OPTIMIZATION OF SOME SELECTED PROCESS FACTORS IN WHEAT PRODUCTION: A RESPONSE SURFACE APPROACH

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ABSTRACT

This study applied the approach of Response Surface Methodology to optimize some selected process factors in wheat production in order to minimize the amount of wheat harvest loss using combine harvester. The factors considered were Grain Moisture Content (GMC), Rotor Speed (RS) and Ground Speed (GS) of the combine harvester. The amount of wheat loss was evaluated in different levels of GMC (10, 15 and 20 %), RS (450, 550 and 650 rpm) and GS (3.5, 4.5 and 5.5 km/h) and the relationship between the specified factors and the amount of wheat harvest loss was established. The study revealed that the 2-factor interaction model with coefficient of multiple determination (R^2) and adjusted coefficient of multiple determination ($\bar{R}^2$) of 79.5% and 76.88% respectively and an insignificant lack of fit (p value of 0.289) best predicts the wheat harvest loss using combine harvester. In the canonical analysis, the Eigenvalues were 10.83, 4.46 and 1.21 which shows that the points 15% for grain moisture content, 650 rpm for rotor speed and 3.5km/h for machine ground speed are points of minimization which give the least wheat harvest loss. The 3-D surface plot for the wheat harvest loss gave a concave up image justifying the points of minimization obtained. The farmer will recover at least 66kg of wheat per hectare if the recommended factor combination is applied.

Keywords: Maize, Irrigation, Poultry manure, Mineral fertilizer; Grain yield

INTRODUCTION

Response Surface Methodology has been used in several areas of science and technology for process optimization (minimization, maximization or prescription). It is a very important tool applied when the values of one or more response variables depends on the levels of two or more input factors and interest is in optimizing the response(s).

Wheat in Nigeria is a very important crop due the wide range of products that can be obtained from it. Some of these products include wheat paste, bread, cakes, confectionaries etc. Despite Nigeria's fertile soil, we still import wheat to service our local industries. This importation has an adverse effect on the nation's economy and the wheat imported into the country are wheat that have been in the foreign farmer's silos for years as such the nutritive value has depreciated, this cannot be compared with the fresh wheat we can produce and consume with its nutrients intact in the country. There is need to increase wheat production to meet the local demand and also have extra for export. This can be achieved basically by encouraging mechanization in wheat production. Harvesting process is one of the most hectic and time-consuming stages in crop production and has thus been advocated by Agriculture Extension Officers to be mechanized using machines like the combine harvester.

The combine harvester is a sophisticated machine capable of cutting and threshing the wheat grain at the same time. The image of the combine harvester is displayed in figure 1 below.

Also, there is need to study loss in food production as (Lundqvist et al., 2008) recorded that as much as 50% of all the crops grown is either lost or wasted before and after it gets to the consumer. Reducing this loss will undoubtedly increase global food supply and farmer's profit. Logically, to eradicate loss in wheat production process is practically impossible but technical approach can be employed to alleviate the pain of farmers by obtaining the levels of the input factors that minimizes the loss using Response Surface Methodology.

Figure 1: Diagram of the combine harvester

In literature, Marvaridi et al., (2008) analyzed the effect of ground speed and cylinder speed on corn combine harvester. Result of the study indicated that the effect of ground speed was significant on header loss and thresher loss while cylinder speed affected thresher loss significantly. The highest total loss suffered as reported in the study was (5%), this was calculated at ground speed and cylinder speed of 2.23km/h and 550rpm respectively. Another study of great importance is the study of King et al., (1995) which revealed through the corn picker field test that snapping roll adjustment and ground speed are the most important factors determining picker losses.

Furthermore, the study of Pishgar-komleh, (2012) applied RSM to optimize harvest loss in corn seed using picker-Husker harvester. The result of the study when the amount of loses in different travel speed levels (3, 4 and 5 km/h) and cylinder speed levels (400, 500 and 600 rpm) was evaluated revealed that the least harvesting loss was 209.88kg/ha. This was obtained at cylinder speed and travel

speed of 600rpm and 3km/h respectively. The study also established that the best model for predicting corn harvest loss using the Picker-Husker harvester is the two-factor interaction model.

Most studies in literature that investigated the effect of cylinder speed and ground speed on mechanized harvest failed to incorporate grain moisture content which is one of the major factors to be considered in studying the amount of grain loss in mechanized harvest. Thus, this study is unique as it involves the effect of cylinder speed, ground speed as well as the grain moisture content on mechanized wheat harvest loss. Studying the relationship between these factors, testing the significance of the factors and establishing an appropriate model for predicting wheat harvest loss will serve as the objectives to achieve the aim of the study which is optimizing wheat harvest loss.

MATERIALS AND METHODS
Response Surface Methodology is the method employed to obtain the optimum settings of the specified factors to minimize wheat harvest loss.

