



Article

Comparative Evaluation of the Multispectral Platforms Sentinel-2, CBERS-04A, and UAV for Nitrogen Detection in Maize Crops

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Abstract

Multispectral images provide valuable indicators of crop nutritional status, playing a key role in strategies to reduce fertilizer use and enable supplementary applications in cases of nitrogen deficiency, thereby ensuring productivity and profitability for farmers. However, the diversity of remote sensing platforms (RSPs) makes the choice challenging, as there are few comparative studies. This study compares the remote sensing platforms Sentinel-2, CBERS-04A, and unmanned aerial vehicle (UAV), assessing their accuracy in detecting different nitrogen doses (NDs) throughout the maize crop cycle in Botucatu-SP, using 10 vegetation indices (VIs). Six NDs were tested (0, 36, 84, 132, 180, and 228 kg ha⁻¹ of nitrogen) in nine assessments during the crop cycle. The results showed that, at the V7 stage, the RSPs were effective in detecting the NDs in eight VIs. However, at the VT stage, only the Sentinel-2 and CBERS-04A satellites demonstrated effectiveness in six VIs. Despite the high correlation among the RSPs, the ability to distinguish the NDs varied depending on the vegetation index (VI) and phenological stage. These findings highlight the importance of selecting the appropriate VI and optimal timing, regardless of the chosen platform.

Keywords: multispectral satellite; UAV; vegetation index



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1. Introduction

Agriculture plays a fundamental role in promoting the Sustainable Development Goals (SDGs), with emphasis on eradicating famine, the sustainable use of natural resources, and tackling climate change [1]. To achieve the goals set by the UN as part of the 2030 Agenda, the FAO recommends adopting practices such as precision agriculture, which involves decision-support systems based on advanced technologies like remote sensing. These remote sensing platforms provide images captured at different wavelengths of the electromagnetic spectrum, offering valuable information about crops that can be expressed through vegetation indices (VIs), thus enabling more efficient and sustainable agricultural production [2].

Multispectral remote sensing includes a variety of platforms, such as satellites, aircraft, unmanned aerial vehicles (UAVs), and agricultural machinery equipped with high-tech sensors. These tools have shown great potential for agricultural monitoring, improving forecast accuracy [3]. Each platform has specific characteristics, such as spatial, spectral, radiometric, and temporal resolutions. UAVs, also known as drones, allow the acquisition of high-spatial-resolution (centimeter-level) images, enabling the capture of details not accessible by satellites. However, UAVs face limitations including wind speed, precipitation, the need for ground operators, and the handling of large volumes of data that require prior processing. In contrast, satellite platforms offer the advantage of rapid and, in some cases, free image acquisition, though they are limited by spatial resolution and cloud cover during image capture [4,5]. Despite these limitations, multispectral remote sensing has advanced significantly, with new technologies offering resolutions as fine as 1 m, better addressing the needs of agriculture. The relationship between spatial resolution and within-field variability is essential for understanding differences in crop productivity. Studies show that as the spatial resolution increases from 3 m to 10 m, 20 m, and 30 m, the explained variability decreases from 100% to 86%, 72%, and 59%, respectively [6]. A comparative analysis of UAVs, aircraft, and nine satellite image providers found that UAVs had higher costs and were not economically viable for variable-rate nitrogen fertilization in grain crops, followed by aircraft and satellites. Although free satellites such as Landsat 7/8 and Sentinel-2 have lower optical quality, the consistency of the data collected proved highly advantageous [7].

The growing number of satellite missions increases opportunities for continuous vegetation monitoring, essential for precision agriculture and environmental sustainability. However, estimating important agronomic characteristics such as nitrogen (N) concentration using data from Landsat 7, Landsat 8, and Sentinel-2 satellites still presents a significant challenge due to different sensor configurations and complex atmospheric interactions [8]. A comparative study evaluated the use of the NDVI index on three remote sensing platforms (tractor and UAV with Micasense Altum multispectral camera, and Sentinel-2 satellite) for variable-rate N application in maize crops. The results indicated a moderately strong correlation among the measurements; however, UAV data yielded higher values due to soil reflectance influence [9]. Over the past two decades, numerous studies have investigated nitrogen status in maize crops using multispectral remote sensing. These studies show that different nitrogen levels can be expressed through vegetation indices (VIs). Some use UAVs equipped with multispectral cameras such as the Sensefly Sequoia and Red Edge MX, while others use satellites like Landsat-8 OLI and QuickBird. Results suggest that multispectral imagery is effective for in-field nitrogen management regardless of variety, as nitrogen levels are closely related to indices such as NDVI, NDRE, GNDVI, GRg, EVI, SAVI, NRI, and NCI [10–13].

Although N is essential for achieving high yields and ensuring global food security, about half of the applied nitrogen fertilizer is not absorbed by crops [14]. This low efficiency is attributed to processes such as volatilization, runoff, leaching, and denitrification, which significantly reduce the return on agricultural investment [15]. Additionally, some of these loss pathways lead to contamination of surface and groundwater, such as nitrate leaching (NO_3^-) and the emission of greenhouse gases like nitrous oxide (N_2O). This contributes to global warming, with the production and use of nitrogen fertilizers accounting for about 5% of global greenhouse gas emissions (GHG). This inefficiency is particularly evident in maize crops, where nitrogen deficiency leads to higher reflectance around 550 nm due to reduced chlorophyll concentration. This decreases radiation absorption and increases reflectance, as the spectral signature of vegetation reflects plant health. Such information is crucial for efficient nitrogen management and to avoid input waste and environmental damage [16,17].

Efficient N management is challenging without accurate knowledge of its status in the crop [18]. Various methods and tools are available for N management, including soil tests, plant tissue analysis, spectral response, and the use of VIs. No single method is considered fully sufficient, but precision agriculture tools such as UAVs and satellites have proven superior to conventional methods, which face numerous challenges like being time-consuming, destructive, and having limited throughput, making efficient lab analysis difficult [19]. The adoption of these technologies can ensure proper nitrogen management, resulting in yield increases of up to 18.8% by providing appropriate nutritional support to the crop. Furthermore, the use of such technologies enables continuous and high-precision monitoring of soil and plant conditions, promoting more sustainable and efficient agricultural production [20,21].

Numerous remote sensing platforms have the potential to monitor crop nutritional status, but it is not yet clear whether they offer equally promising results in specific contexts. The hypothesis of this research is that different remote sensing platforms may provide varying predictive capabilities for identifying nitrogen deficiency in agricultural crops. This study investigates how key factors (spatial, spectral, radiometric, and temporal resolution) influence the accuracy of deficiency detection. It also explores whether the platforms can be complementary or if one outperforms the others in terms of performance. The effectiveness of the platforms may also be influenced by the crop's phenological stage, highlighting the importance of vegetation indices as crucial tools for analysis. Thus, the objective of this article is to compare the multispectral remote sensing platforms Sentinel-2, CBERS-04A, and unmanned aerial vehicle (UAV) to determine whether these platforms can accurately detect different nitrogen doses (NDs) at various phenological stages of maize crops using vegetation indices (VIs).

2. Materials and Methods

2.1. Study Area

Between January and July 2023 (Figure 1), a field experiment was conducted at the Lageado Experimental Farm, which belongs to the Faculty of Agronomic Sciences, located in Botucatu, São Paulo ($22^{\circ}48'50''$ S, $48^{\circ}25'51''$ W, at an altitude of 778 m).

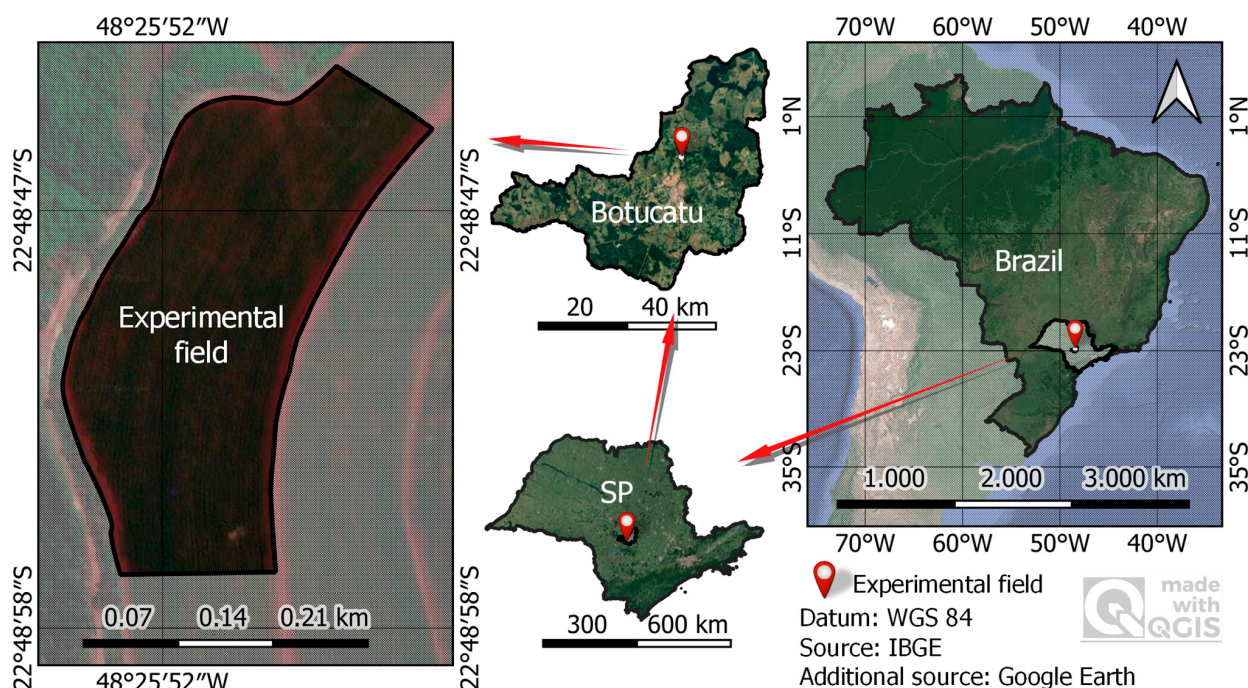


Figure 1. Location of the study area in the municipality of Botucatu, São Paulo, Brazil.

According to Franco et al. [22], the Köppen–Geiger climate classification [23] for Botucatu is type Aw (tropical savanna climate), characterized by hot and rainy summers and cold, dry winters. The average annual temperature is 21.34 °C, with relative humidity around 70% and total annual precipitation of approximately 1500 mm, distributed over 107 days per year. The soil in the experimental area was classified as Typic Rhodudalf [24,25].

2.2. Conducting the Experiment

The experiment was conducted during the 2023/2024 growing season using FS710 hybrid maize (ForSeed®, Changsha, China). Soil preparation was carried out to a depth of 0.30 m using plowing followed by leveling harrowing. At sowing, NPK fertilizer was applied to supply 12 kg ha⁻¹ of N, 42 kg ha⁻¹ of P₂O₅, and 24 kg ha⁻¹ of K₂O, placed 0.05 m below and beside the seeds. Sowing took place on 9 January 2023, with a spacing of 0.90 m between rows and six plants per linear meter, targeting a density of 66,000 plants per hectare.

2.3. Experimental Design and Treatments

The experiment followed a completely randomized design, with six treatments and four replicates. The plots were predefined to ensure a minimum number of pixels and respect the pixel structure and displacement of the multispectral satellite grids. The position of each plot was determined using a Garmin GPSmap 60CSx (Kansas City, Kansas, USA), based on geographic coordinates predefined in QGIS software, version 3.22.10.

