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Autoregressive state spatial modeling of soil bulk density and organic carbon in fields under different tillage system

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ABSTRACT

Uncontrolled transit operations could be responsible of repetitive patterns of soil properties. Cyclic spatial structure patterns of soil bulk density (BD), soil organic carbon (OC) and water content (WC) in farm fields were assessed with spectra and cross spectra analysis in a 100 m-long transect sampled at 1 m apart, on Vertic and Typic Argiudol soils under no tillage (NT) from a commercial farm in San Antonio de Areco, 34° 15′32.42″ S, 59°25′19.93″ W, Ondulate pampa region, Argentina. Although spectrum and cospectrum analysis showed several cyclic locations, only sites at approximately 2.6 m, 4 m and 9 m were significant ($p < 0.05$). These distances are clearly related with tractors axles and combine harvester paths, thus suggesting the importance of those operations on soil variables. An autoregressive state space modeling approach was used to integrate the spatial information and to model BD, WC and OC in different transects at 10 m and 30 m apart. With the spatial relationship between BD and OC we create predictive models that explain 63% of the OC data and 54% of the BD data over a 2740 m-long transect. However, it was not possible to predict WC, despite the spatial correlation observed among the soil variables. The low importance of WC in the modeling process of BD and OC, and the large dominance of the autoregressive part in the final model are pointing out that an important surrogate variable is missing, which could be the key for modeling soil variables at different scale.

1. Introduction

Agricultural activities always determine several alterations of soil ecosystem because it is necessary to modify their natural condition. In strict sense, all farm machineries operations have adverse effects on soil properties. Tractors towing seeder, self-propeller sprayers, and combine harvester with grain carts moving around when harvesting impose a variety of stress loads over the soil. Note that depending on the vehicle, the distance between tires can vary from 1.2 m in tractors to 4 m in a combine harvester. In addition, contractors can use dual or triple tires in the front axle. They also can use different tire pressure or to add loads, depending on the need for sustentation in wet condition (Botta et al., 2012; Seehusen et al., 2014). Despite the size of the equipment and frequency of harvesting procedure, these operations are not often considered in soil degradation studies. However, it becomes evident that the tillage, the terrestrial equipment and the harvesting practices can affect soil properties dynamically in space and time. This evidence is increasing the need to apply spatial and temporal analyses to gain knowledge of the soil use and its behavior, especially in farmer's fields (Strudley et al., 2008). Knowing the spatial distribution of soil properties and their alteration could allow improving soil management practices or assessing their effect on soil quality (Cambardella et al., 1994). Additionally, spatial techniques could define the soil sampling intensity or to improve the sampling scheme for detecting adverse effects on soil functioning (Webster and Oliver, 2001). The alteration of soil properties even under controlled equipment traffic may fluctuate because a variation in landscape features and because the temporal variability could masked the wheel-track effects. Spatial and temporal variability often overshadows specific management effects. Differences in temporal variability depend on spatial locations between rows, within fields at different landscape positions, and between sites with different climates and soil types. Tillage practices have pronounced effects on soil properties but the duration of those effects could vary substantially (Strudley et al., 2008). The reason could be the resilience of the soil properties, as well as the effect of the root system and crop residue on the soil structure (De Varennes and Torres, 2011; Strudley et al., 2008; Abiven et al., 2007). Being the most common soil variables used for tillage comparison, soil bulk density (BD), water content (WC) and soil organic carbon content (OC), received special attention in soil

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studies. Despite all data available, the reviewers still found inconsistent responses about what happens with BD or WC when comparing different tillage practices (Strudley et al., 2008;). For example, Franzluebbers and Arshad (1996) found that tillage-induced BD exhibited large seasonal dynamics similar to WC. On the contrary, Cresswell et al. (1993) demonstrated insensitivity of tillage to WC in a silt loam in New Zealand. Thus, the evidence for changes in WC under tillage has not been generalized, but probably due to the temporal scale is more important than the spatial scale of variability of WC. The scale of variability is an important feature of soil properties, because depend on the soil variable under study. Cambardella et al. (1994) found that BD was moderately spatial-dependent while OC was strongly spatial dependent under tillage systems, conventional tillage and No tillage in central Iowa. They concluded that due to the spatial dependence, is not possible to extrapolate information from one field to another. Soil properties also can exhibit a repetitive or quasi cyclic behavior that could depend on tillage operations (Perfect and Caron, 2002) or cultivation practices (VanWesenbeeck et al., 1988; Nielsen and Alemi, 1989). The cyclic behavior of soil properties or periodicity in the spatial variation can be quantified from the spectral analysis, which approximates a spatial data series by a sum of sine and cosine functions (Nielsen and Wendroth, 2003; Biswas and Si, 2011). The squared amplitude at a given frequency is equal to the contribution of that frequency component to the total variance in the spatial series (Webster, 1977; Shumway, 1988). Frequency domain analysis or spectral analysis (Nielsen and Alemi, 1989) was successfully used for several researchers in soil science to analyze soil properties responsible for water and solute transport (Yang and Wendroth, 2014), effects of land use on leaching (Schwen et al., 2012) or bulk density and gravimetric water content (Perfect and Caron, 2002). In addition, soil data varying along transects can be described as multivariate autoregressive systems in state-space models (Wendroth et al., 1992, 2001). Those models have allowed a better understanding of processes in the field that influence the soils variability. In addition, state-space models were useful in identifying the underlying process that caused different soil function, as well as the yield spatial variability (Li et al., 2002; Wendroth et al., 2003, 2013). Being able to identify soil variables that are related spatially or temporarily allows greater opportunity to understand the mechanisms that create the spatial variation (Morkoc et al., 1985). The goal of this work was to identify the presence of cyclic patterns of selected soil variables (BD, WC and OC) induced for transit operations under NT by using a spectral-cospectral spatial approach. The intention is to assess the cyclic pattern produced by tillage and harvesting operation and to use the spatial relationship to describe and predict soil variables under contrasting tillage system with an autoregressive state space model.