The factors considered in this study are the grain moisture content (%) x_1, the combine harvester rotor speed (rpm) x_2, and the machine ground speed (km/h) x_3 each at three levels. The response variable will be the amount of wheat harvest loss (kg/ha) y.

Before the proper analysis, the actual values of the levels of these factors will be coded as expected to ease computation. This will be done using the equation

$$x_i = \frac{\text{Actual value} - (\text{high level} + \text{low level})/2}{(\text{high level} - \text{low level})/2} \qquad (1)$$

The first-order model
The first-order model given below is the multiple regression model used when the surface is plane.
$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \qquad (2)$$

Where β_0 is the constant term, $\beta_i, i = 1,2,3$ are the model parameters and ε is the error term
The model in (2) can be represented in matrix algebra as

$$Y = X\beta + \varepsilon \qquad (3)$$
Where Y is a nx1 vector of responses, X is a nx3 design matrix, β is a 3x1 vector of parameters and ε is a 3x1 vector of random errors.
Assuming that ε is normally distributed with zero mean and variance $\sigma^2 I_n$, the method of least squares will be used to estimate the model parameters as

$$\hat{\beta} = (X'X)^{-1}X'Y \qquad (4)$$
Provided that the information matrix is invertible. The variance-covariance matrix for the estimated parameters $\hat{\beta}$ is given by

$$\text{Var}(\hat{\beta}) = \sigma^2 (X'X)^{-1} \qquad (5)$$
The estimated first-order response surface model will thus be
$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 \qquad (6)$$

or $\qquad \hat{Y} = X\hat{\beta}$ in matrix algebra.

The fitted model (6) will be subjected to several tests of model adequacy. This will include the following:

The normal probability plot to test if the error term is distributed as $\varepsilon \sim N(0, \sigma^2)$.
The test of significance of regression parameters using Analysis of Variance (ANOVA), where the F-test with the statistic
$$F_0 = \frac{\text{MSR}}{\text{MSE}} = \frac{\text{RSS}/3}{\text{ESS}/(n-3)} \qquad (7)$$
and $\text{RSS} = \hat{\beta}'X'Y - n\bar{Y}^2$, $\text{ESS} = Y'Y - \hat{\beta}'X'Y$ will be used.
The coefficient of multiple determination R^2 and the adjusted coefficient of multiple determination $\bar{R}^2$ given by
$$R^2 = \frac{\hat{\beta}'X'Y - n\bar{Y}^2}{Y'Y - n\bar{Y}^2} = \frac{\text{RSS}}{\text{TSS}} \qquad (8)$$
and

$$\bar{R}^2 = 1 - \frac{(1-R^2)(n-1)}{n-3} \qquad (9)$$
respectively will be used to test how well the estimated model fits the data.
Another important test will be the test of significance of individual regression coefficient using the t-test. This test will decide the inclusion of the input variables into the model. The test statistic will be
$$t_i = \frac{\hat{\beta}_i}{\text{SE}(\hat{\beta}_i)} \text{ for i=1,2,3} \qquad (10)$$
The test of lack of fit will be carried out to know when the estimated first-order model is no longer an appropriate approximation of the true response surface that is when the surface is no longer plane but curved.
If n_d denotes the number of distinct coded treatment combinations z. For each treatment combination for which there is replication, the sample variance S_z^2 of the n_z observations at the treatment combination provides an unbiased estimate of the error variance σ^2. These sample variances can be pooled together to obtain a sum of squares for pure error. That is
$$\text{SSPE} = \sum_z (n_z - 1)S_z^2 \qquad (11)$$
with $n - n_d$ degrees of freedom.
The sum of squares for lack of fit will be obtained from the difference
$$\text{SSLOF} = \text{ESS} - \text{SSPE} \qquad (12)$$
with $n_d - 3$ degrees of freedom
The critical value for the test at α level will be $F_{(n_d-3),(n-n_d),\alpha}$, the F-test is
$$F_0 = \frac{\text{MSLOF}}{\text{MSPE}} = \frac{\text{SSLOF}/(n_d-3)}{\text{SSPE}/(n-n_d)} \qquad (13)$$

Method of Steepest Descent
The method of steepest descent is a procedure for moving sequentially along the path of steepest descent, that is, in the direction of the minimum decrease in the response (Montgomery, 2005).
If the parameters of the estimated first-order model (6) are significant and there is insignificant lack of fit, the model will be used through the path of steepest descent to the vicinity of the optimum as follows:
Given the fitted model (6) $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3$
If $\hat{\beta}_i$ is positive, decrease x_i to decrease the predicted mean response $\hat{y}$, if $\hat{\beta}_i$ is negative, increase x_i to decrease $\hat{y}$. So if the value of x_i is increased by $\vartheta\hat{\beta}_i$ for some real number ϑ, then the level of x_i of the ith factor should be changed by $\vartheta\hat{\beta}_i$ for each other factor.
This exercise is continued until there is a very small or no change in the value of $\hat{y}$ then the process is stopped and another first-order model is estimated and the test for lack of fit it carried out. If

the lack of fit is still insignificant, then the process is repeated until the lack of fit is significant.

