Determination of height in corn (*Zea mays* L.) crops through the use of images produced by UAVs

Jefferson Peres de Oliveira[1], André Luiz Ferreira Oliveira[1], Hugo Manoel de Souza[2], Igor Vinicius dos Santos Araújo[2] & Daniel Noe Coaguila Nuñez[1,3]

[1] Centro Universitário UniBRAS Rio Verde, Rio Verde, Goiás, Brazil

[2] Oro Agri, Rio Verde, Goiás, Brazil

[3] Universidad Nacional de San Agustin de Arequipa, Arequipa, Peru

Correspondence: Jefferson Peres de Oliveira, Centro Universitário do Sudoeste Goiano - UniBras, Rio Verde, Goiás State, Brazil. E-mail: jeffersonperes.agro@gmail.com

Received: December 08, 2023 DOI: 10.14295/bjs.v3i3.519

Accepted: February 29, 2024 URL: https://doi.org/10.14295/bjs.v3i3.519

Resumo

Behind only soybean production, corn is the second most produced grain in Brazil. Remote sensing is generally considered one of the most important technologies for precision agriculture and smart agriculture, enabling producers to monitor various parameters in agricultural crops. This work aimed to determine the height of plants in corn crops through the photogrammetry technique using unmanned aerial vehicles (UAVs). The experiment was conducted in the municipality of Montividiu, State of Goiás, Brazil, in the 2023 harvest. The mapped crop was corn, the georeferenced images were captured via drone, with 249 photos generated during approximately 14 min of flight. The geoprocessing of the orthomosaic and digital surface model was ArcGIS, in which the sketch was plotted on the orthophoto (georeferenced image) to later extract the height data for each treatment. The original data were subjected to the normality test with 5% significance and homogeneity test with 5% significance, then the data were subjected to analysis of variance using the F test with $p < 0.05$ and, when significant, it was used if the *Tukey* test with $p < 0.05$. Block A had the best performance for average plant height with values above 0.8 m. The use of UAVs proved to be an important and efficient tool in determining the height of corn plants for future work on phytopathology, nutrient deficits, areas with leaching or even distinguishing different cultivars.

Keywords: *Zea mays*, remote sensing, precision agriculture, drone.

Determinação de altura na cultura do milho (*Zea mays* L.) através do uso de imagens produzidas por VANT's

Resumo

Atrás apenas da produção da soja, o milho é o segundo grão mais produzido no Brasil. O sensoriamento remoto é geralmente considerado como uma das tecnologias mais importantes para a agricultura de precisão e a agricultura inteligente, possibilitando ao produtor monitorar diversos parâmetros em culturas agrícolas. Este trabalho teve por objetivo determinar a altura de plantas em lavoura de milho através da técnica de fotogrametria utilizando o veículo aéreo não tripulado (VANT's). O experimento foi conduzido no município de Montividiu, Estado de Goiás, Brasil, na safrinha de 2023. A cultura mapeada foi o milho, as imagens georreferenciadas foram captadas via *drone*, com 249 fotos geradas durante aproximadamente 14 min de voo. O geoprocessamento do ortomosaico e modelo digital de superfície foi o ArcGIS, no qual plotou-se o croqui sobre a ortofoto (imagem georreferenciada) para posteriormente extrair os dados de altura de cada tratamento. Os dados originais foram submetidos ao teste de normalidade com 5% de significância e de homogeneidade com 5% de significância, em seguida, os dados foram submetidos a análise de variância pelo teste F com $p < 0,05$ e, quando significativo, utilizou-se o teste de *Tukey* com $p < 0,05$. O bloco A teve o melhor desempenho para altura média das plantas com valores acima de 0,8 m. O uso VANT's demonstrou ser uma ferramenta importante e eficiente na determinação da altura das plantas de milho para futuros trabalhos de fitopatologias, deficit de nutrientes, áreas com lixiviação ou mesmo distinção de diferentes cultivares.

Palavras-chave: *Zea mays,* sensoriamento remote, agricultura de precisão, *drone*.

