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Using GIS and Geostatistics to Monitoring Spatial Variability in Soil Chemical Properties Impacted by Cultivation Practices

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ABSTRACT

The investigation is crucial for understanding and managing the spatial variability of soil chemical properties, which is essential for effective soil management practices and ecological protection on the experimental farm. Therefore, 36 soil samples were taken (0-30 cm depth) from a 100-meter grid of experimental farm is part of the Faculty of Agriculture, Al-Azahar University, Assuit (27° 12′ 16.67″ N latitude and 31° 09′ 36.86″ E longitude). Geographic information systems (GIS) and geo-statistics were practiced to assess the impact of cultivation practices on soil chemical properties and their spatial variability. Spherical model was used to forecast most soil parameters, while Gaussian model was used to estimate soil CO_2-C flux and Exponential model was used to predict available nitrogen (N) and soil EC. The results showed that the coefficient of soil variation values was weak for soil salinity, soil reaction (pH), organic matter (OM) and CO_2-C flux whereas they were moderate for available NPK and carbon storage. Except for soil salinity (EC), which had a range of 480 m, all variables showed a range of less than 55.1 m. All soil qualities have a nugget to sill ratio < 25%, which generally shows a substantial spatial dependence. These maps could be recommended to improve monitoring of soil properties and minimize the spatial variability of soil fertility.

Keywords: Geographic Information System (GIS)**,** Kriged maps, Geo-statistics, Soil chemical properties.

INTRODUCTION

Agricultural expansion is often necessary to meet the growing global demand for food, fiber, and biofuel production. However, this expansion can lead to the conversion of natural ecosystems, loss of biodiversity, and degradation of soil quality. Therefore, it becomes crucial to evaluate the properties of soil, even in degraded areas, to ensure sustainable agricultural practices. Understanding the soil's chemical, physical, and biological characteristics is essential for optimizing crop productivity, mitigating soil erosion, and preserving environmental quality, to account for this continuous variability. Thorough understanding of the specific soil conditions of a given site is necessary to develop appropriate agricultural management plans and policies and to minimize the environmental impact on farming revenue (Snapp 2022). For effective management of soil fertility and land use, the identification of the micronutrient and macronutrient contents of the soil is vital for sustainable agricultural production since plant growth cannot occur without the optimal concentrations of these elements. Also, the structure, functions, and spatial patterns of vegetation are all significantly impacted by the soil's spatial variability over different scales (Guan *et al.*, 2017).

Soil functions depend on their physical, chemical, and biological properties. Both natural disturbances and soil management can affect chemical parameters. Tillage application techniques (conservation tilling, continuous tilling, and adding organic or inorganic fertilizers) can alter soil pH and nitrate levels. The variety of crop varieties, individual farmers' fertilization techniques and field management are the primary causes of the spatial heterogeneity in soil nutrients (Sen *et al.*, 2007).

Soil spatial heterogeneity plays a significant role in crop management, field research trial design, and yield as well as the efficiency of farm inputs (Rahal *et al.,* 2015). Additionally, both the construction of models and actual implementations require an understanding of soil variability. Thus, it may be possible to enhance soil quality, promote efficient land use, and support the preservation of natural environments via comprehending and making use of the spatial variability of soil attributes (Wang *et al.,* 2009). Accurate mapping of soil attributes requires a sampling method that may be defined based on reliable information beyond the scope of spatial correlations. The traditional methods of soil analysis and interpretation require a lot of work, take a long time, and are therefore expensive. In land resource inventories, geostatistical approaches like kriging have come to be recognized as useful spatial interpolation methods (Bhunia *et al.*, 2018).

