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SOIL SCIENCE

Evaluation of the nutritional status of corn by vegetation indices via aerial images

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ABSTRACT: *The objective of this study is to determine the vegetation indices (IV) as a means of identifying the nutritional status of corn, with respect to the soil nitrogen and potassium, using the aerial images received through an RGB camera loaded on an unmanned aerial vehicle. The images were obtained for an experiment of the nitrogen levels (0, 60, 120 and 180 kg ha^{-1}) and potassium levels (0, 50, 100 and 150 kg ha^{-1}), in the random block design, with a factorial scheme of 4 x 4, having three repetitions. Ten leaves were plucked per plot during the flowering phase to assess the total N (NF) and K^+ leaf contents. The Pearson's correlation analysis, as well as the analyses of variance and regression between the IV and the concentrations of N and K_2O. NF, K^+ and the grain yield, responded only to the soil N levels. A significant correlation was observed for the indices of Red Index, Normalized Difference Index and Visible Atmospherically Resistant Index with the NF, which endorses them as favorable in identifying the nutritional standing of corn, with respect to the N level. Not even a single one of the indices evaluated could detect the nutritional ranking of corn in the context of the potassium level.*
Key words: *Zea mays L, RGB images, remote sensing, precision agriculture.*

Avaliação do estado nutricional do milho por índices de vegetação de imagens aéreas

RESUMO: *O estudo teve como objetivo avaliar índices de vegetação (IV) para detecção do status nutricional do milho com relação ao nitrogênio e potássio por meio de imagens aéreas obtidas por câmera RGB embarcada em veículo aéreo não tripulado. As imagens foram adquiridas em ensaio de níveis de nitrogênio (0, 60, 120 e 180 kg ha^{-1}) e potássio (0, 50, 100 e 150 kg ha^{-1}), em blocos ao acaso, fatorial 4 x 4, com três repetições. Coletaram-se dez folhas por parcela na fase de florescimento para avaliação do teor foliar de N total (NF) e K^+. Efetuou-se análise de correlação de Pearson, análise de variância e de regressão entre os IV e os níveis de N e de K_2O. NF, K^+ e a produtividade de grãos responderam apenas aos níveis de N no solo. Houve correlação significativa para os índices Excess Red Index, Normalized Difference Index e Visible Atmospherically Resistant Index com o NF, que os credencia como promissores na detecção do status nutricional do milho em relação ao N. Nenhum dos índices avaliados foi capaz de detectar o status nutricional do milho com relação ao potássio.*
Palavras-chave: *Zea mays L, imagens RGB, sensoriamento remoto, agricultura de precisão.*

INTRODUCTION

For corn to express its productive potential there is a high nutritional demand where nitrogen is the nutrient needed in large amounts. Nitrogen exerts the greatest influence on grain production in corn and is the major factor that contributes to the expenditure involved in its production (MELO et al., 2011).

The next most important element absorbed in high quantities by the corn crop is potassium (BASTOS et al., 2005). Adding potassium during the commercial production of the corn crop is gaining significance due to the high yield of the corn cultivars in response to the application of a combination of potassium and nitrogen (PETTER et al., 2016).

From the findings of several studies, the positive and crucial effect of applying nitrogen and potassium on corn grain production is clearly evident (BASTOS et al., 2005; MELO et al., 2011; PETTER et al., 2016). However, the paucity of studies continues to hinder an accurate evaluation of the nutritional status of the commercial corn crops, in terms of the rational and efficient addition of these nutrients, based on the plant requirement and levels of soil fertility in the regions of production.

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Proximal remote sensing is an excellent and viable tool which enables the nutritional status of agricultural crops to be assessed (LI et al., 2014; CILIA et al., 2014). The proximal detection method is effective in providing possible automation and mechanization applications, like aerial images of the crops, employing unmanned aerial vehicles (UAVs). This enables a substantial reduction in the field operation-related costs. The use of UAVs provides results in terms of the spatial resolution of the images, flexible revisiting time, as well as gives high versatility even when the climatic conditions are unfavorable (TORRES-SANCHEZ et al., 2015)

Using the spectral reflectance of the canopy, the vegetation indices (IV) are simple and successful algorithms, helpful in the quantitative and qualitative evaluation of the vegetation cover, as well as plant vigor and growth dynamics (GITELSON et al., 2002). The remote sensing of the vegetation, principally connected with acquiring multispectral images, can be practically applied. Hence, many IVs have been suggested using multispectral images for remotely estimating the nutritional status of different agricultural crops, particularly from the perspective of the soil nitrogen availability (ISLA et al., 2011; LI et al., 2014; CILIA et al., 2014; VERGARA-DÍAZ et al., 2016). However, studies are still in the nascent stages in determining the nutritional status of potassium (SRIDEVY et al., 2018), and the use of RGB (red-green-blue) images received from the less-expensive cameras (RASMUSSEN et al., 2016).

Thus, this research was performed to remotely assess the nutritional status of the corn crop, with regard to the soil nitrogen and potassium, using the vegetation indices received from the aerial images acquired from an RGB camera, loaded on an unmanned aerial vehicle (UAV).

MATERIALS AND METHODS

The current study was done in a plot in Fazenda Weisul Agrícola, in Magalhães de Almeida, MA, with the coordinates of 3° 22’9.27’’ S and 42° 17’ 28.8’’ W at 85 m altitude. The local climatic conditions are hot, and sub-humid, with moderate water surplus in summer (Aw), annual average temperature of 26 ºC, and annual precipitation of 1,250 mm, particularly between February and May (CORREIA FILHO et al., 2011). During the experimental period, in the area under study, the total precipitation was 1,010 mm, recorded using a rain gauge.