1. Introduction

Behind only soybean production, corn is the second most produced grain in Brazil, whose harvest in 2021/2022 was 113.27 million tons (Conab, 2022), national production in the 2022/2023 harvest was 131. 86 million tons, an increase of more than 16.6% in corn production (Conab, 2023), compared to the previous harvest, and this is due to improvements in precision agriculture techniques (Nascimento et al., 2014; Lopes et al., 2019).

Crop monitoring, with diagnostics especially in a quick, practical and accurate way, is an interesting perspective that can be used in any crop, but a vision that is significantly more relevant for farmers who have adopted precision agriculture (Pereira et al., 2018; Passos et al., 2019; Henrique et al., 2021). According to Tsouros et al. (2019) remote sensing is generally considered one of the most important technologies for precision agriculture and smart agriculture, enabling producers to monitor various crop and vegetation parameters through images of various wavelengths.

One of the most frequent practices to determine the final number of emerged plants was visual inspection of the soil (Bruin; Pederson, 2004). However, it is an activity that demands work and time, demanding a lot from farmers or researchers (Varela et al., 2018). However, we can determine the plant population through the images captured by the drone (Pessi et al., 2020).

Remotely manned aircraft (drones) are an important tool that helps identify the height of plants for different crops among several other agricultural functions. Via drone it provides facilities for defining plant height, as it works with the entire population of plants, and not just 1 linear m or a sample of the plot, for example. In this sense, the technology for monitoring and characterizing the vast corn planting areas is constantly developing, with the use of unmanned aerial vehicles (UAVs) using cameras that allow monitoring, photographing and/or remotely evaluating the crop in the field (Neto et al., 2023).

The use of UAVs has increased in recent years, as they enable cost reduction, as well as advantages such as sampling at low altitudes, which enables the acquisition of data with better and greater resolution for image processing; on-demand mapping and the possibility of using sensors with the most diverse configurations (Neto et al., 2023). In the literature, most studies to estimate plant density and height have been using RGB sensors (Nakarmi; Tang, 2014; Varela et al., 2018). Cameras with RGB (visible spectrum) sensors only collect in the red, green and blue bands (red, green and blue - RGB) (Neto et al., 2023). Thus, digital models of the area are generated from aerial images from an RGB camera onboard the UAVs, with digital surface models (DSM) and orthophotos being the main products of this mapping.

The DSM consists of a model that represents the surface of the terrain as well as any object, vegetation or buildings, so the top of these is represented as the surface in the image (Cruz et al., 2011). The highlight of remote sensing is vegetation indices, which are based on the reflectance values of one or more spectral bands observed in the mapped area (Liu et al., 2019). The Excess Green index (ExG) is one of the vegetation indices that can be used. ExG helps amplify the contrast intensity response between green and background pixels (Varela et al., 2018). There are several vegetation indices that can be worked on, and the visible spectral range (red) allows us to differentiate the characteristics of the vegetation structure, as it is in this spectral range that the absorption of electromagnetic energy by chlorophyll occurs (Fitz, 2008).

This study aimed to determine the height of plants in corn (*Zea mays*) crops through the photogrammetry technique using an unmanned aerial vehicle UAV in the region of the municipality of Montividiu, State of Goiás, Brazil.

2. Materials and Methods

2.1 Work area and experimental design

The experiment was conducted at Rancho Vermelho Farm at the *Instituto Goiano de Agricultura* (IGA), located next to the GO-174 highway, Km-45, on the right, 3.5 km, from the municipality of Montividiu, State of Goiás, Brazil (Figure 1). The experiment was carried out in the 2023 harvest, in March. The soil type in the area is Red Oxisol, with an average temperature for the region varying between 20 and 28 ºC (Climatempo, 2023). The experimental sampled area (Figure 1) was in a randomized block design, with 4 blocks and 10 treatments, totaling 40 plots. The mapped crop was corn.

