CLASSICAL RESPONSE SURFACE DESIGNS FOR FERTILIZER TRIALS IN SESAME (*Sesamum indicum* L.)

by

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THESIS

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DECLARATION

I, hereby declare that this thesis entitled **"CLASSICAL RESPONSE SURFACE DESIGNS FOR FERTILIZER TRIALS IN SESAME (*Sesamum indicum* L.)"** is a bonafide record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title, of any other University or Society.

Place: Vellayani

Date: 17-03-2023

KEERTHANA RAJ K

(2020 -19-002)

CERTIFICATE

Certified that this thesis entitled **"CLASSICAL RESPONSE SURFACE DESIGNS FOR FERTILIZER TRIALS IN SESAME (*Sesamum indicum* L.)"** is a record of bonafide research work done independently by **Ms. Keerthana Raj K (2020-19 -002)** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

Place: Vellayani

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Dr. Pratheesh P. Gopinath
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LIST OF ABBREVIATIONS

%	Per cent
Cm	Centimetre
et al.	And Co-workers
G	Gram
Kg	Kilogram
KAU	Kerala Agricultural University
ºC	Degree Celsius
Fig.	Figure
CCD	Central composite Design
CCC	Central Composite Circumscribed
CCI	Central Composite Inscribed
BBD	Box- Behnken Design
RSM	Response Surface Design
ICAR	Indian Council of Agriculture Research
ORARS	Onattukara Regional Agriculture Research Station
N	Nitrogen
P	Phosphorus
K	Potassium

Introduction

1. INTRODUCTION

Response Surface Methodology analyses and optimizes protocols involving multiple variables affecting a response. RSM develops, enhances, and optimizes a process using a variety of statistical, graphical, and mathematical tools. It is also useful for modeling and finding the optimal settings for an experiment. An approximate functional relationship between a response variable and a group of design variables can be constructed and explored using a variety of experimental techniques, mathematical formulations, and statistical inference. Evaluation of the impact of numerous factors and their interactions on response variables is made possible by the response surface methodology (RSM), which was first introduced by Box and Wilson (1951).

The relationship between the response and the levels of quantitative factors is identified and quantified using the response surface methodology, and the best combinations of levels of different quantitative elements are obtained. RSM is very much useful for finding the optimum N P K levels in fertilizer trials. The response surfaces can be fitted to the region of interest using the data from trials incorporating quantitative components (Prasad *et al*., 2004).

The fundamental benefit of RSM is that it requires fewer experimental trials to examine various parameters and their interactions, making it less time and less laborious than other approaches for process optimization. RSM has been extensively used in the food business to improve conditions and procedures (Shieh *et al*., 1996; Vega *et al*., 1996).

Central composite and Box-Behnken designs are the two most widely utilized designs in response surface modeling. These designs have three or five unique levels for the inputs, but not all possible combinations of these values are used in the design. Embedded factorial or fractional factorial designs with center points that are supplemented with a collection of axial (star) points that enable curvature estimates can be found in central composite designs (Khuri and Mukhopadhyay., 2010).

The three primary types of CCD are Central Composite Faced (CCF), Central Composite Inscribed (CCI), and Central Composite Circumscribed (CCC). The star points are created in the CCC design by stretching each element's low and high values. Depending on the design's desired qualities and the quantity of design-related parameters, the star points are spaced apart from the center at a certain distance "α". The star points provide new low and high values for all factors using these new extremes. The low and high values are the star points in the CCI design, and the system computes appropriate settings for the factorial part of the design inside those boundaries. In CCF design the star points are at the center of each face of the factorial space, so $\alpha = \pm 1$ (Box and Wilson., 1951).

Box-Behnken designs (BBD) are extremely effective response surface designs and it needs a smaller number of runs. BBD reveals the impact of experiment variables and total experimental error. In addition to producing fewer experimental runs than the common CCD and providing more information, these designs have excellent symmetry and rotatability. It is possible to optimize a BBD using both numerical and categorical factors, however using categorical factors typically results in more runs (Beg & Akhter, 2021).

Regression analysis is used in RSM to forecast the response for the specified levels of the process parameters. Understanding the impact of process factors on response is done using response surface plots. The process parameters are then optimized using the response surface methodology's desirability approach and validated by running confirmation tests.

Although widely employed in industrial testing, the response surface approach is not as common in studies involving agriculture, horticulture, and related fields. This might be the case because agricultural science investigations take place in settings that are distinct from those used in industrial experiments. It is generally agreed upon that there are five distinctions: (i) time and factor range; (ii) factor levels; (iii) blocking; (iv) accuracy of observations; and (v) form of the response surface. Taking into account all of these factors, it might be preferable for agricultural experiments to be more reliable, less model-dependent, able to support a more flexible blocking system, and possess equispaced factor values in more combinations than industrial trials. Though theoretically lots of studies were conducted on response designs, their practical application is less (Prasad *et al*., 2004).

The best fertilizer levels in conventional field experimental designs can only be chosen from the applied levels, whereas in RSM the optimum levels can be achieved anywhere between the defined region, I.e., the region of interest could contain the optimum solution.

Sesame (*Sesamum indicum* L.) belongs to the family Pedaliaceae and is one of the most ancient oilseed crops known and used by mankind in the world. It originated in South Western Africa. Numerous names, including Til, Sisim, Gingelly, Ajonjoli, Sisamo, Gergelim Biniseed, etc. are used to refer to it. Because of its simplicity in extraction, high degree of stability, and tolerance to drought, it was an important oilseed crop in the ancient world. In all tropics and subtropics, sesame is grown as a rainfed crop. Although a short-day plant, it may also thrive in locations with lengthy days (Barut *et al*., 2006; Akbar *et al*., 2012)

Due to its high oilseed content and quality, the sesame seed has long been regarded as the "Queen of Oilseeds" and has been classified as a health food in China, Japan, and other Asian nations. Sesame has both nutritional and therapeutic value. Furthermore, seeds contain a high percentage of protein (20–28%) and edible oil (48–55%), as well as lignans that fight free radicals and extend the shelf life of sesame oil. Poor man's ghee is the nickname for sesame oil (Ashakumary., 1999).

Proteins (18–20%) and oil (50%) are both abundant in sesame. The majority of the sesame seed produced in India (78%) is used for oil extraction, followed by sowing (21.5%) and confections and religious Hindu rituals (the remaining 12%). Almost 73% of the oil is utilized for food, 8.8% for hydrogenation, and 4.2% for industrial uses like the production of pesticides, paints, and pharmaceuticals. Fried seeds, seeds combined with sugar, and seeds in various shapes are consumed with sweetmeats. In south India, sesame oil is an important culinary ingredient.

Both in the area and production of sesame India ranks first. India, China, Myanmar, Sudan, Pakistan, Mexico, Ethiopia, Sri Lanka, Burma, and other African nations are among the top sesame-producing nations. The second-largest oilseed crop after groundnuts is sesame. Gujarat, Rajasthan, Madhya Pradesh, Karnataka, Maharashtra, Uttar Pradesh, Tamil Nadu, Andhra Pradesh, Kerala, and Punjab are the primary sesame-growing states in India. Sesame growing and production are well-known in Kerala's Onattukara district.

According to figures for 2019–20, Kerala's area used for sesame farming is 207.94 hectares, and its annual production is 129.4 tonnes. In Kerala, Alappuzha has the biggest area and production of sesame (Farm guide 2022). Sesame is typically planted in Onattukara as a third crop in uplands from August to December and in lowland paddy fields from December to April.

All oilseed crops benefited from balanced fertilization with N and P to reduce negative nutrient extraction and preserve soil health and plant nutrient levels at their optimum levels. One of the most crucial inputs for good crop production is fertilizer. By applying balanced fertilizers, production can be increased sustainably.

For plant nutrition in agricultural ecosystems, nitrogen is vital. It is a crucial component of protein, gives plants their green colour, promotes vegetative growth, and also aids in the manufacture of auxin. Certain facts also suggest that too much nitrogen can have a negative impact on seed oil content. Nitrogen should ideally be used at planting time and, if necessary, top dressed before the first bud emerges. In sandy soil, foliar spraying with urea can boost yield (Nair et al. 1977), but top dressing typically yields comparable results for less money. But according to some reports, with correct fertilization, sesame seed yield can be increased by 50%. (Prakash and Gowda, 1999).

The application of phosphorus is essential for root development, crop maturation, and pathogen resistance as well as for the production and transfer of carbohydrates. It considerably increases the number of seeds/ capsules, capsule/ plant, seed yield, oil, and protein in the sesamum cultivar. In addition, phosphorus is a crucial component for seed growth and filling, which improves yield (Mian *et al*., 2011).

Potassium improves a plant's ability to withstand disease, insect infestation, cold, drought, and other harsh environmental circumstances. It also improves the yield and quality of agricultural produce. It improves the efficiency of the uptake and utilization of N and other nutrients and aids in the formation of a robust and healthy root system. Numerous plant metabolic pathways depend heavily on potassium. Numerous quality characteristics of the crops, especially the oil content in oilseed crops, are improved by sufficient potassium nutrition.

Currently, the fertilizer recommendation for sesame is 30 kg N ha^{-1}, 15 kg P_2O_5 ha^{-1} and 30 kg K_2O ha^{-1} (KAU, 2016). Realizing the importance of nitrogen, phosphorous and potassium in the production of sesame, the present investigation entitled "Classical Response Surface Designs for fertilizer trials in sesame (*Sesamum indicum* L.)" was, therefore, undertaken to evaluate the optimum fertilizer dosage of sesame. The N, P and K levels in this experiment are determined in such a way that new treatment combinations have to produce more economic yield. In this

This study was carried out with the following objectives:

- Obtaining optimum fertilizer dose for sesame.
- Identify the limitations and advantages of the designs and provide suitable modifications.
- Develop open-source software for response surface methodology in agriculture.

The concepts of response surface designs coupled with CCC, CCI, and Box-Behnken designs will be used in the present study to obtain the optimal fertilizer dose for sesame (variety Thilak). An experiment was conducted in Onattukara Regional Agricultural Research Station, Kayamkulam, and yield observations were collected.

1.1 SCOPE OF THE STUDY

The RSM was shown to be useful for the design of experiments investigating the effects of the factors on the response parameters. CCC, CCI, and Box-Behnken design techniques were used to create experimental studies. The response surface methodology reduced the number of experiments for a particular number of components and their levels. The concepts of response surface designs coupled with CCD, CCI, and Box-Behnken designs will be used in the present study to obtain the optimal fertilizer dose for sesame. The software available for implementing RSM is currently proprietary and a few open source packages were available for RSM (rsm package in R)it is not heavily utilized by researchers in agriculture due to the challenges in sufficient programming and computational knowledge To benefit the agricultural researchers a user- friendly GUI based open source software/package needs to be developed.

1.2 LIMITATIONS OF THE STUDY

The experimental runs had only one replication, so the simulation study couldn't be carried out. The study is carried out in the Onattukara region with a single sesame variety over the course of one season. The outcome, therefore, needs to be confirmed by other experimental trials. The outcome is solely the result of computation and statistical analysis. Therefore, additional experiments are required to validate the result.

1.3 PRESENTATION OF THE THESIS

The five sections that make up this thesis are introduction, review of literature, materials and methods, results and discussion, and conclusion. The importance, scope and limitations of the study and the future line of the study are included in the introduction. The review of the literature section presents an overview of related literature and publications. The materials and methods section deals with the statistical methods and procedures employed in this investigation. The data collected are analyzed and interpreted in the fourth section. The conclusion section comprises the summary, reference, appendix and abstract.

1.4 FUTURE LINE OF THE STUDY

The study is limited to just one variety of sesame during a particular season in the Onattukara region. This can be further extended to different varieties during different periods to assess or analyse the optimal dosage of N, P and K for sesame. In this way, it is possible to find the appropriate quantity of fertilizer for different crops such that it will lead to the maximization of yield in a sustainable manner both environmentally and economically. The web application developed incorporates CCC, CCI and BBD, it can be further modified by adding face-centered central composite design. The developed package includes various plots like contour plots, response curve.

Review of Literature

2. REVIEW OF LITERATURE

The findings of previous studies pave the way to understanding the methodologies that may be adopted for the present study. This chapter puts forward the critical reviews of literature related to the current study. In this chapter, an attempt has been made to review the available relevant and up-to-date literature related to the topic “Classical Response Surface Designs for fertilizer trials in sesame (*Sesamum indicum* L.)”.

2.1 Sesame

2.2 Response surface methodology

2.1 Sesame

2.1.1 Kerala

A study on the effects of biofertilizers and chemical fertilization for sesame growing in summer rice fallow was undertaken by Indu and Savithri (2003). A significant increase in sesame seed yield was observed in the summer rice fallow due to the factors like presence of Azospirillum and Azotobacter in nature, the initial medium fertility status of the soil, the incorporation of rice stubbles and FYM, as well as the application of the recommended dose of 30 kg inorganic N ha^{-1}.

In Kerala's Onattukara sandy soil, Jeena *et al*. (2013) conducted a study on the effects of S and B on the production phenology of sesame. The experiment was conducted in the sandy Onattukara soil of Kerala according to a factorial design. The experiment used a factorial randomized block design with four levels of sulphur and boron in each group, and it was found that these two elements function together to increase sesame grain production and yield attributes.

According to Jeena and Sumam (2016), boron and sulphur work together to increase sesame yield and quality (*Sesamum indicum* L.). Field trials were set up in factorial RBD with four levels of sulphur and boron with the variety Thilarani since it is the preferred crop of farmers in the summer rice fallows of Onattukara.

2.1.2 India

According to Kalaiselvan *et al*. (2001), the use of N fertilizers in sesame significantly increases growth and yield characteristics as well as seed production. Plant height, branch count, and dry matter production all rose with each subsequent increase in N level up to 150 kg/ha. In a similar manner, yield components and yield both grew significantly up to 150 kg N/ha.

At the University of Agriculture Faisalabad, Agronomic Research Farm, Malik, *et al*. (2003) studied the effects of different nitrogen levels on sesame (Sesamum indicum L.) productivity under various planting patterns. They found that the application of 80 kg N ha-1 resulted in the highest number of sesame capsules per plant (97.88).

At the Agricultural Research Station in Arsikere, Karnataka, Hanumanthappa and Dalavai (2008) conducted a field experiment to investigate the impact of fertilizer levels on sesamum growth, yield, and quality. The seed yield and yield attributes had been much greater at the fertilizer levels at 100% of the prescribed dose.

Deshmukh *et al.* (2010) conducted a field experiment at Rahuri during the summer of 2007 to examine the impact of integrated nutrient management on the yield of summer sesame. They found that the application of RDF (60:40:20 kg ha^{-1}+ 5 t FYM ha^{-1} + 5 t vermicompost ha^{-1} + seed treatment of Azospirilum + PSB) resulted in the highest dry matter yield.

A field experiment was carried out at the Mahatma Phule Krishi Vidyapeeth, Rahuri, to study the effect of integrated nutrient management on the yield of summer sesamum. It was found that the application of RDF + 5 t FYM + 5 t vermicompost ha^{-1}+ seed treatment of Azospirillum and PSB significantly increased the number of branches per plant (Shaikh *et al.*, 2010).

Shehu *et al*. (2010) conducted a field experiment on nitrogen, phosphorus and potassium nutrition of sesame (*Sesamum indicum L*.) and reported that a higher number of branches (2.11 and 2.03) of sesame were observed when the application of 112.5kg N ha-1 and 22.5 kg P ha^{-1} respectively and found significantly superior to 75 kg N ha^{-1} and 45 kg P ha^{-1} respectively.

In 2007, at the Agricultural Research Station, JAU, Amreli, Vaghani *et al*. (2010) conducted an experiment on medium black calcareous soil to investigate the impact of various amounts of N, K, and S on yield and yield characteristics of Kharif sesame (Sesamum indicum L.) in FRBD using three replications. The results showed that the treatment of N at 100 kg ha^{-1}, K2O at 80 kg ha^{-1}, and elemental S at 40 kg ha^{-1} resulted in considerably higher seed and yield attributes as well as quality measures.

Bhosale *et al*. (2011) conducted a field study at the college instructional farm of Junagadh Agricultural University, Junagadh, during the Kharif season of 2008 to investigate the effects of various levels of potassium and sulphur on sesamum growth, yield, and quality (Sesamum indicum L). Three potassium levels and three sulphur levels were tested. Among the various potash concentrations, 50 Kg ha^{-1} resulted in noticeably increased plant height (94.71 cm), branch count (3.43), seed production (813 kg ha-1), oil content (44.89%), and protein content (27.82%).

The impact of integrated nitrogen management on the growth and yield of sesame (*Sesamum indicum* L) was examined by Ghodke *et al*. (2014). The findings showed that RDF application (60:40 N:P kg ha^{-1}) resulted in the greatest number of functioning leaves $plant^{-1}$ (68.05).

According to Vani *et al*. (2017) applying the recommended nitrogen dose (60 kg/ha) to sesame plants caused the maximum dry matter accumulation per plant (2123.87

kg ha^{-1}) compared to other treatments. At the student farm of the college of agriculture in Rajendranagar, Hyderabad, a field experiment was conducted in the summer of 2013 to determine the impact of integrated nutrient management and foliar application of humic and fulvic chemicals on sesamum. The investigation's findings showed that applying the recommended amount of nitrogen (60 kg/ha) had improved sesamum growth characteristics and yield to a level with applying 100% RDN+1% foliar sprays of humic acid and 100% RDN+1% foliar sprays of fulvic acid, with 75% RDN + 25% N applied through vermicompost coming in second.

In the summer of 2016, Patel *et al*. (2018) conducted a field experiment at the College Farm of the N. M. College of Agriculture, Navsari Agricultural University, Navsari, Gujarat. Three replications of a factorial randomized block design were used to evaluate the experiment, which included 18 treatment combinations with three levels of nitrogen (25, 50, and 75 kg N ha^{-1}), three levels of phosphorus (12.5, 25 and 37.5 kg P2O5 ha^{-1}), and two levels of biofertilizers (no inoculation and seed inoculation with Azotobacter + PSB). The results showed that summer sesamum can be fertilized with N3 (75 kg N ha-1) and P3 (37.5 kg P2O5 ha-1) in the "deep black soil" soil of South Gujarat Agroclimatic Region to produce a superior crop yield with a greater net return.

At the Agronomy Instructional Farm, C.P. College of Agriculture, S.D. Agricultural University, Sardarkrushinagar, during the summer of 2018, Parmar *et al*. (2020) conducted a field experiment. The experiment used a randomized block design with three replications to examine a total of ten integrated nutrient management interventions. The findings demonstrated that nutrient management treatments had a substantial impact on the sesamum plant's growth, yield characteristics, yield, and quality metrics. The treatment of 50% RDF + 5.0 t FYM ha^{-1} + PSB + Azotobactor produced the maximum plant height (77.54 cm), number of branches per plant (4.02), number of capsules per plant (74.30), test weight (3.57 g), seed yield (978 kg ha^{-1}) and stalk yield (2368 kg ha^{-1}).

Suchitha *et al*. (2021) conducted a field experiment during the Zaid season. The experiment was set up in a randomized block design with ten treatments: 30 kg P/ha + 10 kg S/ha, 30 kg P/ha + 15 kg S/ha, 30 kg P/ha + 20 kg S/ha, 40 kg P/ha + 10 kg S/ha, 40 kg

P/ha + 15 kg S/ha, 40 kg P/ha + 20 kg S/ha, 50 kg P/ha + 10 kg S/ha, 50 kg P/ha + 15 kg S/ha, 50 kg P/ha + 20 kg S/ha, and RDF N: P: K 50:40:30, which was replicated three times and showed an effect In terms of growth metrics, applications of 40 kg P/ha with 20 kg S/ha were significantly higher.

2.1.3 World

In the 2004–2005 growing seasons, Abdel (2008) carried out field research at the Nile Valley University Experimental Farm in Darmali, Northern Sudan. Four replications were used in the split-plot design of the experiment. The treatments included five levels of nitrogen (0, 22, 44, 66, and 88 Kg N ha^{-1}) assigned to the subplots and three levels of phosphorus (0, 22 and 44 Kg P2O5 ha^{-1}) applied to the main plots. The number of plants per square meter, the number of branches, the number of capsules per plant, and the seed yield per unit area were all significantly influenced by nitrogen. Under Northern Sudan climate circumstances, the sesame variety Shuak's seed yield and yield components significantly increased after the application of 44 kg N ha^{-1}.

Abdalsalam and Al-Shebani (2010) conducted two field studies at the Educational Farm, Faculty of Agriculture, Sana'a University. The studies were set up using a split-plot design, with the two sesame cultivars (Kod-94 and Local) assigned to the subplots and N levels of 0, 50, 100, and 150 kg N/ha-1 assigned to the main plots. The results showed a significant increase in plant growth, yield per hectare, and yield component growth when nitrogen rates were increased by 0, 50, and 100 up to 150 kg N per hectare.

In order to ascertain the native sesame (Sesamum indicum L.) variety's requirements for nitrogen and phosphate as the second crop on the Harran Plain, Arslan and Gur (2018) conducted a study. This study was conducted in the GAP Training Extension and Research research area. The effects of 5 different nitrogen and 4 different phosphate doses on sesame production are investigated in this study, which is set up as a "split plot" with three replications. The study's findings showed that the average sesame seed yield varied over two years between 116.0 kg/da to 166.5 kg/da. The application of nitrogen and phosphorus had a detrimental impact on yield.

Haghanian *et al.* (2019) demonstrated that the cultivation of the local Behbahan variety with the application of 100 kg N, under Omidieh regional conditions, has improved many sesame traits, including plant height, leaf area index, number of capsules per plant, and 1000 grain weight.

2.2 Response surface methodology

Response surface methodology (RSM) was used by Lee *et al*. (2000) to improve the extraction process for the detection of vitamin E in tomato and broccoli samples. To maximize the extraction and saponification processes, RSM studied the effects of changing the amount of 60% potassium hydroxide (KOH), saponification time, and ultimate ethanol concentration (EtOH) on the tocopherol contents. Ridge analysis was used to acquire the optimal parameters. The experimental values and the values predicted by ridge analysis agreed under the optimum settings.

A thorough explanation of the response surface methodology was provided by Prasad *et al.* (2004). The codes were created using the Statistical Analysis System (SAS) and the Statistical Package for Social Sciences (SPSS) in order to fit second-order response surfaces with and without intercepts, conduct canonical analysis, and explore the response surface close to a stationary point. Additionally, "Response" computer software has been created.

