Temporal variability of vegetation indices and spatial autocorrelation applied to specific management in mountain coffee crops

Igor Araújo Barbosa[1]; Daniel Marçal de Queiroz[1]; Andre Luiz de Freitas Coelho[1]; Domingos Sárvio Magalhães Valente[1]; Michel Castro Moreira[1]; Beatriz Costalonga Vargas[2]

[1] Universidade Federal de Viçosa (UFV), Brazil; [2] EPAMIG, Pitangui Institute of Agricultural Technology (ITAP), Brazil

A paper from 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

Abstract.

The characterization of spatial and temporal variability in agricultural crops is an important stage for the application of precision agriculture, enabling the definition of management zones and the prescription of inputs for variable rate application. In this context, the use of unmanned aerial vehicles (UAVs) equipped with multispectral sensors has enabled the acquisition of spectral data with spatial and temporal resolutions compatible with the objectives of the intended activity. Associated with these data, the calculation of spatial autocorrelation metrics allows for a deeper understanding of crop spatial variability throughout the production cycle. One of the crops that can benefit from this type of analysis is coffee, as it is a perennial crop with management involving various activities. Thus, this study aimed to evaluate the temporal variability of vegetation indices (VIs) and spatial autocorrelation in mountain coffee plantations using multispectral images obtained by UAV. The experiment was conducted throughout 2025 in two coffee production areas (3.1 ha and 3.7 ha) located at Fazenda Oasis, in the municipality of Coimbra, Minas Gerais, Brazil. Fifteen flights were carried out between March and December 2025, using a DJI Mavic 3M UAV with an integrated multispectral sensor. The acquired images were used to generate reflectance orthomosaics and digital surface models (DSM) via Pix4DMapper software, version 4.9.0. The analysis was performed using data from the coffee crop rows, which were automatically segmented using a computer program that utilized the DSM and the Soil-Adjusted Vegetation Index (SAVI) as input data. From the reflectance orthomosaics, the Normalized Difference Vegetation Index (NDVI) and the Red Chlorophyll Index (CI Red) were calculated. Based on these, Moran's Index (MI) was calculated for each VI to evaluate spatial dependence and its variation over time. The results indicated high spatial dependence of the VIs in the first months of the year, with MI values for NDVI ranging between 0.71 and 0.94 in the first area and between 0.81 and 0.90 in the second. For the CI Red, values fluctuated between 0.80 and 0.95 and between 0.84 and 0.91, respectively. These results reflect high spatial homogeneity of the crop during this period, associated with higher VI values. Starting in November, a consistent reduction

The authors are solely responsible for the content of this paper, which is not a refereed publication. Citation of this work should state that it is from the Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture. EXAMPLE: Last Name, A. B. & Coauthor, C. D. (2026). Title of paper. In Proceedings of the 17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture and Brazilian Congress on Precision and Digital Agriculture.

in MI values was observed in both areas, with minimum values near 0.59–0.60 for NDVI and 0.64–0.67 for CI Red, indicating an increase in spatial heterogeneity after harvest and as a result of the crop management techniques adopted. The results demonstrate that using spectral data to calculate spatial autocorrelation metrics constitutes a promising approach for identifying the most suitable periods for characterizing spatial variability and defining management zones in coffee plantations, contributing to the improvement of management strategies within the context of precision agriculture.

Keywords.
Precision agriculture, Coffea arabica, Remote sensing, Spatial autocorrelation, Moran's Index, Vegetation indices, UAV, Temporal variability.

1. Introduction

Coffee farming plays an important role in the economy of several producing countries. Coffee is one of the most widely consumed beverages in the world, sustaining a broad production chain that involves producers, workers, and consumers. According to projections released by the International Coffee Organization, world coffee production will reach 182.5 million 60-kg bags in 2026, an increase of 9.6% compared to the previous year (ICO, 2025). In this crop, field management involves not only the pursuit of high productivity but also the need to produce with quality, since this factor adds value to the final product (Peixoto et al., 2023). For this, it is essential to use technologies that support farmers in the efficient management of their fields.

In this regard, the use of spectrometry is an important strategy for improving crop management. This technique is based on the principle that each material has a unique spectral signature, reflecting electromagnetic radiation in a distinct way (Borém et al., 2022). The spectral response is measured from the characteristics of the electromagnetic waves reflected at different wavelengths (Molin et al., 2015). Remote sensing using multispectral cameras mounted on Unmanned Aerial Vehicles (UAVs) uses these spectral responses to monitor agricultural crops by calculating vegetation indices. Researchers have been using this technique to monitor coffee crops (Silva et al., 2025; Marin et al., 2021a; Wang et al., 2024).

One way of using precision agriculture is by classifying the field into homogeneous regions, called management zones, which allow management to be adapted to the characteristics of each area. Valente et al. (2012) used apparent soil electrical conductivity to define management zones in coffee fields. Marin et al. (2021) used vegetation indices derived from a multispectral camera to classify the coffee crop based on leaf nitrogen content. However, coffee is a crop that undergoes several changes in its structural and physiological characteristics throughout the production cycle, whether in response to management practices or due to environmental conditions (Martello et al., 2022). In view of this, spatial patterns may be continuously changing, making continuous monitoring necessary.

