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Digital Mapping of Soil Properties in the Western-Facing Slope of Jabal Al-Arab at Suwaydaa Governorate, Syria

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Abstract

Digital soil mapping has been increasingly used to produce statistical models of the relationships between environmental variables and soil properties. This study aimed at determining and representing the spatial distribution of the variability in soil properties of western face-sloping of Jabal Al-Arab, Suwaydaa governorate. pH, organic matter (OM), total nitrogen (N), phosphorus (P, as P_2O_5), potassium (K, as K_2O), iron (Fe), boron (B) and zinc (Zn) were studied, thus, Forty-five surface soil samples (0 to 30 cm) were collected and analyzed. Descriptive statistics demonstrated that most of the measured soil variables (except pH, P_2O_5, and Zn) were skewed and ab-normally distributed, and logarithmic transformation was then applied. Kriging was used- as geostatistical tool- in ArcGIS to interpolate observed values for those variables, and the digital map layers were produced based on each soil property. Geostatistical interpolation recognized a strong spatial variability for pH, P_2O5 & Zn, moderate for OM, N, Fe & B, and weak for K_2O. Exponential for P_2O_5, Fe, & Zn, spherical for pH, OM, & K_2O, and Gaussian for N, and B. Models were fitted to the semivariograms of soil properties. These produced maps permit farmers and decision makers to evaluate farm soils, thus allowing them to make easier and more effective management decisions in order to maintain sustainable productivity.

Keywords: Digital soil mapping, Geostatistical models, Jabal Al-Arab, Kriging, Soil properties

1. Introduction

Digital soil-mapping applications which mean spatial prediction of soil properties at unobserved locations using statistical assumption have increasingly used recently since their early development at the beginning of the 19^{th} century. The introduction of geostatistics tools permits researchers to interpolate the spatial distribution of soil variables (Webster, 1994). Digital soil mapping (DSM) is one of most the modern versions of geostatistical soil mapping, including creation of soil spatial information systems using both laboratory and field methods combined with spatial and non-spatial soil inference systems (Lagacherie et al., 2007; Martı´nez-Graña et al., 2016). The spatial distribution of soil variables is determined by relying on observed samples. These surface observed samples data are interpolated to predict soil variables in non-sampled areas (Sanchez et al., 2009). Traditional methods of soil survey are mostly slow, expensive and demanding. Moreover, the current soil database is not usually detailed or even accurate enough to use soil data efficiently (Malone et al., 2017). The existence of soil nutrients is usually one of the most principal indicators of soil quality; therefore it has a considerable impact on the variability of soil productivity and crop production. Various interpolation techniques are used to map the spatial distribution of soil properties (Cambardella and Karlen, 1999). Like Deterministic and stochastic methods (Myers, 1994). Thiessen, density estimation, inverse-distance-weighted (IDW) and splines are examples for deterministic interpolation methods fitting no assessment of errors. Otherwise stochastic interpolation and Kriging methods do provide prediction of error assessments.

Kriging is a geostatistical interpolation method with confirmed competence for predicting values at non-sampled locations based on observed data. The advantages of this method are: supplying the best linear unbiased estimates and information on the estimation of error distribution; presenting robust statistical characteristics (Wang et al., 2009); reducing filed sampling expenses and laboratory analysis, in addition to providing appropriate soil information that depicts the studied area based on restricted soil samples (Johnson et al., 2012). However, the reliability of produced maps of soil variables relies on satisfactory sampling data and accuracy of spatial interpolation method (Yao et al., 2013).

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There is a growing tendency to use DSM as a result of the latest advances in technology on Geographic Information Systems (GIS). For instance, Lopez-Granados et al. (2005) used DSM to map soil properties including organic matter (OM), soil reaction (pH) and potassium (K) by using Kriging method. Santos-France´s et al., (2017a) also used Kriging interpolation method for the spatial distribution of heavy metals in north Spain's soils and north Peru (Santos-France´s et al., 2017b). Likewise, Zhang et al. (2010) mapped the spatial variability for some soil fertility nutrients: nitrogen (N), phosphorus (P) and potassium (K) by using Kriging method in northeast China.

In spite of the success and wide application of DSM all over the world, no single study has tested the use of DSM to study the spatial distribution of soil properties in any part of Syria.

In Syria, Fertilizer recommendation is applied as a normal procedure, where the soil is usually analyzed by random sampling and application of fertilizer recommendation based on soil analysis results without taking into consideration the spatial distribution of soil nutrients and their variation from one place to another. As a result, part of the field may receive an extreme amount of fertilizers, while the other may suffer from shortage, adversely affecting productivity levels. This research aims to determine and map the spatial distribution of some basic soil fertility variables and micronutrients in the western facing-slope of Jabal Al-Arab area in Suwaydaa governorate as a preliminary study to be used for improving the efficiency of using the approved fertilizer recommendation.

