Ensaios e Ciência
ISSN 1415-6938 e ISSN 2178-695X

DOI: https://doi.org/10.17921/1415-6938.2025v29n4p937-951

RGB Remote Sensing Via Drone in Soybean Production Estimation

Sensoriamento Remoto RGB Via Drone na Estimativa de Produção de Soja

Received: March 31, 2025
Accepted: September 29, 2025

Agnaldo da Conceição Brito: Universidade Estadual do Maranhão. MA, Brazil.

Francisco Charles dos Santos Silva: Universidade Estadual do Maranhão. MA, Brazil.

Leticia Carrazana Martinez: Universidade Estadual do Maranhão. MA, Brazil. E-mail: carrazanamartinezleticia@gmail.com

Hítallo Martins Hartmann: Universidade Estadual do Maranhão. MA, Brazil.

Alan Mario Zuffo: Universidade Estadual do Maranhão. MA, Brazil.

José Francisco da Cruz Neto: Universidade Estadual do Maranhão. MA, Brazil.

Fabíola dos Santos Dias: Centro Universitário de Balsas. MA, Brazil.

Abstract

Soybean (*Glycine max* L. Merrill) is the main agricultural commodity in Brazil, playing a significant socioeconomic role. Pre-harvest yield prediction is essential for crop management, logistics, and marketing. Remote sensing with unmanned aerial vehicles (UAVs) equipped with RGB sensors offers a low-cost, high-resolution alternative for this purpose. This study evaluated the relationship between RGB vegetation indices and individual spectral bands, obtained at the R2 stage of soybean, and grain yield. The experiment was conducted in Balsas, Maranhão, with two cultivars (BRASMAX Bônus IPRO and BRASMAX Olimpo IPRO) and three phosphorus rates (0, 50, and 100 kg of P_2O_5 ha^{-1}), in a randomized block design, factorial arrangement, with three replicates. Aerial images were processed to extract ten vegetation indices and the blue (B), green (G), and red (R) bands. The variables were subjected to ANOVA, Pearson's correlation, and partial correlation. The ExGR, ExG, ExR, VEG, and bands B and R showed partial correlations greater than 0.5 and significant ($p<0.05$) correlations with yield. It can be concluded that these variables have high potential for building predictive yield models, contributing to more assertive crop management decisions.

Keywords: Remote Sensing. UAV. Vegetation Indices. Agricultural Yield.

Resumo

A soja (*Glycine max* L. Merrill) é a principal commodity agrícola brasileira, desempenhando papel socioeconômico relevante. A previsão antecipada da produtividade antes da colheita é fundamental para o manejo da lavoura, logística e comercialização. O sensoriamento remoto com veículos aéreos não tripulados (VANTs) equipados com sensores RGB apresenta-se como alternativa de baixo custo e alta resolução para essa finalidade. Este estudo avaliou a relação entre índices de vegetação RGB e bandas espectrais individuais, obtidos no estádio R2 da soja, e a produtividade de grãos. O experimento foi conduzido em Balsas (MA), com duas cultivares (BRASMAX Bônus IPRO e BRASMAX Olimpo IPRO) e três doses de fósforo (0, 50 e 100 kg de P_2O_5 ha^{-1}), em delineamento em blocos casualizados, esquema fatorial, com três repetições. Imagens aéreas foram processadas para extração de dez índices de vegetação e das bandas azul (B), verde (G) e vermelha (R). As variáveis foram submetidas à ANOVA, correlação de Pearson e correlação parcial. Os índices ExGR, ExG, ExR, VEG e as bandas B e R apresentaram correlações parciais superiores a 0,5 e significativas ($p<0,05$) com a produtividade. Conclui-se que essas variáveis possuem elevado potencial para compor modelos preditivos de rendimento, contribuindo para decisões mais assertivas no manejo da cultura.

Palavras-chave: Sensoriamento Remoto. UAV. Índices de Vegetação. Rendimento Agrícola.

---

1 Introduction

Soybean (*Glycine max* L.) holds a prominent position as the main global commodity, and Brazil, in turn, occupies the leading position as the largest producer and exporter of this grain. According to the National Supply Company (CONAB, 2023), Brazilian production is estimated to reach 154.603.4 million tons for the 2023/24 harvest. Moreover, in the previous year, the country achieved a remarkable revenue from exports, registering a record value of USD 46.69 billion, according to data released by the Secretariat of Foreign Trade (SECEX, 2023).

Given this context, the precise application of production estimates for soybean-planted areas is of utmost importance, since early forecasts of grain quantity prior to harvest are vital for production management planning, transportation, processing, storage, and decision-making regarding exports, imports, and domestic market supply (De França *et al*., 2021). Such estimates are also crucial for decisions made by farmers, financial policymakers, governments concerning food security, and commodity traders.

