https://dx.doi.org/10.22161/ijaers.69.5 ISSN: 2349-6495(P) | 2456-1908(O)

Monitoring of Corn Growth Stages by UAV Platform Sensors

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***Abstract*— *Increasing agricultural productivity with economic and environmental sustainability is one of the main challenges in agriculture. The aerial survey platforms known as unmanned aerial vehicles (UAV), so-called drones, allow monitoring, evaluation, and decision support activities to improve the management of crops and herds in farms of any production scale. Vegetation indices are used to map the vegetation cover, mainly on a large scale, using satellite images. However, sensors coupled to UAV platforms provide other indices that can be used to detect the stress load of vegetation at more precise spatial scales. The Visible Atmospherically Resistant Index - VARI and the Green Leaf Index - GLI showed similar performances in the initial vegetative stages of corn crop. Both indices were sensitive to class discrimination at intervals that indicate from bare soil and low vigor (shades of red, orange, and yellow) to the condition of high vegetation vigor (shades of green). The results of vegetation indices in the visible spectrum range prove the applicability of the method for data collection and information extraction related to development and growth of crops. Overall, the indices VARI and GLI appear as a potential alternative for crop monitoring using low cost RGB sensors onboard UAV platforms.*

***Keywords*— *Corn, UAV, Vegetation Index, Remote Sensing*.**

I. INTRODUCTION

In recent years, interest in automated techniques and procedures to monitor crop growth and development has grown greatly [1, 2, 3]. It seems that the next agricultural revolution will be driven by intelligent use of data that can affect productivity growth and contribute to environmental sustainability. This will be achieved through the rational use of resources, especially in the field of food production and land use. In the agricultural sector, the great leap in robotics is becoming clearer, providing interesting and effective solutions for increasing productivity by means of crop monitoring [4].

The use of unmanned aerial vehicles (UAVs) or drones in farms is becoming increasingly evident. The equipment has emerged from a military past and is currently assisting farmers in activities such as cargo transportation (fertilizers or pesticides), and both cattle and crop monitoring. In relation to orbital platforms, UAVs stand out in the so-called smart farms, as they effectively generate data for information extraction from a close panoramic view of the fields, i.e., they allow to assess the crop status more accurately [5].

Crop monitoring with UAVs can assist the farmer in planning and decision making by paying attention to planting characteristics and soil and climate conditions. Productivity may vary due to sowing time, climate characteristics, management, soil heterogeneity [6], weed infestation [7, 8], water stress [9], stand failure [10], and diseases [3].

UAV platforms are lightweight, low-cost aircrafts operated from the ground and can carry sensors for imaging. The most common sensors are those that collect data in the visible range (RGB sensors). However, there is a variety of sensors, including those that capture information only in the near infrared and thermal band or the multispectral type that can extract information in different bands of the electromagnetic spectrum. RGB sensors have a good benefit-to-cost ratio, that is, they allow the generation of spectral indices in the visible range and also allow to extract, from the geoprocessing software, other products such as digital terrain model (MDT), 3D model, orthomosaic images model, volume estimation, and accurate contours.

The advances achieved in recent years have created numerous possibilities of use, showing the importance of the technology for managing the resources used in the field. Therefore, the present study aimed to test the UAV platform coupled to a RGB sensor for monitoring a corn crop at different growth stages.

II. MATERIAL AND METHODS

The experimental area is located in the municipality of Coronel Pacheco-MG, at the José Henrique Bruschi Experimental Field (CEJHB) belonging to Embrapa Dairy Cattle (Figure 1). In this area, Fluvic Neosol (terrace) predominates, with flat relief and varied texture, which are typical of colluvial-alluvial floodplains. The relief forms of the municipality of Coronel Pacheco, MG, consist of 10% flat area, another 10% mountainous, and 80% undulating. The maximum and minimum altitudes are 1,070 m and 409 m, respectively. The municipal headquarters is at 484 m of altitude. The altitude of the corn planting area is around the minimum of the municipality (Figure 1).

The climate of the region is Aw, i.e., tropical with dry winter, according to the Köppen-Geiger classification. Based on the climatological normals of the National Institute of Meteorology (INMET) for the period 1981 to 2010, the average annual air temperature is 21.4ºC and the average annual precipitation volume is 1620.6 mm. The months of July (12.6 mm) and January (355.1 mm) have the lowest and highest rainfall, respectively.

Corn (hybrid RB 9308 VTPRO - Riber KWS) was sown on April 7, 2018. Planting was carried out at spacing of 80 cm between rows and 4.6 seeds per meter to establish a stand of 57.5 thousand plants per hectare, totaling about 310,000 seeds in the area of 5.39 hectares.

