Spanish Journal of Agricultural Research
20 (3), e0205, 10 pages (2022)
eISSN: 2171-9292
https://doi.org/10.5424/sjar/2022203-18808
INIA-CSIC

RESEARCH ARTICLE

OPEN ACCESS

Evaluation of coffee plant attributes by field collection and remotely piloted aircraft system images

Nicole L. Bento, Gabriel A. S. Ferraz, Rafael A. P. Barata, Lucas S. Santana, Rafael O. Faria and Daniel V. Soares
Department of Engineering, Federal University of Lavras (UFLA), Aquenta Sol, 3037 Lavras (MG), Brazil

Abstract

Aim of study: To verify and evaluate the area occupied by coffee plants before and after the manual harvesting of fruits and the difference between such areas; demonstrate the correlation between data on chemical attributes of leaves, yield, vegetation indices, and areas occupied by coffee plants; and estimate yield based on the variable with the best statistical indicator.

Area of study: Bom Jardim Farm in Santo Antônio do Amparo city, Minas Gerais, Brazil.

Material and methods: We studied 52 sampling points composed of four coffee (*Coffea arabica* L.) plants each. Field data on leaf chemical attributes, yield, and aerial images of flights with the Remote Piloted Aircraft System were obtained over the study area. The images were processed in the Pix4D software, and the analyses were performed in the ArcGIS and Orange Canvas software.

Main results: We verified a reduction in the area occupied by coffee plants due to the action of the harvest; no significant correlations were detected between leaf chemical attributes, yield data, and area occupied by coffee plants; and only the NDVI was adequate for determining a linear equation to estimate yield.

Research highlights: The yield correlation and predicting estimates by applying vegetation indices optimize the time spent on field measurements using the remotely piloted aircraft system. The fall of leaves due to the action of harvesting was evidenced and promotes impacts on the next crop's yield.

Additional key words: precision farming; remote sensing; vegetation indices;

Abbreviations used: CPA (Coffee Plant Area); EVI (Enhanced Vegetation Index); GDP (Gross Domestic Product); GNDVI (Normalized Difference Vegetation Index Green); GOSAVI (Green Optimal Soil Adjusted Vegetation Index); GRRI (Green–Red Ratio Index); MPRI (Modified Photochemical Reflectance Index); MTCI (MERIS Terrestrial Chlorophyll Index); NDI (Normalized Different Index); NDRE (Index of the Standardized Difference - Red Edge); NDVI (Normalized Difference Vegetation Index); Post-harvest CPA (post-harvest coffee plant area); Pre-harvest CPA (pre-harvest coffee plant area); RGB (Red/Green/Blue); RPAS (Remotely Piloted Aircraft System).

Citation: Bento, NL; Ferraz, GAS; Barata, RAP; Santana, LS; Faria, RO; Soares, DV (2022). Evaluation of coffee plant attributes by field collection and remotely piloted aircraft system images. Spanish Journal of Agricultural Research, Volume 20, Issue 3, e0205. https://doi.org/10.5424/sjar/2022203-18808

Received: 05 Sep 2021. **Accepted:** 22 Jun 2022.

Funding agencies/institutions	Project / Grant
EMBRAPA Brazilian Coffee Research Consortium	234/2019
Coordination for the Improvement of Higher Education Personnel (CAPES)	
Federal University of Lavras (UFLA)	
National Council for Scientific and Technological Development (CNPq)	
Bom Jardim Farm	

Competing interests: The authors have declared that no competing interests exist.

Correspondence should be addressed to Nicole L. Bento: nicolelbento@gmail.com

Introduction

Coffee refers to one of the leading agricultural products in the Brazilian commodities agenda with effective participation in the Brazilian gross domestic product (GDP), and the country is the largest coffee producer and exporter in the world (https://www.conab.gov.br/). However, the coffee culture demands high production costs, so it is necessary to implement viable techniques to optimize resources to ensure increased crop yield and profitability (Chemura *et al.*, 2017).

Precision agriculture, which in the context of coffee growing is called Precision Coffee Growing, can be defined as the set of techniques and technologies capable of assisting the coffee grower in the management of the crop to maximize profitability and provide higher yield and final product quality (Ferraz *et al.*, 2017). Therefore, technologies for investigation, mapping, and intelligent decision-making about the crops are sought to enhance the field activities (Balastreire, 2000).

It stands out the application of remote sensors coupled to different platforms, aiming to acquire information from the surface of crops through the response of electromagnetic energy interaction (Jensen, 2011). The remotely piloted aircraft system (RPAS) constitutes a typical sub-orbital platform application, with an on-board remote sensor, and makes it possible to obtain products of different resolutions, allows obtaining information capable of anticipating and predicting trends of plant behaviour in response to influences of various agronomic and environmental factors (Tsouros *et al.*, 2019).

Leaf attributes of macro and micronutrients are essential for the plant to reach its stage of maturation and guarantee yield, since each mineral element plays a specific role in the plant's metabolism, ensuring structural and physiological quality (Matiello *et al.*, 2010). Consequently, studies on the attributes of the leaves of the plants are essential since, due to their sensitivity, they promote changes in the development of the plants due to their assimilation and use in important biological functions, affecting several important physiological processes (such as photosynthesis and cellular respiration) that therefore influence the growth and production of cultures.

Such information directly affects the crop yield, resulting from the action of the harvest, a relevant phase in the development of a crop, as results are determined and, consequently, the financial return about profitability (Pereira & Fachini, 2014). However, since the fruits act as drains on the plant, harvesting can also be considered a stress factor. Falling leaves are one of the main damages caused to the coffee plant by the fruit harvesting process (Bártholo & Guimarães, 1997), and it should be studied together with other attributes (genetics, pests and diseases and environmental ones) that can affect future yield values.

