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Article

Optimizing Nitrogen Fertilization in Maize Production to Improve Yield and Grain Composition Based on NDVI Vegetation Assessment

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Abstract

Nitrogen fertilization is essential for balancing maize yield, grain composition, and environmental sustainability. This study aimed to evaluate the relationship between nitrogen (N) supply, grain quality traits, and yield potential using UAV-based Normalized Difference Vegetation Index (NDVI) monitoring in a long-term fertilization field experiment in Eastern Hungary. Six N levels (0–300 kg ha^{-1}) were tested during two consecutive growing seasons (2023–2024) under varying climatic conditions. The obtained results showed that moderate N doses (120–180 kg ha^{-1}) provided the optimal nutrition level for maize, significantly increasing yield compared to the control (+5.086 t ha^{-1} in 2024), while excessive fertilization above 180 kg ha^{-1} did not result in any substantial yield gains; however, it significantly modified grain composition. Higher N supply enhanced protein content (+0.95% between 0 and 300 kg ha^{-1}) and reduced starch percentage, confirming the protein–starch trade-off, whereas oil content was less affected by nitrogen fertilization, similarly to previous results. The strongest correlation between NDVI values and yield was measured at the post-silking stage (112 DAS; R = 0.638 in 2023, R = 0.634 in 2024), indicating the suitability of NDVI monitoring for in-season yield prediction. Overall, NDVI-based monitoring proved effective not just for optimizing N management but also for supporting site specific fertilization strategies to enhance maize productivity and nutrient use efficiency.

Keywords: maize; NDVI; nitrogen supply; nutrient replenishment; remote sensing; yield composition

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1. Introduction

The rate of technological progress in agriculture accelerated during the past decade. In the last ten years, farmers have widely adopted the use of RTK, robotic steering, and, most recently, autonomous machinery. The appearance of drones, i.e., UAVs, both for spraying and remote sensing purposes, is a new step in technological development. The amount of research on the usefulness of the obtained data from remote sensing drones is large, as each pixel carries a single piece of data, which, when correlated to specific factors, can provide many new insights into physiological, biological, and agrotechnical processes. Recently, the use of drones as a proximal data acquisition platform has revolutionized the way precise high-resolution datasets are collected [1,2]. Another advantage of light drones is low financial costs and flexibility [3,4]. Advanced technologies in agriculture, such as drones, offer solutions to many large and small challenges. The main agricultural applications of drones include crop monitoring, soil and field analysis, and bird deterrence [5].

Unmanned aerial vehicles (UAVs) equipped with high-resolution image sensors, LiDAR, and multi- and hyperspectral cameras are widely used to support precision agriculture and digital farming applications, such as plant phenotyping [6–8]. The type of recorded data depends on the various cameras and sensors used by the drone. For today, technological development has reached such a point that these devices can record and analyze individual leaves of a maize plant from a height of 120 m, deducing the water content of the soil, thereby enabling the farm to apply variable amounts of irrigation water. This is how agricultural practices change as a result of drones, thereby providing agricultural information for both farmers and agricultural consultants. Consequently, drone technology is slowly becoming the cornerstone of precision farming [9]. NDVI can be used to quickly and accurately map the nitrogen status and stress levels of plants, enabling the optimization of variable rate fertilization with the aim of improving yield and grain quality [10,11]. In recent years, unmanned aerial vehicles (UAVs) have also proved to be effective in assessing damage due to their relatively high resolution [12], although UAV data have limited spatial coverage and may be subject to uncertainties, such as lighting conditions during flight. For this reason, it is very important to have a precise methodological description of the recording process [13].

Despite its many advantages, NDVI is not always the most accurate index for detecting anomalies in plant yields, especially when detailed data are available between the red and NIR bands [14]. NDRE (Normalized Difference Red-Edge Index) proved to be more beneficial than NDVI for the optimal planning of harvest times, based on the transitions of photosynthesis activity [15].

In precision farming, the use of NDVI data is essential, as mentioned by Ssemugenze et al. (2023) [16], and a drone-mounted NDVI sensor is the ideal solution for the accurate measurement of these data. In addition, Yu et al. (2021) [17] used drones equipped with LiDAR sensors to investigate the growth of the plant flora to estimate the amount of biomass. These innovative technologies offer promising opportunities to promote more efficient and sustainable production in the agricultural sector. As a result, analyzing the normalized vegetation index (NDVI) and the normalized green-red variance index, or NGRDI, to detect weeds, it was found that the NGRDI has slightly better properties [18]. In addition, in some cases, the green visible light vegetation index showed a higher correlation with yield in maize [19]. NGRDI is commonly used to estimate vegetation fractions. It can be considered as a phenological indicator of vegetation index, with which it is possible to estimate biomass [20]. There are many photogrammetric software available to researchers; however, it is important to emphasize that prior experience and knowledge are required to correctly interpret the data [21]. Some software conducts automatic georeferencing to avoid traversal so that the user only needs to enter the field alignment points obtained by manual GPS for the software to successfully match and georeference the photographs [22].

The growth of maize is an important source of data for pre-harvest yield estimation, which can be used to predict the final harvest to some extent. With adequate spectral resolution, satellite and drone remote sensing can be used for a variety of purposes, such as crop condition detection, crop estimation, disease detection, and nutrient deficiency detection [23]. Several previous studies have shown that both true and false spectra taken between the V7 and VT growth stages can be used to predict N deficiency and N requirement in maize [24]. Previous research emphasized the timing of sensing or the value of NDVI for detecting nitrogen deficiency, yet less is known about how NDVI performs in the context of long-term fertilization experiments that reflect cumulative soil-crop interactions across decades. Furthermore, while UAV-based remote sensing is increasingly applied, evidence is still scarce on how it integrates with detailed yield composition traits (protein, starch, oil) under variable climatic conditions. This gap limits the ability to provide site-specific fertilization recommendations that consider both yield quantity and quality. Therefore, this study aimed to combine UAV-derived NDVI with a long-term maize fertilization field experiment to clarify how nitrogen rates affect yield, grain composition, and vegetation dynamics under contrasting growing seasons. In addition, this work also aimed to analyze the development of NDVI dynamics based on the number of days since sowing for each phenological stage, taking into account the different nutrient levels.

2. Materials and Methods

2.1. Description and Location of the Field Experiment

The experiments were carried out at the University of Debrecen, Institutes for Agricultural Research and Educational Farm, Debrecen Educational Farm and Landscape Research Institute (DTTI), and Látókép Crop Production Experiment Site (47° 83, 030″ N, 21° 82, 060″ E, 111 m A.S.L.) (Figure 1). The experimental area is an excellent site for field crop production, with appropriate agrotechnical, biological, and soil conditions (Table 1).

Figure 1. Location of the Látókép Crop Production Experiment Site in northeast Hungary and the aerial view of the experimental site and the long-term experiment with the examined polygons.

