Determining the Leaf Area Index and Percentage of Area Covered by Coffee Crops Using UAV RGB Images

Luana Mendes dos Santos, Gabriel Araújo e Silva Ferraz, Brenon Diennevan de Souza Barbosa, Adriano Valentim Diotto, Marco Thulio Andrade, Leonardo Conti, and Giuseppe Rossi

***Abstract*—Leaf area is a component of crop growth and yield prediction models. Few studies have used the structure from motion (SfM) algorithm, which is based on the principles of traditional stereophotogrammetry, to obtain the leaf area index (LAI). Thus, the objective of this study was to follow the evolution of the LAI and percentage of land cover (%COV) in coffee plants, using pre-established equations and plant measurements obtained from generated 3-D point clouds, combined with the application of the SfM algorithm to digital images recorded by a camera coupled to an unmanned aerial vehicle (UAV). The experiment was conducted in a coffee plantation located in southeastern Brazil. A rotary wing UAV containing a conventional camera was used. The images were collected once per month for 12 months. Image processing was performed using PhotoScan software. Regression analysis and spatial analysis were performed using *R* and GeoDa software, respectively. The resulting %COV data had R^2 and RMSE values of 89% and 3.41, respectively, while those for LAI had R^2 and RMSE of 88% and 0.47, respectively. Significant %COV results were obtained in the months of January, February, and March of 2018. There was significant autocorrelation for the LAI values from January to May 2018, with most blocks in the central and center-west regions presenting LAI values > 3.0. It was possible to monitor the temporal and spatial behavior of the LAI and %COV, allowing for the conclusion that this methodology generated results that are consistent with the literature.**

***Index Terms*—Coffee, leaf area index (LAI), point cloud, structure from motion (SfM), unmanned aerial vehicle (UAV).**

I. Introduction

THE LAI is the ratio between the leaf area (LA) and the surface area covered by the crop [1]. According to [2], the LA of a crop is an indicator of the yield due to the photosynthetic process in the leaves. Thus, by using this parameter, it is possible to infer the photosynthetic efficiency, growth, and development patterns of a crop, as well as growth variations caused by environmental and genetic differences and damage from pests, diseases, and management [3]. LA is a key component of crop growth [4] and yield prediction models [5]–[7] in addition to being a visible aspect of water stress, in which plants under water deficit decrease the show reduced LA [8].

The methods used to determine the LA of a crop may be direct or indirect and destructive or nondestructive. Direct methods are related to the measurements taken directly in the plant, and they are important for proper estimation and representative sampling and have greater precision when applied well. However, this analysis is time-consuming [9]. Some indirect methods are based on direct and/or diffuse light transmission measurements in the canopy, and there are nondestructive methods that enable the user to obtain a larger amount of data compared to direct manual methods.

An example of a nondestructive method is ground and aerial discrete light range and detection (LIDAR) systems, which may provide an additional third dimension of information (Z) for height and volume analysis [10].

Accordingly, LIDAR measurements have made it possible to obtain more detailed measurements of the spatial structure of a canopy and have shown increasing applications in LA estimations [11]. However the cost of this system is still high and the cost of collecting structure from motion (SfM) point clouds is lower compared to LIDAR; therefore, there is a strong interest in using these methods for 3-D modeling [10].

Another nondestructive method is the use of cameras and sensors. Studies in [12] and [13] using portable cameras and sensors achieved good results to estimate some coffee parameters. In addition, Costa *et al.* [13] state that it is also possible to estimate the spatial variability of the water potential of the coffee canopy using an aerial image. This opens up possibilities for studies using SfM-unmanned aerial vehicle (UAV) in this culture.

Indirect and nondestructive methods that accurately estimate the LAI have been researched for the coffee crop. Studies such as [2] allow estimating the LA through equations using volume and the coffee canopy lateral area. Used as an indirect and nondestructive method to estimate the LAI from the leaf volume and plant architecture, requiring only measurements of the height and radius of each plant and the row spacing [7]. According to

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Luana Mendes dos Santos, Gabriel Araújo e Silva Ferraz, Brenon Diennevan de Souza Barbosa, and Marco Thulio Andrade are with the Department of Agricultural Engineering, Federal University of Lavras, University Campus, Lavras, 37200-000, Brazil (e-mail: luanna_mendess@yahoo.com.br; gabriel.ferraz@ufla.br; b.diennevan@outlook.com; marcoengagricola@hotmail.com).

Adriano Valentim Diotto is with the Department of Water Resources and sanitation, Federal University of Lavras, University Campus, Lavras, 37200-000, Brazil (e-mail: adriano.diotto@ufla.br).

Leonardo Conti and Giuseppe Rossi are with the Department of Agricultural, Food, Environment and Forestry (DAGRI), University of Florence, 50145 Florence, Italy (e-mail: leonardo.conti@unifi.it; giuseppe.rossi@unifi.it).

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[12], methods based on biometric relationships such as LA and volume as well as canopy area may be used to estimate coffee LAI with satisfactory accuracy. However, this method may be laborious, which may lead to measurement errors in the field, in addition to not representing the entire area because a limited sample is used to obtain the data.

