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# Characterization of the Chemical Properties of Deposited Red Clay Soil Using GIS Based Inverse Distance Weighted Method in Kirkuk City, Iraq

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## ABSTRACT

This study focuses on the physical and chemical properties of soils and their geographical distribution, with a specific focus on red clay. The inverse distance weighting (IDW) technique, integrated with Geographic Information Systems (GIS), was employed to predict the chemical characteristics of the soil. Sampling was conducted at twenty-one locations in three areas: Bor Mountain, Jambor, and Kirkuk Hills, all located within Kirkuk City. Seven soil properties were examined: acidity, organic matter content, total dissolved salts (TDS), gypsum, chlorides, and sulfates. The chemical analysis revealed that the soil pH ranged within an acidic range. One sample exhibited a high TDS level. Chloride levels varied within a specific range. The concentration of organic matter in the soil exhibited variability. Sulfur trioxide and gypsum concentrations were found to be below average in the study region. The IDW technique effectively mapped the distribution of the different soil parameters within Kirkuk City, demonstrating a range from good to excellent accuracy. Additionally, a cross-validation method was employed to assess the correlation between the fundamental and investigated chemical properties. The results showed good to excellent degrees of correlation in the different structures studied.

**Keywords:** clay, chemical properties, inverse distance weighting, GIS.

## INTRODUCTION

Clay possesses distinctive physical and chemical characteristics (Nadziakiewicza et al., 2019), making it crucial to comprehend the distribution of soil properties in terms of their physical, chemical, and geographic aspects across various land covers (Pradhan et al., 2017; Bellinaso et al., 2021). Soil properties exhibit spatial variation influenced by both extrinsic factors such as soil management methods, fertilizers, and crop rotation, as well as intrinsic soil formation factors like parent materials. Monitoring the spatial and temporal variability of soil properties requires the utilization of spatial methods, which provide continuous data that would otherwise be challenging to obtain through on-site techniques (Shareef et al., 2020; Hasan et al., 2021). Understanding the spatial distribution of physical and chemical soil properties is important for agricultural, ecological, and environmental management. During soil surveys, physical and chemical features of soil are typically recorded at the component level, enabling the generation of maps that depict their spatial distributions (Zhu et al., 2010; Taqi et al., 2016). However, traditional field surveys and laboratory testing for soil sampling are time-consuming and expensive, particularly for national, regional, or global mapping purposes (Dogan and Kılıç, 2013; Forkuor et al., 2017; Mezaal et al., 2017; Mezaal et al., 2018; Mezaal and Pradhan, 2018). Geostatistics, as an important branch of applied statistics, plays a vital role in describing the spatial characteristics of various features and objects, including soils. It serves as a tool for researching and analyzing the spatial features of georeferenced information (Kerry and Oliver, 2004; Raheem et al., 2022). Considering the complexity of soil features, spatial analysis is crucial for enhancing soil planning and assessments (Raheem and Omar, 2021; Raheem et al., 2022; Raheem et al., 2023). The geographical information system (GIS) is a valuable tool for collecting, displaying, and analyzing topographically related information (Noori et al., 2019; Shareef and Hasan, 2020; Maarez et al., 2022; Ahmed et al., 2022; Mahmoud et al., 2022; Mezaal et al., 2022). The integration of geostatistical methods using GIS enables soil scientists to maintain large databases for mapping different soil property types (Vieira et al., 2007; Liu et al., 2014; Shit et al., 2016). Various physio-chemical soil properties are estimated using different interpolation techniques (Morgan et al., 2017; Mousavi et al., 2017). The inverse distance weighting (IDW) interpolation technique is one of the deterministic interpolation methods. It assumes that the rate of correlations and similarities between neighbors is proportional to their distance from each other and can be described as a distance-reversed function of each point from its neighbors. Inverse distance weighting (IDW) has been widely used to anticipate the regional variability of soil parameters in agricultural activities, although efforts have been made to select the most suitable approach (Shareef et al., 2020; Maarez et al., 2022). Several studies have compared IDW with other interpolation techniques to achieve different parameters. For instance, (Robinson and Metternicht, 2006) used three approaches, including inverse distance weighting, kriging, and spline, to estimate electric conductivity and organic carbon. (Gallichand et al., 1992) investigated and evaluated various interpolation methods for preparing surface soil clays and found that IDW, kriging, and co-kriging approaches are comparable. (Reza et al., 2010) evaluated and incorporated some soil chemical parameters using ordinary kriging and inverse distance weighting methods, reporting that ordinary kriging better explains the spatial variability of various soil parameters, except for available nitrogen, compared to the IDW. When compared to IDW, it sometimes performed better than other GIS techniques in different studies (Zhao et al., 2019; Bel-Lahbib et al., 2023).

The aim of this study is to use the inverse distance weighting technique to produce soil maps that show the different chemical properties of the soil in different places of Kirkuk city.

## MATERIAL AND METHODS

### Location and geologic setting of the study area

The study was conducted in northern Iraq, specifically within the coordinates of 35°10′ and 35°30′ north latitude and 44°00′ and 44°40′ east longitude. The research area is characterized by the presence of three prominent structures surrounding Kirkuk City: the Kirkuk Hills, Bor Mountain, and Jambor Hills. These areas are known for their rugged terrain, making them

