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Application of Response Surface Methodology for Determining Optimal Factors in Maximization of Maize Grain Yield and Total Microbial Count in Long Term Agricultural Experiment, Kenya

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Abstract: The Agriculture sector is the main stay of the Kenyan economic development contributing over 70% of the Gross Domestic Product (GDP). The sector is faced with numerous challenges leading to frequent and recurrent food shortages. Declining maize grain yield is one among the major challenges that call for urgent interventions to address the looming food crisis in the country. Maize play a big role in the Kenyan food security and in most case lack of the same is taken to mean food insecurity. It is due the importance attached to the crop that a Long Term Agricultural Experiments (LTAE) was set up specifically to research on the Maize grain yield. Many paper published on the LTAE in the country are only single factors analysis and lack the application of Response Surface Methodology (RSM) approaches in solving challenges facing the low and declining maize grain yield (y_1), total microbe population (y_2) a crucial component of Soil Organic Matter (SOM) and their optimization. The focus of this paper therefore is the application of RSM in maize grain yield and total microbial population optimization. Specifically, the paper determined the most significant factors for maize grain yield and total microbial population (bacteria, fungi, actinomycetes, rhizobia), (screening phase of the paper), constructed of an efficient and appropriate experimental design for evaluating the optimal settings of maize yield and total microbial population count and determined univariate optimal settings for maize grain yield and total microbial population. The primary data was summarized from LTAE in National Agricultural Research Laboratories (NARL) in Kabete under the Kenya Agriculture and Livestock Research Organization (KALRO) and secondary data imputed for experimental points falling outside the set field experimental design points. Two treatment factors were identified as the most significant treatment factors (Farm Yard Manure (FYM) and Nitrogen and Phosphorus (NP)) at their low levels and Circumscribed Central Composite Design (CCCD) with two star points as the most efficient design. CCCD passed most optimal criteria of DAET. Univariately, optimal setting for maize grain yield was realized at $3.8\text{x}10^3$ kg/ha and that of the total microbial population at $3.6\text{x}10^6$ count. The study confirmed that it was possible to optimize the input treatment factor that lead to the optimization of both maize grain yield and maintaining maximal total microbial population count at its optimal levels.

Keywords: Response Surface Methodology, Long Term Agricultural Experiments, Univariate Optimization, Circumscribed Central Composite Design

1. Introduction

Agricultural experiments are key undertaking in the development of most countries. Over the years the growth of scientific agricultural experiments has transformed the agricultural sector, [17]. In agricultural practices, experimentation occupies a crucial undertaking in the improvement of farming practices, [24]. The development of various forms of scientific experiments on crop improvement has led to considerable advancement in finding the optimal agricultural conditions for crop production and the same applies to maize production. Seeking the optimal input and output setting for maize grain yield and total microbial population count is a critical experimental undertaking that solves the food insecurity and hence the decreasing incomes to small scale farmers. Such experimental agenda, give experimenter adequate range of treatment factors (fertilizer, seed among others) to balance for optimum response (yield) in both maize grain yield and total microbes. This has also been motivated by the need to produce more food to feed the increasing world population and also to strike a balance between producing more food and the food safety concept, [8]. Agriculture sector is key in Kenyan Economy, [13].

Long Term Agricultural Experiments (LTAE) is experiments developed to run for a long time and are mainly used to monitor faming systems and soil fertility loss over time.

1.1. Why Response Surface Methodology (RSM)

The increased demand for robust experimental designs across various scientific disciplines has resulted to RSM receiving considerable attention. RSM is concerned with the modeling of one or more response variables using several explanatory variables. RSM is an important concept in the design of experiments as it has continued to provide solution in many fields including agriculture. The initial concept on RSM was introduced by Box and Wilson in 1951, [1]. The number of experimental problems that can be solved using RSM has tremendously increased overtime.

1.2. RSM in Agricultural Experiments

Agricultural field experimentation has evolved over time employing different experimental concepts in solving the challenging aspects. Documented available studies in LTAE have studied single treatment factor at a time which could be misleading in the long run, [23]. The properties of RSM offer a feasible near solution to such due to its robustness and approach. This paper utilizes the RSM advancements made in industrial experiments and in the process optimization to solve challenges in agricultural experimentation and more specifically in LTAE in seeking feasible solutions in soil fertility management options for the small-scale farmers in Kenya who depend on maize crop for their livelihood.

1.3. Optimization Process

In statistics, optimization is the process of making a design as functional and effective as possible. The search for optimal settings in crop (especially in maize grain yield) production naturally presents the need for more than one treatment factor to be optimized (minimized/maximized). Agricultural experiments like any other multi-objective (more than one optimization goal) optimal seeking experiments and systems is expected to balance several production factors (inputs) for benefits (outputs) to ensure that food safety for the future generation is assured and save, [8].

