

Assessment of Spatial Variability of some Alluvial Soil Properties in Egypt

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ABSTRACT

Soil spatial variation is very valuable in deciding the suitable cropping system and appropriate agricultural management of lands. This research paper was done to measure the spatial variation of some soil characteristics, in the western farm of Faculty of Agriculture, Cairo University, Giza province, Egypt. Soils of studied area were classified as Typic Torrifluvents. 100 samples of soil were gathered at depth of 35 cm during 2016. Sampling designee was done by a grid systematic sampling system, using GPS. Samples of soil were gathered at spacing of 30*30 m². Some soil characteristics including EC, pH, CaCO₃, Organic matter (OM), Particle density (Pd), Bulk density (Bd) and Porosity (P) were determined in laboratory. Descriptive statistical analyze were achieved to describe soil properties. Geostatistical procedures of semivariograms and kriging coupled with a GIS were utilized to interpret the variability and mapping of spatial distribution of soil characteristics. The coefficient of variation displayed that the chemical properties the soil were more fickle than the physical properties. Electrical conductivity was the most variable characteristic. Results explained that EC and pH had the maximum and the minimum spatial correlation respectively.

Keywords: Spatial variability, Geostatistics, Soil properties, Egypt.

INTRODUCTION

Soils have a main function in our life and evolution of lands. They are a key ingredient of the ecosystem, particularly for nutrients and water cycling. It is therefore necessary to enhance the protection and maintainable soil resources utilization (FAO, 1988). Information about soil properties can keep time and cash in planning and management. The soil spatial variation within fields has been quite illustrated by soil analyzing results and crop productivity differences. There are diverse reasons of this variation in soil properties, including soil genesis agents (topography, climate, vegetation, origin material and time), cultivation practices and erosion. Land use plays a strong effect on the variation of soil salinity indicating an impact of the land use history on the soil variability (Rosemary *et al.*, 2017). Soil spatial variation is influenced by some bio-physical factors including topography, vegetation, soil microclimate (Chaneton and Avado, 1996). Soil variability impacts on the efficiency of the agricultural management processes and the efficacy of field experiments. Kriging and related geostatistical techniques is very valuable to demonstrate and describe the heterogeneity of the field and identify its affects the studied variables (Bevington *et al.*, 2016).

On a field scale, soil variability causes dissimilar crop evolution and reduces the efficiency of fertilizers (Mulla *et al.*, 1990; 1992). Geostatistical analysis is a valuable tool to decide spatial interrelationships of crop productivity and soil characteristics in the field scale (Usowicz and Lipiec, 2017 and Marinsa *et al.*, 2018). The properties and characteristics of soil vary constantly in the four diminutions, x, y, z and time (Rogerio *et al.*, 2006). Identifying spatial variation of soil is very essential for precision farming, environmental modeling, ecological predictions and natural resources administration (Wang *et al.*, 2009). Soil spatial variation can be applied to delineate the field into distinct management zones and to identify zones or pockets that are critical in terms of material dissipation or

accumulation (Tola *et al.*, 2017 and Beng *et al.*, 2012). Speculation and mapping of soil attributes in un-sampled locations is the master usage of geostatistics in soils. Geostatistics method is the most certain, powerful and widest method for interpolation (Kersic, 1997); he stated that this methodology considers location, spatial variation and distribution of samples. Geostatistics studies are very valuable to suggest recommendations for the suitable management and designing of plant, water and soil relationships in future researches (Kavianpoor *et al.*, 2012). These strategies use statistical and mathematical operations for interpolation and their base is statistical properties of data. This prediction of un-known locations depends on autocorrelation and spatial structure of field points (Zhang and Mc, 2004).

Intrinsic variation of soil attributes cause a highly grade of spatial correlation or dependencies (Barrios *et al.*, 2015). Mapping of soil properties is very powerful method to display their spatial variability well. Soil Spatial variability had been used to minimize and avoid the harmful impact of the compaction resulted from traffic (Barik *et al.*, 2014) and to evolve soil fertility strategies on small and large scales (Bhatti and Bakhsh, 1995; Bhatti and Mulla, 1995; Wasiullah and Bhatti, 2005; Najafian *et al.*, 2012). Ingrained soil and environment spatial variation can strongly effect on the morphological characteristics of artichoke (Long *et al.*, 2014). Assessing and mapping the variation of some soil quality indicators like SOM, texture and C/N ratio is a first stage towards an effective management of natural resources to perform a successful soil conservation practices (Marchetti *et al.*, 2012).

