Soybean production components as indicators of soil variability as a subsidy for precision agriculture

Eduarda Soares Apolinário[1]. Agronomist student: es.apolinario@unesp.br

Wilson José Oliveira de Souza[1]. Professor, PhD: wilson.souza@unesp.br

1. São Paulo State University – UNESP/FCAVR. Rua Nelson Brihi Badur, 430, Vila Tupi. Registro, São Paulo, Brasil. CEP. 11.900-000.

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Abstract.

The soil variability in its physical, chemical and biological parameters can be analyzed using direct methods applicable to each variable studied. Plant responses, manifested in the establishment of the final population, biomass production and grain productivity can reflect the soil conditions, associating them with the variability observed in the area. Localized soil management and the use of machines with variable rate applications, including drones for applications in specific sites, depend directly on the identification of area variability and its causes, allowing decisions to be made that lead to optimization in the use of inputs and reduction of production costs, resulting in greater sustainability of production systems. The objective of the work was to study the area variability based on final stand data and soybean productivity components in Direct Sowing System, aiming to support the adoption of Precision Agriculture techniques in a commercial area. The work was carried out in the municipality of Capão Bonito, SP, at geographic coordinates -24.023598052633503, -48.08443430697025, in soil classified as LVA 35 (RED-YELLOW LATOSSOL), in area of 30.3ha. The area was georeferenced, and 31 points were demarcated in a regular grid, which defined the sampling locations. At each point, Final Stand (FS), Production of dry biomass of plants and grains (DB_{p+g}), Production of dry biomass of soil cover (DB_{bi}), Production of soybean grains (PG) and weight of thousand seeds (WTS). The data were subjected to descriptive analysis, analysis of spatial variability with geostatistics techniques, elaboration of mathematical models between distance (h) and semi-variance [$\hat{y}(h)$] and interpolation by ordinary kriging. Descriptive analyzes of the data, to which the Shapiro-Wilk (W) test was applied, showed normal distribution ($p > 0.05$) for FS, DB_{bi}, PG and WTS data; the values of FS (plants m^{-1}) and PG (kg ha^{-1}) were adjusted to the spherical model (FS with parameters C0 = 0.4374; C1 = 1.437; A1 = 75.00; SSE statistics = 12, 19; RMSE = 0.6599 and AIC = 76.03) and (PG with parameters C0 = 456912; C1 = 9711.1; A1 = 2.422; statistics SSE = 274631187113; RMSE = 99037; AIC = 743.5), with Strong (DSD = 0.2333) and Weak (DSD = 0.9792) Degrees

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of Spatial Dependence, respectively. There was a positive correlation between dry biomass (DB_{bi}*), final stand (FS) and production of dry soybean grains (PG). With the data studied, FS and PG are sensitive to the variability of the area, being able to indicate specific sites with potential for individualized treatment.*

Keywords.
direct sowing, site specific managements.

Introduction

Soybean (*Glicine max* L. Merril) is an oilseed of great importance in Brazil and around the world, as it presents versatility in its use, serving different sectors. In Brazil alone, one of the world's largest soybean producers, production in the 2023/2024 harvest totaled 147.68 million tons, being cultivated in a total area of 45.7 million hectares, according to data from the National Supply Company. (2024). The production of soybean oil supplies the food industry, the by-product generated during grinding, soybean meal, is one of the main sources of energy in animal feed and the biodiesel obtained from its grains, contributes to the reduction of gas emissions greenhouse effect (GHG).

Most of the extensive soybean areas are cultivated in conservationist production systems, involving crop rotation and the adoption of the Direct Sowing System (DSS), essential techniques for conserving the soil, maintaining its productive capacity, reducing environmental impacts and minimizing production costs (Rodrigues et al., 2019). In DSS, the maintenance or increase in crop productivity is related to the physical, chemical and biological effects of soil organic matter (Santos et al., 2021), which in turn directly depends on the phytomass production of the crop and plants used in succession and rotation. Valicheski et al. (2012) cultivated soybeans after black oats and forage turnip in SPD, with different levels of compaction and found that these crops contributed to minimizing the effects of soil compaction on soybean development and productivity, which was attributed to vigorous root development of cover crops and the use of furrowing rods in the seeder to implement the crop. According to Almeida et al. (2020), it was found that soybeans grown in areas with legume coverage had a 15% increase in productivity compared to areas without coverage.

