Assessing the capability of apparent soil electrical conductivity to replace soil texture in the delineation of management zones: a case study

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Abstract.

The delimitation of management zones (MZ) depends on the appropriate selection of information layers used in the clustering process. Traditionally, soil physical attributes with greater temporal stability, such as texture, have been widely employed due to their direct influence on water retention and nutrient availability. However, the acquisition of soil texture data is generally costly, time-consuming, and based on point sampling. In contrast, apparent soil electrical conductivity (ECa) has emerged as an attribute of easy acquisition, high spatial resolution, and strong indirect relationships with soil physical properties. In this context, there is a need to assess whether replacing the soil texture layer with the ECa layer compromises or maintains the quality of MZ delineation. Therefore, this study evaluated the ability of soil ECa to replace soil texture in the generation of MZ while preserving similar spatial patterns. Conducted with producers in two areas of approximately 55 ha each were evaluated, both designated for grain production under a center pivot sprinkler irrigation system in the state of São Paulo, Brazil. ECa data were collected in 2017 at depths of 0–75 and 0–150 cm, while soil samples were collected at the 0–20 cm depth using an ECa-guided sampling strategy. Overall, elevation, cation exchange capacity, organic matter, and yield data for soybean, sorghum, and wheat from 2019 to 2025 were used. MZs were generated under two treatments: one using the ECa layer combined with complementary layers, and the other using the soil texture layer combined with the same set of complementary layers. In addition, four datasets were analyzed across two scenarios, one for each study area. Zone delineation was performed using the unsupervised machine learning algorithm fuzzy c-means. Classification entropy, degree of separation, and variance reduction were used as qualitative evaluation metrics, along with structural similarity analysis between treatments. Results indicated that the ECa layer can replace the soil texture layer, as no statistically significant differences were observed in the qualitative indices, and moderate to high similarity was found between treatments. This resulted in more homogeneous and well-defined zone delineations. This outcome may be associated with the higher sampling density provided by proximal sensing data, which enables a finer understanding of spatial variability. The economic potential of this approach is supported by the reduction in soil sampling requirements, as the initial investment is offset after the fifth growing season under MZ management, resulting in an estimated cost savings of approximately US$ 4 ha^{-1} per season. However, a strong correlation was observed between ECa layers and the soil silt fraction, a condition that may occur in environments with higher water concentration in this textural fraction due to particle approximation in compacted soils, as well as the presence of irrigation in the evaluated fields. Therefore, comparative studies evaluating ECa data acquisition *under irrigated conditions in contrast to rainfed systems are necessary to identify and validate the effects of irrigation on ECa, considering intrinsic differences between these management systems.*

Keywords.
Site-specific management, Proximal sensing and Cost–benefit analysis.

1. Introduction

The spatial variability observed within agricultural fields is one of the main foundations of precision agriculture, as it enables management practices to be adjusted according to the specific conditions of each portion of the field (Cherubin et al. 2022; Gebbers and Adamchuk 2010; Molin et al. 2024). Rather than treating the field as a homogeneous unit, precision agriculture seeks to identify spatial patterns associated with soil, topography, crop performance, and management history, allowing inputs and interventions to be applied more efficiently (Gavioli et al. 2019; Zhang et al. 2012). In this context, the increasing availability of georeferenced data from proximal sensors, yield monitors, remote sensing platforms, and soil sampling has expanded the potential for site-specific crop management (Bullock et al. 2019; A. F. Colaço et al. 2021; André F. Colaço et al. 2025).

Among the strategies used to operationalize spatial variability, management zones (MZs) represent an intermediate and practical approach between uniform field management and highly detailed pixel-based management (Heidari et al. 2026; Reuter et al. 2025). MZs divide the field into regions with similar agronomic behavior, aiming to reduce within-zone variability while preserving meaningful differences among zones (Gavioli et al. 2019; Massruhá et al. 2020; Molin et al. 2015). For this reason, MZs should preferably be based on data layers with agronomic relevance and temporal stability, since unstable or highly seasonal information may generate zones that are difficult to reproduce and less reliable for long-term management decisions (Clarke et al. 2024; Massruhá et al. 2020). This temporal consistency is essential for supporting soil sampling strategies, localized recommendations, and recurrent field operations.

The quality of MZ delineation depends directly on the selection of the data layers used in the clustering process (Gavioli et al. 2019). Soil texture is commonly used for this purpose because it is temporally stable and strongly related to water retention, nutrient availability, root development, and crop yield potential (Grenzdörffer et al. 2025). However, texture data are generally obtained through point-based soil sampling, laboratory analysis, and interpolation procedures, which increase costs and may limit the spatial detail available for zone delineation. These limitations are especially relevant in commercial fields, where the adoption of precision agriculture practices depends not only on technical accuracy but also on operational feasibility.

Apparent soil electrical conductivity (ECa) has emerged as a promising alternative or complementary layer for characterizing soil spatial variability (Farid et al. 2016; Gupta et al. 2019; Molua 2021) When properly acquired, filtered, and interpreted under suitable field conditions, ECa can provide a spatially dense and relatively stable representation of soil variability, similar to other intrinsic soil-related layers such as texture and elevation (Maldaner et al. 2021). Because ECa is indirectly related to soil attributes such as texture, moisture retention, salinity, cation exchange capacity, and other physical-chemical properties, it may capture persistent spatial patterns that influence crop development and yield potential over time(Sanches et al. 2020; Molin et al. 2015; Molua 2021).