Visualization and quantification soil spatial variation using geostatistical analysis can be applied to give effective management actions in mitigating widespread agricultural contamination (Glendell *et al.*, 2014). This work was performed to measure and investigate the spatial variation of some soil characteristics, in the western farm, Faculty of Agriculture, Cairo University, Giza province, Egypt.

MATERIALS AND METHODS

The study site was located at in the western farm of Faculty of Agriculture, Cairo University, Giza province, Egypt. The study site lies between 31° 11' 14" to 31° 11' 30" E and 30° 1' 29" to 30° 1' 43" N. It has 10.76 ha area and 25 m altitude above sea surface (Figure 1). The land use of the studied area was agriculture that land was prepared for wheat cultivation. The climate is semi-arid with temperatures extending from 13°C in January to 27.5 °C in August. The annual mean temperature is 21.2 °C and the annual rainfall is 17 mm. Soils of studied area were classified as Typic Torrifluvents. Studied area is flat to almost flat with a moderately well drained clay soil.

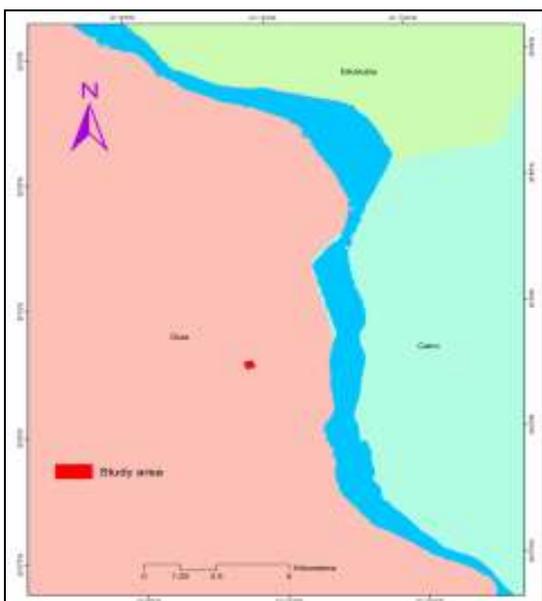


Figure 1 : Location of the study site.

Samples of soil were collected by a grid systematic sampling system. 100 samples were collected with a soil auger at depth of 35 cm from the soil surface during 2016. Samples were taken at spacing of 30*30 m² (Figure 2). Using a GPS, soil samples coordinates were defined to use in spatial variation analysis of soil characteristics.

Samples were air-dried at room temperature (20–22 °C), crushed after stones and other debris were removed, sieved through a 2 mm sieve to prepare them for laboratory analysis. Organic matter, particle density, CaCO₃, bulk density, porosity, soil pH and EC were determined according to USDA, 2014.

Descriptive statistics were done to investigate the distribution of every soil property under assessment and as a basic step before geostatistical analyses (Olea, 2006). Range, mean, minimum, maximum, median, standard deviation (SD), variance, coefficient of variation (CV), Skewness and Kurtosis were calculated for each measured soil property using SPSS 22 software. Geostatistical techniques were utilized to inspect the variability of the soil attributes. The geostatistics approach comprises of two parts: one is the

computation of an experimental variogram and the second is a prediction at un-sampled locations (Burgos *et al.*, 2006). The semivariogram of every soil attribute was built using this equation:

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

Where: $\gamma(h)$ is the semivariance for the interval distance class h ,

$N(h)$ is the number of pairs of the lag interval, $Z(x_i)$ is the measured sample value at point i , and $Z(x_i + h)$ is the measured sample value at position $(i + h)$ (Webster and Oliver, 2001).

Continuous maps of individual characteristics were created by Kriging technique (Candela *et al.*, 1988). Overall Kriging technique is a statistical estimator that grants statistical weight to every observation point so their linear structure's has been unbiased and has the lowest speculation variance (Kumke *et al.*, 2005).

This estimator can use in numerous applications due to minimizing of error variance with equitable estimation (Pohlmann, 1993).

$$Z^*(x_0) = \sum_{i=1}^N \lambda_i Z(x_i)$$

Where, $Z^*(X_0)$ is, estimated variable at X_0 location, $Z^*(X_i)$ is values of inspected variable at X_i location, λ_i is the statistical weight that is offered to $Z(X_i)$ sample located near X_0 , and N is the number of observations in the neighborhood of inspected point.

