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Balancing maize yield and nitrogen use efficiency under dry, optimal and wet production conditions

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ABSTRACT
Nitrogen rate, yield, and NUE (Nitrogen Use Efficiency) are tightly linked, and moisture availability plays a critical role in this relationship. This multi-year trial was established with the aim of optimizing maize grain yield and agronomic nitrogen use efficiency (NUE) under varying moisture conditions. The dataset, covering the period from 2002 to 2020, was obtained from a long-term residue management experiment combined with increasing nitrogen (N) rates. Residue management included two treatments, with and without residue incorporation. When residues were incorporated, six nitrogen rates were applied: 0 (control treatment), 50, 100, 150, 200, and 250 kg N ha^{-1}. In the variant without residue incorporation, three nitrogen rates were applied: 0 (control treatment), 100, and 200 kg N ha^{-1}. A multiobjective approach was employed to analyze the trade-off between yield and NUE under different precipitation regimes, with growing seasons classified as dry, optimal, or wet based on percentile-based precipitation thresholds. This methodology enabled a more precise interpretation of yield responses and nitrogen use efficiency under varying moisture conditions. The results indicated distinct optimal nitrogen rates depending on the precipitation regime. In dry years, the optimal range was between 70 and 77 kg N ha^{-1}, whereas in optimal seasons, it ranged from 118 to 133 kg N ha^{-1}. In wet years, the optimal rates were between 94 and 124 kg N ha^{-1}. These nitrogen rates allowed for achieving near-maximum yields while maintaining nitrogen use efficiency. Further increases in nitrogen application resulted in only modest yield gains while notably reducing NUE. The findings highlight that moderate nitrogen fertilization rates, adjusted to the available moisture conditions, can ensure high and stable maize production. The analysis also confirmed the importance of residue incorporation, which consistently ranked among the optimal solutions in the multiobjective approach.

KEY WORDS
Multiobjective optimization; Pareto; Harvest residues; Nitrogen; Nitrogen Use Efficiency; Yield

Introduction

Given its large-scale cultivation and economic role, optimizing nitrogen use in maize is essential for maintaining productivity and environmental balance (Huang et al., 2021). In Serbia, maize cultivation spans the largest area among all agricultural crops, averaging 1 million hectares and 5.94 million tons production (Grčak et al., 2020). Nutrient management involves the timing, amount, and type of fertilizer application to match crop demands and minimize losses. Nitrogen management particularly plays a critical role in achieving potential yields and high returns in maize farming (Gheith et al., 2022). In Serbia, the usual farmers practice for maize production is to apply 150 kg N ha^{-1}. Around 30% of this is applied together with phosphorus and potassium as complex mineral fertilizers before winter ploughing, while the rest of the N is broadcasted in form of $CO(NH_2)_2$ or NH_4NO_3 and then mixed with soil during pre-sowing cultivation. Over the past three decades, advancements in mineral fertilizers have significantly boosted maize yields, alongside progress in crop selection (Duvick, 2005).

To achieve sustainable production, agricultural practices must enhance productivity while protecting the environment, as well as human and animal health. Enhancing nitrogen use efficiency (NUE) is a key component of this framework (Zhang et al., 2015; Xiong et al., 2018). It is utilized by both Eurostat and the European Environment Agency (EEA) as an agri-environmental indicator to assess the impact of agricultural practices on the environment. They use it to monitor and compare food production, ensuring it is both high-quality and safe for human health, while also meeting environmental standards. This indicator can be applied across different territorial units and various production sectors - whether crop production, livestock farming, or integrated systems (Oenema, 2015). There are numerous approaches to calculate NUE, but the most widespread is agronomic NUE. It is useful to determine how to increase or maintain crop yield while minimizing N inputs, or how much productivity is improved by the application of N (Congreves et al., 2021). It can be broken down into two components: nitrogen uptake efficiency (NupE), which is the proportion of available soil nitrogen that the plant absorbs, and nitrogen utilization efficiency (NUtE), which is the amount of grain produced per unit of nitrogen taken up by the plant. Higher maize yields are typically linked to greater biomass production, and nitrogen uptake tends to increase with both biomass and grain yield.

There are two main strategies to enhance NUE: breeding more efficient genotypes and developing improved fertilization systems. On one side, selecting genotypes that can better absorb nutrients from both soil and fertilizers and utilize them effectively to produce higher yields is crucial (He et al., 2020). For maize, the research has shown that certain hybrids exhibit significant variations in nitrogen accumulation and utilization, indicating the potential for genetic improvement in NUE (Sharifi et al., 2023). The study conducted on the experimental field of the Institute of Field and Vegetable Crops in Novi Sad proved that agronomic NUE was by 25% lower in older maize hybrids NS 444 and NS 640 in comparison to newer hybrids NS 3023 and NS 6140 (Dunđerski et al., 2021). Besides hybrids, NUE also has great variations among maize lines, with 3 of 36 lines having higher N concentration in grains in control treatment in comparison to N treatment (Dragičević et al., 2020). This marks them as the best N users in low-N conditions. However, the authors highlighted 16 lines as the primary focus for further breeding programs, since they don't have only improved NUE, but also high grain yield.

On the other side, achieving high yields with efficient nitrogen management is essential for cereal production in the Pannonian Basin (Moitzi et al., 2020). The same authors concluded that three against two split applications of N in the Pannonian climate region resulted in high-quality wheat for bread-making and for reducing the N loss. Two splits are recommended when aiming only at high GY. The results by Jaćimović et al., 2018 from the experiment conducted on the experimental field at location Rimski Šančevi revealed that the highest efficiency of applied nitrogen fertilizers in wheat was achieved with the application rate of 50 kg N ha^{-1}. However, from the perspective of the combined effect on yield and NUE, the application of a moderate nitrogen rate (100 kg N ha^{-1}) stands out as rational one.

A yield-focused approach is commonly employed to recommend nitrogen fertilizer rates for maize. However, optimizing nitrogen use has become increasingly important due to the environmental and economic costs associated with nitrogen fertilization (Basso et al., 2016).

This study examines the impact of different nitrogen rates on maize yield, and agronomic NUE across three different environmental scenarios: dry, optimal, and wet conditions. We highlight the importance of matching N supply to the season's moisture conditions to optimize yield and NUE. To determine N supply in each scenario, the Pareto front analysis was used to optimize two conflicting objective functions simultaneously. Pareto front analysis has long been used in fields such as engineering and economics to identify efficient trade-offs between competing objectives. For example, in power systems, it assists in evaluating trade-offs between operational costs and environmental impacts like CO_2 emission (Giannelos et al., 2024). Its application in agronomic nutrient management remains scarce. In this study, we frame maize yield and agronomic NUE as dual objectives and construct a Pareto frontier as a set of N-rate treatments for which no increase in yield is possible without a concomitant decrease in NUE, and vice versa. This approach is innovative for three reasons. First, it moves beyond single-objective optimization (maximizing yield or efficiency alone) by identifying treatments that balance agronomic productivity with environmental performance. Second, stratifying the analysis by dry, optimal, and wet years reveals how water availability shifts the shape and position of the frontier. Finally, presenting results as a Pareto frontier provides growers with a clear decision-support tool: they can select N rates that achieve a desired yield level with minimal efficiency loss, or vice versa, rather than relying on arbitrary economic or environmental thresholds. This method aligns with broader sustainability goals by quantifying trade-offs and guiding balanced nutrient management strategies (Alocilja and Ritchie, 1993; Kropp et al., 2019; Karamian et al., 2023).

Materials and Methods

Description of the study cite

A study was conducted to assess the effects of the long-term return of crop residues combined with increasing amounts of nitrogen on maize yield. The research was performed on a long-term, fixed-site field trial known as "ISDV" (Internationale Stickstoff Dauer Versuche). This trial was established in 1971 in a Pannonian environment (PAN3 zone for Serbia) with temperate, moderately wet, and seasonal climate zone (Metzger et al., 2013) and continues to this day. The soil type on the site is chernozem, class A–C (humus-accumulative soil), type—chernozem on loess and loess-like sediments, variety—calcareous, and moderately deep form (40–80 cm, according to A horizon depth)

(Pavlović et al., 2017). It is located on the experimental field of the Institute of Field and Vegetable Crops in Novi Sad. The current article uses results from 2002 to 2020, excluding years 2009, 2014, 2016 (missing data). The cropping system followed a winter wheat-maize-soybean rotation.

