# VARIABILITY OF SOYBEAN AND CORN YIELD AND SOIL TEXTURE IN THE GENERATION OF MANAGEMENT ZONES

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**ABSTRACT:** The spatial representation of soil texture and crop yield allows the formulation of solid and efficient management strategies. Thus, this study aimed to evaluate the spatial variability of soybean/corn yield and soil texture in the generation of management zones. The study was carried out in an area of 130 ha with summer soybean and off-season corn succession. A sample grid was generated with 64 points in a regular grid and 13 random points, totaling 77 points, one for every 1.7 ha. Soil sample collection was performed manually, and soybean (2017/2018 and 2018/2019) and corn (2018 and 2019) yield data were collected from the harvester's yield monitor. Texture and yield data were subjected to descriptive statistics and spatialization. Soybean and corn yield variabilities were influenced by soil texture and climate. Corn and soybean yields presented higher values in regions with more clay under water deficit conditions, whereas soybean yield was higher in regions with more sand under normal conditions. Management zones can be made from this isolated attribute in areas with differing clay content.

**Keywords:** precision agriculture, harvest maps, particle size.

## VARIABILIDADE DA PRODUTIVIDADE DE SOJA E MILHO E DA TEXTURA DO SOLO NA GERAÇÃO DE ZONA DE MANEJO

**RESUMO:** A representação espacial da textura do solo e produtividade das culturas permitem formular estratégias de manejo sólidas e eficientes. Assim, objetivou-se avaliar a variabilidade espacial da produtividade de soja/milho e a textura do solo na geração de zonas de manejo. O trabalho foi realizado em área de 130 ha com sucessão soja verão e milho safrinha. Foi gerado grade amostral, com 64 pontos em malha regular e mais 13 pontos aleatórios, totalizando 77 pontos, um a cada 1,7 ha. A coleta das amostras de solo foi realizada de forma manual e os dados de produtividade de soja (2017/2018 e 2018/2019) e milho (2018 e 2019) foram coletados do monitor de produtividade da colhedora. Os dados de textura e produtividade foram submetidos à estatística descritiva e a espacialização. A variabilidade das produtividades de soja e de milho foi influenciada pela textura do solo e pelo clima. Em condições de déficit hídrico, as produtividades de milho e soja apresentaram maiores valores nas regiões com mais argila, já quando condições normais a produtividade de soja foi maior nas regiões com mais areia. Em áreas com teor de argila discrepantes podem ser feitas zonas de manejo a partir desse atributo isolado.

## 1 INTRODUCTION

With increase in the world population, there is also a great demand for food. The current agriculture to seeks to innovate in machines and technologies that allow using resources rationally. What promotes increase in food production, in a sustainable way, wtih the use of agricultural inputs at varying rates.

The concept of Precision Agriculture (PA) is associated with the use of new technologies that allow for the management of spatial and temporal variability, maximizing profit and minimizing environmental damage, and having greater control over the causes of variation associated with higher amounts of information (TSCHIEDEL; FERREIRA, 2002). According to Cortez et al. (2018a) and Cortez et al. (2018b), the special variability observed by geostatistical methods allows defining specific regions in an area, which enable or require specific local management. Buss et al. (2019) suggest that PA implementation requires prior knowledge about the spatial variability of crops, soil attributes, and the generation of management zones.

The concept of PA uses variable rate application, spatial variability of yield, and other factors (CAMICIA et al., 2018). In the PA context, yield maps describe the spatial variability of the study area and depend on the sampling arrangement and density (GUEDES et al., 2016).

Among the factors considered in the adoption of PA techniques, the spatial of soil texture from the asjustment of models that describe the spatial dependence, has been the subject of numerous studies in the determination of soil physical and chemical soil attributes in usampled locations (OLIVEIRA et al., 2015). However, there are still few studies on the relationship between the variability of these characteristics and crop yield.
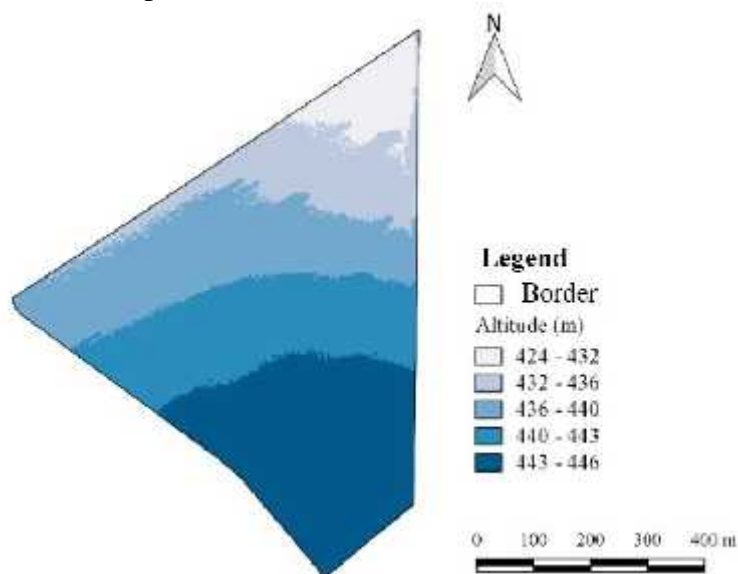
Management Zones (MZ) are included in the larger context of PA. For Molin, Amaral e Colaço et al. (2015) as management zones or differentiated management unit (UGDs) can be defined as regions that contain minimal spatial variability and temporal consistency and that describe the response potential of the area. According to Kuiawski et al. (2017), is an economically viable option that can be delineated using altitude and vegetation indices, showing differences in management zones regarding phosphorus, clay, and silt at the end of the process.

