
# Yield potential zones and their relationship with soil taxonomic classes and management zones

**Amaral[1], L.R.; Oldoni[2], H.; Melo[1], D. D.; Rosin[4], N. A.; Alves[3], M. R.; Demattê[4], J. A. M.**

[1] University of Campinas, School of Agricultural Engineering (FEAGRI/UNICAMP), Campinas – SP, Brazil

[2] University of Campinas, Interdisciplinary Center of Energy Planning (NIPE/UNICAMP), Campinas – SP, Brazil

[3] University of West Paulista (UNOESTE), Presidente Prudente – SP, Brazil

[4] University of São Paulo, "Luiz de Queiroz" Collegue of Agriculture (ESALQ/USP), Piracicaba – SP, Brazil

**A paper from the Proceedings of the**
**16th International Conference on Precision Agriculture**
**21-24 July 2024**
**Manhattan, Kansas, United States**

***Abstract.***
*The use of management zones (MZ) to subdivide agricultural areas based on the variability of yield potential and production factors is increasingly being explored by scientific research and demanded by farmers. However, there is still much uncertainty about which layers of information and procedures should be adopted for this purpose. Thus, our goal was to demonstrate whether simplistic approaches to creating MZ can satisfactorily address the variability of yield potential and soil classes. For such, we used a 109-ha grain-producing field, which harvests two crops a year. We used yield maps, soil taxonomic classification, grid soil sampling, and electromagnetic induction sensing to explore the MZ strategy. We did not observe any major similarities among the information layers used or among the management zones obtained. However, when integrating all data available (20 layers), the subdivision of the area was consistent with the existing variability. This demonstrates the importance of choosing the information layers and, at the same time, how the return with this technique is still dependent on the technical knowledge of the users. Thus, there is still a long way to go before the MZ approach is safe and profitable for farmers.*

***Keywords.***
*Soil survey, soil sensing, pedometric, yield monitor*

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 16th International Conference on Precision Agriculture. EXAMPLE: Last Name, A. B. & Coauthor, C. D. (2024). Title of paper. In Proceedings of the 16th International Conference on Precision Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture.

## Introduction

Agricultural areas are not uniform, and even in small portions of a field, there are differences in production factors that can result in heterogeneous crop development and, consequently, demand for localized treatments. This site-specific management, respecting the spatial variability observed within the fields, is the focus of precision agriculture. Thus, it is a consensus today that agricultural exploration needs to consider crops' spatial and temporal variability to be sustainable and profitable and have a diminished environmental impact (Gebbers & Adamchuk, 2010). In this sense, it is mandatory to identify the variability of agricultural soils since much of the management carried out in crops depends on this knowledge, such as soil preparation, choice of cultivars, fertilization, irrigation, crop rotation, and population rate, among others.

Several approaches have been developed to identify spatial and temporal variability in fields. The proposal for evaluating and managing crops through “management zones” has become popular among them. In its original definition, a management zone (MZ) is a field's sub-region expressing a relatively homogeneous combination of production-limiting factors for which a single input rate or specific crop management is appropriate (Doerge, 2000). This approach divides the crop field into smaller homogeneous units that can be managed individually, making localized management more feasible since detailed and periodic investigation of variability would no longer be required regularly.

As the MZ concept was proposed by the practitioners that initiated precision agriculture, the information layers generally used for this delineation are those that are routinely available in areas applying PA techniques, like information on soil properties in the superficial soil layer (usually 0-0.2 m, sometimes more profound, but generally in the region of interest for fertilizer recommendations), proximal soil sensing data, such as soil apparent electrical conductivity (Peralta & Costa, 2013; Nawar et al., 2017), as they provide information in higher density than sampling and, ideally, historical crop yield maps (Khosla et al., 2008). However, this MZ delineation approach often does not integrate the various production factors present in the field, which can reduce the return on adopting precision agriculture techniques.

The MZ delineation aims to subdivide the agricultural fields, but it is often unclear what each zone's limiting factors and yield potential are. On the other hand, the pedological survey is based on the evaluation of soil horizons, mainly in the subsurface (between 1 and 2 m), seeking to classify the soil according to its natural characteristics, which refers to the dynamics of water and solutes that occur in it; thus, allowing inferences about its productive potential under different climate and cultivation situations in a holistic way. Thus, pedological mapping uses all the specialist's knowledge to divide the areas based on natural soil variations and standardized characterization of each soil type's characteristics, potentials, and limitations. As a result, despite the different conceptual issues, both approaches aim to express the variability of agricultural areas, which leads us to seek a relationship between the MZ technique (which focuses on data collected with high sampling density and often easy to obtain and focus on the surface layer of the soil) and pedology (which focuses on the soil as a whole and also addresses issues related to the subsurface).

This study aimed to verify whether simplistic approaches to creating management zones can satisfactorily address the variability of yield potential and soils in agricultural areas. Thus, in this study, we demonstrate that soil chemical fertility zones and zones generated from electromagnetic induction sensors have a limited relationship with the historical grain yield. Furthermore, we use a detailed pedological map as a reference, demonstrating the importance of integrating the expertise areas (pedology and PA) for a correct understanding of variability at the field level and its yield potential for the sustainable adoption of precision agriculture.

## Material and Methods

The study site consists of a 109 ha grain-producing area, subdivided into ten fields (Fig. 1), located in the interior of the state of São Paulo, Brazil. The region's climate is humid subtropical with dry winter and hot summer (Cwb - Koppen), with an average annual rainfall of 1,300-1,600 mm and an average temperature of 20-22°C.

The area is cultivated in a succession of crops, that is, two crops are grown throughout the year, one being considered the first crop (main harvest), which is sown at the beginning of the rainy season, usually between October and December; the second crop is sown immediately after the harvest of the first crop, seeking to take advantage of the residual soil moisture or the last rains before the beginning of the dry season of the year, usually between February and April. In this study, we used data from three years, i.e., six harvests. As the first crop, soybean was grown in all three years; as second crop, sorghum was cultivated in the 2021 and 2023 seasons, while oats were cropped in the 2022 harvest (Table 1).

**Table 1. Sowing and harvesting time of crops used in the study.**

| Crop | Growth season | Sowing date | Harvesting date |
|---|---|---|---|
| Soybean | 20/21 | Late November 2020 | Middle March 2021 |
| Sorghum | 2021 | Early April 2021 | Early August 2021 |
| Soybean | 21/22 | Late November 2021 | Late March 2022 |
| Oat | 2022 | Late April 2022 | Middle September 2022 |
| Soybean | 22/23 | Early November 2022 | Late March 2023 |
| Sorghum | 2023 | Early April 2023 | Early September 2023 |

The crop was harvested in all seasons with a yield monitor installed on a harvester. The monitor components were checked before harvesting, and the amount of grain harvested was reported to the monitor after finishing the study site harvest to obtain the calibration factor, converting all datasets to a realistic grain yield basis. Even with monitor calibration, evaluating the whole dataset and removing unrealistic data is essential; thus, the raw data were subjected to a step of removal of outliers and inliers (Maldaner et al., 2022).

