ISSN 2175-6813

Revista Engenharia na Agricultura

Viçosa, MG, DEA/UFV - DOI: 10.13083/reveng.v30i1.13390 v.30, p.166-174, 2022

AERIAL IMAGES TO MONITOR GRAPEVINE VEGETATIVE GROWTH

Janielle Souza Pereira[1]*, Gabriel Araújo e Silva Ferraz[1] & Lucas Santos Santana[1]

1 - Federal University of Lavras, Department of Engineering, Lavras, Mina Gerais, Brazil

Keywords:
Precision agriculture
Plant cover
Planting failure
Grape

ABSTRACT

Images obtained by Remotely Piloted Aircraft (RPA) used to monitor the crop can help evaluate leaf mass, plant formation, and plant population. In this context, the objectives of this study were to analyze plant growth in a grapevine crop trained in the trellis system, detect failures and determine the plant covered area using images obtained by RPA. The flight was parameterized with frontal overlap of 75%, lateral overlap of 70%, Ground Sample Distance (GSD) of 60 m, and flight speed of 5 $m.s^{-1}$, using a sensor in the visible range. Processed images showed a stand 3% smaller than projected, an area covered by vine branches occupying 60.8%, undergrowth and invasives represented 5.3%, and exposed soil 33.9%. Vines were identified in the vegetation indices as green points, invasive plants as yellow points, and exposed soil as red points. Image processing obtained with RPA allowed identification of plants in various stages of development, with predominance of vines in the formation process. It was possible to identify the plants and quantify the leaf mass using the MPRI vegetation index, as well as to differentiate exposed soil from plant material. It was also observed that the plot had an incomplete stand at the time the flight was performed.

Palavras-chave:
Agricultura de precisão
Cobertura vegetal
Falhas no plantio
Uva

IMAGENS AÉREAS PARA MONITORAR O CRESCIMENTO VEGETAL DA VIDEIRA

RESUMO

A utilização de imagens obtidas por aeronaves remotamente pilotadas (ARP) para monitorar a lavoura pode auxiliar na avaliação da massa foliar, formação vegetal e população de plantas. Neste contexto, objetivou-se com este trabalho verificar o desenvolvimento vegetal em área de cultivo de videira conduzido em sistema latada. Além de detectar falhas e determinar a área coberta vegetativa, por meio de imagens obtidas por ARP. Para tanto, realizou-se um voo com sobreposição frontal de 75%, lateral de 70%, distância de amostragem do solo de 60 m e velocidade de voo de 5 $m.s^{-1}$, sendo utilizado sensor na faixa do visível. Foram observadas nas imagens processadas estande 3% inferior ao projetado, área coberta por ramos de videira ocupando 60,8%, enquanto que a vegetação rasteira ou ervas daninhas representou 5,3% e o solo exposto 33,9% da área. Foram identificados nos índices de vegetação as videiras como pontos verde, a vegetação rasteira ou plantas daninhas como pontos amarelos e o solo exposto como pontos vermelhos. Assim, o processamento das imagens obtidas por ARP permitiram observar que a área cultivada apresentava plantas em diversas fases de desenvolvimento, com predominância de videiras em processo de formação, resultando em 60,8% de área coberta com ramos da cultura. A partir das imagens obtidas por ARP foi possível detectar 3% de falhas, resultado coerente com o estado do talhão que possuía estande incompleto no momento de realização do voo.

Received 3 Nov, 2021 • Accepted 17 Jan, 2022 • Published 20 Jun, 2022

Email (corresponding author)*: janielle.engenheira@gmail.com

SECTION EDITOR IN CHARGE
Michael Silveira Thebaldi

INTRODUCTION

Technological innovations have been incorporated into the agricultural sector to increase production efficiency, ensure operational and food safety, and minimize the input of resources and effort (AHMAD *et al*., 2021). Therefore, technologies have assisted agricultural development and become indispensable, including information technology, automated systems, precision agriculture, geographic information system, robotics, and remote sensing monitoring (YU *et al*., 2017).

Remote sensing (RS) is based on using sensors to acquire information of phenomena and objects without requiring direct contact, but capturing and recording the energy emitted and reflected by them (GUEDES & SILVA, 2018). To capture this information, the spectral behavior of the object is verified (CARVALHO NETO & RAMOS FILHO, 2021).