Experimental design

Conducted under rain-fed conditions, the experiment was arranged in a randomized complete block design with four replicates. Each replicate consisted of the plots with two factors: (a) residue management (treatments with or without plowing in the crop residues) and (b) nitrogen dosage. The N dosages ranged from 0 to 250 kg N ha^{-1}, in increments of 50 kg, for treatments with residue incorporation, and from 0 to 200 kg N ha^{-1}, in increments of 100 kg, for treatments without residue incorporation. The 50% of the N requirements were incorporated with winter plowing together with 80 kg P_2O_5 ha^{-1} and 80 kg K_2O ha^{-1}, and the remaining 50% were incorporated together with pre-sowing soil preparation. The area of each main plot for fertilizer application was 57 m^2 (6 m long, 9.5 m wide), while for harvest only the central two rows of the plot were considered, from the total of 12 rows in each plot. The distance between rows was 75 cm, while the distance between plants in a row was 25 cm. For yield determination, the ears were hand-harvested at physiological maturity from the two central rows of the plot. The total weight of ears was measured, and then 10 representative ears (ears that represented the average size of the ears in the plot) were chosen. Subsequently, these 10 ears were shelled using an electric sheller that ensured the preservation of every kernel and cob. The kernel and cob weight of each ear were measured with a digital scale and used to calculate the percentage of kernels on the ear. Subsequently, the kernels were combined, and a 100 g portion of the composite was utilized for the determination of moisture content. The measurement of moisture content was conducted by subjecting the samples to constant heat in an oven and measuring the weight loss until constant dry weight was achieved. The weight loss is moisture content in the grains (%). The grain dry matter content (%) was then easily determined as 100 - moisture content (%). Knowing the grain dry matter content and percent of kernels based on 10 representative ears and the total weight of ears from the central two rows of the plot, the grain yield was calculated as:

$$\text{Yield (kg ha}^{-1}\text{)} = (\text{TWK} \times \text{DM})/0.86 \times 1111.11 \qquad (1)$$

where TWK is the total weight of kernels from the central two rows, DM is the grain dry matter content, 0.86 is the correction factor to standardize yield to a moisture content of 14%, and 1111.11 is the conversion factor to express yield per hectare, based on a harvested area of 6 m × 1.5 m.

Statistical Data Analysis

During the 2002–2020 experiment, eight different maize hybrids were planted, and each treatment was replicated four times. To generalize the results, the data were grouped such that neither hybrid identity nor replicate block was treated as a factor in the analysis.

To identify Pareto-optimal treatments, a two-objective framework was adopted, wherein grain yield (kg ha^{-1}) and agronomic nitrogen use efficiency (NUE, kg kg^{-1}) were used as the criteria. Since experimental data were collected at discrete nitrogen levels, Pareto analysis was first applied to the original dataset (with observed values of yield and NUE) within each precipitation category. This initial analysis determined that plowing residue management consistently appeared as the optimal solution in every precipitation category. As a result, further estimation of yield and NUE values was performed only for cases where residues were plowed.

For these plowed-residue cases, various regression curves were fitted to the observed yield and NUE data - specifically, exponential, linear, linear + plateau, quadratic, and square-root models—for each precipitation category. The best model for interpolation in each scenario was selected based on an evaluation of AIC, BIC, R^2, and RMSE. This ensured that an appropriate functional form was used to capture the relationship between yield or NUE and N dose for subsequent interpolation. To evaluate the accuracy of the model-based interpolation, leave-one-out cross-validation (LOOCV) was performed for each dataset. In this approach, each observation was excluded one at a time, and a model was fitted on the remaining data. The excluded value was then predicted using the fitted model, and the squared error was calculated. This process was repeated for all observations, and the root mean squared error (RMSE) was computed as a summary measure of predictive performance.

Using the prediction formulas derived from the selected regression models, estimated values were interpolated for nitrogen doses ranging from 50 to 250 kg N ha^{-1} in 1 kg increments. These interpolated values were then used to identify Pareto-optimal N doses, ensuring that the Pareto front was constructed with a continuous dataset rather than being restricted to the originally tested nitrogen levels. A solution is considered Pareto-optimal if no other treatment exhibits both a higher or equal yield and a higher or equal NUE, with at least one of these metrics being strictly greater.

Following the identification of Pareto-optimal nitrogen doses, the subsequent analysis was confined to this optimal range. A four-tier categorization was implemented, with treatments in the top quartile (75th percentile and above) receiving the highest designation (Q4), those between the 50th and 75th percentiles receiving a high designation (Q3), those between the 25th and 50th percentiles receiving an intermediate designation (Q2), and those below the 25th percentile receiving the lowest designation (Q1). If fewer categories were used, important nuances between different treatments would be lost. On the other hand, a larger number of categories could complicate result interpretation and reduce clarity. However, splitting Pareto-optimal doses into quartiles is an arbitrary choice unless showed that those groups differ statistically. Differences among the four value groups in terms of yield and NUE were tested using one-way ANOVA ($\alpha = 0.05$), with Tukey HSD as the post-hoc test for pairwise comparisons, respecting the assumptions necessary for conduction such tests (normality and homogeneity).

Additionally, linear regression analysis was conducted on the Pareto-optimal NUE and yield values for each dataset. This allowed quantification of the rate at which NUE declines per kilogram increase in yield. By combining the visual cues of conditional formatting with quantitative regression insights, the analysis provides both an immediate overview of treatment performance and a more precise understanding of the trade-offs between yield maximization and nutrient use efficiency.

Agronomic NUE was calculated according to the standard formula:

$$\text{NUE (kg kg}^{-1}\text{)} = \text{(Yield with N) - (Yield without N)/N applied} \qquad (12)$$ (Fageria and Baligar, 2005)

All data manipulation and statistical analyses were performed using statistical software JMP Pro 17.0.0 and R version 4.4.2.

Results

Weather conditions during the research period

This climadiagram (Figure 1) shows seasonal precipitation and mean temperature from April to October for the years 2002–2020. The year 2010 had by far the highest precipitation, exceeding 670 mm, while 2012 had the lowest, just above 200 mm. Mean temperatures generally hovered around 19–20 °C, with peaks in 2003, 2012, and 2018. Notably, 2003 and 2012 had both high temperatures and very low precipitation, which indicate a severe drought year. There's no clear long-term trend, but variability is significant year by year.

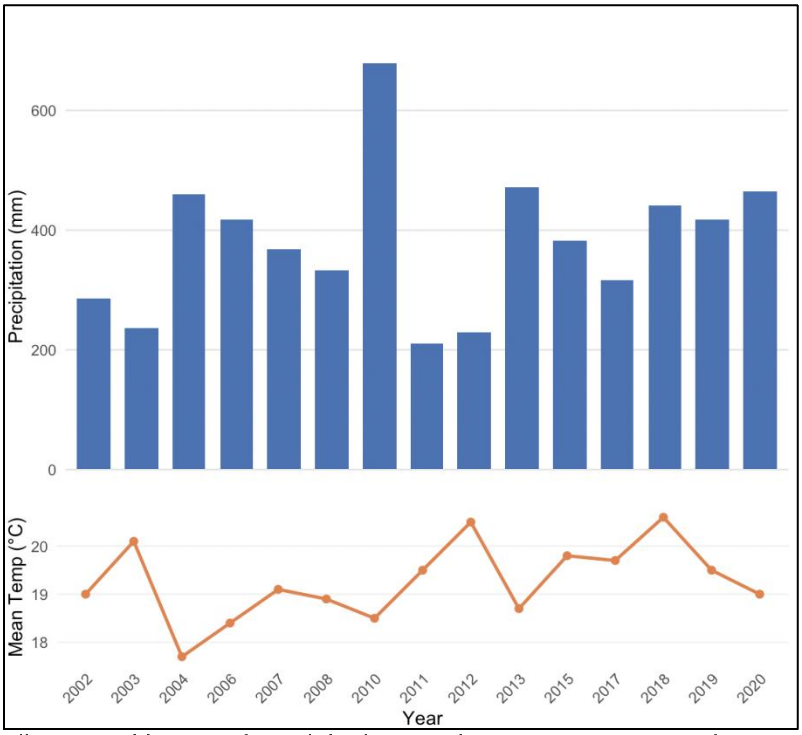


Figure 1. Climadiagram with sum of precipitations and mean temperatures from April to October in experimental years.
Figura 1. Klimadijagram sa sumom padavina i prosečnim temperaturama od aprila do oktobra u godinama istraživanja.

