Mapping of yield, economic return, soil electrical conductivity, and management zones of irrigated corn for silage

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Abstract – The objective of this work was to evaluate the spatial and temporal variability of the dry matter yield of irrigated corn for silage, as well as its economic return. The study was conducted in an irrigated silage corn field of 18.9 ha in the municipality of São Carlos, in the state of São Paulo, Brazil. The spatial variability of the yield of three crop seasons, normalized yield indexes, production cost, profit, and soil electrical conductivity (EC) were modeled using semivariograms. Yield maps were obtained by kriging, and management zones were mapped based on average yield, normalized index, and EC. The results showed a structured spatial variability of corn yield, production cost, profit, and soil EC within the irrigated area. The adopted precision agriculture tools were useful to indicate zones of higher yield and economic return. The sequences of yield maps and the analysis of spatial and temporal variability allow the definition of management zones, and soil EC is positively related to corn yield.

Index terms: *Zea mays*, economic return, management zones, soil electrical conductivity, temporal stability, yield maps.

Mapeamento de produtividade, retorno econômico, condutividade elétrica do solo e zonas de manejo de milho irrigado para silagem

Resumo – O objetivo deste trabalho foi avaliar a variabilidade espacial e temporal do rendimento de milho irrigado para silagem, bem como seu retorno econômico. O estudo foi conduzido em área de 18.9 ha de produção de silagem de milho irrigado, no Município de São Carlos, no Estado de São Paulo. Foram modelados, por meio de semivariogramas, variabilidade espacial da produtividade em três safras, produtividade normalizada, custo de produção, lucro e condutividade elétrica (CE) do solo. Os mapas de produtividade foram obtidos por krigagem, e as zonas de manejo foram mapeadas com base na produtividade média, no índice de normalização e na CE. Os resultados mostraram estrutura da variabilidade espacial do rendimento de milho, do custo de produção, do lucro e da CE do solo dentro da área irrigada. As ferramentas da agricultura de precisão adotadas foram úteis para indicar zonas de maior rendimento e retorno econômico. As sequências de mapas de rendimento e a análise de sua variabilidade espacial e temporal permitem a definição de zonas de manejo, e a CE do solo relaciona-se positivamente à produção de milho.

Termos para indexação: *Zea mays*, retorno econômico, zonas de manejo, condutividade elétrica do solo, estabilidade temporal, mapa de produtividade.

Introduction

Precision agriculture is a management concept that takes into account the spatial variability of an area, aiming to maximize economic return and minimize risks of environmental damage, through agricultural practices based on information technologies (Inamasu et al., 2011). It can be understood as a cycle that begins with data collection, continuing through analyses, interpretation of obtained information, generation of recommendations, and application in the field, aiming the evaluation of results (Gebbers & Adamchuk, 2010).

It reinforces the vision of the knowledge chain, in which machines, applications, and equipment are tools that can support this type of management (Inamasu & Bernardi, 2014). Therefore, differently from the traditional approach of managing whole farming in a homogenous way, precision agriculture considers spatial and temporal variability to define site-specific management zones. According to Doerge (1999), management zones are subregions of a field that have a similar combination of yield-limiting factors.

One way of defining these management zones is by using yield maps. Molin (2002) pointed out that these maps are the most compreenhsive source of information to visualize the spatial variability of crops regarding production factors. Yield maps can be used to investigate causes of variability and can subsidize decisions on soil and crop management (Molin, 2002; Amado et al., 2007; Santi et al., 2013; Vian et al., 2016). However, to reach this goal, it is necessary to monitor and analyze yield maps, considering the history of different cultures during at least three crop seasons, in order to observe spatial and temporal variabilities (Blackmore et al., 2003; Rodrigues et al., 2013). Furthermore, Molin (2002), Blackmore et al. (2003), and Joernsgaard & Halmoe (2003) highlighted the importance of the number of monitored crops, represented in individual maps, since the quality of the information will be greater with a greater data set, and, consequently, the adjustment of the temporal variability measurement will also be better. The information obtained by yield mapping can be used for several analyses and interferences in the field.

Another alternative to establishing management zones is based on soil apparent electrical conductivity (EC) (Moral et al., 2010; Farid et al., 2016). EC measurement integrates soil parameters related to productivity, such as texture, organic matter content and water availability, and can be useful for the interpretation of variations in crop yield (Johnson et al., 2005). Machado et al. (2006) verified that EC values were associated with soil clay content and were convenient to establish the limits of management zones in the soybean [*Glycine max* (L.) Merr.] crop.

Spatial and temporal data are gathered and analyzed by geostatistics and kriging interpolation, generating various maps or surfaces. Modeling by the geographic information system (GIS) enables the fusion of these layers of information, broadening the ability of data interpretation and assisting in decision-making for the management of a production system (Alba, 2014). Therefore, the establishment of management zones enables the best planning and appreciation of a system, since they are a strategy for data simplification (Rodrigues et al., 2013; Moshia et al. 2014).

