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Full Length Research Paper

Spatial variability of soil characteristic for evaluation of agricultural potential in Iran

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Abstract

Analysis and interpretation of spatial variability of soils is a keystone in site-specific farming. Grid soil sampling is typically used for establishing management zones for site-specific application of nutrients. The objectives of this study were to determine the degree of spatial variability of soil chemical properties, soil texture, and variance structure. Spatial distributions for thirteen soil chemical properties and soil texture were examined in a fallow land in Bajgah district, in Fars province, Iran. Soil samples were collected at approximately 60 m square at 0-30 cm depth and coordinates of each of the 100 points were recorded with GPS. The spatial distribution and spatial dependence level varied within location. The range of spatial dependence was found to vary within soil parameters. Phosphorous had the shortest range of spatial dependence (49.50m) and percentage of calcium carbonate equivalent had the longest (181.94m). All parameters were strongly spatially dependent. The results demonstrate that within the same field, spatial patterns may vary among several soil parameters. Soil nutrients were found to be affected by farmer management. Variography and Kriging can be useful tools for designing effective soil sampling strategies and variable rate application of inputs for use in site-specific farming.

Keywords: Kriging, Site-specific farming, Spatial variability, Soil properties, Southern Iran

INTRODUCTION

Site-specific management has received considerable attention due to the three main potential benefits of: 1) increasing input efficiency, 2) improving the economic margins of crop production, and 3) reducing environmental risks. Uniform management of crops grown under spatially variable conditions can result in less than optimum yields due to nutrient deficiencies as well as excessive fertilizer application that may potentially reduce environmental quality (Redulla et al., 1996). Site-specific management of nutrients gives the farmer the potential to apply the exact requirement of nutrients at each given location in a field. Spatial variability in soils occurs naturally from pedogenic factors. Natural variability of soil results from complex interactions between geology, topography, climate as well as soil use (Quine and Zahng, 2002). In addition, variability can occur as a result of land use and management strategies. As a consequence, Soils can exhibit marked spatial variability at the macro– and micro –scale (Vieira and Paz Gonzalez, 2003; Brejda et al., 2000). Demands for more accurate information on spatial distribution of soils have increased with the inclusion of the spatial dependence and scale in ecological models and environmental management systems. This is because the variation at some scales may be much greater than at others (Yemefack et al., 2005). Spatial dependence has been observed for a wide range of soil physical, chemical, and biological properties and processes (Lyons et al.,1998;

Raun and et al,. 1998). Incorporation of functions that relate distance and variance among points (e.g. semivariograms) into spatial analysis of soils data results in more accurate estimates of soil properties and processes than those that consider only spatial independence between points (Warrick and Nielsen, 1980). Semivariograms for soil properties can also be used to reduce the need for expensive and intensive sampling, as in the case of precision agriculture (McBratney and Pringle, 1999). Soil nutrient variability mapping has been reported as an important component for establishing management zones (Castrignano et al., 2000). Although there are reports on recommendations affected by time of sampling (Hoskinson et al., 1999) and by variability in laboratory result (Brenk et al., 1999). Cahn et al. (1994) showed the importance of spatial variation of soil fertility for site specific crop management. Haneklause et al. (1998) also suggested that correctly mapping soil fertility parameters is important for variable-rate application. Therefore, spatial information of nutrient status should be characterized when making fertilizer recommendations. Geostatistical analyses have been done for a number of chemical, physical and Morphological soil properties. In many instances spatial variation is not random but tends to follow a pattern in which variability decreases as distance diminishes between points in space (Warrick and Nielsen, 1980). Geostatistics consists of variography and riging. Variography uses semivariograms to characterize and model the spatial variance of data whereas riging uses the modeled variance to estimate values between samples (Yamagishi et al., 2003). There is a little information in Iran that presents a description of spatial variability of soil parameters in the field-scale. The objective of this study was to describe the variability of some soil fertility indicators at field scale in Bajgah, Shiraz province, Iran.