We performed dense soil sampling for surface characterization of soil chemical fertility and texture (Fig. 1). We collected one composite sample every 40 meters, resulting in a sampling density of six samples per hectare, totaling 656 composite samples. Each sample comprised six subsamples collected within a five-meter radius of the central point and a collection depth of 0-0.2 m, using an automated drill installed on an ATV. In this work, we sought to infer the chemical variability of the soil as a whole and, therefore, we determined in a commercial laboratory (Raij et al., 2001) the following attributes: pH and hydrogen plus aluminum (H+Al), comprising soil acidity parameters; cation exchange capacity (CEC) and organic matter (OM), attributes related to the soil's ability to store nutrients; and, regarding the amount of nutrients available to plants, we used the sum of bases (SB) and the isolated contents of available phosphorus (P) and potassium (K).

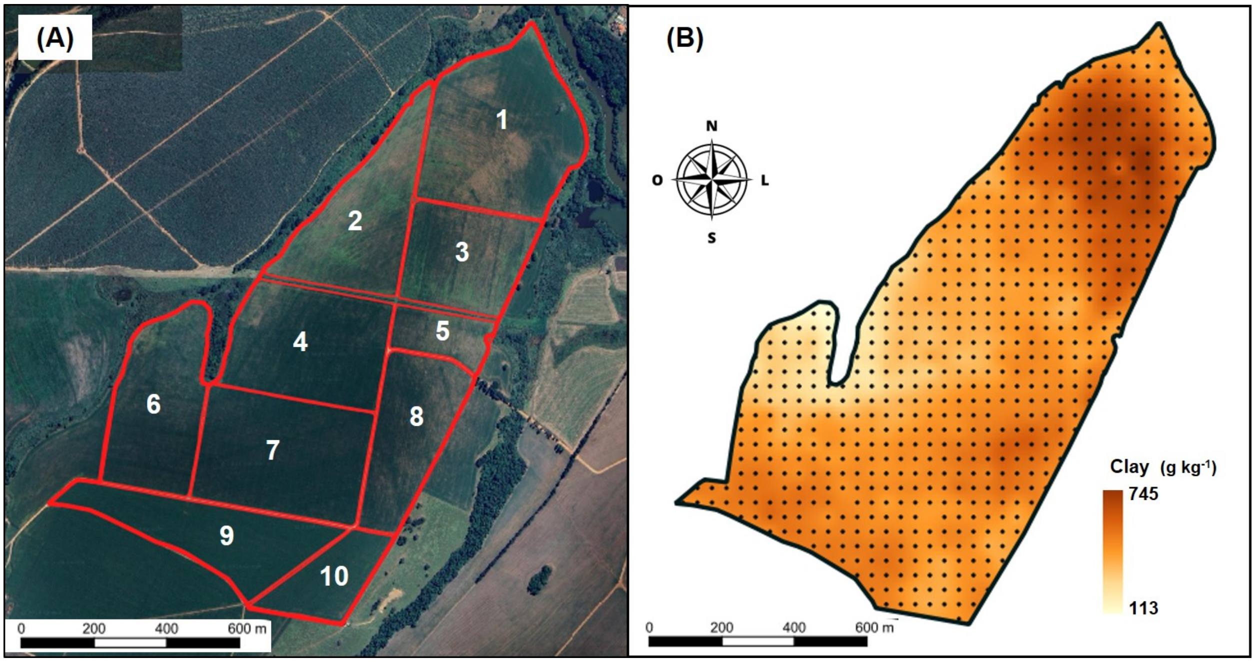


**Fig 1. Experimental area, showing the ten fields (A) and the distribution of the soil sampling points and clay content map (B).**

An electromagnetic induction sensor was also used to quantify soil variability within the study site (EM38-MK2, Geonics). The sensor was driven within the area, collecting data every second (~5 m) along the pass, with passes spaced every 15 m. This sensor records two types of signals: apparent electrical conductivity (ECa) and magnetic susceptibility (MSa). ECa is already widely used in PA (Corwin & Lesch, 2005; Moral et al., 2010), having great potential to indicate soil variability, influenced mainly by soil texture (Sanches et al., 2022). MSa is less explored in PA studies, but there are also reports regarding its feasibility to assist in mapping soil attributes (Ramos et al., 2021) and texture differentiation, mainly because MS is highly influenced by soil mineralogy (Shirzaditabar & Heck, 2022). In addition, as the EMI sensor has two coils that induce the electromagnetic current, measurements can be obtained at two depths; thus, here, we work with measurement depths up to 0.37 m and up to 0.75 m.

All the data mentioned above, i.e., grain yield of the different crop seasons, soil attributes obtained through sampling, and EMI sensor data, were interpolated to obtain continuous maps. For this purpose, we used the *gstat* package available in the R environment (Pebesma, 2004). We performed the variographic modeling according to the recommendations of Oliver and Webster (2014), interpolating values every five meters through ordinary kriging in 30 x 30 m blocks. This block size was defined as being a multiple of the EMI sensor pass (15 m) and close to the width of the harvester platform (9.2 m), with a focus on reducing the "*noise*" present in high-density data sets, but also maintaining this configuration for the soil sampling data to follow the same pattern and ensure correct data colocalization.

Pedological survey was carried out at a detailed level following the methodology proposed by Santos et al. (1995) (Fig. 2A). For this purpose, a synthetic image of bare soil (SySI – Fig. 2B), which represents a direct measurement of soil reflectance on the surface, was obtained using the procedure proposed by Demattê et al. (2018). SySI allows inferences about soil color, texture, and moisture, among other factors. In addition, a digital elevation model (DEM) with a resolution of 12.5 m was obtained from the ALASKA platform (https://www.asf.alaska.edu/) of the PALSAR sensor (Fig. 2D). With the support of the DEM and SySI, sampling points were allocated by the responsible pedologist according to the toposequence method. The soil surveys were carried out at depths of 0-0.2 m, 0.4-0.6 m, and 0.8-1.0 m, followed by physical and chemical analyses of the soil. The sampling points were classified according to the methodology adapted from Santos et al. (2018). These sampling points show the location of occurrence of each soil class in the area, and the boundaries between the classes of these soils in the landscape were delimited according to the DEM and SySI, obtaining a detailed soil map (scale of 1:20,000). The soils found in the study site were Red Latosol with a very clayey texture (LV1) and Red Latosol with a clayey texture (LV2), both classified as Oxysols by the Soil Taxonomy, and Haplic Gleysol with a clayey texture (GX – Entisol).

We implemented different approaches to subdivide the area into management zones for exploratory purposes. They consisted of:

1) Creation of soil chemical fertility zones (SFZ) based on grid sampling performed at the surface (0-0.2 m) since most precision agriculture users have adopted the concept of management zones for fertilizer recommendation purposes (Kerry et al., 2024).

