

DIGITAL IMAGE PROCESSING IN THE EVALUATION OF NITROGEN NUTRITIONAL STATUS IN MAIZE CROP

Katyany Oliveira Mota^{1a}, Murilo Vargas da Silveira^{1b}, Érica de Oliveira Araújo^{1c*}, Ranieli dos Anjos de Souza^{1d}, Iandra Rosa Domiciano^{1e}, and Gabriel Monteiro Paulino^{1f}

^{1a} Department of Agronomy, Federal Institute of Education, Science and Technology of Rondonia, Colorado do Oeste, 76993-000, Brazil

<https://orcid.org/0009-0009-0482-2179>

^{1b} Department of Agronomy, Federal Institute of Education, Science and Technology of Rondonia, Colorado do Oeste, 76993-000, Brazil

<https://orcid.org/0000-0002-0376-6509>

^{1c} Department of Agronomy, Federal Institute of Education, Science and Technology of Rondonia, Colorado do Oeste, 76993-000, Brazil

<https://orcid.org/0000-0003-1996-4849>

^{1d} Department of Agronomy, Federal Institute of Education, Science and Technology of Rondonia, Colorado do Oeste, 76993-000, Brazil

<https://orcid.org/0000-0003-1408-4826>

^{1e} Department of Agronomy, Federal Institute of Education, Science and Technology of Rondonia, Colorado do Oeste, Brazil

<https://orcid.org/0009-0005-6522-6179>

^{1f} Department of Agronomy, Federal Institute of Education, Science and Technology of Rondonia, Colorado do Oeste, 76993-000, Brazil

<https://orcid.org/0009-0007-8946-2891>

* Corresponding author: erica.araujo@ifro.edu.br

ABSTRACT

The use of information derived from conventional digital images can represent a low cost and widely accessible alternative for estimating nitrogen nutrition in various agricultural crops. This study aimed to evaluate the feasibility of using smartphone based digital images in the visible (RGB) spectrum to assess nitrogen status in maize. The experiment was carried out using a randomized block design, with three replicates, in a 2×5 factorial scheme, consisting of the absence and presence of biostimulant and five nitrogen doses (0, 50, 100, 200 and 400 kg·ha⁻¹ of N) applied as topdressing. Relative chlorophyll index measurements were performed using a chlorophyll meter and digital images were obtained using a smartphone at the V8, V10 and R1 phenological stages. At the V10 and R1 phenological stages, leaf samples were collected to determine leaf nitrogen content using the semi-micro Kjeldahl method. Application of the biostimulant did not influence the SPAD index or the nitrogen content of the different maize hybrids. There was a positive linear correlation between the SPAD index and leaf nitrogen content in maize at the V10 and R1 phenological stages, with values of 52.42 and 55.15, respectively. Twelve of the 17 spectral parameters evaluated were effective in assessing the nutritional status of maize plants at the V8, V10 and R1 stages, particularly the R band. Smartphone based image analysis is a valuable tool that enables rapid, non invasive, and non destructive estimation of nitrogen in maize crops directly in the field at low cost, thereby promoting smarter and more sustainable agriculture. Accordingly, the development of a mobile application based on the obtained findings could significantly increase accessibility and usability for stakeholders.

Keywords: *Zea mays* L., plant nutrition, artificial vision, remote sensor, smart farming.

INTRODUCTION

Maize is one of the main agricultural commodities in the world, with Brazil being the third largest producer of this crop. The 2023/2024 harvest recorded 115.7 million tons over an area of 21 million hectares (CONAB, 2024), highlighting the relevance of the crop in the Brazilian trade balance and its contribution to meeting global food demand (USDA, 2024). However, maize yield in Brazil is considered low when compared to countries such as the United States and China, the world's largest producers. The low efficiency in the use of fertilizers, especially nitrogen fertilizers, may be associated with low yield (Frazao et al., 2014).

Nitrogen (N) is the element extracted in greatest quantity by the maize crop and its supply is essential to obtain high yields (Vergutz et al., 2017). This is because N plays important roles in biochemical processes and is a component of chlorophylls, secondary metabolites, proteins, and other enzymes (Elazab et al., 2016; Gabriel et al., 2017), in addition to being vital for stem and leaf growth as well as fruit development (Li et al., 2020). However, N fertilization recommendations are only approximations of the crop's actual needs and yield, since soil N dynamics in the soil are complex, governed by numerous chemical and biological reactions that regulate its availability, and are strongly influenced by edaphoclimatic conditions (Sainju et al., 2017).

In order to identify the optimal N rate, and given that excess N reduces agronomic efficiency, increases production costs, and affects crop productivity, various management strategies have been used to estimate plant nutritional status. The main methods include laboratory analysis of foliar N content and the use of portable sensors. Among the sensors, the SPAD (Soil Plant Analysis Development) chlorophyll meter, which determines the green intensity of the leaves (Fontes, 2016), and the Dualex (dual excitation), a portable device that combines light fluorescence and transmittance to determine N leaf concentration (Tremblay et al., 2009), stand out.

In addition, visible light sensors, such as digital cameras and image analysis software, have been used to quantify leaf greenness as an indirect measure of crop N status, with digital images recording information such as the amounts of red, green, and blue (RGB) light (Bestas et al., 2025; Shi et al., 2021; Rigon et al., 2016). Another method that can be used is remote sensing, which allows evaluating the color of the leaves by means of sensors capable of quantifying the electromagnetic radiation reflected by them,

using as a parameter the spectral bands of the electromagnetic spectrum, which are the ranges of wavelengths of electromagnetic radiation recorded by the remote sensors (Formaggio et al., 2017). Some of these spectral bands are visible through the red, green and blue colors, while others can be converted into visible images. Analysis of certain spectral bands enables the identification of target characteristics, such as vegetation type or condition, as plants absorb, reflect, and transmit electromagnetic radiation in different proportions according to their biochemical and physical properties, allowing the establishment of color parameters that characterize vegetation (Chen et al., 2024; Xin et al., 2024; Devechio et al., 2023; Formaggio et al., 2017). One of the main advantages of this technology is that it allows for surveying large areas in a non invasive and non destructive manner (Lassalle, 2021).

In this context, Wu et al. (2014) found that the analysis of digital images can identify and associate one or more nutrient deficiencies in maize hybrids, allowing determination of the optimal timing and type of nutrient application. Romualdo et al. (2014), in a study evaluating methods for extracting characteristics from digital color images to identify N deficiency in maize hybrids, found high success rates of the methods used, with correct detection rates of 82.5% and 96.5% at the V4 and R1 stages, respectively.

According to Shi et al. (2021), information derived from conventional digital images may represent a low-cost and widely accessible alternative for estimating N nutrition. The present study evaluated the feasibility of using smartphone based digital images in the visible (RGB) spectrum to assess N status in maize, aiming to advance agricultural technologies that promote sustainability and competitiveness of the sector through the integration of technologies that reduce input dependence and production costs, and improve crop production efficiency.

MATERIALS AND METHODS

Experimental area characterization

The experiment was conducted under field conditions from February to April 2022 at the experimental area of the Federal Institute of Education, Science and Technology of Rondônia, Colorado do Oeste Campus, in the municipality of Colorado do Oeste, RO, Brazil (13° 06' S and 60° 29' W), at an average altitude of 407 meters (Fig. 1). The climate of the region is Aw (tropical climate with dry winter) according to the Köppen-Geiger classification (Beck et al., 2018), while the soil is classified as Argissolo Vermelho-Amarelo Eutrófico (PVAe), corresponding to Ultisol in the



Fig. 1. Experimental location. Source: authors' own elaboration (2025).

Soil Taxonomy classification (Santos et al., 2018).

Average temperature (25.6°C) and rainfall (616mm) data during the experiment were obtained from the FieldClimate database (FieldClimate, 2022). Data on the chemical characterization of the soil at 0-20 cm and 20-40 cm depths, from samples collected prior to the experiment, are presented in Table 1.

