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Spatial Analysis of Soil Chemical Properties (pH, EC, and $CaCO_3$%) Using the IDW Method at the Field Scale in Libyan Soil

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A B S T R A C T

Soil chemical properties such as pH, electrical conductivity (EC), and calcium carbonate content ($CaCO_3$%) are important indicators of soil health and fertility, impacting nutrient availability and crop productivity. Accurate mapping of these properties is especially important in arid and semiarid regions, such as Libya, where soil salinity and alkalinity present challenges to agricultural practices. This study assesses the effectiveness of the Inverse Distance Weighting (IDW) method which is a type of spatial interpolation that estimates values at unsampled locations by weighting nearby sampled points based on their distance from the point being estimated. In IDW, closer points have a greater influence on the estimated value, while more distant points contribute less. IDW method is used for interpolating spatial distributions of soil pH, EC, and $CaCO_3$% in a 13,000 square meter area at the Faculty of Agriculture Farm, University of Tripoli, Libya. Using a total of 71 soil samples collected from a depth of 0–30 cm, the spatial variability of these properties through IDW was assessed, a method that estimates values at unsampled locations based on the weighted influence of nearby sampled points. The accuracy of IDW interpolations was evaluated through cross-validation, revealing that IDW provided reliable results for $CaCO_3$%, with R^2 values ranging from 63% to 75%. In contrast, the method demonstrated moderate effectiveness for pH (R^2 values between 41% and 50%) and lower accuracy for EC, with R^2 values as low as 6%. This suggests that soil pH and EC exhibit varying levels of spatial homogeneity, affecting the interpolation accuracy. Alternative methods like Kriging may be more appropriate for EC due to their capacity to account for spatial autocorrelation, a key factor in environmental variables such as soil properties. The findings underscore the importance of selecting appropriate interpolation techniques based on the specific characteristics of soil properties and their spatial distribution.

Key words: Soil salinity (EC) – Soil pH – Soil calcium carbonate content ($CaCO_3$ %) – Spatial or geographical statistics (Geostatistics) – Mapping soil properties – GIS – IDW – Interpolation.

1 Introduction

Soil chemical properties such as pH, electrical conductivity (EC), and calcium carbonate content ($CaCO_3$%) are crucial for understanding soil health and fertility, as they effect nutrient availability and crop productivity (Brady & Weil, 2017). Mapping these properties accurately is needed, particularly in regions like Libya, where soil salinity and alkalinity pose challenges to agriculture (FAO, 2019). Spatial variability in soil properties is driven by factors like soil parent material, climate, and land use, and geostatistical methods, such as Inverse Distance Weighting (IDW), are generally employed to interpolate these properties for spatial distribution maps that assist in precision agriculture (Cambardella et al., 1994; McBratney & Pringle, 1999). Qiu, Cheng, and Wu (2022) also examine IDW's role in assessing soil pH and nutrient patterns across fields, showing how this method improves land management. Furthermore, Banerjee et al. (2023) applied IDW in the Siliguri Sub-Division of India to create soil pH, organic matter, and nutrient maps, demonstrating IDW's value in regions with varying soil parent material and topography. IDW, a deterministic interpolation method, estimates values at unsampled points by weighting the values of nearby sampled points, assuming closer points have more influence (Lu & Wong, 2008). While simple and effective, IDW has limitations, such as sensitivity to sampling distribution and a shortage of consideration for spatial autocorrelation, making methods like Kriging sometimes more accurate (Goovaerts, 1997). However, IDW is frequently used in soil mapping, particularly in data-limited regions (Farahani et al., 2017).

Studies have demonstrated IDW's effectiveness in various agricultural locations. For example, Diacono et al. (2013) used it to map soil pH and EC in Mediterranean fields, and Odeh et al. (1995) mapped soil properties in Australian soils. In Libya, IDW has been used to address issues like salinity and fertility, and recent research has applied it to map pH, EC, and $CaCO_3$% in Northwest Libya, providing valuable insights for soil management (El-Moujabber et al., 2020; Aboukarima et al., 2018). Despite its limitations, IDW remains a practical tool for soil scientists and land managers due to its adaptability and computational efficiency. In **Libyan** soil research by Ghabour et al. (2012) focused on the use of IDW to map soil properties in Libyan fields. Their study stressed the importance of accurate spatial mapping for effective land management in arid and semiarid regions. A more recent study by Ahmed et al. (2020) applied IDW to soil properties at the field scale in Libya, including pH, EC, and $CaCO_3$%. Their findings highlighted the method's effectiveness in providing detailed spatial maps useful for agricultural planning and soil management.

