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AGRARIAN SCIENCES

Seeding rate in soybean according to the soil apparent electrical conductivity

SUZANY S. MOURA, LUIZ T. FRANÇA, VITOR S. PEREIRA,
PAULO EDUARDO TEODORO & FÁBIO H.R. BAIO

Abstract: This work aimed to study different seeding rates in soybean, at management zones determined by the mapping of the soil apparent electrical conductivity (ECa) and its relationships with plant phenology and grain yield (GY). The experiment consisted of a completely randomized design, with six replications. The plant population ranged between 311,000, 360,000, and 422,000 plants ha^{-1}, and the fixed population (360,000 plants ha^{-1}). The management zone with the least yield potential, received the highest seed population. The management zone with the highest plant vigor potential, received the lowest seed population. The variables plant height, Normalized Difference Vegetation Index (NDVI) at 50, 66, and 92 days after emergence (DAE), one hundred-grain weight, and GY were analyzed. ECa maps can be used to decide the seed population of the soybean. The decision strategy of increasing 20% of the seed soybean population on the smaller ECa map zones, and decreasing 20% seed population on higher ECa zones was effective and resulted in similar GY, even with the negative pressure of the high resistance of penetration (RP) values in some zones. GY map variability was influenced by ECa 0-0.2 m, by NDVI at 92 DAE and by RP 0.4-0.6 m soil layer.

Key words: seed population, precision agriculture, vegetation index, soil mechanical resistance to penetration.

INTRODUCTION

Soybean (*Glycine max*. L. Merrill) is the most important legume crop worldwide. It plays an essential role in the Brazilian economy owing to the large volume produced and exported (Yorinori 2007, CONAB 2018). With the increase in the world's population and the demand for food, the constant challenge is to increase production sustainably. To this end, efficient crop management and higher accuracy technologies are crucial for more profitable agriculture (Velandia et al. 2008).

Soybean yield can be affected by several environmental factors, and the soil apparent electrical conductivity can be used as an indicator for the monitoring of soil characteristics, such as salinity, texture, moisture, density, organic matter, and cation exchange capacity (CEC), (Molin & Rabello 2011). Optical, electromagnetic, electrochemical, mechanical, acoustic, and airflow systems have been studied in an attempt to develop techniques to indirectly measure soil properties (Adamchuk et al. 2004).

Some of these operating principles are found in the equipment Veris P4000 (Salina, KS, EUA), which, when in contact with the soil, measures its ECa in depth using a hydraulic probe with sensors and acquires spectral measurements in the Infrared and Red wavelength ranges (Veris 2018). Maps based on the ECa variability can be applied to delimiting management zones

(Fraisse et al. 2001, Molin & Castro 2008). This strategy can increase the efficient use of natural resource and reduce the impact of agriculture on the environment (Luchiari Junior et al. 2011).

Management interventions should be specifically prescribed for each zone, considering yield-limiting factors, with different applications, such as VRT (Variable Rate Technology), which includes the information collected in each unit at a given time and field region. The plant population may vary according to soil characteristics. The number of seeds or plants per unit area can be increased under more favorable conditions. Particular conditions may also occur, such as soil patches containing historically lesser-developed plants. In such cases, increased seeding density is recommended. Thus, the use of the VRT technology is suggested due to the specific seeding density variation for each management zone (Coelho & Silva 2009, Luchiari Junior et al. 2011).

The differences in populations lead to variations in the soybean plant. The increase in the plant population reduces the number of pods, decreases the number of grains per plant, and promotes higher final plant height (Knebel et al. 2006). Higher leaf area indices were observed in treatments with higher density populations of soybean plants per hectare (Luchiari Junior et al. 2011). Also, higher soybean leaf area index indicates higher NDVI values, and they are positively correlated to grain yield (Casa et al. 2018).

Soybean crops can withstand great population reduction without significant yield losses (Vazquez et al. 2008, Embrapa 2011). We hypothesize that the variation of the soybean population based on ECa can affect yield grain. Thus, the study on VRT seeding is fundamental to understand the influence of variable and fixed seeding rate on soybean yield. This work aimed to study soybean VRT seeding in management application zones determined by the soil ECa mapping and VRT relations with plant phenology and grain yield.

