



Validation of UAV-Based NDVI Using Proximal Sensing in Mountain Coffee Plantations

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Abstract.

Unmanned aerial vehicles (UAVs) with multispectral sensors have expanded remote sensing applications in precision agriculture, however validation against ground-truth measurements remains critical, especially for perennial crops in complex terrain such as coffee plantations in mountainous regions. Proximal sensing can be employed as a reference for evaluating the quality of data obtained by remote platforms. This study aimed to evaluate the reliability of Normalized Difference Vegetation Index (NDVI) values obtained by UAV remote sensing by comparing them with proximal sensing measurements. The experiment was conducted on Oasis Farm, a coffee farm located in Coimbra, Minas Gerais, Brazil, across four survey dates during the growing season. Two UAV-sensor combinations were tested: DJI Matrice 350 RTK with MicaSense RedEdge-P camera and DJI Mavic 3M with integrated multispectral camera. Proximal sensing was performed using an ASD HandHeld 2 spectroradiometer and a GreenSeeker active sensor. The data acquisition included sampling 50 points representative of the crop row class and 50 sampling points of the inter-row class, enabling evaluation of different spectral conditions. Multispectral images were processed into reflectance orthomosaics using Pix4DMapper (v4.9.0), and NDVI values were calculated using QGIS (v3.34) and extracted at points corresponding to field measurements. Data from remote and proximal sensors were used to generate NDVI maps through spatial interpolation using the Smart-Map plugin for QGIS. Agreement between UAV-derived and proximal NDVI was assessed using simple linear regression, coefficient of determination (R^2), and root mean square error (RMSE) for both sampling points and interpolated maps. For interpolated maps, the intraclass correlation coefficient (ICC) was also calculated. UAV-derived NDVI showed strong agreement with proximal sensing measurements, with ICC ranging between 0.77 and 0.85, R^2 values exceeding 0.90, and RMSE ranging between 0.040 and 0.095, demonstrating that estimates generated with remote sensing were highly consistent with those obtained by proximal sensing. Remote sensors generally produced values slightly higher than proximal sensors, with differences more evident in the inter-row, which may reflect differences in sensor viewing geometry and ground sampling distance. Nevertheless, consistent behavior was observed in NDVI values obtained by remote sensing for both crop row and inter-row, reflecting the capacity of remote sensors to capture the spectral variability of the production system. Although the two multispectral sensors exhibited distinct behaviors in the linear fit when compared separately to proximal sensing, these differences were not considered significant. The

results demonstrate that UAV remote sensing is a reliable approach for NDVI mapping in coffee plantations located in mountainous regions, supporting crop monitoring and decision-making in precision agriculture environments with complex terrain.

Keywords.

Precision Agriculture, Coffee Crop, NDVI, Multispectral Imaging, Ground Validation

1. Introduction

Spatial variability is an inherent characteristic of agricultural systems and results from the interaction between soil, climatic, topographic, and management factors, directly influencing crop growth, development, and yield. Recognizing this variability represents one of the fundamental principles of Precision Agriculture, since it allows the adoption of site-specific management strategies aimed at optimizing input use, increasing production efficiency, and reducing environmental impacts. In this context, obtaining spatially explicit and temporally representative information on crop status has become one of the main challenges for the effective implementation of intelligent, data-driven agricultural systems (Maes and Steppe, 2019; Bouskour et al., 2023).

Among the different technologies employed to characterize spatial variability, remote sensing stands out for its ability to provide fast, non-destructive, and georeferenced information over large agricultural areas. Traditionally, satellite imagery has been widely used for agricultural monitoring; however, limitations related to spatial resolution, temporal availability, and cloud cover interference often restrict its application in studies requiring a high level of detail. In this scenario, unmanned aerial vehicles (UAVs) emerge as an alternative capable of combining high spatial resolution, operational flexibility, and on-demand data acquisition, enabling the acquisition of information compatible with the scale of variability observed within crop fields (Barata et al., 2023; Cardona et al., 2025).

The advancement of multispectral sensors mounted on UAVs has significantly broadened the possibilities for applying remote sensing in Precision Agriculture. Using these sensors, it is possible to estimate attributes related to vegetative vigor, biomass, nutritional status, and photosynthetic activity of plants through vegetation indices calculated from spectral reflectance. Among these indices, the Normalized Difference Vegetation Index (NDVI) stands out as one of the most widely used metrics in agricultural studies due to its simplicity of acquisition, robustness, and close relationship with biophysical vegetation parameters (Khalesi et al., 2022; Bouskour et al., 2023).

NDVI is based on the characteristic spectral behavior of plants, which exhibit high absorption of electromagnetic radiation in the red region due to the presence of photosynthetic pigments and high reflectance in the near-infrared region due to leaf cellular structure. As a result, this index has been widely used for monitoring plant growth, detecting biotic and abiotic stresses, estimating yield, and characterizing spatial variability in different agricultural production systems (Khalesi et al., 2022; Bouskour et al., 2023).

Despite the widespread use of NDVI in agricultural monitoring studies, the reliability of values obtained by remote sensing remains under investigation (Gomes et al., 2021). Different factors can influence the spectral response recorded by sensors, including the radiometric and spectral characteristics of the equipment, lighting conditions during image acquisition, calibration procedures, sensor spatial resolution, and structural characteristics of the evaluated crop. Additionally, the transfer of information between different observation scales represents an important challenge, since field measurements and estimates derived from aerial images do not necessarily represent the same volume of vegetation or the same spectral composition (Khalesi et al., 2022).