Objectives

Evaluating the spatial distribution of pH, EC, and $CaCO_3$% using the IDW method.
Assessing the accuracy and reliability of the IDW method in mapping these soil chemical properties.
Identifying the optimal parameters (soil sampling number) for the IDW method in the situation of soil property mapping.

2 Materials and Methods

Study Site and Characteristics:
The research site is situated at the Faculty of Agriculture Farm, University of Tripoli, Libya. The site is located in the western part of the farm, as shown in Figure 1. It is bounded to the west by the university road that leads to the southern (Eastern Gate, Salahuddin) entrance, to the north by a farm road that connects to the farm management building from the western gate, to the south by an olive grove, and to the east by a small uncultivated field. The study area extents approximately 13,000 square meters (1.3 hectares).

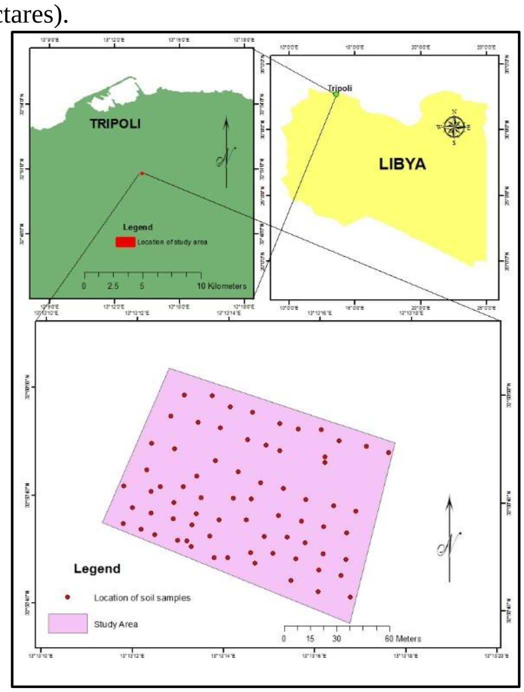


Figure (1) shows the location map of the study area

The topography of the site is mostly flat, with a gentle slope gradient ranging from 0 to 2%, sloping east to west. Roughly half of the southern part of the field is covered with olive trees, while the northern half is lacking of vegetation. The soil in the study area is reddish-brown and free of gravel and stones (Ben-Mahmoud, 1998). The soil formed on wind-deposited parent materials, specifically continental sand deposits, and is characterized as deep, with a light sandy loam texture. It is weakly developed, indicative of a recently formed soil, and contains an Ochric surface horizon, according to the U.S. Soil Taxonomy classification system (Soil Survey Staff, 1999) with no subsurface diagnostic horizons due to limited soil-forming processes.

The primary soil processes involve slight organic matter accumulation on the surface, resulting in the formation of an Ochric horizon and slight calcium carbonate movement within the soil profile (Ben-Mahmoud, 1995; Selkhozpromexport, 1980). The site experiences a Mediterranean climate (Department.M, 2000), and the soil is classified as Xerorthents, a common Mediterranean soil type, according to the U.S. Soil Taxonomy classification system (Soil Survey Staff, 1999).

Soil Sample Collection and Preparation:

The selection of an appropriate soil sampling method is a crucial preliminary step in the interpolation process. Several sampling methods are available, each with distinct advantages and limitations, including Transect, Random, Regular, Contour, Cluster, and Stratified Random sampling (Cochran, W.G., 1977). For this study, the regular sampling technique involves taking samples at fixed intervals across the study area to ensure balanced representation of spatial variability. A GARMIN60CSx GPS device was used to accurately locate sampling points by recording geographic coordinates (latitude and longitude) for each collected sample. Soil samples were collected using an auger at a depth of 0–30 cm. Each sample was labeled with its number, geographic coordinates, depth, and any observations. The samples were immediately transported to the laboratory for preparation and chemical analysis. In the laboratory, the samples were air-dried for 24 hours to remove excess moisture, sieved through a 2 mm sieve, and subsequently oven-dried at 105°C for 24 hours to prepare them for chemical analysis, including soil pH, electrical conductivity (EC), and calcium carbonate content ($CaCO_3$%).