MATERIALS AND METHODS

The experiment was conducted in the experimental area of the Federal University of Mato Grosso do Sul (lat. 0.18°77'19"S; long. 0.52°62'10"W, at 810 m of altitude), in Chapadão do Sul/MS, in the agricultural year 2016/17. The one-hectare area had a history of 15 years of no-tillage system, and maize had been previously used as the cover crop. The climate of the region is Aw type, according to the Koppen's classification, defined as tropical humid, with rainy summer and dry winter (Fig. 1) (Kottek et al. 2006). Between November 2016, and March 2017,

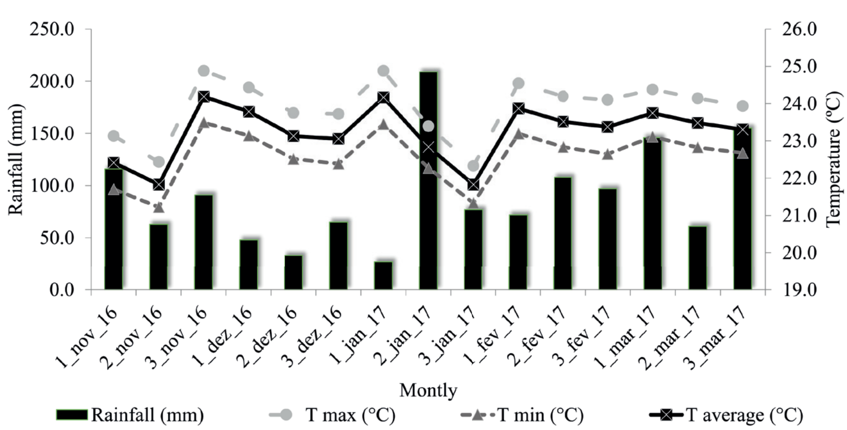

Figure 1. **Rainfall (mm), maximum, minimum, and average temperature (°C) every ten days, during the soybean cultivation in the field. Chapadão do Sul-MS, agricultural year 2016/17.**

the average rainfall in ten days was between 27 and 209 mm, and the average temperature was between 21 and 25 °C.

The experiment consisted of a completely randomized design, with six replications in each treatment (variable seeding rate *versus* fixed seeding rate). The management application zone with the lowest ECa (4.79 to 5.25 mS m^{-1}) received the highest seed population (422,000 seeds per hectare) due to the growth potential of plants that present low biomass and vegetation index. The management application zone with the highest ECa (5.53 to 6.24 mS m^{-1}) represented a higher potential for plant vigor and received the lowest seed population (311,000 soybean seeds per hectare). Soybean was sown on November 16, 2016.

The experiment used the soybean cultivar (*Glycine max*. L. Merrill) Desafio 8433 RR (Brasmax corporation), which has indeterminate growth habit and the average cycle of 110 days. Plants were spaced at 0.45 m between rows. The three management application zones were established with the ECa map at 0.0 to 0.2 m depth. The VRT seeding rates were established in three plant populations in the three management application zones (Fig. 2). The fixed population consisted of 360,000 plants ha^{-1}. For the VRT seed treatment, plant population ranged between 311, 360, and 422 thousand plants per hectare (20% higher and lower than the mean population), based on previous studies on plant population under the same environmental conditions (Knebel et al. 2006, Heiffig et al. 2006).

Thirty-three sites were defined in the different management application zones to measure the response variables, such as phenological indices and grain yield. The 33 sample sites were interpolated by ordinary kriging. The GNSS Trimble Nomad (Sunnyvale, USA) was used for navigation. The geostatistical analysis to determine the semivariograms and elaborate the ECa, RP (soil mechanical resistance to penetration) and VI (vegetation index) maps were performed in the software ArcGIS 10.5 (ESRI, Redlands, CA, USA). The maps allowed a visual analysis of the variability of the variables.

Geostatistical analyses were made modeling the spatial continuities of the regionalized variables, according to Matheron´s theory, and represented by the semivariogram (Equation 1). The spatial dependence index (SD) of the semivariogram models was calculated by the variance percentage of the nugget effect, as it represents the analytical error and indicates the spatial variability that cannot be explained (Trangmar et al. 1985). Spatial dependence was verified by semivariogram adjustments (Vieira 2000), taking into account the inference of intrinsic stationary process. The degree of spatial dependence of the studied variables was analyzed based on the following classification:

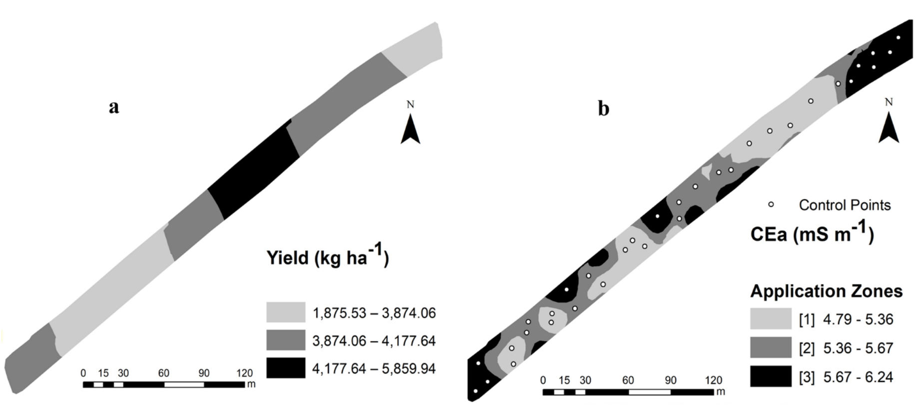

Figure 2. Spatial distribution of soil apparent electrical conductivity (a) based on a regular quadratic grid of 10x10 m, VRT seeding prescription map (b), and sampling points of response variables control in the three management zones.