Table 1. Soil properties of the experimental area.

	pH	Arany's Plasticity Index	$CaCO_3$ [m/m%]	Humus [m/m%]	Nitrogen [mg/kg]	Magnesium [mg/kg]	Sulfur [mg/kg]	Potassium Oxide [mg/kg]	Sodium [mg/kg]	Phosphorus Pentoxide [mg/kg]	Copper [mg/kg]	Manganese [mg/kg]	Zinc [mg/kg]
N0	6.15	38.56	<0.1	2.16	1.17	362.30	0.78	185.28	13.59	52.90	2.26	248.40	0.58
N1	5.81	37.06	<0.1	2.16	1.47	353.00	1.48	287.70	10.08	142.61	2.17	246.40	0.64
N2	5.70	40.28	<0.1	2.23	2.30	346.15	6.88	277.44	9.55	146.65	2.30	259.60	0.59
N3	5.59	38.47	<0.1	2.25	1.98	344.50	4.75	321.18	10.10	200.89	2.17	240.60	0.57
N4	5.40	37.04	<0.1	2.06	1.91	344.85	1.10	315.48	8.59	184.77	2.01	230.10	0.53
N5	5.57	36.81	<0.1	2.02	2.11	359.00	2.81	277.02	9.22	129.12	2.28	252.85	0.59

The experiment was conducted in the framework of a nutrient supplementation long-term experiment established in 1983, where 41 years of unchanged site, agrotechnical parameters, and nutrient supplementation are used (Tables 1 and 2). In the summer of 1983, before the establishment of the experimental site, Béla Martin conducted a soil survey. The investigation revealed that the humus-rich layer extended vertically from the surface down to 80 cm. The humus content ranged between 2.5 and 3.0%, while the pH of the cultivated layer was 6.2. The soil nutrient status was 0.12–0.18 mg/kg nitrogen, 138 mg/kg phosphorus pentoxide (P_2O_5), and (K_2O) 272 mg/kg potassium oxide.

The applied macronutrient doses in the more than 41-year-long field experiment provide nutrient levels that can reveal differences that would not emerge in conventional, short-term field experiments. The N2 and N3 nutrient levels are the closest to practical fertilization regimes, while the high, provocative N5 level serves as an important indicator for detecting the effect of nitrogen. The total area of the long-term field experiment is 1.2 hectares, with 13 different hybrids in the experiment, which were analyzed as the average hybrids in the two years of the study. In 2023, there were 13 examined maize hybrids, ranging between FAO 290 and FAO 510, while in the growing season of 2024, FAO numbers ranged between FAO 340 and FAO 520.

Table 2. The nutrient supply levels used in the experiment are in the amount of active ingredients according to macronutrients.

(kg ha^{-1})	**N**	**P_2O_5**	**K_2O**
N0	0	0	0
N1	60	184	216
N2	120	184	216
N3	180	184	216
N4	240	184	216
N5	300	184	216

The size of the plots used for the tests was approximately 7.6 m^2, 2 rows × 5 m. The experiment has a strip-split-plot design with four replications, with the main plots being the genotypes and the split plots being the fertilizer doses. Crop density was 73,400 plants per hectare, sown at a depth of 5 cm, and row spacing was 76 cm. Plowing was used at a depth of 35 cm, with a spring closure with a combinator in both examined years (Table 3).

Table 3. Dates of agrotechnical interventions of the field experiment in the two growing seasons.

	2023	**2024**
Sowing	20 April 2023	11 April 2024
Weed killer application	14 May 2023	10 May 2024
Row cultivation	18 May 2023	16 May 2024
Harvest	28 September 2023	23 September 2024

2.2. Agroclimatic Conditions

The meteorological databases were obtained from the site's own calibrated weather station located in the experimental area, 500 m from the experiment. The standards of the Hungarian National Meteorological Service (OMSZ) were used for the measurement.

2.2.1. Agroclimatic Conditions of the Growing Season 2023

The 2023 growing season was generally favorable, with moderate temperatures and near-average precipitation. May and July were relatively dry, but stored soil moisture and favorable temperatures prevented significant plant stress. An intense rainfall event in August raised the monthly total despite overall dry conditions (Figure 2).

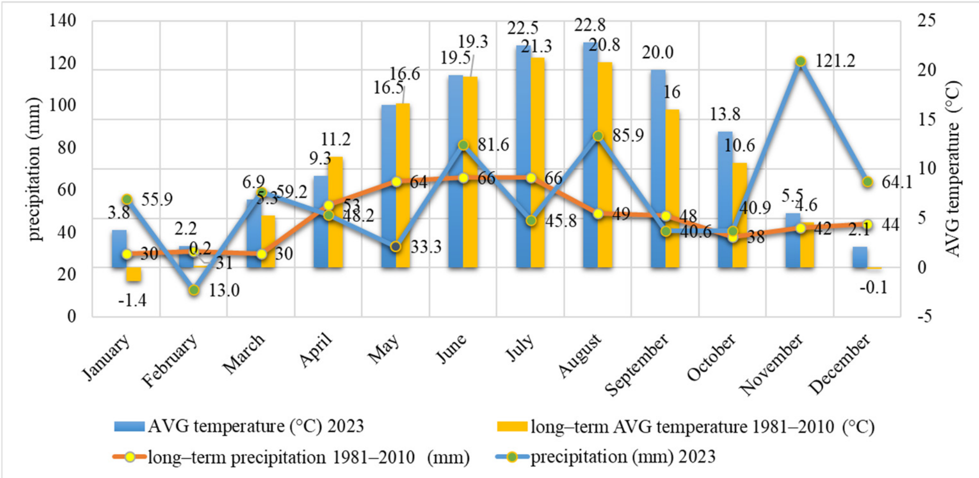

Figure 2. Precipitation data for the experimental area during the growing season comparison with the long-term (1981–2010) weather database in 2023 (AVG = average).

2.2.2. Agro-Climatic Conditions of the Growing Season 2024—f

During the 2024 growing season, February was anomalously warm, with temperatures 5.9 degrees Celsius above the long-term mean and precipitation less than half of the climatological average. March remained markedly dry, while May experienced above-average rainfall, supporting the vegetative phenological phase. From June through September, temperatures exceeded the long-term average by more than two degrees Celsius, and below-average summer precipitation induced water stress. Although September rainfall partially alleviated soil moisture deficits, it occurred too late to enhance generative development (Figure 3).

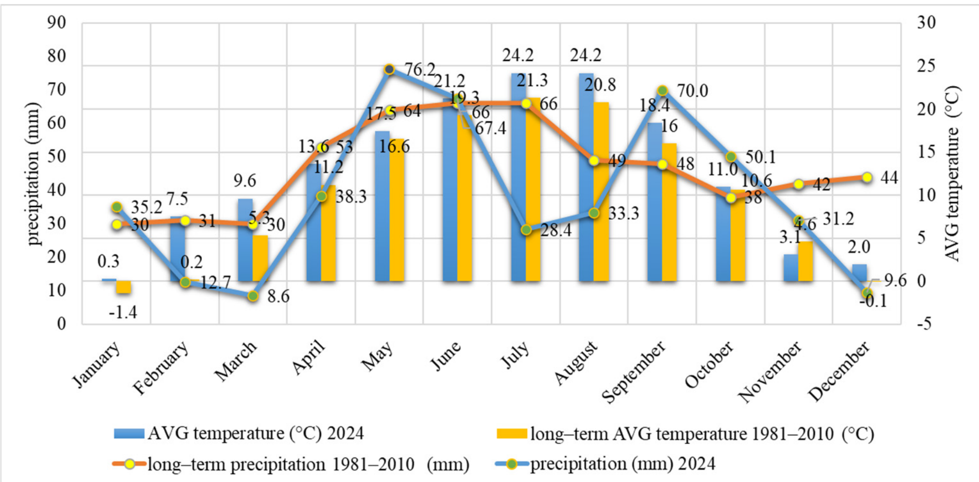

Figure 3. Precipitation data for the experimental area during the growing season compared with the long-term (1981–2010) weather database in 2024 (AVG = average).