2. Materials and Methodology

2.1. Site Description

The study area lies in the western region of Suwaydaa governorate in southern Syria between (32°28'15"N, 36°24'18"E and 32°46'44"N, 36°45'15"E; Figure 1) and covers an area of 523 km^2 (52300 hectares). Altitude ranges between 696 m in west and 1795 m above sea level in the east (Tall Qeni). This area is characterized by the Mediterranean wet climate (Csb) in the highest parts with dry and temperate summer and semi-arid climate (Bsk) to cold in the low areas according to Kopin Classification. The mean annual precipitation is between 250-550 mm and more than 80%, falling between October and April. Agricultural land use is about 83.66 % of study area (AlSafadi, 2016).

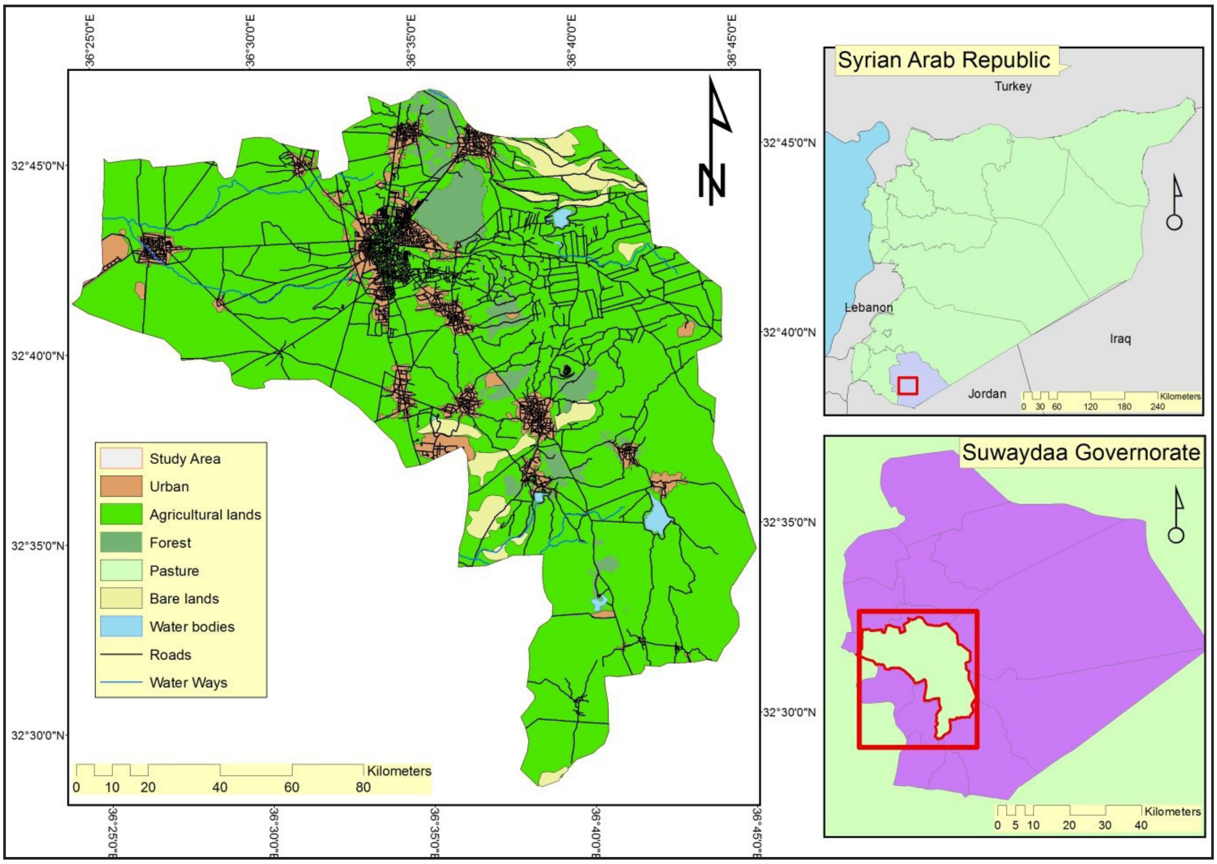

Figure 1. Study area location to Syria and Suwaydaa Governorate

2.2. Soil Sampling and Analysis

Forty-five surface soil samples (0-30cm) were collected during 1-23/4/2016, (Figure 2) and their geographic locations were recorded by using Global Positioning System (GPS). The collected soil samples were air-dried, ground and sieved through a 2mm sieve. The chemical analyses were carried out at Suwaydaa Research Center's laboratory. Organic matter was measured by wet combustion method (Nelson and Sommers, 1982), pH was determined by using pH-meter in 1:2.5 soil water suspension (Jackson, 1973), total N by Kjeldahl (Bremner and Mulvaney, 1982), available P(P_2O_5) was extracted by using sodium bicarbonate ($NaHCO_3$) and then measured by spectrophotometer (Olsen et al., 1954), available K(K_2O) was extracted by ammonium acetate and determined by flame photometry (Toth and Prince,1949), B was estimated by hot water method(Berger and Truog,1939), Fe and Zn by DTPA extraction and measured by atomic absorption (Lindsay and Norvell, 1978). The measured soil properties were categorized (Table 2) based on soil content according to (Costantini, 2009; GCSAR, 2013).

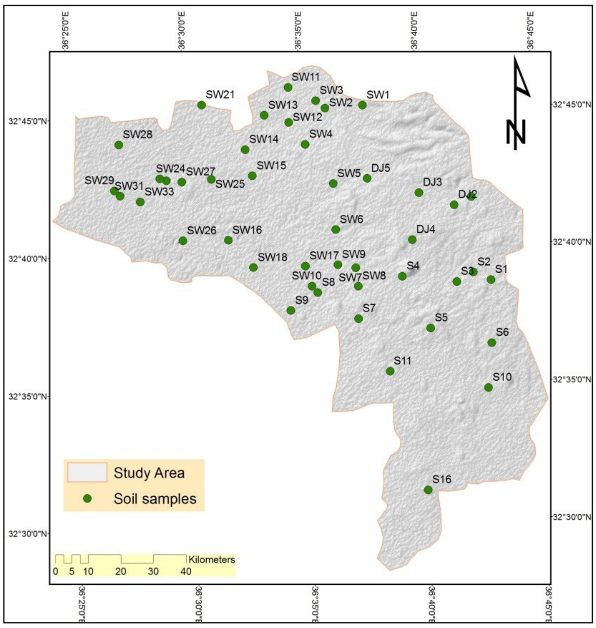

Figure 2. Soil samples locations

2.3. Statistical and Geostatistical Analysis