Among the activities that apply the RS procedures to their operation is the monitoring by aerial platforms. Data collected from these platforms favor obtaining more efficient results on pest control, irrigation, optimal fertilization, harvesting and monitoring of the crop (AHMAD *et al*., 2021; DELAVARPOUR *et al*., 2021). Remotely piloted aircrafts (RPA) stand out among these type of devices, which can be equipped with cameras such as thermal, laser, multispectral, hyperspectral, or RGB sensors, each of these having a distinct spectral resolution (GUEDES & SILVA, 2018; SELS *et al*., 2018).

The RPA technology has become a regularly used tool in building digital maps. These maps assist in creating planting lines, differential application of sanitary products, failure detection, total biomass estimation, monitoring development and vegetation index. The device helps to reduce time and costs of data capture, optimizing agricultural operations (PÁTRIA & FREDIANI, 2021; YU *et al*., 2017).

The grapevine cultivation in the Submiddle San Francisco Valley, located between Bahia and Pernambuco can make use of this technology (SILVA *et al*., 2018). Viticulture in this region can produce two harvests per year, in an environment with average annual temperature of 26º C, high luminosity, irregular rainfall and varied pedology (DE SÁ *et al.,* 2015; SOBRAL *et al.,* 2018). The different soil types associated with the quality of seedlings, irrigation conditions, fertilization and seedling establishment can compromise the plant population per hectare and plant development. These conditions interfere with the final crop productivity and as result the grapevine producer less commercially competitive (REIS & REIS, 2016).

In grape cultivation, the introduction of monitoring by RPA imagery can be of key importance. The discovery of new means to monitor growth and identify invasive plants contributes to rapid and accurate decision-making. One of the ways to collect this information is by using images obtained by remotely piloted aircrafts. This technology contributes to detecting missing plants, leaf mass index, plant growth and vegetation index such as the green of the foliage, enabling the producer to make a more appropriate decision for management (JORGE & INAMASU, 2019; PADOLFI *et al*., 2018).

In this context, this study aimed to verify the plant development in a grapevine cultivation area, detect failures, and determine the percentage of the area covered by branches of the crop through ARP images.

MATERIAL AND METHODS

The study was conducted in a farm located in the Submiddle San Francisco Valley, municipality of Petrolina-PE. The climate of the region is BShw, according to Köopen's classification, with low average annual rainfall (435 mm) and high potential evapotranspiration rate (1520 mm) (JATOBÁ *et al.,* 2017).

The study site is located between coordinates 9° 4' 29.230" S and 40° 29' 55.097" W (Figure 1). The soil is classified as Yellow Red Latosol. The area is part of a 40 ha farm of grapevine planted in the trellis system. The plants belong to variety Arra 15: light green, shiny, waxy and crunchy, long berries (SANTOS *et al.,* 2019).

