SPATIAL VARIABILITY INDEX BASED ON SOIL PROPERTIES FOR NOTILL AND PASTURE SITE-SPECIFIC MANAGEMENT IN BRAZIL.

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ABSTRACT

Quantitative characterization of soil properties spatial variation has first been applied in Brazil using the opportunity index for the Precision Agriculture (PA) adoption. Preliminary index results from four Brazilian research-plots are introduced, in a stepwise process to adapt methods and protocols for different production systems. The model applied uses variogram parameters to quantify the magnitude and the structure of soil properties variation. An electrode-coulter-based sensor was used to map continuous in three no-tillage crop production systems and one pasture system. Results of these different fields and soil depths have fit typical index values and soil variations as previously observed, suggesting that indices could indicate adoption potential with further model calibration for different nutrient management practices.

Keywords: spatial variability, opportunity index, soil electrical conductivity.

INTRODUCTION

Quantitative approaches for the precision agriculture (PA) adoption are demanding decision support tools to better understand the ability of variable rate machinery to react in-field crop production variation. However, the need for characterization of production factor's variability has been mostly supported by customized and detailed geostatistical analyses, which is difficult to implement as general broad information accessible to farm managers. For this matter, few studies have been focused on simple and standardized indicators to support basic decisions at initial phases of PA adoption. Some adoption opportunity indices have been introduced based upon intensive monitoring data (Cambardella *et al.*, 1994; Pringle *et al.*, 2003) regarding operational (Tisseyre & McBratney, 2007) and strategic (de Oliveira & Whelan, 2008) decision support tools, but they are still requiring model calibration and normalization to different crop properties and regional management practices.

The main objective of this research is to fit an opportunity index for the Precision Agriculture (PA) adoption based on apparent soil electrical conductivity, first applying in Brazil a soil-property variability index (S_i) as an indicator for site-specific management. The study is part of a joint research network project, named Brazilian Precision Agriculture Research Network (BPARN), aiming at establishing methods and protocols for the adoption of PA technology for several production systems (*see abstract 1219*).

On-the-go monitoring of apparent soil electrical conductivity (EC_a) is an efficient and affordable (PA) technology, mostly available in Brazil, which may indirectly indicate the degree and the spatial structure of variation for some physical and chemical soil properties. Apparent soil electrical conductivity integrates texture and moisture availability, two soil characteristics that affect productivity while helping with the interpretation of spatial yield variations for certain soils (Kitchen *et al.*, 1999) and related to variation in crop production (Kitchen *et al.*, 1999; Luchiari *et al.*, 2001).

Commercially available instruments can be of two types, an electrode-coulter-based contact sensor or induction-based non-contact sensors (Sudduth *et al.*, 2003). An electrode-coulter-based sensor adapted from Veris 3100 technology to have continuous, via combine subsoiler and combine planter, was described by Rabello *et al.* (2008a,b). These high resolution measures have been evaluated and their typical responses to agricultural soil properties at distinct depths compared for use as input for decision making. They have been applied to a wide range of agricultural operations such as prediction of soil-water regime, salinity management, and characterization of production systems. In Brazil, Machado *et al.* (2006) verified that values of soil EC reflected soil clay content spatial variation and was adequate for establishing the limits of management zones.

Evaluations of depth-weighted responses between different EC_a measurements have shown highly contrasting correlation results were associated with differences in soil parent material, levels of organic matter, drainage classes, profile layering and variations in crop management (Sudduth *et al.*, 2005). These studies have shown that relationships between EC_a and crop yield may vary both spatially due to soil differences, and temporally due to climatic and managerial differences. Yet, electrode-based EC_a variations could be explained to a large extent by considering spatial linear mixed-effects models, where soil organic matter, clay content, presence of gleyic horizons and geological map units could mostly explain field-specific random effects (Kühn *et al.*, 2009). Due to the limited adoption of yield monitor technology in Brazil, the evaluation of quantitative models should be considered with different EC_a data inputs.