In the experimental area the soil is of the Latossolo Amarelo Distrocoeso type and of medium texture (SANTOS et al., 2018). When the chemical and physical characterization of the soil was done initially, in the 0.0 - 0.2 m layer, the following attributes were recorded: pH in H_2O of 5.9; pH in $CaCl_2$ of 5.0; 17.2 mmolc dm^{-3} of potential acidity (H^+ Al); 0.65 mmolc dm^{-3} exchangeable aluminum content; 2.0 mmolc potassium dm^{-3} (K^+); 11.9 mmolc dm^{-3} of calcium (Ca^+_2), 4.1 mmolc dm^{-3} of magnesium (Mg^+_2); 11.6 g kg^{-1} of carbon (C); 18.8 mg dm^{-3} of phosphorus (P) (Mehlich); 35 mmolc dm^{-3} of cation exchange capacity (CTC); 50.5% base saturation (V%); 831.9 g kg^{-1} of the sand fraction; 46.9 g kg^{-1} of the silt fraction; 121.2 g kg^{-1} of the clay fraction and 1.65 g cm^{-3} of soil density. The analyses done adopted the recommendations of the Embrapa Manual of the analysis of soil, plants and fertilizers (SILVA, 2009).

In the experiment performed regarding the nitrogen (N) and potassium (K_2O) levels in corn, aerial images were acquired (Figure 1). The experiment was conducted from February to June 2019, in a rainfed regime, adopting a randomized block design with treatments done in a 4 x 4 factorial scheme (N levels versus K_2O levels), including three replications (T1: 0 N –0 K2O; T2: 0 N - 50 K_2O; T3: 0 N - 100 K_2O; T4: 0 N - 150 K_2O; T5: 60 N - 0 K_2O; T6: 60 N - 50 K_2O; T7: 60 N - 100 K_2O; T8: 60 N - 150 K_2O; T9: 120 N - 0 K_2O; T10: 120 N - 50 K_2O; T11: 120 N - 100 K_2O; T12: 120 N - 150 K_2O; T13: 180 N - 0 K_2O; T14: 180 N - 50 K_2O; T15: 180 N - 100 K_2O and T16: 180 N - 150 K_2O). The experimental plot, extending across an area of 16.0 m^2, included four rows of plants, each row of 8 m length, and the two central lines used for the evaluations (8.0 m^2 of useful area). The spacing between the plant rows was 0.5 m, and plant density was 5 per meter. The corn variety used was the hybrid commercial corn Pioneer 30F35VYHR, sown on 02/13/2019.

First, sowing was performed in parallel furrows at 0.15 m depth and with 0.10 m distance between the sowing lines, manually applying phosphorus and zinc as fertilizers, using 80 kg ha^{-1} of P_2O_5 and 3 kg ha^{-1} of Zn, in the forms of triple superphosphate (TSP) and zinc sulfate, respectively. Fertilization with nitrogen and potassium was accomplished by applying half the quantity of N and K_2O prescribed for each treatment , at the time of sowing, and the remainder was added in cover, performed via haul, at a distance of 0.10 m from the planting line, using moist soil. This was performed during the late afternoon, at the time of the opening of the 6th leaf. Urea and potassium chloride were employed, respectively, as the N and K_2O sources.

During the flowering time, ten corn leaves were collected at random per plot to assess the total

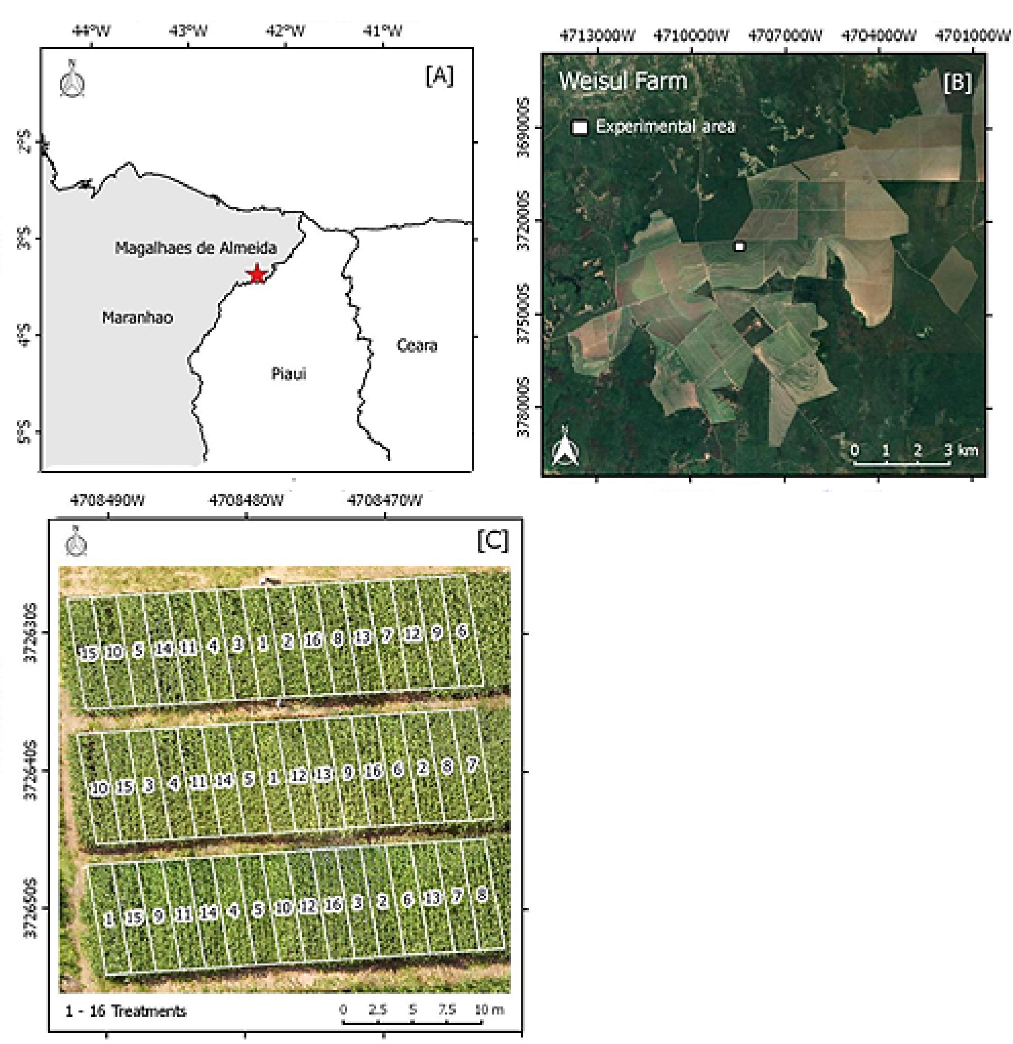

Figure 1 - Location of the experimental area. A: Magalhães de Almeida, MA, Brazil; B: Weisul Farm and C: Aerial image of the experimental area with the disposition of the evaluated treatments.