Prasad (2009) employed modeling and optimization strategies based on response surface methodology (RSM) and multiple response (MR) methodologies to develop ready-to-serve (RTS) beverages based on sugarcane juice. The coefficients of determination (R^2) are significant ($P < 0.01$). Here, the variables taken into account for the sensory responses are sugar and sugarcane juice. The sensory flavour and colour scores' standard errors of estimation were 0.218 and 0.316, respectively, while the coefficients of determination (R^2) were 0.924 and 0.927, respectively.

Prasad (2009) used unique response surface methods (RSM) to examine the impacts of dose, pH, and salt concentration for an optimal condition of colour removal from the distillery wasted wash. Using Moringa oleifera coagulant (MOC), the design was used to create a statistical model for the influence of the parameters examined on colour removal. Using sodium chloride (NaCl) and potassium chloride (KCl) salts, it was discovered that the dosage (20 and 60 ml), pH (7 and 8.5), and concentration of 0.25 M were the ideal conditions for maximal 56% and 67% colour removal, respectively.

Using the response surface (RSM) approach, Singh and Bunkar (2015) improve the nutritional and practical qualities of blended juice. RSM was used in this study to optimize the quantities of juice (50–75 ml pomegranate juice, 25–50 ml orange juice, and 3-5 ml ginger juice). The product was improved based on its physical, chemical, textural, and sensory characteristics. A formulation with 75 ml of pomegranate, 50 ml of orange, and 3 ml of ginger juice, with viscosity indexes of 4.60 g.sec, consistency of 7.36 g.sec, the cohesiveness of 487.45 g, and overall acceptance of 7.29 out of 9.00, was found to be the best among all combinations based on RSM trials.

In contrast to replicated central composite designs (RCCDs), Divecha and Tarapara (2017) developed a technique for creating cost-effective response surface designs (RSDs), which are useful for modeling and optimizing experiments that are asymmetric in some qualitative and quantitative factors with at least two unrestricted quantitative factors while the remaining take two or three levels.

Aydar (2018) employed response surface technology for the extraction of plant material in high yield and quality and to determine optimum conditions for this extraction process. RSM has many advantages when compared to classical methods. It needs fewer experiments to study the effects of all the factors and the optimum combination of all the variables can be revealed. The interaction between factors can be determined. It also requires less time and effort.

Response surface methodology (RSM) was utilized by Manan *et al.* (2019) to determine the ideal conditions for the photo-Fenton oxidation process to degrade PAH-contaminated water. After analysing the reaction duration, pH, and molarity of H_2O_2 and $FeSO_4$, RSM was performed using an aqueous solution. The impacts and interactions of these parameters were assessed using a five-level central composite design with a quadratic model. The regression line's R^2 score of 0.9757 indicates that it adequately matched the data. The maximum Sum of Squares value (15,666.64) with a probability F value of 0.0001 indicates a significant quadratic model according to the lack of fit test. Following the first order of kinetic rates and with R^2 values more than 0.95, the PAHs removal efficiency for samples of potable water ranged from 76.4% to 91%.

Mosaddeghi *et al.* (2020) have looked at the effects of basil mucilage as a plant-based coagulant in combination with alum for the treatment of wastewater from paper recycling. Based on a central composite rotatable design, response surface methodology (RSM) was applied to optimize the chemical coagulation process (CCRD). The analysis of variance was used to produce quadratic models for colour reduction and TSS removal with coefficients of determination of $R^2 > 96$. The removal efficiencies of colour and total suspended solids (TSS) were 85% and 82%, respectively, under ideal circumstances.

Verma *et al.* (2021) developed the response surface model for mixed-level variables. Conditions for the orthogonal estimate of the model's parameters have been derived. A technique for creating designs for mixed-level response surfaces has been put forth. The created designs meet the derived requirements of rotatability. The approach has additionally been expanded to include mixed-level rotatable designs of the form $2^n \times 3^n$.

2.2.1 Central Composite Design

Akram *et al.* (2003) compared the optimality of several Central Composite Designs. The variances of the parameter estimates are affected differently by various combinations of missing observations. Different combinations of these observations provide different levels of information. Compared to the least informative combination of missing observations, the most informative combination increases the maximum variance.

` In order to create microcapsules containing propranolol hydrochloride using the o/o emulsion solvent evaporation approach, Shivakumar *et al*. (2008) used a central composite design. They used a mixture of cellulose acetate butyrate as the coating material and span-80 as the emulsifier. The F test was used to assess the effects of the formulation factors on encapsulation efficiency (Y_1), drug release at 1.5 h, 4 h, 8 h, 14 h, and 24 h, as well as amounts of cellulose acetate butyrate (X_1) and % Span-80 (X_2). On Y_1, both formulation variables had a significant impact (P 0.05), but the degree of cellulose acetate butyrate was the only variable that had a meaningful impact on the other response parameters.

By using Central Composite Design, Koocheki *et al*. (2014) investigated the optimal water, nitrogen, and planting density for canola (*Brassica napus* L.). According to the ANOVA results, both the entire quadratic polynomial equation and its individual parts were significant. Insignificant lack-of-fit results from the polynomial models for the response variables showed that the experimental data were well explained. Results showed that the eco-environmental scenario's application of 2347 m^3 water per hectare and 92 kg of nitrogen per hectare could be improved for resource use, lessen environmental risks, and generate an appropriate amount of canola.

Through the use of an ionotropic gelation process, Nayak *et al*. (2014) developed novel mucoadhesive beads encapsulating metformin HCl using a central composite design. High drug encapsulation (DEE of 86.98 ± 3.26%) and a properly controlled in vitro sustained drug release pattern with super case-II transport mechanism were shown by the optimized mucoadhesive beads carrying metformin HCl over a period of 10 hours. The improved mucoadhesive beads also demonstrated their pH-dependent swelling behavior, good ex vivo mucoadhesivity with the goat intestinal mucosal membrane, and significant in vivo anti-diabetic activity in rats with alloxan-induced diabetes over an extended period of time after oral administration.

Valsartan (VAL), which has high solubility and dissolution, is prepared in stable nanosuspensions by Vuppalapati *et al*. (2016). A bottom-up precipitation method with a five-level complete factorial central composite design was used to create VAL nanosuspensions (CCD). According to the investigation, VAL is substantially more soluble and effective at dissolving in nanosuspension than in its pure form.

In order to maximize watermelon development and yield, Muriithi *et al*. (2017) explored the application of Central Composite Design (CCD) in the formulation of the best usage of organic manure. This study's major goal was to use CCD and RSM to maximize the various responses of watermelon to organic manure. The study suggests collaboration between statisticians and agriculturalists to adequately represent real-world agricultural research challenges using CCD and RSM in order to raise awareness of RSM in agricultural settings.

For magnetorheological finishing of blind hole surfaces using permanent magnet-designed tools and analysis of significant process parameters on the percentage change in surface roughness using newly developed tools, Sirwal *et al.* (2018) used Response Surface Methodology using the Central Composite Design technique.

Levetiracetam, an antiepileptic medication, was developed and optimized utilising the central composite design with response surface methodology (RSM) by Mahapatra *et al*. (2020). To investigate the effects of the acid-base couple on the responses, polynomial equations were created, and model plots (contour plot and 3-dimensional model surface plots) were produced. According to a good linear regression coefficient of 0.9808, 0.9939, and 0.9892 for effervescent time, hardness, and friability, respectively, the study shows that all of the independent variables (citric acid and effersoda) and dependent variables (effervescent time, hardness, and friability) have a good correlation.

Pal *et al*. (2022) optimized the peel-off gel's parameters for extrudability, spreadability, and drying time using the central composite design. This study examines the antibacterial effectiveness of a unique GG/Ag nanoparticle peel-off gel. When Ag nanoparticles are created, UV spectroscopy analysis reveals a distinct peak at 413 nm. TEM images with a resolution of 6 to 18 nm were used to analyze the size and distribution of nanoparticles. According to the findings, the optimal concentrations of GG, PVA, and ethanol were 3.47, 8.30, and 5.80 w/w%, respectively, with 0.02 w/w% Ag nanoparticles.

2.2.1.1 Circumscribed CCD

Through ionotropic gelation, Malakar *et al.* (2013) created cationized starch-alginate beads with sustained aceclofenac release. Using a central composite design, the effects of sodium alginate and cationized starch quantities as independent process factors on drug encapsulation and drug release were optimized. Based on the response surface methodology, the impacts of sodium alginate and cationized starch concentrations as independent process factors on the characteristics of these newly designed beads containing aceclofenac-like drug encapsulation and drug release were optimized and studied

Using a circumscribed central composite factorial design (CCD), Chawla *et al.* (2014) created sustained-release biodegradable polymeric nanoparticles (PNs) containing two anti-tubercular medicines (ATDs), rifampicin (RIF) and isoniazid (INH), and assessed in vivo absorption capability (RPNs). The effects of independent formulation factors, such as drug, polymer ratio (D:P), and surfactant concentration (SC), on the dependent physicochemical characteristics of the drugs, particle size (PS), polydispersity index (PI), and percentage entrapment efficiency (%EE), were investigated using CCD.

Using percolation and pressurized liquid extraction, Kamali *et al*. (2016) conducted a study to separate the extract from aerial sections of *Dracocephalum kotschyi* (PLE). The efficient extraction variables were optimized through a circumscribed central composite (CCC). To get the highest possible extraction yield, total phenolic and flavonoid content from D. *kotschyi*, as well as their antioxidant activity, the PLE working settings were tuned.

The statistical model's excellent correlation suggested that a quadratic polynomial model could be used to refine the extraction parameters and achieve the highest yield, total phenolic and total flavonoid content, and lowest DPPH EC50 using pressured liquid extraction.

Ghelich *et al*. (2019) used a five level, five factor central composite circumscribed design to statistically specify the impact of key process variables, such as the initial PVP polymer concentration (6-14 weight%), applied voltage (10-22 kV), flow rate (4-16 liters per minute), nozzle-collector distance (10-18 cm), and the molar ratio of boron to hafnium (2.2-5.8) on the key response process output variables, such as average diameter, quality, and uniform The analysis of variance (ANOVA) was used to confirm the significance of the components and their interactions with a 95% confidence level (p 0.05).

The impact of maceration temperature and time on Vernonia cinerea's nitrate content is studied by Monton and Luprasong (2019). The study used a circumscribed central composite experimental design. The yield of the extraction and nitrate content were evaluated together with two responses (temperature and duration of time). It was verified to use high-performance liquid chromatography (HPLC) for the quantitative determination of nitrate concentration. The HPLC result was linear in the 10-100 g/mL range (R^2 = 1.000). The HPLC process was certain, exact, and precise. The maceration temperature ranged from 40 to 100 degrees Celsius, while the maceration time ranged from 10 to 60 minutes.

2.2.1.2 Inscribed CCD

To improve the extraction conditions for phenolics (Y1) and flavonoids (Y2) from a by-product of the guava industry, Prasad *et al*. (2010) used Response surface approach. The effects of three independent variables—pH (X1: 2-6), temperature (X2: 40-60 °C), and time (X3: 1–5 h)—on the response variables were examined using a three-factor inscribed central composite design. For phenolics and flavonoids, the corresponding projected values were 336.30 and 427.35 mg per 100 g, respectively. With an R^2 of 0.902, predicted phenolic extraction rates were in good agreement with the experiment results. The model created for flavonoid extraction, with an R^2 of 0.983, was less trustworthy.

A three-factor inscribed central composite design (CCD) was employed by Prasad *et al*. (2011) to optimize total phenolics and antioxidant activity. For TPC and AC, the optimal extraction conditions were 68% ethanol concentration, 55 ° C, and 32.7 ml per kg, respectively. In order to fit the second-order polynomial equations, a multiple regression analysis employing response surface analysis was carried out using the experimental values of phenolic content (Y1) and antioxidant activity (Y2). The values found experimentally for both response variables in this investigation are close to the expected values, suggesting a good model. Based on the coefficients of determination (R^2), which were 0.9936 and 0.9900 for phenolic and antioxidant activity, respectively, it was determined the quality of fit to the second-order polynomial models.

Gulati *et al*. (2016) used response surface methodology with an inscribed central composite rotatable design to examine how the extrusion variables of moisture (17-25%), screw speed (170-250 r.p.m.), and temperature (90-150 °C) affected the extrudates' physical characteristics and antioxidant activity. Bulk density (BD), radial expansion ratio, water solubility index, hardness, colour (L*, a*, b*), and antioxidant activity were the response variables. Extreme low moisture and high screw speed conditions resulted in maximum expansion. The maximum antioxidant activity was likewise consistent with these circumstances. The relationship between screw speed and moisture was by far the most important interaction that had an impact on the process responses.

Gunathilake *et al*. (2019) optimized the extraction parameters of phenolics from *Centella asiatica* leaves using a three-factor inscribed CCD. The total phenolics and carotenoid contents of the experimental data were satisfactorily fit by a second-order polynomial model (R^2 = 84.75%, p 0.004) and 78.74, p 0.019, respectively. For phenolics, the ideal extraction parameters were 6.1% ethanol concentration, 70.2 °C, and 110.5 min of extraction time, while for carotenoids, the ideal values were 100%, 70.2 °C, and 110.5 min.

The effects of replication on the prediction variance performances of inscribe central composite designs, particularly those without replication on the factorial and axial portion (ICCD1), inscribed central composite design with replicated axial portion (ICCD2), and inscribe central composite design whose factorial portion is replicated (ICCD3) were studied by Nwanya and Dozie (2020). These designs were examined using the G-optimal, I- optimal, and FDS plots. While inscribed central composite design with a replicated factorial portion (ICCD3) has a better maximum and average SPV at 5 and 6-factor levels, inscribe central composite design without replicated factorial and axial portion (ICCD1) has a better maximum scaled prediction variance (SPV) at factors k = 2 to 4.

2.2.1.3 Face- Centred CCD

Response surface methodology (RSM) was used to describe the performance of a multilayer tungsten carbide tool by Noordin *et al*. (2004). Cutting tests were carried out in dry-cutting conditions with a constant depth of cut. Cutting speed, feed, and the side cutting edge angle (SCEA) of the cutting edge were the variables examined. Surface roughness and the primary cutting force, or tangential force, were the response factors examined. The face-centered, central composite design served as the foundation for the experiment (CCD). The experimental findings show that, within the parameters of the components under investigation, the recommended mathematical models could adequately characterize the performance indicators.

Using a model azo dye (Azure B) Rosales *et al*. (2012) did a study to enhance the electro-Fenton technique's capacity for the remediation of wastewater contaminated with synthetic dyes. The experiments were created and their interacting effects were assessed using response surface methods and a central composite face-centered experimental design matrix. High coefficient of determination value (R^2 = 0.9835) and reasonable second-order regression prediction was shown by ANOVA analysis. According to Pareto analysis, time and voltage have the biggest effects on the rate of decolorization.

The carrot puree's physical, chemical, and nutraceutical qualities were evaluated by Kaur *et al*. (2022). The face-centered composite design with response surface methodology served as the foundation for the experimental design. The selected responses were used as the basis for process improvement using a desirability function. With d (0.1), d (0.5) as 142.19 and 327.89 m; -carotene (1471.58 g/g); and "a" value (21.42) with composite desirability, ultrasonication for nine minutes followed by mechanical homogenization for one minute, subjected to three passes, produced the best results (0.85). The difference between the experimental and projected values was only 12%.

2.2.2 Box- Behnken Design

An investigation was carried out by Nazzal and Khan (2002) to create and assess an improved, self-nano-emulsified medication delivery system for ubiquinone. The amount of Polyoxyl 35 castor oil (X_1), medium-chain mono- and diglyceride (X_2), and lemon oil (X_3) were employed as independent variables in a 3-factor, 3-level Box-Behnken design for the optimization process. The dependent and independent variables were related using mathematical equations and response surface graphs. The observed responses and the optimized formulation's expected values agreed quite closely.

Francis *et al*. (2003) used a Box-Behnken design and response surface methodology to try and optimize three parameters (incubation temperature, initial substrate moisture, and inoculum size) for *Aspergillus oryzae* NRRL 6270's best production of -amylase during solid-state fermentation (SSF). In order to optimize nutrient supplements, the experimental data were fitted into a polynomial model to predict the yield of enzymes.

Using an agricultural-based adsorbent, sugarcane bagasse fly ash (BFA) Kumar *et al*. (2008) examined the removal of acrylonitrile from wastewater. A Box-Behnken design was used to examine the effects of variables such as adsorbent dosage (w), temperature (T), and time of contact (t) on the sorption of acrylonitrile by BFA with a fixed initial acrylonitrile concentration, C0 = 100 mg/l. The RSM findings show that, within the bounds of the given input parameters, the proposed models satisfactorily predict the responses.

Box-Behnken surface statistical design was used by Tripathi *et al*. (2009) to remove methyl orange (MO) from an aqueous solution using commercial-grade activated carbon (ACC) as an adsorbent. Four input factors were used in the experiments: pH, adsorbent dose (w: 5-20 g/l), contact duration (t: 2-6 h), and temperature (T: 25-55 °C) (pH: 2–8). The experimental data fit the second-order polynomial model well, according to regression analysis, which had an F-value of 10.28 and a coefficient of determination (R^2) of 0.9114

By maximising the four process variables, Dwivedi and Sharma (2015) apply the Box-Behnken response surface methodology to increase the biodiesel yield from Pongamia oil. With a methanol/oil molar ratio of 11.06:1 with KOH as the catalyst (1.43% w/w), a biodiesel production of 98.4% was attained after 81.43 minutes at a temperature of 56.6 °C. The investigation's findings indicate that while PB10 mix can keep its stability without an antioxidant, Pongamia biodiesel's induction period is greatly improved when Pyrogallol (200 ppm) is used. This improvement occurs from 1.83 hours to 6.5 hours.

Thind *et al*. (2018) examined the TiO_2/H_2O_2 mediated UV photocatalytic oxidation of chlorpyrifos (CP) in a lab-scale photo-reactor. The three-stage Box-Behnken factorial design (BBD) technique was used to create the experiments. Polynomial regression models were used to analyze the effects of process parameters such as TiO_2 concentration, H_2O_2 concentration, and beginning pH on response parameters such as COD and CP degradation. With the ideal process conditions and a 3-hour reaction period, approximately 68.29% and 74.38% of COD degradation and CP degradation, respectively, were achieved.

Sharma and Simsek (2020) conducted a laboratory-scale investigation to compare the treatment effectiveness of electro-oxidation (EO) and electrochemical peroxidation (ECP) for the elimination of organic materials. Box-Behnken Design (BBD) was used to optimize the experimental settings for both EO and ECP, and the models produced highly significant quadratic models for both treatment approaches. BBD was used to explore the effects of pH, H_2O_2 dose, current density, and operating time. According to the findings, at pH 5.3, 48.5 mA cm2 of current density, and 393 minutes of operation, EO can remove 75% of organics. The predicted values and measured values had a respectable level of agreement.

Materials & Methods

3. MATERIALS AND METHODS

The aim of the present study is to optimize the fertilizer levels of sesame using response surface methodology. The analysis is based on the primary data recorded from the field experiment conducted at Onattukara Regional Agricultural Research Station (ORARS). A detailed description of methods, procedures and statistical tools used in the study is explained in this chapter. The chapter contents are condensed under the following subsections:

3.1 Study area

3.2 Materials

3.3 Details of the experiment and important characters

3.4 Statistical methods

3.5 Statistical package used

3.6 Development of web package

3.1 Study area

3.1.1 Location

The study was conducted on the Thilak variety of sesame in ORARS, Kayamkulam, Kerala, located at an altitude of 3.09 m above mean sea level, at 9.180503^0 N latitude and 76.518950^0 E longitude.

3.1.2 Climate

The Onattukara region had a warm humid tropical climate.

3.1.3 Soil

A composite soil was taken at a random from 0-15 cm of soil depth and analysed for different Physico-chemical properties prior to the experiment. The results of the soil test were presented in Tables 1 and 2. The soil was loamy sand texture, acidic in soil reaction, low in organic carbon, available nitrogen, available phosphorus and available potassium.

3.1.4 Cropping History

The experimental field was previously utilized for raising rice crops.

Table1. Mechanical composition of the soil prior to the experiment

Sl. No.	Soil Fraction	Content (%)	Method
1	Sand	74.35	Bouyoucous hydrometer method (Bouyoucous, 1962)
2	Silt	20.00	
3	Clay	5.65	
Textural class: Loamy sand			

Table 2. Physico- Chemical properties of the soil prior to the experiment

Sl. No.	Parameter	Content	Rating	Method and Reference
1	pH	5.9	Strongly acidic	1:2.5 soil solution and read in pH meter (Jackson,1973)
2	EC ($dSm^{-1)}$	0.134	Normal	Digital electrical conductivity meter (Jackson, 1973)
3	Organic Carbon (%)	0.69	Low	Walkley and Black rapid titration method (Walkley and Black, 1934)
4	Available N (kg ha^{-1})			Alkaline permanganate method (Subbiah and Asija, 1973)
5	Available P (kg ha^{-1})	3.54	Low	Bray's colorimetric method (Jackson, 1973)
6	Available K (kg ha^{-1})	42.448	Low	Ammonium acetate method (Jackson, 1973)

3.2 Materials

3.2.1 Crop and variety

Thilak (ACV-3) a popular sesame variety having a duration of 80- 85 days released from College of Agriculture, Vellayani (KAU) was used in this study. The important characteristic features of the Thilak variety are drought resistance, brownish black seed and suited for summer rice fallows of the Onattukara region.

3.2.2 Manures and Fertilizers

Urea (46%N), Rajphos (20% P_2O_5) and murate of potash (60% K_2O) were used as a source of N, P and K respectively. Farm yard manure was used as organic manure.

3.3 Details of the experiment and important characters

The experiment was laid out in an area of 4.2 m x 3.6 m. The sesame seeds were sown at a spacing of 30 cm x 15 cm. the field was divided into 55 plots (20 under CCC, 20 under CCI and 15 under BBD) with single replication.