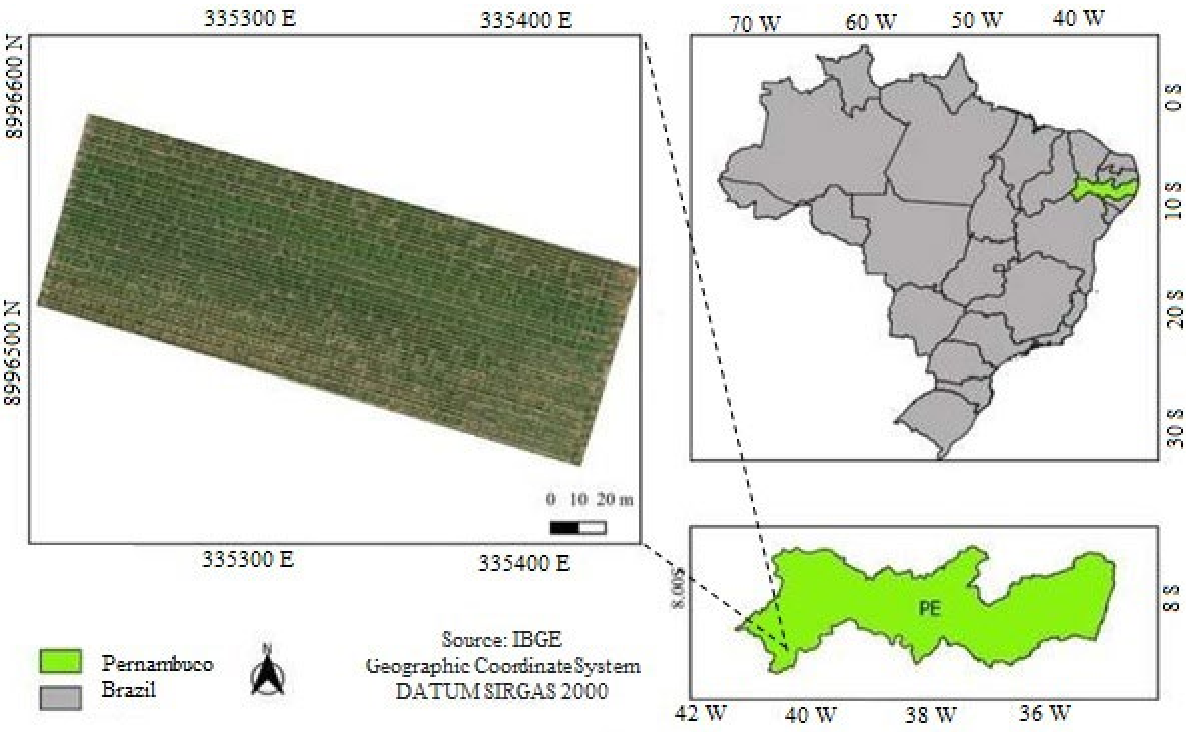

Figure 1. Location of the study site

The plot consisted of 1.38 ha planted with grapevines at the spacing of 2.5 m between plants and 3.5 m between planting rows. It was composed of 20 rows with 79 plants 180 days after planting and 20 days after pruning, a period when individual plants can still be seen.

The images were obtained with a remotely piloted aircraft, DJI's Mavic 2 Pro model. This ARP has a 12MP CMOS sensor coupled to a 20MP RGB camera, a GPS and GLONASS geolocation system and a 31-minute flight autonomy. According to Mendes Santos *et al*. (2019), the flight conditions were evaluated previously, which proposes the verification of wind speed, weather conditions, presence of clouds over the area and presence of objects and trees, takeoff and landing locations.

After analyzing these conditions, the flight plan was defined using the Dronedeploy software, ground sample distance of 60 m above ground, the average speed of 5 $m.s^{-1}$, the frontal overlap of 75% and lateral overlap of 70%, using a sensor in the visible range. Images were captured every 3 seconds with a spatial resolution of 3.5 cm, totaling 79 images in 6 minutes and 33 seconds in three spectral bands.

Initially, the captured RGB aerial images require digital processing to form photogrammetric products. In this study, we used the software Agisoft Metashape Professional, version 1.5.1. This software version is considered superior for orthomosaic generation and digital elevation models (SANTANA *et al.,* 2021a).

The methodology used to process the images followed image alignment steps by photo-triangulation and sparse point cloud generation to materialize the terrain coordinate system (SANTANA *et al*., 2021b). This sparse point cloud goes through the 3D densification process, forming, in 35 min and 05 s, a cloud of 10.150.994 terrain points, which represents the area in more detail. The next step was to build a three-dimensional model to represent accurately the mapped terrain, creating a digital terrain model after filtering the point cloud (Figure 2a). With the application of texture to the previous model, the Digital Terrain Model - DTM (Figure 2b) was built and, after this stage, the orthomosaic was generated.

The models were generated with high-precision ensemble and used for the detection of the parameters evaluated.