nitrogen and potassium contents of the leaf, using the central third of the base leaf of the corn ear, during the planting stage (50% of the plants in the plot were showing the tassel). The morning (between 8 - 11 am) was the best time to collect the leaves on the same day as the flight. To evaluate the N and K^+ content present in the leaves, the semi-micro Kjeldahl method (SILVA, 2009) was followed. On 06/26/2019 the corn was manually harvested, and the dry grain yield was determined at 13% humidity.

To receive the aerial images, a quad-type UAV, DJI brand, model Phantom 3 Professional, was used, which was provided with a DJI sensor model FC300X, (DJI, Nanshan District, Shenzhen, China). This operates in the visible region (red: 660-670 nm, green: 550-560 nm, blue: 470-480 nm), with f / 2.8 aperture, 3.6 mm focal length, and 4000 x 3000 pixels resolution. The following configuration was used at the time of the flight: ISO 100, opening speed 1/800 s and white balance of zero. On the day the leaves were collected between 11:00 am and 12:00 am and analyzed for N and K^+ analysis (04/09/2019), the aircraft was at altitude of 30 m and at speed of 2.5 m/s, with camera angle at 90°. The planning and operation of the flight was done in Pix4D-Capture® software (www.pix4d.com). The configuration of the camera settings was done using the DJI GO® software (www.dji.com).

To ensure the high-quality creation of the orthomosaic, 80% lateral and frontal overlap was employed during the flight, providing 30 aerial photographs in total, to encompass the whole experimental region, with 1.5 cm pixel GSD (ground sample distance). Processing of the orthomosaic of the aerial images was done using the WEB-OpenDroneMap® software (www.opendronemap.org) beta version 0.3.1. The standard configuration of the software enabled a high spatial orthomosaic resolution (2.5 cm / pixel) to be generated.

The orthomosaic was classified under the supervision of the Gaussian Mixture Model method suggested by LAGRANGE et al. (2017). The plugin enabled the mosaic to be to be rasterized into two classes (soil and leaves). This facilitated the pixels classified as soil to be removed from the mosaic, confirming that the estimation of the vegetation index was done using only the pixels classified as leaves. This was accomplished using the QGIS v "dzetsaka" plugin. 2.18 (QGIS, 2016).

Evaluation was done of 18 vegetation indices (IV) (Table 1) estimated from the

Table 1 - RGB vegetation indices evaluated in the study.

Indices	Sigla	Equation	References
Coloration Index	CI	$= \frac{r-b}{r}$	MANDAL (2016)
Color Index of Vegetation Extraction	CIVE	= 18.78745 + (0.44 r) – (0.88 g) + (0.385 b)	YANG et al. (2015)
Carotenoid Reflectance Index 1	CRI-1	$= \left(\frac{1}{b}\right) - \left(\frac{1}{g}\right)$	GITELSON et al. (2002)
Carotenoid Reflectance Index 2	CRI-2	$= \left(\frac{1}{b}\right) - \left(\frac{1}{r}\right)$	GITELSON et al. (2002)
Excess Green Index	EXG	$= (2g) - r - b$	YANG et al. (2015)
Excess Red Index	EXR	$= (1{,}4r) - g$	BENDIG et al. (2015)
Excess Green Minus Red Index	EXGR	$= EXG - EXR$	GITELSON et al. (2002)
Green Leaf Index	GLI	$= \frac{(2g - r - b)}{(2g + r + b)}$	GITELSON et al. (2002)
Modified Green Red Vegetation Index	MGRVI	$= \frac{(g^2 - r^2)}{(g^2 + r^2)}$	BENDIG et al. (2015)
Modified Photochemical Reflectance Index	MPRI	$= \frac{(g - r)}{(g + r)}$	BARBOSA et al. (2019)
Normalized Difference Index	NDI	$= 128\left[\frac{(g - r)}{(g + r)} + 1\right]$	MEYER & CAMARGO NETO (2008)
Normalized Green-Blue Difference Index	NGBDI	$= \frac{(g - b)}{(g + b)}$	BENDIG et al. (2015)
Red Green Blue Vegetation Index	RGBVI	$= \frac{(g^2 - rb)}{(g^2 + rb)}$	BENDIG et al. (2015)
Red Green Index	RGI	$= \frac{r}{g}$	BENDIG et al. (2015)
Triangular Greenness Index	TGI	= 0,5 [(r-b) – (r-g)]– [(r-g) – (r-b)]	BENDIG et al. (2015)
Visible Atmospherically Resistant Index	VARI	$= \frac{(g - r)}{(g + r - b)}$	GITELSON et al. (2002)
Vegetative Index	VEG	$= \frac{g}{(r^{0,667} b^{0,333})}$	HAGUE et al. (2006)
Woebbecke Index	WI	$= \frac{(g - b)}{(r - g)}$	WOEBBECKE et al. (1995)

r, g e b: normalized RGB bands (equations 1 to 3).

orthomosaic RGB bands, employing the QGIS raster calculator (QGIS, 2016). First, the extraction of the RGB bands was done from the orthomosaic and normalized between 0 and 1 (equations 1 to 3) (MARCIAL-PABLO et al., 2019).