The best performance of commercial crops depends on the presence of soil cover. Mendes et al. (2019) studied the effect of corn straw as mulch and found an increase in soil moisture retention and a reduction in temperature, creating more favorable conditions for soybean growth. According to Oliveira et al. (2018), the use of cover crops can increase soybean productivity by up to 20%, due to improvements in soil structure and health. According to Silva et al. (2020) the use of legumes as a cover crop increased nitrogen levels in the soil, directly benefiting soybean growth and, according to Ferreira et al. (2021) areas with vegetation cover showed greater microbial diversity, which contributed to improving soil health and greater resistance to diseases, in addition to (according to Rodrigues et al., 2019) significantly increasing productivity and reducing crop production costs.

An important characteristic of agricultural areas that has been prominently observed in the production process is the variability of its components such as slope, soil type, type of cover and crop productivity. The most found productivity relationships are with chemical and physical attributes of the soil, as found by Gelain et al. (2021), in which soybean productivity showed strong spatial dependence and was strongly positively correlated with phosphorus and moderately with magnesium. Santi et al. (2016) found that the quality of straw distribution during harvest interferes with area variability and can result in greater production variability, which can lead to or indicate the occurrence of microregions with different productive potential, defining different management zones. Management zones allow decision-making to optimize the use of production factors, increasing the efficiency of production systems. Attempts to divide the crop into parcels and treat them differently have already been proposed and tested, but only recently, with the development of appropriate technologies, has it been possible to carry out this type of procedure in a simpler and faster way (Lamparelli et al. , 2001). Alves et al. (2013) studied the identification of different soil management zones based on altitude, electrical conductivity (0-020m and 0.20-0.40m) and organic matter content; the authors found that the management zones that best classified attributes relating to soil texture were those defined based on organic matter maps or electrical conductivity maps; Chemical attributes were better classified from organic matter maps in conjunction with the altitude map and concluded that the attributes soil electrical conductivity and organic matter can be used as indicators of variability in soil properties. Schwalbert et al. (2014), studying the definition of management zones, used overlapping productivity maps of corn (two crops), wheat (two crops), altimetry and electrical conductivity, and arrived at three management zones (low, medium and high productivity) , allowing you to make more assertive decisions regarding the use of inputs. Considering the context, the aim of the work was to study the variability of the area based on final stand data and soybean productivity components in the Direct Planting System, aiming to support the identification of management zones and the adoption of Precision Agriculture techniques in an area commercial.

Material and Methods

The work was carried out in the Capão Bonito county, SP State, at geographic coordinates -24.023598052633503, -48.08443430697025, with an average temperature of 26°C, average precipitation of 140 mm and average altitude of 730m, the studied area has 30.3ha, and the Its soil is classified as LVA 35 (RED-YELLOW OXISOL). The area has been cultivated in a direct sowing system for more than 15 years, following a succession of Soybean crops in the summer and Corn in the autumn/winter.

The cultural treatments carried out in the area for the 2022/2023 harvest were the application of 850 kg ha^{-1} of limestone using the Tatu Marchesan brand distributor, model DCA 5500 T with 5.5 tons capacity, coupled to a Case Maxxum tractor with 110 horsepower (80,96 kW) in the engine, traveling at an average speed of 10 km h^{-1}. The area was desiccated using Finale (2 L ha^{-1}) (c.p.) and Ta 35 (0.5L ha^{-1}), applying 80 L ha^{-1} of syrup, 20 days before soybean sowing. The soybean crop was implemented on October 7th, using the 58160 RSF IPRO BMX LANÇA IPRO variety, inoculated with *Bradyrhizobium japonicum* - ATMO Tradecorp and considering the desired population of 250 thousand plants ha^{-1}. The fertilizer used was Ilsa Gradual Mix 7-12-16 with 350 kg ha^{-1}. The harvest was carried out 145 days after sowing, using a Case/5150/2021 brand/model/year harvester with a 234 kW power engine, 25-foot platform and axial-type track system.