In remote sensing, the use of vegetation indices, which refer to mathematical combinations between the different bands of the electromagnetic spectrum, highlights important issues in the agricultural context, especially when using multispectral bands that detail aspects not visible to the human eye, and may bring different views and decision-making on the behavior of the crop, mainly on final yield information (Bento *et al.*, 2022).

In the literature for orbital sensors, it is possible to find some coffee crops studies that correlate vegetation indices

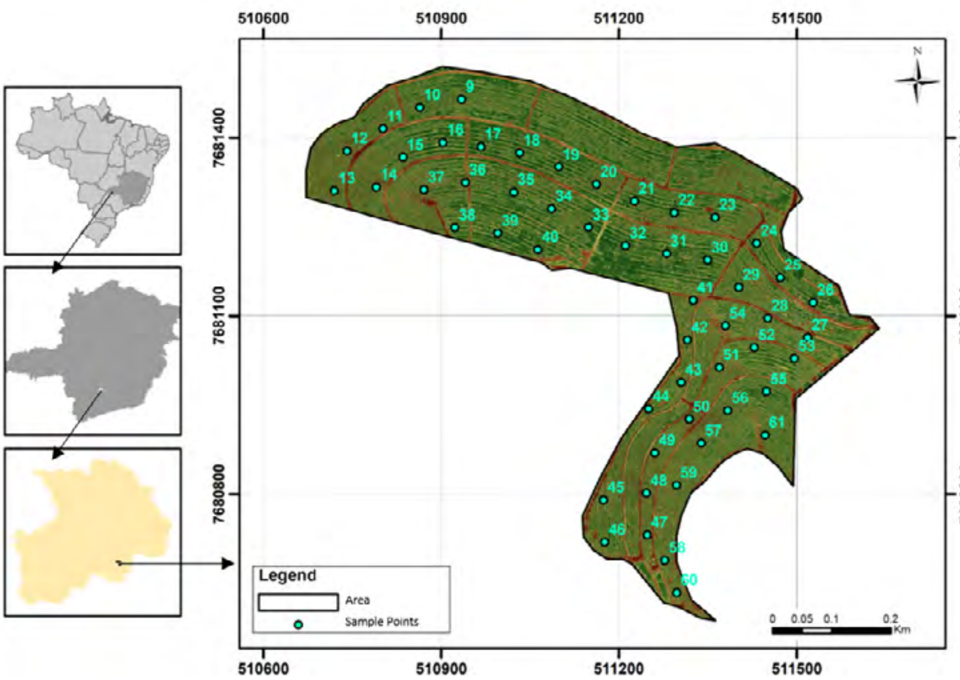

Figure 1. Location of the study area with distribution of the sample points.

Table 1. Vegetation indices used.

Vegetation indices	Acronyms	Equations[1]	References
Normalized difference vegetation index	NDVI	$(R_{NIR} - R_R) / (R_{NIR} + R_R)$	Rouse *et al.* (1974)
Normalized difference vegetation index green	GNDVI	$(R_{NIR} - R_G) / (R_{NIR} + R_G)$	Shanahan *et al.* (2001)
Index of the standardized difference - Red edge	NDRE	$(R_{NIR} - R_{REG}) / (R_{NIR} + R_{REG})$	Buschmann & Nagel (1993)
Green optimal soil adjusted vegetation index	GOSAVI	$(1+0.16)\ (R_{NIR} - R_G) / (R_{NIR} + R_G + 0.16)$	Rondeaux *et al.* (1996)
MERIS terrestrial chlorophyll index	MTCI	$(R_{NIR} - R_{REG}) / (R_{REG} + R_R)$	Dash & Curran (2004)
Modified photochemical reflectance index	MPRI	$(R_G - R_R) / (R_G + R_R)$	Yang *et al.* (2008)
Green–Red ratio index	GRRI	$(R_{GRE}) / (R_{RED})$	Gamon & Surfus (1999)
Normalized different index	NDI	$(R_{GRE} - R_{RED}) / (R_{GRE} + R_{RED} + 0.01)$	Mao *et al.* (2003)

[1] R_{NIR}, reflectance values obtained by the sensor in the near-infrared range. R_{REG}, reflectance in the range between red and infrared. R_R, reflectance in the red range. R_G, reflectance in the green range.

to yield. Jiang *et al.* (2008) found that a more vigorous canopy tends to present a higher potential for crop yield, which is captured by vegetation indices to estimate coffee yield. Brunsell *et al.* (2009) conducted a study to evaluate the feasibility of using MODIS data to monitor coffee yield. Rosa *et al.* (2010) used MODIS low spectral resolution sensor images and agrometeorological data to estimate yield and found a positive correlation for Normalized Difference Vegetation Index (NDVI) when capturing plant leafiness. Bernardes *et al.* (2012) correlated the Enhanced Vegetation Index (EVI) and NDVI vegetation indices derived from the MODIS sensor in estimating yield. Although it is possible to find this kind of study using satellite images, it was not possible to find studies using vegetation indices from RPAS images to coffee yield. In this way, aligning the study of yield and predicting its estimate by applying vegetation indices is fundamental since it optimizes the time spent on field measurements and it is also possible with the use of RPAS.

Thus, the objective of this work was to verify and evaluate the area occupied by coffee plants pre-harvest, post-harvest, and difference area pre and post- manual harvesting of the fruits; demonstrate the correlation between data on chemical attributes of leaves, yield, vegetation indices, and areas occupied by coffee plants; and estimate yield based on the variable with the best statistical indicator.