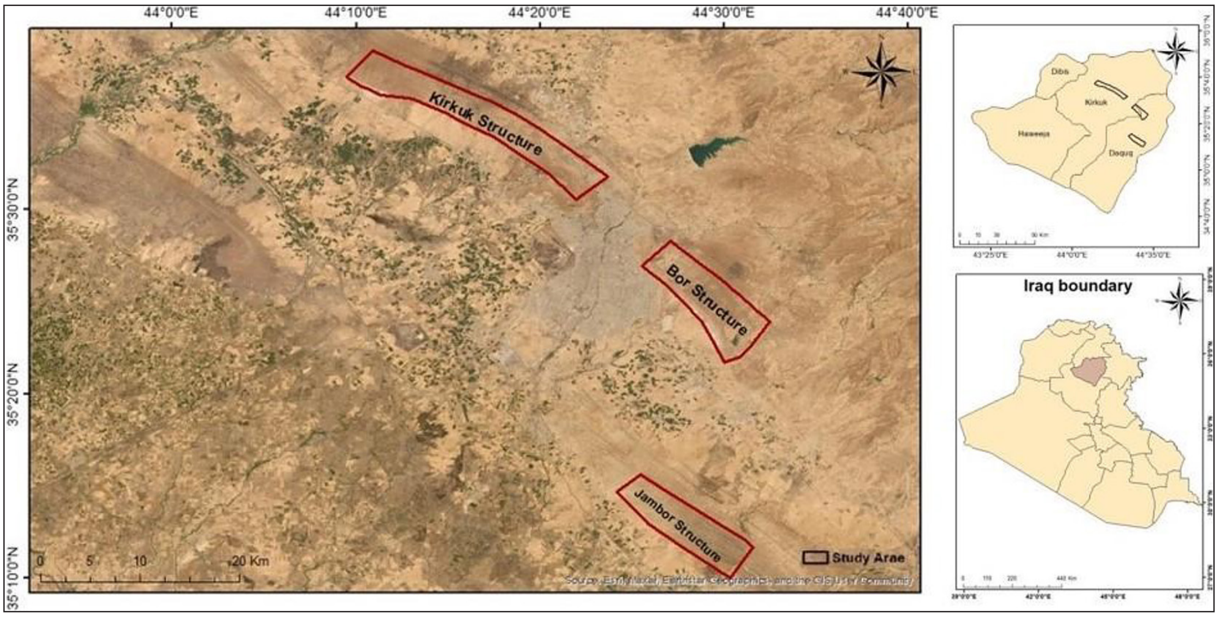


**Figure 1.** Location of the studied area

challenging and costly to access for field testing purposes (Forkuor et al., 2017; Dogan and Kılıç, 2013). A total of 21 soil samples were collected from various observation points distributed across the study area. The sampling points were strategically positioned, forming an irregular network, and were divided into three different sections. Once collected, the soil samples were air-dried and transported to the laboratory for further analysis. The distribution of the sampling stations in the study area is depicted schematically in Figure 1.

Soil samples were collected from a depth of 30 cm, following the removal of the topsoil layer. To facilitate accurate identification of each location, a unique code was assigned to each sampling point. These codes could be used in conjunction with a portable GPS device to precisely determine the coordinates of each location, with an accuracy of approximately ±3.6 units.

In the laboratory, various chemical properties of the soil samples were measured, including pH, electrical conductivity (EC), organic matter content, gypsum content, total dissolved salts (TDS), chloride concentration, and sulfate content. To determine the pH, a pH meter instrument (PCTestr 35) was utilized, providing the hydrogen ion concentration. The electrical conductivity and total dissolved salts of the clay samples were measured using a handheld TDS and EC meter. For the determination of gypsum content, the samples were subjected to a baking process at 150 °C. The percentage of organic matter was calculated through an oven burn at 700 °C, allowing for the estimation of the organic material ratio. Furthermore, chloride concentrations were determined using Mohr's technique, a commonly employed method for measuring chloride levels in soil.

By employing these instruments and techniques, the chemical properties of the soil samples were accurately assessed in the laboratory.

## Interpolation techniques

Spatial interpolation techniques, such as the inverse distance weighting, are geostatistical methods that utilize the concept of spatial autocorrelation. This concept recognizes that neighboring points exhibit greater similarity compared to distant points. These techniques can be categorized as either local or global interpolation methods. Local interpolation techniques estimate the value of an unknown point by analyzing the values of neighboring pixels or sample points. On the other hand, global interpolation methods utilize all available sample points to generate predictions for a single point (Arun, 2013). The effectiveness of spatial interpolation techniques is influenced by various parameters. These parameters include grid size or resolution, stratification, quality of secondary data, variance or normality of the data, and sampling density. Considering these factors is crucial when employing local interpolation techniques like IDW (Li and Heap, 2011).

### *Inverse distance weighting*

The inverse distance weighting is a local interpolation technique used to predict values based on the weighted average of distances between sampled locations and the target point. Each sample site is assigned a weight that is inversely proportional to its distance from the desired location. This ensures that sites closer to the query point have a greater influence on the interpolation process (Arun, 2013, Yao et al., 2013, Almasi et al., 2014).

The formula to determine the unknown value, $Z(X)$, at index $X$, is as follows:

$$Z(X) = \sum_{i=1}^{N} W_I \, Z(X_I) \tag{1}$$

where: $Z(X)$ – the value measured at each sampling site;
$n$ – the number of monitoring stations;
$W_I$ – the weight given to $X_I$, defined as:

$$W_I = \frac{\frac{1}{d_j^k}}{\left(\sum_{i=1}^{n} \frac{1}{d_j^k}\right)} \tag{2}$$

where: $d_j$ – the horizontal distance between the interpolation sites and the observed positions, and $k$ represents the distance power (Yang et al., 2020).

## Chemical properties of soil

### *Potential of hydrogen*

The pH of a solution represents the acidity or alkalinity and is determined by the inverse logarithm of the concentration of hydrogen ions per molecule (Sulyman et al., 2020). pH plays a significant role in nutrient availability for plants, thereby influencing plant growth. Soil pH is typically measured within the range of 4 to 10 (Sulyman et al., 2020; Al-Abbas and Jinnah, 2019). It can be adjusted by incorporating alkaline materials like limestone or granite, or acidic substances such as sulfuric acid (Sulyman et al., 2020; Carter and Gregorich, 2007; McLean, 1983). Several factors influence soil pH, including the presence and concentration of salts, carbonate ions, and carbonate in water (Sulyman et al., 2020).

### *Electrical conductivity*

Electrical conductivity is a parameter that indicates the ability of a substance to conduct electricity when subjected to an electric field. In wet geomaterials, such as soils, the movement of ions in the pore space is the main mechanism responsible for electrical conduction (Klein and Santamarina, 2003). Soil salinity can arise from various sources, including shallow groundwater, irrigation practices, wind and storms carrying salt from nearby regions, and the weathering of minerals present in the Earth's crust (Hendry et al., 1993; Sulyman et al., 2020).

### *Organic material ratio*

The soil's acidity, influenced by factors such as soil composition, temperature, and water dispersion, can have an impact on the quantity of organic matter present (Buee et al., 2007).

Organic matter in soil can be broadly categorized into two types. The first type consists of plant and animal residues that are either fresh or partially decomposed, retaining some physical characteristics that can be linked to their origin. The second type is humus, which forms as a result of decomposition and is more resistant to further breakdown due to its colloidal nature (Balasubramanian, 2017).

### *Gypsum*

The presence of white or gray substances in the soil, such as oxides, can indicate their solubility in groundwater. Among these substances, gypsum is particularly susceptible to leaching, which can significantly impact soil properties (Arutyunyan and Manukyan, 1982; Sulyman et al., 2020). When the gypsum content exceeds 5%, it can have a detrimental effect on the soil quality. However, the specific threshold varies depending on factors such as soil type, particle size distribution, fineness of the gypsum component, and the presence of other salts (Kuttah and Sato, 2015). Achieving optimal soil performance requires maintaining an appropriate concentration of gypsum.