2. Material and methods

The study was performed in San Antonio de Areco, 34°15′32.42″S, 59°25′19.93″W, NE of Buenos Aires province, Argentina. The landscape is lightly undulate with moderate to gently slopes, and it was intensively cultivated from more than 80 years. The weather condition is temperate, humid with mean annual temperature of 17 °C and 1000 mm yr^{-1} total precipitation (decade1995-2005). Two soil series are found in the area, Portela silt loam vertic Argiudol and Rio Tala silt loam typic Argiudol (Soil Survey, 1999). Both soils are well-drained and originated on loess material. They are characterized by high fertility, moderate low acidity (pH 6.5), high cation exchange capacity (CEC), high base saturation and large amounts of exchangeable calcium. A typical crop rotation in this region consists of double cropping wheat (*Triticum aestivum* L.) and soybean (*Glycine max* L. Merr.) followed by corn (*Zea mays* L.)-fallow-soybean (*Glycine max* L. Merr.). Sometimes the double cropping wheat/soybean is repeated several times before rotate with corn. The predominant tillage systems in the area are usually no tillage (NT) and even a combination of NT following wheat under moldboard plowing with disc tillage (MT). Usually this situation occurs when crop rotations include pasture for several years. Three different data sets were used in this study; (a) a 100 m long transect in a field under NT with samples taken every 1 m (NT_{1m}); (b) a 500 m long transect with samples taken every 10- m, in a NT field (NT_{10m}); (c) a 2740 m long transect across different adjacent farms. The soil samples were spaced every 30-m along this transect (NT_{30m}) and included one out of third sampled data taken from the NT_{10m} for predictive purposes. The sampling scheme was displayed in Figs. 1 and 2(a–c) show the soil bulk density (BD), volumetric water content (WC) and soil organic carbon content (OC) data as was found in the different transect. The soil bulk density was determined by the core method (Blake and Hartge, 1986) using undisturbed soil core samples with a volume of a 310 cm^3 and a length of 7.5 cm. The gravimetric water content was determined from these soil cores after dried in oven at 105 °C and converted to volumetric water content with the corresponding BD values. A second set of soil samples were taken in the same location for measuring the OC, which was determined with Walkey Black procedure (Nelson and Sommers, 1982) (Table 1).

In order to apply a frequency domain analysis of variance components, i.e., spectral and cross-spectral analysis (Shumway, 1988; Nielsen and Wendroth, 2003), only data from NT_{1m} transect was used. The frequency domain analysis transforms data to a finite Fourier series that are uncorrelated and have variances equal to the power spectrum. In this way, the presence of multi-collinearity common in soil variables as illustrated in Manns and Berg (2014) is avoided. The power spectrum is the analogue to the analysis of variance, where it is necessary to define the oscillation rate of a time (space) series in terms of its frequency. The total variance in the series is the sum of the variance contributions evaluated at different frequencies (Shumway, 1988). The spectrum formula is as follows:

$$S_{(f)} = 2\int_0^\infty r(h)\cos(2\pi f h)dh \quad (1)$$

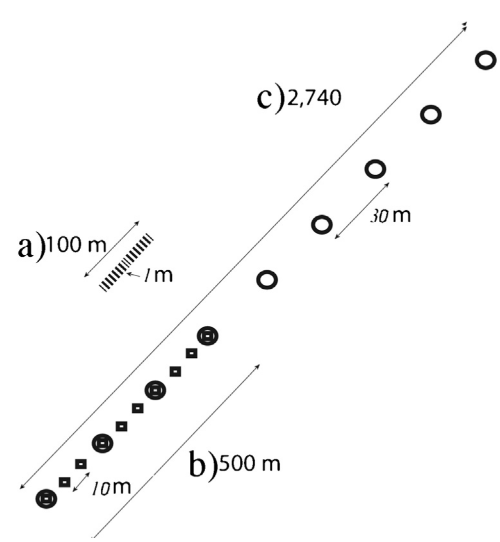

Fig. 1. Sampling scheme of the different transects used in the spatial analysis. (a) 100 m long transect sampled every 1 m; (b) 500 m long transect sampled at 10 m; (c): 2740 m long transect with soil samples taken at 30 m. The scheme is not in scale.

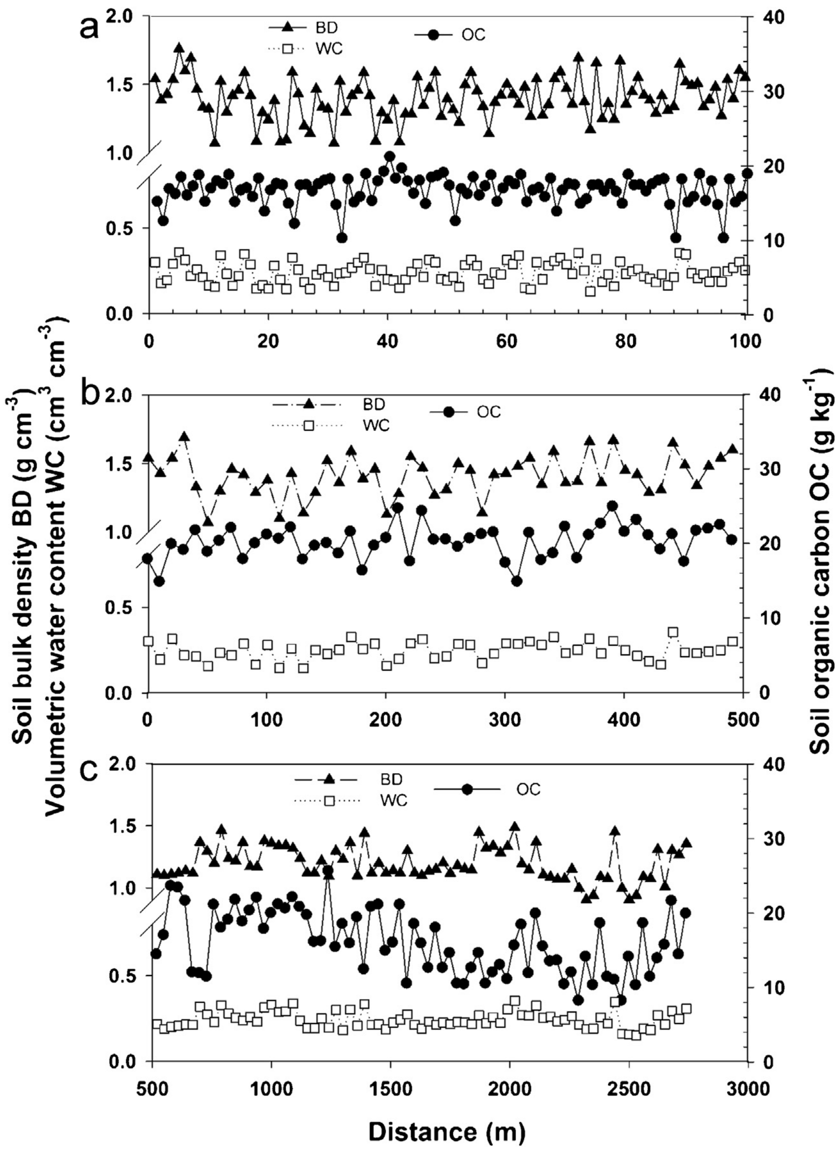

Fig. 2. Mean values of soil bulk density (BD), volumetric water content (WC) and soil organic carbon content (OC) measured in (a) 100 m long transect with samples at 1 m; (b) 500 m long transect with samples every 10 m; (c) 2740 m long transect with samples every 30 m.

where $S_{(f)}$ is the power spectrum, f is the frequency (which is the inverse of the periodicity), r(h) is the autocorrelation function and h is the lag distance.