Descriptive statistics of soil variables (pH ,OM, total N, available P, available K, Fe, B, and Zn) involving mean, minimum, maximum, standard deviation, coefficient of variation, skewness (skew) and kurtosis were calculated by SPSS software. In this study, the ordinary Kriging was used (also called Kriging). Kriging is a linear geostatistical interpolation technique whose theory relies on weighting the sums of adjacent sampled concentrations. Additionally, it is a development over inverse distance weighting (IDW) because prediction estimates in Kriging is less biased and goes along with prediction standard errors. The general formula is formed as a weighted sum of the data:

$$Z(S_0)=\sum_{i=1}^{n} \lambda i\, Z(Si)$$

Where:

$Z(s_i)$ = measured value at i location

λ_i = unknown weight for the measured value at i ocation

s_0 = prediction location

N = number of measured values

For any data distribution, Kriging can give the best-unbiased predictor of values at non-sampled locations. The best estimates of probability maps can be produced as data is closer to normal distribution (Tziachris et al., 2017). Therefore, before doing geostatistical analysis, normality of dataset is vital, due to the high skew and presence of outliers. As coefficient of skew was more than 1 (Table1) except for pH, OM, and Zn, the logarithmic transformation was carried out for Kriging analysis to stabilize the variance (Goovaerts, 1999).

Table 1. Summary statistical overview for selected soil properties of study area

Soil variable	Min	Max	Mean	SD	CV%	Skew	Kurtosis	Skew (Tr)	Kurtosis (Tr)
pH	6.37	7.39	6.95	0.275	3.96	0.155	1.84	-	-
OM %	0.47	1.45	0.99	0.203	20.46	-0.30	2.85	-	-
N %	0.03	0.15	0.067	0.029	42.99	1.236	3.87	0.494	2.63
P_2O_5 (mg/kg)	1.7	94.8	15.91	20.23	127.1	2.11	7.03	0.487	2.48
K_2O (mg/kg)	150.3	883.2	440.3	129.1	29.33	1.09	5.87	-0.65	5.65
Fe (mg/kg)	3.5	35.17	14.74	6.96	47.11	1.03	3.81	-0.33	3.4
B (mg/kg)	0.02	0.7	0.18	0.127	70.56	1.96	7.8	-0.36	3.83
Zn (mg/kg)	1.31	7.69	4.02	1.55	38.59	0.289	2.34	-	-

Min: minimum, max: maximum, SD: standard deviation, CV: coefficient of variation, skew: skewness. Skew and Kurtosis: skewness and kurtosis obtained from original data. Skew (Tr) and Kurtosis (Tr) = skewness and kurtosis obtained from log transformed data.