### *Total dissolved salts ratio*

The salinity ratio is a measure of the amount of water-soluble salt present in the soil relative to the total amount of soil. The solubility of salts in water can vary depending on their chemical composition. Environmental factors such as pH, temperature, dissolved carbon dioxide ($CO_2$), evaporation, and moisture can influence the solubility of substances in the soil (Sulyman et al., 2020; Ali et al., 2023).

### *Chloride*

Chlorides can be found in the soil through the dissolution of various salts in water. The soil naturally contains chlorides, but it is important to maintain chloride levels below 0.02 percent for optimal plant growth. Chlorine salts, which are highly soluble in water, have the ability to alter the physical properties of the soil (Sulyman et al., 2020). The chloride content in soil can be influenced by various factors, including the composition of the parent bedrock, rainfall, irrigation water, fertilization practices, human activities, contributions from basin brines or saline springs, and saltwater intrusion caused by pumping (Geilfus, 2019). Precipitation, irrigation water, nutrient inputs, and human activities can all contribute to the chloride content of the soil.

### *Sulfate trioxide*

Sulfate, a chemical compound, can be found naturally as a mineral and is easily obtained in its purest form with minimal effort. Its presence in the environment is largely influenced by human activities on land and in the atmosphere. The primary source of sulfate is sulfur released through the erosion of evaporate deposits. Additionally, sulfate can originate from rocks and minerals containing sulfide, as well as volcanic activity (Sulyman et al., 2020).

## RESULTS AND DISCUSSION

### Laboratory and statistical analysis

The chemical properties of the measured soil in the studied region have been summarized in Table 1, based on statistical analysis of 21 sampling points. The gypsum content ranged from 0.253% to 41.8814%. The highest gypsum ratio of 41.88% was observed in the Fatha formation within the Kirkuk structure, where gypsum layers are present in various locations and layers. There was a positive relationship between gypsum and sulfate, with sulfate levels ranging from 0.118% to 19.279%, and an average of 3.18%. The Fatha formation in the Kirkuk structure exhibited the highest sulfate value of 19.4749%. The low sulfur percentage can be attributed to the scarcity of sulfur in gypsum, anhydrite, and claystone, as indicated by (Al-Bassam, 2012). The pH values ranged from 6.42 to 7.5, with an average of 6.9. The Jambor structure showed acidic pH levels, ranging from 6.42 to 6.87. The highest pH value was observed in the Injana Formation within the Kirkuk structure, suggesting an increasing trend in pH towards the northern part of Kirkuk, with values ranging from 6.8 to 7.5. Total dissolved solids ranged from 0.745% to 18.8%. The highest TDS value of 18.8% was found in the Injana Formation within the Jambor structure. The TDS value decreased as we moved northward in Kirkuk. Electrical conductivity values ranged from 127 to 2673, with an average of 746. TDS percentage was correlated with EC percentage. The organic matter content in the study area ranged from 0.2% to 6.7%, with an average of 3.9%. The Injana formation within the Kirkuk structure exhibited a higher ratio of organic matter, while the Bor structure showed a lower ratio. The chloride ratio was generally very low across all study areas, ranging from 0.001% to 0.125%, with an average of 0.025%. The chloride content in the Injana Formation ranged from 0.01% to 0.05%

## Spatial analysis based IDW

The distribution of soil properties in the Kirkuk, Bor, and Jambor structures was predicted using the interpolation method known as inverse distance weighting. Seven soil characteristics, including pH, organic matter, total dissolved salts, gypsum, chlorides, electrical conductivity, and sulfates, were analyzed based on data collected from twenty-one locations.

Figure 2 shows the IDW study results for pH levels across the studied region. The pH values in the Kirkuk and Bor structures ranged from 6.74 to 7.5, while the Jambor structures exhibited values between 6.43 and 6.87. The data indicate that the soil pH tends to be acidic in most parts of the region, which is attributed to the presence of red clay soils. The acidity is caused by the leaching of calcium due to precipitation, resulting in increased solution acidity.

**Table 1.** The chemical properties of red clay

| Sample | Formation | Structure | Gypsum, % | Sulfate, % | pH | TDS, % | EC | Organic material, % | Chloride, % |
|---|---|---|---|---|---|---|---|---|---|
| A1 | Injana | Kirkuk | 2.5853 | 1.2025 | 7.5 | 2.3 | 450 | 3.4110 | 0.0125 |
| A4 | Injana | Kirkuk | 3.4232 | 1.5922 | 7.5 | 2 | 400 | 5.2915 | 0.0138 |
| A7 | Fatha | Kirkuk | 41.8814 | 19.4797 | 6.8 | 8.8 | 1781 | 4.5057 | 0.0113 |
| M1 | Fatha | Kirkuk | 3.9632 | 1.8433 | 6.8 | 4.22 | 844 | 6.0574 | 0.01 |
| M2 | Injana | Kirkuk | 4.3139 | 2.0065 | 7.1 | 7 | 1400 | 6.7065 | 0.025 |
| S1 | Injana | Kirkuk | 3.0919 | 1.4381 | 7.1 | 4.59 | 910 | 4.5866 | 0.0375 |
| S6 | Injana | Kirkuk | 2.7519 | 1.2799 | 7.1 | 2.98 | 595 | 6.0922 | 0.0138 |
| SS3 | Injana | Kirkuk | 2.9823 | 1.3871 | 7 | 4.42 | 890 | 5.5051 | 0.015 |
| D1 | Injana | Jambor | 0.571 | 0.266 | 6.87 | 0.975 | 174 | 0.74 | 0.009 |
| D2 | Injana | Jambor | 1.7630 | 0.82 | 6.6 | 2.065 | 398 | 0.89 | 0.003 |
| D3 | Injana | Jambor | 10.470 | 4.87 | 6.42 | 13.112 | 2673 | 1 | 0.018 |
| D6 | Fatha | Jambor | 12.6472 | 5.8824 | 6.7 | 10.5 | 2100 | 4.3089 | 0.025 |
| D7 | Injana | Jambor | 7.1926 | 3.3454 | 6.8 | 18.8 | 3900 | 5.8003 | 0.125 |
| DD4 | Fatha | Jambor | 19.1154 | 8.8909 | 6.8 | 12.2 | 2450 | 5.7153 | 0.05 |
| P1 | Injana | Bor | 7.3180 | 3.404 | 6.7 | 8.845 | 1795 | 0.4 | 0.001 |
| P2 | Injana | Bor | 0.253 | 0.118 | 7.48 | 0.745 | 127 | 0.89 | 0.004 |
| P3 | Injana | Bor | 1.9150 | 0.891 | 6.9 | 4.13 | 824 | 0.2 | 0.004 |
| P4 | Fatha | Bor | 3.2509 | 1.5121 | 7 | 4.32 | 870 | 4.7052 | 0.0125 |
| P8 | Fatha | Bor | 4.7731 | 2.2200 | 7.2 | 2.36 | 470 | 5.4835 | 0.01125 |
| P13 | Injana | Bor | 3.0819 | 1.4335 | 7.4 | 2.25 | 451 | 5.1740 | 0.01 |
| P17 | Injana | Bor | 6.093 | 2.8340 | 6.8 | 10.06 | 2020 | 4.5457 | 0.02 |