Using geo-statistics and GIS technologies to examine the spatial variability of soil parameters has become a popular issue in agricultural ecology and soil research. The foundation for interpreting and interpolating the geographical variability of soil parameters is provided by geo-statistics as a mathematical approach (Haruna and Nkongolo, 2015). In precision agriculture, GIS techniques are applied in various ways which include crop selection and rotation, irrigation, mechanization planning, land use appropriateness assessments, and conservation of significant plant species. Spatial analysis is the most important component of site-specific nutrient management (SSNM) which is determined through the GIS. The SSNM is the real-time feeding of crops with nutrients while recognizing the spatial variability within the field data. This study aims to use Arc GIS and geo-statistics to quantify the geographical variability of soil chemical properties in relation to cultivation practices.

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MATERIALS AND METHODS

Site description.

The site of the experiment is situated 375 km south of Cairo, Egypt, the Experimental Farm is part of the Faculty of Agriculture, Al-Azahar University, Assuit (27° 12′ 16.67″ N latitude and 31° 09′ 36.86″ E longitude) at shown in Fig. (1). The site has a flat terrain and is mostly made up of well-drained Entisols, which have a texture similar to clay loam, are slightly alkaline, have low levels of organic matter, and had acceptable potassium levels in the topsoil layers of the soil (Sayed and El-Desoky, 2018), which are 60 cm deep (Soil Survey Staff, 1996). In winter and summer seasons, the mean temperature values are 22.75 and 39.40 °C, while the relative humidity is 54.7 and 48.5 %, respectively. There is no precipitation as the site is located in arid and semi-arid regions. The farm was subjected to numerous cultivated field crops with different agricultural practices.

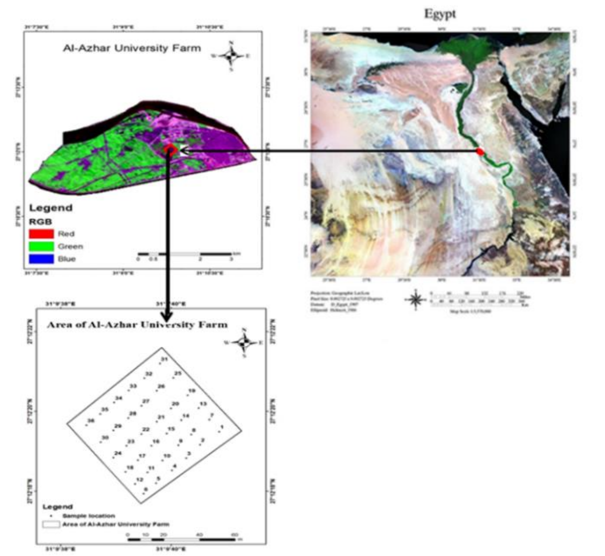

Fig. 1. Location of the study site.

Soil sampling and laboratory analysis

Using a spiral auger at a depth of 0–30 m, thirty-six grid cells (each measuring 10 x 10 m) were taken from the center of each grid cell to gather the soil samples (Fig.1). Then, the plant roots were removed, homogenized, air-dried, powdered, and sieved (particle size < 2 mm) in the lab before being ready for chemical analysis. Soil salinity (EC), (pH) and organic matter content were measured according to Page (1982). Available N, P and K were determined according to Jackson (1973).

Carbon dioxide (CO_2) was trapped in NaOH solution and then determined using the back titration method of the excess NaOH with a dilute hydrochloric acid (Hopkins 2008). Carbon storage (CS) was computed using the following formula, which was developed by Rowell (1994):

CS = % Organic carbon /100 X Bulk density X soil collection area X soil depth.

Statistical and geostatistical analysis

Descriptive statistics analyses for mean, minimum and maximum; standard deviation (SD); coefficient of variation (CV); and Kurtosis (Kurt) and Skeweness (Skew) of each parameter were estimated using SPSS 16.0 software (2000). Geostatistical software GS$^+$TM version 9 (Gamma Design Software, 2000) was used to investigate the spatial correlation. To assess the geographical association of soil chemical characteristics, used was a semivariogram analysis. It is possible to describe a typical semivariogram using the range, nugget effect and sill. Range is the distance at which data are no longer correlated, sill is the plateau where the semivariogram reaches the range, and nugget represents micro-scale variation at h = 0 (Berry, 2005).