Normality test was conducted after logarithmic transformation for soil variables (N, P_2O_5, K_2O, Fe & B). The transformed data resulted in slight skew as shown in (Table 1).The kriging method uses semivariance to evaluate the spatial distribution structure of soil properties (Zandi et al., 2011; Wang and Shao, 2013). Semivariogram modeling and estimation are crucial for structural analysis and spatial interpolation (Chen and Guo, 2017). Geostatistical parameters were developed, including nugget, structural, sill, and range (Wang and Shao, 2013). The study also takes into consideration the spatial dependency (sp.D) of selected soil variables, i.e. ratio of the nugget to sill variance. If the ratio is less than 0.25, then the variance will be strong sp.D, whereas the ratio value between 0.25 and 0.75 suggests moderate sp.D. However, it will be weak if the ratio is more than 0.75 (Orman, 2012). To evaluate the best fit of Kriging (spherical, exponential and Gaussian models), two indicators were calculated: mean error (ME) and root mean square error (RMSE) since ME value is closer to 0 referring to unbiased interpolation method. Likewise, the lowest RMSE value implies the best fit to variogram model.

Table 2. Ranges for selected soil properties (Costantini, 2009; GCSAR, 2013)

Range	OM%	N%	P_2O_5 mg/kg	K_2O mg/kg	Fe mg/kg	B mg/kg	Zn mg/kg
Very low	-	0.05<	0-6.9	0-102	2<	0.2<	0.5<
Low	0.86<	0.05-0.1	6.9-18.4	102-180	2-5	0.2-0.5	0.5-1
Medium	0.86-1.29	0.1-0.2	18.4-32.2	180-300	5-20	0.5-1.2	2-10
High	1.29>	0.2-0.4	32.2-46	300-540	20-50	1.2-2	10-20
Very high	-	0.4>	46>	540>	50>	2>	20>

2.4. Data analysis

IBM SPSS software (version 22) was used to carry out the normality test and descriptive statistics for the selected soil variables. In addition, all maps were developed using ArcMap (version 10.3).Spatial and geostatistical analysis tools were principally used. The structure of spatial variability was examined through semivariogram. Finally, spatial pattern distribution was practically identified by using ArcMap and its spatial autocorrelation (Moran's Index) extension.

3. Results and Discussion

3.1. Descriptive statistics for selected soil variables

The descriptive statistics for selected soil variables: pH, OM, total N, available p, available K, Fe, B and Zn are given in Table 1. The variance of soil variables was interpreted using the coefficient of variance (CV) which was classified as: most (CV< 35%) moderate (CV:15 to 35%) and least (CV>15%) (Wilding, 1985). CV ranged from 3.96% (in pH) to 127.1% (in P_2O_5). Different degrees of heterogeneity

It was also observed that some soil properties (N, P_2O_5, K_2O, Fe and B) were abnormally distributed due to high values of both skew and kurtosis. In order to reduce these values, the logarithmic transformation was used as shown in Table 1, and the transformed values were then used in the spatial analysis. among soil properties were noticed by different CV ranges. The pH values ranged from 6.37 to 7.39 with a mean of 6.95. The soil content of organic matter ranged from low (>0.8%) to moderate (0.8 to 1.45%) with a mean of 0.99%. The macronutrients (N, P, K) were also described in Table 1, showing that total N as very low (0.045-0.05%), low (0.05-0.09%) and moderate (0.09-0.15%) with a mean of 0.067%. Available P (P_2O5) ranged from very low (1.7-10 mg/kg) to high (55-94.1 mg/kg). Available K (K_2O) can be described as high (334-500 mg/kg) to very high (500-883.2 mg/kg) with a mean of 440.3 mg/kg. Three micronutrients were also measured (Fe, B, and Zn). The results revealed Fe from moderate (7.12-20 mg/kg) to high (20-35) with a mean of 14.74 mg/kg. Boron (B) also ranged between very low (0.02 -0.2 mg/kg), low (0.2-0.5 mg/kg) and moderate (0.5-0.7 mg/kg). Finally, the soils of the studied area have moderate zinc (Zn) (1.31-7.69 mg/kg) with a mean of 4.02 mg/kg.

3.2. Kriging-based digital soil maps

Digital maps of selected soil properties were developed by using Kriging method. The results are shown in (Figures 2 through 9). They were grouped into many classes based on Table 2. The estimated area of each class is presented in Table 3.

