

Studying the spatial variability of some chemical traits for the soils of Aljadwal Algharbi district using time series analysis

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ABSTRACT

This study was conducted in the soils of Aljadwal Algharbi district in Karbala province, which is located in the region between the longitude 415656 to 426008 east and the latitude 3597981 to 369564 north, where the soils of part of the district were surveyed and included agricultural soils (cultivated) with an area of (15,252 ha), where 100 locations were identified and for four depths (0-30 cm, 30-60 cm, 60-90 cm, and 90-120 cm) by a Drilling rig (Alokr). It also revealed 8 pedons to be representative of the region, and its coordinates were determined by a GPS device. A path with a length of 14,400 m, which runs through the widest and most repeated units, has been chosen, and the horizons of the pedons have described fundamentally and morphology. It was studied the spatial variabilities for the chemical and fertile traits and for different depths using advanced statistics (time series analysis). The results showed that all chemical traits were variability and it described as highly variability and according to the scale (wilidig, 1994), except for the reaction of the soil, it was slightly variable according to this scale. The most variability traits were the content of organic matter and calcium carbonate, gypsum, Cation-exchange capacity, and electrical conductivity. As for the models that describe the variability of the chemical traits, the Autoregressive model (AR1) was the most suitable and suitable for these traits, with a percentage of (58.33%), the moving-average model (MA1), with a percentage of (29.17%), and the Autoregressive integrated moving average model (ARIMA), with a percentage of (12.5%). The results indicated that calculating the number of required samples for each of the chemical traits by random method which ranged between (3- 135 samples), the lowest samples were for the degree of soil interaction pH, the most number of samples for the soil content of organic matter by the time series analysis method and relying on self-correlation only for the chemical traits which ranged between (3-56 samples), which was the lowest number for soil interactions, and the largest number for gypsum content in the soil.

Keywords: chemical soil traits, Aljadwal Algharbi, spatial variability, time series analysis.

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دراسة التغيرات المكانية لبعض الصفات الكيميائية لترب قضاء الجدول الغربي باستخدام تحليل السلاسل الزمنية

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المستخلص

نفذت هذه الدراسة في ترب قضاء الجدول الغربي في محافظة كربلاء المقدسة التي تقع في المنطقة التي تتحصر بين خطي طول 415656 الى 426008 شرقاً ودائرتي عرض 3597981 الى 369564 شمالاً ، اذ تم مسح ترب جزء من القضاء وشمل مناطق الترب الزراعية (المزروعة) اذ تبلغ مساحتها 15252 هكتار ، اذ تم تحديد 100 موقع ولاربعة اعماق 0-30 سم و 30-60 سم و 60-90 سم بواسطة جهاز الحفر المثقابي (الاوكر) وكشفت ايضاً 8 بيدونات لتكون ممثلة للمنطقة وحددت احداثياتها بواسطة جهاز GPS وقد اختير مسار طوله 14400 متر والذي يمر باوسع الوحدات مساحة واكثرها تكراراً، ووصفت افاق البيدونات وصفاً مورفولوجياً اصولياً . درست التغيرات المكانية للصفات الكيميائية والخصوبية ولمختلف الاعماق وباستخدام الإحصاء المتقدم باستخدام تحليل السلاسل الزمنية Time sereis analysis وقد بينت النتائج بالنسبة للصفات الكيميائية جميعها كانت متغيرة ووصفت بانها عالية التغير وحسب مقياس 1994 wilidig ، ماعدا تفاعل التربة فقد كان قليل التغير حسب هذا المقياس ، اذ كانت اكثر الصفات متغيرة هو محتوى المادة العضوية وكاربونات الكالسيوم ثم الجبسوم والسعة التبادلية للأيونات الموجبة والايسالية الكهربائية اما النماذج التي تصف تغيرات الصفات الكيميائية فقد كان أنموذج الانحدار الذاتي (AR1) الاكثر نسبة وملائمة لهذه