1.4. Challenges Facing Maize Production in Kenya

The main challenge associated with the declining maize grain yields and total microbial population count (measured using Soil Organic Matter (SOM)) has been linked to the declining soil fertility. Soil degradation is a widespread problem. Resource poor, subsistence farming and low-inputs agricultural practices are among the major factors that push further the soil degradation, [5]. These have led to; low productivity, low income, rural-urban migration, household and national food insecurity, [7].

1.5. The Problem

Continuous crop production in the various agricultural LTAE including maize experiments trials has pointed out the decline in essential soil nutrients either through erosion and/or through nutrient loss by crop uptake being the main cause. These has resulted to progressive low maize grain yields, low levels of the optimal total microbial population count and high production costs for sustained production of the crop. LTAE in National Agriculture Research Laboratory (NARL) on soil fertility maintenance concluded that a set of critical treatment factors existed below which it became extremely difficult to maintain maize and beans yields, [10]. To address these changes therefore, different scientific, agronomic and statistical modeling are of paramount value for responding to this noble recommendations to avert food and nutrition insecurity in the country.

1.6. Scope

The paper considered two response variables, maize grain yield (y_1) and the total microbial population count (y_2). The paper presents an analysis of LTAE in KALRO and used sample years (based on data availability and data normalcy) data for building optimal models for maize yield and total population count. Maize grain yield (y_1) was measured and reported in kg/ha. The total microbial population (y_2) was used as an indicator and measure of soil fertility extracted as sum of the total common microbes that included bacteria, fungi, actinomycetes and rhizobia. Optimalities for both treatment factors and response variables y_1 and y_2 were determined.

1.7. A Review of Soil Fertility Studies

Soil fertility management agricultural experiments have been undertaken by both the developed and the developing counties with the aim of understanding the effects of soil fertility on crop yields. In East Africa such initiatives started back in 1930's to address issues of soil fertility through the combination of vegetative fallows and animal manure [34] (Kibunja, 2007). Most of the studies point out to a one dimensional soil fertility maintainance and less use of robust statistical analysis and RSM approaches.

1.8. Screening Experiments

Screening designs are normally performed at the beginning of an investigation when the experimenter intends to characterize a process. In this case, characterizing translated to determining the main treatment factors and investigating the changes of the response by varying each factor [51] (Montgomery, 2009). This identification of the critical process treatment factors can be very useful for later optimization processes because only a subset of the treatment factors have to be considered. Factor screening also play a big role in large experiments with many treatment factors to optimize or consider.

An experiment can have a large number of factors but usually only a handful of the factors are important and significant. A screening experiment employs a design of economical run size to identify the most important treatment factors [13] (Cheng & Wu, 2001). Such experiments are of 1^{st}-order design fractional factorial designs or Plackett-Burman designs with intensive study of the response surface, typically with fewer factors and over a smaller region. 2^{n-k} designs are most commonly used for screening stage [24] (George, Hunter, & Hunter, 2005).

Another useful approach in the identification of key factors is the use of Pareto plots that graphically represents the most important treatment factors in their absolute terms. The plots are weights of the different factors in descending order with less important factors forming the tail of the plot (lower weights). In such plots care is called for as for qualifying a factor that has a significant interaction(s) as in no case that a factors' main effect is rejected and its interaction is qualified.

The goal at this stage (screening) is to find the real important inputs (factors) among the many inputs/output factors that may be changed in a real experiment. Real-world processes are driven by only a few factors, the others being relatively unimportant. With screening designs, responses are taken only for a small fraction of the total possible combinations to reduce the number of runs and hence cost [71] (Wass, 2010).

Specialized designs require screening when a number of factors are too large for even a highly fractionated design [31] (Kelton, 1999). Various screening analyses can be utilized with the most conventional method based on main effects estimation or the Analysis of Variance (ANOVA). A factor is identified as important if its main effects are significant, [2].

1.9. Constructing Robust and Efficient Experiments Designs

Robust Designs of Experiments (DoE) have been constructed to guide the development of various modern experiments. These designs have an extensive statistical element incorporated making them extensively reliable compared to the earlier methods. With the enhanced procedures, DoE have attracted many diverse applications in research work. Most of the initial DoE involved varying of one factor only at a time which presented considerable challenges. Orthogonality property in DoE was later introduced by Taguchi in early 1950's, [26]. However, it was until 1950 that a break through study was carried out by Cox and Cochran that have since been the corner stone for DoE development and advancement, [3]. Despite the above earlier studies that optimized single factors independently, the current paper has extended the concept and optimized two factors simultaneously.

1.10. Response Surface Methodology (RSM)

RSM is a collection of statistical and mathematical techniques that are useful for developing, improving and optimizing experimental and industrial processes. RSM has the ability to produce an approximate function even with a smaller amount of data, [25]. The approach is also easy to use and apply even with minimal knowledge of the underlying process.

In real-world RSM application problems, it is quite common that several responses are of interest, [16]. In RSM setting, the experimenter attempts to find the optimal setting for the input variables that maximizes (or minimizes) the response, [21].