This issue becomes even more relevant in coffee systems grown in mountainous regions.

Brazilian coffee farming is of great economic and social importance, accounting for a significant share of world coffee production. In several producing regions, especially those characterized by steep terrain, environmental heterogeneity strongly influences crop behavior. Variations in altitude, slope, hillside orientation, water availability, and microclimatic conditions contribute to the formation of complex patterns of spatial variability, which can directly affect the spectral response observed by remote sensors. Furthermore, the three-dimensional architecture of the coffee plant, combined with shading effects and exposed soil between rows, increases the complexity of interpreting spectral data obtained by sensors mounted on UAVs (Bento et al., 2023; Zanella et al., 2024).

In this context, proximal sensing has been widely used as a reference tool for validating products derived from remote sensing. Equipment such as spectroradiometers and active optical sensors enable measurements to be taken directly on the target, reducing the influence of atmospheric factors and providing greater control over data acquisition conditions. Thus, the comparison between proximal measurements and estimates derived from aerial images allows the consistency, accuracy, and reliability of vegetation indices used in agricultural applications to be evaluated (Barata et al., 2023; Zanella et al., 2024).

Although the potential of UAV-based remote sensing for agricultural monitoring is widely documented in the literature, studies evaluating the agreement between different multispectral platforms and proximal sensing devices in coffee systems grown in mountainous regions remain limited. Validating these technologies is essential to ensure that vegetation indices obtained by remote sensing adequately represent field conditions and can be confidently used in Precision Agriculture programs. In this context, the present study aimed to evaluate the reliability of NDVI values obtained by remote sensing using two UAV platforms equipped with multispectral sensors, by comparing them with measurements obtained by a spectroradiometer and an active optical sensor in a coffee field.

2. Material and Methods

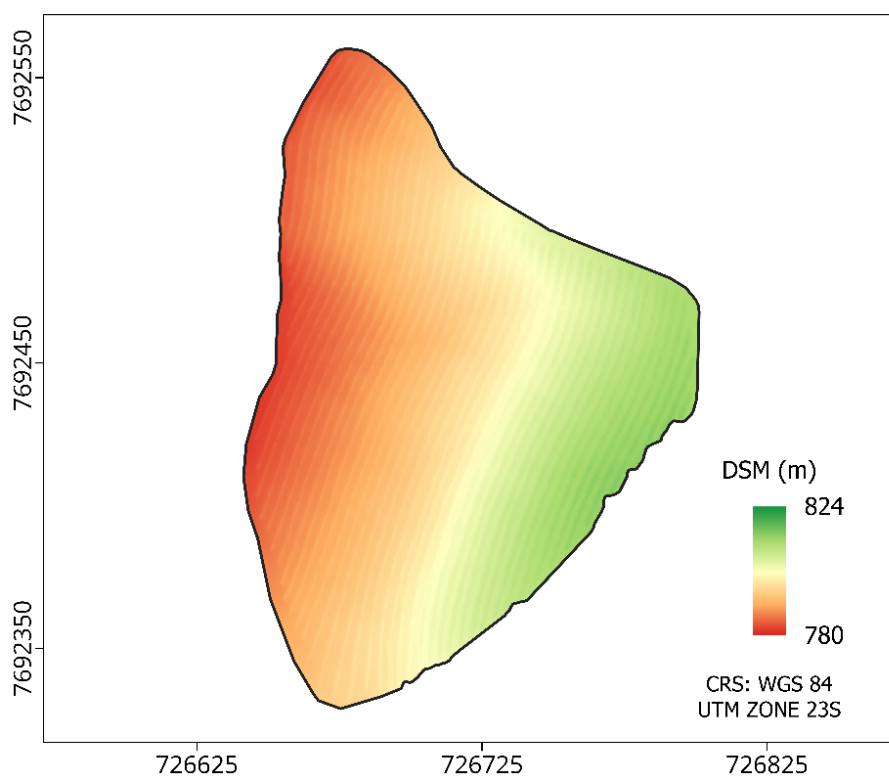
Experimental area

The study was conducted at Oasis Farm, located in the municipality of Coimbra, Minas Gerais, Brazil. The experimental area consisted of a 2.2-hectare coffee plantation established in a mountainous region, a characteristic landscape of the Zona da Mata coffee-growing region of Minas Gerais, as shown in Figure 1. The area exhibits significant topographic variability associated with differences in slope, hillside orientation, and microclimatic conditions, factors that directly influence crop development and its spectral response.

Data acquisition campaigns were conducted on four dates throughout the crop growing season, specifically on June 5 and 12, and July 10 and 16. During each campaign, UAV-based remote sensing surveys and proximal sensing measurements were carried out simultaneously, allowing direct comparison between the different sensing approaches.



(a)



(b)

Fig.1. Characteristics of the experimental area, being: (a) orthomosaic, and (b) digital surface model.

Aerial platforms and multispectral sensors

Two distinct aerial platforms were used to acquire the multispectral images. The first platform consisted of a DJI Matrice 350 RTK UAV (DJI, Shenzhen, China), equipped with a MicaSense RedEdge-P multispectral camera (MicaSense Inc., Seattle, WA, USA). The sensor has five multispectral bands centered in the blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and near-infrared (842 nm) regions, in addition to a high-resolution panchromatic band.

The second platform used was a DJI Mavic 3 Multispectral UAV (DJI, Shenzhen, China), equipped with an integrated multispectral sensor capable of acquiring images in the green (560 nm), red (650 nm), red-edge (730 nm), and near-infrared (860 nm) bands. The UAVs were connected to a GNSS (Global Navigation Satellite System) real-time kinematic (RTK) georeferencing system.