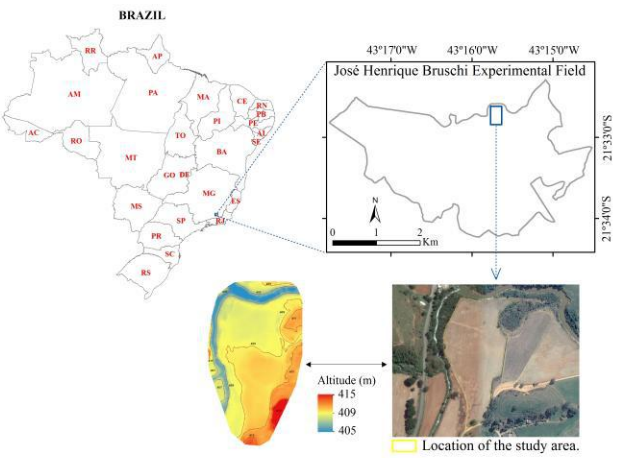

Fig. 1: Location of the study area in the José Henrique Bruschi Experimental Field (CEJHB), Embrapa Dairy Cattle, municipality of Coronel Pacheco, MG.

The aerial survey activities were carried out on April 26, 2018 and May 24, 2018. A rotary-wing UAV Inspire 1 Pro Quadcopter (Figure 2), with exchangeable cameras [from RGB (Red, Green, Blue) to multispectral sensors]. A RGB DJI Zenmuze X5 camera was used for imaging in the visible range. The high precision RGB sensors allowed the evaluation of the planting conditions through the procedures for quantitative measurement of vegetation and the qualitative evaluations through vegetation indices operating in the visible range of the electromagnetic spectrum.

Fig. 2: UAV Inspire 1 Pro flying over cultivated corn crop field. Photo: Marcos La Falce.

Flight plans were created following a standard technical compliance so that the survey results or products could be compared on a similar basis, equalizing variables such as flight height, ground sample distance (GSD), sensor calibration, percentage of image overlap, wind speed, brightness, shadow placement, time of day, angle of view, sun positioning, etc.

The flight plan parameters were set as follows: (i) 90 m flight height; GSD of 2.27 cm; maximum speed 15 m/s, flight time 9.5 minutes on battery use; images had 75% frontal overlap and 85% side overlap. Based on this flight plan configuration, 7 flight lines and 146 images were required to cover the entire area and subsequently generate the orthomosaic model using software Pix4D Mapper Pro 4.125.

Crop vigor, invasive plants, stand failures, and yield were analyzed using the selected vegetation indices according to characteristics and applicability of the visible spectrum Red-Green-Blue (RGB) bands.

Vegetation indices are widely used in studies to identify vegetation stress. These indices may thus assist in classifying targets, for example, separating normal developing vegetation from planting areas affected by pest, diseases, plant nutrient deficiencies, soil nutrient

https://dx.doi.org/10.22161/ijaers.69.5 ISSN: 2349-6495(P) | 2456-1908(O)

deficiencies, damage caused by wildlife such as capybaras (Hydrochoerus hydrochaeris), and others [5].

In the present study, we used the indices VARI (Visible Atmospherically Resistant Index [11]) and GLI (Green Leaf Index [12]) to indicate stress load of vegetation. VARI was developed to reduce possible influences of atmospheric effects by subtracting the blue channel band in the denominator of Equation 1. GLI (Equation 2) has been applied to distinguish photosynthetically active vegetation from dry vegetation with bare soil.

$$VARI = \frac{\rho_{Green} - \rho_{\mathrm{Red}}}{\rho_{Green} + \rho_{\mathrm{Red}} - \rho_{Blue}} \quad (1)$$

$$GLI = \frac{(2\,\rho_{Green} - \rho_{\mathrm{Red}} - \rho_{Blue})}{(2\,\rho_{Green} + \rho_{\mathrm{Red}} + \rho_{Blue})} \quad (2)$$

Where ρ_{Green}, ρ_{Red} and ρ_{Blue} are the spectral bands for the green, red, and blue channels, respectively.

III. RESULTS AND DISCUSSION

The vegetation indices showed the vegetation health and status of the plants at the imaging dates. The results on imaging using RGB cameras onboard the UAV platform are presented in this section. Each class interval defined for the vegetation indices had the area (ha) and the percentage (%) of cover estimated in relation to the total planting area.

As Table 1 shows, the VARI index had intervals of negative values in most of the area (~ 90%). The GLI index had only one class interval with negative values, however, it covered 1.38 ha or 25.58% of the total area. These results indicate little vegetation cover or wide bare soil area. On April 26, 2018, the corn crop was at 19 days after sowing, that is, between the second leaf (V2) and fourth leaf (V4) phenological stages. Subdivisions of the vegetative stages are designated as V1 through Vn, where n represents the stage with the last fully expanded leaf before Vt (tasseling) [13].