However, the relationship between ECa and soil texture is not fixed and may vary according to soil moisture, compaction, clay and silt distribution, salinity, and local management conditions (Cherubin et al. 2022; Lozano-Fondón et al. 2026; Sanches et al. 2020)). In irrigated areas, this interpretation becomes even more complex, since soil water content and traffic-induced compaction can affect the ECa signal and modify its association with textural fractions (Corwin and Lesch 2005; McCutcheon et al. 2006). Therefore, although ECa has operational advantages and potential temporal consistency, its use as a substitute for soil texture requires local validation, especially when the objective is to generate MZs that remain agronomically coherent across different growing seasons (De Feudis et al. 2025; Serrano et al. 2024).

In this context, this study aimed to assess the capability of ECa to serve as a proxy for soil texture in the delineation of management zones in irrigated grain production fields. Specifically, MZs generated using ECa layers were compared with those generated using soil texture layers, while maintaining the same complementary information layers, including elevation, soil fertility attributes, and historical yield data, in order to evaluate whether ECa can reproduce the spatial information typically provided by texture for management zone delineation. The comparison was performed using fuzzy clustering quality indices and structural similarity metrics, allowing the evaluation of whether ECa can preserve the agronomic coherence, temporal rationale, and spatial pattern of texture-based management zones.

2. Materials and Methods

2.1. Study Area

This study was conducted in areas made available to the Precision Agriculture Laboratory, ESALQ-USP. Two fields were evaluated, totaling 110 ha. All fields were irrigated by center pivot and located in the municipalities of Itaí, in the state of São Paulo, Brazil (Figure 1), with mean altitude from 684 m. According to the Köppen classification, the local climate is Cwa, characterized as humid subtropical with a dry winter (Alvares et al. 2013). Mean annual precipitation 1,377 mm, and mean temperature ranges from 20.7 °C. The soil is predominantly classified as a dystrophic Red Latosol with clayey texture. These areas are managed under a crop rotation system, with soybean, sorghum, wheat, and barley as the predominant crops.

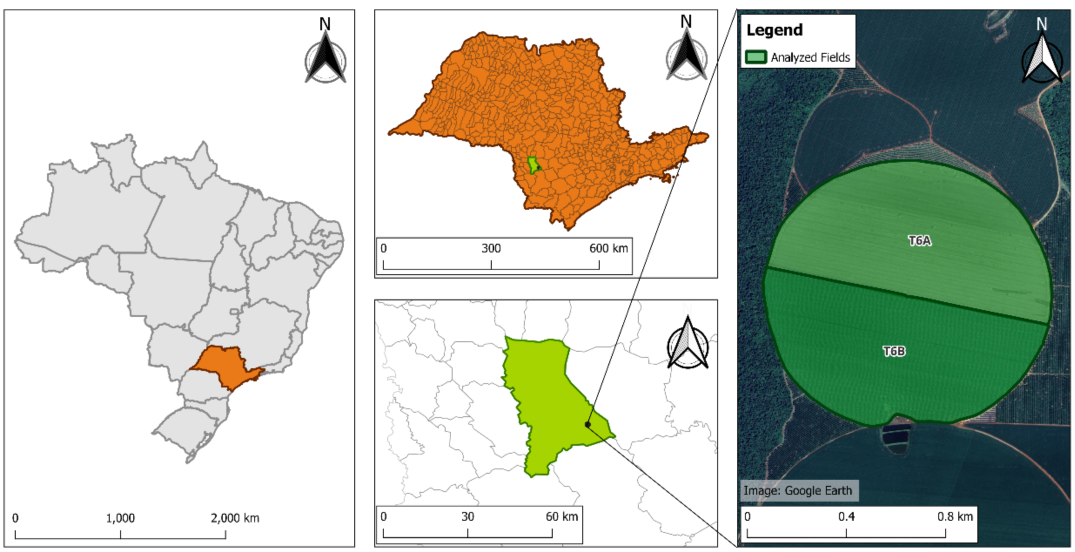

Fig. 1 Analyzed areas, in which T6A has 55 ha and T6B has 53 ha.

2.2. Soil and Yield Data Acquisition

Soil sampling was performed at a depth of 0–0.20 m using a sampling grid of approximately one point every 2 ha. Each composite sample consisted of five subsamples collected within a 5-m radius. The composite samples were then sent to the laboratory for chemical analysis. Samples from fields T6A were collected in February 2024, and field T6B in March 2017. The soil attributes analyzed were organic matter (OM), hydrogen potential (pH), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), cation exchange capacity (CEC), base saturation (V%), and sulfur (S). Elevation data were extracted from the digital elevation model (DEM) generated from elevation points collected by the GNSS receiver installed on the harvester.

Soil ECa was measured using the Elletro II equipment (Geophysical Survey Systems, Inc. — GSSI, Nashua, NH, USA), which performs measurements based on the electromagnetic induction principle at depths of 0–0.75 m and 0–1.50 m. The raw data were collected in March 2017 and georeferenced using a GNSS receiver connected to the equipment. The data were filtered using MapFilter 2.0 software to remove outliers, following the method proposed by Maldaner et al. (2021). Elevation data were extracted from the digital elevation model (DEM) generated from elevation points collected by the GNSS receiver installed on the harvester.

