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تخريط درجة تفاعل التربة (pH) والتوصيل الكهربائي للتربة (الملوحة) باستخدام طريقة كريج البسيطة وكريج العادية في منطقة سهل الجفارة

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Mapping Soil pH and Electrical Conductivity Using Simple Kriging and Ordinary Kriging in Jeffara Plain Region

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الملخص:
تبحث هذه الدراسة في التباين المكاني لدرجة تفاعل التربة (pH) والتوصيل الكهربائي للتربة (EC) في منطقة سهل الجفارة باستخدام منهجيات الكريج البسيط (SK) والكريج العادي (OK). توفر الجيو الإحصائية إطارًا شاملاً لتقييم الأنماط المكانية في خصائص التربة، مما يسهل التنبؤات في المواقع غير المأخوذة بعين الاعتبار ويحسن دقة تقنيات إدارة التربة. يستخدم هذا العمل نماذج شبه التباين لإنشاء خرائط توقعيه للتربة باستخدام طريقتي التداخل SK و OK. تم تحديد منطقة الدراسة، التي تغطي حوالي 150,086 هكتارًا، بعد فحص شامل لـ 250 قطاعا للتربة. تم استخدام ArcGIS لتقييم الارتباطات المكانية والخرائط المتوقعة. ولتحديد صحة خرائط التنبؤ بدرجة تفاعل التربة (pH) والتوصيل الكهربائي للتربة (EC)، تم التحقق من صحة 25 قطاع ممثل للتربة موزعة عشوائيًا في منطقة الدراسة مع نتائج التنبؤ (pH) و(EC) . تشير النتائج إلى أن النموذج الأسي يوفر تنبؤات موثوقة لدرجة تفاعل التربة والتوصيل الكهربائي (EC)، حيث يظهر اعتمادًا جغرافيًا كبيرًا لدرجة حموضة التربة واعتمادًا معتدلاً للتوصيل الكهربائي للتربة. تقدم هذه المنهجية في رسم الخرائط رؤى أساسية لإدارة التربة المستدامة وتسهّل اتخاذ القرارات الاستراتيجية في الأنشطة الزراعية.
الكلمات المفتاحية: كريغينغ العادي (OK)، كريغينغ البسيط (SK) شبه المتغير، والتوصيل الكهربائي، درجة تفاعل

Abstract:
This research examines the spatial variability of soil pH and electrical conductivity (EC) in the Jeffara Plain region utilizing Simple Kriging (SK) and Ordinary Kriging (OK) methodologies. Geostatistics provides a comprehensive framework for evaluating spatial patterns in soil characteristics, facilitating forecasts at unsampled sites and improving the accuracy of soil management techniques. This work utilizes semivariogram models to create forecast soil maps with SK and OK interpolation methods. The designated study area, encompassing roughly 150,086 hectares, was delineated after an exhaustive examination of 250 soil profiles. ArcGIS was employed to evaluate spatial correlations,

and predicted maps. To determine the validation of the predictive soil pH and soil EC maps, 25 reprehensive soil profiles randomly distributed in the study area were cross validated with predicted soil pH and EC results indicate that the Exponential model provides dependable predictions for soil pH and electrical conductivity (EC), exhibiting a large geographical dependency for soil pH and a moderate reliance for soil EC. This mapping methodology offers essential insights for sustainable soil management and facilitates strategic decision-making in agricultural activities.

Keywords.: Ordinary Kriging (OK), Simple Kriging (SK),Electrical Conductivity, Soil pH.

1. Introduction:

In recent decades, advancements in computational resources have facilitated the application of numerical approaches to analyse extensive soil data collected globally. The fact that every observation is related to a specific place in both space and time is a fundamental characteristic of soil information. Understanding an attribute value, such as havey metal concentration, is of minimal significance unless the location and time of measurement, are recognized and incorporated into the analysis. Soil scientists recognize that soil characteristics exhibit spatial variability, having documented significant fluctuations over short distances (Trangmar et al., 1985). Despite a locally inconsistent appearance, a spatial structure is frequently identified, potentially linked to the interplay of processes of multiple physical, chemical, and biological operating at distinct various spatial and temporal scales. The characterisation of soil's spatial variability is crucial for comprehending the intricate relationships between characteristics and environmental influences Afterwards, characteristics at unsampled areas can be predicted using a model of spatial dependency among soil data, improving fertilizer usage recommendations distances (Reza, et al., 2017)..

