Spatial Variability of Plant-available Micronutrients in the Surface and Subsurface Layers of a Calcareous Soil

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Abstract

Geostatistics can be applied for determining fertilizer-needs and predicting nutrient deficiency or toxicity in plants. Spatial variability of available (di-ethilene three amine penta acetic acid, DTPA-extractable) iron (Fe), zinc (Zn), copper (Cu) and manganese (Mn) was studied by sampling 75 points from 0-15 and 15-30 cm depths on a relatively regular design with 50-70 m sampling distance-interval in Dehsheikh area (52º 16´ to 52º 22´ E and29º 37´ to 29º 38´ N) in Fars Province, IR Iran. Statistical analysis showed that except for Mn in 0-15 cm depth and Zn in both studied depths, the other elements was relativelynormally distributed. Available micronutrients had spatial structure and spherical or exponential models were the best fitted models to their experimental semivariograms. In the surface soil the range of spatial dependence (range of influence) varied from 270-2110 m (for Zn and Mn, respectively), whereas, that of subsurface soil varied between 290-3620 m (for Zn and Fe, respectively) indicating that a sampling design with larger sampling distances could be applied. Spatial dependence classes were medium. However, their influence ranges and spatial dependencies in subsurface soil were higher than that of surface-soil. Ordinary kriging was the most suitable approach for estimating available micronutrients concentration in both soil-depths. Generally, spatial analysis of micronutrients could be useful for evaluating soil fertility and soil quality status, as well as developing proper sampling approaches.

Keywords: iron, zinc, copper, manganese, ordinary kriging, inverse distance weighting

Introduction

Soil nutrient availability is one of the vital factor governing net primary productivity (Seastedt et al., 1991 after Sylvie et al., 2001). Soil properties including nutrient elements have spatial and temporal variations from small scales to large scales. Site-specific crop and soil management systems apply agronomic science to manage production practices and inputs to address spatial and temporal variability on the farm (Sylvie et al.,2001). These variations are affected by inherent characteristics (factors affecting soil such as soil parent material) and non-inherent characteristics such as soil management practices and fertilization, (Quine and Zhang,2002;Godwin and Miller,2003). Information about variability of the soil properties and characterizing spatial variability and distribution of nutrient elements is critical for ecological modeling, environmental predictions, precision agriculture, natural resources management (Lin et al.,2004), predicting rates of ecosystem processes (Schimel et al., 1991), understanding how ecosystems work (Townsend et al., 1995), prediction of environmental pollution and nutrient balance (Wang et al., 2014) and assessing the effects of future land use change on nutrient status (Kosmas et al.,2000).Furthermore, spatial variability of soil input data can be highly effective on the results of deductive, experimental and theoretical soil models (Wilding et al.,1994). Due to the aforementioned reasons understanding how nutrient elements vary across landscapes and fields has received increased attention in agricultural and ecological researches (Benning and Seastedt,1995).In the case of spatial variability of nutrient elements and soil attributes, some studies have investigated the formation and development of "fertile islands" in arid and semi-arid region, especially in the African savannas (Okin et al., 2008; Wang et al.,2009) and in the desert ecosystem of North America (Thompson et al., 2006; Ruiz et al., 2008; Butterfield and Briggs, 2009). Furthermore, the spatial heterogeneity of surface soil properties and its influencing factors have also been discussed, respectively, using a traditional statistical method (Schade and Hobbie 2005; Housman et al. 2007; Abril et al. 2009) or a geostatistical method (Chen et al., 2006; Don et al., 2007; Moosavi and Sepaskhah, 2012; Moradi et al., 2016). Furthermore, Rusu and Rusu (2006) also mentioned that kriging is an accurate, time-consuming and complex method among the common interpolation methods; while, some methods such as inverse distance weighting (IDW) method is fast and flexible.

Study of spatial variations and zoning of soil nutrient elements can be applied as a basis for determining fertilizer needs and predicting deficiency or toxicity of the plants required nutrient elements in soil. These spatial variations of soil properties consist of two systematic (structural) and random (nonstructural) components(Saldana et al., 1998). Liu et al. (2004) studied and reported spatial dependence of nutrient elements (iron, manganese, copper and zinc) in rice farmlands of Zhejiang Province located in southeast of China with geostatistics and Geographical Information System (GIS). Spatial distribution of all their studied elements had significant correlation with the factors of soil formation. Sharma et al. (2002) also mentioned that variations in distribution of micronutrients depend on soil factors.

Information about soil characteristics is necessary for management of farmlands and making decision for selection of special strategies for management of soil properties (Franzen et al., 2006). Awareness with these changes is necessary and considerable for increasing productivity, maintenance of soil fertility and applying suitable soil management practices. In Iran due to existence of calcareous soils with high pH and salinity values, deficiency of organic matters in agricultural soils and lack of balance in fertilizer consumption, solubility of nutrient elements particularly micronutrients is very low (Maftoon et al.,2000). Therefore, deficiency of these elements in soil solution and low absorption by plant or lack of balance in ratio of the micronutrients can result in deficiency of these elements in animal and human (Havlin et al.,2013). Although factors and causes of variations are different in different regions, understanding sources of variations will be useful in better management of soil. However, some previous researches were conducted in temperate and tropical regions associated with weak soil erosion (Kosmas et al., 2000), but not in areas with a semi-arid soils like calcareous soils of IR Iran in which essential micronutrients are in deficit conditions. Therefore, considering large area of wheat cultivation and other crops and their important role in nutrient chain in the studied region, recognition of spatial variation of micronutrients in increasing soil quality and improving the management practices for this region is highly important. Due to this reason, the present research was conducted to study the spatial variability of available metal micronutrients in the surface and subsurface layers of a calcareous soil.