2) An approach in which EMI sensor data were grouped (EMI) since most MZ research uses this type of data as the primary information on soil variability (Moral et al., 2010; Serrano et al., 2020). We clustered the four sensor outputs (ECa and MSa at two depths) since we identified slight variations between the maps (Fig. 3), and we wanted the clustering result to be unaffected by the choice of one layer or another.

3) An approach that encompasses all the data available in the survey (from now on referred to as the Integrative Terrain Approach – ILA), i.e., the six yield maps and their standard deviation map (*further explained*), the fertility maps (except P), the four EMI sensor outputs and, in addition, trying to emulate the layers used by the pedologist, we also added the altitude of the area (DEM) and the bare soil image. In this case, we converted the visible color space of the SySI image (RGB) to the HSI space (hue-saturation-intensity space), using the saturation information, also called color purity, to represent the bare soil variability within the study site (Fig. 2C).

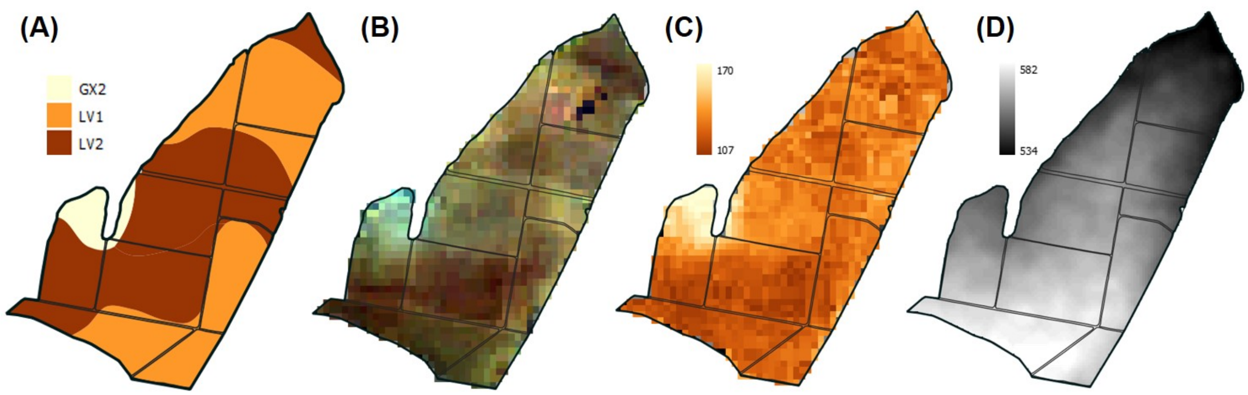


**Fig 2. Soil taxonomic classes (A), RGB bare soil image (SySI - B), saturation from HIS space for bare soil image (C), and area elevation (D).**

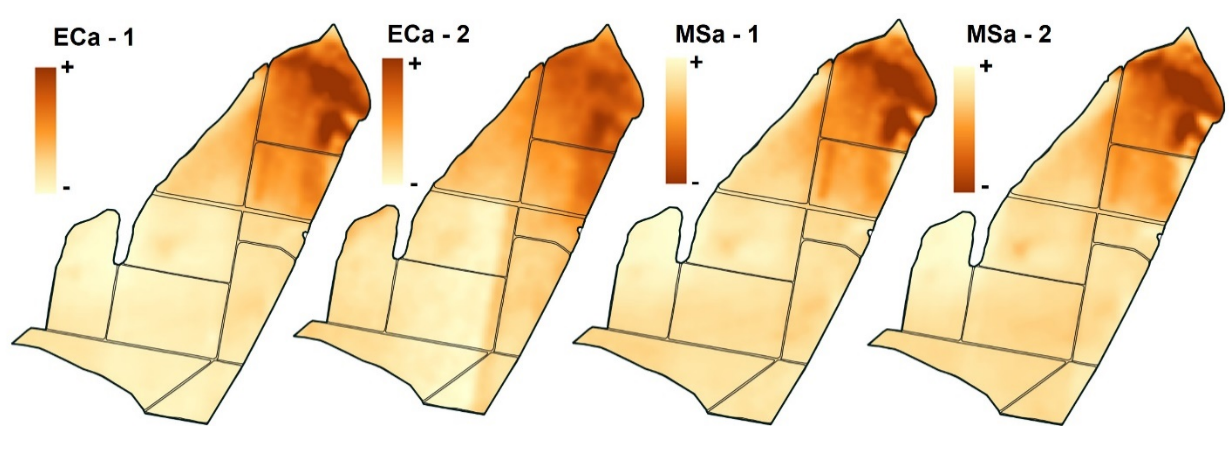

**Fig 3. Soil Electromagnetic Induction Sensing (EMI): apparent electrical conductivity (ECa) and magnetic susceptibility (MSa) in two depths (1 – up to 0.37 m; 2 – up to 0.75 m).**

Furthermore, the yield maps were standardized so that the average of each harvest represented 100%, allowing us to identify where the yield was below or above the average (Suszek et al., 2011). We also averaged these standardized maps. These mean values were extracted for the coordinates of the soil sampling points to calculate the yield variance reduction (Ping & Dobermann, 2003) to evaluate the different MZ scenarios in terms of within-MZ yield homogeneity.

To delineate the MZs using the different approaches, we used the methodology proposed by Córdoba et al. (2016). It consists of applying fuzzy c-means cluster analysis to the spatial principal components (PCs) acquired by multivariate spatial principal components analysis (MULTISPATI-PCA) (Dray et al., 2008) applied to the selected layers. The number of PCs used in the cluster analysis was defined based on the total explained variance, and we adopted a minimum value of 80%. The cluster analysis was applied to 2, 3, 4, and 5 groups (zones), adopting a fuzziness weighting value equal to 1.3 and the Euclidean distance to express the distance between the observations and the centroids of the groups. We obtained the clustering indices FPI (fuzziness performance index) and MPE (modified partition entropy) to indicate the best number of MZ, while the lower their values, ranging from 0 to 1, the better the cluster quality. Finally, we applied the median filter (Gonzalez & Woods, 2008) to the MZ maps to make the zones more continuous and less fragmented.

## Results and Discussion

It was not possible to identify a clear pattern of variability in soybean yield (first crop) among the harvests (Fig. 4A). However, the crops sown as second crop (sorghum and oats) presented some spatial characteristics in common: it is possible to note a region with high production in the center of the area for the three harvests (field 4), in addition to reduced sorghum production in the northern half of the area (fields 1, 2 and 3). The average standardized yield and standard deviation express these patterns (Fig. 4B-C).

MULTISPATI-PCA resulted in different numbers of PCs to explain at least 80% of the total variance of the data in the different MZ input layer scenarios (Table 2). This variation occurs mainly due to the number of input layers and the correlation among them, i.e., the greater the number of variables and the smaller the relationship between them, the greater the number of PCs required for the cluster analysis. In addition, one issue regarding this choice of the number of PCs is the threshold of the explained variance, which can significantly alter the final result. We used the 80% cutoff point, but if we had used 70%, as in some other papers (Gavioli et al., 2016; Miranda et al., 2021), the zoning results could be different. This shows another source of variation in the MZ design strategy.