3.3.1 Design and Layout

Design	: CCC, CCI and BBD
Experimental Runs	: 20 under CCC
	20 under CCI
	15 under BBD
Replication	: Single replication
Season	: Summer 2021-2022
Spacing	: 30 cm x 15 cm
Plot size	: 4.2 m x 3.6 m
Location	: Onattukara Regional Agricultural Research Station

3.3.1.1 Treatment combinations

The maximum and minimum levels of N, P and K for CCC were 32 kg ha^{-1} and 64 kg ha^{-1} for N, 20 kg ha^{-1} and 50 kg ha^{-1} for P and 16 kg ha^{-1} and 34 kg ha^{-1} for K. The maximum and minimum levels of N, P and K for CCI were 38 kg ha^{-1} and 58 kg ha^{-1} for N, 26 kg ha^{-1} and 44kg ha^{-1} for P and 20 kg ha^{-1} and 30 kg ha^{-1} for K. The maximum and minimum levels of N, P and K for BBD were 32 kg ha^{-1} and 64 kg ha^{-1} for N, 20 kg ha^{-1} and 50 kg ha^{-1} for P and 16 kg ha^{-1} and 25 kg ha^{-1} for K. These maximum and minimum values were coded as +1 and -1

3.3.2 Coded values

The different levels of the factors were coded based on the following formula,

$$X = \frac{x_i - a}{b} \quad (1)$$

Where,

X was the coded value

x_i was the uncoded value for the ith factor

a = $\frac{high\ level + low\ level}{2}$

b =$\frac{high\ level - low\ level}{2}$

In this experiment, the coded variables are formed as follows

For CCC

N* = (N –48)/ 16 (2)

P*= (P – 35)/ 15 (3)

K* = (K – 25)/ 9 (4)

For CCI

N*= (N –48)/ 10 (5)

P*= (P – 35)/ 9 (6)

K* = (K – 25)/ 5 (7)

For BBD

N*= (N -48)/ 10 (8)

P*= (P –35)/ 15 (9)

K* = (K –25)/ 9 (10)

3.3.3 Determination of α value

The axial points for Central composite design are determined by finding the value of α.

$$\alpha = \sqrt[4]{2^k} \quad \text{(for k= 2,3,4…)} \qquad (11)$$

In this experiment k = 3, so the value of α = 1.682

The uncoded values of N, P and K for axial points corresponding to α = 1.682 is given by the following formula,

$$N = \pm 1.682 * b + a \qquad (12)$$

$$P = \pm 1.682 * b + a \qquad (13)$$

$$K = \pm 1.682 * b + a \qquad (14)$$

The levels of N, P and K for CCC, CCI and BBD were given in the Table 3, 4 and 5 and experimental runs along with coded values for CCC, CCI and BBD presented in Table 5, Table 6 and Table 7 respectively.

Table 3. The levels of N, P and K for CCC

Levels of the factors					
Factors	-α	Low	Medium	High	+α
	-1.682	-1	0	+1	+1.682
Nitrogen	21	32	48	64	75
Phosphorus	10	20	35	50	60
Potassium	10	16	25	34	40

Table 4. The levels of N, P and K for CCI

Levels of the factors					
Factors	-α	Low	Medium	High	+α
	-1.682	-1	0	+1	+1.682
Nitrogen	31	38	48	58	65
Phosphorus	20	26	35	44	50
Potassium	16	20	25	30	34

Table 5. The levels of N, P and K for BBD

Levels of the factors			
Factors	Low	Medium	High
	-1	0	+1
Nitrogen	32	48	64
Phosphorus	20	35	50
Potassium	16	25	34

3.3.4 Design matrix for N, P and K

The design matrix is a matrix representation of treatments combinations in coded values and the number of treatment combinations vary with no. of factors. The design matrix for CCD and BBD given below,

For CCD

$$\left|\begin{array}{ccc} 1 & -1 & -1 \\ -1 & 1 & -1 \\ 1 & 1 & -1 \\ -1 & -1 & 1 \\ 1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & 1 & 1 \\ -1.682 & 0 & 0 \\ 1.682 & 0 & 0 \\ 0 & -1.682 & 0 \\ 0 & 1.682 & 0 \\ 0 & 0 & -1.682 \\ 0 & 0 & 1.682 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{array}\right|$$

For BBD

$$\left|\begin{array}{ccc} 1 & -1 & -1 \\ -1 & 1 & -1 \\ 1 & 1 & -1 \\ -1 & -1 & 1 \\ 1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{array}\right|$$

Table 6. Treatment combinations for CCC in coded and uncoded form

Experimental Runs	Factors in coded form			Factors in uncoded form		
	N*	P*	K*	N	P	K
1	-1	-1	-1	32	20	16
2	1	-1	-1	64	20	16
3	-1	1	-1	32	50	16
4	1	1	-1	64	50	16
5	-1	-1	1	32	20	34
6	1	-1	1	64	20	34
7	-1	1	1	32	50	34
8	1	1	1	64	50	34
9	-1.682	0	0	21	35	25
10	1.682	0	0	75	35	25
11	0	-1.682	0	48	10	25
12	0	1.682	0	48	60	25
13	0	0	-1.682	48	35	10
14	0	0	1.682	48	35	40
15	0	0	0	48	35	25
16	0	0	0	48	35	25
17	0	0	0	48	35	25
18	0	0	0	48	35	25
19	0	0	0	48	35	25
20	0	0	0	48	35	25

N* = coded form of Nitrogen, P* = coded form of Phosphorus, K* = coded form of Potassium, N = uncoded form of Nitrogen, P = uncoded form of Phosphorus, K = uncoded form of Potassium.

Table 7. Treatment combinations for CCI in coded and uncoded form

Experimental Runs	Factors in coded form			Factors in uncoded form		
	N^*	P^*	K^*	N	P	K
1	-1	-1	-1	38	26	20
2	1	-1	-1	58	26	20
3	-1	1	-1	38	44	20
4	1	1	-1	58	44	20
5	-1	-1	1	38	26	30
6	1	-1	1	58	26	30
7	-1	1	1	38	44	30
8	1	1	1	58	44	30
9	-1.682	0	0	31	35	25
10	1.682	0	0	65	35	25
11	0	-1.682	0	48	20	25
12	0	1.682	0	48	50	25
13	0	0	-1.682	48	35	16
14	0	0	1.682	48	35	34
15	0	0	0	48	35	25
16	0	0	0	48	35	25
17	0	0	0	48	35	25
18	0	0	0	48	35	25
19	0	0	0	48	35	25
20	0	0	0	48	35	25

N*= coded form of Nitrogen, P*= coded form of Phosphorus, K*= coded form of Potassium, N = uncoded form of Nitrogen, P = uncoded form of Phosphorus, K= Uncoded form of Potassium.

Table 8. Treatment combinations for BBD in coded and uncoded form

Experimental Runs	Factors in coded form			Factors in uncoded form		
	N^*	P^*	K^*	N	P	K
1	-1	-1	0	32	20	25
2	1	-1	0	64	20	25
3	-1	1	0	32	50	25
4	1	1	0	64	50	25
5	-1	0	-1	32	35	16
6	1	0	-1	64	35	16
7	-1	0	1	32	35	34
8	1	0	1	64	35	34
9	0	-1	-1	48	20	16
10	0	1	-1	48	50	16
11	0	-1	1	48	20	34
12	0	1	1	48	50	34
13	0	0	0	48	35	25
14	0	0	0	48	35	25
15	0	0	0	48	35	25

N*= coded form of Nitrogen, P*= coded form of Phosphorus, K*= coded form of Potassium, N = uncoded form of Nitrogen, P = uncoded form of Phosphorus, K = uncoded form of Potassium.

3.3.5 Observations Recorded

3.3.5.1 Growth parameters

- Plant height
- Number of leaves per plant
- Number of branches per plant
- Dry matter production

3.3.5.2 Yield attributes

- Day to 50 percent flowering
- No. of capsules per plant
- No. of seeds per capsule
- Seed yield per plant
- Seed yield ha^{-1}
- Haulm yield per plant
- Haulm yield ha^{-1}

3.3.5.3 Price of input and output (Rs. Kg^{-1})

Input	**Price (Rs. Kg^{-1})**
Urea	8
Rock Phosphate	15
Murate of Potash	34
Farm yard manure	10
Seeds	150
Output	
Sesame seed	300

3.3.6 Computed Indices

3.3.6.1 Harvest Index

Harvest index (HI) is the ratio of economical yield to the biological yield.

$$HI=\frac{Economic\ yield}{Biological\ yield} \tag{15}$$

Plate 1. Land preparation

Plate 2. Sowing

Plate 3. Germination Stage

Plate 4. Fertilizer

Plate 5. Weeding

Plate 6. Intercultural operations

Plate 7. Vegetative growth stage

Plate 8. Flowering stage

3.4 Statistical methods

The optimum values of N, P and K for the maximization of yield is done using RSM under CCC, CCI and BBD.

3.4.1 Descriptive Statistics

Descriptive statistics provides the summary of the data recorded. It provides a framework for the initial description of data. Descriptive statistics includes mean, median, maximum and minimum values, standard deviation, coefficient of variation (CV) etc…

3.4.1.1 Mean

It is the average value of the data which represents the whole data. Mean of a set of observations is their sum divided by the number of observations; the arithmetic mean $\bar{x}$ of n observations $x_1, x_2, x_3 \ldots x_n$ is given by,

$$\bar{x} = \frac{1}{n}\sum_{i=.1}^{n} x_i \tag{16}$$

3.4.1.2 Median

Median is the value which divides the whole data set into two equal parts. The median is thus a positional average.

$$Median = \left[\frac{n+1}{2}\right]^{th} \text{term} \tag{17}$$

3.4.1.3 Standard deviation

It is the measure of the spread of observations in terms of the average deviations of observations from the central values. Usually denoted as "σ". It is the positive square root of the arithmetic mean of the squares of the deviation of the given values from their arithmetic mean.

$$\sigma = \sqrt{\frac{1}{n}\Sigma(x_i - \bar{x})^2)} \tag{18}$$

3.4.1.4 Coefficient of variation (CV)

CV is the percentage variation in the mean, standard deviation being considered as the total variation in the mean.

$$cv = \frac{\sigma}{\bar{x}} \times 100 \tag{19}$$

3.4.2 Response surface methodology

RSM is a mathematical and statistical methods for developing empirical models in which on response is influenced by number of factors and the purpose is to optimize the response. The important RSM designs are CCD and BBD.

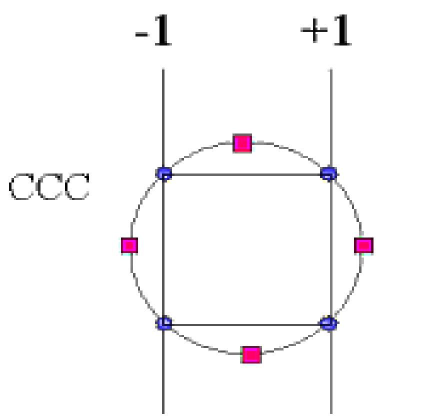


Fig. 1 Circumscribed CCD

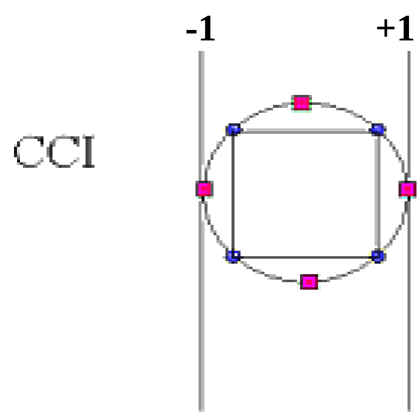


Fig. 2 Inscribed CCD

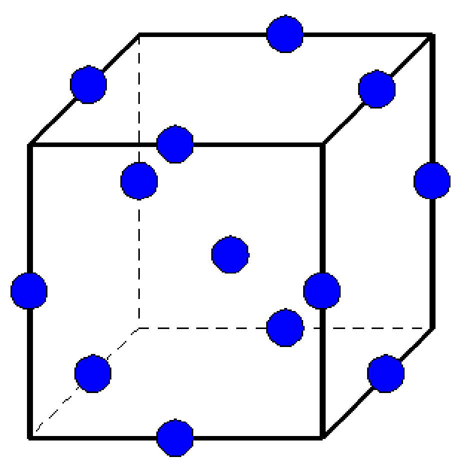


Fig. 3 Box- Behnken Design

In this experiment sesame seed yield was considered dependent variable or response and levels of N, P and K were considered as the independent variable.

3.4.2.1 Second-order model

If there is a complex relation between the response and independent factors, first-order models may not be able to provide an accurate response, so a higher-order polynomial is used. In this study, second-order polynomials were chosen for optimization. The second order model is given below,

$$Y= \beta_0+ \beta_1X_1+ \beta_2X_2+ \beta_3X_3+ \beta_{11} X_1^2+ \beta_{22} X_2^2+ \beta_{33} X_3^2+ \beta_{12} X_1 X_2+ \beta_{13} X_1 X_3+ \beta_{23} X_2 X_3+ \varepsilon \qquad (20)$$

Where ε is the error term which are independently and normally distributed with mean 0 and common variance σ and X_1, X_2, and X_3 were coded values of N, P and K.

3.4.2.2 OLS estimation of Second-order model

The ordinary least square (OLS) technique was used to calculate the regression coefficients. The OLS estimator of the regression coefficients is given as,

$$\hat{\beta} = (x^T x)^{-1} x^T y \qquad (21)$$

Where $\hat{\beta}$ is the estimated regression coefficient vector, X was the design matrix of input variables and Y was the response column vector.

3.4.2.3 ANOVA for response surface model

ANOVA for regression is a statistical method to partition the total sum of squares due to regression and error sum of squares to check the adequacy of the model. ANOVA for response surface model is given in Table 9.

3.4.2.4 R^2 (Coefficient of Determination)

R^2 is a coefficient of determination. It measures how well difference in dependent variable can be explained by the independent variables. The R^2 value ranges from 0 to 1 (i.e. 0 to 100%).

$$R^2 = 1- \left(\frac{RSS}{TSS}\right) \qquad (22)$$

Where,

R^2 = Coefficient of determination

RSS = Sum of squares due to regression

TSS = Total sum of square

Table 9. ANOVA for response surface model

Source of variation	DF	SS	MSS	F value	Pr (>F)
FO (N, P, K)	k	$\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$	MSR=$\frac{SS}{k-1}$	F=$\frac{MSR}{MSE}$	p value of the statistics
TWI (N, P, K)					
SO (N, P, K)					
Residuals	r = n-(k+1)	$\sum_{i=1}^{n}(y_i - \bar{y})^2$	MSE=$\frac{SSE}{r}$		
TSS	n-1	$\Sigma(k-9)^2$			
Lack of fit	n-k-1	$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$			
Pure error		$\sum_{\substack{1\le i \le n \\ 1<j<n}} \left(y_{ij} - \bar{y}\right)^2$			

3.4.2.5 Adjusted R^2

The adjusted R^2 is modified form of R^2. It will never be greater than R^2.

$$R^2 = 1 - \frac{SSE}{TSS} \qquad (23)$$

3.4.3 Testing of Coefficient of estimate

In a multiple linear regression model, to determine the significance of individual regression coefficients, the t- test is used. The t statistic is obtained by dividing the coefficient by its standard error. The standard error is calculated from the standard deviation of the coefficient.

$$t = \frac{\widehat{\beta}}{SE(\widehat{\beta})} \qquad (24)$$

3.4.4 Condition for the optimization by testing of lack of fit

The test hypothesis is

H_0: There is no lack of fit

H_1: There is lack of fit

If the p value is less than 0.05 reject null hypothesis (at 5% significant level).

3.4.5 Graphical methods

3.4.5.1 Contour plot

The contour plots (sometimes called Level Plots) are a way to show a three-dimensional surface on a two-dimensional plane. The same response is joined to form contour lines of constant response. Contour plot can display contour lines for X_1 and X_2 pairings with same Y response value.

3.4.5.2 Three-Dimensional Response surface plot

The graph depicts a response surface in the form of hills, valleys and ridges. It is three dimensional plots.

3.4.6 Estimation of Stationary points using First order derivative

The stationary point is a set of points in which the response is optimum. At stationary points slope of the response surface is zero. Partial differentiation of estimated response equation with respect x values and equating to zero gives the coordinates of the stationary points.

$$\hat{y} = \beta_0 + \beta_1 x + x' A x \tag{25}$$

The first order derivatives,

$$\frac{\partial y}{\partial N*} = \beta_1 + 2\,\beta_{11}\, N^* + \beta_{12} P^* + \beta_{13} K^* \tag{26}$$

$$\frac{\partial y}{\partial P*} = \beta_2 + 2\,\beta_{22}\, P^* + \beta_{12} N^* + \beta_{23} K^* \tag{27}$$

$$\frac{\partial y}{\partial P*} = \beta_3 + 2\,\beta_{33}\, K^* + \beta_{23} P^* + \beta_{13} N^* \tag{28}$$

Equate the above equations to zero

$$\frac{\partial y}{\partial N*} = \beta_1 + 2\,\beta_{11}\, N^* + \beta_{12} P^* + \beta_{13} K^* = 0 \tag{29}$$

$$\frac{\partial y}{\partial P*} = \beta_2 + 2\,\beta_{22}\, P^* + \beta_{12} N^* + \beta_{23} K^* = 0 \tag{30}$$

$$\frac{\partial y}{\partial P*} = \beta_3 + 2\,\beta_{33}\, K^* + \beta_{23} P^* + \beta_{13} N^* = 0 \tag{31}$$

The system of equations can be written in matrix form

$$A = \begin{bmatrix} 2\,\beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{12} & 2\,\beta_{22} & \beta_{23} \\ \beta_{13} & \beta_{23} & 2\beta_{33} \end{bmatrix} \qquad X = \begin{bmatrix} N^* \\ P^* \\ K^* \end{bmatrix} \qquad \beta = \begin{bmatrix} -\beta_1 \\ -\beta_2 \\ -\beta_3 \end{bmatrix}$$

The stationary points are solved using the formula,

$$X = -\frac{1}{2} A^{-1} \beta \tag{32}$$

3.4.7 Second order derivatives or Eigen values

If the eigen values are

- All negative, then at stationary points, the response has a maximum.
- All positive, then at stationary points, the response has a minimum.
- Mixed signs, then at stationary points is a saddle point.

3.5 Statistical package used in the study

In this study rsm package in R was used to perform the Response Surface Methodology. The package was used for design generation, RSM analysis and graph plotting.

3.6 Development of web package

An open- source user friendly R package was developed for RSM in agriculture experiments. The web package was developed using R shiny package.

3.6.1 User Interface

The user interface is the part of the application that handles user input. The control users use to connect with a website or app, such as button displays and gesture controls, are a speciality of web design.

3.6.2 Server function

The server function is the backend that processes these input data to create output results that are then displayed on the website.

3.6.3 Shiny app function

Shiny is a R package that allows us to create interactive web application directly from R.

Results & Discussion

4. RESULTS AND DISCUSSIONS

The present study entitled “Classical Response Surface Designs for fertilizer trials in sesame (*Sesamum indicum* L.)” aims to evaluate the optimum fertilizer dosage of sesame. The N, P and K levels in this experiment are determined in such a way that new treatment combinations have to produce more economic yield. The experiment was carried out in the Onattukara region and data was recorded. The results were analysed using RSM. This chapter discusses the results obtained from the study. Keeping in view the objectives of the study, the results are presented under the following headings.

4.1 Optimization of fertilizer trials

4.2 Advantages and Limitations of RSM

4.3 Development of RSM package

4.1 Optimization of fertilizer trials

4.1.1Central Composite Circumscribed (CCC) Design

4.1.1.1 Summary statistics of Growth parameters

The mean, standard deviation, maximum value, minimum value, median and coefficient of variation of growth attributes like plant height, no. of leaves, no. of branches and dry matter production are given in the Table 10.

Table10: Summary statistics of Growth parameters of Experimental Runs of CCC

Treatments	Plant Height (cm)	No. of leaves	No. of Branches	Dry Matter Production (g/ plant)
T_1	117.6	66	4	12.75
T_2	117.1	70	5	13.48
T_3	114.8	67	5	13.60
T_4	119.9	50	6	14.28
T_5	111.7	56	6	14.46
T_6	116.9	53	8	16.76
T_7	119.2	57	7	15.12
T_8	120.8	56	9	16.99
T_9	117.4	54	6	14.77
T_{10}	118.2	51	7	16.25
T_{11}	120.1	47	6	14.13
T_{12}	116.8	52	6	16.26
T_{13}	116.2	55	4	12.45
T_{14}	118.6	60	7	15.94
T_{15}	119.6	62	8	16.95
T_{16}	119.3	59	8	17.86
T_{17}	116.9	49	7	16.61
T_{18}	119.6	48	7	17.20
T_{19}	115.8	52	7	15.61
T_{20}	120.3	55	6	15.58

Mean	117.84	55.95	6.45	15.35
S. D	2.21	6.41	1.32	1.56
Minimum	111.7	47	4	12.45
Maximum	120.8	70	9	17.86
Median	117.9	55	6.5	15.59
CV (%)	2.0	11.0	20.0	10.0

The average plant height of 20 experimental runs obtained from Thilak variety of sesame was 117.84 cm with a standard deviation of 2.21. the average no. of leaves and average no. of branches were 55.95 and 6.45 with standard deviations of 6.41 and 1.32 respectively. The average dry matter produced by the variety Thilak was 15.35 g per plant with a standard deviation of 1.56. The minimum and maximum plant heights were 111.7 cm and 120.8 cm respectively. The maximum number of leaves was 70 and 47 was the minimum number of leaves. 12.45 g was the minimum dry matter produced and 17.86 g was the maximum. The coefficient of variations of plant height, no. of leaves, no. of branches and dry matter production were 2, 23, 20 and 10 respectively.

4.1.1.2 Summary statistics of yield parameters

The descriptive statistics of yield attributes (days to 50 percent flowering, no. of capsule per plant, no. of seeds per capsule, seed yield per plant, seed yield per ha, haulm yield per plant, haulm yield per ha and harvest index) are presented in the Table 11.

Table11: Summary statistics of Yield attributes of Experimental Runs of CCC design.

Experimental Runs	**Days to 50 percent flowering**	**No. of capsules per plant**	**No. of seeds per capsule**
T_1	34	22.5	34.2
T_2	36	24.4	37.4
T_3	35	25.8	37.2
T_4	36	31.9	41.3
T_5	36	29.1	39.6
T_6	36	44.3	54.8
T_7	37	35.2	46.3
T_8	34	47.1	56.1
T_9	38	28.2	40.8
T_{10}	37	41.6	48.3
T_{11}	36	32.4	42.2
T_{12}	36	34.4	45.4
T_{13}	36	20.7	35.6
T_{14}	36	41.1	50.9
T_{15}	35	46.3	55.1
T_{16}	37	45.8	53.3
T_{17}	37	42.3	51.6
T_{18}	38	44.2	53.7
T_{19}	34	39.5	47.6
T_{20}	36	38.2	49.1

Mean	36	35.75	46.02
S. D	1.17	8.49	7.08
Minimum	34	20.7	34.2
Maximum	38	47.1	56.1
Median	36	36.70	46.95
CV (%)	3.0	24.0	15.0

The mean days to 50% flowering was 36 with a standard deviation of 1.17 and the average no. of capsules per plant was 35.75 with a standard deviation of 8.49. There was an average of 46.02 seed per capsule with a standard deviation of 7.08. The minimum and maximum days required for 50% flowering were 34 days and 38 days respectively. 20.7 and 47.1 were the minimum and maximum no. of capsules per plant respectively and 34.2 and 56.1 were the minimum and maximum no. of seeds per capsule. The coefficient of variation of days to 50% flowering, no. of capsule per plant and no. of seeds per capsule were 3, 24 and 15 respectively.