2.3. Flight Parameters

The DJI Mavic 3 Multispectral UAV was used for the remote sensing measurement. The image sensor of the multispectral cameras was a 1/2.8-inch CMOS with effective pixels: 5 MP (Figure 4). The lens of the cameras: FOV: 73.91° (61.2° × 48.10°), equivalent focal length: 25 mm, aperture: f/2.0, focus: fixed focus. Multispectral Camera Bands: Green (G): 560 ± 16 nm; Red (R): 650 ± 16 nm; Red Edge (RE): 730 ± 16 nm; near-infrared (NIR): 860 ± 26 nm.

(**a**) (**b**)

Figure 4. The type of UAV used (**a**) and the sensor's position (**b**).

The NDVI vegetation index was calculated with this form: [NDVI = (NIR − RED)/(NIR + RED)]. During the flight, the camera was set to automatic, and the weather parameters were the same. The flights were performed every sampling day at the same time (12 am), and there were no clouds. During the flight, the light parameters were constant (Table 4).

Table 4. Flight and camera settings used during the measurements.

Flight Parameters	
Front and side overlap	80%
GSD (Ground Sampling Distance)	4 cm/pixel
Altitude of the flight	90 m AGL
Speed of the UAV during flight	2.7 m/s
RTK base station distance	<20 km
Photo shooting	distance interval
Elevation optimization	turned ON
Angle of the camera	90°
Reprojection error	<1 pixel
Angle of the flight	110°
GCP (Ground Sampling Point)	not used
Light correction during the flight	automatically

Flight and Camera Settings

The orthophotos were taken using WebODM 2.8.4 software, and the images were analyzed using QGIS 3.28 geospatial software. During the analysis, vegetation indices were created using a raster calculator. As a next step, zonal statistics were performed based on the predefined polygons and the corresponding attribute table. When filtering the vegetation indices, values below 0, mainly soil and shade, and outliers above 98% were removed.

For the analysis, the number of days after sowing was used as a comparison to the different vegetation periods under different growing seasons. The difference in days marks the difference between the two years in the time of remote sensing. The time of the remote sensing depended on the prevailing weather conditions (Table 5).

Table 5. Date of the UAV remote sensing in the 2023 and 2024 growing seasons.

Time of the Remote Sensing and the Days After Sowing (DAS), and the Differences Between the Days in the Growing Season		
2023	**2024**	**Difference (Day)**
30	23	−7
46	36	−10
49	49	0

Table 5. *Cont.*

Time of the Remote Sensing and the Days After Sowing (DAS), and the Differences Between the Days in the Growing Season		
2023	**2024**	**Difference (Day)**
64	76	+12
75	85	+10
82	106	+24
98	111	+13
112	122	+10
124	130	+6
145	135	−10

2.4. Measurement of Yield Quality Parameters

At the end of the growing season, the experimental stand was harvested with a Sampo plot harvester, and the grain yield was equalized uniformly in each plot to 14% moisture content to allow for the comparability of yield.

The protein, oil, starch, and grain moisture content of the maize kernels were measured using a Perten DA 7250 NIR analyzer (PerkinElmer Inc., Waltham, MA, USA). Measurements were conducted based on near-infrared reflectance (NIR) spectroscopy. The samples were collected from four biological replications per treatment. Approximately 300 g of clean, undamaged grains were used for each measurement. The instrument was calibrated using the standardized maize models provided by the manufacturer.

2.5. Statistical Analysis

Different statistical analyses were performed in the research. One-way analysis of variance (ANOVA) was applied to determine whether there were significant differences among the means of the treatments. Fisher's Least Significant Difference (LSD) test was used as a post hoc method to compare group means when the ANOVA indicated significant differences. All analyses were conducted at a 5% level of significance ($\alpha = 0.05$). Results were considered statistically significant when the *p*-value was less than 0.05. Pearson correlation analysis was used to detect interactions between yield and NDVI measurements in the different vegetative and generative stages. Statistical analysis and figures were performed in SPSS 29.0.0.0 and Jamovi 2.6 statistical software.

3. Results

In maize production, nitrogen fertilization and vegetation monitoring play an important role in understanding crop performance and planning management decisions, as yield and grain quality are strongly influenced by the rate and timing of fertilizer application.

The effect of nitrogen significantly increased crop yield at nutrient levels of control, 60 kg ha^{-1} N, 120 kg ha^{-1} N, and 180 kg ha^{-1} N. The increase in yield exceeded 3 t ha^{-1} between doses of 0 and 120 kg ha^{-1} N. Between nutrient levels of 120 kg ha^{-1} N and 180 kg ha^{-1} N, the increase in yield was significant, amounting to 0.498 t ha^{-1}. Provocatively high nutrient levels of 240 kg ha^{-1} N and 300 kg ha^{-1} N did not significantly increase crop yield compared to nutrient levels of 120 kg ha^{-1} N and 180 kg ha^{-1} N. The difference in nutrient levels between 120 kg ha^{-1} and 300 kg ha^{-1} N resulted in an increase in yield of only 0.178 t ha^{-1}. The highest yield was achieved with a dose of 180 kg ha^{-1} N in the 2023 growing season. With increasing nutrient levels, the moisture content of the grain yield also increased gradually. The highest grain moisture content was achieved with a dose of 180 kg ha^{-1} N, with a value of 14.139%, compared to the lowest grain moisture content measured in the control with a nutrient level of 0 kg ha^{-1} N, with a value of 13.765%, which represents a difference of 0.374% in grain moisture content. Based on these results, it can be concluded that in the growing season of 2023, grain moisture content increased significantly with increasing yield up to a dose of 180 kg ha^{-1} N. During the starch content analysis, the highest yield was achieved at a nutrient level of 180 kg ha^{-1} N, which was significantly lower than the other nutrient levels, with the lowest starch content of 62.777%. The analysis of grain oil content showed that none of the nutrient treatments resulted in significant differences, but the highest oil content was measured at the control nutrient level, at 3.637%. When examining the protein content, there was no significant difference between the control and the low 60 kg ha^{-1} N nutrient treatment. When analyzing the protein content values, we can divide the examined nutrient levels into two parts: the control, 60 kg ha^{-1}, and the high 240 kg ha^{-1} and 300 kg ha^{-1} nutrient levels. There was a significant difference in protein content between the low and high nutrient levels, with the difference between the control and 300 kg ha^{-1} N nutrient levels exceeding 0.95% (Table 6).

Table 6. The effect of the fertilizers on the yield quality and quantity parameters in 2023. Treatments with different letters are significantly different.

