THE COFFEE NDVI MODELING USING BUILT-IN RGB PASSIVE SENSOR IN UAS

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Abstract: Studies carried out used different sensors and field applications can be accomplished to obtain information and make decisions related to coffee management. The objective of this work was to train machine learning algorithms to estimate the NDVI based on the Greenseeker™ active optical sensor in 20 arabica coffee cultivars in the experimental area of the National Institute of Coffee Science and Technology (INCT of Coffee) using a passive RGB sensor. in unmanned aerial system (UAS) and its relationship with foliage. With the spectral signatures recorded in the RGB images of the 20 coffee cultivars, the relationships with the foliage and the NDVI data obtained with the Greenseeker™ active optical sensor were analyzed. Through machine learning and digital image processing techniques, it was possible to obtain an NDVI equation using the RGB bands based on the NDVI of the Greenseeker TM active optical sensor. The results were satisfactory when compared to in situ data, providing the use of a simple and effective method of evaluating the vegetative vigor of different coffee cultivars.

Index terms: Remote Sensing; NDVI; coffee.

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INTRODUCTION

The proper management of coffee plantations can be accomplished in order to make the plants well-nourished and productive using geospatial and temporal monitoring of coffee trees.

Remote sensing has increasingly been used to assess the increasingly spectral result of digital image processing, in order to obtain agroecosystem variables that enable decision-making based on the electromagnetic reflectance of leaves, individual plants and set of coffee trees (Johnson and Trout, 2012). By imaging spectra from sensors that have two or more bands, it is possible to determine the biophysical patterns of data (Zanzarini et al., 2013).

Studies carried out used different sensors and field applications to obtain information and make decisions related to coffee cultivation, especially related to the use of the active sensor Greenseeker™, which estimates the Vegetation Index by Normalized Difference (Barbosa et al., 2020). Cunha et al. (2019) noted that it is possible to estimate the volume of coffee using unmanned aerial systems (UAS) images to improve pesticide application techniques. Enciso et al. (2019) also noted that it is possible to validate field measurements for tomato varieties using UAS.

Using Machine Learning algorithms, it was possible to determine models of coffee rust (*Hemileia vastatrix*) (Girolamo Neto et al., 2014) and detect necrosis in coffee beans (Miranda et al., 2020), showing the potential of using artificial intelligence in data mining of field variables. According to the studies carried out, obtaining the NDVI in coffee plantations using a passive RGB sensor coupled to UAS can fill a gap in the monitoring of coffee plantations, since it presents, Low cost compared to multispectral sensors; Ease of operation, in addition to being a sensor widely used in surveying (to generate the products: MDS, MDT, Orthophoto mosaic, Point Cloud, etc.), it allows obtaining images in the visible spectrum (which is a great advantage for photointerpretation and data training- machine learning).

Based on the NDVI data obtained with the Greenseeker™ active optical sensor, the objective of this work is to determine an equation capable of generating values close to the NDVI using a passive RGB sensor coupled in UAS for 20 arabica coffee cultivars with different levels of tree foliage using machine learning modeling.