Material and methods

Study area

The study area has a total area of 31.75 ha (Fig. 1) and is located at Fazenda Bom Jardim, in Santo Antônio do Amparo, Campos das Vertentes Zone, Minas Gerais State, Brazil (Baruqui *et al*., 2006), between the meridians 506000 and 508000 meters W and parallels 7680000 and 7690000 meters S, in the UTM zone 23 S projection and geodesic referential SIRGAS 2000. Located in the Atlantic Forest Biome, the soil is classified as Red-Yellow Dystrophic Latosol (Baruqui *et al*., 2006) and the climate is Subtropical Rainy (Cwb) (Alvares *et al*., 2013).

The farm has coffee (*Coffea arabica* L.) cv. ‘Acaiá’ 21-year-old plantations, with 3.60 m spacing between the planting rows and 0.80 m between the coffee plants, and the presence of brachiaria between the rows. In the planted area we distributed systematically, in a homogeneous way, 52 sample points with geographic position determined by GNSS. Each sample point comprises four coffee plants (Fig. 1).

Field data

Considering the pre- and post-harvest study, the focus of this study, we made foliar sampling in May 2020 for chemical foliar attributes evaluation in the 52 sampling points. The foliar sample consisted of removing ten leaves in the medium third of the plant, referring to the 3rd and 4th pair of leaves from the extremity and one side of the plant and another pair of leaves collected from the opposite side. The samples were packed with paper bags labelled (Matiello *et al*., 2010), and sent for laboratory analysis of essential macronutrients (N, P and K), and secondary macronutrients (Ca, Mg and S) in g/kg according to Malavolta *et al.* (1997).

The yield was measured by manual harvesting using a harvest method in the cloth in May 2020. Before starting the harvest, “harvest cloths” were stretched in the soil below the plants at each experimental point. Each sample point corresponds to the average yield of four plants, constituting the experimental plot, and the volume harvested from each plant was measured in a graduated container.

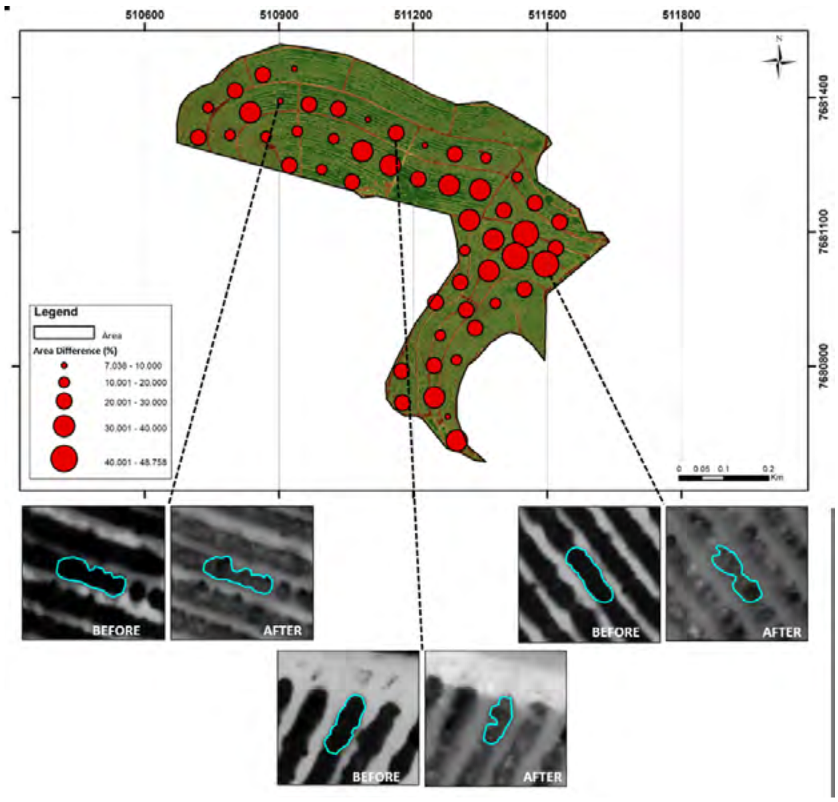

Figure 2. Map of percentage of difference CPA of the harvest and demonstration of zoom.

RPAS data

The images of the area were obtained before (April 2020) and after (May 2020) the harvest event using the Matrice 100 Remotely Piloted Aircraft (https://www.dji.com/br/matrice100), coupling a multispectral camera Parrot Sequoia (https://www.parrot.com/en/), which has reflectance values in the spectral bands of green (550 to 590 nm), red (660 to 700 nm), red edge (735 to 745 nm), near-infrared (760 to 820 nm) and RGB (380 to 720 nm).

The flight planning was performed using the software Precision Flight (https://www.precisionhawk.com/) with a definition of the parameters of the launch and landing site of the aircraft, flight height set at 100 meters, flight speed of 8 m/s, overlap level of 80% × 80% and flight direction of the transverse type to the planting row. The sensor's radiometric calibration procedure was performed before and after the flights, with the aid of a calibration plate. The flights were performed between 11:00 and 13:00 hours.

The PIX4D Mapper software (https://www.pix4d.com/product/pix4dmapper-photogrammetry-software) was used to process the area images, with all processing items set to high resolution. Initially, image positioning corrections were made for each study flight to the SIRGAS 2000 UTM zone 23S. After that, we inserted the calibration plate parameters for the radiometric correction of the images. The images were aligned using automatic triangulation and link points, generating a dense cloud of points and image texture. Finally, the orthomosaic was generated with reflectance data from each sensor for the coffee plantation study area.

Vegetation indices

We calculated eight vegetation indices (Table 1) using reflectance information obtained for images for each sampling point, composed of four coffee plants, in a GIS environment at the ArcGIS 10.4 software (http://www.esri.com/software/arcgis), using the Map Algebra tool.