The treatments consisted of different levels of topdressed nitrogen fertilization. Application was performed manually by broadcast spreading at the V6 vegetative stage (28 days after emergence), using urea as the N source (45% N). The applied nitrogen doses (NDs) were 0, 36, 84, 132, 180, and 228 kg ha⁻¹ of N, corresponding to 0%, 30%, 60%, 90%, 120%, and 150%, respectively, of the recommended 160 kg ha⁻¹ N dosage proposed by Cantarella et al. [26], applied in a single dose.

The experiment occupied a total area of 40,600 m² (considering the plots and the spacing between them), composed of experimental plots of 900 m², with a spacing of 10 m between them. Each treatment level of nitrogen fertilization occupied a total area of 3600 m². The dimensions of each plot were 30 m in the north–south direction and 30 m in the east–west direction.

2.4. Obtaining Images

2.4.1. Unmanned Aerial Vehicle (UAV)

The unmanned aerial vehicle (UAV) used in the experiment was a Phantom 4 Pro (SZ DJI Technology Co., Ltd., Shenzhen, China), equipped with an RGB camera, model FC6310 (SZ DJI Technology Co., Ltd., Shenzhen, China), with a focal length of 8.8 mm and a resolution of 5472 × 3648 pixels, resulting in a pixel resolution of 0.0232 mm. Additionally, it was integrated with an RGN camera, model Survey3W (MAPIR, San Diego, CA, USA), with a focal length of 3.4 mm and a resolution of 4000 × 3000 pixels, providing a pixel resolution of 0.0402 m. This RGN model includes the spectral bands 550 nm (reflectance in the green region), 0.66 µm (reflectance in the red region), and 0.85 µm (reflectance in the near-infrared region) [27].

The average flight time was approximately 12 min and 18 s, covering an area of about 13 ha at an altitude of 80 m above ground level. The data collected by the RGB and RGN cameras were processed using PIX4Dmapper software, version 4.10 (Pix4D S.A., Prilly, Switzerland), which generated orthomosaics and digital maps.

2.4.2. CBERS-04A Satellite

The medium-resolution remote sensing satellite images from CBERS-04A were obtained from the Remote Sensing Data Center (CDSR), responsible for receiving, storing, and processing the images. The data were acquired through the website <http://www.dgi.inpe.br/catalogo/explore> (accessed on 15 June 2025) [28], via the image generation division of INPE | CGOBT | DIDGI.

The imagery was captured using the CBERS-04A's Wide-Field Imager (WPM), which has a spatial resolution of 8 m. The spectral bands used correspond to 0.45–0.52 μm (blue), 0.52–0.59 μm (green), 0.63–0.69 μm (red), and 0.77–0.89 μm (near-infrared). The revisit cycle over a fixed point is 31 days [29].

2.4.3. Sentinel-2 Satellite

Data from the Sentinel-2 satellite constellation were obtained via the Copernicus Space Data Ecosystem, responsible for providing image access, navigation, and metadata export. The images were acquired from <https://browser.dataspace.copernicus.eu/> (accessed on 15 June 2025) [30], via the data distribution service for Sentinel-2 missions.

For data acquisition, the S2B mission, MSIL1C product, and Level-1C level were established. The MSI multispectral sensor has 13 spectral bands; we chose four bands at 10 m, corresponding to 0.49 μm (reflectance in the blue region), 0.56 μm (reflectance in the green region), 0.665 μm (reflectance in the red region), and 0.842 μm (reflectance in the near-infrared region). The period to travel the route is 5 days at the equator with the constellation of 2 satellites, Sentinel 2A and 2B [31].

2.5. Vegetation Indices for UAV, Sentinel-2, and CBERS-04A

After collecting multispectral images from UAV, Sentinel-2, and CBERS-04A platforms, the satellite-provided images were analyzed using the open-source Geographic Information System (GIS) QGIS, version 3.22.10, to verify the presence of clouds that could compromise visualization of the experimental area. Then, the spectral bands were processed using the mathematical formulas for vegetation indices (VIs) (Table 1). The extracted index values were determined based on the mean pixel values within experimental plots.

Table 1. Vegetation indices used in this study.

Index	Fórmula	Authors
greenNDVI	$\frac{(NIR - GREEN)}{(NIR + GREEN)}$	[32]
MCARI2	$\frac{1.5[2.5(NIR - RED) - 1.3(NIR - GREEN)]}{\sqrt{(2NIR + 1)^2 - (6NIR - 5\sqrt{RED})} - 0.5}$	[33]
MGRVI	$\frac{(GREEN)^2 - (RED)^2}{(GREEN)^2 + (RED)^2}$	[34]
MSAVI	$\frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - RED)}}{2}$	[35]
MTVI2	$\frac{1.5[1.2(NIR - GREEN)^2 - 2.5(RED - GREEN)]}{\sqrt{(2NIR + 1)^2 - (6NIR - 5\sqrt{RED})} - 0.5}$	[33]
NDVI	$\frac{(NIR - RED)}{(NIR + RED)}$	[36]
SAVI	$\left[\frac{(NIR - RED)}{(NIR + RED + L)} \right] \times 1 + L$	[37]
SR	$\frac{NIR}{RED}$	[38]
VARI	$\frac{(GREEN - RED)}{(GREEN + RED - BLUE)}$	[39]
WDRVI	$\frac{(a \times NIR - RED)}{(a \times NIR + RED)}$	[40]

greenNDVI = Green Normalized Difference Vegetation Index; MCARI2 = Modified Chlorophyll Absorption Ratio Index; MGRVI = Modified Green Red Vegetation Index; MSAVI = Modified Soil-Adjusted Vegetation Index; MTVI2 = Modified Triangular Vegetation Index; NDVI = Normalized Difference Vegetation Index; SAVI = Soil-Adjusted Vegetation Index; SR = Simple Ratio Index; VARI = Visible Atmospherically Resistant Index; WDRVI = Wide-Dynamic-Range Vegetation Index. BLUE = Reflectance in the Blue Region (nm); GREEN = Reflectance in the Green Region (nm); RED = Reflectance in the Red Region (nm); NIR = Reflectance in the Near-Infrared Region (nm); L = Soil Adjustment Factor; a = Weighting Coefficient.

Throughout the maize growing season, nine data acquisition campaigns were conducted, covering three representative phenological stages: vegetative (V7), early reproductive (VT), and advanced reproductive (R3, R4, and R5). At each stage, all remote sensing platforms flew over the experimental area and collected multispectral images at varying spatial resolutions.

The UAV provided between 1,515,339 and 1,671,849 pixels per plot, due to the exceptionally high spatial resolution of the multispectral camera, which resulted in a greater number of pixels for calculating the average vegetation indices (VIs). For the Sentinel-2 satellite, the average was based on 4 pixels located at the center of the plots, due to their strategic positioning. On the other hand, for the CBERS-04A satellite, the average was calculated using 6 to 9 centrally located pixels within the plots, owing to the higher spatial resolution of its camera, which allows for greater pixel variability within the plots. The different spatial resolutions enabled a detailed analysis of the study area and a comparison between the remote sensing platforms used, as illustrated in Figures 2, A1 and A2 for the UAV, Sentinel-2, and CBERS-04A.

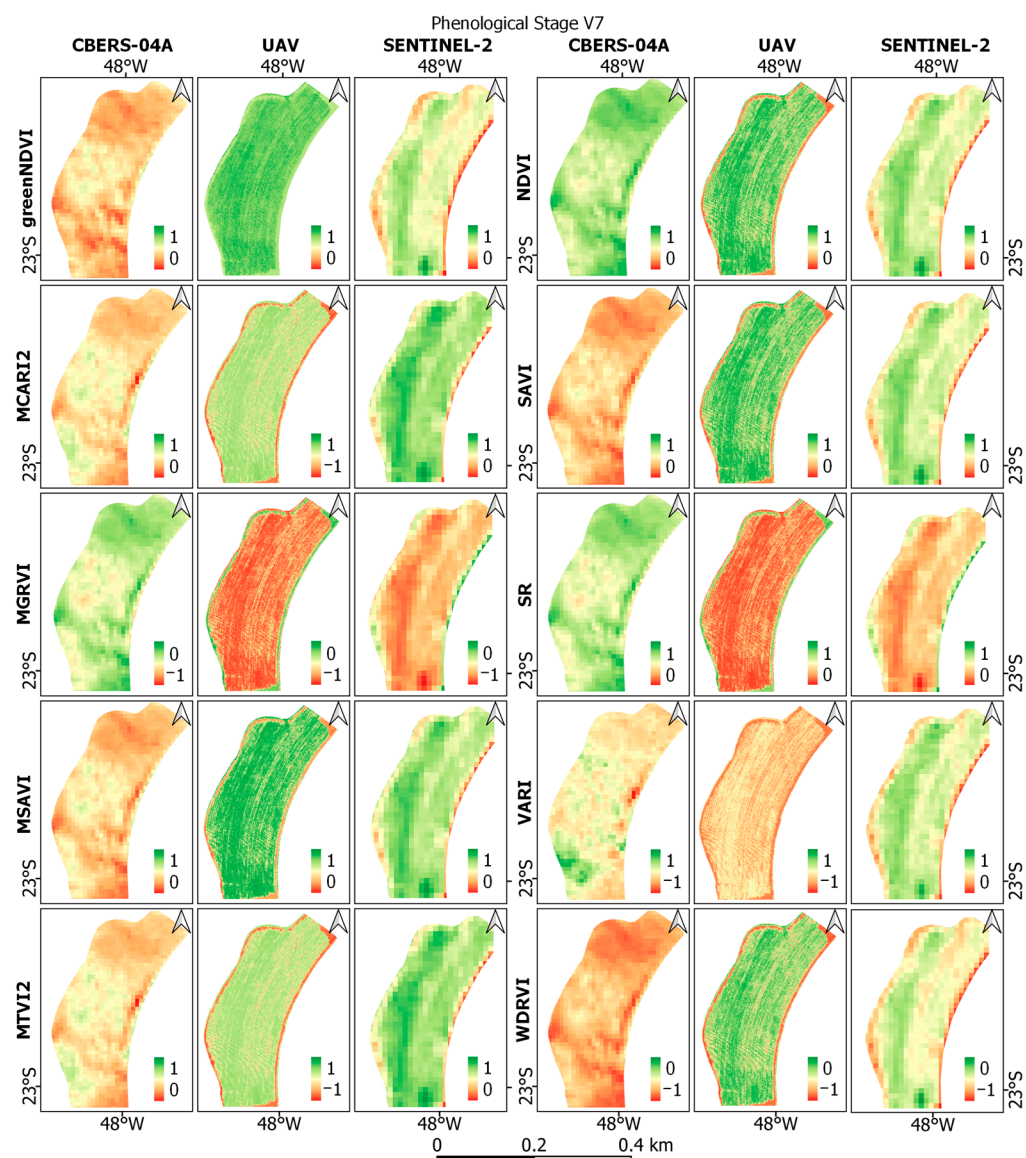


Figure 2. Vegetation indices at the V7 phenological stage of the study area, obtained from the CBERS-04A, UAV, and Sentinel-2 platforms.

2.6. Leaf Sampling and Diagnosis

Fresh plant tissue collection was performed at the R1 stage (flowering), sampling 30 leaves as recommended by Malavolta et al. [41]. The leaves were dried in a forced-air circulation oven at 65 °C until they reached a constant weight. Subsequently, the leaves were ground using a Wiley-type knife mill (1 mm mesh). The nitrogen content in the leaves was determined following the method described by the AOAC [42]. Leaf nitrogen content was determined following AOAC [42] methods, using sulfuric acid digestion to obtain extracts that were distilled by the Kjeldahl method for N quantification via titration.