RSM methodology was introduced by Box and Wilson in 1951, [1] by suggesting the adoption and use of the 1^{st}-degree polynomial in the estimation of response variable. For typical RSM, [21], data from experimental design is used to build a model for approximating the relationship between the outputs (y_i) and inputs (x_i) variables, upon which the optimization is undertaken, [19]. In most cases the univariate optimization has been used in which case only one response variable is optimized.

1.11. Response Surface Methodology in Agricultural Experiments

Mead and Pike in 1975, [18] study was the first to review the role of RSM in agriculture, however, the study ended up recommending the use of non-linear model to address and accommodate biological data. More insights of RSM in agriculture were presented by Edmondson in 1991, [4], in the study that gave crucial findings of RSM in greenhouse experiments, [17]. The study further, presented valuable knowledge on the use of RSM within the agricultural research and experiments as opposed to an industrial setting.

2. Method

2.1. Screening Experiment

This formed an initial step that involved analysis of all the six (6) treatment factors (Control, R, FYM1, FYM2, N_1P_1 and N_2P_2) that were distributed into 4 blocks (Block I, II, III and IV) *(Annex I)*. This enabled screening of the most important treatment factors to form inputs for a robust experimental stage and experimentation purpose.

The screening phase analysis was based on 1st - order regression model *(equation 1)* followed by a more intensive study of the response surface with a fewer treatment factors and over a smaller region based on 2nd -order design (for testing the only significant interaction factors).

$$y = \beta_0 + \beta_1 FYM + \beta_2 NP + \beta_{12} FYM * NP + \varepsilon \quad (1)$$

2.2. Design of Experiments (DoE) for the Study

DoE was used to find out the cause-and-effect relationship between input (FYM and the mineral fertilizers) and output (maize grain yield and total microbial population).

Several treatment factors that affected simultaneously the maize grain yield and total microbial population were given more weight especially the main effects (isolated factor) and the interaction effects. The simplest design tested was represented by a 2^2 factorial designs. Two levels of each treatment factor was denoted as "low" and "high" symbolic presented as "-" at low level and as "+" at high level. For 2^2 yielded 4 runs for full factorial at their main effect was represented in *Figure 1*.

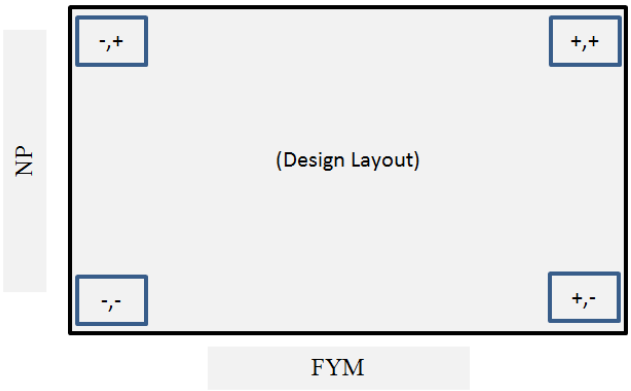

Figure 1. *A 2^2 Factorial Design Layout.*

The general model for full factorial that represented Figure 1 was presented as (2) and a general model (3).

$$y = \beta_0 + \beta_1 FYM + \beta_2 NP + \beta_{12} FYM * NP + \varepsilon \quad (2)$$

and

$$y = \beta_0 + \beta_1 FYM + \beta_2 NP + \beta_{11} FYM^2 + \beta_{22} NP^2 + \beta_{12} FYM * NP + \varepsilon \quad (3)$$

To improve on the above design and arrive at a precise result the study applied a Central Composite Design (CCD) with an embedded factorial design with centre point and an augmented "star points" for curvatures estimation.

Choosing a suitable experimental design was an important step in investigating factors that influenced the response variables (maize grain yield (y_1) and total microbial population (y_2)). The paper used optimal criteria to evaluate the three CCD designs (2^2 - factorial, CCD and the CCCD) and the design with a combination of best optimal criteria was chosen. D-, A-, E-, T-Optimalities (DAET) was applied in this step.

2.3. Optimal Settings for Maize Grain Yield and Total Microbial Population Count

Optimization was achieved by undertaking the following steps:-

1. Screening that involved the determination of factors that influence the outcome variables;
2. Improvement of the process that involved approaches in search of optimum by repeated change of input factor(s) settings and
3. Determining the optimum of the input factors and the optimal settings of response factors (maize yield and total microbial population) settings.

The surface is represented by the response surface equation,

$$\eta = f(x_1, x_2) \quad (4)$$

In the search of optimal region, the following steps were undertaken;

Step I: Finding a suitable approximation for y=f(x) using Least Square Method (LSM) in a low-order polynomial;

Step II: Moving towards the region of optimum (climbing/descending the hill) and

Step III: When curvature was found, locating a new approximation for y=f(x) (generally a higher order polynomial);

Step IV: Performing the response surface analysis proper and

Step V: Optimization of the process for y_1 and y_2.

For screening and for steepest ascent, the 1st-order model was used for each of the response variables (y_1 and y_2) independently. Equation (5) represents maize while (6) represents total microbes;

$$y_1 = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \quad (5)$$

and

$$y_2 = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \quad (6)$$

The 2nd – order was further estimated using the equation (7).

