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Supervised classification and NDVI calculation from remote piloted aircraft images for coffee plantations applications

Sthéfany Airane dos Santos[1], Gabriel Araújo e Silva Ferraz[1], Vanessa Castro Figueiredo[2], Lucas Santos Santana[1], Beatriz Fonseca Dominik Campos[3]

[1]Universidade Federal de Lavras/UFLA, Departamento de Engenharia Agrícola/DEA, Lavras, MG, Brasil
[2]Empresa de Pesquisa Agropecuária de Minas Gerais/EPAMIG, Três Pontas, MG, Brasil
[3]Empresa de Pesquisa Agropecuária de Minas Gerais/EPAMIG, Lavras, MG, Brasil
Contact authors: sthefany.santos1@estudante.ufla.br; gabriel.ferraz@ufla.br; vcfigueiredo@epamig.br; lucas.unemat@hotmail.com; beatriz_dominik@yahoo.com.br
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ABSTRACT

A tool that has been widely used in Precision Agriculture (PA) is the Remote Piloted Aircraft's (RPA's). These tools are used to monitor crops, in addition to checking and quantifying various attributes related to plants. However, there are few studies that evaluate the applicability of this technology in coffee plantations. The objective of this study is to present the applicability of two tools associated with PA and remote sensing to monitoring a coffee plantation. The study was conducted in the municipality of Três Pontas, Brazil, comprised a 1.2 ha coffee plantation. Data were collected during a flight with an eBee SQ RPA, and high spatial resolution images were captured by a Parrot Sequoia multispectral sensor coupled to the aircraft. The images were processed using the software Pix4D, thus creating an orthomosaic that was later uploaded to QGIS software. In this program, a supervised classification of land use and land cover was performed using the maximum likelihood method, and the following classes were obtained: coffee plant, exposed soil, and undergrowth. From the mapping accuracy, an overall accuracy and kappa index of 91% and 85% were obtained, respectively. In addition to the supervised classification of the site, the normalized difference vegetation index (NDVI) was calculated for only the coffee plant class. The NDVI map showed the areas of the plantation coffee crop with higher and lower vegetative vigour.

Key words: Mapping; precision coffee farming; remotely piloted aircraft.

1 INTRODUCTION

The use of technology in the planting field has increasingly expanded. In the most diverse sectors, such as agriculture and livestock production, technology has become a means for increasing productivity and reducing environmental impact.

Because coffee is one of the most important products in Brazilian agriculture, knowledge of the spatial distribution of coffee production is essential for both crop forecasting and agricultural planning. Therefore, the use of remote sensing has become a strategic tool for obtaining thematic information that costs less than conventional methods and that minimizes the subjectivity of indirect methods (Moreira; Barros; Rudorff, 2008).

Some studies have shown that the use of remote sensing in coffee production is significant (Lamparelli; Nery; Rocha, 2011; Bernardes et al., 2012; Chemura; Mutanga; Dube, 2016). However, the main challenge in the analysis of remote sensing data as time series is dealing with the noise present in the images (Lunetta et al., 2006), which can manifest as data loss due to sensor failure or interference from atmospheric components.

The use of RPA's as platforms for remote sensing proves to be advantageous, due to their high accessibility, flexibility and efficiency (Ahmad et al., 2021). Among its many advantages are low cost for image acquisition, obtaining high resolution images (up to 0.2 m) which provides complete spatial coverage, without cloud interference when compared to satellite images (Urbahs; Jonaite, 2013).

The development of remotely piloted aircraft (RPA) in the last decade has facilitated the acquisition of remote sensing images with high spatial and temporal resolution, in addition to providing detailed vegetation information and observation angles different from those of field-level observations (Santos et al., 2020). RPA have boosted precision agriculture (PA) because they have an increasing potential for agricultural monitoring via data collection through remote sensing techniques (Barbosa et al., 2019).

Knowledge of the distribution of vegetation within a cultivation area is the first important step in PA (Torres-Sánchez et al., 2014). In addition to gains in precision, mapping with high spatial resolution images can facilitate the extraction of important plant parameters such as the height, crown diameter, and spacing; the detection of homogeneous patterns and areas; the separation and quantification of weeds; the inspection of anomalies in the field with an aerial view; and the obtaining of field responses faster through an image, which facilitates management and interventions (Santos et al., 2019).