The available yield layers were obtained from a harvester equipped with a yield monitor. Data from 2019, 2020, 2021, 2022, 2023, 2024, and 2025 growing seasons were evaluated. For all seasons, filtering was performed using MapFilter 2.0 software (Maldaner et al. 2021), removing erroneous data and outliers. For statistical filtering, the maximum median variation parameter was set at 50%, while for local filtering it was set at 75%, with a spatial dependence of 89.5 m, corresponding to ten times the width of the harvester platform. Finally, yield points were interpolated by kriging using the SmartMap plugin in QGIS.

2.3. Delimitation and Evaluation of MZs

The delimitation of MZs was performed using the Fuzzy C-Means (FCM) algorithm (Sterle and Molin 2025), with the fuzzy exponent set to 1.25, a maximum of 100 iterations, and a smoothing degree of 3 as default parameters. The optimal number of clusters was defined based on the NCE (Moharana et al. 2020), and VR (Sterle and Molin 2025) indices, considering the greatest increase in variance reduction as the main criterion and, in cases of proximity between solutions, the lowest FPI and NCE values.

The quality of the MZs was evaluated in terms of internal homogeneity, separability among classes, and structural similarity among maps. For this purpose, the FPC (Fuzzy Partition Coefficient), NCE (Normalized Classification Entropy), and VR (Variance Reduction) indices were used, in addition to ARI and NMI indicators, which were employed to compare the spatial and structural agreement among MZs generated from different datasets. ARI was used as a more rigorous point-to-point agreement metric, whereas NMI was used to assess the overall similarity among partitions (Shilpa et al. 2025). The interpretation of these indices was based on performance classes ranging from random segmentation to complete similarity (Table 1). To identify the relative contribution of the variables used in MZ formation, a Random Forest model was fitted using the layers included in each scenario, allowing the importance of each attribute in cluster delimitation to be estimated.

Table 1. ARI and NMI classes used to evaluate structural performance among MZs generated under different treatments.

Range	Performance
1.0 to 0.8	Complete similarity
0.8 to 0.6	High similarity
0.6 to 0.4	Moderate similarity
0.4 to 0.2	Low similarity
0.2 to 0.0	Random segmentation

2.4. Eca influence analysis

To evaluate the influence of ECa, two scenarios were selected, corresponding to fields of approximately 50 ha each, identified as T6A and T6B (Table 2). Initially, Pearson correlation analysis was performed among ECa, soil texture, and yield datasets, adopting a significance level of 5% for correlation acceptance. For each field, two treatments were used for management zone delineation: (i) delineation using soil texture layers and (ii) delineation using ECa layers. In addition to these layers, elevation and soil fertility attributes, including organic matter (OM), pH, and cation exchange capacity (CEC), were incorporated. Yield layers were also included, with management zones generated for each dataset composed of two soybean growing seasons or one second-crop dataset. This approach was adopted to ensure the representativeness of the yield layers and to approximate the analysis to commercial field conditions. Thus, eight datasets were generated for each evaluated field. The FPC, NCE, FPI, and VR parameters were tested for normality and homogeneity and were then submitted to Student’s t-test, considering significant differences at $p < 0.05$.

Table 2. Treatments applied to evaluate the influence of ECa on management zone delineation.

Dataset	Field	Treatment	Yield layer	Complementary layers
1	6A	ECa 0–0.75 m and ECa 0–1.50 m	Soybean 2025 e 2024	Elevation, pH, OM, and CEC at 0–0.20 m from 2024
		Clay, sand, and silt at 0–0.20 m	Soybean 2025 e 2024	
2		ECa 0–0.75 m and ECa 0–1.50 m	Soybean 2023 e 2022	
		Clay, sand, and silt at 0–0.20 m	Soybean 2023 e 2022	
3		ECa 0–0.75 m and ECa 0–1.50 m	Sorghum 2024 e 2021, Wheat 2023	
		Clay, sand, and silt at 0–0.20 m	Sorghum 2024 e 2021, Wheat 2023	
4		ECa 0–0.75 m and ECa 0–1.50 m	Soybean 2021 e 2019	
		Clay, sand, and silt at 0–0.20 m	Soybean 2021 e 2019	
1	6B	ECa 0–0.75 m and ECa 0–1.50 m	Soybean 2025 e 2023	Elevation, pH, OM, and CEC at 0–0.20 m from 2017
		Clay, sand, and silt at 0–0.20 m	Soybean 2025 e 2023	
2		ECa 0–0.75 m and ECa 0–1.50 m	Soybean 2022 e 2021	
		Clay, sand, and silt at 0–0.20 m	Soybean 2022 e 2021	
3		ECa 0–0.75 m and ECa 0–1.50 m	Sorghum 2022 e 2020, Wheat 2021	
		Clay, sand, and silt at 0–0.20 m	Sorghum 2022 e 2020, Wheat 2021	
4		ECa 0–0.75 m and ECa 0–1.50 m	Soybean 2020	
		Clay, sand, and silt at 0–0.20 m	Soybean 2020	

2.5. Economic analysis

An economic analysis was conducted to compare the operational costs of three management strategies: management zones based on apparent soil electrical conductivity (MZ with ECa), management zones based on soil texture (MZ with Texture), and pixel-based management. Commercial reference prices were used, considering US\$ 24.00 ha^{-1} for ECa acquisition, US\$ 4.80 per sample for physical soil analysis, and US\$ 14.08 per sample for chemical fertility analysis (micronutrients, basic fertility, aluminum, and sulfur). For MZ-based management, one sampling point was considered per management zone. As optimal clustering resulted in four zones per field, a total of eight sampling points was used, considering the two fields analyzed. For pixel-based management and the initial texture-based characterization, a sampling density of three points per hectare was adopted, totaling 37 sampling points.

