

Application of the response surface methodology for yield optimization in maize (*Zea mays* L.)


Aplicación de la metodología de superficie de respuesta para la optimización del rendimiento en maíz (*Zea mays* L.)

Aplicação da metodologia de superfície de resposta para otimização de produtividade em milho (*Zea mays* L.)

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Rev. Fac. Agron. (LUZ). 2023, 40(4): e234035
ISSN 2477-9407
DOI: [https://doi.org/10.47280/RevFacAgron\(LUZ\).v40.n4.04](https://doi.org/10.47280/RevFacAgron(LUZ).v40.n4.04)

Crop production

Associate editor: Dr. Jorge Vilchez-Perozo  
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Received: 09-10-2023

Accepted: 22-11-2023

Published: 29-11-2023

Keywords:

Response surface methodology
Yield optimization
Corn
Zea mays L.

Abstract

The objective of this study was based on the application of the response surface methodology (RSM) for yield optimization in maize (*Zea mays* L.). The hybrid INIA SQ-1 was used, and the Response Surface Methodology was used using the Box-Behnken design (DBB), with which the following factors were evaluated: plant density, nitrogen (N) dose and phosphorus (P) dose at three levels each; for the optimization of the response variables: "yield" (kg.ha⁻¹) and the "number of grains per square meter" (g.m²). The response surface method provided a statistically validated predictive model, which through adjustments was adapted to an established optimization process. For the variable "yield", a maximum response was found with the application of 150 kg.ha⁻¹ of N and 90 kg.ha⁻¹ of P. In relation to the number of grains per square meter (g.m²), the optimum was obtained using 75,000 plants.ha⁻¹ and an applied dose of 150 kg.ha⁻¹.

Resumen

El objetivo de este estudio se basó en la aplicación de la metodología de superficie de respuesta (MSS) para la optimización del rendimiento en maíz (*Zea mays* L.). Se utilizó el híbrido INIA SQ-1 y la Metodología de Superficie de Respuesta mediante el diseño Box-Behnken (DBB), con el cual se evaluaron los siguientes factores:

densidad de plantas, dosis de nitrógeno (N) y dosis de fósforo (P) en tres niveles cada una; para la optimización de las variables de respuesta: “rendimiento” ($\text{kg}\cdot\text{ha}^{-1}$) y “número de granos por metro cuadrado” ($\text{g}\cdot\text{m}^2$). El método de superficie de respuesta proporcionó un modelo predictivo validado estadísticamente, que mediante ajustes se adaptó a un proceso de optimización establecido. Para la variable “rendimiento”, se encontró una respuesta máxima con la aplicación de $150 \text{ kg}\cdot\text{ha}^{-1}$ de N y $90 \text{ kg}\cdot\text{ha}^{-1}$ de P. En relación con el número de granos por metro cuadrado ($\text{g}\cdot\text{m}^2$), el óptimo se obtuvo utilizando $75.000 \text{ plantas}\cdot\text{ha}^{-1}$ y una dosis aplicada de $150 \text{ kg}\cdot\text{ha}^{-1}$.

Palabras clave: metodología de superficie de respuesta, optimización de rendimiento, maíz, *Zea mays* L.

Resumo

O objetivo deste estudo baseou-se na aplicação da metodologia de superfície de resposta (RSM) para a otimização da produtividade do milho (*Zea mays* L.). Foi utilizado o híbrido INIA SQ-1 e a Metodologia de Superfície de Resposta foi utilizada por meio do delineamento Box-Behnken (DBB), com o qual foram avaliados os seguintes fatores: densidade de plantas, dose de nitrogênio (N) e dose de fósforo (P) em três níveis cada; para a otimização das variáveis de resposta: “produtividade” ($\text{kg}\cdot\text{ha}^{-1}$) e o “número de grãos por metro quadrado” ($\text{g}\cdot\text{m}^2$). O método de superfície de resposta forneceu um modelo preditivo validado estatisticamente, que, por meio de ajustes, foi adaptado a um processo de otimização estabelecido. Para a variável “rendimento”, foi encontrada uma resposta máxima com a aplicação de $150 \text{ kg}\cdot\text{ha}^{-1}$ de N e $90 \text{ kg}\cdot\text{ha}^{-1}$ de P. Em relação ao número de grãos por metro quadrado ($\text{g}\cdot\text{m}^2$), o ótimo foi obtido com $75.000 \text{ plantas}\cdot\text{ha}^{-1}$ e uma dose aplicada de $150 \text{ kg}\cdot\text{ha}^{-1}$.

Palavras-chave: metodologia de superfície de resposta, otimização de rendimento, milho, *Zea mays* L.