In coffee farming, studies have used images obtained by RPA for monitoring and mapping Guinea grass in coffee plantations (Herwitz et al., 2004) and monitoring fruit ripeness and evaluating the initial harvest period of coffee plantations (Johnson et al., 2004). Crop failure has been detected from RGB images belonging to the RGB (red, green and blue) visible spectrum range (Oliveira et al., 2018), and vegetation volume has been estimated (Da Cunha; Sirqueira; Hurtado, 2019). Additionally, RPA images have been used for mapping land cover (Santos et al., 2019a), analysing flight parameters and georeferencing of images with different control points (Santos et al., 2019b), and analysing flight parameters for the generation of orthomosaics (Santos et al., 2019c). Moreover, biophysical parameters have been evaluated, and the height and diameter of coffee plants have been measured (Santos et al., 2020).

For the management of coffee plantations, the normalized difference vegetation index (NDVI) is an important tool in decision making because, in practice, it is related to various vegetation parameters (leaf area index, yield, biomass, photosynthetically active radiation, and several others) (Pellegrino et al., 2007; Simões; Rocha; Lamparelli, 2009).

Multispectral sensors can be coupled to RPA to capture images at different wavelengths, originating from the reflected spectrum, more specifically encompassing the visible (VIS, 0.4-0.7 µm), near infrared (NIR, 0.7-1.3 µm) and shortwave infrared (SWIR, 1.3- 2.5 µm) regions.

From these images, the vegetation indices can be calculated with mathematical formulas based on various combinations of reflectance values in specific electromagnetic spectrum bands. Knowledge of the spectral behaviour of vegetation is therefore essential for the interpretation of the results (Křížová; Kumhálová, 2017). Vegetation indices can describe the health and condition of agricultural crops, but each index uses a different part of the electromagnetic spectrum, and therefore, each has a different informative value (Stary et al., 2020).

Some studies have used the technology of image acquisition by multispectral sensors coupled to RPA for the detection of coffee leaf rust (Velásquez et al., 2020), early detection of diseases and pests in coffee plants based on imperceptible water stress (Chemura; Mutanga; Dube, 2016), and mapping of nematodes in coffee (Abreu Júnior et al., 2020).

Given the applicability of RPA as support for coffee farming, the objective of this study is to describe two tools that can be used on high-resolution multispectral images obtained by an RPA: supervised classification of land use and land cover and calculation of the NDVI.

2 MATERIAL AND METHODS

2.1 Study site

The study site is located in the southern region of the state of Minas Gerais, south-eastern Brazil, in the municipality of Três Pontas, one of the largest coffee-producing regions in Brazil. Its location is defined by geographical coordinates 2127.8‘20° South and 4512‘29°” West (SIRGAS 2000/ UTM zone 23S). The study area is a 1.2ha experimental field under coffee production. This area aims to generate technical-scientific information for the construction of knowledge and the development of technologies. (Figure 1).