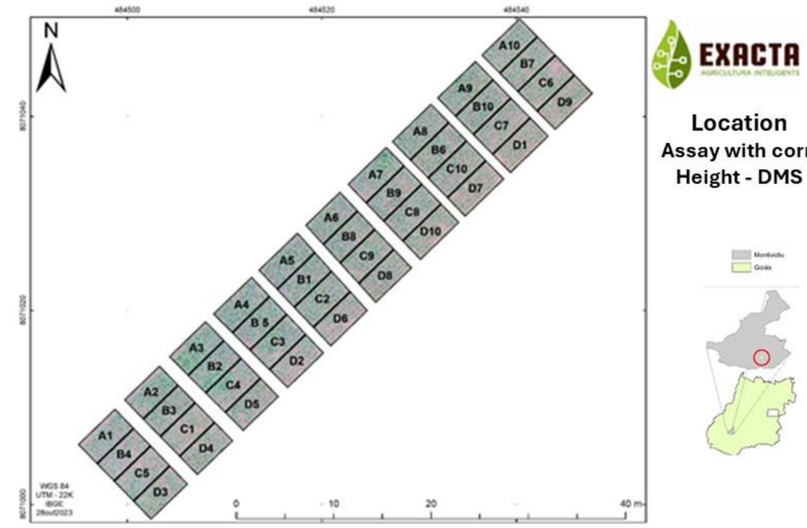

Figure 1. Location of the corn trial, Rancho Vermelho farm at the *Instituto Goiano de Agricultura* (IGA). Source: Authors, 2023.

2.2 Flight planning and mapping

The automatic flight plan for obtaining georeferenced images was through the Drone Deplov application in the test version, using Phantom 4 Pro with the factory RGB camera (1” and 20MP CMOS sensor). The flight plan was carried out at 70m height with frontal and lateral overlap of 75 and 70%, respectively.

The mapping was March 17, 2023, when the crop was already in the fruiting growth phase, at the recommended time (between 10 and 11 am). The mapped area was 201,223.83 m² with 249 photos captured during approximately 14 minutes of flight, with images being captured on the Drone's round trip route (Figure 2). For mapping, the geographic reference system used was the one that comes standard in the equipment (WGS84), with a displacement error of 4.61 m (accuracy). The flight plan always exceeds the area of interest.

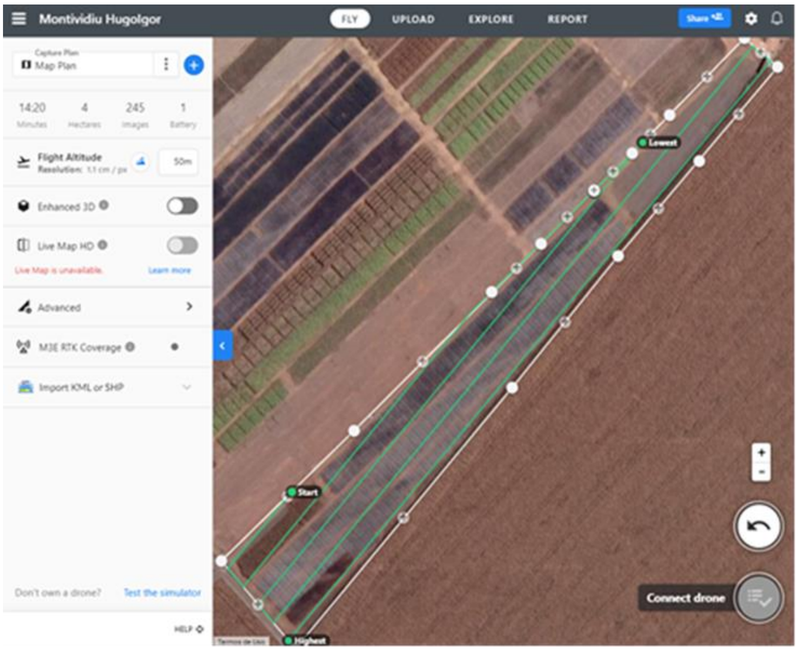

Figure 2. Drone flight plan during area mapping. Source: Authors, 2023.