Opportunity index (O_i) models have been mostly suggested as a function of yield variation (Y_i) and the associated environmental cost/benefits (E), as shown in Equation 1 (Pringle *et al*., 2003).

$$O_i = f(Y_i, E) \tag{1}$$

Pringle *et al*., 2003 have considered concepts on the magnitude and the spatial structure of yield variation that have proven to be relevant when assessing the opportunity for differential crop management. Still, a fair bit of work is still required to establish the environmental-economic component to make a complete opportunity assessment. This preliminary approach used yield monitor data from grape and grain crop production systems from Australia. In France, a technical opportunity index (Tisseyre & McBratney, 2007), takes into account the minimum kernel area that machinery controllers can operate in areas of erosions and dilatations. In spatial terms, patterns are assessed in relation to the smallest area unit of treatment applicable. This operational kernel resolution can be a function of machinery characteristics (Pringle *et al.*, 2003), machinery characteristics plus position inaccuracy (Tisseyre & McBratney, 2007), or changes along the swath (Dillon *et al.*, 2007).

Although supporting a more detailed representation for operational practices, this model has increased complexity, requiring additional morphological data input and skilled interpretations. Further investigations on the O_i model were considered for fields located in three Australian regions (de Oliveira *et al.*, 2007), trying to adjust the O_i to support non-stationary yield variations. In addition, this model was systematically applied to different data inputs, thus: yield monitor (Y_i); EC_a by electrical magnetic induction (S_{i_EM}); and Imagery (I_{i_NDVI}).

MATERIAL AND METHODS

Soil electrical conductivity was gathered using the Veris model 3100 sensor manufactured by Veris Technologies of Salina, KS (Lund et al., 1999) and a prototype model point based readings (Rabello et al., 2010, 2011). Inputs from four fields located in different agroclimatic regions with no-tillage grain crop production systems and an intensive managed pasture were considered to a variety of inputs aiming at a simple numeric distribution validation of contact based opportunity indices (S_{i_Veris}) against previous index distributions computed for Australian grain crop fields (de Oliveira, 2009). Fields are among the first available pilot areas associated to the BPARN project. The three fields that have continuous EC_a measurements are: Field 26 (9 ha) and Field 49 (6 ha), both with soybean after fallow rotation at the Agrishow experimental area, Ribeirão Preto, São Paulo State, and Field 6 (33 ha), located at Cruzeiro Farm, Castelândia, Goiás State, with a soybeans, sorghum, and millet rotation. Point based readings (320 observations), were gathered in an 8 ha field for an irrigated and intensive managed Mombaça-grass (*Panicum maximum*) pasture (*see abstract 1047*) at Embrapa Cattle-Southeast (Canchim Farm), São Carlos, São Paulo State.

Continuous readings were of two depths, 30 cm and 90 cm; and point based for 20 cm and 40 cm.

Pre-processing of Brazilian contact-based index (S_{i_Veris}) computations has considered a step wise protocol as suggested in Taylor *et al.* (2007) for delineation of site-specific management zones. Datasets were georeferenced, organized, and analysed using variogram parameters from Vesper software (Whelan *et al.*, 2001). The selection of the best fitting variogram was undertaken by means of classical evaluation parameters having additional considerations for the practical range in relation to the associated field maximum lag. Detailed discussion of evaluation parameters, such as the Akaike Information Criteria (AIC), is given by Webster & McBratney (1989). Finally, a visual validation of S_{i_Veris} by single field is performed using kriged maps plotted with a normalized colour table legend which considered minimum and maximum EC_a values from all four field-samples using Vesper software (Whelan *et al.*, 2001).