In this context, the knowledge and spatial representation of yield over the years allow for the formulation of more solid and efficient management strategies, such as the division of the property into areas that present higher homogeneity, creating differentiated management units or management zones to adopt the most adequate crop management for each soil condition. Thus, this study aimed to evaluate the spatial variability of soybean and corn yield during two growing seasons associated with soil texture in the generation of management zones.

## 2 MATERIAL AND METHODS

The study was carried out on a commercial farm with approximately 130 ha, located in the municipality of Ponta Porã, MS, Brazil, which is located at latitude 22°22 58 S, longitude 55°10 30 W, and an average altitude of 440 m (Figure 1). The climate is humid tropical with a dry winter. The property is cultivated in the rainfed system and adopts the no-tillage system in straw with a soybean and off-season corn succession for approximately 20 years.

**Figure 1.** Altitude data of the experimental area



**Source:** Author (2020).

The soil in the area is classified as a medium-textured Oxisol (Latossolo Vermelho distrófico, Brazilian Soil Classification System), with a gently wavy relief (SANTOS et al., 2018) and means of 343, 84, and 573 g kg$^{-1}$ of clay, silt, and total sand, respectively. Table 1 shows the chemical attributes in the 0.0–0.20 m layer with their mean values in the area.

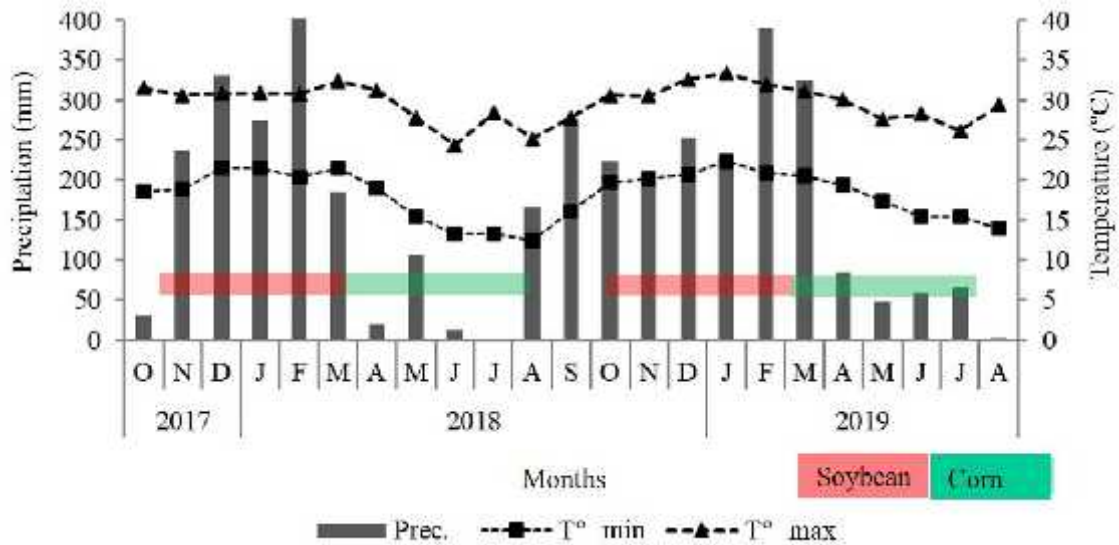**Table 1.** Mean contents of chemical attributes at a depth of 0.00–0.20 m.

| Chemical attributes | | |
|---|---|---|
| pH | | 5.77 |
| OM | g dm$^{-3}$ | 36.00 |
| P | mg dm$^{-3}$ | 12.30 |
| Ca$^{2+}$ | | 5.09 |
| Mg$^{2+}$ | | 1.17 |
| K$^+$ | | 0.18 |
| SB | cmol$_c$ dm$^{-3}$ | 6.44 |
| Al$^{3+}$ | | 0 |
| Al$^{3+}$+H$^+$ | | 2.08 |
| CEC | | 8.52 |
| m | | 0 |
| Ca | | 59.74 |
| Mg | % | 13.73 |
| K | | 2.11 |
| V | | 75.59 |

Cation exchange capacity at pH 7.0 (CEC), sum of bases (SB), base saturation (V), aluminum saturation (m), and mean calcium (Ca), magnesium (Mg), and potassium saturation (K) relative to the total CEC. **Source:** Author (2020).

The meteorological data of maximum and minimum temperature (Figure 2) were collected at the weather station of Embrapa Western Agriculture, Dourados, MS, Brazil, while the precipitation data (Figure 2) were collected in the study area.