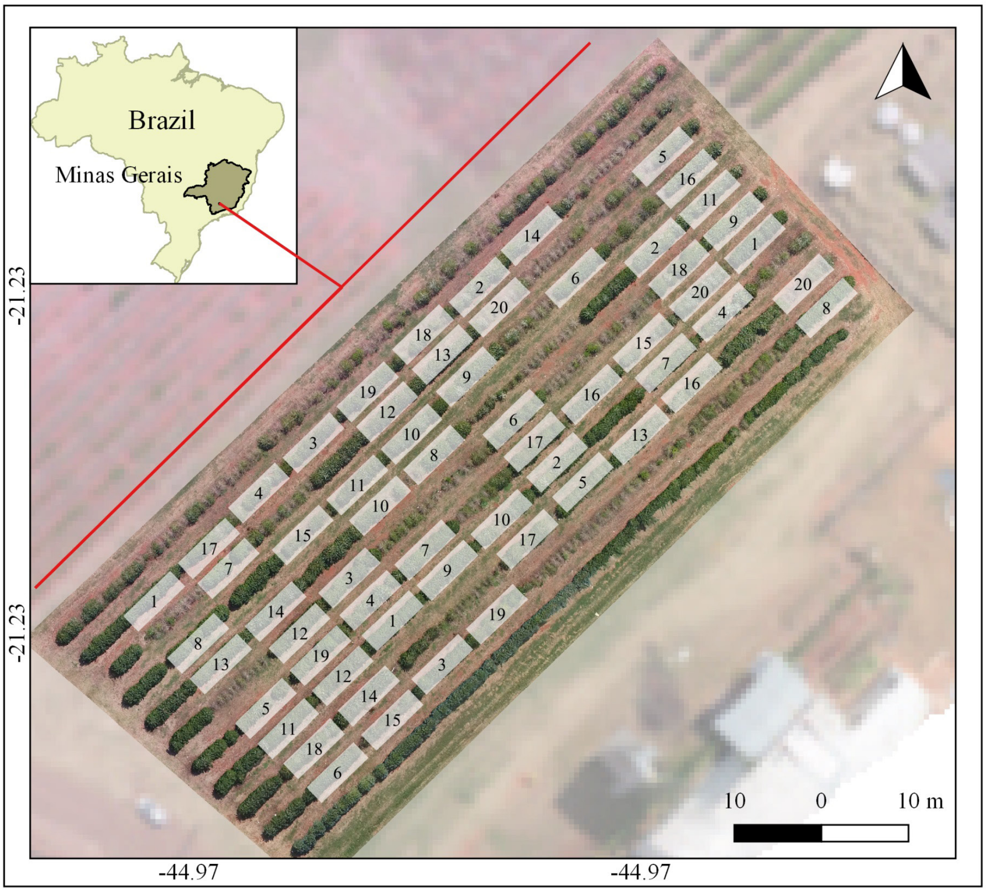
MATERIAL AND METHODS

Study area

The study area is located in the experimental field of the National Institute of Coffee Science and Technology (INCT of Coffee) of the Federal University of Lavras - UFLA, with Latitude: 21° 13'35" S, Longitude: 44°58'14" W, with an average altitude of 941,096 meters. The area was destined for the cultivation of coffee of the species *Coffea arabica* L. The planting date was on 03/30/2015. The plants were spaced 3.5 m between rows and 0.7 m between plants (Figure 1).

Definition of sample points

Ninety detection points (plants) were randomly selected for the Greenseeker™ active optical sensor. Among the 90 points, 20 different cultivars of arabica coffee were selected; MGS Aranãs RV, Araponga MG-1, Catiguá MG-1, Catiguá MG-2, MGS Catiguá 3, Pau Brasil MG-1, Acauã, Acauã



1. Aranãs RV
2.Araponga MG-1
3. Catiguá MG-1
4. Catiguá MG-2
5. Catiguá MG-3
6. Pau-Brasil MG-1
7. Acauã
8. Acauã Novo
9. Arara
10. Clone 224
11. Clone 312
12. Guará
13. Saíra II
14. Siriema
15. Catucaí Amarelo 2SL
16. IAPAR 59
17. IPR 100
18. IPR 102
19. IPR 103
20.Rubi MG-1192.

Figure 1: List of cultivars/genotypes selected for research - "INCT of Coffee" - Federal University of Lavras - UFLA - Minas Gerais – Brazil.

Novo, Arara, Clone 224, Clone 312, Guará, Saíra II, Siriema, Catucaí Yellow 2 SL, IAPAR 59, IPR 100, IPR 102, IPR 103, Rubi MG 1192, with 3 repetitions, totaling 60 points for NDVI evaluation. NDVI data were verified above the orthotropic branch of each coffee plant (Figure 2).

Figure 2: NDVI Measurement with Greenseeker ™ active optical sensor.

In situ evaluation

To determine the NDVI, the Greenseeker ™ optical sensor was used, which was positioned one meter above the plant canopy, as recommended by Ali and Ibrahim (2019) and Barbosa et al. (2020). The collection of the NDVI with the sensor was performed at approximately 11:00 am in order to avoid shading effects. Foliage level was assessed in situ by visual observation score on a scale of 1 to 5 and correlated with the NDVI obtained with the Greenseeker ™ active optical sensor. Note 5 for maximum foliage and 1 for very defoliated plant as performed by Silva and Alves (2013) (Figure 3).

Image acquisition from the passive RGB sensor on board the UAS

The flight plan settings for the UAS were height 70 meters, camera gimbal positioned at 90 degrees to the nadir, 80% longitudinal and 75% lateral overlap (Bater et al., 2011; Rasmussen et al., 2016) and speed of 3 ms^{-1}. It is noteworthy that, due to the oval field of view of the Greenseeker™ active optical sensor, it was kept at a height of 1 meter above the coffee tree canopy. Due to the semi-major axis of the ellipse of the Greenseeker™ optical sensor's field of view being 50 cm, a compatible resolution of 50 cm was used for the images from the passive RGB sensor.

For the geometric correction of the images, 10 control points were used, which were distributed on the edges and in the center of the study area.

The control points for the positional correction of the images obtained with the UAS were georeferenced with the RTK receiver Spectra SP60 L1/L2. For the georeferencing of the control points, the Real Time Kinematic (RTK) technique was used, using as reference the Level Reference Geodetic Station called 3045T of the Brazilian Institute of Geography and Statistics (IBGE), located on the campus of the Federal University of Lavras. UTM coordinates base, SIRGAS 2000 datum.