We performed the MZ delineation based on the yield maps (Fig 5A). However, when analyzing the result of the number of zones indicated by the cluster quality indices (Fig. 5B), only two zones would be indicated to subdivide the study area. However, evaluating the series of yield maps and the spatial variation among the crop seasons, the area subdivision did not reliably represent some crop patterns, especially the higher productivity in the Field 4 surroundings. In addition, the soil map (Fig. 2A), corroborated by the bare soil image (Fig. 2B), showed an area with Gleysol, which would need to be identified when subdividing the area into MZ, since this soil is quite distinct from the Latosols also present in the area. Therefore, we explored other methods to create these grain yield zones, aiming to contemplate the variability present in the area better.

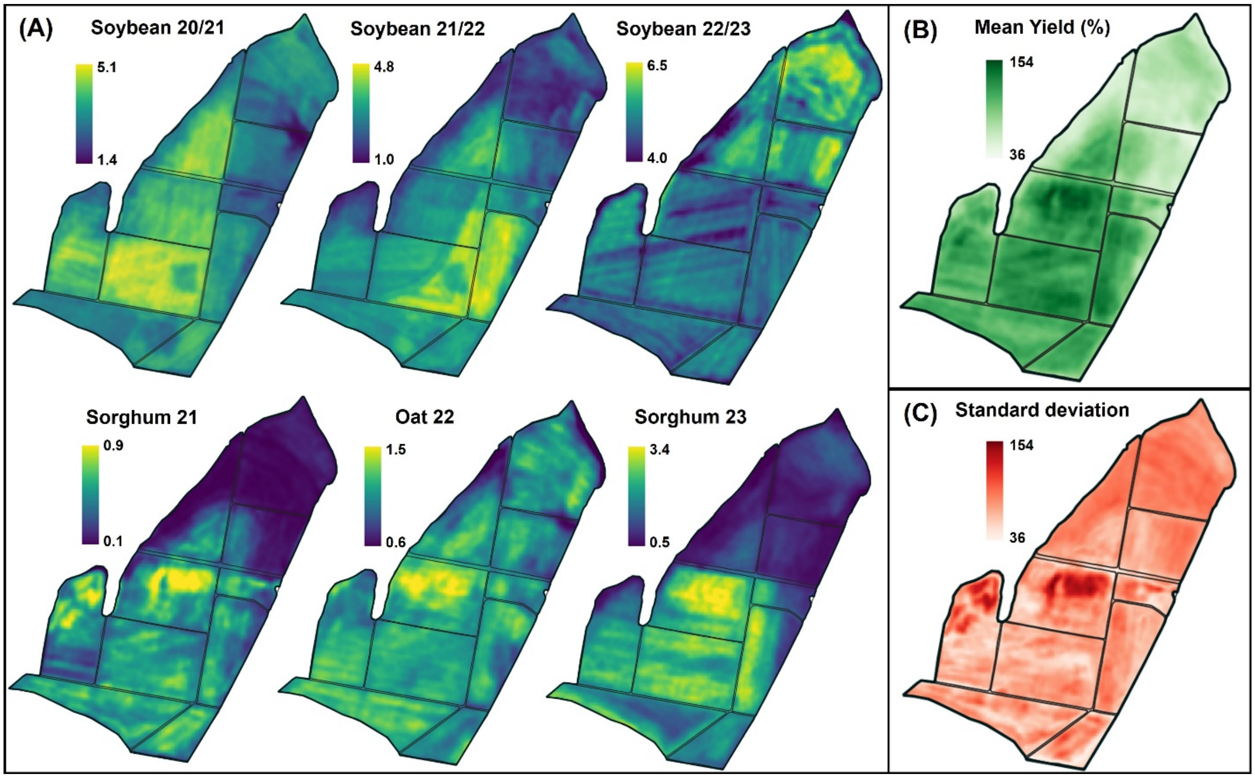


**Fig 4. Grain yield maps of the six crop seasons (A), average standardized yield (B), and standard deviation of the standardized yield of the six harvests (C).**

**Table 2. Explained variance (V) and the total explained variance ($V_{acu}$), in %, of the spatial principal components (PCs) applied to the different scenarios and the number of PCs adopted to reach at least 80% (N).**

| PCs | YZ-1 | | YZ-2 | | YZ-3 | | SFZ | | EMI | | ILA | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | V | $V_{acu}$ | V | $V_{acu}$ | V | $V_{acu}$ | V | $V_{acu}$ | V | $V_{acu}$ | V | $V_{acu}$ |
| 1 | 56 | 56 | 49 | 49 | 56 | 56 | 63 | 63 | 95 | 95 | 53 | 53 |
| 2 | 15 | 71 | 16 | 65 | 44 | 100 | 26 | 89 | | | 15 | 68 |
| 3 | 12 | 83 | 13 | 77 | | | | | | | 9 | 76 |
| 4 | | | 9 | 86 | | | | | | | 6 | 82 |
| N | 3 | | 4 | | 2 | | 2 | | 1 | | 4 | |

YZ-1: yield maps; YZ-2: yield maps + standard deviation; YZ-3: average standardized yield + standard deviation; soil fertility maps (SFZ); EMI sensing (EMI); and the integrative landscape approach (ILA).

Thus, we explored three ways of delimiting yield zones: 1) grouping the maps of the six crop seasons (initial approach - YZ-1); 2) grouping the six crop seasons and adding a layer of the standard deviation of the standardized yield, seeking to express the temporal stability of grain yield (YZ-2); and 3) creating a layer of average standardized yield and, together with the standard deviation layer, grouping the productivity zones (YZ-3). However, evaluating the clustering indices and the reduction of the yield variance (VR) (Fig. 5), it is noted that there is no clear pattern, and the cluster indices even contradict the results of the VR. This result may have been impacted by the fact that we have three crops in the area, grown in two seasons of the year, which can respond differently to the production factors present and climatic conditions occurring during the growth season. This shows that subdividing agricultural areas into smaller zones remains a challenge despite numerous studies outlining protocols and guidelines for such MZ creation (Guastaferro et al., 2010; Córdoba et al., 2016; Javadi et al., 2022). Therefore, we will address the representativeness of the different layers and approaches for MZ delineation in a more subjective and exploratory way.