**Figure 2.** Monthly meteorological data for 2017, 2018, and 2019, with volumes accumulated in the period of soybean and corn cultivation
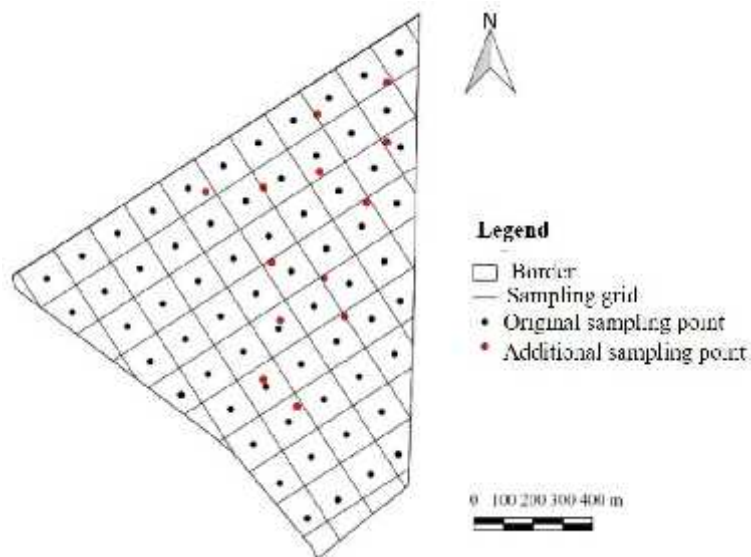


**Source:** Author (2020) and Embrapa Western Agriculture (2020).

A sampling grid with 64 points distributed regularly, with one point every 2.0 ha (143.61 × 143.61 m) plus 13 sampling points (the equivalent of approximately 20% of the points from the original sampling grid), randomly allocated according to the spatial variability of the observed yield in the corn and soybean harvest maps for 2018 and 2019, was generated for the collection of soil data (Figure 2). Therefore, the adopted sampling grid had 77 sampling points at the density of one sample per 1.7 ha. Baio et al. (2021) used 10% additional points in the grid at a distance smaller than the sampling grid to improve the estimation of the semivariogram on the microscale. Molin, Amaral e Colaço et al. (2015) suggested the use of 30% additional points in the sampling grid. Therefore, we decided to use 20% of the additional points in this study.

**Figure 3.** Regular grid with original and additional sampling points for collecting soil samples



**Source:** Author (2020).

Soil samples were collected manually in 2019. To remove the soil was used a Stihl® BT 45 gasoline drill with an Irwin® Mathieson 1 ½ x 18 mm. The composite samples were collected at a depth of 0.00–0.20 m, with 10 subsamples within a radius of 5 m from the

sampling point to be characterized.

Yield data were collected over two years by harvesters equipped with an impact plate mass sensor, monitor, and GNSS receiver capable of collecting data every 1 second. The data obtained the mapping system were filtered using an electronic spreadsheet to eliminate discrepant data (outliers). The criteria adopted for data elimination were as follows: data containing positioning error and/or null geographic coordinates, data with zero grain mass moisture, data collected with a minimum working width of the platform less than 95% of the working width for soybean and 75% for corn for the 2018 growing season and 100% for the 2019 corn growing season (adapted from MENEGATTI; MOLIN, 2004). Considering as the yield data mass is large generated by the mapping system, the values identified as outliers were removed.

Soil texture and crop yield data were subjected to descriptive statistics. The Ryan-Joiner test at the 5% probability was used to verify the fit of the normal distribution.

The geostatistical analysis of the soil texture data was performed using experimental semivariograms (exponential, gaussian or spherical) and the model adjustment was performed based on the lowest sum of squared residuals (SSR) and the best coefficient of determination ($r^2$). The following parameters were defined: nugget effect (Co), contribution (C), sill (Co+C), and range (a). Data were cross-validated to validate the model. The spatial dependence index (SDI) was calculated by the equation SDI=[C0/(C0+C1)]*100. The degree of spatial dependence (DSD) was classified based on SDI as strong, for SDI 25%; moderate, for SDI between 25 and 75%; and weak, for SDI > 75% (CAMBARDELLA

et al., 1994). All texture data were estimated scaled to a 10 m spatial resolution and interpolated by ordinary kriging with QGIS software.

The yield data were subjected to interpolation by the inverse distance weighting (IDW) using the value 2 as a weight, after they had gone through the cleaning process. All data the yields were estimated to a 10 m spatial resolution with QGIS software. The yields values were classified and grouped into five classes.

The management zones were generated after analyzing the data collected annually and temporally, being classified as a function of the clay content according to Santos et al. (2018), in which: medium texture, with material with clay content between 150 and 350 g kg$^{-1}$; clayey texture, material with clay content between 350 and 600 g kg$^{-1}$; and very clayey texture, material with clay content higher than 600 g kg$^{-1}$.

## 3 RESULTS AND DISCUSSION

### 3.1 Granulometry analysis

The spatial variability for soil granulometry attributes (Table 2) has a high range. For clay the values were with minimum of 180.40 g kg$^{-1}$ and maximum values of 580.40 g kg$^{-1}$, showing the variability of this attribute. However, marked variations were observed for silt and sand. The relative dispersion of the coefficient of variation (CV) data for the analyzed attributes was higher for silt despite being classified as medium (CV between 15 and 60%), according to Warrick and Nielsen (1980).

**Table 2.** Descriptive statistics of soil particle size at a depth of 0.0–0.2 m at the study area in Ponta Porã, MS, Brazil.

| Parameter | Clay | Silt | Sand |
|---|---|---|---|
| | ------------ g kg$^{-1}$ ------------ | | |
| Mean/plot | 343.50 | 84.61 | 572.70 |
| SD | 94.80 | 45.37 | 115.20 |
| Variance | 8984.70 | 2058.12 | 13281.80 |
| Minimum | 180.40 | 19.80 | 277.00 |
| Maximum | 580.40 | 309.60 | 750.00 |
| Range | 400.00 | 289.80 | 473.00 |
| CV | 27.61 | 53.62 | 20.12 |
| Sk | 0.48 | 2.82 | −0.31 |
| K | −0.36 | 12.23 | −0.46 |
| RJ | 0.99$^{ns}$ | 0.86* | 0.99$^{ns}$ |

SD: standard deviation; CV (%): coefficient of variation; Sk: skewness; K: kurtosis; RJ: Ryan-Joiner test, where (*) significant at levels of $p < 0.05$ and ($^{ns}$) non-significant distribution. The hypothesis for normal distribution is rejected when it is significant. **Source:** Author (2020).