As further detailed in de Oliveira (2009), the first S_{i_Veris} component considers the magnitude of EC_a variations (M_V) while considering an area related coefficient of variation (CV_A) which is computed by the total average field variance (A_C) minus the nugget effect (C_0). The average covariance is recursively computed between each single sample location and all the other points within the field. The second S_{i_Veris} component regards the spatial structure of EC_a variation (S_V). It is dependent on the application response which can be adjusted to different machinery or commercially available variable-rate applications to be considered. The S_V addresses the maximum length for the average autocorrelated EC_a variation denoted as correlated distance (C_D) and standardized against the operational length (O_L). The final spatial variability index from contact-based on soil EC_a is given in Equation 2.

$$S_{i\_Veris} = \sqrt{M_v \cdot S_v} = \sqrt{\sqrt{\frac{CV_A}{q_{50}\left(CV_A\right)}} \times \frac{C_D}{O_L}} \qquad (2)$$

Where;

M_v – magnitude of variation;
S_v – spatial structure of variation;
CV_A – spatial variation coefficient;
C_D – autocorrelation distance; and
O_L – operational length.

RESULTS AND DISCUSSIONS

Table 1 summarizes the EC_a distribution by individual fields, characterizing the different input data sets. Relatively low values of EC_a ranges for fields T6 and Canchim may reflect typical low soil moisture of these regions. The results derived from the best fitting models (Table 2) have confirmed that continuous monitoring inputs are expected to better support this type of analysis, where the Canchim variogram were still of non-stationary behaviour for both depths even after detrend procedures.

Table 1. EC_a Distribution for available fields at different depths.

Field	Depth (cm)	#	EC_a (mS/m)				CV (%)
			Min.	Med.	Max.	Mean	
T26	30	4868	0.2	6.3	10.6	6.2	28.5
T26	90	3464	0.4	197.3	374.8	180.6	65.8
T49	30	1933	2.1	7.7	16.6	7.9	37.1
T49	90	1933	0.8	10.9	47.6	13.0	62.3
T6	30	7470	0.2	7.1	17.5	6.9	36.2
T6	90	7470	0.1	2.6	7.7	2.6	33.4
Canchim	20	320	0.1	6.2	9.9	6.0	78.1
Canchim	40	320	0.3	4.3	9.6	4.6	73.1

Table 2. Variogram parameters and S_{i_Veris} results for all fields at different depths.

Field	Variogram Model	EC_a (mS/m)			M_v	S_v	S_i
		C_0	C_1	a_1			
T26 (30 cm)	Spherical	2.03	1.99	310	1.73	6.7	3.4
T26 (90 cm)	Spherical	10215	17183	97	4.48	4.1	4.3
T49 (30 cm)	Stable	4.94	2223.7	50000	2.54	13.6	5.8
T49 (90 cm)	Exponential	62.84	21.06	252	2.16	11.2	6.4
T6 (30 cm)	Exponential	3.80	2.48	51	0.91	16.4	3.9
T6 (90 cm)	Spherical	0.48	0.25	183	0.80	5.0	2.0
Canchim (20 cm)	Spherical	4.81	1172.8	50000	0.71	15.0	3.3
Canchim (40 cm)	Spherical	0.68	73.65	10000	1.10	12.8	3.8

Variogram models have indicated that both, stationary and non-stationary trends did not interfere on final index results (Figure 1). This can also be observed in Table 2 with stable response of index components and final results on all fields and depths. For continuous readings only the T49 field (30 cm) had a more laborious variogram fitting. This could be directly related to a more random legacy of soil cover and soil management practices for this experimental plot.

Interpolated maps using ordinary kriging and adjusted for a single legend (Figure 2) can be visually related to the final S_{i_Veris} values as clearly observed in field T49 (90 cm). This field has the highest index result associated to a map showing large magnitude of EC_a variation and well structured spatial patterns.