low, for SD <25%; moderate, for 25% <SD <75%; and strong, for SD> 75% (Trangmar et al. 1985). The methodology used in the interpolation of the sampled data for the variables with spatial dependence had the theoretical models of the semivariogram based on the residual sum of the squares (exponential and spherical), which estimated the ECa and RP at different depths, and the NDVI at different days after emergence.

$$\hat{\gamma}(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[Z(x_i)-Z(x_i+h)\right]^2 \qquad (1)$$

where: $\hat{y}(h)$ is the estimated semivariogram; $N(h)$ is the number of pairs of measured values, $Z(x_i)$ and $Z(x_i+h)$, separated by a vector distance h; $Z(x_i)$ and $Z(x_i+h)$ values of the i-th observation of the regionalized variable, collected at points x and x_i+h(i=1,...,n), separated by a vector h.

Apparent electrical conductivity (ECa) data were collected on the soil profile based on a regular quadratic grid of 10x10 m to define the different management application zones, using the real-time sensor Veris model P4000 (Salina, KS, EUA). This equipment has a hydraulic probe with a set of electrodes, which drives an electrical current through the ground, indicating the apparent electrical conductivity at each depth (Molin & Rabello 2011).

Soil compaction data were collected in kPa to the 0.6 m depth when the soil was in field capacity condition, to study the possible causes of the final grain yield variability. Soil profile readings were performed every other 0.02 m, using the Veris P4000 probe. The device used a load cell to acquire the data on the soil mechanical resistance to penetration by measuring the insertion force required to push the probe into the soil (Veris 2018). The ECa and RP samples were georeferenced by the georeferencing device (GNSS) of the P4000. This tool was coupled to a Valtra tractor, model BL88, which provided hydraulic and electrical power to the system. The ECa and RP values were sampled in 100 sites of a 10 x 10 m rectangular grid. ECa maps were plotted at 0-0.2, 0.2-0.4, and 0.4-0.6 m depths. Ordinary kriging was used as the interpolation method, adjusted in the software ArcGIS 10.5 (ESRI, Redlands, CA, USA).

Deformed samples were collected at the 33 sites, at 0.0-0.2 m depth, for soil chemical analysis (Table I). These analyses were performed after the experiment implantation only for observation of the chemical compounds that influence soil ECa. The gravimetric moisture of the soil was determined by drying the sample in a conventional oven (oven) at 110 °C, for 24 h. The clay content was determined by the granulometric analysis methodology (total dispersion) (Embrapa 1997).

Base fertilization was performed according to the soil analysis, following the recommendations for cultivation in cerrado. Therefore, 150 kg ha^{-1} of Potassium Chloride (00-00-60) was applied at pre-sowing, and 335

Table I. **Mean results of soil chemical analysis.**

pH	H+Al	Ca	Mg	Al	CEC	B	Cu	Fe	Mn	Zn	K	P	OM	Clay	V	m
	cmolc dm^{-3}						g dm^{-3}			%						
4.41	7.2	1.8	0.3	0.4	9.4	0.5	0.9	75.5	9.0	3.9	62.5	15.6	23. 6	456. 7	23.6	16.3

pH CaCl2; H + Al: Potential acidity; Ca: Calcium; Mg: Magnesium; Al: Aluminum; CEC: Cation exchange capacity; B: Boron; Cu: Copper; Fe: Iron; Mn: Manganese; Zn: Zinc; K: Potassium; P: Phosphorus (resin); OM: Organic matter; Clay: Clay content; V: base saturation; m: Aluminum saturation.

kg ha^{-1} of the NPK formulation (05-25-15) was applied at sowing. Phytosanitary treatments and agricultural inputs were applied over the crop's development according to the crop monitoring and the standards for pest control and disease in the region. All the cultural treatments, such as herbicide, insecticide, and fungicide spraying and fertilization were carried out based on the crop's needs, following the recommendation for soybean crops in the region (Embrapa 2011).