N (kg ha^{-1})	Yield (t ha^{-1})	Moisture (%)	Starch (%)	Oil (%)	Protein (%)
0	10.446 ^{d}	13.765 ^{d}	63.662 ^{ab}	3.637 ^{a}	6.255 ^{c}
60	12.607 ^{c}	13.881 ^{cd}	63.748 ^{a}	3.599 ^{a}	6.337 ^{c}
120	13.47 ^{b}	14.036 ^{b}	63.443 ^{ab}	3.550 ^{a}	6.853 ^{b}
180	13.968 ^{a}	14.139 ^{a}	62.777 ^{b}	3.532 ^{a}	7.034 ^{ab}
240	13.553 ^{ab}	13.972 ^{bc}	63.160 ^{ab}	3.582 ^{a}	7.114 ^{a}
300	13.648 ^{ab}	14.027 ^{b}	63.074 ^{ab}	3.561 ^{a}	7.212 ^{a}

During the analysis of NDVI values, the control nutrient level values at 30 DAS in the 2023 growing season differed significantly from the nutrient level of 60 kg ha^{-1} N. The highest NDVI values were obtained at high nutrient levels (240 kg ha^{-1} N, 300 kg ha^{-1} N) with an NDVI value of 0.195, but even 120 kg ha^{-1} N did not cause a significant difference from the group with the highest NDVI value of 0.187. A similar trend was observed at 46 DAS, with vegetation index values falling into three distinct statistical groups. The lowest value was also obtained with the control nutrient level, with an NDVI value of 0.165. The 60 kg ha^{-1} N, 120 kg ha^{-1} N, and 180 kg ha^{-1} N treatments belonged to a different statistical group, with NDVI values between 0.236 and 0.241. In the 49 DAS phenological phase, 0 kg ha^{-1} resulted in a low NDVI value of 0.154, which is significantly different from all other statistical groups. In this phenological phase, 60 kg ha^{-1} significantly increased the NDVI value of the plants with a value of 0.081. The 120 kg ha^{-1} and 180 kg ha^{-1} also belong to different statistical groups compared to the low 0 kg ha^{-1} N and 60 kg ha^{-1} N nutrient levels. The highest NDVI value was obtained with a nutrient level of 300 kg ha^{-1} N with a value of 0.267 NDVI, but this is not significantly different from the values obtained with a lower nutrient level of 240 kg ha^{-1} N compared to the 60 kg ha^{-1} N dose. At 64 DAS and 75 DAS, the 300 kg ha^{-1} N dose did not significantly increase NDVI values compared to the 240 kg ha^{-1} N dose. However, at both points, there was a significant difference between the nutrient levels of 0 kg ha^{-1} N, 60 kg ha^{-1} N, and 180 kg ha^{-1} N. The lowest values were obtained with the control nutrient level of 0 kg ha^{-1} N, 0.209 (64 DAS) and 0.223 (75 DAS). The phenological phase dynamics of 82 DAS differed from the previous dates, as only the control and the low nutrient level differed statistically. In this phenological phase, NDVI values belonged to the same statistical group from a dose of 120 kg ha^{-1} N up to and including a dose of 300 kg ha^{-1} N. Therefore, in this phenological phase, the maximum NDVI value can be achieved with a dose of 120 kg ha^{-1} N from sowing to 82 days in the 2023 growing season (Table 7).

Table 7. The effect of the nutrient levels on the NDVI values in different phenological stages in 2023. Treatments with different letters are significantly different.

	NDVI Values									
N (kg ha^{-1})	DAS 30	DAS 46	DAS 49	DAS 64	DAS 75	DAS 82	DAS 98	DAS 112	DAS 124	DAS 145
300	0.195 ^{a}	0.256 ^{a}	0.267 ^{a}	0.381 ^{a}	0.374 ^{a}	0.352 ^{a}	0.361 ^{a}	0.336 ^{a}	0.310 ^{a}	0.228 ^{a}
240	0.195 ^{a}	0.251 ^{a}	0.258 ^{a}	0.378 ^{ab}	0.370 ^{ab}	0.350 ^{a}	0.359 ^{ab}	0.334 ^{a}	0.301 ^{ab}	0.222 ^{ab}
120	0.187 ^{a}	0.241 ^{b}	0.246 ^{b}	0.368 ^{ab}	0.368 ^{ab}	0.344 ^{a}	0.356 ^{ab}	0.332 ^{a}	0.300 ^{ab}	0.215 ^{bc}
180	0.178 ^{b}	0.240 ^{b}	0.246 ^{b}	0.366 ^{b}	0.361 ^{b}	0.343 ^{a}	0.349 ^{b}	0.329 ^{a}	0.298 ^{b}	0.213 ^{c}
60	0.169 ^{c}	0.236 ^{b}	0.235 ^{c}	0.350 ^{c}	0.335 ^{c}	0.322 ^{b}	0.330 ^{c}	0.304 ^{b}	0.277 ^{c}	0.200 ^{d}
0	0.146 ^{b}	0.165 ^{c}	0.154 ^{d}	0.209 ^{d}	0.223 ^{d}	0.231 ^{c}	0.230 ^{d}	0.203 ^{c}	0.231 ^{d}	0.200 ^{d}

In the 2024 growing season, the highest yield was achieved with a treatment of 240 kg ha^{-1} N, with a value of 12.944 t ha^{-1}, which belonged to the same statistical group as the treatments of 120 kg ha^{-1} N and 300 kg ha^{-1} N. Only the 0 kg ha^{-1} and 60 kg ha^{-1} N treatments were in different, lower statistical groups in terms of yield. It can be stated that between the 0 kg ha^{-1} and 120 kg ha^{-1} N treatments, the plants achieved a yield increase of 5.086 t ha^{-1}. There was no significant difference in the moisture content of the grain yield, which varied between 13.180% and 13.325% depending on the nutrient levels. The analysis of starch content showed that the starch content of grain was significantly higher in the control and the low, 60 kg ha^{-1} N treatment than in the 120 kg ha^{-1} N treatment or higher nitrogen doses.

In the growing season of 2024, none of the nutrient treatment levels had a significant effect on the oil content of the grain yield compared to the control. The oil content ranged from 3.341% to 3.391%. The highest value was measured at 180 kg ha^{-1} N treatment with 3.391%.

The analysis of the protein content shows that nutrient levels increase with nitrogen fertilization, and the percentage of protein in the yield also increases. The lowest protein content was found at the control nutrient level, with a value of 5.839%, while the highest value was found at the most provocatively high treatments of 240 and 300 kg ha^{-1} N, ranging from 6.937% to 6.939% (Table 8).

Table 8. The effect of the fertilizers on the yield quality and quantity parameters in 2024. Treatments with different letters are significantly different.