The periodicity of vegetation index monitoring in coffee fields can be an important strategy for tracking the spatial and temporal evolution of the crop. Thus, data from specific monitoring periods may be more suitable for delineating management zones associated with relevant crop characteristics, such as vegetative vigor, nutritional status, or yield potential. In addition to the temporal variation of these vegetation indices, the variation in the spatial autocorrelation of a given index can be assessed to help identify changes in the spatial patterns of the crop. In this context, Moran's Global Index (MI) is a statistical metric used to quantify the degree of spatial autocorrelation between neighboring observations, indicating whether the values of a variable tend to cluster spatially or to be distributed randomly (Araújo et al., 2019).

Remote sensing using UAVs is effective for identifying changes in crop characteristics, providing data with temporal and spatial resolutions suitable for this type of analysis. In this regard, it is essential to develop studies that assess the temporal dynamics of the coffee crop. Therefore, this study aimed to evaluate the temporal variability of vegetation indices and spatial autocorrelation in mountain coffee plantations using multispectral images obtained by UAV, as well as to evaluate the influence of the monitoring period on the delineation of management zones in coffee fields.

2. Material and Methods

The study was conducted at Fazenda Óasis, located in the municipality of Coimbra, in the state of Minas Gerais, Brazil. The experiment was carried out throughout 2025, between March and December, evaluating two coffee production units called Unit A (Fig. 1a and 1b) and Unit B (Fig. 1c and 1d), both characterized by mountainous terrain, with areas of 3.1 ha and 3.7 ha, respectively.

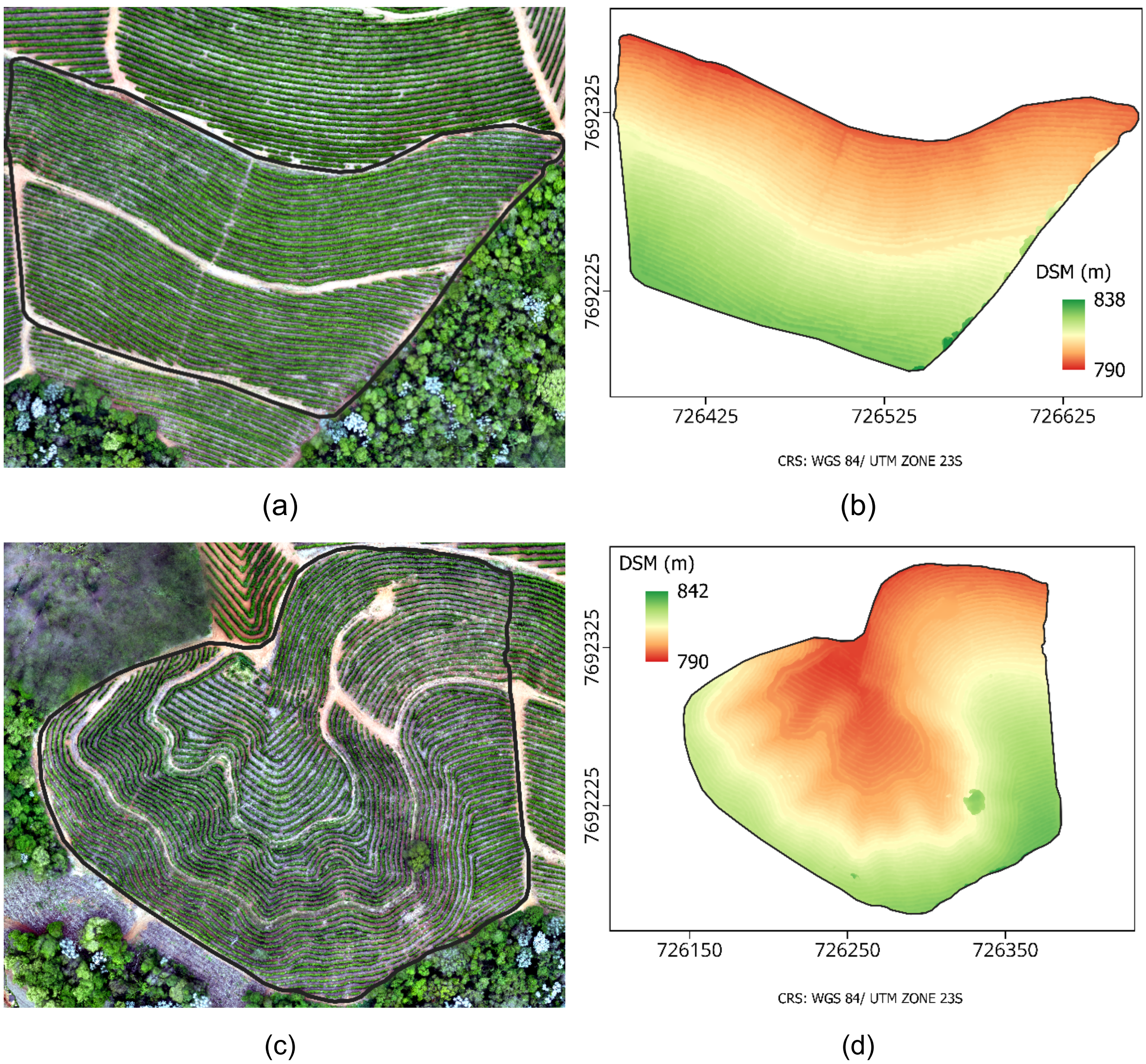


Fig. 1 Characteristics of the production units. (a) Orthomosaic of Unit A, (b) Digital surface model of Unit A, (c) Orthomosaic of Unit B, (d) Digital surface model of Unit B.