For the phenological analysis of the response-variables at each sampling point (33 sites), plant height (PH) and vegetation index (VI) were measured in five plants, which were marked for identification in future evaluations. Plant height was measured at 46, 58, 66, and 92 days after emergence (DAE), in the main trunk, from the soil surface up to the insertion of the last fully expanded leaf. The vegetation index was recorded at 50, 66, and 92 DAE, at different phenological stages of the soybean crop. The Crop Circle equipment measured the NDVI vegetation index, model ACS-470 (Holland Scientific, Lincon, NE), using the 670 nm (red) and 760 nm (NIR - near infrared) filters. This equipment has three optical measurement channels, associated with the positioning of its integrated GPS. The sensor measures crop's reflectance at three wavelengths, according to the lenses selected for measurement. The area was manually scanned at the height of 0.8 m from the plants' canopy, interspersing the experimental field at every two planting rows. Plants were manually harvested at each of the 33 sampling points, in a sample area of 4.05 m^2. Soybean from each plot was weighed, and moisture was corrected to 14%. Afterward, the mean 100-grains weight was calculated.

After verifying the homogeneity between residual variances of each experiment, data were subject to analysis of variance, and the contrast between variable seeding rate (populations of 311,000; 360,000; and 422,000 plants ha^{-1}) and fixed seeding rate (360,000 plants ha^{-1}) was estimated. Subsequently, the principal components analysis (PCA) was performed in order to determine the trend of the variability of the variables, using the Rbio software (Bhering 2017). The method allows identifying the main spatial patterns by considering simultaneously all variables. The PCA is a multivariate covariance modeling technique that linearly transforms an original set of variables, initially correlated to each other, into a smaller set of uncorrelated variables that contains most of the information from the original set. This technique is associated with the idea of reducing data volume, with the lowest possible information loss. The principal components have important properties, *i.e.*, each principal component is a combination (Hongyu et al. 2016).

The study of the autocorrelation for attributes that showed spatial dependency structure was made using Moran´s bivariate (I_{xy}) index analyses (Anselin et al. 2002, Taylor & Bates 2013), via ArcGIS without interpolation. The variables were the same that showed straight correlation with yield by the PCA analyses. Interpolation procedures increase the amount of autocorrelation in the data and is statistically flawed.

$$I_{XY} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} u_i z_j w_{ij}}{s_0\sqrt{s_u^2 s_z^2}} \qquad (2)$$

where: n is the number of points; u_i and z_j are the standardized values of the variables X and Y, respectively; w_j is the element of the normalized neighborhood matrix, corresponding to the spatial weights 0 and 1, being 0 for the areas i and j that do not border each other and 1 for the areas and that border each other; s_0 is the sum of the elements w_i of the symmetric matrix of spatial weights; s^2_u and s^2_z correspond respectively to the variances of variables X and Y.

The relative deviation coefficient (RDC) expresses the dissimilarity between two maps in the module (Coelho et al. 2009). The calculation was performed by Equation 3. All values of the variables were converted to percentual values, in order to compare their different units. The grain yield map was considered the reference (standard) for comparison with the other maps.

$$RDC=\frac{\sum_{i=1}^{n}\left|\frac{P_{ij}-P_{iref}}{P_{iref}}\right|*100}{n} \quad (3)$$

where: n is the number of points; P_{ij} is the value of the variable at the specific point sample; P_{iref} is the value of the reference variable at the same point sample.

RESULTS AND DISCUSSION

Geostatistical analyses

The geostatistical analysis was performed for the most correlated variables with grain yield. Table II shows the parameters and the semivariograms models adjusted to the selected soybean phenology.

The exponential model was adjusted for all variables, according to the cross-validation, except for the variables ECa and RP at 0.0-0.2 m, which presented the best fit of the spherical model. All variables presented spatial dependence (SD). The NDVI at 50 and 66 DAE; the ECa at 0.0-0.2 and 0.4-0.6 m depth; and the RP at 0.2-0.4 m depth presented moderate spatial dependence (from 25% to 75%). The variables NDVI at 92 DAE, ECa at 0.2-0.4 m depth, RP at 0.0-0.2 and 0.4-0.6 m depths, and yield had strong SD (> 75%). The semivariogram must present SD, where the data can be interpolated by ordinary kriging (Cambardella et al. 1994).

Among the critical parameters in the semivariogram study, the range is the most relevant for revealing the limit distance of the spatial dependence, *i.e.*, the maximum distance at which a variable is spatially correlated. The mapped range ensures that all neighbors (within a radius) have spatial continuity and be used to estimate values at any position between them (Machado et al. 2007). The lowest range values were 12.25 and 21.27 m, for the variables NDVI (at

Table II. Parameters of the semivariograms adjusted for the phenological variables and the soybean vegetation index.

