ICPA
17th INTERNATIONAL CONFERENCE ON PRECISION AGRICULTURE
ConBAP 2026
CONGRESSO BRASILEIRO DE AGRICULTURA DE PRECISÃO E DIGITAL
13-16 July 2026 | Porto Alegre, Brazil
ISPA AsBraAP

A paper from the Proceedings of the
17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture
13-15 July 2026
Porto Alegre, Brazil

RELATIONSHIP BETWEEN TEMPORAL VARIABILITY OF SOYBEAN YIELD AND STABLE SOIL ATTRIBUTES

Gabriel K. Seganfredo[1], Luiz G. Kern[1], Luiz F. Pavão[1], André Müllich[1], Emanoel Silva[1], Ivan C. Maldaner[1], Jaqueline Sgarboza[1], Luciano Z. Pes[1], Marcelo S. Farias[1]

[1] Graduando em Agronomia, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (42) 99154-6317, gabrielkseganfredo@gmail.com.

[1] Pós Graduando em Agricultura de Precisão, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (51) 98056-4521, kernluizgustavo@gmail.com.

[1] Pós Graduando em Engenharia Agrícola, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 99152-2828, felipepavao14@gmail.com.

[1] Pós Graduando em Agricultura de Precisão, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 99665-0633, andre.mullich@hotmail.com.

[1] Graduando em Agronomia, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 9713-2400, emanoelrolim80@gmail.com.

[2] Professor Dr. Eng. Agrícola, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 99694-3096, ivan.maldaner@ufsm.br.

[2] Professor Dr. Agronomia, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 99637-8482, sgarbossa.jaqueline@ufsm.br.

[2] Professor Dr. Ciência do Solo, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 99631-7788, lucianopes@politecnico.ufsm.br.

[2] Professor Dr. Agronomia, Depto. de Ensino, Colégio Politécnico, Universidade Federal de Santa Maria, UFSM, Santa Maria, RS, Fone: (55) 99104-7258, Marcelo.farias@ufsm.br.

Abstract.

Management zones are widely used in precision agriculture and can be defined by different factors; however, uncertainties remain regarding their temporal stability when based on a single soil attribute. This study aimed to analyze the relationship between a temporal series of yield from five agricultural fields and four stable soil attributes—clay content, soil organic matter (OM), Topographic Wetness Index (TWI), and apparent electrical conductivity (ECa)—using multiple linear regression and Pearson correlation of residuals.

The study was conducted in an experimental area of the Federal University of Santa Maria (UFSM) and used 28 soybean yield maps from 2011 to 2019 obtained via yield monitor, physical and chemical soil analysis results from 2012 and 2017 sampling campaigns, ECa data, a digital elevation model for TWI generation, and meteorological data. Yield data for each field and year were converted into relative yield (RY) to normalize interannual variability and allow comparisons among fields. Mean yield and TWI values within buffers, aiming at spatial representativeness, were associated with soil sampling points for correlation analysis. The model was structured to explain RY as a function of chemical attributes, so that the residuals represented variability associated with physical and structural soil factors. This approach enabled correlation with stable soil attributes while statistically removing the direct influence of chemical factors. The model was applied under different spatial data grouping strategies, including both individual and combined analyses across fields. For the two fields with ECa data, correlations with yield were performed locally by associating values with buffers, as done for the other attributes, and across the entire field extent, with analyses stratified by field and jointly between them.

In the joint analysis of the five fields, some significant correlations were found, but no consistent response pattern of attributes across the temporal series was observed. In individual field analyses, each field showed temporal trends that were not repeated in others and depended on seasonal water availability. However, for ECa—both in localized analyses and across the whole field—the correlation with yield showed an overall negative trend throughout the series, regardless of rainfall conditions. When considering the entire field extent, this trend became more evident, and all correlations were significant, averaging −20% in the combined analysis and −23% and −17% in the individual analyses. Thus, ECa was the only attribute that remained relatively consistent under different climatic conditions and production environments, reflecting stability across analyses. The results indicate variability in the relationships between certain soil attributes and yield, highlighting ECa as a more consistent indicator of yield potential compared with other isolated attributes, demonstrating its potential for delineating management zones.