MATERIALS AND METHODS

Study area, sampling design and laboratory analysis

The study was conducted in a fallow land in Bajgah, About 15 km northeast of Shiraz, in Fars province, Iran (Figure 1). According to the USDA Soil Taxonomy (Soil Survey Staff, 2006), the soil at the study region was classified as fine, mixed, mesic, Fluventic Calcixerepts. Soil samples were collected (September 2007) at approximately 60 m square at 0-30 cm depth and coordinates of each of the 100 points were recorded with GPS (Figure 1). The soil samples were taken to the laboratory and air-dried over night and passed through a 2-mm sieve. Particle size analysis was performed using Hydrometer method (Day, 1965); available phosphorous (P) was measured by colorimetry using ascorbic acid-ammonium molybdate reagents (Olsen, 1982); pH was measured in saturated paste; available potassium (K) was measured using extraction with ammonium acetate (1N) (Richards, 1954); total Nitrogen (TN) using Kjeldal (Bremner and Mulvaney, 1982); cation exchange capacity (CEC) was determined using extraction with sodium acetate (Page et al., 1987); Electrical conductivity (ECe) was measured with Electroconductimeter, percentage of calcium carbonate equivalent (CCE) was measured by acid neutralization (Salinity Laboratory Staff, 1954); organic matter (OM) content was determined using Walkley–Black, 1934; Manganese, iron, and copper were determined by means of atomic absorption spectrophotometer (Lindsay and Norvell, 1978); calcium and magnesium were measured with titration method(Richards, 1954). (Figure 1)

Descriptive statistics and geostatistical Analysis

Statistical analyses were done in three stages. First, the frequency distributions were analyzed and normality was tested using the Kolmogoroph-Smironoph test (SAS, 1996). Secondly, the distribution of data was described using conventional statistics such as mean, maximum, minimum, median, standard deviation (SD), coefficient of variation (CV), skewness, and kurtosis. These analyses were conducted using the STATISTICA software package (StatSoft Inc., 2001). Thirdly, geo-statistical analysis was performed using the GS+ (Gamma Design Software, 2005) to determine the spatial dependency of soil properties. Isotropic semi-variograms for the soil parameters were computed to determine any spatially dependant variance within the field. Experimental semi variograms were fitted to three models (i.e. exponential, spherical and Gaussian) separately and the best model was selected based on the fit. Using the model semi-variogram, basic spatial parameters such as nugget variance (Co), structural variance (C), range (A) and sill (C + Co) was calculated. Nugget variance is the variance at zero distance, sill is the lag distance between measurements at which one value for a variable does not influence neighboring values; and range is the distance at which values of one variable become spatially independent of another (Lopez Granadoz et al., 2002). Different classes of spatial dependence for the soil variables were evaluated by the ratio between the nugget semivariance and the total semivariance (Cambardella et al., 1994). For the ratio lower than 25%, the variable was considered to be strongly spatially dependent, or strongly distributed in patches; For the ratio between 26 and 75%, the soil variable was considered to be moderately spatially dependent, For the ratio greater than 75%, the soil variable was considered weakly spatially dependent; and for the ratio of 100%, or if the slope of the semivariogram was close to zero, the soil variable was considered non-spatially correlated (pure nugget). In the process of calculating the experimental semivariograms,

