Felix, F.C., Spalevic, V., Curovic, M., Mincato, R.L. (2021): Comparing pixel- and object- based forest canopy gaps classification using low-cost unmanned aerial vehicle imagery. Agriculture and Forestry, 67 (3): 19-29

DOI: 10.17707/AgricultForest.67.3.02

Filipe Castro FELIX [1], Velibor SPALEVIC[2,3],
Milic CUROVIC[2], Ronaldo Luiz MINCATO[4]

COMPARING PIXEL- AND OBJECT- BASED FOREST CANOPY GAPS CLASSIFICATION USING LOW-COST UNMANNED AERIAL VEHICLE IMAGERY

SUMMARY

Forest canopy gaps are an important indicator of ecosystem dynamics. Gap sizes can vary because of several agents, and the spatial distribution is related to abiotic factors. The interest in the study of this forest attribute is old, but the difficulties to detect these areas in situ and with the use of satellite imagery hinder this research approach. Thus, we explore the use of high spatial resolution images obtained with RGB boarded in a multirotor unmanned aerial vehicle (UAV) to evaluate the best method to mapping the forest canopy gaps in Brazil. For this, were utilized the pixel- and object-based approaches, and the algorithms Random Forest (RF) and Support Vector Machine (SVM). The results showed that the ortophotomosaics can overcome the disadvantages of study the forest canopy gaps from conventional methods and reduce the complexity and costs to obtain reliable data of forests remnants. The RF and the pixel-based classification were the best combinations, with an overall accuracy (OA) of 93% in the period of study. However, the SVM presented a satisfactory accuracy to classify the forest canopy gaps, with the precision of user (PU) ranging from 86% to 98% and measure F from 85% to 96%. Therefore, was confirmed the potential of low-cost UAVs boarded with RGB sensors in this research proposal, and the results are promising for future studies.

Key words: Structure from Motion, Random Forest, Support Vector Machine, Forest Remnant, Conservation, Brazil

INTRODUCTION

Gaps in forests canopies represent the result of ecological disturbances and are a key element for understanding forest structure and dynamics (Karki and Hallgren, 2015; Mohammadi *et al.*, 2021). The formation of these openings in the forests varies in size because of several agents, such as the wind, diseases, fire,

[1] Filipe Castro Felix, Agronomic Institute, Campinas, São Paulo, BRAZIL;
[2] Velibor Spalevic, Milic Curovic, University of Montenegro, Biotechnical Faculty, MONTENEGRO;
[3] Velibor Spalevic, University of Montenegro, Geography, Philosophy Faculty, MONTENEGRO;
[4] Ronaldo Luiz Mincato (corresponding author: ronaldo.mincato@unifal-mg.edu.br), Federal University of Alfenas, UNIFAL-MG, Alfenas, Minas Gerais, BRAZIL.
Notes: The authors declare that they have no conflicts of interest. Authorship Form signed online.
Recieved:07/06/2021 *Accepted:14/08/2021*

and cyclones (Bazzaz, 1983). Nevertheless, the spatial distribution of central abiotic factors also plays an important role in the regulation of the formation of the gaps (Getzin *et al.*, 2014).

Therefore, the detection of these areas is an important alternative to monitor the forests remnants because the gaps influence the composition and species richness from microhabitats. Thus, it affects the quality and quantity of available resources, such as light (Kuuluvainen and Linkosalo, 1998), which promotes the natural regeneration of trees and the diversity of understory biota (Burton *et al.*, 2014).

The interest of ecologists in understanding these processes and recognizing the dynamics involved is old (Fisch and Ponzoni, 1995), but the spatial resolution of the satellite’s images and the difficulty of displacement on the ground due to the disturbance of these areas, restrict the studies.

