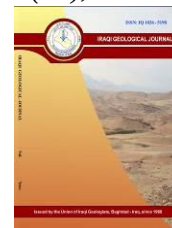




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GIS-Based Spatial Interpolation Approaches for Soil Parameter Assessment: A Case Study from the Taza Khurmatu District, Kirkuk Governorate, Northern Iraq

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Abstract

Geotechnical applications, land management, and land use planning are generally concerned with the soil parameters of the studied areas in order to enable efficient land use. This study used an interpolation technique using Geographic Information System analysis to evaluate the quickly developing Taza Khurmatu District, southern Kirkuk Governorate. A total of thirty samples from different locations within the study area were analyzed using Inverse Distance Weighting and spline interpolation with a 10 x 8 m pixel size as the primary techniques. These techniques are used to find out about some of the most important soil characteristics such as density, moisture content, Liquid Limit, Plastic Limit, Plastic Index, and grain size. Weighted distance measurements for the various sampling techniques have been obtained utilizing the Inverse Distance Weighting technique, which assesses these parameters correctly. Several statistical indicators describing the precision of interpolated surfaces were used, including Root Mean Squared Error, Mean Absolute Error, together with the determination of the R^2 factor. In addition, Inverse Distance Weighting demonstrated high reliability in the parametric estimation of soil density and gravel content variations because these parameters showed substantial local variations. Inverse Distance Weighting demonstrated reliable performance in estimating soil characterization parameters since dry density delivered Root Mean Squared Error values of 0.21 along with R^2 of 0.87, and gravel content reached Root Mean Squared Error levels of 2.12 and R^2 of 0.90, indicating efficient local spatial structures depiction. The Spline interpolation generated precise modeling results for plastic index and clay content because it produced an Root Mean Squared Error of 2.34 and R^2 of 0.88 while effectively modeling smooth spatial transitions. Results from the current study validate how Geographic Information System-based interpolation techniques develop extensive soil property models for southern Kirkuk, which benefits environmental and urban planning operations. In addition to soil properties prediction, future applications should aim at expanding the number and size of the sample, including terrain attributes, and fitting satellite imagery and AI based models to increase the accuracy of the modeling of the generated maps.

Keywords: Geographic Information System (GIS); Physical characteristics; Taza Khurmatu; Interpolation

1. Introduction

The economic effectiveness of land utilization and agriculture is significantly influenced by the quality of land resources, which are, in turn, restricted by the fertility of the soil (Myslyva et al., 2019). Soil texture influences numerous chemical and physical characteristics, such as permeability, adsorption

and absorption characteristics, cation exchange capacity, moisture retention, and soil fertility, and conducting soil property mapping in remote locations via conventional survey methods is challenging and costly (McBratney et al., 2003; Makabe et al., 2009; Akumu et al., 2015). The physical characteristics of soil include soil texture, soil wetness, and soil permeability, whereas the chemical characteristics of soil involve inorganic compounds and pH levels and the presence of numerous inorganic chemicals, such as potassium, magnesium, and zinc (Das and Sobhan, 2014; Manikandababu and Pandian, 2016).

Soil management necessitates thorough soil property examination, fundamentally using the ground measurement for evaluating soil texture; however, these approaches can be costly, labor-intensive, and inefficient because they measure temporal and spatial changes in soil moisture quite poorly. Scientific research has been extensively discussed in the development of remote sensing (RS) products, to enhance accuracy and monitor spatial and temporal coverage of observation under assessment of water resources management and hydrological application (Baghdadi et al., 2016; Ali et al., 2024a).

However, enhanced by the developments in remote sensing, modeling, and Geographic Information Systems (GISs), it has become possible to predict soil properties across landscapes, particularly inaccessible in the past (Akumu et al., 2015). In addition, the use of traditional methods for the indirect determination of soil properties from remote sensing data involves regression analysis models, geostatistical techniques, and information can be categorized, interpreted, and recorded in databases using GIS techniques (Esetlili and Kurucu, 2016; Sridevy et al., 2023).