Kriging Maps were found by the kriging method, the weights depend on the overall spatial arrangement of the measured points as well as the distance between the measured points and the anticipated locations. In ordinary kriging, the weightage is based on any fitted model to the measured points, the distance to the predicted location, and the spatial relationships between the measured and the predicted location (Isaacks and Srivastava, 1989). The spatial autocorrelation must be quantified in the case of using the spatial arrangement in weights. Kriged maps were assigned by using Arc GIS 8.

RESULTS AND DISCUSSION

Soil property description.

From the statistical analysis of the soil chemical properties for the topsoil (0-30 cm) layer listed in Table 1, the data indicated that the EC values varied from 0.86 to 1.17 dS m^{-1} with the mean value of 0.95 dS m^{-1} and soil pH varied from 7.90 to 8.17 while its mean value was 8.03. Organic matter (OM) varied from 18.22 to 29.20 g kg^{-1} with a mean value of 23.59 g kg^{-1}. According to Warrick and Nielsen (1980) the coefficient of variation (CV), which was categorized as low (CV < 12 %), moderate (12 < CV < 62 %), or high (CV > 62 %), among the chemical examined parameters, among the chemical examined parameters, soil pH, soil EC and soil organic matter were found to be weak variables (CV = 0.82, 6.53 and 11.48%, respectively). The available N, P, and K varied from 28.00 to 56.00, from 8.70 to 19.00 and from 138.0 to 492.2 mg kg^{-1}, with mean values of 45.11, 14.82 and 308.3 mg kg^{-1}, respectively, (Table 1). According to the descriptive statistics of soil fertility parameters, available nitrogen, phosphorus and potassium (CV =22.39, 26.52 and 23.18%, respectively) were determined to be moderate variables.

Table 1. Descriptive statistical analysis of some soil properties

Soil Properties	Min.	Max.	Mean	SD	Var.	Skew	Kurt	CV%
EC (dS m^{-1})	0.86	1.17	0.949	0.062	0.0039	1.86	4.32	6.53
pH (1:2.5)	7.90	8.17	8.034	0.066	0.0044	-0.20	-0.14	0.82
Organic matter (g kg^{-1})	18.22	29,20	23.59	2.708	7.3319	0.29	-0.15	11.48
Available N.(mg kg^{-1})	28.00	56.00	45.11	10.10	102.04	-0.37	-0.95	22.39
Available P. (mg kg^{-1})	8.70	19.00	14.82	3.931	15.45	-0.43	-1.54	26.52
Available K. (mg kg^{-1})	138.0	492.2	308.3	71.45	5104.8	0.28	0.34	23.18
CO_2-C flux (g/m^2/7d)	0.15	0.22	0.192	0.019	0.00035	-0.68	-0.61	9.90
Carbon storage (g m^{-3})	74.10	185.6	130.9	27.41	751.374	-0.29	-0.15	20.94

Min. = Minimum, Max. = Maximum, SD = Stander Deviation, Var. = Variance, Kurt = kurtosis, CV = Coefficient of Variation.

The minimum value of CO_2-C flux after 7 days was 0.15 g m^{-2} while the maximum value of CO_2-C emission was 0.22 g m^{-2} with the mean value of 0.02 g m^{-2}. Carbon storage (CS) varied from 74.10 to 185.65 g m^{-3} with the mean value of 27.41 g m^{-3}. Coefficient of variation (CV) was weak and moderate variability for CO_2-C flux and carbon storage, respectively. However, among the chemical properties studied coefficient of variation (CV) was numerically in the order of CO_2-C flux (CV=9.90%) < carbon storage (CV=20.94%).

In general, data indicated that the coefficient of variation values was weak or moderate for the studied attributes (Table 1), in line with the classification that Warrick and Nielsen (1980) suggested high CV values can be caused by many reasons including surface erosion, residual effects from prior fertilization, sample design, and/or exposure to nutrient-poor soils (Montezano et al., 2006 and Cavalcante *et al.,* 2007). It was expected that soil management such as mineral fertilizers application, irrigation and tillage would lead to changes in soil properties on a large scale. A short-term farming practice demonstrated a tendency for soil parameters to homogenize, including EC, pH, OM and CO_2-C flow, also, it exhibited more diversity for (available NPK and carbon storage). A definite sign of cultivation is the variance and variety in chemical properties and texture.

