



Management Zone Delineation for Subsoiling Using Apparent Electrical Conductivity, Elevation, and Soil Moisture

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Abstract.

Soil compaction is among the most pervasive forms of physical degradation in mechanized agricultural systems, constraining root elongation, gas exchange, and water infiltration. Apparent electrical conductivity (ECa) is widely used to delineate management zones (MZs) because it integrates key pedophysical attributes; however, its sensitivity to transient soil moisture fluctuations may obscure spatial patterns related to actual compaction status. This study evaluated whether the explicit incorporation of gravimetric soil moisture and digital terrain attributes — derived from a remotely piloted aircraft system (RPAS) equipped with RTK-GNSS — into a Fuzzy K-means clustering framework could improve the capacity of ECa-based MZs to discriminate zones of distinct soil penetration resistance (SPR). The experiment was conducted on a 10.5-ha experimental field in Pitangui, Minas Gerais, Brazil, undergoing transition from pasture to annual crops. Four variable combinations were tested: (i) ECa alone; (ii) ECa + soil moisture (SMC); (iii) ECa + elevation (ALT); and (iv) ECa + SMC + ALT. Cluster solutions with two, three, and four classes were generated and evaluated by their ability to stratify the field according to required subsoiling depth, estimated from cone penetrometer profiles at 31 georeferenced points. The trivariate scenario (ECa + SMC + ALT) consistently produced the greatest between-zone amplitude in mean decompaction depth (>10 cm), outperforming all other configurations. The final four-class map yielded MZs with mean intervention depths of 23, 27, 29, and 35 cm, substantiating the need for zone-specific tillage prescriptions. These findings demonstrate that decoupling the transient moisture signal from ECa data — while concurrently incorporating topographic gradients that drive particle redistribution — materially enhances the agronomic representativeness of MZs for site-specific soil mechanical management.

Keywords.

soil compaction; apparent electrical conductivity; management zones; Fuzzy K-means; precision agriculture; penetration resistance; RPAS; terrain attributes.

INTRODUCTION

Soil is a non-renewable resource on human timescales, performing critical ecosystem functions that underpin agricultural productivity, including water regulation, nutrient cycling, and structural support for root systems (Doran; Parkin, 1994). Intensive mechanized operations, however, exert substantial compressive stress on the soil matrix, leading to structural deterioration characterized by increased bulk density, reduced macroporosity, and elevated soil penetration resistance (SPR). These alterations impair water infiltration, restrict gaseous exchange, and limit root elongation — collectively depressing crop yields and accelerating erosion processes (Bicki; Siemens, 1991).

Compaction is inherently spatially heterogeneous across cultivated fields, being modulated by both extrinsic factors — notably the intensity and frequency of applied mechanical loads — and intrinsic pedophysical properties, including antecedent moisture content, soil texture, and structural stability (Richart et al., 2005). Superimposed on these drivers, landscape relief amplifies spatial variability by governing erosion dynamics and the differential redistribution of fine particles along hillslope gradients, thereby indirectly conditioning porosity and compaction distribution (Valtera et al., 2015). Characterizing this variability is a prerequisite for targeted mechanical interventions, and SPR mapping has emerged as a practical tool for informing site-specific tillage management decisions (Chig; Oliveira; Crestani, 2014).

Within precision agriculture frameworks, management zone (MZ) delineation offers a means to partition fields into spatially contiguous sub-regions of relatively homogeneous characteristics, enabling the application of zone-differentiated input rates and agronomic practices (Rodrigues Junior et al., 2011). Apparent electrical conductivity of the soil (ECa) has been widely adopted for this purpose, as it provides a continuous, non-invasive spatial signal that integrates attributes such as clay content, salinity, and volumetric water content (Molin; Amaral; Colaço, 2015). Nevertheless, ECa is strongly influenced by transient soil moisture conditions (Rhoades, 1993), which may mask or confound the textural and structural signals relevant to compaction assessment. Concurrently, topographic position influences moisture redistribution and fine-particle accumulation in lower-lying areas, further modulating ECa values and the compaction susceptibility of the soil (Valtera et al., 2015).