Data analysis

We analysed the coffee plant area (CPA) based on pre-harvest CPA (occupied by coffee plants pre-harvest coffee plant area), post-harvest CPA (post-harvest coffee plant area), and difference in CPA (the difference between pre and post-harvest coffee plant areas). Initially, the coffee plants of each sampling point were segmented, removing possible soil interference and allowing the individualization of the plants. Each sampling point comprises four plants in which the occupied area was calculated by inserting the item 'area' in m² into the attribute table with the 'Calculate Geometry' function.

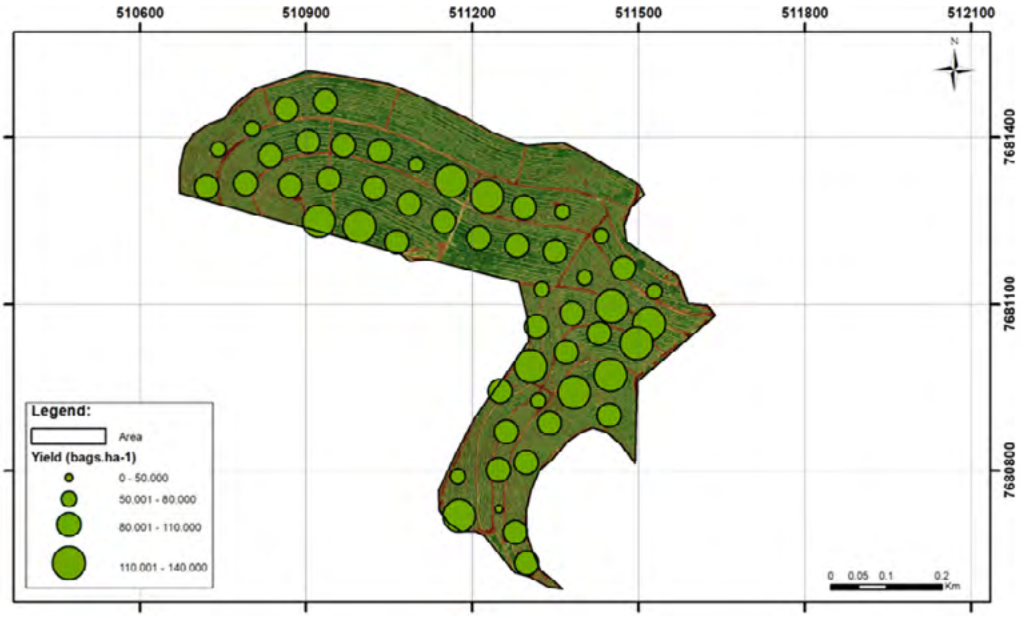

Figure 3. Yield distribution map.

These procedures were performed considering the image obtained from the pre-harvest to calculate occupied by plants pre-harvest (April) coffee plant area (pre-harvest CPA) and the image obtained from post-harvest (May) to calculate the area occupied by the plants post-harvest coffee plant areal (post-harvest CPA). The area of difference between pre and post-harvest coffee plant area (difference in CPA) was calculated by the difference between the initial area and the final area, with differences described in percentage. All procedures for identifying the reduction in the percentage of the area were performed using the ArcGIS 10.4 software (http://www.esri.com/software/arcgis).

To identify and characterize the correlation between data through the Pearson correlation coefficient (R), the software Orange Canvas was used (Demsar *et al.*, 2013) with routines developed in the Python programming language. We analyzed a correlation between yield, chemical foliar attributes, vegetation indices, and CPA (pre-harvest CPA, post-harvest CPA, and difference in CPA) for the sampling points of the study area.

After that, linear regression analysis was performed between yield data and vegetation indices data and difference CPA, with an equation that correlates such information based on the coefficient of determination (R^2) was estimated.

Results

Figure 2 shows the percentage of difference CPA by the loss leaves, fruits, and branches of the harvest for each sample point considering the difference of pre-harvest CPA and post-harvest CPA and the zoom demonstration for three sample points with different scales of percentage. In this study, the difference area values varied from 7.038% for point 58 to 48.758% for point 53.

Since it is described in the literature that the coffee area (CPA) operates in the yield of the following harvests, Fig. 3 shows the distribution of the yield in the study area, with the highest yield value at point 21 of 139.204 bags ha^{-1} and the lowest yield value at point 47 of 48.927 bags ha^{-1}. The distribution was not uniform in the study area. However, it stands out that the northwest area presented higher yield values and refers to the part of the land with the highest elevation of approximately 982,065 m of altitude. The southern area showed lower values of yield with an approximate height of 948,537 m of altitude.

Table 2 shows the values of descriptive statistics for yield, chemical foliar attributes, vegetation indices, and CPA (pre-harvest CPA, post-harvest CPA, and difference in CPA) for the study area's sample points. The values of the chemical foliar attributes, vegetation indices, and CPA varied along with the sampling points, as evidenced by the coefficient of variation (CV). Regarding the vegetations indices, NDRE (Index of the Standardized Difference - Red Edge) showed a high CV value of 22.53%, and a minor variation was observed for the NDVI with a CV of 2.16%.

Table 3 shows the Pearson correlation coefficients (R) between the study variables. The yield showed a correlation with the NDVI. The chemical foliar attribute nitrogen showed no correlation with any other chemical foliar attributes or studied vegetation indices. Normalized Difference Vegetation Index Green (GNDVI) showed correlation with NDRE; Green-Red Ratio Index (GRRI) with Modified Photochemical Reflectance Index (MPRI); Normalized Different Index (NDI) with MPRI and Green-Red Ratio Index (GRRI); and no vegetation indices showed correlation with chemical foliar attributes.

Table 2. Descriptive statistics of the study variables (yield, chemical foliar attributes, vegetation indices), and CPA (pre-harvest CPA, post-harvest CPA, and difference in CPA).