Materials and Methods

Geographical Position of the Study Area

The study area is located near Dehsheikh village, one of the villages of Arjan region in Shiraz, Fars province, IR Iran. This region with approximate area of 1319 ha is located between longitude of 52º 16´ to 52º 22´ andlatitude of 29º 37´ to 29º 38´.The highest and the lowest points of the region are 2045 and 1750 m high above sea level, respectively. Geological formation of the region is of Aghajari formation and climate of the region has been classified as temperate semiarid based on De Martonne’s classification (after Banaei, 1998). Moisture and thermal regimes of the region are xeric and thermic, respectively (Banaei, 1998). Soils of the study area was classified as Typic Xerorthents and Typic Haploxerepts based on Soil Taxonomy (Soil Survey Staff, 1999 after Khormali, 2003) and the common land uses were cultivation (dry lands wheat), garden (apricot) and range (undisturbed).

Sampling

At 75 points on a relatively regular sampling network with distance intervals of 50 to 70 m (Figure 1) composite samples of about 3 kg soil were collected from two depths of 0 to 15 and 15 to 30 cm, separately. The geographical position of each sampling location was recorded with Global Positioning System (GPS) at the beginning of sampling. The samples were air dried after being transferred to the laboratory and passed through 2-mm sieve for further analysis.

Measuring Metal Micronutrients and Some Chemical Properties of Soil

Usual properties of soil such as pH in saturated extract were measured with pH meter, electrical conductivity (EC) of soil saturated extract was measured with conductivity meter in saturated extract, and calcium carbonate equivalent (CCE) was measured with neutralization method with normal hydrochloric acid 1 N and titration with sodium hydroxide (Loeppert and Suarez, 1996). Organic matter (OM) of soil samples was determined by the wet oxidation method (Nelson and Sommers, 1996). Concentration of the available forms of micronutrients (Fe, Zn, Cu and Mn) were measured through extraction with di-ethilene three amine penta acetic acid (DTPA) (Lindsay and Norvell, 1978 after Moosavi et al., 2014) and reading with atomic absorption spectrophotometer.

Statistical and Geostatistical Analyses

Geostatistical analyses were performed with the measured attributes in 75 sampling locations of the studied region. To study frequency distribution and determine descriptive statistics of each soil attributes, the maximum and minimum statistics, mean, standard deviation, skewness and kurtosis were determined. The normality of data was checked according to Kolmogorov-Smirnov's test (Oztuna et al., 2006 after Ghasemi and Zahediasl, 2012) using the SPSS19 software packages (Table 1) and existence of trend was also checked using the aforementioned software packages. In the cases there were significant deviation from normal distribution, logarithmic transformation were used. The correlation coefficients between the concentration of the studied soil micronutrients and some soil properties were also determined.

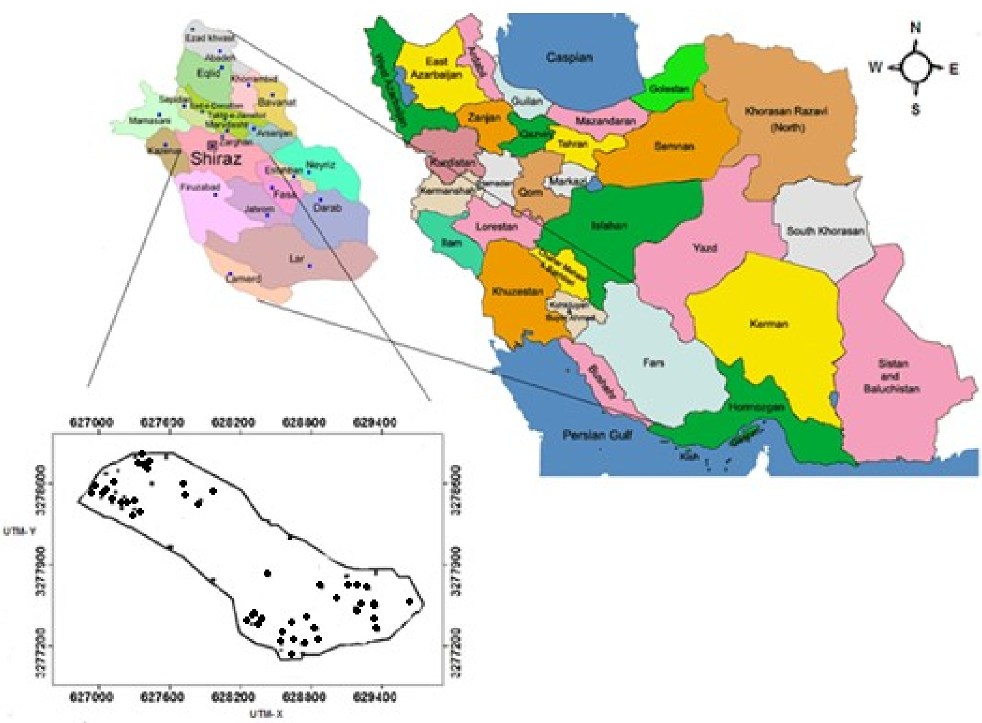

Figure 1 Geographical position of the studied region along with the sampling locations.

Table 1 Descriptive statistics of available (DTPA-extractable) micronutrients (mg kg^{-1}) intwo studied soil depths

Available nutrient (mg kg $^{-1}$)	Depth (cm)	Descriptive statistics[1]							
		Min.	Max.	Mean	Variance	CV (%)	Skewness	Kurtosis	Z[2]
Fe	0-15	1.00	5.80	3.32	1.73	39	-0.03	-0.98	0.703 ^{ns}
	15-30	3.00	5.90	4.20	0.63	18	0.57	-0.74	1.184 ^{ns}
Zn	0-15	0.10	1.40	0.45	0.10	69	1.72	2.24	2.277 **
	15-30	0.16	5.00	0.74	0.40	86	4.17	2.60	1.604 *
Cu	0-15	0.30	1.87	0.87	0.13	41	0.63	0.32	1.057 ^{ns}
	15-30	0.29	1.80	0.89	0.09	34	0.11	-0.17	0.649 ^{ns}
Mn	0-15	1.00	16.0	10.6	7.42	25	-1.10	1.36	1.685 **
	15-30	3.58	17.0	10.8	11.1	30	-0.28	-0.88	1.175 ^{ns}

[1]Min., Max., CV and Z are the minimum value, maximum value, coefficient of variation and Kolmogorov-Smirnov statistic of normality test, respectively.