The flights were carried out on fifteen dates, using a DJI Mavic 3M UAV (DJI Technology Co., Shenzhen, China) with an integrated multispectral camera. The multispectral camera had four channels in the Green, Red, Red Edge and Near Infrared (NIR) bands, which are specified in Table 1. The camera was connected to a DLS (Down-welling Light Sensor), in order to detect the intensity of solar radiation in real time to perform radiometric corrections. In addition, images were captured of a radiometric calibration panel (model RP06, Micasense, Seattle, WA, USA), which were used during the radiometric calibration process. In addition, the UAV operated connected to a GNSS (Global Navigation Satellite System) real-time kinematic (RTK) georeferencing system. The flight parameters were defined with a flight altitude of 100 m AGL (Above Ground Level) and lateral and longitudinal overlaps of 85%. All flights were carried out at times close to local solar noon.

Table 1 Specification of the Mavic 3M multispectral camera bands

Spectral band	Central wavelength (nm)	Bandwidth (nm)
Green	560	16
Red	650	16
Red Edge	730	16
NIR	860	26

The images acquired in these flights were submitted to photogrammetric processing in Pix4D Mapper software, version 4.9.0 (Pix4D, Lausanne, Switzerland). This generated reflectance orthomosaics and digital surface models (DSM) for both areas. Subsequent analyses were performed using the Python programming language, version 3.9. The evaluations considered only values corresponding to the crop rows. In view of this, a computer vision program was used to segment the coffee rows from other regions (Fig. 2). The program used the DSM and the Soil-Adjusted Vegetation Index (SAVI) as input data. This processing was carried out with the aid of the SciPy (Virtanen et al., 2020), Rasterio (Gillies et al., 2013) and GeoPandas (Jordahl et al., 2020).

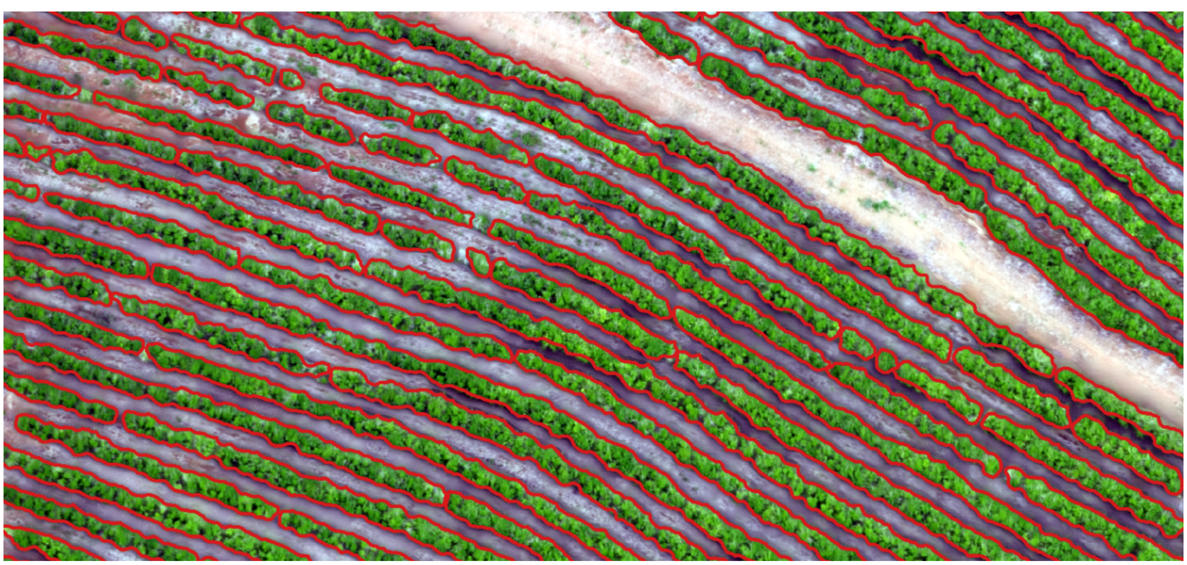
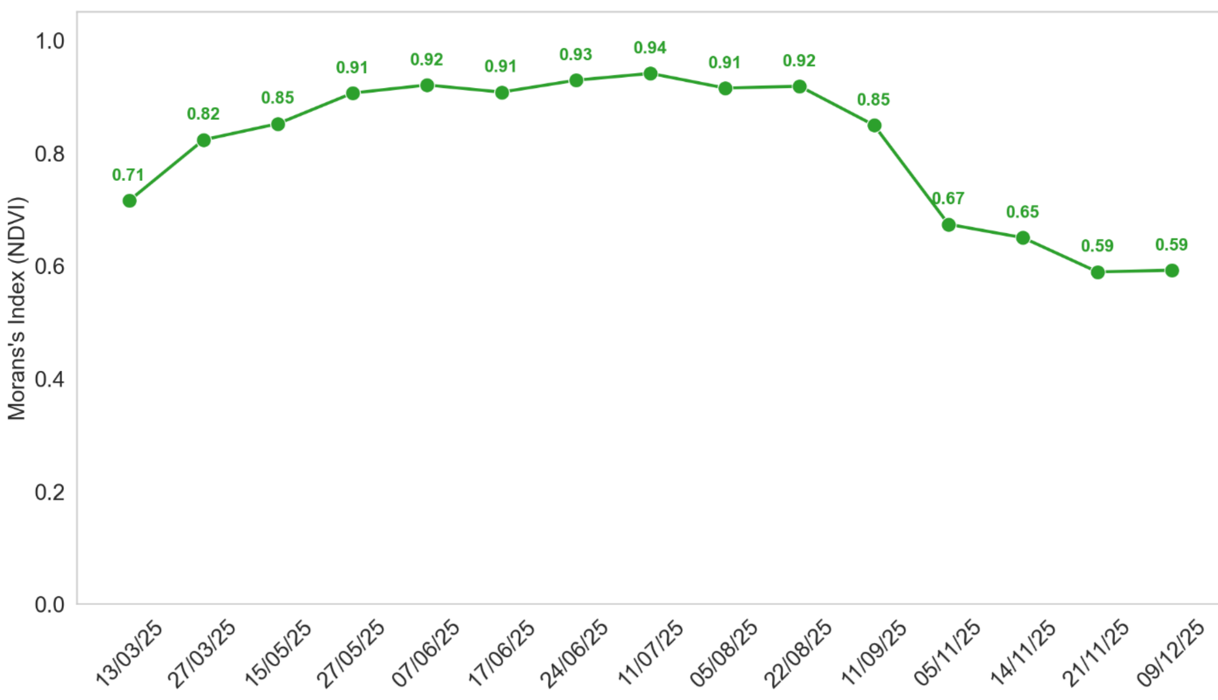