Second-Order Response Surface.

When the estimated first-order model exhibits lack of fit, we are in the vicinity of the optimum. This implies that there is curvature in the surface and a more highly structured model like the second-order model need to be fitted to locate the optimum. For a three-factor study, the second-order model is given as

$$y = \beta_0 + \sum_{i=1}^{3} \beta_i x_i + \sum_{i<j} \beta_{ij} x_i x_j + \sum_{i=1}^{3} \beta_{ii} x_i^2 + \varepsilon \quad (14)$$

The model consists the constant term β_0, linear coefficients β_i, the quadratic coefficients β_{ii} and the interaction coefficients β_{ij}.
The method of least squares can be used to estimate the parameters β_{ij} of the model.

Central Composite Design (CCD)

The CCD is a very efficient design for fitting the second-order model. Generally, the design of n_f factorial or cube runs, n_a axial or star runs and n_0 center runs.
The axial runs added is to allow the quadratic terms to be incorporated into the model and the center runs when there are no replications is to aid the estimation of pure error and additional degrees of freedom for lack of fit.
Locating the Stationary Point and Characterizing the Response Surface
The stationary point is the combination of design variables where the surface is at either a maximum or a minimum in all directions. This can be located using matrix algebra.
The fitted model (14) can be represented in matrix algebra as:
$$\hat{y} = \hat{\beta}_0 + x'b + x'Bx \quad (15)$$

where $x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ $\quad b = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \end{bmatrix}$ and

$$B = \begin{bmatrix} \hat{\beta}_{11} & \hat{\beta}_{12}/2 & \hat{\beta}_{13}/2 \\ \hat{\beta}_{21}/2 & \hat{\beta}_{22} & \hat{\beta}_{23}/2 \\ \hat{\beta}_{31}/2 & \hat{\beta}_{32}/2 & \hat{\beta}_{22} \end{bmatrix}$$

The derivative of $\hat{y}$ with respect to the elements of the vector x equated to zero gives

$$\frac{\partial \hat{y}}{\partial x} = b + 2Bx = 0 \quad (16)$$
The stationary point is the solution to (16) or

$$x_s = -\frac{1}{2}B^{-1}b \quad (17)$$
The predicted response at the stationary point will be obtained by substituting (17) into (16), that is

$$\hat{y}_s = \hat{\beta}_0 + \frac{1}{2}x_s'b \quad (18)$$

The contour and surface plots will be useful in determining the optimum value of y in this study.
Another useful equation in this study is the canonical form of (14) obtained by transforming (14) so that the origin is at the stationary point. That is
$$\hat{y} = \hat{y}_s + \sum_{i=1}^{3} \lambda_i w_i^2 \quad (19)$$

Where $\{w\}$ are the transformed independent variables and $\{\lambda\}$ are the eigenvalues of the matrix **B** known as the canonical coefficients obtained from
$$|B - \lambda I| = 0 \quad (20)$$
the design variables $\{x_i\}$ and the canonical variables $\{w\}$ are related by
$$w = M'(x - x_s) \quad (21)$$

Where **M** is a (3 x 3) orthogonal matrix. The columns of **M** are the normalized eigenvectors associated with the $\{\lambda\}$. That is, if m_i is the ith column of **M,** then m_i is the solution to
$$(B - \lambda_i I)m_i = 0 \quad (22)$$

For which $\sum_{j=1}^{3} m_{ij}^2 = 1$.
In the canonical form, one can immediately tell whether the stationary point is a maximum, a minimum or a saddle point.
If all the $\hat{\lambda}_{ii}'^s$ are negative, then the fitted model is concave down and has a maximum at the stationary point. If all the $\hat{\lambda}_{ii}'^s$ are positive, then the fitted model is concave up and has a minimum at the stationary point. If some of the $\hat{\lambda}_{ii}'^s$ are positive and some are negative, then the stationary point is a saddle point.