Flight missions were planned using the operational parameters recommended for agricultural mapping. Flights were carried out at an altitude of 100 m above ground level with 85% longitudinal and lateral overlap. All acquisitions took place between 11:00 a.m. and 1:00 p.m., aiming to minimize variations related to the solar angle. During flights, the UAVs operated with a terrain-following system, allowing the distance between the sensor and the target to be maintained even in areas with high elevation variation. Before each mission, images of a radiometric calibration panel (model RP06, Micasense, Seattle, WA, USA) for subsequent conversion of digital numbers into reflectance values.

Proximal sensing

Proximal sensing measurements were carried out simultaneously with the imaging campaigns using an ASD HandHeld 2 spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA) and a GreenSeeker active optical sensor (Trimble Inc., Sunnyvale, CA, USA).

The spectroradiometer operates in the spectral range from 325 to 1075 nm, with a spectral resolution of approximately 1 nm, allowing the acquisition of detailed spectral signatures of the evaluated targets. The equipment was calibrated prior to each set of measurements using a Spectralon® reference panel.

The GreenSeeker uses its own light source and directly provides Normalized Difference Vegetation Index (NDVI) values, minimizing interference related to ambient lighting conditions. A total of 100 georeferenced sampling points were established, distributed into two classes of interest:

- 50 points located on the coffee crop row;
- 50 points located in the crop inter-row.

At each experimental point, three consecutive readings were taken with the spectroradiometer, and the average value was used for subsequent analyses. The measurements obtained by the GreenSeeker were recorded simultaneously.

Multispectral image processing

Images acquired by the UAVs were processed using Pix4D Mapper®, version 4.9.0 (Pix4D SA, Lausanne, Switzerland). Image alignment and automatic determination of exterior orientation parameters were performed first. Radiometric calibration was then carried out using the reflectance panel images acquired before each flight. After this step, reflectance orthomosaics were generated for all spectral bands available in each sensor. NDVI values were extracted from the orthomosaics at the same sampling points defined for proximal sensing. The generated

orthomosaics were exported to QGIS®, version 3.34.4, where the spatial analyses and vegetation index calculations were performed.

Vegetation index calculation

The Normalized Difference Vegetation Index (NDVI) was used as the parameter for comparison between the remote and proximal sensors. For the multispectral sensors mounted on the UAVs, NDVI was calculated from the reflectance orthomosaics generated for each platform, using Equation 1. From this procedure, NDVI maps were obtained for the entire experimental area.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (1)$$

where:

NIR = reflectance in the near-infrared band;

RED = reflectance in the red band.

For the GreenSeeker active optical sensor, NDVI values were obtained directly by the equipment during field measurements, with no additional processing step required.

The spectral signatures obtained by the ASD HandHeld 2 spectroradiometer were used to calculate NDVI after spectral resampling of the data, in order to reproduce the spectral bands of the Mavic 3M and MicaSense RedEdge-P sensors. In this way, two sets of NDVI values were generated from the spectroradiometer: one using the bands equivalent to those of the Mavic 3M and another using the bands equivalent to those of the MicaSense RedEdge-P sensor. This procedure made the comparisons more consistent between the proximal and remote sensors, minimizing differences associated with the distinct spectral responses of the equipment.

Subsequently, the sampling points obtained in the field were georeferenced onto the NDVI maps generated from the orthomosaics, enabling the extraction of values corresponding to the same positions evaluated by proximal sensing.

Generation of interpolated maps

NDVI values obtained by remote and proximal sensing were used to generate continuous surfaces of the spatial distribution of the index. Spatial interpolation was performed using the Smart-Map plugin available for QGIS. The generated maps allowed the spatial distribution of NDVI values to be represented for each acquisition method, enabling visual and quantitative comparisons between the different sensing approaches.

Subsequently, scripts developed in the Python language were used for extracting and processing the average values corresponding to the regions of interest, enabling the standardization of the datasets used in the statistical analyses.

Statistical analysis

The agreement between the NDVI values obtained by the remote and proximal sensors was evaluated using the Intraclass Correlation Coefficient (ICC), simple linear regression, the coefficient of determination (R^2), and the root mean square error (RMSE). The coefficient of

determination was calculated using Equation 2:

$$R^2 = 1 - \frac{\sum_{i=1}^n (X_i - Y_i)^2}{\sum_{i=1}^n (X_i - \bar{Y})^2} \quad (2)$$