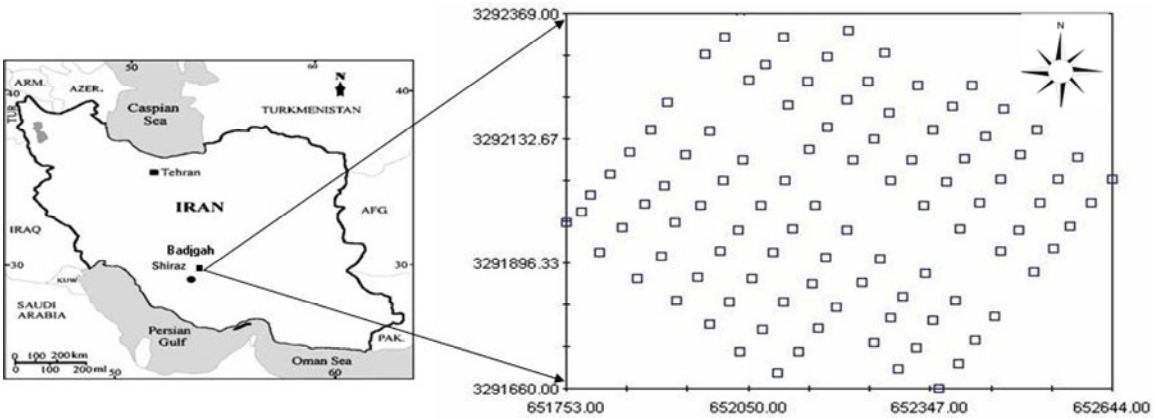

Figure 1. Location of the study area and Sampling pattern in 46.7 ha area

Table 1. Descriptive statistics for variables within the field grid to a depth of 0.3 m

Variable	Unit	Mean	Median	Min	Max	CV (%)	SD	Skewness	Kurtosis
pH	-Log[H+]	8.08	8.08	7.80	8.32	1.30	0.11	-0.03	-0.33
EC	dSm-1	0.60	0.59	0.34	1.20	25.91	0.15	1.09	2.33
sand	(%)	4.23	4.20	0.50	8.50	20.56	0.87	0.17	-0.10
Silt	(%)	40.36	41.00	36.50	43.00	3.90	1.58	-0.50	-0.63
Clay	(%)	55.41	54.60	52.30	58.90	3.42	1.90	0.49	-1.23
TN	(%)	0.07	0.07	0.04	0.14	29.57	0.02	0.82	0.03
P	Mg kg-1	27.28	26.06	22.06	36.70	11.07	3.02	0.93	0.89
K	Mg kg-1	451.39	435.0	387.0	560.0	10.06	45.43	0.89	-0.33
Ca	meq L-1	1.90	1.80	0.20	4.60	42.65	0.81	1.00	1.31
Mg	meq L-1	2.76	2.80	0.20	6.20	45.54	1.26	0.27	-0.12
OM	(%)	1.68	1.55	0.91	3.02	26.06	0.44	0.82	0.03
CCE	(%)	53.02	53.40	47.19	59.63	6.57	3.49	0.04	-1.14
CEC	Cmol kg^{-1}	18.32	17.63	15.43	25.33	9.43	1.73	1.21	2.34
Fe	Mg kg-1	10.97	11.56	6.42	13.76	16.97	1.86	-0.60	-0.42
Cu	Mg kg-1	2.56	2.58	2.12	3.16	8.77	0.22	0.03	-0.80
Mn	Mg kg-1	17.92	17.00	12.02	25.80	21.19	3.80	0.56	-0.88

the active lag distance and the lag class distance interval were changed until the smallest nugget variance in the best model semivariogram was achieved (Mapa and Kumaragamage, 1996). Differences between estimated and experimental values are summarized using the following cross- validation statistics: mean error (ME) and mean square error (MSE) as follows:

ME =∑ni=1(Z*- Z)/n

MSE=∑ni=1(Z*- Z)2/n

Where Z* are the prediction values, Z are the mean values and n is the total number of prediction for each validation case. The ME gives the bias and the MSE gives the prediction accuracy respectively (Utset et al., 2000). Block kriging procedure in GS+ was used to obtain the point estimates of the soil properties at unsampled locations. For each point to be kriged, seventeen neighbors were used within a radius smaller than the range (A) for all soil properties used in the study. The cross-validation analysis provided in the software, which uses the Jack-knifing technique, was used to check the validity of the models and to compare values estimated from the semivariogram model with actual values (Utset et al., 2000).

