Delineation of Management Zones for the Adoption of Precision and Digital Agriculture in Steep-Sloped Arabica Coffee Production Areas

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Abstract.
Precision agriculture in mountainous perennial crops faces unique implementation challenges due to steep topography and restricted accessibility, which limit traditional methods for delineating management zones (MZs). To overcome this, this study evaluated the integration of multi-resolution remote sensing data to delineate and validate temporally stable MZs in topographically complex coffee fields in Caconde, São Paulo, Brazil. The methodology combined a historical time-series of multi-spectral orbital imagery with high-resolution suborbital data acquired via Remotely Piloted Aircraft (RPAs). Stable spatial patterns were mapped by analyzing temporal vegetation indices alongside time-stable variables, such as altimetry, slope, and soil-plant classifications. The clustering quality was evaluated using Silhouette Width (SW) and Variance Reduction (VR) metrics. Results showed a trade-off: while VR suggested a higher number of MZs, SW favored fewer, more cohesive zones (2 to 3 MZs) derived from pixels with high plant incidence (80-90%). The MZs selected by SW proved more operationally feasible for hard-to-reach areas and were successfully validated by altimetry data, presenting distinct topographic profiles. Balancing statistical clustering metrics with topographical validation provides a reliable and cost-effective proxy for establishing practical MZs in steep-slope coffee farming, supporting sustainable site-specific interventions.

Keywords.
Remote sensing, Vegetation Index, Remotely Piloted Aircraft

Introduction

Brazil is the largest producer and exporter of coffee in the world (ICO, 2026; USDA, 2025), especially *Coffea arabica L.*, being predominantly cultivated in Minas Gerais, Espirito Santo and São Paulo states. These regions are characterized by a high diversity of microclimates, altitudes, and soil types, which directly influence crop development and beverage quality (Parreiras et al., 2025). Within this context, the municipality of Caconde, in the state of São Paulo, stands out. Encompassing about 11,000 hectares of coffee plantations, the region is dominated by small-scale properties situated at altitudes exceeding 800 meters with characteristically steep slopes. While these challenging topographical and climatic features are highly conducive to the production of high-quality, value-added specialty coffees, they also introduce significant spatial and temporal variability across the agricultural fields (Ronquim et al., 2023).

Historically, coffee plantations have been managed uniformly, with agricultural inputs applied at constant rates across entire areas. However, modern approaches aim to delimit management zones (MZ) to enhance site-specific applications (Martello et al., 2022). This approach is a simplified way to starts the adoption of Precision Agriculture (PA), essentially for small and medium farmers which initially needs to reduce production costs while at least maintaining the productivity and quality of your product. Although PA has been widely adopted in annual crops cultivated on flat terrains, its implementation in perennial crops located in mountainous regions presents unique challenges due to constrained accessibility and complex topography.

MZs are defined as sub-regions of a field expressing a relatively homogeneous combination of yield-limiting factors, allowing them to receive customized and uniform management (Doerge, 1999). In essence, MZs must accurately represent the natural, underlying variability of the crop area. Furthermore, for a perennial crop like coffee, which exhibits a strong biennial bearing cycle, these zones must remain relatively stable over the years. These temporal stability ensures that the delineated MZs can be effectively and reliably used for long-term management decisions regarding natural resources, fertilization and corrective interventions (Silva et al., 2025). To achieve this temporal stability, the delineation of MZs cannot rely on data from a single season. Instead, historical data reflecting crop and soil behavior must be used to mitigate the confounding effects caused by isolated anthropogenic actions, localized pest infestations, or specific short-term climatic anomalies.