The percentage of land cover (%COV) is an important biophysical parameter for supporting coffee production mechanization, and it is a parameter that is rarely used in coffee crops. Some authors have studied methods for estimating this parameter using satellite images, such as [15]. They evaluated the correlation between the crop parameters and spectral responses of coffee crops (Coffea arabica L.) in TM/Landsat images to establish patterns for identifying this crop by remote sensing [16]. Among the fourteen evaluated variables, the best correlation was between the reflectance measured in the near infrared zone and the percentage of area covered by the plants, which groups or represents other coffee crop variables, such as the size, diameter, density, vegetative vigor, and average production.

Similar results were obtained by Epiphanio *et al*. [17], who also used Landsat 5/TM images and field data to evaluate the effect of the coffee crop parameters on its spectral response. A multiple regression analysis showed the predominant effect of the plant height and percentage of covered area on the spectral response of the coffee canopy.

In contrast to traditional analyses, remote sensing provides a rapid estimation of plant biochemical and biophysical parameters for large areas [18], [19]. However, remote sensing at the orbital level, according to [20], when used to delineate coffee areas in regions with rugged terrain presents challenges and hinders the discrimination of coverage, such as the presence of clouds during data collection and greater shading due to the slope of the terrain. According to the same authors, an alternative would be the combined use of aerial photography as a field reference due to its larger scale and richness of detail.

In recent years, remote sensors and photogrammetry techniques have been developed, and UAVs are currently more accessible and more often used for remote monitoring of agricultural crops. With this type of aircraft, images with high temporal resolution (acquired several times per day) and high spatial resolution (in centimeters and even in millimeters) may be obtained, and it also has low operational costs compared to manned aircraft and especially compared to high spatial resolution satellites. The UAV may be used in smaller areas and in specific locations with easy data acquisition over a shorter time to monitor the growth of several crops.

UAV images may be used to extract crop information with digital elevation models, digital terrain models (DTMs), and 2-D and 3-D models. A study using this technology to obtain the LAI indirectly employed the SfM algorithm. The SfM is based on the principles of traditional stereophotogrammetry, which overlaps with multiple conventional digital RGB images to obtain geometric characteristics for generating a 2-D and 3-D point cloud [21]–[24].

Studies carried out by Santos *et al*. [25] obtained a high correlation ($R = 0.87$) between the height of coffee plants measured in the field and the height obtained by means of an image derived

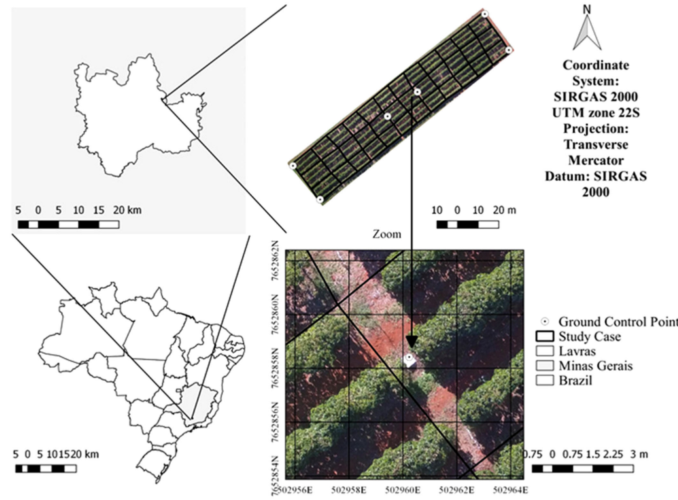

Fig. 1. Location of the study site.

from the SfM-UAV processing. In addition, a correlation of 0.95 was obtained between the diameter of the coffee plants based on field measurements and the diameter obtained through an image derived from SfM-UAV processing. This study shows that the SfM-UAV methodology has the potential to be used for analyses that use biophysical parameters, thus avoiding the need for soil measurements.

Few studies have used this methodology to obtain the LAI and %COV in a coffee culture based on information derived from the SfM point cloud. The authors [10] studied this method and concluded that it was effective, fast, and inexpensive, and that it was able to recreate the grapevine model in digital form. It was also able to correlate the measured LAI in the field with the measurements obtained using the images, with an R^2 of 0.567. Moreover, based on this methodology, it is possible to obtain a map of the geometric characteristics of the entire study area, which can represent the population as a whole, and to estimate various crop parameters by considering a significant number of plants.

Thus, the objective of this study was to follow the evolution of the LAI and %COV in coffee plants across one year, using pre-established equations in the literature, as well as plant measurements obtained from 3-D point clouds and digital images recorded by a camera coupled to a UAV and then processed with the SfM algorithm.

II. Data and Methods

The experiment was performed from June 2017 to May 2018, in a 0.4-ha coffee field established in February 2009, which underwent a pruning process known as esqueletamento (cutting off all the plagiotropic branches 20–30 cm from the orthotropic branch) in July of 2016. This field was the remnant of an experiment with 2.60 × 0.60 m spacing, the treatments of which are described in [26]. The study site is located in the municipality of Lavras, Minas Gerais, Brazil, at latitude 21°13’33“S, longitude 44°58’17”W, and an altitude of 936 m (see Fig. 1).

