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Spatial variability of some soil properties for site specific farming in northern Iran

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Abstract

Evaluating agricultural land management practices requires knowledge of soil spatial variability and understanding their relationships. Spatial distributions for fourteen soil physical and chemical properties were examined in a wheat field in Sorkhankalateh district, in Golestan province, Iran. 101 soil samples at the distances of 5m, 10m and 20m as nested grid were collected at the depth of 0-30cm in early December 2004 just after planting the winter wheat in a plot (1.8 ha area). Data were analyzed both statistically and geostatistically on the basis of the semivariogram. Frequency distribution of all data was normal. The spatial distribution and spatial dependence level varied within location. The range of spatial dependence was found to vary within soil parameters. Nitrate had the shortest range of spatial dependence (23.99m) and K had the longest (93.92m). Eight parameters including pH, EC, sand, silt, clay, P, $CaCO_3$ and organic matter (OM) were moderately spatially dependent whereas saturation percentage (SP), bulk density (D_b), K, N, cation exchange capacity (CEC) and exchangeable sodium percentage (ESP) 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 management.

Keywords: Spatial variability; Semivariogram; Precision agriculture; Site-specific management.

Introduction

An understanding of the distributions of soil properties at the field scale is important for refining agricultural management practices and assessing the effects of agriculture on environmental quality (Cambardella et al., 1994). 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 (Jenny, 1980; 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). The need for intensive grid sampling for evaluating of the spatial variability and/or the diversity of different soil and agronomic properties has been frequently emphasized (Paz-Gonzalez et al., 2000; Cattle et al., 1994). However, most soils studies use bulk sampling from the area analyzed or treated, e.g. the agricultural field. The soil variability therefore is ignored by such sampling. This leads to the question: if this variability could be mapped, how much economic benefit could there be in treating small area of the field differently (Yemefack et al., 2005). This is the motivation for the recent interest in precision agriculture, which has resulted in much work on within-field variability, mostly in context of high-technology farming but also in shifting cultivation (Godwin and Miller, 2003).

The variability of soil properties within fields is often described by classical statistical methods, which assume that variation is randomly distributed within mapping units. In addition, soil properties frequently exhibit spatial dependency. Generally, samples collected close to one another are more similar than samples collected at greater distances. Therefore, parametric statistics are inadequate for analysis of spatially dependent variables because they assume that measured observations are independent in spite of their distribution in space (Miller et al., 1988).

Geostatistical analyses, originally used in the mining industry have proven to be useful to soil science for characterizing and mapping spatial variation of soil properties (Materon, 1963). Many investigations have been conducted that show the spatial distribution of soil properties throughout a region (Burgess and Webster, 1980; Warrick et al., 1986; Odeh et al., 1992; Juang and Lee, 2000). Geostatistics consists of variography and kriging. Variography uses semivariograms to characterize and model the spatial variance of data whereas kriging uses the modeled variance to estimate values between samples (Burgess and Webster, 1980; 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 physical and chemical soil properties at field scale in Sorkhankalateh, Golestan province, Iran.

Materials and methods

Study area, sampling design and laboratory analysis

The study was conducted on a farmer–operated wheat field at the Sorkhankalateh, about 25 km northeast of Gorgan, in Golestan 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, thermic, Fluventic Haploxerepts. Samples of the 0-30 cm horizon were collected before planting in early December 2004 to compare the spatial variation of soil properties at a scale of 1.80 ha (100 × 180m plot) using augers on distances of 20 m, 10 m and 5 m as a nested grid (n=101) (Figure 2). 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); organic matter content was determined using Walkley–Black, 1934; pH was measured in a 0.01 mol KCl–solution; available phosphorous was measured by colorimetry using ascorbic acid-ammonium molybdate reagents (Olsen, 1982); available potassium was measured using extraction with ammonium acetate (1N) (Richards, 1954); total Nitrogen using Kjeldal (Bremner and Mulvaney, 1982); cation exchange capacity and exchangeable sodium were determined using extraction with sodium acetate (Page et al., 1987); Electrical conductivity was measured with Electroconductimeter, Alkaline-earth Carbonate (lime) was measured by acid neutralization (Salinity Laboratory Staff, 1954); bulk density was determined by Method of soil Analysis (1986).