N (kg ha^{-1})	Yield (t ha^{-1})	Moisture(%)	Starch (%)	Oil (%)	Protein (%)
0	7.504 ^{c}	13.253 ^{ab}	63.317 ^{a}	3.361 ^{a}	5.839 ^{d}
60	11.077 ^{b}	13.180 ^{b}	63.435 ^{a}	3.409 ^{a}	6.212 ^{c}
120	12.590 ^{a}	13.306 ^{a}	62.970 ^{b}	3.414 ^{a}	6.731 ^{b}
180	12.916 ^{a}	13.325 ^{a}	62.921 ^{b}	3.391 ^{a}	6.766 ^{b}
240	12.944 ^{a}	13.295 ^{a}	62.822 ^{b}	3.341 ^{a}	6.939 ^{a}
300	12.494 ^{a}	13.254 ^{ab}	62.910 ^{b}	3.369 ^{a}	6.937 ^{a}

In the 2024 growing season, NDVI values increased in the 23 DAS and 36 DAS phenological phases under the 0 and 60 kg ha^{-1} N treatments and then did not change significantly between the 120 kg ha^{-1} N and the 300 kg ha^{-1} N treatments. Based on these results, it can be stated that in the early development phase, NDVI values can be divided into three distinct statistical groups based on nutrient management. In 49 DAS, 76 DAS, and 85 DAS phenological phases, the NDVI values of the plants belonged to the same statistical group from the 60 kg ha^{-1} N treatment to the highest 300 kg ha^{-1} N treatment. In view of these findings, it can be concluded that plant development was more balanced in the phenological phases important for initial yield differentiation, and that maximum NDVI values were already reached at low nutrient levels in terms of nutrient uptake, and that increasing nutrient levels did not result in an increase in NDVI values. In the 106 DAS phenological phase, the lowest NDVI value was measured under the 0 kg ha^{-1} N treatment, compared to which all nutrient treatments significantly increased the NDVI value. In this phenological phase, it can be concluded that the highest NDVI value of 0.334 was already achieved with a treatment of 120 kg ha^{-1} N. In the 111 DAS phenological phase, a decrease in NDVI values can already be observed as a result of high fertilizer application, as the NDVI value decreased from 0.349 with 120 kg ha^{-1} N treatment to 0.334 with 300 kg ha^{-1} N treatment. In the 122 DAS phenological phase, NDVI values were similar to those in the early 23 DAS and 36 DAS phenological phases. At the end of the growing season, in the 130 DAS and 135 DAS phenological phases, NDVI values were similar, but a decrease in NDVI values due to plant drying and the ripening process was observed (Table 9).

Table 9. The effect of the nutrient levels on the NDVI values in different phenological stages in 2024. Treatments with different letters are significantly different.

	NDVI Values									
N	**DAS 23**	**DAS 36**	**DAS 49**	**DAS 76**	**DAS 85**	**DAS 106**	**DAS 111**	**DAS 122**	**DAS 130**	**DAS 135**
300	0.191 [a]	0.191 [a]	0.254 [a]	0.341 [a]	0.358 [a]	0.327 [ab]	0.334 [bc]	0.293 [a]	0.254 [ab]	0.231 [ab]
240	0.193 [a]	0.193 [a]	0.249 [a]	0.340 [a]	0.364 [a]	0.334 [a]	0.340 [ab]	0.306 [a]	0.266 [a]	0.235 [a]
180	0.193 [a]	0.193 [a]	0.253 [a]	0.342 [a]	0.363 [a]	0.332 [a]	0.346 [ab]	0.304 [a]	0.253 [ab]	0.227 [ab]
120	0.191 [a]	0.191 [a]	0.252 [a]	0.352 [a]	0.370 [a]	0.334 [a]	0.349 [a]	0.297 [a]	0.250 [b]	0.224 [b]
60	0.180 [b]	0.180 [b]	0.245 [a]	0.338 [a]	0.362 [a]	0.318 [b]	0.325 [c]	0.221 [b]	0.201 [c]	0.192 [c]
0	0.176 [c]	0.176 [c]	0.176 [b]	0.240 [b]	0.292 [b]	0.219 [c]	0.227 [d]	0.139 [c]	0.166 [d]	0.170 [d]

When analyzing the correlation between NDVI values and crop yield, the highest R value (R = 0.638) was measured in the 112 DAS phenological phase during the 2023 growing season. During the growing season, the degree of correlation increased steadily in the initial phenological phases until the 75 DAS phenological phase, where the R value was 0.617. The strength of the correlation began to decline from 124 DAS. The lowest value was measured at the 145 DAS phenological phase (R = 0.246).

In the growing season 2024, there was a high correlation (R = 0.450) between yield and NDVI values in the early (23 DAS) development phase, which decreased continuously until the 75 DAS phenological phase, where R = 0.147. In the generative phase of the growing season, the correlation strengthened, with an R value of 0.420 in the 82 DAS phenological phase and 0.634 in the 112 DAS phenological phase. At the end of the growing season, in the ripening phase, we also measured a higher-than-usual R value, which was 0.478 in the 2024 growing season (Table 10).

In the growing season of 2023, NDVI values and nutrient levels varied depending on the different phenological phases. In the early phenological phase (30 DAS), the yield decreased in proportion to the increase in NDVI in the 0 kg ha^{-1} control plots, whereas in all other phenological phases, the yield increased in proportion to the increase in NDVI in the control plots. In plots treated with 60 kg ha^{-1} N, crop yield did not increase in many cases in relation to NDVI values, indicating a neutral relationship at this nutrient level. Only at the 75 DAS and 82 DAS phenological phases was there a slight increase in crop yield in conjunction with NDVI values. Under the 120 kg ha^{-1} N nutrient treatment, crop yield increased with increasing NDVI values in the 30 DAS and 46 DAS phenological phases, but in contrast, a decrease was observed in the 49 DAS, 64 DAS, and 75 DAS phenological phases. Under 300 kg ha^{-1} N, NDVI values showed a negative correlation with crop yield from phenological phase 64 DAS to 112 DAS, followed by a positive correlation between the highest nitrogen dose and crop yield at the end of the growing season (Figure 5).

Table 10. Pearson's correlation analyses (R) of the NDVI values with yield under different DAS, averaged over the different nutrient levels. *** = $p < 0.001$.

2023	DAS 30	DAS 46	DAS 49	DAS 64	DAS 75	DAS 82	DAS 98	DAS 112	DAS 124	DAS 145
	0.354 ***	0.498 ***	0.520 ***	0.600 ***	0.617 ***	0.529 ***	0.597 ***	0.638 ***	0.489 ***	0.246 ***
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
2024	DAS23	DAS36	DAS 49	DAS 76	DAS 85	DAS 106	DAS 111	DAS 122	DAS 130	DAS 135
	0.450 ***	0.539 ***	0.337 ***	0.235 ***	0.147 ***	0.420 ***	0.505 ***	0.634 ***	0.558 ***	0.478 ***
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