In this scenario, unmanned aerial vehicles (UAVs) have become an affordable alternative, capable of providing the flexibility and resolution necessary to accurately map the forests (Fassnacht *et al.*, 2003; Chianucci *et al.*, 2015). The combination of these platforms with computer vision algorithms ensures the generation of high-quality products, such as orthophotomosaics and three-dimensional (3D) models, which have the potential to detect and identify flora classes (Felix *et al.*, 2021). Nonetheless, the UAVs can be equipped with different sensors, capable of acquiring information from different portions of the electromagnetic spectrum, like the visible bands (RGB), red edge, and near-infrared (NIR) (Grybas and Congalton, 2021).

According to Castillo *et al.* (2012), the difference in the use of UAVs is the increase in accessibility, performance, and precision in the acquisition of data and orthoimages in high resolutions. Because of this methodological configuration, the limitations of traditional remote sensing techniques are overcome, mainly about significant errors in volumetric calculations.

Studies such as that of Wallace *et al.* (2016), Prošek and Šímová, (2019), and Olivetti *et al.* (2020), have already recognized this potential and achieved satisfactory results in the use of UAVs in different environmental contexts. However, precision agriculture is still considered the area with the greatest potential for its application (Jorge *et al*., 2014).

Thus, in this study we aimed to demonstrate how images acquired with RGB sensor carried on a low-cost UAV can be used for forests gap studies; two different classification approaches (pixel- and object-based) and the algorithms Random Forest (RF) and Support Vector Machine (SVM) were utilized.

MATERIAL AND METHODS

The study area is in the municipality of Lavras, state of Minas Gerais (Figure 1). Forest remnant has 2.81 ha and represents a typical Cerrado (Savanna) physiognomy, with 19 families, 38 species, and 38 genera (H’ = 3.28), with the exclusive occurrence of individuals such as *Bowdichia virgiloides*, *Dalbergia miscolodium,* and *Qualea grandiflora* (Pereira *et al*., 2010).

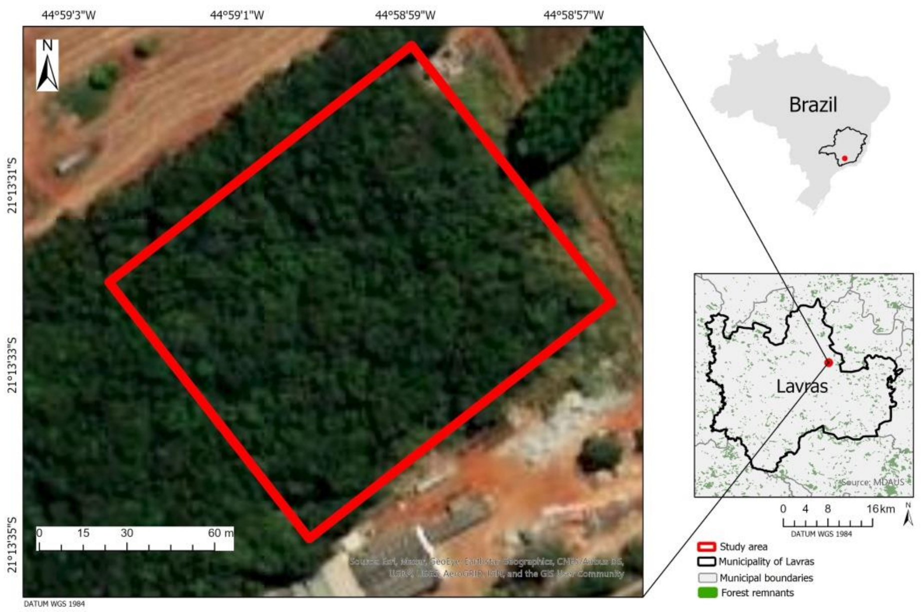

Figure 1. Location map of the study area in the municipality of Lavras, Brazil.

According to the Köppen classification system, the climate of the study area is mesothermal tropical (Cwb) (Sparovek *et al.*, 2007). The average elevation is 918 m, and the mean annual precipitation is 1529.7 mm, with soil classified as dystroferric Red Latosols (FEAM, 2010).