Variable	Unit	Mean	Minimum	Maximum	CV (%)
Yield	bags ha^{-1}	95.68	48.93	139.20	19.67
N	g kg^{-1}	27.61	16.90	33.00	10.21
P	g kg^{-1}	1.64	0.90	2.30	17.86
K	g kg^{-1}	20.97	6.30	32.90	20.85
Ca	g kg^{-1}	17.74	10.40	27.90	19.35
Mg	g kg^{-1}	5.11	3.50	8.10	20.09
S	g kg^{-1}	3.67	2.50	5.40	18.13
NDVI	-	0.85	0.82	0.89	2.16
GNDVI	-	0.73	0.65	0.78	3.79
NDRE	-	0.21	0.07	0.28	22.53
GOSAVI	-	0.63	0.53	0.68	6.46
MTCI	-	0.63	0.19	0.91	21.58
MPRI	-	0.33	0.26	0.50	14.19
GRRI	-	2.04	1.74	3.07	11.75
NDI	-	0.29	0.23	0.45	14.40
Pre-harvest CPA	m²	17.45	9.94	26.48	24.72
Post-harvest CPA	m²	13.26	6.05	21.88	28.56
CPA difference	%	24.19	7.04	48.76	39.67

Variables defined in Table 1. CV: coefficient of variation.

Regarding the chemical foliar attributes, P showed no correlation with any indices and chemical foliar attributes; K showed a correlation with Ca, Mg and S; Ca showed a correlation with K, Mg and S; Mg showed a correlation with K, Ca and S; and S showed a correlation with K, Ca and Mg.

The values of CPA, considering pre-harvest CPA, post-harvest CPA, and difference in CPA, did not correlate with any chemical foliar attributes and vegetation indices. For the study areas only, we detected a correlation between pre-harvest CPA and post-harvest CPA.

Fig. 4 shows the scatter plot of the results. In this study, the yield correlated by vegetation indices and difference CPA by harvest generated determination coefficients (R^2) as 0.501 (NDVI), 0.018 (GNDVI), 0.002 (NDRE), 0.018 (Green Optimal Soil Adjusted Vegetation Index - GOSAVI), 0.016 (MTCI), 0.076 (MPRI), 0.073 (GRRI) and 0.071 (NDI) and 0.008 (difference CPA) with only the NDVI being satisfactory for estimating this variable. This demonstrates the relationship between the set of values, a linear estimation equation, determination coefficient (R^2) and correlation coefficient (R). Fig. 5 shows the NDVI distribution in the study area, since this vegetation index was the only one to present a correlation with the analyzed yield data, allowing the estimation of the prediction equation.

Discussion

As shown in Fig. 2, falling leaves promote a drop-in yield in the following year by reducing the number of leaves and reducing the photosynthetically active radiation intercepted by the canopy of these plants, reflecting the biennial effects of production (Oliveira *et al.*, 2007). The very productive plants tend to become weaker due to the drainage of nutrients from the leaves to the fruit in a year of high yield, leading to physiological disorders in the plant, which promotes leaf fall, reduced photosynthesis, reserves directed to the growth of the leaves and, therefore, low yield in the following year (Bártholo & Guimarães, 1997).

The fall in yield occurs because the high demand for nutrients, both mineral and organic, by the fruits reduces the growth of the new branching, where flowering and fruiting will take place for the next harvest. Therefore, the maintenance of the coffee plant's leaf area at harvest is a determining factor for the subsequent harvest, and therefore attention is required for this production stage of the coffee. The leaf area is of paramount importance for the plant because of the leaf area's more productive potential and crop yield (Manfron *et al.*, 2003). The leaves directly contribute to the supply of photoassimilates and energy required for plant maintenance (Cunha *et al.*, 2004).

Table 3. Pearson's correlation coefficient (R) among the study variables: yield, chemical foliar attributes, vegetation indices, and CPA (pre-harvest CPA, post-harvest CPA, and difference in CPA).