Table12: Summary statistics of Yield attributes of Experimental Runs of CCC design.

Experimental Runs	**Seed yield per plant(g)**	**Haulm yield per plant (g)**
T_1	1.31	2.94
T_2	1.43	3.76
T_3	1.78	3.61
T_4	1.62	4.56
T_5	2.34	4.72
T_6	2.13	6.81
T_7	3.12	5.23

T_8	1.43	7.03
T_9	2.34	4.92
T_{10}	1.56	6.48
T_{11}	2.01	4.38
T_{12}	1.03	6.42
T_{13}	2.43	2.67
T_{14}	2.65	6.02
T_{15}	2.34	6.82
T_{16}	2.23	7.13
T_{17}	2.54	6.32
T_{18}	2.48	6.45
T_{19}	2.31	5.67
T_{20}	2.14	5.23
Mean	2.06	5.36
S. D	0.53	1.38
Minimum	1.03	2.67
Maximum	3.12	7.13
Median	2.18	5.45
CV (%)	26.0	26.0

The average seed yield per plant was 2.06 g with a standard deviation of 0.53 and the average haulm yield per plant was 5.36 g with a standard deviation of 1.38. The minimum and maximum values for seed yield per plant were 1.03 g and 3.12 g respectively.

The minimum haulm yield per plant was 2.67 g and the maximum were 7.13 g. The coefficient of variation for both seed yield and haulm yield per plant was 26.

Table13: Summary statistics of Yield attributes of Experimental Runs of CCC design.

Experimental Runs			**Seed yield (kg/ha)**	**Haulm yield (kg/ha)**	**Harvest Index**
N	**P**	**K**			
32	20	16	277	611	0.312
64	20	16	302	773	0.281
32	50	16	326	798	0.290
64	50	16	415	950	0.304
32	20	34	377	989	0.276
64	20	34	592	1500	0.283
32	50	34	494	1136	0.303
64	50	34	678	1552	0.304
21	35	25	364	1058	0.256

75	35	25	548	1388	0.283
48	10	25	418	917	0.313
48	60	25	458	1389	0.248
48	35	10	257	544	0.321
48	35	40	549	1318	0.294
48	35	25	652	1543	0.297
48	35	25	652	1745	0.272
48	35	25	582	1467	0.284
48	35	25	582	1598	0.267
48	35	25	546	1244	0.305
48	35	25	546	1238	0.306
Mean			480.75	1187.90	0.29

S. D	131.58	346.13	0.02
Minimum	257	544	0.248
Maximum	678	1745	0.321
Median	520	1241	0.29
CV (%)	27.0	29.0	7.0

The average seed yield of 20 experimental runs obtained by the variety Thilak was 480.75 kg ha^{-1} with a standard deviation of 131.58. while the average haulm yield obtained was 1187.90 kg ha^{-1} with a standard deviation of 346.13. In the case of the harvest index, the average was 0.29 with a standard deviation of 0.02. The minimum seed yield produced by the Thilak variety was 257 kg ha^{-1} and the maximum was 678 kg ha^{-1} whereas the minimum haulm yield was 544 kg ha^{-1} and the maximum was 1745 kg ha^{-1}. 0.248 was the minimum harvest index and 0.321 was the maximum. The coefficient of variation (C V) of seed yield, haulm yield and harvest index were 27, 29 and 7 percent respectively.

4.1.1.3 Response surface models

In the investigated 3-factor circumscribed CCD, the treatment combinations of N, P and K were factorial points (8), central points (6) and axial points (6). The levels N, P and K considered as factorial points were 32 kg ha^{-1} and 64 kg ha^{-1} for N, 20 kg ha^{-1} and 50 kg ha^{-1} for P and 16 kg ha^{-1} and 34 kg ha^{-1} for K and these values were coded as +1 and -1 (explained in chapter three). The dosage of N, P and K taken for central points were 48, 35 and 25 respectively and it was coded as 0. The axial points for the design were 21 kg ha^{-1} and 75 kg ha^{-1} for N, 10 kg ha^{-1} and 60 kg ha^{-1} for P and 10 kg ha^{-1} and 40 kg ha^{-1} for K. The coded value for the levels of axial points was -1.682 and +1.682 for each factor.

4.1.1.3.1 Estimation of the response of Seed yield

The estimated coefficients, standard error, p-value and significance of the coefficients of the grain yield calculated using rsm package in R (Russell., 2020) are presented in Table 14.

Table14: Estimated Quadratic response surface model based on seed yield

Factors	Coefficients	Standard Error	t- value	P- value
Intercept	593.011	17.287	34.3033	0.00 ***
N	60.219	11.469	5.2506	0.00 ***
P	31.650	11.469	2.7596	0.02 *
K	96.070	11.469	8.3764	0.00 ***
N P	4.125	14.986	0.2753	0.79
N K	35.625	14.986	2.3772	0.04 *
P K	5.125	14.986	0.3420	0.74

N^2	-46.430	11.163	-4.1592	0.00***
P^2	-52.792	11.163	-4.7291	0.00 ***
K^2	-65.164	11.163	-5.8373	0.00 ***
Multiple R^2		0.9454		
Adjusted R^2		0.8962		

From the table 14 it was clear that the coefficient of the linear effect of N, P, K, interaction effect NK and quadratic terms of N, P and K were significant at 5 percent level of significance. The model has a multiple R^2 of 0.94 which is closer to 1 indicating the high correlation between the dependent variable and independent variables. The adjusted R^2 was 0.89, therefore the estimated model was able to explain 89% variation in the data.

Table15: ANOVA for the estimated Response Model for CCC

	DF	**Sum of Squares**	**Mean Sum of Squares**	**F value**	**Estimated P value**
FO (N, P, K)	3	189268	63089	35.1161	0.00
TWI (N, P, K)	3	10499	3500	1.9480	0.18
PQ (N, P, K)	3	111228	37076	20.6368	0.00
Residuals	10	17966	1797		
Lack of fit	5	6345	1269	**0.5459**	0.74
Pure Error	5	11621	2324		
F- Statistics	(9, 10)			**19.23**	0.00

The P- value for the lack of fit was 0.738 (> 0.05) and the F-value was 0.5459 implying that the estimated model has a good fit and is accepted. Further, the lack of fit is not significant relative to the pure error and it was a good fit model.

The equational form of the Response model where the Seed yield (Y) was the dependent variable and X_1, X_2 and X_3 as the independent variable given as:

$$Y = 593.011 + 60.219 X_1 + 31.650 X_2 + 96.070 X_3 + 4.125 X_1 X_2 + 35.625 X_1 X_3 + 5.125 X_2 X_3 - 46.430 X_1^2 - 52.792 X_2^2 - 65.164 X_3^2$$

Where, X_1, X_2 and X_3 be the coded N, P and K values.

4.1.1.3.2 Comparison between Observed and Estimated Seed yield

The Seed yield estimated based on the coefficients of the model for the 20 experimental runs and corresponding observed values are presented in Table 16.

Table16: Comparison between Observed and Estimated Seed yield under CCC

Experimental Runs			Observed Seed yield (kg/ha)	Estimated Seed yield (kg/ha)
N	**P**	**K**		
32	20	16	277	285.561
64	20	16	302	326.499
32	50	16	326	330.361
64	50	16	415	387.799
32	20	34	377	396.201
64	20	34	592	579.639
32	50	34	494	461.501
64	50	34	678	661.439
21	35	25	364	360.3664
75	35	25	548	562.9431
48	10	25	418	390.4206
48	60	25	458	496.8912
48	35	10	257	247.0642
48	35	40	549	570.2437
48	35	25	652	593.011
48	35	25	652	593.011

48	35	25	582	593.011
48	35	25	582	593.011
48	35	25	546	593.011
48	35	25	546	593.011

4.1.1.4 Determination of optimum levels of N, P and K

4.1.1.4.1 Stationary points

The stationary points for the response surface in coded and uncoded values obtained from rsm package in R (Russell., 2020) are given in the Table 17.

Table 17: The stationary points for the Response Model in coded and uncoded values

	N	P	K
Coded values	1.07	0.39	1.04
Uncoded values	65.06	40.88	34.40

4.1.1.4.2 Eigenvalues and Eigenvectors

The eigenvalues obtained for Circumscribed CCC are presented in the Table 18.

Table18: Eigenvalues obtained for CCC

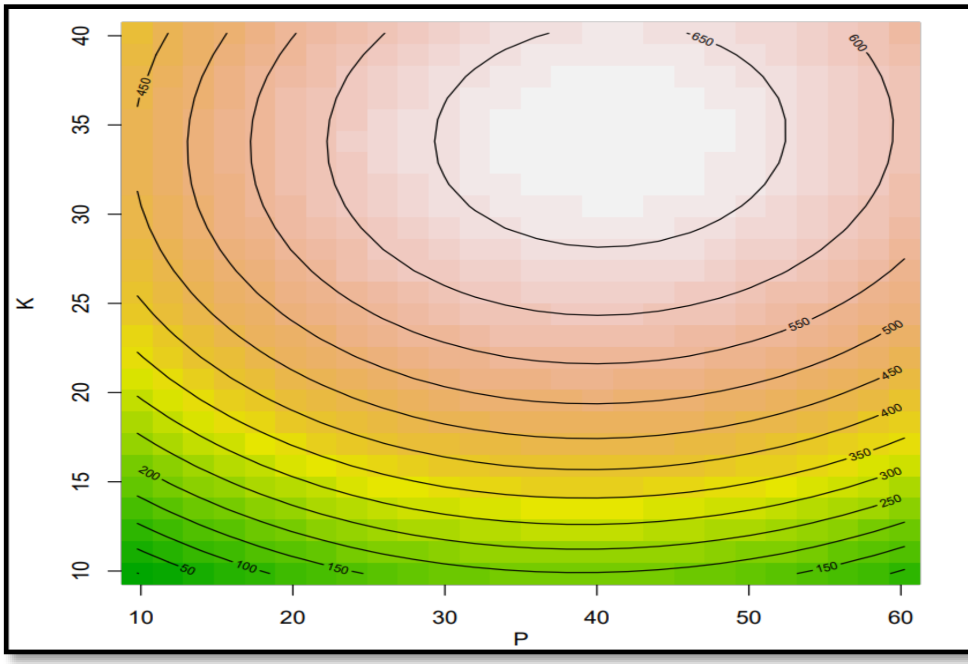
	N (λ_1)	P (λ_2)	K(λ_3)
Eigen Values	-35.13	-53.28	-75.98

The eigenvalues obtained were -35.13, -53.28 and -75.98. Since all the eigenvalues were negative the stationary point was maximizing the response.

4.1.1.5 Contour Plot

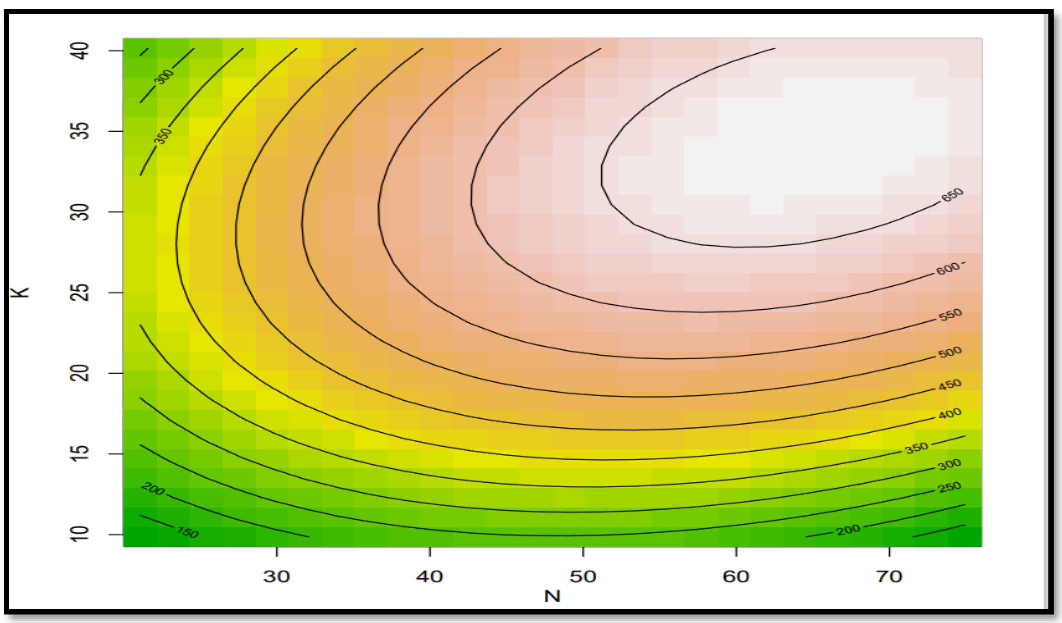
The contour plots (sometimes called Level Plots) are a way to show a three-dimensional surface on a two-dimensional plane. The same response is joined to form contour lines of constant response. Fig 4. shows that when N is kept at 65.06 kg ha^{-1} the values of P above 30 kg ha^{-1} and K beyond 30 kg ha^{-1} were found to be in the optimum range. The yield was maximum beyond 550 kg ha^{-1} as the plot become circular ring-shaped from annular ring indicating optimization. Fig 5. reveals that when P is at 40.88 kg ha^{-1}, the N and K values above 55 kg ha^{-1} and 30 kg ha^{-1} were indicating higher yield. The yield was maximum beyond 550 kg ha^{-1} From Fig 6. it was clear that when K is kept at 34.40 kg ha^{-1}, the values of N and P were found to be the optimum and yield was maximum beyond 550 kg ha^{-1}. Here the plot had more circular rings. The optimum values of N, P and K obtained under CCC design were 65.06, 40.88 and 34.40 kg ha^{-1} respectively.

Fig 7. was the 3D representation of the maximization of yield with P and K keeping N value constant and it shows that the yield was maximum beyond 500 kg ha^{-1}. The 3D representation of N and K with constant P level were presented in Fig 8. The 3D plot also showed a rise in regions beyond 500 kg ha^{-1}. Fig 9. presented the 3D representation of N and P. The graph had a peak at a region beyond 500 kg ha^{-1} while keeping K at a constant level of 36 kg ha^{-1}.It can be concluded that the optimum range of N, P and K were 65.06, 40.88 and 34.40 kg ha^{-1} and the optimum yield was beyond 500 kg ha^{-1}.



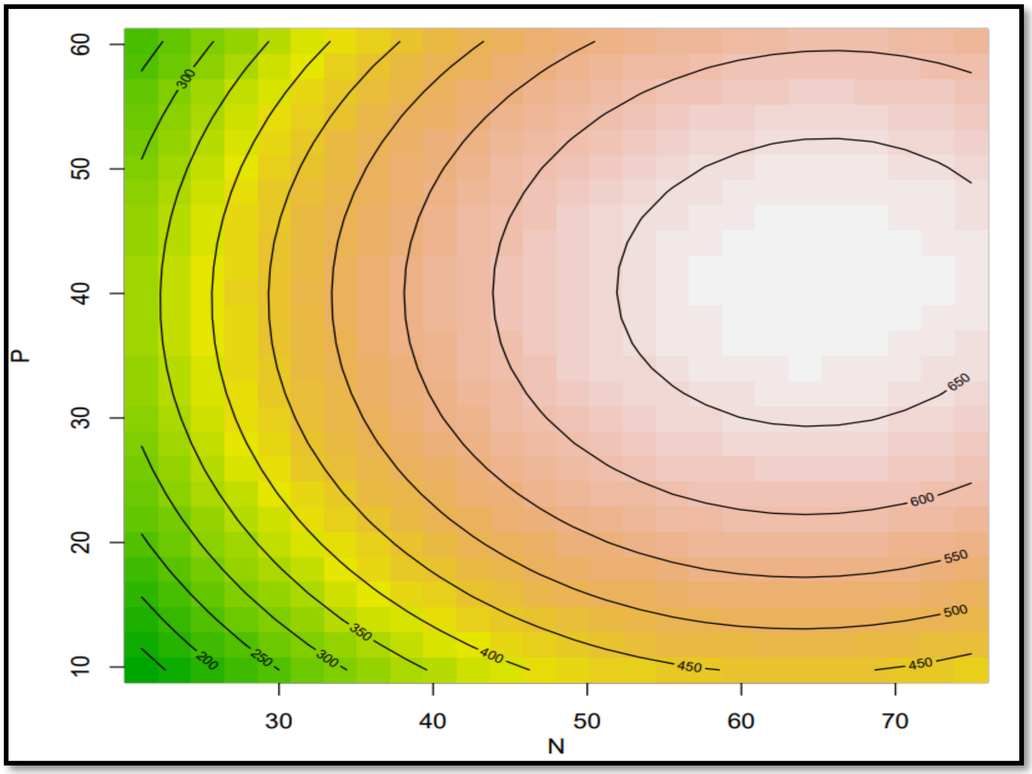
Slice at N= 65.06

Fig 4. Contour plot between P and K keeping N at 65.06



Slice at P = 40.88

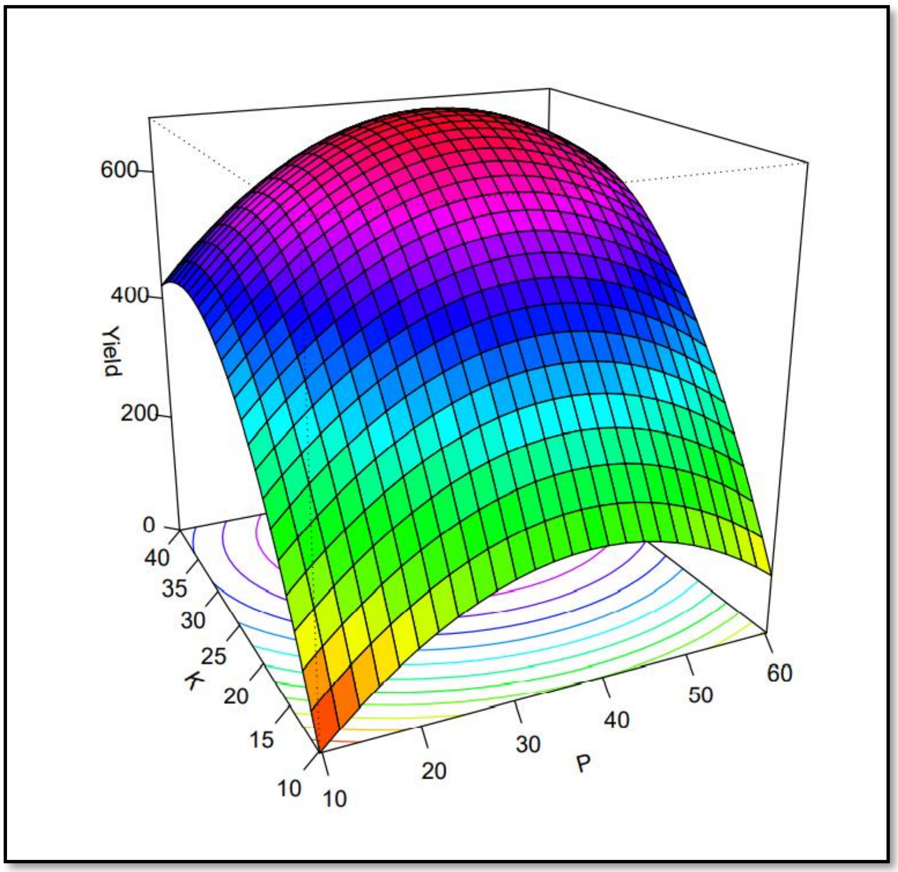
Fig 5. Contour plot between N and K keeping P at 40.8



Slice at K=34.4

Fig 6. Contour plot between N and P keeping K at 34.4

3D Response Surface Plot



Slice at N= 65.06

Fig 7. 3- D Surface plots of P and K when N = 65.06

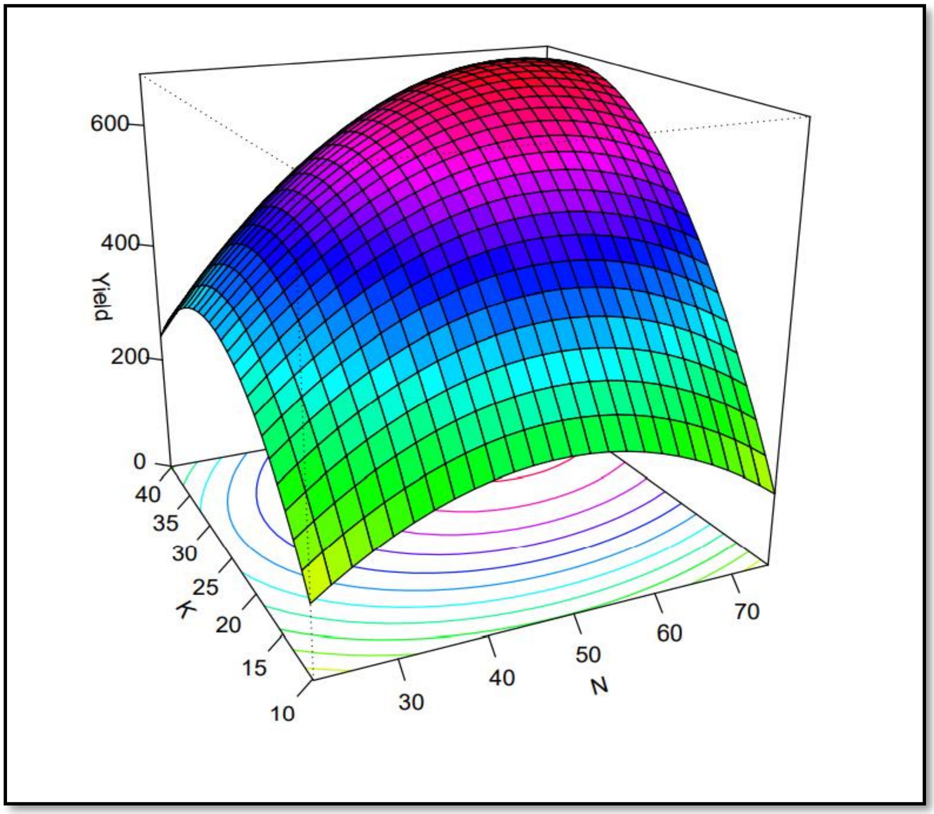
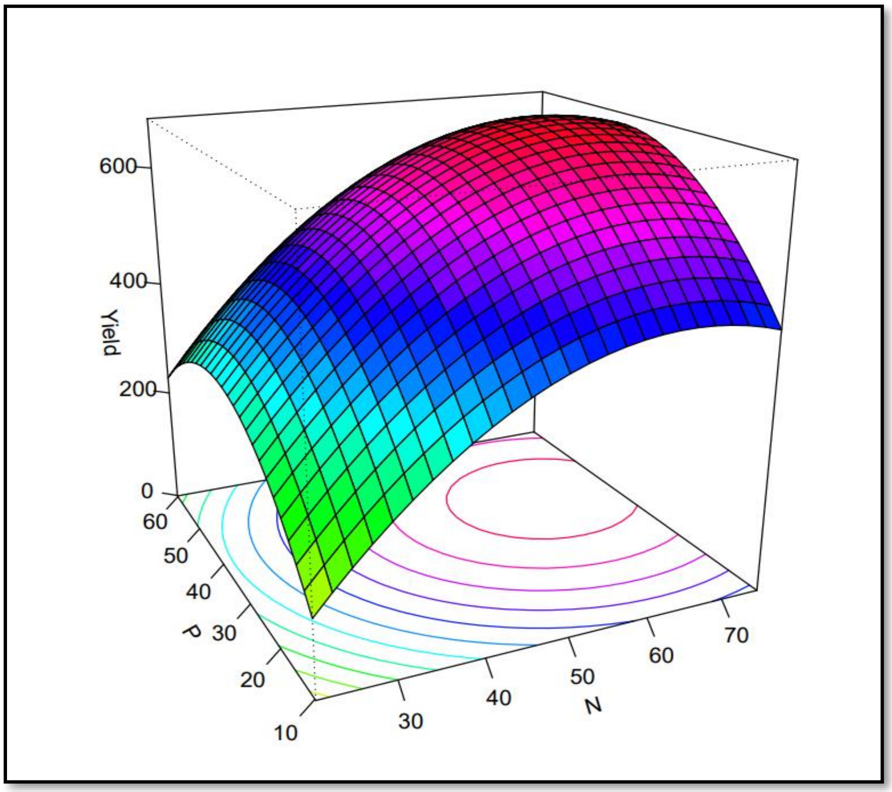


Fig 8. 3- D Surface plots of N and K when P = 40.88



Slice at K=34.4

Fig 9. 3- D Surface plots of N and P when K = 34.4

4.1.2 Central Composite Inscribed (CCI) Design

4.1.2.1 Summary statistics of Growth parameters

The mean, standard deviation, maximum value, minimum value, median and coefficient of variation of growth attributes like plant height, no. of leaves, no. of branches and dry matter production are given in the Table 19.