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum \sum_{i<j}^{k} \beta_{ij} x_i x_j + \varepsilon \quad (7)$$

2.4. Optimization in Case of Single (Y_1 and Y_2) Response Experiment

This was achieved using the following methods;

1. Graphically (through contours in case of 2 factors) and
2. Analytically (for validating the method 1).

3. Results

3.1. Significant Treatment Factors for the Maize Grain Yield (Y_1)

From the regression analysis three factors levels significantly explained the maize grain yield N_1P_1+FYM_1 (x_1), NIL and NIL+R and FYM_1 (in the intercept) all with p-value<0.001, R^2=96.4% and adjusted R^2 = 94.6%. However, treatments with NIL (controls) had a negative (-ve) influence on the maize grain yield *(Annex II)*. The treatments were also significant (p-value<0.001) while that of blocks were not statistically significant. The intercepts was large enough to be ignored and therefore it was retained for modeling the maize grain yield. The blocks effects were not significant which was due to their insignificance from the initial descriptive plots. This was an encouraging result as blocks were only intended for local control and further random error. The largest positive effects on the maize grain yields were realized with N_1P_1+FYM_1, N_1P_1+FYM_1+R and FYM_1+R treatments while the greatest negative effects were from NIL, NIL+R treatments. This is a clear indication that the combination of chemical fertilizers and the FYM had better yields for maize.

Further, the study evaluated the model adequacies which were met.

3.2. Significant Factors for Total Microbial Population Count (y_2)

The 1st-order model for the total microbial population count did not reflect significant (p>0.05). This led to the undertaking of a full model, normally proposed in such cases to get the significance in higher levels models *(Annex III)*.

Only interaction between, NIL: Block-II and FYM_1: R: Block-II turned significant in the full model. This indicated that their main factors need to be considered in the optimization stage as primary treatment factors. This implies that NIL (control) and FYM_1+R were important. R-square improved from 24% to 69% from the reduced model to the full model (2nd – order).

3.3. Efficient and Appropriate Experimental Design for Optimal Setting for Maize Yield and Total Microbial Population

Efficient design for the two responses variables (maize and total microbes) that lead to the optimal region step by step is proposed.

The baseline (centre point - (0, 0)) was taken as the usual farmers practice (status quo) FYM_1 and N_1P_1 and also the same factors that were statistically significant in the prediction of the two response factors. To represent the same mathematically, the study used coded values to link the two (coded and natural values). The responses were computed from the average of the different levels of the factor treatments. To measure the model disturbances, crop residues were added in the design as they were likely to affect the maize yields and the subsequent treatment levels. The estimated responses were arrived at by averaging yields and microbial population count from the different factor levels using statistical intra and extra-polation procedures. The computed values were later compared with the model estimated values to assess model fit and to map the next design points.

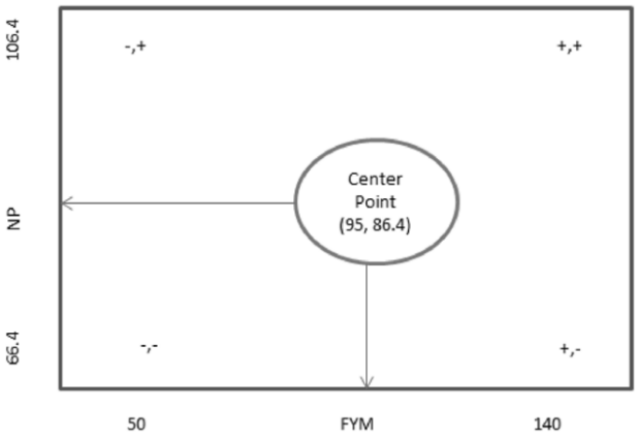

Figure 2. *Design 1 Indicating the Link between Coded and Natural Values.*

Using figure 1, the design points and model in *Table 1* and *2* were generated.

Table 1. *Design I Layout for the Treatment Factors and the Corresponding to the Imputed Values for Responses.*

Experiment	FYM	NP	fym	np	maize yield	Total Microbes	Model
Current Point	95	86.4	0	0	3,259.0	3,252,158.5	1
1	50	66.4	-1	-1	3,239.0	3,095,105.0	1
2	50	106.4	-1	1	3,264.0	3,023,695.0	1
3	140	66.4	1	-1	3,275.0	3,480,621.0	1
4	140	106.4	1	-1	3,300.0	3,409,212.0	1

Table 2. *Design 1 Model for Maize Yield (y_1).*

Parameter	Estimate	se	t-value	p-Value
Intercept	3269.5	0	5.5	<0.001
fym	18	0	2.7	<0.001
np	12.5	0	1.91	0.001
fyp:np	0	0	0.02	0.988

With the corresponding model given by;

$$\hat{y}_1 = 3.3x10^3 + 18\,fym + 12.5np + 0\,fym:np \qquad (8)$$

For the total microbial population count the model became

$$\hat{y}_2 = 3.3x10^6 + 1.9x10^5\,fym - 3.6x10^3\,np + 0.25\,fym:np \qquad (9)$$