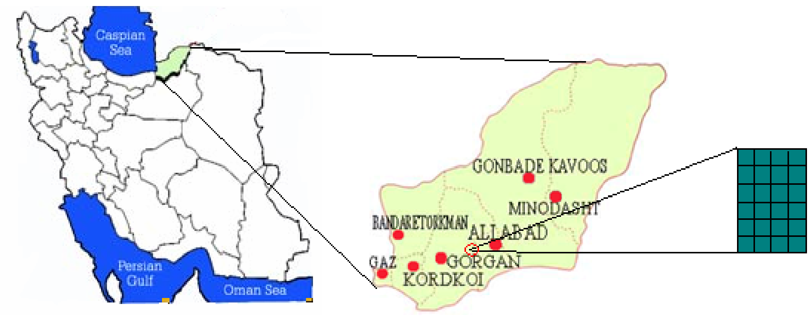

Figure 1. Location of the study area.

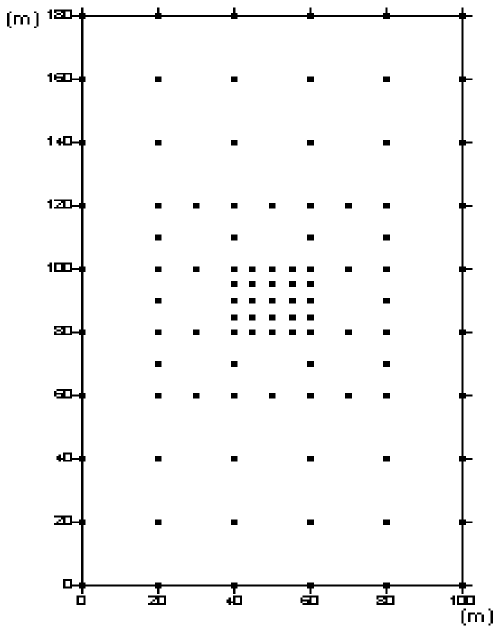

Figure 2. Sampling pattern in 1.8 ha area (100×180m plot).

Statistical analysis

Exploratory statistical analysis

Data were analyzed statistically. Classical descriptors such as mean, median, minimum, maximum, coefficient of variation (%CV), standard deviation (SD), skewness and kurtosis of data distribution were determined using the Statistical Analysis System (SAS institute, 1985). Also normality of the data was examined by Kolmogoroph-Smironoph test (SAS, 1985).

Geostatistical analysis

The soil properties were analyzed using geostatistics. An isotropic semivariogram was calculated for each soil property using VARIOWIN software (Pannatier, 1996). Semivariance is defined by the following equation (Cahn et al., 1994; Lopez-Granadoz et al., 2002):

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

where $\gamma(h)$ is the experimental semivariogram value at distance interval h; N(h) is number of sample value pairs within the distance interval h; and z (x_i+h) is sample value at two points separated by the distance interval h. All pairs of points separated by distance h (lag h) were used to calculate the experimental semivariogram. Several semivariogram functions were evaluated to choose the best fit with the data. Spherical or Gaussian models were fitted to the empirical semivariograms. Spherical model that is the most commonly used model in soil science (Burgess and Webster, 1980) is defined in the following equations:

$$\gamma(h) = C_0 + C_1 \left[3h/2a - \tfrac{1}{2}(h/a)^2\right],\ h \le a \qquad (2)$$
$$\gamma(h) = C_0 + C_1,\ h > a$$

Gaussian model is described with the following equation (Cetin and Kirda, 2003):

$$\gamma(h) = C_0 + C_1 \left(1 - e^{-3(h/a)2}\right) \qquad (3)$$

Where C_0 is the nugget effect, C_1 is the structural variance and is the range of spatial dependence.