RESULTS AND DISCUSSION

The summary of the statistics of soil parameters are shown in Table 1. The descriptive statistics of soil data suggested that they were all normally distributed (according to Kolmogrov-Smironov test). Coefficient of variation for all of variables was very different; The greatest variation was observed in the magnesium whereas the smallest variation was in PH. Phosphorus, Silt, PH, clay, CCE, CEC, potassium, and copper low variation (CV <15%) whereas all other properties exhibited a medium variation (CV 15-50%) according to the guidelines provided by Warrick (1998) for variability of soil properties. In order to identify the possible spatial structure of different soil properties, semivariograms were

Table 2. Parameters for variogram models for different soil properties.

Variable	Unit	Model	Nugget	Sill	Range	Spatial Ratio(%)	Spatial class	ME	MSE	R^2
pH	-Log[H+]	Exponential	0.00097	0.01104	109.50	0.08	S	-0.0006	0.01	0.351
EC	dSm-1	Gaussian	0.00001	0.01292	51.70	0.0007	S	0.1678	0.0619	0.451
sand	(%)	Spherical	0.001	2.221	120.4	0.0004	S	-0.0122	2.208	0.407
Silt	(%)	Gaussian	0.278	2.552	57.20	0.09	S	-0.033	2.211	0.374
Clay	(%)	Exponential	0.000001	0.00142	148.90	0.0007	S	-0.0059	1.291	0.80
TN	(%)	Gaussian	0.0001	0.06350	62.5	0.001	S	-0.0025	0.0004	0.487
P	Mg kg-1	Spherical	0.00032	0.01262	49.50	0.02	S	0.026	7.860	0.459
K	Mg kg-1	Gaussian	0.01252	0.00001	79.10	1	S	0.046	2.182	0.592
Ca	meq L-1	Gaussian	0.0001	0.08380	71.20	0.0012	S	-0.56	0.8658	0.447
Mg	meq L-1	Gaussian	0.001	1.7610	54.50	0.00057	S	-0.0186	1.2020	0.528
OM	(%)	Gaussian	0.0001	0.0570	64.0	0.00175	S	-1.2055	1.594	0.524
CCE	(%)	Spherical	0.0001	0.06190	181.94	0.0017	S	-0.162	9.4243	0.514
CEC	Cmol kg 1	Gaussian	0.00001	0.00882	91.0	0.00113	S	-0.0049	1.562	0.725
Fe	Mg kg-1	Gaussian	0.010	3.4780	50.70	0.0029	S	0.0396	2.912	0.402
Cu	Mg kg-1	Exponential	0.0001	0.04820	135.70	0.0021	S	0.0036	0.026	0.693
Mn	Mg kg-1	Gaussian	0.0001	0.04510	112.40	0.0023	S	-0.0215	6.245	0.779

Spatial ratio=nugget semivariance / total semivariance, total semivariance=nugget + sill.
Spatial class: S=strong spatial dependency.

