ICPA 17th INTERNATIONAL CONFERENCE ON PRECISION AGRICULTURE
ConBAP 2026 CONGRESSO BRASILEIRO DE AGRICULTURA DE PRECISÃO E DIGITAL
13-16 July 2026 | Porto Alegre, Brazil

SELECTION OF UAV-BASED VEGETATION INDICES FOR THE PREDICTION OF LEAF CHLOROPHYLL CONTENT IN MAIZE USING A NORMALIZED PARTIAL LEAST SQUARES REGRESSION (PLSR) REDUCTION APPROACH

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A paper from the Proceedings of the

17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture

13-15 July 2026

Porto Alegre, Brazil

Abstract. *The accurate monitoring of the nutritional status is essential for optimizing nitrogen (N) fertilization and maximizing maize grain yield. Variations in N availability directly affect agronomic parameters such as leaf chlorophyll content, which can be estimated using optical sensors. This study assessed the effects of urease inhibitors and nitrogen application rates on leaf chlorophyll content and predicted total leaf chlorophyll content in maize using relevant vegetation indices under field conditions. The experiment was conducted under field conditions at the Agronomic Experimental Station of UFRGS (Federal University of Rio Grande do Sul), in Eldorado do Sul, southern Brazil, using the hybrid DKB 358 sown on October 23rd, 2025, in a randomized block design with four replications, totaling 40 experimental plots. Treatments consisted of three nitrogen rates (90, 180 and 360 kg N ha* $^{-1}$*) applied at V13 (thirteen fully developed leaves) and R1 (flowering) growth stages, combined with different nitrogen sources (conventional urea and two commercial urease inhibitors). Total leaf chlorophyll content using a hand-held chlorophyll meter model CFL2060 (Falker Automação Agricola Ltda.) was measured from four leaves per plot, with two readings per leaf. Image acquisition was carried out using a DJI Phantom 4 RTK multispectral drone, equipped with sensors that capture the bands blue (450 nm ± 16 nm), green (560 nm ± 16 nm), red (650 nm ± 16 nm), red-edge (730 nm ± 16 nm) and near-infrared - NIR (840 nm ± 26 nm). Flight height above ground level was 35 meters, with 75% frontal and 75% side overlap and pixel size of 2 cm. Twenty-one vegetation indices were extracted from multispectral images and subsequently selected using a normalized Partial Least Squares Regression (PLSR) reduction method to compose a new reduced input dataset with the most relevant spectral bands. The PLSR algorithm was used to train (70% of the dataset) and test (30% of the dataset) the leaf chlorophyll estimation model. For the vegetative growth stage V13, the model achieved a coefficient of determination (* R^2*) of 0.70 and a Root Mean Square Error (RMSE) of 3.10. In the reproductive stage (R1-flowering), the model obtained a* R^2 *of 0.76 and an RMSE of 3.68. The vegetation indices most associated with leaf chlorophyll variation during the vegetative stage (V13) were the Normalized Difference Red-Edge Vegetation Index (NDRE), the Normalized Difference Vegetation Index (NDVI), and the Green Leaf Index (GLI), whereas during the reproductive stage the most relevant indices were NDRE, Excess Red Minus (EXRM), and Soil-Adjusted Vegetation Index (SAVI). These results indicate that spectral indices, particularly those sensitive to the red-edge region, can support the prediction of leaf chlorophyll content and contribute to more precise nitrogen management in maize.*

Nogueira, B. S., Bender, E., de Carvalho, D. A., Salem, M. C., Muller, L. E., Gonçalves Junior, S. R. S., Souza, G. E., Klassmann, J. V. M., Gallo, B. B., Bredemeier, C. (2026). Selection of UAV-based vegetation indices for the prediction of leaf chlorophyll content in maize using a normalized partial least squares regression (PLSR) reduction approach. In Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture and Brazilian Congress on Precision and Digital Agriculture.