	Model	Nugget Effect (Co)	Sill (Co+C)	Range (m)	SD	r
NDVI 50 DAE	Exponential	0.0012	0.0018	35.28	0.35	0.67
NDVI 66 DAE	Exponential	0.0004	0.0006	22.04	0.36	0.43
NDVI 92 DAE	Exponential	0.0005	0.0026	12.25	0.81	0.85
ECa 0.0-0.2 m	Spherical	0.4382	1.5111	64.70	0.71	0.87
ECa 0.2-0.4 m	Exponential	0.0000	3.8100	21.27	1.00	0.46
ECa 0.4-0.6 m	Exponential	0.3574	1.0212	24.91	0.65	0.57
RP 0.0-0.2 m	Spherical	0.0000	5.2901	53.31	1.00	0.53
RP 0.2-0.4 m	Exponential	1.3984	3.6800	68.29	0.62	0.95
RP 0.4-0.6 m	Exponential	0.0000	1.9228	49.97	1.00	0.47
Yield	Exponential	0.0000	3.8105	24.91	1.00	0.45

ECa: Soil Apparent electrical conductivity; RP: soil mechanical resistance to penetration; SD: Spatial dependence [1-(C/Co+C)]; r: Cross-validation regression coefficient.

92 DAE) and ECa (at 0.2-0.4 m depth), respectively. The highest ranges, 68.29 m, and 64.70 m, were recorded for the variables RP (at 0.2-0.4 m depth) and ECa (at 0.0-0.2 m depth), respectively. This study revealed a low magnitude of the nugget effect (Co), which represents the unexplained variance, or the random variance, usually caused by measurement errors or property variations that cannot be detected in the sampling scale.

Researchers state that when the semivariance is constant at a certain level; regardless of the increase in distance, the model has a pure nugget effect (Mendes et al. 2008). These results suggest that besides the random distribution, samples are independent of the classical statistical methods and dependent on the distance that separates the sampling points (Motomiya et al. 2012).

Contrasts between variable seeding rate and fixed seeding rate

Table III presents the contrasts between the results for the variable seeding rate and fixed seeding rate for the NDVI evaluated at different days after emergence. The contrast at 92 DAE revealed significance, indicating the difference between the management of the different seed populations for this variable. This result can be

Table III. F calculated values for NDVI, soil apparent electrical conductivity (ECa) and soil mechanical resistance to penetration (RP) evaluated at different depths (m), plant height (PH) evaluated at different days after emergence (DAE), 100-grain weight (100GW), and grain yield (GY) evaluated at different days after emergence of soybean cultivated under variable seeding rate and fixed seeding rate.

Variable		F calculated values			Overall mean	CV (%)
		Fixed seeding rate (FSD)	Variable seeding rate (VSR)	FSR vs. VSR		
NDVI	50 DAE	1.84^{ns}	1.24^{ns}	0.18^{ns}	0.89	1.39
	66 DAE	0.38^{ns}	0.05^{ns}	0.29^{ns}	0.89	1.59
	92 DAE	0.95^{ns}	0.95^{ns}	5.71*	0.70	4.19
ECa (mS m^{-1})	0.0-0.2 m	2.46^{ns}	2.55^{ns}	37.28*	5.48	4.10
	0.2-0.4 m	9.36^{ns}	3.11^{ns}	10.25*	4.11	7.11
	0.4-0.6 m	8.18^{ns}	0.71^{ns}	2.73^{ns}	3.25	12.72
RP (kPa)	0.0-0.2 m	0.82^{ns}	0.10^{ns}	2.85^{ns}	3040.24	12.20
	0.2-0.4 m	0.80^{ns}	2.09^{ns}	20.78*	2631.97	7.45
	0.4-0.6 m	1.81^{ns}	4.55^{ns}	27.91*	1851.65	7.82
PH (m)	46 DAE	2.24^{ns}	0.13^{ns}	2.22^{ns}	0.64	5.79
	50 DAE	0.04^{ns}	0.41^{ns}	0.29^{ns}	0.80	8.73
	66 DAE	4.14^{ns}	5.21^{ns}	1.25^{ns}	0.83	6.66
	92 DAE	0.30^{ns}	0.23^{ns}	0.36^{ns}	0.88	4.68
100GW (g)		2.21^{ns}	3.51^{ns}	1.18^{ns}	15.24	2.72
GY (kg ha^{-1})		2.32^{ns}	1.71^{ns}	0.94^{ns}	3941.34	13.56

^{ns} and *: not significant and significant at 5% probability by the F test, respectively; CV: coefficient of variation.

explained by the fact that, at this stage, plants already present uniform size without plant density variation, limiting the perception about changes in the NDVI (Mercante et al. 2009, Groff et al. 2013). For this reason, significant contrasts were not detected at 50 DAE and 66 DAE.

NDVI increased gradually from 50 to 66 DAE (Fig. 3). However, this VI decreased by 92 DAE. This event happened because the dry matter increment rate in soybean plants increases gradually during the vegetative development stages until the R1 stage. Around the R2 stage, the daily rate of dry matter accumulation is constant, but a gradual decrease occurs during the grain filling stage (shortly after the R6 stage). Dry matter accumulation ends after the R6.5 stage (Ritchie 2000).