Precipitation data from the 2002–2020 period (covering the typical maize growing season from April to October) were obtained from the Republic Hydrometeorological Service of Serbia (RHMZ). Using the percentile method, each year in this interval was classified as a dry year (precipitation below the 25th percentile), an optimal year (precipitation between the 25th and 75th percentile), or a wet year (precipitation above the 75th percentile) (Figure 2). The entire dataset was then divided into these three categories, and all subsequent statistical analyses were performed separately for each category.

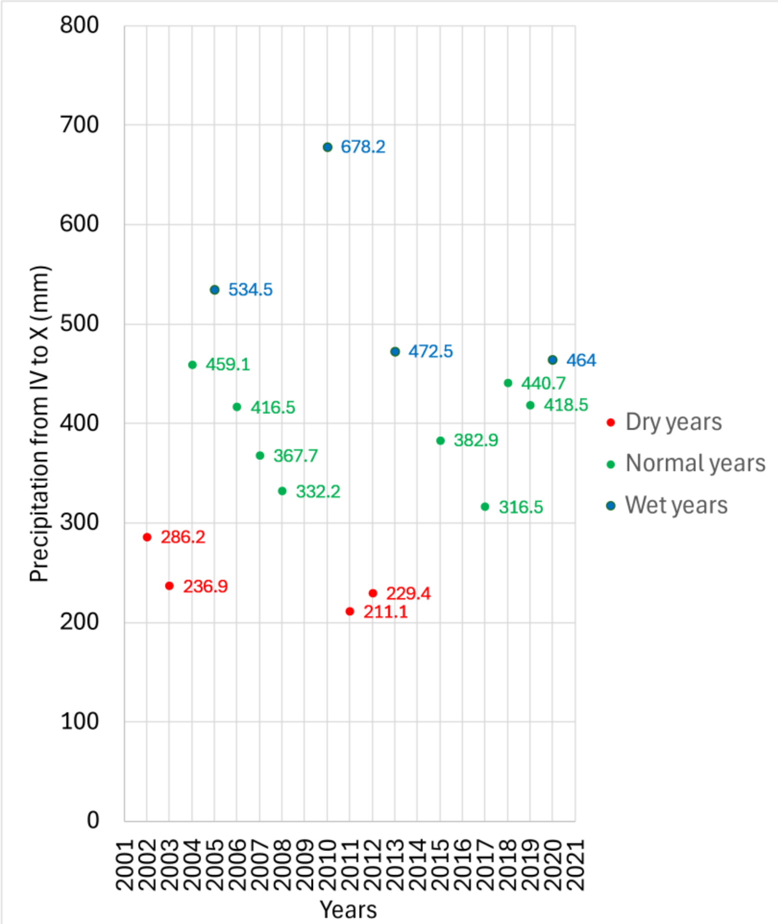


Figure 2. Grouping of the years based on maize in season precipitation using percentile method.
Figura 2. Grupisanje godina na osnovu količine padavina tokom vegetacije kukuruza primenom metode percentila.

Validation of precipitation-based year classification

To confirm if percentile method to classify years into three categories based on precipitations from IV-X is suitable, we used nonparametric multiple-comparison test (Steel–Dwass) to see if these categories differ statistically. The reason to use nonparametric test is because the precipitation data did not follow a normal distribution (Table 1). Welch's ANOVA showed that the differences between the precipitation groups are statistically highly significant (Table 2). Effect-size measures evidenced very large effects: eta-squared for the ANOVA was 0.776 (rainfall category explained 77.6 % of the variance), and Cliff's delta for all pairwise contrasts was |δ| = 1.00 (95 % CI [–1.00, –0.999]). All three pairwise comparisons are highly significant, indicating that each category differs from the others in median precipitation (Table 3). The Steel–Dwass results confirm that these three categories are indeed distinct in terms of growing-season rainfall.

Table 1
Shapiro-Wilk test results to examine the normality of the data
Tabela 1
Shapiro-Wilk test za ispitivanje normalnosti podataka

Rainfall Category	W Statistic	p-value
Dry	0.779	< 0.001
Optimal	0.905	< 0.001
Wet	0.729	< 0.001

Table 2
Welch's ANOVA results
Tabela 2
Rezultati Welch's ANOVA

F (df1, df2)	F statistic	p-value	Eta-squared
F (2, 56.73)	255.13	< 0.0001	0.776

Table 3
Steel–Dwass pairwise comparisons of precipitation among dry, optimal, and wet years
Tabela 3
Steel–Dwass poređenja količine padavina između sušnih, optimalnih i vlažnih godina

Condition	- Condition	Score Mean Difference	p-Value	Cliff's Delta |δ|	95% CI
optimal	dry	41,97321	<0.0001**	1.0	[-1.00, -0.999]
wet	optimal	41,97321	<0.0001**	1.0	[-1.00, -0.999]
wet	dry	27,96429	<0.0001**	1.0	[-1.00, -0.999]

** statistically significant at p < 0.01

Comparative model performance in explaining yield and NUE across contrasting moisture regimes

The analyses of the relationships between N dose and both NUE and yield reveal distinct optimal model choices across moisture regimes (Table 4a, 4b). For yield, the quadratic model consistently outperformed the alternatives in all datasets. In the dry dataset, the quadratic model yielded an AIC of 68.29, a BIC of 66.73, an R^2 of 0.804, and an RMSE of 100.49, indicating a better fit compared to the exponential, linear, or square root formulations. Similar performance was observed in the optimal and wet datasets, where the quadratic formulation provided the lowest AIC and BIC values and the highest R^2 values. Notably, the linear-plateau model emerged as the second-best model in both the optimal and wet datasets, offering competitive performance with slightly higher AIC and BIC values than the quadratic model. However, in the dry dataset, the linear-plateau model could not be fitted, because the dry dataset did not exhibit a pronounced plateau phase which contributed to the singularity problem.

To assess interpolation accuracy for the yield across dry, optimal, and wet year categories, we performed leave-one-out cross-validation (LOOCV) of interpolation across N doses, which yielded an RMSE of 164.78, 145.28 and 220.61 kg ha^{-1} for dry, optimal and wet dataset, respectively. For the dry dataset, this error corresponds to an average deviation of about 1.9% of the mean yield and covering ~26% of the total yield range, indicating that interpolation provides reasonably precise estimates of unobserved values. For the optimal dataset, the leave-one-out interpolation RMSE was 145.28, meaning that interpolated yields differ from the true values by about 1.5% of the mean yield and 15.5% of the total range. The LOOCV interpolation RMSE of 220.61 kg ha^{-1} for wet category means that predictions miss the true value by about 220 kg ha^{-1} on average. Since the mean yield is 10107 kg ha^{-1}, this corresponds to around 2.2% average error and around 12.5% of the full 1762 kg ha^{-1} yield range.

Table 4
Summary of model fit indices (AIC, BIC, R^2, and RMSE) across dry, optimal, and wet year categories. Below are the equations for best fitted models for each condition.
Tabela 4
Pregled indeksa prilagođenosti modela (AIC, BIC, R^2 i RMSE) u kategorijama sušnih, optimalnih i vlažnih godina. U nastavku su prikazane jednačine najbolje prilagođenih modela za svaki od uslova.