	Yield	N	P	K	Ca	Mg	S	Indices								CPA		
								NDVI	GNDVI	NDRE	GOSAVI	MTCI	MPRI	GRRI	NDI	Pre	Post	Diff.
Yield	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
N	-0.127^{ns}	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
P	0.043^{ns}	-0.041^{ns}	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
K	0.228^{ns}	-0.024^{ns}	0.237^{ns}	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Ca	-0.107^{ns}	-0.110^{ns}	0.423^{ns}	0.674*	1	-	-	-	-	-	-	-	-	-	-	-	-	-
Mg	-0.287^{ns}	0.048^{ns}	0.288^{ns}	0.617*	0.839*	1	-	-	-	-	-	-	-	-	-	-	-	-
S	-0.196^{ns}	0.020^{ns}	0.418^{ns}	0.772*	0.845*	0.941*	1	-	-	-	-	-	-	-	-	-	-	-
NDVI	0.708*	0.185^{ns}	0.067^{ns}	0.210^{ns}	-0.143^{ns}	-0.212^{ns}	-0.160^{ns}	1	-	-	-	-	-	-	-	-	-	-
GNDVI	0.137^{ns}	0.080^{ns}	0.051^{ns}	-0.040^{ns}	-0.089^{ns}	-0.105^{ns}	-0.112^{ns}	0.399^{ns}	1	-	-	-	-	-	-	-	-	-
NDRE	0.048^{ns}	-0.100^{ns}	-0.053^{ns}	-0.113^{ns}	-0.060^{ns}	-0.171^{ns}	-0.168^{ns}	0.192^{ns}	0.704*	1	-	-	-	-	-	-	-	-
GOSAVI	0.133^{ns}	0.170^{ns}	-0.123^{ns}	-0.067^{ns}	-0.075^{ns}	-0.036^{ns}	0.007^{ns}	0.134^{ns}	-0.109^{ns}	0.084^{ns}	1	-	-	-	-	-	-	-
MTCI	0.129^{ns}	-0.113^{ns}	0.075^{ns}	0.006^{ns}	-0.192^{ns}	-0.192^{ns}	-0.149^{ns}	-0.029^{ns}	-0.085^{ns}	0.094^{ns}	0.387^{ns}	1	-	-	-	-	-	-
MPRI	-0.275^{ns}	0.001^{ns}	-0.240^{ns}	-0.217^{ns}	-0.144^{ns}	-0.117^{ns}	-0.185^{ns}	-0.287^{ns}	-0.052^{ns}	-0.183^{ns}	-0.398^{ns}	-0.340^{ns}	1	-	-	-	-	-
GRRI	-0.272^{ns}	-0.013^{ns}	-0.250^{ns}	-0.237^{ns}	-0.165^{ns}	-0.138^{ns}	-0.217^{ns}	-0.281^{ns}	-0.047^{ns}	-0.177^{ns}	-0.415^{ns}	-0.319^{ns}	0.992*	1	-	-	-	-
NDI	-0.267^{ns}	0.007^{ns}	-0.251^{ns}	-0.223^{ns}	-0.132^{ns}	-0.105^{ns}	-0.179^{ns}	-0.267^{ns}	-0.041^{ns}	-0.183^{ns}	-0.366^{ns}	-0.375^{ns}	0.996*	0.988*	1	-	-	-
Pre CPA	0.107^{ns}	-0.141^{ns}	0.125^{ns}	0.151^{ns}	0.049^{ns}	-0.068^{ns}	-0.018^{ns}	0.007^{ns}	-0.265^{ns}	0.022^{ns}	-0.025^{ns}	-0.264^{ns}	-0.016^{ns}	-0.063^{ns}	0.007^{ns}	1	-	-
Post CPA	0.118^{ns}	-0.082^{ns}	0.075^{ns}	0.090^{ns}	-0.059^{ns}	-0.086^{ns}	-0.044^{ns}	0.041^{ns}	-0.300^{ns}	-0.090^{ns}	-0.065^{ns}	-0.186^{ns}	-0.006^{ns}	-0.042^{ns}	0.009^{ns}	0.887*	1	-
Diff. CPA	-0.092^{ns}	-0.135^{ns}	0.063^{ns}	0.087^{ns}	0.242^{ns}	0.096^{ns}	0.091^{ns}	-0.134^{ns}	0.113^{ns}	0.202^{ns}	0.103^{ns}	-0.075^{ns}	-0.062^{ns}	-0.073^{ns}	-0.053^{ns}	-0.083^{ns}	-0.520^{ns}	1

*5% significant correlation; ns: non-significant correlation.

The limits values presented by the chemical foliar attributes (Table 2) are close to the limits and critical ranges expressed in literature for healthy plant conditions (Malavolta *et al.*, 1997; Mills & Jones Junior, 1996). The most significant variation was observed for the difference in CPA with a CV of 39.67%, demonstrating that the area values fluctuated considerably in the study area, evidenced by manual harvesting, which, due to human activity, suffers various interferences for the sampling points. For NDRE this more significant variation presented is justified by the presence of the red edge transition band and near-infrared in its equation, which consequently has greater sensitivity and faster perception of the transition from healthy to initially stressed plants (Rodriguez *et al.*, 2006).

The CPA values did not correlate with the yield data (Table 3). Silva *et al.* (2010) found that manual harvesting promoted more significant falling leaves in places of higher yield, but this fact was not verified in this study since the point of most excellent falling leaves does not refer to the highest yield and the lowest falling leaves to the lowest yield, as described by Pearson's correlation coefficients (R) (Table 3).

It is noteworthy that the harvest promotes removing fruits and, consequently, leaves and branches. In this way, the aerial images capture all the canopy's integration, justifying the low correlation between the data to the difference CPA and the yield data.

Based on vegetation indices, only the NDVI had a significant correlation with the yield at Pearson's correlation rate of 0.708 (Table 3). The low correlations of the other vegetation indices with the chemical foliar attributes explain the stress presented by the coffee plants. Plants under stress conditions decrease the leaves' chlorophyll concentration, affecting light absorption in the visible, red-edge, and near-infrared region, reflected in the vegetation indices values (Marin *et al.*, 2019). This low correlation between the other vegetation indices and yield (except for NDVI) was justified by combining spectral bands in the equations involving indices, which were not enough to describe the changes presented by yield in the field.

Although yield did not show a trend with falling leaves data, an intense depletion of coffee plants was observed in this study due to harvesting, resulting in reduced vegetation indices values and area occupied by plants compared to pre and post-harvest periods. Understanding the behaviour of falling leaves caused by fruit harvesting directly influences the yield and profitability of the crop and should therefore be the focus of research.

In conclusion, it was observed a reduction in the area occupied by coffee plants due to the manual harvesting of fruits. No significant correlations were detected between leaf chemical attributes, yield data, and the area occupied by pre and post-harvest coffee trees. Only the Normalized Difference Vegetation Index (NDVI) presented adequate correlation and determination coefficients to describe a linear equation to estimate coffee yield.