Table 19: Summary statistics of Growth parameters of Experimental Runs of CCI

Treatments	Plant Height (cm)	No. of leaves	No. of Branches	Dry Matter Production (g/ plant)
T_1	120.5	23	5	13.92
T_2	122.5	32	6	14.97
T_3	119.7	31	6	13.66
T_4	118.4	30	7	14.63
T_5	112.3	37	7	13.74
T_6	114.4	38	8	14.93
T_7	123.5	42	8	16.56
T_8	112.0	39	5	17.06
T_9	113.4	41	6	14.32
T_{10}	99.5	40	7	16.73
T_{11}	107.6	47	8	12.67
T_{12}	113.5	36	7	15.42
T_{13}	115.6	39	8	13.12
T_{14}	110.7	37	8	16.74
T_{15}	117.2	42	9	16.03

T_{16}	108.7	34	5	14.23
T_{17}	111.6	41	7	15.02
T_{18}	118.6	46	8	16.12
T_{19}	119.1	37	6	18.02
T_{20}	118.5	39	8	16.12
Mean	114.36	37.55	6.95	15.2
S. D	5.84	5.60	1.19	1.44
Minimum	99.5	23	5	12.67
Maximum	123.5	47	9	18.02
Median	113.95	38.5	7	15
CV (%)	5.0	15.0	17.0	9.0

The average plant height of the Thilak variety of sesame in the 20 experimental runs was 114.36cm with a standard deviation of 5.84 and the average no. of leaves was 37.55 with a standard deviation of 5.6. Thilak variety of sesame under CCI experimental runs had an average of 6.95 branches with a standard deviation of 1.19. The mean dry matter produced by the variety was 15.2 g per plant with a standard deviation of 1.44. The plant's minimum and maximum height attained were 99.5 cm and 123.5cm respectively. 23 was the minimum no. of leaves and 47 was the maximum no. of leaves whereas the minimum no. of branches was 5 and the maximum no. of branches was 9. The minimum dry matter production was 12.67 g per plant and the maximum was 18.02 g per plant.

4.1.2.2 Summary statistics of yield parameters

The descriptive statistics of days to 50 percent flowering, no. of capsule per plant, no. of seeds per capsule, seed yield per plant, seed yield per ha, haulm yield per plant, haulm yield per ha and harvest index are presented in the Table 20.

Table 20: Summary statistics of Yield attributes of Experimental Runs of CCI design.

Experimental Runs	Days to 50 percent flowering	No. of capsules per plant	No. of seeds per capsule
T_1	38	26.8	34.7
T_2	34	30.2	41.8
T_3	37	27.3	36.1
T_4	38	31.5	42.1
T_5	37	28.4	38.2
T_6	37	37.1	45.9
T_7	34	36.8	46.3
T_8	39	44.6	54.2
T_9	35	29.3	40.2
T_{10}	36	43.1	53.1
T_{11}	37	20.4	32.4
T_{12}	38	41.2	48.4
T_{13}	34	23.1	34.3
T_{14}	34	43.7	52.7
T_{15}	36	33.6	43.6
T_{16}	34	34.7	44.7
T_{17}	38	38.3	46.4
T_{18}	38	38.9	46.2
T_{19}	37	41.2	49.7
T_{20}	38	42.7	50.2

Mean	36.45	34.65	44.06
S. D	1.70	7.24	6.52
Minimum	34	20.4	32.4
Maximum	39	44.6	54.2
Median	37	35.75	45.3
CV (%)	5.0	21.0	15.0

The mean days to 50% flowering was 36.45 with a standard deviation of 1.70 and the average no. of capsules per plant was 34.65 with a standard deviation of 7.24. There was an average of 44.06 seed per capsule with a standard deviation of 6.52. The minimum and maximum days required for 50% flowering were 34days and 39 days respectively. 20.4 and 44.6 were the minimum and maximum no. of capsules per plant respectively and 32.4 and 54.2 were the minimum and maximum no. of seeds per capsule. The coefficient of variation of days to 50% flowering, no. of capsule per plant and no. of seeds per capsule were 5, 21 and 15 respectively.

Table 21: Summary statistics of Yield attributes of Experimental Runs of CCI design.

Experimental Runs	**Seed yield per plant(g)**	**Haulm yield per plant (g)**
T_1	1.26	3.82
T_2	1.75	4.89
T_3	1.42	3.04
T_4	1.84	4.24
T_5	1.53	3.69
T_6	2.33	4.84
T_7	2.31	6.77
T_8	2.85	7.23

T_9	1.58	4.41
T_{10}	2.68	6.46
T_{11}	1.14	2.56
T_{12}	2.59	5.38
T_{13}	1.21	3.22
T_{14}	2.78	6.88
T_{15}	2.08	6.14
T_{16}	2.17	4.17
T_{17}	2.39	4.97
T_{18}	2.42	6.04
T_{19}	2.59	8.16
T_{20}	2.62	5.94
Mean	2.08	5.14
S. D	0.56	1.53
Minimum	1.14	2.56
Maximum	2.85	8.16
Median	2.24	4.93
CV (%)	27.0	30.0

The mean seed yield per plant was 2.08 g with a standard deviation of 0.56 and the average haulm yield per plant was 5.14 g with a standard deviation of 1.53. The minimum and maximum seed yield per plant were 1.14 g and 2.85 g respectively. 2.56 g was the minimum haulm yield per plant and 8.16 g was the maximum. The coefficient of variation of seed yield per plant and haulm yield per plant were 27 and 30 respectivel

Table 22: Summary statistics of Yield attributes of Experimental Runs of CCI design.

Experimental Runs			Seed yield (kg/ha)	Haulm yield (kg/ha)	Harvest Index
N	P	K			
38	26	20	280	849	0.248
58	26	20	388	1087	0.263
38	44	20	315	676	0.318
58	44	20	408	943	0.302
38	26	30	341	819	0.294
58	26	30	518	1076	0.325
38	44	30	518	1505	0.256
58	44	30	634	1606	0.283
31	35	25	352	981	0.264
65	35	25	618	1435	0.301
48	20	25	253	568	0.308
48	50	25	576	1196	0.325
48	35	16	269	716	0.273
48	35	34	618	1528	0.288
48	35	25	462	1364	0.253
48	35	25	482	927	0.342
48	35	25	532	1105	0.325
48	35	25	538	1343	0.286
48	35	25	576	1814	0.241

48	35	25	582	1320	0.306
Mean			463	1142.90	0.29
S. D			127.07	340.01	0.03
Minimum			253	568	0.24
Maximum			634	1814	0.34
Median			500	1096	0.29
CV(%)			27.0	30.0	10.0

The average seed yield of 20 experimental runs obtained by the variety Thilak was 463 kg ha^{-1} with a standard deviation of 127.07, while the average haulm yield obtained was 1142.90 kg ha^{-1} with a standard deviation of 340.01. In the case of the harvest index, the average was 0.29 with a standard deviation of 0.03. The minimum seed yield produced by the Thilak variety was 253 kg ha^{-1} and the maximum was 634 kg ha^{-1} whereas the minimum haulm yield was 568 kg ha^{-1} and the maximum was 1814 kg ha^{-1}. 0.24 was the minimum harvest index and 0.34 was the maximum. The coefficient of variation (C V) of seed yield, haulm yield and harvest index were 27, 30 and 10 respectively.

4.1.2.3 Response surface models

In the investigated 3-factor inscribed CCD, the treatment combinations of N, P and K were factorial points (8), central points (6) and axial points (6). The levels N, P and K considered as factorial points were 38 kg ha^{-1} and 58 kg ha^{-1} for N, 26 kg ha^{-1} and 44kg ha^{-1} for P and 20 kg ha^{-1} and 30 kg ha^{-1} for K and these values were coded as +1 and -1 (explained in chapter three). The dosage of N, P and K taken for central points were 48, 35 and 25 respectively and it was coded as 0. The axial points for the design were 31 kg ha^{-1} and 65 kg ha^{-1} for N, 20 kg ha^{-1} and 50 kg ha^{-1} for P and 16 kg ha^{-1} and 34 kg ha^{-1} for K. The coded value for the levels of axial points was -1.682 and +1.682 for each factor.

4.1.2.3.1 Estimation of the response of Seed yield

The estimated coefficients, standard error, p-value and significance of the coefficients of the grain yield calculated using rsm package in R (Russell., 2020) are presented in Table 23.

Table 23: Estimated Quadratic response surface model based on seed yield

Factors	Coefficients	Standard Error	t- value	P- value
Intercept	529.230	20.583	25.7121	0.00 ***
N	68.926	13.655	5.0475	0.00 ***
P	65.256	13.655	4.7788	0.00 ***
K	88.552	13.655	6.4716	0.00 ***
N P	-9.500	17.843	-0.5324	0.60
N K	11.500	17.843	0.6445	0.53
P K	29.750	17.843	1.6674	0.13
N^2	-19.131	13.291	-1.4394	0.18

P^2	-44.051	13.291	-3.3142	0.00**
K^2	-33.800	13.291	-2.5430	0.03*
Multiple R^2		0.917		
Adjusted R^2		0.8423		

From the table it was clear that the coefficient of the linear effect of N, P and K and the quadratic terms of P and K were significant at 5 percent level of significance. The coefficient of quadratic terms of N was not significant and also the interaction terms were not significant (at 5 percent). The model has a multiple R^2 of 0.92 which is closer to 1 indicating the high correlation between the dependent variable and independent variables. The adjusted R^2 was 0.84, therefore the estimated model was able to explain 84% variation in the data.

Table 24: ANOVA for the estimated Response Model.

	DF	**Sum of Squares**	**Mean Sum of Squares**	**F value**	**Estimated P value**
FO (N, P, K)	3	229718	76573	30.0652	0.00
TWI (N, P, K)	3	8860	2953	1.1597	0.37

PQ (N, P, K)	3	42725	14242	5.5918	0.01
Residuals	10	25469	2547		
Lack of fit	5	13664	2733	**1.1574**	0.44
Pure Error	5	11805	2361		
F- Statistics	(9, 10)			**12.27**	0.00

The P- value for the lack of fit was 0.438 (> 0.05) and the F-value was 1.1574 implying that the estimated model has a good fit and is accepted. Further, the lack of fit is not significant relative to the pure error and it was a good fit model.

The equational form of the Response model where the Seed yield (Y) was the dependent variable and coded X_1, X_2 and X_3 as the independent variable given as:

$$Y = 529.230 + 68.926 X_1 + 65.256 X_2 + 88.373 X_3 - 9.500 X_1 X_2 + 11.500 X_1 X_3 + 29.750 X_2 X_3 - 19.131 X_1^2 - 44.051 X_2^2 - 33.800 X_3^2$$

Where, X_1, X_2 and X_3 be the coded N, P and K values.

4.1.2.3.2 Comparison between Observed and Estimated Seed yield

The Seed yield estimated based on the coefficients of the model for the 20 experimental runs and corresponding observed values are presented in Table 25.

Table 25: Comparison between Observed and Estimated Seed yield

Experimental Runs			Observed Seed yield (kg/ha)	Estimated Seed yield (kg/ha)
N	P	K		
32	20	16	280	335.689
64	20	16	388	375.295
32	50	16	315	331.455
64	50	16	408	427.307
32	20	34	341	335.689
64	20	34	518	515.541
32	50	34	518	544.701
64	50	34	634	686.553
21	35	25	352	359.172
75	35	25	618	591.040
48	10	25	253	294.844
48	60	25	576	514.365
48	35	10	269	284.962
48	35	40	618	582.249
48	35	25	462	529.23
48	35	25	482	529.23
48	35	25	532	529.23

48	35	25	538	529.23
48	35	25	576	529.23
48	35	25	582	529.23

4.1.2.4 Determination of optimum levels of N, P, and K

4.1.2.4.1 Stationary points

The stationary points for the response surface in coded and uncoded values obtained from rsm package in R (Russell., 2020) are given in Table 26.

Table 26: The stationary points for the Response Model in coded and uncoded values

	N	P	K
Coded values	2.16	1.26	2.23
Uncoded values	69.58	46.35	36.15

4.1.2.4.2 Second-order derivative and Eigenvectors

The eigenvalues obtained for Inscribed CCD are presented in the Table 27.

Table 27: Eigenvalues obtained for CCI

	N (λ_1)	P (λ_2)	K(λ_3)
Eigen Values	-17.14	-23.78	-56.07

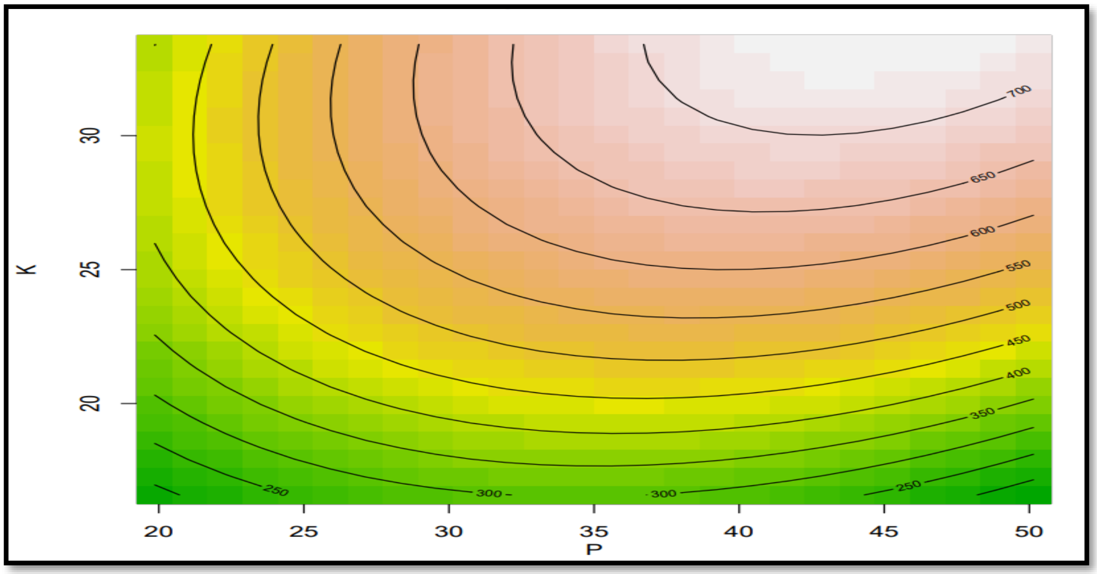
The eigenvalues obtained were -17.14, -23.78 and -56.07. Since all the eigenvalues were negative the stationary point was maximizing the response.

4.1.2.5 Contour Plot

Fig 10. shows that when N is kept at 69.58 kg ha^{-1} the values of P above 35 kg ha^{-1} and K beyond 30 kg ha^{-1} were found to be in the optimum range. The yield was maximum beyond 550 kg ha^{-1} as the plot become circular ring-shaped from annular ring indicating optimization. Fig 11. reveals that when P is at 46.78 kg ha^{-1}, the N and K values beyond 50 kg ha^{-1} and 30 kg ha^{-1} yield were increasing. The yield was maximum beyond 550 kg ha^{-1}. From Fig 12. it was clear that when K is kept at 37.56 kg ha^{-1}, the values of N and P were found to be the optimum and yield was maximum beyond 550 kg ha^{-1}. Here the plot had more circular rings. The optimum values of N, P and K obtained under CCC design were 69.58, 46.35 and 36.15 kg ha^{-1} respectively.

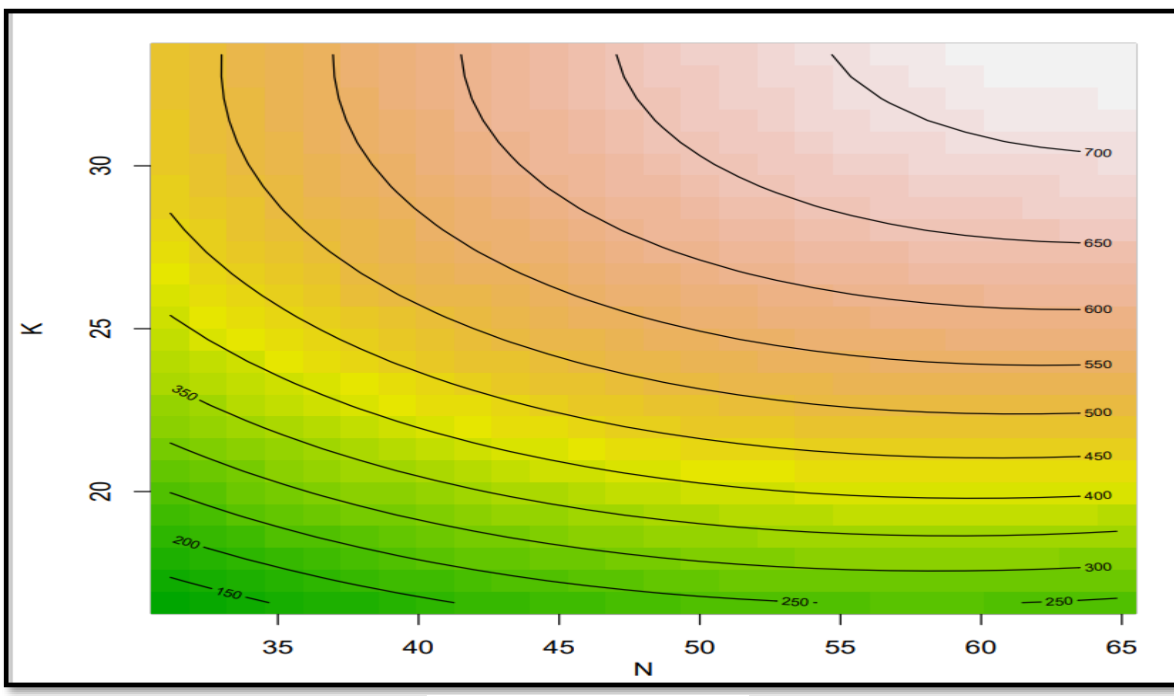
4.1.2.6 3D Response Surface Plot

Fig 13. was the 3D representation of the maximization of yield with P and K keeping N value constant and it shows that the yield was maximum beyond 500 kg ha^{-1}. The 3D representation of N and K with constant P level was presented in Fig 14. The 3D plot also showed a rise in regions beyond 500 kg ha^{-1}. Fig 15. presented the 3D representation of N and P. the graph had a peak at a region beyond 500 kg ha^{-1} while keeping K at a constant level of 36 kg ha^{-1}. It can be concluded that the optimum range of N, P and K were 69.58, 46.35 and 36.15 kg ha^{-1} and the optimum yield was beyond 500 kg ha^{-1}.