Traditionally, MZ delineation has relied on dense grid soil sampling, mechanical yield mapping or proximal field sensing, such as apparent soil electrical conductivity (ECa). However, in steep-slope farming of perennial crops, dense manual sampling is physically arduous and economically prohibitive, and the mechanization required for automated yield mapping is severely restricted by the terrain (Sassu et al., 2021). In these challenging topographies, orbital and suborbital remote sensing technologies have emerged as an indispensable alternative for proximal data collection, providing a viable and highly accurate approach to mapping spatial variability. The acquisition of multi-spectral images, characterized by different spatial, spectral, and temporal resolutions, allows for the continuous monitoring of crop vigor and biomass. Through the use of historical series of vegetation indices (VI), it is possible to assess the dynamic of the crop response to the environment over multiple seasons without the need for frequent, costly, and labor-intensive trips to hard-to-access fields. Additionally, suborbital platforms, such as Remotely Piloted Aircraft (RPAs), besides providing high-resolution multi-spectral data capable of capturing variations on a refined scale at the level of individual plants, also provide point clouds that allow the calculation of digital terrain and surface models (DTM and DSM), which are important for defining the spatial variability of sloping areas (Bento et al., 2025).

Despite the proven potential of remote sensing technologies, the integration of multi-temporal spectral data to define stable MZs in complex mountain coffee systems remains insufficiently explored in the scientific literature. Therefore, the hypothesis of this study is that analyzing a historical time-series of multi-spectral orbital imagery combined with ultra-high-resolution maps of time-stable variables, such as altimetry, slope and soil-plant classification obtained from suborbital imagery, can accurately identify temporally stable spatial patterns, serving as a reliable proxy for delineating MZs in topographically complex coffee fields. Consequently, the primary objective of this research was to evaluate the use of data provided by different resolution imagery to delineate and validate stable MZs in mountainous Coffea arabica sites, aiming to support sustainable decision-making.

Materials and Methods

Figure 1 shows an illustrative flowchart with different stages of the data analysis process used in this study, related to data acquisition, data processing, MZ delineation and validation, described in more detail throughout this section.

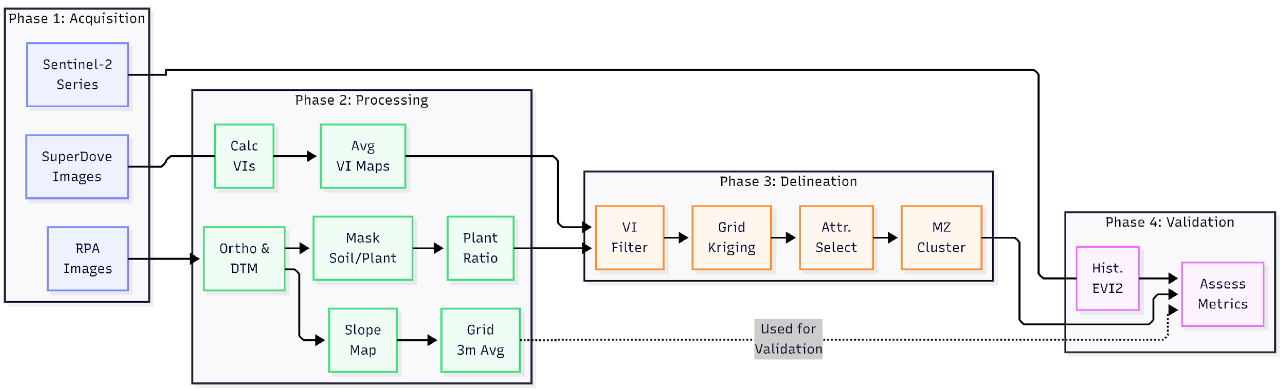


Fig 1. Illustrative flowchart of the data analysis process used in this study.