2.7. Statistical Analysis

2.7.1. Analysis of Variance

The data were analyzed using RStudio software (version 2022.07.1+554 “Spotted Wakerobin”). Data normality was verified using the Shapiro–Wilk and Royston tests, while the homogeneity of variances was assessed using Bartlett’s test. For data that did not meet the assumptions, transformations were applied using the “bestNormalize” package. One-way ANOVA was used to evaluate the nitrogen content in the leaves, followed by a quadratic regression analysis performed with the “stats” package. The corresponding graph was generated using the “dplyr” package.

Two-way ANOVA was applied to assess the effects of nitrogen doses (NDs) and remote sensing platforms (RSPs) on vegetation indices (VIs). Three phenological stages of the maize crop were analyzed (V7, VT, and the reproductive stages R3, R4, and R5, which were analyzed together), allowing for a comprehensive comparison of the variables throughout the plant’s development. When significant differences were observed, the Least Significant Difference (LSD) multiple comparison test was applied at a 5% significance level.

2.7.2. Principal Component Analysis and Pearson Correlation

Principal component analysis (PCA) was used to reduce data dimensionality and identify relevant patterns among the variables. The analyses were carried out using RStudio software, version 2022.07.1+554 “Spotted Wakerobin”, with the statistical packages “FactoMineR” and “factoextra”, which enabled the extraction and visualization of quantitative and categorical variables. Additionally, Pearson’s correlation was calculated using the same variables, with the aid of the “corrplot” package.

3. Results and Discussion

3.1. Analysis of Variance

3.1.1. Leaf Diagnosis

The analysis of variance (ANOVA), presented in Table 2, shows the results for N content in maize leaves. Foliar nitrogen content differed significantly as a function of the different nitrogen doses (NDs). Figure 3 illustrates the quadratic regression analysis of leaf nitrogen content as a function of the NDs. The regression coefficient $R^2 = 0.663$ indicates that approximately 66.3% of the variation in the data is explained by the quadratic relationship between the variables, suggesting a moderate correlation between them. The frequency of nitrogen content in the leaves indicates a consistent foliar N level in response to the topdressed NDs.

The absence of N fertilization (0 kg ha^{−1} of N) resulted in the lowest foliar nitrogen content, showing a reduction of approximately 15% compared to the 36 kg ha^{−1} N dose and 28% in relation to the other doses (Figure 3). As the NDs increased, foliar N content remained consistent between the 84 and 228 kg ha^{−1} N doses. These results are in line with the findings of Mondal et al. [43], who reported lower foliar N content in the control treatment (0 kg ha^{−1} N) at 55 days after emergence (DAE) of maize. In that

study, a slight increase in foliar N was observed at 40 kg ha⁻¹ N, while doses between 80 and 240 kg ha⁻¹ N maintained uniform nitrogen content. This suggests physiological saturation, indicating that nitrogen uptake and assimilation are limited by genetic and metabolic factors, regardless of increased N supply.

Table 2. Nitrogen content in maize leaves at the flowering stage, grown under different topdressed nitrogen doses.

NDs (kg ha ⁻¹)	N (g kg ⁻¹)
Reference	25 and 35
CV(%)	8.81%
<i>p</i> -value	0.0002 *

Reference: Leaf nutrient concentrations considered adequate for maize (corn), as established by Cantarella et al. [26]. (*) = Significant at significance level of 5%.

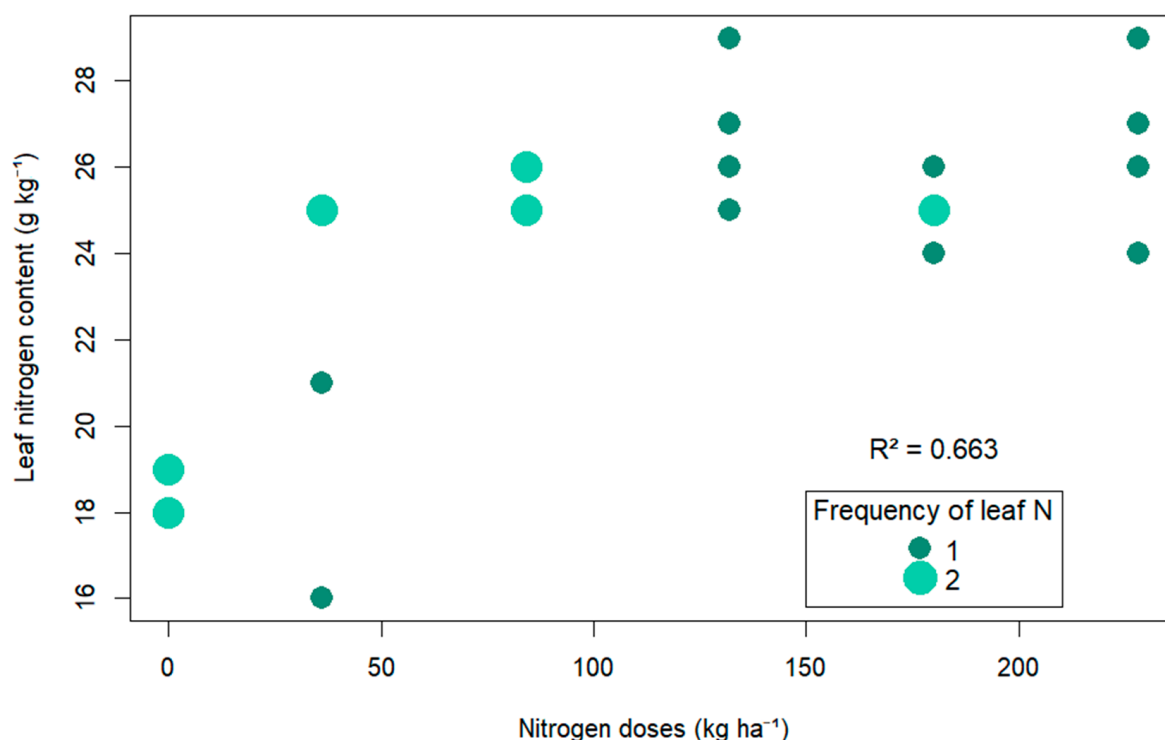


Figure 3. Scatter plot with a quadratic regression line, illustrating leaf nitrogen content as a function of nitrogen doses of 0, 36, 84, 132, 180, and 228 kg ha⁻¹.

Furthermore, Cantarella [26] states that the ideal N content in maize leaves should range between 25 and 35 g kg⁻¹ to ensure maximum yield or crop growth. The results of this study showed that foliar N levels ranged between 18 and 29 g kg⁻¹, with the highest value of 29 g kg⁻¹ observed with a nitrogen dose of 132 kg ha⁻¹. The adequacy of foliar N content relative to recommended levels may be influenced by factors such as genotype characteristics and fertilization management practices. Recent studies emphasize that nutrient composition is affected by genotype effects, with two maize hybrids showing maximum N concentrations in stems and leaves when fertilized with 300 kg ha⁻¹ N [44].

3.1.2. Phenological Stage V7

According to the analysis of variance (ANOVA) for phenological stage V7 (Table 3), the greenNDVI and VARI indices did not show significant differences in response to nitrogen doses (NDs). Previous studies [45] have indicated that greenNDVI displayed a weaker response to nitrogen supply during early growth stages; however, this response became

stronger at later stages. These results are consistent with the findings of Han et al. [46], who evaluated nitrogen in maize from the VT to R6 stages and found that VARI had the lowest accuracy ($R^2 = 0.311$) among the six indices analyzed.

Table 3. Results of the two-way ANOVA for the variables (NDs and RSPs) at the V7 stage.

Variables	geenNDVI	MCARI2	MGRVI	MSAVI	MTVI2
<i>p</i> -value (RSPs)	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (NDs)	0.08 ^{ns}	0.01 *	0.02 *	0.02 *	0.01 *
<i>p</i> -value (I)	0.94 ^{ns}	0.89 ^{ns}	0.92 ^{ns}	0.91 ^{ns}	0.89 ^{ns}
Variables	NDVI	SAVI	SR	VARI	WDRVI
<i>p</i> -value (RSPs)	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (NDs)	0.03 *	0.03 *	0.02 *	0.09 ^{ns}	0.04 *
<i>p</i> -value (I)	0.89 ^{ns}	0.89 ^{ns}	0.92 ^{ns}	0.96 ^{ns}	0.86 ^{ns}

(RSPs) = Remote Sensing Platforms. (NDs) = Nitrogen Doses (kg ha^{-1} of N). (I) = Interaction between RSPs and NDs. (*) = Significant. (^{ns}) = Not significant at the 5% significance level.

On the other hand, the VIs MCARI2, MGRVI, MSAVI, MTVI2, NDVI, SAVI, SR, and WDRVI showed significant differences for both factors: remote sensing platforms (RSPs) and nitrogen doses (NDs). Thus, the results indicate that the remote sensing source did not exert a substantial impact on predicting differences in NDs, although variations were observed among the indices. All RSPs proved suitable for assessing the different nitrogen doses at this phenological stage (Table 3). These consistent findings reinforce the conclusions of Croft et al. [11], who suggested that multispectral reflectance data can be used to estimate chlorophyll content, enabling the use of both satellite- and UAV-based multispectral sensors to guide fertilization and maintain adequate nitrogen levels throughout the growing season.

These results align with the recommendations of Zhang et al. [47], who emphasized that seeking a balance between nitrogen inputs, crop yield, and quality can benefit from combining traditional indices such as NDVI, NDRE, and GNDVI with innovative indices to provide valuable insights across different crop types and development stages. The indices MCARI2, MSAVI, MTVI2, NDVI, SAVI, and WDRVI showed higher average values for nitrogen doses between 84 and 180 kg ha^{-1} , as well as for indices obtained via Sentinel-2 (Table A1). These findings validate the predictive capacity for nitrogen deficiency, where maize shows chlorosis in leaves after this stage, progressing to senescence. These leaves did not elongate properly, and plant growth was stunted. Similar symptoms were reported by Romualdo et al. [48] in maize cultivated with 40% of the recommended N dose, especially after stage V7, where chlorosis extended along the midrib and led to necrosis and rupture, in addition to thin stems.

Interestingly, the indices MGRVI and SR showed similar patterns in distinguishing between the averages of the factors (RSPs and NDs), as did the indices MCARI2 and MTVI2 (Table A1). These VIs, proposed by Haboudane et al. [33] as improved estimators of leaf area index, are enhanced variants of indices originally designed to measure photosynthetically active radiation (TVI and MCARI). These results are consistent with earlier findings, such as those by Nguy-Robertson [49], who noted that MCARI2 and MTVI2 are mathematically identical; therefore, using only one of them is recommended to optimize time and effort.

Unlike the other indices analyzed, MGRVI and WDRVI presented negative average values throughout the maize growth cycle (Tables A1–A3). This interpretation can be clarified by considering that WDRVI incorporates a weighting coefficient below 1 in its mathematical formulation, providing a more robust determination of the crop's physiological and phenological characteristics by reducing the disparity between near-infrared (NIR) and red reflectance contributions to NDVI [40]. Meanwhile, MGRVI, or the modified GRVI,

captures reflectance differences due to chlorophyll a and b absorption and is defined as the normalized difference of the squared green and red reflectance, amplifying reflectance differences [34].

3.1.3. Phenological Stage VT

Table 4 presents the ANOVA results for the vegetation indices (VIs) related to the VT phenological stage. The factors (RSPs) and (NDs) were significant for the VIs MCARI2, MGRVI, MTVI2, and VARI. Therefore, for these specific indices, the remote sensing platform did not significantly influence the prediction of NDs. As such, all RSPs were suitable for evaluating the different NDs based on these indices and phenological stage. Our findings align with those of Ye et al. [50], in which crop growth stages directly impacted remote sensing performance, as canopy reflectance is influenced by biomass before the V12 stage and by plant nitrogen content after this stage.

Table 4. Results of the two-way ANOVA for the variables (NDs and RSPs) at the VT stage.