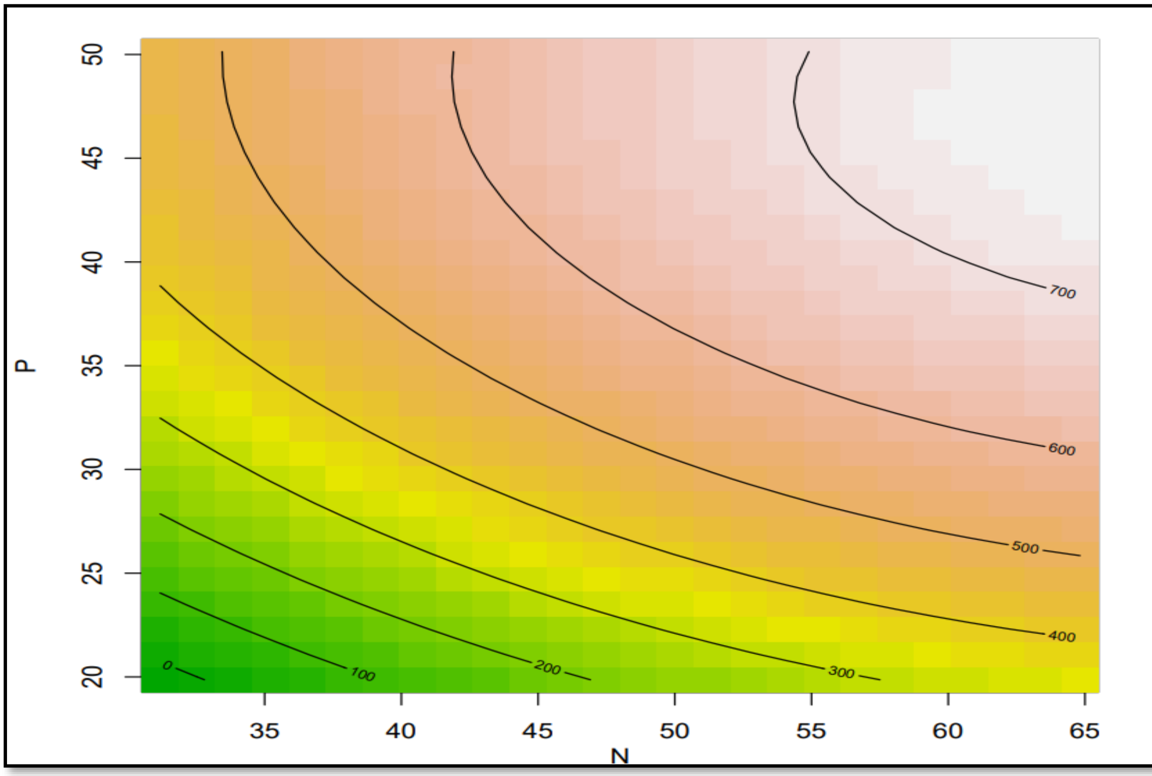
Slice at N= 69.58

Fig 10. Contour plot between P and K keeping N at 69.58



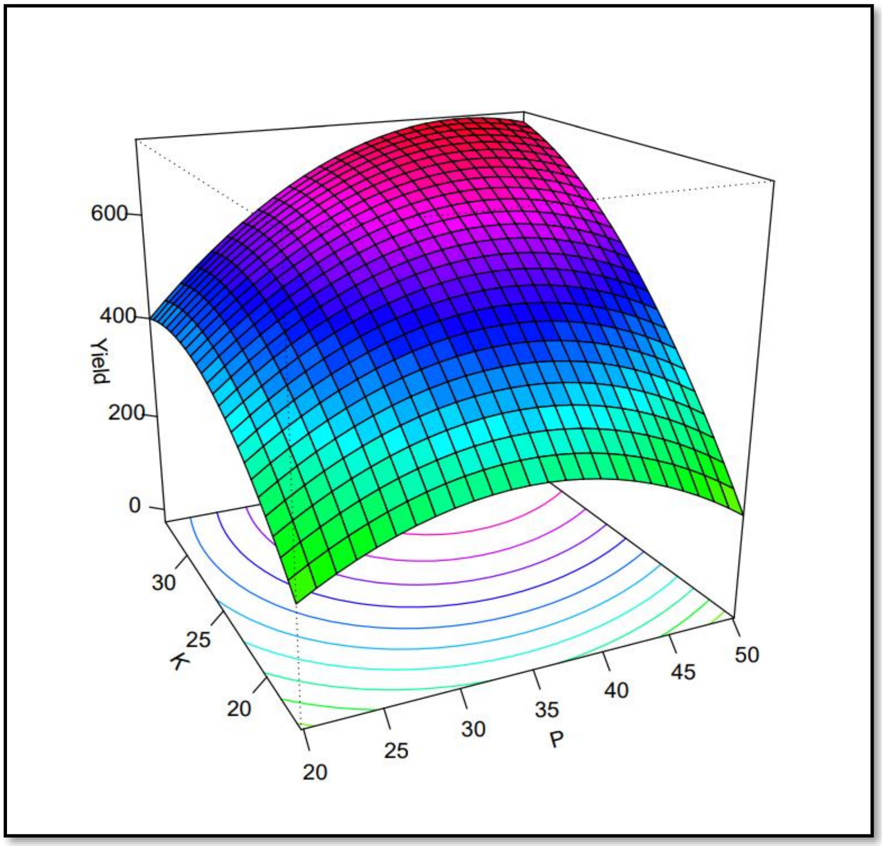
Slice at P= 46.35

Fig 11. Contour plot between N and K keeping P at 46.35



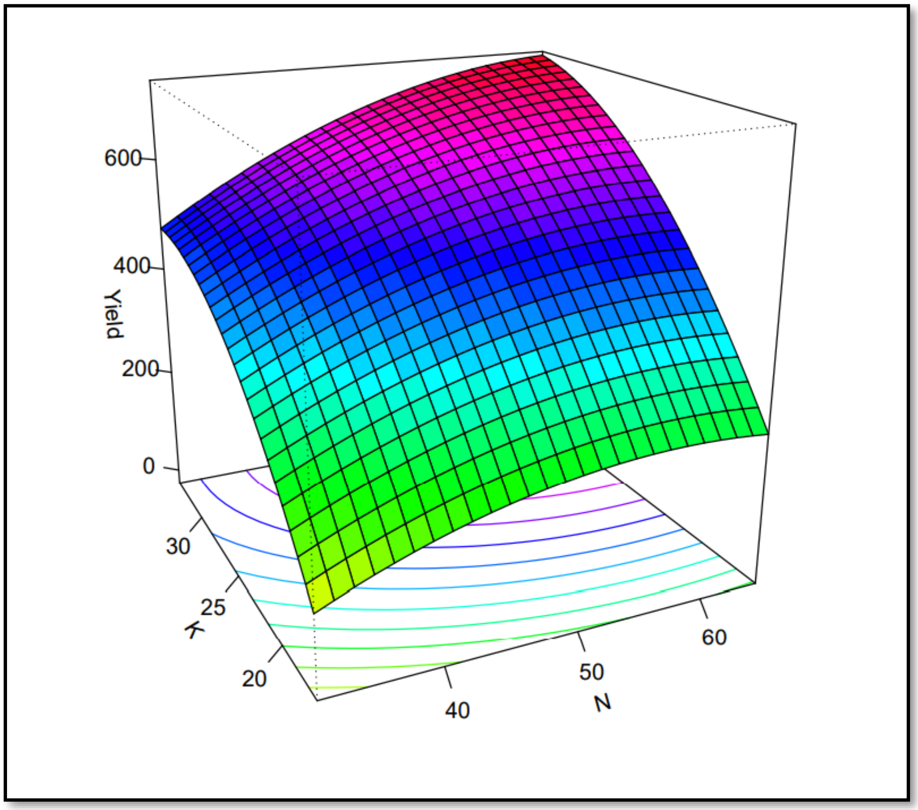
Slice at K= 36.15

Fig 12. Contour plot between N and P keeping K at 36.15



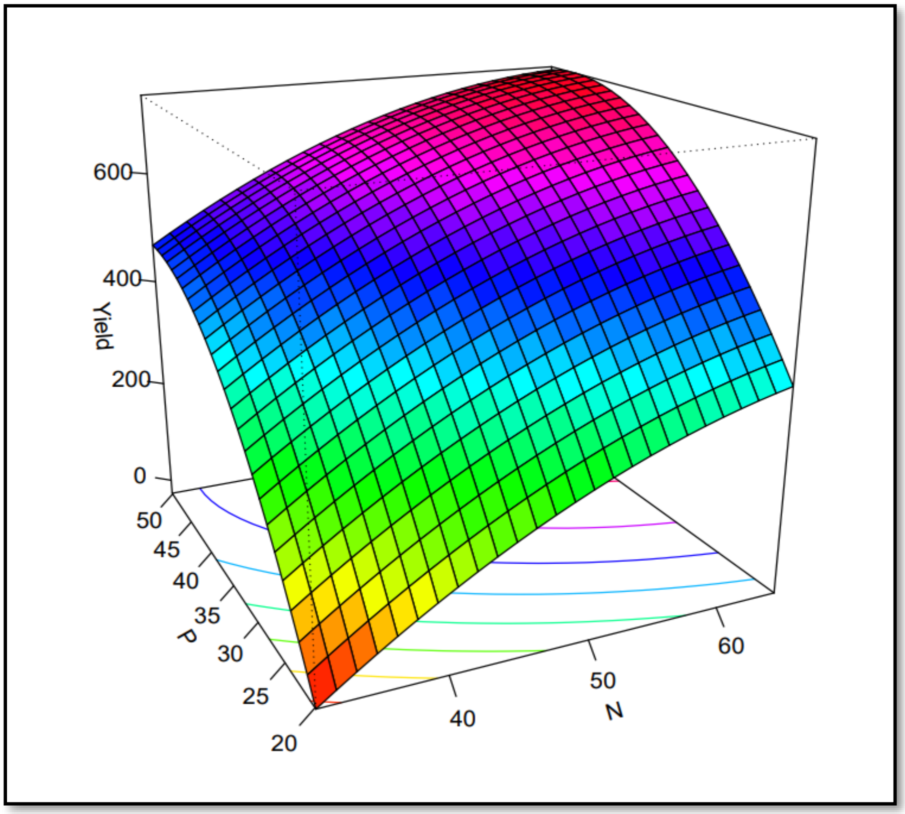
Slice at N= 69.58

Fig 13. 3- D Surface plots of P and K when N = 69.58



Slice at P= 46.35

Fig 14. 3- D Surface plots of N and K when P = 46.35



Slice at K= 36.15

Fig 15. 3- D Surface plots of N and P when K = 36.15

4.1.3 Box-Behnken Design (BBD)

4.1.3.1 Summary statistics of Growth parameters

The mean, standard deviation, maximum value, minimum value, median and coefficient of variation of growth attributes like plant height, no. of leaves, no. of branches and dry matter production are given in the Table 28.

Table 28: Summary statistics of Growth parameters of Experimental Runs of BBD

Treatments	Plant Height (cm)	No. of leaves	No. of Branches	Dry Matter Production (g/ plant)
T_1	118.4	56	6	12.08
T_2	121.5	58	7	14.06
T_3	116.8	61	6	16.51
T_4	120.9	47	6	16.01
T_5	120.4	51	4	12.12
T_6	117.8	63	5	13.86
T_7	119.1	52	8	14.09
T_8	114.3	49	9	16.80
T_9	121.2	53	5	12.74
T_{10}	117.7	62	5	12.80
T_{11}	113.6	56	6	14.21
T_{12}	118.2	49	7	17.79
T_{13}	117.3	55	8	15.67
T_{14}	120.0	61	8	15.68
T_{15}	116.6	54	7	15.44

Mean	118.25	55.13	6.47	14.66
S. D	2.36	5.08	1.41	1.77
Minimum	113.6	47	4	12.08
Maximum	121.5	63	9	17.79
Median	118.2	55	6	14.21
CV(%)	2.0	9.0	22.0	12.0

The average plant height of 15 experimental runs obtained from Thilak variety of sesame was 118.25 cm with a standard deviation of 2.36. The average no. of leaves and average no. of branches were 55.13 and 6.47 with standard deviations of 5.08 and 1.41 respectively. The average dry matter produced by the variety the Thilak was 14.66 g per plant with a standard deviation of 1.77. The minimum and maximum plant heights were 113.6 cm and 120.4 cm respectively. The maximum number of leaves was 63 and 47 was the minimum number of leaves. 12.08 g was the minimum dry matter produced and 17.79 g was the maximum. The coefficient of variations of plant height, no. of leaves, no. of branches and dry matter production were 2, 9, 22 and 12 respectively.

4.1.3.2 Summary statistics of yield parameters

The descriptive statistics of yield attributes (days to 50 percent flowering, no. of capsule per plant, no. of seeds per capsule, seed yield per plant, seed yield per ha, haulm yield per plant, haulm yield per ha and harvest index) are presented in the Table 29.

Table 29: Summary statistics of Yield attributes of Experimental Runs of BBD

Experimental Runs	**Days to 50 percent flowering**	**No. of capsules per plant**	**No. of seeds per capsule**
T_1	34	24.7	31.6
T_2	32	35.7	36.4
T_3	36	46.1	35.1
T_4	37	43.2	36.2
T_5	36	25.9	36.5
T_6	36	32.4	37.5
T_7	33	34.6	38.2
T_8	37	51.6	34.3
T_9	35	26.5	32.3
T_{10}	34	28.3	36.1
T_{11}	36	31.5	37.7
T_{12}	34	49.1	35.6
T_{13}	34	44.1	37.1
T_{14}	35	37.9	38.9
T_{15}	37	39.2	37.1
Mean	35.07	36.72	36.04
S. D	1.53	8.68	2.04

Minimum	32	24.7	31.6
Maximum	37	51.6	38.9
Median	35	35.7	36.4
CV(%)	4.0	24.0	6.0

The mean days to 50% flowering was 35.07 with a standard deviation of 1.53 and the average no. of capsules per plant was 36.72 with a standard deviation of 8.68. There was an average of 36.04 seeds per capsule with a standard deviation of 2.04. The minimum and maximum days required for 50% flowering were 32 days and 37 days respectively. 24.7 and 51.6 were the minimum and maximum no. of capsules per plant respectively and 31.6 and 38.9 were the minimum and maximum no. of seeds per capsule. The coefficient of variation of days to 50% flowering, no. of capsule per plant and no. of seeds per capsule were 4, 24 and 6 respectively.

Table 30: Summary statistics of Yield attributes of Experimental Runs of BBD

Experimental Runs	Seed yield per plant(g)	Haulm yield per plant (g)
T_1	1.28	3.37
T_2	2.03	4.54
T_3	2.41	6.47
T_4	2.34	6.05
T_5	1.37	3.23
T_6	1.82	4.49
T_7	2.11	4.53
T_8	2.58	6.51
T_9	1.48	3.89
T_{10}	1.59	3.72

T_{11}	1.78	4.87
T_{12}	2.47	7.54
T_{13}	2.32	5.72
T_{14}	1.92	5.90
T_{15}	2.05	5.66
Mean	1.97	5.10
S. D	0.41	1.28
Minimum	1.28	3.23
Maximum	2.58	7.54
Median	2.03	4.87
CV (%)	21.0	25.0

The average seed yield per plant was 1.97 g with a standard deviation of 0.41 and the average haulm yield per plant was 5.10 g with a standard deviation of 1.28. The minimum and maximum values for seed yield per plant were 1.28 g and 2.58 g respectively. The minimum haulm yield per plant was 3.23 g and the maximum was 7.54 g. The coefficient of variation for both seed yield and haulm yield per plant were 21 and 25.

Table 31: Summary statistics of Yield attributes of Experimental Runs of BBD.

Experimental Runs			**Seed yield (kg/ha)**	**Haulm yield (kg/ha)**	**Harvest Index**
N	**P**	**K**			
32	20	25	288	748	0.278
64	20	25	468	1008	0.317
32	50	25	582	1439	0.288
64	50	25	563	1345	0.295

32	35	16	326	719	0.312
64	35	16	432	998	0.302
32	35	34	476	1007	0.321
64	35	34	638	1447	0.306
48	20	16	318	864	0.269
48	50	16	368	827	0.308
48	20	34	427	1082	0.283
48	50	34	629	1675	0.273
48	35	25	563	1271	0.307
48	35	25	525	1311	0.286
48	35	25	524	1258	0.294
Mean			475.13	1133.27	0.30
S. D			113.26	284.76	0.02
Minimum			288	719	0.27
Maximum			638	1675	0.32
Median			476	1082	0.30
CV (%)			21.0	25.0	5.0

The average seed yield of 15 experimental runs obtained by the variety Thilak was 475.13 kg ha^{-1} with a standard deviation of 113.26, while the average haulm yield obtained was 1133.27 kg ha^{-1} with a standard deviation of 284.76. In the case of the harvest index, the average was 0.30 with a standard deviation of 0.02. The minimum seed yield produced by the Thilak variety was 288 kg ha^{-1} and the maximum was 638 kg ha^{-1} whereas the minimum haulm yield was 719 kg ha^{-1} and the maximum was 1675 kg ha^{-1}. 0.27 was the minimum harvest index and 0.32 was the maximum. The coefficient of variation (C V) of seed yield, haulm yield and harvest index were 21, 25 and 5 percent respectively.

4.1.3.3 Response surface models

In the investigated 3-factor circumscribed BBD, the treatment combinations of N, P and K were factorial points (8) and central points (7). The levels N, P and K considered as factorial points were 32 kg ha^{-1} and 64 kg ha^{-1} for N, 20 kg ha^{-1} and 50 kg ha^{-1} for P and 16 kg ha^{-1} and 25 kg ha^{-1} for K and these values were coded as +1 and -1 (explained in chapter three). The dosage of N, P and K taken for central points were 48, 35 and 25 respectively and it was coded as 0.

4.1.3.3.1 Estimation of the response of Seed yield

The estimated coefficients, standard error, p-value and significance of the coefficients of the grain yield calculated using rsm package in R (Russell., 2020) are presented in Table 32.

Table 32: Estimated Quadratic response surface model based on seed yield

Factors	Coefficients	Standard Error	t- value	P- value
Intercept	537.333	17.871	30.0679	0.00***
N	53.625	10.944	4.9002	0.00 ***
P	80.125	10.944	7.3217	0.00***
K	90.750	10.944	8.2926	0.00***
N P	-49.750	15.476	-3.2146	0.02*
N K	14.0	15.476	0.9046	0.40
P K	38.0	15.476	2.4553	0.05
N^2	-14.792	16.108	-0.9183	0.40
P^2	-47.292	16.108	-2.9358	0.03*

K^2	-54.542	16.108	-3.3859	0.02
Multiple R^2		0.9733		
Adjusted R^2		0.9253		

From the table, it was clear that the coefficient of the linear effect of N, P and K, the quadratic term of P and the interaction term N P were significant at 5 percent. The model has a multiple R^2 of 0.97 which is closer to 1 indicating the high correlation between the dependent variable and independent variables. The adjusted R^2 was 0.92, therefore the estimated model was able to explain 92% variation in the data.

Table 33: ANOVA for the estimated Response Model.

	DF	**Sum of Squares**	**Mean Sum of Squares**	**F value**	**Estimated P value**
FO (N, P, K)	3	140250	46750	48.7953	0.00
TWI (N, P, K)	3	16460	5487	5.7268	0.04
PQ (N, P, K)	3	18093	6031	6.2950	0.04
Residuals	5	4790	958		
Lack of fit	3	3802	1267	**2.5636**	0.29

Pure Error	2	989	494		
F- Statistics	(9, 10)			**20.27**	0.00

The P- value for the lack of fit was 0.293 (> 0.05) implying that the estimated model has a good fit and is accepted. Further, the lack of fit is not significant relative to the pure error and it was a good fit model.

The equational form of the Response model where the Seed yield (Y) was the dependent variable and coded X_1, X_2 and X_3 as the independent variable given as:

$Y= 537.333 + 53.625\, X_1 + 80.125\, X_2 + 90.750\, X_3 – 49.750\, X_1 X_2 + 14.0\, X_1 X_3 +38.0\, X_2 X_3 – 14.792\, X_1^2 – 47.292\, X_2^2 – 54.542\, X_3^2$

Where, X_1, X_2 and X_3 be the coded N, P and K values.

4.1.3.3.2 Comparison between Observed and Estimated Seed yield

The Seed yield estimated based on the coefficients of the model for the 20 experimental runs and corresponding observed values are presented in Table 34.

Table 34: Comparison between Observed and Estimated Seed yield

Experimental Runs			Observed Seed yield (kg/ha)	Estimated Seed yield (kg/ha)
N	P	K		
32	20	25	288	291.75
64	20	25	468	498.50
32	50	25	582	551.50
64	50	25	563	559.25
32	35	16	326	337.62
64	35	16	432	416.87
32	35	34	476	491.12

64	35	34	638	626.37
48	20	16	318	302.62
48	50	16	368	386.87
48	20	34	427	408.12
48	50	34	629	644.37
48	35	25	563	537.33
48	35	25	525	537.33
48	35	25	524	537.33

4.1.3.4 Determination of optimum levels of N, P, and K

4.1.3.4.1 Stationary points

The stationary points for the response surface in coded and uncoded values obtained from rsm package in R (Russell., 2020) are given in the Table 35.

Table 35: The stationary points for the Response Model in coded and uncoded values

	N	P	K
Coded values	1.20	0.71	1.23
Uncoded values	67.17	45.69	36.11

4.1.3.4.2 Eigenvalues and Eigenvectors

The eigenvalues obtained for Box-Behnken Design are presented in the Table 36.

Table 36: Eigenvalues obtained for Box-Behnken Design

	N (λ_1)	P (λ_2)	K(λ_3)
Eigen Values	-1.15	-37.50	-77.97

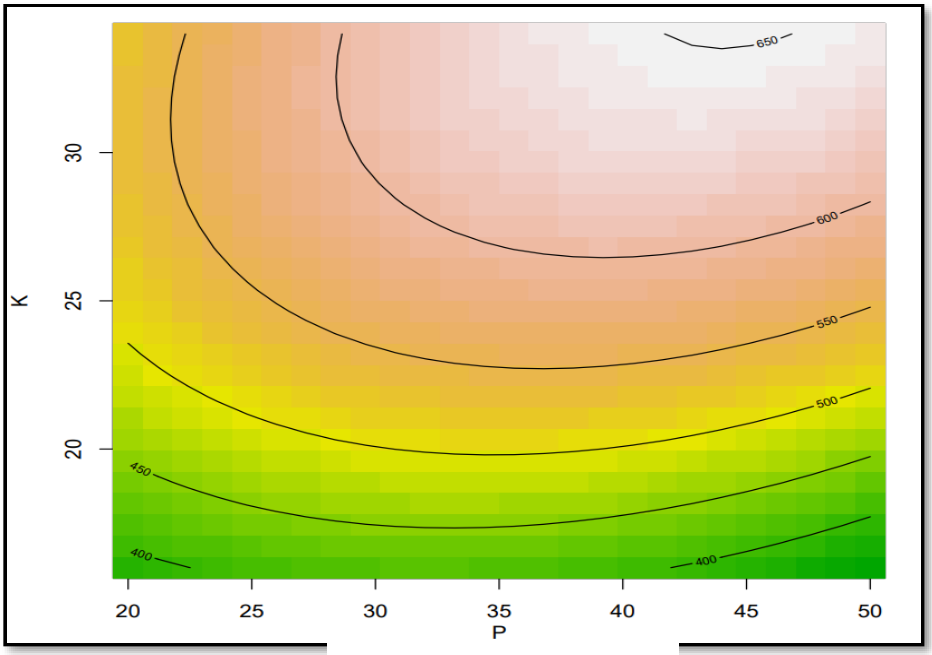
The eigenvalues obtained were -1.15, -37.50 and -77.97. Since all the eigenvalues were negative the stationary point was maximizing the response.