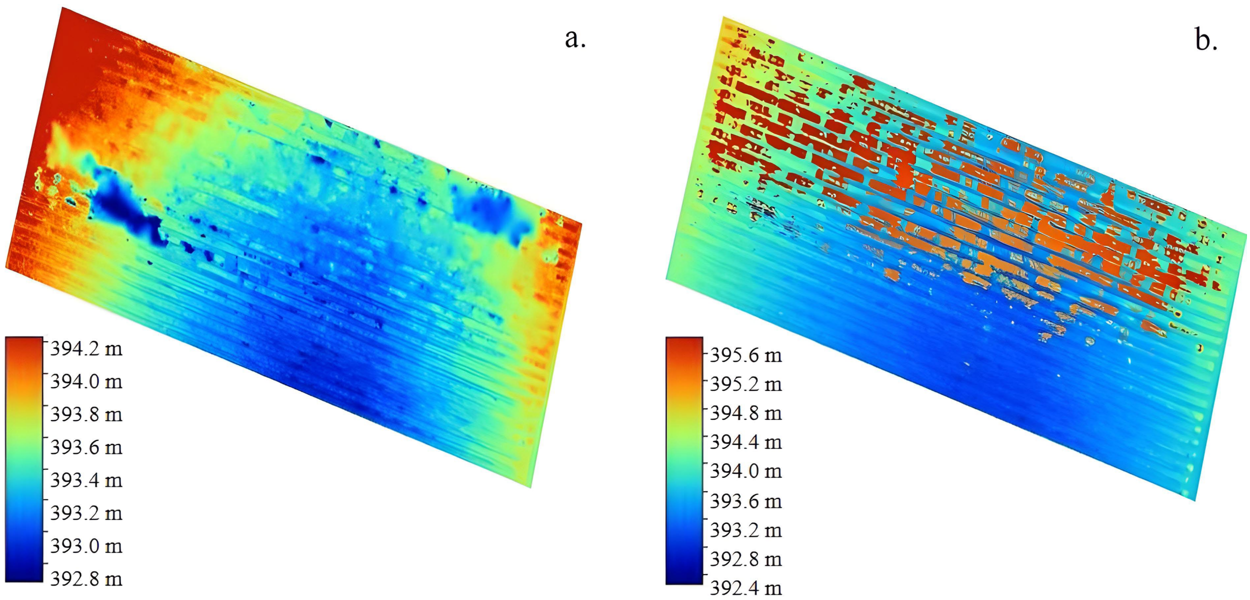

Figure 2. Digital Terrain Model (A) and Digital Surface Model (B)

The identification of number of plants and crop failures was carried out using the SAGA GIS software. Gaussian filters were applied to reduce the noise present in the image and segmentation filters were applied to optimize the mapping quality, creating a grid of points with the probable identification and location of each plant.

The orthomosaic created by Agisoft and the point grids were exported to ArcMap software. The points of the grid were overlaid on the orthomosaic to verify the location and point counting generated by the software algorithms.

When performing this step, one can observe the presence of outliersthat need to be removed by hand for better result accuracy. The count of enabling points present in the area represented the number of plants in the field and failure detection. Validation of results in the photogrammetric process was carried out by verifying them in the area.

The Modified Photochemical Reflectance Index (MPRI) was determined. This index seeks to explore the spectral properties of photosynthetically active plant components, indicating the activity of the vegetation cover (BERGER *et al.*, 2019).

After performing the separation of the RGB bands in the ArcMap software, the index was calculated using the equation proposed by Yang *et al.* (2008) (Equation 1):

$$MPRI = \frac{Green\text{-}Red}{Green+Red} \qquad (1)$$

where,
Green = green band expresses the reflectance at the green wavelength;
Red = red band expresses the reflectance at the red wavelength.

This index was chosen because of the good results for agricultural crop analyses reported by Linhares *et al.* (2014) and Schadeck *et al.* (2019).

From the MPRI image, to determine the area with vegetation biomass and the exposed soil of the plot, the image was reclassified using the ArcMap software algorithm and the QGIS 3.16,7 software. Post-processing was performed for the supervised image classification, creating three classes corresponding to the spectral bands (RGB) through the Semi-Automatic Classification Plugin (SPC) complement. This also provided the percentage of the total analyzed area that each layer covered through the table of attributes generated for each class.

RESULTS AND DISCUSSION

After processing the images, the orthomosaic was generated with the point grids, identifying the location of each plant in the plot (Figure 3). The points were counted and 1533 plants were identified, which was less than the projected number (1580 plants), representing about 3% less plants, indicating the missing plants, as observed in the field (Figure 4).

Lower quality seedlings may explain the presence of these gaps, leading to low survival rates when they are planted in the field. These results corroborate Nóbrega *et al*. (2017) and Pereira *et al.* (2013), who identified the seedling quality as a primary factor for establishing a complete crop stand.