الصفات بنسبة 58.33% ثم أنموذج الأوساط المتحركة MA(1) بنسبة 29.17% ثم الانموذج المختلط ARIMA بنسبة 12.5% أشارت النتائج إلى إن حساب عدد العينات المطلوبة لكل صفة من الصفات الكيميائية بالطريقة العشوائية قد تراوحت بين 3- 135 عينة ، وكانت اقل العينات لدرجة تفاعل التربة pH ، وأكثر عدد عينات لمحتوى المادة العضوية في التربة وبطريقة تحليل السلاسل الزمنية والاعتماد على الارتباط الذاتي فقط للصفات الكيميائية تراوحت بين 3-56 عينة ، والذي كان اقل عدد لتفاعل التربة ، وأكثر عدد لمحتوى الجبسوم في التربة.

الكلمات المفتاحية : صفات التربة الكيميائية ، الجدول الغربي ، التغيرات المكانية ، تحليل السلاسل الزمنية
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1. INTRODUCTION

The study of the spatial variability for soil traits has great importance in managing soils for different agricultural applications. The studies of spatial variabilities today are also an important means to raise the efficiency of soil survey work and their classification and interest in its study have emerged in recent years because of its significant effects on soil survey operations and its management. The main objective of studying the spatial variability for the different soil traits is to obtain a logical explanation for these variabilities and also to predict the values of different soil traits at the locations from which field soil samples were not taken (Borrough, 8). Ersahin, (10) emphasized that the study of spatial variability is important in studying soil traits and it has particular importance in taking samples from the soil where knowing the variability presence in the soil can be benefited to develop the model used to study the traits of the soil and describing them accurately. Stutter et al., (19) showed that studying the variabilities of soil traits has particular importance in developing a sampling method and that taking variance into account when taking samples reduces time, effort and cost, perhaps in half. The coefficient of variation for total calcium carbonate (CaCO_3), pH, EC, and organic soil carbon in the Iran soils was the lowest variability is the pH traits, where their values amounted to (1.54, 11.01, 22.76, 19.84), respectively, and When using advanced statistics, the carbon of organic soil was the most variability with a variation distance of (538.50 m, for pH 740.1 m, EC 584.1 m, and calcium carbonate 867.0 m. The reason attributed this to the accuracy of advanced statistics, where it is noted that pH and calcium carbonate is the least variability.

Knowing the existing types of soils is real knowledge, which results in the validity of the representation of the extracted sample. The validity of laboratory analysis does not rise to the integrity of the sample and its representation for its statistical community. In order to give a clearer vision and a broader understanding of the statistical method in studying the variability of soil traits and obtaining samples accurately, it is necessary to understand the modern statistical method and one of these methods or statistical analyzes is the time series analysis. Due to the lack of studies in applying this analysis in studying soil variability, We have laid a basic building block for this approach within the group of biosciences to study variabilities of soil traits and applying it within agricultural soils for their importance in the Aljadwal Algharbi district in Karbala province in order to studying the spatial variabilities for soil traits and forecasting the traits of subsequent locations and placing more accurate and efficient sampling system.

2. MATERIALS AND METHODS

Information was obtained from the Directorate of Agricultural in Karbala province, A field visit was conducted to the Aljadwal Algharbi district, which is located in the region between the longitude 415656 to 426008 east and the latitude 3597981 to 369564 north, where the soils of part of the district were surveyed and included agricultural soils (cultivated) with an area of (15,252 ha), where 100 locations were identified and for four depths (0-30 cm, 30-60 cm, 60-90 cm, and 90-120 cm) by a Drilling rig (Alokr). It also revealed 8 pedons to be representative of the region, with the Networking engineering system required by the spatial analysis procedures proposed by (Lark,

2009) and using the satellite image to conduct the scanning process, as shown in Figure (1). The soil is classified according to the series classification (Alagidi, 5) has been chosen, and The coordinates of the locations were determined and samples were obtained from each depth, a cartographic analysis of the map was then conducted to know the percentage and frequency for each unit of soil units. It revealed 8 pedons, Its coordinates are determined by the GPS device, and The horizons of the pedons have described fundamentally and morphology according to the principles stated in (Soil Survey Staff, 18). Samples were obtained from each horizon. The samples were preserved and brought to the laboratory and prepared for laboratory measurements. The following chemical measurements were estimated:

1- Electrical conductivity

The EC conductivity and the pH of a soil sample extract and water with a ratio of (1: 1 soil: water) were measured as reported in (Richards, 1954; USDA Handbook 60, 1954), and the cation exchange capacity (CEC) was measured by (Papanicolaou, 17). The organic matter in the soil was estimated by a method of wet oxidation, as mentioned in (Jackson, 11) by oxidizing it with potassium dichromate and adding concentrated sulfuric acid as a source of heat and then titration with ferrous-zalamonic sulfate. Total calcium carbonate was also measured using hydrochloric acid (3N) by determining the weight loss of CO₂ gas as reported in (Richards, 1954) and described in (USDA Handbook 60 1954). Gypsum is estimated by precipitation with acetone, according to the method described in (Page et al. 16).

Statistical analysis

The statistical analysis included the following:

- 1- Converting the district map to the GIS system so that we can isolate the soil units and conducting cartographic analysis to determine the most units of

soil series with the area and frequently repeated and mapping the soil units series for Aljadwal Algharbi district.

2- Time series analysis, which includes the following:

- 1- Building time series models describing traits variability

The models were built using the computer for data entry and knowing the appropriate models for the spatial variabilities for each trait of the study soil and using the statistical analysis program (SPSS). The models were built according to the steps, model reviews, diagnosis, assessment, suitability checking, and forecasting according to (Box and Jenkins, 6).

- 2- Calculating Autocorrelation with distance (Lag).
- 3- Drawing the Correlogram, which represents the Autocorrelation with the lag distance to know the correlation distance.
- 4- Calculating the number of samples required to represent the community in the following methods: -
 - A- Autocorrelation method.
 - B- Using one of the random laws according to (Al-Nasir and Al-Marzouk, 4).

$$N = t^2 \alpha \sigma^2 / (\alpha x)^2 \text{ ----- (1)}$$

where:

N = number of required samples, $t\alpha$ = value of t dependent on degrees of freedom, σ^2 = variance.

α = significant level (0.05), X = average.

3. RESULTS AND DISCUSSION

The spatial variability of some chemical traits for the soils of the study region using time series analysis

1- Soil salinity EC

Table (1) shows the values of the variability for soil salinity represented by the electrical conductivity EC, where it is clear from the table

that the conductivity values were distributed with an average of (4.19, 4.33, 4.35, 4.3 dS.m⁻¹) for depths (30, 60, 90, 120 cm), respectively, with a deviation of (2.52, 2.54, 2.81, 2.15), respectively for each depth and depending on the criteria for time series analysis, it became clear that the appropriate form for expressing about the trait variability for the salinity is AR(1) model. The reason is this model was more appropriate in terms of it was the least error-variability model and the lowest of the Akaike information criterion (AIC). The predicted values for five subsequent distances ranged from 3.56 - 3.76 dS.m⁻¹ for depth of 30 cm, 3.66-4.09 dS.m⁻¹ for depth of 60 cm, 3.82-4.22 dS.m⁻¹ for depth of 90 cm, 3.81-4.2 dS.m⁻¹ for depth of 120 cm, with an increase of (0.2, 0.43, 0.4, 0.39 %), respectively. It is noted that the EC at these depths was low and the forecasting values were close to their previous averages, and these results agree with (Davis and Brockwell, 8) in terms of suitability of models and this series is stable at their arithmetic means.