The methodology that was explicitly explained in the previous slides can be summarized using the flowchart by Dean and Daniel, (1999).
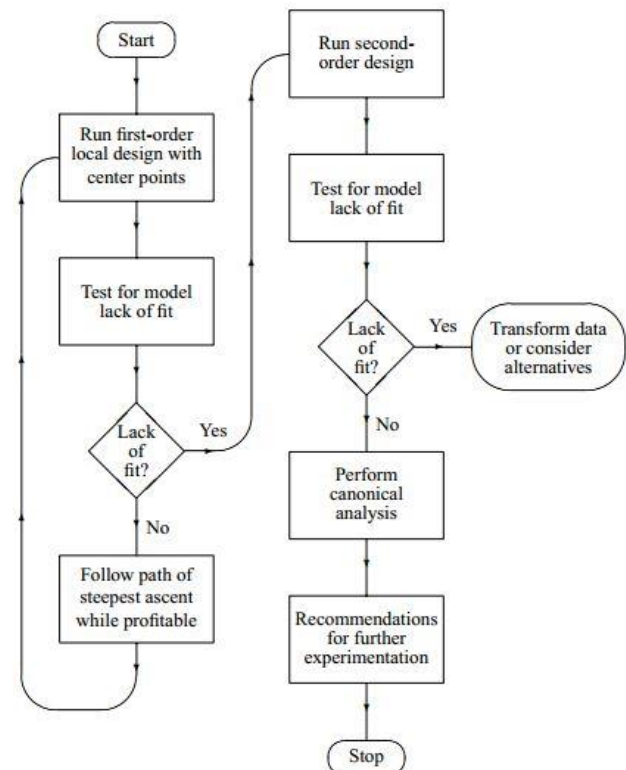

Figure 2. Flowchart Representation of Response Surface Methodology

Data Description

The data for this study were secondary data obtained from an experiment consisting three input factors (grain moisture content,

rotor speed and ground speed of the combine harvester) each at three level and the experiment was replicated twice in a factorial setting, this gave a total of $3^3 * 2 = 54$ runs.

RESULTS AND DISCUSSION

To prepare the data for statistical computation, the three levels of the independent variables (grain moisture content, rotor speed and ground speed) where coded using (1) which produced table 1.

Table 1: Independent Variables Levels

Independent variables (unit)	Levels		
	-1	0	1
Grain moisture content (%)	10	15	20
Rotor speed (rpm)	450	550	650
Ground speed (km/h)	3.5	4.5	5.5

As specified by the flowchart, the results first of order design are represented in tables 2 and 3.

Table 2 shows that the three independent variables significantly contribute to wheat harvest loss at 5% level of significance. Table 3 shows that the first order design has a significant lack of fit, this implies that the surface cannot be represented by the first order model. Thus, there is need to run a second order design

Table 2: Estimated First Order Regression Coefficients for Wheat Harvest Loss

Source of var.	Coefficients	Standard dev.	t-value	P-value
Constant	228.680	2.437	93.853	0.000
X_1	5.919	2.289	2.586	0.020
X_2	15.775	2.289	6.553	0.000
X_3	17.640	2.289	7.640	0.000

Table 3: Lack - of - Fit Test for the First Order Model

Source of var.	DF	Sum of Sq.	Mean Sq.	F-value	P-value
Regression	3	21231	7077.0	22.08	0.000
Linear	3	21231	7077.0	22.08	0.000
Residual Error	50	16029	320.6		
Lack of fit	23	12066	524.6	3.57	0.001
Pure Error	27	3964	146.8		
Total	53	37261			

Table 4 shows the results of the second order design, revealing the terms to be included in the model and table 5 shows the associated lack - of - fit test.

Table 4: Estimated Second Order Regression Coefficients for Wheat Harvest Loss

Terms	Coefficients	Standard deviation	t-value	P-value
Constant	231.346	3.964r	49.890	0.000
X_1	5.919	2.147	2.758	0.008
X_2	15.775	2.147	7.349	0.000
X_3	17.489	2.147	8.147	0.000
X_1^2	-3.931	3.718	-1.057	0.296
X_2^2	2.503	3.718	0.673	0.504
X_3^2	-2.572	3.718	-0692	0.493
$X_1 X_2$	-6.833	2.629	-2.599	0.013
$X_1 X_3$	6.592	2.629	2.507	0.016
$X_2 X_3$	16.108	2.629	6.127	0.000

R^2=80.4% $\overline{R}^2$=76.4%

Table 5: Lack - of - Fit Test for the Second Order Model

Source of var.	DF	Sum of sq.	Mean sq.	F-value	P-value
Regression	9	29962.0	3329.1	20.07	0.000
Linear	3	21231.1	7077.1	42.66	0.000
Square	3	340.0	113.3	0.68	0.567
Interaction	3	8391.0	2797.0	16.86	0.000
Residual Error	44	7298.6	165.9		
Lack of fit	17	3334.9	196.2	1.34	0.244
Pure Error	27	3963.6	146.8		
Total	53	37260.5			

From table 4, the main effects and the 2-factor interaction of all the three factors are significant at 5% level significance but all the square terms are insignificant.

From table 5 the model for predicting the wheat harvest loss in coded units is as follows

$$\hat{y} = 231.35 + 5.92X_1 + 15.78 X_2 + 17.50X_3 - 6.83 X_1X_2 + 6.59 X_1X_3 + 16.11 X_2X_3 \qquad (23)$$

This can be thought of as a 2-factor interaction model with relatively high coefficient of multiple determination and adjusted coefficient of multiple determination.