The attribute silt did not follow a normal frequency distribution (Table 2), which was confirmed by the skewness coefficient shifted to the right (Sk > 0) and kurtosis with a leptokurtic distribution (Ck > 0), confirmed by the Ryan-Joiner test (RJ). However, the attributes clay and total sand presented values close to zero for the skewness and kurtosis coefficients so that the frequency distribution tends to normality, which can be verified by the result of the RJ test.

A strong spatial dependence was observed for the attributes sand, clay, and silt (Table 3), with an exponential semivariogram model more suitable for the three fractions. The cross-validation test showed that all estimators have a regression coefficient close to 1.0, measuring the reliability of the adopted models.

Range (A) values (Table 3) showed that the use of a regular grid (original grid) with a density of one sampling point for every 2.06 hectares, associated with random points (additional points) at a density of 20% of the regular grid, allocated according to soybean and second crop corn yield variability for a period of two years, was efficient to identify the spatial dependence of soil texture attributes in the study area, all of which were classified as strong. Molin, Amaral e Colaço et al. (2015) state that adding points to the regular grid improves the quality of investigation and analysis of spatial dependence.

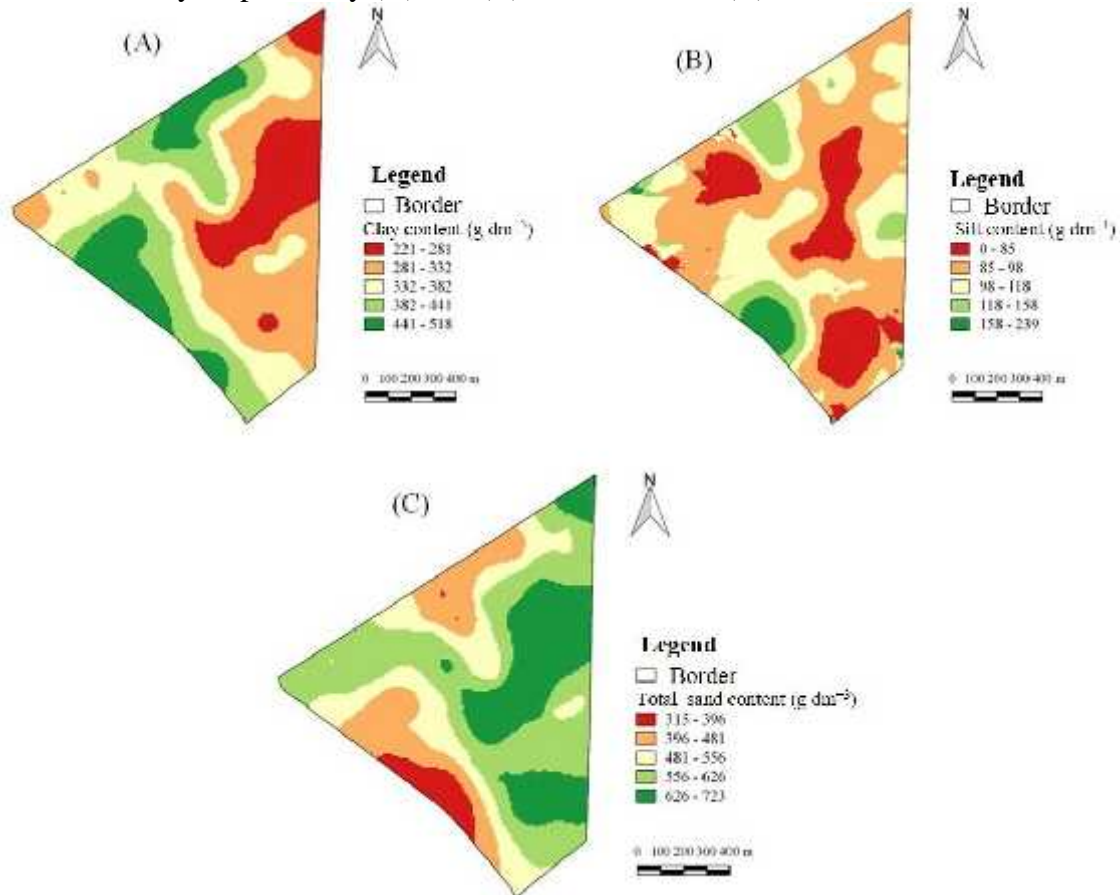**Table 3.** Parameters for the semivariogram adjustment regarding soil texture.

| Attribute | Model | Co | Co+C | A (m) | SSR | SDI | DSD | r$^2$ |
|---|---|---|---|---|---|---|---|---|
| Clay | Exponential | 10.00 | 11.050.00 | 621.00 | 7.69 | 0.09 | Strong | 0.93 |
| Silt | Exponential | 118.00 | 2.389.00 | 300.00 | 2.73 | 4.94 | Strong | 0.52 |
| Total sand | Exponential | 10.00 | 17.990.00 | 606.00 | 1.74 | 0.06 | Strong | 0.94 |

Co: nugget effect; Co+C: sill; A: range; SSR: sum of squared residuals; SDI: spatial dependence index; DSD: degree of spatial dependence; r$^2$: determination coefficient. **Source:** Author (2020).