The region is part of the upstream portion of the Rio Grande watershed and makes up the geomorphological Atlantic Plateau unit in Varginha Complex crystalline rocks (CPRM 2014). The vegetation is characterized by the transition of the Atlantic Forest to the Cerrado (Savanna), with the presence of the remnants of Montana Semi Deciduous Forest (Oliveira-Filho *et al*., 2001).

PROCEDURE

1. Unmanned aerial vehicle (UAV):

We used the multirotor Phantom 3 (Professional) with an RGB sensor, camera model Sony EXMOR ½.3", which captures images in real colour with lens 94° FOV 20 mm (Figure 2).

Considering that the occurrence of gaps is seasonal, being more frequent during the rainy season when the fall of trees and branches is also amplified by the strong winds (Sarukhán, 1978), two flights were scheduled. One to run in the middle of the dry season (24 August 2017) and the other after the rainy season (1 February 2018), at a height of 60 m and with 80% forward and side overlap. The grid adopted was 50 x 50 m and the mapping was planned and executed using the GCS (Ground Control Station) Pix4DCapture.

Figure 2. DJI Phantom 3 equipped with an RGB sensor.

The images were processed using the commercially available structure-from-motion (SfM) Agisoft Photoscan Professional® v1.2.7 software with the configurations: "*Align Photos*" = high; "*Accuracy*" = generic / pair pre-selection and 40 000 points features per image; "*Tie points*" = 10 000. No ground control points (GCPs) were used for image orthorectification.

2. Segmentation:

Segmentation considers the radiometric information of the pixels, the semantic properties of each segment, and other background information that describes the connection of adjacent pixels, such as the intensity, texture, shape, and dimensional relations (De Luca *et al*., 2019).

Thus, the object-based image analysis (OBIA) aimed to group pixels into homogeneous classes, allowing the use of multiple descriptive statistics and contextual information during the classification process (Blaschke, 2010).

In this study, the OBIA method was based in the multi-resolution segmentation algorithm implemented on eCognition 8.3. After iterative tests, the parameters selected were: "*scale*" = 40; "*shape*" = 0.3 and "*compactness*" = 0.8.

Since the texture features are one of the important characteristics used for identifying objects (Haralick, 1979), the measure GLCM was implemented. Thus, after the segmentation, the mean, the standard deviation, the homogeneity, the entropy of the Red band, the maximum difference, and the brightness were extracted for each sample, resulting in 12 attributes. Therefore, 200 objects were selected as training data, which were grouped into 5 classes: (1) bare land, (2) branches, (3) canopies, (4) gaps, and (5) shadows.

3. Pixel-based approach:

Reference polygons were selected by visual interpretation of the ortophotomosaics, using the true colour composition. A total of 200 reference polygons were selected as training samples to five classes described in section 2. Nonetheless, the variables extracted for each sample were only the mean of the bands, resulting in three attributes.

4. Ortophotomosaics classification:

The RF algorithm (Breiman, 2001) is a non-parametric and robust algorithm used for images classification. A couple of studies presented satisfactory results on the employment of RF in land use and species classification approaches (Belgiu and Dragut, 2016).

In this study, the RF was grown with the parameters "*ntree*" = 500 and "*mtry"* with the square root of the number of the variables included in the model as described in sections 2 and 3.

On the other hand, the SVM (Cortes and Vapnik, 1995) are based on statistical learning theory, defining the optimal hyperplane as a linear decision function between the vectors of two classes (Deur *et al*., 2020). We used the radial basis function kernel in this study.

Thus, each singular date of imagery was classified in R open-source statistical programming environment, and the training samples were randomly divided into training (70%) and validation (30%) datasets.

The accuracy of these classifications was assessed using the error matrix approach. After, were obtained the overall accuracy (OA), the accuracy of classes, and the kappa index (Congalton, 1991). For each matrix, the precision of the classes was determined by calculating the precision of user (PU) and producer (PP) (Story and Congalton, 1986), and to summarize PU and PP in a single metric, measure F was calculated (Equation 1).

$$F = 2 * \frac{(PU*PP)}{(PU+PP)} \qquad \text{(Equation 1)}$$

RESULTS AND DISCUSSION

UAV imagery reached 2 cm spatial resolution, which facilitates the detection of classes by visual interpretation using the true colour composition.