Study Area and Data Acquisition

The study was conducted in municipality of Caconde, São Paulo, Brazil (21.5294° S, 46.6439° W), at an elevation of 860 m above sea level. In a property named Sítio Progesso, two sets of plots were analyzed: Field 1 (F01), planted in 2022, with 5.2 ha of area, altitude from 898 to 950 m and slope from 7 to 46 degrees; and Field 2 (F02), planted in 2023, with 3.3 ha of area, altitude from 861 to 922 m and slope from 10 to 41 degrees. In a property named Sítio Santa Rosa, were analyzed a set of plots planted in 2018, with 3 ha of area, altitude from 902 to 961 m and slope from 6 to 46 degrees (Field 3 - F03). Since all studied fields are sets of smaller plots, only pixels from orbital sensing images internal to each plot were considered; that is, the pixels corresponding to the separation carriers between the plots were ignored from the beginning.

Multi-spectral satellite images composed by 8 bands (Coastal Blue, Blue, Green I, Green II, Yellow, Red, Red Edge and Near-Infrared) were obtained from the Super Dove sensor (PSB.SD), with spatial resolution of 3 m and daily revisit (Planet Team, 2026), provided by RedeMAIS/MJSP. For F01 and F02, only images from the 2024-2025 crop season were obtained due to their recent planting. For F03, images from the four previous crop seasons were obtained (from 2021-2022 to 2024-2025). For each crop season, only images in corresponding phenological stages of the general development of the fruits (from October to December months) and of the full development of the fruits (from January to March months) were collected. For each of these intervals, representative images of sub-intervals between 10 and 15 days were obtained, all of them without cloud cover or cloud shadows. Therefore, a total of 10 images from F01 and F02, and 44 images for F03 were obtained. Additionally, suborbital images were collected by a Remotely Piloted Aircraft (RPA), model DJI Mavic 3M (DJI Science and Technology Co., Shenzhen, China), equipped with RTK positioning correction, on a single date (in April 2025). Finally, in order to have historical data for each area that would help validate the obtained MZs, average maps of the EVI2 vegetation index (Jiang et al., 2008) were generated from the Sentinel-2 satellite (European Space Agency, 2026), considering time series from the studied periods, images without cloud cover or cloud shadow. The source of this data was the Google Earth Engine platform (Gorelick et al., 2017).

Data Processing and Canopy Masking

The processing of satellite images was carried out similarly for the studied fields. Initially, the vegetation indexes NDVI, NDRE, EVI2, and SAVI, widely used in the literature for identifying spatial variability of agricultural crops, were calculated for all collected images (Maia et al., 2023; Vera-Esmeraldas et al., 2025). Then, for each crop season, maps were generated with average values of each index for each phenological stage studied, totaling 8 maps for F01 and F02 and 32 maps for F03. This processing was performed using functions of *FieldImageR* package (Matias et al., 2020), available for the R software.

On the other hand, from RPA images, orthomosaics in the visible spectrum (RGB) and multi-spectral spectrum (Red-Green-RedEdge-NIR) were generated, both with an approximate GSD (Ground Sample Distance) of 2 cm; and digital terrain models (DTM) from the point cloud generated by the RPA, with an approximate GSD of 5 cm – this model actually contains the altimetry values for each field. For this processing, the OpenDroneMap software (OpenDroneMap, 2026) was used. Based on the RGB orthomosaic, a new binary orthomosaic was generated for each field, identifying pixels corresponding to soil or plant, using the *fieldMask* function from the *FieldImageR* library. From the DTM, a slope map was also generated, with values in degrees, for each field, considering the *Slope* tool available in QGIS software version 3.42.3.

Since raster data with different spatial resolutions were obtained, a grid standardization was necessary to use all of them for the process of delineating MZs. Regarding that most of the attributes used in the analysis are derived from remote sensing images with a spatial resolution of 3 m, the resolution of the altimetry and slope data has been degraded based on average values of their pixels contained within the 3 m pixels. For the binary orthomosaic, instead of average values, the ratio of the count of pixels identified as plants to the total number of pixels inside each pixel of 3m-resolution was used, creating a new attribute called *perc_plant* ranging from 0 to 1. Thus, in addition to vegetation indices at different phenological stages for different growing seasons, the final dataset for each field, with a spatial resolution of 3 m, also integrated time-invariant attributes of altimetry, slope, and *perc_plant*. Theses processing steps were performed combining zonal statistics and raster calculator tools also available in QGIS.