2.3 Processing

Afterwards, the photos were downloaded from the Drone to the computer using the Open Drone Map software (WebODM 2.0.3; https://opendronemap.org) and the vegetation index algorithm used was ExG to identify the vegetation, thus obtaining the orthophoto and subsequently the digital surface model (DMS; Figure 3A and 4). The program used for the geoprocessing of the orthomosaic and DMS was ArcGIS 10.4 (Esri®), with a pixel of 1.3 cm (distance between pixel points), in which the sketch was plotted on the orthophoto (georeferenced image) as shown in (Figure 4), to later extract plant height data from each treatment and the entire plot (Figure 3B). Using the orthomosaic, the object of study was classified, which were only the surfaces of the images containing corn plants.

As shown in Figure 4, the orthophoto was processed with the ExG vegetation index to identify only the plants from the entire plot. Right after coloring, in this case the exposed soil and plants, but we only used the reflectance corresponding to the vegetation. After extracting the height values (m^2) from each plot, spreadsheets were generated and exported to Excel so that statistical procedures could be carried out to calculate whether there was a statistical difference between the treatments.

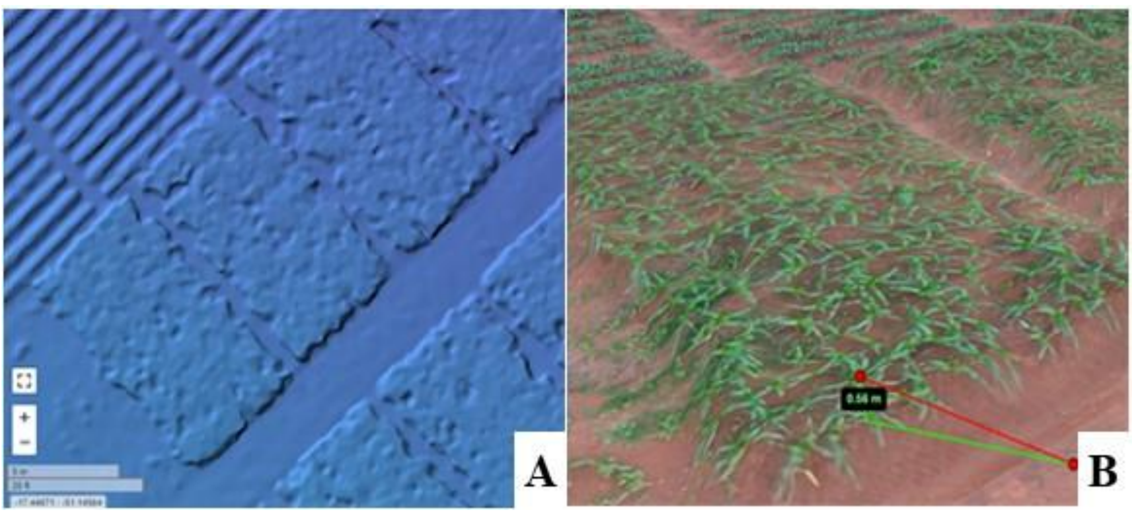

Figure 3. Digital surface model (**A**) and orthomosaic superimposed on the digital surface model (**B**). Source: Authors, 2023.

Figure 4. Sketch of the corn trial in the experimental area of the Goiano Institute of Agriculture. Letters and numbers are blocks and treatments, respectively. Source: Authors, 2023.

2.4 Statistical analysis

The original data were subjected to the *Shapiro-Wilk* normality test with 5% significance and the *Bartlett* homogeneity test with 5% significance. Data that did not present normal distribution and/or homoscedasticity were transformed using the Box-Cox family of transformations (Box; Cox, 1964). Then, the data were subjected to analysis of variance using the F test with $p < 0.05$ and, when significant, the *Tukey* test with $p < 0.05$ was used in the qualitative analysis to compare the means. All analyzes were carried out using the statistical software R, version 4.2.0 (Ferreira et al., 2014; Team, 2018).