Despite the widespread use of ECa for MZ delineation, critical knowledge gaps remain regarding the systematic integration of soil moisture and terrain variables to produce MZs that more faithfully represent the spatial distribution of actual compaction. The present study was designed to address this gap by investigating whether the concurrent incorporation of gravimetric soil moisture data and digital elevation model (DEM) derivatives into a multivariate clustering algorithm generates MZs with superior capacity to discriminate zones of distinct compaction severity, relative to ECa-only and bivariate approaches.

MATERIAL AND METHODS

The experiment was conducted on a 10.5-ha field at the Instituto Tecnológico em Agropecuária de Pitangui (ITAP), managed by the Empresa de Pesquisa Agropecuária de Minas Gerais (EPAMIG), located in the municipality of Pitangui, Minas Gerais, Brazil (19°42'39" S; 44°54'20" W). The field was undergoing the conversion from degraded pasture to annual cropping systems, a transition that commonly involves significant soil disturbance legacy and mechanization-induced compaction. The soil was classified as a Hapludult (Argissolo Vermelho-Amarelo Distrófico in the Brazilian Soil Classification System), characterized by a texture gradient between the A and B horizons.

Apparent electrical conductivity of the soil was measured in the 0–0.25 m depth layer using a Terram® electromagnetic induction sensor (Falker Automação Agrícola, Porto Alegre, Brazil). All georeferenced ECa measurements underwent a two-stage quality control procedure. In the first

stage, negative values, null readings, and statistical outliers exceeding two standard deviations from the mean were removed using the Pandas library (Python/Spyder environment). The second stage consisted of a geostatistical filtering based on the Local Moran's Index (LISA) implemented in GeoDa software, applying an inverse distance weight matrix with a bandwidth of 9 m, corresponding to the inter-pass spacing of the tractor during data acquisition. This procedure effectively eliminated spatial anomalies attributable to sensor noise or abrupt operational conditions.

Gravimetric soil moisture content (SMC) was determined by the standard oven-drying method (105–110 °C, 48 h) on samples collected from the 0–0.25 m layer. Sampling was conducted on a regular grid with 58 × 58 m spacing, totalling 31 georeferenced points. Moisture content was calculated as the mass ratio of water to oven-dry soil, expressed as a percentage ($\text{g g}^{-1} \times 100$).

Soil penetration resistance was measured at the same 31 grid points using a digital recording cone penetrometer (SoloStar PLG5500, Falker), equipped with a Type 2 cone with a 13.5-mm base diameter and 30° semi-included angle, per ASABE S313.3 specifications. Readings were recorded at 1-cm depth increments to a maximum depth of 40 cm. A critical threshold of 2,000 kPa was adopted as the limiting value for root elongation of annual crops (Sá et al., 2005). The required decompaction depth at each sampling point was operationally defined as the deepest depth at which SPR equalled or exceeded this threshold, representing the minimum tillage depth necessary to alleviate root-restricting compaction at that location.

Topographic data were obtained via aerial survey using a DJI Mavic 3M remotely piloted aircraft system (RPAS) equipped with a multispectral sensor and an integrated RTK-GNSS module. The flight was conducted at 120 m above ground level with 70% lateral and 80% frontal image overlap. A digital elevation model (DEM) was generated through photogrammetric processing in Agisoft Metashape Professional software using Structure-from-Motion (SfM) algorithms. Point cloud densification, mesh generation, and DEM export followed standard photogrammetric workflows.

The spatial dependence of ECa and SMC was assessed using the Global Moran's I index (pseudo-p-value, $\alpha = 0.05$). Variables exhibiting statistically significant spatial autocorrelation were interpolated onto a regular grid via ordinary kriging (OK) using the Smart Map plugin for QGIS. Terrain elevation values were extracted directly from the DEM at locations coinciding with the kriged grid nodes, eliminating the need for additional interpolation of topographic data.