The parameters of the model e.g. nugget semivariance, range and sill were also determined. Nugget semivariance 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).

Then Semivariogram models were cross- validated (trial and–error procedure) to check the validity of the models and to compare values estimated from the semivariogram model with actual values (Utset et al., 2000). Difference between estimated and experimental values are summarized using the following cross- validation statistics: mean error (ME) and mean square error (MSE) as follows:

$$ME=\Sigma^{n}_{i=1}(Z^{*} - Z)/n \qquad (5)$$

$$MSE=\Sigma^{n}_{i=1}(Z^{*} - Z)^{2}/n \qquad (6)$$

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). Once cross–validated, the parameters of the semivariogram models described above were used in the construction of maps by kriging for each soil property. Ordinary block kriging was performed on a regular grid of 5 m using GEOEAS software (Englund, 1980) and contour maps were generated using SURFER8 (Golden software, 2002).

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). Skewness values (Table 1) also confirmed that all soil variables were normally distributed. Therefore no transformation was used for geostatistical analyses. Coefficient of variation for all of variables was low; the highest and lowest CV% was related to ESP (12.36%) and pH (0.59%) respectively. Generally, CV values for selected soil properties in this study were lower than those reported in other references, indicating probably to the homogenizing effect of the long-term cultivation and homogenous management on top soil. This finding is also in accordance with Paz Gonzalez et al. (2000).

Classical statistics could not show the spatial variability of soil parameters. The spatial behavior of soil attributes was evaluated through their semivariograms along with the models fit to them, as shown in Figure 3 and the parameters for the models corresponding to the semivariograms are presented in Table 2. 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 23.99 m for total N up to 93.92 m for K). 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 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.

Table1. Descriptive statistics for variables within the field grid (100×180 m) to a depth of 0.3 m.

Variable	Unit	Mean	Median	Min	Max	CV(%)	SD	Skewness	Kurtosis
pH	-log[H^+]	7.86	7.86	7.75	7.96	0.59	0.047	-0.106	-0.502
EC	dSm^{-1}	0.83	0.84	0.64	1.05	11.20	0.093	0.322	-0.033
SP	(%)	68.58	68.41	67.17	70.02	1.04	0.712	0.031	-0.875
sand	(%)	2.17	2.17	1.90	2.36	4.01	0.087	-0.600	1.179
VC-sand	(%)	0.17	0.17	0.13	0.22	12.35	0.021	-0.009	-0.814
C-sand	(%)	0.29	0.29	0.20	0.35	11.03	0.032	-0.341	-0.67
M-sand	(%)	0.39	0.40	0.30	0.45	8.72	0.034	-0.635	-.118
F-sand	(%)	0.61	0.61	0.40	0.72	8.69	0.053	-0.791	1.570
VF-sand	(%)	0.70	0.70	0.60	0.81	5.42	0.038	-0.060	0.110
Silt	(%)	41.51	41.76	38.32	44.66	2.76	1.147	-.525	0.402
Clay	(%)	56.32	56.08	53.18	59.50	2.02	1.140	0.477	0.308
D_b	g cm^{-3}	1.80	1.81	1.65	1.85	2.33	0.042	-0.701	1.990
P	mg kg^{-1}	27.16	27.40	24.00	29.50	4.68	1.271	-0.385	-.761
K	mg kg^{-1}	334.59	335.26	321.11	352.56	2.43	8.127	0.230	-0.578
$CaCO_3$	(%)	27.10	27.00	22.00	31.00	7.34	1.989	-0.119	-0.516
OM	(%)	2.57	2.58	1.82	3.00	8.52	0.219	-0.416	0.107
N	(%)	0.13	0.13	0.091	0.178	8.46	0.011	0.379	4.011
CEC	$Cmol_{(+)}$ Kg^{-1}	31.06	31.10	28.75	32.65	2.55	0.793	-0.519	0.421
ESP	(%)	5.88	5.90	4.69	7.80	10.39	0.611	0.592	1.072