Keywords.
Apparent electrical conductivity, soil attributes, time series, spatial variability, management zones.

Introduction

Site-specific crop management has established itself as an ecologically and economically sustainable solution to the constant pressure for profitability and lower environmental impact in agricultural production. There is a growing demand for strategies that optimize profit margins without compromising environmental sustainability. At the same time, farmers seek management practices that maintain and increase profitability. In this sense, this practice not only allows for savings on inputs but also prevents them from being used excessively and running the risk of being leached.

It is well known that the soil is not a homogeneous environment and that its variations impact crop yield. As described by Rabello (2014), the spatial variability of production stems from inherent soil factors (morphological, nutritional), the biological complex of the system, anthropic interference (such as compaction, machinery traffic), topography, and climate. With the exception of climate, all these factors are, to some extent, related to soil properties and contribute to spatial variability. Thus, it is of fundamental importance to understand the relationship between yield and inherent soil factors in order to establish effective site-specific management zones.

Different methods have been employed to analyze soil variability, focusing on the different attributes to be analyzed. Georeferenced soil sampling aims to understand the spatial dispersion of different chemical and physical soil attributes, such as texture and the mineral components of fertility. Apparent soil electrical conductivity (ECa) is another attribute linked to the soil's water retention capacity and fertility. The spatial analysis of ECa has been highlighted for being a low-cost process, offering greater speed when compared to the previous method, and presenting a behavior of low temporal change (Moral et al., 2010). Less commonly used for this purpose, the Topographic Wetness Index (TWI) indicates the probability of an area accumulating water in a given relief, and it has already been demonstrated that it has a direct relationship with expected yield loss in flooding situations (Smith et al., 2021).

Given this context, the present study aimed to analyze the relationship between the temporal variability of soybean yield and stable soil attributes. To do so, it correlated a historical series composed of 28 soybean yield maps with attributes of greater temporal stability, namely clay, organic matter (OM), cation exchange capacity (CEC), TWI, and ECa.