In this context, the sustainability analysis of any system must consider agricultural, environmental, and economic aspects. Moshia et al. (2014), Bernardi et al. (2016), and Verruma et al. (2017) used precision agriculture tools to estimate the economic return of different production systems. Massey et al. (2008) concluded that transforming corn (*Zea mays* L.), soybean, and sorghum [*Sorghum bicolor* (L.) Moench] yield maps into profit maps containing economic thresholds that represent profitability zones could improve site-specific decisions. Particularly, the use of precision agriculture could be used to indicate spatial and temporal variations in crop yield, establish management zones, and indicate the potential economic return of production areas.

In the case of the corn crop, cultivated in 16.4 million hectares in Brazil, in the 2017/2018 growing season, with an average production of 5.1 Mg ha^{-1} (Acompanhamento..., 2018), yield has recently increased due to technological changes, such as plant breeding, balanced soil liming and fertilization, modernization of agricultural mechanization, and use of irrigation and precision agriculture tools. Irrigation can avoid water stress during critical reproductive growth stages of the crop, resulting in significantly higher yield, which has led to its expanded use in commercial crops throughout the country (Vian et al., 2016).

The objective of this work was to evaluate the spatial and temporal variability of the dry matter yield of corn for silage, as well as its economic return.

Materials and Methods

The study was conducted at Embrapa Pecuária Sudeste, in the municipality of São Carlos, in the state of São Paulo, Brazil (21°57'15S, 47°50'53.5W, at 856 m altitude), in an 18.9-ha area with a Latossolo Vermelho-Amarelo distrófico (Calderano Filho et al., 1998), i.e., an Oxisol, containing 730 g kg^{-1} sand, 17 g kg^{-1} silt, and 253 g kg^{-1} clay, with a sandy clay textural class. The climate, according to Köppen-

Geiger's classification, is CWa tropical of altitude, with 1,502 mm of annual rainfall and average minimum and maximum temperatures of 16.3°C in July and 23°C in February, respectively. The corn cultivar DKB390PRO2 was sown in December 2010, 2011, and 2013 in a no-tillage system, on the straw of the natural vegetation sprouted during the off-season. Liming was performed annually with dolomitic limestone (70% effective calcium carbonate equivalent) to raise base saturation to 70%. The following fertilizers were applied annually: 40, 140, 80, and 4 kg ha^{-1} N, P_2O_5, K_2O, and Zn, respectively, at planting; and 100, 25, and 100 kg ha^{-1} N, P_2O_5, and K_2O as topdressing at the three-leaf (V3) growth stage. The population used consisted of five plants per meter, spaced at 0.8 m between lines. Sprinkler irrigation was performed by the center pivot irrigation system, and water management (amount and frequency) was established based on the balance between climate demand (evapotranspiration) and the edaphic conditions (available water storage) of the site. Only half of the irrigated area was cultivated with corn (Figure 1).

The yield of irrigated corn for silage was evaluated between April and May 2011, 2012, and 2014 (years 1, 2, and 3 of the experiment), when the crop was harvested at the dough stage, with dry matter between 28 and 35%. Biomass production was manually estimated in a regular grid of 40 georeferenced points (Figure 1), representing 2.1 samples per hectare. In each sampling point, 4.0-m length subsamples of corn aboveground biomass were collected from two lines to form a composite sample. Samples from the harvested material were taken to a forced-air circulation drying