The cost structure varied according to the management strategy and year of evaluation. In the first year, the MZ with ECa strategy included the cost of ECa acquisition, whereas the MZ with Texture and pixel-based strategies included both physical and chemical soil analyses. From the second year onward, only chemical fertility analyses were considered, using eight samples for MZ-based management and 37 samples for pixel-based management. Annual costs were calculated from the number of samples and their respective analysis costs, expressed on a per-hectare basis. The evaluation was performed over a ten-year period, assuming that MZs remained stable and could be reused over time. The accumulated difference was calculated as the cumulative balance between pixel-based management and MZ with ECa.

3. Results and Discussion

3.1. Influence of ECa use as a proxy for soil texture

The ECa is widely recognized as an efficient tool for characterizing the spatial variability of soil physical and chemical properties. Farahani et al. (2005) and Heil and Schmidhalter (2012) demonstrated that ECa can be used to characterize soil spatial variability, mainly because it is influenced by attributes related to soil texture, water content, and ion concentration in the soil solution (McCutcheon et al. 2006). In general, stronger relationships are commonly reported between ECa and finer soil fractions, especially clay, due to the higher water retention capacity and greater surface reactivity of these particles. The greater water content retained in micropores favors the presence of dissolved ions in the aqueous phase, facilitating the conduction of electrical current and, consequently, increasing ECa values. Although the correlations shown in Fig. 2 are consistent with observations reported in the literature, indicating that ECa was associated with textural variation in the evaluated areas, the strongest relationship in this study was observed with the silt fraction. This suggests that the ECa response was not exclusively controlled by clay content. This behavior reinforces that ECa should be interpreted as an indirect and integrated soil response, influenced not only by particle-size distribution, but also by soil moisture, pore arrangement, dissolved ions, and the physical condition of the soil at the time of data acquisition (Serrano et al. 2024).

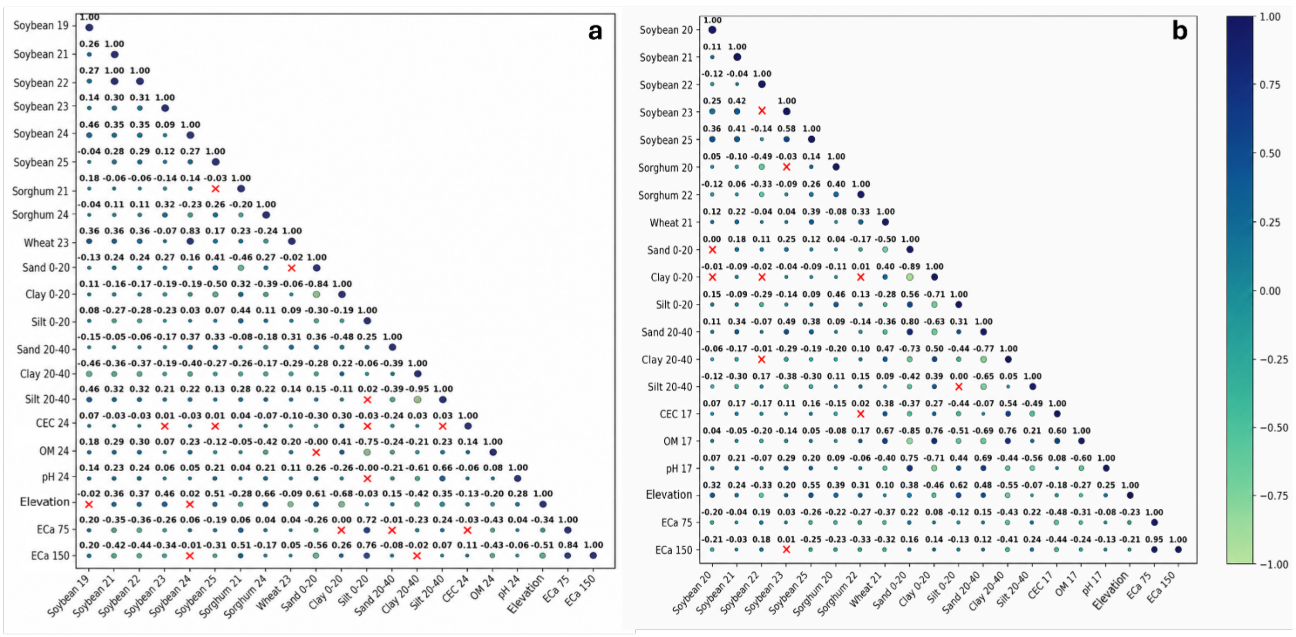

Fig. 2 Pearson correlation between processed yield layers of soybean, sorghum, and wheat from the 2019 to 2025 growing seasons, soil texture at depths of 0–0.20 m and 0.20–0.40 m, and ECa at 0–0.75 m and 0–1.50 m; (a) field 6A and (b) field 6B. The "X" indicates non-significant correlations at the 5% significance level (p-value > 0.05).