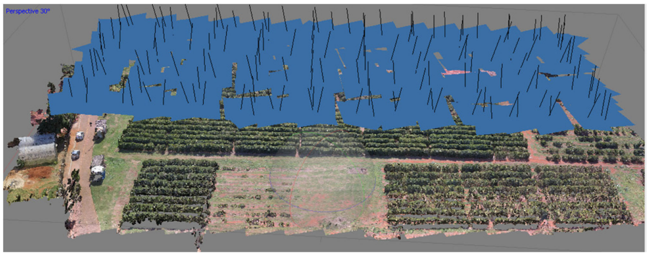

Fig. 2. Dense point cloud.

Four coffee plants were sampled from the 36 blocks distributed over the area for a total of 144 plants, according to the sampling methodology proposed in [27]. In addition, field data, such as height and canopy diameter, were collected to correlate with the data obtained from the images. Six ground control points (GCPs) were also evenly distributed throughout the area to correct the georeferencing of the images, in accordance with studies in [28] (see Fig. 1). The positions of both the plants and the GCPs were taken using a Differential Global Navigation Satellite System (DGNSS; Trimble Navigation Limited, Sunnyvale, California, USA), model SP60, with a horizontal and vertical precision of 0.07 m.

The aircraft used here, a model DJI Phantom 3 (DJI, Shenzhen, China) professional, is classified as a rotary wing UAV with four rotors (quadcopter) and flight autonomy of up to 23 min. This item is equipped with a digital camera coupled with its gimbal. The camera is a Sony model EXMOR 1/2.3", with 4000 × 3000 pixels (12 megapixel) resolution in true colors (Red-R, Green-G, Blue-B) and a 20-mm lens with an optical aperture of f/2.8. The gimbal compensates for the UAV (pitch and roll) movement during flight and ensures the collection of near-nadir images [24]. In this study, the captured images were stored on an SD card for further analysis.

Images were taken monthly, from June 2017 to May 2018, totaling one year of collection. Prior to the flights, the GCPs were delineated. The images were collected 30 m above ground level. The overlap was 80% for both the frontlap and sidelap, and the aircraft speed was 3 m/s. The flights were planned using the DroneDeploy application (Infatics Inc., San Francisco, CA, USA), which is free software that is installed on Android devices. According to [29], the RGB images are strongly influenced by hourly, daily, and seasonal lighting changes; thus, during the collection period, photographs were always taken between 11:00 A.M. and 2:00 P.M., which constitutes the period of highest luminosity in the area.

Agisoft PhotoScan Professional Edition software version 1.2.4 (Agisoft LLC, St. Petersburg, Russia) was used to identify homologous points in the image and create a continuous region for the stereoscopic generation of a point cloud.

Fig. 2 shows the point cloud produced for one month of study. From the dense point cloud, models can be constructed from which the height and diameter values of the plants can then be extracted.

The images were first aligned and optimized using the inertial unit of measurement (IMU) and onboard GNSS/GPS [30]. This software was used to create an orthomosaic and to generate the digital surface model (DSM) and the DTM.

Point cloud classification was performed to obtain the DSM and DTM according to the methodology described in [23] and [31]; the parameters were defined as the maximum angle (deg): 15, maximum distance (m): 0.1, and cell size (m): 40.

The DSM, DTM, and orthomosaic created in the PhotoScan software were exported in a GeoTiff file for Quantum GIS software ver. 2.16.3 (QGIS Development Team, Open Source Geospatial Foundation). All were georeferenced in the Universal Transverse Mercator (UTM) coordinate system, in the SIRGAS 2000 zone 23 S datum, according to the coordinates of the control points collected in the study area and by drawing a polygon of the area of interest in the shapefile (.shp) format.

To obtain the plant height, the methodology proposed in [23] and [25] was used, in which a canopy height model (CHM) is obtained by subtracting the DSM from the DTM. To accurately extract the plant height values, the Focal Statistics tool in ArcGIS version 10.5 (ESRI, Redlands, California, USA) was used. This tool identifies the highest pixel value in the tree canopy of the CHM, avoiding lower or larger pixel values in the tree canopy. Once tabulated, the plant height data were obtained by using the plug-in Point Sampling Tool in QGis software.

The crown diameter of the plants was extracted from the orthomosaic using the QGis measurement tool.

Processing was performed for all 12 months of data obtained through the UAV.

To calculate the LAI, (1) was used, as reported in [2]. This equation takes into account the volume of the canopy and, consequently, the height and diameter of the lower section of the canopy (coffee canopy) and may be used to estimate the leaf area index (LAI) of the coffee tree with an R^2 of 0.99. This parameter was calculated using field data and data extracted from the UAV images

$$\mathrm{LAI} = 0.0134 + 0.7276 \times {D_c}^2 \times h \quad (1)$$

where

D_c - crown diameter, m, and

h - plant height, m.