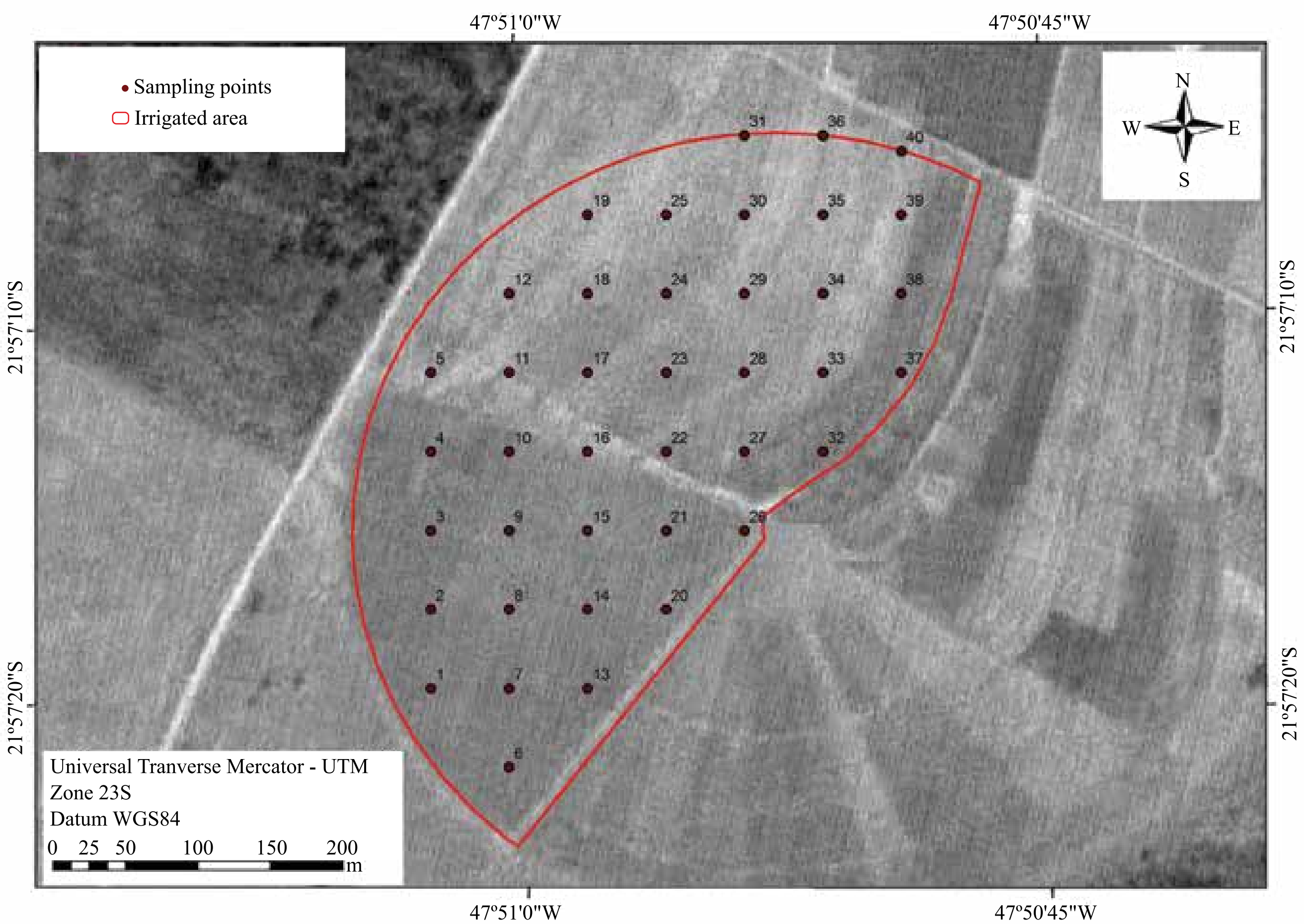

Figure 1. Location and sampling points for yield evaluation of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil.

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oven at 65ºC, until constant weight, for dry matter determination.

The yield data of the three evaluated years were subjected to the procedures of Blackmore (2000) and Molin (2002). The yield of each crop was normalized, and the average yield per plot in the three crops was calculated; the percentage of this average was obtained for each sampling point. The standard deviation and coefficient of variation (CV) were also calculated for each sampling point, representing the temporal variability of corn yield. From these values, yield was classified as: high, yield $_{i}$ > 105% yield $_{average,}$ CV < 30%; median, 95% ≤ yield $_{I}$ ≥ 105% yield $_{average}$, CV < 30%; low, yield $_{I}$ < 95% yield $_{average}$, CV < 30%; and inconsistent, CV ≥ 30%.

Based on the methodology proposed by Xu et al. (2006), management classes were established for each sampled point, considering the spatial (average yield of each point) and temporal stability (CV) trends. Five classes were taken into account in the present study: class 1, yield > yield $_{average}$ and CV <15%; class 2, yield > yield $_{average}$ and 15% ≤ CV_i <25%; class 3, yield < yield $_{average}$ and CV <15%; class 4, yield < yield $_{average}$ and 15% ≤ CV_i <25%; and class 5, CV_i ≥ 25%.

Apparent soil EC was measured with the soil EC 3100 sensor (Veris Technologies, Salina, KS, USA). The geographical coordinates of each measured point were obtained with the GPSMAP 60CSx handheld GPS (Garmin International Inc., Olathe, KS, USA). By May 2011, the equipment collected measurements at two different depths: 0.0–0.3 and 0.0–0.9 m.

The items and coefficients for production cost and profit simulations of the corn crop for silage were obtained based on the spreadsheets of Tupy et al. (2015). In this case, corn production costs considered: inputs, such as seeds, limestone, plaster, fertilizer, and agricultural pesticides; machines, used for pulverization, liming, plastering, sowing, fertilization, and harvest; and labor, including planting, cultural traits, harvest, and ensilage. Profit was calculated using the reference system of milk production described by Tupy et al. (2015), with Holstein cows producing an average of 25 kg milk per day, when feed: Tobiatã grass [*Megathyrsus maximus* (Jacq.) B.K.Simon & S.W.L.Jacobs] pasture, alfalfa (*Medicago sativa* L.), and concentrated food in summer; and corn silage, alfalfa, and concentrated food in winter. The prices were converted to American dollar at the quotation of US$ 1.00 = R$3.417.