Different methods have been employed to predict crop yields, including informal techniques based on crop knowledge or practical rules, as well as statistical models constructed as matrices with historical production data and agrometeorological parameters such as precipitation and temperature (Mladenova *et al*., 2017).

Remote sensing is a relatively low-cost alternative for crop yield forecasting. The literature reports numerous examples of its use for agricultural production prediction (De França *et al*., 2021).

The use of spectral bands, either combined or individually, as well as vegetation indices, has been successfully applied in agronomy for monitoring agricultural areas, since there are relevant interactions between plant biomass and the radiation reflected by vegetation (Hereher, 2013).

There are different types of vegetation indices, including RGB indices, which are derived from visible light bands encompassing red, green, and blue wavelengths. These indices provide information related to leaf pigmentation and plant vitality, with chlorophyll production serving as an indicator of plant health and vigor. Conventional RGB (Red, Green, Blue) images are commonly used for these purposes due to their cost-effectiveness, portability, and widespread availability of cameras and sensors when compared to thermal, multispectral, or hyperspectral imaging (Sampaio *et al*., 2020).

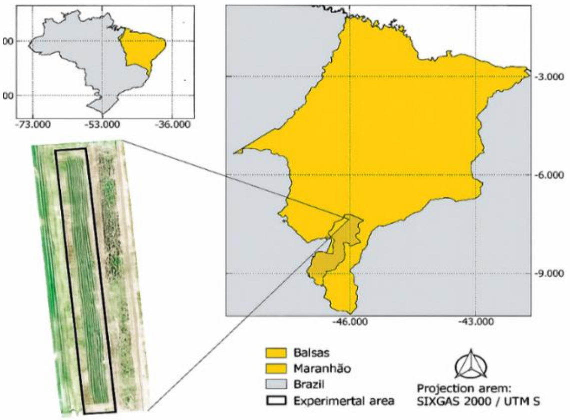
Such sensors can be mounted on remotely piloted aircraft (RPAs), commonly known as drones. The main advantage of this equipment lies in its low operational cost compared to other conventional options. Furthermore, drones provide the ability to capture images with higher spatial resolution than satellites or manned aircraft, at times specifically chosen by the user (Da Silva; Elias; Do Rosário, 2022). Although vegetation indices derived from satellite imagery are commonly used, the use of RPAs enables applications at a superior level, mainly due to advantages such as high spatial resolution, lower costs, shorter intervals between observations, and the possibility of customizing the equipment to meet specific needs (Lacerda, 2017).

Could RGB indices collected by drones be used to estimate soybean yield?To address this question, the objective of this study was to analyze the feasibility of using RGB indices and/or spectral bands to estimate soybean yield through images collected by drones.

2 Material and Methods

The experiment was conducted in the experimental field of the *Fazenda Pequizeiro*, owned by Accert – Research and Agronomic Consulting, located in the municipality of Balsas (Maranhão State, Brazil), at latitude 7°53'23.37" S and longitude 46°16'03.98" W, with an average altitude of 283 meters. The region has a tropical climate with dry winters and rainy summers (Aw), according to the Köppen climate classification (Maranhão, 2002). The soil in the area is classified as a Yellow Latosol with sandy texture (Santos *et al*., 2012).

Figure 1 – Experimental area



Source: the authors.

The experiment was conducted following a randomized complete block design (RCBD) in a split-plot factorial scheme with three replications, which was sufficient to perform basic statistical analyses (ANOVA, mean comparison, and regression).

The main plots consisted of two soybean cultivars: BMX BÔNUS IPRO (maturity group 7.9, indeterminate growth habit) and BMX OLIMPO IPRO (maturity group 8.0, also with indeterminate growth habit). The subplots corresponded to three rates of phosphorus fertilizer application, namely 0 (control), 50, and 100 kg of P_2O_5 ha^{-1}. Each subplot measured 2 meters in width by 3 meters in length.

It is important to emphasize that the six treatments implemented in the experiment (two soybean cultivars subjected to three phosphorus fertilizer rates) were used solely to induce controlled variability in soybean grain yield potential. As there was no interest in investigating the interaction between factors, but rather in ensuring the existence of yield variability within the experimental area, the collected data were analyzed using a randomized complete block design with six treatments.