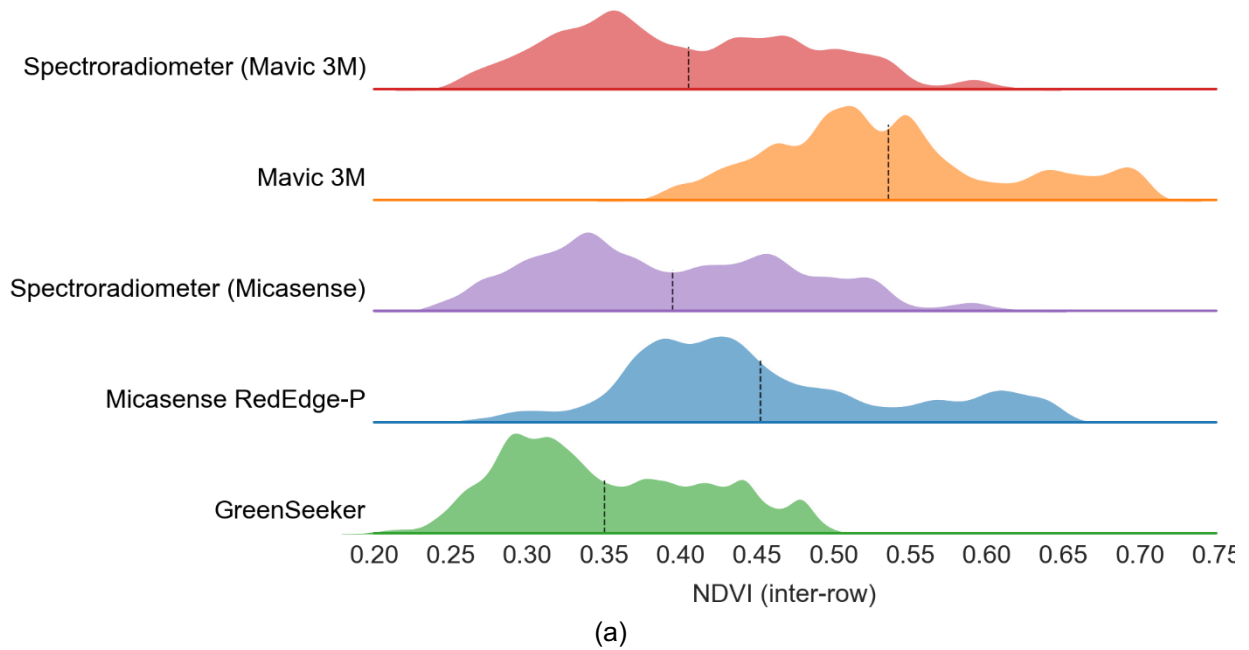
The root mean square error was obtained using Equation 3:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}} \quad (3)$$

The intraclass correlation coefficient (ICC) was used to assess the degree of agreement between the datasets obtained by remote and proximal sensing. For this analysis, two independent groups were defined. The first group was composed of the NDVI values obtained by the Mavic 3M sensor, the values provided by the GreenSeeker, and the NDVI values calculated from the spectral signatures of the ASD HandHeld 2 spectroradiometer after spectral resampling to reproduce the Mavic 3M bands. The second group was composed of the NDVI values obtained by the MicaSense RedEdge-P sensor, the GreenSeeker values, and the NDVI values calculated from the spectroradiometer after spectral resampling to reproduce the bands of the MicaSense RedEdge-P sensor.

3. Results and Discussion

A consistent behavior was observed between the acquisition methods, showing that both the proximal sensors and the multispectral sensors embarked on the UAVs were able to identify the patterns of spectral variability present in the coffee field (Figure 2).



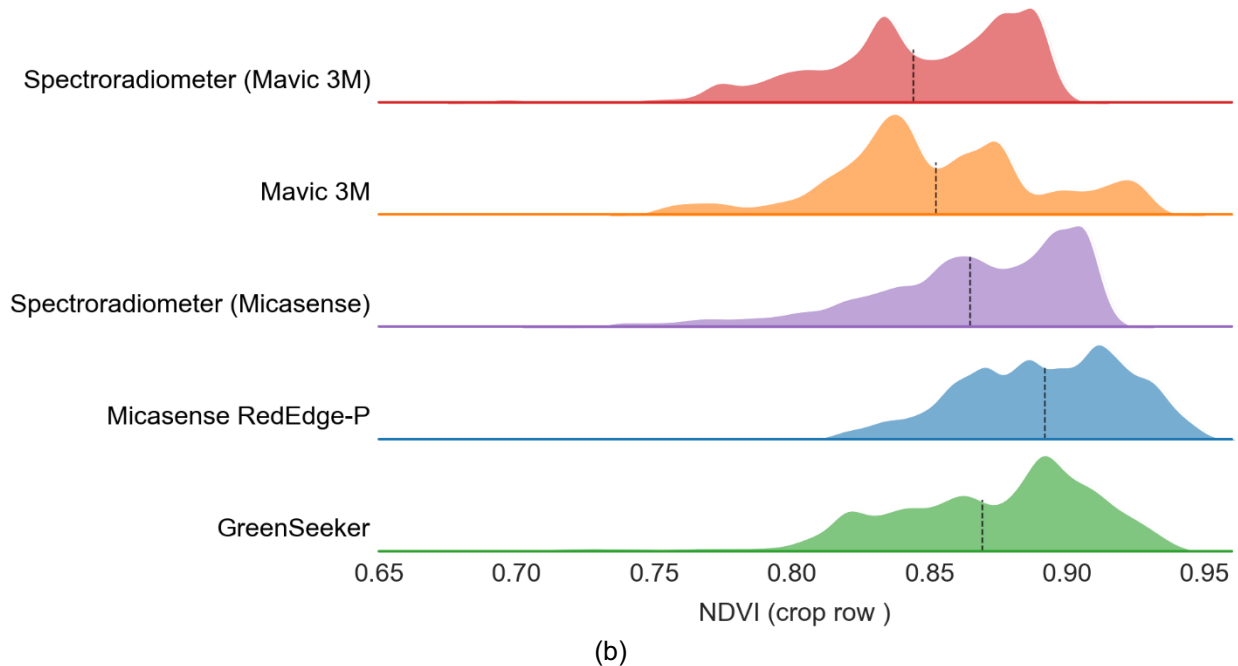


Fig. 2. Distribution of values based on the interpolated maps. (a) NDVI values on the coffee crop row. (b) NDVI values in the inter-row. The dashed line in the graphs represents the mean of the values.