In this frequency domain approach, the relationship between two variables could be analyzed as well, using the frequency-dependent correlation function, the cross spectrum and the quadrature spectrum. The cross spectrum is a complex cosine function that measures the association of two series, i.e., the covariance of the two series. The formula is as follows:

$$Co_{(f)} = 2\int_{0}^{\infty} r_c(h)\cos(2\pi f h)dh \quad (2)$$

Table 1
Descriptive statistics of selected soil variables in the different transect used in the study.

Descriptive statistics	NT_{1m}			NT_{10m}			NT_{30m}		
	BD $g\,cm^{-3}$	WC $cm^3\ cm^{-3}$	OC $g\,kg^{-1}$	BD $g\,cm^{-3}$	WC $cm^3\,cm^{-3}$	OC $g\,kg^{-1}$	BD $g\,cm^{-3}$	WC $cm^3\,cm^{-3}$	OC $g\,kg^{-1}$
Mean	1.21	0.23	17.84	1.22	0.24	17.08	1.28	0.24	17.78
Minimum	1.07	0.12	10.34	1.10	0.14	10.50	0.91	0.15	8.30
Maximum	1.45	0.35	23.02	1.46	0.35	22.70	1.69	0.35	23.70
SD	0.10	0.06	2.64	0.10	0.05	4.15	0.17	0.04	4.10
CV%	10.53	25.26	24.85	8.91	21.40	24.34	13.78	19.75	23.05

Abbreviations: NT_{1m} = No till sampled at 1 m; NT_{10m} = No till sampled at 10 m; NT_{30m} = No till sampled at 30 m; BD = soil bulk density; WC = Volumetric water content; OC = soil organic carbon content; SD = standard deviation; CV = coefficient of variation.

where *Co* is the cross spectrum, *f* the frequency (or periodicity $^{-1}$) and $r_c(h)$ the autocorrelation function and *h* is the lag.

The quadrature spectrum is a sine function that measures the contribution of the different frequencies to the total covariance (Nielsen and Wendroth, 2003). The procedure identifies the lag between two series that are correlated at the same frequency.

$$Q_{(f)} = 2\int_0^\infty r_c'(h)\sin(2\pi fh)dh \quad (3)$$

The quadrature spectrum $[Q_{(f)}]$ is a sine function, which is as modeling the linear filtering of the frequency content. It is a time series analogue of the simple linear regression. To test the strength of the spatial cross correlation the squared coherency $[K_{(f)}]$ value was obtained with the following formula (Nielsen and Wendroth, 2003):

$$K_{(f)} = \frac{Co^2(f) + Q^2(f)}{S_1(f) + S_2(f)} \quad (4)$$

Where $S_{1(f)}$ and $S_{2(f)}$ are the spectra of the two sets of observations in the study and $Co^2{}_{(f)}$ and $Q^2{}_{(f)}$ are cross spectra and quadrature as defined previously.

A triangular spectral window for smoothing the periodogram was used to produce the spectral density estimate. The mean was subtracted to the data to prevent a large first periodogram ordinate from distorting the scale of the plot (SAS, 2010). Previous to perform the frequency analysis, data was tested for white noise (Ljung and Box, 1978).

For the second part of the objective, an autoregressive state space model (or multivariate state space) was used. This approach for calculating the conditional expectations, i.e. the unknown observation of interest in the analysis, was considered an advantage in this study. The reason is that a state space model does not require an equally-spaced sampling scheme, the series does not have to be stationary and relatively short series can be used, unlike spectral and cross spectral analysis. The state space model consists of two parts, a model equation and an observation