Delineation of Management Zones

Since the main objective of this study was to verify the differences in MZ obtained using vegetation indexes (VIs) calculated from orbital images filtering pixels containing different percentages of plants identified by suborbital images, slope and altimetry attributes were not used during the process, but rather in the validation of the MZ. That being said, different pre-filters based on the *perc_plant* attribute were tested for all fields, considering pixels containing at least 10% up to at least 90% of plants, regarding steps of 10%. As this type of pre-filtering removes samples and makes the data grid irregular, in all cases a 3m-regular grid reconstruction for orbital VIs was performed using ordinary kriging, considering semivariogram adjustments and automatic interpolations available from the *automap* package (Hiemstra, 2013), available in the R software. In this way, for each field were used nine distinct datasets of VIs, with the aim to verify different capabilities to delineate MZs with different levels of influence of plant reflectance.

The pre-processed datasets also went through an attribute pre-selection process using the *hclust* function (using standard parameters) from *stats* native package available on R software. The goal of this variable selection was to reduce the dimensionality and multicolllinearity of each dataset to improve the performance of the clustering algorithm used in MZs delineation. The standard dendrogram cutoff used was 0.2, which allowed the creation of clusters of highly correlated attributes. From each of them, a unique attribute was randomly selected to compose the final dataset. Finally, the Ward Hierarchical Clustering Algorithm (Murtagh and Legendre, 2014) also available in the *hclust* function by setting the method parameter to Ward.D2, was used to clustering processes. For each case, were used dendrogram cutoffs from k=2 to k=5 clusters, regarding the ranges of MZs most commonly used in practice. For MZs validation, were used the Silhouette Width (SW) (Rouseew et al., 1987) and Variance Reduction (VR) (Schenatto, et al. 2017) metrics, regarding as target attribute the EVI2 average maps mentioned in session 2.1.

Results

Based on the process defined in section 2.3, 36 distinct MZs maps were obtained for each field, considering four amounts of MZs (2 to 5) and 9 filtering levels according to *perc_plant* attribute. Figures 2, 3 and 4 show the results of VR and SW for these cases and the optimal MZ maps according to SW and VR achieved in F01, F02 and F03 respectively.