Keywords.
nitrogen management, Urease inhibitors, machine learning, Precision agriculture

Introduction

Urea is the main nitrogen (N) source used in maize cultivation due to its high N content (approximately 44%) and low cost (Lara-Cabezas et al. 1997). However, losses through ammonia volatilization can reduce its agronomic efficiency (Pan et al. 2016). The use of urease inhibitors is a strategy to slow urea hydrolysis and improve nitrogen availability to plants (Cantarella et al. 2018).

Nitrogen is directly related to leaf chlorophyll content, which is widely used as an indicator of crop nutritional status (Schlemmer et al. 2005). Traditional methods for chlorophyll assessment are limited in terms of scale and efficiency, whereas the use of multispectral sensors enables the extraction of vegetation indices sensitive to changes in canopy structure and pigment content, allowing indirect estimation of plant nutritional status and chlorophyll content (Broge and Leblanc 2001; Gitelson Gritz and Merzlyak, 2003).

In general, the most used vegetation indices include the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), Normalized Difference Red Edge (NDRE) (Barnes et al., 2000) and Soil-Adjusted Vegetation Index (SAVI) (Huete 1988). In addition, machine learning methods, such as Partial Least Squares Regression (PLSR), allow these relationships to be modeled with greater accuracy (Wold Sjöström and Eriksson 2001). Thus, the present study aims to evaluate the effects of urease inhibitors and nitrogen rates on leaf chlorophyll content and to predict total leaf chlorophyll content in maize using relevant vegetation indices under field conditions.

Material and Methods

The experiment was conducted in Area 11 of the Federal University of Rio Grande do Sul Experimental Agronomic Station (EEA), located in the municipality of Eldorado do Sul, RS, Brazil (30°06'39.3"S 51°40'51.5"W), on BR-290 Highway, Country Club 1 – km 146, Eldorado do Sul, RS, 92990-000.

A randomized block design with four replications was adopted, totaling 40 experimental plots. The treatments consisted of nitrogen (N) topdressing rates distributed into two main ranges (90 kg N/ha and 180 kg N/ha) and one complementary range with phosphorus (P) treated with rates of 180 kg N/ha and 360 kg N/ha. In the main ranges, six treatments were evaluated: white urea, 3 kg Volit, 2 kg Volit, 2.5 kg Prokit, commercial treatment, and no N application (control). In the range with treated P, only the 3 kg Volit treatment was evaluated at two rates (180 kg and 360 kg N/ha).

Sowing was carried out on 10/23/2025 at the Experimental Agronomic Station (EEA), using the maize variety DKB 358, sown in five rows with 0.5 m spacing. After emergence, the plots were delimited to an area of 5 m², maintaining a population of 4 plants/m² (approximately 100 plants per plot). Image acquisition was performed using a DJI Phantom 4 RTK Multispectral equipped with sensors capable of capturing the Blue (450 nm ± 16), Green (560 nm ± 16), Red (650 nm ± 16), Red-Edge (730 nm ± 16), and NIR (840 nm ± 26) spectral bands. The flight was conducted at an altitude of 35 m, with 75% frontal and lateral overlap, generating an image per each spectral band. The NDVI data were obtained using the GreenSeeker active sensor, which emits light in two spectral ranges (red and near infrared), using the formula described in table 1.

This measurement was performed by passing the sensor through the center of each plot and recording the average value obtained (Fig. 1).

Figure 1. Methodology used: (a) planted maize field area; (b) NDVI acquisition using the GreenSeeker sensor; (c) calibration and multispectral imaging; (d) Experimental plots subjected to different nitrogen (N) rates and urease inhibitors captured by drone.

Image processing was performed using the Agisoft Metashape® software to generate orthomosaics, which were associated with information from eight ground control points generated by GNSS-RTK to perform geometric correction of the images. Spectral information was extracted from orthomosaics (multispectral image) using the QGIS software through the raster calculator plugin for the calculation of twenty-one vegetation indices to characterize the spectral response of the crop. The indices with the highest importance for prediction are presented in Table 1.