$$r = \frac{\left(\frac{R}{Rmax}\right)}{\left(\frac{R}{Rmax}\right)+\left(\frac{G}{Gmax}\right)+\left(\frac{B}{Bmax}\right)} \tag{1}$$

$$g = \frac{\left(\frac{G}{Gmax}\right)}{\left(\frac{R}{Rmax}\right)+\left(\frac{G}{Gmax}\right)+\left(\frac{B}{Bmax}\right)} \tag{2}$$

$$b = \frac{\left(\frac{B}{Bmax}\right)}{\left(\frac{R}{Rmax}\right)+\left(\frac{G}{Gmax}\right)+\left(\frac{B}{Bmax}\right)} \tag{3}$$

Where r, g and b: normalized RGB bands; Rmax = Gmax = Bmax = 255 in 8-bit color images per band.

The values of the vegetation indices were extracted using the QGIS v 2.18 zonal statistical plugin (QGIS, 2016). For each plot, the zonal statistics plugin gives a series of statistical attributes including the maximum, minimum, average, and standard deviation values. To achieve this, a vector file which contained the useful area of the experimental plots was used. To create this vector file, the useful area of the experimental plot was distinguished into two parts, producing six polygons (subplots), each having an area of 4.0 m^2, which were utilized to statistically analyze the data. This step was done using the QGIS v 2.18 "divider polygon" (QGIS, 2016).

Pearson's correlation analysis was done of the mean values of the vegetation indices with the N and K_2O levels present in the soil, as well as the N and K^+ present in the leaves. The analyses of variance and regression were done to assess the response of the vegetation indices, N and K^+ concentration in the leaves and grain yield after the treatment was applied. The statistical analysis using the ExpDes.pt package from R (FERREIRA et al., 2014) was conducted. For those variables which revealed significant interaction between the N and K_2O levels, the response surfaces were produced together with the supplement of Excel Real Statistics Resource Pack (ZAIONTZ, 2020) and the Surfer® software. In figure 2A the flowchart shows the steps of the process.

First, the vegetation indices were adjusted to the polynomial regression models, and the degree to which this adjustment occurred was evaluated by the coefficient of determination (R^2), standard error of the regression (S) (equation 4), square root of the mean square error (RMSE) (equation 5) and the normalized percentage of RMSE (nRMSE) (equation 6). The S represents the average distance of the recorded values with respect to the regression line. The RMSE indicates the magnitude of the recorded values versus the values determined by the models, while the nRMSE refers to the normalized measure of the RMSE, which enabled a comparison of the performances of the different regression models (LI et al., 2014).

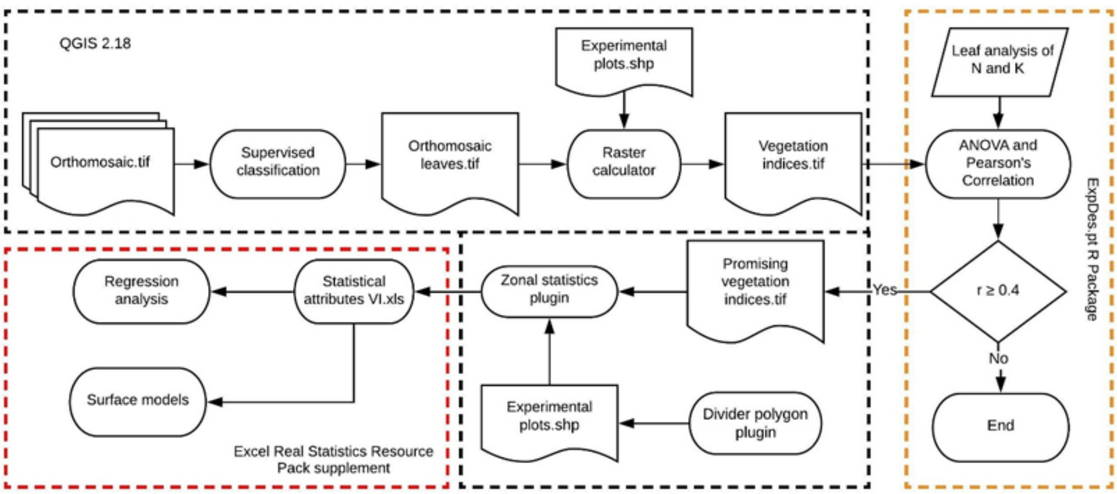

Figure 2 - Flowchart containing the image processing steps.

$$S = \sqrt{\frac{1}{(n-2)}\left[\sum(Yi - \bar{Y}i)^2 - \frac{[\sum(Xi-\bar{X}i)(Yi-\bar{Y}i)]^2}{\sum(Xi-\bar{X}i)^2}\right]} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Yi-Yi')^2}{n}} \quad (5)$$

$$nRMSE = \frac{RMSE}{(Ymax-Ymin)}100 \quad (6)$$

Where n represents the number of observations, Yi refers to the observed values of y, Yi' are the values assessed by the regression models, Xi includes the observed values of x, Ymax is the maximum observed y value, and Ymin is the minimum observed y value.

RESULTS AND DISCUSSION

The N and K levels in leaves and grain yield

From the analysis of variance, it was evident that the N content in the leaves (NF), the K^+ level in the leaves (KF) and grain yield (PGS) showed a response solely to the soil N levels ($P < 0.001$) (Table 2). The results from a few studies revealed that corn shows greater response when nitrogen is applied to the soil, than to when the potassium is added (CARDOSO et al., 2007; MELO et al., 2011). When 165.0 kg ha^{-1} of N was applied to the soil the maximum PGS (8,536.8 kg ha^{-1}) was obtained (Figure 3). In a study to assess the N levels (0, 50, 100, 150 and 200 kg ha^{-1}) and corn seeding densities (2.5; 5.0; 7.5 and 10.0 plants m^{-2}), using hybrid BR3060, CARDOSO et al., (2007) reported maximum grain yield of 8893.0 kg ha^{-1}, after applying 160.6 kg ha^{-1} of N related to a sowing density of 7.45 plants m^{-2}, a value which almost corresponds to the maximum value observed in the current work, with sowing density of 10 plants m^{-2}.