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

Variable	Unit	Model	Nugget	Sill	Range	Spatial Ratio(%)	Spatial class	ME	MSE
pH	-log[H^+]	Spherical	0.0011	0.001	24.39	53.84	M	0.00096	0.0022
EC	dSm^{-1}	Gaussian	0.0048	0.0043	57.23	53.05	M	-0.00146	0.0063
SP	(%)	Gaussian	0.89	8.9	55.09	9.09	S	0.0036	0.443
TotalSand	(%)	Gaussian	0.0054	0.0032	91.41	40.0	M	-0.0025	0.0065
VC-sand	(%)	Spherical	0.00028	0.00019	38.14	59.57	M	0.00032	0.0014
C-sand	(%)	Spherical	0.00065	0.00049	24.00	57.01	M	-0.00063	0.0011
M-sand	(%)	Spherical	0.00051	0.00069	37.64	42.50	M	0.00018	0.0013
F-sand	(%)	Spherical	0.00137	0.00152	66.14	47.40	M	0.0011	0.0021
VF-sand	(%)	Gaussian	0.00063	0.00089	41.02	41.44	M	0.0004	0.0004
Silt	(%)	Spherical	0.628	0.72	24.39	46.34	M	0.013	1.333
Clay	(%)	Spherical	0.67	0.656	25.83	50.75	M	-0.0082	1.302
Db	(%)	Spherical	0.00048	0.0014	72.07	24.64	S	0.00033	0.0018
P	g cm^{-3}	Spherical	1.075	0.570	35.58	65.34	M	0.028	1.695
K	mg kg^{-1}	Spherical	17.16	62.403	93.92	21.56	S	0.143	40.104
$CaCO_3$	mg kg^{-1}	Spherical	1.387	2.53	42.92	35.29	M	-0.0108	3.369
OM	(%)	Spherical	0.025	0.019	29.28	56.42	M	0.00061	0.035
N	(%)	Gaussian	0.000006	0.00010	23.99	5.66	S	0.00006	0.00007
CEC	$Cmol_{(+)}$ Kg^{1}	Gaussian	0.084	0.599	52.28	12.29	S	0.0066	0.5729
ESP	(%)	Spherical	0.024	0.40	76.41	5.66	S	0.0103	0.432

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

The different ranges of spatial correlation for nutrients may be related to the mobility of the ions. In the present study, total N, the most mobile of the three ions studied, had the shortest range (23.99m) of spatial dependence, whereas K and P, presumably the least mobile, were spatially correlated across the longer distance (93.92 m). In addition, spatial distribution of total N appeared to be correlated with OM. The ranges of total N and OM from the 1.8 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 90m for K indicates that K values influenced neighboring values of K over greater distances than other soil variable (Table 2).

The soil properties displayed differences in their spatial dependence, as determined by their semivariograms (Fig.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). Our sampling schemes were designed to allow the calculation of semivariance at small value of h relative to the size of the sampling grid. Isotropy was checked with variogram surface calculated by VARIOWIN software.

There was no anisotropy evidence in the variograms surfaces for any of the soil properties.