To remove redundancy among variables and identify the most relevant vegetation indices, a Partial Least Squares Regression (PLSR) variable reduction approach was applied. Variable Importance in Projection (VIP) scores derived from the PLSR model were used to rank the contribution of each vegetation index to chlorophyll prediction. The highest-ranked indices were subsequently selected as inputs for the final predictive model.

The dataset was divided into two subsets, with 70% of the samples used for model training and the remaining 30% used for testing predictive performance. Model efficiency was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE), metrics used to assess, respectively, the explanatory capacity and the accuracy of the estimates generated by the model. Processing was done in Python, using library packages of pandas, numpy, matplotlib, seaborn, scikit-learn, imbalanced-learn, scipy and statsmodels.

Table 1. Vegetative indices with the highest importance values for prediction.

Type	Index	Equation
	Green Leaf Index (GLI) (Hunt 2013)	(2G - R - B) / (2G + R + B)

RGB	Raw Excess Green minus Raw Excess Red (ExGR) (Meyer and Neto 2008)	ExG - ExR
RE-NIR	Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974)	(NIR - R) / (NIR + R)
	Soil-Adjusted Vegetation Index (SAVI) (Huete 1988)	[(NIR - R) (1 + L)] / (NIR + R + L)
	Normalized Difference Red Edge Index (NDRE) (Barnes et al. 2020)	(NIR - RE) / (NIR + RE)

*R = red; G = green; B = blue; RE = red edge; NIR = near infrared

Results and Discussion

At the vegetative stage V13, the model showed a coefficient of determination (R^2) of 0.70, and a root mean square error (RMSE) of 3.10 (Fig 2a). In the reproductive stage (R1 – flowering), the model achieved an R^2 of 0.76 and an RMSE of 3.68 (Fig. 2b). The higher R^2 observed during the reproductive stage suggests that the relationship between spectral response and chlorophyll content became more consistent at flowering. During this stage, structural changes in the canopy become more pronounced, especially among plots subjected to different nitrogen conditions. In addition, the reproductive stage corresponds to the period in which the crop canopy reaches maximum vegetative development, factors that can influence reflectance patterns and increase spectral variability (Hatfield et al. 2008).

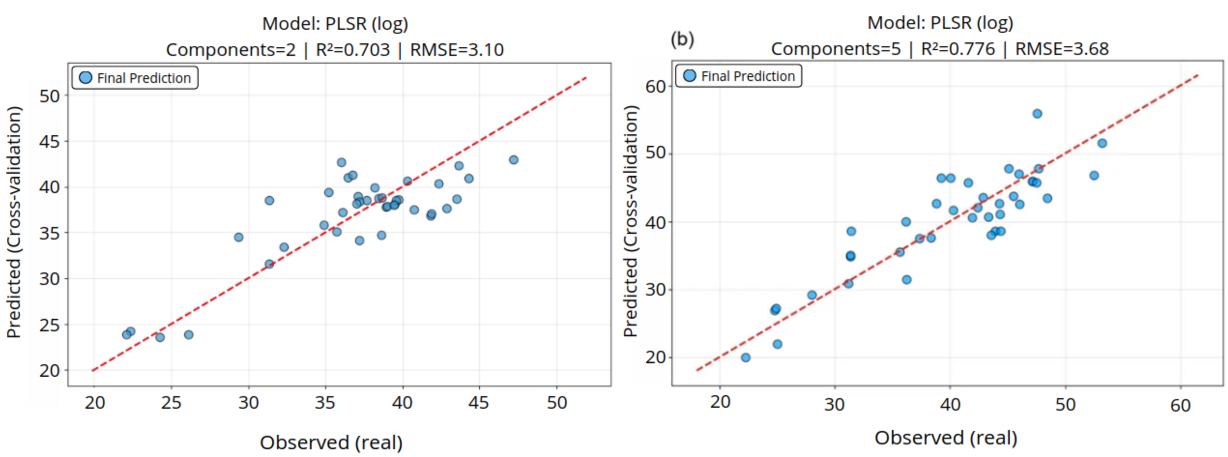

Figure 2. Predictions performance of the PLSR model for chlorophyll content across two acquisition dates: (a) V13 vegetative stage and (b) R1-flowering stage.