Fig. 2 Segmented coffee crop rows.

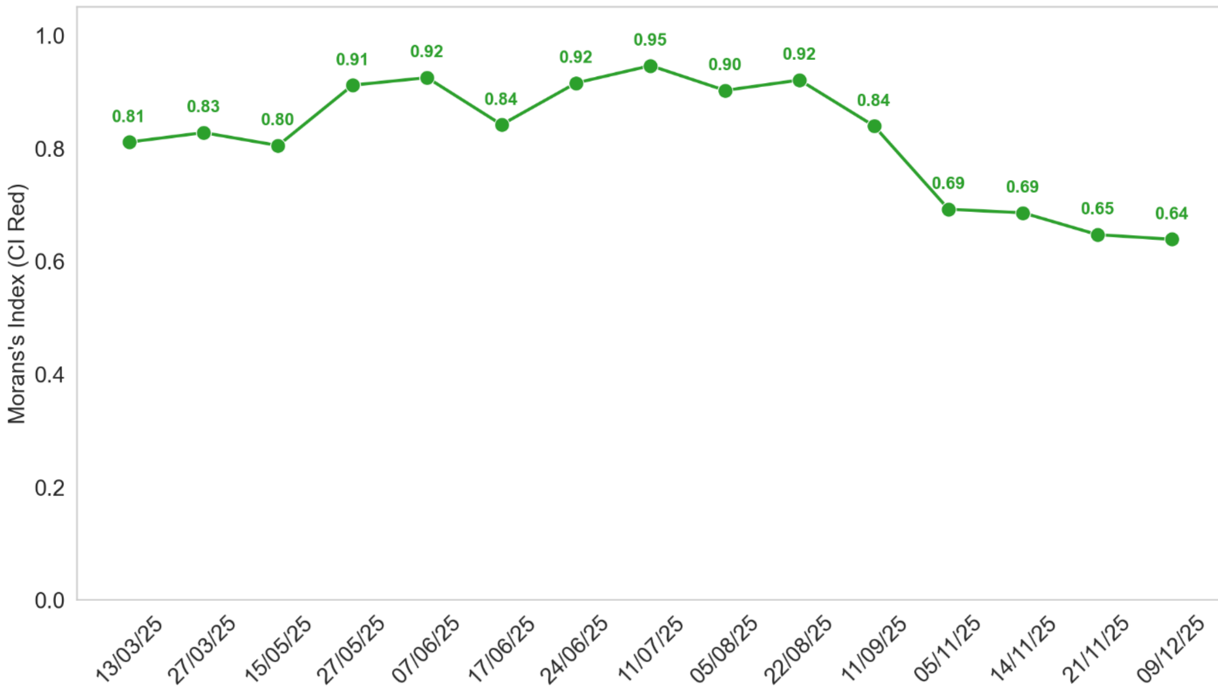
From the reflectance orthomosaics, the Normalized Difference Vegetation Index (NDVI) and the Red Chlorophyll Index (CI Red) were calculated. Spatial autocorrelation was analyzed separately for each date and each vegetation index using the Global Moran's Index, which was calculated using the ESDA (Exploratory Spatial Data Analysis) module of the PySAL library (Rey & Anselin, 2007). In addition, a temporal analysis of NDVI values in the crop rows was performed for both areas. To assess the effects of temporal changes in the production units, the areas were classified into management zones under two distinct situations, considering the NDVI and CI Red vegetation index values at two periods of the year.

3. Results and Discussion

The Moran's Index values shown in Fig. 3 and 4, for both units, considering the NDVI and CI Red vegetation indices, indicated high spatial dependence between March and September. In this period, in Unit A, the MI associated with NDVI ranged between 0.71 and 0.94 (Fig. 3a), while in Unit B the range was between 0.81 and 0.90 (Fig. 4a). Considering the MI associated with CI Red in the same period, the range was 0.80 to 0.95 in Unit A (Fig. 3b) and between 0.84 and 0.91 in Unit B (Fig. 4b). In all cases, a significant drop in MI was observed in the period between September 11, 2025 and November 5, 2025, with the November and December values being the lowest observed. In these months, the MI associated with NDVI reached minimum values of 0.59 in Unit A (Fig. 3a) and 0.60 in Unit B (Fig. 4a). The minimum MI values in this period associated with CI Red were 0.64 in Unit A (Fig. 3b) and 0.67 in Unit B (Fig. 4b).