Clay, silt, and total sand spatialization (Figure 4) indicate high variability in the area. Moreover, the behavior of clay and sand are antagonistic, that is, regions where clay contents were higher (441 to 518 g kg⁻¹) had

lower sand contents (315 to 396 g kg⁻¹). This fact was already expected and also confirmed by Lima et al. (2014) who found an inverse spatial distribution of the clay and total sand fractions.

**Figure 4.** Variability maps of clay (A), silt (B), and total sand (C) contents



**Source:** Author (2020).

Soil texture characteristics may vary due to the relief, which can affect crop yield. Thus, clay content decreases as altitude decreases (Figure 1). Kuiawski et al. (2017) stated that there are several associations of the soil-plant-atmosphere relationship that affect yield and the terrain altimetry associated with vegetation indices shows greater agreement with the yield zones of the soybean crop. Cortez, Anghinoni e Arcoverde et al. (2020) observed that one of the factors that affect yield is soil compaction and machinery traffic.

## 3.2 Grain yield

Soybean and corn yield data (Table 4) showed high variability, indicated by the data range. The relative dispersion of the data, according to Warrick and Nielsen (1980), was classified as low (CV lower than 15%) for the soybean and medium (CV between 15 and 60%) for corn in both growing seasons. Skewness values were negative and kurtosis values were close to three for the two soybean and corn growing seasons, characterizing the non-normal distribution of data, attested by the RJ normality test (Table 4).

**Table 4.** Descriptive statistics of soybean (2017/2018 and 2018/2019) and corn (2018 and 2019) yield at the study area in Ponta Porã, MS, Brazil.
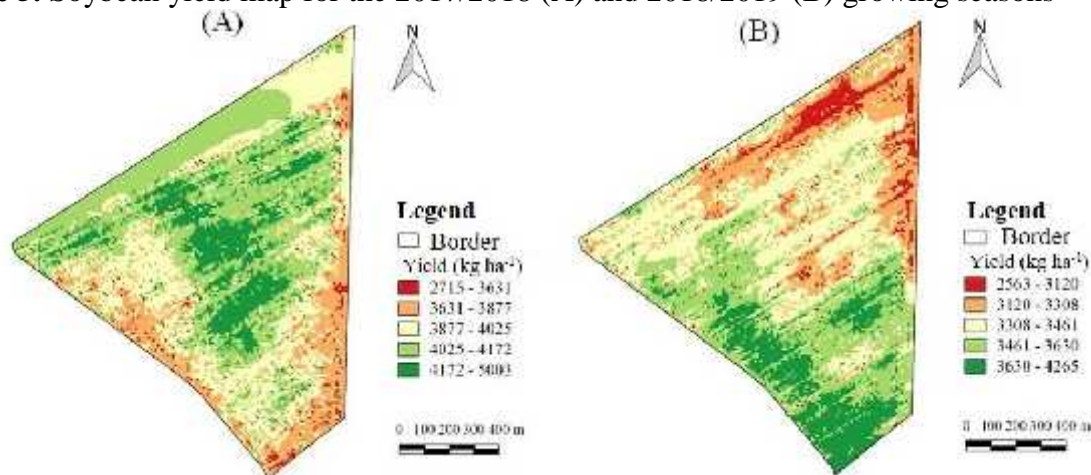
| Parameter | Soybean | | Corn | |
|---|---|---|---|---|
| | 2017/18 | 2018/19 | 2018 | 2019 |
| | ------------------- kg ha$^{-1}$ ------------------- | | | |
| Mean/plot | 4,013.10 | 3,458.01 | 2,823.70 | 5,085.57 |
| SD | 428.98 | 319.33 | 800.37 | 912.02 |
| Variance | 183920.71 | 101972.95 | 640585.00 | 831784.64 |
| Minimum | 2,506.30 | 2,428.00 | 351.10 | 2,103.00 |
| Maximum | 5,517.60 | 4,486.00 | 5,289.60 | 8,019.30 |
| Range | 3,011.30 | 2,058.00 | 4,938.50 | 5,916.30 |
| CV | 10.69 | 9.23 | 28.34 | 17.93 |
| Sk | −0.14 | −0.30 | −0.55 | −0.40 |
| K | 3.87 | 3.43 | 3.36 | 3.60 |
| RJ | 1.00* | 1.00* | 0.99* | 0.99* |

SD: standard deviation; CV (%): coefficient of variation; Sk: skewness; K: kurtosis; RJ: Ryan-Joiner test, where (*) significant at levels of $p < 0.05$ and ($^{ns}$) non-significant distribution. The hypothesis for normal distribution is rejected when it is significant. **Source:** Author (2020).

The higher ranges observed in both growing seasons for corn yield showed the "elasticity" of C4 plants relative to C3 plants when compared to the range of soybean yield data. According to Santi et al. (2013), this behavior is due to the higher productive potential of corn compared to other crops, such as soybean.

The yield achieved in the 2019 corn growing season was higher than in 2018 (Table 4). It can be explained by the climate conditions (Figure 2). Because as the accumulated rainfall in the region during the crop cycle (from sowing to harvest) was 585 mm in 2019, a volume 29.4% higher for the period compared to 2018.