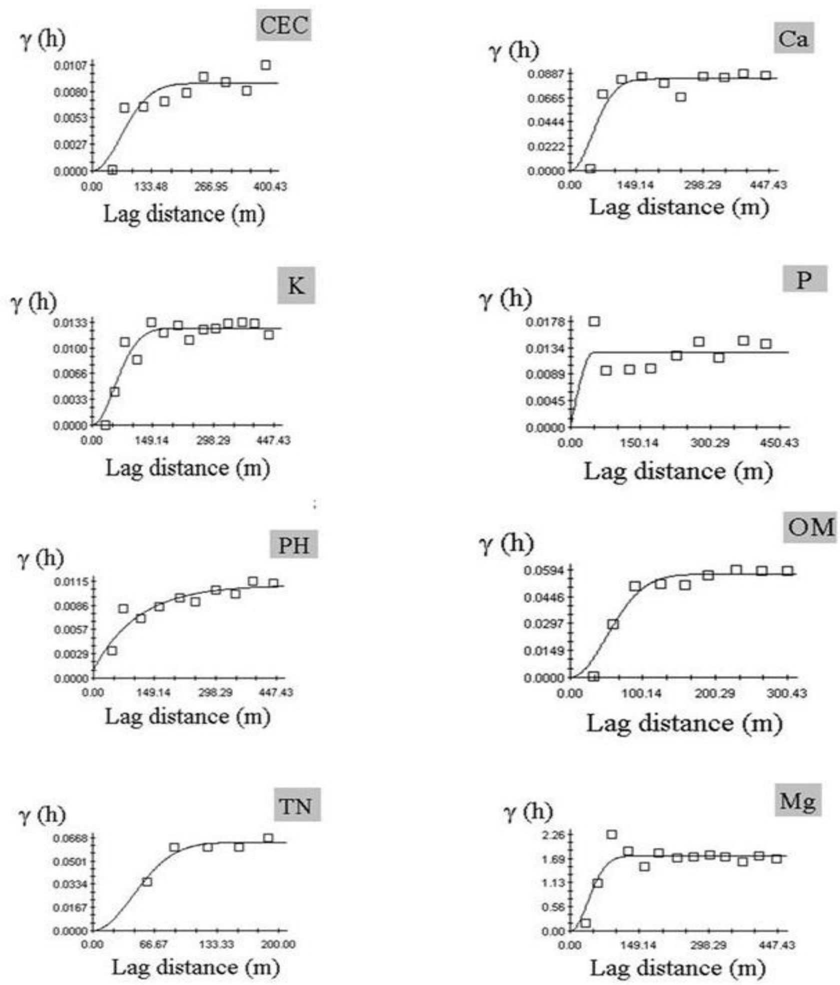

Figure 2. Omnidirectional semivariogram for soil parameters

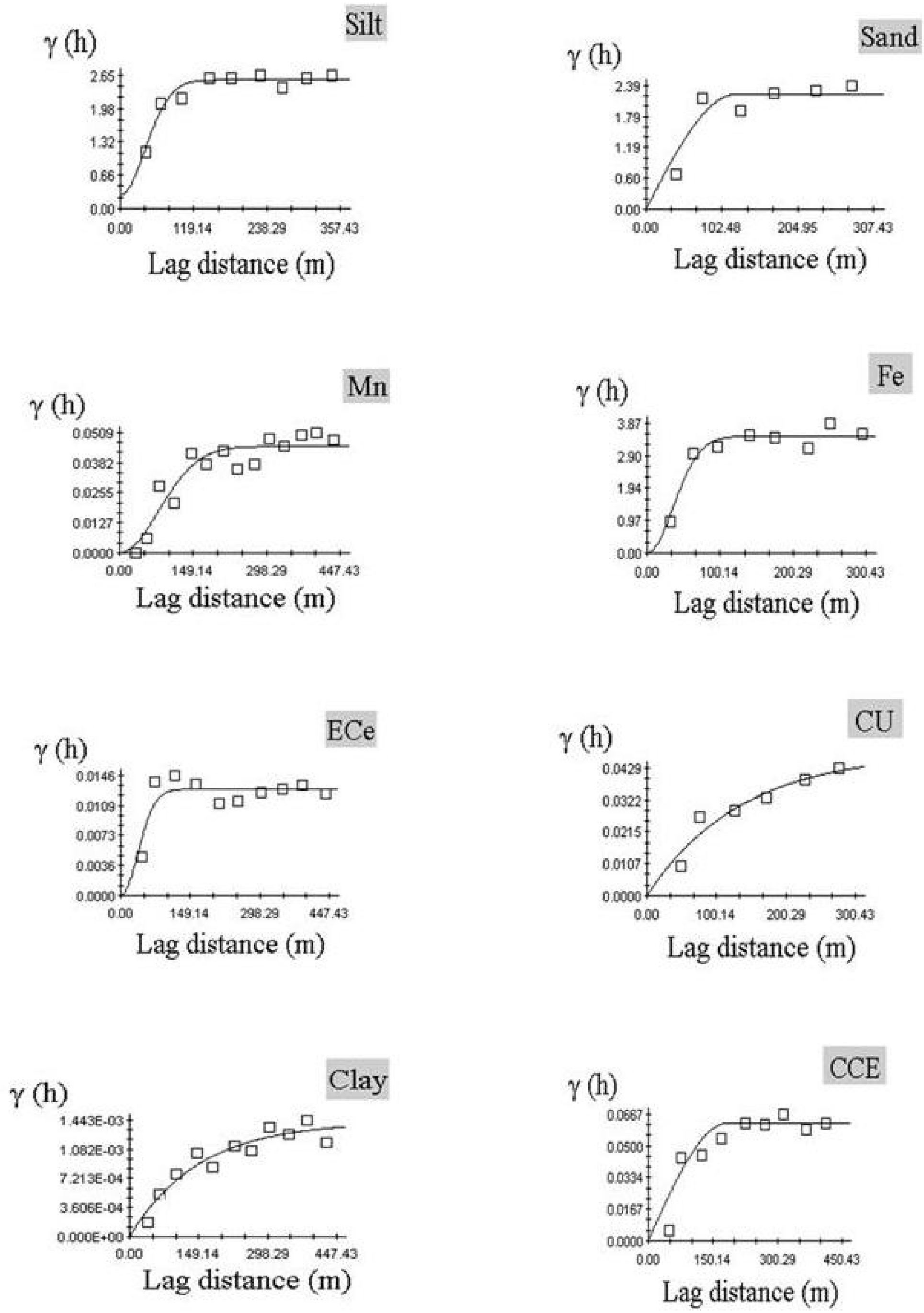

Figure 3. Omnidirectional semivariogram for soil parameters

calculated and the best model that describes these spatial structures was identified. The results are given in Table 2 and depicted in Figure 3. The geostatistical analysis presented different spatial distribution models and spatial dependence levels for the soil properties. As seen, the ranges of spatial dependences show a large variation (from 49.50 m for phosphorous up to 181.94 m for percentage of calcium carbonate equivalent). Knowledge of the range of influence for various soil properties allows one to construct independent datasets to perform classical statistical analysis. Furthermore, it aids in determining where to resample if necessary, and in the design of future field experiments to avoid spatial dependency. The range values showed considerable variability among the parameters (Table 2). There were great differences between ranges of the different soil variables, as had been already reported in several studies. Weitz et al. (1993) found most of the soil properties had variable range between 30 and 100 m. Doberman (1994) fitted the spherical models to