[2]ns means that distribution follow the normal distribution. * and ** mean that the distribution departure from the normal distribution at the probability levels of 0.05 and 0.01, respectively.

To study spatial variations of the studied properties, experimental semivariograms were calculated for all variables in different directions as shown in the following Eq.:

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

where $\gamma(h)^*$ is semivariogram (SV) value in distance of h, $Z(x_i+h)$ is the measured value of variable in spatial position (x_i+h);$Z(x_i)$ is the measured value of variable in position (x_i) and $N(h)$ is the number of paired comparisons in distance of h in the studied zone. Then different theoretical models including spherical (Eq. 2) and exponential (Eq. 3) models were fitted to the calculated SV of each attribute and the suitable model was obtained based on the values of coefficient of determination (R^2) and the residual sum of squares (RSS). The model which had the maximum R^2 and the minimum RSS was selected as the best SV model (*Robertson,* 2008). To study anisotropy and isotropy of variations in the concentration of each studied micronutrients, two techniques of drawing SV in four main directions and drawing surface SVwere used. Surface SV of the studied variables showed that their variability in the region was independent of geographical direction andanisotropy ratio is equal to 1. Therefore, isotropic (omnidirectional) SV were used to study the structure of spatial variations of the studied variables. where C_o is nugget effect (the minimum value of SV which has been calculated) that indicates the discontinuity of the SV curve near originof coordinate which reflects the variance of sampling and laboratory analysis errors and spatial variance in shorter distances from the sampling distances (Li and Heap, 2008).C_1 is SV sill (total nugget effect (C_o) and structured part of SV (C) which is equivalent to total variance of the studied variable and relatively constant value with random variations is called sill), a is range of influence (the distance in which SV is fixed and reaches the sill value), and h is separation distance. To determine different classes of spatial dependence of the studied variables, ratio of spatially structured variance to total variance was used. If the ratio of spatially structured variance (C) to sill ($C+C_0$) is less than 25% , between 25 and 75% and more than 75%, the studied variable will be in the range of weak, medium and strong spatial dependence class (Wu et al., 2008).

Spherical model:
$$\gamma(h) = C_0 + C_1\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] \quad \text{for } h \le a \quad (2)$$
$$\gamma(h) = C_0 + C_1 \quad \text{for } h > a$$
$$\gamma(0) = 0 \quad \text{for } h = a$$

Exponential model:
$$\gamma(h) = C_0 + C_1\left(1 - e^{\frac{h}{a}}\right) \quad (3)$$

Considering the parameters of the best fitted model to the experimental SV and the measured values of each studied attribute, their values were estimated at the un-sampled locations with the Ordinary Kriging, KRIG (Eq. 4) and the Inverse Distance Weighting (IDW) methods (Eq. 5). All of the aforementioned steps for a geostatistical analysis have been shown as a flowchart (Figure 2).

Kriging is a weighted moving average and is defined as follows (Pang et al., 2011):

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \qquad i= 1,\dots,n \qquad (4)$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

Where $Z^*(x_i)$ is the estimated value, $\lambda_i$is the weight which is given to the sample and X, $Z(x_i)$ is value of the i-th sample. The Inverse Distance Weighting method is defined as follows:

$$\lambda_i = \frac{D_i^{-\alpha}}{\sum_{i=1}^{n} D_i^{-\alpha}} \qquad (5)$$

Where D_i is the distance between the i-th observed point and the estimated point, α is the inverse distance weighting power and n is the number of neighborhood points. To determine the most suitable method of estimation, several indices of evaluation including coefficient of determination, R^2, mean bias error, MBE, (Eq. 6), mean absolute error, MAE, (Eq. 7) were used simultanesouly (Whitmore, 1991). The MBE and MAE indicates bias and accuracy of each applied estimation method. If the MAE value is low, the values estimated by the model and the real values are closer to each other and the model has lower error. In the case of MBE, difference between the measured and estimated values is calculated algebraically, therefore, this index can present useful information about underestimation or overestimation of the applied model or estimation approach. Positive values of MBE indicate overestimation of the model and its negative values correspond to underestimated results. where $Z^*(x_i)$ is the estimated value in point X, $Z(x_i)$ is the observed value in point X_i and n is the number of points.

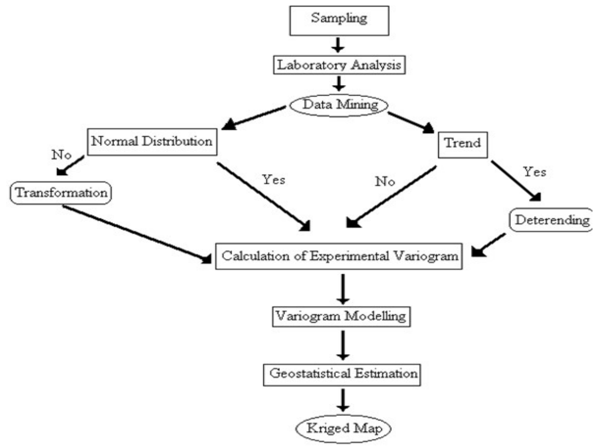

Figure 2 Schematic description of steps should be followed in a geostatistical analysis.

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n} (Z^*(x_i) - Z(x_i))}{n} \qquad (6)$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n} (Z^*(x_i) - Z(x_i))}{n} \qquad (7)$$

Where $Z^*(x_i)$ is the estimated value in point X, $Z(x_i)$ is the observed value in point X_i and n is the number of points.

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Results and Discussion

Statistical Description

Statistical description of the measured available micronutrients at 75 points of the study area has been shown in Table 1. Results of Kolmogorov-Smirnov's test (Oztuna et al., 2006 after Ghasemi and Zahediasl, 2012) showed that all of the studied micronutrients except Mn and Zn in depth of 0 to 15 cm and Zn in depth of 15 to 30 cm relatively followed a normal distribution (Table 1). The results of skewness coefficients (Table 1) and histogram analysis (Figures 3 and 4) confirm the aforementioned normal distributions results.In the cases there were significant deviations from normal distribution i.e., high skewness and kurtosis (Table 1 and Figures 3 and 4) which could damage structure of SV in geostatistical analyses and reduce accuracy of estimation, the data were transformed using logarithmic transformation. In other words, by performing suitable logarithmic transformation, the distribution of data got close to normal distribution as far as possible.