Materials and methods

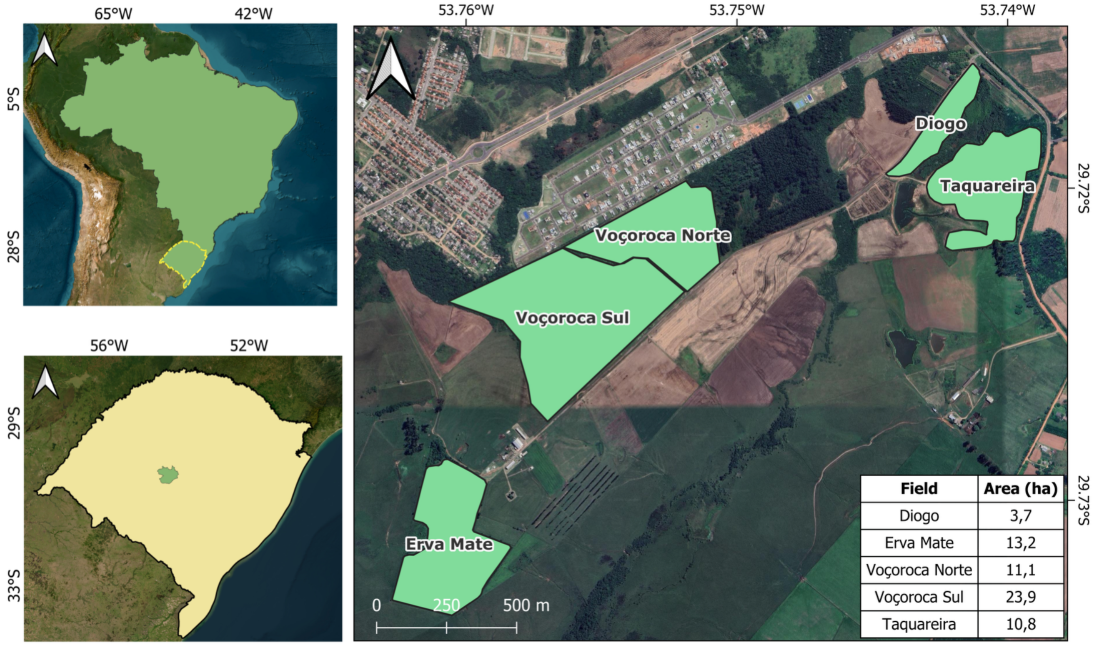
Study area

The study was conducted in the agricultural area of the Colégio Politécnico of UFSM (Federal University of Santa Maria). The area is located in the municipality of Santa Maria, in the central region of the state of Rio Grande do Sul, Southern Brazil, at coordinates 29°S, 53°W. The climate of the region is Cfa, according to the Köppen climate classification, characterized as humid subtropical, presenting average temperatures of 24°C in the summer and 18°C in the winter, with an average annual precipitation of 1778 mm (INMET). The area belongs to the Colégio Politécnico and is used for practical training of students under conditions that simulate commercial farming systems. The cultural practices and mechanization used represent typical annual grain production in the region, with soybean and winter crops under a rainfed system.

Five fields on the property, located close to one another, were selected. They feature a soil classified as Argissolo vermelho alumínico, in a survey conducted by IBGE at a 1:250,000 scale (BDiA), this classification is according to the Brazilian Soil Classification System and corresponding to an Ultisol class of Soil Taxonomy (Embrapa). The total area occupied by the selected fields is 62,7 ha, with the largest being 23,9 ha and the smallest 3,7 ha (Figure 1).

The yield maps available between the 2010/2011 and 2018/2019 harvest seasons were chosen, designated by the year they were harvested (2011-2019). Among these maps, soybean was the selected crop, as it was the most planted during the period. In total, 28 soybean yield maps were used in the study.

Fig 1. Location of the property.



Data collection, processing, and analysis

Yield data were obtained by a self-propelled grain harvester equipped with yield, moisture, position, and header sensors, recording data approximately every 2 meters. This data was extracted and exported to the precision agriculture platform Sensix FieldScan, which performed outlier elimination, yield correction to 13% moisture, kriging interpolation, and the generation of harvest maps. The data was downloaded in shapefile format, containing 2,500 yield points per hectare already corrected for moisture. The Sensix FieldScan platform was chosen over manual processing due to the software's efficiency in data cleaning and because this tool was available for the Advanced Farm 360 project. To spatially analyze the yield results alongside the attributes in the field, the average of the yield values in 40-meter buffers around the sampling grid points was used. Thus, the soil values of each sampling point could be analyzed with the average yield within a 40-meter radius.

Soil sampling was performed in a georeferenced manner by the precision agriculture company Drakkar, using a regular grid sampling method of 1 point per hectare at a depth of 0 - 20 cm. Consequently, the number of collection points in the fields varied from 3 in the Diogo field to 23 in the Voçoroca Sul field, totaling 62 points used. The samples were analyzed at the UFSM soil analysis laboratory, which follows the extraction methods indicated for interpretation by the Fertilization and Liming Manual of RS and SC (SBCS, 2016). These were conducted in the years 2012 and 2017, after the soybean harvest, utilizing the same sampling grid. Thus, the values correspond to the soil's nutritional condition in the previously harvested seasons, including the season designated by the collection year. According to the interpretation suggested by the manual, the levels of P (phosphorus) and K (potassium) were classified into classes: very low, low, medium, high, and very high, based on the levels of each nutrient and the clay and CEC levels. To accurately define these classes, the values used were those reported in the individual analysis for each point collected in that same year. However, for the subsequent correlation of yield with stable soil attributes, it was standardized that the physical levels (clay, OM, and CEC) used at each sampling point would be those reported in the 2017 analysis, as there were minor differences in these values between the 2012 and 2017 analyses due to random errors stemming from sampling and analysis.

The Topographic Wetness Index (TWI) data were obtained through processing in the QGIS software based on the Copernicus Global DSM 30m digital surface model (DSM) extracted from each field. Although the DSM did not have high spatial resolution (30 meters), the analysis was not compromised. To correlate this attribute and compare it with the soil analysis attributes (clay, OM, and CEC), it was necessary to calculate the average at the points present within a 40 m radius of each point on the sampling grid.