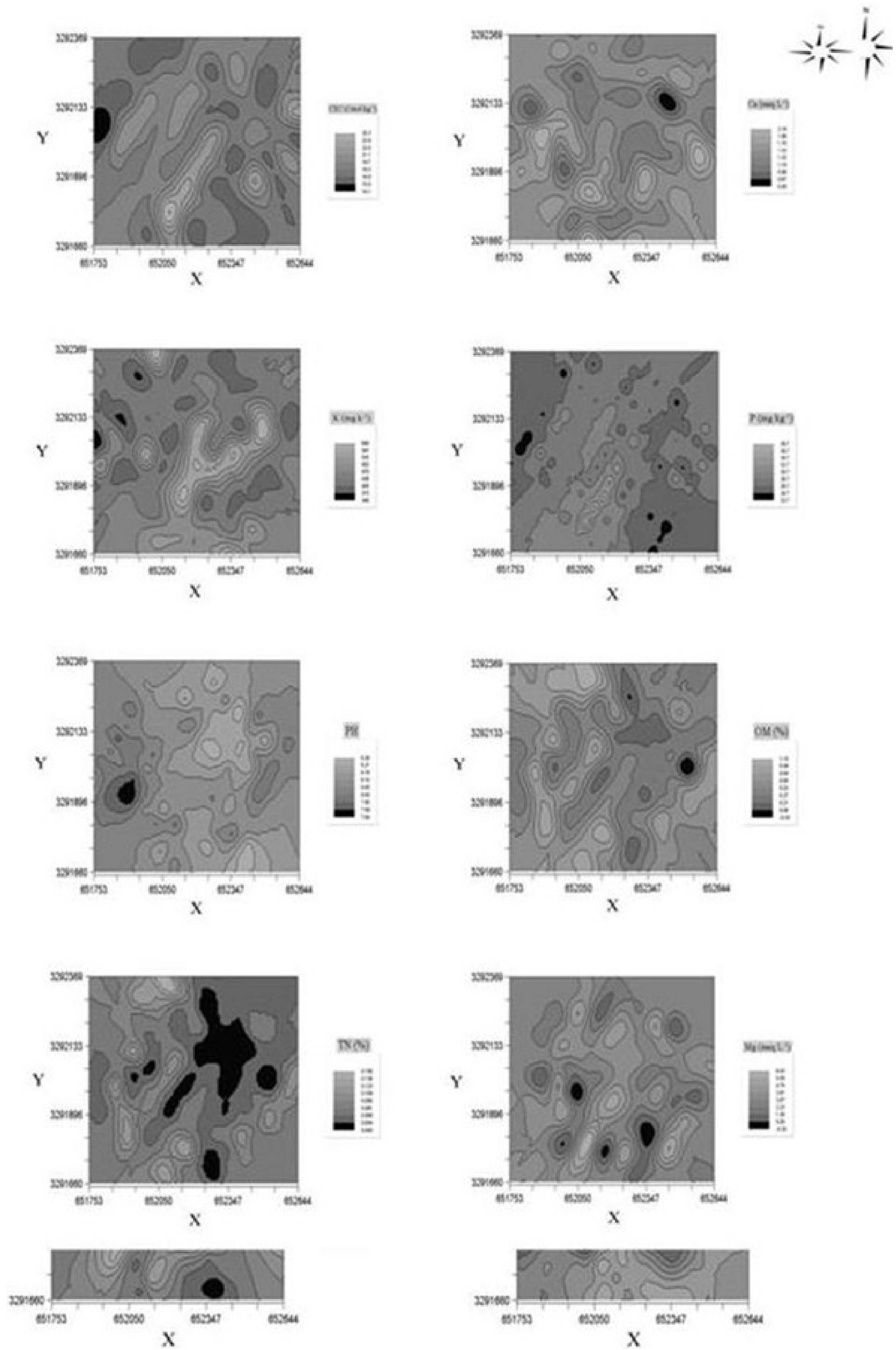

Figure 4. Digital maps of soil properties prepared by ordinary Kriging

variograms with range between 80 to 140 m. Cambardella et al., (1994) reported it was 80 m for total organic N at a farm from Iowa, USA. In site-specific management it is always advantageous to look for a soil property with a greater spatial correlation due to practical reasons. Lauzon et al. (2005) observed that the current 100 m sampling grid in southern Ontario for site-specific P fertilizer management is not reliable as there was no spatial correlation for available P in spacing of more than 30 m. The different ranges of spatial correlation for nutrients may be related to the mobility of the ions. In the present study spatial distribution of total N appeared to be correlated with OM. The ranges of total N and OM from the 46.7 ha plot were similar (Table 2). These results are in accordance with the results of Cahn et al. (1994).A large range indicates that observed values of the soil variable are influenced by other values of this variable over greater distances than soil variables which have smaller ranges (Lopez–Granadoz et al., 2002). Thus a range of more than 182 m for CCE indicates this variable values influenced neighboring values of CCE over greater distances than other soil variable (Table 2). The soil properties displayed differences in their spatial dependence, as determined by their semivariograms (Figure 3). Semivariance ideally increases with distance between sample locations, or lag distance (h), to a more or less constant value (the sill or total semivariance) at a given separation distance, i.e. the range of spatial dependence. Samples separated by the distances closer than the range are related spatially, and those separated by the distance greater than the range are not spatially related. Semivariogram ranges depend on the spatial interaction of soil processes affecting each property at the sampling scale used (Trangmar et al., 1985). The semivariance at h=0 is called the nugget variance. It represents field and experimental variability, or random variability that is undetectable at the scale of sampling (Webster and Oliver, 1992). Semivariograms were calculated both isotropically and anisotropically. The anisotropic calculations were performed in four directions (0˚, 45˚, 90˚ and 135˚) with a tolerance of 22.5˚ to determine whether semivariogram functions depended on sampling orientation and direction (i.e., they were anisotropic) or not (i.e., they were isotropic).Isotropy was checked with variogram surface calculated by GS+ software. There were no distinct different among the structures of directional semivariograms for soil properties. Gaussian models were defined for TN, K, Ca, Mg, EC, CEC, Silt, Fe, Mn and Spherical models were defined for CCE, sand, P and exponential models defined for PH, clay, and Cu. The semivariogram for clay, EC, and CEC shows almost zero nugget effect value and a low range of spatial dependence. The zero nugget effect value indicates a very smooth spatial continuity between neighboring points. On the other hand, the lowest range of spatial dependence (49.50 m) indicates that this continuity disappear