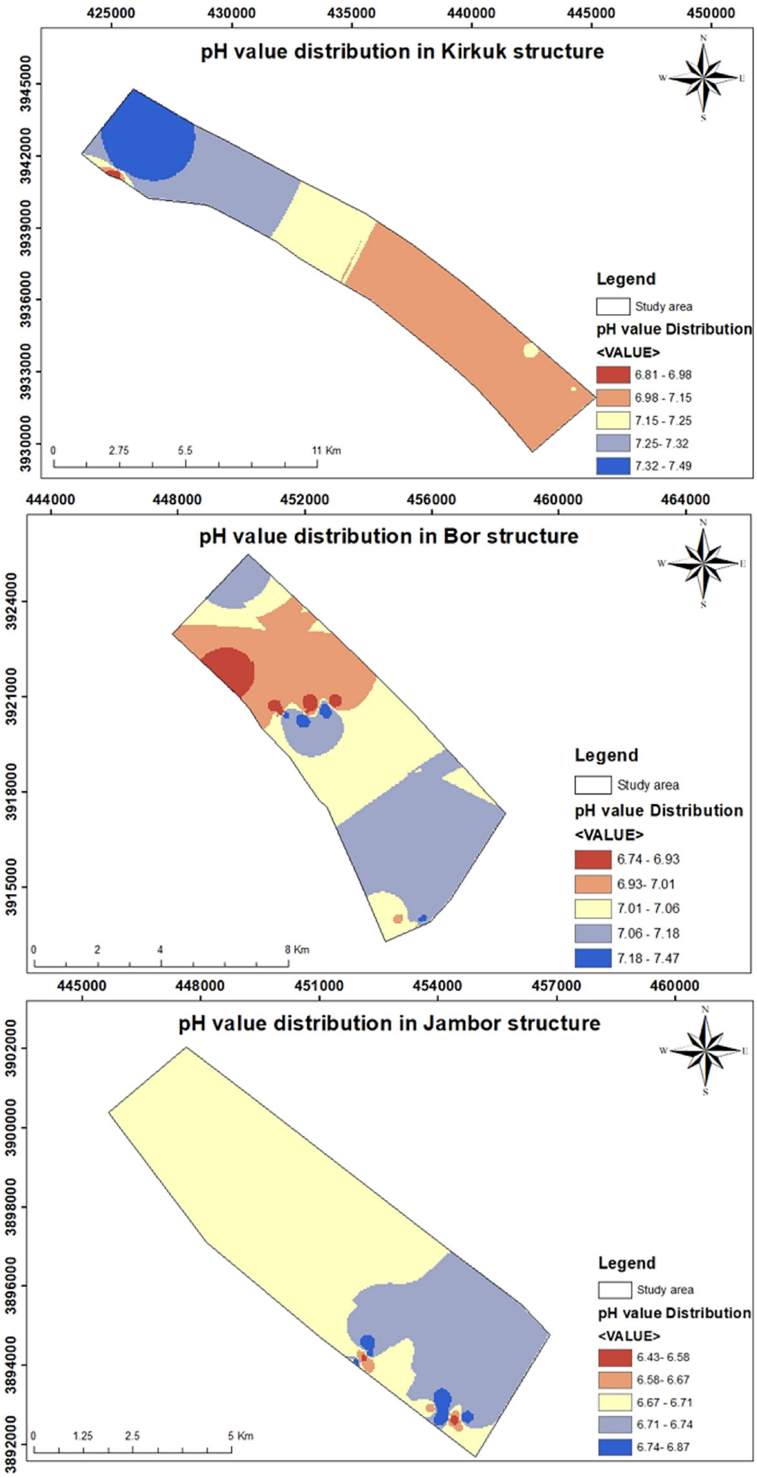


**Figure 2.** IDW representation of pH value

Figure 3 displays the distribution pattern of electrical conductivity obtained from the IDW analysis. The Kirkuk structure exhibited a range of 404 to 1794 S/cm, the Bor structure ranged from 151 to 2006 S/cm, and the Jambor structure ranged from 217 to 3888 S/cm. The variations in electrical conductivity levels indicate differences in soil salinity across the structures.

The IDW analysis findings for organic matter distribution are presented in Figure 4. In the Kirkuk structure, organic matter content ranged from 3.43% to 6.09%, while in the Bor structure, it varied from 0.24% to 6.7%. The Jambor structure exhibited a range of 0.79% to 5.78%. Fine-textured soils such as clay and silt loams tend to have higher organic matter content