This interpretation is particularly important under irrigated conditions, in which successive wetting and drying cycles caused by frequent water input and redistribution can modify soil structure over time, especially in soils with low aggregate stability (Liu et al. 2024; Wang et al. 2022). This process may favor particle rearrangement, reduce macroporosity, and increase soil bulk density, resulting in a compacted condition that alters water dynamics and pore distribution. Consequently, the relationship between ECa and textural attributes may be modified, since water retention and movement depend not only on texture, but also on structural changes induced by irrigation management and possible compaction caused by recurrent machinery traffic. In clayey soils, greater water retention is expected due to the higher proportion of micropores, which tends to increase ECa values. In contrast, sandier fractions generally show negative relationships with ECa because of their lower water retention capacity and greater drainage. However, when soil structure is modified, intermediate fractions such as silt, and even sandy fractions in specific conditions, may contribute more strongly to water retention and electrical conduction, helping to explain the pattern observed in the evaluated areas.

Because crop response is sensitive to soil physical processes, yield variability can also be interpreted in relation to ECa and soil physical attributes. In field 6A, the highest correlations with yield were observed for soybean in 2022 and sorghum in 2021, whereas in field 6B, soybean in

2025 and wheat in 2021 showed the strongest relationships. This trend may be associated with the ability of ECa to indirectly reflect variations in texture, moisture, and soil structure, attributes that directly influence water availability, root development, and, consequently, crop performance (Molin; Faulin, 2013). The similarity between the coefficients of variation (CV) of the yield layers and ECa reinforces this interpretation. In field 6A, soybean in 2022 and sorghum in 2021 presented CV values of 3.55% and 7.05%, respectively, which were close to those observed for ECa at 0–0.75 m and 0–1.50 m, with values of 4.79% and 4.94%. In field 6B, this similarity was mainly observed for wheat in 2021, which presented a CV of 23.70%, compared with 15.77% and 22.09% for ECa at 0–0.75 m and 0–1.50 m, respectively. These results indicate that, in specific growing seasons, yield variability showed a magnitude similar to the spatial variability captured by ECa.

Thus, although ECa does not directly represent yield, it can assist in identifying regions with different yield potentials, especially when soil patterns control water availability and crop response over time(Molua 2021). This characteristic is particularly relevant for the delineation of MZs since these units should be based on layers capable of representing persistent and agronomically interpretable spatial patterns (De Feudis et al. 2025; Serrano et al. 2024). Therefore, when obtained at high sampling density and properly processed, ECa can contribute to the identification of zones with higher and lower productive potential, supporting its use as a substitute or complementary layer to soil texture.

To verify whether ECa could act as a proxy for soil texture layers in MZ delineation, Table 3 presents the qualitative evaluation of the MZs generated by the FCM algorithm in fields 6A and 6B, considering an optimal number of four clusters for treatment comparison. Overall, replacing soil texture layers with ECa layers did not compromise MZ quality, since the NCE and FPC indices showed similar values and no statistical differences between treatments. Low NCE values indicate low uncertainty in cluster classification, whereas high FPC values confirm that the generated partitions had good definition and low overlap among clusters. This behavior demonstrates that, regardless of the layer used, ECa or texture, the algorithm was able to form well-defined groups with low ambiguity in zone boundaries. Thus, the results suggest that ECa provided sufficient spatial information to generate MZs with fuzzy quality similar to that obtained using soil texture layers. Among the evaluated indices, only variance reduction (VR) showed a significant difference in field 6A.

Table 3. Qualitative evaluation of MZs generated using ECa and soil texture layers, considering an optimal number of four clusters for all datasets. Different letters within the same column and field indicate statistically significant differences by Student's t-test at the 5% significance level.

Index	Field 6A		Field 6B	
	ECa	Texture	ECa	Texture
NCE	0,16 a	0,17 a	0,13 a	0,14 a
FPC	0,88 a	0,88 a	0,89 a	0,90 a
VR	0,49 a	0,45 b	0,41 a	0,46 a

In this case, the ECa treatment showed higher VR than the texture treatment, indicating greater internal homogeneity of the MZs generated using the ECa layer. This result shows that replacing soil texture with ECa did not reduce the segmentation capacity. On the contrary, in field 6A, the higher spatial density of ECa may have favored the identification of local variability gradients, resulting in zones with lower internal variance. In field 6B, no statistical differences were observed between treatments, indicating equivalent performance between ECa and soil texture. In addition to the comparison using four clusters, differences were observed in the optimal number of clusters indicated for each treatment. The MZs generated with soil texture showed the best fit with four clusters, whereas those based on ECa indicated five clusters as the optimal solution. This difference was directly reflected in the reduction of intra-MZ variance, which reached approximately 45.07% for the texture treatment and 49.67% for the ECa treatment. This behavior suggests that ECa, due to its higher sampling density, captured more detailed spatial variability, requiring a greater number of zones to adequately represent the gradients present in the field.