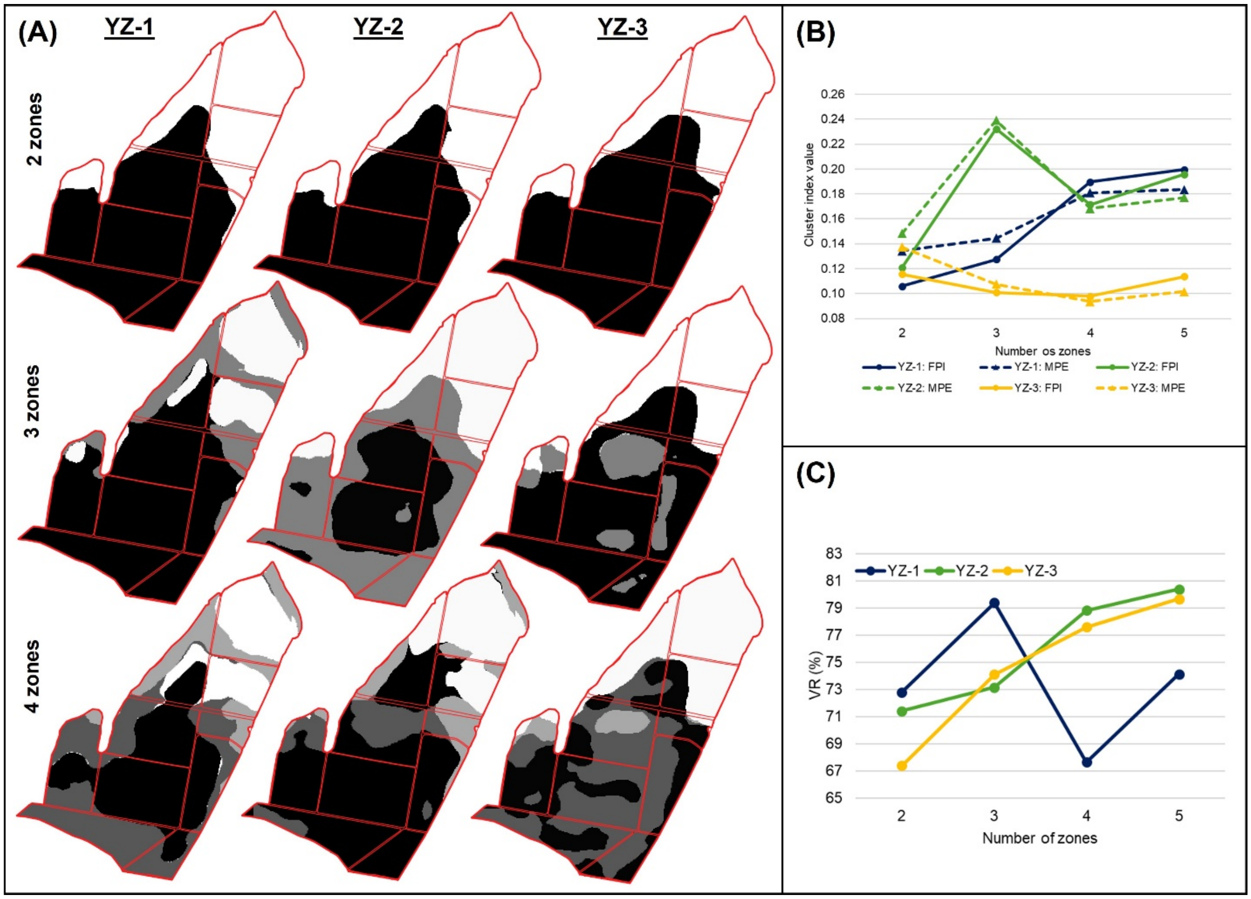


**Fig 5. Yield zones created through three approaches (YZ-1: yield maps; YZ-2: yield maps + standard deviation; YZ-3: average standardized yield + standard deviation for two to four zones (A), cluster quality indices (MPE and FPI) (B), and variance reduction (VR %) of yield data for one to five zones (C).**

The grain yield variability throughout the growth seasons (Fig. 4) and the yield zones obtained with the different approaches (Fig. 5) did not present explicit agreement with the soil maps (pedological classification – 2A; soil color – 2B; electromagnetic induction – Fig. 3; and fertility maps – Fig. 6A). Some points to consider when comparing the yield zones with the soil information: 1) Although Gleysol is morphologically distinct from Latosols and, therefore, has a different yield potential and distinct management demand, the yield zones were not able to identify such soil class; 2) regions with high levels of soil fertility in the surface layer (Fig. 6A) should supposedly be more productive, but this trend was not observed in the study area; 3) regions with high ECa tend to have higher yield potential since it indicates more clayey soil with greater water retention capacity, but this was also not observed. In a way, this relatively low level of agreement between the yield and soil maps is expected since crop productivity depends on several other factors, such as planting quality, pest attacks, weather during the growth season, harvesting efficiency, among others. However, these results show the complexity of agricultural production and how decision-making based on a few production factors can be limited. If the practitioner uses only plant information (yield maps or even vegetation indices from remote sensing), it would not be possible to identify regions with different soils since the plant information layer showed variable behavior within the crop seasons. Therefore, the choice of information layers used in the MZ delineation must be carefully made based on the survey's goals, seeking information layers that complement each other to explain crop productivity and soil characteristics.

Among the seven parameters used to infer soil chemical quality, only one demonstrated excessively variable spatial behavior (available P – Fig. 6A). Evaluating the P map, it is clear that this is an attribute with a highly random distribution, which has already been reported in several studies (Bottega et al., 2013; López-Castañeda et al., 2022). Therefore, this attribute was not considered in the delimitation of soil fertility zones, since MZ with a certain spatial continuity are sought. It is possible to identify two main spatial behaviors when analyzing the other fertility maps: 1) there is a visual relationship between most of the attributes, with a region with higher CEC, OM, SB and K contents in the northern part of the area, mainly Fields 1 and 3, while also presenting higher potential acidity (H+Al), which corresponds to the region with more clayey soil on the surface (Fig. 1B); and 2) there was a region that presented higher pH (Field 4), with values close to the neutrality range (pH between 6 and 7) and, consequently, with lower potential acidity (H+Al), which corresponded to the region with the highest sorghum yield, perhaps because it favors rooting and makes the crop less susceptible to lack of water throughout its growth during the dry season. MULTISPATI-PCA captured precisely these two behaviors by selecting the first two PCs (Table 2), as is evident in the PC score maps (Fig. 6B).