By decoding the coded variables to the actual values, (23) changed to (24) as

$$WHL = 411 + 7.48GMC - 0.637RS - 67.7GS - 0.01367GMC * RS + 1.318GMC * GS + 0.1611RS * GS \qquad (24)$$

Where WHL is the wheat harvest loss, GMC is the grain moisture content, RS is the rotor speed and GS is the ground speed of the combine harvester.

Since the square terms in second-order model are insignificant at 5% level of significance, it is reasonable to fit a 2-factor interaction model to the data for better prediction of the wheat harvest loss.

Table 6: Estimated 2-Factor Interaction Regression Coefficients for Wheat Harvest Loss

Terms	Coefficients	Standard deviation	t-value	P-value
Constant	228.68	1.73	131.82	0.000
X_1	5.919	2.12	2.79	0.008
X_2	15.775	2.12	7.42	0.000
X_3	17.489	2.12	8.23	0.000
X_1X_2	-6.833	2.60	-2.63	0.01
X_1X_3	6.592	2.60	2.53	0.015
X_2X_3	16.108	2.60	6.19	0.000

R^2=79.50% $\bar{R}^2$=76.88%

From table 6 the required model for predicting the wheat harvest loss in coded units is

$$\hat{y} = 228.68 + 5.92X_1 + 15.78 X_2 + 17.50X_3 - 6.83 X_1X_2 + 6.59 X_1X_3 + 16.11 X_2X_3 \qquad (25)$$

The 2-Factor interaction regression model is thus suitable for the prediction of wheat harvest loss considering three explanatory variables this is in line with the study of Pishgar-Komleh (2012) where two input factors were considered.

Table 7: Lack - of - Fit Test for 2-Factor Interaction Regression Model

Source of var.	DF	Sum of sq.	Mean sq.	F-value	P-value
Regression	6	29622.0	4937.0	30.38	0.000
Linear	3	21231.0	7077.0	43.54	0.000
Interaction	3	8391.0	2797.0	17.21	0.000
Residual Error	47	7639.0	162.5		
Lack of fit	20	3675.0	183.7	1.25	0.289
Pure Error	27	3964.0	146.8		
Total	53	37261.0			

Table 7 shows that the 2-Factor interaction regression model has an insignificant lack-of-fit. By decoding the coded variables to the actual values, (25) changed to (26) as

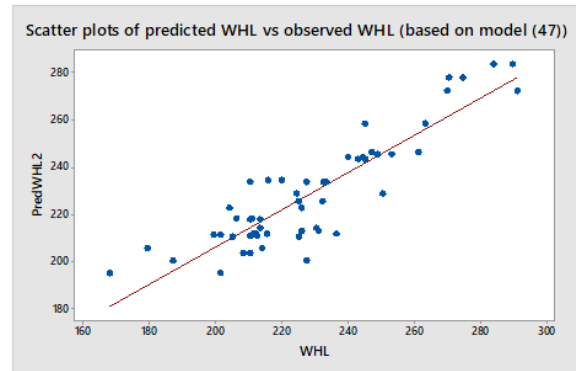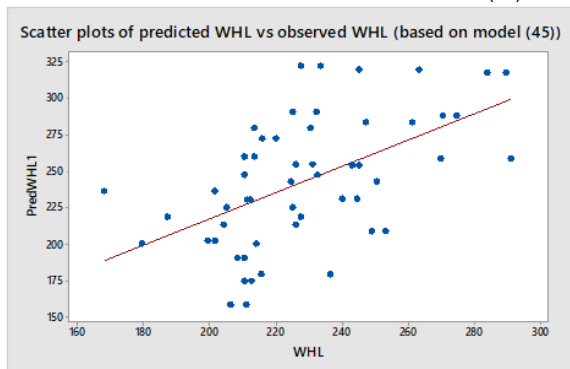$$WHL = 420.4 + 2.77GMC - 0.362RS - 90.9GS - 0.01367GMC * RS + 1.318GMC * GS + 0.1611RS * GS \qquad (26)$$

Figure 3: Linear Correlation between Predicted and Actual Values

As it can be seen in figure 3, the actual values were distributed relatively close to the predicted values for the model in (26) than for the model in (24). Thus, the model in (26) can predict the wheat harvest loss better.

Canonical Analysis
Having obtained the required model for predicting wheat harvest loss using combine harvester, there is need to locate the stationary point using (17), obtain the predicted response at the stationary point and characterize the stationary point as either minimum, maximum or saddle point using (20).