4.1.3.5 Contour Plot

Fig 16. shows that when N is kept at 67.17 kg ha^{-1} the values of P and K above 30 kg ha^{-1} were found to be in the optimum range. The yield was maximum beyond 600 kg ha^{-1} as the plot become circular ring-shaped from annular ring indicating optimization. Fig 17. reveals that when P is at 45.69 kg ha^{-1}, the N and K values were 55 kg ha^{-1} and 30 kg ha^{-1} indicating higher yield. The yield was maximum beyond 600 kg ha^{-1}. From Fig 18. it was clear that when K is kept at 36.11 kg ha^{-1}, the values of N and P were found to be the optimum and yield was maximum beyond 600 kg ha^{-1}. Here the plot had more circular rings.

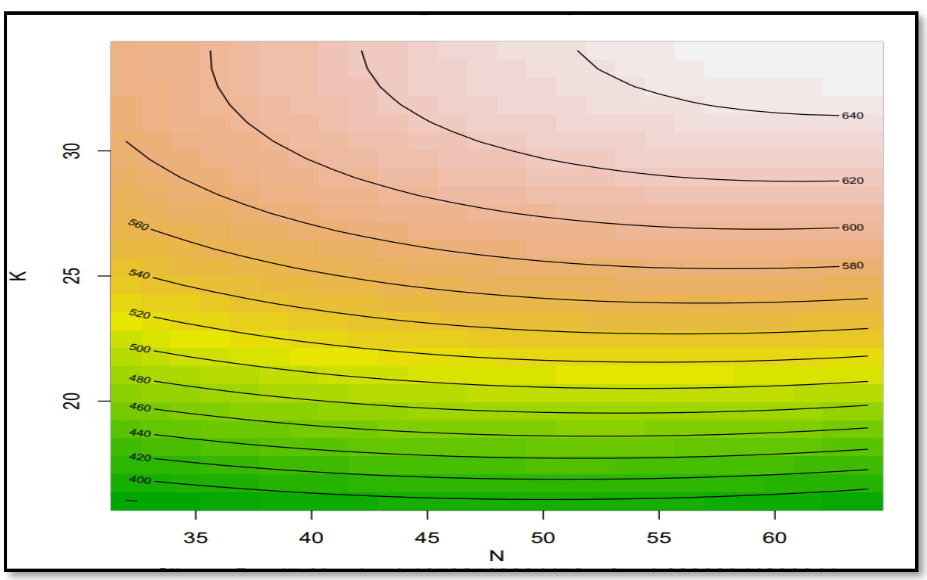
4.1.3.6 3D Response Surface Plot

Fig 19. was the 3D representation of the maximization of yield with P and K keeping N value constant and it shows that the yield was maximum beyond 600 kg ha^{-1}. The 3D representation of N and K with constant P level was presented in Fig 20. The 3D plot also showed a rise in regions beyond 600 kg ha^{-1}. Fig 21. presented the 3D representation of N and P. the graph had a peak at a region beyond 600 kg ha^{-1} while keeping K at a constant level of 36.11 kg ha^{-1}. It can be concluded that the optimum range of N, P and K were 67.17, 45.69 and 36.11 kg ha^{-1} and the optimum yield was beyond 600 kg ha^{-1}.



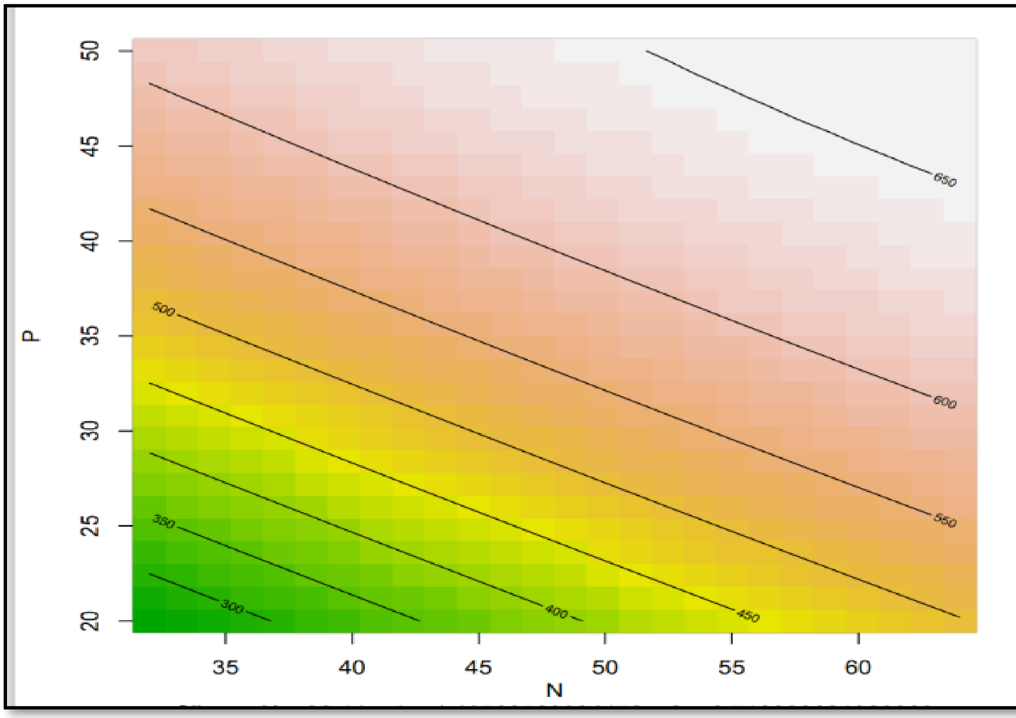
Slice at N =67.17

Fig 16. Contour plot between P and K keeping N at 67.17



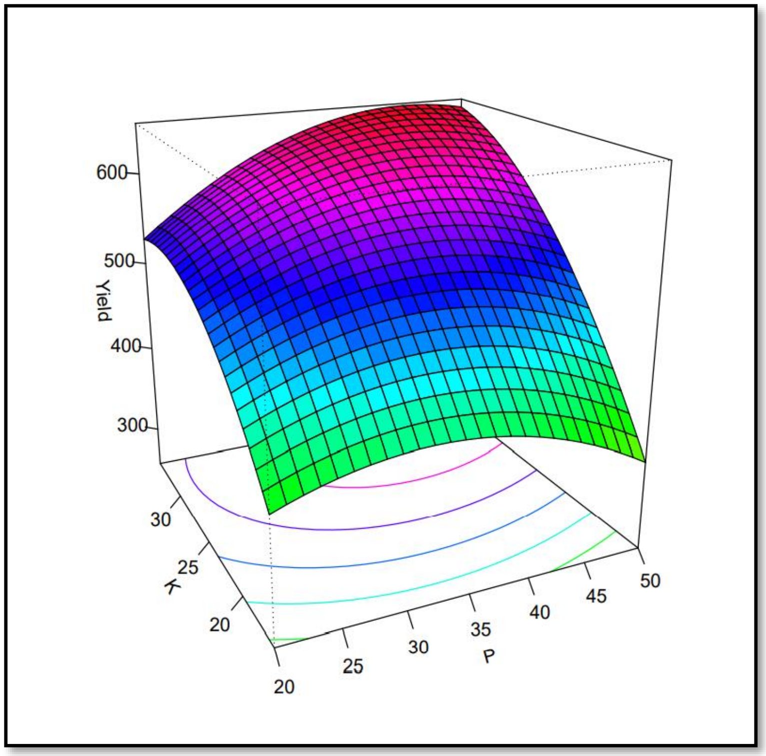
Slice at P = 45.69

Fig 17. Contour plot between N and K keeping P at 45.69



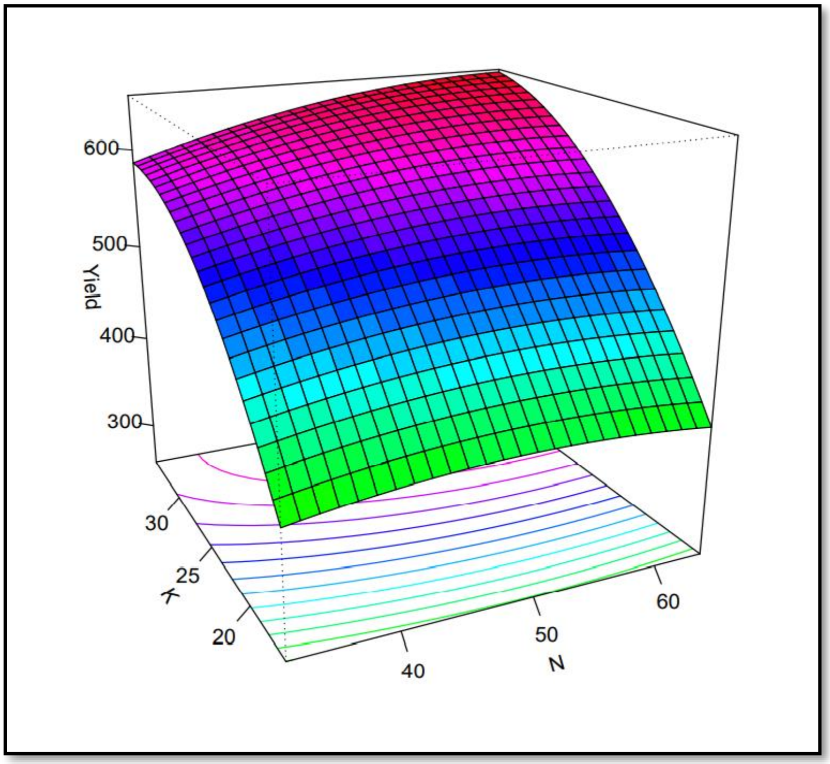
Slice at K= 36.11

Fig 18. Contour plot between N and P keeping K at 36.11



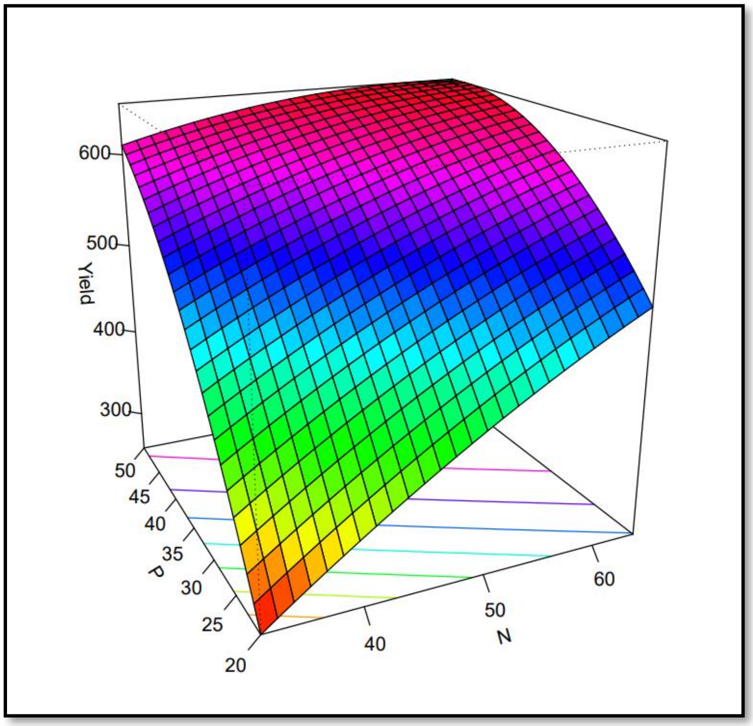
Slice at N = 67.17

Fig 19. 3- D Surface plots of P and K when N = 67.17



Slice at P = 45.69

Fig 20. 3- D Surface plots of N and K when P = 45.69



Slice at K = 36.11

Fig 21. 3- D Surface plots of N and P when K = 36.11

Conclusion

The three fitted models under CCC, CCI, BBD were a good fit with an insignificant lack of fit ($p > 0.05$) at the 95% confidence level. The multiple R^2 and adjusted R^2 values gives a good view of the result. The BBD model has multiple R^2 and adjusted R^2 values that are greater than the CCD for the response. Multiple R^2 values of 0.94, 0.92, and 0.97 were found for the quadratic models created using CCC, CCI, and BBD, respectively. The quadratic models' adjusted R^2 scores were 0.89, 0.84, and 0.92. In all three models, R^2 values were found to be greater than 0.8 indicating a good fit of the models. Among the three models, BBD had higher R^2 values than CCC and CCI, so the quadratic model developed through BBD had good predictability compared to other models. In addition, BBD has the advantage of requiring fewer experiments (15 batches for 3 variables), i.e.; BBD provides yield optimization with a low number of runs. At a 95% confidence level, the resulting models were determined to be significant, sufficient, and predictive. RSM is an effective and economically viable technique that can be adapted for optimizing fertilizer trials. According to the results of this study, the predictability of designs, BBD has better prediction rather than the other designs.

The optimum fertilizer dose of N, P and K obtained under the three designs were given in the Table 37.

Table 37: The optimum fertilizer dose and R^2 values obtained under three designs

Design	**N (kg ha^{-1})**	**P (kg ha^{-1})**	**K (kg ha^{-1})**	**R^2**	**Adj. R^2**
CCC	65.06	40.88	34.40	0.94	0.89
CCI	69.58	46.35	36.15	0.92	0.84
BBD	67.17	45.69	36.11	0.97	0.92

The results show that the model developed under BBD was best-fit, so the optimum N, P and K doses for the Thilak variety of sesame were 67.17, 45.69, and 36.11 kg ha^{-1}. In the Onattukara region, the recommended dose of N, P and K as per the package of practice recommendations for sesame is 30:15:30 kg/ha (KAU, 2016). The obtained N, P and K ratio was higher compared to the recommended levels, this may be because of the fact that the initial soil nutrient levels were low (results were mentioned in Materials & Methods chapter). Since the soil in Onattukara is sandy, there will be more nutrient leaching. This could also contribute to greater N, P, and K levels obtained. The obtained N, P and K levels are closer to the recommended dose of sesame in Maharashtra and Chhattisgarh under summer conditions (Sesame- Technology for maximizing production; ICAR). On further experimentation, we will be able to understand that the above-given values are optimum N, P and K for maximization of yield.

4.2 Advantages and limitations of RSM

The response surface method is useful for analysing the problem when several independent variables influence the dependent variable or response. RSM is used in developing new processes and optimizing their performance and obtaining optimum combinations of levels of various quantitative factors. RSM produces an empirical polynomial model which gives an approximation of the true response surface over a factor region. It gives optimal settings for process factors so, researchers can minimize, maximize or stabilize the response of interest. By overlaying contour maps from multiple responses, RSM can be used to find the region of operability. In response surface designs more levels for each of the factors can be accommodated and still the design can be conducted in fewer runs.

The application of response surface methods in industrial research has been extensive, but it doesn't seem to be as common in studies involving agriculture and related fields of study. This can be because the experimental settings used in agricultural sciences differ from those used in industrial experiments. The agricultural experiments take more time i.e., a year or more to complete. A wider region of factor space needs to be included when analysing agricultural trial data. In the agriculture field, it is very difficult to manipulate or control factor levels. Because of this, in agricultural studies unequally spaced factor levels and numerous levels of a factor are undesirable. In some agricultural research, elaborate blocking is needed for controlling environmental variability and sometimes it may also require splitting of experimental units or plots. The elaborate blocking and splitting of experimental units make the experimental system more complex. A simple quadratic response function over the region of interest could not offer a good approximation. For this reason, designs for fitting response surfaces in agricultural experiments must provide both an estimate of the coefficients and test the "goodness of fit" of an assumed quadratic response surface. Taking into account all of these factors, it might be preferable for agricultural experiments to be more reliable, less model-dependent, able to support a more flexible blocking system and possess equispaced factor values in more combinations.

4.3 Development of rsm package

For the development of an open- source package based on Response Surface Methodology, a set of R codes were constructed. The package consists of two types of central composite designs (CCC and CCI) and Box- Behnken design (BBD). Each of these is made for 2 and 3 factors.

4.3.1 Algorithm

4.3.1.1 Design Matrix

The design matrix is a matrix representation of treatment combinations in coded value and the number of treatment combinations vary with the number of factors.

4.3.1.1.1 For 2 factors

The matrix used for 2 factors and α = 1.414 is presented below.

For CCD

$$\begin{vmatrix} -1 & -1 \\ 1 & -1 \\ -1 & 1 \\ 1 & 1 \\ 0 & 0 \\ 0 & 0 \\ -1.414 & 0 \\ 1.414 & 0 \\ 0 & -1.414 \\ 0 & 1.414 \\ 0 & 0 \\ 0 & 0 \end{vmatrix}$$

For BBD

$$\begin{vmatrix} -1 & -1 \\ 1 & -1 \\ -1 & 1 \\ 1 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{vmatrix}$$

The design matrix of CCD consists of 4 factorial points, 4 axial points and 4 central points in case of 2 factors with α = 1.414. The design matrix BBD consists 4 factorial points and 4 central points in case of 2 factors with α = 1.414.

4.3.1.1.2 For 3 factors

For CCD

$$\begin{vmatrix} -1 & -1 & -1 \\ 1 & -1 & -1 \\ -1 & 1 & -1 \\ 1 & 1 & -1 \\ -1 & -1 & 1 \\ 1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & 1 & 1 \\ -1.682 & 0 & 0 \\ 1.682 & 0 & 0 \\ 0 & -1.682 & 0 \\ 0 & 1.682 & 0 \\ 0 & 0 & -1.682 \\ 0 & 0 & 1.682 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{vmatrix}$$

For BBD

$$\begin{vmatrix} -1 & -1 & -1 \\ 1 & -1 & -1 \\ -1 & 1 & -1 \\ 1 & 1 & -1 \\ -1 & -1 & 1 \\ 1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{vmatrix}$$

The design matrix of CCD consists of 8 factorial points, 6 axial points and 6 central points in case of 3 factors with $\alpha = 1.682$. The design matrix BBD consists 8 factorial points and 7 central points in case of 3 factors with $\alpha = 1.682$.

4.3.2 Algorithm for Design matrix and response surface model

4.3.2.1 Algorithm for CCD

Step1. Input the number of factors

Step2. Input the minimum value and the maximum values of the factors

Step3. Determine mid-point of each factor

Step4. Determine the value of α ($\alpha = \sqrt[4]{2^k}$ for k= 2,3,4…)

Step5. Generate the design matrix

Step6. Input the responses based on the design matrix

Step7. Perform response surface models

Step8. Choose the best model

Step9. Find the stationary points

Step10. Check for the second-order condition

Step11. Check stationary points are outside or inside the specified range

Step12. Check for optimum using contour plots also

Step13. If the stationary points are outside the range of the levels of the factors, choose ridge analysis to find the optimum level of each factor

Step14. stop

4.3.2.2 Algorithm for BBD

Step1. Input the number of factors

Step2. Input the minimum value and the maximum values of the factors

Step3. Determine mid-point of each factor

Step4. Generate the design matrix

Step5. Input the responses based on the design matrix

Step6. Perform response surface models

Step7. Choose the best model

Step8. Find the stationary points

Step9. Check for the second-order condition

Step10. Check stationary points are outside or inside the specified range

Step11. Check for optimum using contour plots also

Step12. If the stationary points are outside the range of the levels of the factors, choose ridge analysis to find the optimum level of each factor

Step13. Stop

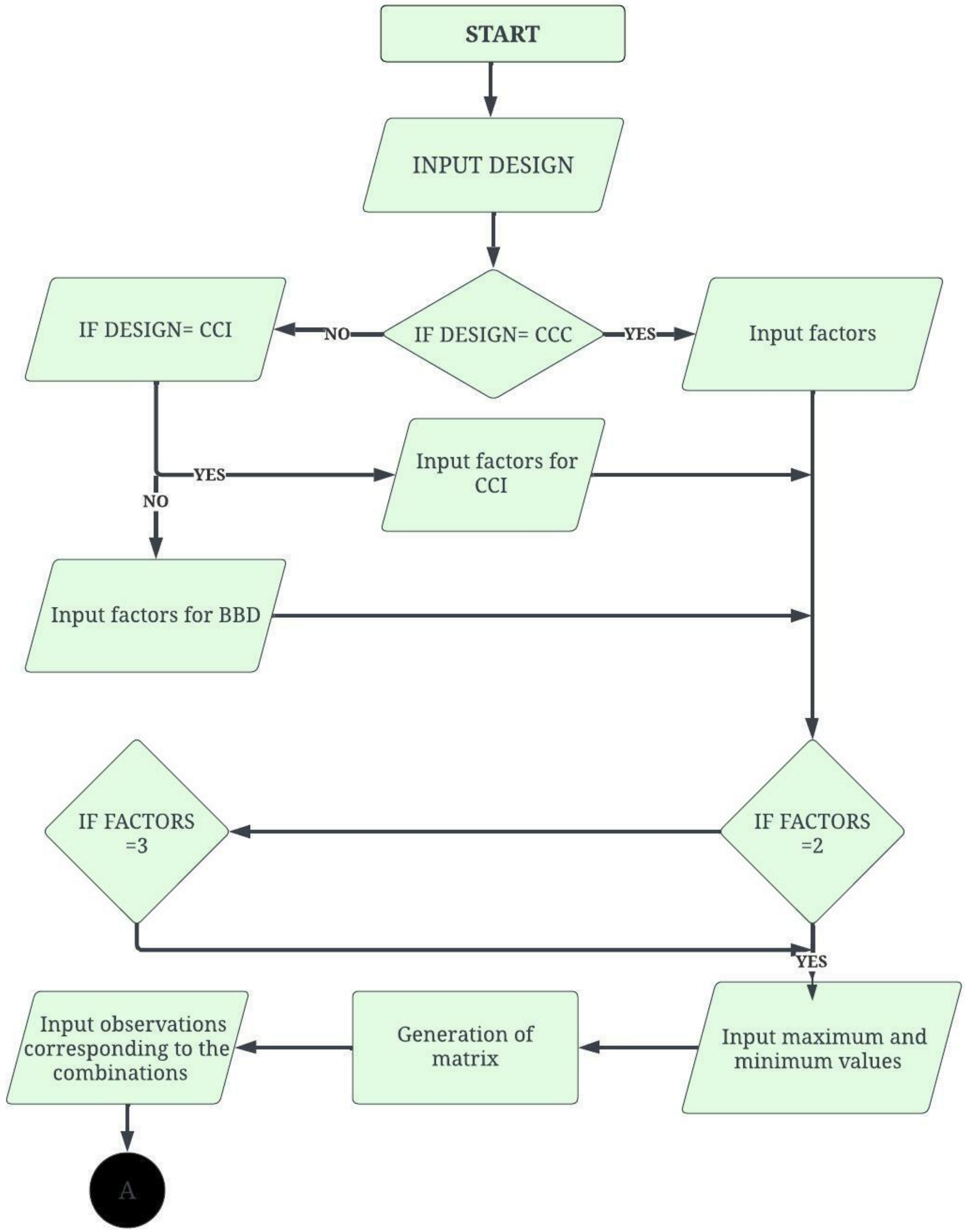
The algorithm presented in sections 4.3.2.1 and 4.3.2.2 were combined together to develop the web application based on shiny in R. The application will be hosted from cloud server. The shiny web application will be converted into an R package. The different steps adopted for solving RSM are represented in the flowchart.