Introduction

Corn is an important crop in the Venezuelan vegetable agricultural sector, considered one of the most important strategic and priority crops of the nation, due to its importance in the daily diet of Venezuelans. In addition, corn is a source of employment, due to the large number of people who grow it throughout almost the entire national geography, being concentrated mainly in the states of Portuguesa, Barinas, Cojedes, Guárico, Apure and Yaracuy; 80 % of the production is used for the manufacture of precooked flour and the rest for the processing of corn flour and animal consumption. Hence, precooked corn flour represents the first source of calories and the third source of protein in the Venezuelan diet, generating a great demand for corn at levels that are not covered by domestic production, according to FAO-ESS (2021) (Erenstein *et al.*, 2022). Therefore, it is convenient to evaluate the factors affecting the agricultural practices of the crop,

to increase the yield per hectare of the crop and in turn improve the final quality of the grain, and thus satisfy the requirements of national consumption that contributes to the sustainability of the corn circuit, of great strategic importance for the Venezuelan diet.

The reduction in crop yield can be attributed to several factors, mainly the use of varieties with low productive potential, water deficiency, low fertility of cultivated soils, inadequate planting time, planting density and inadequate control of insects and harmful plants (Masood *et al.*, 2011). However, fertilization and plant density are some essential technological components within modern agriculture, considering nitrogen fertilization as one of the key aspects in corn crop management because, among other aspects, it plays a fundamental role in plant growth and yield and, above all, in increasing the number of grains (Moreno *et al.*, 2017; Vargas *et al.*, 2021). Similarly, the application of phosphorus contributes to the formation of nucleic acids, cellular respiration, and metabolic activity which, when applied together with nitrogen, influence grain yield, forage quality, plant height and number of leaves per plant (Medina *et al.*, 2018; Romero *et al.*, 2022). Thus, the interest in growing corn using reduced spacing has grown in recent years in different producing regions, mainly among producers who work with planting densities higher than $50,000 \text{ plants}\cdot\text{ha}^{-1}$, as reported by Rodríguez *et al.* (2021). In this sense, planting density has been one of the factors that producers frequently modify to increase grain yield, although they do not always establish the correct density, increasing competition for light, water, and nutrients, causing a decrease in root volume, number of ears, grain quantity and quality per plant (Sharifi *et al.*, 2014; Bouras *et al.*, 2021). Indeed, there is a challenge to increase crop productivity and efficiency in the use of fertilizers, leading to the search for new ways that lead to a more sustainable agriculture, being necessary the application of tools to evaluate different scenarios and to obtain an optimal performance (Yaguas, 2017; Torralbo *et al.*, 2023).

Therefore, the objective of this study was based on the application of the response surface methodology for yield optimization in corn (Ganugi *et al.*, 2022), evaluating the factors plant density ($\text{plants}\cdot\text{ha}^{-1}$), nitrogen (N) dose and phosphorus (P) dose; for the response variables “yield” ($\text{kg}\cdot\text{ha}^{-1}$) and “number of grains per square meter” ($\text{g}\cdot\text{m}^2$).

Materials and methods

Study area

The present investigation was carried out during the rainy period (May-October) of 2020, in the farm “El Angel”, specifically in the rural area of Mariara, Diego Ibarra Municipality, Carabobo State, Venezuela, at the coordinates $10^{\circ}17'16''$ North and longitude $67^{\circ}43'10''$ West, at an altitude of 442 masl. This area is characterized by average annual rainfall and temperature of 800 msl. And 28°C respectively. The climate of the area corresponds to dry tropical, according to the Köppen climate classification. The material used corresponded to the INIASq-1 hybrid.

Experimental units were used, made up of plots of $3.6 \times 4.0 \text{ m}$, with four rows of 4 m long and 0.9 m apart, the distance between plants was 0.20 m. The size of the useful plot was 10 m^2

Variables

Corn yield ($\text{kg}\cdot\text{ha}^{-1}$)

Ten squared meters were harvested manually in each experimental unit; the harvested ears were threshed manually and grain moisture at

physiological maturity was determined with a moisture meter. Yield was expressed at 12 % grain moisture.

Number of grains per square meter (g.m²)

The number of grains per m² was calculated as the quotient between yield (on a dry basis) and individual grain weight. The latter variable was determined by averaging two samples of 200 grains each and dried in a forced-air oven for 10 days.