Results showed that the mean concentrations of Fe, Zn, Cu and Mn were 3.3, 0.45, 0.87 and 10.6 mg kg^{-1} in depth of 0 to 15 and were 4.2, 0.74, 0.89 and 10.7 mg kg^{-1}in depth of 15 to 30 cm. Considering the adequacy levels of Fe, Zn, Cu and Mn in soil which are 5 to 25, 0.5 to 6, 0.3 to 2.5 and 5 to 30 mg kg^{-1}, respectively (Havlin et al.,2013), the mean value of Fe in both of studied soil depths and the mean value of Zn in depth of 0 to 15 cm is below their critical limits; while, the mean values of available soil Cu and Mn concentrations are adequate. Zinc is one of the micronutrients which are essential for optimal growth of plants, animals and human in low concentration. The available concentration of Zn and its absorption by plant root is restricted in calcareous (alkaline), alkali (sodic) and organic soils (Subrahmanyam et al.,1991). Zinc deficiency is one of the most prevalent nutrient deficiencies in calcareous soils due to the low available Zn concentration, while the total concentration of Zn is almost adequate. When the organic and chemical fertilizers are added to soil, its recovery is almost below 5% which indicates high capacity of calcareous soils to preserve zinc (Maftoon et al., 2000; Kuo and Mikkelsen, 1980 after Zahedifar et al., 2012).

Availability of Mn is affected by pH more than any other factors; however, the other factors like organic matter and aeration are also effective; therefore the consumed fertilizers by farmers particularly organic fertilizers reduce pH and increase the availability of Mn and Cu (Gambrell and Patrik,1982). Results showed that the maximum and minimum variances in soil depth of 0-15 cm correspond to Mn and Zn, respectively; whereas, the maximum and minimum variances in soil depth of 15-30 cm correspond to Mn and Cu, respectively. Based on the criterion proposed byWilding (1985), if the variation coefficient of a variable is below 15%, 16 to 35%, and more than 35 %, the variable will be in low, moderate and high variability classes, respectively. Variations coefficient of the studied micronutrients in depth of 0 to 15 cm revealed that Mn is included in high variability class, while Fe, Zn and Cu are included in the medium variability class.

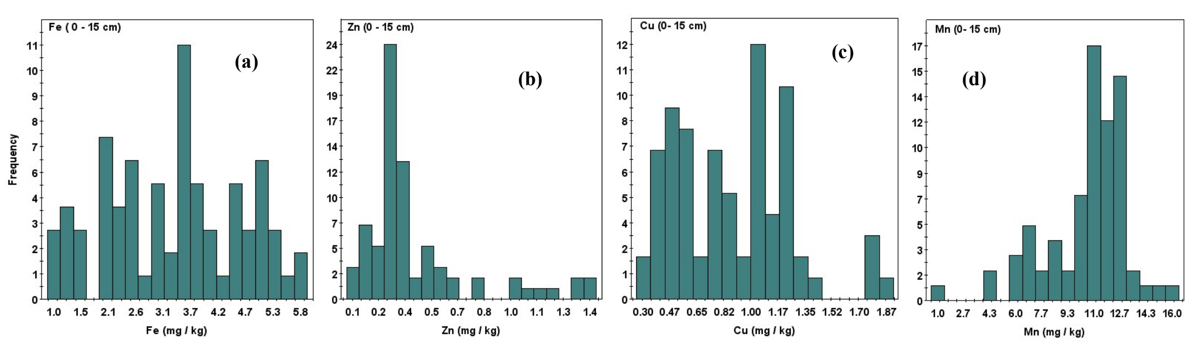

Figure 3 Histogram of available (DTPA-extractable) iron (a), zinc (b), copper (c) and manganese (d) in surface layer (0-15 cm depth) of studied soil.

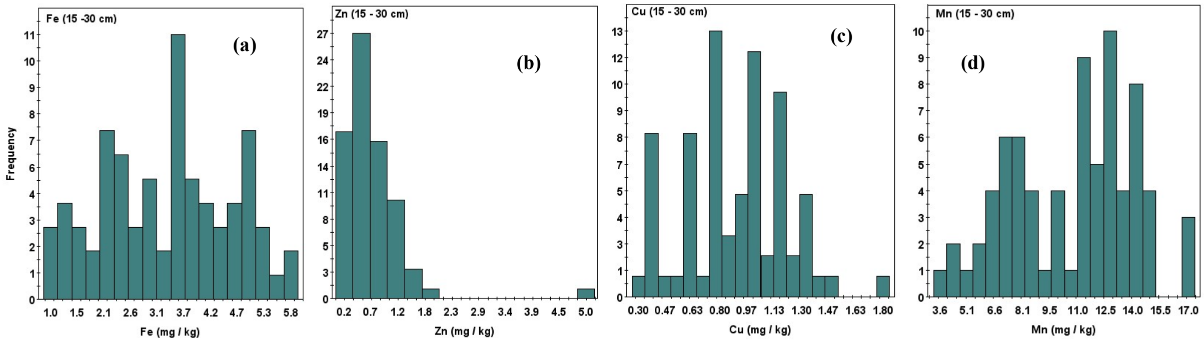

Figure 4 Histogram of available (DTPA-extractable) iron (a), zinc (b), copper (c) and manganese (d) in surface layer (15-30 cm depth) of studied soil

Results also indicated that the available concentration of Fe, Mn, and Cu in 15-30 cm depth were located in the moderate variability class, but Zn was located in the high variability class. In general, our findings revealed that the CV values of available Fe and Cu in surface layer of studied soils were higher than those of subsurface layers; whereas, the reverse trend was observed for Zn and Mn. The aforementioned variability trends between the studied nutrient elements of surface and subsurface layers of soil revealed that the variation of Fe and Cu mainly correspond to the variation of management practices, whereas variation of Zn and Mn may relate to the variation of pedogenic factors in a greater extent.