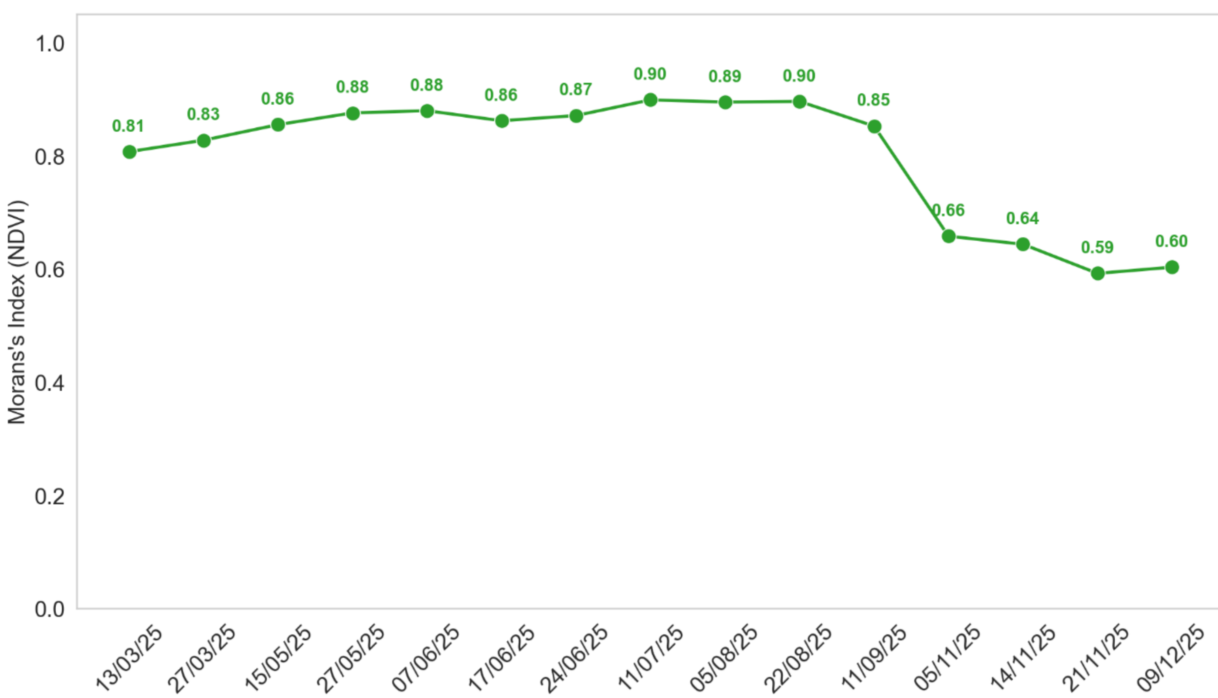


(a)

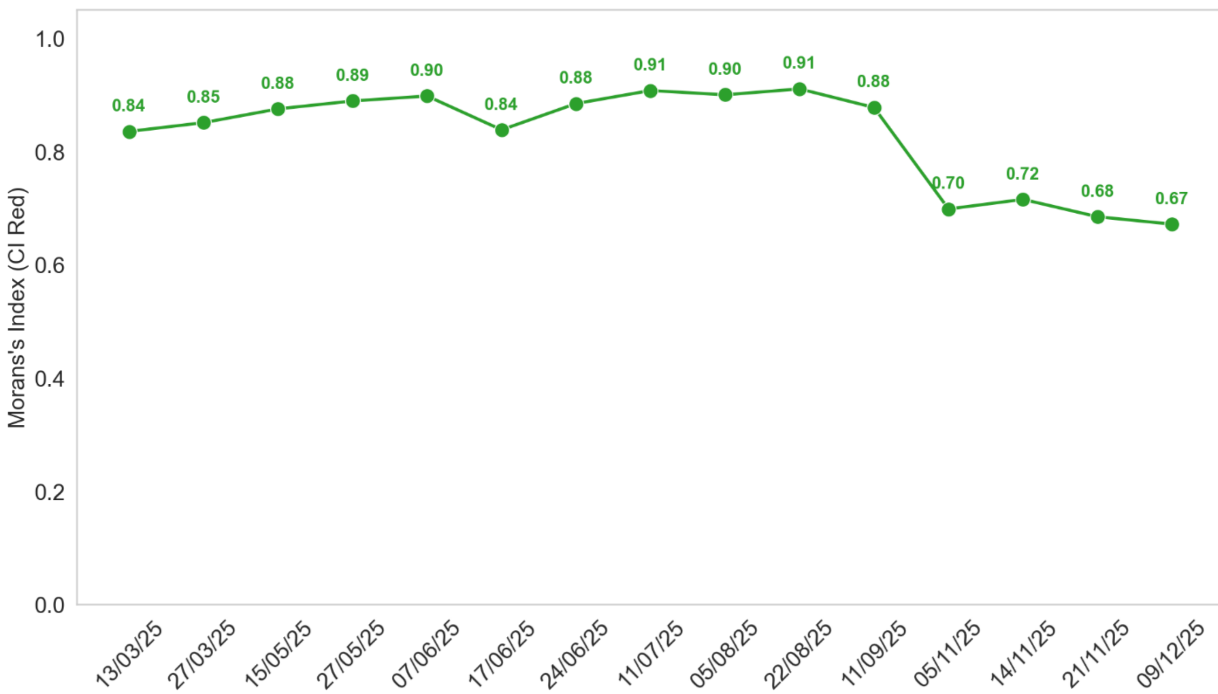


(b)

Fig. 3 Temporal distribution of Moran's Index in Unit A. (a) Moran's Index associated with NDVI and (b) Moran's Index associated with CI Red.