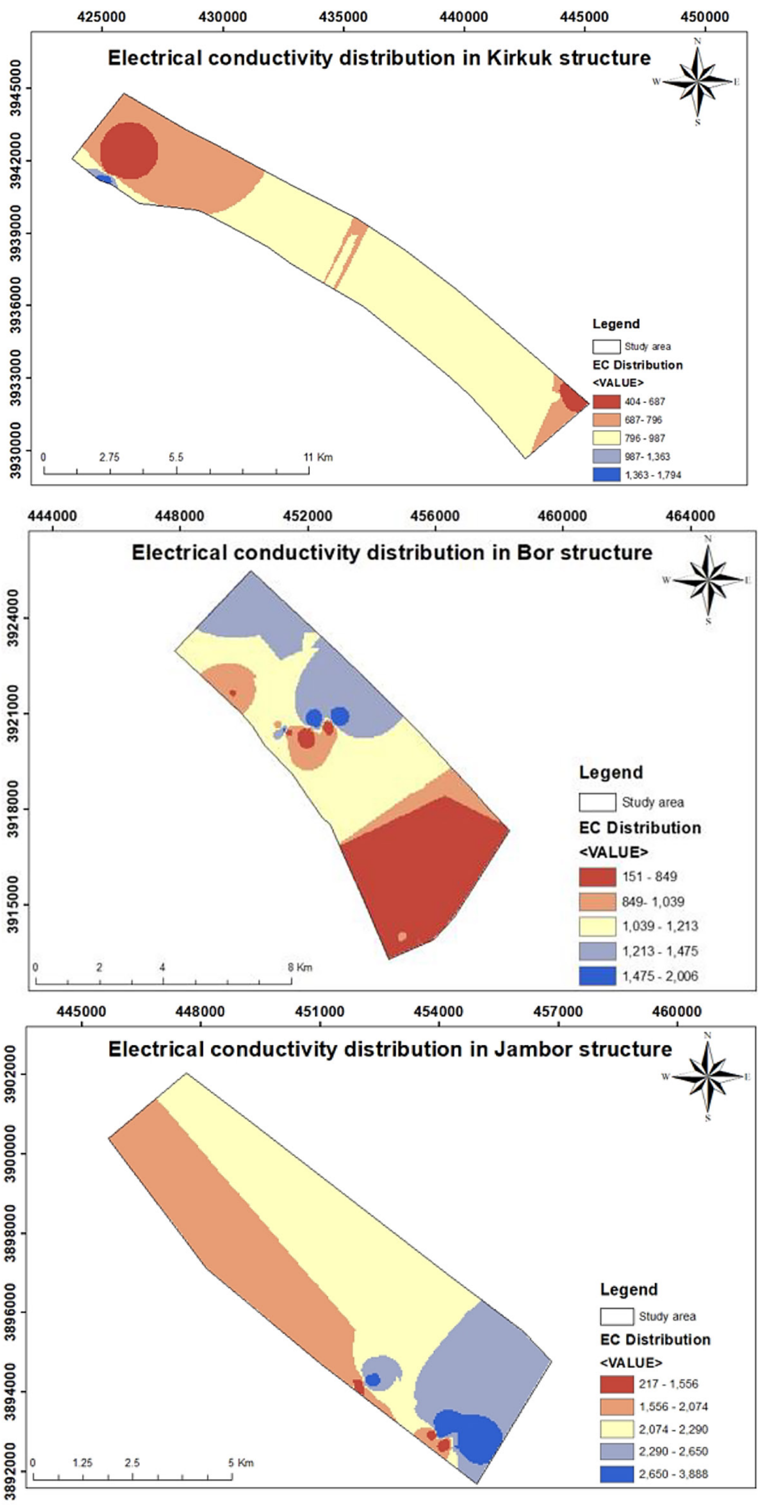


**Figure 3.** IDW representation of electrical conductivity

compared to coarser-textured soils like sands and sandy loams.

Figure 5 illustrates the distribution of total soluble salts obtained from the IDW analysis. The Kirkuk structure had a TDS percentage range of 2.04% to 8.84%, the Bor structure ranged from 0.86% to 9.99%, and the Jambor structure ranged from 1.19% to 18.75%. Salinity in soils can arise from the release of ions during weathering processes and atmospheric depositions from various sources.

The geographical distribution of chloride contents is shown in Figure 6. The Kirkuk and Bor structures exhibited chloride content ranging from

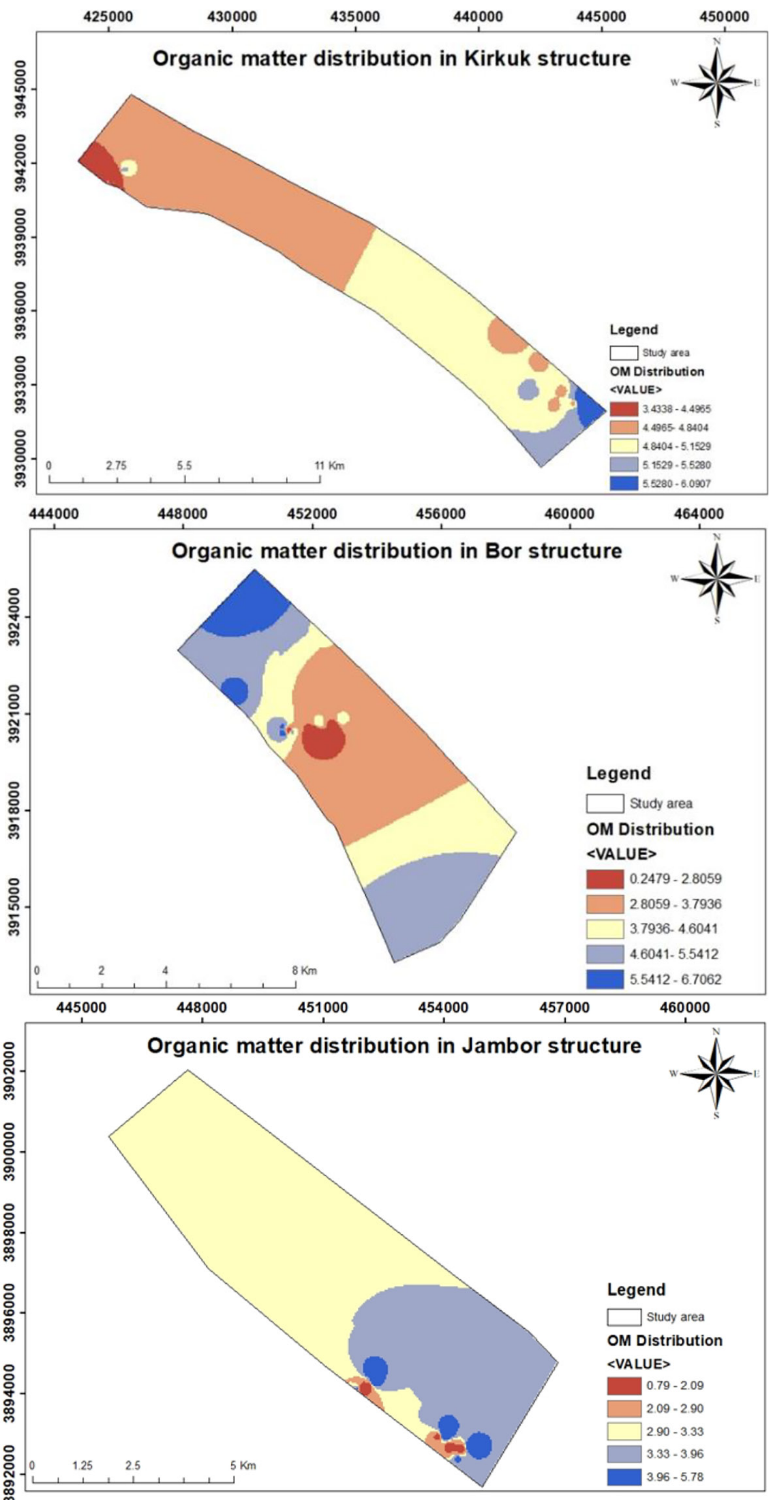


**Figure 4.** IDW representation of organic matter

0.00113% to 0.0379%, while the Jambor structure ranged from 0% to 0.12%. Chlorine content can significantly impact soil fertility, and human activities often contribute to excessive accumulation of chloride anions in soils (Geilfus, 2019).