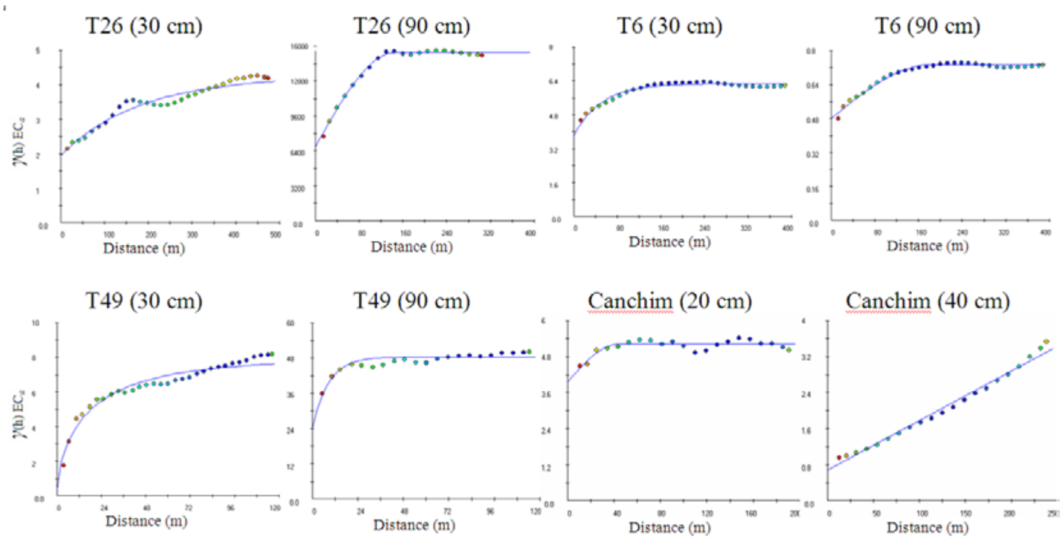

Figure 1. Variogram fitting for available fields at different depths.

Finally, the O_i distributions have shown that the proposed model could have a stable response when applied to different PA technologies at different management practices (Table 3). Importantly, correlations between index values and its associated components could also reflect an ability to incorporate both the magnitude and spatial nature of the encountered production variability in a manner that matches the physical understanding of the data produced by the respective sensing systems. In this case, the more continuous and less variable nature of the soil EC_a data at field scale contributes to the relatively lower values.