The NDVI calculation (Huete et al., 1997) basically consists of the normalized difference between the NIR and Red bands (Equation 1):

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

Regarding the RGB sensor images on board UAS, the normalized proportion between the Green and Red (NPGR), Green and Blue (NPGB) and Red and Blue (NPRB) bands (Equation 2, 3 and 4) was calculated.

$$\mathrm{NPGR} = \frac{\mathrm{Green} - \mathrm{Red}}{\mathrm{Green} + \mathrm{Red}} \tag{2}$$

$$\mathrm{NPGB} = \frac{\mathrm{Green} - \mathrm{Blue}}{\mathrm{Green} + \mathrm{Blue}} \tag{3}$$

$$\mathrm{NPGR} = \frac{\mathrm{Red} - \mathrm{Blue}}{\mathrm{Red} + \mathrm{Blue}} \tag{4}$$

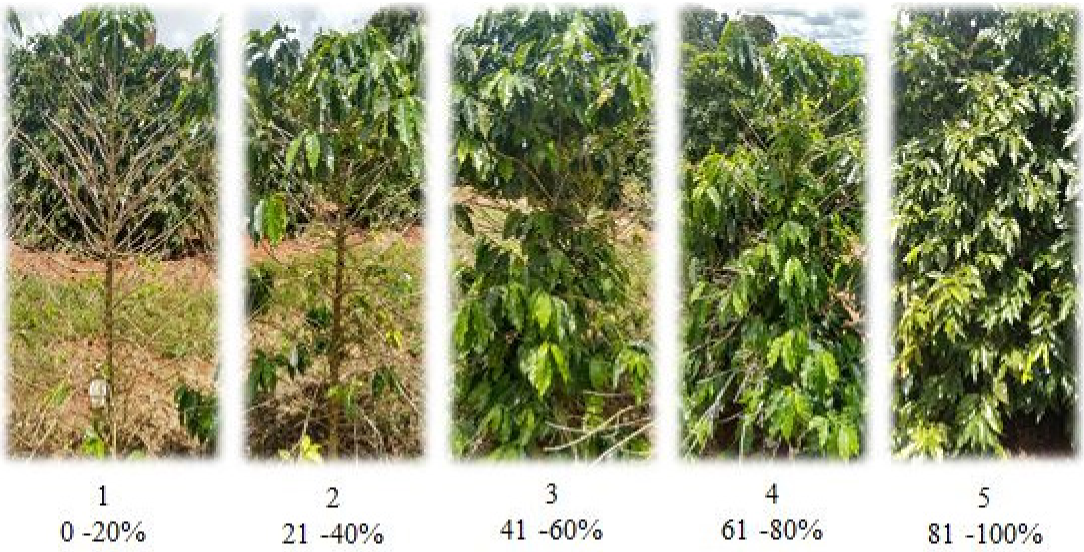


Figure 3: Visual classification notes for planting at foliage level in coffee plantations.

Machine learning for leafing estimation and NDVI

As the images from the RGB sensor were adjusted to a spatial resolution of 50 cm to approximately correspond to the coverage radius of the Greenseeker™ optical sensor, the values of the bands, red, green and blue, as well as the normalized ratio between the bands for the sampled points.

To adjust the model that calculates the NDVI values with data from the RGB sensor based on the Greenseeker™ active sensor, the Machine Learning Random Forest and Linear Regression algorithms were used. Random Forest was adjusted considering a mean absolute error as a criterion for branching and training the ruleset, using 500 decision trees.

To classify the RGB sensor images, in terms of foliage classes, the Random Forest algorithm was used with 500 decision trees, considering in this case the input as a branching criterion and a set of rules.

The model was validated using the Leave one out method, which consists of repeating the validation process of a point, where in each process a single point is removed from the training set and the interaction is performed until all points are predicted.

The models were submitted to mean absolute error, mean square error and coefficient of determination. As for the classification, global precision and balanced global precision were applied. Being an overall precision, a proportion of the total number of samples, a balanced overall precision, a proportion of the mean between the sensitivity and specificity of the model.

RESULTS AND DISCUSSION

Spatial distribution of foliage level was similar to the NDVI average figure with the Greenseeker™ optical sensor. Some plants with developmental level of low spectral water behavior that indicate they are suffering from some ailment of disease or nutrition. The NDVI is a numerical indicator that fluctuates throughout the phenological cycle of some crops, such as coffee (Herwitz et al., 2004; Zerbato et al., 2016; Almeida et al., 2017). Based on the field analysis, a high ratio between the foliage level and the NDVI can be observed ($r = 0.97$, p value < 0.01) (Figure 4 and 5).

Visual perception of foliage level is a simpler and more intuitive method, and NDVI can be considered a more assertive method for evaluating plant vigor.

Note that there is a link between the methods as both are linked to the state of the coffee leaves. According to Moreira et al. (2004), as the leaves of plants are configured as the most important object, as all reactions are the most photochemical reactions of the plant, in addition to other vital reactions, such as respiration and transpiration.