Experimental design

The experimental design was randomized blocks, with three replicates, in a 2×5 factorial scheme, consisting of the absence and presence of biostimulant and five N rates (0, 50, 100, 200 and 400 kg·ha⁻¹N) applied as top-dressing (Banzato and Kronka, 2006). Seeds of the single hybrids SYN7G17 TLTG Viptera and DKB 390 PRO3, from the brands Syngenta and Dekalb, were used for planting.

Soil preparation and planting

Planting and fertilization furrows were mechanically opened at depths between 4 and 7 cm, according to the determined spacing. The single hybrids SYN7G17 TLTG Viptera and DKB 390 PRO3 were sown on previously desiccated *Crotalaria juncea* straw using a seeder-fertilizer machine, with 0.50 m row spacing, targeting a population of 65,000 plants ha⁻¹. Each experimental unit measured 3 m x 6 m, with a usable area of 8m², excluding the two outer rows and 1m from each end.

At the time of sowing, basal fertilization was applied at 500 kg·ha⁻¹ of fertilizer (04-30-10 (N-P₂O₅-K₂O), supplying 20 kg·ha⁻¹ N, 150 kg·ha⁻¹

P₂O₅ and 50 kg·ha⁻¹ K₂O. An additional 150 kg·ha⁻¹ K₂O was applied as top-dressing across the plot in two equal split applications at the V2 and V4 phenological stages.

The biostimulant used was Bioenergy®, registered as a foliar fertilizer obtained from seaweed (*Ascophyllum nodosum* L.) extract and added with glycine, applied at a rate of 250 mL·ha⁻¹ at the V5 and V11 phenological stages. The top-dressing N rates (0, 50, 100, 200 and 400 kg·ha⁻¹N) were applied in the form of urea (45%), in two equal splits at the V4 and V6 phenological stages across the entire experimental plot. Crop development was monitored using the scale proposed by Ritchie et al. (1993). Pest, disease, and weed management was carried out following standard recommendations for maize cultivation.

Determination of chlorophyll index and nitrogen content

Relative chlorophyll index (RCI) measurements were obtained using the Minolta SPAD-502 chlorophyll meter, and performed at the V8, V10 and R1 phenological stages, in five plants per experimental unit, with four readings per plant in the two newly expanded leaves. Readings were taken at two thirds of the distance from the tip of the leaf blade to the stem, on opposite sides of the midrib and equidistant between the midrib and the leaf margin. The RCI of the experimental unit was calculated as the average value of twenty readings, according to Argenta et al. (2004).

At the V10 and R1 phenological stages, five plants per experimental unit were sampled, with collection of the last fully expanded leaf (V10)

Table 1. Soil chemical characteristics prior to the experiment.

Layer (cm)	pH H ₂ O	pH CaCl ₂	OM g/kg	P mg/dm ³	K	Na	Ca cmolc/dm ³	Mg cmolc/dm ³	Al	H+Al
	cmolc/dm ³									
0-20	5.84	5.04	23.37	11.92	198.45	5.56	4.21	1.58	0	4.81
20-40	5.87	4.98	14.95	3.74	97.32	5.56	4.05	0.77	0	3.75
Layer (cm)	Cu	Fe	Mn	Zn	SB	CEC	V (%)	cmolc/dm ³		
	mg/dm ³				cmolc/dm ³					
0-20	4.34	26.3	83.5	8.35	6.32	11.13	56.77			
20-40	4.88	12.89	81	3.77	5.09	8.83	57.56			

and the leaf opposite to and below the ear (R1). The sampled leaves were cleaned, cut, properly identified, packed in paper bags and dried in a forced air circulation oven at a temperature of 65 °C until reaching constant mass. Subsequently, the dried material was weighed on a semi-analytical scale, ground in a Wiley-type mill and sent for laboratory analysis to determine N content by the semi-micro-Kjeldahl method, as described by Malavolta et al. (1997).

Determination of spectral parameters

At the V8, V10 and R1 phenological stages, digital images of the last fully expanded leaf of four plants per experimental unit were collected using a smartphone with a 48megapixel camera, Samsung brand and Galaxy A32 model, and a flashlight with a light source of 1 LED of 3 watts and 130 lumens, Original brand.

The flashlight was positioned in the abaxial part of the maize leaf, and the smartphone camera was positioned in the adaxial part, adjacent to the leaf, to ensure that only spectral information (RGB) of the leaf was collected in the images. Subsequently, the RGB spectral values were decomposed using the Microsoft Paint program, with radiometric resolution of 8 bits per band, selecting 3 points of each sample with the 'color selector' tool, to later calculate the averages of each treatment (Fig. 2).

Statistical analysis

The data were subjected to joint analysis of variance for each variable, enabling comparison of two experiments when the ratio of residual mean squares between them was less than 7. Regression analysis was performed to evaluate the effect of the quantitative factor, N rate, on the variables analyzed. The regression models were chosen based on the significance of the regression coefficients, using the "t" test and coefficient of determination ($R^2 = SS_{\text{Regression}}/SS_{\text{Treatment}}$). Statistical analyses were carried out using the

statistical program Sisvar (Ferreira, 2019).

For image analysis, 17 parameters were used, as defined by Barman et al. (2022). These parameters consist of band combination forming indices based on the visible region of the electromagnetic spectrum, namely: R, G, B, (R-B)/(R+B), R + G + B, (G + B)/R, G/R, (R + G + B)/R, (G-R)/(G + R), (G-R), (G+R), G/(R + G + B), R/(R + G + B), B/(R + G + B), (R-B), (G-B)/(R + G + B) and (R+B). Each parameter was calculated based on the average values of R, G and B of each treatment and analyzed using the Sisvar statistical software (Ferreira, 2019).

RESULTS AND DISCUSSION

Application of the biostimulant based on *Ascophyllum nodosum* algae extract did not influence the SPAD index or leaf N content of maize hybrids (Table 2). N contents accumulated in the leaf and the SPAD index were higher according to the phenological development of maize plants, showing a positive linear correlation at the V10 and R1 stages (Table 3 and Fig. 3).

The spectral parameters R, R-B and (R+B) decreased with the progress of the phenological stages of maize plants; on the other hand, the spectral parameters G, B, R+G+B, (G+B)/R, G/R, (R+G+B)/R, (G-R) and (G+R) showed a decrease in values at V10 with a subsequent increase at R1, while the opposite was observed for the parameter (R-B)/(R+B). For the other spectral parameters, values remained constant at the V8 and V10 stages, with only a slight variation at R1 (Table 3).

Decomposition of the double interaction between maize hybrids and biostimulant application showed no significant difference ($p < 0.05$) for the SPAD index at the different phenological stages. However, the SPAD index values gradually increased with plant phenological stage, reaching their highest levels at R1, the onset of flowering (Table 2). Gonzaga et al. (2023) and Souza-Netta et al. (2022) also reported

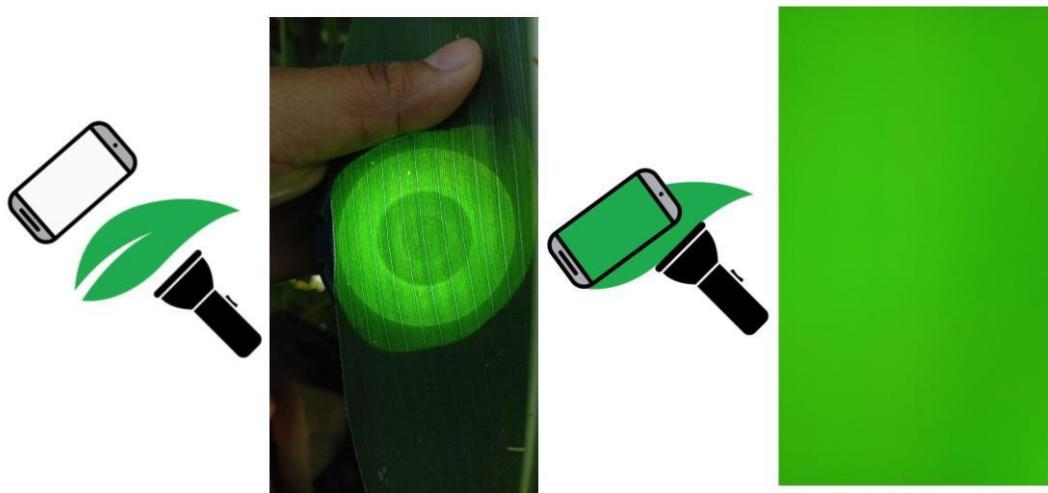


Fig. 2. Demonstration of leaf color image acquisition using a smartphone and flashlight.