The spatial analysis of the MZs shown in Fig. 3 complements the interpretation of the qualitative indices. The MZs generated from datasets that included second-crop yield layers showed a different behavior compared with those based on first-crop layers, especially in field 6A. In this case, greater irregularity was observed in the segments, mainly associated with the 2024 sorghum yield layer, which showed the second-highest relative importance in the Random Forest model. This behavior can be explained by the high variability of this layer, which presented a coefficient of variation of 20.59%, the highest among the crops analyzed in the field. When a highly variable layer has high importance in the clustering process, its influence tends to be directly reflected in the spatial configuration of the MZs, increasing fragmentation and reducing segment continuity. The greater heterogeneity observed in the second-crop yield map may be associated with the combination of different crop species. Under these conditions, each crop may present different moisture conditions, canopy structures, and yield levels, reducing the spatial consistency of the final yield layer. Consequently, this may intensify artificial variability patterns and contribute to the increased noise observed in the MZs.

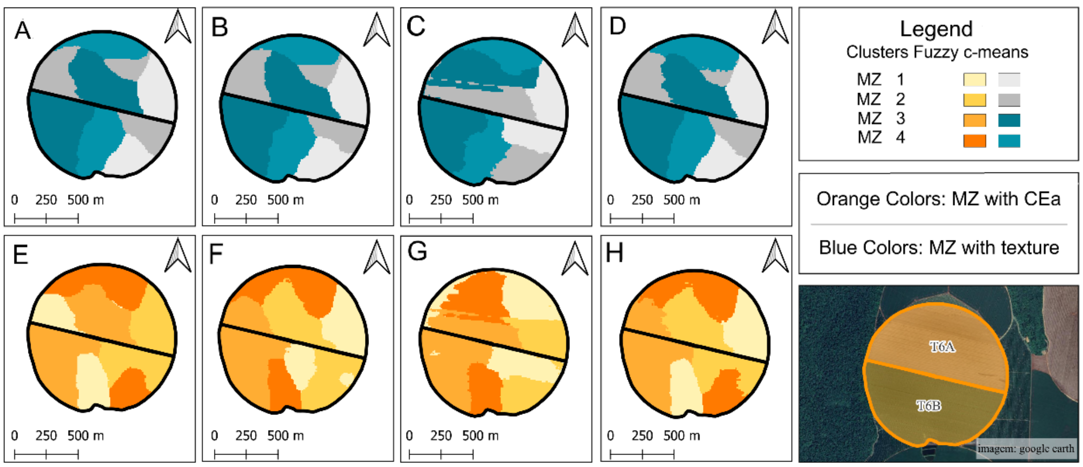

Fig. 3 Representation of fields 6A and 6B segmented into four clusters. Panels A, B, C, and D represent datasets 1, 2, 3, and 4, respectively, generated using the soil texture treatment, whereas panels E, F, G, and H represent datasets 1, 2, 3, and 4, respectively, generated using the ECa treatment.

Table 4 presents the structural similarity indices between the MZs generated using ECa layers and those generated using soil texture layers. Overall, ARI and NMI values indicated moderate to high spatial agreement between treatments, demonstrating that replacing soil texture with ECa preserved an important part of the spatial organization of the zones. The highest similarity was observed in field 6B, which may be related to the greater relative influence of the layers shared by both treatments, such as CEC, OM, pH, elevation, and yield. When these shared variables have similar influence on cluster formation, the difference between using ECa or soil texture tends to be reduced, favoring greater structural agreement between segmentations. In field 6B, the differences in the importance of soil chemical attributes between models were lower, with amplitudes of 0.01, 0.04, and 0.06 for CEC, OM, and pH, respectively. This behavior suggests that the common layers contributed to stabilizing the MZ structure and reducing divergence between treatments. In field 6A, the lower structural similarity may be explained by the greater difference in the relative importance of the shared variables between treatments. The amplitudes observed for CEC, OM, and pH were 0.03, 0.08, and 0.07, respectively, indicating that these layers contributed less uniformly to cluster formation. These results reinforce that the similarity between MZs does not depend only on the replaced layer, but also on the interaction among all variables used in the clustering process. Although ECa and soil texture represent important edaphic components, the final organization of the zones is also conditioned by complementary layers related to soil fertility, elevation, and yield.

Table 4. Similarity indices between MZs obtained using ECa layers and MZs generated using soil texture layers. ARI:

Adjusted Rand Index; NMI: Normalized Mutual Information.

Dataset	Field 6A		Field 6B	
	ARI	NMI	ARI	NMI
1	0.63	0.66	0.73	0.70
2	0.62	0.65	0.71	0.68
3	0.40	0.48	0.69	0.66
4	0.67	0.69	0.71	0.67
Mean	0.58	0.62	0.71	0.68

On the other hand, NMI showed slightly lower mean values, 0.62 for field 6A and 0.68 for field 6B, indicating moderate structural similarity between zoning methods. However, because NMI is based on the mutual information shared between partitions, it tends to smooth small local divergences. The local differences observed in Fig. 3 may be associated with the intrinsic nature of the layers used. Soil texture layers are derived from point-based sampling and interpolation, which tends to smooth spatial variability. In contrast, ECa is obtained at higher sampling density and may capture more detailed local variations, especially in areas where changes in soil moisture, soil structure, or particle-size distribution affect the sensor response. Therefore, differences in cluster spatial distribution do not necessarily indicate loss of quality, but rather that each data source represents soil variability at different spatial scales and intensities.