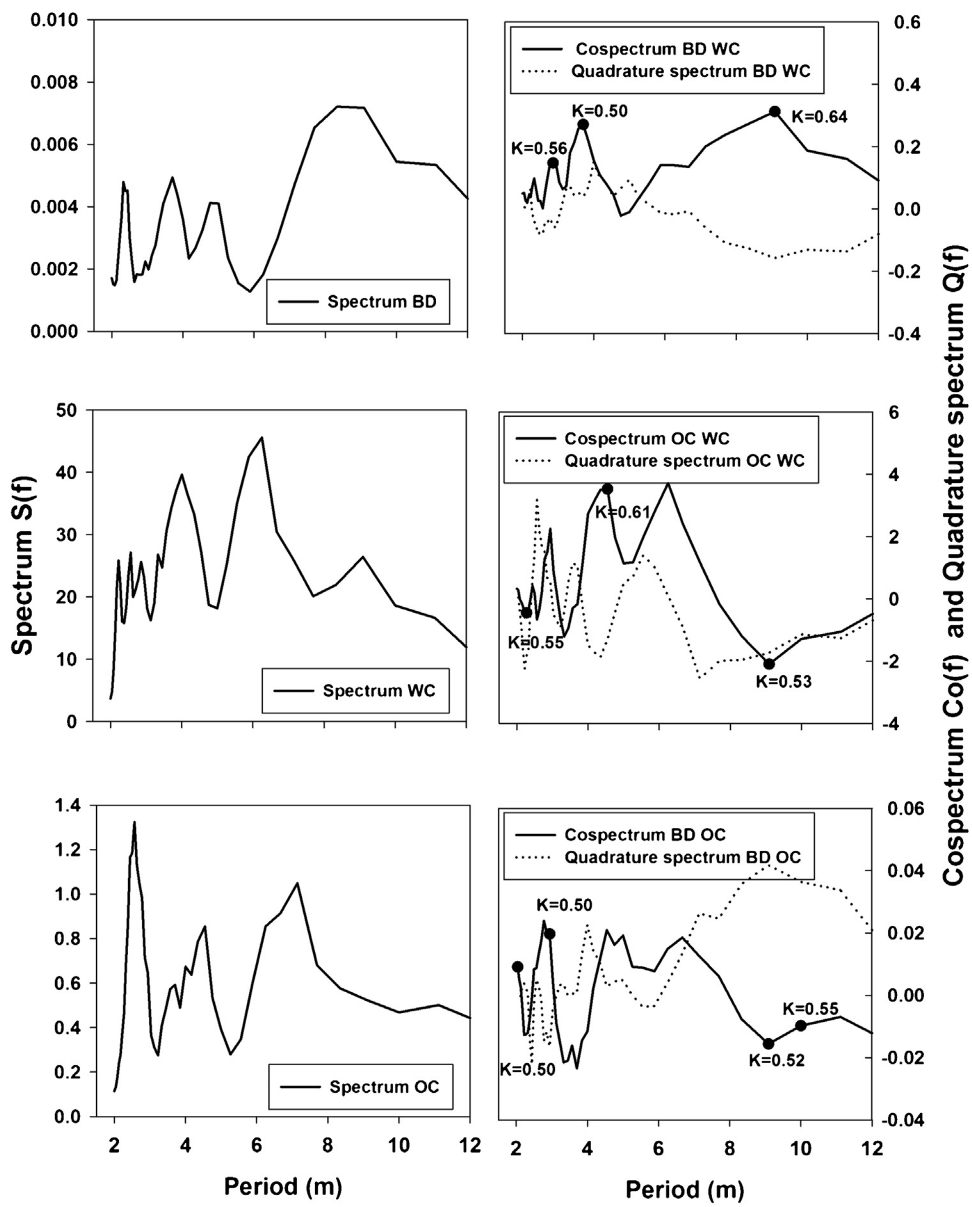

Fig. 3. Spectra, cospectra and quadrature spectra of soil bulk density (BD), volumetric water content (WC) and soil organic carbon content (OC) evaluated from data taken at 1 m in 100 m long transect. Numbers close to the mark identifies the corresponding coherence values.

equation.

$$X_i = \Phi X_{i-1} + \omega_i \quad (5)$$

Where X_i is a state vector of p variables, $\boldsymbol{\Phi}$ is a transition matrix of variables $(p \times p)$ composed by autoregressive coefficients, X_{i-1} represents the previous time or point in the space and ω_i is an error term with independent zero mean noise with covariance matrix $\boldsymbol{Q}$ $(q \times \mathrm{q})$. This matrix represents the variance per unit of space and it is directly related to the sampling interval. Notice that due to the error term contains systematic error created by the model itself and other underlying sources, the magnitude and the significance of the transition coefficients produce important information about the nature of the process under study.

The observation equation will calculate the variable of interest Y_i, the indirect measure of the true state, $\mathrm{X_i}$, a measurement matrix $\boldsymbol{M}_i$, and an independent zero mean measurement error that determine the noise covariance matrix $\boldsymbol{R}$. The elements of this matrix are the observation noises υ_i.

$$Y_i = \mathbf{M}_i X_i + \upsilon_i \quad (6)$$

The behavior of the state space vector X_i is determined by its initial value X_0, which is assumed to be random, and the formulated state equation (Shumway, 1988). The unknown parameters and the state vector X_i are solved recursively by Kalman filter (Kalman, 1960; Kalman and Bucy, 1961). In accordance to the procedure of Akaike (1971), a sequence of unrestricted vector autoregressive (AR) models are fits tentatively to the data and the Akaike's information criterion (AIC) is calculated for each model. The vector autoregressive models are estimated using the sample autocovariance matrices and the Yule-Walker equations. The order of the AR model that produces the smallest AIC is chosen as the order (number of previous lags) to use in the canonical correlation analysis. The elements of the state vector are then determined via a sequence of canonical correlation analyses of the sample autocovariance matrices. Only variables that yield significant correlations are added to the state vector. The importance of the correlation is judged on the basis of the AIC. After the state vector is determined, the state space model is fit to the data. During the recursive calculation procedure, the missing values are replaced for the smoothed estimators and the