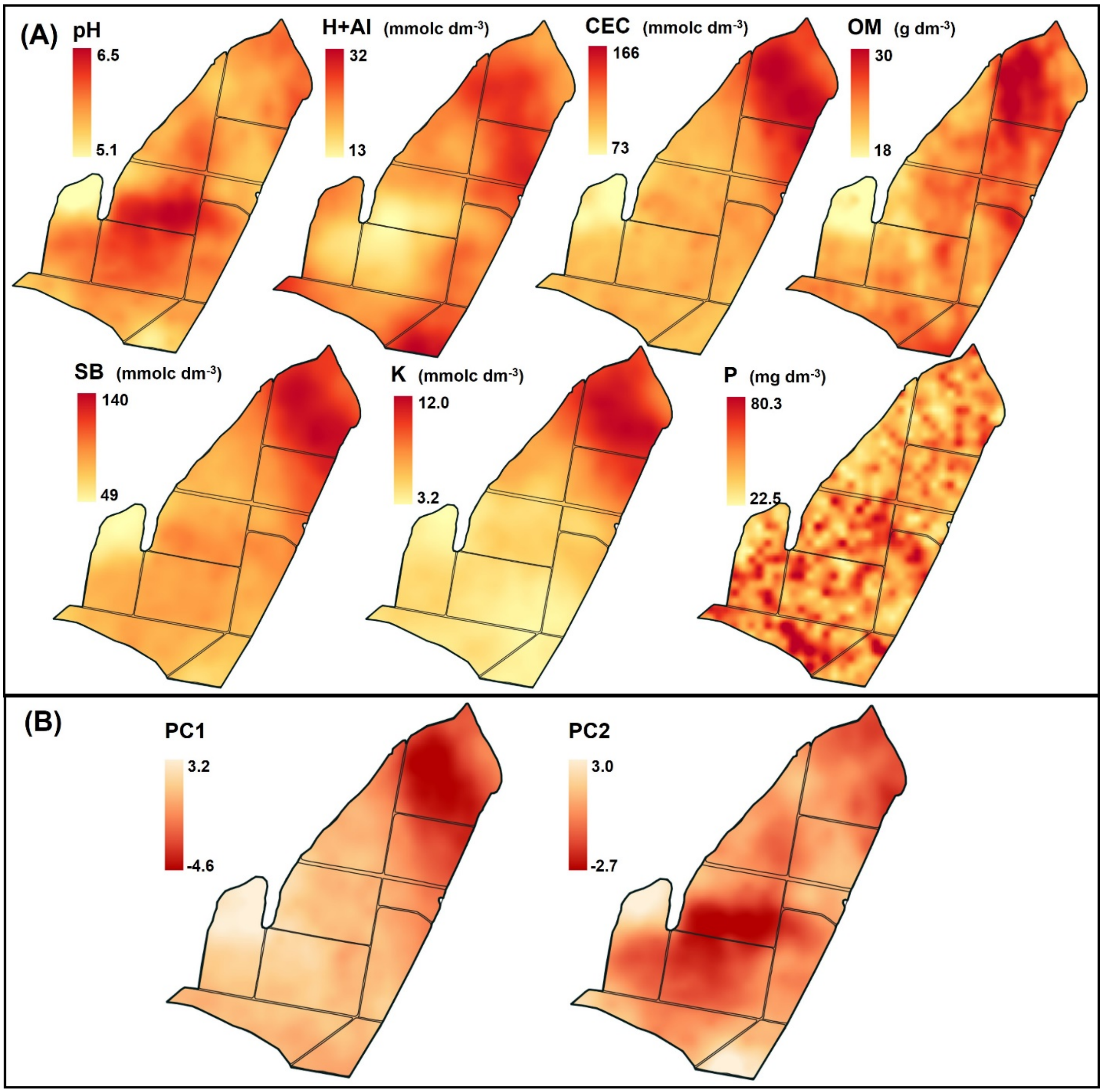


**Fig 6. Soil chemical fertility maps interpolated by ordinary kriging (A) and the score values for Principal Components 1 and 2 (B).**

The EMI sensor measures two signals (ECa and MSa) at two depths each, but the maps of each one were similar (Fig. 3). The PCA corroborated that, as 95% of the total variance was explained by the first PC (Table 2). However, observing the spatial distribution of the EMI maps, it is noted that they were unable to capture the Gleysol region, but it did present a visual relationship with the pattern of high soil fertility (Fields 1 and 3), which is probably due to this region also presenting a higher clay content (Fig. 1B). However, even though the Gleysol region had a lower clay content, the EMI sensor was unable to identify this, resulting in zones that do not include this location (Fig. 7B). In contrast, the bare soil image clearly shows this region (Fig. 2B). This shows that the information present in the different sensing methods is complimentary. Thus, although there are studies that use only the ECa or MSa information to divide soil zones (Moral et al., 2010; Sanches et al., 2022), such variation must be complemented with other information, seeking to contemplate more variability factors in the definition of management zones.

After constructing all these scenarios for delimiting MZa (Fig. 7), it is again clear that such a task is quite variable and challenging. Below are some more observations on the different approaches results:

- Soil fertility zones (SFZ): According to the clustering indices (FPI and MPE – Fig. 8), the area should be divided into two fertility zones, which would present around 60% similarity with the same yield zone. However, taking into account the knowledge already acquired through the exploration of data from different sources, the subdivision of the area into four zones seems to encompass better the variability present within the central zone of the area, mainly composed of Field 4, which presents a different pattern of soil acidity (pH and H+Al) and higher sorghum yield. In addition, it also highlights the Gleysol region and the low average yield in the northern part of the area (Fields 1 and 3).

- Zones obtained with the EMI sensor (EMI): The clustering indices indicate the definition of three zones (Fig. 8). However, even using a larger subdivision (5 zones – Fig. 7B), it is not possible to identify the fertility zones (Fig. 7A) or to have a good relationship with the soil pedological classification (Fig. 2A). This confirms that each technique has its potential to deliver information and their integration is essential to quantify the variability present within the fields.

- Integrative Landscape Approach (ILA): This approach better captured the most contrasting regions within the study area (Fig. 7C), which would be expected since 20 information layers were used, requiring four PCs to represent at least 80% of the data variance (Table 2). When the area was subdivided into four zones (Fig. 7C), it was possible to identify the region composed by the Gleysol, the center of the area with the highest and most variable yield (Field 4), and the north of the area, which presents the highest ECa/MSa and fertility levels (Fields 1-3). Thus, this approach could be adopted to encompass the most significant possible variability of production factors.