3. Results and Discussion

In Figure 5 the blocks that stand out in height were blocks A and D, and in turn the block that had the lowest performance was B. The mentioned performance may have been influenced by the adjacent road that separates the tests (Figure 4). Since there was no problem with shadows in the mapping, which differs from what was observed by García-Martínez et al. (2020), where three classifications were required regarding the orthophoto: soil, shade and vegetation, where they presented shading in the mapping of the area under study. For Olson et al. (2019), researchers evaluated the relationship between vegetation index and corn productivity at different stages, where it was possible to verify that the success of drone-based remote sensing depends on changes in the sensitivity of vegetation indexes and crop growth stages .

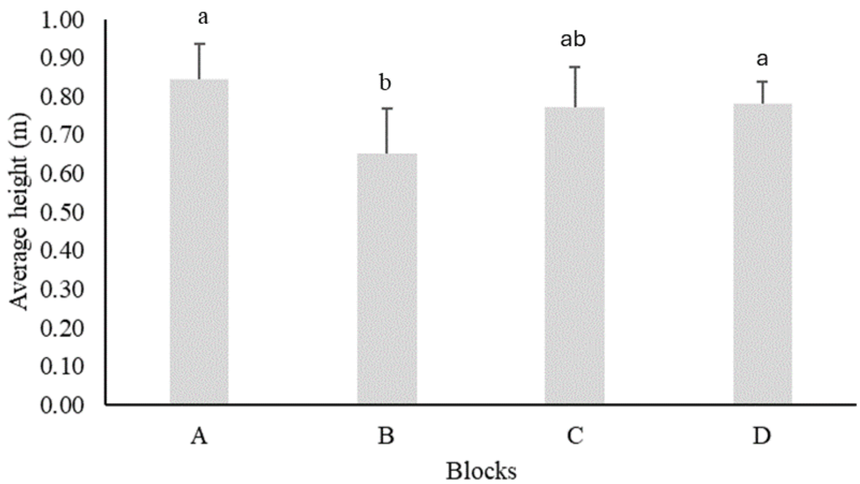

Figure 5. Average height (m) with 4 blocks for corn cultivation obtained from images captured by an unmanned aerial vehicle (UAV). Source: Authors, 2023.

On the other hand, when we analyzed by treatments (Figure 6), no significant statistical difference was observed between them, however it can be observed that treatment 10 had the lowest standard deviation, indicating greater uniformity between the results.

Furthermore, the height values were less than 0.8 m in all treatments evaluated, different from what was observed between the blocks, where block A had an index greater than 0.8 m (Figure 5). It is also possible to observe that the standard deviation of the treatments were higher than the standard deviation observed in the blocks. This demonstrates greater variability of data between treatments.

The average plant height between treatments was 0.7 to 0.8 m, thus DMS proved to be efficient for estimating corn height in the field, corroborating Ferraz et al. (2022). The authors determined the height of corn plants using images from a remotely piloted aircraft and did not observe a statistically significant difference between the results from aerial images and manual collection in the field.

The use of UAVs in agriculture makes it possible to collect data in places that are difficult to access and with precision (Ferraz et al., 2022) and through digital models it allows the monitoring of crops in the field at all stages, and the evaluation of other parameters such as productivity and physiological data (Neto et al., 2023).