Variables	GreenNDVI	MCARI2	MGRVI	MSAVI	MTVI2
<i>p</i> -value (RSPs)	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (NDs)	0.00 *	0.01 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (I)	0	0.28 ^{ns}	0.10 ^{ns}	0.05 *	0.27 ^{ns}
Variables	NDVI	SAVI	SR	VARI	WDRVI
<i>p</i> -value (RSPs)	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (NDs)	0.00 *	0.00 *	0.00 *	0.03 *	0.00 *
<i>p</i> -value (I)	0.02 *	0.02 *	0.05 *	0.24 ^{ns}	0.00 *

(RSPs) = Remote Sensing Platforms. (NDs) = Nitrogen Doses (kg ha⁻¹ of N). (I) = Interaction between RSPs and NDs. (*) = significant; (^{ns}) = not significant at significance level of 5%.

For the indices MCARI2, MTVI2, and VARI, the CBERS-04A satellite provided the highest average values, as did the doses ranging from 84 to 228 kg ha⁻¹ of N, which did not differ significantly from each other. Interestingly, for the MGRVI index, higher mean values were observed at doses of 0 and 36 kg ha⁻¹ of N, which were statistically similar to each other and differed from the other NDs (Table A2). These results are in agreement with previous findings by Sharifi [51], in which Sentinel-2 data proved effective in mapping N uptake in maize. In that study, indices such as TCARI, MCARI, MTVI2, and GNDVI demonstrated high predictive capacity for nitrogen content at the biomass peak, being more sensitive to variations in chlorophyll concentration, as also observed in the present study. In contrast, indices such as NDVI, SR, and NDRE did not show sensitivity in regions of low nitrogen uptake due to saturation effects and non-linear relationships with canopy absorption.

ANOVA analysis revealed that the interaction between the factors (I) was significant for the VIs greenNDVI, MSAVI, NDVI, SAVI, SR, and WDRVI. Thus, the LSD test confirmed that, for these indices, the image acquisition source significantly influenced the predictive capacity to diagnose nitrogen doses in the crop. Therefore, only the Sentinel-2 and CBERS-04A satellites proved efficient in identifying the NDs, whereas the UAV was not effective (Table A2). This contradicts the findings of Cai et al. [52], in which multispectral sensors based on UAVs and CubeSat satellites showed similar performance in detecting N stress in maize under different N management practices. A possible explanation for this discrepancy between the current results and those cited in the literature could be the interference of soil background noise in maize canopy images acquired with the UAV, as previously demonstrated by Qiao et al. [12], who showed that soil background segmentation methods can reduce image texture complexity and enable noise rejection to improve the diagnostic accuracy of maize canopy chlorophyll content in the field.

For the VIs greenNDVI, MSAVI, NDVI, SAVI, and WDRVI derived from Sentinel-2, the absence of nitrogen fertilization (0 kg ha^{-1} of N) was comparable to the reduced dose of 36 kg ha^{-1} of N, which, in turn, did not differ from the dose of 84 kg ha^{-1} of N. In contrast, for the same indices obtained via CBERS-04A, the absence of nitrogen fertilization (0 kg ha^{-1} of N) was clearly identified by the VIs, differing from the other NDs. For the SR index, a distinct pattern was observed compared to the other VIs, as the absence of nitrogen fertilization (0 kg ha^{-1} of N) showed the highest average and differed from the other NDs when analyzed using CBERS-04A imagery (Table A2). These findings reflect those previously reported by Maresma et al. [53], who observed in their study that the absence of nitrogen fertilizer resulted in lower values for the indices NDVI, WDRVI, and GRVI, clearly distinguishing it from treatments with nitrogen fertilization.

3.1.4. Phenological Stages R3, R4, and R5

Table 5 presents the ANOVA results for different phenological stages of the maize crop. The UAV captured images at the R3 stage, Sentinel-2 acquired imagery at the R4 stage, and CBERS-04A captured images at the R5 stage. The reason for these differing growth stages was the presence of clouds during image acquisition and the long revisit period of the CBERS-04A satellite, which is 31 days.

Table 5. Results of the two-way ANOVA for the variables (NDs and RSPs) at stages R3, R4, and R5.

Variables	GreenNDVI	MCARI2	MGRVI	MSAVI	MTVI2
<i>p</i> -value (RSPs)	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (NDs)	0.29 ^{ns}	0.58 ^{ns}	0.38 ^{ns}	0.39 ^{ns}	0.58 ^{ns}
<i>p</i> -value (I)	0.82 ^{ns}	0.81 ^{ns}	0.82 ^{ns}	0.81 ^{ns}	0.81 ^{ns}
Variables	NDVI	SAVI	SR	VARI	WDRVI
<i>p</i> -value (RSPs)	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *
<i>p</i> -value (NDs)	0.43 ^{ns}	0.43 ^{ns}	0.38 ^{ns}	0.84 ^{ns}	0.47 ^{ns}
<i>p</i> -value (I)	0.78 ^{ns}	0.78 ^{ns}	0.81 ^{ns}	0.99 ^{ns}	0.74 ^{ns}

(RSPs) = Remote Sensing Platforms. (NDs) = Nitrogen Doses (kg ha^{-1} of N). (I) = Interaction between RSPs and NDs. (*) = significant. (^{ns}) = not significant at significance level of 5%.

The analysis revealed differences only for the factor (RSPs) across all VIs. No significant differences were identified for the factors (NDs) and (I) (Table 5). The underlying cause of this result may be related to the phenological stages at which the images were acquired. At stages R3, R4, and R5, detecting nitrogen supply in the crop becomes challenging due to canopy closure, nitrogen consumption, and biomass presence. These results support the observations by Sumner et al. [45], who evaluated the response of VIs to different nitrogen doses in maize. It was observed that the magnitude of VI values varied depending on the growth stages, the year, and the sensing platforms. As the growing season progresses and the maize canopy closes, the usefulness of these indices in detecting differences in nitrogen supply appears to diminish.

Similarly, these estimates are consistent with research conducted by Colovic et al. [54], which showed that several VIs do not demonstrate high sensitivity to maize crop parameters. It is crucial to consider that the relationship between canopy-level spectral signals and target properties can be influenced by structural factors such as plant size, age, and leaf angle. The texture characteristics of multispectral images of the maize canopy become more complex as the growing period progresses. This occurs because, as maize grows, the soil background may be mistakenly classified as part of the crop due to the complexity of plant structures and increased shading from overlapping leaves, which adds to the complexity of the canopy structure [12].

3.2. Principal Component Analysis

3.2.1. Remote Sensing Platforms

In this study, the results obtained from the principal component analysis (PCA) for the variables of the remote sensing platforms (RSPs) Sentinel-2, CBERS-04A, and UAV, presented in Figure 4, highlight that two principal components explain 98.4% of the cumulative variance of the dataset. The first principal component (PC1) accounts for 93.8% of the total variance, while the second (PC2) contributes 4.6%. It can be observed that the RSP vectors exhibit strong associations, suggesting a direct correlation between them, and are well represented by components PC1 and PC2 (Figure 4a).

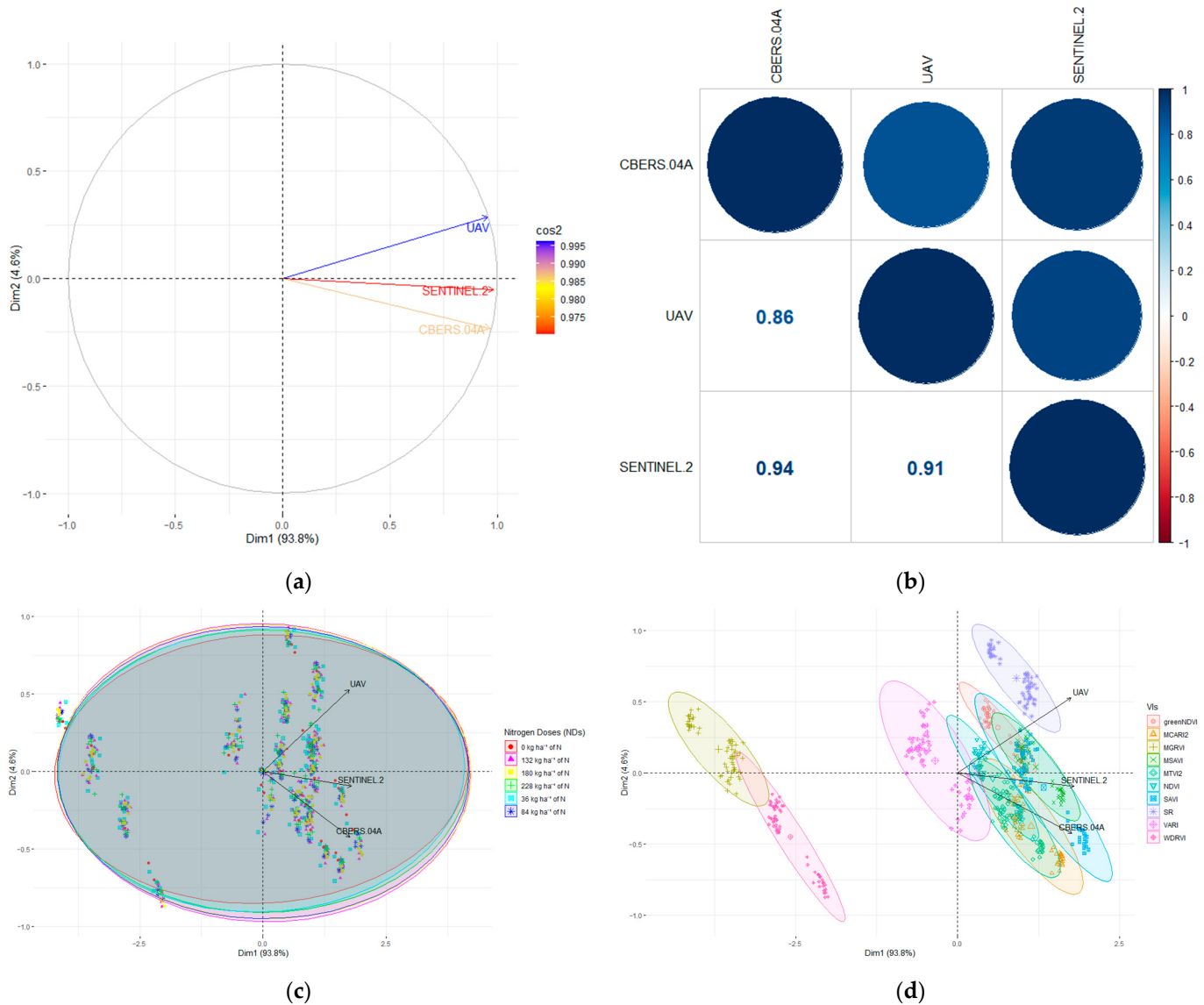


Figure 4. (a) PCA biplot for RSPs; (b) Pearson correlation plot between RSPs; (c) PCA biplot for RSPs and NDs; (d) PCA biplot for RSPs and VIs.

Pearson correlation analysis (Figure 4b) confirms the strong correlation between the RSPs, corroborating the evidence from the PCA. The highest correlation coefficient was found between Sentinel-2 and CBERS-04A ($r = 0.94$), followed by the correlation between Sentinel-2 and UAV ($r = 0.91$), and between CBERS-04A and UAV ($r = 0.86$). These results highlight the similarity between the RSPs despite differences in spatial, radiometric, and temporal resolutions, as well as differences in camera imaging characteristics. The correlation results among the RSPs in this study align with findings from Santos et al. [55],

who identified similarities among the evaluated images and found that even with different spatial scales, the platforms showed high correlation coefficients ($r = 0.73$) between UAV and Sentinel-2, and a moderate correlation between UAV and Landsat 8 ($r = 0.65$). Furthermore, the urgency of large-scale monitoring in precision agriculture becomes evident. The fusion of drone and satellite images could be an adaptive approach, minimizing the repetitive use of drones [56].