The correlation coefficient between the concentration of available micronutrients and pH, EC, organic matter (OM) and (CCE) values in the studied soil depths have been summarized in Tables 2 and 3. There are significant (P<0.01) negative correlations between soil pH and concentration of the studied micronutrients (except for Cu in depth of 15 to 30 cm) indicating that decrease of pH has increased the availability of micronutrients. Results showed that there is significant (P<0.05) positive correlation between OM and concentration of Cu and Fe in depth of 0 to 15 cm and between OM content and concentration of Zn in depth of 15 to 30 cm. Liu et al. (2008) showed that there was significant positive correlation between concentration of Zn and OM content of soil. Findings also revealed that there was significant positive correlation between concentration of Fe and other studied nutrient elements, while Zn had no significant correlation with the other elements (except Fe) and there was negative correlation between the Cu and Mn concentration in both of studied soil depths.

Spatial Correlation Analysis

Results showed that all of the studied available micronutrients had spatial structure and the spherical and exponential models were the best fitted models to their experimental SV (Table 4 and Figures 5 and 6). Results also indicated that exponential model was the best fitted model to the SV of Fe (at 15-30 cm depth) and Mn (at both studied soil depths), but the spherical model was the best fitted model to the other SV. Cetin and Kirda (2003) also reported that the spherical model was one of the common geostatistical models for the SV of soil attributes. Zhang et al. (2008) reported that the best fitted model to SV for Fe, Mn and Cu are exponential, Gaussian and spherical models, respectively. Results showed that the minimum nugget effect (0.011) correspond to the SVof Zn in depth of 0 to 15 cm indicating that relative variance and sampling size are suitable for clarifying the spatial structures, while the maximum nugget effect (0.227) correspond to Mn indicating strong random variance in short intervals resulting from sampling and measurement errors, small range variations in shorter distance from the shortest sampling intervals. In depth of 15 to 30 cm, the minimum and maximum nugget effects correspond to the SVof Cu and Mn. Results showed that the minimum and maximum sill values between the SV of studied micronutrients in both depths, respectively observed for Cu and Mn indicating that the variation of Cu is more spatially structured; whereas, variation of Mn is more random or less

Table 2 Correlation coefficient between the concentration of available micronutrients and some of soil chemical properties in depth of 0 to 15 cm.

Soil variable	Fe	Zn	Cu	Mn	pH	ECe	OM	CCE
Fe	1							
Zn	0.500**	1						
Cu	0.584**	0.165	1					
Mn	0.497**	0.199	0.376**	1				
pH	-0.519**	-0.530**	-0.429**	-0.310**	1			
ECe	0.172	0.307**	0.222	0.087	-0.406**	1		
OM	0.236*	0.183	0.289*	0.133	-0.376**	0.168	1	
CCE	0.11	-0.012	0.144	0.011	-0.292*	0.349**	0.123	1

** and * mean that the correlation coefficients is significant at the probability levels of 0.01and 0.05, respectively.

Table 3 Correlation coefficient between the concentration of available micronutrients and some of soil chemical properties in depth of 15 to 30 cm.

Soil variable	Fe	Zn	Cu	Mn	pH	ECe	OM	CCE
Fe	1							
Zn	0.284*	1						
Cu	0.326**	0.115	1					
Mn	0.431**	0.174	0.316**	1				
pH	-0.426**	-0.315**	-0.045	-0.391**	1			
ECe	0.484**	0.458**	0.051	0.470**	-0.625**	1		
OM	0.051	0.236*	-0.107	0.01	-0.22	0.296*	1	
CCE	-0.008	-0.056	-0.089	0.166	-0.215	0.237*	0.134	1

** and * mean that the correlation coefficients is significant at the probability levels of 0.01and 0.05, respectively

Table 4 Coefficients of the best fitted model to experimental semivariograms of micronutrients in two depths of the studied area

DTPA-extractable (mg kg $^{-1}$)	Depth (cm)	Model	Nugget	Sill	Range (m)	$C/(C_0+C)^{2}$ **	Spatial class	R^2	RSS[3]
Fe	0-15	Spherical	0.047	0.156	510	0.702	M	0.62	0.00087
	15-30	Exponential	0.537	1.07	3620	0.50	M	0.73	0.00258
Zn	0-15	Spherical	0.011	0.0394	270	0.628	M	0.51	0.00017
	15-30	Spherical	0.095	0.2827	290	0.66	M	0.66	0.00030
Cu	0-15	Spherical	0.013	0.029	360	0.67	M	0.74	0.00009
	15-30	Spherical	0.038	0.099	430	0.62	M	0.88	0.00048
Mn	0-15	Exponential	0.227	0.433.8	2110	0.51	M	0.90	0.00032
	15-30	Exponential	9.00	18.01.3	2110	0.50	M	0.75	0.00079

[2]The ratio of structured variation (C) to total variation ($C+C_0$) of less than 25%, between 25 and 75% and more than 75%, that specification will be in range of weak, moderate and strong spatial dependence (Camberdella et al., 1994 after Moosavi and Sepaskhah, 2012)
[3]RSS is Residual sum of squares and $R^2$is coefficient of determination

spatially structured as compared to those of the other studied elements. In other words, the total variance of all samples has been used in calculation of their SV was high.

The minimum and maximum ranges of influence among the studied elements in depths of 0 to 15 cm were 270 and 2110 m that corresponded to the semivariogramsof Zn and Mn, respectively. This indicate that available Zn can influenceits values on the adjacent locations strongly; whereas, available Mn content can influence the adjacent locations, weakly. Results indicated that the maximum range