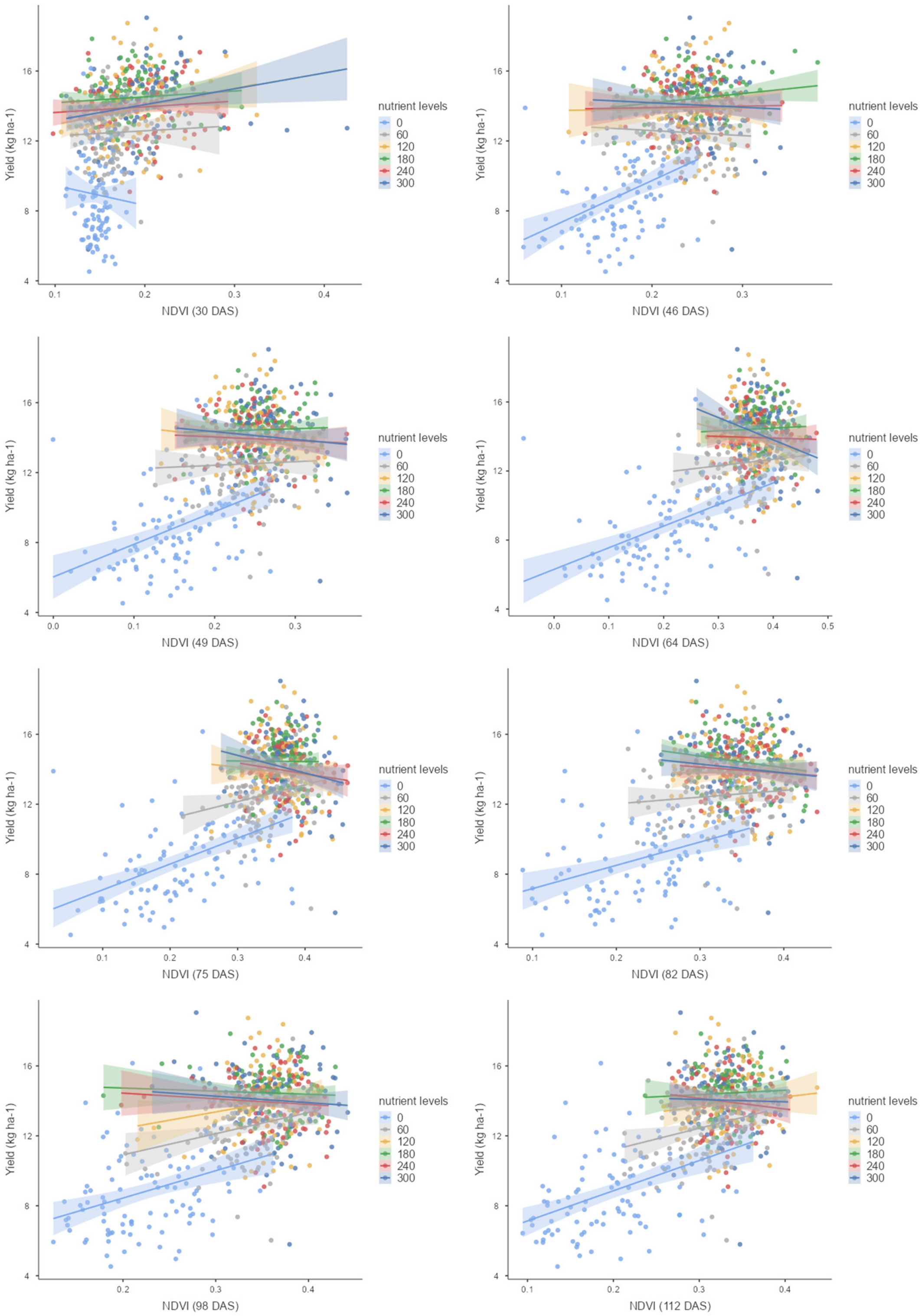

Figure 5. *Cont.*

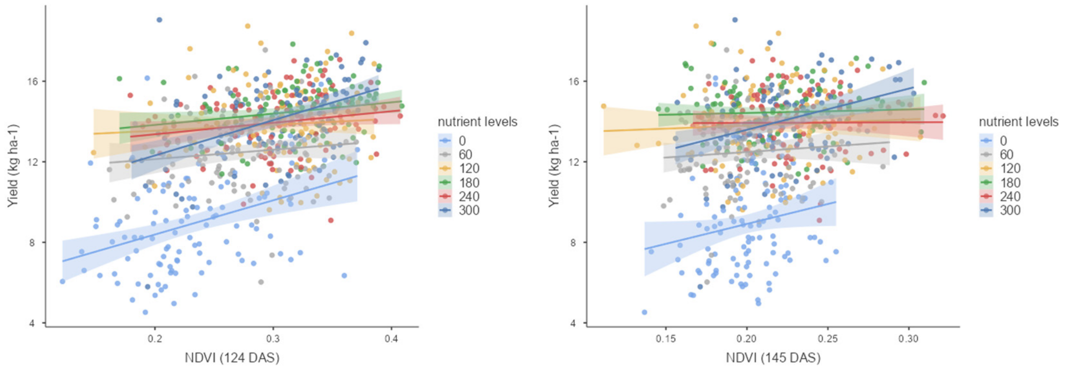

Figure 5. Evaluation of the NDVI values and amount of the yield under different nitrogen levels and DAS in the 2023 growing season.

In the 2024 growing season, the correlation between NDVI and yield at the control nutrient level was different from that in the previous growing season of 2023. In the early phenological phases, 23 DAS and 36 DAS, an increase in NDVI values resulted in an increase in yield, but this trend reversed and became negative until the phenological phases 49 DAS–122 DAS. Only at the end of the growing season, in the last third of the generative phase, was the correlation between NDVI values and yield positive again at the control nutrient level. At the nutrient level of 60 kg ha^{-1} N, NDVI and yield showed a positive trend until phenological phase 49 DAS, after which NDVI values decreased in proportion to yield until phenological phases 76 DAS–111 DAS. Based on these results, it can be stated that increasing nutrient levels are often inversely related to yield when evaluated based on NDVI values. Therefore, it is important to analyze the correlation at each nutrient level and provide recommendations to farmers and researchers on trends that can guide the analysis of the correlation. In many cases, the effect of control and high nitrogen fertilization resulted in different trends in the relationship between NDVI and yield (Figure 6).