Statistical methods

Response Surface Methodology was used to optimize yield (kg.ha⁻¹) and number of grains per square meter (g.m²) in corn. Response Surface Methodology is a collection of mathematical and statistical techniques used to develop, improve, and optimize processes. It is also applicable in the design, development, and formulation of new products, as well as the improvement of existing product designs. One of the most widespread applications of these techniques is to model and analyze problems in which a response of interest (there may be more than one) is influenced by several quantitative factors, being the objective to optimize this response by determining the optimal values of the factors involved (Montgomery, 2004). The relationship will be given by:

$$y = f(x_1, x_2) + \epsilon \quad (1)$$

Which is assumed to be continuous, in E where represents the noise or error observed in the response, whose distribution is assumed to be normal with zero mean. The variables in the equation (2) are natural variables since they are expressed in the natural units of measurement. However, it is common to transform them into coded variables. The variables, without dimensions, with zero mean and the same standard deviation. Thus, the actual value expected to be taken by the response variable implies a relationship that can be represented by a hypersurface called response surface.

$$\eta = f(x_1, x_2, \dots, x_k) \quad (2)$$

The form of the true response function is unknown, so we must approximate it and the choice of appropriate factors is therefore important. The success of applying the MSR technique also lies in the fact that the response can be fitted to a polynomial of first or second degree.

Box-Behnken Design

We used the Box-Behnken design (DBB), designed by Box and Behnken (1960), often used to refine models after important factors have been determined using screening designs or factorial designs, especially if curvature of the response surface is suspected. The mathematical model fit to a DBB is determined by the following equation:

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

Where β_0 is the independent term, β_i are the coefficients of the i -s main effects and their quadratic effect respectively, β_{ij} is the interaction coefficient between the i -s and the j -s factor and ϵ is the random error. This equation, having quadratic terms, provides a response surface with some curvature, thus better approximating the real model than in the case of the k -factor design.

Factors evaluated

In the present work, the factors plant density (plants.ha⁻¹), n dose and p dose were evaluated. Table 1 shows the levels used for each

of these factors with their respective coding. The details of the Box-Behnken design are presented in table 2, where each of the levels used for each factor are shown in table 1.

Table 1. Treatment levels and coded values of the factors evaluated.

FACTORS	LEVELS		
	-1	0	1
Density of plants (plants.ha ⁻¹)	50000	75000	100000
Nitrogen dosage (kg.ha ⁻¹)	100	150	200
Phosphorus dosage (kg.ha ⁻¹)	60	90	120

Table 2. Box-Behnken design matrix for response surface analysis, with natural and coded factors.

Randomization Order	CODED FACTORS			NATURAL FACTORS		
	Density	Nitrogen	Phosphorus	Density	Nitrogen	Phosphorus
8	-1	-1	0	50	100	90
7	-1	1	0	50	200	90
11	1	-1	0	100	100	90
12	1	1	0	100	200	90
1	-1	0	-1	50	150	60
4	-1	0	1	50	150	120
14	1	0	-1	100	150	60
2	1	0	1	100	150	120
13	0	-1	-1	75	100	60
3	0	-1	1	75	100	120
15	0	1	-1	75	200	60
9	0	1	1	75	200	120
6	0	0	0	75	150	90
5	0	0	0	75	150	90
10	0	0	0	75	150	90

The use of the results obtained here is not directly applicable in the field. The way the treatments were assigned to the experimental units was an unrestricted randomization, where each treatment, including the control, had the same probability of being assigned to any of the available experimental units. Table 2 shows the order of randomization.

Results and discussion

Corn yield (kg.ha⁻¹)

Table 3 shows the results of the analysis of variance for the variable "yield" (kg.ha⁻¹), showing that the model studied is significant ($p < 0.05$), which indicates that at least one of the factors evaluated has a significant influence on the measured response. The non-significance of the lack of fit ($p > 0.05$) allows inferring that the model fits the data adequately. Likewise, it is observed that the linear effect of the density and nitrogen factors, in addition to the quadratic effect of the density factor and all interactions, did not present significant differences; therefore, their effects are considered negligible and are eliminated to increase the model fit.

Table 3. Analysis of variance for yield variable (kg.ha⁻¹).

	df	Sum of squares	Mean squares	Fc	p
Model	9	500867	55652	5.65	0.0355*
Density	1	14113	14113	1.43	0.2854
Nitrogen	1	7080	7080	0.72	0.4349
Phosphorus	1	46512	46512	4.72	0.0818
Density*density	1	3142	3142	0.32	0.5961
Nitrogen*nitrogen	1	312985	312985	31.75	0.0024*
Phosphorus* phosphorus	1	66682	66682	6.76	0.0483*
Interactions	3	50323	16774.33	1.70	0.2491
Error	5	49289	9857.8		
Lack of adjustment	3	25724	8574.67	0.73	0.6321
Pure error	2	23565	11782.5		
Total	14	540126			