2- Soil reaction (pH)

Table (1) shows that the soil reaction for the depths of the study soil was distributed with an average of (7.63, 7.42, 7.40 and 7.50 for the depths of (30, 60, 90, 120 cm), respectively. The results of the statistical analysis indicated that the appropriate models to describe the variabilities of pH is the moving-average model (MA1). It is appropriate to describe its variability in depths of (30 and 60 cm), while the Autoregressive model (AR1) is appropriate to describe the soil interaction in depths of (90 and 120 cm). Perhaps the reason is attributed to the fact that those models are the most appropriate to the nature of data and the most representative in drawing the series and this result agrees with (Harvey, 12). As for the forecasting values, the results indicated that the soil reaction values at depths of (30 and 90 cm) are higher than their previous averages, where they ranged between 8.11-8.14 at the depth of 30 cm and between 8.19-8.2 at the depth 90 cm. Whereas the forecasting values for depths of

(60 and 120) are close to their previous averages, where they ranged between 7.0-7.9 at the depth of 60 cm and between 7.8-8.0 at the depth of 120 cm. Perhaps the reason is due to the type of soil material (calcareous) that affects the raise of the soil reaction and considering it a homogeneous pattern in all locations.

3- The organic matter in the soil

Table (1) shows that the variability of the organic matter was moderate in general, in all depths of the study soil, where its averages in the soil depths amounted to (7.51, 5.88, 4.93, 3.81 g.kg⁻¹), for depths of (30, 60, 90, 120 cm), respectively. The reason for the spatial variability of the values of organic matter can be attributed to the variability of the bio-mass expected to be present at the surface depths due to the variation in the activity of the root system of the natural plant and the cultivated plants in the soils of that region. The results of the statistical analysis indicated that the appropriate model for this trait was the moving-average model (MA1) at the depths of (30 and 60 cm) and the auto-regression model (AR1) at the depths of (90 and 120 cm). As for the forecasting values for the values of the soil reaction were higher than previous averages. These results agree with (Mohammed et al., 15).

4- Cation-exchange capacity

Table (1) shows that the appropriate model that describes its variability is the moving-average model (MA1) at a surface depth of 30 cm. As for the rest of the depths (60 and 90 cm), the auto-regression model (AR1) was appropriate to describe the variability of this trait at these depths, while the Autoregressive integrated moving average model (ARIMA) (1,1) is the appropriate model for this trait at the subsurface depth of 120 cm. This is due to the fluctuation in the variability of this trait and pattern of data, as well as the lack of Akaike information criterion (AIC) in these models. We also note from drawing the series at such depths that it is a stable series and that the distance between one

location and another is related to each other. The reason is that the series showed some staticity and stability in the pattern of its drawing, which means that the static variability ranged between (4.64 - 7.90) in its values for this trait. These results agree with (Miswan et al., 14) in their study of electrical load using ARIMA models. As for the forecasting values

of the following locations for the CEC trait, the results showed that their values are close to their averages in the previous locations. while the auto-regression model (AR1), It is a suitable model for depths of (90, 120 cm) due to the convergence of the values of carbonate minerals in those depths.

Table 1: Statistical analysis for the traits of chemical soil for the study region using time series analysis.