The apparent soil electrical conductivity (ECa) data were obtained by a Veris equipment coupled to a tractor and measured at a depth of 0-20 cm. The entire length of the field was covered to measure values every 3 meters, thus creating a point file with a resolution similar to that of the yield files. Data collection was performed in a period subsequent to the yields analyzed in this study, in the year 2022; however, due to the temporal stability of this attribute, the analysis was not compromised. Still, only the Erva Mate and Taquareira fields had their data collected, as the others were no longer in use at the time of this data collection. Thus, it was only possible to perform the analyses with ECa in these two fields.

Data on the loss of yield potential due to the water conditions of the harvest season were extracted from the SISDAGRO software, which utilizes historical meteorological data from INMET. It calculates the crop's climatological water balance based on the planting date and cycle, thereby providing estimated values of yield potential loss.

Aiming to understand the correlation of yield with stable soil attributes without the interference of fertility, a multivariate linear regression model was used to estimate the interference of fertility on yield in each of the fields for each season, so that it could be excluded prior to the correlation analysis. Thus, we sought to create a model that attempted to estimate the interference of soil fertility and established that the residual, or the error of the model, was precisely the actual yield without chemical interference. This model was developed in the R software using the "stats" library. It was identified that soil fertility affected yield through three main factors: phosphorus (P) availability, potassium (K) availability, and soil pH.

To enable the comparison of yield values between points within the fields with the other attributes proportionally to the production of each season, Relative Yield (RY) values were used for each field. First, a reference maximum yield is established based on the upper 95th percentile of yield observations, where RY = 100%. Then, the average yield values of the buffers defined at each point of the sampling grid are selected and compared with the field's maximum potential value to be transformed into RY.

The interference of nutrient levels in the soil does not follow a linear behavior with yield, but rather an asymptotic exponential curve, as demonstrated by Mitscherlich's Law (response curve), and may even present a decrease due to toxicity at high concentrations. However, the pH level in the soil does not exhibit the same behavior regarding yield, generally being described as an inverted parabola. Therefore, to make it possible to use a linear regression model, it was necessary to interpret these levels and assign them different weights. Another alternative would be the use of non-linear multivariate regression models; however, this would require analyzing curves with different characteristics, which would make the analysis even more complex. Thus, the most practical and reliable approach was to classify nutrient levels according to the fertility manual of the region: Manual de Adubação e calagem do Estado do rio Grande do Sul e Santa Catarina (SBCS, pg 90, 2016) and the definition of weights, which represent the expected yield potential (in %RY) for being in that class, according to the manual (Table 1). For the values referring to pH levels, values were sought in the literature regarding possible curve behaviors, since the Manual neither presents classes nor suggests expected relative yield.

Table 1. Weights used in the classification of the classes for each variable.

P and K Classes	P and K Weights
Very low	35
Low	60
Medium	85
High and very high	100

pH	pH Weight
< 4.8	50
> 4.8	70
> 5.2	90
> 5.6	100

Legend: P and K classes defined according to the Manual (SBCS, 2016).

Weights represent the expected Yield Potential (%RY) for being in that class.

The model was structured to respect the following equation (Equation 1):

Equation 1: $$FI = \beta 0 + \beta 1*(P\ Weight) + \beta 2*(K\ Weight) + \beta 3*(pH\ Weight) \quad (1)$$

Where:

FI = Fertility interference;

β_0 = Model intercept;

β_1, β_2, β_3 = Partial regression coefficients, indicating the slope of the line for each attribute, calculated by the software;

P, K and pH Weights = Values representing the expected Yield Potential (%RY) for that sampling point, based on the class of the respective nutrient or indicator.

In this way, the best fit of the coefficients is calculated jointly among the different factors for each field in each harvest season. For each point on the sampling grid, the model determines the interference on yield and, consequently, generates a residual, which measures the model's deviation when estimating the yield. Thus, the residual symbolizes the yield estimate, in RY, without the effect of fertility (Equation 2):

Equation 2: $$Residual = RY\ FI \quad (2)$$

Where:

Residual = The error present in the model estimating fertility interference, representing the estimated yield without chemical interference;

RY = The relative yield of that grid point (in %) compared to the 95th percentile of the highest values observed in the field;

FI = Fertility Interference calculated by the regression model.