Other studies reported no response in the corn from the perspective of grain yield to the potassium applied to the soil. In fact, BASTOS et al. (2005) observed no productive response in corn, hybrid BRS-3123, in their assessment after five levels of N (0, 50, 100, 150 and 200 kg ha^{-1}) and five levels of K_2O (0, 30, 60, 90 and 120 kg ha^{-1}) were applied to the soil categorized as Oxisol Yellow-Alic, and sandy / medium in texture. In their work, MELO et al. (2011) found that potassium fertilization on maize gave positive effects which were confirmed in sandy soils, as well as in soils having a K^+ level below 2.3 mmolc dm^{-3}, up to a depth of 0-0.2 m. In such conditions, a dosage of up to 60 kg ha^{-1} of K_2O induced the best response. In the experimental area, the soil contains a K^+ level of 2.0 mmolc dm^{-3}, in the 0-0.2 m layer, almost within the limit of the potassium response.

Regarding the leaf N content, 28.6 g kg^{-1} was the maximum value recorded after 175.0 kg ha^{-1} of N was applied to the soil; the maximum KF content (29.5 g kg^{-1}) was reached after 122.3 kg ha^{-1} of N was added to the soil. In fact, some studies noted that with the rise in the soil N levels a quadratic increment was seen in the total nitrogen content of the leaves. Another study by MELO et al. (2011) reported maximum NF values in corn, (of the simple hybrid BRS 1001 variety), of 28.0 g kg^{-1}, after 175.0 kg ha^{-1} of N was applied in relation to 7.5 plants m^{-2}, concurring with the findings of the current study.

When examining the potassium in the leaves, it became evident that the quadratic response was induced only due by the soil N levels and not by the K_2O levels, as mentioned in the literature (PETTER et al., 2016). In fact, PETTER et al. (2016) in their study on dystrophic Yellow Latosol, having

Table 2 - Analysis of variance (MS) for the nitrogen content of the leaves (NL), potassium in the leaves (K^+) (KL) and grain yield (GY) as a function of the levels of N and K_2O in the soil.

SV	DF	-------------NL---------------		------------KL-------------		---------------GY-----------------	
Blocks	2	3.7950	*	37.420	*	1810519	*
Nitrogen (N)	3	15.4022	***	51.866	***	19439535	***
Potassium (K_2O)	3	0.7095	ns	15.726	ns	115619	ns
N versus K_2O	9	2.0585	ns	5.943	ns	651722	ns
Residue	30	0.9200		7.038		440954	
CV (%)		3.47		9.26		11.47	

SV: source of variation; N: nitrogen levels in the soil; K_2O: potassium levels in the soil; DF: degrees of freedom; CV (%): coefficient of variation (%); NF: N content in leaves; KF: K^+ content in the leaves; GY: grain yield at 13% humidity. Significance levels by the F test: ns $p > 0.1$; ° $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

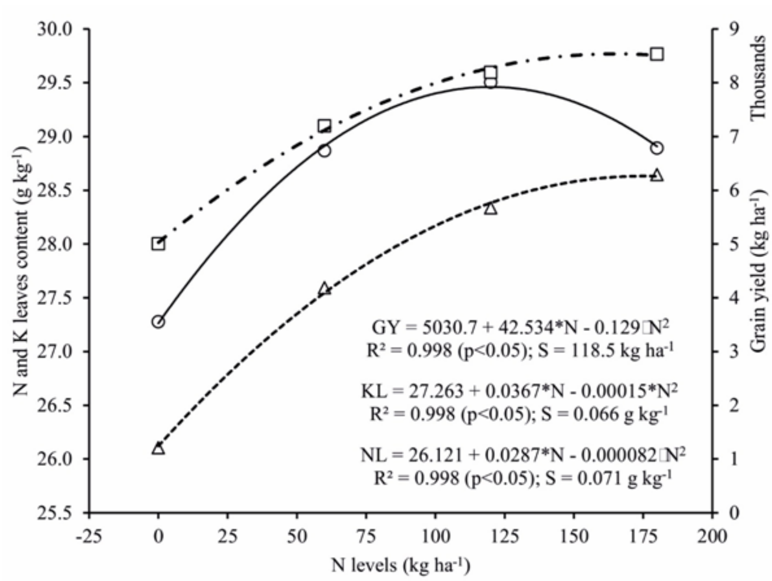

Figure 3 - Regression equations for leaf N content, grain yield and leaf K^+ content as a function of soil N levels. Magalhães de Almeida, MA, 2019.

a sandy-loam texture, noted a significant linear rise in the K^+ level in the corn leaves, in response to increasing the K_2O levels added to the soil. A maximum K_2O level of 120.0 kg ha^{-1} induced the leaves to accumulate 25.4 g kg^{-1} of K^+. However, this K^+ level rise in the leaves had no effect on the relative total chlorophyll content, revealing the absence of any direct correlation between the K^+ concentration in the leaves and chlorophyll synthesis. However, in the present study, this trend was not observed, likely because the soil K^+ concentration in the experimental area prevented the expression of the K_2O levels applied, as emphasized earlier.