(a)

	Model	AIC	BIC	R^2	RMSE	Durbin-Watson test	Breusch-Pagan test
Dry	Exponential	71.48664	70.31495	0.4470561	168.9707		
	Linear	71.43272	70.26104	0.4529864	168.0621		
	Quadratic*	68.29045	66.72820	0.8044103	100.4948	p = 0.04	p = 0.80
	Square Root	72.27845	71.10677	0.3521757	182.8940		
	Exponential	74.53493	73.36325	0.5535508	229.19083		
	Linear	74.41501	73.24332	0.5641315	226.45867		
Optimal	Quadratic**	59.97084	58.40859	0.9837433	43.73486	p = 0.07	p =0.77
	Square Root	72.96006	71.78838	0.6741780	195.79491		
	Linear+Plateau	60.93304	59.37079	0.9802935	48.15213		
	Exponential	78.68503	77.51334	0.7022665	347.08309		
	Linear	78.34877	77.17708	0.7216311	335.60618		
Wet	Quadratic***	65.79502	64.23277	0.9848470	78.30126	p = 0.14	p =0.67
	Square Root	76.50462	75.33294	0.8074959	279.08703		
	Linear+Plateau	69.03613	67.47388	0.9710254	108.27504		

* Yield = 8319.02 + 7.5 * Ndose - 0.03 * $Ndose^2$
** Yield = 8298.66 + 19.58 * Ndose - 0.05* $Ndose^2$
*** Yield = 7595.82 + 31.05 * Ndose - 0.08 * $Ndose^2$

(b)

	Model	AIC	BIC	R^2	RMSE	Ljung-Box p-value	slope p-value
	Exponential*	6.647767	5.476081	0.9991481	0.2581636	p =0.26	p = 0.15
	Linear	29.453395	28.281708	0.9184794	2.5254037		
Dry	Quadratic	7.562191	5.999942	0.9993143	0.2316056		
	Square Root	24.605766	23.434079	0.9690823	1.5552527		
	Linear+Plateau	21.631896	20.069648	0.9885664	0.9457766		
	Exponential	20.03156	18.85988	0.8879729	0.9843416		
Optimal	Linear	16.92498	15.75329	0.9398149	0.7214874		
	Quadratic**	15.23744	13.67519	0.9712132	0.4989772	p =0.11	p = 0.71
	Square Root	20.23881	19.06713	0.8832318	1.0049552		
	Exponential***	27.04176	25.87007	0.9763996	1.984242	p =0.45	p = 0.48
	Linear	33.47775	32.30606	0.9145048	3.776645		
Wet	Quadratic	28.34931	26.78706	0.9794518	1.851493		
	Square Root	29.22975	28.05807	0.9634434	2.469552		
	Linear+Plateau	33.81890	32.25666	0.9386440	3.199363		

* NUE = 46.88 * exp(-0.0097 * Ndose)
** NUE = 13.99 - 0.003 * Ndose - 0.0001 * $Ndose^2$
*** NUE = 70.43 * exp(-0.0061 * Ndose)
* Durbin-Watson and Ljung-Box test were used to assess autocorrelation. Breusch-Pagan and p-value of the slope coefficient from a regression of squared residuals on fitted values were used to assess heteroscedasticity, respectively.

The evaluation of agronomic NUE demonstrated model selection that varied with environmental moisture. In the dry and wet datasets, the exponential model emerged as the best fit. In the dry dataset, although both the exponential and quadratic models showed very high coefficients of determination (R^2 values exceeding 0.999), the exponential model achieved a slightly lower AIC (6.65 versus 7.56 for the quadratic) and comparable RMSE values, supporting its selection as the superior model. A similar pattern was observed in the wet dataset where the exponential model had an AIC of 27.04 and an RMSE of 1.98, outperforming the quadratic model despite both models explaining a large portion of the variance in NUE. In contrast, for the optimal dataset, the quadratic model provided the best fit, with an AIC of 15.24, a BIC of 13.68, and an R^2 of 0.971, outperforming the exponential model whose performance metrics were inferior.

The dry dataset with a mean NUE of 13.71 kg ha^{-1} and a total span of 24.27 kg ha^{-1}, this corresponds to about 2.5% of the mean and 1.4% of the range. The exponential fit therefore delivers very tight interpolation across the N interval. In the optimal dataset, LOOCV RMSE = 2.33 kg ha^{-1}. Against a mean NUE of 10.13 kg ha^{-1} and a span of 7.45 kg ha^{-1}, the error represents roughly 23% of the mean and 31% of the range. For applications focusing on NUE shifts exceeding ~2.3 kg ha^{-1}, this model captures the response curve well. For the wet dataset, LOOCV RMSE for the exponential NUE model is 4.85 kg kg^{-1}. Since the mean NUE is 31.09 and the full range is 37.43 kg kg^{-1}, this error represents roughly 15.6% of the mean and about 13% of the range.

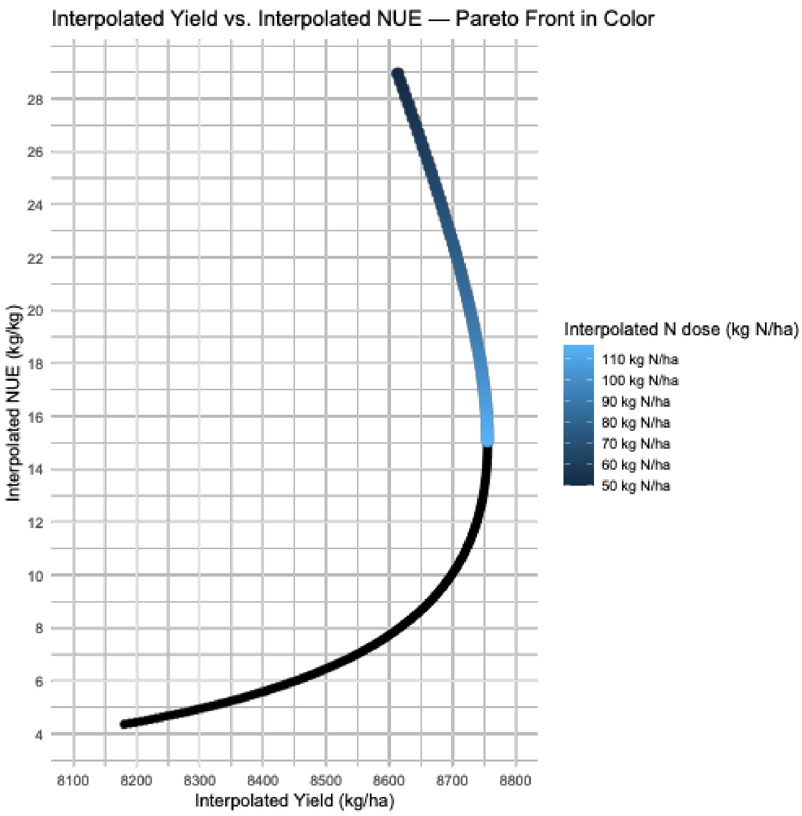
The quadratic models in all datasets suggest that yield initially increases with nitrogen dose until a maximum is reached, after which further increases in nitrogen lead to a decline in yield. The coefficients of the linear term increase from 7.5 in the dry condition to 31.05 in the wet condition, indicating that the responsiveness of yield to nitrogen application is much stronger under more favorable moisture conditions. Conversely, the negative quadratic coefficients become more pronounced (from –0.03 to –0.08), reflecting a sharper curvature in the yield response when moisture is ample. The formula reveals that under dry conditions the estimated N dose for theoretical maximum yield is approximately 125 kg N ha^{-1}, while in both optimal and wet conditions the dose shifts to around 194–196 kg N ha^{-1}. This pattern indicates that under water-limited conditions the yield response is subdued and peaks at a lower nitrogen rate, whereas in environments with optimal or abundant moisture, maize yield responds more noticeably to increasing nitrogen, albeit with a steeper eventual decline.

For NUE, the best-fit models differ with moisture regimes. In the wet and dry dataset, the equations indicate that NUE decreases exponentially as nitrogen dose increases, a common phenomenon as higher doses often lead to diminishing returns in nitrogen uptake and utilization. Notably, the decay constant is higher in the dry dataset (0.0097 versus 0.0061 in the wet dataset), suggesting that under drought conditions the efficiency with which plants use applied nitrogen declines more rapidly with increasing dose. In contrast, for the optimal dataset, the quadratic model was best fitted for NUE. The model shows a gradual decline in NUE with increasing nitrogen dose. Specifically, at the lower bound of 50 kg N ha^{-1}, the predicted NUE is about 13.9, whereas by 250 kg N ha^{-1}, it decreases to around 8.5. This milder quadratic response indicates a more moderate decrease in efficiency as nitrogen increases. It suggests that, while overapplication of nitrogen can still reduce efficiency, the penalty is less steep when moisture is neither limiting nor excessive.