Moreover, although the dataset expresses multiple concentrations, this behavior is not due to the different N application doses shown in Figure 4c. Instead, it reflects the data's behavior in relation to the VIs, which play a key role in clustering the data. The indices MGRVI and WDRVI, in particular, show a distinct dispersion compared to the other VIs, presenting an opposite orientation to the vectors, validating the findings from the ANOVA throughout the entire crop growth cycle, in which these indices consistently showed negative values (Figure 4d).

3.2.2. Vegetation Indices

In this study, the results obtained from the PCA for the independent variables of the determined VIs (greenNDVI, MCARI2, MGRVI, MSAVI, MTVI2, NDVI, SAVI, SR, VARI, and WDRVI) shown in Figure 5 reveal that only two principal components explain 98.5% of the cumulative variance in the dataset, with PC1 and PC2 accounting for 88.5% and 10% of the total variance, respectively. The results indicate that the VIs MCARI2, MSAVI, MTVI2, NDVI, SAVI, and WDRVI show a strong association and robust contribution to PC1. In contrast, the VIs greenNDVI and VARI diverge from the others, presenting only a moderate association among the vectors (Figure 5a).

The Pearson correlation shown in Figure 5b supports these findings, highlighting strong correlations among MCARI2, MSAVI, MTVI2, NDVI, and SAVI, with coefficients ranging from $r = 1$ to $r = 0.91$. This suggests multicollinearity among these variables and indicates that the VIs respond in a similar manner, reflecting vegetation vigor and common environmental factors such as vegetation density, atmospheric conditions, solar illumination geometry, soil moisture, color, and brightness. Therefore, in line with the ANOVA results for the V7 phenological stage, these VIs confirm their capacity to predict nitrogen (N) deficiency, regardless of the remote sensing platform used (Table 3). Additionally, these indices showed negative correlations with the VIs MGRVI and SR, which were strongly correlated with each other ($r = 1$). The VIs greenNDVI and VARI exhibited a correlation coefficient of $r = 0.86$. These results confirm findings from previous studies, which indicate that vegetation indices have different sensitivities to specific factors. Although they may show similarities, each index captures distinct aspects of the interaction between vegetation and the environment, as no single index can evaluate vegetation universally and precisely [57,58].

The effects of nitrogen doses (NDs) on maize are illustrated in Figure 5c. The subtle displacement of the ellipses suggests a tendency in data dispersion for the 0 and 36 kg ha⁻¹ N doses compared to the other NDs, although all exhibited non-uniform data dispersion. This behavior may be attributed to the influence of RSPs, as shown in Figure 5d, highlighting their fundamental role in data clustering. The UAV data showed greater concentration, with a smaller ellipse, indicating lower measurement variability. In contrast, the data from CBERS-04A showed excessive dispersion. Sentinel-2, on the other hand, demonstrated moderate dispersion compared to CBERS-04A and greater dispersion than the UAV. The abundance of pixels captured exclusively by the UAV contributes significantly to the robustness of the data. In this context, Zhang et al. [47] emphasize that optimizing flight parameters and rigorous sensor calibration are essential for ensuring the accuracy and reliability of the measurements obtained. Moreover, when using satellite platforms, it is

important to consider the lower image resolution, as atmospheric influence may increase data dispersion [4].

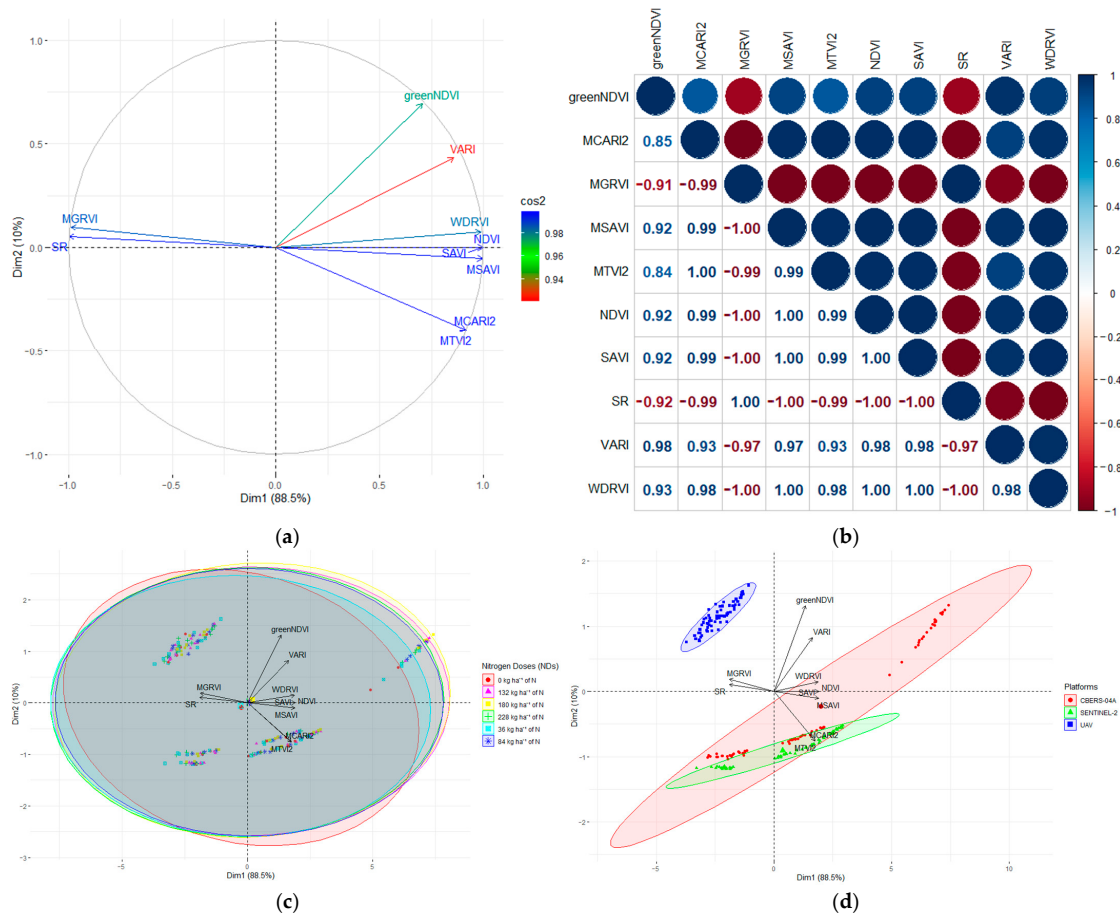


Figure 5. (a) PCA biplot for VIs; (b) Pearson correlation graph between VIs; (c) CA biplot for VIs and nitrogen doses (NDs); (d) PCA biplot for VIs and remote sensing platforms (RSPs).

3.2.3. Phenological Stage

According to the PCA presented in Figure 6, it was possible to identify the relationships between the phenological stage of the maize crop at the time of multispectral image acquisition and the RSPs. Based on the data obtained by UAV, there is a high degree of data aggregation for all phenological stages monitored by this platform, V7, VT, and R3. This concentration is particularly notable when compared to the satellite-acquired data.

For the CBERS-04A data, there is visible clustering corresponding to the V7, VT, and R5 stages. Notably, during the VT stage, the CBERS-04A data show a distinct displacement and elongation of the ellipse compared to the other stages. Uniquely, the Sentinel-2 data stand out due to a dense clustering of points, especially in the R4 phenological stage.

Reflections on the crop's different growth stages are always relevant. In the V7 stage, which occurred approximately 36 days after emergence (DAE), the maize crop had recently received the nitrogen treatments. At this stage, the influence of structural factors such as plant size and biomass quantity is significant, along with the presence of exposed soil. This may explain the larger ellipse sizes compared to other stages. As growth progresses past 59 DAE, the canopy fully develops, increasing photosynthetic activity and reducing the influence of earlier factors. Finally, from 93 DAE onward, water supply decreases due to reduced rainfall in the region during May, leading to more intense leaf senescence during the grain filling period, a natural process in which the plant redirects nutrients to the developing grains.

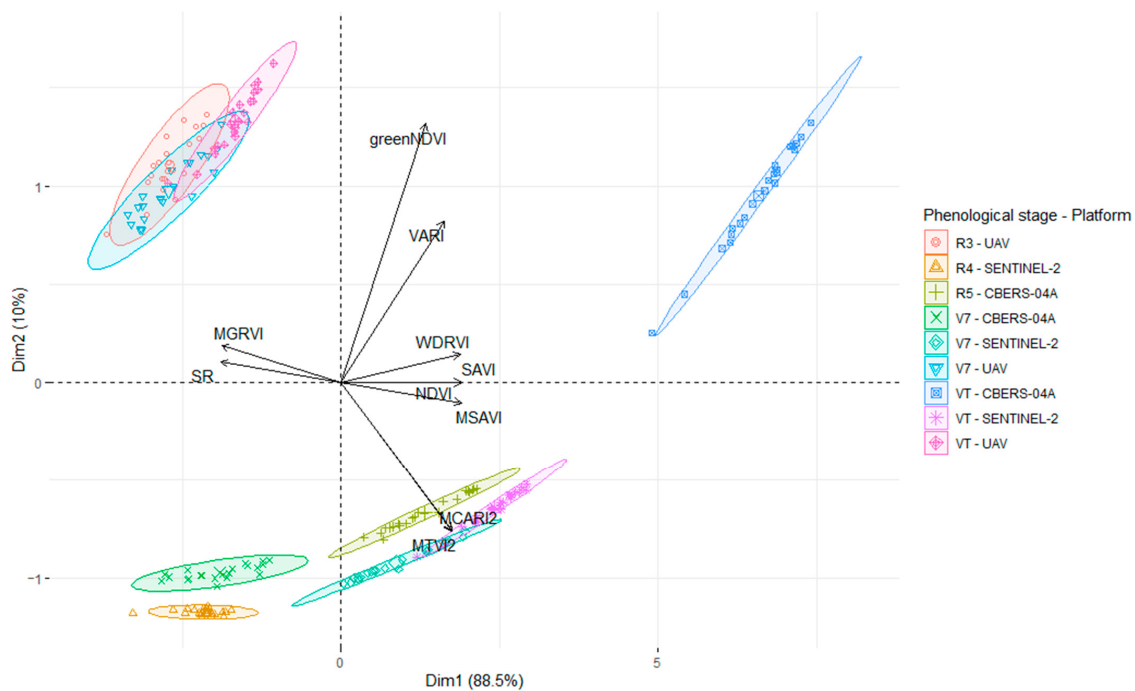


Figure 6. PCA biplot for VIs in relation to phenological stages and RSPs.

These observations are explored by Venâncio et al. [59], who, based on maize crop development, observed an inverse relationship between the amount of photosynthetic vegetation and soil coverage. At 13 DAE, all VIs had low values, indicating the early growth phase. In contrast, at 61 DAE, the amount of photosynthetic vegetation increased, reflected in peak values for most indices. However, by 77 DAE, during the reproductive phase, photosynthetic vegetation began to decline as the plants reached their maximum height. This decrease in VIs results from loss of vegetative vigor, which becomes more evident as the harvest approaches.

4. Conclusions

The results of this study demonstrate that multispectral images obtained from different remote sensing platforms (RSPs) such as the Sentinel-2 and CBERS-04A satellites and an unmanned aerial vehicle (UAV) are effective for accurately detecting varying nitrogen doses. However, the selection of vegetation index (VI) and the phenological stage at the time of image acquisition play a critical role in the effectiveness of remote sensing for identifying nitrogen deficiency in maize crops.