Traits	Thickn ess	Model	Parame ter	Appreciat ion	Error varian ce	AIC	AC F	SD	mea n	C.V .	forecasting				
EC	30 -0	AR(1)	$\phi 1$	0.498	0.087	200.1 4	- 0.5 0	064	4.19	15.4 0	3.76	3.72	3.68	3.64	3.56
	60	AR(1)	$\phi 1$	0.296	0.096	258.8 5	0.3 1	0.87	4.33	20.0 0	4.09	3.98	3.87	3.76	3.66
	90	AR(1)	$\phi 1$	0.385	0.093	238.3 9	0.3 9	0.83	4.35	18.9	4.22	4.13	4.05	3.89	3.82
	120	AR(1)	$\phi 1$	0.350	0.095	261.7 5	0.3 5	0.88	4.41	19.9 1	4.20	4.10	4.00	3.90	3.81
pH	30-0	MA(1)	$\theta 1$	-0.378	0.094	68.88	0.3 2	0.33	7.63	4.30	8.14	8.14	8.13	8.13	8.12
	60-30	MA(1)	$\theta 1$	0.085	0.010	73.82	0.4 7	0.34	7.56	4.5	8.00	7.90	7.81	7.71	7.62
	90-60	AR(1)	$\phi 1$	0.-040	0.101	55.82	0.4 5	0.31	7.56	4.10	8.20	8.20	8.20	8.19	8.19
	120-90	AR(1)	$\phi 1$	0.074	0.101	59.57	- 0.1 2	0.31	7.58	4.2	7.90	7.89	7.89	7.88	7.88
SOM	30-0	AR(1)	$\phi 1$	-0.363	0.224	402.4 7	0.4 2	1.72	7.51	32.8 0	8.16	7.92	7.69	7.47	7.26
	60-30	MA(1)	$\theta 1$	-0.347	0.096	389.9 2	0.4 2	1.68	5.88	28.5 0	7.31	7.03	6.76	6.51	6.26
	90-60	AR(1)	$\phi 1$	0.200	0.100	364.7 1	- 0.2 1	1.48	4.93	30.0	6.97	6.58	6.20	5.85	5.52
	120-90	ARIMA(1 ,1)	$\theta 1$	-0.032 -0.385	0.285 0.263	253.3 4	0.3 0	0.84	3.81	22.1	3.69	3.59	3.48	3.38	3.29
CEC	30-0	MA(1)	$\theta 1$	-0.379	0.094	470.7 8	0.4 9	2.52	26.0 8	9.70	26.4 0	26.2 9	26.1 7	26.0 6	25.9 5
	60-30	AR(1)	$\phi 1$	0.519	0.086	417.8	0.5	2.54	24.3	10.4	23.7	23.6	23.5	23.4	23.3

						1	2		3	0	9	9	8	7	7
	90-60	AR(1)	$\phi 1$	0.482	0.089	492.1 5	0.4 8	2.81	21.5 0	13.1 0	18.5 4	18.3 8	18.2 3	18.0 7	17.9 2
	120-90	ARIMA(1 ,1)	$\theta 1$	0.585 0.054	0.159 0.193	439.4 1	0.5 2	2.15	19.7 3	10.9	18.3 1	18.2 3	18.1 40	18.0 6	17.9 7
CaCO ₃	30-0	MA(1)	$\theta 1$	-0.529	0.886	1112. 32	0.6 9	64.4 2	235. 97	27.3 0	233. 36	228. 91	224. 54	220. 26	216. 06
	60-30	ARIMA(1 ,1)	$\theta 1$	0.766 0.162	0.093 0.145	1113. 09	0.6 9	64.6 7	240. 06	26.9 0	235. 33	230. 47	225. 70	221. 04	216. 47
	90-60	AR(1)	$\phi 1$	0.673	0.074	1122. 10	0.6 8	67.6 8	242. 29	27.9 0	235. 18	229. 79	224. 52	219. 37	214. 34
	120-90	AR(1)	$\phi 1$	0.653	0.076	1121. 86	0.6 6	67.6 1	242. 33	27.9	150. 87	93.0 6	57.4 0	35.4 0	21.8 4
Gypsum	30-0	AR(1)	$\phi 1$	0.687	0.073	336.3 6	0.6 9	1.29	5.80	22.3 0	4.82	4.73	4.65	4.57	4.49
	60-30	AR(1)	$\phi 1$	0.522	0.087	346.5 6	0.5 2	1.35	5.36	25.1 0	3.58	3.46	3.35	3.24	3.14
	90-60	MA(1)	$\theta 1$	-0.417	0.092	343.5 9	0.4 6	1.33	5.11	26.0 0	3.77	3.63	3.51	3.39	3.23
	120-90	AR(1)	$\phi 1$	0.485	0.088	344.5 9	0.4 9	0.13	5.01	26.6 0	3.86	3.72	3.59	3.46	3.33