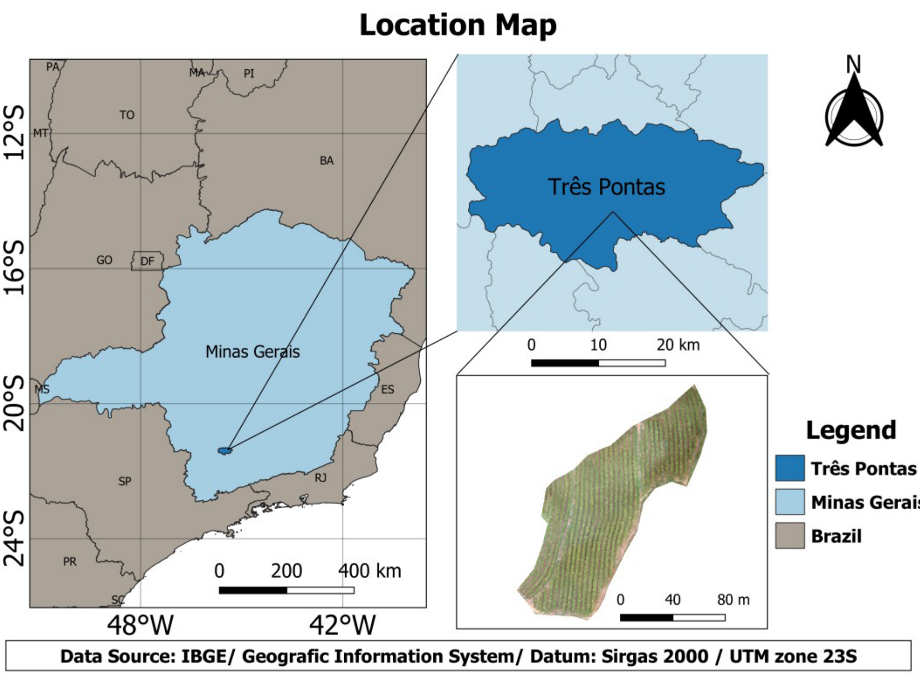

Figure 1: Location map.

This area belongs to the Agricultural Research Corporation of Minas Gerais (Empresa de Pesquisa Agropecuária de Minas Gerais - EPAMIG). The coffee plantation was established in 1998 and is cultivated with the species *Coffea arabica* cv. Topázio MG 1190, with 3.70 m spacing between rows and 0.70 m between plants.

According to the Köppen classification, the climate is characterized as warm and temperate (Cwa), and it rains much more in summer than in winter. The mean annual temperature is 20° C, with a total annual rainfall recorded in 2019 of between 1800 and 2000 mm (Instituto Nacional de Meteorologia - INMET, 2020).

2.2 Obtaining images by remotely piloted aircraft

To capture images, a flight was performed on November 19, 2019 with an RPA, model eBee SQ (Figure 2), manufactured by a Swiss company founded in 2009 called senseFly, which is a commercial RPA subsidiary of Parrot Group. This aircraft had a fixed wing design with a 110 cm wingspan, a radio range of 3 km (nominal), a cruising speed of 40-110 km h^{-1}, a wind resistance up to 45 m h^{-1} (12 m s^{-1}), an electric motor, a maximum payload of 1.1 kg (including a camera and batteries), and a flight autonomy of up to 55 minutes.

The RPA was equipped with a Parrot Sequoia multispectral sensor (Figure 3), which had a high-resolution RGB camera with a 4608 × 3456 pixel sensor, pixel size of 1.34 µm, and focal length of 4.88 mm; the ground sampling distance (GSD) was 1.9 cm at 70 m above ground level (AGL).

The Sequoia sensor had four monochromatic cameras sensitive to the following spectral bands: green (G, 530-570 nm), red (R, 640-680 nm), red edge (RE, 730-740 nm) and near infrared (NIR, 77-810 nm). The resolution was 1280 × 960, with a pixel size of 3.75 µm and focal length equal to 3.98 mm; the GSD was 6.8 cm at a flight height of 50 m AGL, which was adopted for the described study.

The flight planning consisted of an initial step where parameters such as the altitude, coverage area, and appropriate speed were defined so that the images obtained were of high quality and met the expected objectives. There are several software programs available on the market to perform flight planning that can be used in an office or through smartphones and tablets, where the flight plan is sent to the RPA.

During flight planning, the image resolution was defined, and as a result of this and of the sensors used, a flight height and route were defined. It was necessary to ensure a minimum of 60% lateral overlap and 70% longitudinal overlap of the images for subsequent processing.

The flight time was set between 11 am and 1 pm to obtain good lighting conditions, as recommended by Bater et al. (2011), who reported that RGB camera images are strongly influenced by hourly, daily, and seasonal lighting changes.

The flight plan was created through the base station, developed by the same aircraft manufacturer (senseFly), with the following components: eMotion software, responsible for flight scheduling and execution of the aircraft path, and a transmitting antenna, which facilitated real-time monitoring of the flight and the sending of landing, direction change and image capturing commands. The program interface showed important information about the battery level, ambient temperature, altitude, position, flight duration and speed, wind speed, resolution and longitudinal and latitudinal overlap of the area to be flown, altitude, and radio link. The following parameters were established in the flight plan (Table 1).