Table 8: Stationary Points for the Response Surface in Coded Units

X_1	X_2	X_3
0.3050835	0.5813979	-1.3240082

Table 9: Stationary Point of the Response Surface in Natural Units

GMC	RS	GS
16.5254175	608.13979	3.1759918

Eigen Analysis

Table 10: $values

10.829033	4.464382	1.214918

Table 11: Vectors

	[, 1]	[, 2]	[, 3]
X_1	0.6337895	0.3512793	0.68913988
X_2	-0.5381984	-0.4396370	0.71907007
X_3	-0.5555658	0.8266330	0.08957932

From table 10, it can be deduced that the Eigenvalues are all with positive signs, this implies that the stationary point represents a point of minimum response as required.
At this point of the study there is need to represent the response surface pictorially as earlier stated. This will be done using the surface plot and contour plots.

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Table 9 shows that stationary points in natural units are fairly close to the experimental points 15%, 650rpm and 3.5km/h which represents the intermediate, high and the low levels for the grain moisture content (GMC), rotor speed (RS) and the ground speed (GS) respectively.
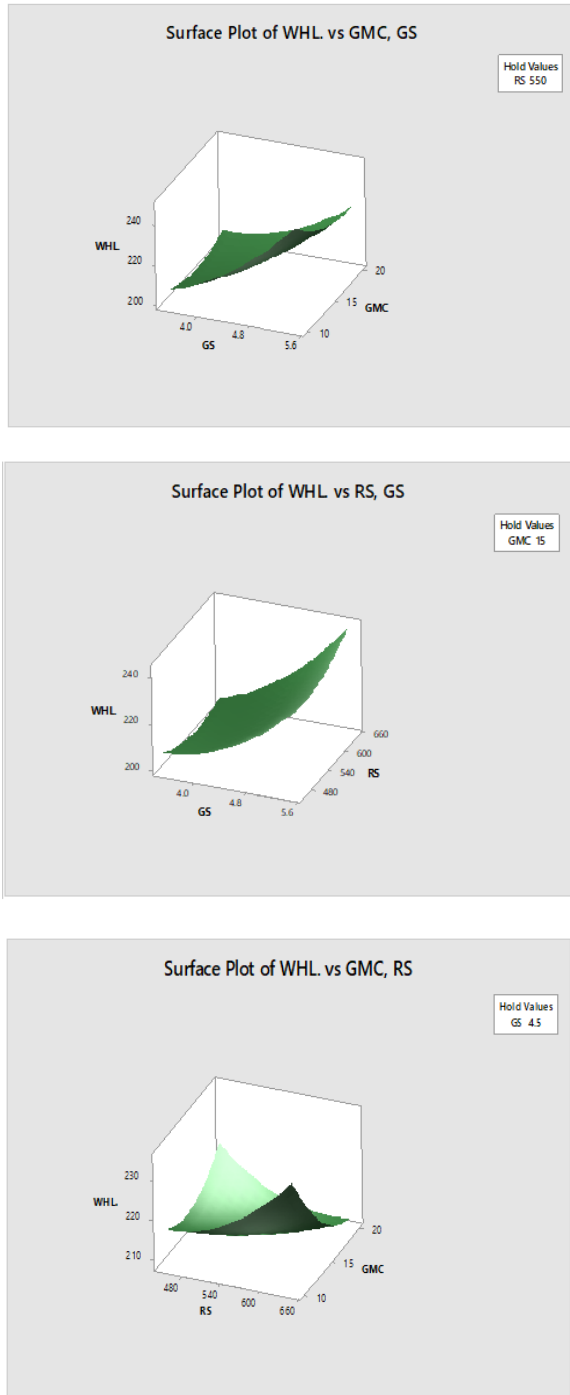
Displaying Response Surface