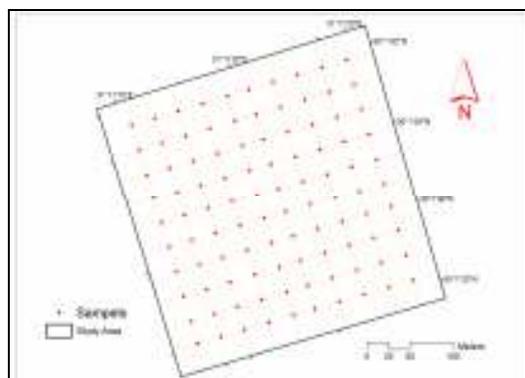


Figure 2. Systematic sampling system in the study area.

The semivariogram can be fitted with spherical, exponential, or Gaussian models. In this study, geostatistical analysis of the data was performed with the ArcGIS10.0 geostatistical analyst tool.

RESULTS AND DISCUSSION

Classical statistics:

Chemical properties: Soil pH reflects the nature of medium in which the chemical responses occur and their effect on the growth, productivity and management of agricultural crops. Table 1 shows that the pH values ranged between 8.02 – 8.59 indicating that soils are moderately to medium alkaline, this could be ascribed to the fact that the soil is alluvial sediment and the

origin material is basal rocks. Values of soil pH are a reflection of the components of the materials which the soil is derived from (Park and Vlek, 2001), low OM content and the warm climate of the investigated area.

Table 1 shows that CV of soil pH was 1.13% with standard deviation (SD) 0.10, also results displayed that the pH values had a negatively-skewed (-2.97) distribution. pH had lowest CV, which could be a result of the symmetric conditions in the studied district such like slight changes in slope degree and slope aspect that led to symmetry of soils. Kavianpoor *et al.* (2012), Weindorf and Zhu (2010) and Kamare *et al.* (2010) found comparable results. EC values of saturated soil paste indicate to the concentration of soluble salts and the severity of soil salinization whether on the surface or in different depths. Results in Table 1 illustrated that soil EC values ranged between 0.33 – 1.17 dS m⁻¹ indicating the soil is slightly saline. Table 1 indicates that CV of soil EC was 21.99 % with SD 0.12, also results explained that the EC values had a positively-skewed (1.54) distribution. This variation could be a

result of soil management and the un-completely level of soil surface. Results in Table 1 showed the SOM content and its distribution in the studied area, it is noted that the general decline in SOM content, ranging between 1.86 – 2.66 %. This is due to scarcity of vegetation, Low rainfall or precipitation as well as the high temperature which lead to the rapid oxidation and decomposition of organic matter (Marchetti *et al.*, 2012). Table 1 presents that the CV of SOM is 7.23 % with SD 0.16. Results illustrated that the SOM values had a positively-skewed (0.08) distribution. Results displayed that soils of studied area had low content of CaCO₃ (Table 1). CaCO₃ values ranged between 3.62 – 5.37 %, this is due to the origin material and its low content of calcium carbonate. Table 1 indicates that CV of soil CaCO₃ was 8.81 % with SD 0.41, also results indicate that the CaCO₃ values had a negatively-skewed (- 0.11) distribution. This can be attributed to the variability in activity of capillary from place to another place in addition to the incompletely level of soil surface.

Table 1. Statistical analysis of soil attributes.

Soil attributes	Unit	Range	Min	Max	Mean	S.D.	CV %	Variance	Skewness
EC	dS m ⁻¹	0.84	0.33	1.17	0.55	0.12	21.99	0.01	1.54
pH	-log [H ⁺]	0.57	8.02	8.59	8.42	0.10	1.13	0.01	-0.97
CaCO ₃	%	1.75	3.62	5.37	4.61	0.41	8.81	0.16	-0.11
OM	%	0.80	1.86	2.66	2.20	0.16	7.23	0.03	0.08
Ps	gcm ⁻³	0.28	2.50	2.78	2.61	0.08	2.90	0.01	0.34
Pb	gcm ⁻³	0.41	1.11	1.52	1.26	0.06	4.97	0.00	1.24
P	%	17.02	42.13	59.15	51.90	2.69	5.17	7.21	-1.03