Figure 2: eBee SQ RPA.

Figure 3: Parrot Sequoia multispectral camera.

Table 1: Defined flight plan parameters.

Camera	Parrot Redwood
RGB camera resolution	16 megapixels
Multispectral camera resolution	1.2 megapixels
Focal length	3.98 mm
Side overlap	70%
Longitudinal overlap	70%
Spatial resolution	5 cm
Flight altitude	50 m
Flight speed	12 m s^{-1}
Imaged area	2.6 ha

2.3 Image processing

Image processing was performed using the program Pix4DMapper. The digital processing consisted of phototriangulation of the image blocks, obtaining the exterior and interior orientation parameters of the images, the production of the digital surface model (DSM) and the generation of the orthomosaic.

To perform the phototriangulation of the images, five control points were distributed evenly throughout the property. The points were surveyed using a dual-frequency Trimble global navigation satellite system (GNSS) receiver operating in real time kinematic (RTK) mode with positional accuracy of less than 1 mm in a 1 Hz band.

Next, radiometric correction of the orthomosaics was performed, i.e., conversion of the values into digital numbers (DNs) for surface reflectance. This processing was also performed in Pix4DMapper, with resources from Parrot Sequoia.

Before the flight, a calibration plate placed on the ground was recorded with the Sequoia camera so that the sensor could determine the local calibration conditions. Using the values of this plate, the software could calibrate and correct the image reflectance taking into account the lighting conditions at the time of flight.

To perform the radiometric correction it is necessary to follow a workflow. First, the individual images undergo a specific sensor correction that is divided into steps: exposure calibration, vignette correction and irradiance normalization.

Exposure calibration was performed to adjust the different exposure settings. Vignette is the radial decrease in pixel values that results in darker areas near the edges of images (Goldman, 2010). Then, irradiance normalization was applied to no r malize the images for variability in irradiance.

The corrected images were then processed with structured motion techniques to create an orthomosaic with all saturated pixels masked. Finally, the empirical line method (Stow et al., 2019) was applied to the orthomosaic to create a reflectance map, that is, an orthomosaic where pixel values are converted into surface reflectance.

Stow et al. (2019) and Olsson et al. (2021) present in detail all the workflow and detailed calculations that are involved in this image transformation process.

2.4 Supervised classification

The principle of supervised classification is based on the use of algorithms to determine the pixels that represent the characteristic reflection values of a certain class. Supervised classification has become the most commonly used type for the quantitative analysis of remotely sensed images (Belgiu; Draˇgu¸t, 2014; Ma et al., 2017; Costa; Foody; Boyd, 2018).

In this study the supervised classification was performed to define the spectral signatures present in the area. Digital image processing was performed using the pixel-by-pixel classification technique by the maximum likeli hood method. This method has a training area, where model pixel areas are selected in the image that are representative of each land cover target (Moreira; Barros; Rudorff, 2008).

The objective of this classification was to divide the study area into three classes (coffee, exposed soil and undergrowth). For this, 90 training samples were collected, being 30 samples for each intended class. These samples were collected randomly under the composition of RGB bands (visible spectrum).

2.5 Mapping accuracy

Classification accuracy was determined from the kappa coefficient, overall accuracy, producer accuracy and user accuracy which were derived from the error (confusion) assessment as analyzed by Congalton (2009).

Considering that this study did not present data collected in the field (field truth) and in order to have a comparison between the classification results and the mapping accuracy, 30 accuracy samples were used (10 samples for each class). These samples were also collected under the composition of RGB bands and at different locations from the training samples.

The global accuracy represents the results in percentage of hits, and the minimum accepted for land use maps is 85%, a value that is within the reliability interval created by Jensen (1996).

The kappa index, proposed by Landis and Koch (1977), considers the entire confusion matrix in its calculation, which represents the disagreements in the classification, the authors characterized three clusters for the kappa index: a value greater than 0.80 (that is, >80%) represents strong agreement; a value between 0.40 and 0.80 (ie, 40-80%) represents moderate agreement; and a value below 0.40 (i.e. <40%) represents poor agreement.