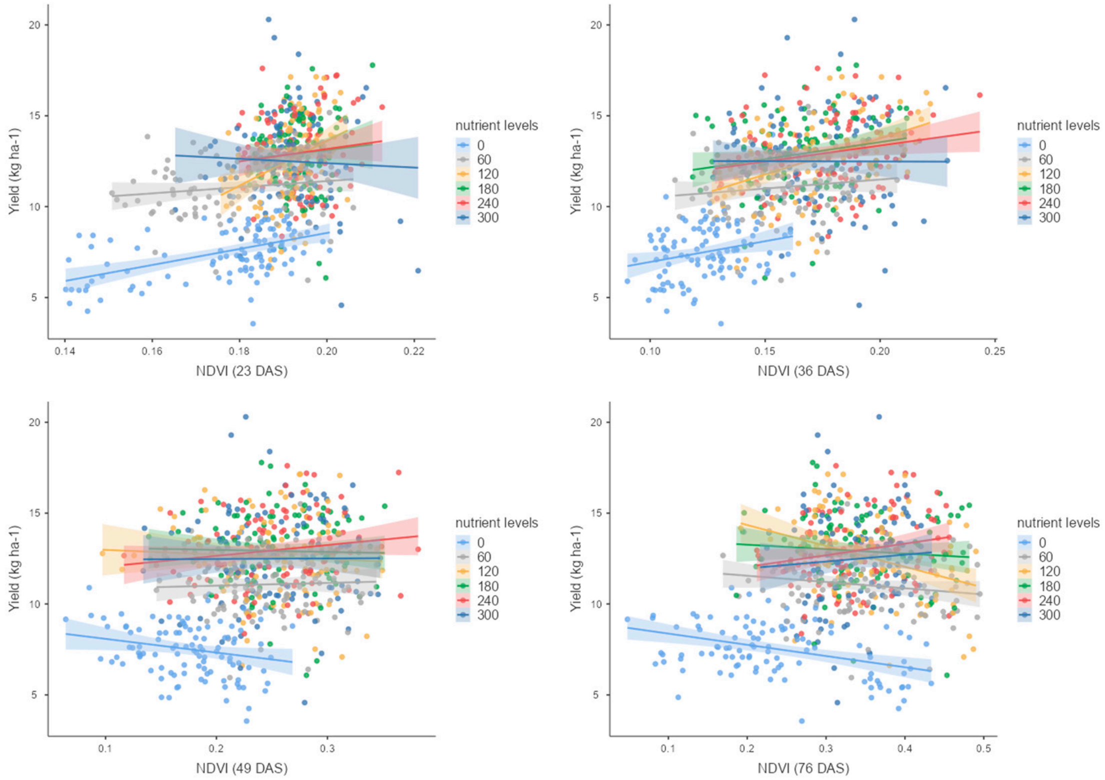

Figure 6. *Cont.*

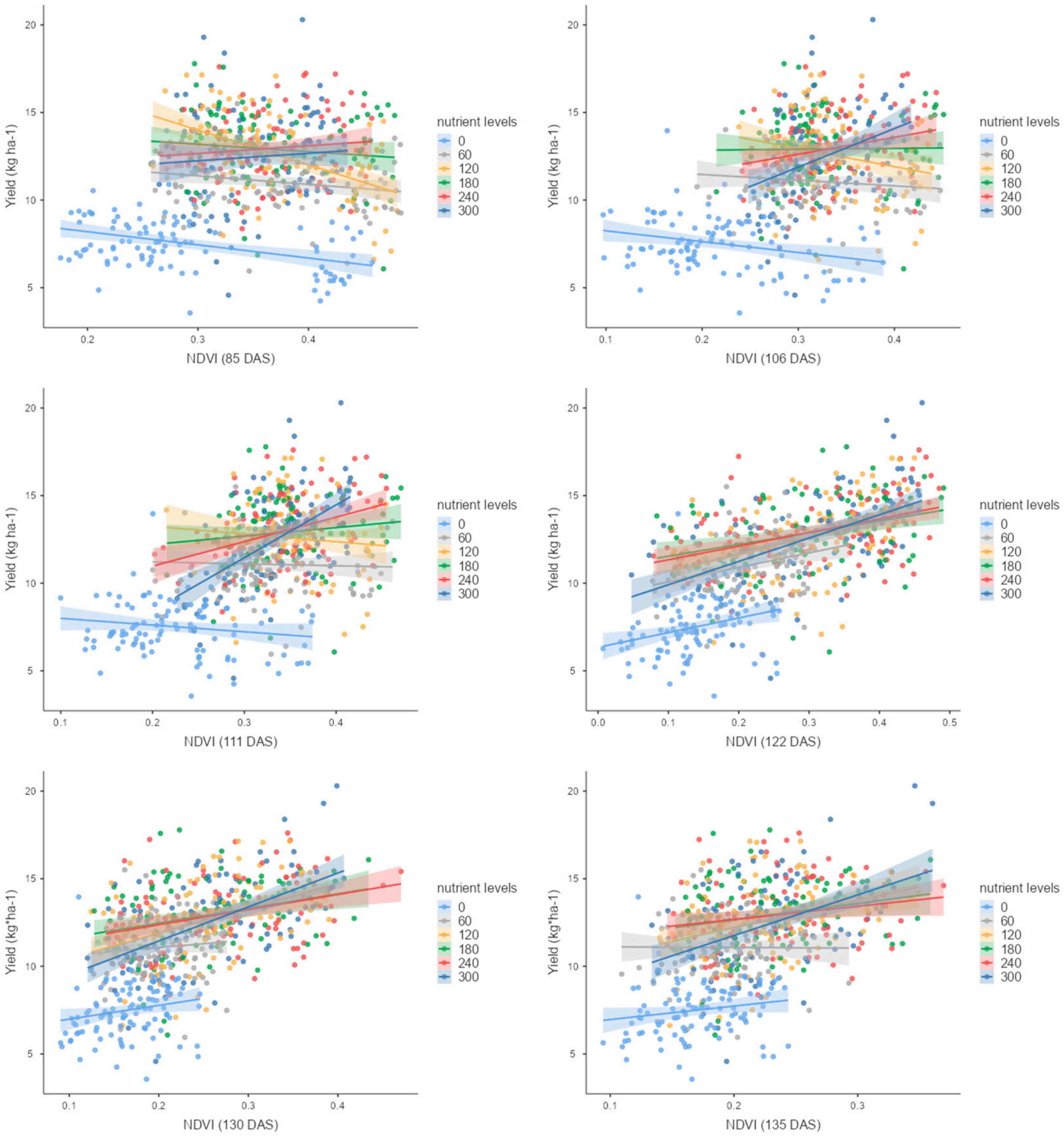

Figure 6. Evaluation of the NDVI values and amount of the yield under different nitrogen levels and DAS in the 2024 growing season.

4. Discussion

4.1. The Influence of Nitrogen on Yield

Maize yield estimation and its relationship with fertilization have been increasingly studied through remote sensing approaches, particularly NDVI-based methods, due to their ability to monitor crop vigor and nutrient responses across diverse environments. Several studies highlight that NDVI is closely linked to maize biomass accumulation and grain yield under varying fertilization conditions [25,26]. However, the predictive power of NDVI is highly dependent on timing, with mid-season measurements generally providing the most accurate yield forecasts [27,28]. These approaches consistently demonstrate that NDVI can reflect crop responses to fertilization intensity and population density, improving yield prediction models [29]. Beyond NDVI, empirical models combining multispectral data and crop management information have also proven effective in estimating maize yield under diverse agroclimatic conditions [30,31]. Furthermore, several research studies indicate that the integration of remote sensing with agronomic knowledge is particularly important in complex and resource-limited agriculture, where fertilization practices are limited [32].

Overall, these previous results suggest that combining NDVI-based monitoring with optimized fertilization strategies offers a powerful tool to enhance maize yield prediction and improve nutrient management efficiency in different maize production systems.

The results of this long-term maize fertilization experiment provide important insights into the relationship between nitrogen fertilization, grain yield, grain quality traits, and vegetation indices derived from UAV-based NDVI measurements. The findings confirm that while N fertilization significantly enhances crop performance, excessive application beyond the optimum threshold does not proportionally increase yield and may negatively influence grain composition. This study demonstrated that optimal yields were achieved at moderate nitrogen levels (120–180 kg N/ha), consistent with earlier reports highlighting the diminishing returns of high N inputs. Ciampitti and Vyn (2014) [33] reported that maize yield response typically plateaus at medium N levels, with additional fertilization primarily enhancing protein concentration rather than yield. Similarly, Mueller et al. (2012) [34] emphasized that excessive N application reduces nitrogen use efficiency (NUE) and contributes to environmental risks without consistent yield benefits.

Grain quality responses followed expected physiological trends. Increasing N fertilization enhanced grain protein content while reducing starch proportion, confirming the protein-starch interaction observed in previous studies [35,36]. Oil content, however, showed limited sensitivity to N fertilization, consistent with observations by Uribelarrea et al. (2004) [37], who reported that maize oil concentration is less responsive to nutrient supply than protein or starch.