Physical properties: The soil real density of the soil is a reflection of its mineral composition. Table 1 illustrated that the real density values ranged between 2.5 – 2.78 g cm⁻³ with a low CV 2.9 % and SD 0.08, this is due to the homogeneity in mineralogical composition of studied soils. The real density values had a positively-skewed (0.34) distribution. Bulk density of the soil is a reflection of its structure and the compaction resulting from various agricultural tillage operations. Bulk density values ranged between 1.11 – 1.52 g cm⁻³ with CV 4.97 % and SD 0.06. Results illustrated that bulk density is more variable than the real density where the first is strongly depended on tillage operations. Bulk density values had a positively-skewed (1.24) distribution. Soil porosity represents the pores spaces between solid soil particles, both mineral and organic, or aggregates of these particles. Porosity plays a significant role in determining soil permeability. Results in Table 1 showed the soil porosity values ranged between 42.13 – 59.15 %. As displayed in Table 1 CV of soil porosity was 5.17 % with SD 2.69. The porosity values had a negatively-skewed (-1.03) distribution.

Geostatistical analysis

In this research study, samples of soil were gathered by grid systematic sampling method with equal space between them because random sampling method can produce points that are very close together so

decreases accuracy of these studies as mentioned by Weindorf and Zhu (2010). The grid sampling strategy provides more precise results compared to random pattern, and precision increased with growing sample size (Wang and Qi, 1998 and McBratney and Webster, 1983). Soil spatial variations cannot be shown only by descriptive statistics therefore the spatial behavior of the different soil properties was studied through geostatistical and semivariogram analysis. By utilizing ordinary kriging methods, Spatial distribution maps of soil characteristics were gotten based on the observed semivariogram parameters. Soil spatial variability maps and semivariograms are demonstrated in Figures 4, 5, 6 and 7. Spatial dependence i.e. the effect of ratio between nugget and sill expressed as a percent was used to determine the strength of the spatial dependence of soil properties. According to Cambardella *et al.* (1994), the EC showed a strong spatial dependence (C0/C0+C < 25%). CaCO₃, pH, porosity and bulk density showed a moderate spatial dependence (25% < C0/C0+C < 75%) whereas the OM and real density showed a weak spatial dependence (C0/C0+C > 75%).

Physical properties: Results in Table 2 indicates that the spatial dependence of soil real density was weak (80.44%) and the fitted semivariogram model was spherical. The nugget effect (C0) was 0.0007 and sill effect (C0+C) was 0.0009. Real density had a high effective range 152.90 m.

Table 2. Calculated semi-variograms properties of soil factors

Soil properties	Model	Range A0 (m)	Nugget (C0)	Partial Sill (C)	Sill (C0+C)	Nugget /Sill ratios C0/(C0+C), %	Spatial dependence
CaCO ₃	Spherical	56.20	0.0034	0.0044	0.0078	43.13	moderate
OM	Exponential	103.64	0.0045	0.0009	0.0055	83.24	weak
pH	Spherical	60.82	0.0000	0.0001	0.0001	42.32	moderate
EC	Gaussian	53.59	0.0106	0.0384	0.0489	21.56	strong
P	Exponential	68.66	0.0016	0.0019	0.0035	45.60	moderate
Ps	Spherical	152.90	0.0007	0.0002	0.0009	80.44	weak
Pb	Exponential	56.20	0.0014	0.0014	0.0028	51.69	moderate