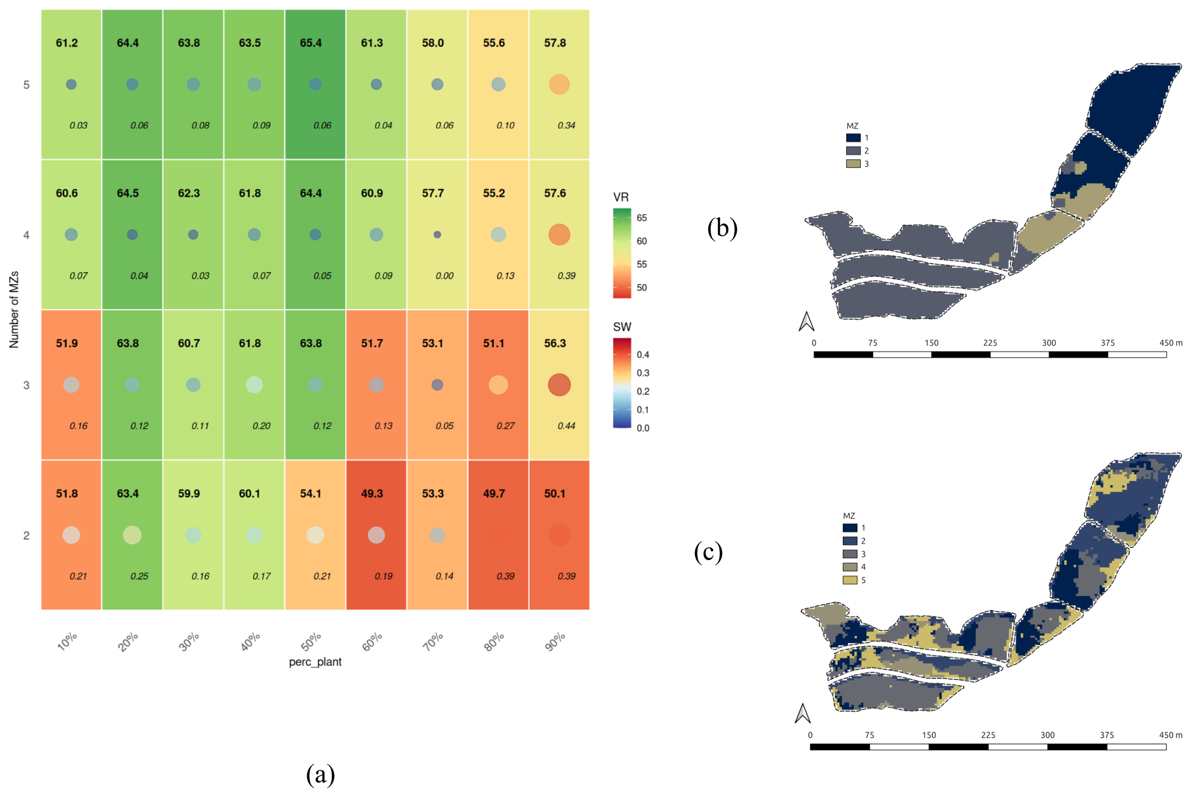
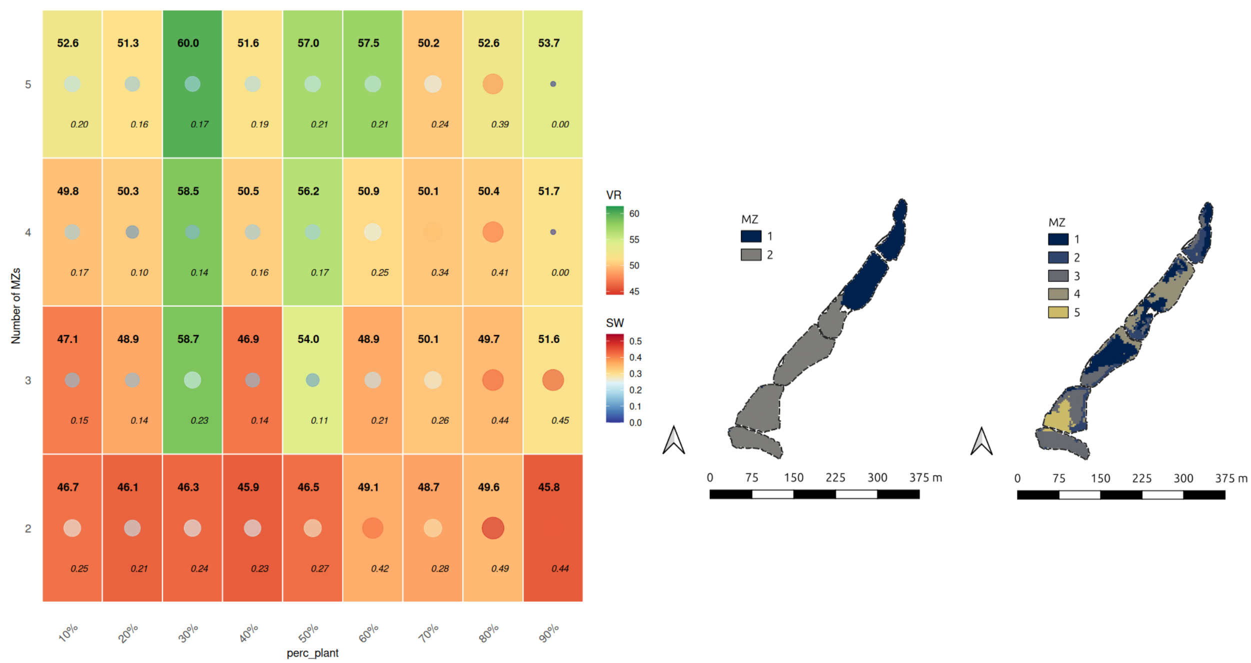