- For images captured by UAV, the vegetation indices (VIs) greenNDVI, MSAVI, NDVI, SAVI, SR, and WDRVI did not perform satisfactorily during the VT phenological stage. In contrast, during the V7 stage, the influence of image source was less significant, allowing for more reliable predictions.
- The use of the Sentinel-2 satellite is recommended due to its excellent temporal resolution and free access to imagery. Moreover, employing multiple VIs is advisable to ensure effective nutritional assessments and minimize adverse effects. It is also essential to conduct monitoring at an appropriate growth stage to ensure the accuracy and relevance of nutritional analysis.
- This study paves the way for future research to further explore the specificities of different multispectral remote sensing platforms and how the images generated can be applied to monitor nutrient deficiencies in crops. It highlights the importance of

thoughtful selection of monitoring technologies, which can enhance the efficiency of site-specific management enabled by precision agriculture.

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Data Availability Statement: The data used in this study are publicly accessible, including those obtained from the CBERS-04A satellite, available through the catalog of the National Institute for Space Research (INPE) at link <http://www.dgi.inpe.br/catalogo/explore> (accessed on 15 June 2025), and from the Sentinel-2 satellite constellation, available on the Copernicus Open Access Hub at <https://browser.dataspace.copernicus.eu/> (accessed on 15 June 2025).

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

RSPs	Remote Sensing Platforms
UAV	Unmanned Aerial Vehicle
VI	Vegetation Indices
NDs	Nitrogen Doses
SDGs	Sustainable Development Goals
UN	United Nations
FAO	Food and Agriculture Organization of the United Nations
GHG	Greenhouse Gases
greenNDVI	Green Normalized Difference Vegetation Index
MCARI2	Modified Chlorophyll Absorption Ratio Index
MGRVI	Modified Green–Red Vegetation Index
MSAVI	Modified Soil-Adjusted Vegetation Index
MTVI2	Modified Triangular Vegetation Index
NDVI	Normalized Difference Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
SR	Simple Ratio Index
VARI	Visible Atmospherically Resistant Index
SR	Wide-Dynamic-Range Vegetation Index
AOAC	Association of Official Analytical Chemists
ANOVA	Analysis of Variance
PCA	Principal Component Analysis
I	Interaction between RSPs and NDs
LSD	Least Significant Difference
INPE	National Institute for Space Research (Brazil)
CGOBT	Earth Observation Management Commission
DIDGI	Directorate of Geospatial Data Intelligence and Information
CDSR	Remote Sensing Data Center

Appendix A

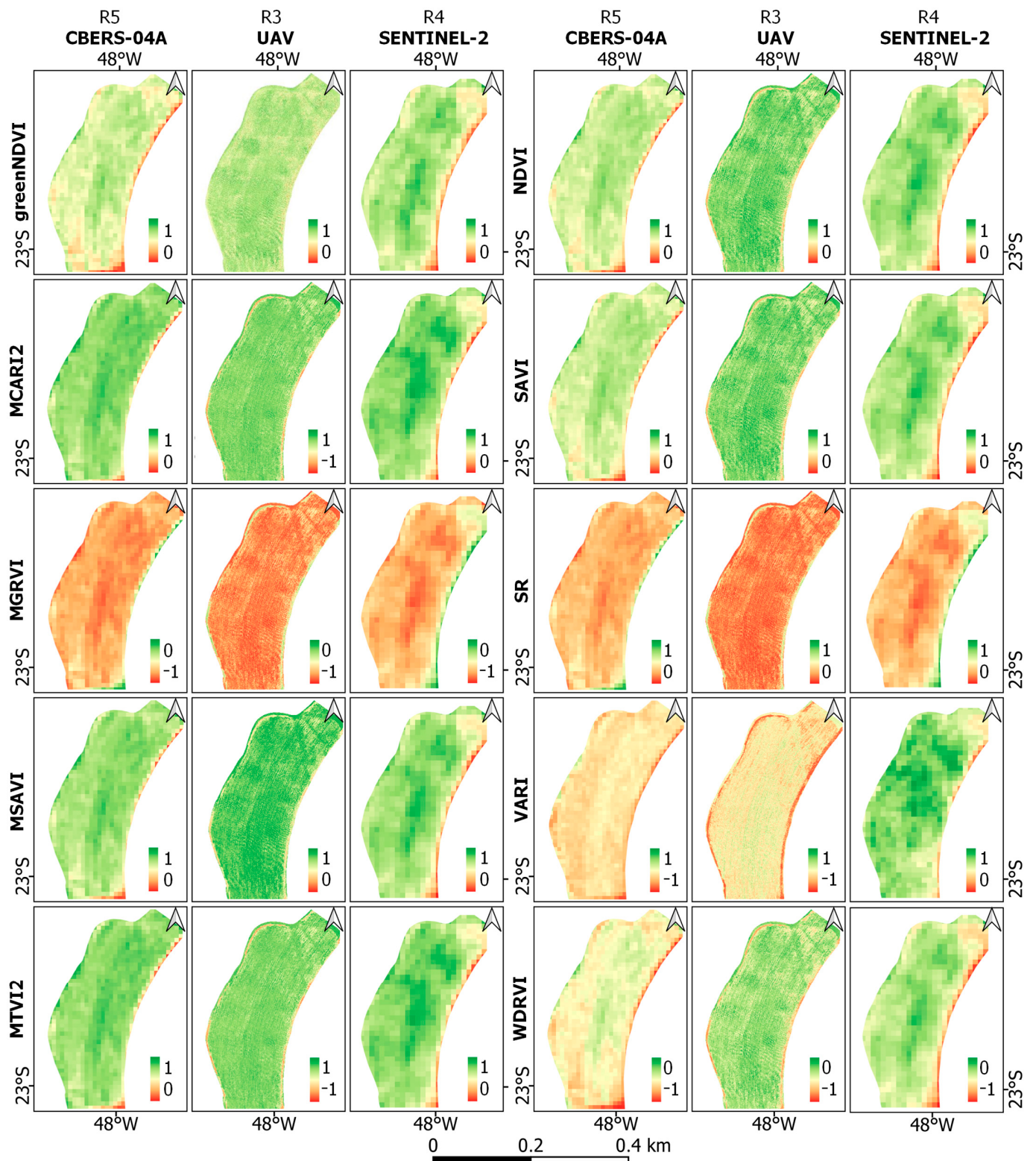


Figure A1. Vegetation indices at the VT phenological stage in the study area, obtained from the CBERS-04A, UAV, and Sentinel-2 platforms.

Appendix B

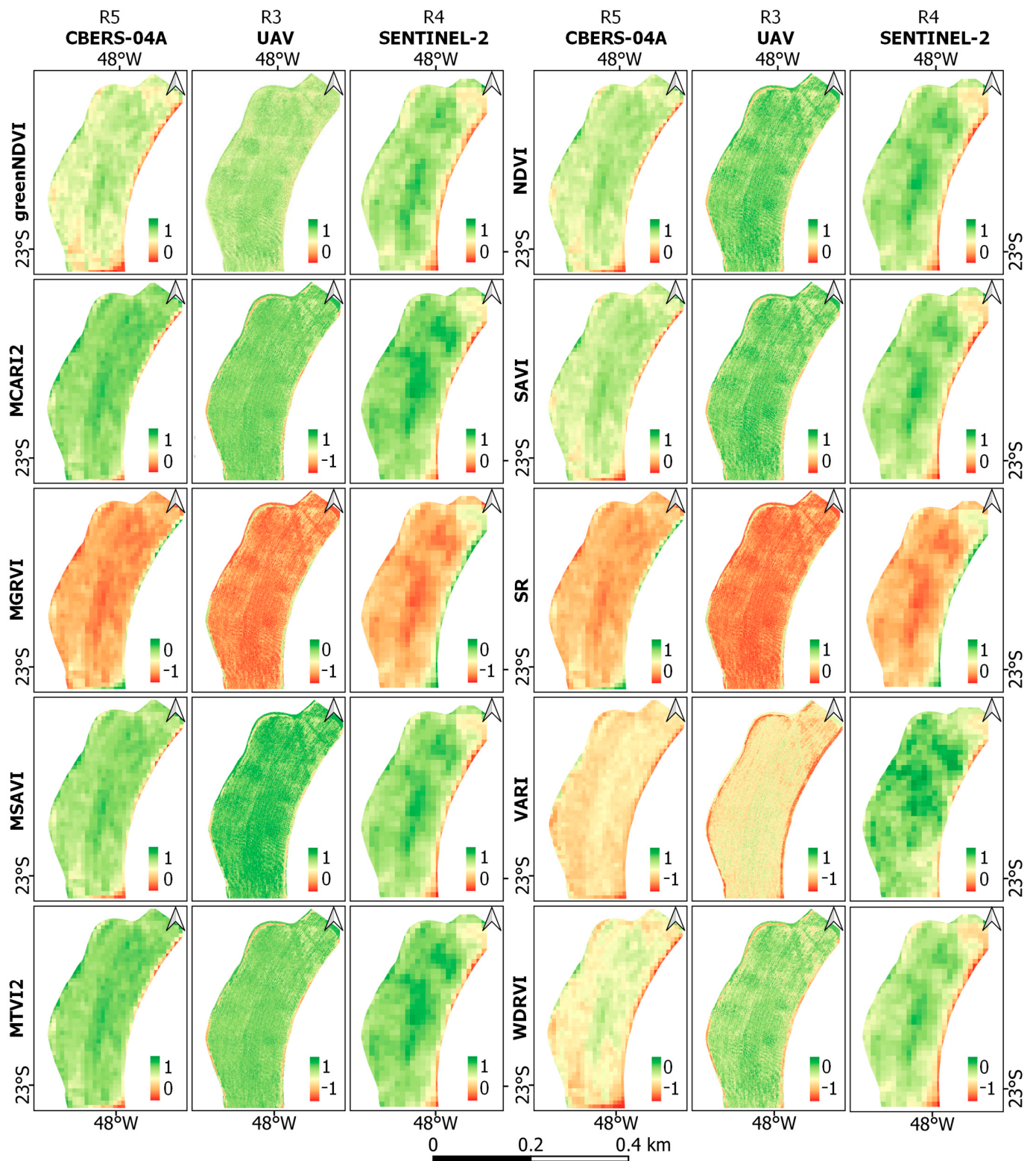


Figure A2. Vegetation indices at the R3, R4, and R5 phenological stages in the study area, obtained from the CBERS-04A, UAV, and Sentinel-2 platforms.

Appendix C

Table A1. Results of the LSD test for the variables (NDs and RSPs) at the V7 stage.

Factors	Variables	GreenNDVI	VARI		
(RSPs)	CBERS-04A	0.31 c	0.01 c		
	UAV	0.40 a	0.11 b		
	Sentinel-2	0.35 b	0.17 a		
Factors	Variables	MCARI2	MGRVI	MSAVI	MTVI2
(RSPs)	CBERS-04A	0.49 b	−0.57 b	0.48 b	0.43 b
	UAV	0.28 c	−0.51 a	0.43 c	0.25 c
	Sentinel-2	0.67 a	−0.71 c	0.58 a	0.60 a
(NDs)	0	0.47 bc	−0.59 ab	0.49 bc	0.42 bc
	36	0.46 c	−0.58 ab	0.49 bc	0.41 c
	84	0.49 abc	−0.60 abc	0.50 abc	0.43 abc
	132	0.49 ab	−0.60 bc	0.51 ab	0.43 ab
	180	0.50 a	−0.61 c	0.51 a	0.44 a
	228	0.46 c	−0.58 a	0.48 c	0.41 c
Factors	Variables	NDVI	SAVI	SR	WDRVI
(RSPs)	CBERS-04A	0.31 b	0.47 b	0.53 b	−0.48 b
	UAV	0.27 c	0.41 c	0.57 a	−0.48 c
	Sentinel-2	0.41 a	0.62 a	0.41 c	−0.35 a
(NDs)	0	0.33 bc	0.49 bc	0.51 ab	−0.43 b
	36	0.32 bc	0.49 bc	0.52 ab	−0.43 b
	84	0.34 abc	0.51 abc	0.50 abc	−0.42 ab
	132	0.34 ab	0.51 ab	0.50 bc	−0.42 ab
	180	0.45 a	0.52 a	0.49 c	−0.41 a
	228	0.32 c	0.48 c	0.52 a	−0.44 b

(RSPs) = Remote Sensing Platforms. (NDs) = Nitrogen Doses (kg ha^{-1} of N). (I) = Interaction between RSPs and NDs. Means followed by the same letter (a, b, c) do not differ by LSD test. At the 5% significance level.