Possessing the residual data and the stable attributes for each point, the correlation analysis between them was performed. The stable attributes analyzed were clay, cation exchange capacity at pH 7.0 (CEC), organic matter (OM) content, and apparent soil electrical conductivity (ECa). The Pearson correlation coefficient was used at a 5% significance level. The correlation coefficients and their respective statistical significance values (p-value) were determined, discarding correlations with $p > 0.05$ as non-significant.

Shortly after soil sampling, management practices were carried out aimed at correcting the levels presented in the analyses. Thus, the nutritional levels indicated in the analysis reports corresponded only to the soil situation in the seasons prior to sampling. It was also considered that over the seasons, nutritional levels change; therefore, there could be an error in assuming that the values reported in the analysis correspond to soil levels in seasons retroactively exceeding three years. For this reason, in the present study, the 2011 and 2012 seasons used the values indicated in the 2012 analysis, and the 2016 and 2017 seasons used the values indicated in the 2017 analysis. For the 2014, 2018, and 2019 seasons, the fertility estimation model was not applied to avoid errors, as there was no reliable fertility data available for use. Consequently, these seasons did not have their yield values altered by the regression model, and the correlation was performed directly with the raw RY values.

The data were analyzed in four distinct situations: (i) individualized data analysis by field, aiming to understand if there were heterogeneous yield responses among the different areas; (ii) generalist analysis of the fields, as if all 62 sampling points of the analyzed dataset formed a single field, aiming to find a common response of the entire area to the factors; (iii) generalist analysis with ECa data for the Erva Mate and Taquareira fields.

In situation (i), the behavior of four fields was analyzed, omitting the Diogo field due to the fact that it only has three sampling points, an insufficient quantity to enable the application of the regression model. Additionally, in this stage, the fields that contained ECa mapping were correlated with this variable. In situation (ii), all five fields were included in the integrated analysis; however, the ECa factor was disregarded in this modeling because the database for this attribute was not available for all areas. For this reason, in situation (iii), a integrated analysis was conducted restricted to the fields that had electrical conductivity mapping.

The ECa data were correlated with yield in two ways: (1) "ECa Buffer": This consisted of correlating the model residual with the average value contained within a 40-meter radius around the sampling grid points, following the same approach used for the TWI analysis. (2) "ECa FullMap": Based on correlating the entire density of continuously collected points in the field with the total area yield map, utilizing a 10 m × 10 m grid, without restriction to the soil sampling points. It is important to emphasize that this latter methodology generates a point density approximately 100 times greater than that restricted to the soil sampling grid. This results in a larger number of analyzed points, increasing the probability of the correlation being statistically significant while decreasing the probability of observing a strong correlation coefficient. Both ECa processing methodologies were replicated for scenarios (i) and (iii).

Resultados e discussão

The field-specific approach demonstrated that the study areas exhibited distinct responses across growing seasons with respect to the stable soil attributes evaluated. Certain fields showed specific patterns under particular conditions that were not replicated in the remaining areas. However, ECa was the only variable that displayed a consistent behavior under the analyzed conditions, both in the localized approach (Buffer) and across the entire field extent (FullMap) (Table 2).

Table 2. Results of the field-specific analysis among the evaluated fields (i).

Taquareira

Year	WL%	R²	OM	Clay	CEC	TWI	ECa Buffer	ECa FullMap
2011	38,4	0,77	6%	-16%	-48%	-5%	-44%	**-11%**
2012	63,2	0,27	55%	-41%	-33%	0%	**-65%**	**-34%**
2014								
2016	24,1	0,54	49%	-17%	-31%	-26%	-47%	**-30%**
2017								
2018								
2019	53,4	NA	**86%**	-22%	-25%	-35%	-61%	**-21%**

Erva Mate

Year	WL%	R²	OM	Clay	CEC	TWI	ECa Buffer	ECa FullMap
2011	38,4	0,03	-26%	6%	-27%	-14%	-23%	**-17%**
2012	63,2	0,16	28%	-11%	32%	6%	-38%	**-22%**
2014	57,4	NA	**-52%**	**66%**	8%	-3%	6%	**-19%**
2016	24,1	0,20	-10%	20%	-20%	21%	-38%	**-9%**
2017	26,4	0,26	9%	-25%	-25%	3%	-10%	**-25%**
2018	50,1	NA	11%	-41%	**-54%**	-21%	-18%	**-23%**
2019	53,4	NA	**73%**	-45%	33%	**-73%**	-8%	**-7%**