Data were assigned to the respective geo–coordinates and exported to a GIS domain, the ArcGIS software, version 10.1 (Environmental Systems Research Institute, Redlands, CA, USA), as a shapefile for the geostatistical analysis. Geostatistical analyses were performed for all variables in order to evaluate spatial dependence and continuity. The models of empirical omni-directional semivariograms were calculated using the Vesper software (Oliveira, 2015), according to the equation:

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

where $Z(x_i)$ and $Z(x_i + h)$ are the values observed for Z in the x and x + h location, respectively; h is the separation distance; and N(h) is the paired comparison number at an h distance. From the adjusted mathematical model, the following coefficients of the semivariogram model, $\hat{\gamma}(h)$, were calculated: nugget effect (C_0), structural variance (C_1), and reach (a). Contour maps were estimated by kriging using the Vesper software (Oliveira, 2015). The contour maps for each of the analyzed variables were obtained with the ArcGIS software, version 10.1 (Environmental Systems Research Institute, Redlands, CA, USA).

A 1,033-virtual sampling point grid was created in the GIS environment, and values of average yield, normalized yield, management classes, production cost, profit, and apparent soil EC at the 0.0–0.3 and 0.0–0.9-m depths were obtained; then, Pearson's correlations – tested by Student's t-test, at 5.0, 1.0, and 0.1% probability – were established between them.

Results and Discussion

The yield data of the three evaluated years, average and normalized yields, cost and profit present asymmetry and kurtosis values compatible with normality (Table 1), since theoretical values of asymmetry (<0.5) and kurtosis (<3.0) indicate normal distribution of data (Vian et al., 2016). The results of the descriptive statistics indicated that all variables were symmetric data, while the distribution of EC at 0.0–0.9 m ($EC_{0.0\text{-}0.9}$) skewed to the right. This observation was also supported by the closeness of mean and median values (Table 1). In the geostatic analysis, normal distribution is not narrowly required, but, if met, can lead to more consistent results. Kriging also shows better results when data normality is satisfied (Grego & Oliveira, 2015). Average and normalized yields, as well as cost and profit, had a low CV (<10%). Yields in the three years of evaluation presented CVs considered medium (between 10 and 20%), while those of EC at 0.0–0.3 ($EC_{0.0\text{-}0.3}$) and $EC_{0.0\text{-}0.9}$ were high.

The experimental semivariograms were calculated, and all adjusted models delimited for each year of sampling (Table 2). The observations within the range of variogram (A) are considered spatially correlated (Grego & Oliveira, 2015). Therefore, this range indicated the existence of spatial correlation for plant and soil parameters over a long distance of >58 m and > 473 m, respectively. A sampling interval of less than half of the range of a variogram is recommended for the adequate spatial characterization of parameters. Therefore, a sampling distance shorter than 29 m can be used as a sampling interval for the spatial characterization of parameters such as corn yield, whereas a longer distance, i.e., a wider sampling interval, of <237 m can be adopted for soil EC.

Table 1. Statistical parameters of average dry matter yield (DMY), normalized yield, management classes, production cost, profit, and apparent soil electrical conductivity at the 0.0–0.3 ($EC_{0.0\text{-}0.3}$) and 0.0–0.9-m ($EC_{0.0\text{-}0.9}$) depths of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil(1).

Variable	Average	Median	Minimum	Maximum	SD	Asymmetry	Kurtosis	CV (%)	Number
DMY - Year 1	14,137	13,911	9,810	20,104	2,401	0.340	0.010	16.99	40
DMY - Year 2	13,897	13,996	9,419	18,543	1,929	0.069	0.121	13.88	40
DMY - Year 3	13,952	13,442	11,511	18,231	1,626	0.909	0.587	11.66	40
Average DMY (3 crops)	13,995	14,270	11,627	16,705	1,327	-0.072	-0.874	9.48	40
Normalized yield	99.51	101.85	83.08	115.25	9.484	-0.17	-1.05	9.11	40
Cost	102.50	100.14	85.64	122.91	9.947	0.39	-0.75	9.29	40
Profit	1,225.96	1,244.39	1,083.89	1,359.90	73.043	-0.31	-0.84	5.96	40
$EC_{0.0\text{-}0.3}$	3.96	3.84	2.05	7.63	0.94	0.448	-0.341	23.8	14,815
$EC_{0.0\text{-}0.9}$	5.53	4.79	1.90	19.01	2.65	1.784	4.340	48.0	14,793

(1)SD, standard deviation; and CV, coefficient of variation.

Table 2. Estimates of the parameters of the semivariogram models adjusted to average dry matter yield (DMY), normalized yield, management classes, production cost, profit, and apparent soil electrical conductivity at the 0.0–0.3 ($EC_{0.0\text{-}0.3}$) and 0.0–0.9-m ($EC_{0.0\text{-}0.9}$) depths of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil(1).