The area was georeferenced using GPS navigation (Garmin 60Cx) with an accuracy of 6.0 m and 31 points were demarcated in a regular grid, following the map generated by the Falker Map program, which defined the sampling locations. At each point, Final Stand (EF), Production of dry biomass of plants and grains (DB_{p+g}), Production of dry biomass of soil cover (DB_{bi}), Production of soybean grains (PG) and weight of thousand seeds (WTS). Data collection was carried out in the 2022/2023 harvest of soybeans, carried out manually with the aid of a GPS to locate the points, upon arrival to determine the Final Stand, 2 meters were measured on the sowing line, in two lines , counting the number of soybean plants, with conversion into number of plants per linear meter and per hectare. Dry Biomass of Plants and Grains were measured 2 meters on the sowing line, in two lines, in which the plants (with pods) were collected and weighed to obtain the wet weight, they were taken to LAMMEC (Conservationist Machinery and Mechanization Laboratory) where they were taken to an oven with forced air circulation for 24-48 hours, at 60-70° C. The dry material (constant weight) was weighed to obtain dry weight. Production of Soil Coverage Biomass A metal frame measuring 0.50m x 0.50m was launched and the biomass contained in it was collected. The material was weighed to obtain the wet weight and sent to an oven with forced air circulation for 24-48 hours, at 60-70°C, removed and weighed again, then obtaining dry weight, which was converted to kg per hectare.

The data were subjected to descriptive analysis and the Shapiro-Wilk Normality Test, correlation analysis between variables and regression analysis between variables (PIMENTEL-GOMES & GARCIA, 2002) with a correlation coefficient greater than 0.60 ($R > 0.60$). Based on geostatistics, analyzes of the structure and spatial dependence were carried out, based on the shape of the semivariogram with its respective parameters (c= spatial variance, c0= nugget effect, c+c0= plateau, a= range) which were estimated using- if vesper v.1.60 (minasny et al., 2005). Both the structure and the spatial dependence between the observed values can be shown by the relationship expressed in equation 1.

$$\gamma\ (h) = \tfrac{1}{2}\,\{\mathrm{var}\ [z\ (t) - z\ (t + h)]\} \qquad (1)$$

on that,

γ (h)= semivariance as a function of the separation distance (h) between pairs of points; h= separation distance between pairs of points, m.

After obtaining the experimental semivariograms, the Gaussian, spherical and exponential models were tested and then the one that provided the appropriate adjustment to the square root of the mean calibration error (RMSE) method whose values closest to 1 and 0 were the estimates obtained for β1 and β0, respectively, the better the interpolation method or spatial dependence model; Akaike Index (AIC) whose model with the lowest value is considered the best fitting model, and the highest value of the spatial dependence evaluator (GDE), according to Dalchiavon et al. (2011). Characterizing the degree of variability consisted of analyzing the coefficient of variation (CV) values of the attributes, as recommended by Warrick & Nielsen (1998), which considers low variability when CV <12%; average for the range 12 – 60%, and high variability when CV > 60%. The degree of spatial dependence of the variables was determined and classified according to the parameters proposed by Cambardella et al., (1994) using Equation 2.

$$\mathrm{DSD} = (C_0/C + C_0) \times 100 \qquad (2)$$

on that,
DSD= Degree of spatial dependence;
C0= Nugget effect (represents the random variation of the studied phenomenon);
C0+C= threshold (total variation of the phenomenon evaluated).

The interpretation of the degree of dependence was determined according to the criteria established by Cambardella et al. (1994) which are described in Table 1.

. Table 1. Parameters for interpreting the degree of spatial dependence for variables analyzed by semivariance.

DSD - Degree of spatial dependence				
Interpretation	**STRONG**	**MODERATE**	**WEAK**	**INDEPENDENT**
Value	<25	25<GDE<75	75<GDE<1,0	=1,0
Meaning	Nugget effect less than or equal to 25% of the threshold	Nugget effect represents between 25% and 75% of the level	Relationship between nugget effect and plateau is between 75% and 100%	Relationship between nugget effect and threshold equal to 1. Pure nugget effect

Font: Adaptaded from Cambardella et al., (1994).

Results and discussion

The data obtained was subjected to descriptive analysis and the results are presented below. The normality analysis indicated that the final stand (EF) and soybean production components presented a normal distribution (W > 0.05), except total dry mass (MSp+g) which presented W = 0.9205 (p = 0. 0243) and non-normal distribution, as can be seen in Table 2.