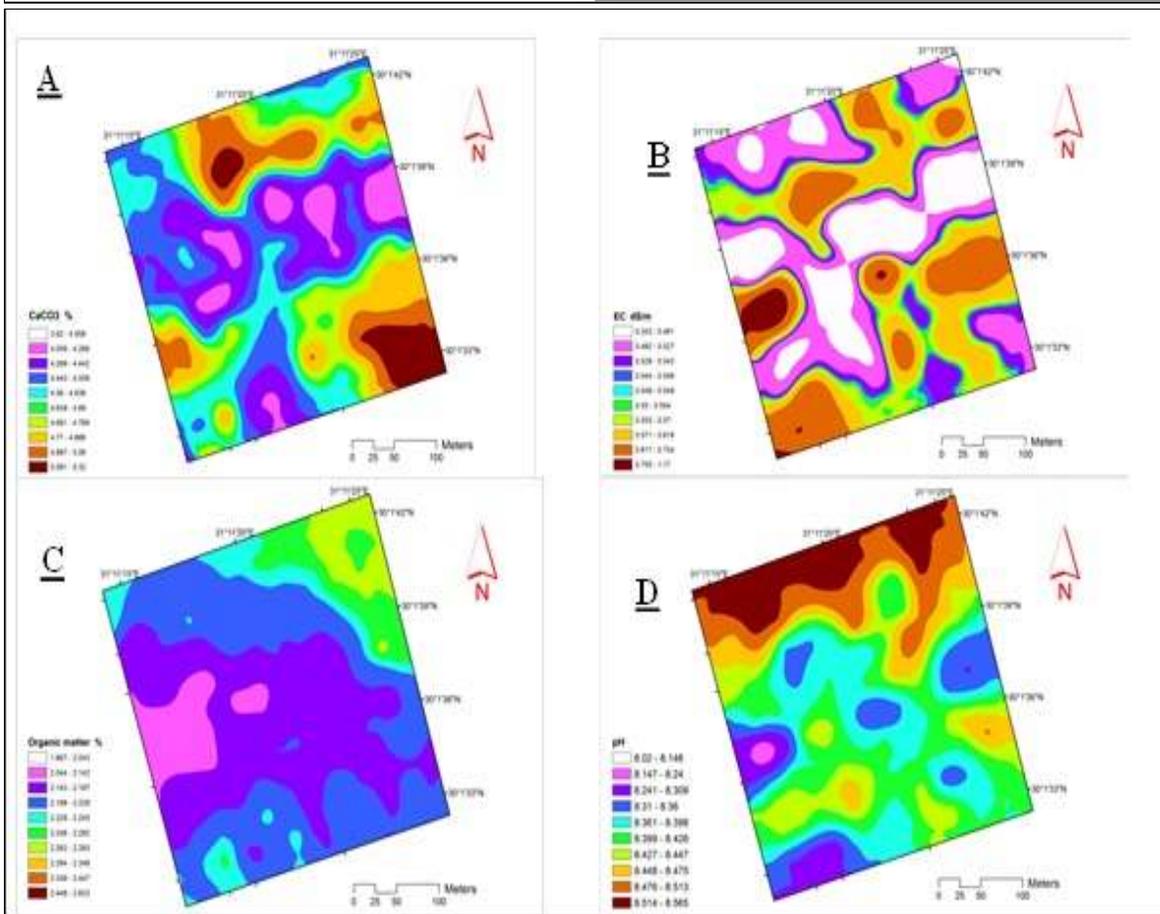
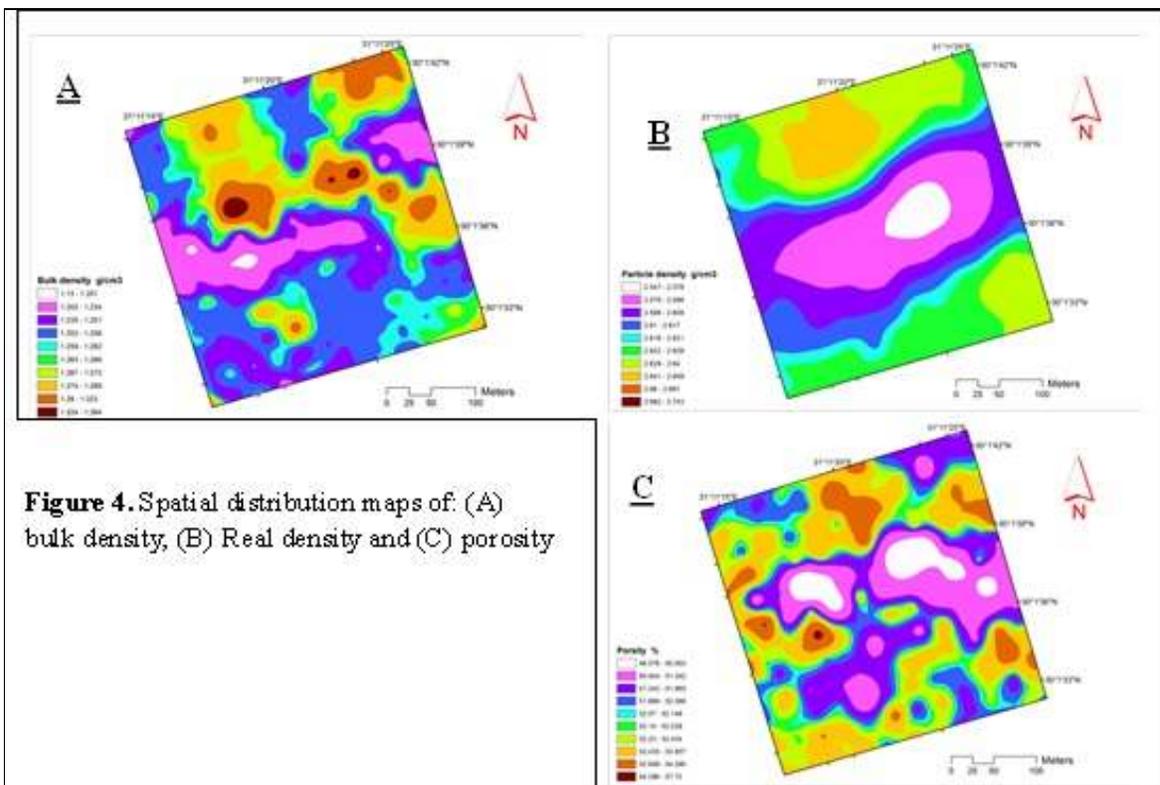
The spatial dependence of soil bulk density was moderate (51.69 %) as displayed in Table 2, where it has a coefficient of variation higher than real density as shown in Table 1 and the effective range (56.20 m) is lower than real density. The fitted semivariogram model was Exponential similar to what had been illustrated in research of Usowicz and Lipiec (2017). While the nugget effect (C0) was 0.0014 and sill effect (C0+C) was 0.0028. Bulk density had moderate spatial dependence similar to what had been illustrated in research of Marinsa *et al.* (2018), Glendell *et al.* (2014), Kavianpoor *et al.* (2012) and Jafarian *et al.* (2009). Data in Table 2 shows that the spatial dependence of soil porosity was moderate (45.60 %) and the fitted semivariogram model was Exponential. Also the result showed that the nugget effect (C0) was 0.0016 and sill effect (C0+C) was 0.0035. Porosity had effective range 152.90 m. Porosity had moderate spatial dependence similar to what had been illustrated in research of Marinsa *et al.* (2018)