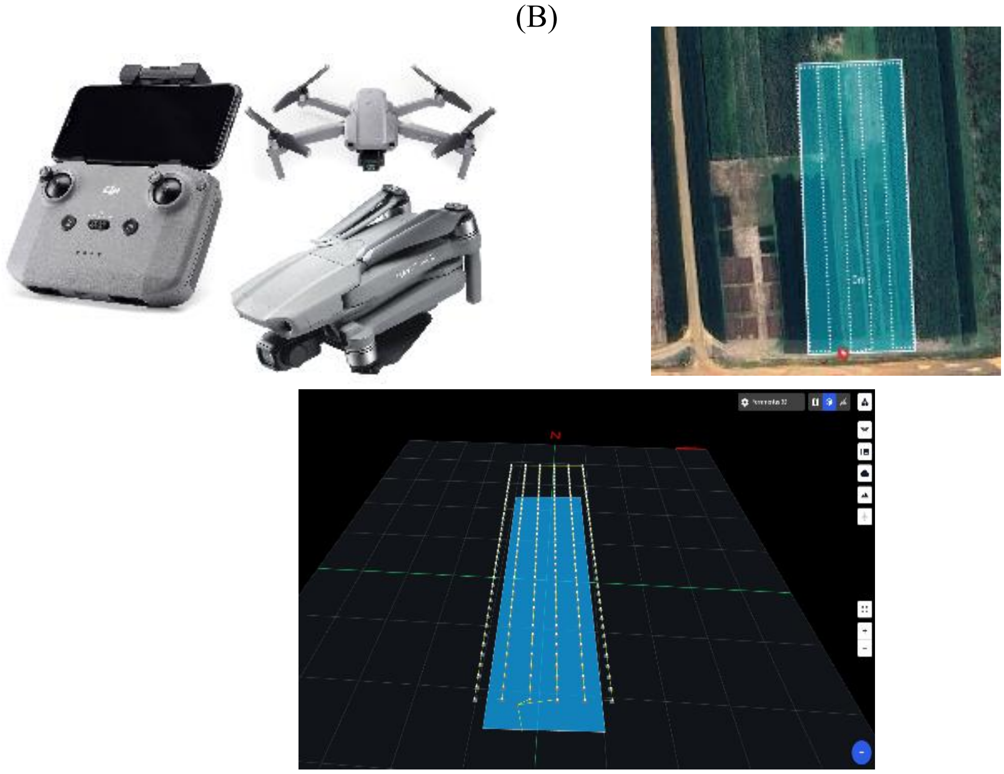
Sowing was performed manually at a depth of approximately 3.5 cm. The row spacing was 0.50 meters, with a final plant stand of 17 plants per meter, totaling approximately 340,000 plants per hectare. When the plants reached the harvest stage (R8), the useful area of each subplot—corresponding to the four central rows—was harvested using a threshing machine. Subsequently, the grain mass was weighed, and moisture content was adjusted to 13% to determine grain yield, expressed in kg ha^{-1}.

The collection of spectral information was carried out when the soybean plants reached the R2 growth stage, corresponding to full flowering. Data acquisition was performed using an RGB sensor mounted on a Mavic Air 2s drone (class 3 aircraft, according to ANAC, 2023).

The Mavic Air 2 camera is a key component, equipped with a 1/2-inch CMOS sensor with RGB spectral resolution, capable of capturing images at 48 megapixels. To ensure image stability and precision, the camera is supported by a three-axis stabilization system, which significantly reduces shaking and vibrations during flight (DJI, 2024) (Figure 2A).

Figure 2 - Image (A) drone and RGB sensor (DJI, 2024); images (B and C) schematic representation of the flight plan used in the study

(A) (B) (C)



Source: the authors.

For the development of the flight plan, which is essential for obtaining reliable data, the Drone Harmony application was used. Weather conditions, including factors such as wind direction and intensity, were taken into account to ensure optimized drone performance. In addition, key parameters were established, including a flight altitude set at 20 meters and a flight area extending 10% beyond the target area, along with a longitudinal and lateral overlap rate of 75%. This configuration resulted in a total of six flight lines to minimize the likelihood of overlap inaccuracies during image processing (Figure 2B and 2C

The captured images were subsequently processed using the OpenDroneMap software to generate the orthomosaic, which was then employed to obtain the vegetation indices listed in Table 1, as well as the individual green, blue, and red bands, with the aid of QGIS software version 3.28.11 (QGIS, 2022).

Table 1 - RGB Vegetation Indices adopted in the study

Indices	Formulas	References
Normalized Green Red Difference Index	$NGRDI = (G - R)/(G + R)$	Tucker (1979)
Redness Index	$RI = (G - R)/(G + R)$	Escadafal and Huete (1991)
Excess Green Index	$ExG = 2G - R - B$	Woebbecke *et al.* (1995)
Excess Red Vegetative Index	$ExR = 1.4R - G$	Meyer *et al.* (1998)
Vegetative	$VEG = \frac{G}{R^{a}B^{(1-a)}}$	Marchant and Onyango (2002)
Color Index of Vegetation Extraction	$CIVE = 0{,}441.R - 0{,}811.G + 0{,}385.B + 18{,}78745$	Kataoka *et al.* (2003)
Excess green minus Excess red	$ExGR = ExG - ExR$	Camargo-Neto (2004)
Combination	$COM = 0{,}36ExG + 0{,}47\ CIVE + 0{,}17VEG$	Guerrero *et al.* (2012)
IAFMiranda (2017)	$IAF = -25{,}838(\sqrt{R} + B^2 - \sqrt{G}) + 2{,}354$	Miranda (2017)
IAF2 Miranda (2017)	$IAF = -0{,}2013\left(\frac{e^B + log_2 G}{log_{10} R}\right) + 3{,}8408$	Miranda (2017)

R: Red band; B: Blue band; G: Green band; “a” is an experimental constant (a = 0.667).
Source: research data.