The percentage of area covered by %COV was calculated according to [15], which accounts for the area occupied by the plants, by considering a plant spacing that was less than or equal to the average plant diameter (in a close-planted hedgerow system), as shown in the following equation:

$$\%COV = \left(\frac{D}{SR}\right) \times 100 \quad (2)$$

where

D - plant diameter, m, and

SR - spacing between planting rows, m.

This parameter was also calculated using field data and data extracted from UAV images. To obtain parameters such as the LAI and %COV, the average of the four plants sampled in the image from the 36 blocks of area was used, both for the field data and data obtained from the image.

The linear regression model was applied to the 36 LAI and %COV values obtained for the 12 months of study. Pearson's correlation coefficient (R) was calculated to measure the degree of the linear relationship between the variables under study. The coefficient of determination, R-square (R^2), mean absolute error (MAE) and root mean square error (RMSE) were also calculated to assess the goodness and accuracy of the regression. The larger the R^2 value, the stronger the correlation. The smaller the RMSE value, the higher the predicted accuracy. All analyses were carried out with the R software package.

Electronic spreadsheets were used for the calculations (%COV and LAI) and data organization, and GeoDa free software was used for the spatial analysis [32]. Spatial analyses are essential for visualizing the spatial distribution of these variables throughout the field. In addition, such analyses allow for the analysis of the temporal distribution of the %COV and LAI, to understand their behavior in the studied site.

To estimate the spatial variability of the data from the study area, a spatial weight matrix was calculated using GeoDa, based on the "queen" criterion, i.e., by considering second-order neighbors, so that $w_{ij} = 1$ if the ith block shares at least one side with the jth block, and $w_{ij} = 0$ otherwise. The pseudo-significance test was applied with $p < 0.05$ to validate the statistic.

The global Moran's index of spatial autocorrelation (I) proposed by [33] describes the spatial arrangement of objects given by the following equation:

$$I = \frac{n}{W}\left(\frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum\limits_i z^2{}_i}\right) \forall i \neq j \tag{3}$$

where

n - number of observations;

w_{ij} - element of the weight matrix for pair i and j;

W - sum of the weights of the matrix;

z_i and z_j - deviations from the mean (z_i - z), (z_j - z); and

z - mean.

According to [34], the Moran index ranges from -1 to 1, with 0 to 1 indicating a positive direct autocorrelation and 0 to -1 indicating an indirect and negative autocorrelation.

III. RESULTS

A. Percentage of Area Covered and LAI Estimation

The biophysical parameters showed a strong spatial correlation. Linear regression showed a strong relationship between the estimated and measured %COV ($R = 0.89$) To improve the regression model, we also calculated the residuals. More specifically, the %COV R^2, RMSE, and MAE were 0.79, 3.41, and 2.59, respectively (see Fig. 3).

Linear regression showed a strong relationship between the estimated and measured LAI ($R = 0.88$) and the R^2, RMSE, and MAE accuracy for LAI were 0.77, 0.47, and 0.38, respectively (see Fig. 4).

B. Percentage of Area Covered by Coffee Plants

With the data obtained from the images, it was possible to obtain the %COV during the study period and to monitor the evolution and cover of coffee plants in the area. The crop underwent the pruning process during the third week of July 2016. Thus, it was possible to monitor coffee growth and development remotely throughout the study.

A classification scheme (see Table 1) was proposed that allowed for the %COV to be monitored in the study area over the course of the year.

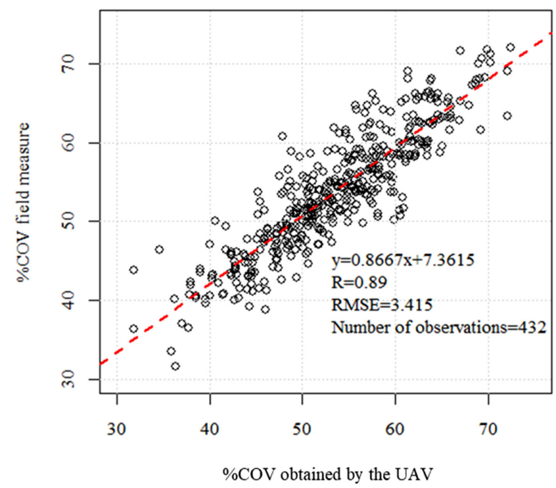

Fig. 3. Linear regression models of the estimated (UAV) and measured (ground truth) for %COV.

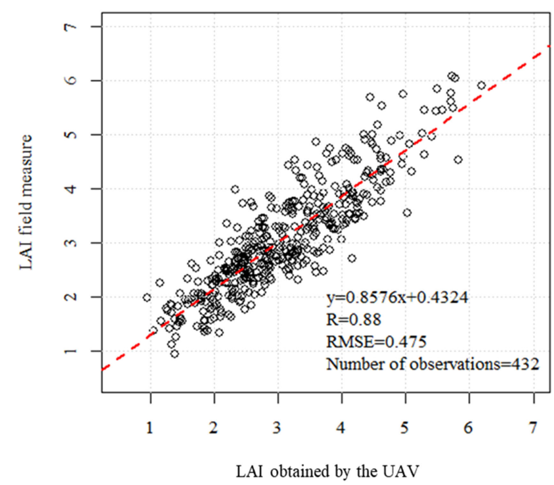

Fig. 4. Linear regression models of the estimated (UAV) and measured (ground truth) for LAI.