Chemical properties: Table 2 display that the spatial dependence of soil EC was strong (21.56 %) and the fitted semivariogram model was Gaussian. The nugget effect (C0) was 0.0106 and sill effect (C0+C) was 0.0489. EC had effective range 53.59 m. Rosemary *et al.* (2017) found that EC had strong spatial dependence but But Kavianpoor *et al.* (2012) found that EC had moderate spatial dependence because they worked in different conditions in northern Iran. Data in Table 2 indicates that the spatial dependence of soil pH was moderate (42.32 %) and the fitted semivariogram model was Spherical. Also the result showed that the nugget effect (C0) was 0.0000 and sill effect (C0+C) was 0.0001. pH had effective range 60.82 m. pH had moderate spatial dependence according to results of Vasu *et al.* (2017) and Usowicz and Lipiec (2017). But Kavianpoor *et al.* (2012) and Weindorf and Zhu (2010) found that pH had strong spatial dependence because they worked in different conditions in northern Iran and New Mexico, USA respectively. The results in the Table 2 showed that the spatial dependence of soil OM was weak (83.24 %) and the fitted semivariogram

model was Exponential similar to what had been illustrated in research of Weindorf and Zhu (2010) and Usowicz and Lipiec (2017). Also the result showed that the nugget effect (C0) was 0.0045 and sill effect (C0+C) was 0.0055. Soil OM had effective range 103.64 m. Organic matter had weak spatial dependence according to results of Rosemary *et al.* (2017) but Vasu *et al.* (2017) and Kavianpoor *et al.* (2012) found that OM had moderate spatial dependence because they worked in different conditions. The results in the Table 2 displayed that the spatial dependence of soil CaCO₃ was moderate (43.13 %) and the fitted semivariogram model was Spherical according to results of Kavianpoor *et al.* (2012). Also the result showed that the nugget effect (C0) was 0.0034 and sill effect (C0+C) was 0.0078. Soil CaCO₃ had effective range 56.20 m. Kavianpoor *et al.* (2012) found that CaCO₃ had strong spatial dependence because they worked in different conditions.