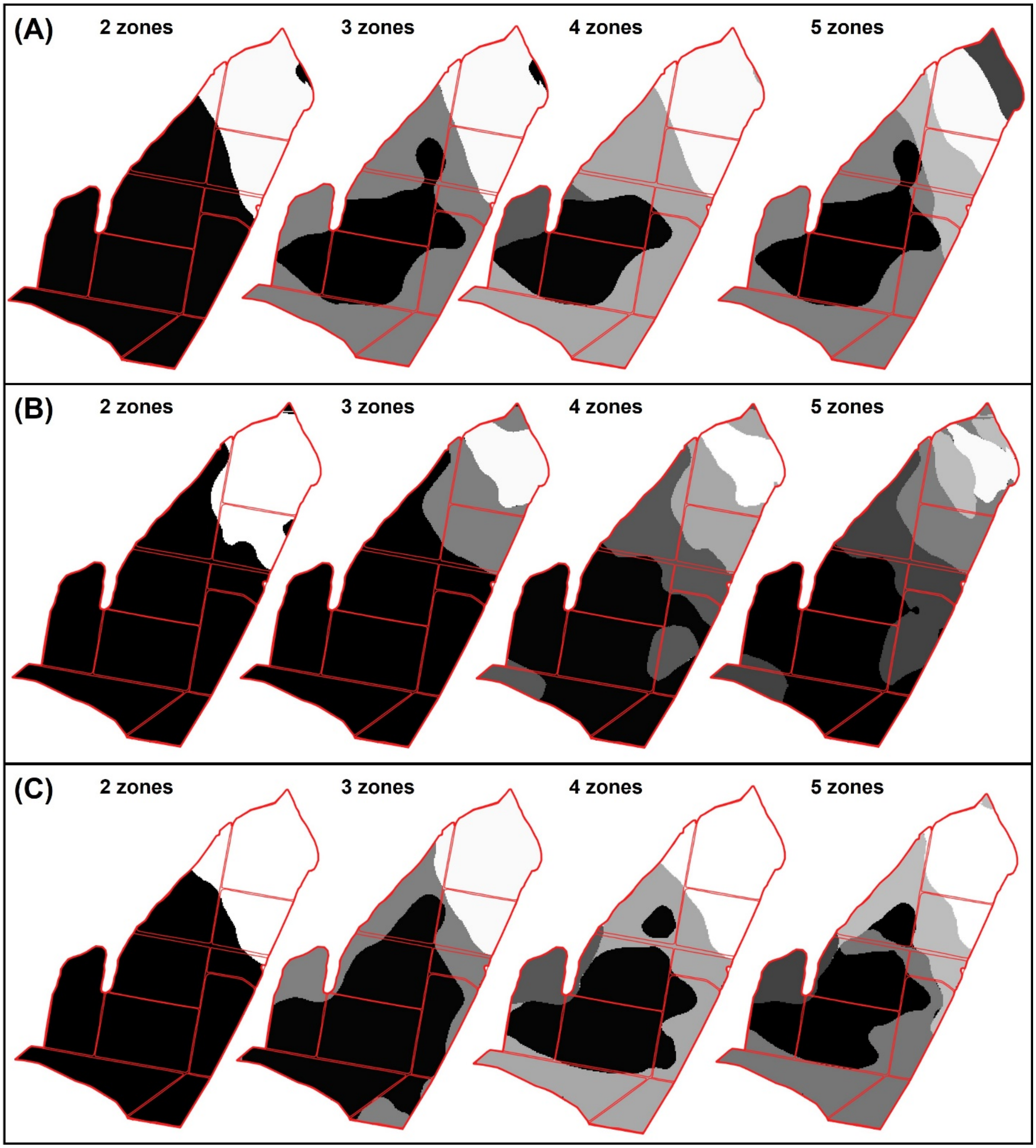


**Fig 7. Management zones (2 to 5 zones) created through three different variable groups: soil fertility maps (A); EMI sensing (B); and the integrative landscape approach (C).**

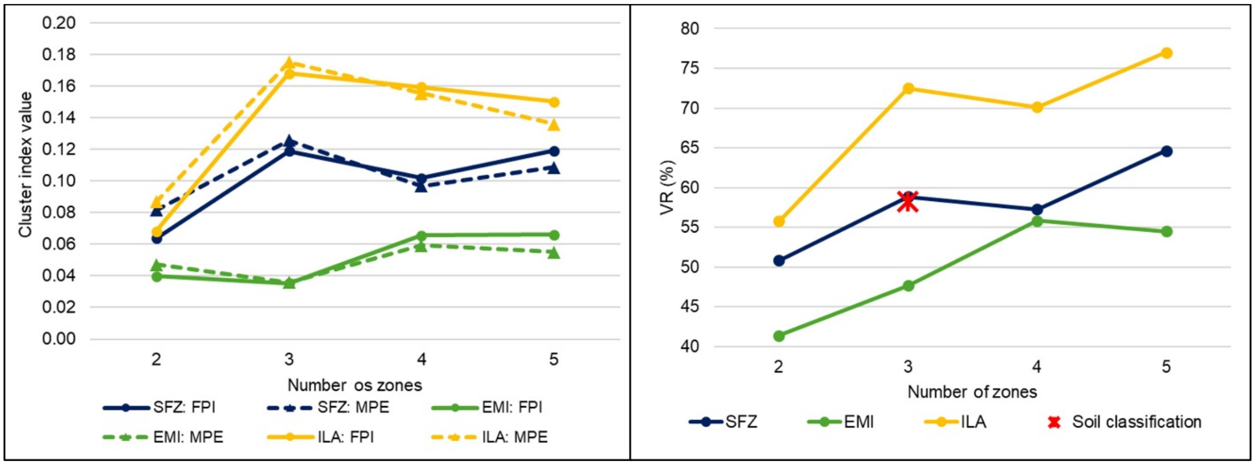


**Fig 8. Cluster quality indices (MPE and FPI) (A) and variance reduction (VR %) of yield data for one to five zones according to the management zones approach (B): soil fertility maps (SFZ), EMI sensing (EMI), and the integrative landscape approach (ILA). Additionally, the VR for the soil classification map is also presented.**

According to the cluster quality indices, based on the SFZ, the area should be divided into two zones; evaluating only the EMI sensor, the ideal would be three zones; for the ILA (with all available data), the best subdivision would be four or five zones. However, we found that none of these combinations of zones satisfactorily covers all the variation in average grain yield over the years: for the SFZ, the VR would indicate the delimitation of three zones, for EMI it would be four zones, and the ILA would indicate the need for five zones. Thus, such results again highlight that the definition of MZ remains challenging, as well as the evaluation of this approach, as there is a lack of studies demonstrating the return generated by this site-specific management. Furthermore, it is a fact that several studies used the reference (or similar) approach that we used here (Gavioli et al., 2016; Miranda et al., 2021; Ouazaa et al., 2022). However, in general, these studies do not demonstrate the impact that slight variations in the process have on the final zoning result, such as the choice of a different information layer or which algorithms and grouping metrics are considered for delimiting the zones. Therefore, any type of proposal for creating MZ is still quite subjective and dependent on the analyst's experience and field checks, in addition to exploring more information layers to determine the best option for each situation. Thus, the path to greater adoption and return on the subdivision of areas into MZ involves the integration of knowledge from pedology and geotechnology, combined with the concepts and tools of precision agriculture.

# Conclusion

Here, we presented several ways of subdividing an agricultural area with a succession of grain crops, including exploration of yield maps, soil taxonomic classification, and soil sampling and sensing techniques. However, despite the range of approaches explored for creating management zones, we found that there is still a long way to go to make this approach suitable so that it becomes less dependent on information layer selection and the analyst's knowledge. Research in this subject needs to focus on integrating tools and knowledge from pedology, geotechnology, and precision agriculture to make it more viable for safe and profitable use by farmers.


## Acknowledgments

The authors would like to thank the owner and manager of the São José farm and everyone who collaborated in data collection. We praise the support from CNPq-Brazil with the Level-2 Productivity Grant to the first author (306867/2022-2) and to São Paulo Research Foundation - FAPESP for financial support for this research (Process number 2022/03160-8). We also thank FAPESP for the scholarship granted to the third author (Process number 2023/02592-4).

## References


Bottega, E. L., Queiroz, D. M., Pinto, F. A. C., & Souza, C. M. A. (2013). Spatial variability of soil attributes in no a no-tillage system with crop rotation in the Brazilian savannah. *Revista Ciência Agronômica*, 44(1), 1–9.