TABLE I
SCALE, PERCENTAGE OF AREA COVERED BY COFFEE PLANTS

	%Cover	Level of Cover
Classes	< 20	Low
	20 - 39	Noticeable
	40 - 60	Moderate
	61 - 80	High
	> 80	Voluminous

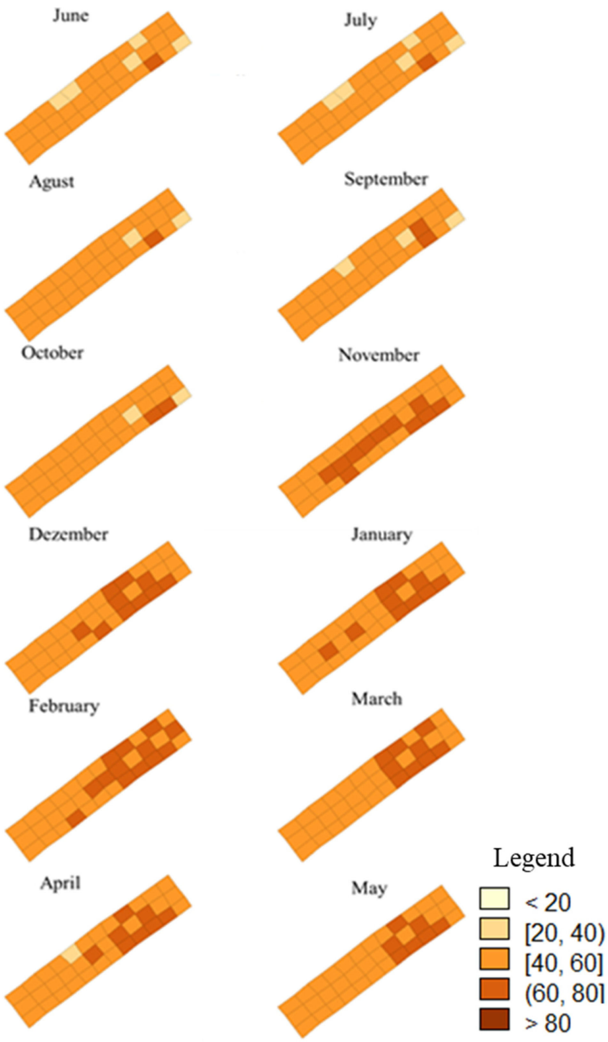

Fig. 5. Spatial distribution for the percentage of area covered by coffee plants during the study months, as generated by GeoDa software with data obtained from the UAV.

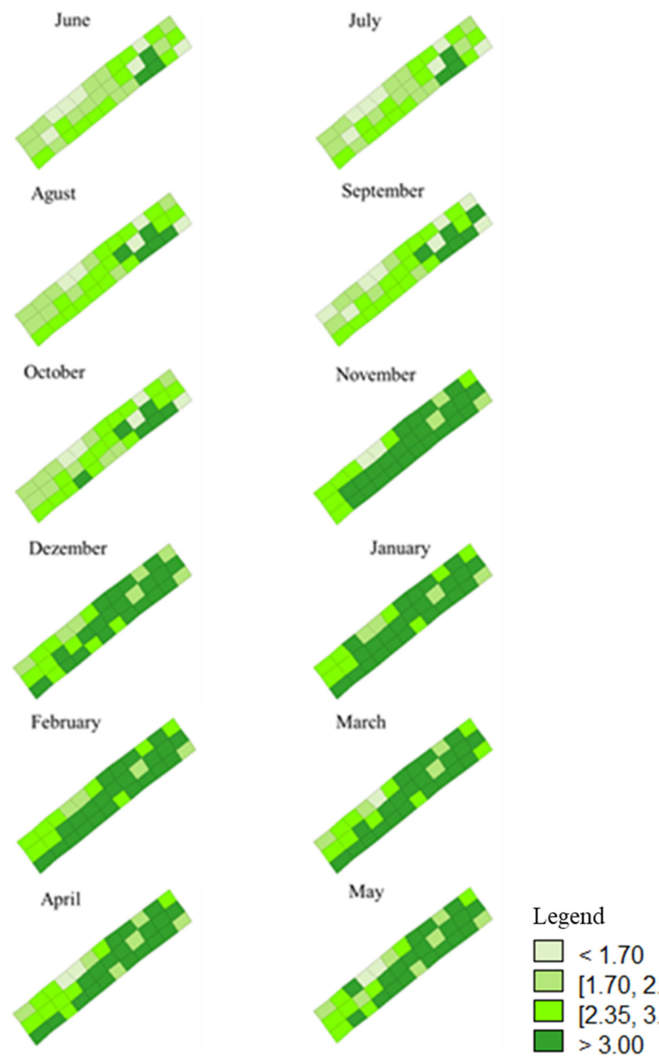

Fig. 6. LAI of the coffee plants during the study months.