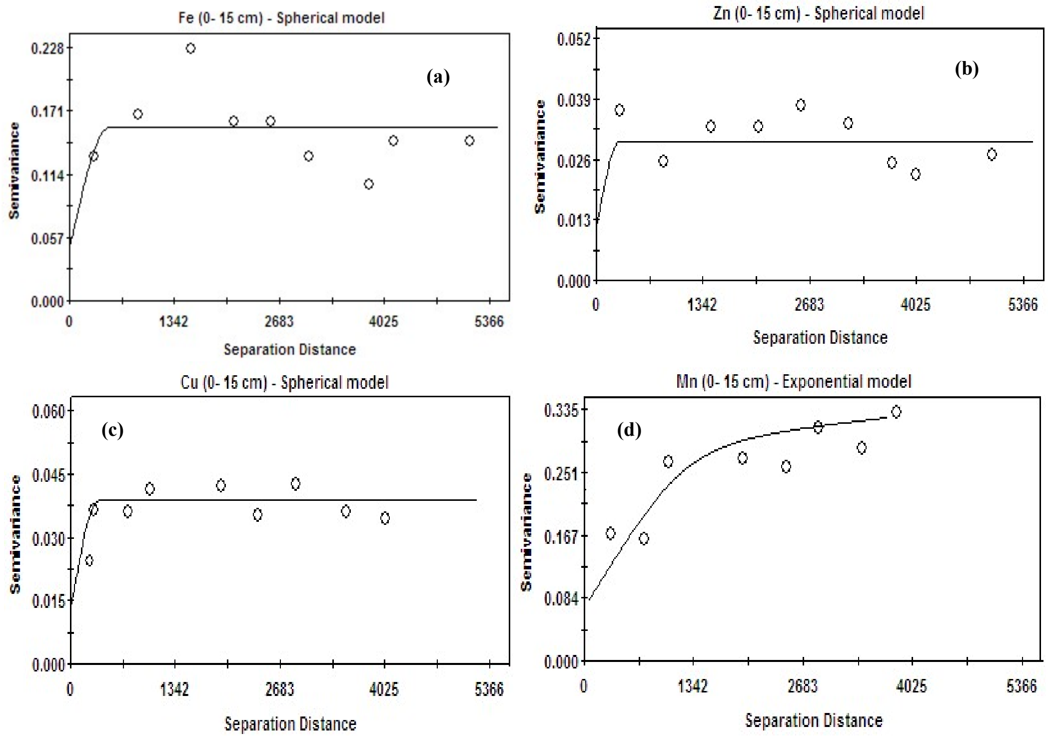

Figure 5 Experimental semivariogram of available (DTPA-extractable) iron (a), zinc (b), copper (c) and manganese (d) in surface layer (0-15 cm depth) of studied soil along with the best fitted theoretical models.

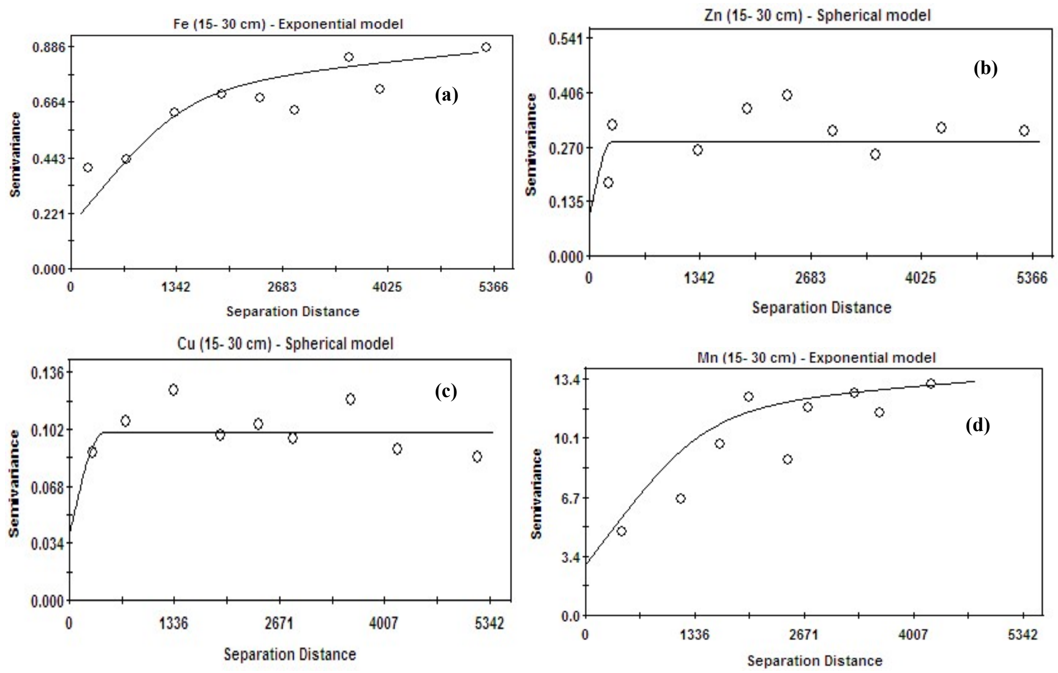

Figure 6 Experimental semivariogram of available (DTPA-extractable) iron (a), zinc (b), copper (c) and manganese (d) in surface layer (15-30 cm depth) of studied soil along with the best fitted theoretical models.

of influence among the studied elements in depth of 15 to 30 cm is 3620 m that corresponded to the SV of available Fe; whereas, the minimum range of influence (290 m) was obtained for SV of available Zn. Results indicated that due to the lower variability of studied elements in the subsurface layer of soil, the range of influence and spatial dependency of studied elements were higher than that of the surface layer. Lower variability (higher spatial correlation) of the studied metal micronutrients in the subsurface layer of studied soil may correspond to the lower disturbance of soil materials, penetration of plant roots, number of soil organisms and the biological, biophysical and biochemical reaction and activities, and also lower influences of human born managerial factors in the subsurface parts of soil in comparison to that of surface parts.

In general, as the range of influence increases, the sampling distances can increase and the number of required samples for mapping can reduce, as a consequence the costs of sampling and mapping can reduced. In this study, the range of spatial dependence varied between 270 and 3620 m, indicating that the applied grid scale for sampling was not adequate for assessing the spatial variability of micronutrients in the studied area. Therefore, for reducing the cost of sampling, a sampling design with larger sampling interval should be applied.