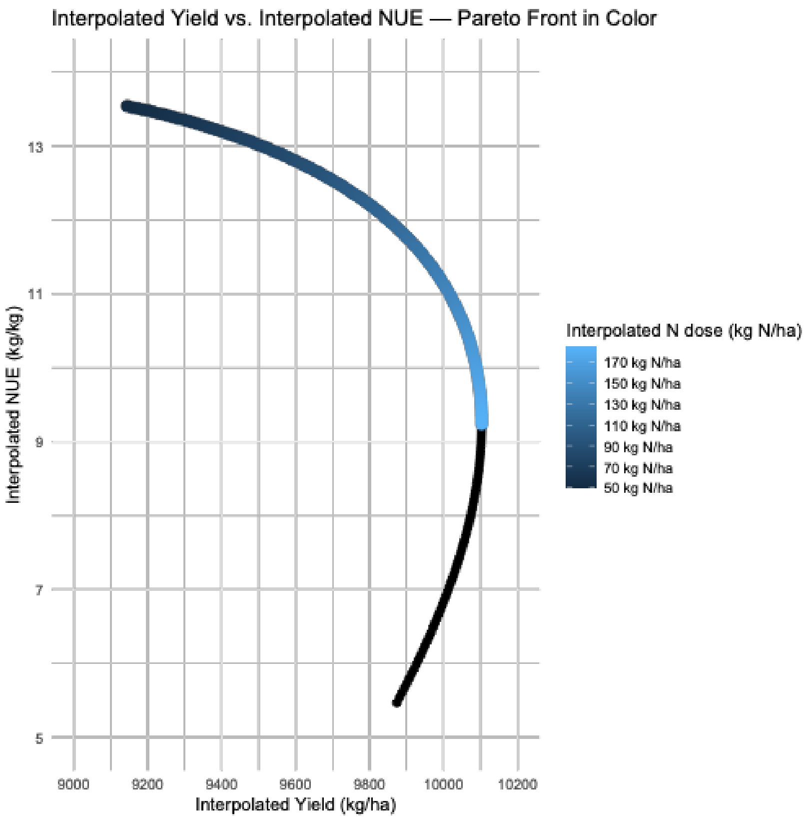
Multiobjective optimization of nitrogen fertilization: balancing yield and efficiency across moisture regimes

The Figure 3a, 3b, 3c represent points on the Pareto front for each moisture regime, which reflects a compromise between yield and NUE for a given N dose. In a multiobjective sense, one cannot increase yield further without sacrificing NUE, or vice versa, along these solutions.

(a)


Interpolated Yield vs. Interpolated NUE — Pareto Front in Color
Interpolated NUE (kg/kg)
28
26
24
22
20
18
16
14
12
10
8
6
4
8100
8200
8300
8400
8500
8600
8700
8800
Interpolated Yield (kg/ha)
Interpolated N dose (kg N/ha)
110 kg N/ha
100 kg N/ha
90 kg N/ha
80 kg N/ha
70 kg N/ha
60 kg N/ha
50 kg N/ha

(b)


Interpolated Yield vs. Interpolated NUE — Pareto Front in Color
Interpolated NUE (kg/kg)
13
11
9
7
5
9000
9200
9400
9600
9800
10000
10200
Interpolated Yield (kg/ha)
Interpolated N dose (kg N/ha)
170 kg N/ha
150 kg N/ha
130 kg N/ha
110 kg N/ha
90 kg N/ha
70 kg N/ha
50 kg N/ha

(c)

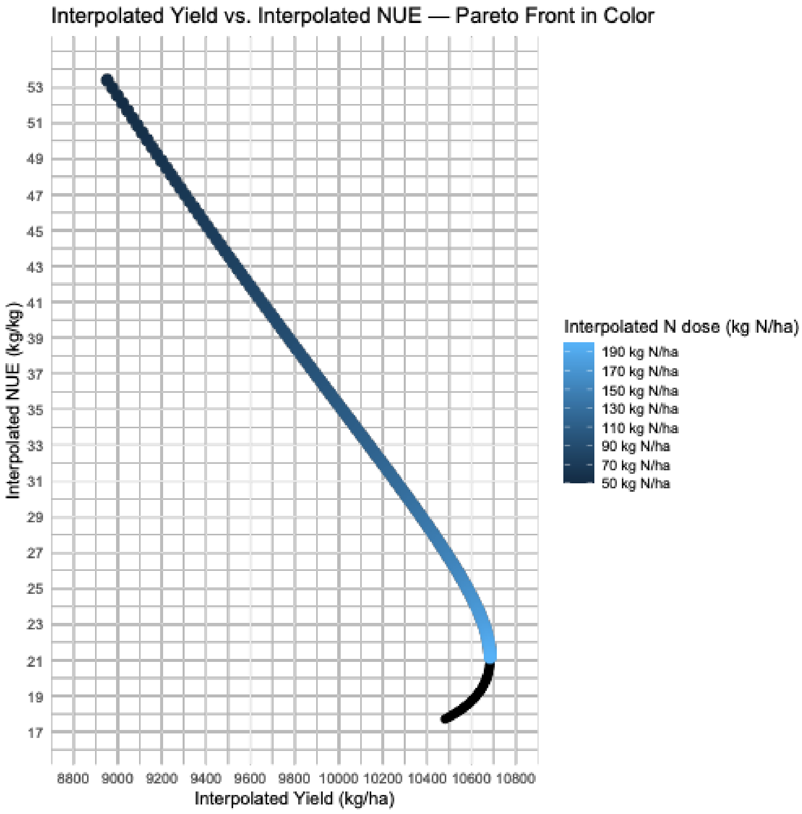


Figure 3. Pareto front of yield and NUE under: **(a)** Dry conditions, **(b)** Optimal conditions, **(c)** Wet conditions. Black points represent non-optimal solutions, while colored points form the Pareto front. Color indicates the nitrogen dose (kg N ha^{-1}).

Figura 3. Pareto front prinosa i agronomske efikasnosti korišćenja azota (NUE) u uslovima: **(a)** suše, **(b)** optimalne vlažnosti, **(c)** prekomerne vlažnosti. Crne tačke predstavljaju neoptimalna rešenja, dok obojene tačke čine Pareto front. Boja označava dozu azota (kg N ha^{-1}).

In each dataset, the categories formed using the percentile-based method were checked for statistical differences using one-way ANOVA (α = 0.05), with Tukey HSD as the post-hoc test. Checking statistical differences between categories shows that the groups created by quartiles capture real differences in yield and NUE, not random noise. It proves low (Q1), intermediate (Q2), high (Q3), and highest (Q4) N-rate bands differ in performance. ANOVA showed that mean NUE values differed significantly across categories in dry conditions. Tukey HSD confirmed all pairwise differences (all p-values < 0.001) (Table 5). Similarly, ANOVA for yield across categories revealed a significant difference, and Tukey HSD showed that all four groups differed from each other ($p < 0.001$). This was the case for both optimal and wet conditions also. Normality assumptions Shapiro-Wilk test didn't show normality of the residuals; however, the one-way ANOVA was still applied because the Levene test showed that the homogeneity was present in the data (Table 6). According to Blanca et al. (2017), the F-test of ANOVA is still a valid statistical procedure for data that do not have a normal distribution, only if the variances between groups are homogeneous.

Table 5
ANOVA and pairwise differences in NUE and yield between quartile categories in dry, optimal and wet conditions
Tabela 5
ANOVA i razlike između grupa u NUE i prinosu između kvartilnih kategorija u sušnim, optimalnim i vlažnim uslovima

Condition	NUE category	NUE difference	p-value	Yield category	Yield difference	p-value
Dry	Q2-Q1	3.525241	<0.001	Q2-Q1	36.87030	<0.001
	Q3-Q1	7.000848	<0.001	Q3-Q1	73.83448	<0.001
	Q4-Q1	10.544336	<0.001	Q4-Q1	114.06691	<0.001
	Q3-Q2	3.475608	<0.001	Q3-Q2	36.96418	<0.001
	Q4-Q2	7.019095	<0.001	Q4-Q2	77.19660	<0.001
	Q4-Q3	3.543487	<0.001	Q4-Q3	40.23242	<0.001
Pr(>F)	<0.001			<0.001		
Optimal	Q2-Q1	1.087731	<0.001	Q2-Q1	245.3157	<0.001
	Q3-Q1	2.175858	<0.001	Q3-Q1	491.7635	<0.001
	Q4-Q1	3.284517	<0.001	Q4-Q1	763.2242	<0.001
	Q3-Q2	1.088126	<0.001	Q3-Q2	246.4479	<0.001
	Q4-Q2	2.196785	<0.001	Q4-Q2	517.9086	<0.001
	Q4-Q3	1.108659	<0.001	Q4-Q3	271.4607	<0.001
Pr(>F)	<0.001			<0.001		
Wet	Q2-Q1	6.550950	<0.001	Q2-Q1	439.8553	<0.001
	Q3-Q1	13.014554	<0.001	Q3-Q1	882.4098	<0.001
	Q4-Q1	19.565504	<0.001	Q4-Q1	1377.0039	<0.001
	Q3-Q2	6.463604	<0.001	Q3-Q2	442.5545	<0.001
	Q4-Q2	13.014554	<0.001	Q4-Q2	937.1485	<0.001
	Q4-Q3	6.550950	<0.001	Q4-Q3	494.5941	<0.001
Pr(>F)	<0.001			<0.001		

* Q4-75th percentile and above, Q3-between the 50th and 75th percentiles, Q2-between the 25th and 50th percentiles, Q1-below the 25th percentile.