Soybean yield variation in the study area (Figure 5) indicates an antagonistic behavior in regions of high and low yield in the 2017/2018 and 2018/2019 growing seasons, associated with the rainfall regime and clay contents. Rainfall volume and distribution in both growing seasons (Figure 2), 558 and 486 mm, respectively, during the phenological stages R1 to R7, the time of highest water demand, associated with clay and sand contents (Figure 4), justify this behavior. The occurrence of deficits during the reproductive phase of the soybean crop leads to a higher reduction in yield (Nunes et al., 2016).
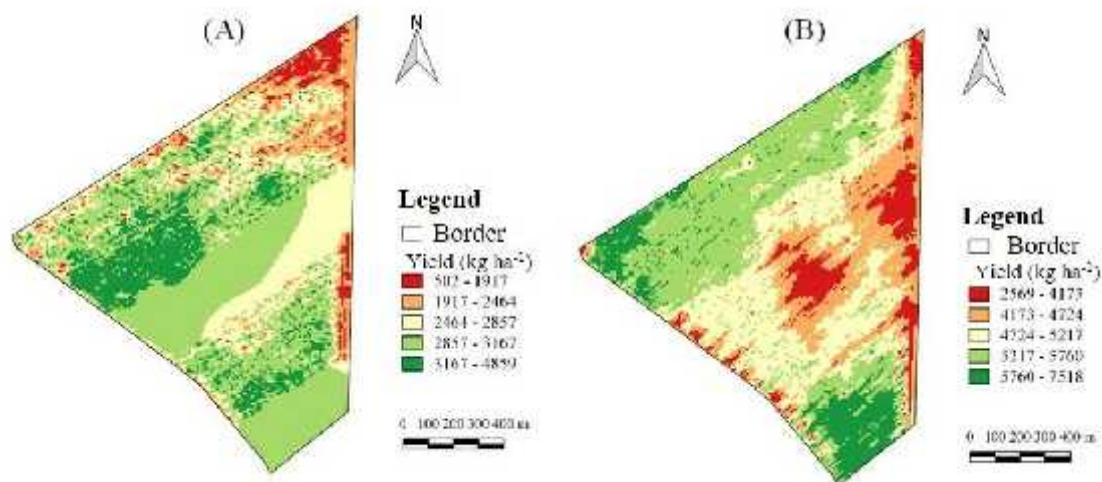
**Figure 5.** Soybean yield map for the 2017/2018 (A) and 2018/2019 (B) growing seasons



**Source:** Author (2020).

Proper management allows obtaining best soybean yields in sandy soils in the Cerrado region, which is in line with the yield found in the 2017/2018 growing season (Figure 5A). Soybean yield for the 2018/2019 growing season (Figure 5B) reflects the regional climate instability effects, with a lower yield in the area with the highest amount of sand. Buss et al. (2019) studying a spatial variability of soybean yield and soil physical attributes, observed that soybean yield was inversely related to coarse and fine sand content in the 0-0.20 m layer.

The 2018 second crop corn yield map failed in the process of recording it on a flash drive by the harvester at the harvest time (Figure 6A). This failure proved to be irreversible, leaving part of the field without information. Corn yield (Figure 6) showed similar behavior to soybean yield (Figure 5). The red regions in the corn harvest map represent lower yields, corroborating with regions with the lowest amount of clay in the soil. This behavior can be explained by the soil water storage capacity. Soils with more clay influence water retention in the soil (CARDUCCI et al., 2011).

**Figure 6.** Corn yield map second crop for the 2018 (A) and 2019 (B)



**Source:** Author (2020).

Precipitation volume (Figure 2) accumulated in the 2018 growing season throughout the corn cycle (from sowing to harvest) in the region was 133 mm lower (452 mm – 585 mm) compared to the 2019 growing season. The occurrence of two droughts, the first in the period from 04/04 to 11/05 (lasting 37 days) and the second from 06/06 to 08/02 (57 days), coinciding with the beginning of the definition of the productive potential, flowering, and grain filling, affected the corn crop development and yield. Caetano and Casaroli (2017) observed that water deficit causes a reduction in sugarcane yield. Souza et al. (2020) found that the water deficit imposed on the cowpea crop favored a lower yield. Rocha et al. (2021) found that the characteristics of corn most affected by water deficit were male flowering, plant and ear

height and yield. This fact justified the behavior of the low yield region, located in the plot where the soil has the highest total sand content (Figure 4), that is, the soil with higher macroporosity and possibly less water retention capacity.
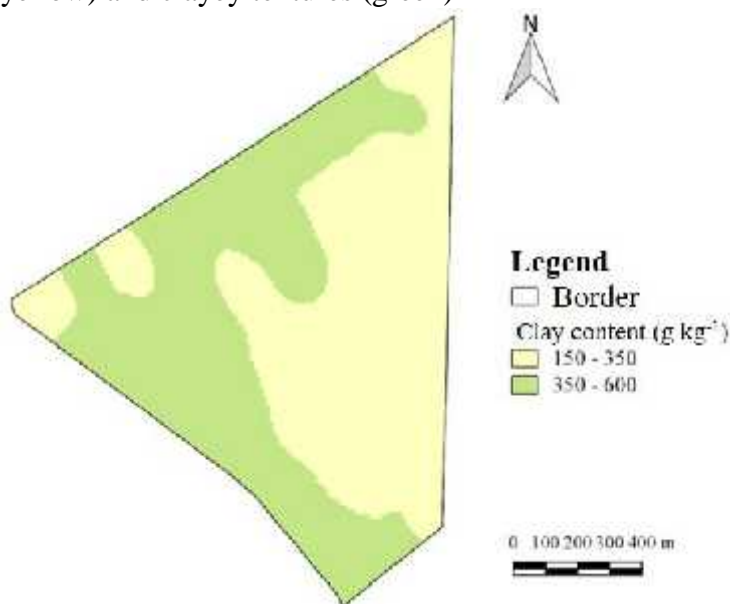
In general, the regions with the highest corn yields are located in areas with the highest clay content. On the other hand, the highest soybean yield depends on the water regime, associated with soil clay content. However, Corassa et al. (2018) found that a low crop yield is associated with high clay content in Oxisols under no-tillage systems in the Rio Grande do Sul region and that organic matter was the indicator of high yields. Thus, the literature presents contradictory results regarding the reasons that affect high yields, requiring further research on the subject.