Spherical models were defined for $CaCO_3$, clay, ESP, K, OM, D_b, pH, Silt and Gaussian models were defined for EC, CEC, sand, total N and SP. The semivariogram for total N 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 (23.99 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 moderate spatial dependence for all variables except for CEC, K, Db, total N and Sp that had strong spatial dependence (Table 2). Strongly spatially dependent properties may be controlled by intrinsic variations in soil characteristics, such as texture and mineralogy. Extrinsic variations, such as fertilizer application and tillage, may control the variability of weakly spatially dependent parameters. In this case, P had an approximately weaker spatially dependence than the other parameters. This parameter may be spatially dependent at scales smaller than those

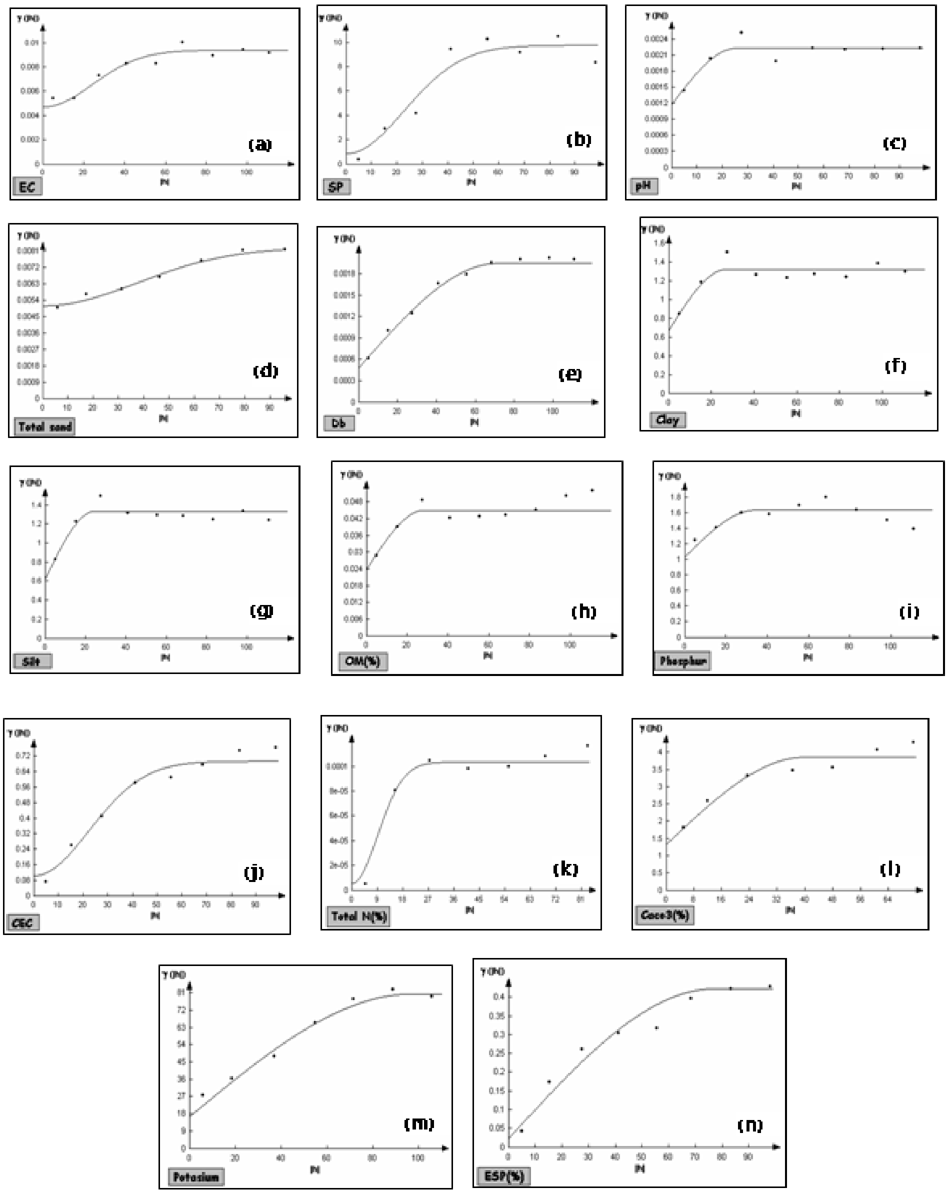

Figure 3. Omnidirectional semivariogram for soil parameters: (a) EC, (b) SP, (c) pH, (d) total sand, (e) bulk density, (f) clay, (g) silt, (h) organic matter, (i) phosphorous, (j) cation exchange capacity, (k) total N, (l) $CaCO_3$, (m) potassium, (n) exchangeable sodium percentage.