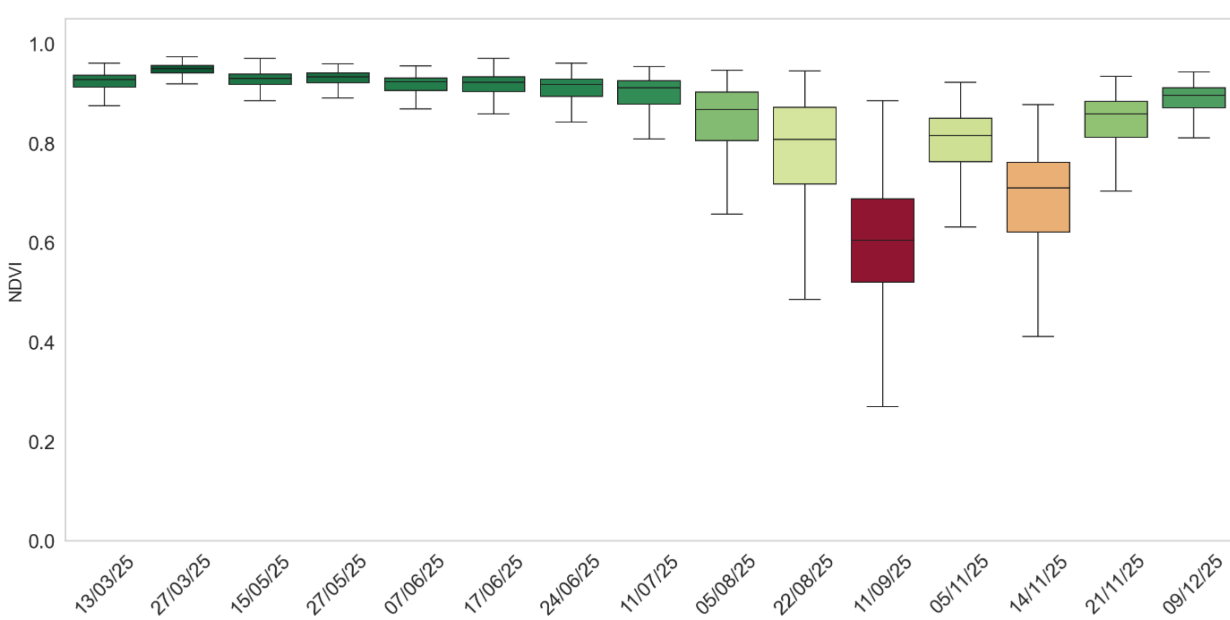
(a)



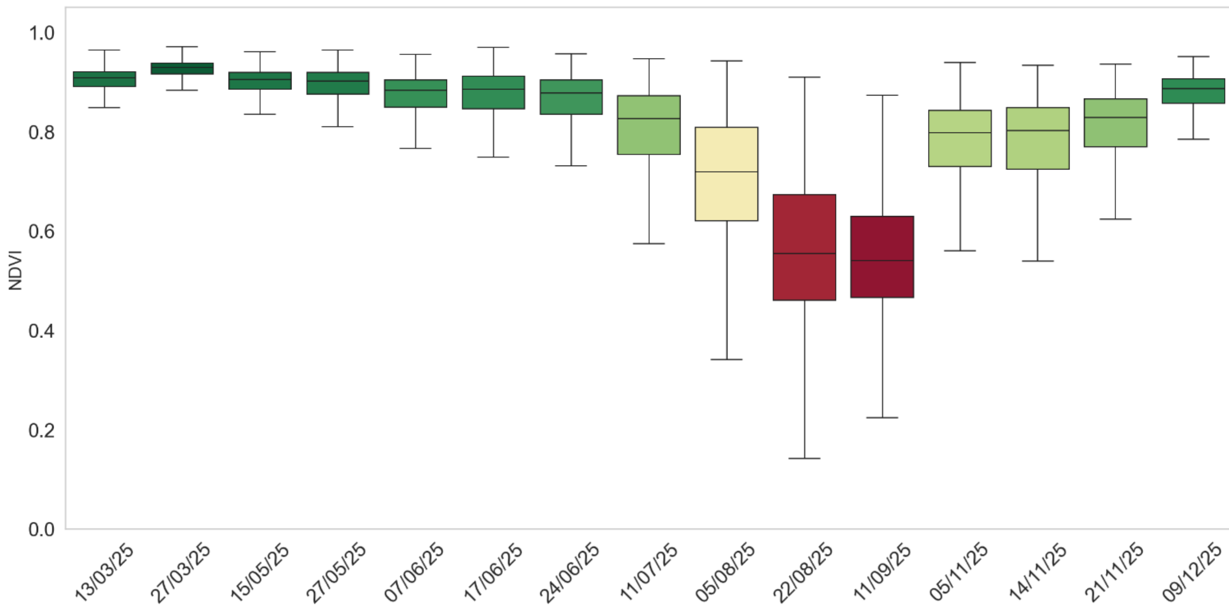
(b)

Fig. 4 Temporal distribution of Moran's Index in Unit B. (a) Moran's Index associated with NDVI and (b) Moran's Index associated with CI Red.