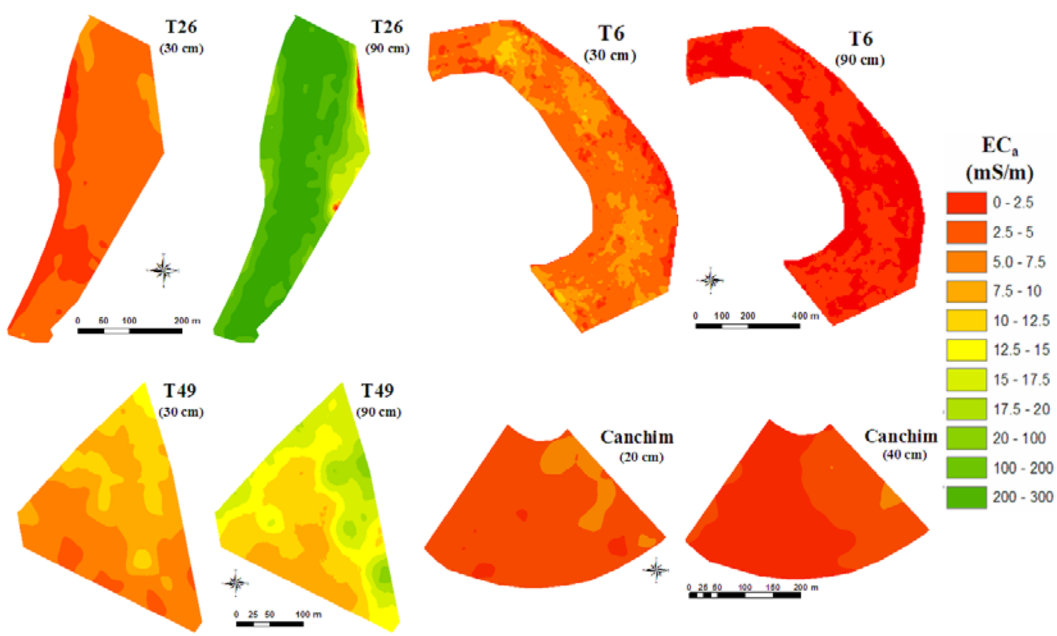

Figure 2. Interpolation of EC_a maps for available fields at different depths.

Table 3. Distribution of index values and its component correlations using different sensors as input for the PA adoption opportunity index.

Sensor	#	Opportunity Index (O_i) Min.	Med.	Max.	r (S_v)	r (M_v)
Yield (Y_i)	218	1.6	5.2	17.3	0.82	0.85
Imagery (I_{i_NDVI})	97	2.6	7.7	18.1	0.82	0.71
EC_a by induction (S_{i_EM})	44	2.0	3.7	9.0	0.83	0.94
EC_a by contact (S_{i_Veris})	8	2.0	3.8	6.4	0.53	0.72

Results from this preliminary application of the opportunity index on the electrode-coulter-based contact sensor (S_{i_Veris}) for different fields and depths have fit within typical S_{i_EM} values reported for non-contact electromagnetic-induction sensors in Australia (Table 3). Furthermore, S_{i_Veris} values for all fields have shown spatial relationship with topography and the spatial distribution of soil variation previously observed. Variogram fitting and index parameters could be mostly explained by current agronomic knowledge on specific no-tillage production systems, suggesting that adjusted indices could show actual potential for the adoption of PA technology.

The rationale for an opportunity index as first overviewed on the spatial variation of soil properties aims at identifying the farm areas where the cost of gathering further site-specific data is best matched by site-specific management results. Once adjusted and standardized across different production systems and regions, opportunity indices could support quantitative threshold information to determine whether the observed variability warrants differential treatment. It can also give some extra insights of factors affecting variability. With the large volume of data obtained upon the adoption of PA by family farms and producer associations, the field median indices could be used to rank the opportunity of fields per farm. If a fair distribution of samples is available, farm median indices could be used to rank the opportunity of farms per region.

CONCLUSIONS

Opportunity indices calculated from on-the-go soil EC_a sensors and crop reflectance imagery have shown potential support for farmer’s decisions on the adoption of PA technology when spatially dense data on crop yield are unavailable. The applied method has proven to be stable and robust over a variety of crop management systems and input data characteristics for Australian and Brazilian applications. Yet, model calibration is required to reflect the actual adoption opportunity for Brazilian standards on variable-rate machinery and operational management practices. As an example, the adjustment of the machinery related kernel area to operate.

Results from this preliminary application of the opportunity index with data from an adapted electrode-based contact sensor (S_{i_Veris}) may justify a systematic application of methods for additional production areas related to the Brazilian

Precision Agriculture Research Network. Model parameters could be mostly explained by specific knowledge on no-till production systems, suggesting that adjusted indices could support the adoption of PA technology.

General index results suggest that new input data applications could be considered for the original yield-monitor data related concept (O_i**).** Therefore, several within-field variability aspects can be estimated using alike parametric methods in accordance to a specific adopted technology; as: yield and soil EC_a sensors, or several imagery derived vegetation and plant related indices (e.g. Y_i, S_{i_EM38V}, S_{i_EM38H}, S_{i_EM31V}, S_{i_Veris}, I_{i_NDVI}, $I_{i\_PlantCellDensity}$).

Combined with local field management knowledge over multiple seasons, normalized indices could provide a valuable indicators supporting efficiency in crop management. Still, there is a need to face a greater challenge surrounding the incorporation of ecological and economic aspects in order to achieve a further understanding of the opportunity assessment.

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