Table 2. Decomposition of the interaction between maize hybrids and the application of *Ascophyllum nodosum* based biostimulant on SPAD index across different phenological stages.

Biostimulants	Hybrids			Means	CV%
	DKB 390	SYN7G17			
Without	V8	49.12	48.36	48.74 ^a	4.01
With		49.31	47.47	48.89 ^a	
Means		49.21 ^A	47.92 ^A	48.57	
Without	V10	53.18	51.68	52.46 ^a	3.79
With		52.68	52.24	52.40 ^a	
Means		52.93 ^A	51.93 ^A	52.43	
Without	R1	57.06	53.66	55.36 ^a	3.70
With		56.34	53.58	54.96 ^a	
Means		56.70 ^A	53.62 ^A	55.16	

Means followed by the same letter, lowercase in the column and uppercase in the row, do not differ significantly by Tukey test at the 5% probability level. V8: eight fully developed leaves; V10: tenth fully developed leaf; R1: full flowering.

no positive effect of Stimulum® biostimulant application on chlorophyll a and contents in the maize cultivar AS 1820 Agroceres. Several studies report similar, comparable, or divergent results regarding the use of biostimulants based on seaweed extract, fungi, or bacteria, often combined with hormones, L-amino acids and/or mineral formulations in economically-important grain crops such as maize, beans, soybeans, and sorghum (Ferreira et al., 2018; Francischini et al., 2018; Tejada et al., 2018).

Leaf N content was higher and showed good performance as nutritional index up to the V10

phenological stage, decreasing as the plant matured (Table 3). However, its determination required laboratory analysis, which prevents correcting N deficiency within the same growing season, making it useful only as an indication for supplementation in subsequent crops (Argenta et al., 2002).

The SPAD index increased with maize phenological stage, reaching its highest values at V10 and R1 (Table 3), constituting a strategic tool for assessing plant N status. Argenta et al. (2001) suggest that adequate N levels in maize plants are indicated by SPAD values of 45.4, 52.1, 55.3

Table 3. Mean and standard deviation of the parameters collected from maize leaves at different phenological stages.

Parameter	Phenological stages of maize		
	V8	V10	R1
N	—	35.70 +/- 5.33	31.11 +/- 4.07
SPAD	48.56 +/- 4.48	52.42 +/- 3.93	55.15 +/- 4.022
R	68.20 +/- 8.68	64.82 +/- 7.31	63.09 +/- 7.57
G	198.45 +/- 8.12	185.46 +/- 6.44	199.42 +/- 7.69
B	14.26 +/- 1.65	13.20 +/- 1.41	14.10 +/- 2.45
(R-B)/(R+B)	0.65 +/- 0.037	0.66 +/- 0.032	0.63 +/- 0.068
R+G+B	280 +/- 12.12	263.50 +/- 10.88	276.62 +/- 10.43
(G+B)/R	3.16 +/- 0.42	3.10 +/- 0.34	3.43 +/- 0.47
G/R	2.95 +/- 0.40	2.89 +/- 0.33	3.20 +/- 0.43
(R+G+B)/R	4.16 +/- 0.42	4.10 +/- 0.34	4.43 +/- 0.47
(G-R)/(G+R)	0.48 +/- 0.053	0.48 +/- 0.044	0.52 +/- 0.048
(G-R)	130 +/- 12.77	120.64 +/- 9.47	136.32 +/- 11.44
(G+R)	266.65 +/- 10.93	250.29 +/- 10.01	262.51 +/- 10.12
G/(R+G+B)	0.70 +/- 0.025	0.70 +/- 0.021	0.72 +/- 0.022
R/(R+G+B)	0.24 +/- 0.025	0.24 +/- 0.021	0.22 +/- 0.023
B/(R+G+B)	0.050 +/- 0.0045	0.050 +/- 0.0043	0.051 +/- 0.009
R-B	53.93 +/- 8.17	51.61 +/- 6.83	48.98 +/- 8.34
(G-B)/(R+G+B)	0.65 +/- 0.026	0.65 +/- 0.023	0.67 +/- 0.024
(R+B)	82.47 +/- 9.44	78.03 +/- 8.026	77.20 +/- 7.56

and 58.0 at the stages of three to four leaves, six to seven leaves, ten to eleven fully expanded leaves and silking, respectively. According to Rocha et al. (2005), SPAD index measurement is a low-cost, practical tool for early diagnosis of N status, enabling timely decision-making on topdressing N fertilizer applications without compromising yield, as the period of greatest N demand for maize occurs between flowering onset and the beginning of grain formation.

The spectral parameters R, R-B and (R+B) showed a reduction with the progress of the phenological stages of the maize plant, while the spectral parameters G, B, R+G+B, (G+B)/R, G/R, (R+G+B)/R, (G-R) and (G+R) showed a decrease in values at V10 with a subsequent increase at R1, and the opposite was observed in the parameter (R-B)/(R+B). For the other spectral parameters, the values remained constant at the V8 and V10 stages, with variation at R1 (Table 3).

The correlation between SPAD index and leaf N content is well established in the literature and was confirmed in the present study, showing positive linear correlation at the V10 and R1 phenological stages (Fig. 3). This indicates that as leaf N content increases, chlorophyll content rises proportionally, suggesting that SPAD measurements can effectively replace leaf N

content analysis for the diagnosis of plant N status. Argenta et al. (2001) demonstrated that relative chlorophyll content measured with a portable SPAD meters a reliable indicator of N level in cereals. Similarly, Shivashankar et al. (2025) reported a significant positive linear relationship between SPAD-derived nutritional status and maize grain yield.

When analyzing the correlation coefficients of N content and SPAD index with the spectral parameters of maize leaves collected by smartphone based digital images, the R band (red) appeared to be the most effective for evaluating the nutritional status of maize plants at the V8, V10 and R1 stages (Table 4). Similarly, other parameters calculated based on the values of R, G and B seem promising, namely: (R-B)/(R+B), (G+B)/R, G/R, (R+G+B)/R, (G-R)/(G+R), (G-R), G/(R+G+B), R/(R+G+B), (R-B), (G-B)/(R+G+B) and (R+B), as shown in Figs. 5, 6, 7 and 8. In line with the results found, Barman et al. (2022) evaluated the digital chlorophyll measurement method based on smartphone acquired images to estimate the chlorophyll value of citrus leaves at different stages of maturation. The authors found that the color parameters R and (R+B) were highly correlated and (G+R) showed moderate correlation with chlorophyll in immature leaves;