## 3.3 Management zones

One of the simplest ways to make management zones (MZ) is through the spatialization of clay, using the classification proposed by Santos et al. (2018), which allowed us to simplify the spatial variability

(Figure 7). In this sense, medium clay (150 to 350 g kg$^{-1}$) and clayey regions (350 to 600 g kg$^{-1}$) were distinguished in the area and the yield maps (Figures 5 and 6) correlate and express the responses as a function of years with or without rainfall.

**Figure 7.** Map of management zones considering the clay content in the plot, representing the medium (yellow) and clayey textures (green)



**Source:** Author (2020).

The use of clay as a delimiter of management zones was efficient in plots that showed marked variations in clay content (spatial variation), in which the effect of this granulometry variation can be observed in the yield maps throughout the growing seasons (temporal variation). Leal et al. (2015) state that clay is one of the effective estimators in estimating second crop corn yield when using neural networks as techniques. Therefore, clay content becomes a reliable component to define management zones.

Comparing the maps of corn productivity with the map of management zones, it can be seen that the regions with the highest productivity are related to the MZ with the highest clay content. For soybean yield, this behavior was not observed. Considering the use of the MZ map as a management tool to be adopted in the corn and soybean crop, some decisions could be based on the spatial distribution of the clay content of the area, including the establishment of cover plants

(aiming to increase of organic matter and consequently of cation exchange capacity in the more sandy regions) and also the plant population to be sown in each MZ. According to Vian et al. (2016), in a study of the spatial variability of corn yield, state that obtaining high grain yields is conditioned by the final plant population, with uniform spatial distribution of plants in the area.

## 4 CONCLUSIONS

The attributes clay, silt, and total sand have strong spatial dependence and one point every two hectares, added to 20% of random points, are efficient for identifying spatial dependence.

The spatial variability of soybean and corn yields is influenced by soil texture.

Corn and soybean yield under water deficit conditions showed higher values in regions with higher clay content. On the contrary, soybean yield without water deficit

was higher in regions with more sand.

Areas with contrasting clay content values allow the generation of management zones using this attribute.

## 5 REFERENCES

BAIO, F.H.R.; NEVES, D.C.; ALIXAME, D.; TEODORO, P.E.; ROQUE, C.G.; OLIVEIRA, J.T. Mais assertivos. **Cultivar Máquinas**, Pelotas, n.216, p.29-31, 2021.

BUSS, R.N.; SILVA, R.A.; SIQUEIRA, G.M.; LEIVA, J.O.R.; OLIVEIRA, O.C.C.; FRANÇA, V.L. Spatial and multivariate analysis of soybean productivity and soil physical-chemical attributes. **Revista Brasileira de Engenharia Agrícola e Ambiental**, Campina Grande, v.23, n.6, p.446-453, 2019.

CAETANO, J.M.; CASAROLI ,D. Sugarcane yield estimation for climatic conditions in the state of Goiás. **Revista Ceres**, Viçosa, n. 64, n.3, p.298-306, 2017.

CAMBARDELLA, C. A.; MOORMAN, T. B.; NOVAK, J. M.; PARKIN, T. B.; KAREN, D. L.; TURCO, R. L.; KONOPKA, A. E. Field-scale variability of soil properties in Central Iowa soils. **Soil Science Society of America Journal**, Madison, v.58, p.1501-1511, 1994.

CAMICIA, R.G.M.; MAGGI, M.F.; SOUZA, E.G.; BAZZI, C.L.; KONOPATZKI, E.A.; MICHELON, G.K.; PINHEIRO, J.B.S. Productivity of soybean in management zones with application of different sowing densities. **Ciência Rural**, Santa Maria, v.48, n.12, p.e20180532, 2018.

CARDUCCI, C. E.; OLIVEIRA, G. C.; SEVERIANO, E. C.; ZEVIANI, W. M. Modelagem da curva de retenção de água de Latossolos utilizando a Equação Duplo Van Genuchten. **Revista Brasileira de Ciência do Solo,** Viçosa, v.35, n.1, p.77-86, 2011.

CORASSA, G.M.; SANTI, A.L.; SILVA, V.R.; BARON, F.A.; REIMCHE, G.B.; FIORESI, D.; FLORA, D.P.D. Soil chemical attributes restricting grain yield in Oxisols under no-tillage system. **Pesquisa Agropecuária Brasileira**, Brasília, v.53, n.11, p.1203-1212, 2018.

CORTEZ, J.W.; ANGHINONI, M.; ARCOVERDE, S.N.S. Seed metering mechanisms and tractor-seeder forward speed on corn agronomic components. **Engenharia Agrícola**, Jaboticabal, v. 40, n.1, p.61-68, 2020.

CORTEZ, J.W.; CAVASSINI, V.H.; MOTOMIYA, A.V.A.; ORLANDO, R.C.; VALENTE, I.Q.M. Spatialization of soil resistance to penetration for localized management by precision agriculture tools. **Engenharia Agrícola**, Jaboticabal, v.38, n. 5, p.690-696, 2018a.