Pearson correlation between the N, K^+ content in the leaves and vegetation indices

The correlation found between the N and K^+ leaf contents and the N and K_2O soil levels were $r = 0.684$ ($p < 0.001$) and $r = 0.284$ ($p < 0.05$), respectively, establishing the higher N response in terms of the yield performance of corn, as discussed prior (Table 2). Regarding the N concentration in the leaves, a significant correlation was seen for ten indices, particularly on the EXR ($r = -0.479$; $p < 0.001$), NDI ($r = 0.454$; $p < 0.001$) and VARI ($r = 0.412$; $p < 0.001$), which are shown to be the most promising in detecting the nutritional status of corn in relation to N (Figure 4A). The other indices also revealed a significant correlation; however, with the r values below 0.4, such as MGRVI, MPRI, GLI, RGI, EXG, CIVE and CI (Figure 4A). As for the K^+ content in the leaves, the RGI index alone showed significant correlation ($p < 0.05$). The $r = 0.222$ was regarded as low, according to the classification of HOPKINS (2000), which disqualifies it as a good indicator for the detection of the K^+ level in the maize leaves (Figure 4B).

These vegetation indices are understood to offer promise, even if the use of the RGB bands alone was sufficient to distinguish between the spectral responses of the corn canopy, depending upon the N doses added to the soil. Variations in detecting the spectral response of the corn canopy via vegetation indices with regards to the levels of soil fertility and N concentration in the leaves were also noted in the research performed by LI et al. (2014), CILIA et al. (2014) and VERGARA-DÍAZ et al. (2016).

In fact, VERGARA-DIAZ et al. (2016) derived different vegetation indices using the digital RGB images at the levels of the leaf and canopy and assessed as inexpensive tools in corn fertilization management. The effectiveness of the RGB indices was compared with that of the other indices that employ bands in the near infrared region, like the

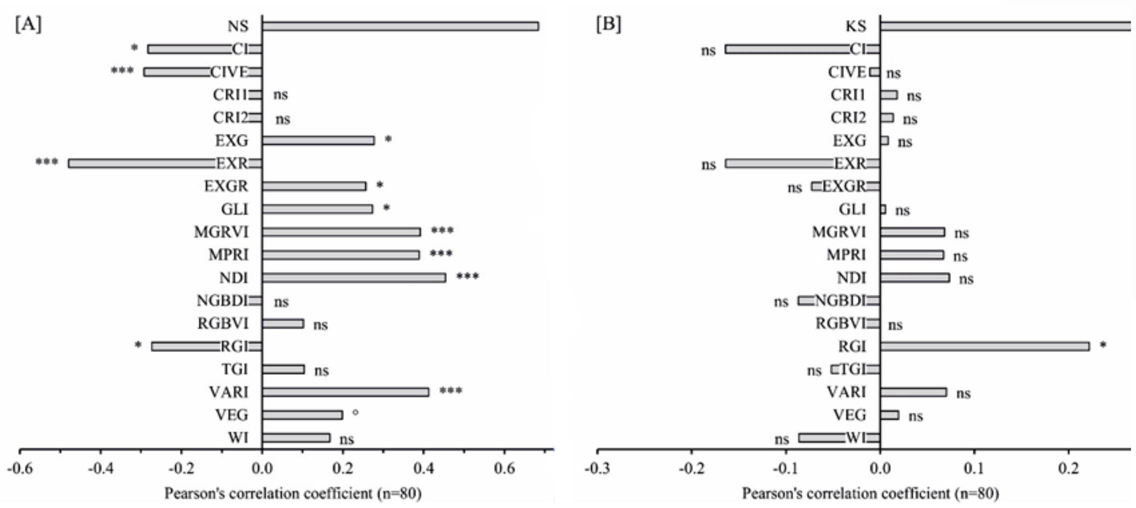

Figure 4 - Pearson's correlation between vegetation indices and the content of N and K^+ in the leaves in response to the levels of N and K_2O applied in the soil. A: N content in leaves; B: K^+ content in the leaves. Significance levels by the t test: ns $p > 0.1$; ° $p < 0.1$; * $p< 0.05$; ** $p< 0.01$; *** $p < 0.001$.

NDVI (Normalized Difference Vegetation Index), and the leaf chlorophyll concentration (LCC - Leaf Chlorophyll Content) during flowering. The conclusion drawn by the authors was that the grain productivity and N levels in the leaves at the evaluated levels of fertilization were emphatically anticipated by the majority of the RGB indices (with $R^2 \pm 0.7$), closely corresponding to the NDVI and LCC.

It was CILIA et al. (2014) who employed the vegetation indices of the hyperspectral remote sensing images to assess the techniques of mapping the nitrogen levels in the corn crop. Based on the Nitrogen Nutrition Index (NNI) the nitrogen status was determined, interpreted as the ratio between the N content of the leaves and the minimum N content necessary for the maximum dry biomass yield. The best performances were seen by the MCARI / MTVI2 index (Modified Chlorophyll Absorption Proportion Index / Modified Triangular Vegetation Index 2) in evaluating the N content in the leaves (R2 = 0.59) and MTVI2 in determining the dry biomass ($R^2 = 0.80$). The NNI map concurred with the estimated NNI using field data, employing the traditional destructive measurements ($R^2 = 0.70$), to confirm the potential of using the remotely detected indices in the assessment of the nutritional status of corn related to N levels.

In their study, ABRAHÃO et al. (2009) estimated the nutritional status of Tanzania grass at different levels of soil N (0, 80, 60 and 320 kg ha^{-1}) employing RGB vegetation indices. They determined that not only did the VARI index best discriminate the nitrogen added, at all the times of the evaluation being investigated, it also revealed the highest correlation with the readings of the chlorophyll and dry mass. Later, ISLA et al. (2011) indicated that the GNDVI and GRVI indices showed much promise as well, in the detection of the nutritional status of corn with respect to N, particularly during the developmental stages of V6-V8. It was GHOLIZADEH et al. (2011) who identified a high degree of correlation between the EXR index and N level in the rice leaves induced by the soil N levels (0, 85 and 170 kg ha^{-1}).

It was also noteworthy that the Pearson's correlation values of 0.3 to 0.6 were commonly identified in works done to assess the nutritional status of agricultural crops by the use of RGB vegetation indices (LI et al., 2014; CILIA et al., 2014; VERGARA-DÍAZ et al., 2016; RASMUSSEN et al., 2016).