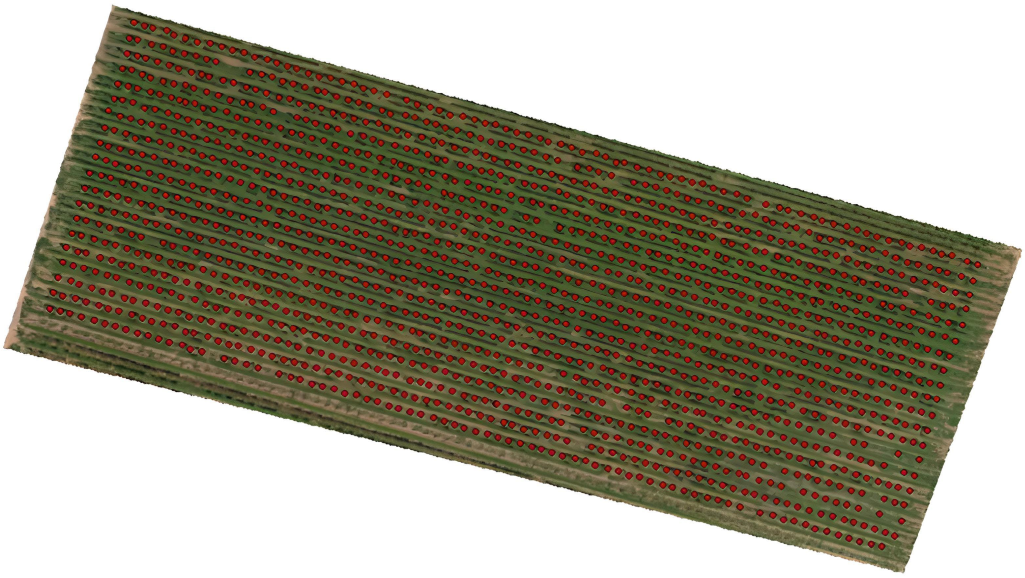

Figure 3. Orthomosaic showing dots identifying each plant present in the area

Figure 4. Missing plants (a) and present plants (b) in the study area

When evaluating the population density in the plot, considering the expected productivity of 24 kg per plant, this lower stand would result in the loss of about 1,128 kg of grapes and consequently, a reduction in the income of the farmer. In addition, the loss of profitability would be due to the quantity harvested and the waste of water, fertilizers and pesticides, considering that the crop stand planned is complete.

A study by Rech *et al.* (2019) indicates that for the establishment and production of a grapevine hectare in the first three years, each plant costs an average of BRL 63.00. When applying this information to our study, we verify that multiplying it by the number of plants in the plot (47 plants), in this period, the vineyard will already present an unnecessary investment of BRL 2,961.00. Some inputs such as water, fertilizer and pesticides continue to be applied to the plot without considering the missing plants.

Returning to the site evaluated we confirmed the results and verified that 38 plants were missing, representing 2.4% of the stand designed. Thus, it is clear that the image processing differed by only 0.6% of the observation in the field, demonstrating accuracy of results obtained by remotely piloted aircraft.

The difference in the results may have occurred due to the non-uniformity of the plot, with plants at various stages of growth (Figure 5), since grapevines were planted at different times in an attempt to recompose the stand. Furthermore, the flight height made it difficult for verification of the existence or not of a grapevine plant in the orthomosaic created by the software.

These results corroborate with Barbosa *et al.* (2021), who state that canopy non-uniformity can promote large errors in processed image analysis. Besides compromising the quality of processing, the lack of uniformity also makes management operations less efficient (SANTANA *et al.,* 2021a).

The interference of the flight height in the determination of the plant stand by image processing compared to the growth observed in the field is also corroborated at in the flight altitudes selected by Jurado *et al.* (2020) and Santana *et*

Figure 5. Area with plants at different stages of growth

al. (2021a). The ground sample distance adopted in this study (60 m) is twice those selected in the cited studies, which may limit the image resolution when approaching it for object identification.