Variable	Model of adjustment	C_0	C_1	A	Dependence $100[C_0 (C_0 + C_1)^{-1}]$	Correspondence
DMY - Year 1 (kg ha^{-1})	Spherical	2,593,802	3,061,068	208.2	84.7	Weak
DMY - Year 2 (kg ha^{-1})	Exponential	2,509,430	1,411,262	98.8	177.8	Weak
DMY - Year 3 (kg ha^{-1})	Exponential	1,419,596	1,362,045	58.3	104.2	Weak
Average DMY (kg ha^{-1})	Exponential	205,370	2,107,606	144.8	9.7	Strong
Normalized yield	Spherical	0.27	1.06	227.0	25.47	Moderate
Management class	Exponential	0.26	1.032	170.0	20.1	Strong
Cost (US$ per hectare per year)	Spherical	0.19	1.08	242.0	17.7	Strong
Profit (US$ per megagram)	Spherical	0.25	1.07	245.0	23.4	Strong
$EC_{0.0\text{-}0.3}$ (mS cm^{-2})	Exponential	0.51	56.6	10,000.0	0.89	Strong
$EC_{0.0\text{-}0.9}$ (mS cm^{-2})	Spherical	10.7	18.4	473.0	36.6	Moderate

(1)C_0, nugget effect; C_1, structural variance; and A, range.

The exponential model was considered appropriate for the experimental variograms of years 2 and 3, average yield, management class, and $EC_{0.0\text{-}0.3}$ parameters; however, for all others, the spherical model stood out. The ratio between nugget effect (C_0) and sill (C_0 + C), expressed as percentage, was used to determine the strength of the spatial dependence of the studied parameters. These values characterize the random component of field data spatial variability and also quantify the measurement of spatial dependence for the studied variables. The spatial dependencies of the yields in the three experimental years can be considered weak, as they showed C_0 above 76% of the threshold. Normalized yield and $EC_{0.0\text{-}0.9}$ had moderate dependencies between 25 and 75%, whereas average yield, cost, profit, and $EC_{0.0\text{-}0.3}$ presented strong dependencies, with $C_0 \leq 25\%$ of the threshold.

The obtained maps (Figure 2 A, B, and C) indicate similarities among the three crops, grown in three different years, i.e., seasons. However, the variation in spatial distribution, considering average yield, is a steadier result, as already observed by Godwin et al. (2003). Therefore, the average yield map (Figure 2 D) shows the spatial trend for the period and reveals that yield ranges may vary in approximately 39%, with greatest yield zones located in the northern and northeastern regions of the map, and the lowest ones in the central-west. Results from Vian et al. (2016) are also indicative of the high spatial variability of corn yield even under irrigation.