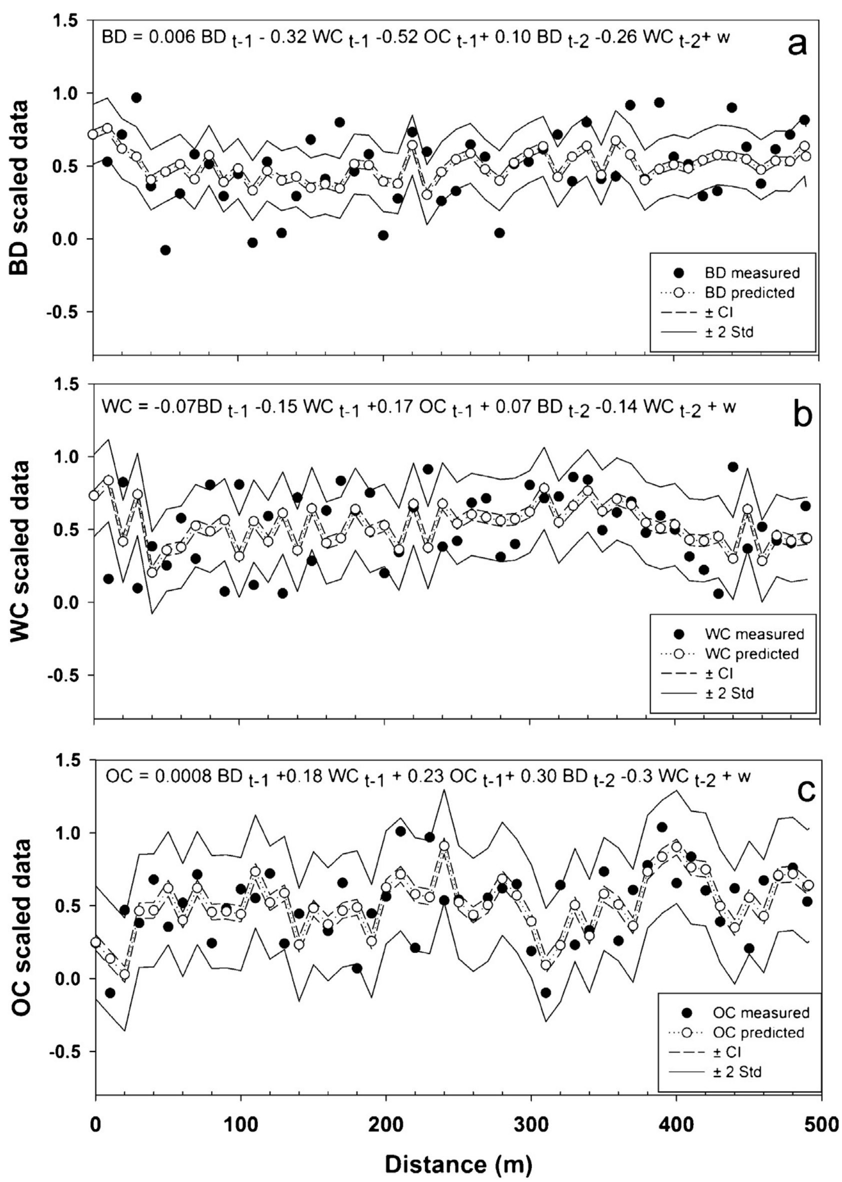

Fig. 4. State space model created to predict (a) soil bulk density (BD); (b) volumetric water content (WC) and (c) soil organic carbon content (OC) with data taken at 10 m from a 500 m-long transect.

covariance functions (Shumway, 1988). To remove differences in magnitude among the variables, the original data were normalized (y_{sc}), resulting in a mean (μ_y) of 0.5 and a standard deviation (σ_y) of 0.25, by using the following equation (Nielsen and Wendroth, 2003):

$$y_{sc} = \left[y_i - \left(\mu_y - 2\sigma_y\right)\right]/4\sigma_y \quad (7)$$

The statistical packages PROC SPECTRA and PROC STATESPACE provided for SAS (2010) were used to analyze the data.

3. Results:

3.1. spectral analysis for identifying cyclic spatial structure in a field under tillage and harvesting operations

The values of the soil variables measured taken in different transects are displayed in Fig. 2. The 1-m-sampled transect (NT_{1m}) is displayed in Fig. 2a, the 10-m-sampled transect (NT_{10m}) in Fig. 2b and the 30-m-sampled transect (NT_{30m}) in Fig. 2c. The corresponding descriptive statistics are included in Table 1. No significant differences were observed in BD. Transects NT_{1m} and NT_{30m} present no significant differences in OC but their values were higher than NT_{10m} ($p < 0.05$). The WC was the lowest in NT_{1m} ($p < 0.05$), and no significant differences in WC were found in transects NT_{10m} compared to NT_{30m}. In addition, we can observe that a wave patterns becomes evident for all transects (Fig. 2a–c). The evaluation of the cyclic spatial structure through the spectra analysis (Fig. 3a–c) shows several positions with repetitive pattern for all the soil variables considered. For example, the spectrum for BD (Fig. 3a) has several peaks at 2.56, 3.7, 5 and 9 m, approximately. These peaks also occurred at similar location for WC, with three points from 2.23 to 2.8 m, two high peaks at 4 and 6.3 m and one located at 9 m (Fig. 3b). In the case of OC, three peaks are evident at 2.56, 4.54 and 7.2 m (Fig. 3c). The cross spectral analysis confirms that the series BD, WC and OC are spatially correlated and the quadrature spectrum identifies the importance of several peaks on the total variance. This result is confirming the complex spatial relationships among these soil variables in a farm with uncontrolled transit. We observe that at positions 2.9 m, 3.7 and 9 m the cospectrum between BD and WC are positive, with high values of coherence (Fig. 3d). Note that coherence is the analog to the correlation in regression analysis. The results were different for the cross spectral analysis between OC and WC (Fig. 3e). The relationships are negative at positions 2.20 and 9.2 m (coherence value of 0.55 and 0.53, respectively) but positive at position 4.48 m (coherence value of 0.61). The spatial relationship between BD and OC also shows a change from positive to negative. At short range, 2 and 3 m (coherence of 0.5), the cross spectra is positive. At long range, 9 and 10 m, the cyclic variations show a negative relationship.

3.2. State space modeling of BD, WC and OC

A space state model was fitted to the data measured every 10 m on a 500-m long transect (NT_{10m},Fig. 4a–c). The BD, WC and OC were displayed with a confidence interval and two standard deviations from the mean. Notice that was necessary to use a second lag, validating an autoregressive model of order 2 (Table 2). The RMSE values and the r^2 confirm that the prediction was poor. The samples taken every 10 m capture a large proportion of variance in the short distance, which conspire with the prediction success. In order to evaluate the impact for reducing the variability, the next step was to model the same dataset but using only 30% of the data. In other words, we take one out of three positions, generating a new transect of 500-m long but as if it has been sampled every 30 m. As result, the models are simpler (only one previous stage is used). As denoted for the transition coefficients, the previous position of the variable becomes very important in explaining the variation in the current position (Table 2). The prediction improves, manifested for the value of RMSE and r^2 (Table 2). The RMSE decreased from 0.22 to 0.14 for BD, from 0.29 to 0.25 for WC and from 0.21 to 0.17 in the case of OC. The r^2 increases for all the variables, but still the model is showing a poor prediction of WC. To observe how the data was modeled in this different sampling scheme, the real data was included in Fig. 5 (a–c). Notice that for the BD, some extreme data was not captured for the model (Fig. 5a). For the WC, the results were similar (Fig. 5c). The variability in the WC was not captured by the surrogate variables. The smooth pattern defined for the model is not enough to describe the behavior of the WC (Fig. 5b). In contrast, the prediction of OC was better than the others (Fig. 5c). Even the data that were not used in the modeling process were captured inside of the two standard deviations from the mean. Moreover, most of them were located inside of the confidence interval from the mean.

The next step was to model all the data included in the 2740 m-long transect, spaced every 30 m (NT_{30m}). In this case the prediction was poor for the BD as denoted for the r^2 that was reduced from 0.54 to 0.30 (Table 2). Despite the complexity of the model, the BD was not well described by the surrogate variables and several points are almost outside of the 95% confidence

Table 2
Results of autoregressive state-space analysis for modeling the selected soil variables in different transects.