Figure 3A shows the mosaic of RGB images (visible bands). Areas with bare soil predominate. Corn planting rows start to appear in small areas on the north and south edges. The central region concentrates most of the negative values of class intervals for the VARI and GLI indices, with the yellow, orange, and red classes in the VARI index (Figure 3B) and the orange and red classes in the GLI index (Figure 3C). The indices indicate the nonuniformity of crop development from the early vegetative stages. In this case, it may have been influenced by water variability or the chemical and physical constituents of the soil. Soil analyses may clarify this issue.

Vegetation indices can assist in identifying areas of the crop with normal development or with some deficiency. According to Hunt Jr. et al. [12], vegetation indices have fundamental application in the extraction of information from remote sensing data; however, these methods can mitigate, but not eliminate, the effects of soils, topography, and view angle.

Table 1. Class intervals of vegetation indices VARI (Visible Atmospherically Resistant Index) and GLI (Green Leaf Index) with respective areas, as percentage, for the aerial survey on April 26, 2018

Class	Vegetation indices					
	VARI			GLI		
	Class intervals	Area (ha)	Percentage	Class intervals	Area (ha)	Percentage
(dark green)	0.02 to 0.53	0.08	1.56	0.10 to 0.48	0.04	0.66
(light green)	-0.05 to 0.01	0.60	11.09	0.04 to 0.09	0.21	3.84
(yellow)	-0.09 to -0.06	2.14	39.41	0.02 to 0.03	1.12	20.66
(orange)	-0.12 to -0.10	1.96	36.18	0.00 to 0.01	2.67	49.26
(red)	-0.62 to -0.13	0.64	11.75	-0.27 to -0.01	1.38	25.58

The VARI and GLI vegetation indices calculated for the aerial survey carried out on 24/05/2018 showed positive class intervals in more than 85% of the planting area (Table 2). Of the total area (5.39 ha), only 13.13% (0.72 ha) and 14.78% (0.78 ha) were classified with negative intervals using the VARI and GLI indices, respectively.

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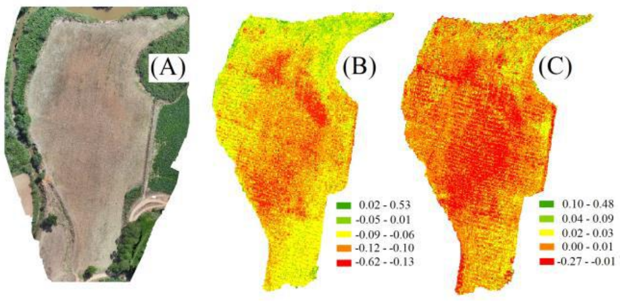

Fig. 3: RGB mosaic image (A) and class interval ranges for the vegetation indices VARI (B) and GLI (C), on April 26, 2018.

Table 2. Class intervals of vegetation indices VARI (Visible Atmospherically Resistant Index) and GLI (Green Leaf Index) with respective areas, as percentage, for the aerial survey on May 24, 2018

Class	Vegetation indices					
	VARI			GLI		
	Class intervals	Area (ha)	Percentage	Class intervals	Area (ha)	Percentage
	0.24 to 0.60	0.76	13.96	0.20 to 0.50	0.53	9.81
	0.18 to 0.23	1.70	31.14	0.16 to 0.19	1.12	20.50
	0.11 to 0.17	1.31	24.05	0.12 to 0.15	1.53	28.10
	0.02 to 0.10	0.97	17.72	0.07 to 0.11	1.49	27.31
	-0.21 to 0.01	0.72	13.13	-0.06 to 0.06	0.78	14.78

As can be seen in Figure 4A, the corn canopy has completely closed (47 days after sowing, between stages V8 and V9). However, stand failures are visible, especially in the middle of the area. Comparing the VARI (Figure 4B) and GLI (Figure 4C) maps clearly shows that GLI is more sensitive to green vegetation, which can be explained by the index formula, as the green spectral band has weight 2 relative to the blue and red bands. Thus, positive GLI values represent both green leaf and green stem characteristics.

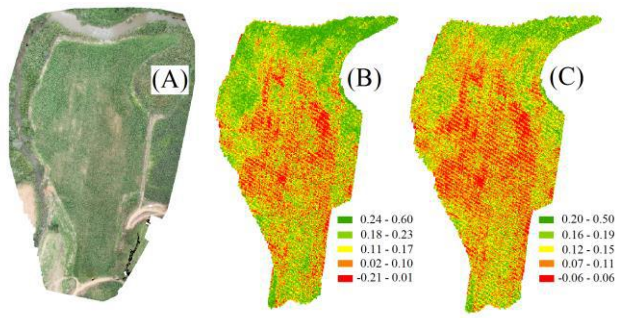

Fig. 4: RGB mosaic image (A) and class interval ranges for the vegetation indices VARI (B) and GLI (C), on May 24, 2018.