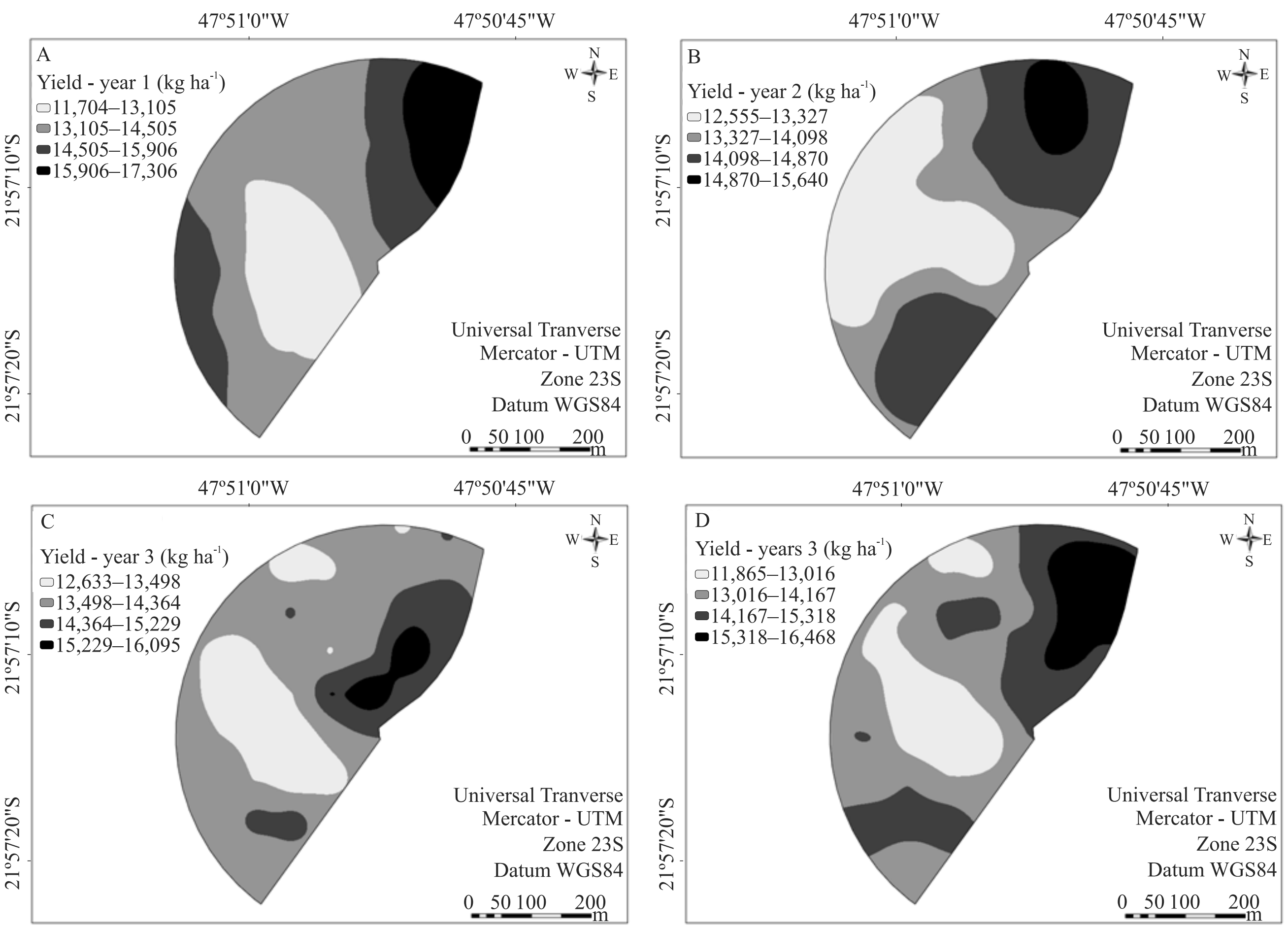

Figure 2. Spatialized maps of dry matter yield of irrigated corn (*Zea mays*) crop for silage in the 2010 (A), 2011 (B), and 2013 (C) harvests, as well as average yield (D) of the three growing seasons, in the municipality of São Carlos, in the state of São Paulo, Brazil.

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The averages of the sampling points for the three analyzed crops were considered consistent, with CV>30%, indicating the repeatability of these values throughout the sampled period and the consistency of the presented map, classifying the area into three distinct management zones of low, medium, and high yield potential. The definition and spatialization of the management zones for this corn field allow identifying the areas in which the yield of the system was similar in the defined period (Figure 3 A).

A trend in spatial variability could be expected for the three studied crops, as the chemical, physical and biological properties of the soil, essential for crop yield, can be relatively stable throughout time, despite spatial variability (Joernsgaard & Halmoe, 2003). However, the differences observed across crop seasons might derive from external factors, such as climate and agricultural practices (Amado et al., 2009; Vian et al., 2016), which can interact with soil properties and create different patterns of crop yield variation from one year to the other.

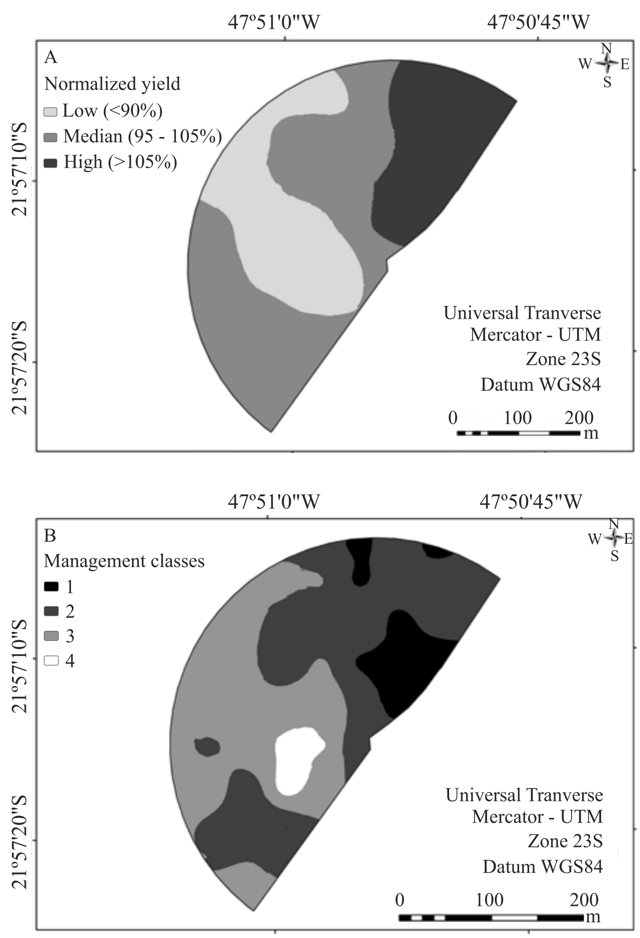

Figure 3. Spatialized maps of normalized yield (A) and management classes (B) of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil.