The spectral data and grain yield from the plots were subjected to analysis of variance (ANOVA) to verify the existence of significant differences within the experiment. The F-test results from ANOVA were presented as boxplot graphs.

This statistical and graphical approach allowed for a detailed analysis of discrepancies among samples from the same treatment, enhancing data interpretation and improving the understanding of the results.

The ability of each vegetation index and spectral band (blue, green, and red) to estimate soybean yield was determined using Pearson’s correlation analysis. Vegetation indices and spectral bands showing correlation coefficients greater than 0.5 were further subjected to partial correlation analysis to ensure greater reliability of the results.

The Pearson correlation coefficient is a measure that assesses the linear relationship between two quantitative variables. It is represented by the letter “r” and ranges from -1 to 1. When $r = 1$, this indicates a perfect positive correlation, meaning that both variables increase together linearly. When $r = -1$, it indicates a perfect negative correlation, meaning that as one variable increases, the other decreases linearly. Finally, when $r = 0$, there is no linear relationship between the variables

(Figueiredo *et al.*, 2009, p.115).

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \times \sum(Y_i - \bar{Y})^2}}$$

Where:

• $X_i$and $Y_i$are the individual values of variables X and Y, respectively;

• $\bar{X}$and $\bar{Y}$are the means of variables X and Y, respectively;

• Σdenotes summation over all values.

Partial correlations, on the other hand, are statistical measures that examine the relationship between two variables while controlling for the effects of one or more confounding variables. Essentially, they allow the evaluation of the association between two variables while keeping constant other variables that may influence this relationship. This helps to isolate the specific effect of the variables of interest, providing a more accurate understanding of their interrelationships.

$$r_{XY.Z} = \frac{r_{XY} - (r_{XZ} \times r_{YZ})}{\sqrt{(1 - r_{XZ}^2)(1 - r_{YZ}^2)}}$$

Where:

• $r_{XY.Z}$is the partial correlation between X and Y, controlling for Z;

• $r_{XY}$is the correlation between X and Y;

• $r_{XZ}$is the correlation between X and Z;

• $r_{YZ}$is the correlation between Y and Z;

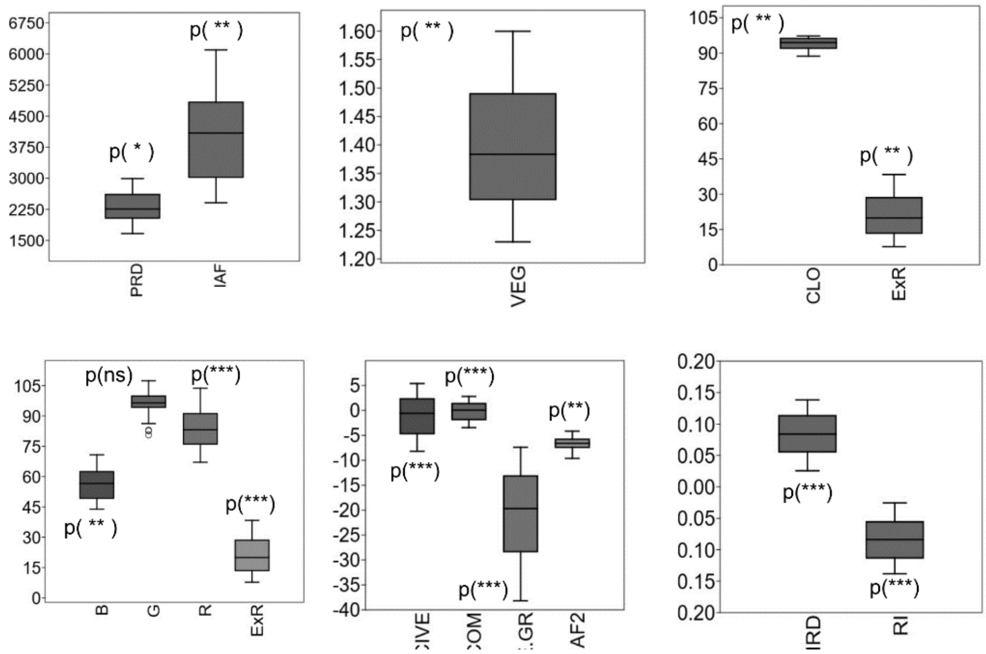
• *sqrt* denotes the square root.