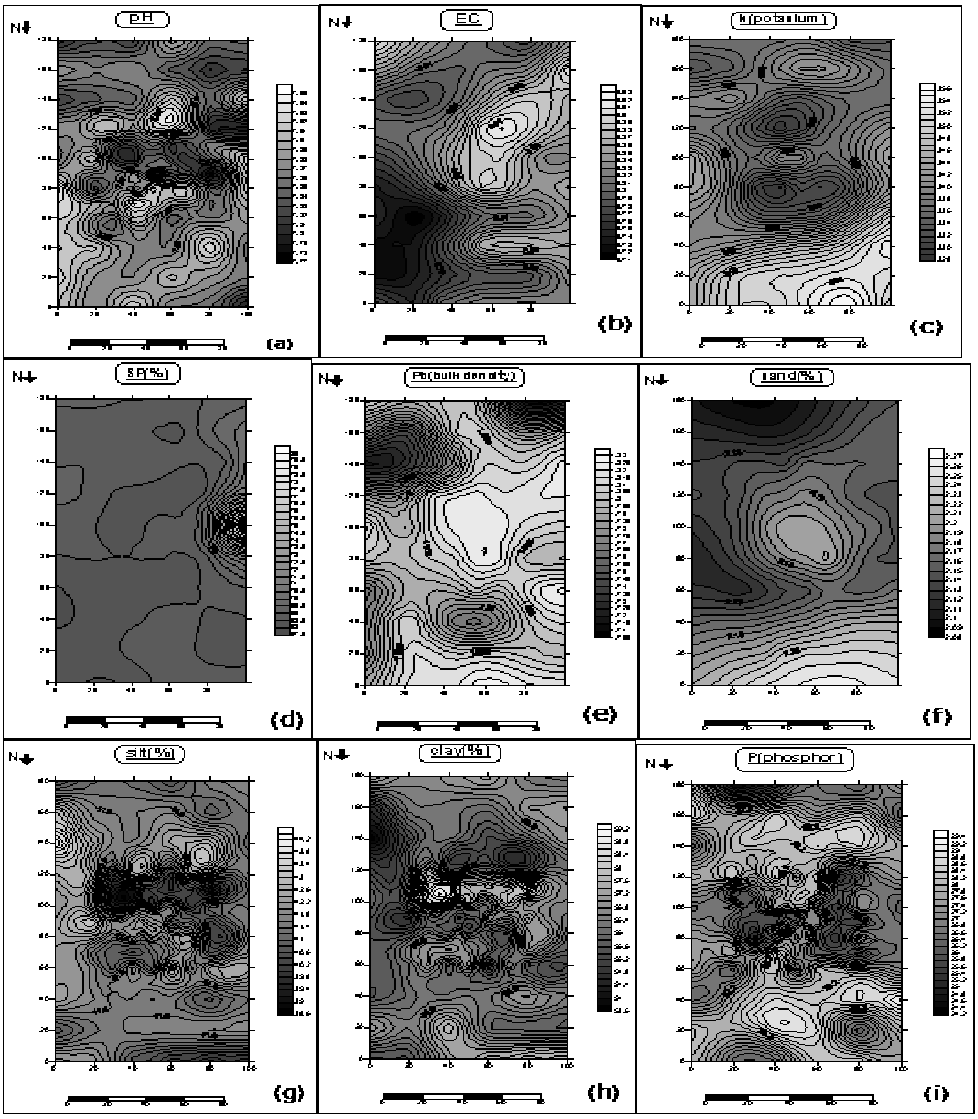

Figure 4. Contour maps of soil properties prepared by ordinary kriging: (a) pH, (b) EC, (c) K, (d) SP, (e) D_b, (f) sand, (g) silt, (h) clay, (i) P, (j) CEC, (k) ESP, (l) Total N, (m) $CaCo_3$ and (n) OM.