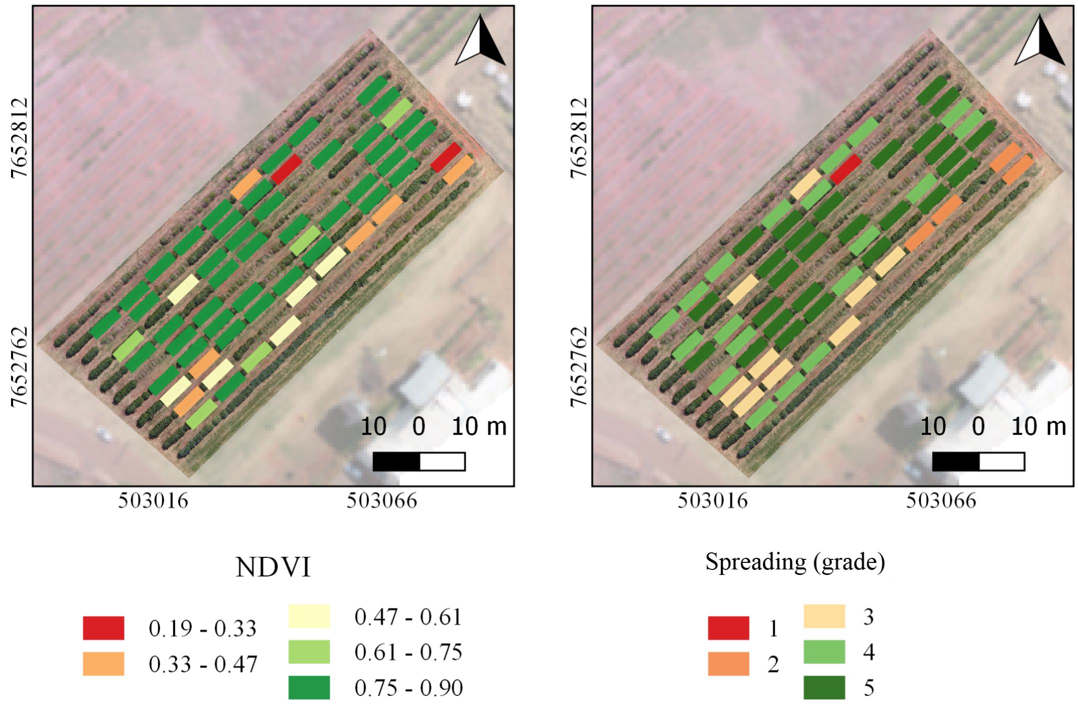


Figure 4: Leafing level classification and spatial distribution of the mean NDVI™ by the Greenseeker ™ active sensor.

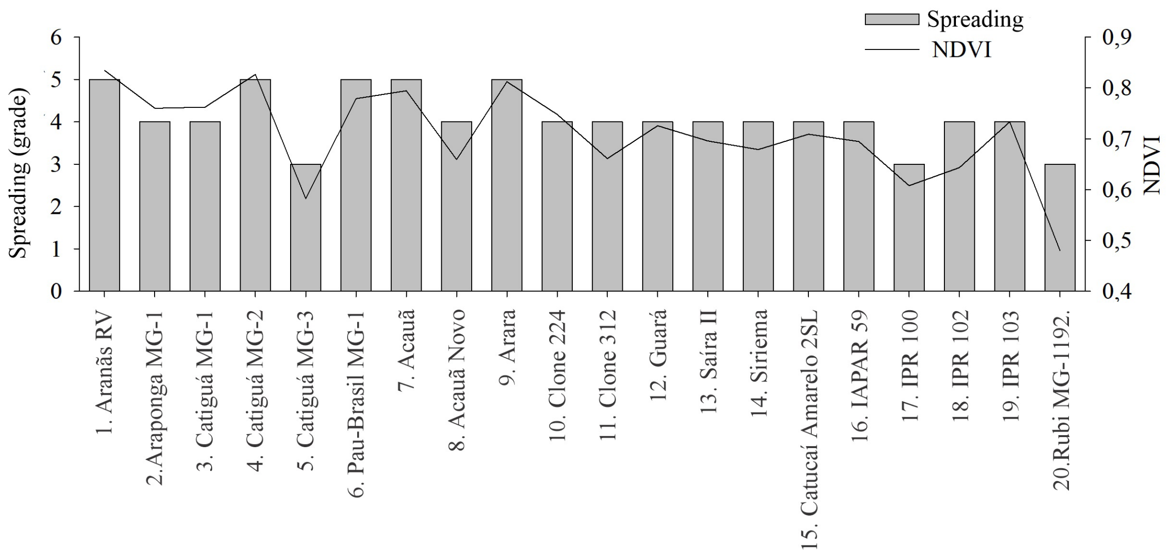


Figure 5: NDVI figure and average leaf level for medium cultivars.

The Greenseeker™ active optical sensor captures the signal directly on the leaves and as it is an active optical sensor, the signal suffers little interference in the path between the emission and reception of electromagnetic energy.

In the NIR spectral range, plants tend to reflect electromagnetic energy in a greater proportion than the other bands, in this sense, with the presence of greater coffee foliage, there will be greater NIR reflectance, but the RGB sensor maintains the same color tone.

The correlation between the UAS's RGB sensor and the Greenseeker™ active optical sensor's NDVI was significant (Table 1). As the Greenseeker™ captures reflectance at a short distance from the target, it tends to represent information with less spectral mixing, thus maintaining a more accurate value of the target's spectral behavior. The 50 cm spatial resolution of the image provided by the RGB UAS sensor in this analysis, detailed an area with only coffee leaves, and therefore, may have contributed to the higher correlation between the RGB sensor in relation to the Greenseeker™ active optical sensor. In studies with tomato (Enciso et al., 2019), a low correlation (P>0.05) was observed between the NDVI of the Greenseeker™ active optical sensor and the NDVI estimated with a multispectral sensor embedded in UAS, since the Greenseeker™ measurements pointed to the canopy, while the UAS measured the NDVI of the entire vegetative area, resulting in an R less than 0.45. In this study, the NDVI observed with the passive RGB sensor was for each plant observed with the Greenseeker™ active optical sensor.