Voçoroca Sul

Year	WL%	R²	OM	Clay	CEC	TWI
2011	38,4	0,38	-5%	36%	6%	-11%
2012	63,2	0,41	-15%	-20%	-21%	26%
2014	57,4	NA	-33%	-20%	-25%	-29%
2016	24,1	0,12	16%	**58%**	28%	-8%
2017	26,4	0,20	10%	**56%**	26%	-17%
2018	50,1	NA	-6%	12%	-26%	**56%**
2019						

Voçoroca Norte

Year	WL%	R²	OM	Clay	CEC	TWI
2011						
2012	63,2	0,23	13%	2%	-23%	-43%
2014	57,4	NA	5%	-2%	-37%	-51%
2016	24,1	0,49	-62%	4%	-5%	35%
2017	26,4	0,50	31%	-12%	-15%	-15%

2018	50,1	NA	-1%	2%	-34%	-42%
2019	53,4	NA	20%	16%	-22%	**-75%**

Legend: WL% = Water limitation, percentage loss of yield potential due to water-related constraints.
NA = Not applicable.
Correlation coefficients shown in bold are significant at the 5% level ($p < 0.05$).
Underlined coefficients are classified as strong correlations (> 0.5 or < -0.5).

The coefficient of determination (R^2) represents the degree of efficiency of the model fit to the dataset, as it expresses the proportion of total variation explained by the independent variables. In the present study, this index reflects the overall magnitude of the influence of soil fertility on crop yield within each field. Consequently, the relative residual variance ($100 - R^2$) represents the fraction of total variation not captured by the model and, therefore, corresponds to the proportion of yield variability available for correlation with the stable soil attributes. Growing seasons in which R^2 is reported as "NA" were those in which soil analyses were considered incapable of estimating nutrient levels with sufficient accuracy.

It can be observed that R^2 values were similar among growing seasons that used data from the same soil sampling campaign and preceded corrective management practices. Therefore, the model proved to be consistent in estimating the influence of soil fertility on crop yield and in reducing noise in the correlation analysis caused by external influences. Fields that initially exhibited low fertility-related limitations (Voçoroca Norte and Erva Mate) showed higher R^2 values in subsequent years, suggesting insufficient nutrient replenishment over time. In contrast, the Voçoroca Sul field displayed the opposite behavior, indicating that the fertility correction strategy adopted in this area was effective.

For this analytical approach, some attributes exhibited recurring patterns despite the occurrence of exceptions. The TWI showed negative correlations during years characterized by greater water limitation (2012, 2014, 2018, and 2019), with the exception of the Voçoroca Sul field in 2018, which presented a strong, positive, and statistically significant correlation. CEC displayed a behavior similar to that of clay content in the Taquareira and Voçoroca Sul fields, whereas in Voçoroca Norte and Erva Mate it behaved more similarly to TWI, with minor variations during years of lower water stress. Clay content exhibited highly variable responses among fields: weak correlations in Voçoroca Norte, predominantly negative correlations in Taquareira, and mainly positive correlations in Voçoroca Sul during years with lower water limitation. Organic matter (OM) also showed considerable variability, displaying a clear pattern only in Taquareira, where it was positively associated with yield. Notably, in the Erva Mate and Taquareira fields, OM and clay content exhibited opposite behaviors.

The only attribute that showed a clear and consistent pattern across years and among fields was ECa, which exhibited a negative correlation with crop yield in both analytical approaches and in both evaluated areas. As expected, the FullMap analysis resulted in statistically significant correlations for all growing seasons due to the substantial increase in the number of observations included in the analysis.

The behavior observed for TWI was opposite to what would be expected. Since negative correlations were observed during years with greater water limitation, the results indicate that areas with a greater tendency for water accumulation produced proportionally less under drier conditions. This response may be partially explained by the physical characteristics of the soil. Because the soils are classified as Ultisols with a clay-enriched subsurface horizon (argillic horizon), the area is susceptible to surface sealing and temporary waterlogging, particularly in lowland zones, whenever high-intensity rainfall events occur, even if total seasonal precipitation remains below average.