3.2.1 Soil reaction pH

Soil reaction (pH) varied from slight acid (6.1-6.5) in 1.74% to slight alkaline in 8.01% of the total study area, whereas the rest (90.52%) was neutral soil reaction (Table 3, Figure 3). These results are in agreement with Habib's study (2006), who claimed that slight acid pH reflects the nature of soil components leaching soil process, especially $CaCO_3$. Though it was reported that it could be an indication for further pH decrease in the future. Lulu (1980) reported that the majority of soils in the study area tend to be neutral (pH: 6.6-7.3) which is favorable for most crops and soil management.

3.2.2. Soil organic matter

The results demonstrated that all the studied lands (100%) have low organic matter content (0.8-1.15%). (Table 3 and Figure 4). The low organic carbon content in soil can be generally attributed to lack of organic matter sources in the study area and rapid mineralization due to high soil and air temperature or low huminification rate (Habib, 2006).

3.2.3. Total nitrogen N

Nitrogen is the most important soil nutrient that affects crop growth, quality and yield. The geostatistical results showed that more than 91% of the total area had low N content (Figure 5) with values (0.05-0.0812%), while that of the remained area (8.97%) was very low (>0.05%). These results are in agreement with Al-Hinawi (2012). The differences in N content in different parts of the study area are due to soil management, and application of organic manures and mineral fertilizers to the previous crops.(Sherchan and

Gurung, 1995). The severe shortage of nitrogen can be explained by low organic matter of soil, increased organic matter mineralization rates, inefficient use of nitrogen fertilizers on grown crops, which are depleted by crops in the study area (Vasu et al., 2017).

3.2.4. Available phosphorus

The available P_2O_5 varied from very low (2.32-6.9 mg/kg) with 18.95% to very high (<46 mg/kg) with 0.11 % of the total area (Figure 6). However, most soils had low P_2O_5 (6.9-18.4 mg/kg) with 60.38% of the area. The low levels of available P_2O_5 may be explained by low organic matter content in soils. In contrast, the high levels of available P_2O_5 may be due to dissolution of Ca-P under neutral pH (Pal et al., 2012). The amount of available P_2O_5 is affected by soil reaction pH, soil content of organic matter, and amount of applied phosphorus fertilizer. However, it is lost from soils by surface runoff and erosion (Panday et al., 2018).

3.2.5. Available potassium

The majority of soils in the study area had high levels of available K_2O (300 -540 mg/kg) in 91.39% of the total area (Table 3, Figure 7), whereas 8.61% of the area had very high K_2O (<540 mg/kg). These high levels of K_2O were also found by Al-Hinawi (2012). Soil reaction pH has a great effects on K_2O availability, since pH is greater than 7 (most of the area pH <7). Ca cations displaced K cations on the clay surfaces (exchange K by Ca), increasing K_2O concentration in soil solution. Another possible reason is the clay mineral type as the presence of smectite and mica was reported by Al-Hinawi (2012) which are the key sources of exchangeable K.

3.2.6. Micronutrients Fe, B, and Zn

The results showed that most of the study area was medium in Fe and Zn and very low in B (Table 3, Figures 8-10). These results were in agreement with studies conducted by Habib (2006) and Al-Hinawi (2012). The low levels of micronutrients may be explained by the low concentration of these substances in parent materials and low organic matter in the soils. On the other hand, the intensive cropping patterns resulted in high uptake of micronutrients by crops. In spite of sufficient levels of Fe (relatively high in some areas) (Table 3), plants root may not absorb Fe because of the dominant phosphate inion P_2O_5 in soil solution (Habib, 2006; Al-Hinawi, 2012).

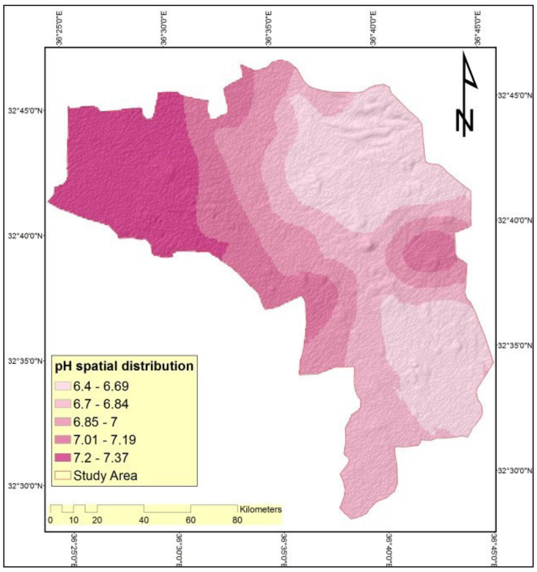

Figure 3. pH spatial distribution.