3 Results and Discussion

The data for each vegetation index used in the crop evaluation are presented in boxplot diagrams in Figure 3. In the boxplots, the median is represented by a horizontal line within the central rectangle, while the ends of the rectangle indicate the range containing the central 50% of the data. The whiskers extend to the maximum and minimum observed values in the dataset.

The F-test results from the analysis shown in the boxplots revealed significant differences at the 5% significance level for soybean yield, crop cycle, and spectral variables — including vegetation indices and individual bands — except for the green band (Figure 3).

Figure 3 - Result of the F-test obtained by ANOVA and behavior of vegetation indices and individual bands using a box plot. R: Red Band; B: Blue Band; G: Green Band; PRD: Production; IAF: Leaf Area Index; VEG: Vegetative Index; CLO: Cycle; ExR: Excess Green Index; CIVE: Vegetation Extraction Color Index; COM: Combination Index; IAF2: Leaf Area Index 2; NIRD: Near-infrared-red difference index; RI: Redness Index; p***, p** and p* significant at 0.1%, 1% and 5% probability respectively by the F-test



Source: the authors.

The fact that the green band did not show significant differences indicates that, under the conditions in which the study was conducted, even with variations in nutrient availability interacting with two different cultivars, there was no variation in chlorophyll concentration among the treatments. This is consistent with the relationship between green radiation reflectance and plant chlorophyll concentration, as reported by Gao *et al*. (2020).

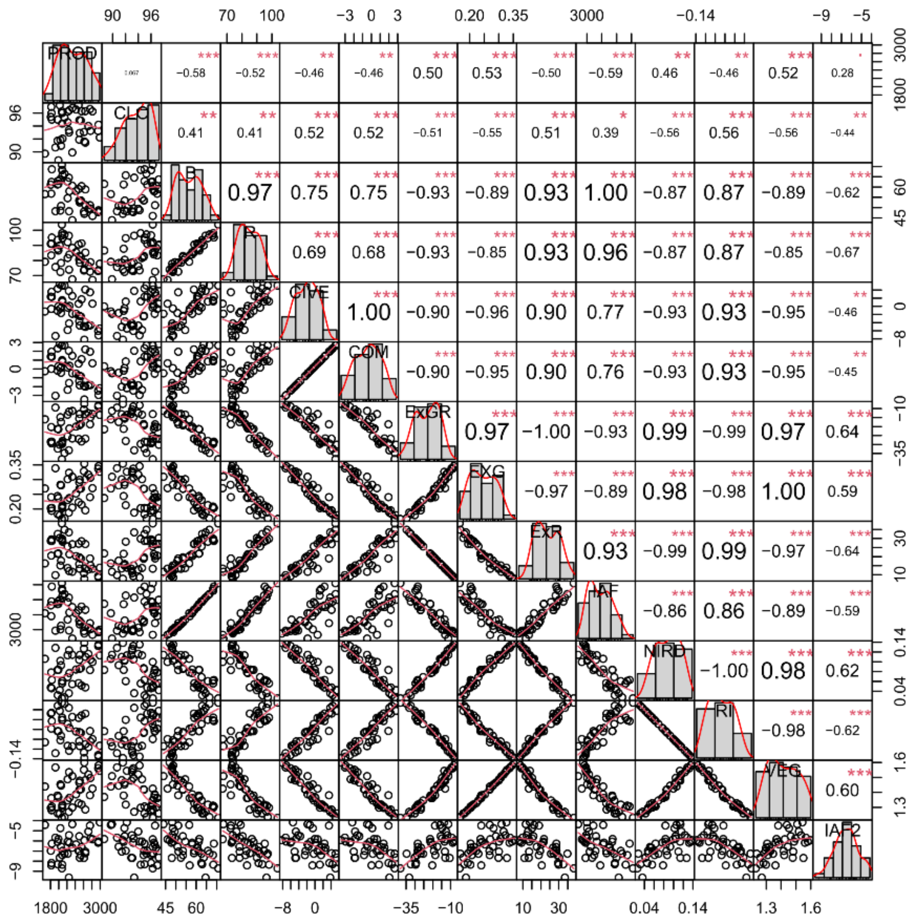
For the variables that did show significant differences, it can be inferred that the variability in productive capacity of the trial is related to the combined effect of the different cultivars used and the various doses of phosphate fertilizer applied.

The significance of the analyzed variables (Figure 3) is crucial for subsequent statistical analyses in this study, since the presence of variability in the productive capacity of the area allows for the quantification of these differences through remote sensing.

Thus, it is reasonable to infer the possibility of identifying one or a combination of vegetation indices and/or an individual spectral band that, when measured in the soybean crop, could optimize yield prediction models.