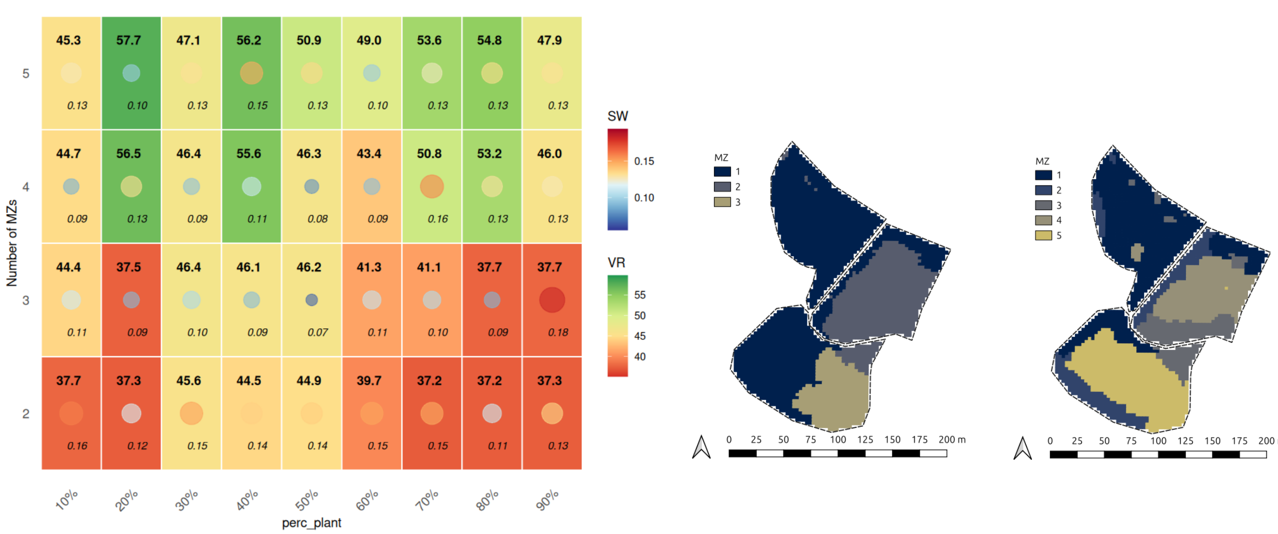
Fig. 2 Summary table containing VR and SW values for each combination of *perc_plant* and number of MZs (a), MZ map for the best result according to the SW metric (k=3, SW=0.44 and *perc_plant*=90%) (b) and MZ map for the best result according to the VR metric (k=5, VR=65.4% and *perc_plant*=50%) (c) for F01.



(a)

(a) (b) (c)

Fig. 3 Summary table containing VR and SW values for each combination of perc_plant and number of MZs (a), MZs map for the best result according to the SW metric (k=2, SW=0.49 and perc_plant=80%) (b) and MZs map for the best result according to the VR metric (k=5, VR=60% and perc_plant=30%) (c) for F02.



(a) (b) (c)

Fig. 4 Summary table containing VR and SW values for each combination of perc_plant and number of MZs (a), MZ map for the best result according to the SW metric (k=3, SW=0.18 and perc_plant=90%) (b) and MZ map for the best result according to the VR metric (k=5, VR=57.7% and perc_plant=20%) (c) for F03.