To ensure improved productivity, which is the most desired outcome in agricultural production, Da Silva *et al.* (2010) point out that it is essential to monitor the formation of the stand, helping the producer to minimize or avoid losses in the harvest and the use of inputs, as observed in the plot analyzed in this study.

The determination of the vegetation index for the area studied using the MPRI resulted in satisfactory data as shown in Figure 6, with the grapevine plants being identified by the green points, undergrowth or invasives by the yellow points, and the exposed soil as red points.

The identification obtained coincides with the parameters defined by Padolfi *et al.* (2018). The MPRI vegetation index shows values ranging from -1 to 1, with the red pigmentation representing the points with values close to -1. The yellow points with values close to 0 express areas with low vegetation density. At the same time, the green pigmentation indicates values relative to 1 and represents the area with a high density of vegetation.

After post-processing the image for this index, it was possible to determine the amount of the studied area that was covered with vegetation biomass and the amount that showed exposed soil of the plot. The results indicated that 60.8% of the area was covered with grapevine branches, 5.3% indicated undergrowth or weeds, and 33.9% showed exposed soil.

These results show the characteristics of the area with an incomplete stand, plants at different stages of development, predominantly those in the formation process and branches not having enough biomass to occupy a larger area.

CONCLUSION

- Image processing obtained with ARP allowed us to observe that the cultivated area had plants at different stages of growth, with a predominance of grapevines in the formation process.
- It was possible to identify the plants and quantify the leaf mass using the MPRI vegetation index, which was able to differentiate exposed soil from plant material.
- In addition to being observed that the plot had an incomplete stand at the time the flight was performed.

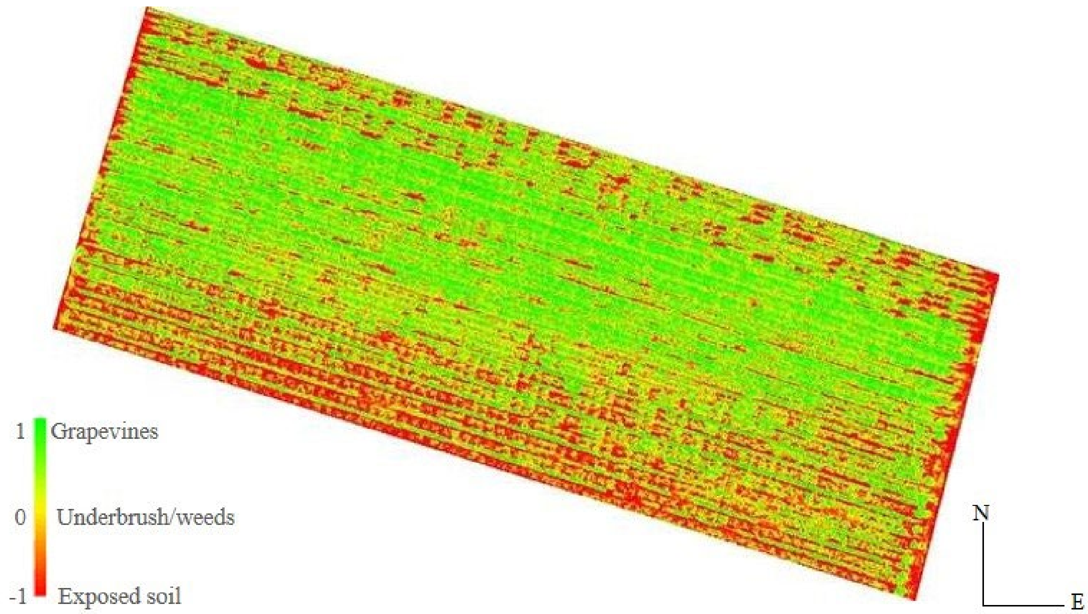

Figure 6. Modified Photochemical Reflectance Index (MPRI)

AUTHORSHIP CONTRIBUTION STATEMENT

PEREIRA, J.S.: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing; **FERRAZ, G.A.S:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing; **SANTANA, L.S.:** Investigation, Methodology, Writing – review & editing.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

AHMAD, A.; ORDOÑEZ, J.; CARTUJO, P.; MARTOS, V. Remotely piloted aircraft (RPA) in agriculture: a pursuit of sustainability. **Agronomy**, v. 11, n. 7, p. 1-25, 2021.