Regarding the importance of vegetation indices at the V13 stage, the indices most strongly associated with variation in leaf chlorophyll content were the Normalized Difference Red Edge Index (NDRE), the Normalized Difference Vegetation Index (NDVI), and the Green Leaf Index (GLI) (Table 1) and (Fig 3a). In the reproductive stage, the most relevant indices were NDRE, Excess Red Minus (EXRM), and the Soil-Adjusted Vegetation Index (SAVI) (Table 1) and (Fig. 3b)

At the vegetative stage (V13), NDRE, NDVI, and GLI showed stronger relationships with chlorophyll content because of their greater sensitivity to photosynthetic activity, vegetative vigor, and leaf greenness intensity (Gitelson 2004). Among these indices, NDRE stood out because it uses the red-edge region, which is less susceptible to saturation under conditions of high leaf density and more sensitive to variations in chlorophyll concentration (Gitelson, Gritz, and Merzyak 2003). This spectral region, which corresponds to the transition between the red and near-infrared wavelengths, has been extensively employed to estimate variations in leaf chlorophyll content and to serve as an indicator of vegetation stress (Cho and Skidmore 2006).

During the reproductive stage, the greater importance of NDRE, EXRM, and SAVI was associated with their lower susceptibility to band saturation caused by increased biomass and the onset of leaf senescence (Gitelson 2004). Under these conditions, indices related to the red-edge region, pigment variation, and soil influence tend to provide better performance and improved accuracy in chlorophyll estimation (Delegido et al. 2011).

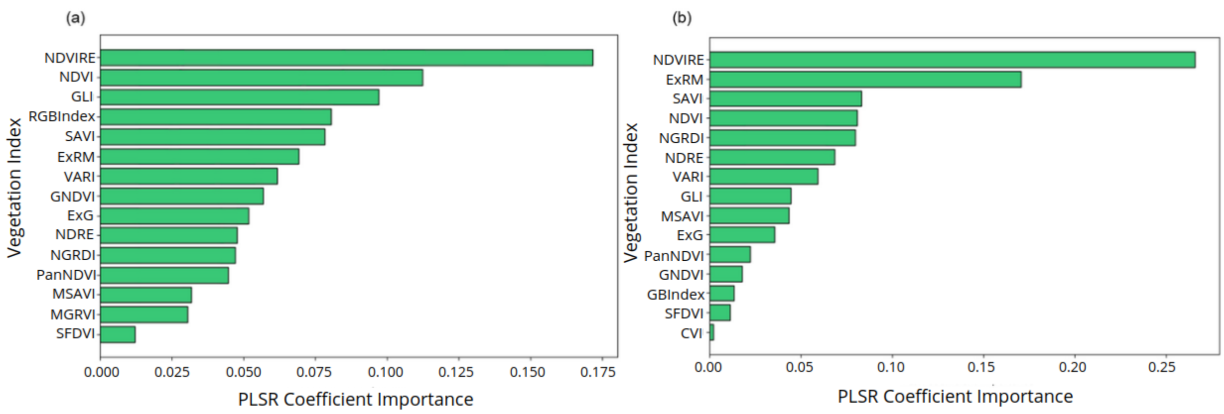

Figure 3. Coefficients of importance of the PLSR model for vegetation indices (VIs) at two acquisition dates: (a) V13 vegetative stage and (b) R1 flowering stage.