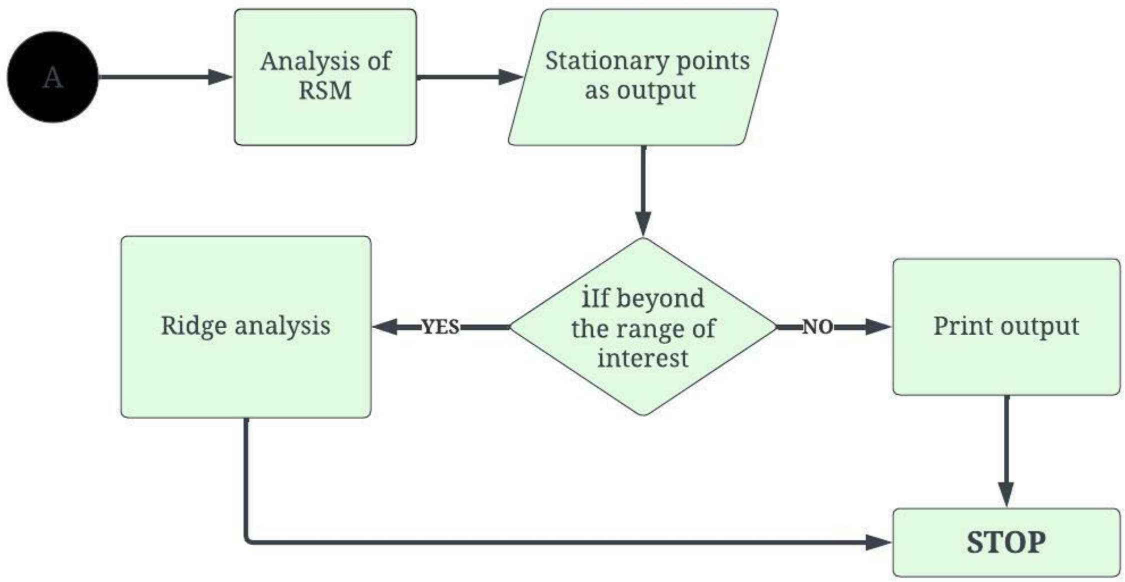
This open-source user-friendly R package aims for benefiting agricultural researchers in optimizing the response of interest. This R package is based on Central composite design and Box-Behnken design (BBD) in Response surface methodology. The software consists of two types of Central composite design (i.e., circumscribed CCD and inscribed CCD) and Box-Behnken design. Each of these is made for 2 and 3 factors. The package has 3 sections. The first section is for design generation where one can generate CCD and BBD designs without any code. In the second section, one can do the analysis of the CCD and BBD. The third section consists of graphs and plots, here the users can generate the 2D contour plots and the 3D surface plots for further analysis.

FUTURE LINE OF STUDY

- This type of study has to be conducted in multilocation in different seasons to confirm the results.
- This study can be extended to other varieties of sesame.
- Similar studies can be undertaken for crops other than sesame.
- The package can be modified with the addition of other designs.
- An option for further analysis, if the stationary point is a saddle point, could be incorporated into the package.

4.3.3 Flowchart for RSM




A
Analysis of RSM
Stationary points as output
iIf beyond the range of interest
YES
NO
Ridge analysis
Print output
STOP

4.3.4 DISPLAY OF RSM PACKAGE

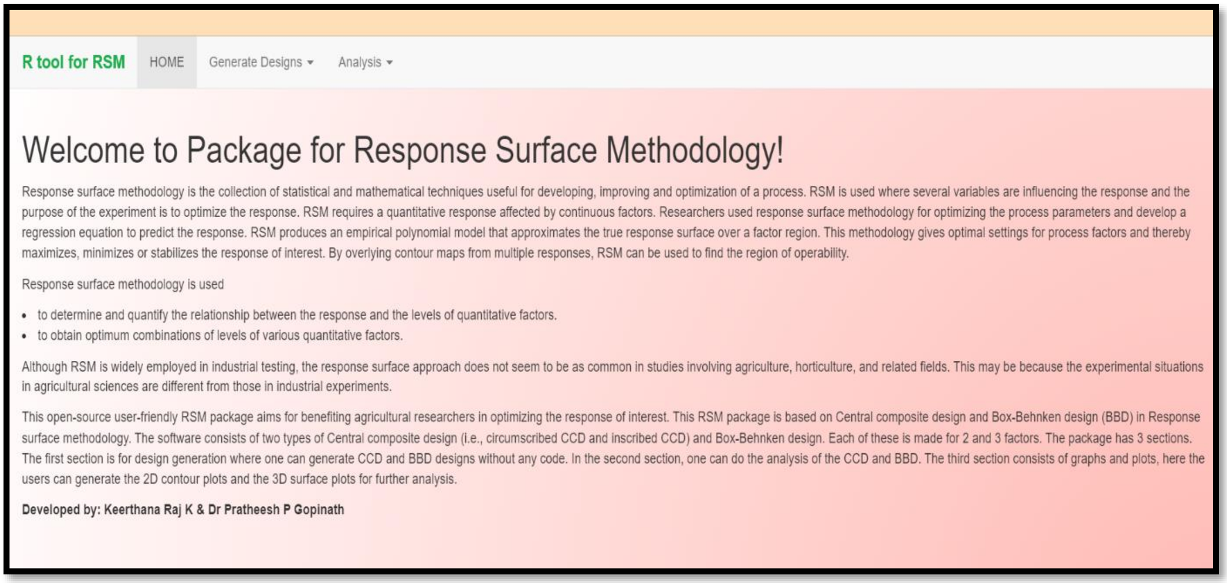


Fig 22. Display of the home page of the package

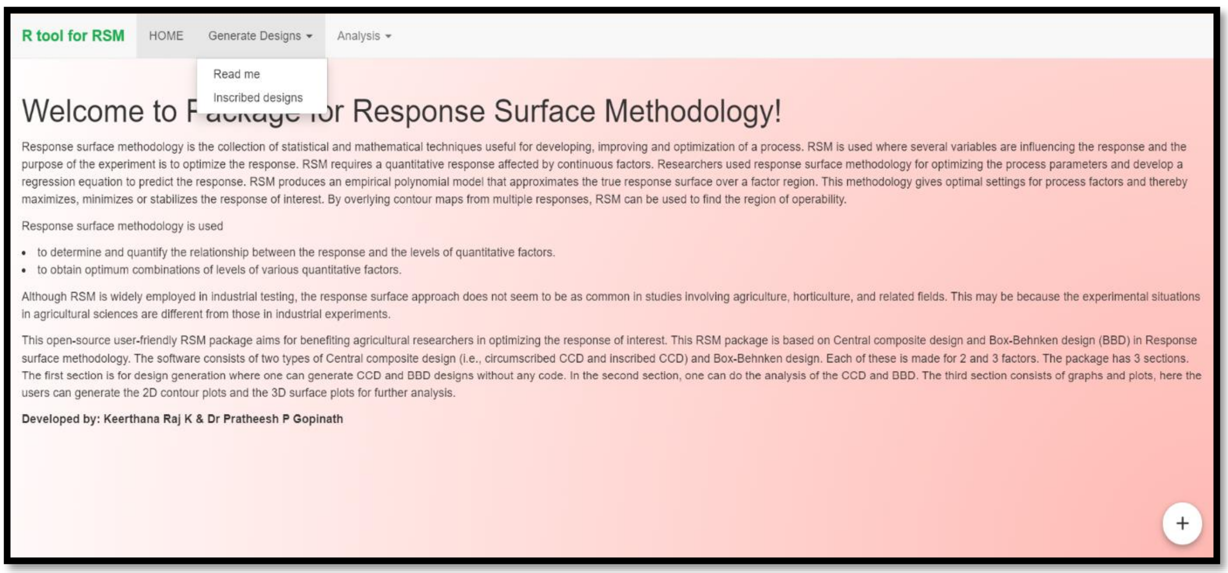


Fig 23. Selection of Design

Fig 24. Design Generation

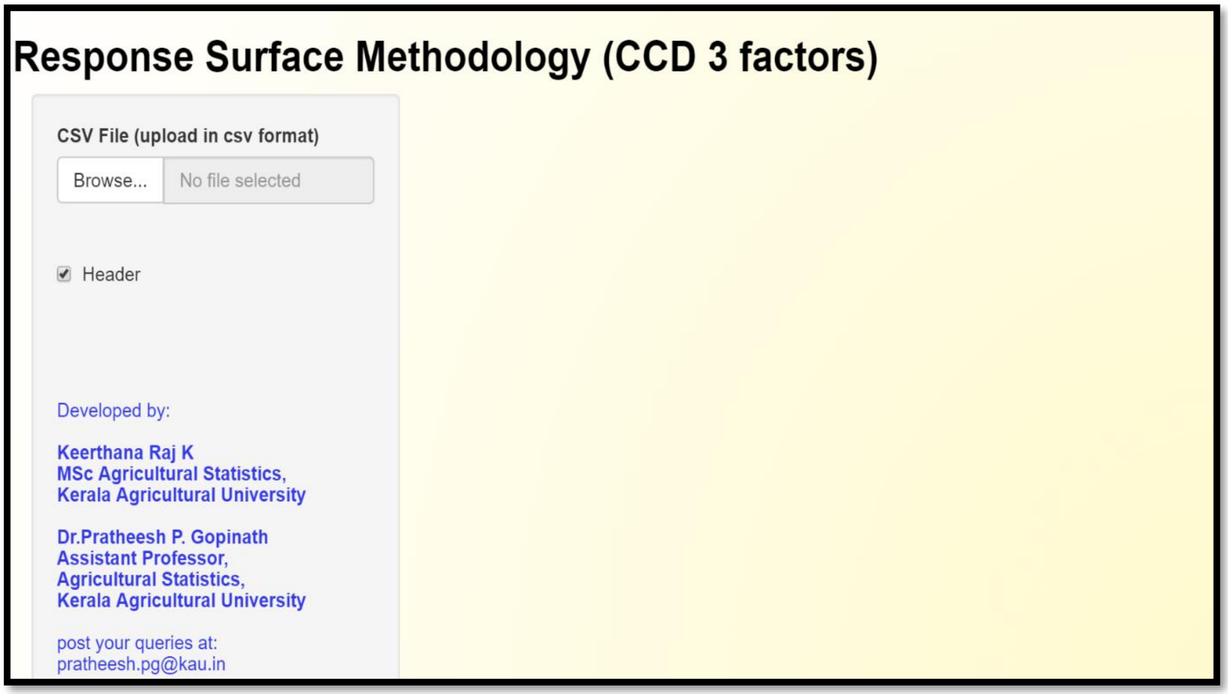


Fig 25. RSM analysis

Summary

5. SUMMARY

The research work entitled “Classical response surface designs for fertilizer trials in sesame (*Sesamum indicum* L.)” was carried out at Onattukara Regional Agricultural Research Station, Kayamkulam and College of Agriculture, Vellayani during 2020-2022. The objectives of the study were to identify classical response surface designs suitable for obtaining optimum fertilizer dose for sesame, identify the limitations and advantages of the designs and provide suitable modifications, and also to develop open-source software for response surface methodology in agriculture.

The concepts of response surface designs coupled with CCC, CCI, and Box-Behnken designs will be used in the present study to obtain the optimal fertilizer doses for sesame. Thilak variety of sesame was selected for the experimental trial. At present, the recommended dose of N, P and K as per the package of practice recommendations for sesame is 30:15:30 kg/ha (KAU, 2016). The N, P and K levels in this experiment were determined based on the recommended levels. The dosage of N, P and K taken for central points were 48, 35 and 25 respectively. Since three factors were chosen for the experiment, the α value was $\pm$ 1.682. 20 treatment combinations were used under CCC and CCI design. The BBD design consists of only 3-factor levels, so under BBD, only 15 combinations were used. The experiment was conducted as per the design layout and yield observations were recorded.

The sesame crops were harvested and observations were recorded separately for the different designs. For the three different designs average seed yield and haulm yield were computed and based on the data descriptive statistics were also calculated. The average seed yield obtained under CCC, CCI and BBD were 480.75 kg ha^{-1}, 463 kg ha^{-1}and 475.13 kg ha^{-1} respectively. In the case of haulm yield, the average obtained under CCC, CCI and BBD were 1187.90 kg ha^{-1}, 1142.90 kg ha^{-1} and 1137.27 kg ha^{-1} respectively. The computed harvesting index had an average of 0.29 for CCC and CCI and 0.30 for BBD design.

The estimated second-order response model obtained under the three different designs are presented below

$$Y = 593.011 + 60.219\, N^* + 31.650\, P^* + 96.070\, K^* + 4.125\, N^* P^* + 35.625\, N^* K^* + 5.125\, P^* K^* - 46.430\, N^{*2} - 52.792\, P^{*2} - 65.164\, K^{*2} \quad (1)$$

$$Y = 529.230 + 68.926\, N^* + 65.256\, P^* + 88.373\, K^* - 9.500\, N^* P^* + 11.500\, N^* K^* + 29.750\, P^* K^* - 19.131\, N^{*2} - 44.051\, P^{*2} - 33.800\, K^{*2} \quad (2)$$

$$Y = 537.333 + 53.625\, N^* + 80.125\, P^* + 90.750\, K^* - 49.750\, N^* P^* + 14.0\, N^* K^* + 38.0\, P^* K^* - 14.792\, N^{*2} - 47.292\, P^{*2} - 54.542\, K^{*2} \quad (3)$$

Equation (1) represents the response model obtained under CCC. Similarly, equations (2) and (3) are the equational form of response models developed under CCI and BBD.

In all three models, the coefficients of individual effects were found to be significant. The three models (CCC, CCI, BBD) created in this study were a good fit with an insignificant lack of fit ($p > 0.05$) at the 95% confidence level. Multiple R^2 values of 0.94, 0.92, and 0.97 were found for the quadratic models created using CCC, CCI, and BBD, respectively. The quadratic models' adjusted R^2 scores were 0.89, 0.84, and 0.92. In all three models, R^2 values were found to be greater than 0.8 indicating a good fit of the models. Among the three models, BBD had higher R^2 values than CCC and CCI, so the quadratic model developed through BBD had good predictability compared to other models. According to the results of this study, the predictability of designs, BBD has better prediction rather than the other designs.

The optimum levels of N, P and K for the Thilak variety obtained under CCC were 65.06 kg ha^{-1}, 40.88 kg ha^{-1} and 34.40 kg ha^{-1} respectively. The optimum N, P and K levels obtained under CCI were 69.58 kg ha^{-1}, 46.35 kg ha^{-1} and 36.15 kg ha^{-1}. Under BBD the optimum levels of N, P and K obtained were 67.17 kg ha^{-1}, 45.69 kg ha^{-1} and 36.11 kg ha^{-1}. The results show that the model developed under BBD was best-fit, so the optimum N, P and K doses for the Thilak variety of sesame were 67.17, 45.69, and 36.11 kg ha^{-1}. In the Onattukara region, the recommended dose of N, P and K as per the package of practice recommendations for sesame is 30:15:30 kg/ha (KAU, 2016). The obtained N, P and K ratio was higher compared to the recommended levels, this may be because of the fact that the initial soil nutrient levels were low. Since the soil in Onattukara is sandy, there will be more nutrient leaching. This could also contribute to greater N, P, and K levels obtained.

The application of response surface methods in industrial research has been extensive, but it doesn't seem to be as common in studies involving agriculture and related fields of study. Taking into account all of the limitations in the agriculture experiment, it might be preferable for agricultural experiments to be more reliable, less model-dependent, able to support a more flexible blocking system and possess equispaced factor values in more combinations.

2-D contour plot for the response was drawn for two factors by keeping the other factor constant and from that plot, the optimum yield levels were obtained. The optimum seed yield for the variety was beyond 550 kg ha^{-1}. A 3-D response surface curve was drawn to locate the maximum of yield also suggesting the range for grain yield as 550-600 kg ha^{-1}.

An open-source user-friendly RSM package aimed for benefiting agricultural researchers in optimizing the response of interest was developed. This RSM package was based on Central composite design and Box-Behnken design (BBD) in Response surface methodology. The software consists of two types of Central composite design (i.e., circumscribed CCD and inscribed CCD) and Box-Behnken design. The package has 3 sections. The first section is for design generation where one can generate CCD and BBD designs without any code. In the second section, one can do the analysis of the CCD and BBD. The third section consists of graphs and plots, here the users can generate the 2D contour plots and the 3D surface plots for further analysis.

The results of RSM analysis using CCC, CCI and BBD concluded that BBD was the good fit model with higher multiple and adjusted R^2 values. The optimum dose of N, P and K for the Thilak variety of sesame obtained under BBD was 67.17, 45.69 and 36.11 kg ha^{-1}. A web application for RSM in agriculture with CCD and BBD for 2 and 3 factors was also developed using R.

5.1 SUGGESTIONS

- This type of study has to be conducted in multilocation in different seasons to confirm the results.
- This study can be extended to other varieties of sesame.
- Similar studies can be undertaken for crops other than sesame.
- The package can be modified with the addition of other designs.
- An option for further analysis, if the stationary point is a saddle point, could be incorporated into the package.

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CLASSICAL RESPONSE SURFACE DESIGNS FOR FERTILIZER TRIALS IN SESAME (*Sesamum indicum* L.)

by

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ABSTRACT

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ABSTRACT

The research work entitled “Classical response surface designs for fertilizer trials in sesame (*Sesamum indicum* L.)” was carried out at Onattukara Regional Agricultural Research Station, Kayamkulam and College of Agriculture, Vellayani during 2020-2022. The study's objectives were to identify classical response surface designs suitable for obtaining optimum fertilizer dose for sesame, identify the limitations and advantages of the designs and provide suitable modifications, and develop open-source software for response surface methodology in agriculture. Response surface methodology will be used to find the optimal fertilizer dose of sesame under Central Composite Circumscribed (CCC), Central Composite Inscribed (CCI) and Box- Behnken Design (BBD). And the designs will be compared based on the best-fit model. The CCC and CCI design consists of 20 experimental runs and under the BBD design there were 15 experimental runs.

The dosage of N, P and K taken for central points were 48, 35 and 25 respectively. The levels were selected based on the package of practice recommendations (KAU, 2016) and on the basis of preliminary soil tests. Since three factors were chosen for the experiment, the α value was ± 1.682. The experiment was conducted and observations were recorded. The average seed yield obtained under CCC, CCI and BBD were 480.75 kg ha^{-1}, 463 kg ha^{-1} and 475.13 kg ha^{-1} respectively.

From analysis, it was observed that all the eigenvalues were negative so the stationary point maximized the response. The three models (CCC, CCI, BBD) created in this study were a good fit with an insignificant lack of fit ($p > 0.05$) at the 95% confidence level. Statistically, the better models are influenced by the multiple R^2 and adjusted R^2 values. Both R^2 values are essential for model fitting. A higher value of R^2 showed that the model could explain the result successfully. Multiple R^2 values of 0.94, 0.92, and 0.97 were found for the quadratic models created using CCC, CCI, and BBD, respectively. The quadratic models' adjusted R^2 scores were 0.89, 0.84, and 0.92. In all three models, R^2

values were found to be greater than 0.8 indicating a good fit of the models. Among the three models, BBD had higher R^2 values than CCC and CCI, so the quadratic model developed through BBD had good predictability compared to other models.

The response models were estimated using R for seed yield. The best model was obtained under the design BBD. The equational form of the Response model was given,

$$Y = 537.333_{(17.871)} + 53.625\, N^*_{(10.944)} + 80.125\, P^*_{(10.944)} + 90.750\, K^*_{(10.944)} - 49.750\, N^* P^*_{(15.476)} + 14.0\, N^* K^*_{(15.476)} + 38.0\, P^* K^*_{(15.476)} - 14.792\, N^{*2}_{(16.108)} - 47.292\, P^{*2}_{(16.108)} - 54.542\, K^{*2}_{(16.108)}$$

Where the Seed yield (Y) was the dependent variable and coded N^*, P^* and K^* as the independent variable. The optimum levels of N, P and K for the Thilak variety obtained under CCC were 65.06 kg ha^{-1}, 40.88 kg ha^{-1} and 34.40 kg ha^{-1} respectively. The optimum N, P and K levels obtained under CCI were 69.58 kg ha^{-1}, 46.35 kg ha^{-1} and 36.15 kg ha^{-1}. Under BBD the optimum levels of N, P and K obtained were 67.17 kg ha^{-1}, 45.69 kg ha^{-1} and 36.11 kg ha^{-1}. The results show that the model developed under BBD was best-fit, so the optimum N, P and K doses for the Thilak variety of sesame were 67.17, 45.69, and 36.11 kg ha^{-1}. In the Onattukara region, the recommended dose of N, P and K as per the package of practice recommendations for sesame is 30:15:30 kg/ha (KAU, 2016). The obtained N, P and K ratio was higher compared to the recommended levels, this may be because of the fact that the initial soil nutrient levels were low. Since the soil in Onattukara is sandy, there will be more nutrient leaching. This could also contribute to greater N, P, and K levels obtained.

An open-source user-friendly RSM package aimed for benefiting agricultural researchers in optimizing the response of interest was developed. This RSM package was based on Central composite design and Box-Behnken design (BBD) in Response surface methodology. The software consists of two types of Central composite design (i.e., circumscribed CCD and inscribed CCD) and Box-Behnken design. The package has 3 sections. The first section is for design generation where one can generate CCD and BBD designs without any code. In the second section, one can do the analysis of the CCD and BBD. The third section consists of graphs and plots, here the users can generate the 2D contour plots and the 3D surface plots for further analysis.

The results of RSM analysis using CCC, CCI and BBD concluded that BBD was the good fit model with higher multiple and adjusted R^2 values. The optimum dose of N, P and K for Thilak variety of sesame obtained under BBD was 67.17, 45.69 and 36.11 kg ha^{-1}. A web application for RSM in agriculture with CCD and BBD for 2 and 3 factors was also developed using R

Appendices

Appendix 1

The rsm package developed is open source. The code for the web package is available in GitHub. The GitHub link: https://github.com/pratheesh3780/grapesRSM