very fast. It is also confirmed by the results of Vieira and Paz-Gonzalez (2003). Test of validation was checked with the ME and MSE values (Table 2). These values are low indicating that kriging predictions of soil properties are equally accurate. To determine distinct classes of spatial dependence for soil variables, the ratio of nugget/total variance was used. Semivariograms indicated strong spatial dependence for all variables (Table 2). Strongly spatially dependent properties may be controlled by intrinsic variations in soil characteristics, such as texture. Figure 4 shows the digital maps obtained by kriging for soil properties. The comparison of these maps may be useful in the interpretation of the results, for example spatial variability maps showed that available P content is high in the study area with variable distribution around the study area. This is probably due to high input of P_2O_5 mostly through Di-ammonium Phosphate, to crops in this area. Visual inspection of distribution maps of soil nutrients such as N and P with distribution map of OM shows that they are not very identical, indicating that nutrient distributions within the field are influenced by fertilizing management and heterogeneous management on top soil. In addition, the quantitative information obtained from these maps could be used to facilitate site-specific management in the study region and applying Variable-rate Technology (VRT) in field for best management. These maps could be used to design site-specific management strategies to increase crop yields while minimizing the environmental pollution and input costs.

CONCLUSION

The generation of maps for soil properties is the most important and first step in precision agriculture. These maps will measure spatial variability and provide the basis for controlling spatial variability. The results demonstrated that the spatial distribution and spatial dependence level of soil properties can be different even within a similar former agricultural management. Variograms are a helpful tool for characterizing the spatial variability of a soil property in the presence of irregular sampling designs, as it reduces the fluctuation variance of the sample variogram and makes the spatial structure more discernible and interpretable. Long-term field management histories should be well known since even the same farming practice clearly affected both spatial distribution and the level of spatial dependence. Geostatistical techniques offer alternative methods to conventional statistics for the estimation of parameters and their associated variability. The findings of this study showed that spatial structure exist in the soil properties at the field scale in the study area. The soil properties usually have spatial dependence and understanding of such structure may provide new insights into soil behavior for site-specific management. These digital maps could be used to delineate management zones for variable rate fertility in site-specific management systems. The analysis of spatial variation using variograms shows that many standard models could be fitted to soil properties in the area.

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