Table 1: Pearson's correlation of NDVI from Greenseeker™ in relation to the red, blue, green bands and the normalized relationship between the UAS RGB sensor bands.

RGB Sensor Bands	Greenseeker NDVI
Red	-0.74**
Green	-0.78**
Blue	-0.70**
NPGR	-0.16^{NS}
NPGB	-0.76**
NPRB	0.59**

* Significant at 5%; ** Significant at 1%; NS Not significant for t test.

The methodology used in the treatment of spectral data in images obtained by a passive RGB sensor coupled in UAS, provided simple and direct detection by NDVI based on data from an active optical sensor (RGB). Therefore, the developed technique can be used for a detailed analysis at the plant level. Allied to remote sensing techniques, the use of RGB sensors coupled to the UAS helps in the efficiency of the control of the coffee plantation and in the decision making.

The modeling of the RGB sensor bands to estimate the NDVI using the Greenseeker™ active optical sensor obtained the best fit (R^2 0.72), with the multiple linear regression (Figure 6).

$$NDVI = 0,04Red - 0,03Green - 119,5NPGR + 118,2NPGB + 123,8NPRB + 0,25 \quad (5)$$

Considering the average of the estimates for the cultivars, the errors were relatively low compared to the Greenseeker™, which may indicate that the main errors were the outlier points that tend to be reduced by the average of the NDVI values of the cultivars (Figure 7).

In the classification of RGB images, being the green band and the NPGB, they obtained greater importance for the definition of the notes of tree leafing. The greater the tree leafing, the greater the color of the image in green tones and consequently the relationship in this spectral range (Table 2).

The general accuracy was 0.43 and the BAC was 0.45, as well as the produced accuracy (52.78%) and the user (60.64%) with the highest values in detecting plants with a 5 leafing score (Table 3). The spatial variability of foliage estimated by Random Forest was centered on

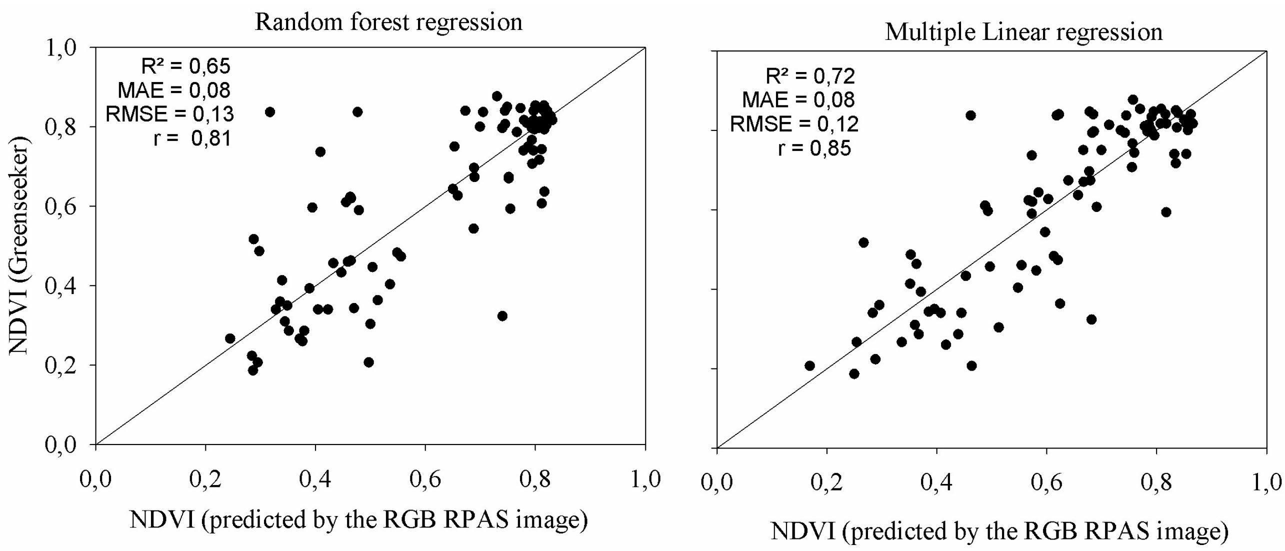


Figure 6: NDVI estimation with Greenseeker™ active optical sensor using passive RGB sensor image in UAS with Random Forest and multiple linear regression methods.