Chemical Analysis of Soil Samples:

Soil pH: The pH of each soil sample (71 samples) was measured using a 1:1 soil-water extract ratio, with a calibrated pH meter. The meter was calibrated using standard buffer solutions of known pH values to ensure accuracy.

Electrical Conductivity (EC): The electrical conductivity was assessed using a 1:1 soil-water extract ratio, measured with an EC meter to determine salt concentrations within the samples The EC meter was calibrated with a 0.01 N KCl solution, which provides a reading of 1.4118 mS/cm at 25°C.

Calcium Carbonate Content: The calcium carbonate content was determined using the back-titration method. An excess of diluted hydrochloric acid (HCl) was added to a measured soil sample, reacting with the carbonates. The unreacted acid was then titrated with a sodium hydroxide (NaOH) solution to determine the remaining acid, allowing for the calculation of $CaCO_3$% in the soil samples. (Rhoades, 1996)

Preparation of Primary Data (Field and Laboratory Analysis Results):

To ensure precise data processing and analysis, the primary field and laboratory results for each soil sample were thoroughly recorded in digital formats. Essential parameters, including sample number, geographic coordinates (latitude and longitude), pH, electrical conductivity (EC), and calcium carbonate content ($CaCO_3$%), were compiled into electronic tables using spreadsheet software. This systematic arrangement allowed efficient data analysis and whole integration into geographic information system (GIS) software for spatial analysis. Digitally structuring data made it easier to manipulate, visualize, and interpret using geostatistical methods.

Each soil sample's pH was measured using a soil-water suspension, EC was determined to reflect the salt concentration, and $CaCO_3$% was calculated through back-titration, providing essential insights into the soil's chemical properties. This structured dataset worked as the foundation for conducting spatial interpolation, enabling a better understanding of soil variability across the study area.

Spatial Statistical Analysis Using the IDW Method:

Spatial analysis of the soil properties was performed using ArcGIS software, utilizing its Geostatistical Analyst extension. This tool facilitated both descriptive and spatial statistical analyses, which are critical for understanding the spatial distribution of soil characteristics across the study site. The software produced interpolated maps for pH, EC, and $CaCO_3$%, effectively visualizing variations within the study area. Additionally, the software evaluated the accuracy of these interpolations by employing cross-validation techniques and error statistics to assess the reliability of the predicted values (ESRI, 2012; Rosenbaum & Ell, 1996).

The spatial statistical approach allowed for the identification of patterns in soil variability, which are important in managing agricultural practices, optimizing resource use, and supporting precision agriculture efforts.

Inverse Distance Weighting (IDW) Method:

The Inverse Distance Weighting (IDW) method was used for the spatial interpolation of un-sampled points based on the values of neighboring measured points. IDW is a deterministic interpolation procedure that assumes that the values of un-sampled locations are more similar to nearby measured points than to those farther away. The method calculates the estimated value at an un-sampled location by assigning weights to each surrounding measured point, with the weights being inversely proportional to the distance between the sampled and un-sampled points.

The IDW equation is expressed as:

$$z(\mathbf{x}) = \sum_i w_i z_i \Big/ \sum_i w_i \quad w_i = 1 \big/ d_i^2$$

Where:

- Z(x): The point to be estimated or predicted.
- Z: The measured point (known).
- di^2: The distance between the measured point and the point to be estimated or predicted.
- Wi: The weight.

A number of factors influence the accuracy and reliability of the IDW method, including: **Distance**: The closer the sampled point is to the un-sampled location, the greater its influence on the predicted value. **Power Parameter (p)**: The value of p determines how quickly the influence of a sampled point reduces with increasing distance. Greater values of **p** give more weight to closer points, resulting in a more localized interpolation. **Number of Samples**: The number of sampled points used in the estimation affects the accuracy of the predicted values. More samples provide a better estimation, especially in areas with high spatial variability.