Geostatistics offers a collection of statistical methodologies for integrating the spatial and temporal coordinates of observations in data analysis, facilitating the characterization and modelling of spatial patterns, forecasting at unsampled sites, and evaluating the degree of uncertainty associated with these forecasts. Following the initial applications of Geostatistics to soil data in the early 1980s see (Zhang et al., 1997). Geostatistical approaches have gained prominence in soil research, as evidenced by the rising many of soil studies documented in the literature (Zhang et al., 1997, Goovaerts, 2000 and Song et al., 2020,). The characteristics of soil change with depth, throughout the terrain, and in accordance with regional variations in parent material and climate.. Alterations in soil characteristics at the order classification level typically, but not invariably, occur over considerable distances, frequently spanning substantial climatic and/or geographic gradients. Soil qualities exhibit considerable variation within fields and across short distances, even among areas classified under a same soil order (Mulla and McBratney, 2000). Soil diversity exists among soil series and units, with the extent varying based on diverse soil-forming causes. The geographical heterogeneity of physical or chemical soil characteristics in soils derived from identical parent materials may be minimal yet present within the same soil unit (Song et al., 2020). The characteristics exhibit constant variation over the field and are not universally measurable. Consequently, comprehending the regional diversity of soil attributes will facilitate improved soil and crops management in the farmland. Geostatistical approaches are relevant in soil research for quantifiable qualities that exhibit continuous spatial variation. In regions that have not been investigated or where few samples have been collected, the geostatistical approach is used to estimate the values of soil properties (Owais, et al., 2024). This technique is utilized across various domains of soil investigations, including spatial variation in physical and chemical of soil characteristics (Zhang et al., 1997; Denton, et al., 2017., Vandana et al. 2024; Tang et al., 2017, and Vasu et al., 2017). The geostatistical method is highly effective when a sample value is anticipated to be influenced by its location and its correlation with neighboring values, as indicated by semivariograms and variograms. The parameters of variograms furnish crucial spatial information for Kriging, a technique for optimal estimate of the variable, and it is an impartial estimator characterized by low and known variance (Journel and Huijbergts, 1978; Samra and Singh, 1990; Webster and Burgess, 1980). According to Burgess (1981) Kriged estimations are readily produced from observations of constantly variable attributes on equilateral or square grids or from unevenly distributed data.

Utilizing geostatistical techniques for the analysis of soil physical property data facilitates a reduction in the quantity of field observations required. Vieira and Paz (2003) determined that a minimum of (128) samples sufficed to acquire almost equivalent information as (1280) samples within an area o f (55 x 160 meter). Chang et al. (1988) determined from their research on electrical conductivity and soil texture (sand content) maps which produced by Kriging might offer valuable insights for the design of experiments, including plot size, layout, and soil sample strategies for the management and reclamation of saline soils. The Kriged estimations can be shown as isoaarithmic maps to illustrate the variety. Hajrasuliha et al. (1980) utilized maps of anticipated Kriged salinity of soil to enhance the positioning of sprinklers within an irrigation system. Numerous further research (Goovaerts, 2000; Vieira and Paz 2003; Behera and Shukla, 2015; Ferreiro et a l., 2016) employed Kriging to delineate regionalized soil characteristics. Numerous studies have delineated the spatial variation of soil (EC) employing traditional statistical methods (Sousa et al., 2021; Molin and Faulin, 2013) alongside geostatistical techniques (Reza, et al., 2017). The primary objective of this paper was to use the basic Kriging and ordinary Kriging methods to examine and describe the spatial variability of soil pH and electrical conductivity.

2. Materials and Methods:

2.1. Study Area Location:

The Jeffara Plain region is triangular, spanning from the west of AlKhoums city in Libya to the Tunisian border, The territory examined in this study is situated in the northwest of the Jeffara Plain region, positioned between Tripoli and AlAziziyah city, with longitudes ranging from 12° 45' to 13° 15' east and latitudes from 31° 52' to 32° 52' north, and covers approximately 150086ha (Figure1).