Model	Variable predicted	lag	RMSE	r^2	Transition coefficients				
					BD $_{(x-1)}$	WC $_{(x-1)}$	OC $_{(x-1)}$	BD $_{(x-2)}$	WC $_{(x-2)}$
$SSNT_{10m}$	BD	2	0.22	0.17	0.006	−0.32	−0.520	0.100	−0.26
	WC	2	0.29	0.00	−0.070	−0.15	0.170	0.070	−0.14
	OC	2	0.21	0.28	0.001	0.18	0.230	0.300	−0.30
$SSNT_{10m}$*	BD	1	0.14	0.54	−0.330	0.05	−0.180		
(only 30% of data)	WC	1	0.25	0.14	0.230	−0.67	−0.280		
	OC	1	0.17	0.59	0.100	0.06	−0.430		
$SSNT_{30m}$	BD	2	0.20	0.30	−0.070	−0.66	−0.090	−0.200	
	WC	2	0.21	0.26	0.100	0.08	−0.470	0.230	
	OC	2	0.15	0.63	0.009	0.33	−0.005	0.001	

Abbreviations: $SSNT_{10m}$ = State space model created with data from the transect of 500 m long sampled at 10 m on a farm under no tillage; $SSNT_{10m}$* = State space model created with only one out of three data from the data set sampled at 10 m (NT_{10m}); $SSNT_{30m}$ = State space model created with data from the transect of 2740 m long sampled at 30 m. This data include the NT_{10m}* data set; BD = soil bulk density; WC = water content; OC = soil organic carbon content; (x−1), (x−2) = refers to previous location; RMSE = root mean square error; r^2 = coefficient of determination.

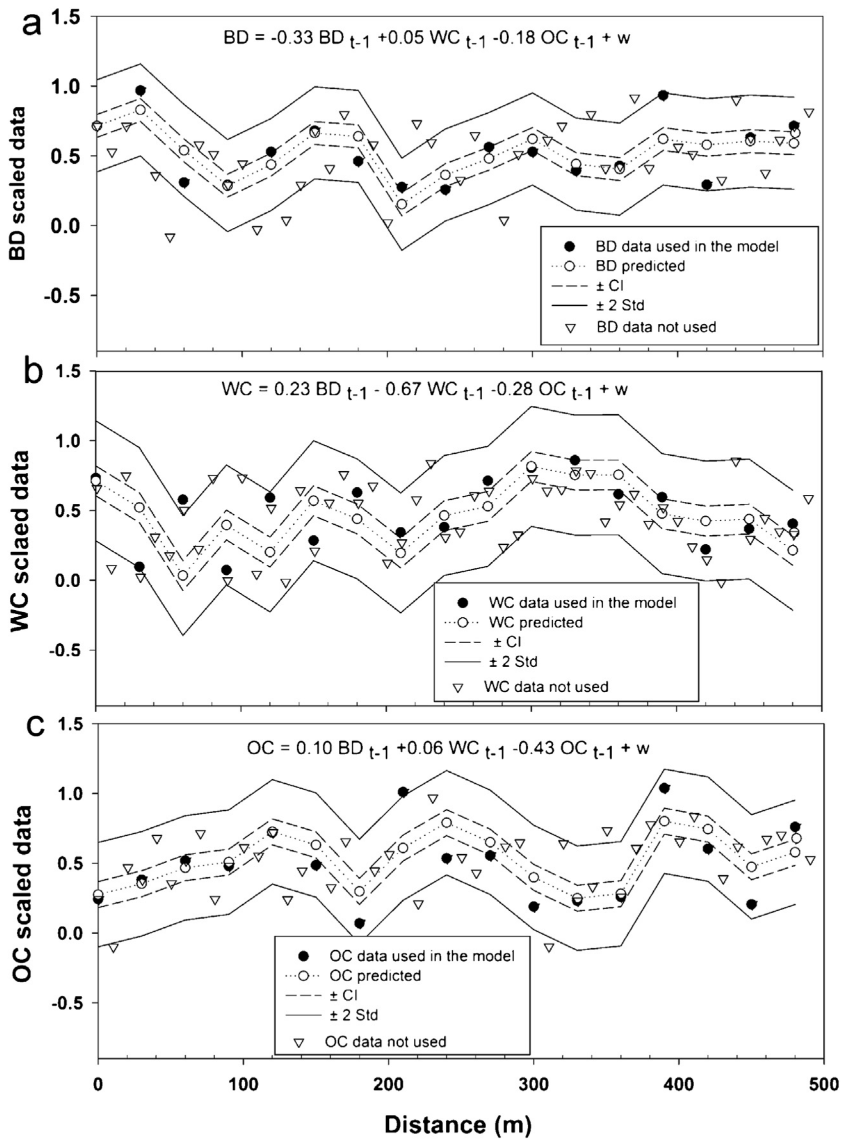

Fig. 5. State space model created to predict (a) soil bulk density (BD); (b) volumetric water content (WC) and (c) soil organic carbon content (OC) with data from a 500 m-long transect that include only samples at 30 m apart.

interval (Fig. 6a). However, the prediction improved for WC and OC. The r^2 values obtained were 0.26 and 0.63, respectively (Table 2). The prediction for WC shows several points that were not captured (Fig. 6b), but the model describe properly the OC variations (Fig. 6c). To explore the value of the WC as a surrogate variable, it was removed from the state vector and a new model was built. The RSME obtained for BD and OC was 0.18, and the r^2 was 0.46 and 0.50, respectively (Table 3). This result could imply that WC does not contain useful information for modelling OC or BD. To allow for comparison, a single regression model was created between OC and BD. The result was included in Table 3; the r^2 was null probing that the single regression model was useless, due to the cyclic behavior of the variables in this field.

4. Discussion

4.1. The cyclic pattern of soil properties as detected with spatial analysis

The repetitious fluctuations observed at different distance in the fields could be explained if we observed the common planting and harvesting distances. This support the observations of Mahboubi et al. (1993) and Logsdon et al. (1999), empowering the rationale to assess the traffic operations to improve the benefits of the tillage system, especially when NT is used. The tractors, the combine harvester and the grain carts are imposing a variety of distances according to the machinery. Moreover, the load capacity of the combine harvester, the dimension of the plots and the yield could modify the need to empty the harvester's grain tank, and consequently the transit of the grain carts varies. The spectrum for BD is showing these different distances. The short range could be due to the transit of tractors towing seeder and self-propeller row-crop sprayer (Fig. 3a). The long range (the region around 9 m) seems to identify the position where the combine harvester is unloaded to a parallel grain cart (Fig. 3a). Barik et al. (2014) also found a significant spatial distribution in BD. They observed that the BD was not equally affected in all directions after the traffic operation, which could be a consequence of the tires strips. The contact area under a track could be different than the common assumption of long and flat strips (Antille et al., 2013; Contreras et al., 2013), which could explain the variability of those data. In the case of WC, the peaks at similar period that those observed with BD