Management zones were delineated using the Fuzzy K-means clustering algorithm, which allows partial membership of observations in multiple clusters — a property particularly suited to the continuous and overlapping nature of soil attribute variation. Cluster solutions with 2, 3, and 4 classes were tested for four variable combinations: (i) ECa alone; (ii) ECa + SMC; (iii) ECa + elevation (ALT); and (iv) ECa + SMC + ALT. The quality of each scenario in partitioning the field according to compaction severity was evaluated by extracting SPR sampling points within each zone boundary and computing the mean and standard deviation of the required decompaction depth per zone. Scenarios yielding greater between-zone differences in mean decompaction depth and lower within-zone standard deviations were considered superior for characterizing spatial compaction variability.

In post-processing, polygons with an area below 1,000 m² were merged into the adjacent zone exhibiting the greatest mean decompaction depth. This conservative approach minimized spatial fragmentation, improved operational compatibility with agricultural machinery, and ensured that no area requiring deeper tillage intervention was inadvertently underestimated.

RESULTS AND DISCUSSION

Following quality control procedures, ECa values ranged from 1.6 to 9.0 mS m^{-1} , with values predominantly concentrated between 2.5 and 5.0 mS m^{-1} (mean $\approx 4.0 \text{ mS m}^{-1}$; SD = 1.0 mS m^{-1}). The interpolated ECa map revealed a spatially structured pattern, with values near the field mean distributed across most of the area and localized elevated readings ($>6.0 \text{ mS m}^{-1}$) concentrated in the lower-left portion and in scattered patches in the upper and central sectors (Figure 1).

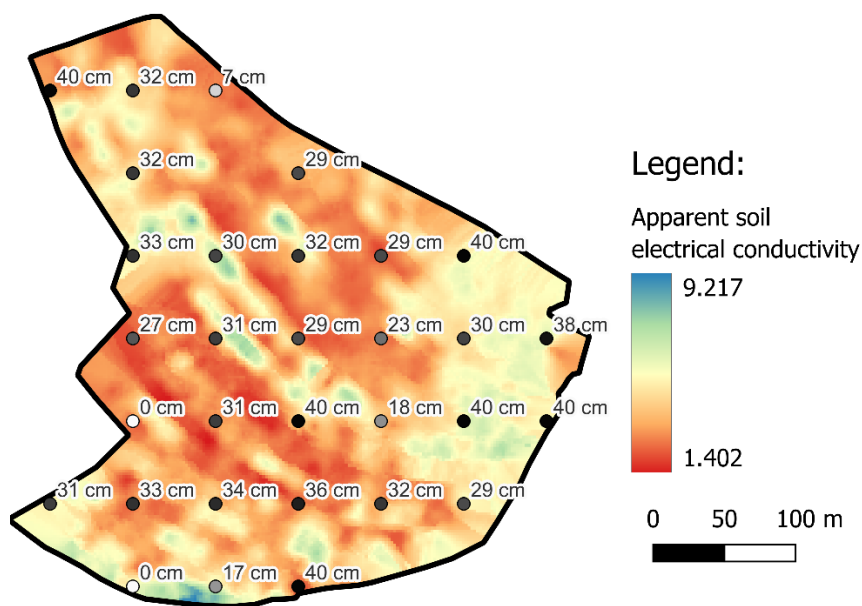


Figure 1 — Interpolated ECa map and required decompaction depths at sampled points

The observed ECa spatial pattern is consistent with heterogeneous pedophysical conditions that modulate soil electrical conductivity, including variability in clay content, organic matter, and volumetric water content (Molin; Amaral; Colaço, 2015). Zones with ECa exceeding 6.0 mS m^{-1} may be associated with elevated clay fractions or impeded drainage conditions, both of which promote water retention and enhanced electrical conductance (Corwin; Lesch, 2005). Critically, given that soil moisture is among the primary determinants of ECa (Rhoades, 1993), the observed spatial pattern may partly reflect temporal water content fluctuations at the time of sampling rather than permanent pedophysical attributes. This observation underscores the rationale for explicitly incorporating moisture as an independent covariate in the MZ delineation process to disentangle its transient signal from the permanent structural properties underpinning compaction.