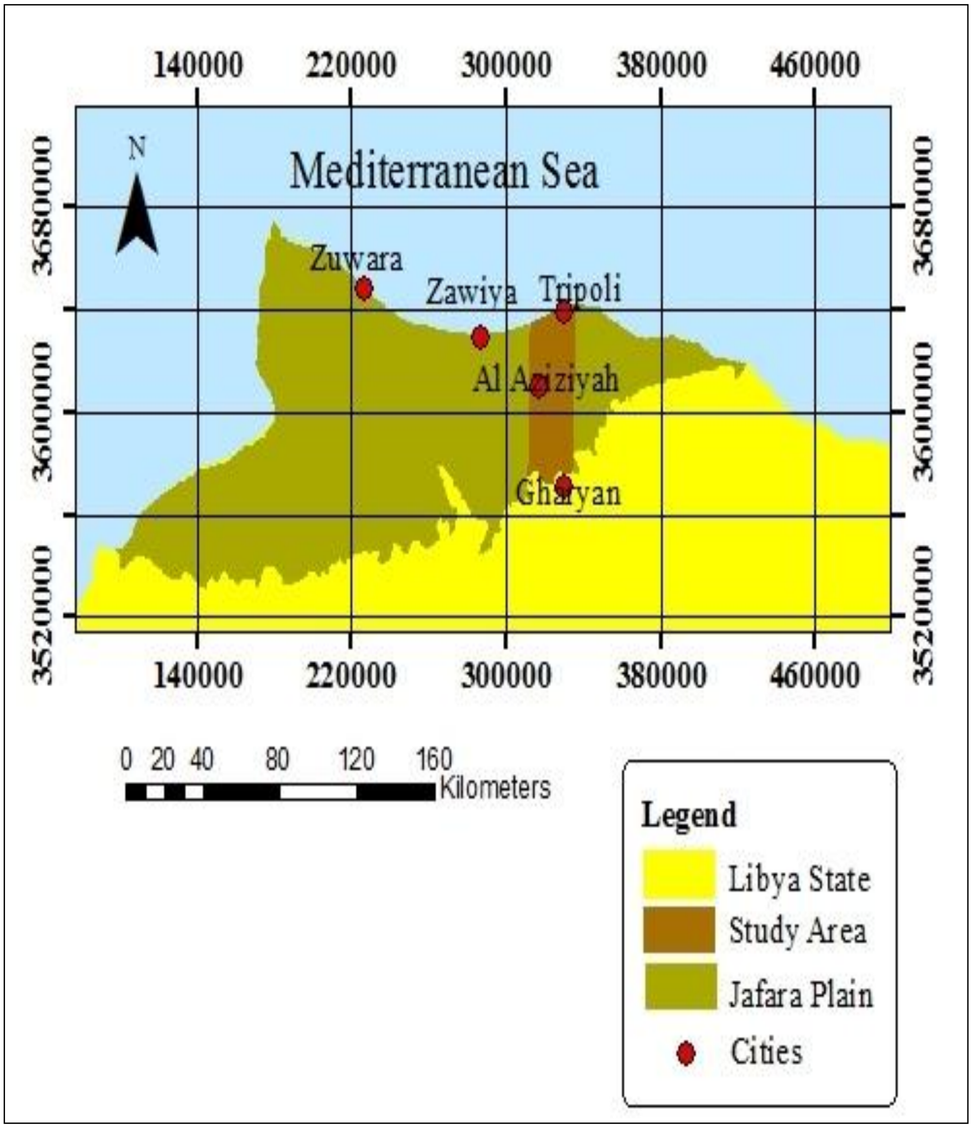

Figure 1. Study Area Location

The soil investigations in the study area were conducted by the Soil Ecological Expedition of v/o Selkhozpromexport, Agricultural Research Centre, University of Tripoli, and the Ministry of Agriculture (Selkhozpromexport, 1980). The soil units in the study region were defined based on morphological criteria. Soil samples were collected from several genetic strata, and auger sampling was conducted at a rate of one sample per

60 hectares; this density was also applied to the depth samples. Data from 250 sample soil profiles were gathered within the study region for the purpose of mapping soil pH and electrical conductivity (EC) (Figure 2).