TABLE 2. Result of the descriptive analysis and normality test for data on Final Stand (EF), Dry Mass of plants and grains (MSp+g), Dry Mass of soil cover biomass (DBbio), Grain production (PG) and Weights of a Thousand Seeds (WTS) in the 2022-23 agricultural year, in Pilar do Sul, SP, Brazil.

Parameter	n	M	Md	s^2	s	CV%	W	*p* value	Re
FS (pl m^{-1})	31	11,89	12,41	2,1785	1,4760	12,42	0,9674	$0,4514^{NS}$	N
DB_{p+g} (kg ha^{-1})	*31*	*14645,16*	*11844,44*	*$5,2369.10^6$*	*2288,4390*	*15,63*	*0,9205*	*0,0243**	*NN*
DB_{bio} (kg ha^{-1})	31	9109,68	7800,00	$1,0133.10^7$	3183,2221	34,94	0,9490	$0,1462^{NS}$	N
PG_s (kg ha^{-1})	31	5632,6159	5633,33	$5,0281.10^5$	709,0939	12,59	0,9773	$0,7331^{NS}$	N
WTS (kg)	31	0,1677	0,1650	0,0001	0,0099	5,92	0,9420	$0,0940^{NS}$	N

n = number of points sampled, M = arithmetic mean; Me = median; Md = mode; s = sampling variance; s2 = standard deviation of the mean; CV = coefficient of variation; W= Normality test value; EF= Final soybean stand; MSp+g= dry mass of plants with soybeans; MSbio = dry mass of soil cover biomass; PG = soybean grain production (dry); PMSe = weight of 1000 seeds; NS = not significant (normal distribution - N).*= significant at 5% probability level (non-normal distribution).**= significant at 1% probability level (non-normal distribution - NN).

Analyzing the data on the production components, the lowest CV value was obtained for PMSe, considered low in the classifications proposed by Pimentel-Gomes (1985) and Costa et al. (2002). The EF and PG values showed CV values close to 12% considered average (PIMENTEL-GOMES, 1985; COSTA et al., 2002), as well as MSp+g. Biomass production (Pbi) showed a CV value of 34.94%, considered high by the cited authors, indicating that it is the variable with the greatest discrepancy between the sampled points. A possible explanation for the observed variability may be the poor distribution of straw over the surface during the harvest of the previous crop, as pointed out by Schwalbert et al. (2014). Despite the greater variability of these data, the amount of ground cover biomass produced was greater than what is considered ideal, 6 t ha-1 (ALVARENGA et al., 2001). EF correlated linearly and positively with soybean PG (Figure 1), as well as MSp+g, as shown in Figure 2. These data are in line with other studies, such as Dalchiavon and Carvalho (2012), which also found positive correlations between number of pods and soybean grain production. The authors also considered pod production per plant and grain production per plant as good indicators for estimating soybean productivity.

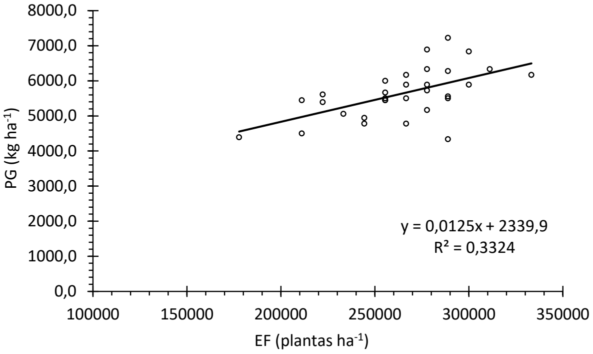

Fig 1. Regression analysis between FS, (plants ha-1) and PG (kg ha-1) in the soybean harvest in the direct sowing system, in the agricultural year 2022/23, in the of Capão Bonito county, SP.