CORTEZ, J.W.; MATOS, W.P.S.; ARCOVERDE, S.N.S.; CAVASSINI, V.H.; VALENTE, I.Q.M. Spatial variability of soil resistance to penetration in no tillage system. **Engenharia Agrícola**, Jaboticabal, v.38, n.5, p.697-704, 2018b.

EMBRAPA AGROPECUÁRIA OESTE. **GUIA clima**. Dourados: Embrapa Agropecuária Oeste. Disponível em: http://www.cpao.embrapa.br/clima/. Acesso em: 2 fev. 2020.

GUEDES, L.P.C.; RIBEIRO JUNIOR, P.J.; URIBE-OPAZO, M.A.; BASTIANI, F. Soybean yield maps using regular and optimized sample with different configurations by simulated

annealing. **Engenharia Agrícola**, Jaboticabal, v.36, n.1, p.114-125, 2016.

KUIAWSKI, A.C.M.B.; SAFANELLI, J.L.; BOTTEGA, E.L.; OLIVEIRA NETO, A.M.; GUERRA, N. Vegetation indexes and delineation of management zones for soybean. **Pesquisa Agropecuária Tropical,** Goiânia, v.47, n.2, p.168-177, 2017.

LEAL, A.J.F.; MIGUEL, E.P.; BAIO, F.H.R.; NEVES, D.C.; LEAL, U.A.S. Redes neurais artificiais na predição da produtividade de milho e definição de sítios de manejo diferenciado por meio de atributos do solo. **Bragantia**, Campinas, v.74, n.4, p.436-444, 2015.

LIMA, J.S.S.; BONA, D.A.O.; FIEDLER, N.C.; PEREIRA, D.P. Distribuição espacial das frações granulométricas argila e areia total em um Latossolo Vermelho-Amarelo. **Revista Árvore**, Viçosa, v.38, n.3, p.513-521, 2014.

MENEGATTI, L.A.A.; MOLIN, J.P. Remoção de erros em mapas de produtividade via filtragem de dados brutos. **Revista Brasileira de Engenharia Agrícola e Ambiental**, Campina Grande, v.8, n.1, p.126-134, 2004.

MOLIN, J.P.; AMARAL, L.R.; COLAÇO, A.F. **Agricultura de precisão**. Piracicaba: Oficina de Textos, 2015.

NUNES, A.C.; BEZERRA, F.M.L.; SILVA, R.A.; SILVA JÚNIOR, J.L.C.; GONÇALVES, F.B.; SANTOS, G.A. Agronomic aspects of soybean plants subjected to deficit irrigation. **Revista Brasileira de Engenharia Agrícola e Ambiental**, Campina Grande, v.20, n.7, p.654-659, 2016.

OLIVEIRA, I.A.; CAMPOS, M.C.C.; AQUINO, R.E.; SILVA, D.M.P.; CUNHA, J.M.; SOUZA, Z.M.; SOARES, M.D.R.; FREITAS, L. Spatial variability of physical attributes of cambisol under cassava cultivation in Southern Amazonas. **African Journal of Agricultural Research**, Nairobi, v.10, n.49, p.4414-4423, 2015.

ROCHA, D. S.O.; RODRIGUES, C.S.; GALLO, P.B.; TICELLI, M.; PATERNIANI, M.E.A.G.Z. Drought tolerance in intervarietal maize hybrids. **Revista Caatinga**, Mossoró, v. 4, n.1, p. 80-89, 2021.

SANTI, A.L.; AMADO, T.J.C.; EITELWEIN, M.T.; CHERUBIN, M.R.; SILVA, R.F.; DA ROS, C.O. Definição de zonas de produtividade em áreas manejadas com agricultura de precisão. **Revista Brasileira de Ciências Agrárias**, Recife, v.8, n.3, p.510-515, 2013.

SANTOS, H.G.; JACOMINE, P.K.T.; ANJOS, L.H.C.; OLIVEIRA, V.A.; LUMBRERAS, J.F.; COELHO, M.R.; ALMEIDA, J.Á.; ARAÚJO, J.C.; OLIVEIRA, J.B.; CUNHA, T.J.F. **Sistema Brasileiro de Classificação de Solos**. 5 ed. Brasília: Embrapa, 2018.

SOUZA, P.J.O.P.; FERREIRA, D.P.; SOUSA, D.P.; NUNES, H.G.G.C.; BARBOSA, A.V.C. Trocas Gasosas do Feijao-Caupi Cultivado no Nordeste Paraense em Resposta à Deficiência Hídrica Forçada Durante a Fase Reprodutiva. **Revista Brasileira de Meteorologia**, São José dos Campos, v.35, n.1, p.13-22, 2020.

TSCHIEDEL, M.; FERREIRA, M.F. Introdução à agricultura de precisão: conceitos e vantagens. **Ciência Rural**, Santa Maria, v.32, n.1, p.159-163, 2002.

VIAN, A.L.; SANTI, A.L.; AMADO, T.J.C.; CHERUBIN, M.R.; SIMON, D.H.; DAMIAN, J.M; BREDEMEIER, C. Variabilidade espacial da produtividade de milho irrigado e sua correlação com variáveis explicativas de planta. **Ciência Rural**, Santa Maria, v. 46, n.3, p.464-471, 2016.

WARRICK, A.W.; NIELSEN, D.R. Spatial variability of soil physical properties in the field. In: HILLEL, D. (org.). **Applications of soil physics**. New York, Academic Press, 1980. p. 319-344.