The highest pixel-based classification accuracy was obtained for the RF algorithm on both dates, with OA = 93%, and kappa = 0.88 and 0.90, respectively (Table 1 and Table 2). Concerning the forest gaps, the highest accuracy was obtained for RF (PU ranged from 92% to 94% and the measure F ranging from 93% to 95%).

Although the SVM presented the worst result than RF in the classification accuracy for forest gaps (PU ranged from 92% to 98% and the measure F ranging from 90% to 96%), the performance of the algorithm was satisfactory.

Table 1. Accuracy assessment of pixel-based classification with RF and SVM on 24 August 2017.

RF								
Prediction	**B.L.**	**Branches**	**Canopies**	**Gaps**	**Shad.**	Total	**PU**	**F**
Bare land	975	28	3	15	46	1 067	91%	85%
Branches	75	10 298	664	53	7	11 097	93%	92%
Canopies	13	908	25 331	161	29	26 442	96%	96%
Gaps	65	91	171	39 540	3 089	42 956	92%	95%
Shadows	83	63	3	532	1 638	2 319	70%	46%
Total	1 211	11 388	26 172	40 301	4 809	**OA** = 93%		
PP	80%	90%	97%	98%	34%	**Kappa** = 0.88		
SVM								
Bare land	4 014	453	1 768	340	0	6 575	96%	93%
Branches	35	8 559	6 642	610	0	15 846	86%	47%
Canopies	42	15 924	21 952	413	0	38 331	67%	69%
Gaps	294	926	251	18 403	0	19 874	92%	90%
Shadows	0	0	0	900	2 345	3 245	72%	84%
Total	4 385	25 862	30 613	20 576	2 345	**OA** = 35%		
PP	91%	33%	71%	89%	100%	**Kappa** = 0.50		

PP: precision of producer; PU: precision of user; and F: measure F.

Table 2. Accuracy assessment of pixel-based classification with RF and SVM on 1 February 2018.

RF							
Prediction	**Bare land**	**Branches**	**Canopies**	**Gaps**	**Total**	**PU**	**F**
Bare land	3 967	60	29	79	4 135	96%	93%
Branches	110	23 821	1 590	417	25 938	92%	92%
Canopies	59	1 491	28 649	556	30 755	93%	93%
Gaps	249	490	345	18 714	19 798	94%	94%
Total	4 385	25 862	30 613	19 766	**OA** = 93%		
PP	90%	92%	93%	94%	**Kappa** = 0.90		
SVM							
Bare land	951	9 658	6 370	391	17 370	5%	9%
Branches	54	20 661	4 653	233	25 601	80%	72%
Canopies	11	942	24 940	4	35 897	69%	60%
Gaps	18	33	142	11 565	11 758	98%	96%
Total	1 034	31 294	46 105	12 193	**OA** = 31%		
PP	92%	66%	54%	95%	**Kappa** = 0.17		

PP: precision of producer; PU: precision of user; and F: measure F.

In the case of the OBIA classification, the RF also showed the best results in both dates and in the detection of the forest gaps (Table 3 and 4). The OA ranging from 78% to 88%, the PU from 85% to 89%, with a measure F of 96% and 90%.

Table 3. Accuracy assessment of object-based classification with RF and SVM on 24 August 2017.