Fig. 5 shows the percentage of area covered over the 12-month study. In June 2017, the coffee field was recovering from pruning; most blocks, i.e., 30 blocks, had a moderate %COV; and the calculated Moran index had a positive spatial autocorrelation but a weak autocorrelation of 0.008. During this month, the variable was not statistically significant, allowing for the acceptance of the null hypothesis with a significance level of 0.05, i.e., there was no spatial autocorrelation for the %COV variable in the month of June 2017, indicating that the space did not influence the %COV variability in the area.

For the months of July, August, September, and October, whose Moran indices were 0.008, 0.021, 0.091, and 0.047, respectively, the %COV was moderate in most blocks, and for these months, there was no spatial autocorrelation.

For November and December, the Moran indexes were 0.023 and 0.089, respectively, and there was a small increase in the blocks with high %COV values; however, most remained at a moderate cover level. Even so, during these months, there was no significant spatial autocorrelation.

In the months of January, February, and March, the Moran index increased in comparison to the previous months, with values of 0.134, 0.133, and 0.206, respectively.

The %COV results obtained for the months of April and May were less than those of the previous months. The Moran index also decreased compared to the previous months, with values of 0.069 for April and 0.117 for May; during both months, there was no significant spatial autocorrelation.

C. *LAI Obtained by the UAV*

Fig. 6 shows the evolution of the LAI as calculated for each month in the study. In June and July, the LAI remained between 1.7 and 3.0 for most blocks, and the Moran Indexes (I) were 0.079 and 0.086, respectively. During these months, there was no spatial autocorrelation because the LAI variable was not statistically significant, so it was possible to accept the null hypothesis at a significance level of 0.05. This result is due to the spatial variability derived from the previously used treatments.

In the months of August, September, and October, the LAI was 2.5 to 3.0 for most blocks; during these months, the Moran's I values were 0.084, 0.182, and 0.124, respectively, remaining nonsignificant.

Over these months, there was an increase in the Moran's I, with values of 0.135 for the month of December, 0.163 for January, 0.168 for February, and 0.278 for March, and an increase in the LAI value, with values greater than 3.0.

For January, February, and March, there was a significant autocorrelation, and consequently, the LAI values were influenced by the space; that is, the LAI values observed in a given region were found to be dependent on the LAI values in the neighboring locations, as shown in Fig. 6. Most of the blocks of the central and central-west regions had LAI values > 3.0, as represented by the darker green color.

In April and May, the Moran's I values decreased in comparison to the values for the previous months, with values of 0.111 for April and 0.183 for May, and although the pseudo-significance test was significant, the LAI decreased.

IV. Discussion

A. Percentage of Area Covered and LAI Estimation

In this study, we obtained a strong correlation between %COV and LAI data from UAV RGB images. This result is mainly attributed to the high image resolution that can be obtained from UAV platforms and the configured flight parameters. However, studies in which such parameters are obtained for coffee crops are still incipient, such that it would be recommended, whenever possible, to test flight parameters (height, overlap, speed) because these may significantly interfere with the results. A significant advantage of the used method was its ability to demonstrate the reliability of using a common RGB camera to obtain the biophysical parameters of coffee trees. With this, there is a reduction in the cost of camera equipment when compared, e.g., with thermal, multispectral [35], and hyperspectral cameras. In addition, this option is particularly interesting for UAV applications, because it allows biophysical and biochemical parameters to be obtained indirectly, using a rapid and economical approach [18], [19].

There are no precedent studies on the use of UAV images to estimate %COV. However, researchers have used satellite images to correlate this parameter with vegetation indices. The authors of [36] studied the correlation between culture parameters and the spectral response of coffee culture, using data from Landsat/TM images. The results showed that among the culture variables evaluated, the %COV of coffee plants showed a significant response when correlated with the spectral response of the culture in band 4.

The study presented in [15] investigated %COV using satellite high-spatial-resolution images. These authors found that the vegetation indexes evaluated did not obtain significant results for the %COV parameter. Their results can be attributed to the conditions of the crops studied, where crops with coverages less than 50% may not be practical for the extraction of remote information from images collected from orbital platforms, e.g., satellites. Thus, our research using platforms closer to the target is essential and justified. Future research that entails this approach of correlating vegetation indexes with biophysical parameters obtained from UAVs is recommended.

Previous studies using UAVs have shown similar results in regard to LAI determinations. The authors of [37] used the SfM-UAV methodology for vineyards. Another study uses the SfM-UAV methodology to obtain forest biomass and LAI values [38].

Our study varies from those cited above in several capacities. The differences are mainly due to the use of different data sources and different types of vegetation, biomass, and canopy density. Therefore, the specific characteristics of coffee crops must be studied and incorporated into future studies with greater accuracy. However, this study demonstrated our ability to carry out constant evaluations of crop %COV and LAI using the SfM approach based on images obtained by a UAV with an RGB camera. In addition, this study confirmed that canopy height and diameter may be important and appropriate parameters for remotely monitoring and analyzing LAI and %COV in coffee crops.