The variable importance analysis, presented in Fig. 4 and estimated using the Random Forest model, showed that when the ECa layer was used, yield-related variables, especially soybean and sorghum, had greater importance in the model compared with the MZs generated from soil texture layers. This behavior indicates that, when ECa replaced the texture layers, the segmentation process relied more strongly on the remaining layers available to represent field spatial variability. Although the importance of yield layers was still lower than that of some soil and elevation attributes, their greater contribution suggests that these variables helped identify spatial patterns complementary to those captured by ECa. Thus, MZ formation was not determined by a single layer, but by the interaction among ECa, yield, soil fertility, and elevation. The greater relative contribution of yield layers in the ECa-based treatments may also be associated with the spatial density of these data. Yield maps, similarly to ECa data, are obtained at higher sampling density than texture layers derived from point-based sampling and interpolation. This characteristic increases the ability of the model to identify local variability gradients, favoring the formation of clusters that are more sensitive to spatial changes within the field.

In contrast, soil texture layers, because they are obtained from a smaller number of sampling points, tend to show greater spatial smoothing after interpolation. This smoothing may reduce the level of detail of local variations and cause other layers shared between treatments, such as CEC, OM, pH, and elevation, to assume greater influence in zone delineation. Therefore, the differences observed in variable importance reinforce that ECa and soil texture represent soil variability at different spatial scales: texture expresses a more generalized and stable pattern, whereas ECa can capture more detailed spatial variations associated with the soil physical-hydric condition. Overall, the variable importance analysis confirms that replacing soil texture with ECa does not eliminate the agronomic coherence of the MZs, but changes the relative contribution of the layers in the clustering process. This result reinforces the interpretation that ECa can act as an operational proxy for soil texture, provided that it is analyzed together with complementary layers capable of representing yield history, soil fertility, and elevation. Thus, MZ delineation should be understood as the result of integrating multiple sources of information, rather than as the isolated effect of a single variable.

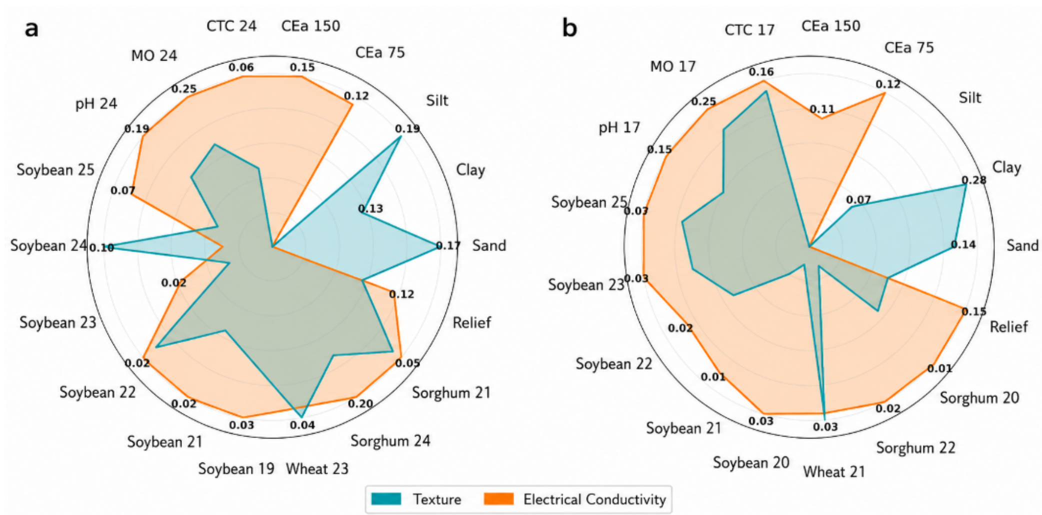

Fig. 4 Mean importance of the variables used for MZ delineation, estimated using the Random Forest prediction model; (a) variables used in field 6A and (b) variables used in field 6B.

3.2. Economic implication of ECa-based management zones

In addition to the agronomic and spatial coherence observed for the MZs generated with ECa, the adoption of this approach also has relevant economic implications. The comparison among MZ management with ECa, MZ management with soil texture, and pixel-based management shows that the economic feasibility of each strategy depends not only on the initial cost of data acquisition, but also on the possibility of reusing the zones over time. While pixel-based management requires more recurrent sampling and laboratory analyses every year, MZ-based management tends to dilute the initial investment, since the zones can be used as a basis for recommendations in subsequent growing seasons, provided that they maintain agronomic coherence and temporal stability.

Thus, Fig. 5 presents the evolution of the financial balance over a ten-year production period. In the first year, MZ management with ECa had the highest cost due to the initial acquisition and processing of the ECa layer. In comparison, both MZ management with soil texture and pixel-based management had an initial cost of US\$ 6.35 ha^{-1}. However, from the second year onward, the annual cost of MZ management decreased to US\$ 1.02 ha^{-1} for both the ECa-based and texture-based approaches, whereas pixel-based management maintained an annual cost of US\$ 4.74 ha^{-1}. This behavior demonstrates that the main economic benefit of MZs is the reduction in recurrent costs associated with soil sampling and recommendation procedures (Clarke et al. 2024; Rattalino Edreira et al. 2017). When comparing MZ management with ECa to pixel-based management, the higher initial investment is offset over time. The accumulated balance between the strategies remains negative until the fifth year, indicating that, during this period, pixel-based management still presents a lower accumulated cost. However, from the sixth year onward, the accumulated balance becomes positive, with an accumulated saving of US\$ 0.95 ha^{-1} in favor of MZ management with ECa. At the end of ten years, the accumulated cost of MZ management with ECa was US\$ 33.22 ha^{-1}, while pixel-based management reached US\$ 48.97 ha^{-1}, resulting in an accumulated saving of US\$ 15.76 ha^{-1}.