To achieve this objective, Pearson correlation coefficients were initially calculated between soybean yield data and the values of each of the 10 vegetation indices and 3 individual bands (R, G, B). These calculations were performed using each of the 42 experimental plots, aiming for a comprehensive understanding of the relationships among these variables. Given the size of the resulting correlation matrix and to facilitate interpretation of the results, a graphical analysis was performed (Figure 4).

Figure 4 - Correlation table of vegetation indices, individual spectral bands, and evaluated agronomic characters. R: Red Band; B: Blue Band; G: Green Band. PRD: Production; IAF: Leaf Area Index; VEG: Vegetative Index; CLO: Cycle; ExR: Excess Green Index; CIVE: Vegetative Extraction Color Index; COM: Combination Index; IAF2: Leaf Area Index 2; NIRD: Near-infrared-red difference index; RI: Redness Index; p(ns): not significant; p***, p**, and p* significant at 0.1, 1, and 5% probability, respectively, by the F-test



Source: the authors.

The graphical analysis showed that both the crop cycle and the indices CIVE, COM, NIRD, RI, and IAF2 exhibited low-magnitude correlations, below ±0.5. Thus, these indices, when obtained at the R2 stage (full flowering), are not efficient for predicting soybean yield.

Based on the correlation analysis results, the indices EXGR, EXG, EXR, IAF, VEG, and the individual bands R and B showed high-magnitude correlations, above 0.5, with soybean yield, suggesting that they can be used as tools for crop yield prediction.

In a study conducted by Alberto (2024), the potential for determining soybean yield using vegetation indices and individual bands obtained from drones was demonstrated. These devices stand out in agricultural and environmental monitoring applications due to their high spatial resolution, lower costs, and greater flexibility in customization (Tsouros*;* Bibi; Sarigiannidis*,* 2019). Compared to satellite images, drones allow for detailed and frequent data capture, ideal for specific analyses such as crop yield prediction.

In general, the main spectral vegetation indices used for estimating agronomic variables via remote sensing are based on bands in the visible spectrum (mainly red) and near-infrared (Formaggio; Sanches, 2017). However, an alternative approach that has received growing attention is the use of indices based on visible spectrum bands, such as RGB indices. These indices use combinations of the red (R), green (G), and blue (B) bands to infer information about vegetation (Feldmann *et al*., 2023).

The advantages of RGB indices include their simplicity in formulation and interpretation, as they are directly related to visible colors and are therefore intuitive for visual analysis. Moreover, RGB indices can capture information about the spectral and structural distribution of plants in ways that traditional indices based on specific bands cannot. This is especially useful in contexts where vegetation exhibits complex characteristics or spectral mixtures that may not be well represented by traditional vegetation indices.

It should be noted that correlation studies do not allow conclusions about cause-and-effect relationships; correlation is only a measure of association, and the magnitude and direction of a correlation measure can be influenced by other variables. In such cases, partial correlation analysis can be used to eliminate the influence of other independent variables on the correlation magnitude between two variables (Trivisiol *et al*., 2024).

Partial correlation analysis allowed the identification of the most efficient indices and individual bands for determining crop yield. In this study, the blue (B) and red (R) bands, as well as the indices ExGR, ExG, ExR, and VEG, showed partial correlations above 0.5 and were significant according to the T-test, whereas the leaf area index (IAF) showed a non-significant correlation (Table 2).

Table 2 - Simple and partial correlations of variables B, R, ExGR, ExG, ExR, IAF, and VEG with soybean yield

Variable Pairs	r (simple)	r (partial)	T-test (5%)
Yield × B	-0.583	-0.719	*
Yield × R	-0.5153	-0.708	*
Yield × ExGR	0.5008	0.604	*
Yield × ExG	0.5252	0.502	*
Yield × ExR	-0.5005	-0.501	*
Yield × IAF	-0.5882	-0.146	Ns
Yield × VEG	0.5175	0.441	*

Note: B = Blue band; R = Red band; ExGR, ExG, ExR, VEG = vegetation indices; IAF = Leaf Area Index; Ns = not significant; * = significant at 5% level.
Source: research data.

Based on the results of this study, it can be stated that, for soybean crops, the values of the individual blue (B) and red (R) bands, as well as the indices EXGR, EXG, EXR, and VEG, provide the basis for developing models to predict soybean yield. This enables informed decision-making by producers, governmental agencies, commodity traders, and others involved in grain production.

As reported by Fortunato (2023), the results of this study demonstrate the feasibility of using UAVs to determine crop yield through RGB vegetation indices and individual bands, with particular emphasis on the red (R) and blue (B) bands.