Table 6
Results of Shapiro–Wilk and Levene's tests before applying ANOVA under dry, optimal, and wet conditions
Tabela 6
Rezultati Shapiro–Wilk i Levene testa pre primene ANOVA u sušnim, optimalnim i vlažnim uslovima

Condition	Test	Response	P-value
Dry	Shapiro–Wilk	Yield	0.007
		NUE	0.012
	Levene	Yield	0.996
		NUE	0.992
Optimal	Shapiro–Wilk	Yield	<0.001
		NUE	<0.001
	Levene	Yield	0.995
		NUE	0.997
Wet	Shapiro–Wilk	Yield	<0.001
		NUE	<0.001
	Levene	Yield	0.999
		NUE	0.993

In the dry dataset (Figure 3a) from 50 kg N ha^{-1} (yield = 8,613 kg ha^{-1}, NUE = 29 kg kg^{-1}) up to 116 kg N ha^{-1} (yield = 8,755 kg ha^{-1}, NUE = 15 kg kg^{-1}), the Pareto- optimal points show a steady tradeoff: modest increases in yield at the cost of a rapid decline in efficiency. Past 116 kg N ha^{-1} NUE continues dropping, underscoring the limited yield potential under water- stressed conditions and the sharply diminishing returns from additional nitrogen. Conditional formatting based on percentile distribution reveals that under dry conditions, the optimal N dose range where yields are increasing and NUE stays stable is between 70 and 77 kg N ha^{-1} (Figure 4a). When compared with the 116 kg N ha^{-1}, the optimal N dose range produced roughly 0.7% lower yield while achieving a substantially higher NUE - approximately 52% greater.

(a)

N dose	Yield	NUE
69	8683.03	23.95
70	8686.06	23.71
71	8689.01	23.47
72	8691.91	23.24
73	8694.73	23.01
74	8697.50	22.79
75	8700.20	22.56
76	8702.83	22.34
77	8705.40	22.12
78	8707.91	21.90

(b)

N dose	Yield	NUE
117	9862.19	11.95
118	9869.28	11.92
119	9876.27	11.88
120	9883.15	11.85
121	9889.93	11.82
122	9896.60	11.78
123	9903.17	11.75
124	9909.63	11.72
125	9915.98	11.68
126	9922.22	11.65
127	9928.36	11.62
128	9934.40	11.58
129	9940.33	11.55
130	9946.15	11.51
131	9951.86	11.47
132	9957.47	11.44
133	9962.97	11.40
134	9968.37	11.37

(c)

N dose	Yield	NUE
93	9808.30	41.05
94	9824.75	40.87
95	9841.05	40.70
96	9857.20	40.52
97	9873.19	40.35
98	9889.02	40.17
99	9904.70	40.00
100	9920.22	39.83
101	9935.58	39.65
102	9950.79	39.48
103	9965.84	39.30
104	9980.74	39.13
105	9995.48	38.95
106	10010.07	38.78
107	10024.49	38.60
108	10038.77	38.43
109	10052.88	38.25
110	10066.84	38.08
111	10080.65	37.90
112	10094.30	37.73
113	10107.79	37.55
114	10121.13	37.38
115	10134.31	37.20
116	10147.33	37.03
117	10160.20	36.86
118	10172.91	36.68
119	10185.47	36.51
120	10197.87	36.33
121	10210.11	36.16
122	10222.20	35.98
123	10234.13	35.81
124	10245.91	35.63
125	10257.53	35.46

Figure 4. (a) The table shows the response of maize to varying nitrogen (N) doses under dry conditions, with N dose (kg ha⁻¹), yield (kg ha⁻¹), and nitrogen use efficiency (NUE; kg grain per kg N) represented in columns. The optimal N dose range (70–77 kg N ha⁻¹), highlighted in yellow, corresponds to high values for both yield and NUE, as indicated by the golden-colored markers. Doses below 70 or above 77 kg N ha⁻¹ are associated with reduced performance, which could be seen from different colored markers in either yield or NUE. **(b)** Under optimal moisture conditions, the optimal N dose range for simultaneously achieving high yield and NUE is between 118 and 133 kg N ha⁻¹ (highlighted in yellow). Within this range, yield values are among the highest recorded (green-colored markers), while NUE remains stable (golden-colored markers). **(c)** Under wet conditions, the optimal N dose range for balancing high yield and NUE lies between 94 and 124 kg N ha⁻¹ (highlighted in yellow). Doses under 94 or over 124 kg N ha⁻¹ result in reduced performance, indicated by different coloured markers in yield or NUE.

*The full dataset includes N doses from 50 to 250 kg N ha⁻¹, but only values near the optimal range (one below and one above) are shown here for better visibility.

Figura 4. (a) Tabela prikazuje odgovor kukuruza na različite doze azota u uslovima suše, sa kolonama koje sadrže dozu azota (kg ha⁻¹), prinos (kg ha⁻¹) i agronomsku efikasnost korišćenja azota (NUE; kg zrna po kg N). Optimalni opseg doze azota (70–77 kg N ha⁻¹), označen žutom bojom, odgovara visokim vrednostima i prinosa i NUE, što je prikazano zlatnim markerima. Doze ispod 70 ili iznad 77 kg N ha⁻¹ povezane su sa smanjenim učinkom, što se vidi po markerima druge boje u kolonama prinosa ili NUE. **(b)** U uslovima optimalne vlažnosti, optimalni opseg doze azota za istovremeno postizanje visokog prinosa i visoke NUE iznosi između 118 i 133 kg N ha⁻¹ (označeno žutom bojom). U ovom intervalu, vrednosti prinosa su među najvišima zabeleženima (označene zelenim markerima), dok NUE ostaje stabilna (zlatni markeri). **(c)** U uslovima prekomerne vlažnosti, optimalni opseg doze azota za balansiranje visokog prinosa i visoke NUE nalazi se između 94 i 124 kg N ha⁻¹ (označeno žutom bojom). Doze ispod 94 ili iznad 124 kg N ha⁻¹ dovode do smanjenja performansi, što je prikazano različitim bojama markera u kolonama prinosa i NUE.

* Kompletan skup podataka obuhvata doze azota u rasponu od 50 do 250 kg N ha⁻¹, ali su ovde prikazane samo vrednosti u blizini optimalnog opsega (jedna doza ispod i jedna iznad), radi bolje preglednosti.

The Figure 5 illustrates the trade- off between yield and NUE under a dry scenario using interpolated data points for nitrogen doses from 50 kg N ha⁻ ¹ up to 116 kg N ha⁻ ¹. The labeled points at 50 kg N ha⁻ ¹ and 116 kg N ha⁻ ¹ mark the extremes of this trade- off: lower nitrogen rates maintain higher efficiency at the cost of reduced yield, whereas higher rates push yield upward but diminish efficiency. The steep negative slope highlights the diminishing returns in agronomic efficiency once yield approaches its upper limit under these dry conditions. The linear equation quantifies how NUE declines as yield increases under these dry conditions. Specifically, the slope of -0.093 means that for every 1 kg ha⁻ ¹ increase in yield, NUE decreases by about 0.093 kg kg⁻ ¹.