In the distributions corresponding to the points located on the crop row (Figure 2a), the highest NDVI values were observed for the sensors embarked on the UAVs, especially for the MicaSense RedEdge-P sensor, followed by the Mavic 3M sensor. The proximal sensors presented slightly lower values, although maintaining a similar behavior. This result suggests that the remote sensors tend to moderately overestimate NDVI when compared to measurements taken directly above the canopy, possibly due to differences in observation geometry, sampled area, and spatial resolution.

For the inter-row condition (Figure 2b), greater dispersion of values and a widening of the differences between sensors were observed. This behavior was expected due to the greater influence of spontaneous vegetation, plant residues, and exposed soil present between the coffee rows. Even under these conditions of greater spectral heterogeneity, the remote sensors maintained a pattern similar to that observed by the proximal sensors, indicating an adequate capacity to represent the spatial variability of the area.

In the comparison between the values obtained by the Mavic 3M sensor and the spectroradiometer, the linear regressions obtained from the sampling points yielded a coefficient of determination of $R^2 = 0.917$ and an RMSE of 0.081 (Figure 3a), indicating high agreement between the methods. A similar result was observed in the comparison between the Mavic 3M sensor and the GreenSeeker (Figure 3b), with $R^2 = 0.900$ and RMSE of 0.095.