The IDW method is particularly useful when the distribution of sample points is dense and uniform, and when there is an assumption that spatial autocorrelation (the similarity of points over space) decreases with distance. However, the method does not account for directional trends or anisotropy in the data, which can be limitations in certain circumstances. Despite these constraints, IDW is widely used in environmental and agricultural studies for its simplicity and effectiveness in interpolating spatial data.

In this study, IDW was applied to generate continuous spatial predictions of soil pH, EC, and $CaCO_3$%, allowing for the creation of detailed soil property maps that enhance understanding of the spatial distribution and variability within the study site. These maps are instrumental in informing land management strategies and optimizing agricultural inputs.

3 Results and discussion

Histograms were generated for each dataset to assess their distribution and determine whether they follow a normal distribution, which is important for the application of spatial interpolation techniques like Inverse Distance Weighting (IDW). Outliers were identified and mapped to assess whether they represent legitimate data variation or potential errors in the sampling process. The shape of each histogram was analyzed to check for multimodal distributions, which might indicate different groups or land uses within the dataset, such as water bodies, agricultural land, or forests A series of statistical metrics were calculated, including sample size, minimum and maximum values, mean, median, standard deviation, skewness, kurtosis, and variance, which helped confirm the distribution characteristics and the normality of the soil property data. Table 1 below summarizes the statistical analysis for key soil properties (pH, Electrical Conductivity (EC), and Calcium Carbonate content ($CaCO_3$%)) based on the 71 field samples, providing further details on their distribute

Initiation of Interpolation Processes:

To create continuous surfaces representing the spatial distribution of each soil property, interpolation was conducted using the Inverse Distance Weighting (IDW) method. The IDW method was applied through the Geostatistical Analyst extension in ArcGIS, which facilitated both descriptive and spatial statistical analysis, ultimately producing interpolated maps for pH, EC, and $CaCO_3$%.

Property	pH	EC	%$CaCO_3$
Number of Samples	71	71	71
Min	7.7	0.13	0.25
Max	8.1	0.34	9.75
Median	8	0.202	5.366
Mean	8	0.2	6.25
Skewness	0.17	0.7	-0.311
Kurtosis	2.36	3,47	1.68

Table 1: Statistical Summary of Analysis Data for All Field Samples

The interpolation was performed using different sample sizes: initially, maps were generated using all 71 samples, followed by maps using 75% (53 samples) and 50% (35 samples) of the total samples. This allowed an evaluation of how the number of samples impacted the quality and accuracy of the interpolated maps.

Presentation of Interpolation Results:

The results of the interpolation processes are presented as continuous surface maps for the key soil properties (pH, EC, and $CaCO_3$%). For each interpolation, statistical measures such as the Root Mean Square Error (RMSE), correlation coefficient (r), and coefficient of determination (R^2) were calculated. These metrics were derived through Cross-Validation to assess the accuracy and uncertainty of the interpolation.

Figures 2 through 19 show the results of the interpolation processes, which include nine maps (three for each property: pH, EC, and $CaCO_3$%). These maps were created using the three different sample levels (71, 53, and 35 samples). Alongside the maps, correlation

graphs are provided to evaluate the relationship between the measured and interpolated values.
The following tables (table 2a and 2b) presents the RMSE, correlation coefficient (r), and R^2 values for the different sample sizes used in the interpolation process.

Number of Samples	pH (RMSE)	EC (RMSE)	%$CaCO_3$ (RMSE)
71	0.112	0.02	0.139
53	0.11	0.021	0.145
35	0.139	0.034	0.160

Table 2a: RMSE Values for Interpolated Data

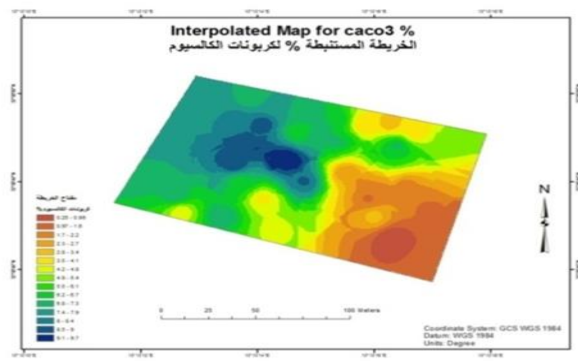
Number of Samples	pH (R^2 %)	EC (R^2 %)	%$CaCO_3$ (R^2 %)
71	48	69	75
53	50	71	70
35	41	64	63