Spatial autocorrelation analysis of SPR data yielded a non-significant Global Moran's I (pseudo- $p > 0.05$), precluding geostatistical interpolation and indicating that compaction exhibited a spatially random distribution at the scale of the adopted sampling grid. This randomness likely reflects fine-scale variability driven by localized factors — such as heterogeneous traffic patterns, micro-topographic irregularities, and point-scale moisture conditions at the time of soil trafficking — that operate at spatial scales below the $58 \times 58 \text{ m}$ grid spacing (Richart et al., 2005; Valtera et al., 2015). The marked variability in required decompaction depths across sampling points highlighted the necessity of field partitioning into sub-management units with differentiated tillage prescriptions.

The mean SPR depth profile revealed pronounced compaction in the surface layer, with a peak near 5 cm depth where mean SPR substantially exceeded the 2,000 kPa critical threshold (Figure 2). Mean SPR remained above this limit to approximately 32 cm depth, indicating that mechanical intervention requirements extend well into the subsoil — beyond the effective working depth of conventional chisel plows.

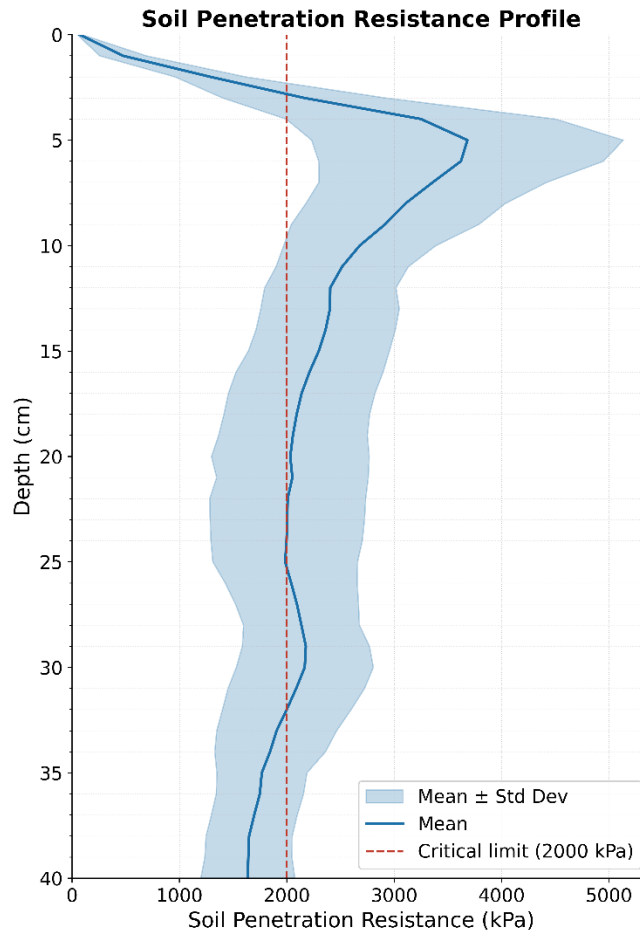


Figure 2 — Mean SPR depth profile across all sampling points

The intensity and depth of compaction in the surface layer is attributable to the history of unmanaged continuous livestock grazing. Repeated animal treading exerts cyclical impact loads on the soil surface, progressively reducing macropore continuity, compressing aggregates, and consolidating the upper soil horizon (Cunha et al., 2009). The resulting structural degradation impairs macroporosity and saturated hydraulic conductivity, creating root-restricting conditions for subsequent annual crops (Fagundes; Silva; Bonfim-Silva, 2014). The persistence of critical SPR to 32 cm on average implies that remediation may require subsoilers operating at depths that exceed those achievable with standard chisel plows, necessitating site-specific calibration of tillage implements.

Gravimetric soil moisture content ranged from 16% to 23% in the 0–0.25 m layer, exhibiting a well-defined spatial pattern: moisture contents above 20% were concentrated in the upper portion of the field, whereas values below 18% predominated in the lower terrain positions. The higher moisture content at elevated topographic positions suggests a concurrent influence of soil texture — specifically elevated clay content — on water retention capacity, as fine-textured soils exhibit greater field-capacity water storage (Tormena; Silva; Libardi, 1998). This interpretation is supported by the spatial coincidence of patches with $\text{ECa} > 6.0 \text{ mS m}^{-1}$ and areas with $\text{SMC} > 20\%$, indicating a plausible co-variation among clay fraction, moisture content, and electrical conductance.