RF								
Prediction	**B.L.**	**Branches**	**Canopies**	**Gaps**	**Shadows**	**Total**	**PU**	**F**
Bare land	0	0	0	0	0	0	100%	0%
Branches	1	12	3	0	0	16	75%	79%
Canopies	1	5	17	0	0	23	74%	85%
Gaps	0	0	0	18	3	21	85%	96%
Shadows	0	0	0	0	0	0	100%	0%
Total	2	17	20	18	3	**OA** = 78%		
PP	0%	70%	85%	100%	0%	**Kappa** = 0.68		
SVM								
Bare land	0	0	0	0	0	0	100%	0%
Branches	0	8	2	0	0	10	80%	87%
Canopies	2	9	18	0	0	29	62%	66%
Gaps	0	0	0	18	3	21	86%	89%
Shadows	0	0	0	0	0	0	100%	0%
Total	2	17	20	18	3	**OA** = 73%		
PP	100%	95%	72%	93%	100%	**Kappa** = 0.61		

PP: precision of producer; PU: precision of user; and F: measure F.

Table 4. Accuracy assessment of object-based classification with RF and SVM on 1 February 2018.

RF							
Prediction	**Bare l.**	**Branches**	**Canopies**	**Gaps**	**Total**	**PU**	**F**
Bare land	2	0	0	0	2	100%	66%
Branches	0	16	0	0	16	100%	94%
Canopies	1	1	20	2	24	89%	92%
Gaps	1	1	1	15	18	93%	90%
Total	4	18	21	17	**OA** = 88%		
PP	50%	89%	95%	88%	**Kappa** = 0.83		
SVM							
Bare land	1	0	0	0	1	100%	40%
Branches	0	6	3	0	9	93%	48%
Canopies	2	12	18	4	36	54%	66%
Gaps	1	0	0	13	14	97%	85%
Total	4	18	21	60	**OA** = 63%		
PP	25%	33%	86%	76%	**Kappa** = 0.46		

PP: precision of producer; PU: precision of user; and F: measure F.

These results indicating that the best approach of the study was the pixel-based classification with the RF, and the RGB sensor is a feasible alternative to monitor the forest dynamics (Figure 3).

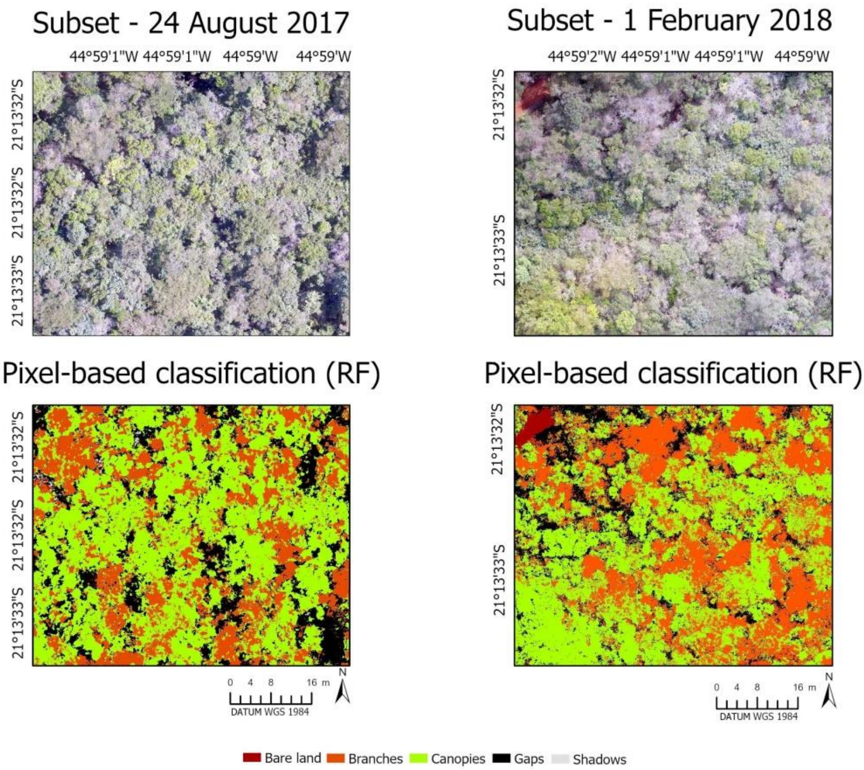

Figure 3. Example subsets of pixel-based classification with the Random Forest algorithm in both dates of study.