Therefore, only establishing management zones might not be enough for decision-making. Other criteria may also be necessary, such as the coefficient of management (Blackmore, 2000; Xu et al., 2006), which considers the spatial and temporal variability of yield. The map of management classes, based on Blackmore (2000), is a synthesis of the spatial and temporal stability trends of the three crop seasons (Figure 3 B). Therefore, the maps obtained according to Blackmore (2000) and Molin (2002) can be an excellent management tool and be adequately used for harvest estimation, since they are prepared considering the trend of different growing seasons, as recommended by Rodrigues et al. (2013).

For average yield, a significant linear correlation coefficient was observed between normalized yield (0.99) and management class (-0.82) (Table 3). This result is essential, as it shows that both indexes allowed identifying differences in the assessed corn field.

The information from yield maps and management zones is used to simplify spatial complexity, and the division of fields into subfields may support agronomic management decisions (Rodrigues et al., 2013; Moshia et al., 2014) as, for example, the optimization of the use of lime and fertilizer in areas of different yield potential. Another strategy is the intervention in low yield fields, with a more detailed diagnosis, followed by a response based on the limiting factors detected. However, the strategies for intervention in an area depend on several factors such as land use history, adopted production system and agricultural practices, and, as emphasized by Molin (2002), economic and financial aspects.

The production cost and profit (net income) maps incorporated the yield data of the three experimental years and provided a scenario of the economic return of the irrigated corn field (Figure 4 A and B). Three classes of production cost (US$ per megagram) were identified; the highest cost was on average 12 and 22% higher, respectively, than the average (US$ 98 to 111 per megagram) and low (US$ 85 to 98 per megagram) costs. Regarding profitability, differences of 6 to 12% were observed between the class with the highest

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economic return and the others. The cost and profit estimates allow to establish economic benchmarks and indicate what areas of the field were above or below the limit. Moreover, the cost and net profit maps translate yield data, which may be being collected by farmers for several years, as an understandable

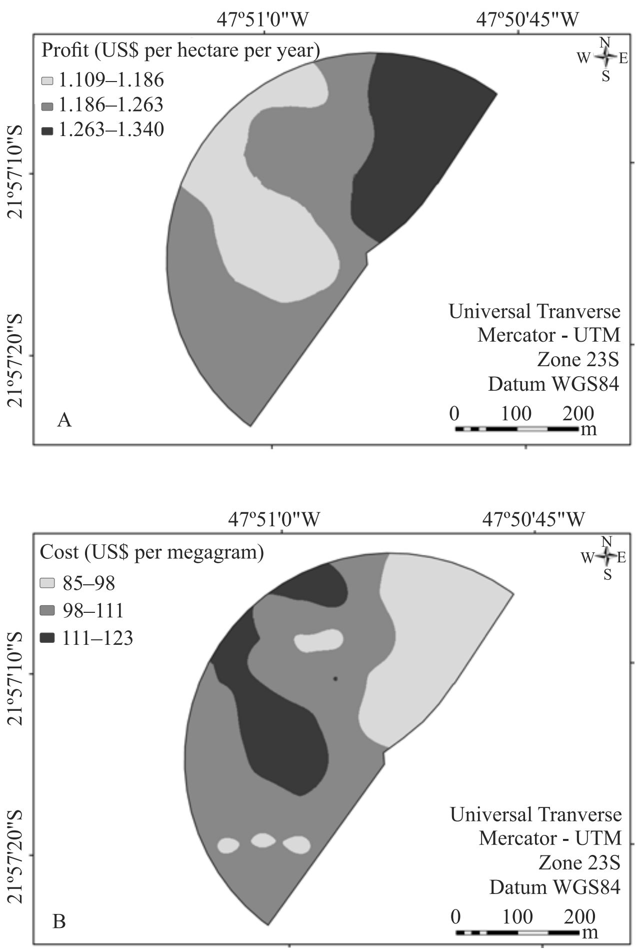

Figure 4. Spatialized maps of the production cost (A) and profit (B) of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil.