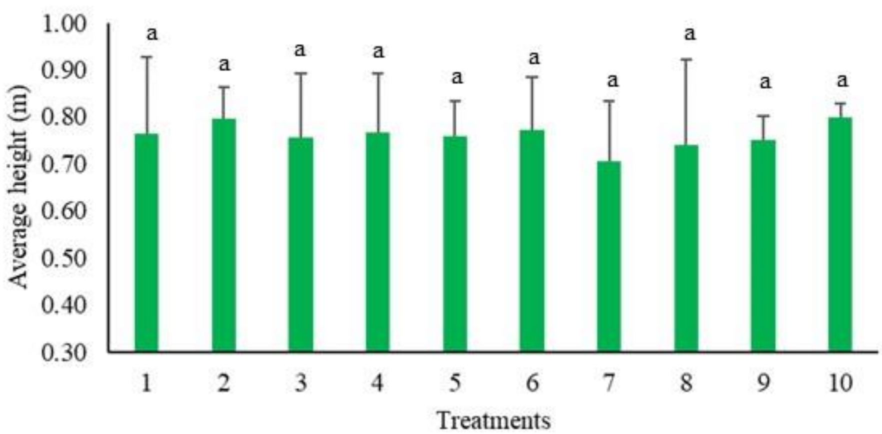

Figure 6. Average height values (m) in relation to treatments. Source: Authors, 2023.

4. Conclusions

The determination of plant height through UAV images demonstrated in this study, a viable and efficient alternative that can help in decision making or make it possible to monitor corn cultivation in places with difficult access, where agricultural machinery, for example, can damage the crops plants.

5. Acknowledgments

To the UniBRAS University Center Rio Verde, Rio Verde, Goiás, Brazil.

6. Authors'Contributions

Jefferson Peres de Oliveira: study design, writing, imaging, data search and presentation of results. *André Luiz Ferreira Oliveira:* study design, drone manipulation, writing and reading the study. *Hugo Manoel de Souza*: data collection and data analysis. *Igor Vinícius dos Santos Araújo*: drone flights and data collection. *Daniel Noe Coaguila Nuñez*: statistical collection and analysis, guidance and supervision, writing, reading, translation and publication.

7. Conflicts of Interest

No conflicts of interest.

8. Ethics Approval

Not applicable.

9. References

Box, G. E. P., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society*. Series B (Methodological), 26(2), 211-252. https://doi.org/10.1111/j.2517-6161.1964.tb00553.x

Bruin, J., & Pedersen, P. (2004). Early season scouting; extension and outreach. IC-492:7; Iowa State University: Ames, IA, USA, 33-34.

Climatempo. *Climatologia e histórico de previsão do tempo em Montividiu, BR*. Available in: https://www.climatempo.com.br/climatologia/2740/montividiu-go. Access in November 08, 2023.

Conab. (2022). Companhia Nacional De Abastecimento. *Acompanhamento da safra brasileira – Grãos*: *safra 2021/2022*. 12º Levantamento, 9(12), 51 p.

Conab. (2023). Companhia Nacional De Abastecimento. *Acompanhamento da safra brasileira – Grãos*: *safra 2022/2023*. 12ª Levantamento, 10(12), 58 p.

Cruz, C. B. M., Barros, R. S., Cardoso, F. V., Reis, F. B., Rosário, L. S., Barbosa, S. S, Rabaco, L. M. L., & Lourenço, J. S. Q. (2011). Avaliação da exatidão planialtimétrica dos modelos digitais de superfície (MDS) e do terreno (MDT) obtidos através do LIDAR. *In*: Anais XV Simpósio Brasileiro de Sensoriamento Remoto - SBSR, Curitiba: INPE, 5463 p.

Ferraz, M. A. J., Pereira, J. L. A. R., Ferraz, G. A. J., & Santos, N. L. R. C. (2022). Determinação de altura de plantas de milho através da análise de imagens aéreas obtidas com ARP. *Brazilian Journal of Development*, 8(1), 6900-6917. https://doi.org/10.34117/bjdv8n1-465

Ferreira, E. B., Cavalcanti, P. P., & Nogueira, D. A. (2014). ExpDes: An R Package for ANOVA and Experimental Designs. *Applied Mathematics*, 05(19), 2952-2958. https://www.scirp.org/html/4-7402250_51204.htm

Fitz, P. R. (2008). *Geoprocessamento sem compilação*. São Paulo: Oficina de Texto.