Giving;

Table 3. *Design 1 Contour Plots for Total Microbial Population.*

Parameter	Estimate	se	t-value	p-Value
Intercept	3252158	0.17	18776345	<0.001
fym	192758.3	0.19	995399.3	<0.001
np	-35704.8	0.19	-184379	<0.001
fyp:np	0.25	0.11	2.24	0.2677

The interaction between fym and np (fym:np) was very small relative to the main effects coefficients (large values) and it is also not significant; dropping this, the new model for microbial population as;

$$\hat{y}_2 = 3.3x10^6 + 1.9x10^5\,fym - 3.6x10^3\,np \qquad (10)$$

For the steepest ascent, the two equations, indicates that moving from low levels of FYM_1 to higher levels of FYM_1 (in coded values), the maize yield increases by 18 kg/ha and moving from low level for N_1P_1 to the higher levels N_1P_1+R the maize yield increases by 12.5kg/Ha. Similarly, moving from low levels of FYM_1 to higher levels of FYM_1, the microbial population increases by $1.9x10^5$ and moving from low level for N_1P_1 to the higher levels of N_1P_1 the microbial population count decreases by $3.6x10^4$.

This was expected from the descriptive analysis that portrayed that the addition of artificial fertilizers had decreasing effects on the microbial population count. This also indicated that maize grain yields registered improved performances when the both treatments are at their high factor levels. This assertion is further portrayed in the contour plots for the two response variables

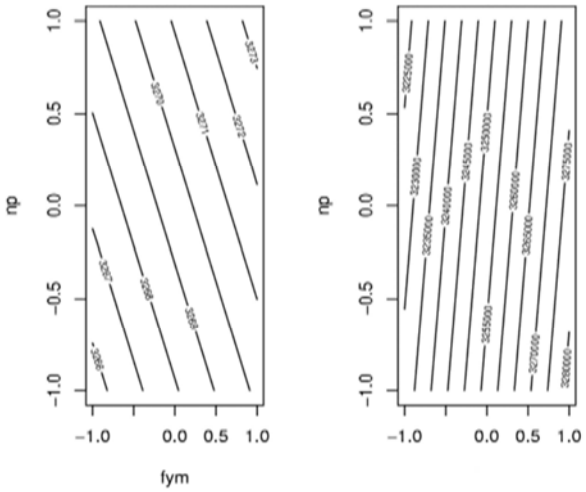

Figure 3. *Design 1 Contour Plots for Maize Yield and Total Microbial Population.*

The 3 designs criteria proposed section 3, when applied gave D-, E- and A- optimality values as in *Table 4*. With these results the study concluded that a Circumscribed Central Composite Design (CCCD) design was the most appropriate. Using the CCCD as the efficient design for the maize grain yield and total microbial population count with two star points the response factors are generated

Table 4. *D. A. E. T for the 3 Designs.*

Optimality	Factorial	FCD	CCCD	Criterion
D	80	182.25	442.4	Larger the better
A	0.7	0.71	0.4	smaller the better
E	0.25	0.22	0.17	smaller the better
T	7.5	9.5	7.7	smaller the better

3.4. Estimating the Response (Outcome) Variables from the Best Design

Having established the appropriate best design for the experiment, the results reported from the main experiment were used to estimate the maize grain yield and total microbial population count using both extra and intra-polation approaches at various treatment factor levels outside the LTEA formulation. This was deemed necessary as efficient design called for extra design points not within the LTEA. For instance, at center point (0, 0) the maize yields and total microbial population were calculated using simple average. For other design points, we used the extrapolation and simulation formula model that gave.

Table 5. *Estimation of Response Values outside the normal LTAE design points.*

Experimental Point	Maize Yield (y_1)	Microbial Population (y_2)
0,0	(3202+3226)/2	(4126373+2063837)/2
-1,-1	$Extrapolation_1$	$Extrapolation_2$
-1+1	$Extrapolation_3$	$Extrapolation_4$
+1,+1	$Extrapolation_5$	$Extrapolation_6$
0,+1.41	$Extrapolation_7$	$Extrapolation_8$
-1.41,0	$Extrapolation_9$	$Extrapolation_{10}$
+1.41,1	$Extrapolation_{11}$	$Extrapolation_{12}$
0,-1.41	$Extrapolation_{13}$	$Extrapolation_{14}$

The extrapolation formulas were used in estimating the response values outside the experiment and the resulting output. The resultant data was used in the next testing determining the optimal inputs that gave the optimal outputs value. The extrapolation values of the response values were determined using equation (11).

$$y_1 + \frac{x - x_2}{x_2 - x_1}(y_2 - y_1) \qquad (11)$$

3.5. Determining the Optimal Settings for Maize Grain Yield and Total Microbial Population Count

The optimization for this section was derived for maize yield and total microbial population count response variable independently using results from the Table 6.