Positive correlations between clay content, OM, and crop yield are generally expected, especially under water-limited conditions, due to improved water retention, greater natural fertility, and the presence of colloids that enhance soil structure. However, previous studies have reported that soil compaction may exert a direct negative effect on crop productivity, and areas with higher clay contents are generally more susceptible to compaction, which may explain the occurrence of negative correlations in some scenarios. The negative correlations observed for OM may also be explained by the fact that soil organic carbon tends to accumulate in depositional landscape positions and water-accumulation zones (Singh et al., 2016), which are generally associated with higher TWI values. Consequently, similarly to the TWI response, crop performance may be reduced in areas with greater OM accumulation due to waterlogging stress.

The variable behavior observed for CEC may be associated with the effectiveness of the statistical modeling approach employed. This variable tended to resemble either the behavior of clay content or that of TWI, suggesting that it remained associated with structural soil characteristics after the influence of fertility had been isolated during the previous modeling stage.

Regarding ECa, the results are consistent with findings reported in the Brazilian literature. Bottega et al. (2017) and Alcântara et al. (2012) observed similar relationships when correlating soybean yield with ECa, reporting correlation coefficients of -0.18 and -0.25, respectively, in studies conducted in Brazil. International studies have also reported this same pattern of weak negative correlations (Singh et al., 2016).

The divergence between ECa and the other analyzed variables may be explained by the inconsistent spatial relationship between ECa and other soil properties. Singh et al. (2016) reported that ECa can be significantly influenced by topographic conditions. Likewise, the correlation between clay content and ECa varies according to slope and landscape position and is generally weak and positive. In addition to physical soil properties, the relationship between electrical conductivity and nutrient concentrations also varies according to topographic position. This may explain why ECa exhibited a distinct behavior relative to the other variables, despite being associated with them under certain conditions.

In approaches (ii) and (iii), which considered all sampling points as belonging to a single dataset and aimed to identify the overall behavior of the study area, a tendency toward a similar response pattern among ECa and the remaining variables was observed (Tables 3 and 4).

Table 3. Results of the pooled analysis including all five fields (ii)

Year	WL%	R^2	OM	Clay	CEC	TWI
2011	38,4	0,08	8%	11%	-14%	**-28%**
2012	63,2	0,09	2%	-13%	-18%	12%
2014	57,4	NA	**-45%**	5%	-2%	-1%
2016	24,1	0,13	-17%	-6%	0	5%
2017	26,4	0,12	20%	2%	-5%	-22%
2018	50,1	NA	-22%	-10%	-16%	28%
2019	53,4	NA	3%	-27%	10%	-30%

Table 4. Results of the pooled analysis including the Erva Mate and Taquareira fields (iii)

Year	WL%	R²	OM	Clay	CEC	TWI	ECa Buffer	ECa FullMap
2011	38,4	0.116	-19%	7%	-5%	-3%	-15%	**-14%**
2012	63,2	0.085	35%	-2%	17%	0%	-27%	**-12%**
2014	57,4	NA	**-52%**	**66%**	8%	-3%	6%	**-19%**
2016	24,1	0.316	22%	-37%	**-40%**	3%	**-63%**	**-29%**
2017	26,4	0.256	9%	-25%	-25%	3%	-10%	**-25%**
2018	50,1	NA	11%	-41%	**-54%**	-21%	-18%	**-23%**
2019	53,4	NA	**65%**	-38%	-9%	**-50%**	**-46%**	**-20%**

When data from all five fields were pooled in approach (ii), the variables exhibited behaviors different from those observed in the field-specific analyses. Although OM and TWI showed statistically significant correlations in specific scenarios, neither attribute displayed a consistent pattern. This outcome reflects the heterogeneous behavior of individual fields regarding these variables. In contrast, ECa was the only attribute that maintained the same behavior observed in the individual analyses when evaluated in approach (iii), highlighting the consistency of its response across the two analyzed fields.

Once again, ECa exhibited weak negative correlations regardless of seasonal water limitations and irrespective of the analytical methodology employed (Buffer or FullMap), reinforcing the trend observed previously.