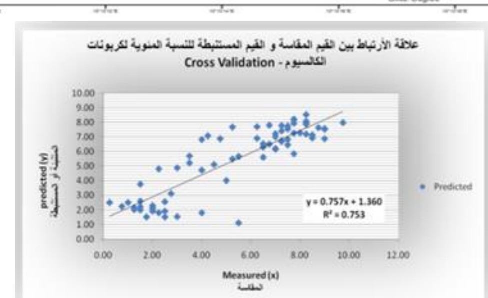
Table 2b: R^2 Values for Interpolated Data

The results in Tables 2a and 2b indicate that the interpolated maps for calcium carbonate (%$CaCO_3$) were the most accurate at all sample levels, with R^2 values ranging from 63% to 75%. In contrast, the maps for salinity (EC) displayed the least accuracy, with R^2 values as low as 6% when only 35 samples were used. The pH maps demonstrated moderate accuracy, with R^2 values ranging from 41% to 50%.
One notable finding is that the smoothness of the interpolated surfaces was not significantly affected by the sample size for most properties, except for the salinity maps derived from only 35 samples, which displayed considerable inaccuracies. This suggests that the IDW method performs well for properties like calcium carbonate but may be less suitable for salinity mapping**.**

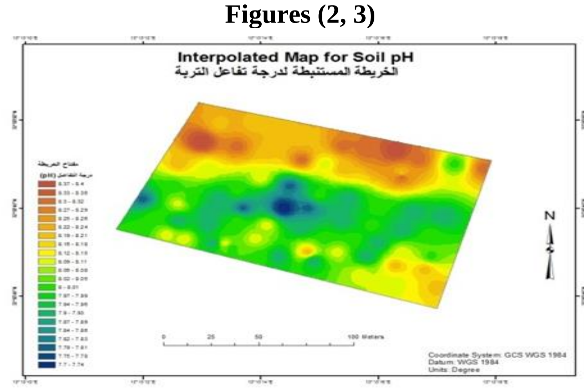
4 Conclusions

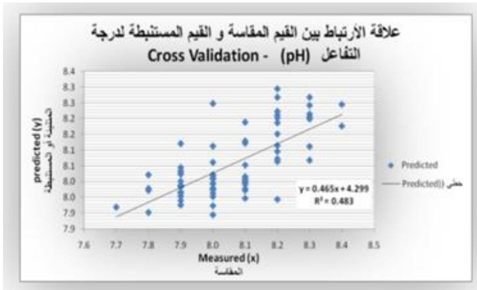
The Inverse Distance Weighting (IDW) method demonstrated strong performance for estimating calcium carbonate ($CaCO_3$) content, showing low RMSE (Root Mean Square Error) and high R^2 values even with smaller sample sizes. This indicates that IDW can be effective for properties like $CaCO_3$ with relatively uniform distribution patterns, making it suitable for similar applications in areas with consistent environmental conditions. The simpler spatial nature of $CaCO_3$ distribution means that IDW's distance-based weighting can accurately capture the variations without requiring more complex spatial models.
However, IDW proved less effective for predicting soil pH values and especially for Electrical Conductivity (EC), where the spatial complexity is significantly higher. Soil pH often exhibits moderate spatial variability due to factors like vegetation, organic matter, and land management practices. In such cases, alternative methods like Kriging may offer better accuracy. Kriging's ability to incorporate spatial autocorrelation allows it to model the influence of both distance and spatial relationship, which can better capture the elusive variations in pH over space.
For Electrical Conductivity (EC), the high spatial variability, often associated with localized salinity concentrations, presents a notable challenge for the IDW method. IDW's limitations become evident as it struggles to accurately capture these fine-scale variations. In contrast, geostatistical methods such as Kriging, which incorporate spatial autocorrelation and account for variability, may be better suited for interpolating EC. These approaches can effectively handle sharp gradients and clustered salinity patterns, providing a more accurate representation of EC distribution.