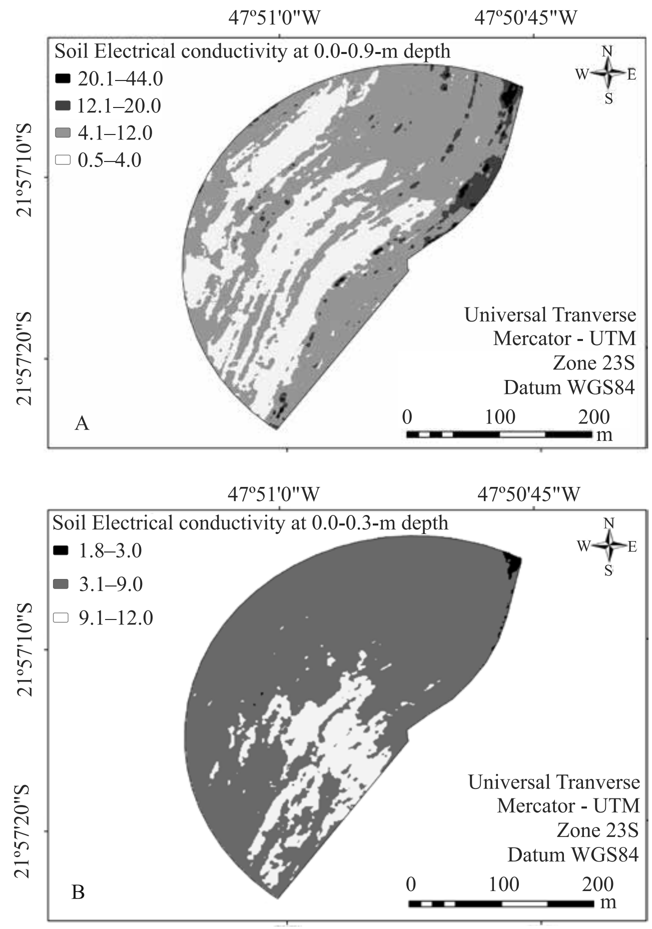

Figure 5. Spatialized maps of apparent soil electrical at the 0.0–0.3 (A) and 0.0–0.9-m (B) depths of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil.

Table 3. Pearson's correlation coefficients between average yield, normalized yield, management classes, production cost, profit, and apparent soil electrical conductivity (EC) at the 0.0–0.3 ($EC_{0.0\text{-}0.3}$) and 0.0–0.9-m ($EC_{0.0\text{-}0.9}$) depths of irrigated corn (*Zea mays*) crop for silage in the municipality of São Carlos, in the state of São Paulo, Brazil.

Variable	Normalized yield	Management class	Cost	Profit	$EC_{0.0\text{-}0.3}$	$EC_{0.0\text{-}0.9}$
Average yield	0.992***	-0.817**	-0.975***	0.993***	0.529*	0.431*
Normalized yield		-0.832**	-0.962***	0.995***	0.533*	0.437*
Management class			0.776**	-0.819**	-0.526*	-0.423*
Cost				-0.971***	-0.524*	-0.417*
Profit					0.434*	0.461*
$EC_{0.0\text{-}0.3}$						0.451*

*, ** and ***Significant at 5.0, 1.0, and 0.1% probability, respectively.

feedback that can be directly applied to improve site-specific management, as indicated by Massey et al. (2008). Significant correlation coefficients were found between corn yield and cost ($r=-0.98^{***}$) and net profit ($r=0.99^{***}$) (Table 3), confirming the importance of both maps to aid farmers and technicians in interpreting field variations and to support management decisions (Blackmore, 2000; Blackmore et al., 2003; Rodrigues et al., 2013).

Therefore, these results confirm that precision agriculture can help both in the detection of limiting factors (Inamasu et al., 2011; Inamasu & Bernardi, 2014) and in decision making regarding site-specific management strategies to improve crop profitability (Xu et al., 2006; Massey et al., 2008; Bernardi et al., 2016; Verruma et al., 2017).

The zones that need particular attention were identified in the present study and could be treated by specific measures. Therefore, it is recommended that limiting factors be diagnosed and, whenever possible, corrected before the application of spatially variable issues.

The spatial distribution of the soil EC evaluated at two different soil depths ($EC_{0.0\text{-}0.30}$ and $EC_{0.0\text{-}0.90}$) showed spatial patterns similar to those of corn yield (Figure 5 A and B). The shallow depth of 0.0–0.3 m presented EC values between 1.8 and 12 dS m^{-1}, and the deeper one of 0.0–0.9 m, between 0.5 and 44 dS m^{-1}. As the EC value is positively influenced by soil clay content (Johnson et al., 2005; Machado et al., 2006), the regions with higher EC reflect the quantity of clay (Moral et al., 2010). Consequently, regions with high clay typically indicate soil with a high organic matter content, cation exchange capacity, and available ions to the soil solution, conditions that increase soil yield potential. Corroborating the previous findings of Johnson et al. (2005) and Moral et al. (2010), average and normalized yields, as well as management class maps, were significantly related to the soil $EC_{0.0\text{-}0.3}$ and $EC_{0.0\text{-}0.9}$ values (Table 3) measured by the Veris sensor (Veris Technologies, Salina, KS, USA).

Conclusions

1. There is a structured spatial variability of corn (*Zea mays*) yield, production cost, profit, and soil electrical conductivity within the irrigated area.

2. The evaluated precision agriculture tools are useful to indicate zones of higher yield and economic return.

3. The sequences of yield maps and the analysis of spatial and temporal variability allow the definition of management zones.

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