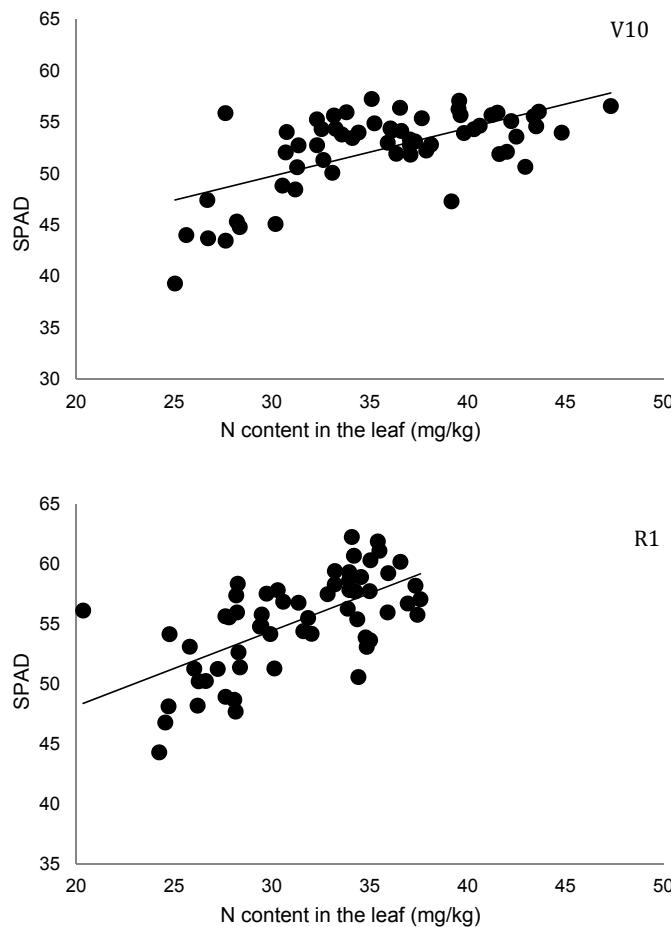


Fig. 3. Correlation between SPAD index and leaf nitrogen content in maize at the V10 and R1 phenological stages.

(G+B)/R, G/R, (R+G+B)/R, (G-R)/(G+R), (G-R), G/(R+G+B), R/(R+G+B), R-B and (R+B) showed a high correlation with the chlorophyll content in tender leaves; and B and B/(R+G+B) showed the strongest correlation in mature leaves. Likewise, Shi et al. (2021) studied the estimation of N nutrition in rice plants through RGB images and reported significant correlations between some image indices and nutritional parameters of rice. Several studies support the differential role of R and B bands in detecting N-related pigment changes (Bestas et al., 2025; Liu et al., 2021; Zhang et al., 2020).

N rates significantly influenced SPAD index and N content in maize leaves, with the results described by a quadratic model. The highest relative chlorophyll contents (SPAD readings) were detected at the R1 stage (Fig. 4). According to the models, the metabolic potential of

chlorophyll production by the maize hybrids evaluated (maximum response point) as a function of N supply was reached with the N rates of 281, 275 and 313 kg·ha⁻¹ at the V8, V10 and R1 stages, respectively, while the N rates for the maximum accumulation of N in the leaves were 257 and 333 kg·ha⁻¹ at the V10 and R1 phenological stages, respectively. The presence of N in the soil is approximately proportional to the chlorophyll content in the leaf, and thus plants with higher N content showed greater growth and development and, consequently, higher leaf area index, which led to greater carbohydrate synthesis by photosynthesis. In addition, increased N also improves carbohydrate allocation to the root system, resulting in a larger root network and more efficient N uptake from both soil and fertilizer. Additionally, Chen et al. (2024) have reported that SPAD values of maize

Table 4. Pearson's linear correlation coefficient between the nutritional and spectral parameters of maize leaf.

Parameter	Phenological stages of maize				
	V8	V10		R1	
	SPAD	SPAD	N	SPAD	N
R	-0.325*	-0.5778**	-0.6354**	-0.560**	-0.450**
G	0.720**	0.4300**	0.1189 ^{ns}	0.471**	0.279*
B	0.236 ^{ns}	-0.1114 ^{ns}	-0.2160 ^{ns}	0.286 *	0.213 ^{ns}
(R-B)/(R+B)	-0.500**	-0.4361**	-0.4067**	-0.504**	-0.397**
R+G+B	0.282*	-0.1483 ^{ns}	-0.3849**	0.008 ^{ns}	-0.071 ^{ns}
(G+B)/R	0.500**	0.6564**	0.6373**	0.637**	0.497**
G/R	0.491**	0.6564**	0.6386**	0.634**	0.493**
(R+G+B)/R	0.500**	0.6564**	0.6373**	0.637**	0.497**
(G-R)/(G+R)	0.516**	0.6895**	0.6525**	0.659**	0.502**
(G-R)	0.679**	0.7387**	0.5715**	0.688**	0.486**
(G+R)	0.277*	-0.1453 ^{ns}	-0.3875**	-0.061 ^{ns}	-0.124 ^{ns}
G/(R+G+B)	0.485**	0.6798**	0.6464**	0.601**	0.453**
R/(R+G+B)	-0.525**	-0.6888**	-0.6513**	-0.667**	-0.508**
B/(R+G+B)	0.171 ^{ns}	-0.0705 ^{ns}	-0.0851 ^{ns}	0.285*	0.228 ^{ns}
R-B	-0.392**	-0.5958**	-0.6358**	-0.593**	-0.471**
(G-B)/(R+G+B)	0.434**	0.6484**	0.6199**	0.443**	0.329**
(R+B)	-0.257*	-0.5464**	-0.6174**	-0.468**	-0.381**

^{ns} not significant at the 5% probability level; * significant at the 5% probability level; and ** significant at the 1% probability level.

canopies treated without N application (N0) were significantly lower than those subjected to N treatments across all four growth stages. Notably, differences in canopy SPAD values between different N application rates were more pronounced during vegetative stages (V6 and V9) and diminished during reproductive stages (R1 and R2).

When associating maize nutritional status measurements to topdressing N rates, the parameters R, (R-B)/(R+B), (G+B)/R, G/R, (R+G+B)/R, (G-R)/(G+R), (G-R), G/(R+G+B), R/(R+G+B), (R-B), (G-B)/(R+G+B) and (R+B) effectively reflected N status from the V8 phenological stage (Figs. 5, 6, 7 and 8). Additionally, the quadratic regression model showed acceptable accuracy and precision, with mean correlation coefficients (R^2) exceeding 0.80, corroborating findings by Xin et al. (2024) and Jia et al. (2014). Furthermore, as plants matured, the R^2 values increased, indicating that spectral parameters provided more accurate assessment of N status at the R1 stage (full flowering).

Smartphone-based image analysis is a viable, high-potential technology for rapid, non-invasive, non-destructive, and low-cost assessment of N status in maize. It can be

performed by anyone, requires no specific camera or controlled environment, and allows images to be collected over time, archived, and later compared to evaluate temporal changes in crops. The results of this study enable the advancement of research and the development of tools or applications for in-field image processing, promoting sector competitiveness and efficiency through technological integration for smarter, more sustainable agriculture. Future research should extend to other crops, building datasets from leaf images captured with different cameras, lighting conditions, and resolutions to evaluate the performance of N estimation algorithms.

CONCLUSIONS

Application of a biostimulant based on *Ascophyllum nodosum* algae extract did not influence the SPAD index or leaf nitrogen content of the different maize hybrids.

Appositive linear correlation was observed between the SPAD index and leaf nitrogen content in maize at the V10 and R1 phenological stages, with values of 52.42 and 55.15, respectively.