BARBOSA, B. D. S.; FERRAZ, G. A. S.; DOS SANTOS, L. M.; SANTANA, L. S.; MARIN, D. B.; ROSSI, G.; CONTI, L. Application of RGB Images Obtained by UAV in Coffee Farming. **Remote Sensing**, v. 13, 2021.

BERGER, R.; DE SILVA, J. A. A.; FERREIRA, R. L. C.; CANDEIAS, A. L. B.; RUBILAR, R. Índices de vegetação para a estimativa do índice de área foliar em plantios clonais de *Eucalyptus* saligna Smith. **Ciência Florestal**, v. 29, n. 2, p. 885-899, 2019.

CARVALHO NETO, L. M. de; RAMOS FILHO, R. Análise temporal (2008-2018) do uso e ocupação do solo na microbacia do Córrego Barreiro, no município de Uberaba (Minas Gerais). **Revista Brasileira de Sensoriamento Remoto**, v. 2, n. 1. p. 68-78, 2021.

DELAVARPOUR, N.; KOPARAN, C.; NOWARZKI, J.; BAJWA, S.; SUN, X. A technical study on UAV characteristics for precision agriculture applications and associated practical challenges. Remote Sensing, v. 13, 2021.

GUEDES, J. C. F.; SILVA, S. M. P. da. Sensoriamento remoto no estudo da vegetação: princípios físicos, sensores e métodos. **ACTA Geográfica**, v. 12, n. 29, p. 127-144, 2018.

JATOBÁ, L.; SILVA, A. F.; GALVÍNCIO, J. D. A dinâmica climática do semiárido em Petrolina – PE. **Revista Brasileira de Geografia Física,** v. 10, n. 01, p. 136-149, 2017.

JORGE, L. A. de C.; INAMASU, R. Y. **Uso de veículos aéreos não tripulados (VANT) em Agricultura de Precisão.** Available in: https://www.alice.cnptia.embrapa.br/bitstream/doc/1003485/1/CAP8.pdf. Access in: Jun. 17, 2021.

JURADO, J. M.; PÁDUA, L.; FEITO, F. R.; SOUSA, J. J. Automatic Grapevine Trunk Detection on UAV-Based Point Cloud. **Remote Sensing**, v. 12, n. 3043, 2020.

LINHARES, M. M. A.; AMARAL, B. A. S.; COSTA, A. P.; ROCHA, N. C. C.; CÂNDIDO, L. G. Vant's aplicados ao monitoramento da evolução vegetativa de culturas agrícolas. *In*: CONGRESSO BRASILEIRO DE AGRICULTURA DE PRECISÃO. São Pedro, 2014. **Anais** [...], São Pedro: ConBAP, 2014.

DA NÓBREGA, E. P.; SARMENTO, M. I. de A.; RODRIGUES, M. L. de M.; DE OLIVEIRA, P. R. R.; FERREIRA NETO, J.; MARACAJÁ, P. B. Desenvolvimento inicial de mudas de goiabeira irrigadas com diferentes tipos de água. **Revista de Agroecologia no Semiárido**, v. 1, n. 2, p. 01-09, 2017

PADOLFI, A. S.; RAMALDES, G. P.; DOS SANTOS, O. L. Análise de índice de vegetação através de imagens obtidas por VANT. **Revista Científica da FAESA**, v. 14, n. 1, p. 145-165, 2018.

PÁTRIA, H. I.; FREDIANI, M. Voos cada vez mais altos: cresce o uso de drones no Agronegócio Brasileiro. **Revista Agrimotor**, n. 107, p. 7-14, 2021.

PEREIRA, L. R.; MARCILIO, G. S.; MOTA, F. M.; SANT'ANA, B. T.; DARDENGO, M. C. J. D. Qualidade de mudas do café conilon vitória produzidas em viveiros do Sul Capixaba. **Enciclopédia Biosfera**, v. 9, n. 17, p. 2213-2220, 2013.

RECH, V.; GONÇALVES, R. B.; VIEIRA, G. B. B. Estudo comparativo dos custos de produção de uvas pelos métodos orgânico e convencional. **Custos e Agronegócio online**, v. 15, 2019.