User accuracy refers to commission errors, which is the error made when assigning a pixel to a class when it belongs to some other class, referring to an excessive delimitation of the category (Cho et al., 2021). Whereas producer accuracy refers to omission errors, being the probability of a reference pixel be correctly classified (Sarmiento et al., 2014).

2.6 NDVI calculation

From the land use and land cover classification, a mask layer containing only the polygons that made up the coffee plant class was extracted. From this layer, the images obtained by the Parrot Sequoia camera in the red and NIR bands were used to calculate the NDVI for only the coffee plant class.

The NDVI was calculated using the formula (Equation 1).

$$NDVI = \frac{NIR + RED}{NIR - RED} \tag{1}$$

Where NIR: near-infrared spectral band reflectance; RED: red spectral band reflectance.

The NDVI ranges from -1 to 1, and the closer to 1, the greater the vegetative activity at the site represented by the pixel. Negative values or values close to 0 indicate areas with water, buildings, and bare soil, in short, where there is little or no chlorophyll activity (Zhang et al., 2016; Cordeiro et al., 2017).

3 RESULTS

The land use and land cover map, produced by the maximum likelihood method, is shown in Figure 4. Using the supervised classification method, it was possible to define three classes (coffee plant, exposed soil, and undergrowth). The small number of classes was favorable for mapping by interpretation of images at this site.

Table 2 represents the land cover classes, total areas occupied by each, and the representative percentages in relation to the total area. Coffee plants occupied most (47, 21%) of the total 1.2 ha area.

The confusion matrix is presented in Table 3.

Table 4 presents the user and producer accuracy data for the maxver algorithm by supervised classification.

The RED and NIR bands were cut through a mask layer obtained by the coffee class (Figure 5) which generated an NDVI map only for this class (Figure 6).

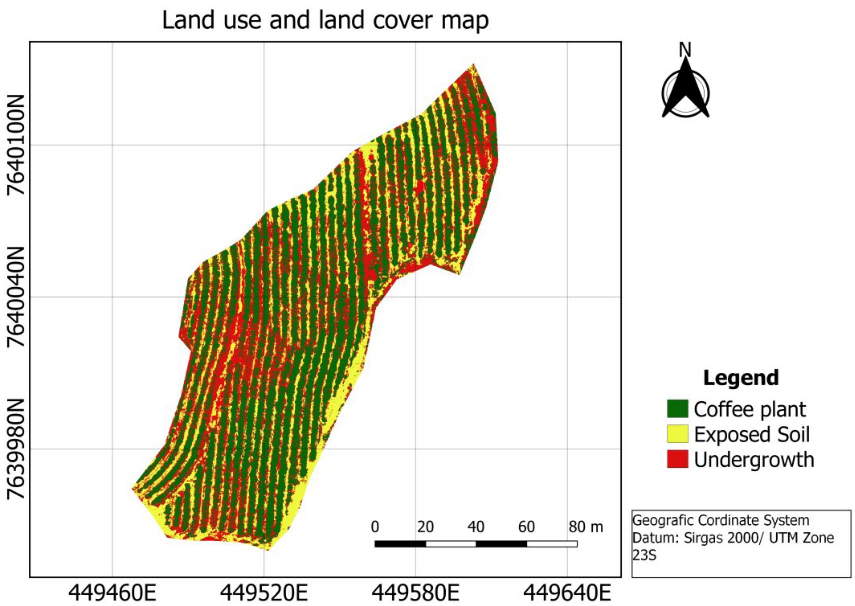

Figure 4: Land use and land cover map.

Table 2: Sizes and percentages of each land cover class.

Land cover	Area (ha)	Percentage (%)
Coffee plant	0.4743	47.21
Exposed soil	0.2202	21.93
Undergrowth	0.3100	30.85
Total	1.2055	100.00

Table 3: Confusion matrix.

Classification Data	Reference Data			
	Coffee (m²)	Exposed Soil (m²)	Undergrowth (m²)	Total (m²)
Coffee	0.4583	0.0000	0.0138	0.4721
Exposed Soil	0.0000	0.2193	0.0000	0.2193
Undergrowth	0.0771	0.0011	0.2304	0.3086
Total	0.5354	0.2204	0.2442	1

Table 4: User and producer's accuracy.