Soil characterization is important in geotechnical engineering, agricultural planning and management, and sustainable development, especially in areas under intense urbanization. Recent studies have shown the potential of combining GIS and spatial interpolation techniques to map and evaluate soil variability on different landforms. In the study done in Kirkuk City, Inverse Distance Weighting (IDW) was utilized to predict HV red clay soils, which correctly identified chemical contents such as pH, TDS, gypsum, and chlorides (Salahalden et al., 2024b). Furthermore, other studies proved that IDW is useful in physical soil parameters modeling from 65 samples for sustainable land management, underscoring the achievement of the method (Mohamed et al., 2020). Consequently, Salahalden et al. (2024) incorporated IDW with the multiple linear regression method for predicting Atterberg limits and grain size for the economical effectiveness of red clay behaviour. Also, both Sentinel 1-C SAR data and ML algorithm were used to model the topsoil characteristics of Laylan in Kirkuk, and the outcome shows that the ML models were even superior to random forest classifiers, even when they were trained with few samples (Ali et al., 2024a). Altogether, these works support the use of GIS, statistical modeling, and remote sensing in increasing the chances of assessing soil properties.

However, limited studies have extensively focused on the spatio-temporal variability of soil characteristics in Taza Khurmatu District, an intensifying urban area in Kirkuk Governorate, with diverse geology and inconsistent land use patterns. This gap has led to the design of the present study, which determine the spatial distribution and relation of the key soil indicators in the area using of GIS-based interpolation techniques. The main aims of the study are: (1) The assessment of thirty samples of soil collected from thirty different sites in Taza Khurmatu. 2. to apply both IDW and Spline interpolation methods to map geotechnical parameters, including dry density, moisture content, Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), and grain size distribution. 3. to compare and validate the performance of the two interpolation methods using Root Mean Squared Error (RMSE) and the R^2 values. The generated soil maps can contribute to informed decision-making regarding infrastructure development, land use planning, environmental conservation, and sustainable management of the study area.

2. Study Area

The study area is situated in the Taza Khurmatu district, Northern Iraq, approximately 230 km from Baghdad governorate, and 10 km from Kirkuk governorate. It is delineated by latitudinal and longitudinal lines extending from 3904000 to 3910000 N and 437000 to 441000 E, respectively (Fig. 1).