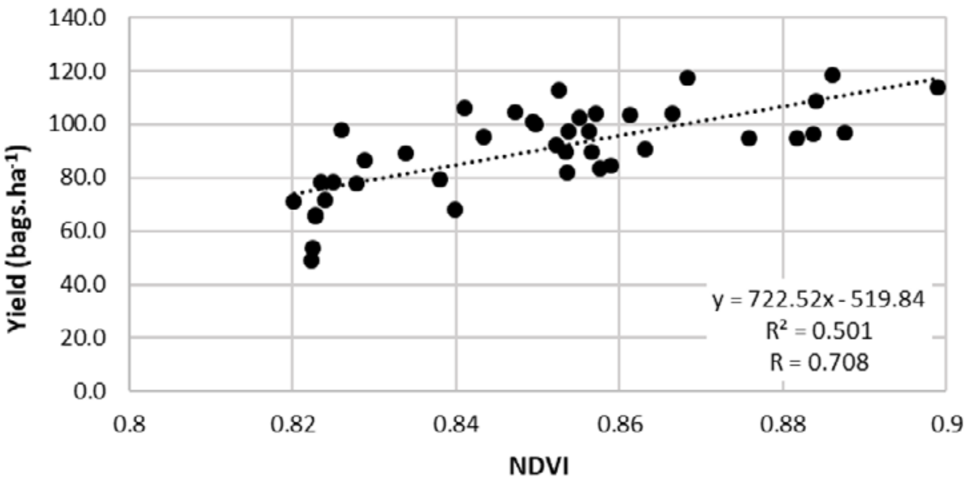

Figure 4. Scatter plot of the results of the set of yield and NDVI values, linear equation, determination coefficient (R^2) and correlation coefficient (R).

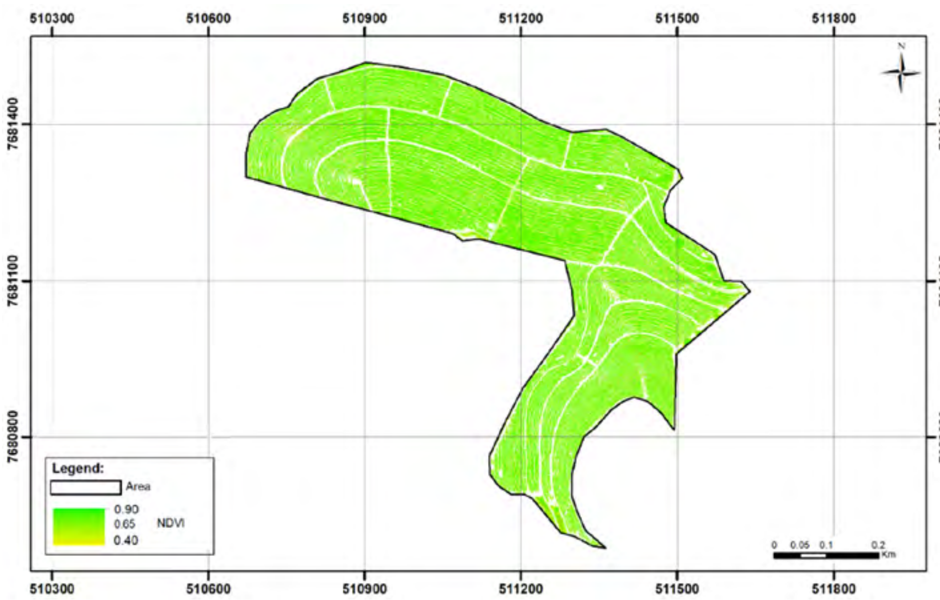

Figure 5. NDVI distribution in the study area.

Authors' contributions

Conceptualization: N.L. Bento, G.A.S. Ferraz, R.O. Faria, D.V. Soares.
Data curation: N.L. Bento, R.A.P. Barata, L.S. Santana, R.O. Faria, D.V.Soares.
Formal analysis: N.L. Bento, G.A.S. Ferraz.
Funding acquisition: N.L. Bento, G.A.S. Ferraz.
Investigation: N.L. Bento, R.A.P. Barata, L.S. Santana, R.O. Faria, D.V.Soares.
Methodology: N.L. Bento, G.A.S. Ferraz.
Project administration: N.L. Bento, G.A.S. Ferraz, R.O. Faria, D.V. Soares.
Resources: N.L. Bento, G.A.S. Ferraz, R.A.P. Barata, L.S. Santana, R.O. Faria, D.V.Soares.
Software: N.L. Bento, G.A.S. Ferraz.
Supervision: G.A.S. Ferraz.
Validation: N.L. Bento, G.A.S. Ferraz.
Visualization: N.L. Bento, G.A.S. Ferraz.
Writing – original draft: N.L. Bento, G.A.S. Ferraz.
Writing – review & editing: N.L. Bento, G.A.S. Ferraz.

References

Alvares CA, Stape JL, Sentelhas PC, De Moraes Gonçalves JL, Sparovek G, 2013. Köppen's climate classification map for Brazil. Meteorologische Zeitschrift 22(6): 711-728. https://doi.org/10.1127/0941-2948/2013/0507