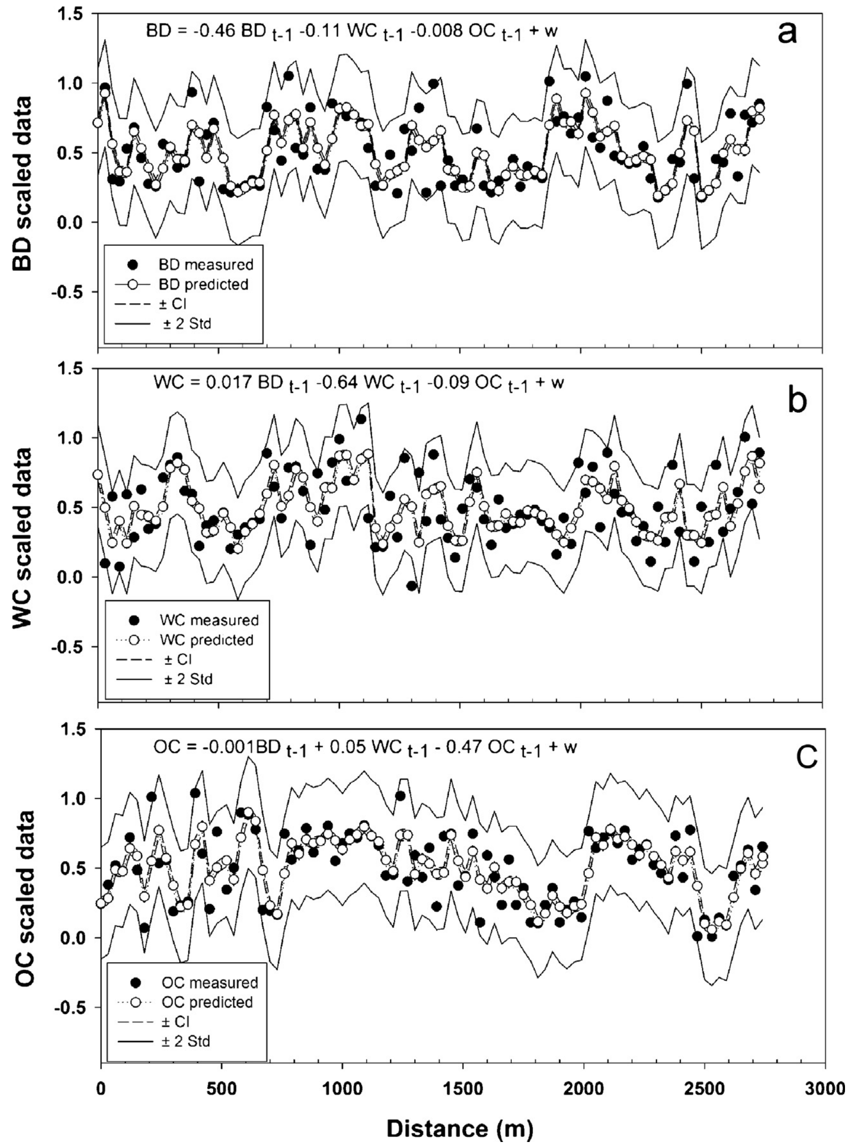

Fig. 6. State space model created to predict (a) soil bulk density (BD); (b) volumetric water content and (c) soil organic carbon content (OC) with data from a 2740 m-long transect with samples taken every 30 m.

could refer to a depression created for the traffic in soil surface. We observe that at positions 2.8, 3.6 and 9 m the cospectrum between BD and WC are positive (Fig. 3d). It is clear that a micro relief governs the water distribution in soil surface. A depression, natural or induced by traffic, will collect more water independently of the BD value, producing uncommon situations (Ball et al., 1997). The WC has a direct interaction with the soil compaction status, i.e., soil structure will be more affected for the machinery when the WC exceeds the optimal liquid limit, thus determining high values of BD (Ball et al., 2000; Contreras et al., 2013; Dexter and Bird, 2001).

A repetitive pattern in soil variables also was described by Perfect and Caron (2002) in silt loam soils of Kentucky, at periods of 5.6 m for WC and at 1, 1.4 and 4.5 m for BD. Only controlled harvesting operations were performed in those plots, thus they conclude that past activities should create those patterns. Schwen et al. (2012) in a silt loam soil was comparing pasture with

Table 3
Results of autoregressive state-space analysis for modeling soil bulk density and soil organic carbon by excluding volumetric water content, in comparison with the results of a simple regression model.

Model	Variable predicted	lag	RMSE	r^2	Regression parameter (OC)	Transition coefficients			
						BD_{x-1}	OC_{x-1}	BD_{x-2}	OC_{x-2}
$SSNT_{30m}$	BD	2	0.18	0.46		0.09	0.015	0.05	0.08
	OC	2	0.18	0.50		−0.10	0.17	−0.15	0.20
Sreg	BD-OC	–	0.24	0.00	0.034	–			

Abbreviations: $SSNT_{30m}$ = Bivariate state space model with data from a long transect (2740 m) sampled at 30 m from a field under no-till (NT); Sreg = simple regression; BD = soil bulk density; OC = soil organic carbon content; x−1, x−2 = refers to the previous location; RMSE = root mean square error; r^2 = coefficient of determination.

cropsand found that BD had periods at 4 and 6.5 m. They also attributed this features to traffic or tillage because these peaks were not manifested in the pasture. The values at long period are similar to those we found, thus reinforcing our observations about the consequences of harvesting operations. However, Perfect and Caron (2002) found a negative relationship between BD and OC that only was found in one position under our conditions. Most of the relationship between BD and OC in our study was positive, which it has no clear answer. One of the reasons could be the overlapping action of the combine's chopper tailboard that spread residues at the same distance. Several examples exist in literature about the cyclic variations in the OC (Liu et al., 2015, 2012; Ogunwole et al., 2014; Sampaio et al., 2010). Notice that is expected to find a large spatial variability of OC in the field because the crop residue has no a perfect distribution (Kumar et al., 2012). The rows could present more OC than the furrow, leading to markedly different OC values at short distances (Grigera et al., 2007). Additionally, the OC transformations can be diminished in sites with temporal anoxia and low temperature, which makes likely to find low OC values associated with high WC in the landscape (Lu et al., 2015). The opposite also could be true, as a consequence of different organic groups that affect the soil wettability, thus determining high OC values with low WC (Hurrass and Schaumann, 2006). In our study, most of the positions showed positive relationships, but at long range (9 m approximately), a negative relationship was also found. This is a region that not only showed a positive relationship between BD and WC (Fig. 3d) but also a negative relationship between BD and OC (Fig. 3f).