The significance of ECa in the soil surface layer (Table III) can be associated to the organic matter accumulation, which is restricted to the surface layers, influencing the soil physical, chemical, and biological conditions (Araújo et al. 2016). The organic matter accumulation in the no-tillage system increases soil CEC (Ciotta et al. 2003), which is highly related to the soil apparent electrical conductivity (Araújo et al. 2016). Although the VSR plots showed lower ECa, indicating lower potential fertility, and presented greater compaction in depth, the NDVI indices at 50 and 66 DAE were equal, *i.e.*, they agreed with the plant height. This result reflected in the grain yield; with a lower ECa and higher RP, the yield value was the same, showing that the variation in the seed population provided similar grain yield. This phenomenon shows that management application zones were well established and precision agriculture was similar to FSR.

Soil mechanical resistance to penetration and depth are directly proportional since the RP increased with the increase in the depth (Table III). The less compacted surface layer is explained by the non-compaction in the furrow caused by fertilizer machines, leading to non-compaction between depths of 0.08 and 0.12 m, and also by the seeder machine (Baio et al. 2017). The degree of soil compaction can be expressed by the measurement of soil mechanical resistance to penetration since its quantification indicates the growth and development dynamics of the root system (Silveira et al. 2010).

The variables related to plant height (PH) evaluated at different development stages (100-grain weight [100GW] and grain yield [GY]) presented no significant contrast when cultivated under variable and fixed seeding rates (Table III). Taller plants were expected at higher population density due to the possible etiolation caused

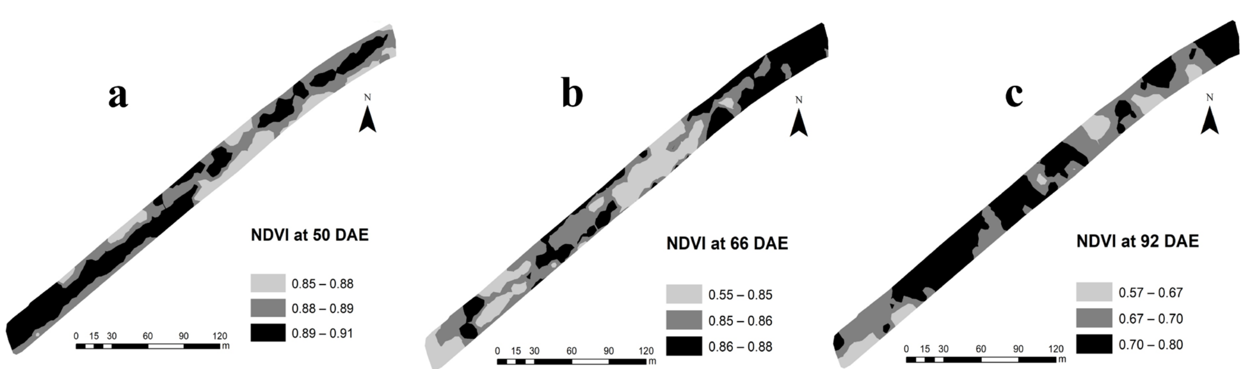

Figure 3. Spatial distribution of NDVI with five classes, according to the readings performed at 50 (a), 66 (b), and 92 DAE (c).

by shading. This fact is because the increase in seeding density increases the intraspecific competition for light (Mauad 2010). However, this behavior was not verified for plant height evaluated at different phenological stages (Table III) and was not significant for any of the plant populations (311, 360, or 422 thousand plants per hectare). This result was also observed in a similar study (Monteiro et al. 2015).

These events indicate that the differences between the different seeding populations influenced the agronomic behavior of the soybean crop, which was possibly due to the small variation in the plant population. Moreover, the number of pods per plant, which varies according to population increase or reduction, is a plant production component that contributes to higher tolerance to population variation (Peixoto et al. 2000).

Principal component analysis (PCA)

ECa at 0-0.2 m depth and NDVI at 92 DAE presented the highest factorial load in the first principal component and are directly correlated to each other and to yield (Fig. 4), contributing with most of the total variability observed. This result demonstrates that the management application zones to soybean seed rate were well defined based on the ECa at that given depth. The inverse occurred with soil mechanical resistance to penetration at the three depths evaluated (0-0.2, 0.2-0.4, and 0.4-0.6 m) and soybean yield.

Several factors can contribute to the explanation of the yield variation correlated to the ECa. The soil apparent electrical conductivity can be attributed to the different clay contents in each area (Molin & Rabello 2011). Clay is more efficient in retaining water when compared with silt and sand and is one of the determining factors in the ability of the soil to conduct electric current. However, other factors also influence soil ECa, such as salinity, water content, texture, and some chemical properties of agricultural interest (*e.g.*, cation exchange capacity [CEC]) (Molin & Rabello 2011).