Figure 4: 3-D Surface Plot for Wheat Harvest Loss
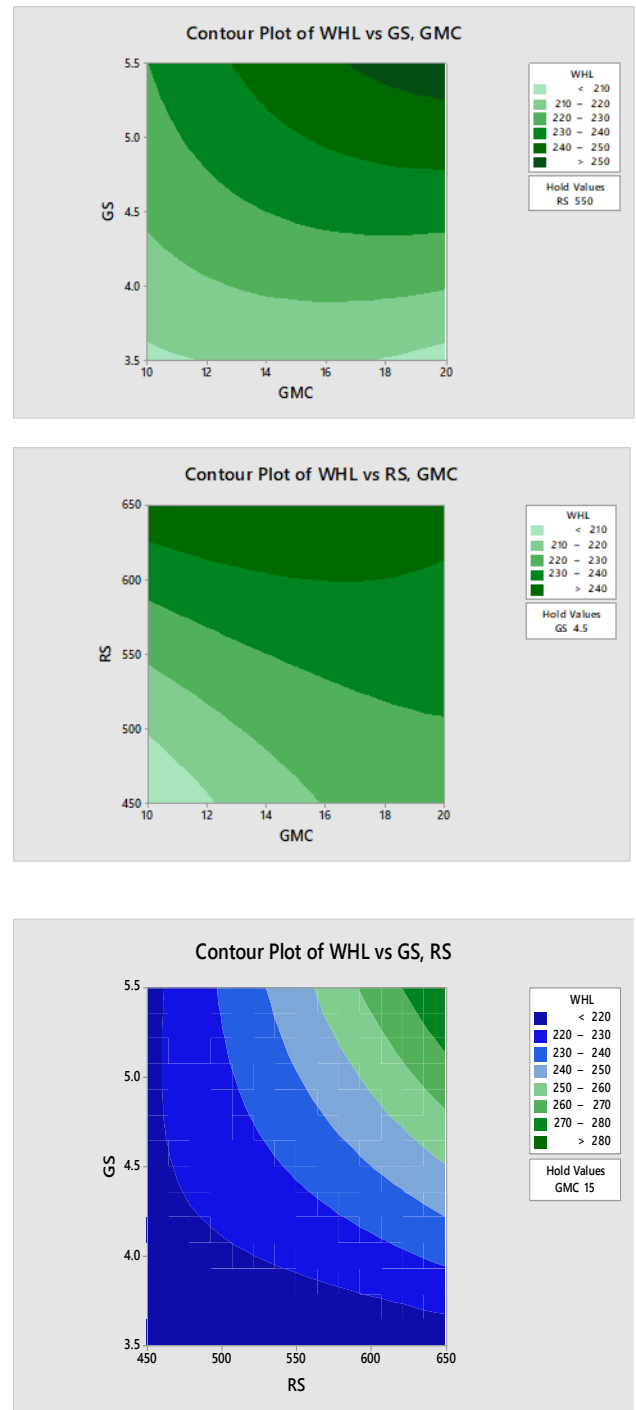

Figure 5: Contour Plot for Wheat Harvest Loss

The contour plots in fig. 5 shows the line connects the pairs of the independent variables and the corresponding wheat harvest loss
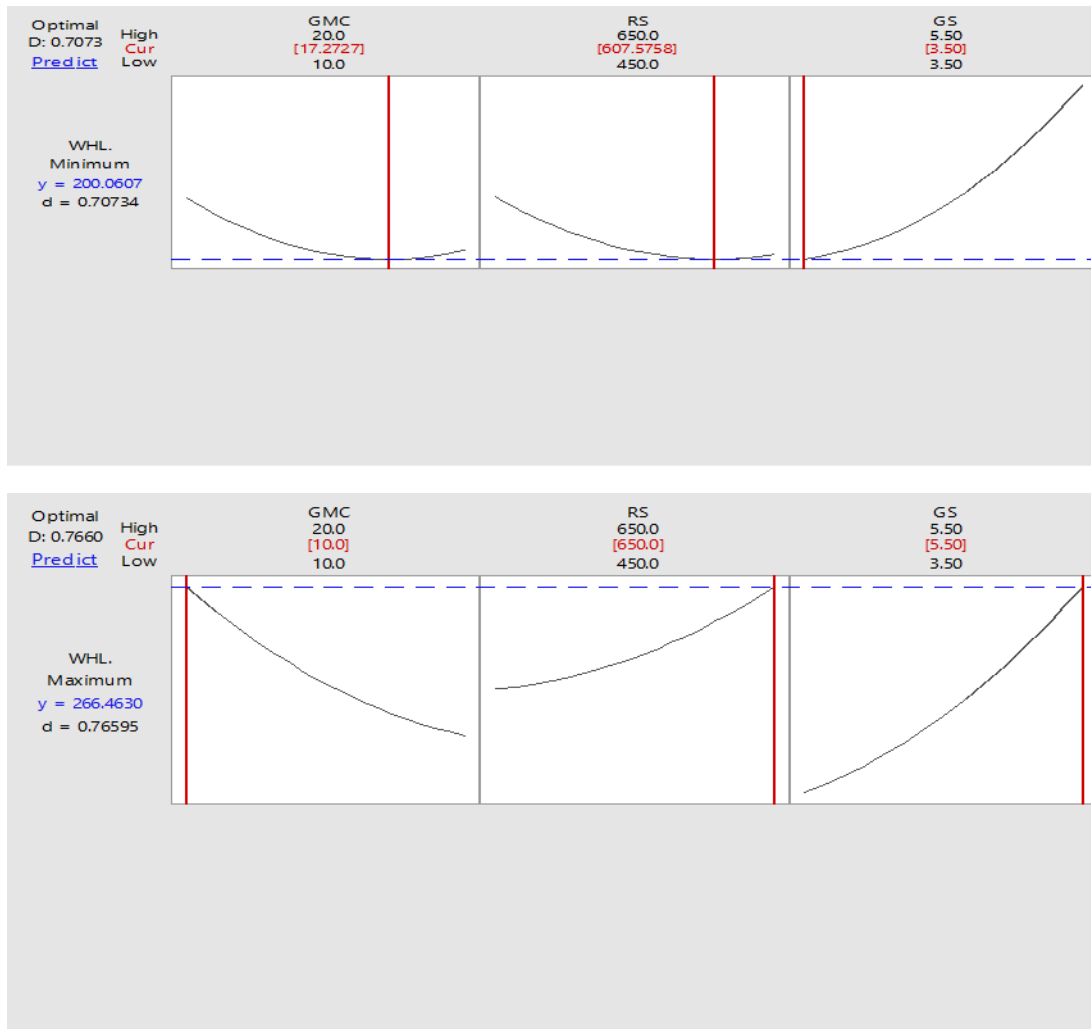
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Figure 6: Optimization Plot for Wheat Harvest Loss