The spectral parameters R, (R-B)/(R+B), (G+B)/R, G/R, (R+G+B)/R, (G-R)/(G+R), (G-R),

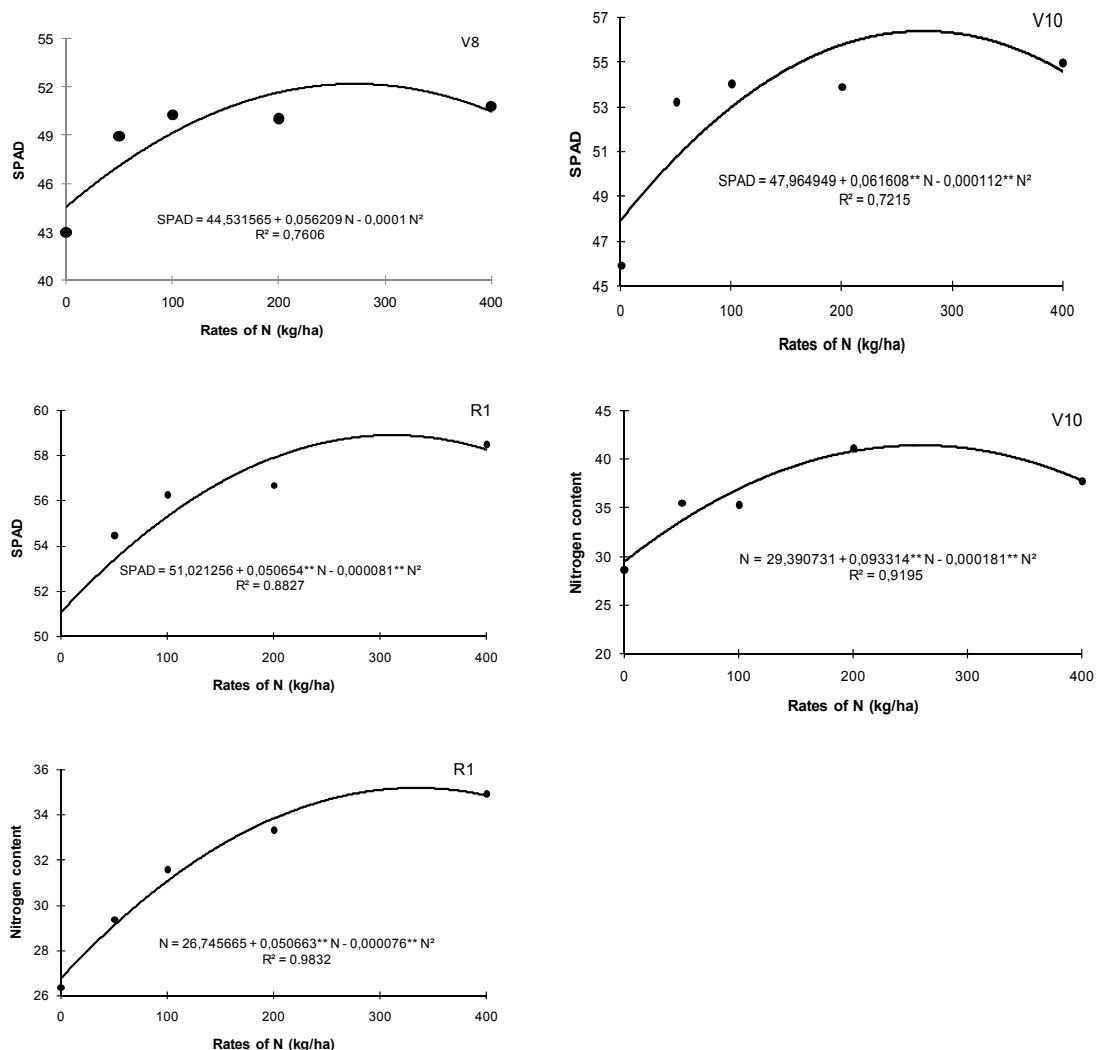


Fig. 4. Effect of nitrogen fertilization on SPAD index and leaf nitrogen content in maize at the V8, V10 and R1 phenological stages.

G/(R+G+B), R/(R+G+B), (R-B), (G-B)/(R+G+B) and (R+B) of the digital image are effective for assessing the nutritional status of maize plants at the V8, V10 and R1 stages, besides having the potential to estimate nitrogen status in other crops.

Smartphone-based image analysis is a technology that facilitates rapid, non-invasive, non-destructive, and low-cost nitrogen estimation in maize, directly in the field, promoting smarter and more sustainable agriculture. Converting this research into a mobile application could significantly increase accessibility and usability for stakeholders, thereby supporting the practical implementation of the findings and recommendations of the present study.

ACKNOWLEDGMENTS

The authors thank the Federal Institute of Rondônia, Colorado do Oeste Campus, the Office of Research, Innovation and Graduate Studies and the National Council for Scientific and Technological Development (CNPq) for providing infrastructure, resources and awarding a scientific initiation scholarship to the first author through Notice 10/2021/PROPESP. The research was conducted at the Federal Institute of Rondônia, Colorado do Oeste, Brazil.

Declaration of conflict of interest

The authors declare no conflict of interest.

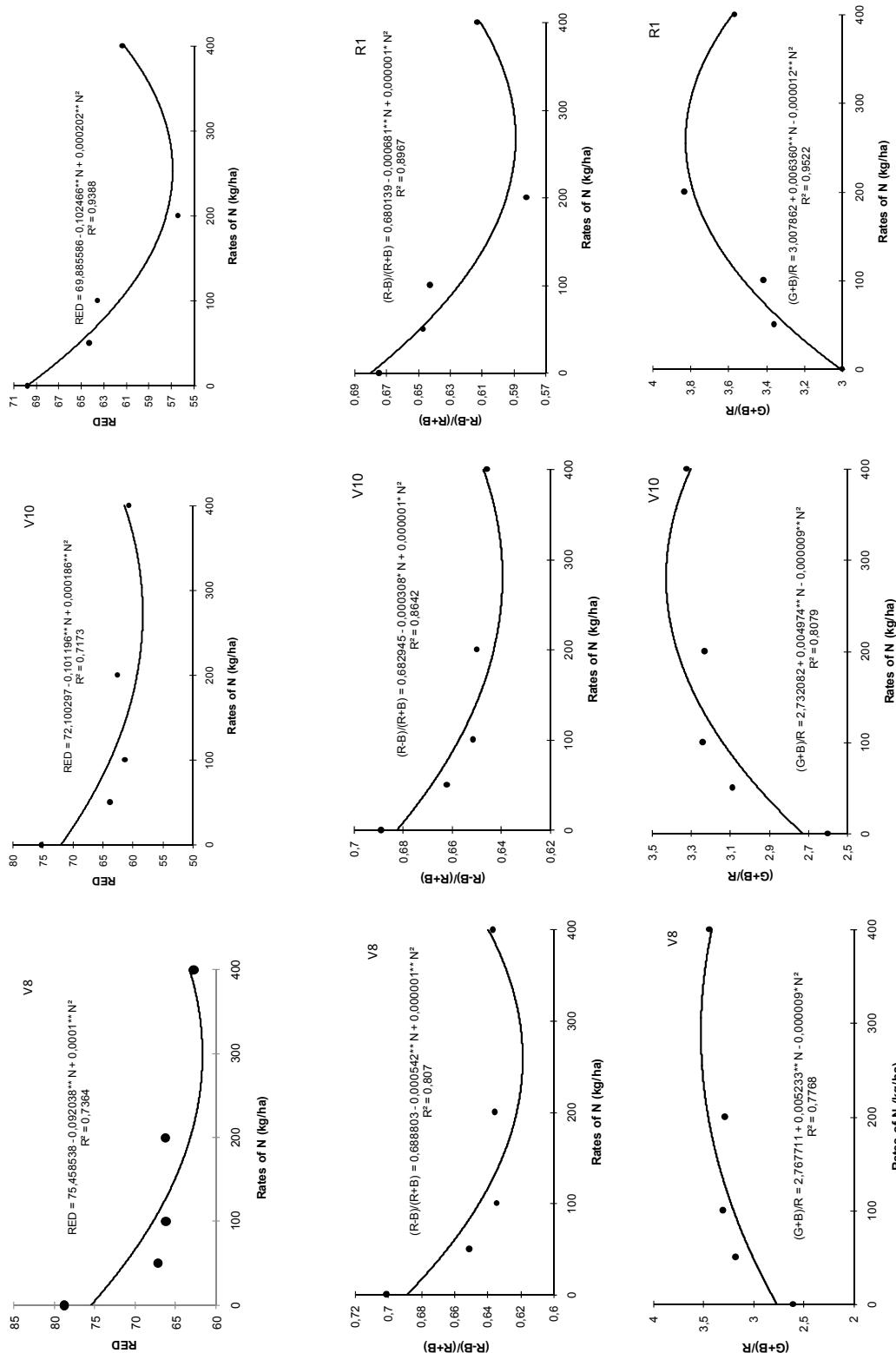


Fig. 5. Spectral parameters R, $(R-B)/(R+B)$ and $(G+B)/(R)$ in leaves of maize at the V8, V10 and R1 stages in response to topdressing nitrogen rates.