It should be emphasized that crop yield is the result of a complex interaction among numerous variables and follows the principle of Liebig’s Law of the Minimum, whereby a deficiency in a single factor can limit the entire production system. Consequently, factors other than soil fertility and the stable soil attributes evaluated in this study may influence yield. Variables unrelated to soil properties, including pest and disease pressure, weed competition, crop protection practices, and operational errors, may also interfere with and mask spatial correlations. Furthermore, random errors may have occurred during data collection, whether associated with yield monitoring, georeferenced soil sampling, or long-term digital management of the databases. These factors may partially explain results that deviated from the dominant patterns observed.

Nevertheless, considering the substantial volume of data analyzed, the results presented here are considered highly reliable for interpretation. Furthermore, as reported by [REFERENCE], water availability and adequate nutrient supply are among the principal yield-limiting factors in soybean production systems of southern Brazil. In addition, recognizing that crop yield is a multifactorial and complex variable that may be constrained by a single limiting factor further reinforces the importance of identifying a spatial attribute with a consistent correlation pattern across seven growing seasons, as observed for ECa.

Conclusions

The study identified temporal variations among fields regarding the correlations between stable soil attributes and soybean yield. Distinct response patterns were observed among the evaluated areas, reflecting the complexity of crop productivity and its susceptibility to multiple interacting factors, even after attempts to remove the influence of soil fertility through the regression model.

Unlike the other variables, ECa exhibited a consistent temporal pattern across growing seasons, characterized predominantly by weak negative correlations in most analyses. Therefore, despite the influence of environmental and management-related factors, the temporal stability of this attribute indicates that apparent soil electrical conductivity has strong potential as a basis for delineating site-specific management zones within the evaluated fields.

References

Alcântara, G.R.; Reis E.F.; Queiroz, D.M. (2012). Produtividade de culturas correlacionada com condutividade elétrica aparente de um solo sob plantio direto. **Revista Agrotec**, 3(2), 62-72, doi: 10.12971/2179-5959.v03n02a06

Banco de Dados de Informações Ambientais - BDiA. Mapeamento de Recursos Naturais: escala 1:250 000. https://bdiaweb.ibge.gov.br/#/consulta/pedologiahttps://bdiaweb.ibge.gov.br/#/consulta/pedologia. Accessed 02 June 2026.

Bottega, E.L.; de Queiroz, D.M.; de Assis de Carvalho Pinto, F.; de Souza, C.M.A.; Valente, D.S.M (2017). Precision agriculture applied to soybean: Part I-Delineation of management zones. Aust. J. **Crop Sci**. 11(5), 573–579, doi: 10.21475/ajcs.17.11.05

EMBRAPA. Sistema Brasileiro de Classificação de Solos. https://www.embrapa.br/solos/sibcs/correlacao-com-wrb-fao-e-soil-taxonomy. Accessed 02 June 2026.

INMET - Instituto Nacional de Meteorologia. Ministério da Agricultura, Pecuária e Abastecimento. Normais Climatológicas do Brasil 1991-2020. https://clima.inmet.gov.br/GraficosClimatologicos/RS/83936. Accessed 02 June 2026.

Moral FJ, et al (2010). Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. **Soil Till Research**, 106(2), 335-343, doi:10.1016/j.still.2009.12.002.

Rabello, L., Bernardi, A., Inamasu, R. (2014). Condutividade elétrica aparente do solo. Agricultura de precisão: um novo olhar (pp 48-57). São Carlos, Brasil: Embrapa Instrumentação.

Smith, S. D., Bowling, L. C., Rainey, K. M., & Cherkauer, K. A. (2021). Quantifying Effects of Excess Water Stress at Early Soybean Growth Stages Using Unmanned Aerial Systems. **Remote Sensing**, 13(15), 2911, doi: 10.3390/rs13152911.

Singh, G., Williard, KWJ, & Schoonover, JE (2016). Relação espacial da condutividade elétrica aparente do solo com a produtividade das culturas e propriedades do solo em diferentes posições topográficas em uma pequena bacia hidrográfica agrícola. Agronomy , 6(4), 57, doi: 10.3390/agronomy6040057.

Sociedade Brasileira de Ciência Do Solo - SBCS (2016). Manual de Calagem e Adubação para os estados do Rio Grande do Sul e Santa Catarina (Ed 11). Brasil: SBCS – Núcleo Regional Sul.