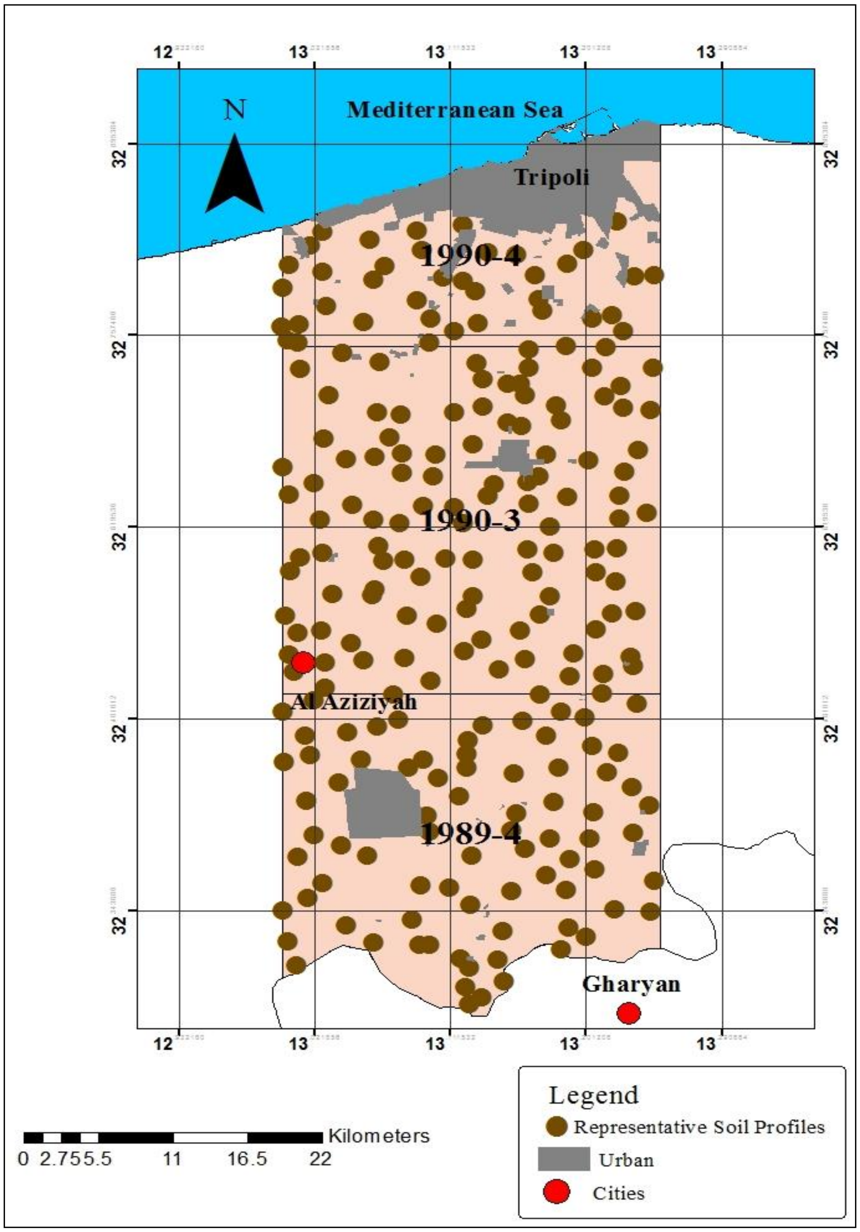

Figure 2. Representative Soil Profiles in the study area.

2.2 Simple and Ordinary Kriging for Mapping soil pH and soil EC in the Study Area:

Kriging is a significant method within geostatistical approaches. Kriging is a technique for linear interpolation. that yields the ideal linear an impartial estimation for spatially varying values. Kriging evaluates are computed as weighted aggregates of the neighboring sampled concentrations. If data exhibit high spatial continuity, locations in proximity to estimated values are assigned greater weights than those further away (Goovaerts, 2000). Kriging is considered the as the most reliable way to perform spatial forecasting. in theory, it is a weighted moving average (Zhang et al., 1997):

$$Z(\chi_0) = \sum_{i=1}^{n} \lambda_i Z(\chi_i) \qquad (1)$$

The value to be estimated at the position of $\chi 0$ is denoted as $Z\chi i$, which represents the known value at the sampling site χi, and n signifies the number of sites within the search neighbourhood utilized for the estimation. The variable n is determined by the user and is contingent upon the dimensions of the moving window.

Kriging's weighting is no longer arbitrary, which sets it apart from earlier techniques like Inverse Distance Weighting (IDW). The weight is contingent upon the parameters of the semivariogram model and the sample configuration, determined under the criteria of impartiality and reduced estimate variance (Zhang et al., 1997).

Numerous kriging methods exist, with Simple Kriging (SK) being a prevalent approach in soil science; it estimates values of continuous random spatial variables from data without bias and with minimal variance. Ordinary Kriging (OK) is another kriging method where the weights of the values total to one. OK use an average of a selection of adjacent points to generate a specific interpolation point (Thangavelu, et al., 2022). OK predicts the value at an unsampled location by using an estimated mean of a specific soil attribute at a known location (Kingsley, et al., 2021).

Kriging methods employ the variogram methodology or (semiviariogram) to assess the spatial variability of a localized variable, supplying the necessary input criteria for kriging spatial interpolation (Goovaerts, 2000 and Zhang et al., 1997). This study employed the semivariogram to examine discrete soil samples. Semivariograms are essential in the theory of regionalized variables and consist of three components: sill, range, and nugget, which grow with the lag between samples; semivariance rises to a maximum asymptotic value (sill). Due to this lag, Semivariance approximates the observed variance. This lag is referred to as the range beyond which variables exhibit independence and lack relationships. Nugget arises when the semivariogram does not commence precisely at the intersection of coordinates, typically because to laboratory testing inaccuracies, abrupt variations in soil characteristics, or when the sample distance exceeds the range. The initial slope strength in the semivariogram demonstrates variability based on distance and a decrease in correlation among samples (Robinson, and Metternich 2006).). The semivariogram is calculated as half the mean squared difference between the elements of data pairings (Goovaerts,, 2000). The function is articulated as:

$$\gamma(h) = \frac{1}{2\,n\,(h)} \sum_{i=1}^{n} [Z\,(\chi_i) - Z\,(\chi_i + h)]^2 \qquad (2)$$

Where $n\,(h)$ is the total number of data pairs separated by a distance; h; Z represents the measured value for soil property; and χ is the position of soil samples (Shi et al., 2007).

2.3. 3 Data analysis:

In this study, data for 250 whole representative soil profiles were encoded in the database. Data for 225 representative soil profiles was analyzed and using classical statistics: (mean, maximum, minimum, median, Standard Deviation, skewness, Kurtosis, 1-st Quartile and 3-st Quartile) were performed using ArcGIS 10.1and 25 representative soil profiles were used to evaluate the maps produced using SK and OK method.