Figures (2, 3)





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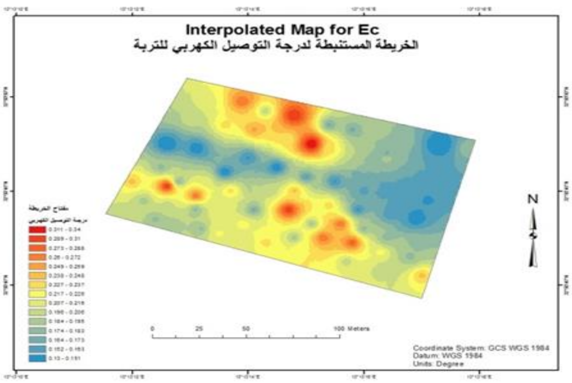
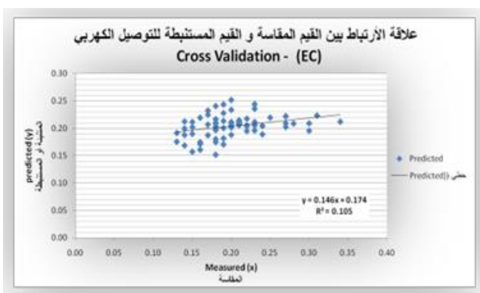
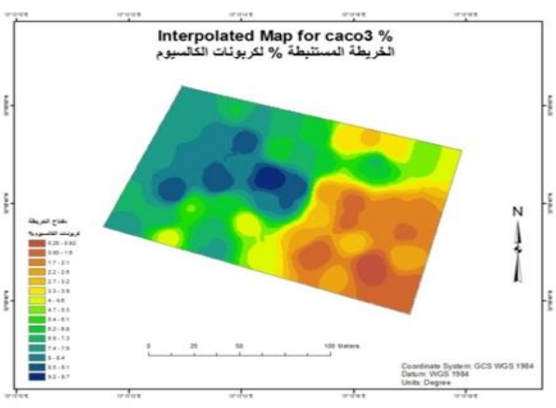
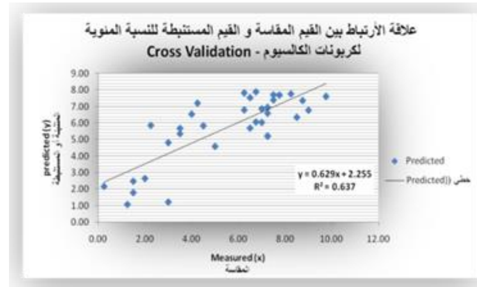




Figures (6, 7)

Interpolation results from 71 measured samples





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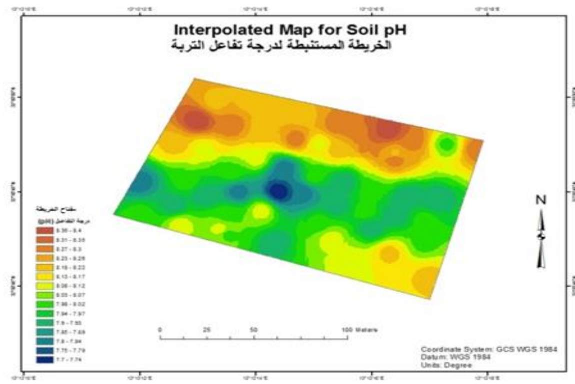