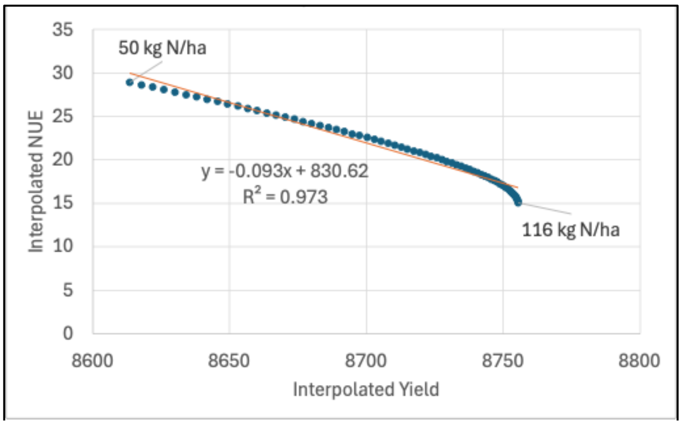


Figure 5. Relationship between maize yield and NUE in dry conditions.
Figura 5. Odnos između prinosa kukuruza i agronomske efikasnosti korišćenja azota (NUE) u uslovima suše.

Under optimal moisture, the Pareto front spans a broader range (Figure 3b). At the low end (50 kg N ha^{-1}), yield is around 9,145 kg ha^{-1}, with NUE ≈ 13.5 kg kg^{-1}. As N input increases toward 141–167 kg N ha^{-1}, yield goes above 10,000 kg ha^{-1} but NUE declines into the 10–11 kg kg^{-1} range. The plateau near 10,100 kg ha^{-1} emerges at 184 kg N ha^{-1}, where NUE settles at 9.24 kg kg^{-1}. Each step along this Pareto front highlights how optimal moisture conditions allow for higher yields than the dry scenario but still require accepting a reduced efficiency at high N doses. Conditional formatting based on percentile distribution indicates that, under optimal moisture conditions, the optimal nitrogen application rate for stable yields and nitrogen use efficiency is between 118 and 133 kg N ha^{-1} (Figure 4b). Compared to the 50 kg N ha^{-1}, the intermediate range yielded about 8.4% more but exhibited a 13.9% reduction in NUE. In contrast, relative to the high nitrogen rate, the intermediate range produced roughly 1.8% lower yield while enhancing NUE by approximately 26.2%.

Under optimal moisture, the negative slope of -0.0041 reveals that as yield increases by 1 kg ha^{-1}, NUE declines by 0.0041 kg kg^{-1} (Figure 6). This decline in efficiency is less steep than in more water-limited scenarios, suggesting that under these conditions, producers can increase yield with only a moderate penalty to NUE.

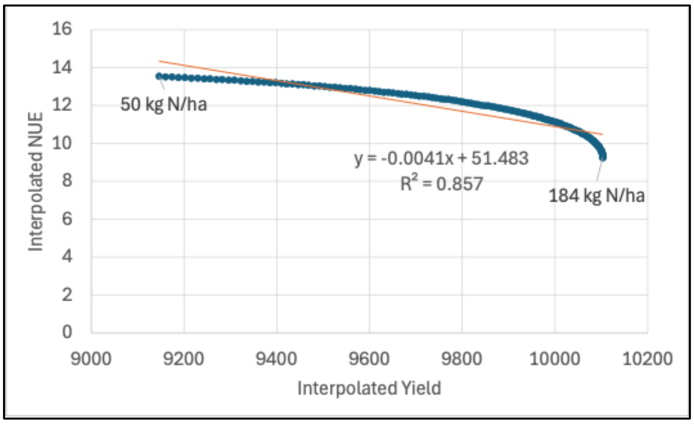


Figure 6. Relationship between maize yield and NUE in optimal conditions.
Figura 6. Odnos između prinosa kukuruza i agronomske efikasnosti korišćenja azota (NUE) u optimalnim uslovima vlage.

In the wet environment in the Figure 3c, the Pareto front starts with high NUE – around 48 kg kg^{-1} at 50 kg N ha^{-1} and yields nearly 9,000 kg ha^{-1}. As N increases toward 150–160 kg N ha^{-1}, yield can exceed 10,500 kg ha^{-1}, but NUE simultaneously drops to around 25–27 kg kg^{-1}. The highest yields (≈ 10,690 kg ha^{-1}) appear at 200 kg N ha^{-1}, where NUE is closer to 21 kg kg^{-1}. Although wet conditions enable the largest absolute gains in yield, the Pareto front still reveals a pronounced efficiency penalty for each additional unit of nitrogen once the crop's high yield potential is approached. Conditional formatting reveals that in the wet environment, the optimal N dose range where yields are increasing and NUE stays stable is between 94 and 124 kg N/ha (Figure 4c). The intermediate range provided a yield increase of roughly 12.1% relative to the 50 kg N ha^{-1}, albeit with a reduction in NUE of about 21.2%. When contrasted with a high nitrogen rate of 199 kg N ha^{-1}, the intermediate range exhibited a yield approximately 6.1% lower, yet its NUE was improved by approximately 69.7% than that observed at the high nitrogen rate.

Compared with the corresponding graphs under dry and optimal conditions, this wet-environment graph highlights a stronger yield potential but also a steeper decline in NUE as yield increases. The negative slope of -0.0141 reveals that as yield increases by 1 kg ha^{-1}, NUE declines by 0.0141 kg kg^{-1} (Figure 7).

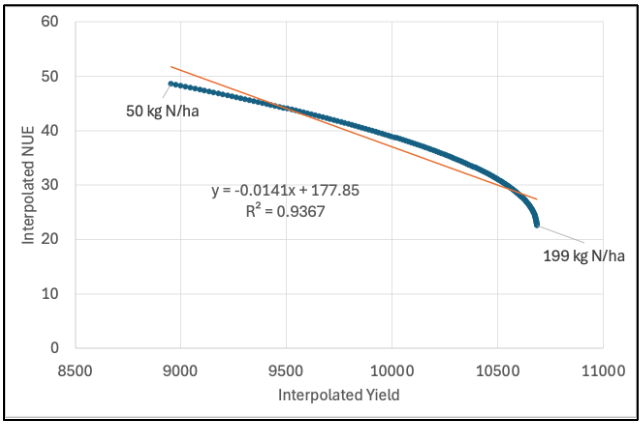


Figure 7. Relationship between maize yield and NUE in wet conditions.
Figura 7. Odnos između prinosa kukuruza i agronomske efikasnosti korišćenja azota (NUE) u uslovima prekomerne vlage.

Discussion

Multiobjective optimization of maize yield and nitrogen use efficiency

The Pareto front is a curve consisting of all outcomes where you cannot improve one objective without worsening the other (Röglin, 2020). By plotting yield on one axis and NUE on the other for various N rates and different moisture scenarios, we obtain a frontier of optimal points. Our results showed that under each moisture condition, the location and shape of the Pareto-optimal region change. Under each condition, a different segment of the interpolated yield–NUE curve becomes Pareto-optimal. This results in a different set of optimal trade-off points along the curve, rather than a uniform shift of the entire frontier. In a well-watered condition, the frontier extends to higher yields with a broader NUE loss, whereas in a drought condition, the maximum achievable yield and thus the Pareto front is lower, and trying to reach for it causes steeper NUE penalty. This multiobjective view reinforces recommendations to avoid chasing 100% of maximal yield at disproportionate cost to efficiency. In other words, as you apply more nitrogen to reach the highest possible yield, each additional unit of yield requires much more nitrogen, so NUE drops rapidly. It quantitatively shows how backing off slightly from the yield maximum can improve NUE.