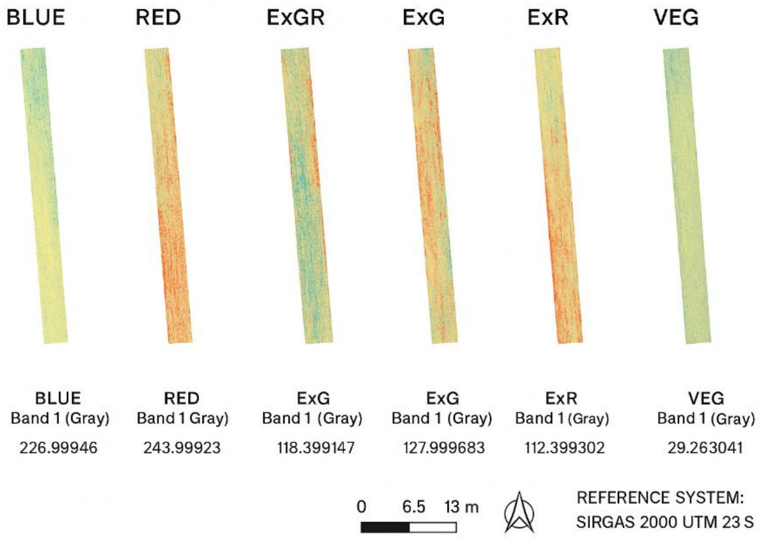
Table 2 shows the negative relationship between the reflectance of the blue (B) and red (R) bands and soybean yield. That is, the lower the reflectance of these bands, the higher the crop's productive capacity.

Among plant organs, leaves play the most relevant role in the spectral behavior of vegetation due to their position and function. In the visible spectrum, for example, the presence of chlorophyll leads to significant absorption of solar energy in the red wavelength range, resulting in low reflectance and a dark tone in remote sensing imagery; a similar behavior occurs in the blue wavelength range.

Jensen and Epiphânio (2009) reported that plants absorb more blue light through chlorophyll b and more red light through chlorophyll a. The absorbed energy is used in photosynthesis, so higher absorption of blue and red energy corresponds to lower reflectance at these wavelengths, higher photosynthetic activity, and consequently greater plant productive capacity, which explains the results obtained in the present study.

Figure 5 shows, in the experimental area, the vegetation indices and spectral bands that exhibited significant partial correlations with soybean yield.

Figure 5 - Vegetation indices and spectral bands that showed significant partial correlations with soybean productivity; RED: Red band; BLUE: Blue band; VEG: Vegetative index; ExGR: Index of excess green minus excess red; ExG: Index of excess green; ExR: Index of excess red



Source: the authors.

The ExGR index shows significant positive correlations, suggesting a favorable relationship with soybean yield (Table 2). This variable, which reflects plant vigor, indicates that areas with higher ExGR values tend to have higher soybean productivity. This highlights the importance of monitoring plant vigor to predict and improve crop yield.

The ExG index, which indicates the quantity and quality of green vegetation present in an area, also shows a significant positive correlation with soybean yield (Table 2). This suggests that areas with more green vegetation, relative to other reflected bands, tend to exhibit higher soybean productivity. This relationship can be explained by the fact that healthy vegetative growth is directly associated with increased grain production.

In contrast, the ExR index, which is associated with the amount of red light reflected by plants, showed a negative partial correlation (-0.501) with soybean yield (Table 2). This indicates that areas with greater absorption of red light tend to have higher soybean productivity. This relationship suggests better physiological status of plants in these areas, contributing to superior yield.

The Leaf Area Index (IAF), which measures the amount of foliage present in the vegetation, showed a non-significant partial correlation with soybean yield. The absence of correlation indicates that the observed variation in soybean leaf area (Figure 3) was not large enough to impact plant productivity (Table 2).

Finally, the VEG variable, which represents plant vigor characteristics, also showed a positive correlation with soybean yield, indicating that areas with more vigorous plants tend to achieve higher productivity, as expected.

Together, these correlations reveal the complexity of factors influencing soybean yield and underscore the importance of considering multiple spectral variables to understand and maximize the predictive capacity of crop yield. These findings contribute significantly to agricultural knowledge and have practical implications for soybean management and increased crop production.

However, as no single vegetation index or spectral band showed a partial correlation equal to one (1), further studies are needed to develop mathematical models that combine the most promising spectral information for accurate prediction of soybean yield.

4 Conclusions

The individual blue and red bands, as well as the EXGR, EXG, EXR, and VEG indices, show high potential for predicting soybean grain yield.

References

ANAC - Agência Nacional de Aviação Civil. Disponível em: https://www.gov.br/anac/pt-br/assuntos/drones/classes-de-drones. Acesso em 25 ago. 2025.

ALBERTO, M.H. Índices de vegetação obtidos por RPA e redes neurais artificiais na determinação de áreas de produção de sementes de soja (*Glycine max* (L.) Merrill). Santa Maria: Universidade Federal de Santa Maria, 2024.

CANDIDO, A.F. Estimativa de safra do algodoeiro com produtos de sensoriamento remoto. João Pessoa: Universidade Federal da Paraíba, 2022.