The points sample sites 22, 28, 30, and 32 were closer to the NDVI at 92 DAE and ECa at 0.0-0.2 m depth, being very close to the yield vector. In these sites, seed management was carried out at a variable rate, *i.e.,* precision agriculture was applied. The corresponding values of these sites were the seed rate of 360 and 311 thousand seeds per ha^{-1}. Regarding yield, this variation was not much different since the soybean crop can withstand massive population reductions without significant yield losses. The difference between soybean populations does not interfere with the physiological quality, size, and seeds mass (Vazquez et al. 2008).

In experiments with precision agriculture techniques are more difficult to control experimental field factors that can affect the results. Several times, experimental field results are influenced by all variables together, making it difficult to be interpreted. PCA can help with this experimental field situation. In this study, the difference in the seed population was influenced by the ECa at 0-0.2 m and promoted higher values of NDVI values at 92 DAE (Figure 5).

Map similarities between significative variables and yield

Table IV presents the spatial autocorrelation (Moran´s index) and similarities between maps by the RDC to the variables yield, ECa, RP, and NDVI at 50, 66, and 92 DAE. Moran´s index showed that all analyzed variables presented spatial autocorrelation defined by the clustered zones on their maps, corroborating to the geostatistical analyses. The yield map presented the higher index (0.99), showing that there is a straight positive correlation between the values of a point and its neighbors (original

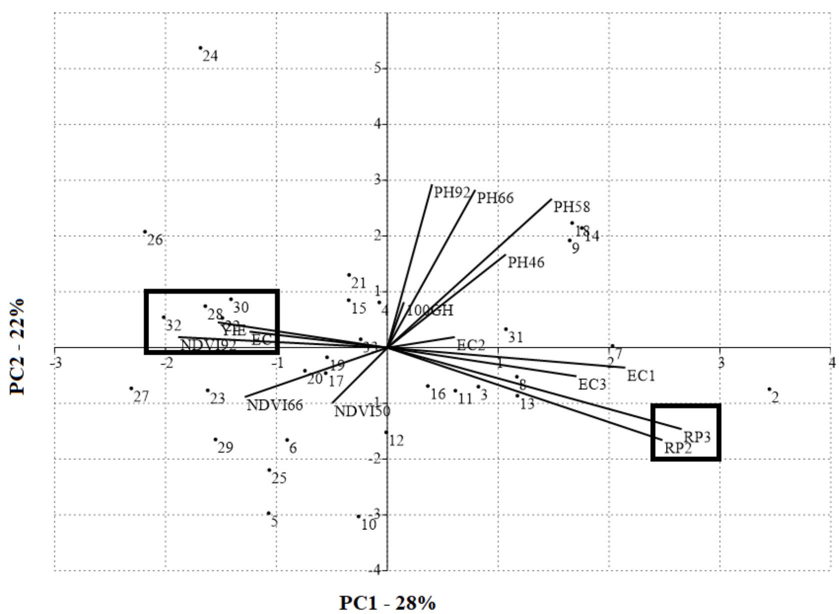

Figure 4. **Principal component analysis applied to the different sample sites evaluated under variable seeding rate and fixed seeding rate.**

samples). Significant spatial autocorrelation is generally higher than 0.3 (Jung et al. 2006), but all measured variables presented statistical significance level (p-value < 0.01). Thus, this is possible to confirm that the spatial variability of the measured variables was not random.

The smallest difference between two maps (presenting the higher correlation) was measured between NDVI at 50 and 66 DAE (1.0 % - Table IV). Small difference between subsequent VI maps is expected, mainly at the beginning of the crop cycle. The correlation between yield and ECa 0-0.2 m maps presented the smallest RDC index when comparing yield, showing only 40% of the difference between their relative variability values. This result corroborates with previous PCA analyses, presenting the same trend. There is no RDC value considered as optimum, and the choice of an acceptable RDC percentage value depends on the degree of accuracy desired by the user. Based on that, an RDC of 15% is considered a suitable value for guiding the interpretation of the results (Martins et al. 2018). The higher RDC index (or higher relative variability difference) was observed between yield and NDVI at 66 DAE maps.

When analyzing VI maps, NDVI at 92 DAE presented the highest correlation that influenced yield (Table IV). This fact may have occurred due to the difference in plant mass reflecting on the NDVI vegetation index in this period. Around R2, the daily dry matter accumulation rate by the plant is constant. Stages from R1 to R6 describe better the development of the plant. Plant mass accumulation depends on nutrients assimilation by the plants over their cycle, which increases until the final production stage and decreases after grain filling, being responsible for the soybean yield (Ritchie 2000).

Even with the negative influence of compaction at 0.4-0.6 m depth, the yield was satisfactory, with a mean of 3,941.34 kg ha^{-1}. Considering that ideal climatic conditions might have minimized the effects of soil with a compaction trend, the crop's root system might have obtained adequate water and nutrients at the non-compacted soil layer, which provided good yields even at locations with compacted subsurface layers (Drescher et al. 2012).