Additionally, regarding the best results illustrated by figures above, the average slope and altitude values were calculated for each MZ, in order to verify if the obtained MZs reflect significant differences with respect to these attributes. All studied fields have most of its slopes within the strongly undulating class (between 20 and 45 degrees) (Embrapa, 1979) which corroborates the need for limited use of machinery. Despite the steep slope, the average slope values within each MZ for these results are very close, ranging from 22.5 degrees (for MZ3 on the map in Figure 2c) to 31.7 degrees (for MZ4 on the map in Figure 3c), that is, all within the range of the strong undulating class and, therefore, showing no significant variations between the MZs. On the other hand, when we observe the average altimetry values for the same MZs (Table 1), the differences between the results are more enhanced.

Table 1. Average altimetry values (m) for each MZ obtained for each selected map of each field, regarding SW and VR metrics.

Field	Selected Maps - SW			Selected Maps - VR					
	MZ1	MZ2	MZ3	MZ1	MZ1	MZ2	MZ3	MZ4	MZ5
1	908	918	928		918	912	928	919	918
2	882	904	-		890	889	907	890	915
3	937	940	914		946	927	932	943	916

Discussion

Results shown in the previous session demonstrate that VR and SW metrics can offer distinct interpretations of the achieved results. In any case, for sloping areas with difficult access, such as those used in this study, obtaining MZs that are feasible in practice and that bring significant operational gains for the farmer is a challenge.

For F01, we can observe that the SW metric indicated the use of a map containing 3 MZs obtained from pixels with at least 90% of plants (Figure 2b), while the VR metric indicated the use of a map containing 5 MZs obtained from pixels with at least 50% of plants (Figure 2c). For F02, we can observe something similar: SW metric indicating the use of a map containing 2 MZs obtained from pixels with at least 80% of plants (Figure 3b); and VR metric indicating the use of a map with at least 30% of plants (Figure 3c). These results indicate that there is no convergence between what is indicated as the choice by the SW and VR metrics in both cases; however, the results of these metrics for different fields indicate a trend provided by different ways of analyzing the generated clusterings.

The VR metric verifies a percentage reduction in the variance of a target variable (in this case, average historical values of EVI2 were used as a possible indicator of natural spatial variability) in relation to the different MZ maps delineated, indicating whether, for a given situation, it is worthwhile to split the field into MZs or not. Thus, this metric shows a trend to obtain higher VR values for larger amounts of MZs, reaching VR increase plateaus in an intermediate number of clusters. On the other hand, SW is a traditional measure of cluster quality, indicating whether there is a balance in intra-cluster variability and inter-cluster separation, considering the attributes used to perform the clustering. In this case, the metric tends to provide higher values for cohesive clusters that are well separated statistically. Thereby, an intuitive way to analyze the results obtained for F01 and F02 is to start with SW and then, considering the context of MZ, analyze the result provided by the VR metric.

In this sense, we can see that, for both F01 and F02, it makes more sense to use the maps containing 2 and 3 MZs (figures 2b and 3b, respectively), selected by their greater SW value. In addition to providing a more simplified visualization in map form, thus simplifying the use of agricultural machinery that allows variable-rate interventions in hard-to-reach areas, the VR obtained for these maps is slightly lower than that obtained by the maps in figures 2c (9.1% less) and 3c (10.4% less), that is, a non-significant difference if we consider the idea of a plateau provided by the VR metric. On the other hand, if VR value were prioritized, we would be using MZs maps generated by clusterings resulting in SW values very close to 0 (0.06 and 0.17 respectively), which likely indicates the formation of random clusters. Another important issue is related to the percentage of plants within the pixels. The maps provided by figures 2b and 3b were obtained by initially considering pixels with a high incidence of plants (90% and 80%, respectively). Although the input data for these cases have a larger number of pixels with interpolated values, the lower presence of pixels classified as soil gives greater reliability to the vegetation indices obtained.