CONAB - Companhia Nacional de Abastecimento. Acompanhamento da safra brasileira de grãos – Decimo primeiro levantamento, safra 2022/23. Brasília: CONAB, 2023.

DA SILVA, M.H.; ELIAS, A.R.; DO ROSÁRIO, L.L. Análise da cultura da soja a partir de índices de vegetação (ExG–GLI–TGI–VEG) advindos de imagens RGB obtidas com ARP. *Rev Bras. Geomát.*, v.10, n.2, p.140-154, 2022.

DE FRANÇA, J. *et al*. Previsão da produção de soja utilizando imagens de satélite e Lógica Fuzzy. *Ens. Ciênc.*, v.25, n.2, p.232-238, 2021. doi: https://doi.org/10.17921/1415-6938.2021v25n2p232-238.

DUFT, D.G. Uso de sensoriamento remoto para aplicações de agricultura digital em cana-de-açúcar. São Paulo: USP, 2022.

DJI. Mavic Air 2 - Especificações. 2020. Disponível em: https://www.dji.com/br/mavic-air-2/specs. Acesso em: 20 jun. 2025.

FELDMANN, N.A. *et al*. Índice de vegetação baseado no espectro visível para monitoramento de cultivares de trigo submetidas a diferentes doses de nitrogênio. *Rev Inov. Gestão Tecnol. Agron.*, v.2, p.227-254, 2023.

FIGUEIREDO, D.B.; SILVA, J.A. Desvendando os Mistérios do Coeficiente de Correlação de Pearson(r). *Rev. Pol. Hoje*, v.18, n.1, p.115-146, 2009.

FORMAGGIO, A.R.; SANCHES, L.D. Sensoriamento remoto em agricultura. Oficina de Textos, 2017.

FORTUNATO, I.V. Análise da fisiológica e índices de vegetação para diferentes cultivares de soja no Espírito Santo. Colatina: Instituto Federal do Espíritos Santos, campus Itapina, 2023.

GAO, L. *et al*. Remote sensing algorithms for estimation of fractional vegetation cover using pure vegetation index values. A review. ISPRS, v.159, p.364-377, 2020. doi: https://doi.org/10.1016/j.isprsjprs.2019.11.018.

HEREHER, M.E. The status of Egypt's agricultural lands using MODIS Aqua data. *Egy. J. Remote Sens. Space Sci.*, v.16, n.1, p.83-89, 2013.doi: https://doi.org/10.1016/j.ejrs.2013.03.001.

JENSEN, J.R.; EPIPHANIO, J.N. Sensoriamento remoto do ambiente: uma perspectiva em recursos terrestres, 2009.

LACERDA, V.S. Estimativa do índice de severidade de Ferrugem Asiática na cultura da soja por meio de imagens obtidas com aeronave remotamente pilotada. Ponta Grossa: Universidade Estadual de Ponta Grossa, 2017.

MARANHÃO - Governo do Estado do Maranhão. Gerência de Planejamento e Desenvolvimento Econômico - GEPLAN. Atlas do Maranhão. São Luís: Universidade Estadual do Maranhão, 2002.

MLADENOVA, I. *et al*. Intercomparison of soil moisture, evaporative stress, and vegetation indices for estimating corn and soybean yields over the US. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, v.10, n.4, p.1328-1343, 2017. doi: 10.1109/JSTARS.2016.2639338.

QGIS Development Team. Geographic Information System (QGIS) software, version 3.28.11. Open-source geospatial foundation project,2019.

SAMPAIO, H. *et al*. Comparação entre índices de vegetação obtidos por imagens aéreas com veículo aéreo não tripulado (VANT) e satélite. *Rev. Bras. Eng. Biossist.*, v.14, n.2, p.111-124, 2020. doi: https://doi.org/10.18011/bioeng2020v14n2p111-124.

SANTOS, H. *et al*. Aplicação de plataforma de sensoriamento remoto de baixa altitude (LARS) para monitoramento do crescimento de culturas e infestação de plantas daninhas em uma plantação de soja. *Agricul. Prec.*, v.13, p.611-627, 2012.

SECEX - Secretaria de Comércio e Exterior. Disponível em: https://www.gov.br/produtividade-e-comercio-exterior/pt-br/assuntos/comercio-exterior. Acesso em. agosto de 2023.

TRIVISIOL, V. *et al*. Correlações parciais entre caracteres produtivos e proteína em grãos de trigo. Rev. Caatinga, v.37, p.e12312-e12312, 2024. doi: https://doi.org/10.1590/1983-21252024v3712312rc.

TSOUROS, D.C.; BIBI, S.; SARIGIANNIDIS, P.G. A review on UAV-based applications for precision agriculture. *Information*, v.10, n.11, p.349, 2019. doi: https://doi.org/10.3390/info10110349.