Terrain elevation ranged from 630 to 660 m a.s.l., with a mean slope of approximately 7%, classifying the landscape as gently undulating (EMBRAPA, 2021). Although the absolute altitudinal range of 30 m is moderate, slope gradients in this range are sufficient to drive selective laminar erosion and the differential downslope translocation of fine soil particles, altering texture and porosity gradients along the hillslope and indirectly modulating compaction susceptibility

(Valtera et al., 2015; Fanning; Fanning, 1989). These complementary spatial patterns of moisture and terrain attributes provided the empirical basis for hypothesizing that their explicit incorporation into the clustering framework would enhance the pedophysical representativeness of the resulting MZs.

Management zones with 2, 3, and 4 classes were generated for all four variable combinations. Visual comparison of the four-class maps revealed substantial differences in the spatial configuration of zones across scenarios (Figure 3). The trivariate scenario (ECa + SMC + ALT) produced a spatially coherent pattern with greater zonal continuity, and the zone boundaries exhibited perceptible correspondence with observed topographic gradients and moisture distribution patterns. In contrast, the ECa-only, ECa + SMC, and ECa + ALT scenarios generated zones with less spatial coherence relative to the measured pedophysical characteristics of the terrain.

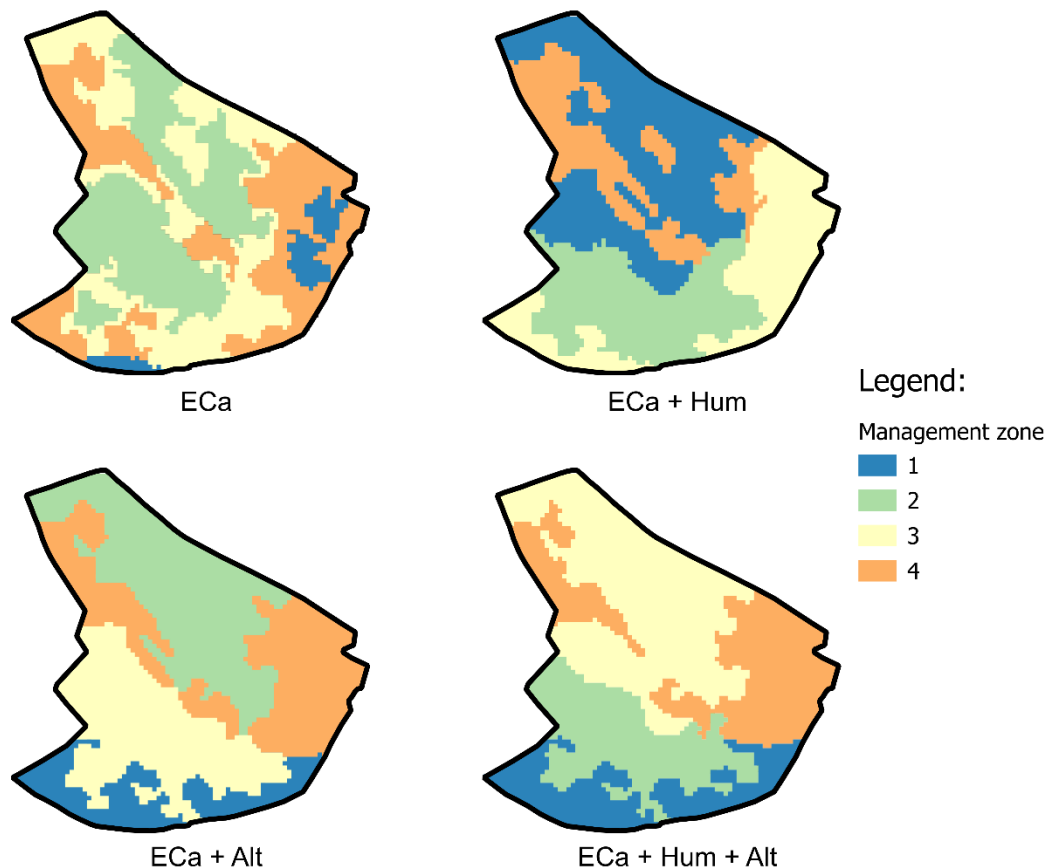


Figure 3 — Comparative MZ maps (4-class solution) for the four variable combination scenarios