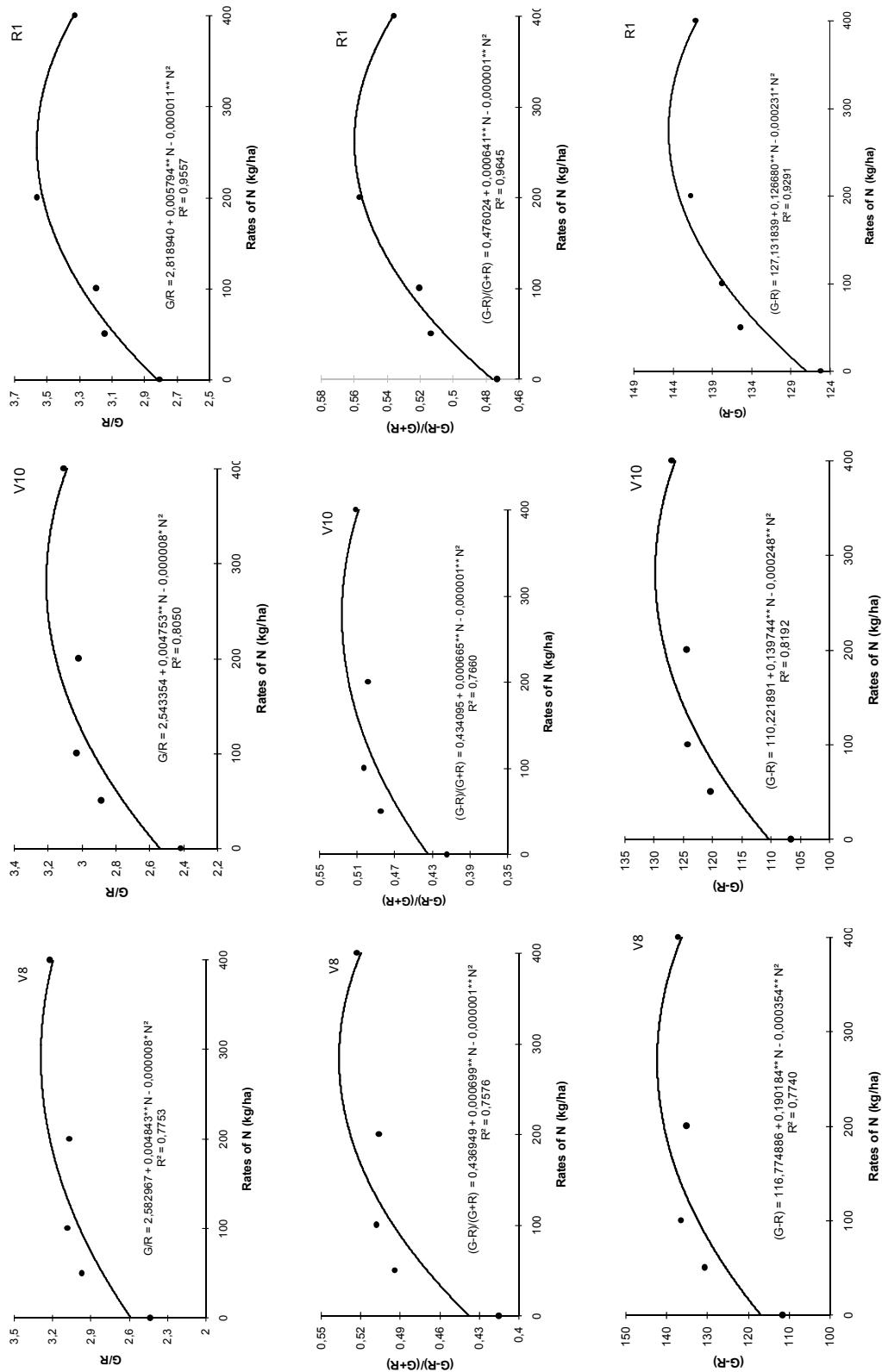


Fig. 6. Spectral parameters G/R, (G-R)/(G+R), (G+R) in leaves of maize at the V8, V10 and R1 stages in response to topdressing nitrogen rates.

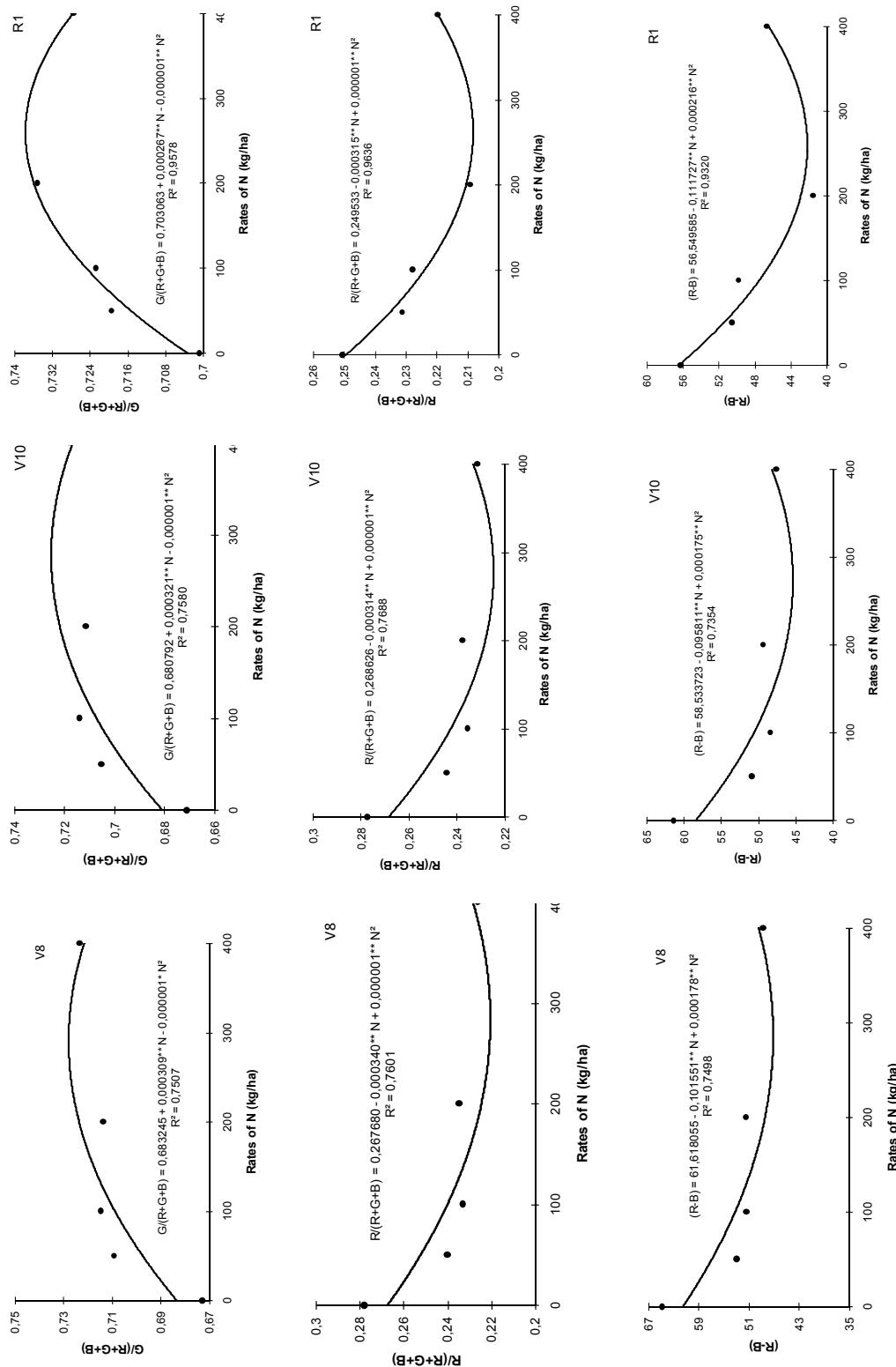


Fig. 7. Spectral parameters $G/(R+G+B)$, $R/(R+G+B)$ and $(R-B)$ in leaves of maize at the V8, V10 and R1 stages in response to topdressing nitrogen rates.