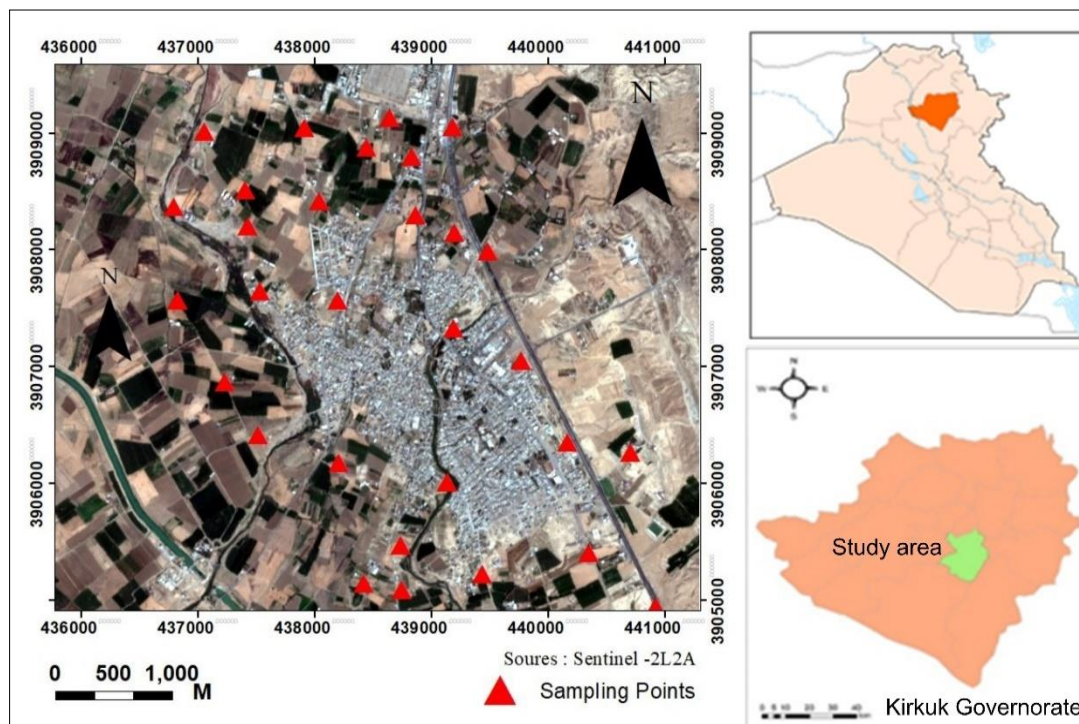


Fig. 1. Study area and sampling location

In addition, structurally, the study area is located within the Makhoul–Hamrin subzone, within a low-fold zone of Iraq. The Khasas River (Khasas Su) is a seasonal river that runs through the study area (Jassim and Goff, 2006). The study area is covered by an alluvial fan, which has been preserved in several places throughout the study area; these deposits overlie folded rocks from pre-Quaternary formations to create flat summits of small plateaus (Jassim and Goff, 2006; Sissakian and Saeed, 2012; Jabbar, 2015; Gharib et al., 2021; 2024). Additionally, the study area is located between semiarid and Mediterranean climates, which are distinguished by hot, dry summers and cool winters; the majority of precipitation occurs between December and March, while the warmer months experience very little rainfall.

3. Materials and Methods

To determine the physical and chemical characteristics of the soil samples, several parameters and measurements were used, including field measurements (Table 1), Sentinel-2L2A satellite imagery obtained on 7 October 2024, and GIS tools (interpolation techniques) in conjunction with a linear regression model, Atterberg limits, dry density, water content, and soil texture. Fig. 2 illustrates the general methodology flowchart.

Table 1. Details of the satellite data used in the study

Image type	Image format	Image resolution	Datum	Date source name	Sensing data	Cloud cover
True color	32-bit –	1468×672	WGS 84	Sentinel -	2024-10-7	0%