Quantitative evaluation based on the mean required decompaction depth within each zone corroborated this pattern (Figure 4). The trivariate combination (ECa + SMC + ALT) consistently yielded the greatest between-zone amplitude in mean decompaction depth — with differences between class means exceeding 10 cm — across all cluster configurations. In the univariate and bivariate scenarios, between-zone differences in mean decompaction depth were typically below 5 cm, substantially limiting their practical utility for prescribing differentiated tillage depths.

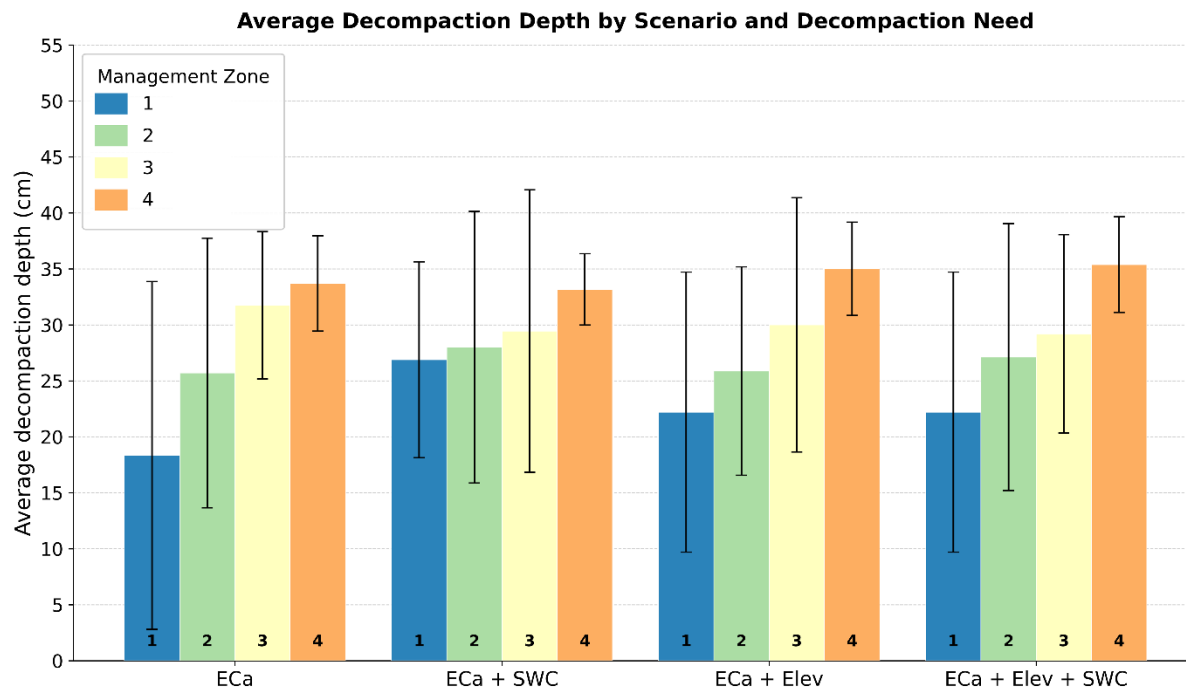


Figure 4 — Mean required decompaction depth per MZ for the four scenarios (4-class solution)