Vegetation indices in response to soil N and K_2O levels

From the analysis of variance, the interaction between the N and K_2O showed significance for the vegetation indices EXR ($p < 0.05$) and NDI ($P < 0.05$), while the VARI ($p < 0.001$) responded to the N application alone (Table 3). It is significant that the EXR and NDI indices could detect the spectral

Table 3 - Analysis of variance (MS) for the vegetation indices in response to the levels of N and K_2O in the soil. Magalhães de Almeida, MA, 2019.

SV	DF	------------EXR-----------		--------------NDI-------------		--------------VARI--------------	
Blocks	2	0.00642	***	277.850	***	0.01515	***
Nitrogen (N)	3	0.00328	***	76.426	***	0.00332	***
Potassium (K_2O)	3	0.00004	ns	6.714	ns	0.00078	ns
N versus K_2O	9	0.00070	*	16.464	*	0.00068	ns
Residue	30	0.00024		5.409		0.00050	
CV (%)		12.03		1.72		23.20	

SV: source of variation; N: nitrogen levels in the soil; K_2O: potassium levels in the soil; DF: degrees of freedom; CV (%): coefficient of variation (%); EXR: Excess Green Index; NDI: Normalized Difference Index; VARI: Visible Atmospherically Resistant Index. Significance levels by the F test: ns p>0.1; ° p<0.1; * p<0.05; ** p<0.01; *** p<0.001.

response of the interaction between the soil N and K_2O concentrations; however, this interaction was absent with respect to the agronomic response to the N and K^+ levels in the leaves and grain productivity (Table 2).

For the EXR index, the response surface was adjusted to a 1st degree polynomial model ($y = a + bx + by + dxy$), with $R^2 = 0.656$, with significance at 5% by the F test, with the model coefficients showing significance at 0.1% (b) and 10% (c and d), by t test, and the standard error of estimate equal to 0.0104. The EXR values are lowered as the rise in the soil N and K_2O levels reach up to 100 kg ha^{-1} of N, following which the decrease in the EXR begins to take place by a drop in the soil K_2O levels. The NDI showed a similar trend which was also adjusted to the 1st degree polynomial model, just as it was adjusted for the EXR (Figures 5A and 5B). A nutritional evaluation work done by VERGARA-DIAZ et al. (2016) on corn in relation to N (0, 10, 20, 80 and 160 kg ha^{-1}) using RGB images, found that the indices showing promise in identifying the N showed sensitivity to the variations in the N content of leaves up to the 80 kg ha^{-1} level of N; however, none of them was significantly related to the 160 kg ha^{-1} level of N.

The highest EXR (0.146) value was seen with the combined lowest doses of N and K_2O (0 N - 0 K_2O); the lowest value (0.104) value was noted with 180 kg ha^{-1} level of N and 0 kg ha^{-1} level of K_2O. From the isoquants, the ranges of the EXR and NDI values associated with the different levels of N and K_2O present in the soil can be identified (Figures 5C and 5D), which facilitates the detection of the nutritional status of corn based on these indices. When the EXR value is 0.146 it means that the soil has both N and K_2O in low levels (0 to 20 kg ha^{-1}); however, when the EXR is 0.118 it suggests that the soil N levels (160 to 180 kg ha^{-1}) and K_2O levels (120 to 140 kg ha^{-1}) are high. With respect to the NDI, a value of 134.0 indicates that the soil has low N and K_2O levels (0 to 20 kg ha^{-1}). When the NDI value is 138.8 it implies that the soil has high N (160 to 180 kg ha^{-1}) and K_2O levels (120 to 140 kg ha^{-1}).

High levels of soil N and K_2O are indicated when the EXR value is 0.117 and the NDI is 138.8. This is linked to a high average grain productivity of around 8,520.4 kg ha^{-1}, while the values of EXR and NDI, 0.146 and 134.0, respectively are linked to low average grain production (5,430.2 kg ha^{-1}). This has been attributed to the low N and K2O availability in the soil (Figure 3). Therefore, for the farmer, the use of remote detection of the nutritional status of corn through the EXR and NDI indices is very useful in helping him to decide whether to increase or decrease the application of the nitrogen and / or potassium fertilizers, to optimize the grain yield.

The VARI index adjusted to a polynomial model of the 1st degree, as a response to the soil N levels, shows higher quality of the indicators R^2, RMSE, nRMSE and S when compared with the other models (Figure 6). High VARI values of 0.1283 suggest high N levels in the soil (180 kg ha^{-1}), which induces high grain productivity on average (8,520.4 kg ha^{-1}) (Figure 3). However, the low VARI values (0.097) reveal lowered N levels in the soil, which are unfavorable to achieving satisfactory grain yield (5,430.2 kg ha^{-1}) (Figure 3).

It was CILIA et al. (2014) and VERGARA-DÍAZ et al. (2016) who obtained the linear relationship