The pH values showed low CV (Table 2) since it is considered to be the log-transformed H^+ concentration. Similar findings were reported by Grego *et al.,* (2010), who discovered that pH had the lowest CV (3.5%) and the low variation. In all sampling periods and both locations, pH was the only one with minimal change (Castro *et al.,* 2016). Additionally, high and low pH values of geographic variability have been documented in earlier research (Caniego *et al., 2005* & Vidal Vázquez *et al.,* 2013). Because irrigation water has a high percentage of salt, soil pH was higher than in native grasslands (Kilic *et al.,* 2012). The CV was low for organic matter (Table 1) is likely due to the combination of a low amount of organic material intake and high temperatures that accelerate the decomposition of organic matter. Organic matter (9.13%) was found to be less variable in the field based on the CV values of the soil properties (Gulser *et al.,* 2016). Peter-Jerome *et al.,* (2022) report that, in comparison to the soil fertility ratings suggested by Esu, (1991), the available phosphorus content and organic carbon content are significantly lower. While the organic carbon was moderate, it was high for available phosphorus. According to reports by Karaman *et al.,* (2001) and Ga *et al.,* (2020), the available phosphorus is usually more variable than most other macronutrients.

Spatial variation in soil properties

Geostatistics is basically a technique to estimate the variation of properties in space in different dimensions (Webster 1991). Different spatial distribution models and levels of spatial dependency for soil properties were found using geostatistical analysis. The nugget effect values were used to estimate the spatial variability. The nugget, sill, and range parameters were examined for every empirical semivariogram (Table 2 and Fig. 2). Various models (Spherical, Gaussian, Exponential and Linear) were applied for different soil chemical properties.

The variations of organic matter and soil pH were better described by the Spherical model, with a low correlation coefficient (R^2) value of 0.01, while soil salinity was best fitted by the exponential model, which had an R^2 value of 0.87. The variable shows strong spatial dependence if the value is less than 25%, moderate spatial dependence if the value is between 25 and 75%, and weak spatial dependence if the value is greater than 75% (Cambardella *et al.,* 1994). Data also, show that Nugget/ sill effect was 0.22, 0,00682 and 0.0148% for EC soil pH and OM, respectively, indicating strong spatial dependence.

Soil fertility values in Table (2) indicated that the available N, P and K were fitted to the Exponential, Spherical and Linear models respectively. It is observed that a high R^2 value of 0.91 was noticed for available phosphorus followed by available potassium (R^2= 0.61) and available nitrogen (R^2= 0.12). Range of spatial correlation for available N, P and N were 11.1, 25.8 and 52.5 m respectively. The data showed that the Nugget/ sill effect was 0.0647, 0.00061 and 1.00% for available N, P and K, respectively, indicating strong spatial dependence, according to Cambardella *et al.,* (1994).

When other variables are adjusted to dimensional models, it is shown that the average values of the variables do not exhibit distinct trends in any direction, indicating that they satisfy the isotropy assumption. Using these models to generate estimates at unsampled sites offers a sufficient spatial representation of each variable behavior in the field (Viera and González, 2003). The nugget to sill ratio of soil properties is generally < 25%, suggesting a substantial geographical dependence, according to the data. variances in intrinsic soil qualities may be the cause of these variances (Laekemariam *et al.,* 2018; Guan *et al.,* 2017). Reza *et al.,* (2016) also showed a substantial geographical dependence (nugget/sill, 12%) for soil pH in India. The spherical model was used to forecast most soil parameters, while the Gaussian model was used to estimate the CO_2-C flux in the soil and the exponential model was used to predict the available N. This outcome agrees with the findings of Gorai and Kumar (2013) and Laekemariam *et al.,* (2018).