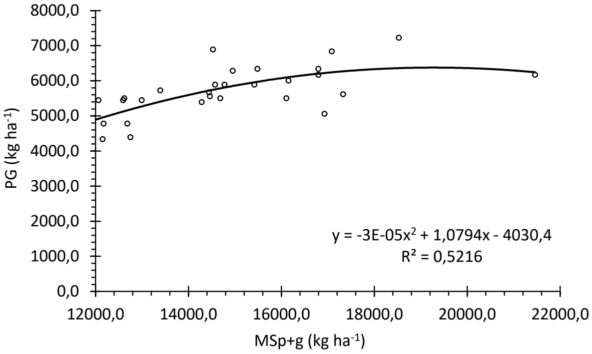

Fig 2. Análise de regressão entre DBp+g (kg ha-1) e PG (kg ha-1) in the soybean harvest in the direct sowing system, in the agricultural year 2022/23, in the of Capão Bonito county, SP.

Data evaluation using geostatistical methods showed that most of the variables studied present spatial variability, but low spatial dependence (Table 3), with the Spherical model being the one that best adjusted the data. The greatest spatial dependence was observed for the Final Stand (EF), with 23.3%, defined by strong (GDE < 0.25) according to Cambardella et al. (1994) and the adjusted model is presented in Figure 3. Studies carried out by Tagliari-Balestrin et al. (2021)

showed that the variability of straw distribution during the soybean harvest influenced the final stand of oats grown in succession. However, the EF obtained by the authors showed weak spatial dependence, different from that obtained in this work.

TABLE 3. Results of geostatistical analysis of data on Final Stand (FS), Dry Mass of plants and grains (DBp+g), Dry Mass of soil cover biomass (DBbio), Grain Production (PG) and Thousand Weights Seeds (WTS) in the 2022-23 agricultural year, in Pilar do Sul county, SP, Brazil.

Variável	Modelo	Co	C	Co+C	A1	AIC	RMSE	GDE
EF (pl m^{-1})	*Spherical*	*0,4374*	*1,437*	*1,8744*	*75,00*	*76,02*	*0,6599*	*0,233*
MS$_{p+g}$ (kg ha^{-1})	Exponential	4844259,0	2127,0	4846386,0	2,422	894,2	1461221,0	0,999
MS$_{bio}$ (kg ha^{-1})	Spherical	9242509,0	10000,0	9252509,0	2,422	940,6	3345778,0	0,999
PG (kg ha^{-1})	Spherical	456912,0	9711,3	466623,3	2,42	743,5	99037,0	0,979
PMSe (kg)	Spherical	77,36	1,523	78,883	56,00	290,9	30,6	0,981

FS= Final soybean stand; DBp+g= dry mass of plants with soybeans; DBbio = dry mass of soil cover biomass; PG = soybean grain production (dry); WTS = weight of 1000 seeds; Co= nugget effect; Co+C= plateau; Ao= (autocorrelation) proportion of variation explained by the distance between samples; A1 = range (amplitude); RMSE= root mean square error; GDE= degree of spatial dependence, calculated according to the nugget effect and the threshold calculated for the model defined for the variable.

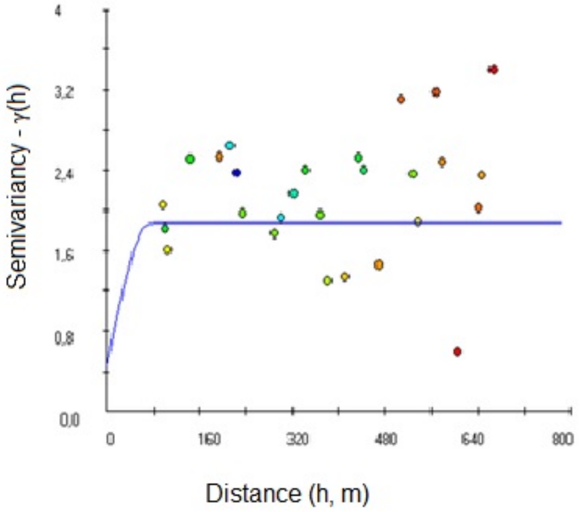

Figure 3. Semivarigram adjusted to the Spherical model, of the Final Stand data (EF, pl m-1) of the soybean crop in the

agricultural year 2022/23, in the municipality of Pilar do Sul, São Paulo, Brazil.

Conclusion or Summary

Considering the objective of this work, the data obtained can be used in studies of spatial variability;

Allows assistance in the history of the area for management in specific sites and adoption of precision agriculture technologies;

The Final Stand (EF) and total Mass Production (Pp+g) helped in estimating soybean productivity (PG) in SPD.

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