Table 6. *Estimated Data for CCCD with star points.*

partten	fym	np	yield	microbial
+-	1	1	3264	3095105
-+	-1	1	2160.11	2433104
00	0	0	3264	3095105
--	-1	-1	2113.17	2003824
A0	1.41	0	4211.79	3470620
00	0	0	3264	3095105
++	1	1	4414.83	3689516
0A	0	1.41	4744.46	4148661
0a	0	1.41	3018.81	2352240
a0	-1.41	0	2269.23	2204914

The real values are for farm yard =120.65kg/ha equivalent to 13.3 tons/ha of fym. This should contain an estimated 64.34kg N and 32.17 kg P at the optimal region. For np the real values are 11.6 kg/ha equivalent to almost 1.5 bags/ha. The optimal values for fym and np are 120.65kg/ha and 11.6 kg/ha that yields to the maximal yield of 3.80×10^3. This gave the contour and response surface plots in *Figures 4-8.*

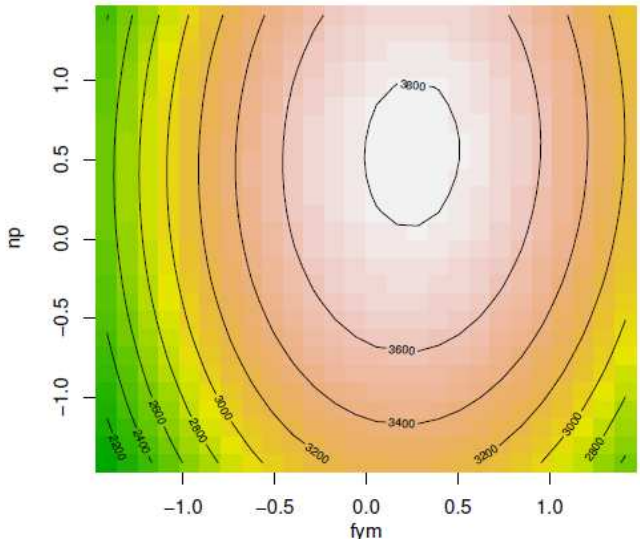

Figure 4. *Contours at the Optimal Region for Maize Yield (y_1).*

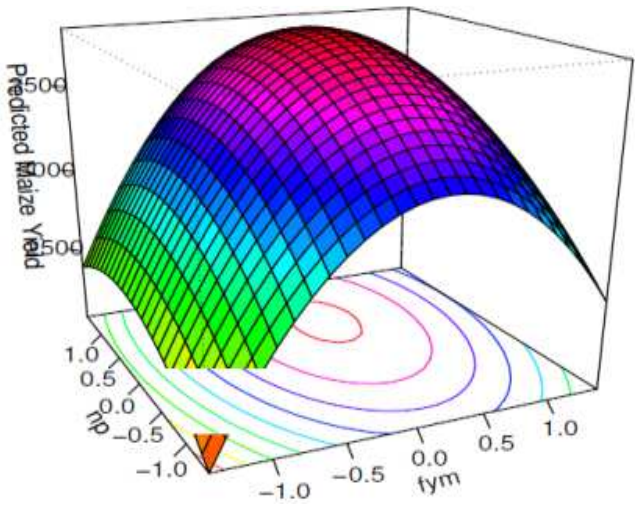

Figure 5. *Response Surface Plot for Maize Yield (y_1).*

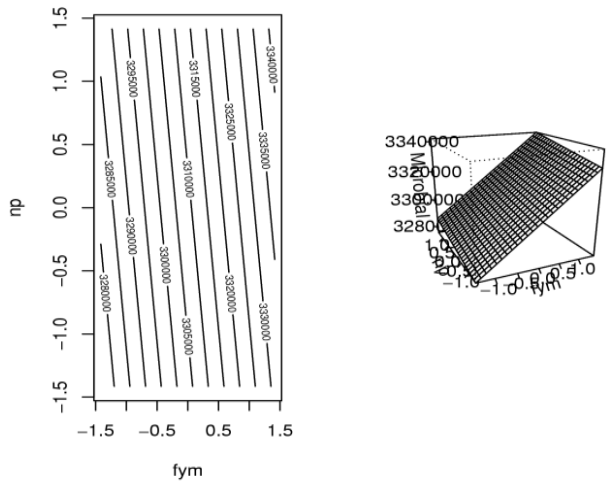

Figure 6. *Contours and Response Surface for model total microbial population.*

The 2nd model fitted the data well and were used for searching the path of steepest ascent.