Our results were somehow different to the findings of Zhang et al. (2008) who reported that the range of influence for SV of Fe, Mn and Cu are 5, 58 and 3 km, respectively. Results showed that the highest ratio of spatially structured to unstructured variation of SV in depth of 0 to 15 cm is 0.70 that correspond to the SV of available Fe. This indicates that 70% of Fe variations in the surface soils of studied area are spatially structured variation and only 30% of its variation is random. While the lowest ratio (0.51) of spatially structured to no spatially structured variation corresponded to the SV of available Mn in depth of 0 to 15 cm. This indicates that the half of Mn variations in the surface soil is spatially structured variation and the other half is random.

In the subsurface soil (depth of 15-30 cm) the highest (0.66) and the lowest (0.50) ratio of spatially structured to unstructured variation of SV corresponded to the available Zn and available Fe or Mn, respectively. Results showed that spatial dependence classes of all available studied micronutrients at both of studied soil depths were medium indicating that the influence of inherent factors such as parent materials and managerial factors on the variability of these elements is relatively similar. Our findings were similar to those of Tutmez et al. (2009) who reported medium spatial dependence class for microelements. Whereas, Zhang et al. (2008)stated that the spatial dependence class of Zn and Cu is strong and inherent factors such as parent materials has greater effect on the variability of these elements. Medium spatial dependence classes for the studied elements means that application of geostatistical approaches can be useful in analysis of their spatial variability patterns and mapping their variations. Strong spatial dependence class of soil properties can be dependent on inherent properties of soil i.e., soil formation (Cambardella et al., 1994 after Moosavi and Sepaskhah, 2012). While medium spatial dependence is mainly attributed to external factors such as soil management approaches. Therefore, in each region, difference in the variability of soil properties and nutrient elements depends on both variation of land management practices and the variation of soil forming factors (soil formation processes).

Results showed that in the surface and subsurface layers of studied soils, estimations of available micronutrients with kriging method had higher coefficient of determination and lower MBE and MAE (Table 5). In the other word, the values of MBE and MAE statistics were close to zero indicating that the introduced estimation method predicts the studied attributes well at un-sampled locations. Therefore, for prediction of available micronutrients, kriging was more accurate than IDW and the maps (Figures 7 and 8) were prepared using the kriged values.

Results showed that the maximum amounts of available micronutrients in depth of 0 to 15 cm were found in northern to northwestern parts of the study area, while the minimum amounts were found at the central (Fe, Cu, and Mn) or southeastern (Zn) parts. In depths of 15 to 30 cm, the maximum amounts of Fe, Zn and Mn was found in the north to northwestern (Fe, Mn, Cu, and Zn) or southwestern

Table 5 Applied estimation methods for estimation of available micronutrients in two studied soil depths along with the calculated statistical criteria for evaluation of their accuracy and performance

DTPA-extractable (mg kg $^{-1}$)	Depth (cm)	Method[1]	R^2 [2]	MBE[2]	MAE[2]
Fe	0-15	KRIG	0.6	0.0007	0.01
		IDW	0.55	0.0009	0.010
	15-30	KRIG	0.45	-0.0007	0.008
		IDW	0.4	-0.0005	0.007
Zn	0-15	KRIG	0.65	-0.00006	0.002
		IDW	0.59	0.0007	0.002
	15-30	KRIG	0.5	-0.0004	0.003
		IDW	0.51	0.0009	0.003
Cu	0-15	KRIG	0.3	-0.0004	0.003
		IDW	0.2	0.0003	0.003
	15-30	KRIG	0.45	0.0001	0.003
		IDW	0.4	0.00001	0.003
Mn	0-15	KRIG	0.5	0.00001	0.027
		IDW	0.4	-0.001	0.026
	15-30	KRIG	0.6	-0.001	0.036
		IDW	0.6	-0.001	0.035

[1]IDW and KRIG are inverse distance weighting and ordinary kriging, respectively.
[2]R^2, MBE and MAE are coefficient of determination between the measured and predicted values, mean bias error and mean absolute error, respectively.

(Cu) parts of the study area. The kriged maps also revealed that the variation of studied micronutrients in the surface layer of soil was higher than that of subsurface layer. However, in general, relatively the same spatial structures can be seen for all micronutrients at each depth. Variations in micronutrients may result from the interactions between different factors such as the amount of these elements in soil, chemical and physical properties of soil particularly pH (Hue et al., 1998) and organic matter content, type of rotation, the rate and type of chemical and organic fertilizers consumption and type of farmland management practices. In the other words, it seems that the spatial structure and pattern of variations in these elements are more affected by managerial factors and non-inherent variability. For instance, the local short-range variations mainly are controlled by fertilization with the relatively parallel spatial patterns to the crop rows. However, some parts of the local anomalies in spatial variations can be attributed to their inhomogeneity. The same conclusions but for clay and nitrogen contents of central Italian soils also has been reported by Castrignano et al. (2000).

Conclusions

The available forms of micronutrients studied in this research have spatial structures that are more affected by non-inherent variability and managerial factors. The spherical and exponential models were the best fitted models to their experimental semivariograms. Spatial dependence classes of micronutrients were medium to strong. However, their ranges of influence and their spatial correlation in subsurface soil were higher than that of the surface soil. In both of studied soil depths the range of spatial dependence (range of influence) were obtained higher than the applied sampling distances. This indicates that the applied grid scale for sampling was not adequate for assessing the spatial variability of aforementioned micronutrients in the studied area and for reducing the cost of sampling, a sampling design with larger sampling interval is recommended. Furthermore, statistical evaluation of the predicted values showed that ordinary kriging was the most suitable approach for estimation of available micronutrients in both of studied soil depths. Therefore, application of Ordinary Kriging is recommended for spatial