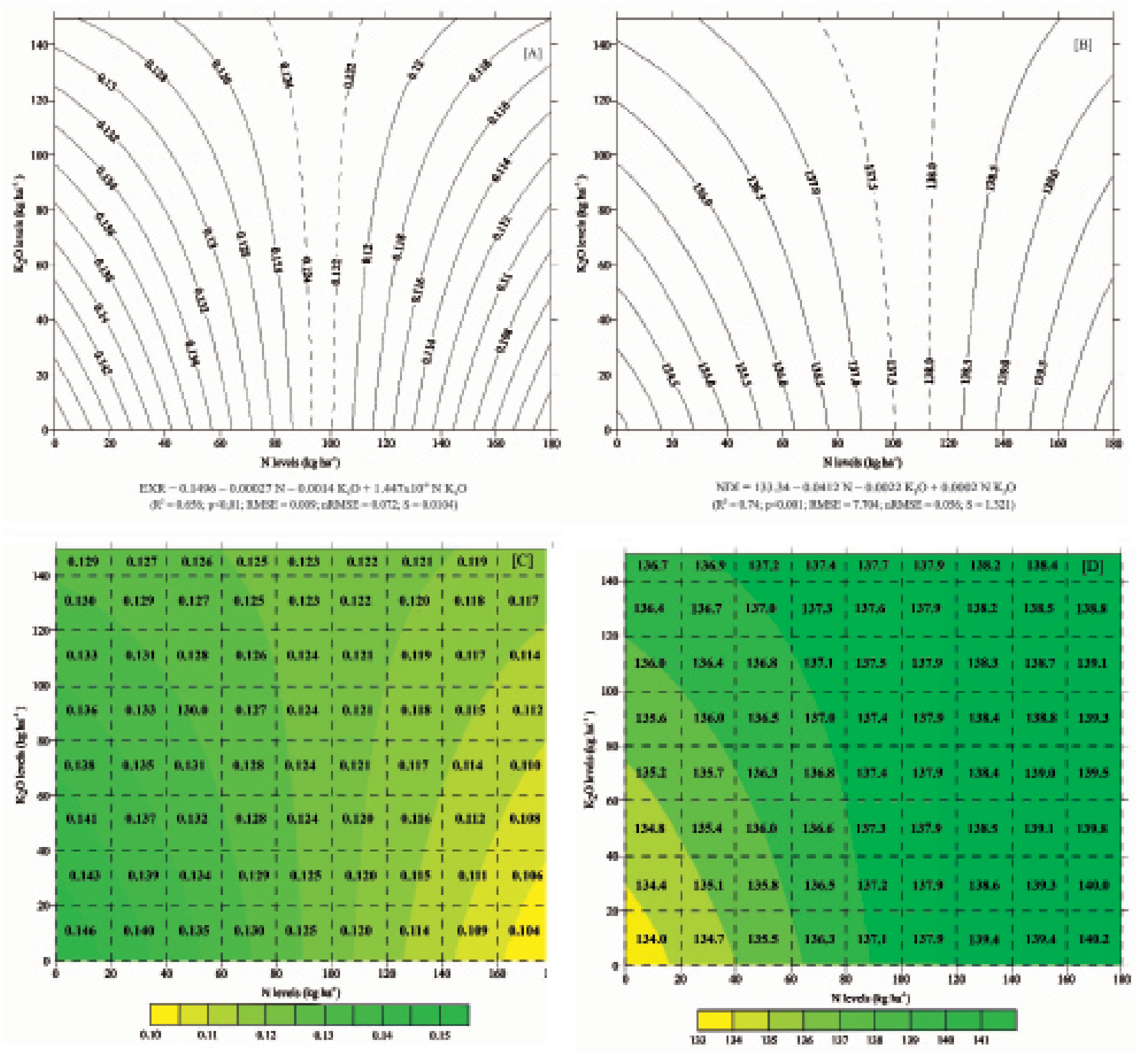

Figure 5 - Response surfaces for the EXR (A, C) and NDI (B, D) indices as a function of the levels of N and K_2O in the soil. Magalhães de Almeida, MA, 2019.

between the N concentration in the corn leaves and vegetation indices. This trend was also noted for the N level in the leaves and the grain produced (Figure 3). In fact, VIÑA et al. (2004) in their assessment of the phenological development of corn with the help of RGB images, came to understand that the VARI index is highly sensitive to the response to the leaf chlorophyll content. From these authors it is evident that this index may be indicative of an early stress phase in the crop because one of the symptoms suggestive of stress with respect to N is the drop in the leaf chlorophyll content (SRIDEVY et al., 2018).

CONCLUSION

Significant correlation was observed for the EXR, NDI and VARI indices with the leaf N content, which endorses them as encouraging in the identification of the nutritional status of corn with respect to N.

The nutritional status of corn could not be detected with regards to potassium, by even one of the indices assessed. The EXR and NDI indices were able to capture the interaction between the N and K_2O levels in the soil.

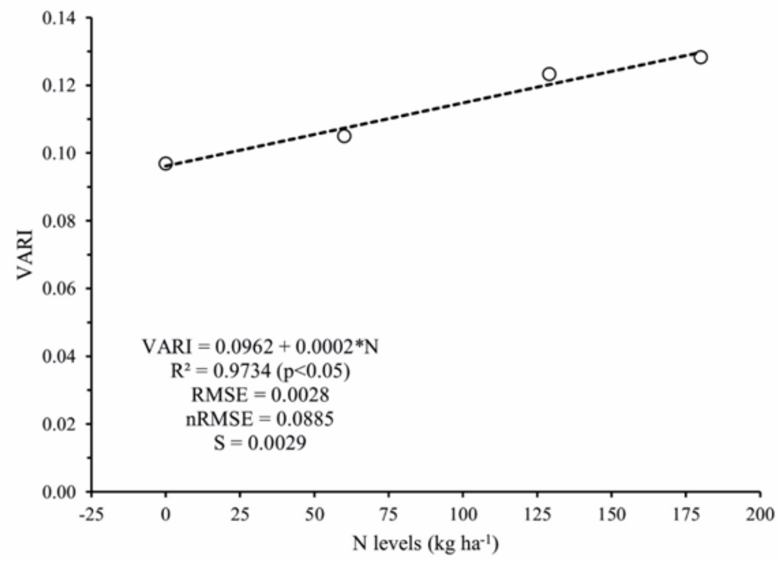

Figure 6 - Regression to the VARI index in response to soil N levels. Magalhães de Almeida, MA, 2019.

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DECLARATION OF CONFLICT OF INTEREST

The authors have no conflict of interests to declare. Sponsors did not play any part in the design of the study. They neither had any role in the data collection, its analysis or interpretation nor in the manuscript writing and the decision to publish the findings.

AUTHORS' CONTRIBUTIONS

All the authors have made equal contributions towards the design and writing of the manuscript. All the authors have critically reviewed the manuscript and given their approval for the final version.

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