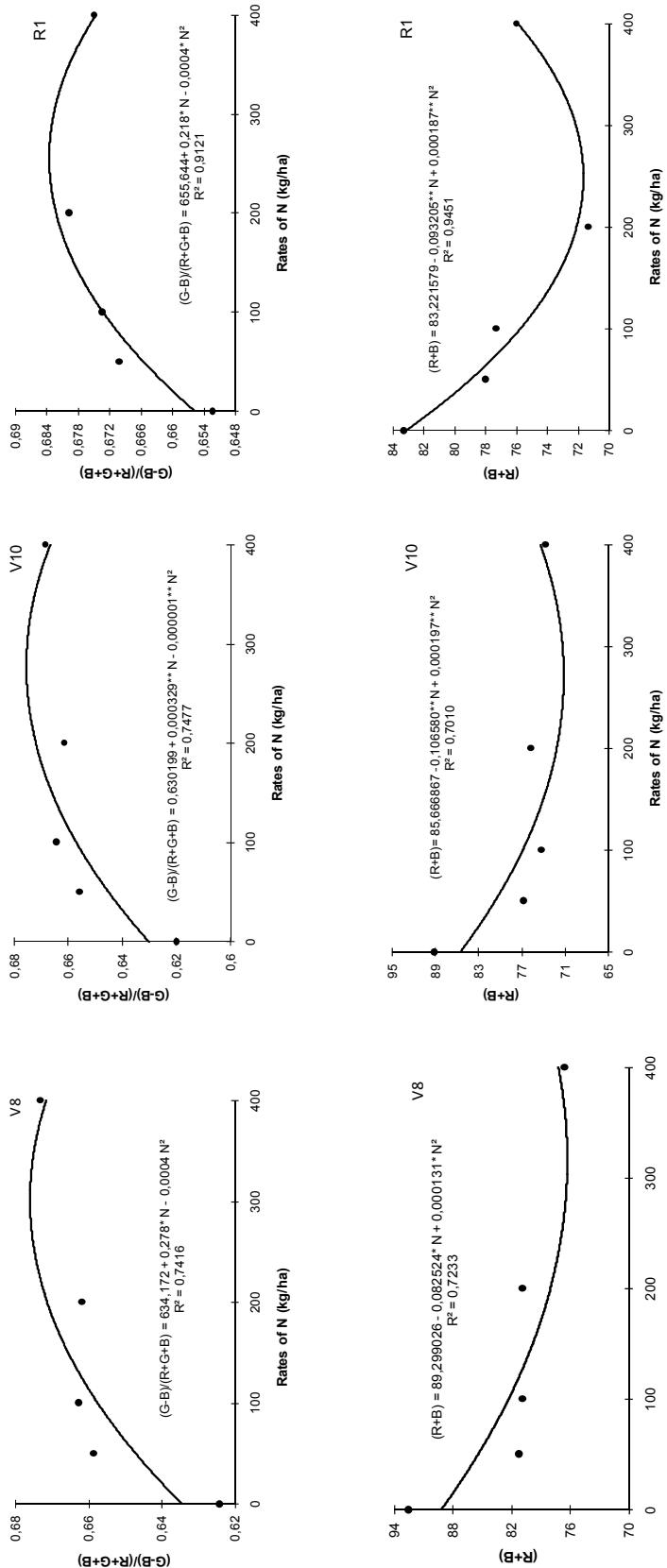


Fig. 8. Spectral parameters $(G-B)/(R+G+B)$ and $(R+B)$ in leaves of maize at the V8, V10 and R1 stages in response to topdressing nitrogen rates.

Author contributions

Katyany Oliveira Mota and Murilo Vargas da Silveira: Active participation in research conceptualization and methodology development; Érica de Oliveira Araújo: Writing and review of the final version of the article; Ranieli dos Anjos de Souza: Active participation in the discussion of the results; Iandra Rosa Domiciano and Gabriel Monteiro Paulino: Active participation in field supervision and bibliographic review.

LITERATURE CITED

Argenta, G., P.R.F. Silva, and L. Sangoi. 2004. Leaf relative chlorophyll content as an indicator parameter to predict nitrogen fertilization in maize. *Rural Science* 34:1379-1387. <https://doi.org/10.1590/S0103-84782004000500009>

Argenta, G., P.R.F. Silva, J. Mielińczuk, and C.G. Bortolini. 2002. Plant parameters as indicators of nitrogen status in maize crop. *Brazilian Agriculture Research* 37:519-527. <https://doi.org/10.1590/S0100-204X2002000400014>

Argenta, G., P.R.F. Silva, and C.G. Bortolini. 2001. Leaf chlorophyll as an index of nitrogen status in cereals. *Rural Science* 31:715-722. <https://doi.org/10.1590/S0103-84782001000400027>

Barman, U., and R.D. Choudhury. 2022. Smartphone image based digital chlorophyll meter to estimate the value of citrus leaves chlorophyll using Linear Regression, LMBP-ANN and SCGBP-ANN. *Journal Computer and Information Science* 34:2938-2950. <https://doi.org/10.1016/j.jksuci.2020.01.005>

Banzato, D.A. and Kronka, S.N. 2006. Agricultural experimentation. 4. ed. Jaboticabal.

Beck, H.E., N.E. Zimmerman, T.R. McVicar, N. Vergopolan, A. Berg, and E.F. Wood. 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data* 5: 180214. <http://dx.doi.org/10.1038/sdata.2018.214>

Bestas, Z., M.E. Harold, W.D. Philpot, K. Cavender-Bares, and D.G. Rossiter. 2025. High-resolution sensing of maize nitrogen status through under-canopy RGB imaging using a mobile platform. *Precision Agriculture* 26:71. <https://doi.org/10.1007/s11119-025-10262-0>

Chen, B., G. Huang, X. Lu, S. Gu, W. We, W. Wang, W. Chang, X. Guo, and C. Zhao. 2024. Prediction of vertical distribution of SPAD values within maize canopy based on unmanned aerial vehicles multispectral imagery. *Frontiers Plant Science* 18(14):1253536. <https://doi.org/10.3389/fpls.2023.1253536>

Devechio, F.F.S., P.H.C. Luz, L.M. Romualdo, M.M. Baesso, T.L. Silva, and V.R. Herling. 2023. Use of image analysis to detect nutrient deficiencies in maize cultivated in the field subjected to omission of nitrogen. *Brazilian Journal of Animal and Environmental Research* 6: 177-188. <https://doi.org/10.34188/bjaerv6n1-016>

Elazab, A., R.A. Ordóñez, R. Savin, G.A. Slafer, and J.L. Araus. 2016. Detecting interactive effects of N fertilization and heat stress on maize productivity by remote sensing techniques. *European Journal of Agronomy* 73:11-24. <https://doi.org/10.1016/j.eja.2015.11.010>

Ferreira, D.F. 2019. Sisvar: a computer analysis system to fixed effects split plot type designs. *Brazilian Journal of Biometric* 37: 529-535. <https://doi.org/10.28951/rbb.v37i4.450>

Ferreira, L.L., B.R. Souza, A.I.A. Pereira, C.R.S. Curvelo, C.S. Fernandes, N.S. Dias, and E.K.A. Nascimento. 2018. Biostimulant and gradual release nitrogen in the performance of sorghum. *Nativa* 7:330-335. <https://doi.org/10.31413/nativa.v7i4.6656>

FieldClimate: manual. [S.l.]: Pessl Instruments, 2022. Available at: <https://metos.global/pt/fieldclimate-manual/>. Accessed on: 22 dec 2022.