Balastreire LA, 2000. A estado-da-arte da agricultura de precisão no Brasil, 1st ed. Ed. Piracicaba, v. 1. 224 pp.
Bártholo GF, Guimarães PTG, 1997. Care in harvest and prepare of coffee. Informe Agropecuário [Agricultural Report], Belo Horizonte 19(187): 33-42.
Baruqui AM, Naime UJ, Motta PEF da, Carvalho Filho A de, 2006. Levantamento de reconhecimento de média intensidade dos solos da Zona Campos das Vertentes - MG. Embrapa Solos - Boletim de Pesquisa e Desenvolvimento 96. bpd962006levantcamposvertentes.pdf
Bento NL, Ferraz GAS, Barata RAP, Soares DV, Santos LM, Santana LS et al., 2022. Characterization of recently planted coffee cultivars from vegetation indices obtained by a remotely piloted aircraft system. Sustainability 14: 1446. https://doi.org/10.3390/su14031446
Bernardes T, Moreira MA, Adami M, Giarolla A, Rudorff BFT, 2012. Monitoring biennial bearing effect on coffee yield using MODIS remote sensing imagery. Remote Sens 4(9): 2492-2509. https://doi.org/10.3390/rs4092492
Brunsell NA, Pontes PPB, Lamparelli RAC, 2009. Remotely sensed phenology of coffee and its relationship to yield. GIScі Remote Sens 46(3): 289-304. https://doi.org/10.2747/1548-1603.46.3.289
Buschmann C, Nagel E, 1993. In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation. Int J Remote Sens 14(4): 711-722. https://doi.org/10.1080/01431169308904370
Chemura A, Mutanga O, Dube T, 2017. Integrating age in the detection and mapping of incongruous patches in coffee (*Coffea arabica*) plantations using multi-temporal Landsat 8 NDVI anomalies. Int J Appl Earth Observ Geoinform 57: 1-13. https://doi.org/10.1016/j.jag.2016.12.007
Cunha RL, Mendes ANG, Chalfoun SM, 2004. Practices of coffee rust control related to yield and leaves retention. Agrotechn Sci 28(5): 990-996. https://doi.org/10.1590/S1413-70542004000500004
Dash J, Curran PJ, 2004. The MERIS terrestrial chlorophyll index. Int J Remote Sens 25: 5403-5413. https://doi.org/10.1080/0143116042000274015
Demsar J, Curk T, Erjavec A, Gorup C, Hocevar T, Milutinovic M *et al.,* 2013. Orange: Data mining toolbox in Python. J Machine Learn Res 14(1): 2349-2353.
Ferraz GAS, Da Silva FM, De Oliveira MS, Da Silva FC, Carvalho LCC, 2017. Comparison between the soil chemical attributes sampled conventionally and in grid. Coffee Sci 12(1): 17-29.
Gamon JA, Surfus JS, 1999. Assessing leaf pigment content and activity with reflectometer. New Phytol 143: 105-117. https://doi.org/10.1046/j.1469-8137.1999.00424.x
Jensen JR, 2011. Remote sensing of the environment: A perspective on terrestrial resources. Ed. Parêntese, São José dos Campos, SP, Brazil.
Jiang Z, Huete AR, Didan K, Miura T, 2008. Development of a two-band enhanced vegetation index without a blue band. Remote Sens Environ 112(10): 3833-3845. https://doi.org/10.1016/j.rse.2008.06.006
Malavolta E, Vitti GC, Oliveira SA, 1997. Assessment of the nutritional status of plants: principles and applications, 2nd ed. POTAFOS, Piracicaba. 319 pp.
Manfron PA, Dourado Neto D, Pereira AR, Bonnecarrére RAG, Medeiros SLP, Pilau FG, 2003. Model of the leaf area index of maize culture. Brazil J Agrometeorol 11: 333-342.
Mao W, Wang Y, Wang Y, 2003. Real-time detection of between-row weeds using machine vision. Proc ASAE Annual Meeting, Las Vegas, USA.
Marin DB, De Carvalho Alves M, Pozza EA, Belan LL, De Oliveira Freitas ML, 2019. Multispectral remote sensing in the identification and mapping of biotic and abiotic coffee tree variables. Ceres 66(2): 142-153.
Matiello JB, Santinato R, Garcia AWR, Almeida SR, Fernandes DR, 2010. Cultura de café no Brasil: Manual de recomendações. MAPA/Procafé, Rio de Janeiro.
Mills HA, Jones Junior JB, 1996. Plant analysis handbook II: A practical sampling, preparation, analysis, and interpretation guide, 2nd ed. Micro-Macro Publ, Athens, GA, USA. 422 pp.
Oliveira E, Silva FM, Guimarães RJ, Souza ZM, 2007. Elimination of lines in dense coffee plants using semi-mechanized means. Sci Agrotechnol 31(6): 1826-1830. https://doi.org/10.1590/S1413-70542007000600033
Pereira V, Fachini M, 2014. Globalización, especialización territorial y división del trabajo: Patrocínio y el café del Cerrado de Minas Gerais [Globalization, territorial specialization, and division of labor: Patrocínio and the coffee from the Cerrado of Minas Gerais]. Cuad Geogr Rev Colomb Geogr 23(2): 239-254. https://doi.org/10.15446/rcdg.v23n2.37333
Rodriguez D, Fitzgerald GJ, Belford R, Christensen LK, 2006. Detection of nitrogen deficiency in wheat from spectral reflectance indices and basic crop eco-physiological concepts. Aust J Agric Res 57(7): 781-789. https://doi.org/10.1071/AR05361
Rondeaux G, Steven M, Baret F, 1996. Optimization of soil-adjusted vegetation indices. Remote Sens Environ 55: 95-107. https://doi.org/10.1016/0034-4257(95)00186-7
Rosa VGCD, Moreira MA, Rudorff BFT, Adami M, 2010. Coffee crop yield estimate using an agrometeorological-spectral model. Pesqu Agropec Bras 45(12): 1478-1488. https://doi.org/10.1590/S0100-204X2010001200020
Rouse JW, Haas RH, Deering DW, Schell JA, Harlan JC, 1974. Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. Type III Final Report. NASA/GSFC, Greenbelt, MD, USA.
Shanahan JF, Schepers JS, Francis DD, Varvel GE, Willhelm WW, Tringe JM et al., 2001. Use of remote-sensing imagery to estimate corn grain yield. Agron J 93: 583-589. https://doi.org/10.2134/agronj2001.933583x

Silva CF, Silva FM, Alves MC, Barros MM, Sales RS, 2010. Behavior of the coffee fruit detachment force throughout the harvest period. Sci Agrotechnol 34(2): 468-474. https://doi.org/10.1590/S1413-70542010000200028

Tsouros DC, Bibi S, Sarigiannidis PG, 2019. A review on UAV-based applications for precision agriculture. Information 10(11): 349. https://doi.org/10.3390/info10110349

Yang Z, Willis P, Mueller R 2008. Impact of band-ratio enhanced AWIFS image to crop classification accuracy. Proc 17th William Pecora Memorial Remote Sensing Symp, Denver, CO, USA, pp: 18-20.