The spatial correlation among measured sample locations was analyzed via semivariogram functions in ArcGIS 10.1. In addition to identifying the optimal fitting model that intersects the points in the semivariogram Experimental anisotropy semivariograms were analyzed to model the spatial relationships within the dataset Spherical, Exponential, Gaussian, and Circular models were employed to ascertain the optimal fit in SK and OK interpolation methods. Model selection for semivariograms was conducted by evaluating the discrepancy between estimations and measured data, alongside executing a cross-validation test throughout the complete dataset. The mean error (ME), root mean square error (RSME), mean standardized error (MSE), and root mean square standardized error (RMSSE) were calculated to evaluate the efficacy of the optimal theoretical models. Geostatistical characteristics, including range, nugget, and nugget ratio values, were computed for pH and electrical conductivity (EC). Sill is the lag distance between measurements at which one value in a dataset has no effect on its neighboring values. The range is the distance at which the variogram attains the sill value. In theory, the semivariogram value at a separation distance of zero (i.e., lag = 0) is zero. At an infinitesimal separation distance, the semiviariogram frequently exhibits a nugget effect, indicating a value exceeding zero. The geographical dependence of soil parameters was assessed according to the nugget variance effect. The qualities were deemed strongly dependent if the rate was (25% or below), reasonably dependent if it ranged from (25%-75%), and weakly dependent if it was (75% or higher) (Robinson, and Metternich 2006 and Abass et al., 2023).

2.4. Statically analysis:

The statistical analysis used in the provided table is called the "Independent Samples T-Test." This test is used to compare means between two independent groups, in this case, the "Patient" group and the "Control" group, to determine whether there is a statistically significant difference between them based on important values such as the p-value (P-value). In this context, the test was used to analyze the differences in the mentioned biochemical parameters between the "Patient" and "Control" groups.

3. Results and Discussions:

3.1 Statistical Analysis of Simple and Ordinary Kriging Models Results:

TheTrend analysis on soil samples revealed that soil pH was normally distributed without using any transformation type, while soil EC was not normally distributed, therefore Logarithmic transformation (log) was applied to obtain normal distribution trend for soil EC mapping. The results of the summary statistics of applying the traditional statistics on available dataset are displayed in Table 1, Figures 3, and 4.

Table 1. Statistical Analysis of 225 representative soil profiles for mapping pH and EC in the study area.

	pH	EC
Transformation Type	None	Logarithmic
Min	7.86	-1.20
Max	8.90	3.03
Mean	8.35	0.14
Median	8.37	0.013
Std.Dev	0.21	0.709
Skewness	0.05	1.78
Kurtosis	2.50	7.059
1-st Quartile	8.2	-0.23
3-st Quartile	8.5	0.282

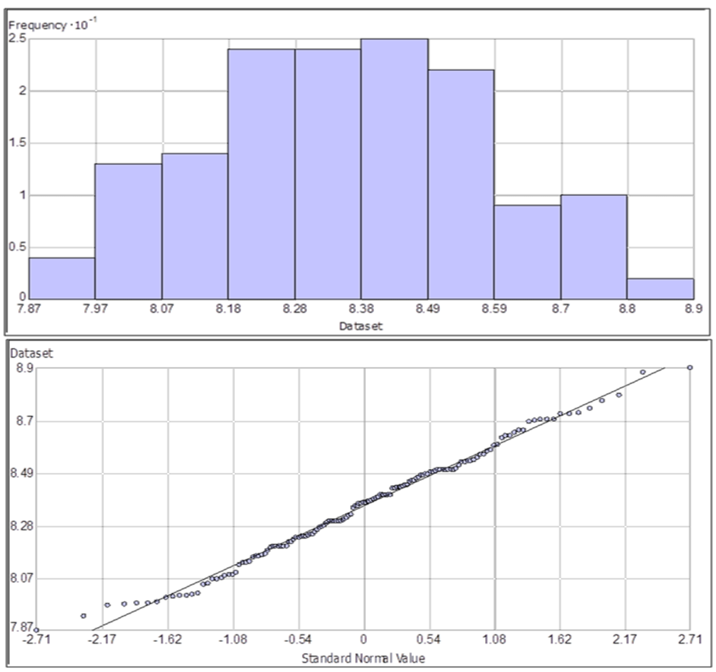

Figure 3. The Histogram and normal QQplot (none transformation) and cumulative variation of soil pH.