Figure 7 displays the dispersion of gypsum across the structures. In the Kirkuk structure, gypsum content ranged from 2.686% to 41.4836%, in the Bor structure it ranged from 0.3258% to 7.0360%, and in the Jambor structure, it ranged from 0.7% to 18.73%. Gypsum is commonly found in various locations, except for a few limited areas.

The outcome of the sulfate trioxide dispersion is presented in Figure 8, with a range of 0.1537% to 19.3395%. The examined region generally exhibited lower levels of sulfate trioxide content.

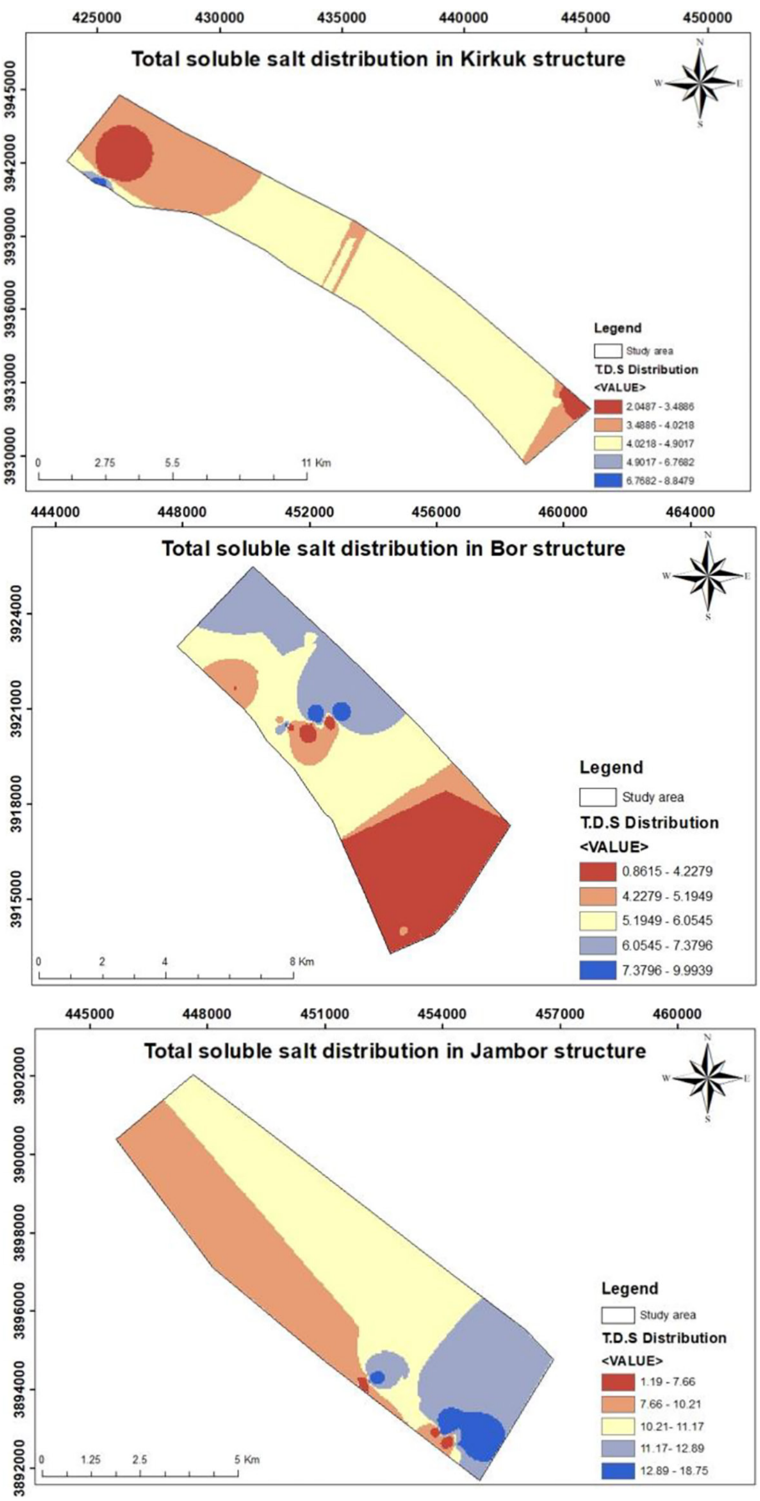


**Figure 5.** IDW representation of total dissolved salt

## Validation and accuracy assessment

In order to assess the accuracy of different interpolation techniques, the cross-validation method is employed. This involves testing the estimation approach at the locations of known samples. At a specific position, the sample value is temporarily excluded from the dataset, and the value at that location is then calculated using the remaining samples. The estimated value is compared to the actual sample value that was previously omitted from the dataset. This process is repeated for each available sample. Once completed, statistical methods are used to compare the actual and estimated values. To evaluate the accuracy of each interpolation technique, the