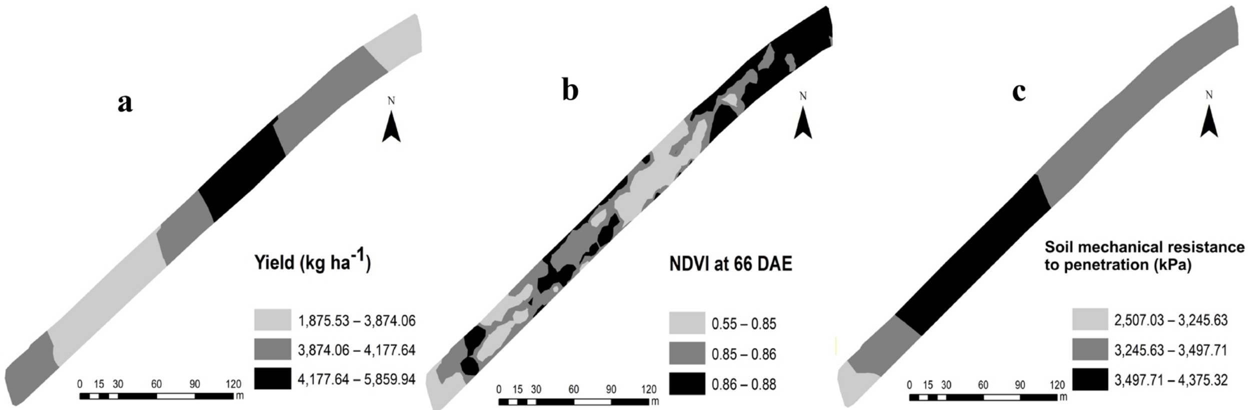

Figure 5. Spatial variability of grain yield (a), NDVI at 66 DAE (b), and soil mechanical resistance to penetration (c) measured at 0.4-0.6 m soil layer.

Table IV. Spatial autocorrelation (Moran´s index) and similarities between maps by the relative deviation coefficient (RDC %) to the variables yield, apparent electrical conductivity (ECa), soil resistance to the penetration (RP) and NDVI at 50, 66 and 92 DAE (ND).

	Moran´s index				Relative deviation coefficient (RDC %)					
	index	z-score	p-value	class	Yield	ECa	RP	ND 50	ND 66	ND 92
Yield	0.9874	11.1	<0.0001	clustered	0.0	4.0	7.1	7.9	8.9	5.5
ECa	0.9518	10.7	<0.0001	clustered	4.0	0.0	6.2	6.4	6.8	4.7
RP	0.9376	10.6	<0.0001	clustered	7.1	6.2	0.0	5.0	5.4	5.4
ND 50	0.2705	3.1	<0.0016	clustered	7.9	6.4	5.0	0.0	1.0	7.8
ND 66	0.2317	2.8	<0.0052	clustered	8.9	6.8	5.4	1.0	0.0	8.3
ND 92	0.5388	6.1	<0.0001	clustered	5.5	4.7	5.4	7.8	8.3	0.0

CONCLUSIONS

ECa maps can be used to decide the seed population of the soybean crop, applying precision agriculture techniques. The decision strategy of increasing 20% of the seed soybean population on the smaller ECa map zones, and decreasing 20% seed population on higher ECa zones was effective and resulted in similar grain yield, even with the negative pressure of the high RP values in some zones.

The soybean yield map variability was influenced by ECa 0-0.2 m, by NDVI at 92 DAE and by RP 0.4-0.6 m soil layer.

Based on these findings, Brazilian Cerrado farmers will be able to use variable rate sowing based on ECa maps. This technique may contribute to increased soybean grain yield.

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SUZANY S. MOURA
https://orcid.org/0000-0002-2795-8871

LUIZ T. FRANÇA
https://orcid.org/0000-0001-7852-4857

VITOR S. PEREIRA
https://orcid.org/0000-0002-9314-0453

PAULO EDUARDO TEODORO
https://orcid.org/0000-0002-8236-542X

FÁBIO H.R. BAIO
https://orcid.org/0000-0002-9522-0342

Universidade Federal de Mato Grosso do Sul, Departamento de Agronomia, Rodovia MS 306, Zona Rural, 79560-000 Chapadão do Sul, MS, Brazil

Correspondence to: **Paulo Eduardo Teodoro**
E-mail: eduteodoro@hotmail.com

Author contributions

S.S. de Moura wrote the manuscript. S.S. de Moura, L.T. França and V.S. Pereira conducted the experiment; P.E. Teodoro performed the statistical analysis; F.H.R. Baio guided the research; All authors read the final version of the manuscript.