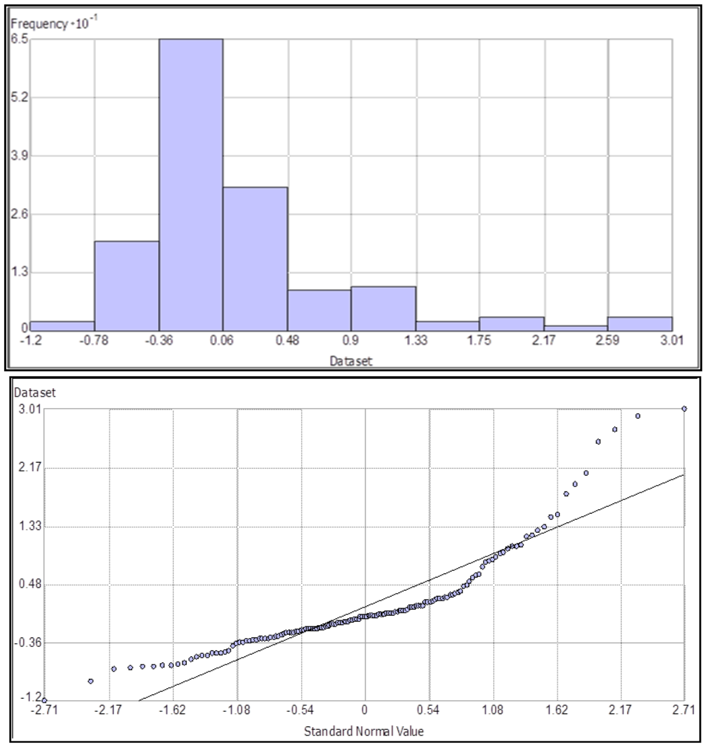

Figure 4. The Histogram and normal QQplot (Logarithmic transformation) and cumulative variation of soil EC.

All models were cross validated to assess the predictability of the theoretical model by computing Prediction error statistics. The optimal model was chosen according to criteria: (the standardized mean closet zero, the minimal Root-Mean-Squared Error (RMSSE)), tests for the standardized root-mean-squared error (RMSSE) closest to one, and the lowest Nugget-Sill ratio (%). This study identified the Exponential spherical, Gaussian, and Circular models as the most suitable models using crossvalidation testing. The parameters of the chosen semiviariogram models and the cross-validation tests for soil pH and soil electrical conductivity (EC) are reported in Tables 3 and 4.

Table 2. Cross validation and selected semiviariograms models results for pH.

Kriging Type	Model	Nugget	Partial Sill	Sill	Nugget-Sill (%)	RMSE	RMSSE
SK	Gaussian	0.02	0.02	0.04	50	0.21	0.98
	Circular	0.02	0.02	0.04	50	0.21	0.99
	Spherical	0.02	0.02	0.04	50	0.21	0.99
	Expotinatil	0.003	0.044	0.047	6.38	0.21	0.99
OK	Gaussian	0.02	0.02	0.04	50	0.23	1.00
	Circular	0.02	0.02	0.04	50	0.23	1.00
	Spherical	0.02	0.02	0.04	50	0.23	1.00
	Expotinatil	0	0.05	0.05	0	0.23	1.00

Table 3. Cross validation and selected semivariograms models results for soil EC.

Kriging Type	Model	Nuggeet	Partial Sill	Sill	Nugget Sill (%)	RMSE	RMSSE
SK	Gaussian	0.45	0.03	0.48	93.75	2.74	2.22
	Circular	0.44	0.04	0.48	91.6	2.74	2.24
	Spherical	0.44	0.04	0.48	91.6	2.75	2.25
	Expotinatil	0.45	0.03	0.48	93.75	2.75	2.27
OK	Gaussian	0.35	0.18	0.53	66	2.73	1.73
	Circular	0.29	0.24	0.53	54	2.72	1.73
	Spherical	0.25	0.28	0.53	47	2.72	1.74
	Expotinatil	0.17	0.37	0.54	31	2.73	1.73

Table 3 showed that Nugget-Sill ratio (%) for Expotinatil model was 0 using OK and this means there is strongly spatially dependency (i.e. Nugget-Sill between 0 to 25). The spatial prediction soil pH map of OK with Nugget-Sill ratio (%) = zero % based on Expotinatil model is presented in the Figure 5.