Table A2. Results of the LSD test for the variables (NDs and RSPs) at the VT stage.

Factors	Variables	MCARI2	MGRVI	MTVI2	VARI		
(RSPs)	CBERS-04A	0.88 a	−0.92 c	0.77 a	0.46 a		
	UAV	0.32 c	−0.56 a	0.29 c	0.18 c		
	Sentinel-2	0.74 b	−0.78 b	0.65 b	0.21 b		
(NDs)	0	0.63 c	−0.74 a	0.56 c	0.25 c		
	36	0.64 bc	−0.74 a	0.56 bc	0.26 bc		
	84	0.65 ab	−0.76 b	0.57 ab	0.29 ab		
	132	0.65 a	−0.76 b	0.58 a	0.29 ab		
	180	0.66 a	−0.76 b	0.58 a	0.30 a		
	228	0.66 a	−0.76 b	0.58 a	0.30 a		
Factors	Variables	greenNDVI			MSAVI		
(RSPs)		CBERS-04A	UAV	Sentinel-2	CBERS-04A	UAV	Sentinel-2
(NDs)	0	0.53 aD	0.45 bA	0.38 cC	0.76 aC	0.47 cA	0.62 bC
	36	0.56 aC	0.44 bA	0.39 cBC	0.78 aB	0.47 cA	0.63 bBC
	84	0.58 aAB	0.44 bA	0.41 cAB	0.80 aAB	0.47 cA	0.65 bAB
	132	0.59 aAB	0.44 bA	0.43 bA	0.81 aA	0.47 cA	0.67 bA
	180	0.61 aA	0.44 bA	0.43 bA	0.81 aA	0.47 cA	0.67 bA
	228	0.58 aBC	0.45 bA	0.42 cA	0.80 aAB	0.48 cA	0.66 bA

Table A2. Cont.

Factors	Variables	NDVI			SAVI		
(RSPs)		CBERS-04A	UAV	Sentinel-2	CBERS-04A	UAV	Sentinel-2
(NDs)	0	0.61 aC	0.31 cA	0.45 bC	0.92 aC	0.47 cA	0.68 bC
	36	0.64 aB	0.31 cA	0.46 bBC	0.96 aB	0.46 cA	0.70 bBC
	84	0.67 aA	0.31 cA	0.48 bAB	0.10 aA	0.46 cA	0.73 bAB
	132	0.68 aA	0.31 cA	0.50 bA	1.01 aA	0.46 cA	0.75 bA
	180	0.68 aA	0.31 cA	0.50 bA	1.03 aA	0.46 cA	0.75 bA
	228	0.66 aAB	0.32 cA	0.49 bA	0.99 aAB	0.48 cA	0.74 bA
Factors	Variables	SR			WDRVI		
(RSPs)		CBERS-04A	UAV	Sentinel-2	CBERS-04A	UAV	Sentinel-2
(NDs)	0	0.24 cA	0.53 aA	0.38 bA	−0.09 aD	−0.45 cA	−0.31 bC
	36	0.22 cB	0.53 aA	0.37 bAB	−0.04 aC	−0.45 cA	−0.29 bBC
	84	0.20 cBC	0.53 aA	0.35 bBC	0.00 aB	−0.45 cA	−0.27 bAB
	132	0.19 cC	0.53 aA	0.34 bC	0.02 aAB	−0.45 cA	−0.25 bA
	180	0.19 cC	0.53 aA	0.33 bC	0.04 aA	−0.45 cA	−0.25 bA
	228	0.20 cBC	0.52 aA	0.34 bC	−0.01 aB	−0.44 cA	−0.26 bA

(RSPs) = Remote Sensing Platforms. (NDs) = Nitrogen Doses (kg ha^{−1} of N). (I) = Interaction between RSPs and NDs. Means followed by the same lowercase letter in the column (a, b, c) and uppercase letter in the row (A, B, C, D) do not differ from each other. At significance level of 5%.

Table A3. Results of the LSD test for the variables (NDs and RSPs) at stages R3, R4, and R5.

Factors	Variables	GreenNDVI	MCARI2	MGRVI	MSAVI	MTVI2
(RSPs)	CBERS-04A	0.40 a	0.67 a	−0.74 c	0.61 a	0.59 a
	UAV	0.40 a	0.27 c	−0.51 a	0.43 c	0.24 c
	Sentinel-2	0.26 b	0.51 b	−0.54 b	0.45 b	0.45 b
Factors	Variables	NDVI	SAVI	SR	VARI	WDRVI
(RSPs)	CBERS-04A	0.44 a	0.66 a	0.39 c	0.13 a	−0.32 a
	UAV	0.27 c	0.41 c	0.57 a	0.13 a	−0.48 c
	Sentinel-2	0.29 b	0.44 b	0.54 b	0.08 b	−0.46 b

(RSPs) = Remote Sensing Platforms. (NDs) = Nitrogen Doses (kg ha^{−1} of N). (I) = Interaction between RSPs and NDs. Means followed by the same letter (a, b, c) do not differ by LSD test. At significance level of 5%.

References

- United Nations. *Transforming Our World: The 2030 Agenda for Sustainable Development*; Department of Economic and Social Affairs: New York, NY, USA, 2015.
- Santos Valle, S.; Kienzle, J. *Agriculture 4.0—Agricultural Robotics and Automated Equipment for Sustainable Crop Production*; FAO: Rome, Italy, 2020.
- Barbosa Júnior, M.R.; Moreira, B.R.d.A.; Carreira, V.d.S.; de Brito Filho, A.L.; Trentin, C.; de Souza, F.L.P.; Tedesco, D.; Setiyono, T.; Flores, J.P.; Ampatzidis, Y.; et al. Precision Agriculture in the United States: A Comprehensive Meta-Review Inspiring Further Research, Innovation, and Adoption. *Comput. Electron. Agric.* **2024**, *221*, 108993. [\[CrossRef\]](#)
- Silva, L.; Conceição, L.A.; Lidon, F.C.; Maças, B. Remote Monitoring of Crop Nitrogen Nutrition to Adjust Crop Models: A Review. *Agriculture* **2023**, *13*, 835. [\[CrossRef\]](#)
- Alvarez-Vanhard, E.; Corpetti, T.; Houet, T. UAV & Satellite Synergies for Optical Remote Sensing Applications: A Literature Review. *Sci. Remote Sens.* **2021**, *3*, 100019. [\[CrossRef\]](#)
- Skakun, S.; Kalecinski, N.I.; Brown, M.G.L.; Johnson, D.M.; Vermote, E.F.; Roger, J.C.; Franch, B. Assessing Within-Field Corn and Soybean Yield Variability from WorldView-3, Planet, Sentinel-2, and Landsat 8 Satellite Imagery. *Remote Sens.* **2021**, *13*, 872. [\[CrossRef\]](#)
- Sozzi, M.; Kayad, A.; Gobbo, S.; Cogato, A.; Sartori, L.; Marinello, F. Economic Comparison of Satellite, Plane and UAV-Acquired NDVI Images for Site-Specific Nitrogen Application: Observations from Italy. *Agronomy* **2021**, *11*, 2098. [\[CrossRef\]](#)

8. Dehghan-Shoar, M.H.; Pullanagari, R.R.; Kereszturi, G.; Orsi, A.A.; Yule, I.J.; Hanly, J. A Unified Physically Based Method for Monitoring Grassland Nitrogen Concentration with Landsat 7, Landsat 8, and Sentinel-2 Satellite Data. *Remote Sens.* **2023**, *15*, 2491. [CrossRef]
9. Miller, J.O.; Mondal, P.; Sarupria, M. Sensor-Based Measurements of NDVI in Small Grain and Corn Fields by Tractor, Drone, and Satellite Platforms. *Crop Environ.* **2024**, *3*, 33–42. [CrossRef]
10. Bausch, W.C.; Khosla, R. QuickBird Satellite versus Ground-Based Multi-Spectral Data for Estimating Nitrogen Status of Irrigated Maize. *Precis. Agric.* **2010**, *11*, 274–290. [CrossRef]
11. Croft, H.; Arabian, J.; Chen, J.M.; Shang, J.; Liu, J. Mapping Within-Field Leaf Chlorophyll Content in Agricultural Crops for Nitrogen Management Using Landsat-8 Imagery. *Precis. Agric.* **2020**, *21*, 856–880. [CrossRef]
12. Qiao, L.; Gao, D.; Zhang, J.; Li, M.; Sun, H.; Ma, J. Dynamic Influence Elimination and Chlorophyll Content Diagnosis of Maize Using UAV Spectral Imagery. *Remote Sens.* **2020**, *12*, 2650. [CrossRef]
13. Santana, D.C.; Cotrim, M.F.; Flores, M.S.; Rojo Baio, F.H.; Shiratsuchi, L.S.; da Silva Junior, C.A.; Teodoro, L.P.R.; Teodoro, P.E. UAV-Based Multispectral Sensor to Measure Variations in Corn as a Function of Nitrogen Topdressing. *Remote Sens. Appl.* **2021**, *23*, 100534. [CrossRef]
14. Martínez-Dalmau, J.; Berbel, J.; Ordóñez-Fernández, R. Nitrogen Fertilization. A Review of the Risks Associated with the Inefficiency of Its Use and Policy Responses. *Sustainability* **2021**, *13*, 5625. [CrossRef]
15. Govindasamy, P.; Muthusamy, S.K.; Bagavathiannan, M.; Mowrer, J.; Jagannadham, P.T.K.; Maity, A.; Halli, H.M.; G. K., S.; Vadivel, R.; T. K., D.; et al. Nitrogen Use Efficiency—A Key to Enhance Crop Productivity under a Changing Climate. *Front. Plant Sci.* **2021**, *14*. [CrossRef] [PubMed]
16. Roy, P.S. Spectral Reflectance Characteristics of Vegetation and Their Use in Estimating Productive Potential. *Proc. Indian Acad. Sci.* **1989**, *99*, 59–81. [CrossRef]
17. Torres-Madronero, M.C.; Goez, M.; Guzman, M.A.; Rondon, T.; Carmona, P.; Acevedo-Correa, C.; Gomez-Ortega, S.; Durango-Flórez, M.; López, S.V.; Galeano, J.; et al. Spectral Library of Maize Leaves under Nitrogen Deficiency Stress. *Data* **2022**, *8*, 2. [CrossRef]
18. Li, X.; Ata-UI-Karim, S.T.; Li, Y.; Yuan, F.; Miao, Y.; Yoichiro, K.; Cheng, T.; Tang, L.; Tian, X.; Liu, X.; et al. Advances in the Estimations and Applications of Critical Nitrogen Dilution Curve and Nitrogen Nutrition Index of Major Cereal Crops. A Review. *Comput. Electron. Agric.* **2022**, *197*, 106998. [CrossRef]
19. Sharma, L.K.; Bali, S.K. A Review of Methods to Improve Nitrogen Use Efficiency in Agriculture. *Sustainability* **2017**, *10*, 51. [CrossRef]
20. Moises, C.; Andrade, F.H.; Monzon, J.P.; Reussi Calvo, N.I.; Cerrudo, A. Nitrogen Deficiency in Maize Fields of the Southern Pampas Does Not Affect Kernel Number but Reduces Weight per Kernel. *Field Crops Res.* **2024**, *312*, 109394. [CrossRef]
21. Gong, X.; Li, J.; Ma, H.; Chen, G.; Dang, K.; Yang, P.; Wang, M.; Feng, B. Nitrogen Deficiency Induced a Decrease in Grain Yield Related to Photosynthetic Characteristics, Carbon–Nitrogen Balance and Nitrogen Use Efficiency in Proso Millet (*Panicum miliaceum* L.). *Arch. Agron. Soil Sci.* **2020**, *66*, 398–413. [CrossRef]
22. Franco, J.R.; Pai, E.D.; Calça, M.V.C.; Raniero, M.R.; Dal Pai, A.; Sarnighausen, V.C.R.; Sánchez-Román, R.M. Atualização Da Normal Climatológica e a Classificação Climática de Köppen Para o Município de Botucatu-SP. *Irriga* **2023**, *28*, 77–92. [CrossRef]
23. Köppen, W.; Geiger, R. *Klima Der Erde (Climate of the Earth)*; Justus Perthes: Gotha, Germany, 1954.
24. dos Santos, H.G.; Jacomine, P.K.T.; dos Anjos, L.H.C.; de Oliveira, V.A.; Lumberras, J.F.; Coelho, M.R.; de Almeida, J.A.; de Araujo Filho, J.C.; de Oliveira, J.B.; Cunha, T.J.F. *Sistema Brasileiro de Classificação de Solo*, 5th ed.; Embrapa: Brasília, DF, Brazil, 2018; ISBN 9788570358004.
25. *Soil Survey Staff Keys to Soil Taxonomy*, 13th ed.; USDA-Natural Resources Conservation Service: Washington, DC, USA, 2022.
26. Cantarella, H.; Quaggio, J.A.; Mattos, D., Jr.; Boaretto, R.M.; Van Raij, B. *Boletim Técnico 100: Recomendações de Adubação e Calagem Para o Estado de São Paulo*; Cantarella, H., Mattos, D., Jr., Boaretto, R.M., Quaggio, J.A., Van Raij, B., Eds.; Instituto Agrônomo de Campinas (IAC): Campinas, Brazil, 2022.
27. Survey3W Camera—Red+Green+NIR (RGN, NDVI). Available online: <https://www.mapir.camera/en-gb/products/survey3w-camera-red-green-nir-rgn-ndvi> (accessed on 11 March 2025).
28. INPE—Ministério Da Ciência, Tecnologia e Inovação—Instituto Nacional de Pesquisas Espaciais—Catálogo. Available online: <https://www.dgi.inpe.br/catalogo/explore> (accessed on 11 March 2025).
29. Instituto Nacional de Pesquisas Espaciais—Câmeras Imageadoras. Available online: <https://www.gov.br/inpe/pt-br/programas/cbers/sobre-o-cbers-1/cbers-04a/cameras-imageadoras> (accessed on 11 March 2025).
30. Copernicus Browser. Available online: <https://browser.dataspace.copernicus.eu/> (accessed on 11 March 2025).
31. S2 Mission—Overview of Sentinel-2 Mission. Available online: <https://sentiwiki.copernicus.eu/web/s2-mission> (accessed on 11 March 2025).