At a depth of 0–30 cm, the range (A_0) values revealed reduced variability among the measured soil chemical properties (Table 2). With the exception of soil salinity (EC), which had a range of 480 m, all variables showed a range of less than 55.1 m. It is implied that random variation exists when samples separated by distances more than the range are not geographically associated and that samples separated by distances closer than the range are spatially related (Nethononda *et al.,* 2012).

Table 2. Semivariogram parameters values of soil properties.

Soil Properties	Model	Nugge C_0	Sill C_0+C	Nugget% C_0/ C_0+C	Proportion C/ C_0+C	Range A_0 (m)	R^2
EC	Exponential	0.00244	0.0111	0.21982	0.780	480.9	0.87
pH	Spherical	0.00003	0.0044	0.00682	0.993	11.8	0.01
Organic matter	Spherical	0.11000	7.4270	0.01481	0.985	11.8	0.01
Available N.	Exponential	6.70000	103.500	0.06473	0.935	11.1	0.12
Available P.	Spherical	0.01000	16.4600	0.00061	0.999	25.8	0.91
Available K.	Linear	5053.998	5053.998	1.00000	0.000	52.5	0.61
CO_2-C flux	Gaussian	0.000072	0.000488	0.14754	0.852	55.1	0.99
Carbon storage	Spherical	12.00000	761.1000	0.01577	0.984	11.8	0.01

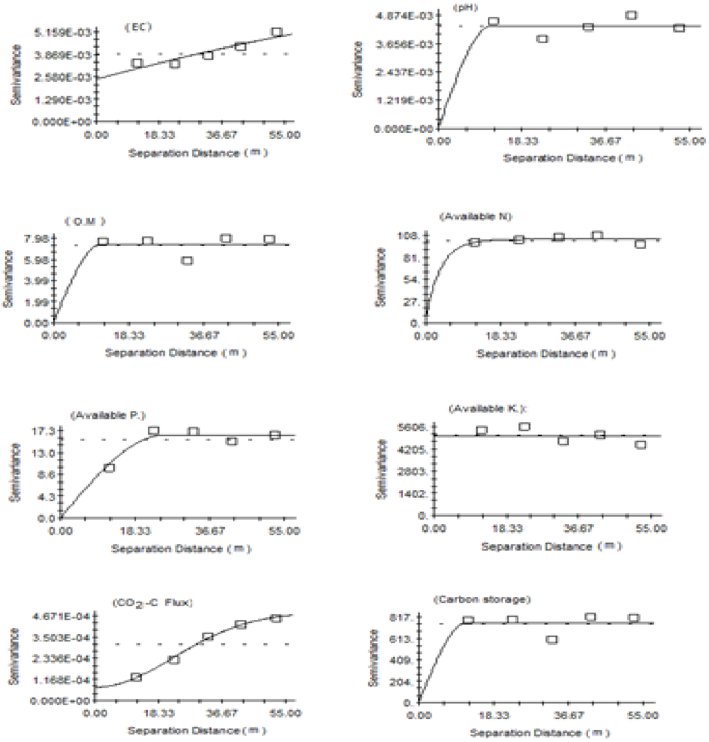

Fig. 2. Semi-variogram analysis of soil properties

Kriged maps of soil properties.

Understanding spatial variability and its influences were observed by using the interpolation maps that are produced using geostatistics. The spatial distribution of the soil chemical properties studied at 0–30 cm depth is depicted in (Fig. 3 & 4).