According to Deur et al. (2020), the OBIA was the best method to work with high spatial products, but as demonstrated in our results the performance was lower than the pixel-based method. A couple of studies also indicated that the SVM algorithm is the best alternative to OBIA classification (Belgiu and Dragut, 2016), which wasn't confirmed in this research because the SVM showed the worst results obtained with the two classification methods.

Despite that, our results confirmed the potential reported to other studies in the evaluation of forest canopy gaps with UAVs (Bagaran *et al*., 2018, Bourgoin *et al*., 2020), and reinforce the capacities of low-cost equipment configuration in these interest front.

The spatial resolution of orthophotomosaics allowed the identification of a significant number of small gaps ($\leq 1\text{m}^2$), especially in February 2018. In the last years, the discussion on the minimal gap size restricts the threshold from 1 m^2 to 5 m^2 (Nieschulze *et al*., 2012, Boyd *et al*., 2013). Therefore, our results point to the importance of a better evaluation about the metrics adopted in the studies of forest canopy gaps from remote sensing. However, we agree with Tanaka and Nakashizuka (1997) and Getzin *et al*. (2014), that the monitoring of small gaps should be analyzed in the long-term, because the disturbances around these areas cannot be explained simply as gap expansion but should be considered the regeneration and successional dynamics of the understory.

Thus, we recognize the promising results obtained with the use of UAVs, still, we emphasize that the use of these technologies does not replace the evaluation of these areas *in situ*. In the case of Brazil, with the recent availability of pan sharpened very high spatial resolution of CBERS-4A satellite (2 m), as well as the free Planet satellite imagery (3-5 m), the integrated use of these platforms can allow the monitoring of long-term forest dynamics. Furthermore, this configuration offers a great opportunity to overcome the satellite's limitations in other areas and can be an alternative to evaluate the forest canopy gaps with the climate changes.

Last, this research compared the performance of two methods to classification and identifying forest attributes, but we do not disqualify the use of the SVM or the OBIA method for future studies. After all, the algorithm and classification method are historically consolidated and can contribute to several mapping approaches. Because, as confirmed in Table 1 and Table 2, the SVM presented a highest accuracy for gaps classification with the pixel-based method.

Thus, our results represent directions for future researchers aiming the mapping and monitoring forests attributes, especially in Tropical areas.

CONCLUSIONS

The use of unmanned aerial vehicles to detect and monitoring forest dynamics can reduce the costs and provide promising results in mapping the forest canopy gaps. RGB sensor represented a feasible alternative to overcome the limitations of satellite data, but the combined use of these platforms provides a great opportunity to maintain the landscape. The Random Forest algorithm confirmed its robustness and capabilities to use in different contexts. Nonetheless, Support Vector Machine also represents an alternative for future research aiming at the study of forest canopy gaps.

ACKNOWLEDGEMENTS

To the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) for granting a scholarship to the first author. To the contributions of Professor Marx Leandro Naves Silva, from Federal University of Lavras, Minas Gerais, Brazil. Study was partially funded by the CAPESx - Financial Code 001.

REFERENCES

Bagaram, M. B., Giuliarelli, D., Chirici, G., Giannetti, F., & Barbati, A. (2018): UAV remote sensing for biodiversity monitoring: are forest canopy gaps good covariates? Remote Sensing, 10(9): 1397.

Bazzaz, F. A. (1983): Characteristics of populations in relation to disturbance in natural and man-modified ecosystems. In Disturbance and ecosystems (pp. 259-275). Springer, Berlin, Heidelberg.

Belgiu, M; Dragut, L. (2016): Random forest in remote sensing: A review of applications and future directions. ISPRS journal of photogrammetry and remote sensing, 114: 24-31.

Blaschke, T. (2010): Object based image analysis for remote sensing. ISPRS journal of photogrammetry and remote sensing, 65(1): 2-16.