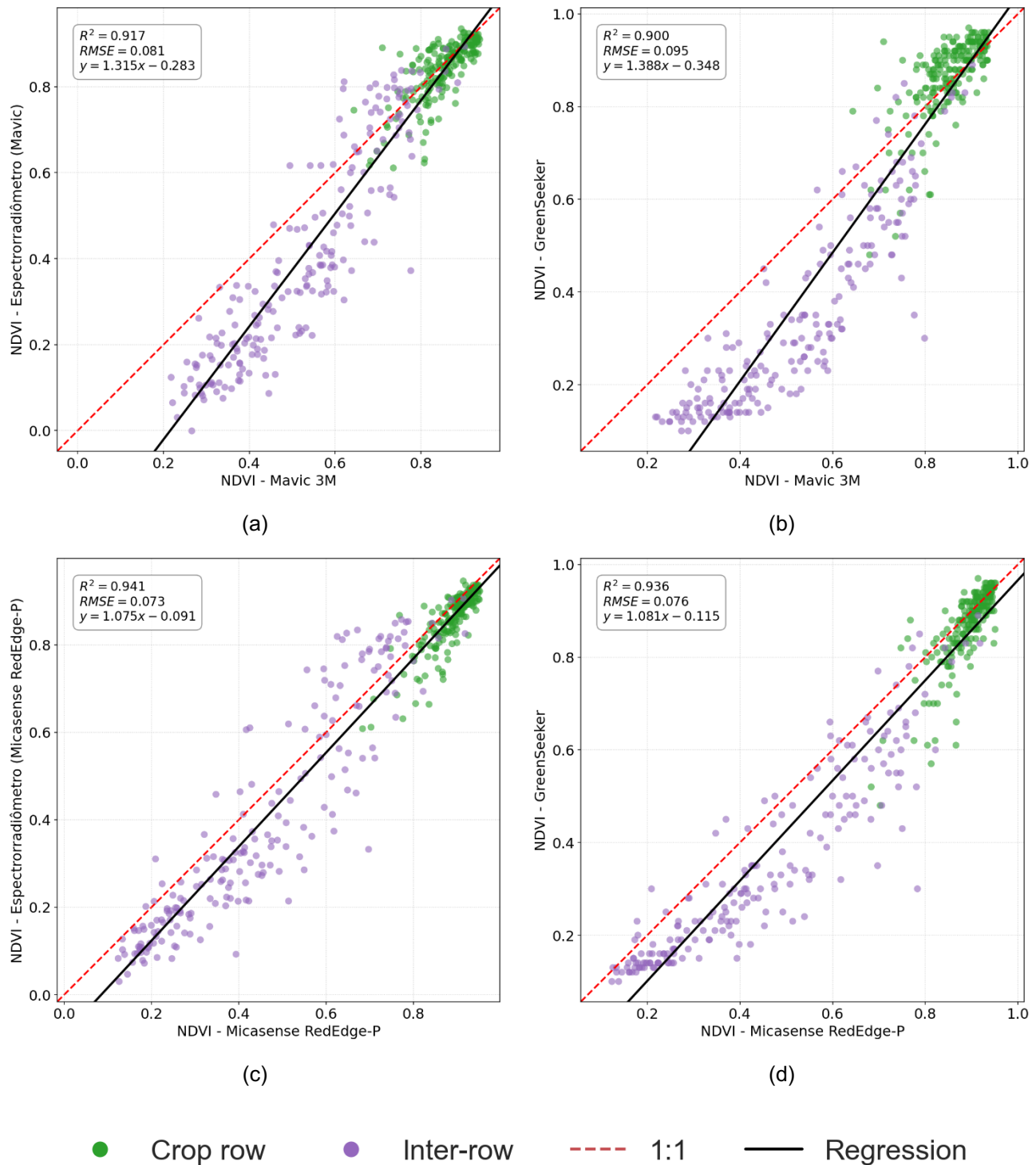


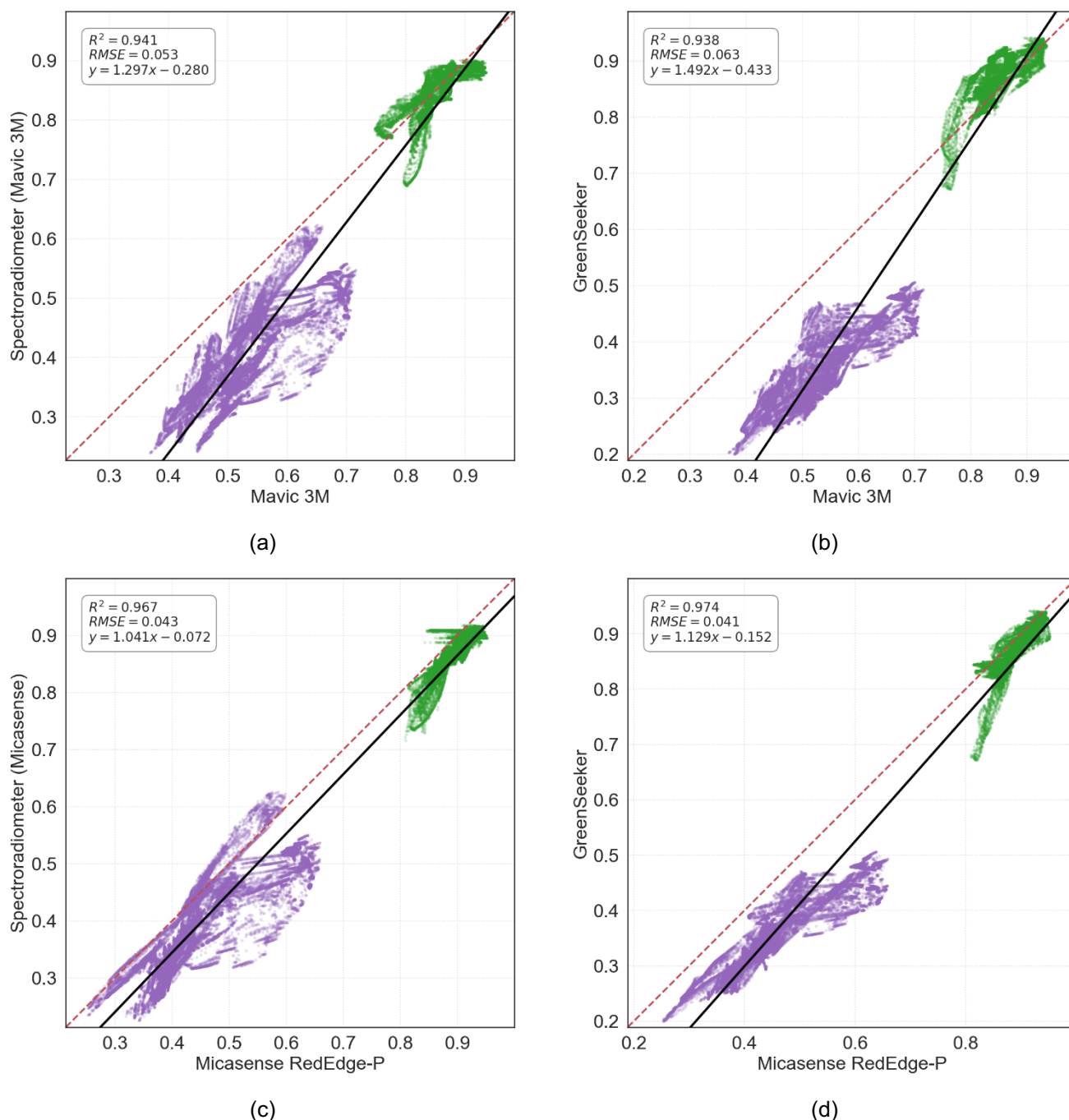
Fig. 3. Scatter plots between NDVI values from remote and proximal sensing, based on the sampling points: (a) Spectroradiometer and Mavic 3M, (b) GreenSeeker and Mavic 3M, (c) Spectroradiometer and MicaSense RedEdge-P, and (d) GreenSeeker and MicaSense RedEdge-P.

For the MicaSense RedEdge-P sensor, the coefficients of determination were even higher. In the comparison with the spectroradiometer, the coefficient of determination was $R^2 = 0.941$ and the RMSE was 0.073 (Figure 3c), while the comparison with the GreenSeeker resulted in $R^2 = 0.936$ and RMSE of 0.076 (Figure 3d). These results show that both sensors embarked on the [Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture: 13-15 July, 2026, Porto Alegre, Brazil](#)

UAVs were able to satisfactorily reproduce the values obtained by the proximal sensors, with a slight superiority of the MicaSense system in terms of statistical fit being observed.

The regression equations obtained slopes greater than unity for all comparisons, ranging from 1.075 to 1.388. This behavior indicates a tendency toward overestimation of NDVI values by the remote sensors relative to the proximal sensors, mainly in the intermediate ranges of vegetative vigor. This effect may be associated with the larger spectral integration area observed by the sensors embarked on the UAVs, which simultaneously capture different canopy components and reduce the influence of small local variations recorded by the proximal sensors.

The coefficients of determination observed were higher than those obtained in the analysis based exclusively on the sampling points, showing a high spatial agreement between the evaluated methods (Figure 4).