The temporal analysis of NDVI values in the crop rows for both areas indicated that between March and June the index values were higher, accompanied by lower spatial variability (Fig. 5). Between July and September, the indices decreased while the variability of the values increased, with the NDVI reaching minimum values in both units during this period. In November and December, NDVI increased again, with a reduction in variability.



(a)



(b)

Fig. 5 Temporal distribution of NDVI values. (a) Unit A and (b) Unit B.

The combined analysis of the temporal variation of MI and NDVI values in both units showed that in the early months of the year the fields had high vigor and were more homogeneous, reflecting high spatial dependence. After this period, the spatial structure was altered, leading to an increase in spatial heterogeneity. These changes occurred as a result of the harvest stage and the management techniques adopted. In August and September, the units showed less vigorous plants, whereas in the following months a vigor recovery process took place for the next cycle.

To evaluate the change in the spatial pattern of the units, the areas were segmented into management zones considering the NDVI and CI Red values on June 24 and July 11 (Fig. 6a and 6c), periods with higher MI, and also considering these indices on November 5 and November 14 (Fig. 6b and 6d), periods with lower MI. The units were segmented into management zones considering classes 1, 2 and 3, which predominantly presented low, medium and high vigor values, respectively. It was observed that the change in the spatial pattern of the units resulted in a change in the classification of the areas when considering the two periods evaluated.

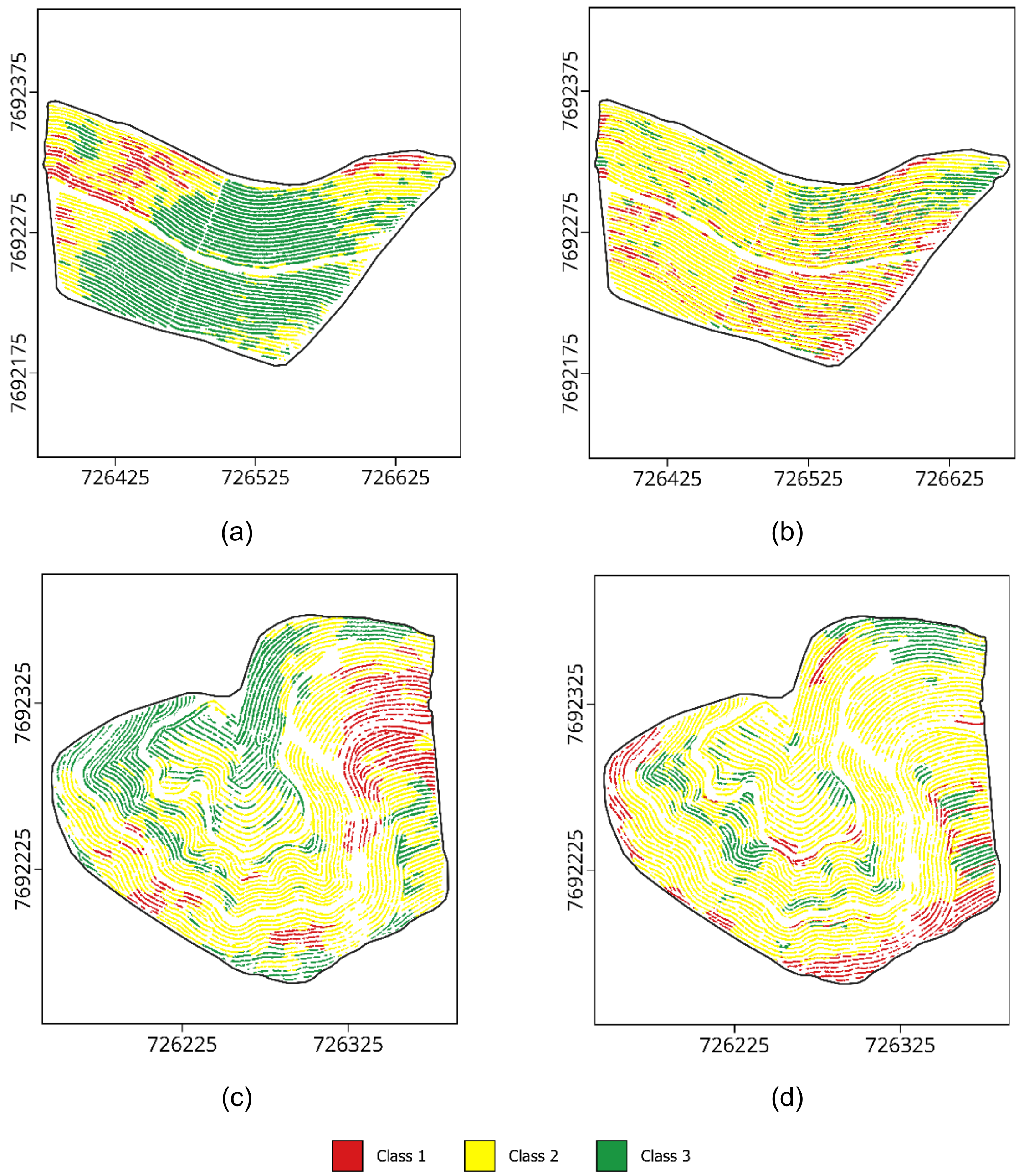


Fig. 6 Segmentation of the fields into management zones. (a) Unit A segmented based on data from June 24 and July 11, (b) Unit A segmented based on data from November 5 and November 14, (c) Unit B segmented based on data from June 24 and July 11, (d) Unit B segmented based on data from November 5 and November 14.