Adjust= 74.45 %; * p<0.05

Table 4 shows the analysis of variance excluding the non-significant effects from the previous table, showing how the model fit goes from 74.45 % (table 3) to 90.28 %, which indicates that 90.28 % of the corn yield is explained by the new model.

$$\hat{y} = 9104,63 + 6,879 * Phosphorus - 0,0241 * Phosphorus^2 + 0,003524 * Nitrogen^2 \quad (4)$$

Table 4. Analysis of variance for yield variable (kg.ha⁻¹).

	df	Sum of Squares	Middle Management	Fc	p
Model	3	500867	166956	14.82	0.0028*
Phosphorus	1	46512	46512	4.13	0.0667
Nitrogen*Nitrogen	1	312985	312985	27.78	0.0002*
Phosphorus*Phosphorus	1	66682	66682	5.92	0.0332*
Error	11	123947	11267.91		
Total	14	540126			

Adjust= 90,28 %; * p<0.05

Figure 1 shows the maximum curvature reached by the maize yield variable; when studying the surface, it is established that this optimum point is achieved when using a medium level of N doses (150 kg.ha⁻¹), and a medium level of the phosphorus factor, that is, an application of 90 kg.ha⁻¹ of P. Similar results were obtained by barrios *et al.* (2018), who obtained higher yields (9763 kg.ha⁻¹) with doses of 150 kg.ha⁻¹ of N, determining that higher doses of N did not significantly influence yield, thus allowing a more efficient use of N at a lower dose. Barrios *et al.* (2016) also reported that excess n accumulates in leaf tissues, saturating the N absorption capacity of the crop, resulting in a poor root system, soft tissue, weak plants, delayed production, and lower yields. Gómez *et al.* (2016) indicated that 200 kg.ha⁻¹ of n were required to obtain maximum grain yield; however, with the application of 90 kg.ha⁻¹ of P, they obtained higher values in plant and ear height, ear health and grain yield. However, there are studies (Guo *et al.*, 2016) indicating the case of the loess plateau of China where a potential yield of 98 to 108 % was achieved; varying the optimum dose of N from 207 to 222 kg.ha⁻¹ with a ratio of 65 to

80 kg of grain/kg of N applied. In relation to planting density, it was showed that the effect was not significant, allowing to establish that the three density levels evaluated had no effect on the yield variable. These results agree with those reported by Tadeo *et al.* (2020), who determined that plant density is not a factor that influences grain yield; however, they recommend the use of a population of 65,000 plants.ha⁻¹ to avoid spending more seed. Similarly, Youngerman *et al.* (2018) indicated that yield at low density did not differ from the standard, suggesting no significant changes.

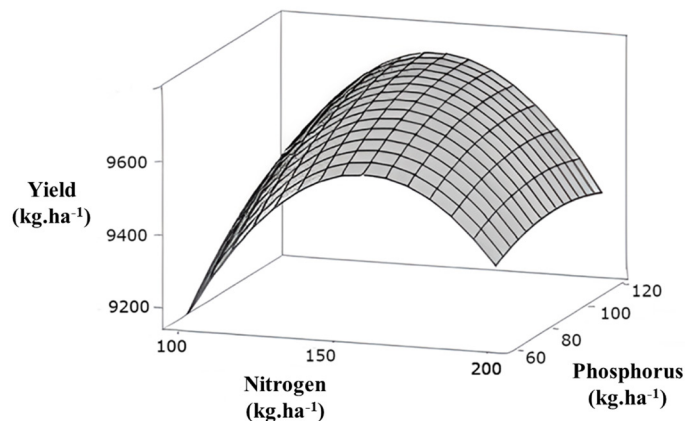
**Figure 1. Response surface for the response variable yield (kg.ha⁻¹).**

Table 5 shows the analysis of variance for the variable “grains per square meter”, finding significance (p<0.05) for the proposed model, which indicates that at least one of the selected factors has a significant influence on the evaluated variable, this effect being either linear or quadratic. The non-significance of the lack of adjustment allows us to establish that the model proposed achieves a good adjustment for the variable studied. Likewise, the effect of linear density, quadratic phosphorus and the different interactions that form the factors studied, did not present significant effects; therefore, these effects were eliminated from the model to improve its fit.

Table 6 shows that the significant effects are nitrogen, both linearly and quadratically, and plant density quadratically, which indicates that these factors allow finding an optimal response for the measured variable. The improvement in the model fit, from 89.79 % to 93.5 %, is noteworthy.