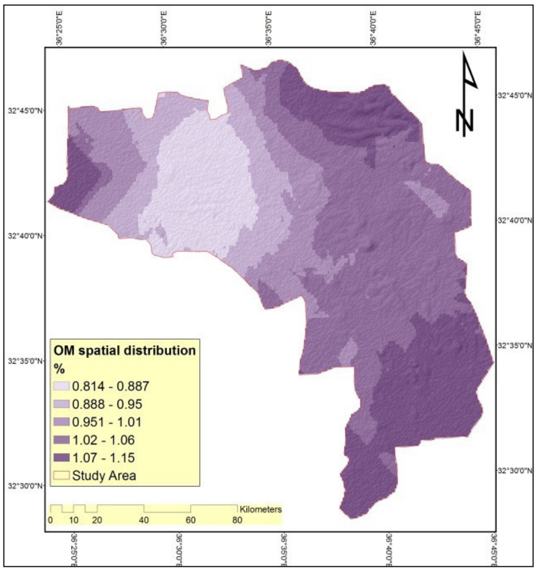

Figure 4. Organic matter spatial distribution.

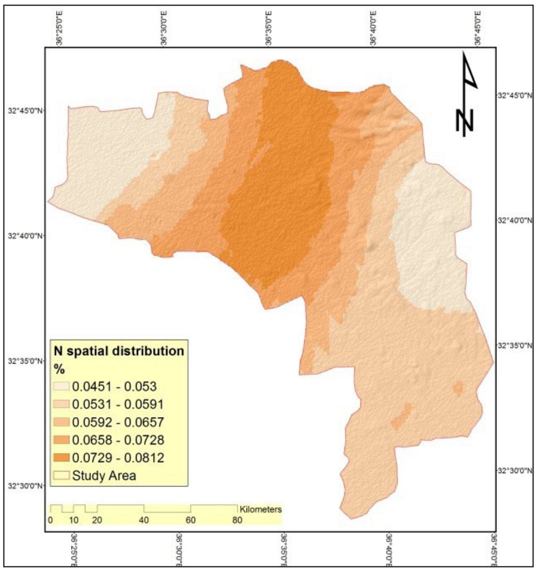

Figure 5. N spatial distribution.

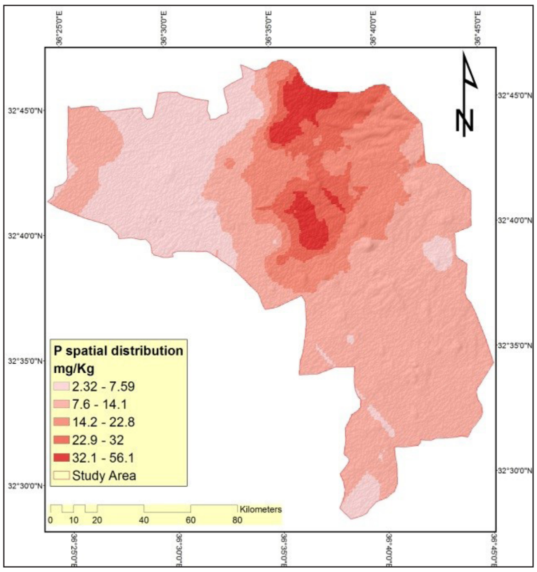

Figure 6. P(P_2O_5) spatial distribution.

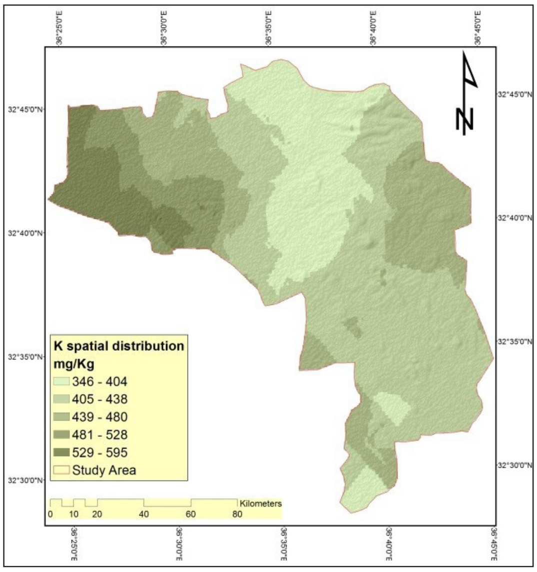

Figure 7. K(K_2O) spatial distribution

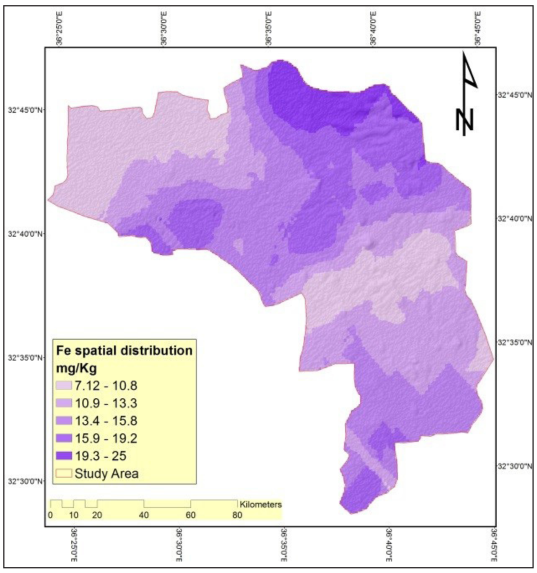

Figure 8. Fe spatial distribution.