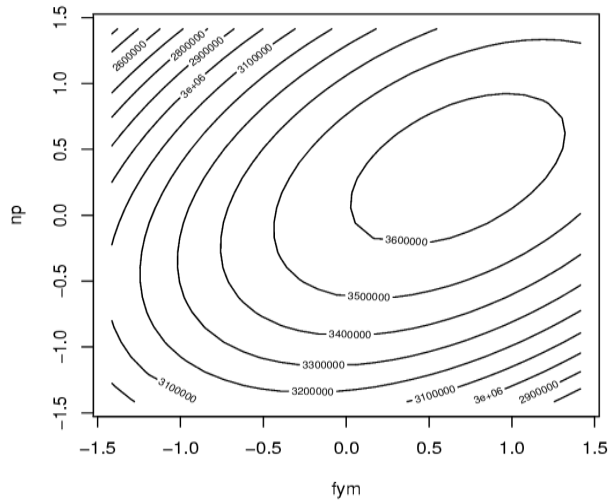

Figure 7. *Steepest Ascent for Total Microbial population (y_2).*

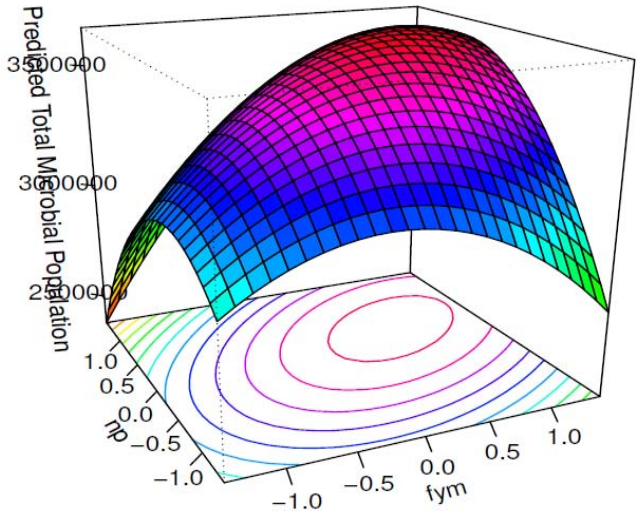

Figure 8. *Response Surface plot for Microbial Population (y_2).*

Solving this gives coded values, the real values are for farm yard =92.75kg/ha equivalent to 10.2 tons/ha. This will contain an estimated 76.82 kg N and 15.93 kg P at the optimal region. For np the real values are 12.4 kg/ha equivalent to almost bags 5.4 kg/ha of N and 7.00 kg/ha of P. Under these settings the optimal microbial population was estimated at $3.6x10^6$.

Table 7 below gives a summary of the univariate optimization achieved that will led to the optimal levels of the maize grain yield and total microbes population count.

Table 7. *Summary of Univariate Optimalities, y_1 and y_2.*

fym	np	optimal yield	optimal microbial population
120.65kg/ha	64.34 kg/ha	3.8 103	-
92.75 kg/ha	12.5 kg/ha	-	3.6x106

4. Discussions

The largest positive effects on the maize yields were realized with N_1P_1+FYM_1, N_1P_1+FYM_1+R and FYM_1+R treatments while the greatest negative effects were from NIL, NIL+R treatments. This is a clear indication that combination of chemical fertilizers and the FYM produces better yields for maize. These results are in consistent with earlier studies in LTEA and in Embu, Kenya that concluded that use of the inorganic fertilizers had higher response to high yields when supplemented with the FYM that retained the SOM an able condition of multiplication of the microbe.

From the two 1st-order models selection a parsimonious set of treatment factors were identified for the subsequent phase of experimental design for optimizing both the responses. Considering the significant factors and impact of the factors and through informed consultation with the LTEA experts on the commonly used practices by small-scale farmer in the Country and also due to its significance size, the FYM_1+ N_1P_1 treatment factor was identified for optimizing the two responses (Maize yield and the total microbial population count). These include combination of the FYM (organic-manure application of 5 ton/Ha "boma" manure (about 75 kg N and 20 kg P)) and the use N1P1 (chemical fertilizers – N1 60 kg N/Ha as Calcium Ammonium Nitrate (CAN), P1-26.4 kg/ha P as Triple Superphosphate (TSP)). The current practice for the treatment factors were taken as the baseline (center points, (0,0)) during the design of the experiments simulation and extrapolation procedure. The significant treatment factors FYM and NP selected were simulated to assess the possible levels for MOO maize yield and the total microbial population count.

5. Conclusions

It was evident that the maize yields from the LTEA were experiencing yields decline over years despite the continuous soil management option practices. The maize yields had declined to lows of about 2,100kg/ha in some treatments/soil management options. This calls for an integrated reversal approach in the retention of soil fertility. These points to a possible conclusion that the current operating soil fertility options are not optimal for the future soil fertility retention and for sustained maize yields.

Two treatment factors were isolated during the screening phase as the most significant and important treatment factors from a possible range of input and controllable factors. These were farm yard manure (FYM_1) and chemical fertilizers at level N_1P_1 at their lower levels. The two treatment factors significantly explained the maize yield and total microbial population. These two treatment factors were important in for ensuring the optimal maize yields while retaining the required threshold for total microbial population.

The study established that using the CCCD within the CCD with two star experimental points provided the best efficient and appropriate design for the MRSM and MOO in maize yield and total microbial population count.