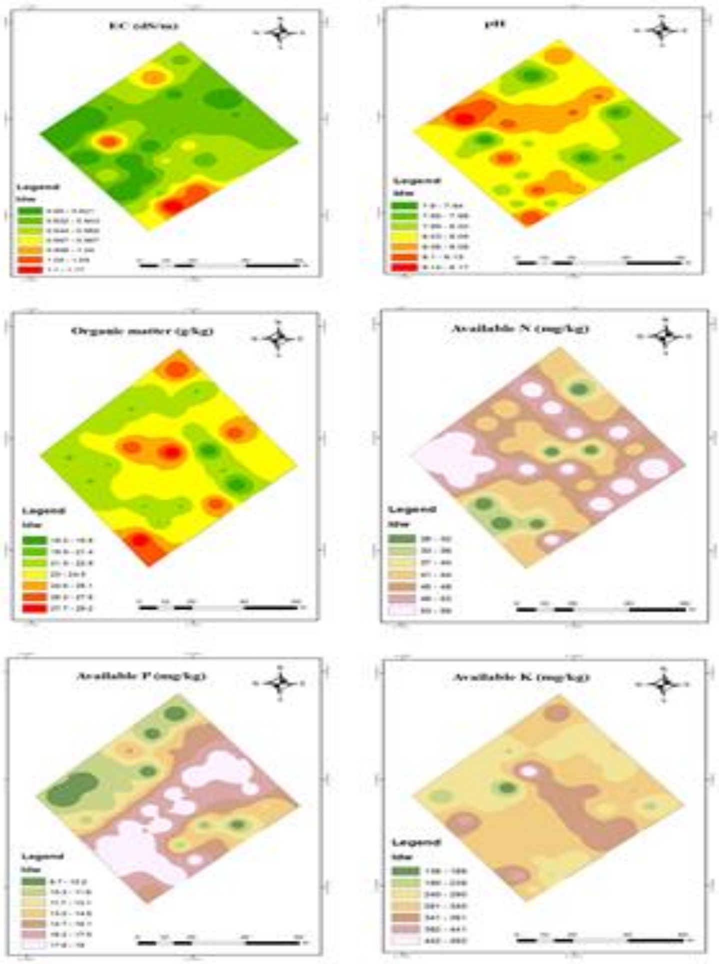

Fig. 3. Spatial distribution map of EC, pH, O.M and available NPK.

Most of the soil properties displayed clustered spatial distribution patterns with varying ranges of patches. There was significant variation in the distribution of soil EC values in the middle north and southeast of the field, ranging from 0.94 to 0.96 dS m^{-1}, while low variability of soil EC values distribution between the range 1.1 to 1.17 dS m^{-1} was observed at the southeast part of the study area. The isorithmic map provides the estimation variance for each transect to indicate the spatial distribution of soil pH (Fig. 3). The high pH values concentrated from 8.03 to 8.05 in the middle of the studied field near the west border and northeastern region of the field. The distribution tends to gradually decrease in the middle of the studied field near the north part of the field.

The average value of soil organic matter was 53% which was greater than 24.3 g kg^{-1}, while the average value of 47% of the soils was between 18.2 and 24%. There was significant variation in the distribution of organic matter levels in the central and southeast sections of the field, ranging from 23.0 to 24.5 g kg^{-1} (Fig. 3). The eastern region, which stretches towards the western region, has a highly accessible nitrogen concentration ranged between 41.0 and 44.0 mg kg^{-1}. High P values with a range of 17.6 to 19.0 mg kg^{-1} were found in the field's southwest area and extended across a wider area from the center to the eastern regions. A wider distribution of low P values was observed between 8.7 and 10.2 mg kg^{-1} in the northeastern (Fig. 3). There was significant variation in the distribution of potassium values in the middle southwest and northeastern regions of the field, ranging from 291.0 to 340.0 mg kg^{-1} (Fig. 3).

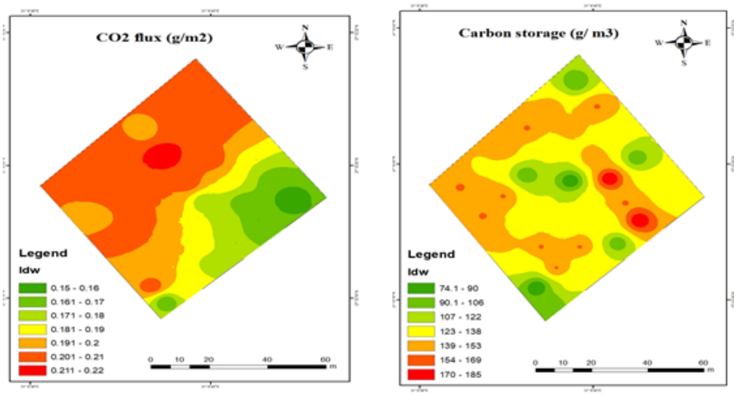

Fig. 4. Spatial distribution map of CO_2-C flux and carbon storage.