B. Percentage of Area Covered by Coffee Plants

In July, August, September, and October, there was no spatial autocorrelation. This period corresponds to the drier and colder months, which resulted in lower crop development. According to [39], the end of the second phase of crop growth in coffee plants occurs in July and August for the study region, during which the plants enter a period of relative dormancy. September and October constitute months in which the coffee plants enter the third phase, the first of the second phenological year, initiating flowering and the formation of small green coffee berries. In this area, flowering occurred in October.

For November and December, for which there was no spatial correlation, this result may be explained by the forced variability in the area due to the treatments used in the prior experiment and their residual effects. However, because the treatments did not continue throughout the study, this variability tended to decrease, and the area tended to become more stable and had more similar neighbors, as may be observed during the subsequent months.

In January, February, and March, the pseudo-significance test was significant, indicating the presence of spatial autocorrelation. It may be said that the treatments no longer had an effect on the blocks; thus, the area tended to be more uniform, resulting in a majority of the blocks with a moderate percentage of cover. In addition, it can be concluded that space has a stronger effect on plant development, and therefore, neighboring plants tended to be similar due to their spatial location (see Fig. 5).

The lack of spatial correlation for the %COV parameter during the final months, April and May, can be explained by disease-induced variability. For those two months, the crop was affected by a disease, Cercospora leaf spot, which is also known as brown eye spot of coffee. January to May is the period with the highest incidence of Cercospora leaf spot in the field, in which adult plants experience severe defoliation, maturation and the premature dropping of fruits, an increase in the number of empty grains in addition to the adherence of the pulp to the husk, which hinders pulping, causing a decrease in the yield and quality of the final product [40], [41]

Disease susceptibility occurred due to nutritional deficiency in the area because of the discontinuation of treatments in the field. In the literature, several authors have indicated that deficient or unbalanced nutrition has a direct effect on the intensity of attacks by Cercospora leaf spot [40], [42],[43]. During these two months, the %COV continued to be moderate for most blocks, although the number of blocks with a high %COV decreased, as shown in Fig. 5.

The %COV of coffee plants is a biophysical parameter that allows for the monitoring of crop development, and it may support, among other management practices, mechanization because crops with voluminous cover may hinder the entry of machinery for use in mechanized management systems. One of the mechanized operations performed in coffee production is harvesting, and according to [44], a mechanized coffee harvesting system has a lower operational cost and yields better fruit quality compared to a manual harvesting system.

According to [45], some self-propelled coffee harvesters have a gantry with the ability to work at a maximum height of 2.10 m and a 1.40–1.80 m crown diameter. For crops, such as that in this study, from the vegetative period onward at a spacing of 2.6 m between rows, this diameter threshold would result from 54 to 69%COV, i.e., moderate to high, hindering the entry of machinery into the field. However, values greater than 69% COV, i.e., high and voluminous, would no longer allow for the entry of this type of harvester into the field, or if used, it could result in low harvesting efficiency and the excessive snapping of branches. Thus, analyzing the percentage of cover may help manage machinery in the fields.

C. LAI Obtained by the UAV

The highest LAI values are typically found in November, December, and January, according to [39]. Coffee plants are in the vegetative period during November and December, based on the climatic conditions of Brazil. The related results show that the crop recovered following pruning.

In April and May, the LAI decreased due to the Cercospora leaf spot disease. The coffee plants became susceptible due to the discontinuation of fertilization treatments, which influenced the leaf development of the plants, as observed for the %COV parameter.

The studies performed by [2] reported similar values compared to those in this study. The authors found LAI values equal to 2.34 for coffee plants at 30 months after planting and LAI values of 3.41 for coffee plants at 35 months after planting.

In addition to [2], other authors have used (1) in an adapted manner to estimate the volume or LAI of coffee trees. The authors of [46] used (1) to conclude that it is possible to reliably determine the volume of coffee vegetation by digitally processing the images captured by UAVs.

The studies carried out by [8] reached values of LAI at the upper part of the plant of 1.78 and of 6.5, on average, at the lower portion. In another study, Costa *et al*. [47] concluded that the LAI value was between 0 and 6.

Due to the pruning performed at the end of 2016, there was a significant decrease in the LA of the coffee trees during our period of study. However, from June 2017 to March 2018, it was possible to observe a recovery in the crop and an increase in the ratio between the LA and the area covered by the coffee plants and to monitor this evolution throughout the study. The values found in [2], are close to those found in the present study, although the plants were not of the same age. However, it should be noted that pruning led to a decrease in the number of leaves and consequently a decrease in the LAI.

According to [48], knowledge of the temporal variation in the LAI is important for defining better irrigation management strategies in addition to the crop's yield potential. The yield may be monitored by using the LAI because any variation in this index caused by frost, storms, defoliation, drought, management practices, etc., may change the yield [49]. In this study, the LAI generally increased, with a decrease observed during the last months of analysis. As found in [49], the LAI is variable throughout the year and is strongly affected by the harvest and the occurrence of pests and diseases, as observed in this study, during which a decrease in the LAI occurred due to disease.