The univariate optimal of maize yield and total microbial population count where higher compared to the multi-objective optimal that presented lower levels of both yield and microbial population. This is a confirmation that optimization of a single variable at a time can provide misleading conclusions and hence multi-response optimization offers the best solutions in cases were more than one factors of interest to the experimenter/Decision Maker (DM) are considered.

Appendix

Appendix I: Treatments Factors

Variable	Variable.Type	Description	Derivation.of.the.Variable	Optimization.Goal
Yield (Y_1)	Response	Achieved yield	Yield from the soil management	Maximum
Microbial Population (Y_2)	Response	Bacteria, Fungi Actinomycetes, Rhizobia	Total microbe	Maximum
Control (x_1)	Dependent	Controlled input		
Control+R (x_2)	Dependent	Controlled input		
FYM_1+R (x_3)	Dependent	Controlled input		
N_1P_1 (x_4)	Dependent	Controlled input		
N_1P_1+R (x_5)	Dependent	Controlled input		
N_1P_1 (x_6)	Dependent	Controlled input		
N_1P_1+FYM_1 (x_7)	Dependent	Controlled input		
N_1P_1+FYM_1+R (x_8)	Dependent	Controlled input		

Appendix II: Model 1 for Maize Yield (y_1)

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3,302.0000	130.1283	25.37	< 0.001
FYM1+R	74.7125	99.7414	0.75	0.4621
N1P1	8.5056	99.7554	0.09	0.9329
N1P1+FYM1	565.0319	99.7554	5.66	< 0.001
N1P1+FYM1+R	182.7125	99.7414	1.83	0.0812
N1P1+R	-111.7444	99.7554	-1.12	0.2753
NIL	-1340.2181	99.7554	-13.44	< 0.001
NIL+R	-658.5375	99.7414	-6.60	< 0.001
Block II	-6.8500	153.9698	-0.04	0.9649
Block III	-57.0224	154.1145	-0.37	0.7151
Block IV	63.8724	154.1145	0.41	0.6827

Appendix III: Model for Treatment Factors for Microbial Population (y_2)

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3966945.0000	2621550.5784	1.51	0.1451
FYM1+R	583301.8500	2009380.4688	0.29	0.7744
N1P1	-602307.6421	2009661.7173	-0.30	0.7673
N1P1+FYM1	-870015.4579	2009661.7173	-0.43	0.6695
N1P1+FYM1+R	-1271214.6500	2009380.4688	-0.63	0.5338
N1P1+R	-2041483.3921	2009661.7173	-1.02	0.3213
NIL	-583133.2079	2009661.7173	-0.29	0.7745
NIL+R	-2818243.1500	2009380.4688	-1.40	0.1754
BlockII	750926.6000	3101860.4755	0.24	0.8111
BlockIII	-655484.4316	3104774.3892	-0.21	0.8348
BlockIV	542267.8316	3104774.3892	0.17	0.8630

Appendix IV: Full Model 2 Treatment Factors for Microbial Population (y_2)

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3966945.0000	2911982.4700	1.36	0.2153
FYM1+R	-2859536.0000	4118165.1024	-0.69	0.5098
N1P1	723679.0000	4118165.1024	0.18	0.8655
N1P1+FYM1	-2725349.5000	3566435.5957	-0.76	0.4697
N1P1+FYM1+R	-6144462.0000	4118165.1024	-1.49	0.1793
N1P1+R	-6047450.0000	4118165.1024	-1.47	0.1854
NIL	-5641030.0000	3566435.5957	-1.58	0.1577
NIL+R	-5986798.0000	4118165.1024	-1.45	0.1893
BlockII	-1933865.0000	4118165.1024	-0.47	0.6529
BlockIII	-769801.0000	4118165.1024	-0.19	0.8570
BlockIV	3341376.0000	4118165.1024	0.81	0.4439
FYM1+R:BlockII	7013594.0000	5447820.3594	1.29	0.0238*
N1P1:BlockII	558494.0000	5823964.9399	0.10	0.9263
N1P1+FYM1:BlockII	3340852.5000	5447820.3594	0.61	0.5591
N1P1+FYM1+R:BlockII	8176981.5000	5447820.3594	1.50	0.1771
N1P1+R:BlockII	5637904.0000	5823964.9399	0.97	0.3653
NIL:BlockII	11632650.0000	5447820.3594	2.14	0.0701*
NIL+R:BlockII	5272073.5000	5447820.3594	0.97	0.3654
FYM1+R:BlockIII	2428955.0000	5823964.9399	0.42	0.6891
N1P1:BlockIII	-2874062.0000	5447820.3594	-0.53	0.6141
N1P1+FYM1:BlockIII	1281375.5000	5447820.3594	0.24	0.8208
N1P1+FYM1+R:BlockIII	5823818.0000	5823964.9399	1.00	0.3506
N1P1+R:BlockIII	5250139.5000	5447820.3594	0.96	0.3673
NIL:BlockIII	5799829.0000	5447820.3594	1.06	0.3224
NIL+R:BlockIII	4814864.0000	5823964.9399	0.83	0.4357

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