● Crop row ● Inter-row - - - - 1:1 — Regression

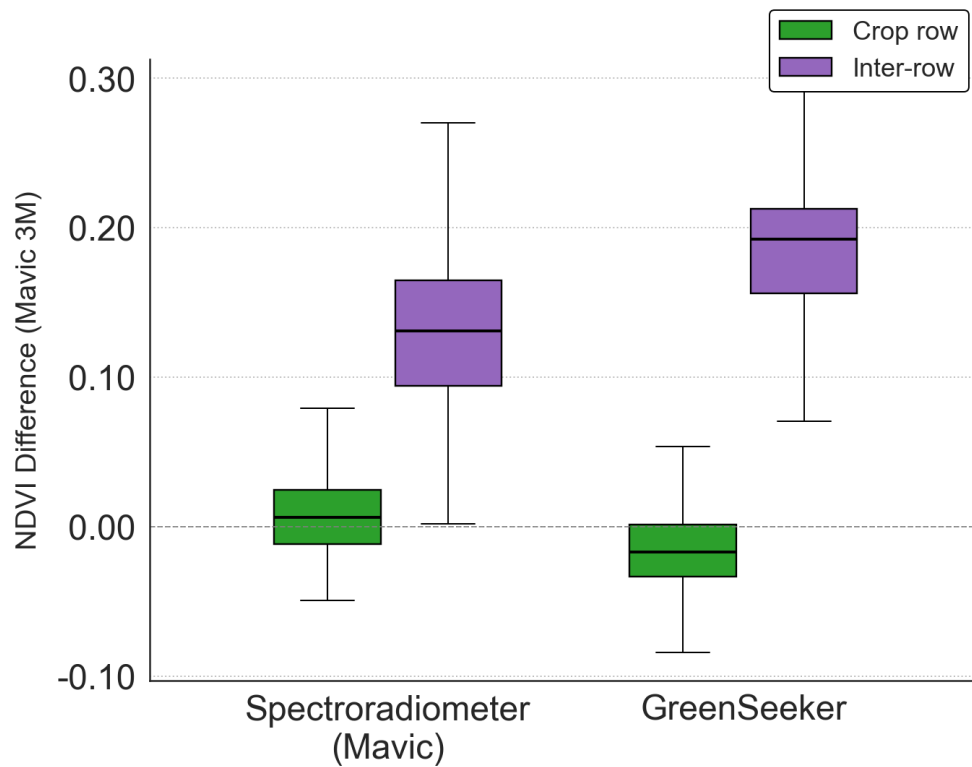
Fig 4. Scatter plots of the coefficient of determination and RMSE values between remote and proximal sensing, based on the interpolated maps: (a) Spectroradiometer and Mavic 3M, (b) GreenSeeker and Mavic 3M, (c) Spectroradiometer and MicaSense RedEdge-P, and (d) GreenSeeker and MicaSense RedEdge-P.

The comparison between the interpolated maps generated by the Mavic 3M sensor and the spectroradiometer presented $R^2 = 0.941$ and $RMSE = 0.053$ (Figure 4a), while the comparison between the Mavic 3M sensor and the GreenSeeker resulted in $R^2 = 0.938$ and $RMSE = 0.063$ (Figure 4b). These results demonstrate that the spatial distribution of NDVI obtained by the sensor embarked on the UAV adequately reproduced the patterns observed by the proximal sensors, even after the interpolation step.

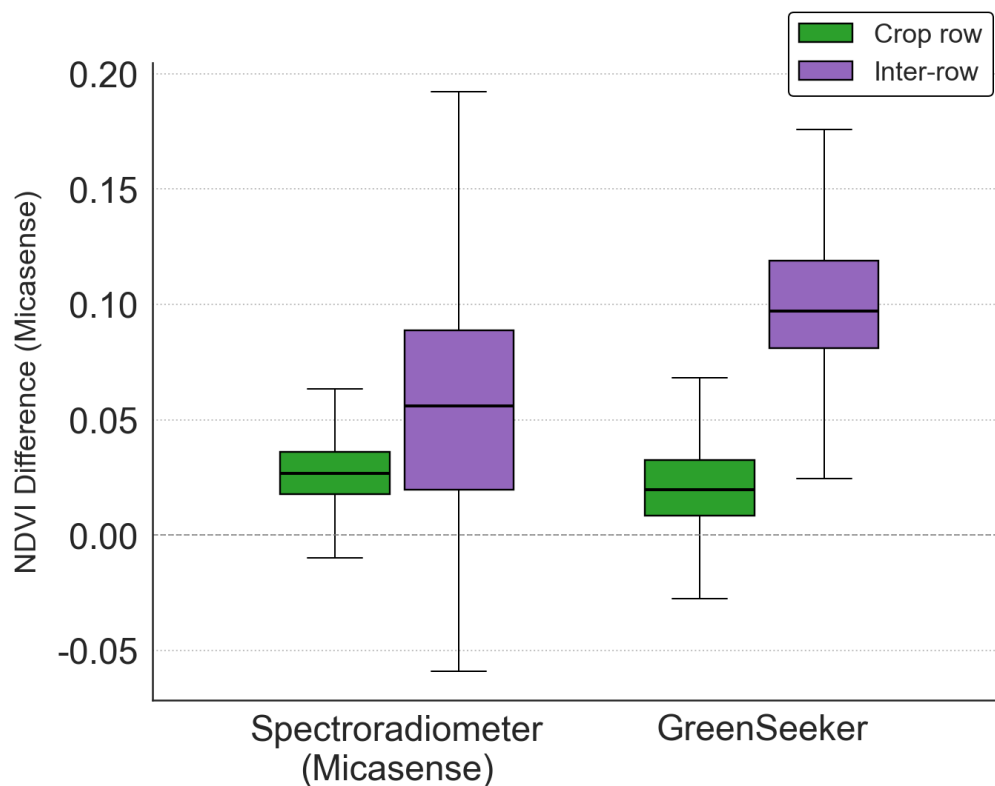
For the MicaSense RedEdge-P sensor, the best performances among all the comparisons performed were observed. The regression between the maps derived from the MicaSense and the spectroradiometer obtained $R^2 = 0.967$ and $RMSE = 0.043$ (Figure 4c), while the comparison with the GreenSeeker resulted in $R^2 = 0.974$ and $RMSE = 0.041$ (Figure 4d). The high coefficients of determination and the low errors obtained show the high capacity of the sensor to represent the spatial variability of the crop's vegetative vigor.