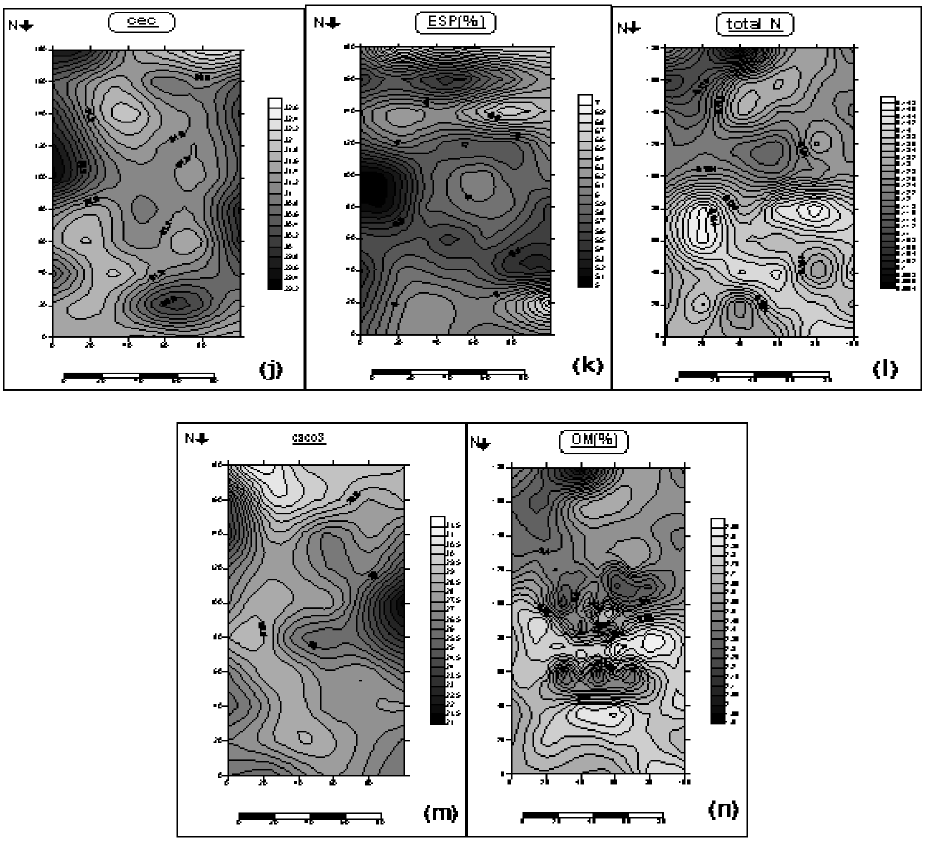

Figure. 4. cont. - Contour maps of soil properties prepared by ordinary kriging: (a) pH, (b) EC, (c) K, (d) SP, (e) D_b, (f) sand, (g) silt, (h) clay, (i) P, (j) CEC, (k) ESP, (l) Total N, (m) $CaCo_3$ and (n) OM.

used for these studies. The existence of this spatial dependency for some soil properties at this scale is consistent with results shown in previous studies (Cambardella et al., 1994; Lopez–Granadoz et al., 2002).

Figure 4 shows the contour maps obtained by kriging for soil properties. The comparison of these maps may be useful in the interpretation of the results. 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. In addition, the quantitative information obtained from these maps could be used to facilitate site-specific management in the study region.

Conclusion

The results demonstrated that the spatial distribution and spatial dependence level of soil properties can be different even within a similar former agricultural management. These results support the importance of collecting information in every agricultural region to know how a site-specific system should be undertaken. 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.

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