The optimization plots above provided further justification the experimental point that optimizes (minimizes and maximizes) the wheat harvest loss. From the first optimization plot, the point that minimizes the wheat harvest loss is close to the experimental point 15%, 650rpm and 3.5km/h for the grain moisture content, rotor speed and the ground speed respectively. This is closely related with the result obtained by Marvaridi et. al., (2008). The plot revealed that the estimated minimum wheat harvest loss at this point is 200kg/h.

Also, the second optimization plot revealed that the experimental point that maximizes the wheat harvest loss is 10%, 650rpm and 5.5km/h for the grain moisture content, rotor speed and the ground speed respectively. Pishgar-Komleh (2012) in his study revealed that farmers can lose up to 209.88kg|ha of corn with wrong adjustment of the input factors and the plot in this study also revealed that the estimated maximum wheat harvest loss at this point is 266kg/h.

With this, any farmer that adheres to this setting stands to recover 66kg/h wheat.

Conclusion
The Response Surface Methodology (RSM) has proven its ability to model situations in which a response variable depends on two or more explanatory variables and interest is in obtaining the best setting of the explanatory variables that optimizes the response. In this study, RSM has established that the relationship between wheat harvest loss (dependent variable) and grain moisture content, rotor speed and machine ground speed (independent variables) can be approximated using the 2-factor interaction model. Also, through hypothesis testing, it has been confirmed that the three factors considered in this study (grain moisture content, rotor speed and machine ground speed) significantly contribute to wheat harvest loss. Ultimately, RSM has also established that harvesting the wheat grain at the moisture level of 15 % and operating the combine harvester at 650 rpm rotor speed and 3.5 km/h ground speed will produce the least wheat harvest loss and the maximum wheat loss will be obtained when the process is operated at 10 % moisture content, 650 rpm rotor speed and 5.5 km/h ground speed. This setting saves the farmers from losing 66kg/h wheat grain or more

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APPENDIX

Table 12: Observed responses for mechanized wheat harvest loss.

s/n	GMC	RS	GS	WHL	s/n	GMC	RS	GS	WHL
1	10	450	3.5	179.5	28	10	450	3.5	214.2
2	10	450	4.5	187.4	29	10	450	4.5	227.6
3	10	450	5.5	168.4	30	10	450	5.5	201.8
4	10	550	3.5	236.7	31	10	550	3.5	215.6
5	10	550	4.5	204.3	32	10	550	4.5	226.2
6	10	550	5.5	210.6	33	10	550	5.5	232.7
7	10	650	3.5	211.1	34	10	650	3.5	206.5
8	10	650	4.5	253.2	35	10	650	4.5	249.2
9	10	650	5.5	291	36	10	650	5.5	270.1
10	15	450	3.5	211.6	37	15	450	3.5	212.4
11	15	450	4.5	226	38	15	450	4.5	231.3
12	15	450	5.5	230.6	39	15	450	5.5	213.5
13	15	550	3.5	199.7	40	15	550	3.5	201.6
14	15	550	4.5	224.6	41	15	550	4.5	250.5
15	15	550	5.5	247.4	42	15	550	5.5	261.3
16	15	650	3.5	212.7	43	15	650	3.5	210.5
17	15	650	4.5	244.5	44	15	650	4.5	240.1
18	15	650	5.5	274.6	45	15	650	5.5	270.5
19	20	450	3.5	213.7	46	20	450	3.5	210.6
20	20	450	4.5	232.4	47	20	450	4.5	225.3
21	20	450	5.5	233.5	48	20	450	5.5	227.5
22	20	550	3.5	205.4	49	20	550	3.5	225.1
23	20	550	4.5	215.9	50	20	550	4.5	220.1
24	20	550	5.5	263.4	51	20	550	5.5	245.1
25	20	650	3.5	208.5	52	20	650	3.5	210.6
26	20	650	4.5	245.3	53	20	650	4.5	243.2
27	20	650	5.5	284.1	54	20	650	5.5	289.5