5- Carbonate minerals

Table (1) shows that the appropriate model that describes its variability in this trait at a depth of 30 cm was the moving-average model (MA1) and at the depth of 60 cm, the appropriate model was the Autoregressive integrated moving average model (ARIMA) (1,1) while the auto-regression model (AR1) is the appropriate model for depths of (90 and 120 cm) due to the convergence of carbonate mineral values in those two depths. It is noted that the models describing the variability of carbonate minerals in the regions of the study soil have varied due to the reason that most of the carbonate in sedimentary soil origin materials are primary minerals that were transported with Tigris and Euphrates water and deposited in fine particles, Therefore, the sedimentary soil content of lime was high. This result agrees with (Buringh, 7). In addition to that carbonates are also deposited secondarily from irrigation water and high groundwater from the bottom when the

appropriate conditions are available for that (Zubaidi, 1). As for the predicting or forecasting values for the subsequent locations, the results showed that they are values that are close to their values in the previous locations, with a rise in some locations and a decrease in other locations, where the prediction values in the locations for the depth of (30 cm) ranged between (216.06 - 233.36 g.kg⁻¹), at the depth of 60 cm ranged between (216.47 - 235.33 g.kg⁻¹), and at the depth (90 cm) ranged between (214.34 - 235.18 g.kg⁻¹). At the depth of 120 cm, these predicted values ranged from the locations close to the previous locations. The further away we are from the location, its previous values were decreased except for the 120 cm depth.

6- Gypsum

Table (1) shows that the model that describes the gypsum variability in the depths of the study soils, Autoregressive model (AR1) was at all depths except the depth of (90 cm). The moving-average model (MA1) was the one that describes gypsum variability in that depth and The reason is attributed to the homogeneous distribution of gypsum content in the depths of the study soils. As for the prediction values for the subsequent locations for the depths of the soil, which ranged between (4.49 - 4.82 g.kg⁻¹), at a depth of 30 cm and a depth of 60 cm ranged between (3.14 - 3.59 g.kg⁻¹), at the depth of 90 cm ranged between (3.23-3.77 g.kg⁻¹), and at the depth 120 cm ranged between (3.23-3.77 g.kg⁻¹), and rising it to the depth of 30 cm is observed and approaching it from their previous averages. This is due to the distribution pattern of gypsum values in the

depths of the study soils, and this result agrees with (Al-Quraishi, 2).

Sampling system

Table (2) indicates that the values of auto-regression model (AR1) were low where the distance at which the highest auto-regression model (AR1) was taken (more than 0.1), where the distance with the highest correlation for chemical traits ranged between (256 - 5736 m), where it was the lowest distance for a trait of Gypsum at depth of (0-30 cm) and the highest distance for soil reaction pH at depth of (0-30 cm). It is noted from the table of calculating the number of samples (2) that the number of samples for chemical traits when using time series analysis ranged between (3- 56 samples), where the lowest number of samples for soil reaction pH was at the depth (0-30 cm), and the highest number of samples was for the gypsum content at depth (0 - 30 cm). The reason for this may be attributed to melting and varying gypsum while moving down.

CONCLUSIONS

It is clear from the above that the greater the variance leads to the greater the number of samples and whenever the smaller the variance leads to the smaller the number of samples. The results also show that the number of samples for most of the traits of the chemical soil was a smaller number when using time series analysis compared to when using traditional statistics (one of the random rules), These results agree with (Al-Muhaimid, 3; Al-Quraishi, 2).

Table 2: Calculating the number of samples by statistical methods for the traits of study soils.

Traits	Depth or horizon	number of samples by a random method	The distance at maximum auto-correlation	Number of samples by an auto-correlation
EC	30	35	668	22
	60	60	684	21
	90	53	508	28
	120	60	577	25
Ph	30	3	5736	3
	60	18	2226	6
	90	3	1750	8
	120	3	1441	10
SOM	30	85	562	26
	60	122	700	21
	90	135	704	20.
	120	74	770	19
CEC	30	14	787	18
	60	16	630	23
	90	26	918	16
	120	18	985	15
CaCO ₃	30	112	600	24
	60	109	1120	13
	90	118	4374	3
	120	117	916	16
Gypsum	30	74	256	56
	60	94	390	37
	90	102	390	37.
	120	107	406	35

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