These results demonstrate that ancillary variables provide spatial information that ECa alone cannot adequately capture. While ECa integrates pedophysical attributes including texture, salinity, and moisture (Corwin; Lesch, 2005), when moisture varies spatially — as observed here, with a 7 percentage-point range across the field — it introduces a spatially structured signal that may confound compaction-related patterns (Rhoades, 1993). By treating SMC as an independent dimension in the Fuzzy K-means clustering, the algorithm effectively partitioned moisture-driven variability from compaction-related variability, improving the correspondence between MZ boundaries and actual compaction severity. Similarly, the incorporation of elevation data — with a 30-m range across the field — provided information on topographic gradients that govern differential particle redistribution and moisture dynamics along the hillslope (Valtera et al., 2015). These are precisely the processes that indirectly determine compaction susceptibility but that ECa alone does not represent with sufficient spatial fidelity.

All scenarios exhibited elevated within-zone standard deviations for the required decompaction depth, reflecting substantial intra-zone variability. This behaviour is largely attributable to the low SPR sampling density — 31 points across 10.5 ha, corresponding to approximately one observation per 3,387 m² — which yields few observations per zone as the number of classes increases, diminishing the statistical representativeness of zonal mean estimates and inflating standard deviations. Increasing the penetrometer sampling density and incorporating attributes with well-documented relationships to soil compaction — such as clay fraction and bulk density — could mitigate this limitation and improve the statistical robustness of the clustering outcomes (Khosla et al., 2010).

Following spatial post-processing, the final MZ map consolidated four spatially contiguous zones with mean required intervention depths of 23 cm (MZ 1), 27 cm (MZ 2), 29 cm (MZ 3), and 35 cm (MZ 4). The conservative approach of merging fragmented polygons into adjacent zones with the greater decompaction requirement ensured that no area with deeper intervention needs was underestimated, preserving agronomic safety and reducing operational interruptions for implement adjustment.

The 12-cm amplitude between mean decompaction depths across zones — ranging from 23 cm (MZ 1) to 35 cm (MZ 4) — substantiates the spatial heterogeneity of compaction across the field and clearly demonstrates the inadequacy of uniform tillage management. A uniform prescription

calibrated to the maximum depth requirement (35 cm) would entail unnecessary mechanical disturbance and energy expenditure in MZ 1, where 23 cm is sufficient. Conversely, a prescription based on the field-mean depth (≈ 32 cm) would leave MZ 4 inadequately treated, compromising root system establishment and crop performance. Importantly, MZ 4 — with a mean intervention depth of 35 cm — necessitates the deployment of a subsoiler rather than a chisel plow, as the required working depth exceeds the operational range of the latter. This distinction has direct implications for machinery selection, tractor power requirements, fuel consumption, and cost-effectiveness of the mechanical operation (Chig; Oliveira; Crestani, 2014). The adoption of MZ-based prescriptions for site-specific subsoiling represents a tangible operational and agronomic gain, aligned with the principles of precision agriculture and site-specific soil management (Bernardi et al., 2014; Fu et al., 2010).

CONCLUSIONS

The integration of gravimetric soil moisture and terrain elevation with apparent electrical conductivity in a Fuzzy K-means clustering framework proved to be an effective strategy for improving the delineation of soil compaction management zones. The trivariate scenario (ECa + SMC + ALT) consistently outperformed univariate and bivariate alternatives in discriminating zones with distinct required decompaction depths, confirming the central hypothesis of this study.

The final four-class MZ map generated by the ECa + SMC + ALT scenario produced zones with mean intervention depths ranging from 23 to 35 cm — a 12-cm amplitude that underscores the spatial heterogeneity of compaction across the study area and substantiates the need for zone-differentiated tillage prescriptions. A uniform management approach would result in operational inefficiency and inadequate compaction relief in the most severely affected zones.

The primary limitation of the study was the low SPR sampling density, which resulted in elevated within-zone variability and reduced the statistical power of between-scenario comparisons. Future research should employ higher-density penetrometer sampling designs and incorporate complementary soil physical attributes — notably clay fraction and bulk density — to enhance zonal delineation accuracy and increase confidence in zone-specific tillage depth prescriptions. Additionally, the temporal stability of the proposed MZs across seasons and crop cycles warrants investigation to establish their robustness as decision-support tools in precision agriculture systems.

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