Conclusion

These results indicate that spectral indices, especially those related to the red-edge region, have good potential for predicting leaf chlorophyll content, because they are sensitive to changes in the physiological condition of the plants. Thus, these indices can help improve the monitoring of nitrogen status in maize. In this way, their use may contribute to more accurate nitrogen management, increasing fertilizer efficiency, and supporting more sustainable crop production.

Acknowledgements

This work has been partially funded by the project AgroSAT supported by the **Center for Embedded Devices and Research in Digital Agriculture (CEDRA) of SENAI-RS**, with financial resources from the PPI IoT/Manufatura 4.0 / PPI HardwareBR of the MCTI, grant number 053/2023, signed with EMBRAPII.

References

Barnes, E. M., Clarke, T. R., Richards, S. E., Colaizzi, P. D., Haberland, J., Kostrzewski, M., et al. (2000). Coincident detection of crop water stress, nitrogen status, and canopy density using ground-based multispectral data. In *Proceedings of the Fifth International Conference on Precision Agriculture* (pp. 1–10). Bloomington, MN, USA.

Broge, N. H., & Leblanc, E. (2001). Comparing prediction of power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. *Remote Sensing of Environment, 76*(2), 156–172.

Cantarella, H., Otto, R., Soares, J. R., & Silva, A. G. B. (2018). Agronomic efficiency of NBPT as a urease inhibitor: A review. *Journal of Advanced Research, 13*, 19–27.

Cho, M. A., & Skidmore, A. K. (2006). A new technique for extracting the red edge position from hyperspectral data: The linear extrapolation method. *Remote Sensing of Environment, 101*(2), 181–193.

Delegido, J., Verrelst, J., Alonso, L., & Moreno, J. (2011). Evaluation of Sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. *Sensors, 11*, 7063–7081.

Gitelson, A. A. (2004). Wide dynamic range vegetation index for remote quantification of crop biophysical characteristics. *Journal of Plant Physiology, 161*(2), 165–173.

Gitelson, A. A., Gritz, Y., & Merzlyak, M. N. (2003). Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *Journal of Plant Physiology, 160*, 271–282.

Hatfield, J. L., Gitelson, A. A., Schepers, J. S., & Walthall, C. L. (2008). Application of spectral remote sensing for agronomic decisions. *Agronomy Journal, 100* (Suppl. 3), S117–S131.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment, 25*(3), 295–309.

Hunt, E. R., Jr., Doraiswamy, P. C., McMurtrey, J. E., Daughtry, C. S. T., Perry, E. M., & Akhmedov, B. (2013). A visible band index for remote sensing leaf chlorophyll content at the canopy scale. *International Journal of Applied Earth Observation and Geoinformation*, 21, 103–112.

Lara-Cabezas, W. A. R., Korndörfer, G. H., Motta, S. A., & Santana, D. G. (1997). Volatilização de N-NH3 na cultura de milho: I. Efeito da irrigação e substituição parcial da ureia por sulfato de amônio. *Revista Brasileira de Ciência do Solo, 21*, 481–487.

Meyer, G. E., & Neto, J. C. (2008). Verification of color vegetation indices for automated crop imaging applications. *Computers and Electronics in Agriculture*, 63(2), 282–293.

Pan, B., Lam, S. K., Mosier, A., Luo, Y., & Chen, D. (2016). Ammonia volatilization from synthetic fertilizers and its mitigation strategies: A global synthesis. *Agriculture, Ecosystems & Environment, 232*, 283–289.

Rouse, J. W., Jr., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *Proceedings of the Third Earth Resources Technology Satellite-1 Symposium*, 1, 309–317.

Schlemmer, M. R., Francis, D. D., Shanahan, J. F., & Schepers, J. S. (2005). Remotely measuring chlorophyll content in corn leaves with differing nitrogen levels and relative water content. *Agronomy Journal, 97*, 106–112.

Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS regression: A basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems*, 58(2), 109–130.