Figure 2 shows the maximum curvature reached for the number of grains per square meter (g.m²), achieving this optimum value with a planting density of 75,000 plants.ha⁻¹, and an N dosage of 150 kg.ha⁻¹. This is in agreement with what was reported by Tadeo *et al.* (2012), where the stocking density of 70,000 plants.ha⁻¹ presented numerically higher yields for a given hybrid, compared to other densities. In case the number of plants per area goes beyond the optimum, there would be detrimental consequences for ear ontogeny, resulting in sterility and a decrease in the number of grains per square meter (g.m²), according to Jun *et al.* (2017). In other study (Martinez *et al.*, 2017) the components ear length, mean ear diameter and mean ear diameter were sensitive to the increase in plant population per hectare, recommending a density of 65,000 plants.ha⁻¹. With respect to the dose of N applied, it has been previously showed that the number of grains per square meter (g.m²) had a positive and significant response to the intermediate dose of N (150 kg.ha⁻¹ of N), favoring the size and number of grains per ear, important components in determining the level of yield in corn (Barrios *et al.*, 2018).

Table 5. Analysis of variance for the variable “number of grains per square meter” (g.m²).

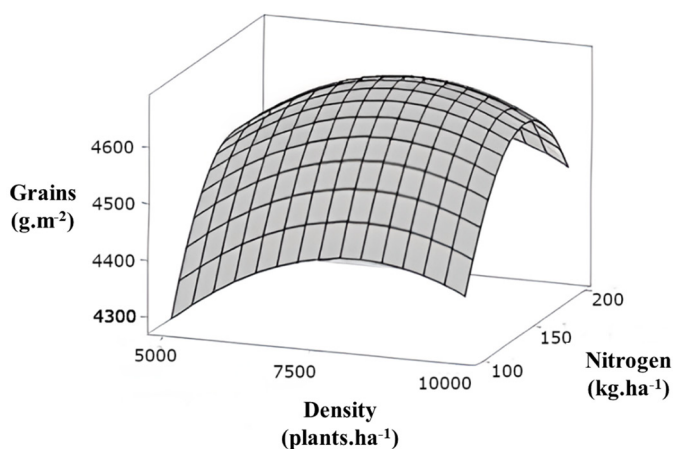
	df	Sum of squares	Mean squares	Fc	p
Model	9	215407	23934	4.95	0.0468
Density	1	8522	9522	1.97	0.2854
Nitrogen	1	32381	32381	6.69	0.0491*
Phosphorus	1	5555	6555	1.35	0.0818
Density*density	1	34416	34416	7.11	0.0445*
Nitrogen*nitrogen	1	116768	116768	24.13	0.0044*
Phosphorus*phosphorus	1	2725	2725	0.56	0.4879
Interactions	3	15040	5013	1.04	0.2491
Error	5	24200	4840		
Lack of adjustment	3	18080	6027	1.97	0.6321
Pure error	2	6121	3060		
TOTAL	14	239607			

Adjustment: 89.79 %; * p< 0.05

Table 6. Adjusted analysis of variance for the variable “number of grains per square meter” (g.m²).

	df	Sum of Squares	Middle Squares	Fc	p
Modelo	3	183656	61219	12.02	0.0008*
Nitrógeno	1	32381	32381	6.36	0.0283*
Densidad*-densidad	1	34416	34416	6.76	0.0247*
Nitrógeno*-nitrógeno	1	116768	116768	22.92	0.0001*
Error	11	56042	5095		
Total	14	239607			

Adjustment: 93.5 %; *significant difference at 5 %.

**Figure 2. Response surface for the response variable “grain” (g.m²).**

The response surface method provided a statistically validated predictive model, which through adjustments was adapted to an established optimization process. For the variable “yield”, a maximum response was found with the application of 150 kg.ha⁻¹ of N and 90 kg.ha⁻¹ of P. In relation to the number of grains per square meter (g.m²), the optimum was obtained using 75,000 plants.ha⁻¹ and an applied dose of 150 kg.ha⁻¹.

Conclusions

The present study demonstrates that the response surface methodology is a valuable tool to optimize maize yield in Venezuela. The results indicate that planting density and the amount of nitrogen are key factors affecting maize yield, and that the optimal planting density to maximize the number of grains per square meter was 75,000 plants per hectare. In addition, it was found that the improvement in the fit of the model, from 89.79 % to 93.5 %, is significant and demonstrates the effectiveness of the response surface methodology in optimizing maize yield. These results are important for corn production in Venezuela since corn is an essential crop for the economy and diet of the population.

Increasing the yield per hectare can improve the economy of Venezuela and guarantee the food security of the population. In addition, improving the quality of corn production can reduce the need to import corn from other countries, which can have a positive impact on the trade balance not only locally, but also regionally.

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