Fontes, P.D. 2016. Mineral nutrition of plants: anamnesis and diagnosis. Viçosa, Brazil.

Formaggio, A.R., and I.D.A. Sanches. 2017. Remote sensing in agriculture. São Paulo: Text Workshop, Brazil.

Francischini, R., A.G. Silva, and D.J. Tessmann. 2018. Effectiveness of biostimulants and fungicide on agronomic and economic traits in the green corn crop. *Brazilian Journal of Corn and Sorghum* 17:274-286.

Frazao, J.J., A.R.D. Silva, V.L.D. Silva, V.A. Oliveira, and R.S. Correa. 2014. Increased efficiency nitrogen fertilizers and urea in corn cultivation. *Brazilian Journal of Agriculture and Environment* 18: 1262-1267. <http://dx.doi.org/10.1590/1807-1929/agriambi.v18n12p1262-1267>

Gabriel, J.L., P.J. Zarco-Tejada, P.J. López-Herrera, E. Pérez-Martín, M. Alonso-Ayuso, and M. Quemada. 2017. Airborne and ground level sensors for monitoring nitrogen status in a maize crop. *Biosystems Engineering* 160:124-133. <https://doi.org/10.1016/j.biosystemseng.2017.06.003>

Gonzaga, B.A., C.L.L. Andrade, and F.R. Cabral Filho. 2022. Corn seed treatment with biostimulant. *Brazilian Journal of Science* 2: 46-53. <https://doi.org/10.14295/bjs.v2i3.248>

Jia, B., H. He, F. Ma, M. Diao, G. Jiang, Z. Zheng, J. Cui, and H. Fan. 2014. Use of a digital camera to monitor the growth and nitrogen status of cotton. *Science World Journal* 6:602-647. <https://doi.org/10.1155/2014/602647>

Lassalle, G. 2021. Monitoring natural and anthropogenic plant stressors by hyperspectral remote sensing: recommendations and guidelines based on a meta-review. *Science of the Total Environment* 788:147758. <https://doi.org/10.1016/j.scitotenv.2021.147758>

Li, D., C. Li, Y. Yao, M. Li, and L. Liu. 2020. Modern imaging techniques in plant nutrition analysis: A review. *Computers and Electronics in Agriculture* 174:105459. <https://doi.org/10.1016/j.compag.2020.105459>

Liu, W., G. Liu, Y. Yang, X. Guo, B. Ming, R. Xie, Y. Liu, K. Wang, P. Hou, and S. Li. 2021. Spatial variation of maize height morphological traits for the same cultivars at a large agroecological scale. *European Journal of Agronomy* 130:e126349. <https://doi.org/10.1016/J.EJA.2021.126349>

Malavolta, E., C.G. Vitti, and A.S. Oliveira. 1997. Assessment of the nutritional status of plants: principles and applications. Piracicaba: Potafos.

National Supply Company (CONAB). 2024. Monitoring of the Brazilian Grain Harvest 2023/2024: Eleventh Survey, Brazil, 134p.

Rigon, J., S. Capuani, D. Fernandes, and T. Guimarães. 2016. A novel method for the estimation of soybean chlorophyll content using a smartphone and image analysis. *Photosynthetica* 54:559-566. <https://doi.org/10.1007/s11099-016-0214-x>

Ritchie, S.W., and J.J. Hanway. 1993. How a cornplantdevelops? Ames: Iowa State University of Science and Technology.

Rocha, R.N.C., J.C.C. Galvão, P.C. Teixeira, G.V. Miranda, E.L. Agnes, P.R.G. Pereira, and U.T. Leite. 2005. Relation ship of the SPAD index determined by the chlorophyll meter with nitrogen content in the leaf and grain yield in three maize genotypes. *Brazilian Journal of Corn and Sorghum* 4:161-171.

Romuldo, L.M., P.H.C. Luz, F.F.C. Devechio, M.A. Marin, A.M.G. Zúniga, O.M. Bruno, and V.R. Herling. 2014. Use of artificial vision techniques for diagnostic of nitrogen nutritional status in maize plants. *Computers and Eletronics in Agriculture* 104:63-70. <https://doi.org/10.1016/j.compag.2014.03.009>

Santos, H.G.D., P.K.T. Jacomine, L.H.C. Anjos, J.F. Lumbreiras, M.R. Coelho, J.A. Almeida, J.C. Araújo Filho, J.B. Oliveira, and T.J.F. Cunha. 2018. Brazilian Soil Classification System. 5. ed. Brasília.

Sainju, U.M. 2017. Determination of nitrogen balance in agroecosystems. *MethodsX* 4:199-208.

Souza-Neta, M.A., A.C.P. Menezes-Filho, H.R.F. Batista-Ventura, C.L.L. Andrade, M.V.A. Ventura. 2022. Stimulation of germination and initial development of corn cultivar AS1820 with biostimulant Stimullum. *Brazilian Journal of Science* 11:100-107. <https://doi.org/10.14295/bjs.v1i1.220>

Shi, P.H., Y. Wang, J. Xu, Y. Zhao, B. Yang, Z. Yuan, and Q. Sun. 2021. Rice nitrogen nutrition estimation with RGB images and machine learning methods. *Computers and Electronics in Agriculture* 180:105860. <https://doi.org/10.1016/j.compag.2020.105860>

Shivashankar, K., M.P. Potdar, S. Gawdiya, A. Golshetti, A.K. Kanade, B. Balol, D.P. Biradar, K.K. Math, N. Al-Ansari, S. El-Hendawy, M.A. Mattar, and A. Salem. 2025. SPAD dynamics in maize crop with precision nitrogen management under rain-fed and irrigated conditions. *Scientific Reports*. 15(1):22842. <https://doi.org/10.1038/s41598-025-05255-y>

Tejada, M., B. Rodríguez-Morgado, P. Peneque, and J. Parrado. 2018. Effects of foliar fertilization of a biostimulant obtained from chicken feathers on maize yield. *European Journal of Agronomy* 96:54-59. <https://doi.org/10.1016/j.eja.2018.03.003>

Tremblay, N., Z. Wang, and C. Belec. 2009. Performance of Dualex in spring wheat for crop nitrogen status assessment, yield prediction and estimation of soil nitrate content. *Journal of Plant Nutrition* 33: 57-70. <https://doi.org/10.1080/01904160903391081>

United States Department of Agriculture (USDA). 2024. Grain and Feed Update: Brazil.

Vergutz, L., R.F. Novais, and R.V. Valadares. 2017. Recomendation of corrective agents and fertilizers. In: Borém A, JCC Galvão, MA Pimentel (ed.) Corn: from planting to harvestig. 2 ed. Viçosa, Brazil, 150p.

Xin, Q.I., Y. Wang, Y. Huang, Y. Ye, Y. Guo, and Y. Zhao. 2024. Nitrogen Nutrition Diagnosis Method Based on Mobile Phone Image of Summer Maize Canopy. *Scientia Agricultura Sinica* 57: 4094-4106. <https://doi.org/10.3864/j.issn.0578-1752.2024.20.014>

Wu, L., X. Chen, Z. Cui, W. Zhang, and F. Zhang. 2014. Establishing a Regional Nitrogen Management Approach to Mitigate Greenhouse Gas Emission Intensity from Intensive Smallholder Maize Production. *Plos One* 9:1-11. <https://doi.org/10.1371/journal.pone.0098481>

Zhang, J., H. Sun, D. Gao, L. Qiao, N. Liu, M. Li, and Y. Zhang. 2020. Detection of canopy chlorophyll content of corn based on continuous wavelet transform analysis. *Remote Sensing* 12: 21-20. <https://doi.org/10.3390/rs12172741>