CONCLUSION

The spatial dependence of EC was very strong but bulk density, porosity, Calcium carbonate (CaCO₃) and pH had moderate spatial dependence. Particle density and organic matter had weak spatial dependence. Particle density had maximum effective range with 152.90 and EC had the lowest effective range among the studied soil characteristics with 53.59 meter. In order to define the needs of soil to upgrade crop growth in terms of fertilization, requirements of lime or gypsum and water requirement, Geostatistics can be utilized to design soil sampling for these applications and also for prediction and mapping soil properties. Stockholders and farmers can utilize these maps to decrease the amount of fertilizers and insecticides utilized by applying inputs only where they are required and in suitable quantities. The outcomes from this study refer to the effective role that can be played by GIS, especially in the interpolation and producing thematic maps such as the maps of chemical and physical soil properties.



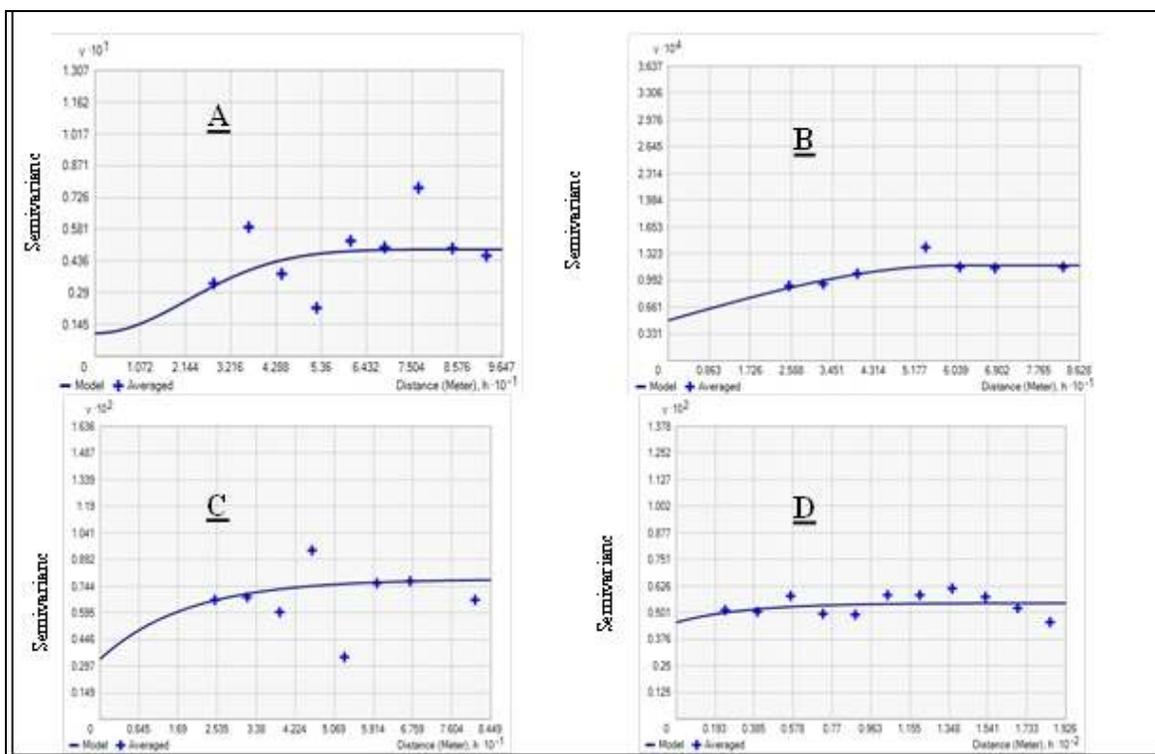


Figure 6. Semi-variograms of (A) EC, (B) pH, (C) CaCO₃ and (D) organic matter

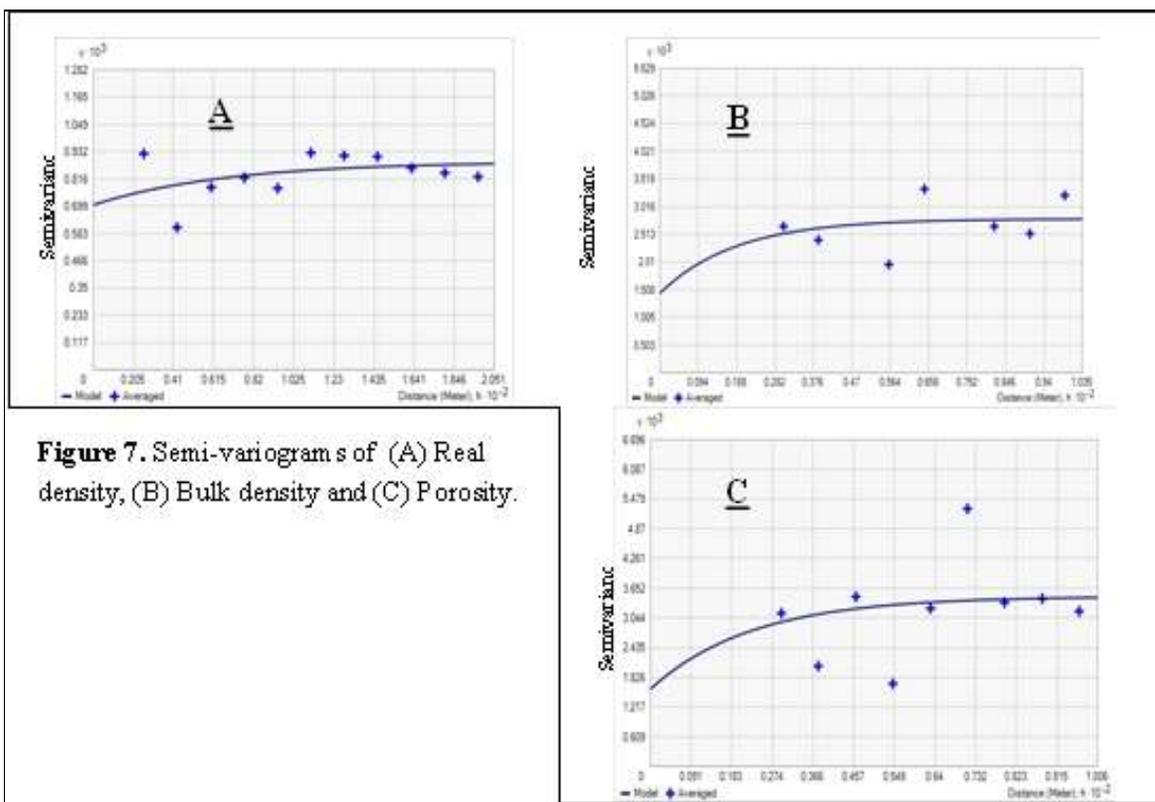


Figure 7. Semi-variograms of (A) Real density, (B) Bulk density and (C) Porosity.

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تقييم التباين المكاني لبعض خصائص التربة الرسوبية - مصر