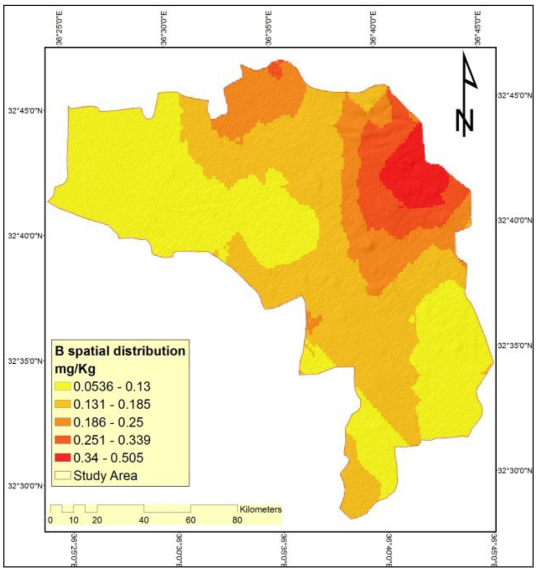

Figure 9. B spatial distribution

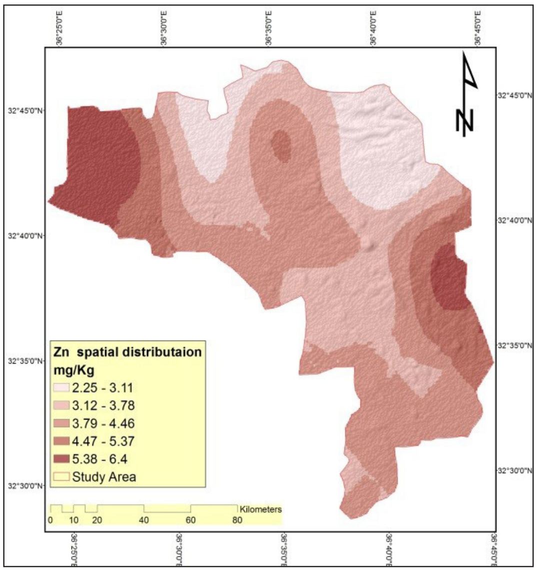

Figure 10. Zn spatial distribution

3.3. Geostatistics for selected soil properties

3.3.1 Semivariogram analysis

Some geostatistical parameters and semivariogram model analysis are shown in Table 4. According to the lowest root mean square (RMSE), three theoretical semivariogram models (spherical, exponential, and Gaussian) were examined for the significant fit of soil properties. (Robertson, 2008)

The results showed that spherical model provided the best fit to semivariogram for pH, OM and available K(K_2O), whereas exponential model was the best fit to semivariogram for available P (P_2O_5), Fe, and Zn. Finally, Gaussian model was the best fit to total N, and B. Because of its ability to explain the maximum variability (Venteris et al., 2013). Many findings recommend exponential model for estimating spatial soil distribution (Lark, 2000; Tripathi et al., 2015).

Spatial dependency (Sp. D) ranged from 0 in pH to 0.92 in available K. Clearly, Sp. D was strong (in pH, available P and Zn), and moderate (in OM, N, Fe and B) versus weak in available K. These results may be counted to external factors such as variable rates of applied K fertilizers in the study area. Spatial dependency ranges were large and varied between 3551 m in available P and B and 15208 m in total N, indicating that the optimum sampling interval varies greatly among different soil properties. The range values give an idea about the correlation between different soil sampling locations, along with the maximum spatial dependency distances between them (Akpa et al., 2014).