García-Martínez, H., Flores-Magdaleno, H., Ascencio-Hernández, R., Khalil-Gardezi, A., Tijerina-Chávez, L., Mancilla-Villa, O. R., & Vázquez-Peña, M. A. (2020). Corn Grain Yield Estimation from Vegetation Indices, Canopy Cover, Plant Density, and a Neural Network Using Multispectral and RGB Images Acquired with Unmanned Aerial Vehicles. *Agriculture (Switzerland)*, 10(277). https://doi.org/10.3390/agriculture10070277

Henrique, I. G., Bosqueiro, R. O., Kotsubo, R. M., & Botelho, S. C. C. (2021). Déficit hídrico e a germinação de sementes de híbridos de milho. *Nativa*, 9(3), 240-246. https://doi.org/10.31413/nativa.v9i3.9686

Liu, T. D. J., Shanga, J., Ma, B. Q. B., Kovacs, J. M., Waltersb, D., Jiao, X., Genga, X., & Shia, Y. (2019). Assessment of red-edge vegetation indices for crop leaf area index estimation. *Remote Sensing of*

Environment, 222, 133-143. https://doi.org/10.1016/j.rse.2018.12.032

Lopes, J. R. F., Dantas, M. P., & Ferreira, F. E. P. (2019). Variabilidade da precipitação pluvial e produtividade do milho no semiárido brasileiro através da análise multivariada. *Nativa*, 7(1), 77-83. https://doi.org/10.31413/nativa.v7i1.6243

Nakarmi, A. D., & Tang, L. (2014). Within-row spacing sensing of maize plants using 3D computer vision. *Biosystems Engeenering*, 125, 54-64. https://doi.org/10.1016/j.biosystemseng.2014.07.001

Nascimento, R. T., Pavan, B. E., Guerra, E. D., & Lima, F. N. (2014). Seleção em variedades de milho crioulo no sul do Piauí. *Nativa*, 2(2), 114-118. https://doi.org/10.31413/nativa.v2i2.1500

Neto, E. V. L., Silva, A. V., Silva, J. H. B., Silva, C. M., Costa, T. R. S., & Mielezrski, F. (2023). Índices espectrais de vegetação no monitoramento do milho (*Zea mays* L.) submetidos à bioestimulantes. *Nativa*, 11(3), 323-330. https://doi.org/10.31413/nat.v11i3.13779

Olson, D., Chatterjee, A, Franzen, D. W., & Day, S. S. (2019). Relationship of drone-based vegetation indices with corn and sugarbeet yields. *Soil Fertility and Crop Nutrition*, 111(5), 2545-2557. https://doi.org/10.2134/agronj2019.04.0260

Passos, E. G. C, Xavier, A. R., Neves, L. O., Masiero, F. C., & Araújo, J. C. (2019). Uso de imagens aéreas obtidas por drone no monitoramento do desenvolvimento da cultura do milho. *In*: XII MICTI e VI IFcultura.

Pereira, C. S., Giese, E., Fiorini, I. V. A., & Lange, A. (2018). Épocas de semeadura de milho na região norte de Mato Grosso. *Nativa*, 6(3), 241-245. https://doi.org/10.31413/nativa.v6i3.5471

Pessi, D. D., José, J. V., Mioto, C. L., & Silva, N. M. (2020). Aeronave remotamente pilotada de baixo custo no estudo de plantas invasoras em áreas de cerrado. *Nativa*, 8(1), 66-80. https://doi.org/10.31413/nativa.v8i1.8433

Team, R. D. C. (2018). A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria. Available online at https://www.r-project.org/

Tsouros, D.C., Bibi, S., & Sarigiannidis, P. (2019). A review on uav-based applications for precision agriculture. *Information*, 10(349), 1-26. https://doi.org/10.3390/info10110349

Varela, S., Dhodda, P. R., Hsu, W. H., Vara Prasad, P. V., Assefa, Y., Peralta, N. R., Griffin, T., Sharda, A., Ferguson, A., & Ciampitti, I. A. (2018). Early-season stand count determination in corn via integration of imagery from unmanned aerial systems (UAS) and supervised learning techniques. *Remote Sensing*, 10(343), 1-14. https://doi:10.3390/rs10020343

Funding

Not applicable.

Intitutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.