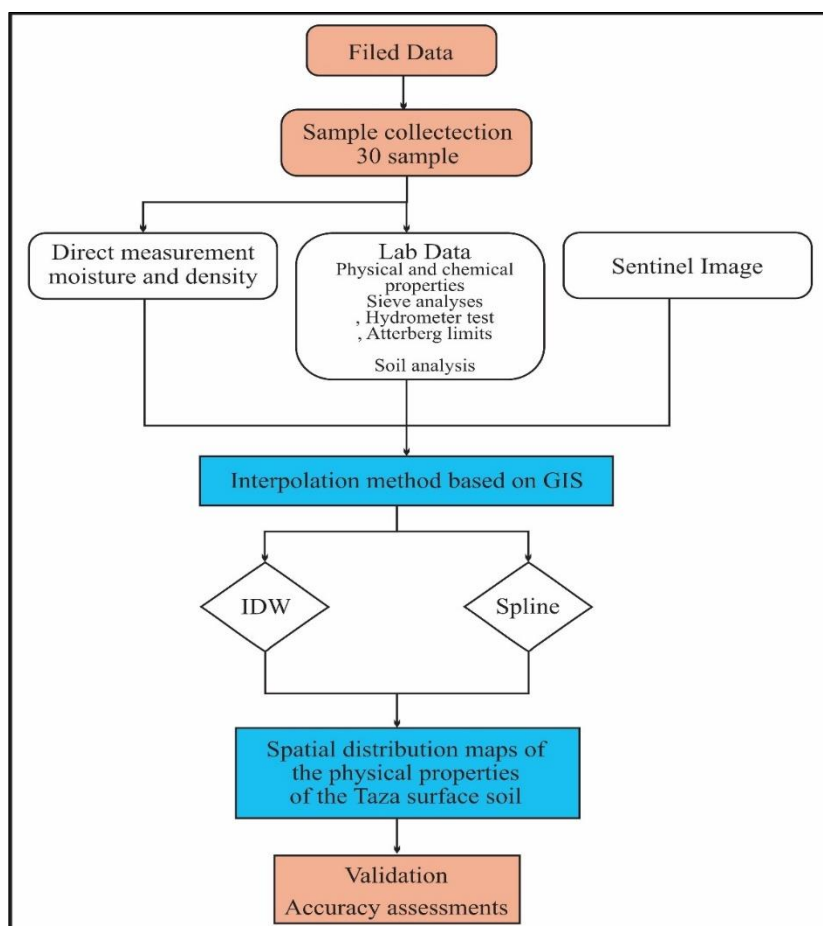


Fig. 2. Flowchart of the map preparation process of Taza District, Iraq

3.1. Physical Properties

Thirty soil sampling points were selected in the Taza Khurmatu region, Kirkuk, Iraq. The GPS device was used to obtain precise coordinates for these points with an accuracy value of $\pm 3.6\%$. The field measurements of dry density and water content were recorded by using an HS-5001EZ moisture/density meter. The soil samples were extracted from a depth of 30 cm for each sampling point after removing the topsoil layer. Before the laboratory examinations, samples were dried. The laboratory examined multiple tests that measured the essential physical properties of the soil samples (Table 2). The sieve analysis methodology classified the soil particles into different categories, comprising clay, silt, sand, or gravel. The ASTM D7928 standard serves as a basis for this methodology to differentiate clay from silt through the use of a hydrometer (ASTM International, 2021).

The Casagrande method assessed the Atterberg limits throughout the calculation of the LL and PL. This followed the ASTM D7928 procedure by the American Society for Testing and Materials (ASTM), (ASTM, 2017). The specific gravity measurement is followed by calculating sand, silt, and clay contents via a hydrometer apparatus. All assessment procedures followed the guidelines set by ASTM.

3.2. Interpolation Methods

Spatial interpolation involves estimating values at unsampled locations using measurements from nearby sampled sites, making it an essential tool for generating continuous spatial data (Tan and Xu, 2014). It relies on data from neighboring points with known value to predict missing information in areas lacking direct measurements.

Table 2. A geotechnical analysis of soil parameters combined with classification using USCS standards

Point	Density	moisture	L.L	P.L	P.I.	G.S	Gravel %	Sand%	Silt%	Clay%	Group symbol	Group name
1	1.849	6.8	45	30	15	2.71	0	3.16	55.95	40.89	ML	silt
2	1.652	15.2	49	33.5	15.5	2.7	0.14	5.02	52.82	42.02	ML	silt
3	1.721	4.6	47.2	33.9	13.3	2.71	0.36	5.08	62.09	32.47	ML	silt
4	1.505	14.7	39.6	27.6	12	2.72	0.52	5.26	54.43	39.79	ML	silt
5	1.747	6.6	42.5	31.5	11	2.7	0.2	6.32	57.69	35.79	ML	silt
6	1.582	3.6	35.5	26.5	9	2.69	0.6	21.46	54.25	23.69	ML	silt, sand
7	1.538	2.9	-	-	-	2.66	0	65.06	29.84	5.1	SM	silty sand
8	1.675	1.7	-	-	-	2.65	23.22	57.04	16.08	3.66	SM	silty sand, gravel
9	1.821	3.4	-	-	-	2.67	41	17.88	33.49	7.63	GM	Siltygravel, sand
10	1.851	2.2	-	-	-	2.65	19.6	39.16	33.59	7.65	SM	silty sand, gravel
11	1.714	11	15	9	6	2.76	0.24	9.42	46.84	43.5	ML-CL	silty clay
12	1.979	8.2	15.5	10.5	5	2.78	6.66	7.56	41.09	44.69	ML-CL	silty clay
13	1.612	10.5	22.1	16.6	5.5	2.76	0.06	13.5	43.24	43.2	ML-CL	silty clay
14	1.403	2.8	32	24	8	2.69	0.4	16.5	58.8	24.3	ML	silt, sand
15	1.585	4.8	17.5	11.5	6	2.75	0	11	46.14	42.86	ML-CL	silty clay
16	1.62	2.2	37.5	28.5	9	2.7	0	24.69	49.48	25.83	ML	silt, sand
17	1.701	2.9	34.8	25.5	9.3	2.68	0.1	26.1	52.6	21.2	ML	silt, sand
18	1.831	5	40	34	6	2.7	0	24.5	52.55	22.95	ML	silt, sand
19	1.533	2.3	45.5	36.5	9	2.67	0.06	34.26	48.31	17.37	ML	sandy silt
20	1.632	4.5	22	13	9	2.72	0.04	21	36.66	42.3	CL	clay, sand
21	2.005	3.3	36	30	6	2.73	0.32	37.4	43.35	18.93	ML	sandy silt
22	1.67	4.7	42	27.7	14.3	2.7	0.38	8.04	63.75	27.83	ML	silt
23	1.868	3.1	32	25	7	2.7	0.32	17.32	57.33	25.03	ML	silt, sand
24	2.07	3.9	38	27	11	2.71	0.7	12.32	58.83	28.15	ML	silt
25	1.863	4.1	45	33	12	2.75	0.07	10.2	60.53	29.2	ML	silt
26	1.66	6.4	44	35	9	2.73	0.02	15.1	54.29	30.59	ML	silt, sand
27	1.455	4.9	37	26	11	2.72	0.36	37	41.13	21.51	ML	sandy silt
28	1.687	4.5	43	30.5	12.5	2.71	0.06	17.9	58.72	23.32	ML	silt, sand
29	1.716	4.1	38	27	11	2.65	5.62	34.88	46.11	13.39	ML	sandy silt
30	1.87	4	41	32	9	2.7	0.32	12.12	59.22	28.34	ML	silt