4.2. The state spatial modeling of soil variables

The basic idea in the state spatial modeling technique is that the process is not dominated by 'noisy data coming for the measurement uncertainty (Cassel et al., 2000). In the NT_{10m} scheme we observe that it was necessary to use two lags, which implies that the spatial dependence increases (Table 2). The model was more complex but even with the additional information from previous two lags, the prediction did not improve. Notice that the coefficient of determination was lower and the RSME was larger in NT_{10m} than the model with only 30% of the data (NT^*_{10m}, Table 2). This could be a direct consequence of the complexity of the relationship among the soil variables observed at a period of 9 m, as was discussed in the cross spectral analysis. Dyck and Kachanoski, (2011) working with soil porosity in a loamy sand soil found that the pronounced variability at short distances decreases with more spaced samples. They showed that it was as result of an increase in covariance more than a decrease in the individual spatial variance. They also found that as result of the agricultural activities, the autocorrelation of soil variables increases compared to an unaltered soil. The consequence of the cultivation was to reduce the local variability of micro topography and the complex spatial covariance patterns among topography, soil morphology and hydrology. The low importance of WC in the modeling process and the large dominance of the autoregressive part in our final models are pointing out the lack of knowledge about how the soil variables are interacting under uncontrolled traffic. A surrogate variable other than those used in this study could be more appropriate to improve the prediction. For example, micro relieves data as obtained through LiDAR imageries at short range could clarify the relationship between WC and BD. Other interesting surrogate variable could be the soil texture, despite that the cost to measure it in a long transect could be prohibitive. Timm et al. (2004) found a significant WC predictions trough a state space model with OC and clay content. This was accomplished despite the WC was not cross correlated to the other variables, thus supporting the use of such models with spatial data. Our findings support the study of Timm et al. (2004), despite the weak WC prediction in our conditions. Likely, a remarkably difference in the clay content between soils contribute to observe a low relationship between OC and WC. The Vertic and Typic Argiudol soils that we sampled only have 260 g kg^{-1} of clay content compared to the 530 g kg^{-1} of the Rhodic Kandiacualf soil in Timm et al. (2004). Another reason could be the different temporal scale in WC compared to BD or OC. A long transect cannot be sampled at the same day, which increase the source of variability in WC. Manns and Berg (2014) observed a strong lineal relationship between OC and WC. Our study could not found the lineal relationship between OC and WC, likely due to the differences in soil textures involved. It is interesting to note that Manns and Berg (2014) used clayey soils, not silt loam soils in their study. This issue is alerting about a soil textural component in the relation OC, WC or BD. For example, Liu et al. (2012) observed that silt content performed better than clay content at regional scale to predict OC. Their findings could be related to the process observed for Six et al. (2002) in the sense that silt plus clay lead to a better association with mycrobial derivate carbohydrates. Hence, the relationship between soil texture and OC is far more complex than for building pore system or controlling soil bulk density (Schnitzer and Kodama, 1992; Oades, 1993; Ball et al., 1997; Abiven et al., 2007). This is clearly a topic that deserves more attention because to find the best combination of surrogate variables is a key for improving the prediction at different scales. Similarly to Timm et al. (2004), Sampaio et al. (2010) and Schwen et al. (2012), our observations demonstrate that even with complex spatial relationship among the soil variables, it is possible to build a predictive model by using an autoregressive state space approach. Our bivariate model explained 50% of the OC data and 46% of the BD data (Table 3), but also with different scenarios multivariate models could explain 63% of OC or 54% of BD (Table 2). Liu et al. (2012) working over a large area with soil samples taken 40 km apart, found that using OC and BD as surrogate variable, the OC prediction reaches 76.3%, which confirm the importance of the scale on those variables. The variations observed in the quality of the predictions were likely a consequence of differences in spatial covariance, which clearly depend on the scale (Dyck and Kachanoski, 2011). Thus, is necessary to determine precisely the better scenario for each pairs of selected surrogates. Further efforts would be addressed to analyze soil variables that could be directly or indirectly related to BD or OC and measured reasonably with proximal or remote sensors. This would open several windows of opportunities to increase our knowledge, especially with the advances in drones and satellites applied in agriculture. For example, to obtain contemporary WC, BD and OC data over a large region is cost-prohibitive. However, with the availability of the NASA soil moisture mission to obtain WC data (Entekhabi et al., 2010; Phillips et al., 2014; Temimi et al., 2014) and NIR spectrometry to predict OC data (Reeves et al., 2006; Bartholomeus et al., 2008; Rienzi et al., 2013) these soil variables could be acquired in real time. Thus, approaches as multivariate state space modeling would be very useful for predicting, calibrating and modeling soil variables over large areas without a significant lost in reliability. This would reduce significantly the cost of the land survey and it would allow creating thematic maps for evaluating C sequestration issues or soil quality status in real time.

5. Conclusion

The effects of agriculture on soil variables cannot be understood completely if only the planting process is assessed. Our studyfound evidence of cyclic patterns on three common soil variables (BD, WC and OC) that could be related to the transit of equipment used during diverse tillage operations and harvesting process. The effect of uncontrolled transit during planting and harvesting procedures on BD, WC and OC could mask or null their relationships, thus distorting results that are missing the spatial nature of this process. The spectral and cross spectrum analysis put in evidence the cyclic nature of the soil variables, identifying patterns at short (2–4 m, approximately) and long periods (9 m) associated with uncontrolled traffic operation. A direct implication of this finding would be the need to improve the tillage system efficiency by evaluating the total farming operation procedures. For example, to replace wheels for track systems should be important for improving soil quality, especially under NT. In addition, the autoregressive state space model showed a way to use spatial related data more efficiently. Our observations demonstrate that, even though the complex spatial variability among the soil variables, it was possible to build a predictive model by using this approach. The spatial relationship between BD and OC allows creating a predictive model that explains 63% of the OC data and 54% of the BD data. However, no useful relationships were found to model WC in a proper way. Some evidences point out to a soil textural interaction among the soil variables, but also could be related with the different temporal scale of variation of WC compared to BD or OC. This is an important issue that would deserve further attention, because to understand these relationships is a key for modeling soil variables at different scales.

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