4. Conclusions

The use of remote sensing with UAVs is an effective practice in the context of precision agriculture for the continuous monitoring of coffee fields. The analysis made it possible to identify, during the evaluated period, changes in the spectral response of the crop, as well as changes in the spatial pattern of the production units.

The effect of these changes was evaluated by segmenting the production units into management zones. It was found that segmentation based on data from different periods altered the clustering patterns of the fields.

The results demonstrate that the use of spectral data for temporal evaluation and for calculating spatial autocorrelation metrics constitutes a promising approach for identifying the most suitable periods for characterizing spatial variability and defining management zones in coffee fields, contributing to the improvement of management strategies in the context of precision agriculture.

The results demonstrate that the use of spectral data for temporal evaluation and for calculating spatial autocorrelation metrics constitutes a promising approach for identifying the most suitable periods for characterizing spatial variability and for defining management zones in coffee fields. Thus, the methodology contributes to the improvement of management strategies in the context of precision agriculture.

5. Acknowledgments

The present study was carried out with support from the Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES) - Funding Code 001, the Minas Gerais State Research Support Foundation - Process APQ-00750-23 (Artificial Intelligence Models from Digital Agriculture Data for Mountain Coffee Crop Management), and the National Council for Scientific and Technological Development - Brazil (CNPq).

6. References

Araújo, M. L. S. de, Sano, E. E., Bolfe, É. L., Santos, J. R. N., dos Santos, J. S., & Silva, F. B. (2019). Spatiotemporal dynamics of soybean crop in the Matopiba region, Brazil (1990–2015). *Land Use Policy*, 80, 57–67. https://doi.org/10.1016/j.landusepol.2018.09.040. Accessed 12 June 2026.

Borém, A., Queiroz, D. M. de, Valente, D. S. M., & Pinto, F. A. de C. (Orgs.). (2022). *Agricultura digital* (2ª ed.). Oficina de Textos.

Gillies, S., Ward, B., & Petersen, A. S. (2013). *Rasterio: Geospatial raster I/O for Python programmers* [Software]. GitHub. https://github.com/mapbox/rasterio. Accessed 12 June 2026.

ICO – International Coffee Organization. (2026). *Coffee Market Report – April 2026*. https://ico.org/. Accessed 12 June 2026.

Jordahl, K., Van den Bossche, J., Fleischmann, M., Wasserman, J., McBride, J., & Gerard, J. (2020). *geopandas/geopandas: v0.8.1* [Software]. Zenodo. https://doi.org/10.5281/zenodo.3946761. Accessed 12 June 2026.

Marin, D. B., Ferraz, G. A. e. S., Schwerz, F., Barata, R. A. P., de Oliveira Faria, R., & Dias, J. E. L. (2021). Unmanned aerial vehicle to evaluate frost damage in coffee plants. *Precision Agriculture*, 22(6), 1845–1860. https://doi.org/10.1007/s11119-021-09815-w. Accessed 12 June 2026.

Marin, D. B., Ferraz, G. A. e. S., Guimarães, P. H. S., Schwerz, F., Santana, L. S., Barbosa, B. D. S., et al. (2021). Remotely piloted aircraft and random forest in the evaluation of the spatial variability of foliar nitrogen in coffee crop. *Remote Sensing*, 13(1471). https://doi.org/10.3390/rs13081471. Accessed 12 June 2026.

Martello, M., Molin, J. P., Angnes, G., & Acorsi, M. G. (2022). Assessing the temporal and spatial variability of coffee plantation using RPA-based RGB imaging. *Drones*, 6(10). https://doi.org/10.3390/drones6100267. Accessed 12 June 2026.

Molin, J. P., Amaral, L. R. do, & Colaço, A. F. (2015). *Agricultura de precisão*. Oficina de Textos.

Peixoto, J. A. B., Silva, J. F., Oliveira, M. B. P., & Alves, R. C. (2023). Sustainability issues along the coffee chain: From the field to the cup. *Comprehensive Reviews in Food Science and Food Safety*, 22(1), 287–332.

Rey, S. J., & Anselin, L. (2007). PySAL: A Python library of spatial analytical methods. *Review of Regional Studies*, 37(1), 5–27.

Silva, A. S., S., Ferraz, G. A. e. S., Figueiredo, V. C., Valente, G. F., Volpato, M. M. L., & Machado, M. L. (2025). Soil moisture spatial variability and water conditions of coffee plantation. *AgriEngineering*, 7(4). https://doi.org/10.3390/agriengineering7040110. Accessed 12 June 2026.

Valente, D. S. M., Queiroz, D. M., Pinto, F. A. C., Santos, N. T., & Santos, F. L. (2012). Definition of management zones in coffee production fields based on apparent soil electrical conductivity. *Scientia Agricola*, 69(3), 173–179.

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., et al. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods*, 17(3), 261–272. https://doi.org/10.1038/s41592-019-0686-2. Accessed 12 June 2026.

Wang, X., Zhang, C., Qiang, Z., Liu, C., Wei, X., & Cheng, F. (2024). A coffee plant counting method based on dual-channel NMS and YOLOv9 leveraging UAV multispectral imaging. *Remote Sensing*, 16(20). https://doi.org/10.3390/rs16203810. Accessed 12 June 2026.