Table 4. Semivariogram analysis of spatial structure in soil properties

Soil parameter	ME	RMSE	Model	Range	Lag size	Nugget	Partial	sill	Sp.D	DES Sp.D
pH	0.142	0.147	S	1871	989	0	0.065	0.065	0	ST
OM	0.2	0.19	S	12067	1718	0.34	0.071	0.15	0.32	M
N	0.026	0.027	G	15208	1798	0.11	0.056	0.169	0.65	M
$P(P_2O_5)$	29.2	16.2	E	3551	407	0.135	0.947	1.082	0.12	ST
$K(K_2O)$	143.92	127.38	S	6957	580	0.085	0.006	0.091	0.92	W
Fe	7.7	6.36	E	7085	590	0.11	0.126	0.236	0.46	M
B	0.13	0.104	G	3551	446	0.187	0.171	0.351	0.53	M
Zn	1.38	1.344	E	7350	1628	0.507	1.89	2.397	0.21	ST

ME: mean error, RMSE: root mean square error, E: Exponential, G: Gaussian, S: Spherical, ST: strong, M: Moderate, and W: Weak. Unit for range and lag size, m. Sp.D: spatial dependency, DES. Sp.D: descriptive of spatial dependency.

Table 5. Areas of different soil groups based on soil parameters classes

Parameter	Unit	Rating	Existing class	Area(h)	% of total area
pH	-	6.1-6.5	Slightly acidic	766.62	1.47
		6.5-7.3	Neutral	46913.4	90.52
		7.3-7.8	Slightly alkaline	4619.89	8.01
OM	%	0.86-1.26	Low	52300	100
N	%	0.05<	Very low	5114.24	8.97
		0.05-0.1	Low	47185.46	91.04
$P (P_2O_5)$	mg/kg	0-6.9	Very low	9824.16	18.95
		6.9-18.4	Low	31299.36	30.38
		18.4-32.2	Medium	8695.23	16.77
		32.2-46	High	1965.82	7.79
		46>	Very high	45.8	0.11
$K (K_2O)$	mg/kg	300-540	High	47359.23	91.39
		540>	Very high	4461.762	8.61
Fe	mg/kg	6-20	Medium	49524.42	95.55
		20-50	High	2301.9	4.45
B	mg/kg	0.2<	Very low	42050.39	81.13
		0.2-0.5	Low	9738.97	19.79
		0.5-1.2	Medium	510.64	0.08
Zn	mg/kg	2-10	Medium	52300	100

3.3.2 Spatial autocorrelation

It is assumed, at the beginning of the study, that the spatial pattern of soil properties distribution is random. Therefore, the Moran`s index was calculated by using ArcMap to identify the spatial pattern, which varies depending on the feature locations and value of soil properties between dispersed, random and clustered samples (Moran, 1950). According to ESRI (2017), the spatial pattern does not reflect random distribution if the p-value is less than 0.05 and Z-score is either (very high) < 1.96 or (very low) > -1.96. As presented in Table 5 and according to the test of significant values, most of the studied soil chemical properties (pH, OM, N, P_2O5, and B) had clustered distribution, whereas the spatial pattern of K_2O, Fe, and Zn was not different at p-value less than 0.05 from random distribution.

Table 5. Test of significance for the spatial pattern of studied soil properties

soil parameter	Moran`s index	Variance	p-value	Z-score
pH	0.385	0.0020	0.00	8.65
OM	0.065	0.0021	0.057	1.89
N	0.107	0.0021	0.004	2.819
P_2O_5	0.08	0.0019	0.01	2.410
K_2O	-0.01	0.0020	0.701	0.261
Fe	0.02	0.0021	0.350	0.93
B	0.12	0.0019	0.00	3.48
Zn	0.004	0.0021	0.55	0.589

It is assumed, at the beginning of the study, that the spatial distribution is close to random. On the other hand, positive Moran`s index value indicates neighboring values are similar, referring to spatial dependency, while the negative Moran`s index value implies that neighboring values are dissimilar, referring to the opposite of spatial dependency. Also, the zero Moran`s index value points out shortage of spatial pattern (Lloyd, 2010; Al-Ahmadi and Al-Zahrani, 2013). As showen in the Table, except $K_2O$, most of the selected soil properties demonstrated positive Moran`s index values that indicate spatial dependency.

4. Conclusions

The application of geostatistical approach involving descriptive statistics and semivariogram analysis improved the description of spatial variability for soil chemical properties at 0 to 30 cm deep. The descriptive statistics showed that most of measured soil variables were skewed and abnormally distributed, and the available K_2O data were highly variable (338 to 595 mg/kg). Geostatistical interpolation identified that exponential, spherical or Gaussian models provided the best fit to semivariograms, depending on the soil chemical variable, showing in general strong, moderate or weak spatial dependency for all variables.

Kriging maps of soil variables were found effective in interpreting the distribution of soil properties in non-sampled locations based on sampled data. These maps help farmers in making efficient management decisions based on their proper understanding of the conditions of existing farm soils. These results show that Kriging-geostatistical analysis is an effective prediction tool for exploring the spatial variability of soil nutrients. Generally speaking, this tool is recommended for future soil sampling campaigns in Syria.

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