ابراهيم عطيه حسين يوسف
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الاختلافات المكانية لخصائص التربة لها قيمة كبيرة في تحديد التركيب المحصولي الامثل والإدارة الزراعية المناسبة للأراضي. أجريت هذه الدراسة لقياس التباين المكاني لبعض خصائص التربة الفيزيائية والكيميائية، في المزرعة الغربية لكلية الزراعة، جامعة القاهرة، محافظة الجيزة، مصر. تتبع اراضى منطقة الدراسة رتبة الاراضى الحديثة Typic Torrifluvents. تم جمع ١٠٠ عينة تربة سطحية باستخدام الاوچر بعمق ٣٥ سم من سطح التربة خلال عام ٢٠١٦. وتمت عملية أخذ العينات بالنظام الشبكي المنتظم وذلك باستخدام جهاز تحديد المواقع العالمي (GPS). أخذت عينات على مسافات ٣٠ * ٣٠ م. تم تقدير بعض خصائص التربة الفيزيائية والكيميائية في المعمل بما في ذلك التوصيل الكهربائي (EC)، رقم الحموضة (pH)، الكثافة الحقيقية (Pd)، الكثافة الظاهرية (Bd)، كربونات الكالسيوم (CaCO₃)، المسامية (P) والمادة العضوية (OM). تم إجراء التحليل الاحصائي الوصفي لوصف خصائص التربة. تم استخدام تقنيات الاحصاء الجيولوجى ودالة التباين النصفى مقترنا بنظام المعلومات الجغرافية (GIS) لتفسير الاختلافات المكانية لخواص التربة وعمل خرائط لها. وقد أشار معامل الاختلاف إلى أن الخصائص الكيميائية للتربة كانت أكثر تبايناً من الخصائص الفيزيائية، وكان التوصيل الكهربى الأكثر تبايناً. وأظهرت نتائج الدراسة ان التوصيل الكهربى (EC) ودرجة الحموضة (pH) كان لهما اعلى وافل ارتباط مكاني على التوالي.