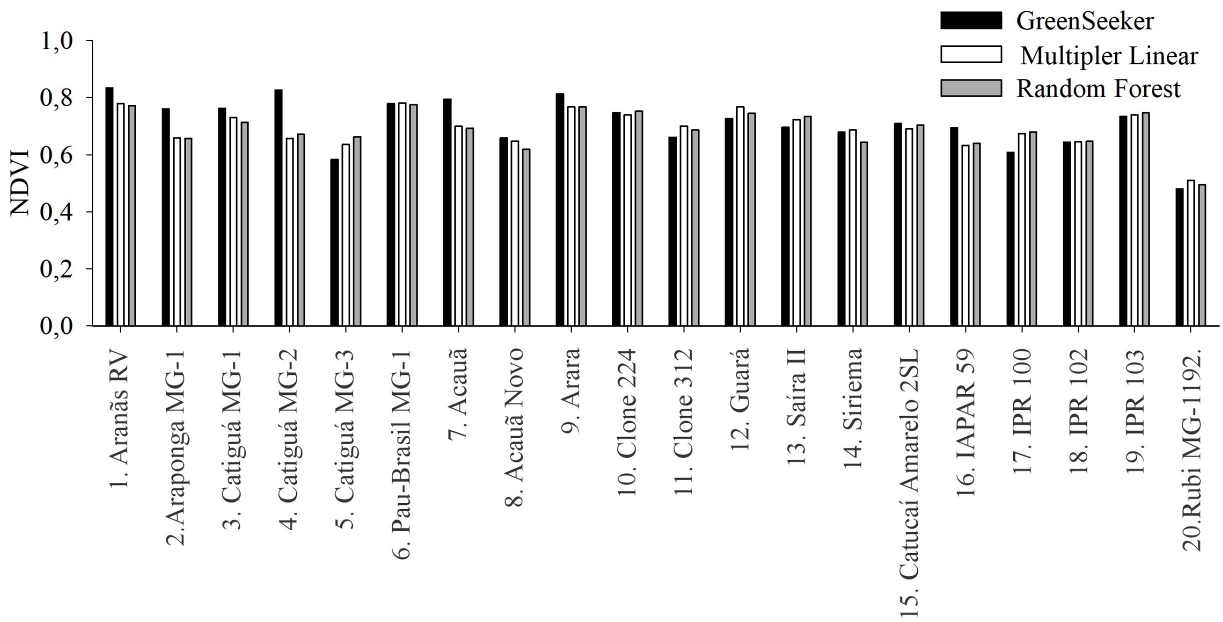


Figure 7: Average NDVI for cultivars observed with the Greenseeker™ optical sensor and estimated by Random Forest and multiple linear regression.

classes 3 and 4, with the in situ foliage centered on class 5 (Figure 8).

Table 2: Importance of the RGB sensor bands to decrease entropy in the estimation of the tree leafing note.

Bands	Decreased RF Entropy
Red	15.20%
Green	21.17%
Blue	14.71%
NPGR	12.88%
NPGB	21.79%
NPRB	14.24%

Table 3: Accuracy produced and user in the classification of RGB images according to the foliage note by the Random Forest algorithm.

Leafing level (note)	Accuracy Produced	User Accuracy
1	23.08%	15.79%
2	38.78%	44.19%
3	39.58%	38.78%
4	36.54%	29.23%
5	52.78%	60.64%

In the mean of the values for cultivar, the observed errors were of the order of one class. It is noteworthy that this visual method for leafing notes can be subjective depending on the evaluator, therefore, note errors above or below the forecast are expected results.

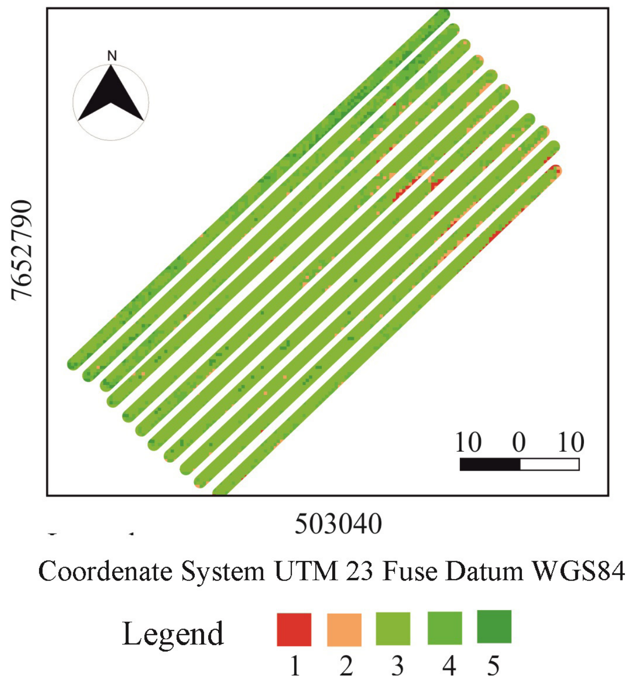


Figure 8: Classification of the Random Forest algorithm in prediction of leafing using UAS RGB sensor image.

The average productivity of the cultivars obtained values that follow the trend of NDVI in which the low productivity obtained a direct relation with the index. The cultivar Rubi MG-1192 showed lower productivity, NDVI and leafing (Figures 9 and 10), this cultivar has the characteristic of small size, being indicated for the manual handling of the culture (Pereira et al., 2014). However, this characteristic can infer about low tree leafing, but productivity below 30 sc/ha is not common for culture, which indicates that there is a phytosanitary problem.