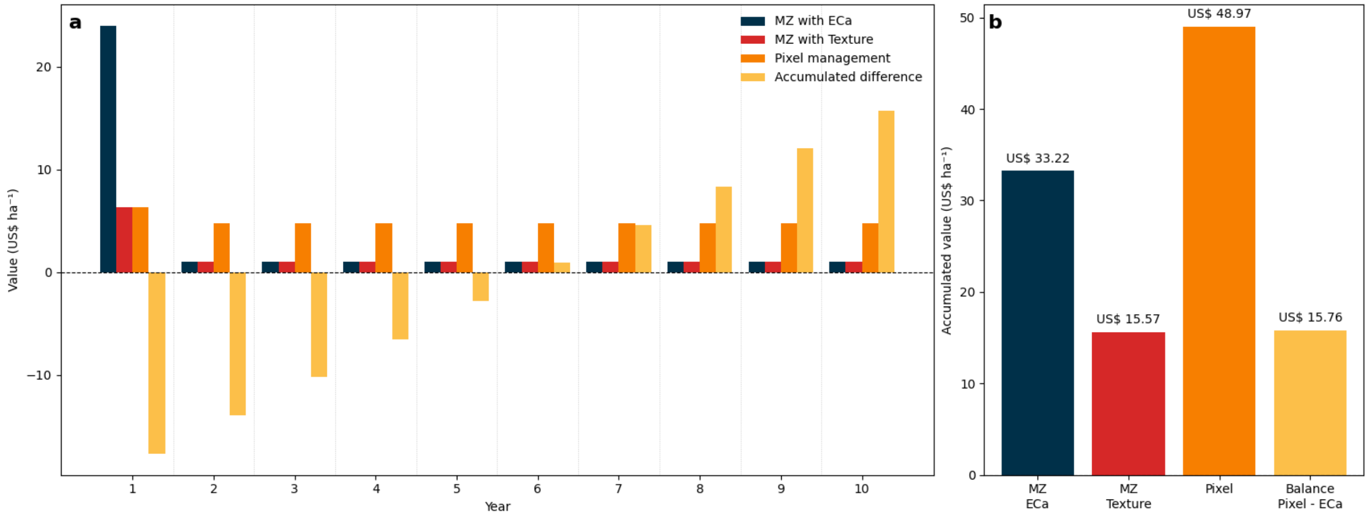

Fig. 5 Economic comparison among management strategies over a ten-year period. (a) Annual costs of MZ with ECa, MZ with Texture, pixel-based management, and accumulated balance between pixel-based management and MZ with ECa. (b) Total accumulated costs and final economic balance after ten years. Values are expressed in US$ ha^{-1}.

The MZ management approach based on soil texture showed the lowest accumulated cost over the evaluated period, totaling US$ 15.57 ha^{-1} after ten years. This result was expected, since, in this simulation, the texture-based approach did not include the same initial cost associated with ECa acquisition. However, the economic comparison should be interpreted together with the agronomic and spatial results. Although soil texture presented the lowest direct cost in this scenario, its acquisition depends on point-based sampling and interpolation, which may limit the spatial detail of the generated zones. In contrast, ECa has a higher initial cost, but provides information at higher spatial density and has the potential to represent stable edaphic patterns over time. Therefore, the economic analysis reinforces that the use of ECa as a proxy for soil texture becomes more advantageous when evaluated over a multi-year horizon. The economic return of adopting ECa occurs from the sixth year onward when compared with pixel-based management, while its agronomic benefits are associated with greater spatial detail and the potential to reduce dependence on intensive soil sampling. Thus, the feasibility of ECa-based MZ management depends on the temporal stability of the generated zones, their reuse in subsequent growing seasons, and the reduction of the initial investment required for ECa data acquisition at the field scale.

4. Conclusion

This study showed that ECa can be used as an operational proxy for soil texture in the delineation of management zones under irrigated grain production conditions. ECa was associated with soil textural variation and yield-related spatial patterns, although its response reflected an integrated soil condition influenced not only by clay content, but also by silt, soil moisture, pore arrangement, dissolved ions, and management-related structural changes. Replacing texture layers with ECa did not compromise the quality or spatial coherence of the generated management zones. The fuzzy validity indices indicated similar classification performance between ECa and texture, based zones, while the structural similarity analysis showed moderate to high agreement between maps, especially in field 6B. These results indicate that ECa preserved an important part of the spatial organization obtained with texture layers, while capturing local variability at higher spatial density.

The economic analysis showed that ECa-based management zones require a higher initial investment, but this cost is diluted when zones are reused over multiple seasons. Compared with pixel-based management, the accumulated balance became positive from the sixth year onward, reaching an estimated saving of US$ 15.76 ha^{-1} after ten years. Overall, ECa represents a technically and economically viable alternative for supporting management zone delineation, combining high spatial density, agronomic coherence, and potential reduction in recurrent soil sampling costs. However, its interpretation should consider soil moisture, compaction, and local management conditions, and should be supported by proper filtering and complementary agronomic layers.

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