Class	User Accuracy (%)	Producer's Accuracy (%)
Coffee	97.0	85.6
Exposed Soil	100.0	99.5
Undergrowth	74.6	94,3

4 DISCUSSION

According to Moreira (2007), the quality of a thematic map is evaluated based on two criteria: mapping precision and exactness or accuracy. While the mapping precision means that the area of each class reflects the truth in the field, the accuracy is a number that evaluates the positioning of the spatial distribution of each of the classes that are mapped.

Statistics indicate a kappa index of 85%, which represents a strong agreement, taking into account the criteria of Landis and Koch (1977). According to Lillesand, Kiefer and Chipan (2004), this index serves as an indicator of the degree to which the percentage of correct values of the error matrix is due to the "truth" versus the "probability" of agreement. The global accuracy was 91%, considered "acceptable" according to the classification quality of Jensen (1996).

The results also showed that the overall accuracy values were higher than the kappa index values, and similar results were found by Lamparelli, Nery and Rocha (2011) and Sarmiento et al. (2014).

Through the confusion matrix (Table 3) it was possible to evaluate that there was a confusion of 0.0771 m² (14.4%) of coffee area that was classified as exposed soil area and the 0.4583 m² (85.6%) of the coffee area has been classified correctly. Regarding the exposed soil class, 0.0011 m² (0.5%) was classified as undergrowth and 0.2193 m² (99.5%) was classified properly. For the undergrowth class, 0.0138 (5.65%) of undergrowth area was classified as coffee and 0.2304m² (94.35%) were correctly classified.

Regarding user and producer precision data (Table 4), it was observed that for user precision, coffee classes (97.0%), exposed soil (100%) and undergrowth (74.6 %) represent the same category as the field. The producer's precision indicated 85.6%, 99.5% and 94.3% of correct answers in relation to the reference data, respectively, for coffee, exposed soil and undergrowth.

Santos et al. (2019), in their study of land cover mapping in coffee plantations using the minimum distance method in images obtained by RPA, found overall accuracy and kappa index values of 85% and 75%, respectively. The study by Abreu Júnior et al. (2020) on nematode mapping in coffee plantations using images obtained by RPA and using the maximum likelihood method found overall accuracy and kappa index values of 81% and 72%, respectively.

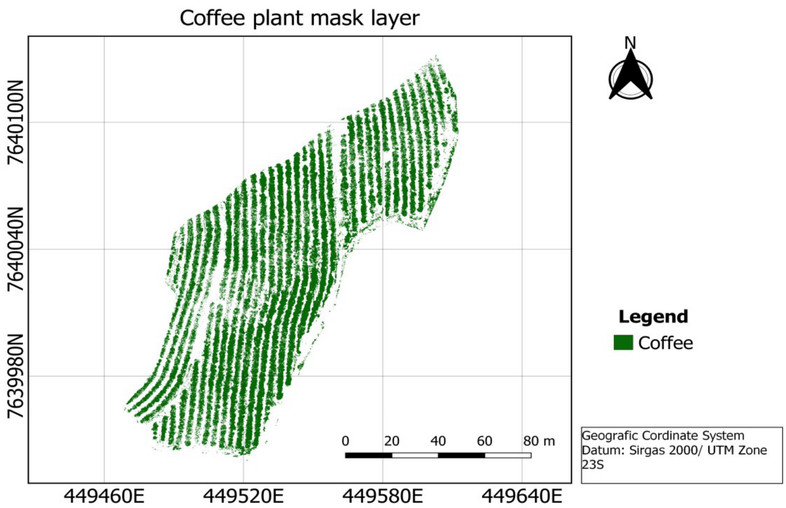

Figure 5: Coffee plant mask layer.