On the other hand, the cultivar New Acuã, showed a greater divergence between NDVI and productivity. Comparative studies between cultivars show that Acauã Novo has a higher percentage of cherry, dry and green fruits compared to other cultivars such as Caiá Cerrado-MG 1474; World New IAC 379-19; Bourbon Amarelo IAC J10; Catuaí Vermelho IAC 99 (Fernandes et al., 2020). This divergence in maturation indicates that the cultivar does not produce homogeneously, which may have occurred.

Although the data are insufficient to obtain a model of yield prediction for each cultivar,

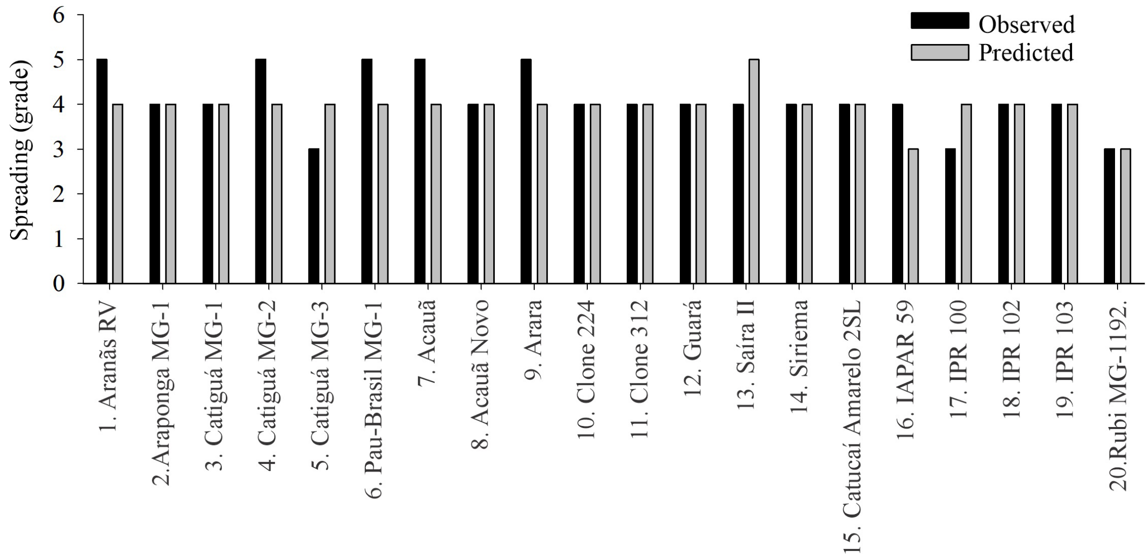


Figure 9: Average tree leafing score for cultivars observed in situ and estimated by Random Forest in UAS RGB sensor image.

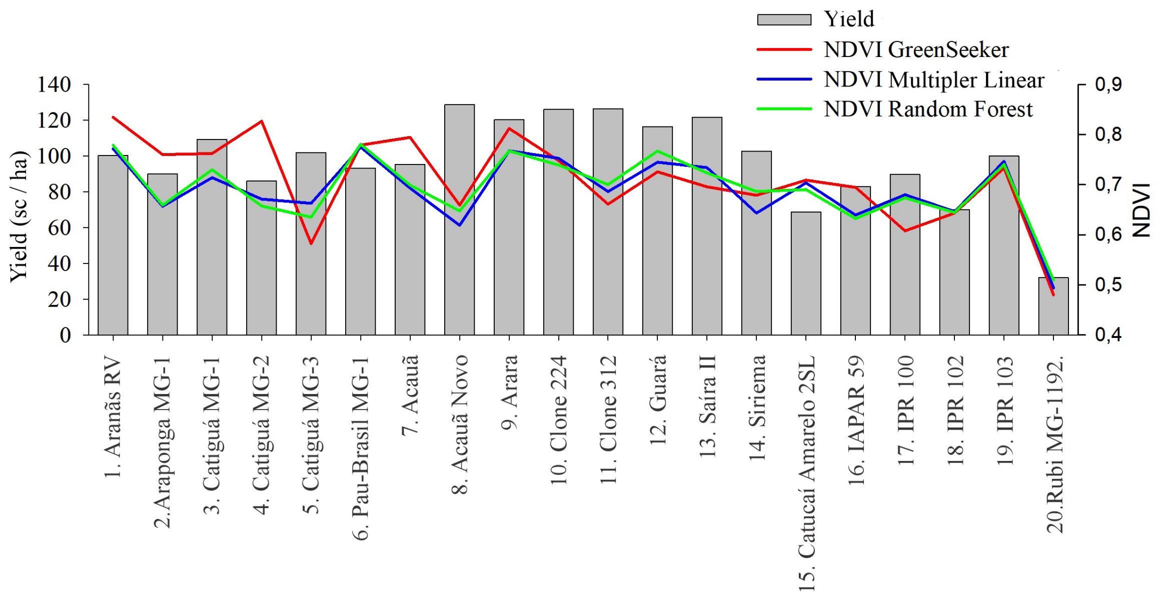


Figure 10: Relationship of average yield and NDVI estimated by different regression methods for each cultivar evaluated.

it was possible to observe a pattern for some cultivars such as IPR 100, Catucaí Amarelo 2SL, Aranãs RV in which they can be targets of further studies. However, when studied all cultivars together, you can observe a correlation between productivity and NDVI (Figure 11). The NDVI obtained by the multiple linear regression with the best results in relation to the other estimate of the index stands out.