IV. CONCLUSION

The vegetation indices VARI and GLI showed similar performance in the initial vegetative stages of the corn crop. The indices were sensitive to class discrimination at intervals that indicate from bare soil and low vigor (shades of red, orange, and yellow) to the condition of high vegetation vigor (shades of green). Overall, the indices VARI and GLI appear as a potential alternative for crop monitoring using low cost RGB sensors onboard UAV platforms.

REFERENCES

[1] Zhang, C.; Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: a review. Precision Agriculture, 13(6), pp. 693-712.

[2] Ribeiro-Gomes, K.; Hernandez-Lopez, D.; Ballesteros, R.; Moreno, M. A. (2016). Approximate georeferencing and automatic blurred image detection to reduce the costs of UAV use in environmental and agricultural applications. Biosystems Engineering, 151, pp. 308-327.

[3] Zhang, D.; Zhou, X.; Zhang, J.; Lan, Y.; Xu, C.; Liang, D. (2018). Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multispectral imaging. PLOS ONE, v. 13(5), e018747, pp. 1-14.

[4] Tripicchio, P.; Satler, M.; Dabisias, G.; Ruffaldi, E.; Avizzano, C. A. (2015). Towards Smart Farming and Sustainable Agriculture with Drones. International Conference on Intelligent Environments. IEEE Computer Society, pp. 140-143. Available at: <https://ieeexplore.ieee.org/document/7194284>. Consulted on: August 13, 2019.

[5] Andrade, R. G.; Hott, M. C.; Magalhaes Junior, W. C. P. de; Oliveira, P. S. d'; Oliveira, J. S. (2019). Uso de veículo aéreo não tripulado (VANT) como plataforma para monitoramento da produção agropecuária: estudo de caso para o milho forrageiro. Juiz de Fora: EMBRAPA Gado de Leite, 20p. (Documentos, 233). Available at: <http://ainfo.cnptia.embrapa.br/digital/bitstream/item/195875/1/DOC-233-Uso-de-VANT-como-plataforma-p-

https://dx.doi.org/10.22161/ijaers.69.5 ISSN: 2349-6495(P) | 2456-1908(O)

monitoram-da-prod-agropecuaria.pdf>. Consulted on: May 17, 2019.

[6] Vieira, S. R.; Gonzalez, A. P. (2003). Analysis of the spatial variability of crop yield and soil properties in small agricultural plots. Bragantia, 62(1), pp. 127-138.

[7] Calha, I. M.; Sousa, E.; González-Andújar, J. L. (2014). Infestation maps and spatial stability of main weed species in maize culture. Planta Daninha, 32(2), pp. 275-282.

[8] Cutti, L.; Lamego, F. P.; Aguiar, A. C. M.; Kaspary, T. E.; Rigon, C. A. G. (2016). Winter cover crops on weed infestation and maize yield. Revista Caatinga, 29(4), pp. 885-891.

[9] Gago, J.; Douthe, C.; Coopman, R. E.; Gallego, P. P.; Ribas-Carbo, M.; Flexas, J.; Escalona, J.; Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. Agricultural Water Management, 153, pp. 9-19.

[10] Pontes, G. R.; Freitas, T. U. (2015). Monitoramento de plantios de eucalipto utilizando técnicas de sensoriamento remoto aplicadas em imagens obtidas por VANT. In: Simpósio Brasileiro de Sensoriamento Remoto - SBSR, 17., 2015, João Pessoa. Anais... João Pessoa: SBSR/INPE, pp. 4057-4064. Available at: <http://www.dsr.inpe.br/sbsr2015/files/p0801.pdf>. Consulted on: August 13, 2019.

[11] Gitelson, A. A.; Stark, R.; Grits, U.; Rundquist, D.; Kaufman, Y.; Derry, D. (2002). Vegetation and soil lines in visible spectral space: a concept and technique for remote estimation of vegetation fraction. International Journal of Remote Sensing, 23(13), pp. 2537-2562.

[12] Hunt Jr., E. R.; Doraiswamy, P. C.; Mcmurtrey, J. E.; Daughtry, C. S. T.; Perry, E. M. (2013). A visible band index for remote sensing leaf chlorophyll content at the canopy scale. International Journal of Applied Earth Observation and Geoinformation, 21, pp. 103-112.

[13] Magalhães, P. C.; Durães, F. O. M. (2006). Fisiologia da produção de milho. EMBRAPA Milho e Sorgo, 10p. (Circular Técnica, 76). Available at: <https://www.infoteca.cnptia.embrapa.br/bitstream/doc/490408/1/Circ76.pdf>. Consulted on: June 03, 2019.