The results of the study conducted in two consecutive growing seasons under varying climatic conditions revealed that in 2023, the highest grain yield was obtained with the 180 kg ha^{-1} N treatment (12.841 t ha^{-1}), which significantly exceeded the yield of the control (0 kg ha^{-1} N) and lower N treatments. Based on the differing growing seasons, in 2023 a moderate nitrogen level (180 kg ha^{-1}) proved to be optimal, whereas in 2024 a higher rate (240 kg ha^{-1}) was more favorable, likely due to the warmer and drier summer conditions. In 2023, the 240 and 300 kg ha^{-1} treatments resulted in only minimal yield increases (+0.178 t ha^{-1}). However, further increases in the 240 and 300 kg ha^{-1} N treatments did not result in significant yield increases, but only a 0.178 t ha^{-1} increase compared to the 180 kg ha^{-1} dose. The grain moisture content was the highest at the 180 kg ha^{-1} N treatment (14.139%), while in the control it was 13.765%, a difference of 0.374%. Among the composition values, the starch content decreased with higher N doses (e.g., 180 kg ha^{-1} N: 62.777%), while the protein content increased, reaching 6.789% at 300 kg ha^{-1} N compared to 5.839% in the control (+0.95%). The oil content also changed to a lesser extent, but in some cases it was not significant. In 2024, the highest yield was achieved with a dose of 240 kg ha^{-1} N (12.944 t ha^{-1}), but there were no significant differences within the range of 120–300 kg ha^{-1}. The difference in yield between the control and 120 kg ha^{-1} N exceeded 5 t ha^{-1} (5.086 t ha^{-1}), indicating the critical role of nitrogen supply. Grain moisture values remained relatively balanced (13.180–13.325%), and the content parameters also showed similar trends to the previous year. Starch content was highest in the control, while higher N treatments reduced it. Protein and oil content increased with N doses, but the differences varied in significance from year to year. Inter-annual variation in yield response emphasizes the interaction between N management and climate. In 2023, balanced rainfall allowed plants to efficiently utilize applied nitrogen, resulting in a clear positive response at 180 kg ha^{-1} (12.841 t ha^{-1}). In contrast, heat stress during the 2024 growing season constrained yield potential despite higher N rates, aligning with Sinclair and Rufty (2012) [38], who emphasized that nutrient benefits are strongly moderated by environmental conditions. The reduced predictive power of NDVI in late stages (e.g., DAS

145, R = 0.246) further confirms that senescence, leaf yellowing, and canopy closure limit spectral sensitivity at maturity [27].

4.2. The Significance of NDVI in Different Phenological Phases

Numerous studies demonstrate that nitrogen availability is a key factor of yield variability and that NDVI and related vegetation indices provide effective methods for monitoring crop responses to fertilization. Széles et al. (2024) [39] showed that advanced precision technologies, integrating NDVI with fertilization and irrigation regimes, significantly improved maize yield prediction under Hungarian field conditions. Similarly, UAV and multispectral imaging approaches have proven useful for optimizing nitrogen applications and forecasting yield, with Maresma et al. (2016) [40] and Vergara-Díaz et al. (2016) [41] confirming the capacity of vegetation indices to discriminate between fertilization levels and predict yield outcomes. Field-scale studies further revealed that NDVI can be used in-season to calibrate nitrogen fertilization rates, enabling dynamic management decisions to enhance both yield and nitrogen use efficiency [42–44].

NDVI analysis provided valuable insights into vegetation dynamics across different growth stages. The strongest correlation between NDVI and yield was observed in the post-silking stage (~112 DAS), highlighting this growth phase as critical for remote sensing-based yield prediction. This finding aligns with studies by Zaman-Allah et al. (2015) [23], who also identified this phenological stage as important for predicting maize yield. The reduced predictive power of NDVI in late phenological stages is consistent with earlier work [45], where canopy senescence and saturation effects limit the accuracy of NDVI as a yield predictor. Based on vegetation indices, the strongest positive correlation between yield and NDVI occurred between 112 and 122 DAS in both years (2023: R = 0.638; 2024: R = 0.634). At the end of the growing season (e.g., DAS 145), this correlation decreased significantly (R = 0.246–2023), suggesting that NDVI is less suitable for yield prediction at this stage. Significant differences were observed between the 2023 and 2024 growing seasons, underlining the strong interaction between nitrogen management and climate scenarios. In 2023, favorable and balanced rainfall allowed maize plants to respond more efficiently to applied nitrogen, while in 2024, heat stress during critical summer months decreased yield potential despite higher fertilization. Such interactions between nutrient availability and climate variability are widely recognized in previous research results [38,46]. These results further emphasize the need for adaptive, site-specific fertilization strategies that consider seasonal weather conditions. In both growing seasons, UAV-based NDVI monitoring effectively captured crop responses to nitrogen fertilization, particularly during the post-silking stage (~112 DAS) (2023: R = 0.638; 2024: R = 0.634). The main difference between the two growing seasons is in the interaction between climate and crop response to nitrogen. In 2023, favorable precipitation allowed moderate nitrogen rates to efficiently enhance yield, whereas in 2024, heat stress during critical summer months reduced the yield-enhancing effect of nitrogen, even at higher application rates.

The relationship between NDVI, nitrogen fertilization, and yield observed in this study can be explained by the physiological role of nitrogen in chlorophyll synthesis and canopy development. Adequate N supply increases chlorophyll concentration, enhancing photosynthetic activity and biomass accumulation, which are captured as higher NDVI values due to stronger absorption in the red spectrum and reflectance in the near-infrared range [47,48]. This mechanism supports the clear differences observed among treatments in the early to mid-vegetative phases. Similar findings were reported by Tamás et al. (2023) [25] and Kumar et al. (2022) [26], who showed that NDVI reliably tracks biomass and yield potential in maize under different fertilization regimes.

From a precision agriculture perspective, UAV-based NDVI monitoring proved effective for differentiating nitrogen treatments and tracking crop development. The observed yield–NDVI relationships suggest that UAV remote sensing can be integrated into variable-rate fertilization systems to optimize N management and improve NUE. This is consistent with findings by Ma et al. (2023) [49], who demonstrated that UAV-derived indices can provide real-time information for nitrogen management in maize.

Overall, the study highlights that nitrogen fertilization between 120 and 180 kg ha^{-1} provides the optimal nutrition level, enhancing yield, grain quality, and environmental sustainability, respectively. UAV-based NDVI monitoring enhances decision-making by enabling in-season adjustments and reducing the risk of over-fertilization. These findings support the integration of remote sensing technologies with long-term fertilization trials for advancing sustainable maize production.

5. Conclusions

Based on the results of the experiment, nitrogen doses of 120–180 kg ha^{-1} had the most favorable effect on maize yield, parameters, and vegetation activity. The strongest correlation between the NDVI and yield was found at 112 DAS in the 2023 growing season (R = 0.638), which may help with yield prediction. During the growing season, physiological processes related to developmental stages (e.g., vegetative and generative phases) have a significant impact on the development of vegetation indices, and their effects can result in similar patterns even under different environmental conditions at different times.

Overall, the different growing seasons and the agrometeorological conditions during the growing season, together with nutrient supply, significantly influenced the strength and direction of the relationship between yield and NDVI. Based on our results, it is important to note that NDVI is an effective vegetation index in the near-infrared range, but not all physiological changes can be detected by this indicator. For the practice, it is important to recognize that the effects of different growing seasons and nutrient levels, particularly the amount of nitrogen, substantially influence NDVI values during the vegetation period.

Finally, the strength of the relationship between NDVI values and yield parameters varied across the different growth stages. This has clear implications for the development of yield estimation methodologies, as well as for decision-making during crop production, including supplementary fertilization, nitrogen top-dressing, or biotic and abiotic stress management, which will shape the directions of our future research.

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