Bourgoin, C., Betbeder, J., Couteron, P., Blanc, L., Dessard, H., Oszwald, J., Le Roux, R., Cornu, G., Reymondin, L., Mazzei, L., Sist, P., Läderach, P. & Gond, V. (2020): UAV-based canopy textures assess changes in forest structure from long-term degradation. Ecological Indicators, 115: 106386.

Boyd, D. S., Hill, R. A., Hopkinson, C., & Baker, T. R. (2013): Landscape scale forest disturbance regimes in southern Peruvian Amazonia. Ecological applications, 23 (7): 1588-1602.

Breiman, L. (2001): Random forests. Machine learning, 45(1): 5-32.

Burton, J. I., Mladenoff, D. J., Forrester, J. A., & Clayton, M. K. (2014): Experimentally linking disturbance, resources and productivity to diversity in forest ground layer plant communities. Journal of Ecology, 102(6): 1634-1648.

Castillo, C., Pérez, R., James, M., Quinton, J., Taguas, E. V., & Gómez, J. A. (2012): Comparing the accuracy of several field methods for measuring gully erosion. Soil Science Society of America Journal, 76: 1319-1332.

Chianucci, F., Disperati, L., Guzzi, D., Bianchini, D., Nardino, V., Lastri, C., & Corona, P. (2016): Estimation of canopy attributes in beech forests using true color digital images from a small fixed-wing UAV. International journal of applied earth observation and geoinformation, 47: 60-68.

Congalton, R. G. (1991): A review of assessing the accuracy of classifications of remotely sensed data. Remote sensing of environment, 37(1): 35-46.

Cortes, C., & Vapnik, V. (1995): Support-vector networks. Machine learning, 20(3): 273-297.

CPRM, C. Mapa Geológico do Estado de Minas Gerais. Escala, 1(1.000).

De Luca, G., N Silva, J. M., Cerasoli, S., Araújo, J., Campos, J., Di Fazio, S., & Modica, G. (2019): Object-based land cover classification of cork oak woodlands using UAV imagery and Orfeo ToolBox. Remote Sensing, 11(10): 1238.

Deur, M., Gašparović, M., & Balenović, I. (2020): Tree Species Classification in Mixed Deciduous Forests Using Very High Spatial Resolution Satellite Imagery and Machine Learning Methods. Remote Sensing, 12(23): 3926.

Fassnacht, F. E., Schmidt-Riese, E., Kattenborn, T., & Hernández, J. (2021): Explaining Sentinel 2-based dNBR and RdNBR variability with reference data from the bird's eye (UAS) perspective. International Journal of Applied Earth Observation and Geoinformation, 95: 102262.

FEAM - Gerais, M. (2009): Fundação Estadual do Meio Ambiente. Inventário de resíduos sólidos industriais e minerários: ano base.

Felix, F. C., Avalos, F. A., Lima, W. D., Candido, B. M., Silva, M. L., & Mincato, R. L. (2021): Seasonal behavior of vegetation determined by sensor on an unmanned aerial vehicle. Anais da Academia Brasileira de Ciências, 93.

Fisch, S.T.V., & Ponzoni, F.J. Estudo da dinâmica florestal através de técnicas de sensoriamento remoto.

Fisch, S.T.V.; Ponzoni, F.J. (1995): Estudo da dinamica florestal atraves de tecnicas de sensoriamento remoto. Revista Biociencias, 1 (1): 7-24. Congresso de Ecologia do Brasil, 2 (5-9 dez. 1994).

Getzin, S., Nuske, R. S., & Wiegand, K. (2014): Using unmanned aerial vehicles (UAV) to quantify spatial gap patterns in forests. Remote Sensing, 6(8): 6988-7004.

Grybas, H., & Congalton, R. G. (2021): A Comparison of Multi-Temporal RGB and Multispectral UAS Imagery for Tree Species Classification in Heterogeneous New Hampshire Forests. Remote Sensing, 13(13): 2631.

Haralick, R. M. (1979): Statistical and structural approaches to texture. Proceedings of the IEEE, 67(5): 786-804.