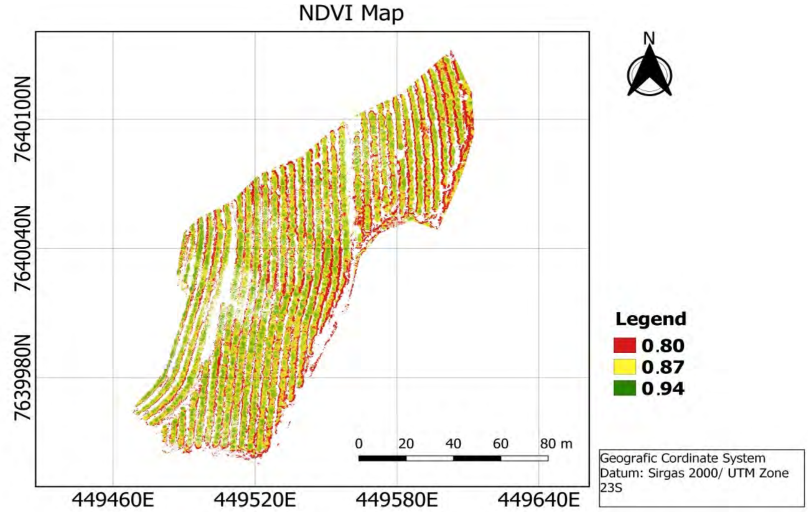

Figure 6: NDVI map.

Despite the good overall accuracy and kappa index results, it was possible to visually observe some confusion between coffee plants and undergrowth. This occurred because the coffee plant and undergrowth classes had similar characteristics and therefore very similar spectral responses. Spectral confusion between targets was also observed in the study by Sarmiento et al. (2014), where the coffee, forest, and pasture classes showed spectral confusion.

The analysis of the NDVI map shows that this parameter predominantly ranged from 0.80 to 0.94 and that a large part of the area was represented by shades of green and yellow, that is, NDVI values in the range of 0.87 to 0, 94, indicating that there was high photosynthetic activity in this coffee crop and very vigorous coffee plants.

Felix et al. (2020) obtained high-resolution images of a coffee plantation in the municipality of Lavras, Minas Gerais, Brazil, using a multispectral sensor on board a RPA. The authors calculated three vegetation indices from the images: excess green (ExG), excess red minus green (ExRmG) and NDVI. Their objective was to evaluate the seasonal behaviour of the crop regarding the availability of surface soil water.

The results showed a strong association between the spectral response of *Coffea* spp. and the moisture availability. The authors concluded that there is great potential for the use of these platforms in different agro-environmental settings, demonstrating how commercial models and sensors can be relevant to natural resource conservation, ecosystem resilience, and the productivity of agricultural crops, such as coffee.

Supervised classification is a quantification tool that can help producers quickly monitor their crops and calculate the size of each type of land use and cover class with the least possible labor. The NDVI is a qualitative tool that can help farmers identify the health of their crops.

This work presents an alternative methodology to obtain information within the coffee plantation. Through the supervised classification, it was possible to distinguish and divide the crop into classes of land use and occupation, quantify the density and percentages of classes, especially coffee, which is the predominant class within this study area. In terms of the NDVI map, its benefits are numerous, because through it is possible to evaluate several parameters within the crop, such as its health, vegetative vigor, density and even the identification of probable outbreaks of pests and diseases.

The supervised classification presented satisfactory results that were presented by the confusion matrix, which exhibited good relationships with the validation data. However, in future works, we intend to analyze the mapping accuracy and the NDVI evaluation, through data from the field, thus making the data validation even more accurate and true.

5 CONCLUSIONS

From the images acquired by a multispectral sensor coupled to an RPA, supervised classification was performed by the maximum likelihood method. The efficiency of the classification was confirmed by the kappa index (85%), which was very close to 1 and is a very good result according to the references used in this study. In addition, an NDVI map was created for only the coffee plant class, which was produced by clipping the classification through a mask layer, and this index ranged from 0.80 to 0.94, with most of the map represented by the range of 0.87 to 0.94.

It is concluded that RPA are excellent platforms for remote sensing, returning images with very high resolution at a high level of detail without unforeseen issues in terms of temporal resolution, and that this tool, combined with PA techniques, has great value for crop management.

6 ACKNOWLEDGMENTS

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7 AUTHORS' CONTRIBUTION

SAS wrote the manuscript and performed the experiment, GASF supervised and co-worked the manuscript, VCF supervised the experiment, LSS co-worked the manuscript and BFDC assisted in the statistical analyses.

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