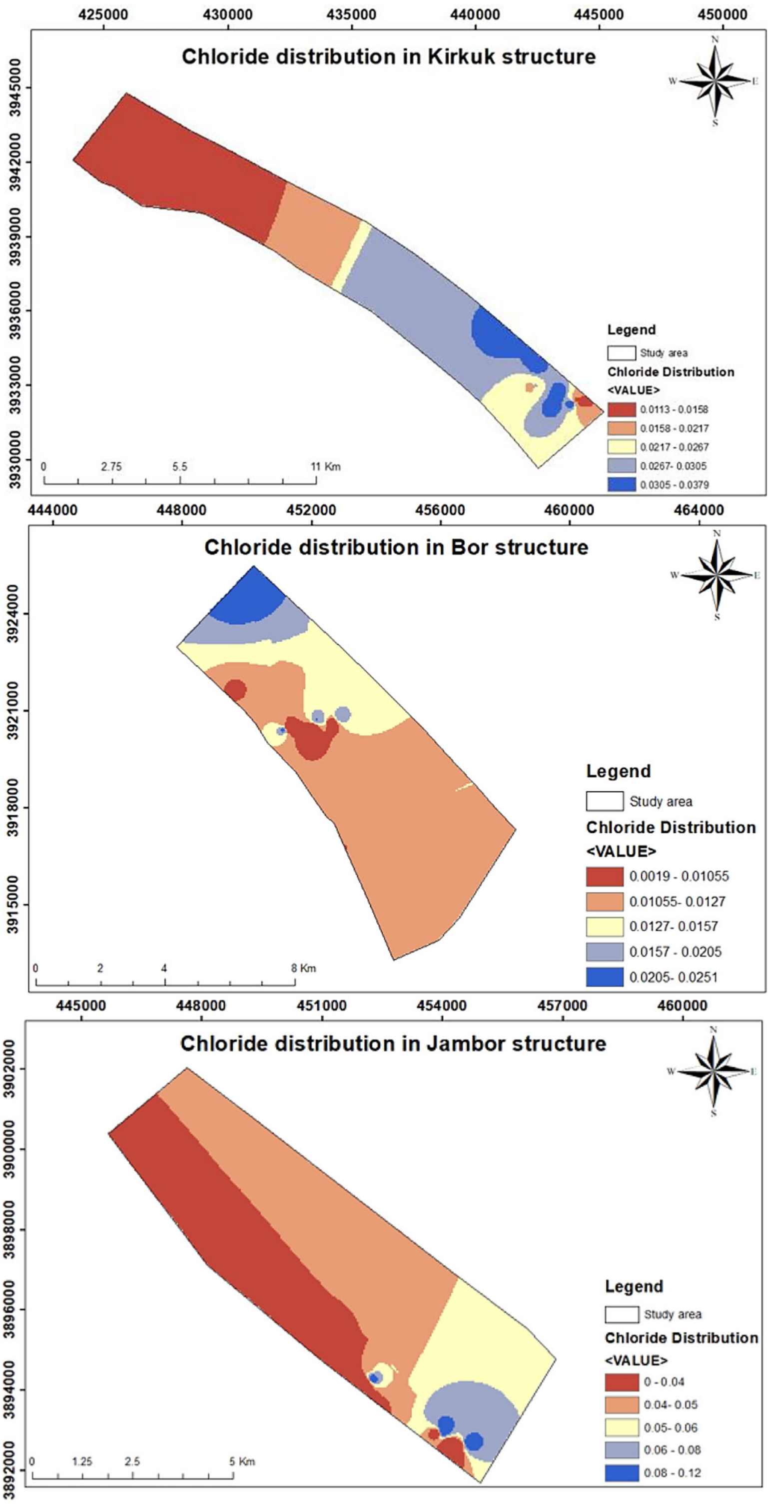


**Figure 6.** IDW representation of chloride

error between the estimated and actual values is determined (Ding et al., 2011; Yao et al., 2013). The root mean squared error (RMSE) is considered a crucial criterion for cross-validation. This criterion takes into account both stationary points and extremes, and it can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_i - Z)^2} \quad (3)$$

The result of the RMSE and $R^2$ shown in Table 2.