Jorge, L.D.C., & Inamasu, R.Y. (2014): Uso de veículos aéreos não tripulados (VANT) em agricultura de precisão. Embrapa Instrumentação-Capítulo em livro científico (ALICE).

Karki, L., & Hallgren, S. W. (2015): Tree-fall gaps and regeneration in old-growth cross timbers forests. Natural Areas Journal, 35(4): 533-541.

Kuuluvainen, T., & Linkosalo, T. (1998): Estimation of a spatial tree-influence model using iterative optimization. Ecological modelling, 106(1): 63-75.

Mohammadi, M., Khaledi Darvishan, A.K., Spalevic, V., Dudic, B., Billi, P. (2021): Analysis of the Impact of Land Use Changes on Soil Erosion Intensity and Sediment Yield Using the IntErO Model in the Talar Watershed of Iran. Water 2021, 13, 881. https://doi.org/10.3390/w13060881

Nieschulze, J., Zimmermann, R., Börner, A., & Schulze, E.D. (2012): An assessment of forest canopy structure by LiDAR: derivation and stability of canopy structure parameters across forest management types. Forstarchiv, 83(6): 195-209.

Oliveira-Filho, A.D., Curi, N., Vilela, E.A., & Carvalho, D.A. (2001): Variation in tree community composition and structure with changes in soil properties within a fragment of semideciduous forest in south-eastern Brazil. Edinburgh Journal of Botany, 58(1): 139-158.

Olivetti, D., Roig, H., Martinez, J. M., Borges, H., Ferreira, A., Casari, R., & Malta, E. (2020): Low-Cost Unmanned Aerial Multispectral Imagery for Siltation Monitoring in Reservoirs. Remote Sensing, 12(11): 1855.

Pereira, I.M., van den Berg, E., Pinto, L.V.D.A., Higuchi, P., & Carvalho, D.A.D. (2010): Avaliação e proposta de conectividade dos fragmentos remanescentes no campus da Universidade Federal de Lavras, Minas Gerais. Cerne, 16: 305-321.

Prošek, J., & Šímová, P. (2019): UAV for mapping shrublands vegetation: Does fusion of spectral and vertical information derived from a single sensor increase the classification accuracy? International Journal of Applied Earth Observation and Geoinformation, 75: 151-162.

Sarukhan, J. (1978): Studies on the demography of tropical trees. Tropical trees as living systems, pp 163-184, Cambridge, Cambridge University Press.

Sestras, P., Salagean, T., Bilasco, S., Bondrea, M., Nas, S., Fountas, S., Spalevic, V., & Cimpeanu, S. (2019). Prospect of a GIS based digitization and 3D model for a better management and land use in a specific micro-areal for crop trees. Environmental Engineering and Management Journal, 18(6): 1269-1277.

Sparovek, G., De Jong Van Lier, Q., & Dourado Neto, D. (2007): Computer assisted Koeppen climate classification: a case study for Brazil. International Journal of Climatology: A Journal of the Royal Meteorological Society, 27(2): 257-266.

Story, M., & Congalton, R. G. (1986): Accuracy assessment: a user's perspective. Photogrammetric Engineering and remote sensing, 52(3): 397-399.

Tanaka, H., & Nakashizuka, T. (1997): Fifteen years of canopy dynamics analyzed by aerial photographs in a temperate deciduous forest, Japan. Ecology, 78(2): 612-620.

Tavares, A.S.; Uagoda, R.E.S.; Spalevic, V.; Mincato, R.L. (2021): Analysis of the erosion potential and sediment yield using the IntErO model in an experimental watershed dominated by karst in Brazil. Agriculture and Forestry, 67 (2): 153-162

Wallace, L., Lucieer, A., Malenovský, Z., Turner, D., & Vopěnka, P. (2016): Assessment of forest structure using two UAV techniques: A comparison of airborne laser scanning and structure from motion (SfM) point clouds. Forests, *7*(3): 62.