REIS, L. P.; REIS, P. C. M. dos R. Viabilidade econômica do cultivo de uva irrigada no município de Petrolina, PE. **Enciclopédia Biosfera**, v. 13, n. 24, p. 1089-1099, 2016.

DE SÁ, N. C.; SILVA, E. M. S.; BANDEIRA, A. da S. A cultura da uva e do vinho no Vale do São Francisco. **Revista de Desenvolvimento Econômico**, v. 17, p. 461-491, 2015.

SANTANA, L. S.; FERRAZ, G. A. S.; CUNHA, J. P. B.; SANTANA, M. S.; FARIA, R. de O.; MARIN, D. B.; ROSSI, G.; CONTI, L.; VIERI, M.; SARRI, D. Monitoring Errors of Semi-Mechanized Coffee Planting by Remotely Piloted Aircraft. **Agronomy**, v. 11, n. 1224, 2021a.

SANTANA, L. S.; FERRAZ, G. A. S.; MARIN, D. B.; BARBOSA, B. D. S.; DOS SANTOS, L. M.; FERRAZ, P. F. P.; CONTI, L.; CAMICIOTTOLI, S.; ROSSI, G. Influence of flight altitude and control points in the georeferencing of images obtained by unmanned aerial vehicle. **European Journal of Remote Sensing**, v. 54, n. 1, 2021b.

SANTOS, L. H. R.; DA SILVA, J. C.; NETO, F. A.; SILVA, E. P.; AZEVEDO, T. H.; COSTA, J. D. S. Qualidade de uva 'arra 15' armazenada em atmosfera modificada em bolsões de filme plástico. **Revista Iberoamericana de Tecnología Postcosecha**, v. 20, n. 2, 2019.

SANTOS, L. M.; FERRAZ, G. A. S.; ANDRADE, M. T.; SANTANA, L. S.; BARBOSA, B. D.S.; MACIEL, D. T.; ROSSI, G. Analysis of flight parameters and georeferencing of images with different control points obtained by RPA. **Agronomy Research**, v. 17, n. 5, p. 2054–2063, 2019.

SCHADECK, A.; ROSA, H. A.; BORTOLINI, J. Influência da altura de voo no índice MPRI obtido com Veículo Aéreo Não Tripulado (VANT). **Revista Cultivando o Saber**, v. 12, n. 4, p. 454-464, 2019.

SELS, S.; BOGAERTS, B.; VANLANDUIT, S.; PENNE, R. Easy sensor localization using an RGB camera. **Op3mech**, n. 1, 2018.

SILVA, C. de A.; DE MENEZES, M. A.; DE OLIVEIRA, R. V. Às margens do desenvolvimento: o trabalho das mulheres e a luta por direitos no polo de fruticultura de Petrolina/PE-Juazeiro/BA. **Cadernos Pagu**, v. 52, 2018.

DA SILVA, J. B.; LAZARINI, E.; DA SILVA, A. M.; RECO, P. C. Ensaio comparativo de cultivares de soja em época convencional em Selvíria, MS: características agronômicas e produtividade. **Bioscience Journal**, v. 26, n. 5, p. 747-754, 2010.

SOBRAL, M. do C.; DE ASSIS, J. M. O.; DE OLIVEIRA, C. R.; DA SILVA, G. M. N.; MORAIS, M.; CARVALHO, R. M. C. Impacto das mudanças climáticas nos recursos hídricos no Submédio a Bacia Hidrográfica do Rio São Francisco – Brasil. **Revista Eletrônica do Prodema**, v. 12, n. 3, p. 95-106. 2018.

YANG, Z.; WILLIS, P.; MUELLER, R. Impact of Band-Ratio Enhanced AWIFS Image to Crop Classification Accuracy. *In*: PECORA – THE FUTURE OF LAND IMAGING: GOING OPERATIONAL, 17., 2008, Denver. **Anais** […]. Denver: ASPRS, 2008.

YU, I. A.; YA, P. L.; SMINORV, I. G.; KOLESNIKOVA, V. A.; MARCHELO, L. A. Substantiation of parameters of unmanned aerial vehicles for pesticides and fertilizers application in precision farming system. **International Scientific Journal "Mechanization In Agriculture"**, p. 168-170, 2017.