Córdoba, M. A., Bruno, C. I., Costa, J. L., Peralta, N. R., & Balzarini, M. G. (2016). Protocol for multivariate homogeneous zone delineation in precision agriculture. *Biosystems Engineering*, 143, 95–107.

Corwin, D.L. & Lesch, S.M. (2005). Characterizing soil spatial variability with apparent soil electrical conductivity: I. Survey protocols. *Computers and Electronics in Agriculture*, 46(1–3), 103-133.

Demattê, J. A. M., Fongaro, C. T., Rizzo, R., & Safanelli, J. L. (2018). Geospatial Soil Sensing System (GEOS3): A powerful data mining procedure to retrieve soil spectral reflectance from satellite images. *Remote Sensing of Environment*, 212, 161-175.

Doerge, T.A. (2000). *Management Zone Concepts*. Potash & Phosphate Institute, Norcross, GA. Available at: < http://www.ipni.net/publication/ssmg.nsf/0/C0D052F04A53E0BF852579E500761AE3/$FILE/SSMG-02.pdf>.

Dray, S., Saïd, S., & Débias, F. (2008). Spatial ordination of vegetation data using a generalization of Wartenberg's multivariate spatial correlation. *Journal of Vegetation Science*, *19*(1), 45–56.

Gavioli, A., Souza, E. G., Bazzi, C. L., Guedes, L. P. C., & Schenatto, K. (2016). Optimization of management zone delineation by using spatial principal components. *Computers and Electronics in Agriculture*, 127, 302-310.

Gebbers, R., & Adamchuk, V. I. (2010). Precision Agriculture and Food Security. *Science*, 327, 828–831.

Gonzalez, R. C. & Woods, R. E. (2008). *Digital Image Processing* (3rd ed.). Upper Saddle River: Pearson Prentice Hall.

Guastaferro, F., Castrignanò, A., De Benedetto, D., Sollitto, D., Troccoli, A., & Cafarelli, B. (2010). A comparison of different algorithms for the delineation of management zones. *Precision Agriculture,* 11, 600–620.

Javadi, S. H., Guerrero, A., & Mouazen, A. M. (2022). Clustering and smoothing pipeline for management zone delineation using proximal and remote sensing. *Sensors*, 22(2), 645.

Kerry, R., Ingram, B., Oliver, M., & Frogbrook, Z. (2024). Soil sampling and sensed ancillary data requirements for soil mapping in precision agriculture I. delineation of management zones to determine zone averages of soil properties. *Precision Agriculture*, 25, 1181-1211.

Khosla, R., Inman, D., Westfall, D.G. et al. (2008). A synthesis of multi-disciplinary research in precision agriculture: site-specific management zones in the semi-arid western Great Plains of the USA. *Precision Agriculture*, 9, 85–100.

López-Castañeda, A., Zavala-Cruz, J., Palma-López, D. J., Rincón-Ramírez, J. A., & Bautista, F. (2022). Digital mapping of soil profile properties for precision agriculture in developing countries. *Agronomy*, 12(2), 353.

Maldaner, L. F., Molin, J. P., & Spekken, M. (2022). Methodology to filter out outliers in high spatial density data to improve maps reliability. Scientia Agricola, 79(1), e20200178.

Miranda, D. A. R., Alari, F. O., Oldoni, H., Bazzi, C. L., Amaral, L. R., & Magalhães, P. S. G. (2021). Delineation of management zones in integrated crop-livestock systems. *Agronomy Journal*, *113*(6), 5271–5286.

Moral, F. J., Terrón, J. M., & Marques da Silva, J. R. (2010). Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. *Soil and Tillage Research*, 106(2) 335-343.

Nawar, S., Corstanje, R., Halcro, G., Mulla, D., & Mouazen, A. M. (2017). Delineation of soil management zones for variable-rate fertilization: a review. *Advances in Agronomy*, 143, 175–245.

Oliver, M. A. & Webster, R. (2014). A tutorial guide to geostatistics: computing and modelling variograms and kriging. *Catena*, 113, 56-69.

Ouazaa, S., Jaramillo-Barrios, C. I., Chaali, N., Amaya, Y. M. Q., Carvajal, J. E. C., & Ramos, O. M. (2022). Towards site specific management zones delineation in rotational cropping system: Application of multivariate spatial clustering model based on soil properties. *Geoderma Regional*, 30, e00564.

Pebesma, E. J. (2004) Multivariable geostatistics in S: the gstat package. *Computers & Geosciences*, 30, 683–691.

Peralta, N. R. & Costa, J. L. (2013). Delineation of management zones with soil apparent electrical conductivity to improve nutrient management, *Computers and Electronics in Agriculture*, 99, 218-226.

Ping, J. L. & Dobermann, A. (2003). Creating spatially contiguous yield classes for site-specific management. *Agronomy Journal*, *95*(5), 1121–1131.

Raij, B. Van, Andrade, J. C., Cantarella, H., & Quaggio, J.A. (2001). Chemical analysis to evaluate the fertility of tropical soils (Análise química para avaliação da fertilidade de solos tropicais). Instituto Agronomico, Campinas, Brazil. (book in Portuguese).

Ramos, P. V., Inda, A. V., Barrón, V., Teixeira, D. D. B., & Marques, J. (2021). Magnetic susceptibility in the prediction of soil attributes in southern Brazil. *Soil Sci. Soc. Am. J.*, 85, 102–116.

Sanches, G. M., Otto, R., Adamchuk, V., & Magalhães, P. S. G. (2022). Spatial variability of soil attributes by an electromagnetic induction sensor: A framework of multiple fields assessment under Brazilian soils. *Biosystems Engineering*, 216, 229-240.

Santos, H.G., Hochmuller, D.P., Cavalcanti, A.C., Rêgo, R.S., Ker, J.C., Panoso, L.A., & Amaral, J.A.M. (1995). *Normative procedures for soil survey* (Procedimentos normativos de levantamento pedológico). EMBRAPA, Brasília, Brazil. (*in Portuguese*)

Santos, H.G. et al. (2018). Brazilian system of soil classification (Sistema Brasileiro de Classificação de Solos) 5. Ed. EMBRAPA, Brasília, Brazil. (*in Portuguese*)

Serrano, J., Shahidian, S., Marques da Silva, J., Paixão, L., Moral, F., Carmona-Cabezas, R., Garcia, S., Palha, J., & Noéme, J. (2020). Mapping management zones based on soil apparent electrical conductivity and remote sensing for implementation of variable rate irrigation — case study of corn under a center pivot. *Water*, 12(12), 3427.

Shirzaditabar, F. & Heck, R.J. (2022). Characterization of soil magnetic susceptibility: a review of fundamental concepts, instrumentation, and applications. *Can. J. Soil Sci*., 102, 231–251.

Suszek, G., Souza, E. G., Uribe-Opazo, M. A., & Nobrega, L. H. P. (2011). Determination of management zones from normalized and standardized equivalent produtivity maps in the soybean culture. *Engenharia Agrícola*, 31(5), 895–905.