Studies with orbital imaging have already observed a relationship between the index and productivity. They are generally used in spectral agrometerological models, with NDVI being the spectral component representing the leafing aspects of the crop (Picini, 1998; Rosa et al., 2010; Silva et al., 2011; Bernardes et al., 2012; Almeida et al., 2017). The NDVI multiple regression equation obtained by UAS images, can be used in large-scale mapping, enabling to estimate productivity at the plant level and thus exercise greater accuracy in precision agriculture.

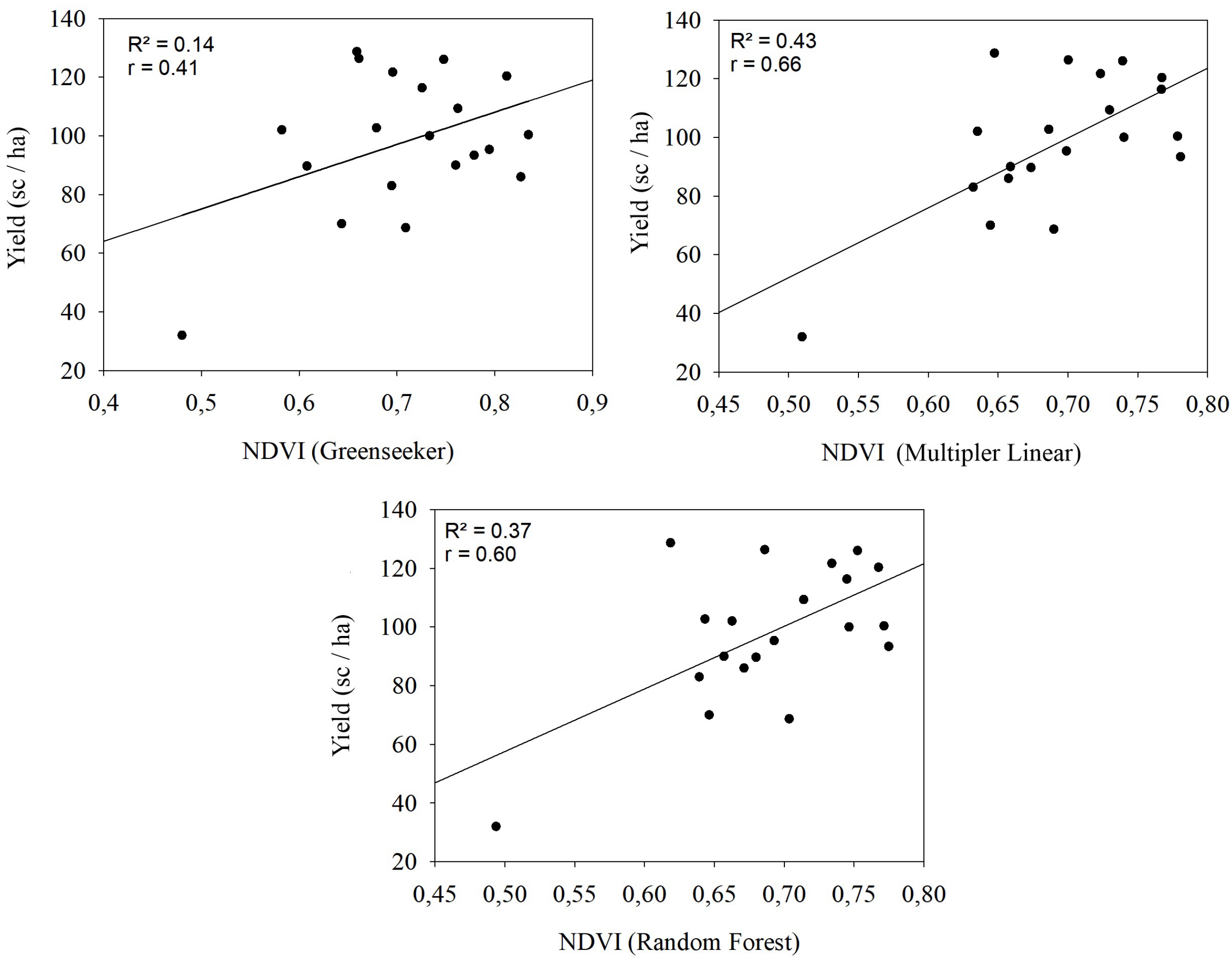


Figure 11: Relationship between NDVI estimated by different regression methods and yield for all cultivars.

CONCLUSIONS

The methodology used in the treatment of spectral data with images obtained by a passive RGB sensor coupled in UAS, provided simple and direct detection of NDVI based on data from an active optical sensor (RGB). Therefore, the developed technique can be used for a detailed analysis at the coffee crop. Remote Sensing techniques using RGB sensors coupled to UAS can help in the monitoring of coffee tree foliage and in the decision making of coffee growing.

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