The findings from this study confirm a well-known agronomic pattern: increasing N fertilizer boosts maize yield up to a point, but excessive N leads to diminishing returns in yield and a sharp drop in efficiency (Su et al., 2020; Ju et al., 2015). Moisture conditions modulate this optimum – adequate water allows the crop to respond fully to N, whereas drought or excessively wet or soil where nitrogen is washed below the root zone and becomes unavailable to plants can stunt the response (Wani et al., 2021). Sufficient soil moisture promotes robust root growth, increasing the root surface area and depth. This expansion allows for greater exploration of the soil profile, facilitating more efficient absorption of N and other essential nutrients (Ma et al., 2023). Adequate water availability supports optimal transpiration rates, which drive the mass flow of nutrients, including N, from the soil to the root surfaces. This process enhances the delivery of N to the plant, supporting growth and metabolic functions (Plett et al., 2020). When water is scarce, the crop's ability to use N is impaired, so yield plateaus at a lower N rate and any N above that reduces NUE (Capurro and Sawchik, 2015), which aligns with our results. A drought-year trial reported that a base rate of 120 kg N ha^{-1} was optimal, as additional N did not improve yield due to lack of rain. Likewise, excess moisture can limit yield response by inhibiting root function and N uptake. In that case, maize roots suffer oxygen deprivation and nutrient uptake is disrupted, meaning even if ample N is present, the plant cannot absorb it efficiently (Kaur et al., 2020). Our results showed that there wasn't much difference in terms of yield and optimal N dose between optimal and excess moisture conditions, which confirms finding from (Kaur et al., 2020). It also aligns with the results from (Latković et al., 2006) who state that the calculated highest yield was achieved by applying 195 kg N ha^{-1}. Our study suggests that the peak in yield is achieved with 184 and 199 kg N ha^{-1} in optimal and wet conditions, respectively. Considering the economy of production, as well as the nitrogen balance, the same authors further state that the optimal amount of nitrogen would be 110–150 kg N ha^{-1}, if the harvest residues are plowed. That is the similar range of N as in our study (Figures 4b, 4c). However, in drought conditions the optimal N rate shifts between 70 and 77 kg N ha^{-1} (Figure 4a).

Environmental considerations

Research shows that very high N may only raise yield slightly more than moderate N rates, while reducing NUE and risking environmental losses. In recent years, agricultural regions and settlements have experienced accelerated contamination of groundwater with nitrogen-containing substances (Rogožarski and Marjanović, 2012) due to the excessive use of mineral fertilizers, applied in quantities exceeding what plants can utilize. A study by Rajković et al. (2014) reported that in certain regions of Serbia, the most common causes of drinking water contamination were elevated concentrations of nitrates (up to 20 times above the permissible limit) and nitrites (up to 10 times above the limit). While there are many ways to reduce the amount of nitrate and nitrite entering the water, one of the approaches is to reduce N fertilizer added to the field. Additionally, adopting nutrient management techniques that consider soil testing, crop requirements, and environmental conditions can further enhance nitrogen use efficiency. This approach ensures that the applied nitrogen meets crop needs without contributing to environmental pollution (Clarke and Beegle, 2014).

For instance, in rice cultivation, applying more than 315 kg N ha^{-1} led to reduced grain yield and NUE. The optimal application rate was identified as 210 kg N ha^{-1}, which balanced high grain yield with efficient nitrogen utilization (Liang et al., 2021). One long-term study found that reducing N by 25% caused almost no yield penalty (<4% yield drop) but significantly improved NUE in maize. Similarly, another experiment noted that cutting N by about 30% did not decrease maize biomass or yield, and it achieved the highest NUE at that reduced rate, whereas further N increases only lowered NUE (Shi et al., 2016). Sensor-based fertilization strategies have demonstrated that reducing N input by up to 20% from the optimal rate can result in only about a 5% yield loss, thereby enhancing NUE and minimizing nitrogen surplus (Mittermayer et al., 2024).

Modeling approaches in fertilizer management

Our analyses consistently showed that a quadratic model best described the relationship between N rate and maize grain yield across different moisture regimes. Many agronomic studies have used quadratic models to represent this nutrient response pattern (Zou et al., 2024; Li et al., 2020; Qiu et al., 2015; Latković, 2010). However, it is important to note that while the quadratic model is prevalent, it may not always provide the most accurate representation of yield responses, especially at higher nutrient application rates. Alternative models, such as the quadratic-plus-plateau model, have been suggested to better capture the plateau effect observed in crop yields at higher nutrient levels (Wang et al., 2020). However, we didn't use it in this study because the quadratic-plus-plateau model is constituted from four parameters, and we had five data points – using it would promote overfitting in such situations. In our case, the linear-plus-plateau model (three parameters) was the second best after the quadratic-plus-plateau model.

For agronomic NUE the relationship with N rate under extreme moisture conditions was explained by an exponential decay model. Here, the NUE against N curve became very steep initially and then quickly flattened near zero, a shape characteristic of exponential decay. Under optimal conditions, NUE typically declines as N rate increases, often in a smooth curvilinear way. These results corroborate many other studies that investigated the relationship between NUE and fertilizer rates (Hegedus et al., 2023).

Conclusion

The findings from this study highlight a pronounced trade-off between yield maximization and agronomic nitrogen use efficiency (NUE) in maize production across distinct moisture conditions. Dry years showed a lower optimal nitrogen rate, whereas optimal and wet years supported higher N applications before returns on yield began to diminish. However, the optimal rate in optimal years was slightly higher than in wet years, by 7-25%. Quadratic models adequately captured the yield response to nitrogen in each scenario, and exponential decay models frequently explained the decline in NUE as N rates rose. By focusing on nitrogen ranges below the absolute yield peak, growers can realize substantial improvements in NUE (ranging 26.2-69.7%), reducing input costs and mitigating potential nitrate leaching risks. This approach supports more resource-conscious maize production, emphasizing strategic nitrogen applications tailored to site-specific precipitation patterns. Such practices can stabilize yields while preserving water quality and ecosystem integrity. Overall, results underscore the value of aligning nitrogen doses with prevailing moisture conditions and show that 70-77 kg N ha^{-1}, 118-133 kg N ha^{-1} and 94-124 kg N ha^{-1} in dry, optimal and wet conditions respectively, can meet productivity targets without incurring excessive environmental costs.

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Optimizacija prinosa kukuruza i efikasnosti korišćenja azota u sušnim, optimalnim i vlažnim proizvodnim uslovima

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SAŽETAK

Doze azota, prinos zrna kukuruza i efikasnost korišćenja azota (NUE) su usko povezani, a režim padavina ima značajnu ulogu u toj vezi. Višegodišnji ogled postavljen je sa ciljem optimizacije prinosa zrna kukuruza i agronomske efikasnosti korišćenja azota u različitim uslovima vlažnosti. Podaci, koji obuhvataju period od 2002. do 2020. godine, dobijeni su iz dugoročnog eksperimenta upravljanja žetvenim ostacima u kombinaciji sa rastućim dozama azota (N). Upravljanje žetvenim ostacima obuhvatalo je dva tretmana, sa i bez zaoravanja ostataka. Kada su žetveni ostaci bili zaorani, primenjeno je šest nivoa azota: 0 (kontrolni tretman), 50, 100, 150, 200 i 250 kg N ha^{-1}. U varijanti bez zaoravanja biljnih ostataka, primenjene su tri doze azota: 0 (kontrolni tretman), 100 i 200 kg N ha^{-1}. Za analizu je primenjen višeciljni pristup, koji je omogućio uvid u kompromis između prinosa i NUE u zavisnosti od režima padavina, pri čemu su se vegetacione sezone klasifikovale kao suve, optimalne i vlažne, na osnovu percentilskih pragova padavina. Ova metodologija omogućila je precizniju interpretaciju reakcije prinosa i efikasnosti korišćenja azota u različitim uslovima vlažnosti. Rezultati su ukazali na različite optimalne doze azota u zavisnosti od režima padavina. U suvim godinama, optimalni raspon kretao se od 70 do 77 kg N ha^{-1}, dok je u sezonama sa uobičajenim padavinama iznosio od 118 do 133 kg N ha^{-1}. U vlažnim godinama, optimalne doze su bile između 94 i 124 kg N ha^{-1}. Ove doze omogućile su ostvarenje prinosa bliskih maksimalnim vrednostima, uz održavanje efikasnosti korišćenja azota. Dalje povećanje količine azota donosilo je samo skromna povećanja prinosa, uz istovremeno izraženiji pad NUE. Rezultati naglašavaju da umereni nivoi đubrenja azotom, prilagođeni raspoloživoj vlažnosti, mogu obezbediti visoku i stabilnu proizvodnju kukuruza. Analiza je takođe potvrdila značaj zaoravanja biljnih ostataka, koje se dosledno pokazalo kao jedno od optimalnih rešenja u okviru višeciljnog pristupa.

KLJUČNE REČI

Višeciljna optimizacija; Pareto; žetveni ostaci; azot; iskorišćenje azota; prinos

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