The spatial distribution of CO_2-C flux at 0–30 cm depth is depicted in (Fig. 4). There was significantly high CO_2-C flux with high values concentrated in the northwestern, middle and mid-northwestern parts of the field. Low CO_2-C flux values range between 0.15 to 0.17 g m^{-2} were observed in the southeastern region of the field. A visual map analysis showed that at a depth of 0–30 cm, clear and gradual areas predominated for carbon storage (Fig. 4). The carbon storage varied from 74.1 to 185.0 g m^{-3} with most values remaining high at 122.0 g m^{-3} in nearly the entire area. High variability of carbon storage values distribution between 123.0 and 138.0 g m^{-3} was observed in the middle region of the field and southeastern part.

CONCLUSIONS

It could be concluded that understanding how the chemical properties of soil vary spatially is crucial for figuring out how much to apply in each region and for dividing the field into suitable management zones. GIS could be used as an effective tool for determining the spatial distribution of chemical properties. From Kriged maps by GIS, it is evident that most of the study area was low to medium in soil fertility. Based on these maps recommendations can be given for soil fertility management techniques that mainly concentrate on boosting and maintaining soil OM, nutrients, and pH are advised in order to improve soil conditions.

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استخدام نظم المعلومات الجغرافية والتحليل الجيولوجي لرصد التغيرات المكانية في الخواص الكيميائية للتربة المتأثرة بالممارسات الزراعية.

ياسر عبد العال سيد ومصطفي يونس خلف الله

قسم الاراضي والمياه - كلية الزراعة جامعة الازهر اسيوط - مصر.

الملخص

تتأثر خواص التربة ووظائفها بشكل كبير بالإختلافات المكانية. يمكن اكتساب المعرفة الواقعية حول إدارة التربة والحماية البيئية من التوزيع المكاني للخواص الكيميائية للتربة. ولذلك، تم أخذ 36 عينة من التربة (0-30 سم عمق) من نظام شبكة 100 متر من المزرعة التجريبية المختارة. تم إستخدام نظم المعلومات الجغرافية (GIS) والتحليل الجغرافي لتقييم تأثير ممارسات الزراعة على الخواص الكيميائية للتربة وإختلافاتها المكانية. تم إستخدام النموذج Spherical للتنبؤ بمعظم خواص التربة، بينما تم استخدام النموذج Gaussian لتقدير تدفق ثاني أكسيد الكربون في التربة والنموذج Exponential للتنبؤ بالنيتروجين الميسر (N) وملوحة التربة EC. أظهرت النتائج أن معامل قيم إختلاف التربة كان ضعيفاً بالنسبة لملوحة التربة وحموضة التربة (pH) والمادة العضوية (OM) وتدفق ثاني أكسيد الكربون (CO_2-C) أو متوسطاً بالنسبة لتوافر NPK والكربون المخزن. بإستثناء ملوحة التربة (EC)، والتي كان نطاقها 480 مترًا، أظهرت جميع الخواص نطاقًا أقل من 55.1 مترًا. جميع خواص التربة لديها نسبة nugget to sill < 25%، والتي تظهر عموماً إعتمادًا مكانيًا كبيراً. حتى في الحالات الزراعية ذات الموارد المحدودة، تعد الإحصاء الجيولوجية وسيلة قيمة لرسم خرائط المتغيرات المكانية للخصائص الكيميائية للتربة. ويمكن التوصية بهذه الخرائط لتحسين خصائص التربة وتقليل التغير المكاني لخصوبة التربة.