A validation of the MZ considering altimetry data should also be taken into account for F01 and F02. According to the data in Table 1, it can be observed that, for the maps indicated by the SW metric, there are well-defined altimetry differences for F01 (10 meters difference between MZs) and F02 (22 meters difference between MZs). However, for the best maps indicated by the VR metric, this difference is not observed - three of the five MZs have practically the same average altitude for F01 and F02. This allows for a more consistent validation and definition of the maps in Figures 2b and 3b as the most suitable for defining the MZs for F01 and F02, respectively.

Regarding F03, the variations in *perc_plant* showed a better result according to the VR metric for 20%, and according to the SW metric for 90%, that is, compatible with the results of F01 and F02 according to this parameter. The maximum VR value of 57.7% is also consistent with previous results; however, a significant difference is observed in the best SW value (0.18), which is very low compared to the other. Additionally, for the result with this SW value, one of the lowest VR values (37.7%) was observed, making it difficult to choose the best solution in the same way as was done for the other fields. Regarding the validation considering the altimetry data from Table 1, the map in Figure 4b shows very similar altimetry values for MZ1 and MZ2, with a significant difference (approximately 25 meters) for MZ3, suggesting that, in terms of practical use, MZ1 an MZ2 could be merged into a single MZ. Already the map in Figure 4c shows altimetry compatibility between MZ1 and MZ4 (946 and 943 m) and MZ2 and MZ3 (927 and 932 m), also suggesting the merging of these MZs. Regarding MZs 2 and 3, it is still possible to observe that both appear to be more related to a border effect caused by the clustering algorithm than to the shaping of MZs themselves. This effect can also be seen in parts of MZ1 of the map in Figure 4b. For these cases, a solution may be to use windowed image filtering algorithms, such as mean and mode filters, to improve the final result. Another solution could be to choose a result that provides a fair balance between the practical use of MZs and the values obtained from the VR and SW metrics, such as the map containing two MZs obtained from the dataset with *perc_plant*=30%, which provides an average altitude of 941 m for MZ1 and 915 m for MZ2 (Figure 4).

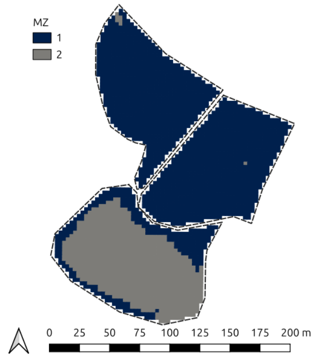


Fig. 4 Feasible MZ map for F03 , considering in a balanced way the best values obtained for SW and VR metrics and practical use.

Conclusion

This research successfully evaluated the use of different image sources to delineate and validate stable management zones (MZs) in steep-slope *Coffea arabica* fields, aiming to support sustainable and practical agricultural decision-making. Our findings reveal a divergence between Variance Reduction (VR) and Silhouette Width (SW) metrics when determining the optimal number of MZs. For complex, sloping terrains, relying solely on VR tends to over-segment the field, generating operationally impractical and seemingly random clusters. Instead, prioritizing the SW metric—combined with high-incidence plant pixels (80–90%) — produced the most reliable and cohesive results. As demonstrated in fields F01 and F02, this approach delineated a manageable number of zones (two to three) that were successfully validated by significant altimetry differences. However, field F03 highlighted the inherent challenges of this methodology, such as algorithm-induced border effects and less distinct metric convergence. In such cases, achieving practically feasible MZs requires either post-processing filtering or a strategic compromise between SW and VR values. Ultimately, emphasizing cluster quality and topographic validation over pure variance reduction provides farmers with robust, implementable MZ maps, enhancing operational efficiency in hard-to-access agricultural environments. For future work, the use of additional data sources is planned to allow for better identification of spatial soil variability, such as georeferenced fertility and texture samples and apparent electrical conductivity. The trend is that this data will complete the information from the images, which primarily reflect plant characteristics, and allow for improved MZs delineation by considering the soil-plant system in a balanced way.

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