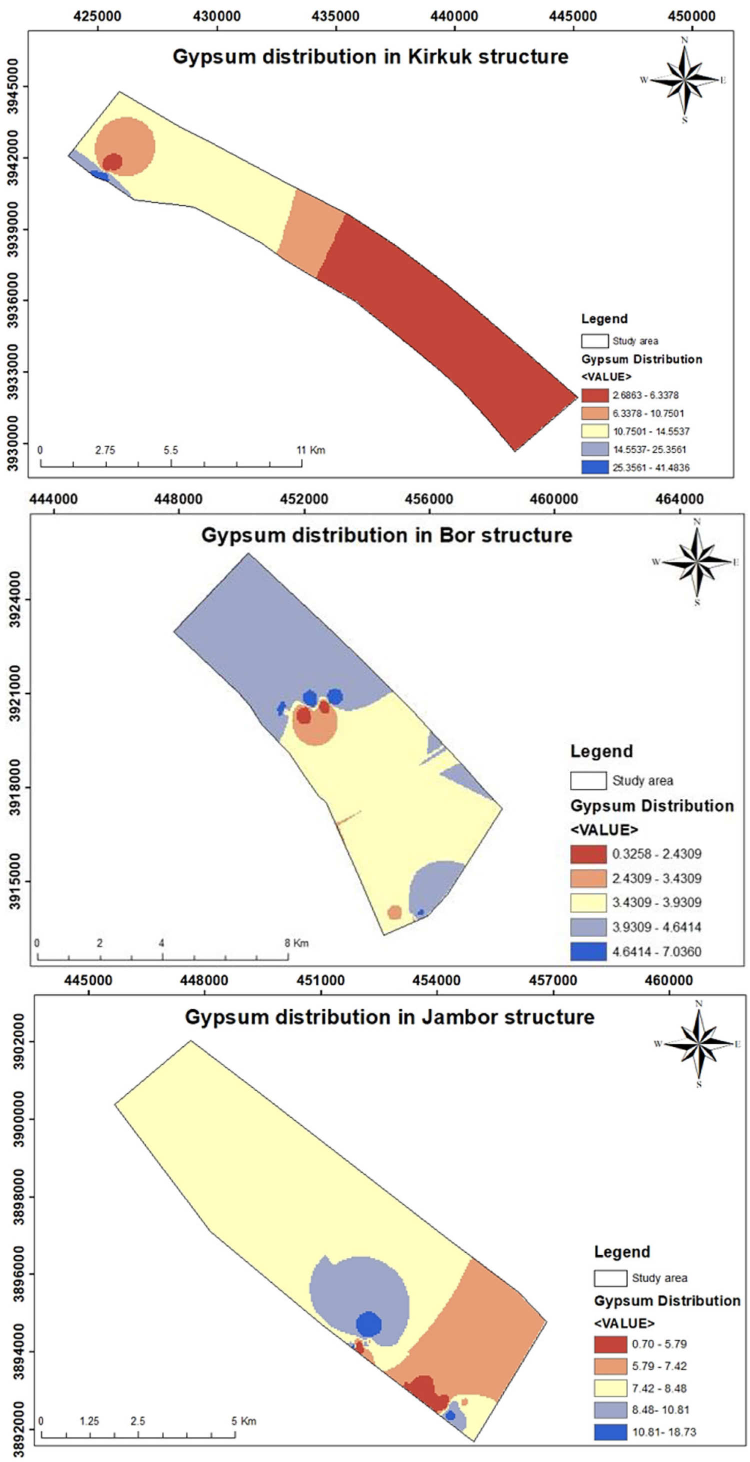


**Figure 7.** IDW representation of gypsum

**Table 2.** The root mean squared error (RMSE) and $R^2$ for maps

| Chemical properties | Kirkuk hills | | Bor mountain | | Jambor hills | |
|---|---|---|---|---|---|---|
| | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ |
| pH | 0.0075 | 0.91 | 0.0149 | 0.894 | 0.029 | 0.872 |
| Gypsum | 0.027 | 0.88 | 0.021 | 0.884 | 0.059 | 0.85 |
| Sulfate | 0.013 | 0.897 | 0.008 | 0.907 | 0.077 | 0.827 |
| TDS | 0.022 | 0.883 | 0.12 | 0.795 | 0.064 | 0.843 |
| Chloride | 0.0011 | 0.93 | 0.0004 | 0.95 | 0.0018 | 0.923 |
| EC | 0.28 | 0.77 | 0.45 | 0.74 | 0.39 | 0.76 |
| Organic | 0.018 | 0.886 | 0.059 | 0.85 | 0.062 | 0.845 |

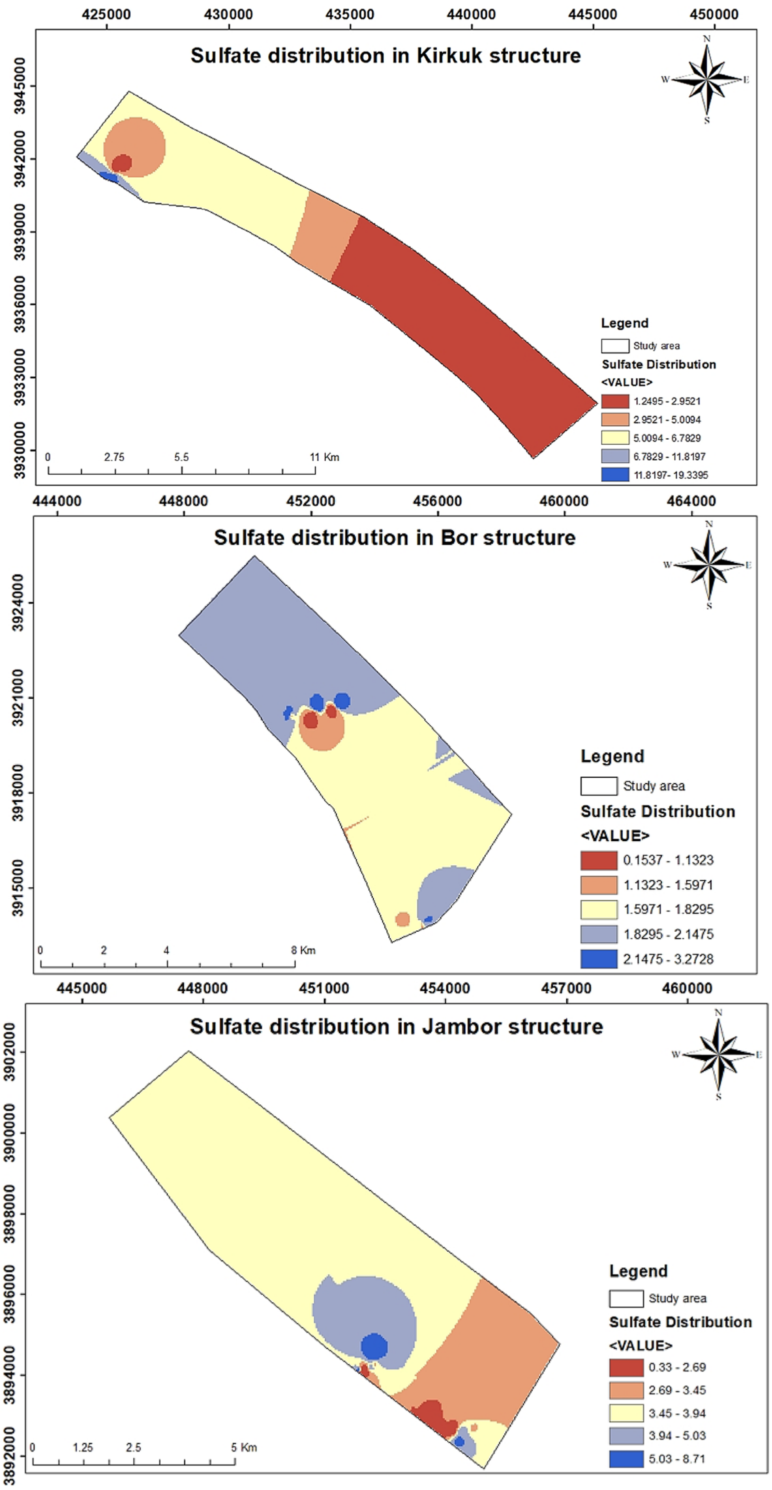


**Figure 8.** IDW representation of sulfate

## CONCLUSIONS

The present study showcased the remarkable capabilities of geographic information systems and geostatistical systems in spatially analyzing and zoning various chemical properties of soil. The investigated variables exhibited distinct spatial structures, as evidenced by the cross-validation fitting results, making them well-suited for assessing changes in the researched attributes. Across all soil chemical parameters, the lowest mean bias error and highest coefficient of determination (R square) were achieved, indicating the excellent performance of the interpolation techniques employed. Particularly, in zoning the properties within Kirkuk city, the inverse distance weighting method proved to be a suitable estimator, considering the applied error indices.

The spatial correlation analysis utilizing IDW interpolation shed light on the distribution patterns of soil properties. The pH levels were generally found to be acidic throughout the region, with variations observed across different structures such as Kirkuk, Bor, and Jambor. Electrical conductivity exhibited variations across these structures, suggesting disparities in soil's conductivity. The organic matter content displayed variations across different structures, with higher concentrations observed in fine-textured soils. Total dissolved salts showed variations across the structures, each with its distinct range. Chloride contents were relatively low overall, with variations observed among the different structures. The distribution of gypsum and sulfate content also varied across the structures, each exhibiting its specific range.

In conclusion, this study provides valuable insights into the chemical properties of red clay soil in the examined region. It highlights the variations in gypsum, sulfate, pH, TDS, EC, organic matter, and chloride content across different structures. The utilization of IDW analysis helps visualize the spatial distribution patterns of these soil properties. The accuracy assessment of the interpolation techniques affirms the reliability of the predicted values, further enhancing our understanding of the soil characteristics in the area.

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