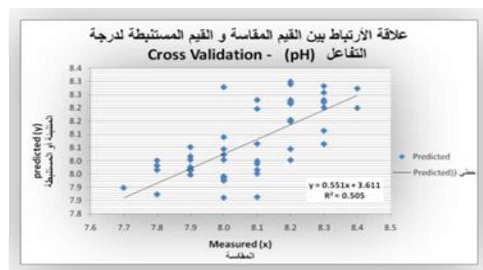

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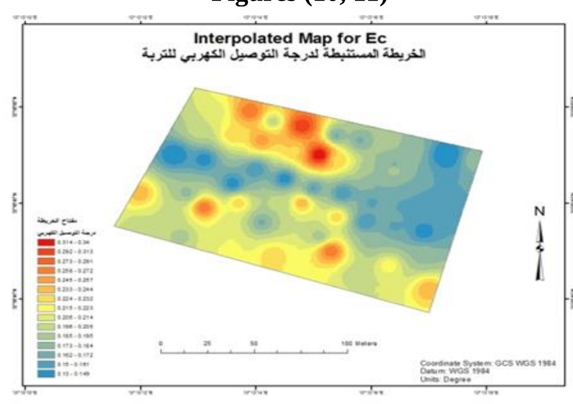
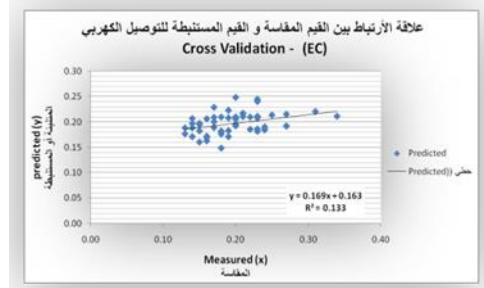
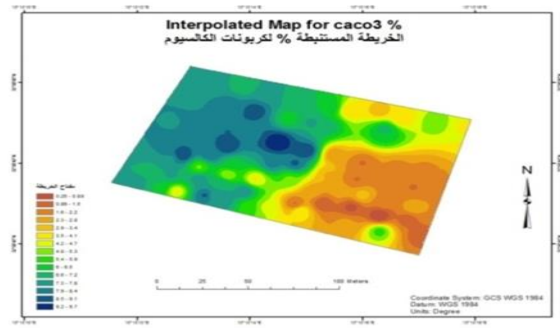
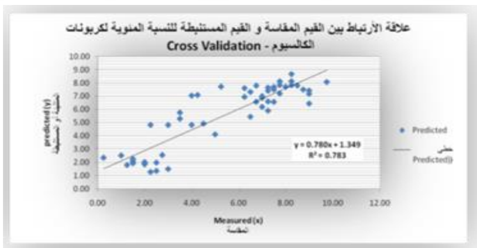




Figures (12, 13)

Interpolation results from 53 measured samples





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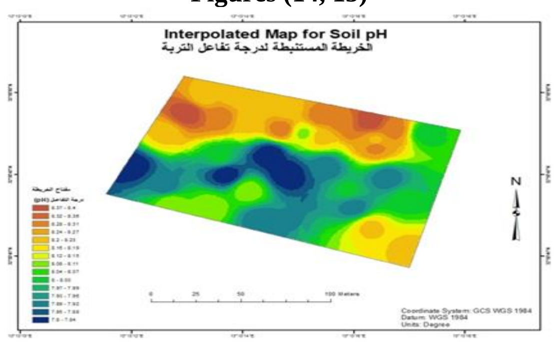

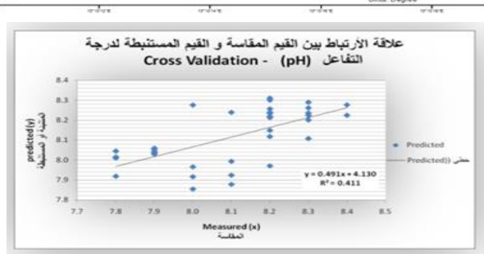

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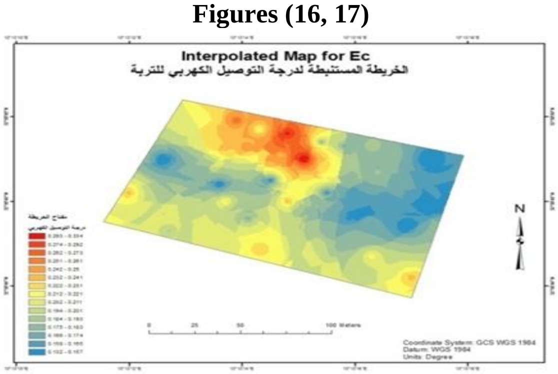

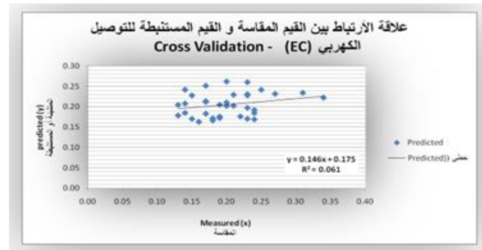

Figures (18, 19)
Interpolation results from 35 measured samples

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