32. Gitelson, A.A.; Kaufman, Y.J.; Merzlyak, M.N. Use of a Green Channel in Remote Sensing of Global Vegetation from EOS-MODIS. *Remote Sens. Environ.* **1996**, *58*, 289–298. [\[CrossRef\]](#)
33. Haboudane, D.; Miller, J.R.; Pattey, E.; Zarco-Tejada, P.J.; Strachan, I.B. Hyperspectral Vegetation Indices and Novel Algorithms for Predicting Green LAI of Crop Canopies: Modeling and Validation in the Context of Precision Agriculture. *Remote Sens. Environ.* **2004**, *90*, 337–352. [\[CrossRef\]](#)
34. Bendig, J.; Yu, K.; Aasen, H.; Bolten, A.; Bennertz, S.; Broscheit, J.; Gnyp, M.L.; Bareth, G. Combining UAV-Based Plant Height from Crop Surface Models, Visible, and near Infrared Vegetation Indices for Biomass Monitoring in Barley. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *39*, 79–87. [\[CrossRef\]](#)
35. Qi, J.; Chehbouni, A.; Huete, A.R.; Kerr, Y.H.; Sorooshian, S. A Modified Soil Adjusted Vegetation Index. *Remote Sens. Environ.* **1994**, *48*, 119–126. [\[CrossRef\]](#)
36. Jackson, R.D.; Huete, A.R. Interpreting Vegetation Indices. *Prev. Vet. Med.* **1991**, *11*, 185–200. [\[CrossRef\]](#)
37. Huete, A.R. A Soil-Adjusted Vegetation Index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309. [\[CrossRef\]](#)
38. Jordan, C.F. Derivation of Leaf-Area Index from Quality of Light on the Forest Floor. *Ecology* **1969**, *50*, 663–666. [\[CrossRef\]](#)
39. Gitelson, A.A.; Kaufman, Y.J.; Stark, R.; Rundquist, D. Novel Algorithms for Remote Estimation of Vegetation Fraction. *Remote Sens. Environ.* **2002**, *80*, 76–87. [\[CrossRef\]](#)
40. Gitelson, A.A. Wide Dynamic Range Vegetation Index for Remote Quantification of Biophysical Characteristics of Vegetation. *J. Plant Physiol.* **2004**, *161*, 165–173. [\[CrossRef\]](#)
41. Malavolta, E.; Vitti, G.C.; de Oliveira, S.A. *Avaliação Do Estado Nutricional Das Plantas: Principios e Aplicações*—E. Malavolta—Google Livros, 2nd ed.; Piracicaba: Piracicaba, Brazil, 1997.
42. Latimer, G.W., Jr. *Official Methods of Analysis of AOAC International*, 20th ed.; AOAC International: Rockville, MD, USA, 2016; Volume 2, ISBN 978-0935584875.
43. Mondal, S.; Kumar, R.; Mishra, J.S.; Dass, A.; Kumar, S.; Vijay, K.V.; Kumari, M.; Khan, S.R.; Singh, V.K. Grain Nitrogen Content and Productivity of Rice and Maize under Variable Doses of Fertilizer Nitrogen. *Heliyon* **2023**, *9*, e17321. [\[CrossRef\]](#)
44. Bojtor, C.; Mousavi, S.M.N.; Illés, Á.; Golzardi, F.; Széles, A.; Szabó, A.; Nagy, J.; Marton, C.L. Nutrient Composition Analysis of Maize Hybrids Affected by Different Nitrogen Fertilisation Systems. *Plants* **2022**, *11*, 1593. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Sumner, Z.; Varco, J.J.; Dhillon, J.S.; Fox, A.A.A.; Czarnecki, J.; Henry, W.B. Ground versus Aerial Canopy Reflectance of Corn: Red-Edge and Non-Red Edge Vegetation Indices. *Agron. J.* **2021**, *113*, 2782–2797. [\[CrossRef\]](#)
46. Han, N.; Zhang, B.; Liu, Y.; Peng, Z.; Zhou, Q.; Wei, Z. Rapid Diagnosis of Nitrogen Nutrition Status in Summer Maize over Its Life Cycle by a Multi-Index Synergy Model Using Ground Hyperspectral and UAV Multispectral Sensor Data. *Atmosphere* **2022**, *13*, 122. [\[CrossRef\]](#)
47. Zhang, J.; Hu, Y.; Li, F.; Fue, K.G.; Yu, K. Meta-Analysis Assessing Potential of Drone Remote Sensing in Estimating Plant Traits Related to Nitrogen Use Efficiency. *Remote Sens.* **2024**, *16*, 838. [\[CrossRef\]](#)
48. Romualdo, L.M.; Luz, P.H.C.; Devecchio, F.F.S.; Marin, M.A.; Zúñiga, A.M.G.; Bruno, O.M.; Herling, V.R. Use of Artificial Vision Techniques for Diagnostic of Nitrogen Nutritional Status in Maize Plants. *Comput. Electron. Agric.* **2014**, *104*, 63–70. [\[CrossRef\]](#)
49. Nguy-Robertson, A.L. The Mathematical Identity of Two Vegetation Indices: MCARI2 and MTVI2. *Int. J. Remote Sens.* **2013**, *34*, 7504–7507. [\[CrossRef\]](#)
50. Ye, H.; Huang, W.; Huang, S.; Wu, B.; Dong, Y.; Cui, B. Remote Estimation of Nitrogen Vertical Distribution by Consideration of Maize Geometry Characteristics. *Remote Sens.* **2018**, *10*, 1995. [\[CrossRef\]](#)
51. Sharifi, A. Using Sentinel-2 Data to Predict Nitrogen Uptake in Maize Crop. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 2656–2662. [\[CrossRef\]](#)
52. Cai, Y.; Guan, K.; Nafziger, E.; Chowdhary, G.; Peng, B.; Jin, Z.; Wang, S.; Wang, S. Detecting In-Season Crop Nitrogen Stress of Corn for Field Trials Using UAV-and CubeSat-Based Multispectral Sensing. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2019**, *12*, 5153–5166. [\[CrossRef\]](#)
53. Maresma, Á.; Ariza, M.; Martínez, E.; Lloveras, J.; Martínez-Casasnovas, J.A. Analysis of Vegetation Indices to Determine Nitrogen Application and Yield Prediction in Maize (*Zea mays* L.) from a Standard UAV Service. *Remote Sens.* **2016**, *8*, 973. [\[CrossRef\]](#)
54. Colovic, M.; Yu, K.; Todorovic, M.; Cantore, V.; Hamze, M.; Albrizio, R.; Stellacci, A.M. Hyperspectral Vegetation Indices to Assess Water and Nitrogen Status of Sweet Maize Crop. *Agronomy* **2022**, *12*, 2181. [\[CrossRef\]](#)
55. dos Santos, C.V.B.; Moura, M.S.B.d.; Galvêncio, J.D.; Carvalho, H.F.d.S.; Miranda, R.d.Q.; Montenegro, S.M.G.L. Comparação de Imagens Multiespectrais Utilizando Satélites e VANT Para a Análise de Mudanças Estruturais Em Área de Floresta Seca. *Rev. Bras. Geogr. Física* **2021**, *14*, 2510–2522. [\[CrossRef\]](#)
56. Murugan, D.; Garg, A.; Singh, D. Development of an Adaptive Approach for Precision Agriculture Monitoring with Drone and Satellite Data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2017**, *10*, 5322–5328. [\[CrossRef\]](#)
57. Bannari, A.; Morin, D.; Bonn, F.; Huete, A.R. A Review of Vegetation Indices. *Remote Sens. Rev.* **1995**, *13*, 95–120. [\[CrossRef\]](#)

58. Zeng, Y.; Hao, D.; Huete, A.; Dechant, B.; Berry, J.; Chen, J.M.; Joiner, J.; Frankenberg, C.; Bond-Lamberty, B.; Ryu, Y.; et al. Optical Vegetation Indices for Monitoring Terrestrial Ecosystems Globally. *Nat. Rev. Earth Environ.* **2022**, *3*, 477–493. [[CrossRef](#)]
59. Venacio, L.P.; Mantovani, E.C.; do Amaral, C.H.; Neale, C.M.U.; Gonçalves, I.Z.; Filgueiras, R.; Eugenio, F.C. Potential of Using Spectral Vegetation Indices for Corn Green Biomass Estimation Based on Their Relationship with the Photosynthetic Vegetation Sub-Pixel Fraction. *Agric. Water Manag.* **2020**, *236*, 106155. [[CrossRef](#)]

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