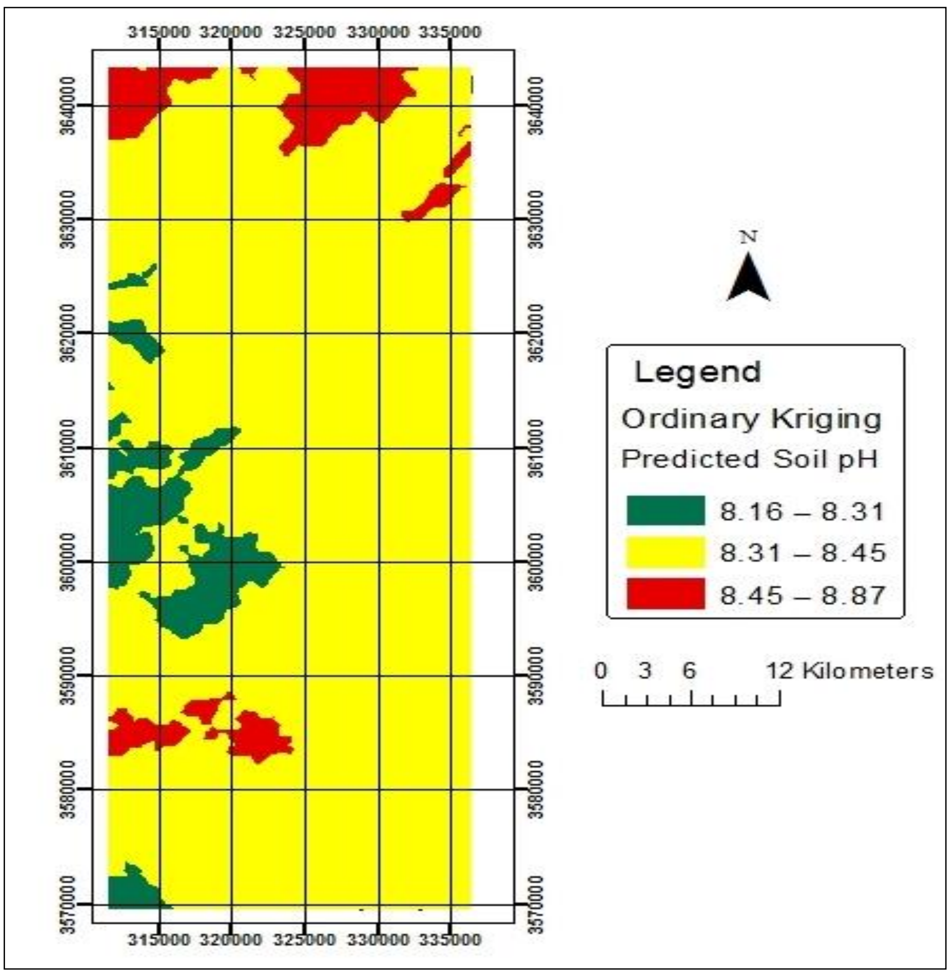

Figure 5. The spatial prediction soil pH map of OK with Nugget-Sill ratio (%) = zero % based on Expotinatil model.

Table 4 illustrates that Expotinatil model using Ordinary Kriging was the best fitted model for mapping soil EC and the Nugget-Sill ratio (%) was 31 % (i.e. fairly dependency), while Simple Kriging was unsuitable model for mapping soil EC in the study area due to spatial dependency was more than 75 % and this means there is weakly dependent. The spatial prediction soil EC map of OK with Nugget-Sill ratio (%) = 31 % based on Expotinatil model is presented in the Figure 6.

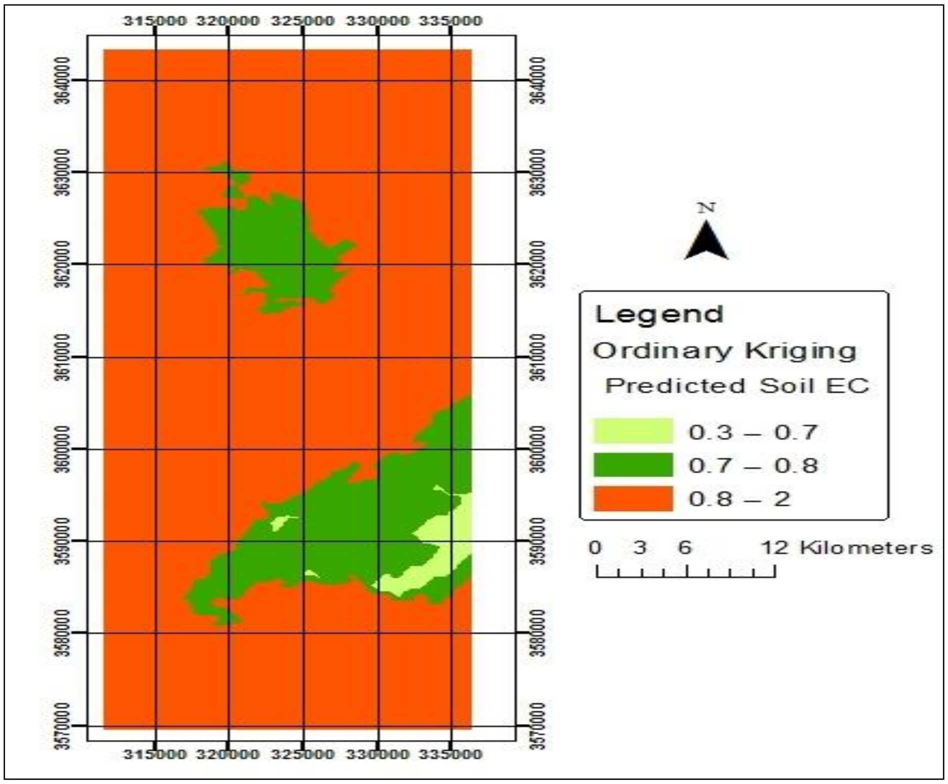

Figure 6. The spatial prediction soil EC map of OK with Nugget-Sill ratio (%) =31 % based on Expotinatil model

3.2 Validation of the Predictive Maps:

To determine the validation of the predictive soil pH and soil EC maps, 25 reprehensive soil profiles (measured data) randomly distributed in the study area were cross validated with predicted soil pH and EC results. The results of this investigation indicated that through using ordinary kriging method and Expotinatil model it is possible to produce highly reliable soil pH and soil EC maps. This is confirmed by the very low values obtained for the determination coefficient (R2) as a precision indicator of the model prediction.