V. Conclusion

In this study, we determined that it is possible to use a UAV-coupled digital camera to obtain the biophysical parameters of coffee plants, such as %COV and LAI, using a nondestructive method, 3-D point cloud, and SfM algorithm. The %COV and LAI estimated in the recorded images were shown to be strongly correlated with the field data %COV and LAI. It was also possible to monitor the temporal and spatial behavior of the LAI and %COV such that we were able to conclude that the presented methodology yields results that are consistent with those in the literature.

The main advantage of the coffee monitoring methodology presented here is that it is nondestructive, simple, and time-efficient for calculating LAI and% COV.

It is a methodology that could assist farmers in the monitoring of crop growth and development, weed control, canopy cover, crop anomalies and mechanization management, pest and disease management, and crop management in coffee crops.

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Luana Mendes dos Santos received the B.S. degree in agricultural environmental engineering from the Rural Federal University of Rio de Janeiro, Seropédica, Brazil, in 2016, the M.S. degree in agricultural engineering from the Federal University of Lavras, in 2018, and a work safety engineering certificate from Unilavras Lavras, Lavras, Brazil. She is currently working toward the Ph.D. degree in agricultural engineering at the Federal University of Lavras.

Her research interests include precision agriculture, unmanned aerial vehicles, precision coffee farming, and interesting GIS problems in agriculture.

Gabriel Araújo e Silva Ferraz received the B.S. degree in agricultural engineering, the M.S. degree in agricultural engineering with concentrations in agricultural machinery and automation, and the Ph.D. degree in agricultural engineering from the Federal University of Lavras, Lavras, Brazil, in 2008, 2010, and 2010, respectively.

From 2011 to 2014, he was a Professor with the Rural Federal University of Rio de Janeiro, Seropédica, Brazil. In 2017, he commenced a Post-Doctoral position with the National University of Colombia, Medellin, Colombia. From 2019 to 2020, he was a Visiting Professor with the University of Florence, Florence, Italy. Since 2014, he has been a Professor with the Agricultural Engineering Department, Federal University of Lavras. He has authored more than 65 articles published in scientific journals, 15 book chapters, and more than 180 conference papers. His research interests include precision agriculture, unmanned aerial vehicles, geostatistics, GIS, and agricultural machinery.

Brenon Diennevan de Souza Barbosa received the B.S. degree in agricultural and environmental engineering from the Federal University of Minas Gerais, Belo Horizonte, Brazil, in 2014, the M.S. degree in water resources in agriculture systems, in 2016, from the Federal University of Lavras, Lavras, Brazil, where he is currently working toward the Ph.D. degree in agricultural engineering. His research interests include precision agriculture, irrigation, engineering irrigation, water resources, energy in irrigated agriculture systems, and unmanned aerial vehicles in agriculture.

Adriano Valentim Diotto received the B.S. degree in agronomist engineering and the Ph.D. degree in irrigation and drainage from the University of São Paulo, São Paulo, Brazil, in 2002 and 2013, respectively.

From 2013 to 2015, he was a Research Assistant with the University of Nebraska-Lincoln, Lincoln, NE, USA. Since 2016, he has been an Associate Professor with the University of Lavras, Lavras, Brazil. His research interests include water and energy use efficiency in agricultural systems and irrigation system designs and management.

Marco Thulio Andrade received the title of Technician in agriculture and zootechnics from the Federal Institute of Science and Technology, Bambuí, Brazil, in 2013, and the B.S. degree in agricultural engineering from the Federal University of Lavras in Lavras, Brazil, in 2020.

Leonardo Conti the B.S. degree in forest sciences with a specialization in environmental management and soil conservation and the Ph.D. degree in agricultural and forest engineering from the University of Florence, Florence, Italy, in 1999 and 2004, respectively.

From 2005 to 2007, he was a Contract Professor in “Rural building,” also at the University of Florence. Since 2007, he has been an Assistant Professor with the Department of Agriculture, Division Agricultural and Forest Biosystems Engineering, the University of Florence. He has authored 70 peer-reviewed papers and conference proceedings. His research interests include precision agriculture, applications of GPS-GIS technologies to rural landscape planning, and unnamed aerial vehicles.

Giuseppe Rossi received the B.S. degree in agricultural science and technology and the Ph.D. degree in agroforestry engineering from the University of Florence, Florence, Italy, in 2005 and 2012, respectively.

From 2007 to 2016, he was a Research Fellow with the Department of Agriculture, Environment, Food and Forestry, the University of Florence. Since 2017, he has been Assistant Professor with the Department of Agriculture, Environment, Food and Forestry, the University of Florence. He has authored one book, more than 35 articles published in national and international journals, and a co-owner of two national patents and one international patent.

Dr. Rossi is a member of Italian Society of Agricultural Engineering and since 2015 has served as an Expert Advisor for the Italian Agency for Development Cooperation, Italian Ministry of Foreign Affairs.