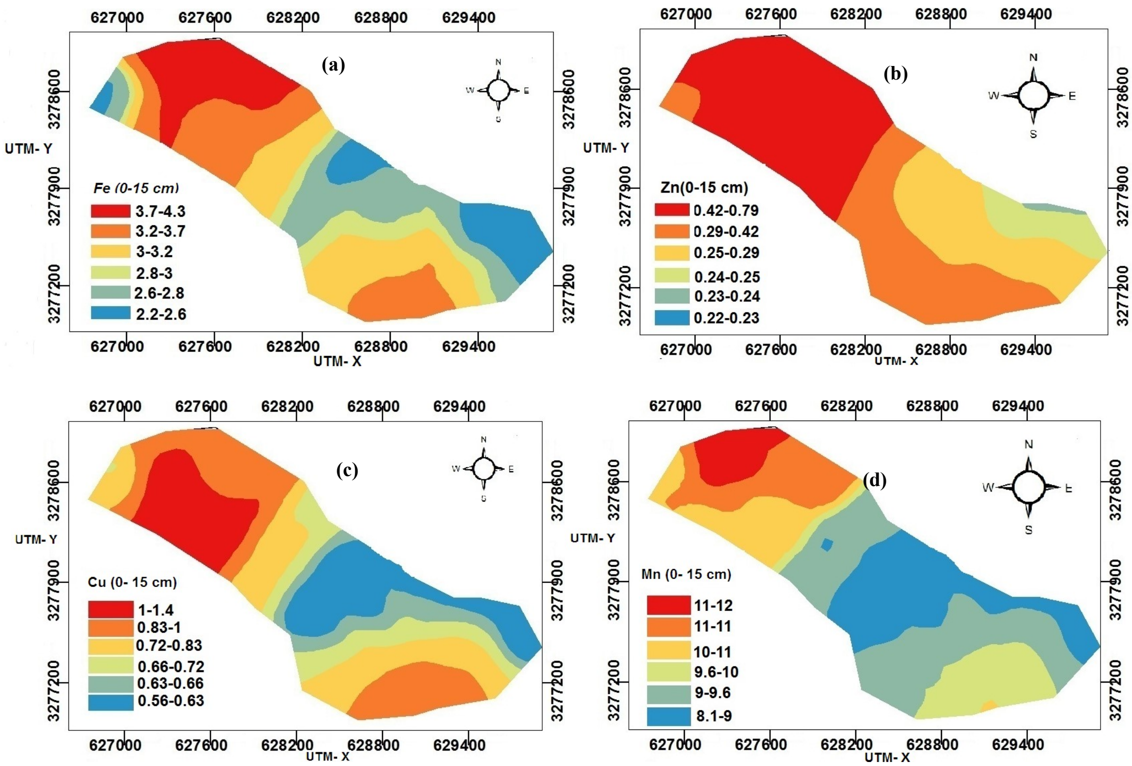

Figure 7 Kriged maps of available (DTPA-extractable) iron (a), zinc (b), copper (c) and manganese (d) concentrations (mg kg^{-1}) in surface layer (0-15 cm depth) of studied soil.

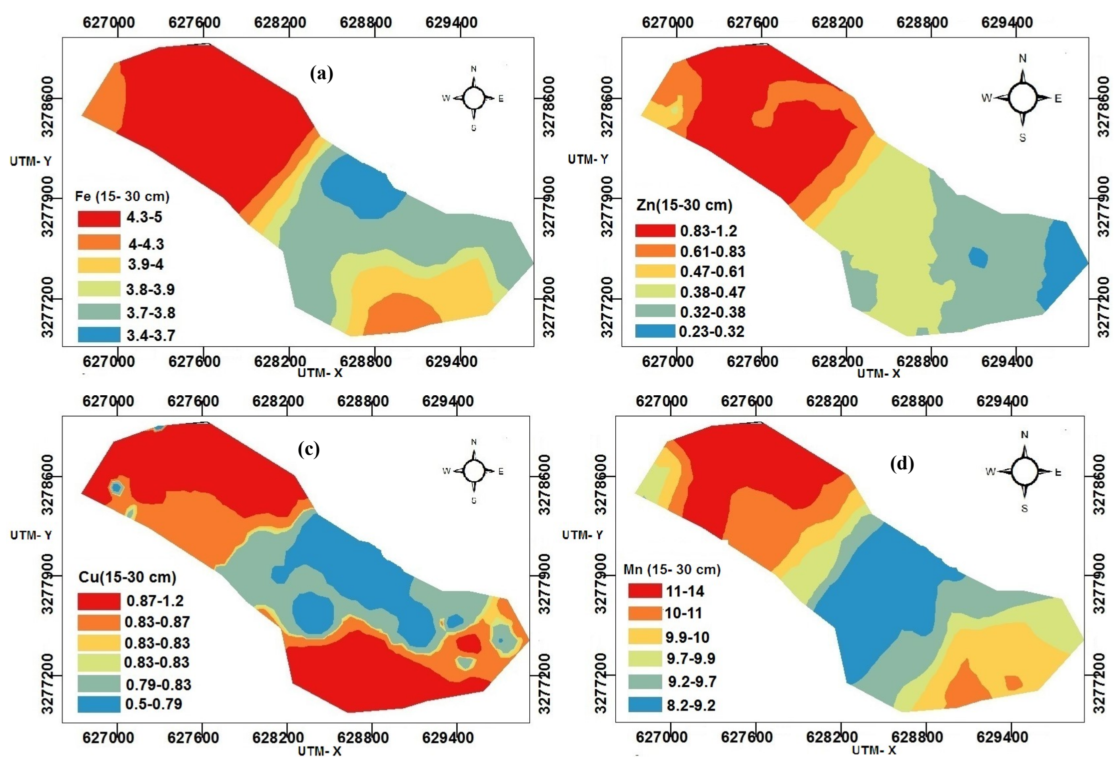

Figure 7 Kriged maps of available (DTPA-extractable) iron (a), zinc (b), copper (c) and manganese (d) concentrations (mg kg^{-1}) in subsurface layer (15-30 cm depth) of studied soil.

analysis of micronutrients that is a useful approach for evaluating soil quality and soil fertility status, as well as developing proper sampling approaches and making appropriate intelligent soil management decisions. As a result this type of accurate and intelligent management in farming can save agricultural inputs, protect environment, reduce production costs and also reduce risks resulting from the excessive consumption of chemical fertilizers. In the other words, utilization of geostatistical approaches and zoning of farmlands and creation of equal areas in terms of managerial needs will lead to better management of soil and environment, prevent waste of fertilizer sources and environmental pollution. However, it is necessary to note that spatial variations pattern of different soil properties such as nutrient elements should be studied for other zones and their maps should be prepared.

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