A high linear correlation with a regression coefficient of 0.9868 and 0.9997 for soil pH and soil EC respectively were found between the spatial variation of soil pH and soil EC concentration in the study area (Figure 7 and 8).

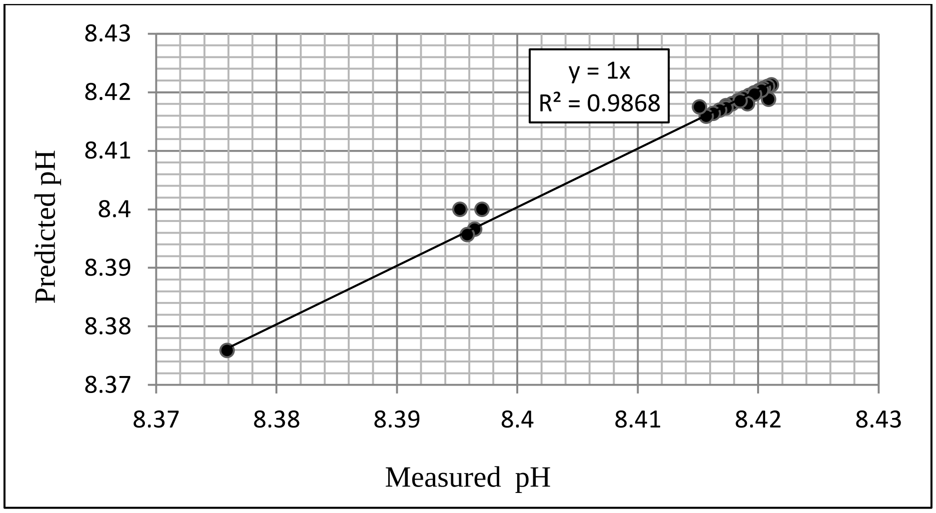

Figure 7. The relationship between measured pH and Predicted pH.

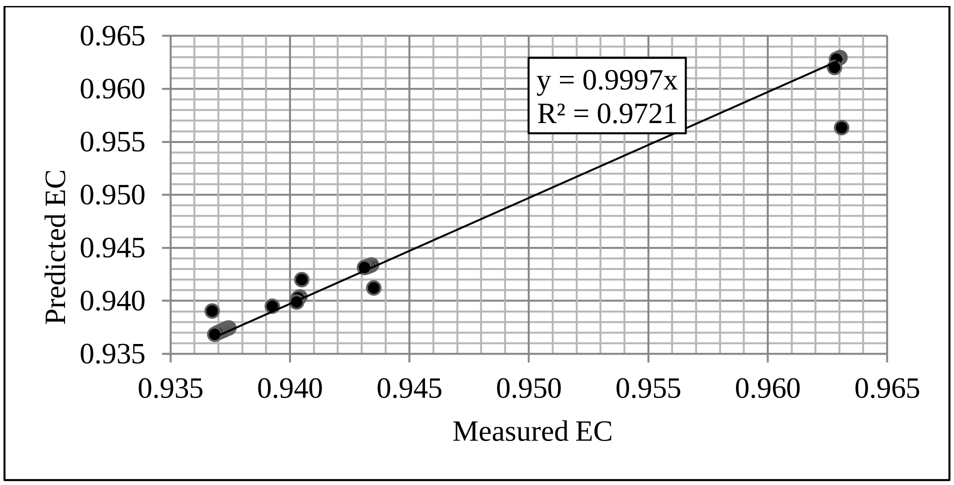

Figure 8. The relationship between measured EC and Predicted EC.

4.. Conclusions

This study emphasizes the efficacy of Ordinary Kriging and Exponential semivariogram models in precisely mapping soil pH and electrical conductivity in the Jeffara Plain region. The results indicated a robust regional dependency for pH and a moderate dependency for EC, confirming the efficacy of OK in predicting soil attributes. According to geostatistical statistics, the spherical model fit for EC and the best, whereas the exponential model fit for pH. This result is consistent with the results of a number of previous studies, such as the study (Salman, et al., 2022 and Tagore, et al., 2022). The prediction maps from the study are essential tools for enhancing soil management methods and increasing agricultural yield. Future research may investigate the incorporation of supplementary soil characteristics to enhance spatial variability models and facilitate sustainable land use planning.

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