The regression equations indicated slopes greater than unity for most comparisons, mainly for the Mavic 3M sensor, whose angular coefficients ranged from 1.297 to 1.492. This behavior suggests a tendency toward amplification of the spatial contrasts of NDVI relative to the proximal sensors. In contrast, the MicaSense sensor achieved angular coefficients closer to unity (1.041 and 1.129), indicating behavior closer to the ideal equivalence between the acquisition methods. This result may be related to the radiometric characteristics of the sensor, the greater stability of the radiometric calibration, and the spectral quality of the bands used to calculate the index.

The difference maps in Figure 5 allow the spatial evaluation of the magnitude of the deviations between the products generated by remote and proximal sensing. In Figure 5a, corresponding to the Mavic 3M sensor, a greater range of differences distributed throughout the experimental area is observed, indicating greater sensitivity to the spectral variations existing between the row and inter-row. Despite this, the spatial patterns remained compatible with those obtained by the proximal sensors.



(a)



(b)

Fig 5. NDVI differences between interpolated maps produced by remote and proximal sensing: (a) Spectroradiometer (Mavic 3M) and GreenSeeker for row and inter-row, and (b) Spectroradiometer (MicaSense) and GreenSeeker for row and inter-row.

In both maps, the regions corresponding to the crop rows, identified in green, presented high agreement between the acquisition methods. In these areas, the predominance of the coffee canopy favors more uniform spectral responses and reduces the influence of non-vegetated components. In contrast, the inter-row areas, identified in purple, exhibited greater variability in the observed differences, an expected result due to the presence of exposed soil, weeds, crop residues, and shading effects.

Although local differences were identified for both sensors, the observed deviations were relatively small when compared to the total range of NDVI values recorded in the experimental area. Thus, the maps reinforce the results of the statistical analyses, demonstrating that both UAV-embarked sensors were able to adequately represent the spatial variability of the crop's vegetative vigor, with a tendency toward better performance of the MicaSense RedEdge-P sensor in reproducing the patterns observed by the proximal sensors.

The intraclass correlation coefficient (ICC) values obtained for the interpolated maps ranged from 0.775 to 0.855 (Table 1), all of which were classified as having good reliability according to the criteria proposed by Koo and Li (2016). These results indicate high agreement between the products generated by remote and proximal sensing, confirming that the spatial patterns of NDVI were consistently reproduced by the sensors embarked on the UAVs.

Tab 1. ICC between interpolated maps from remote and proximal sensing.

Group	Region	Paired points	ICC	Classification
Mavic set	Crop Row	14892	0.775	Good
Mavic set	Inter-row	28641	0.828	Good
MicaSense set	Crop Row	14892	0.817	Good
MicaSense set	Inter-row	28641	0.855	Good

Source: A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research (Koo and Li, 2016).

The highest ICC values were obtained for the MicaSense RedEdge-P sensor, both for the row (ICC = 0.817) and the inter-row (ICC = 0.855), corroborating the high coefficients of determination and the lower errors observed in the regressions of the interpolated maps. In turn, the Mavic 3M sensor presented ICC values of 0.775 for the row and 0.828 for the inter-row, also classified as good reliability.

The results indicate that both sensors were able to adequately represent the spatial distribution of NDVI in the experimental area. However, the combination of the ICC, R^2 , and RMSE results suggests a tendency toward greater agreement between the data obtained by the MicaSense RedEdge-P sensor and those from the proximal sensors. This tendency is also consistent with the smaller magnitude of the differences observed in the comparative maps, reinforcing the robustness of the estimates generated by this sensor for monitoring coffee crops in mountainous regions.

4. Conclusion

Remote sensing using unmanned aerial vehicles equipped with multispectral sensors proved to be a reliable tool for obtaining NDVI values in coffee crops located in mountainous regions. The high coefficients of determination, the low RMSE values, and the intraclass correlation coefficients classified as good showed high agreement between the data obtained by remote sensing and those measured by proximal sensing.

The agreement observed between the methods was maintained both in the analyses performed on sampling points and in the interpolated maps, demonstrating that the sensors embarked on the UAVs were able to adequately represent the spatial variability of the crop's vegetative vigor. This result reinforces the potential of the technology for applications in Precision Agriculture, since management decisions are generally based on spatial information obtained through maps.

Although both evaluated platforms produced reliable NDVI estimates, the MicaSense RedEdge-P sensor showed a tendency toward greater agreement with the proximal sensors, reflected by higher R^2 values, lower RMSE values, and higher intraclass correlation coefficients. However, the differences observed did not compromise the practical applicability of either platform for crop monitoring.

Therefore, the results confirm that remote sensing by UAVs constitutes a robust alternative for NDVI mapping in coffee systems conducted in environments with complex relief, contributing to crop monitoring, the characterization of spatial variability, and decision-making support in Precision Agriculture.

5. Acknowledgments

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