L.L = Liquid Limit, P.L = Plastic Limit, P.I = Plasticity Index, GS = Grain Size, ML = Silt with low plasticity, CL =Low-plasticity clay, SM = Sand with Silt, GM = Gravel with Silt

One of the main challenges is selecting the most appropriate surface replication method from the many available options, especially since point data collection allows for evaluating different interpolation techniques.

Furthermore, interpolation approaches are vital in various Earth surface-related fields because they support the continuous spatial variables estimation (Caruso and Quarta, 1998; Tan and Xu, 2014). Among the many available interpolation techniques, this study selected two methods for evaluation and comparison.

IDW is a well-known deterministic spatial interpolation technique used in geostatistics and GIS to predict unknown values by incorporating mapped point values (Myslyva et al., 2019). IDW follows a basic principle that states that nearer points in relation to the observation location have a stronger impact on the forecast results than points located farther away under conditions of spatial autocorrelation (Borges et al., 2016). This method provides the most accurate predictions, mainly when data is highly distributed (Li and Heap, 2014).

Moreover, IDW presents a commonly used method that combines simple data analysis with spatial interpolation techniques. It has become a standard tool in many fields, including environmental science and resource management, and meteorology, due to its straightforward nature, which makes it easy to apply and interpret (Li and Heap, 2011).

The equation of the IDW interpolation determination is presented as:

$$Z(x_0) = \frac{\sum_{i=1}^n \frac{Z(x_i)}{d(x_0, x_i)^p}}{\sum_{i=1}^n \frac{1}{d(x_0, x_i)^p}} \quad (1)$$

Where $Z(x_0)$ is the estimated value at the location that is not specified, $Z(x_i)$ represents the known values at surrounding points, $d(x_0, x_i)$ is the distance between the known and unknown points, P is the power parameters that determining the influence of distance on weights (typically $P = 2$), and n is the total of known points considered in the model (Tan and Xu, 2014).

In addition, the Root Mean Square Error (RMSE) is considered a primary cross-validation metric (Zhang et al., 2008). The calculation method appears below:

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

The number of values used for estimation (n) and the number of selected parameters in the empirical equation (m) define this calculation, together with the estimated value (Z) and the measured value at sampling point (Z_i), where i goes from 1 to n (Zhang et al., 2008). Additionally, the Mean Absolute Error (MAE) provides an average error size value that ignores the error direction. The validity of a prediction improves by lowering the MAE value. Both RMSE and MAE were used for the validation and assessment the accuracy of the map modeling.

Mathematical functions known as splines are widely used for interpolation, approximation, and validation of datasets. They are also effective of data smoothing being defined as piecewise polynomials that connect smoothly at specified knot points while preserving continuity in the first and second derivatives. This capability makes splines highly effective for modeling continuous, smooth curves across multiple scientific applications (Perperoglou et al., 2019).

The mathematical definition of splines evolved from flexible drawing tools that shipbuilders and designers used to create smooth lines.

Localized control offered by splines surpasses global polynomial interpolation methods, because splines divide the data into smaller intervals and apply low-degree polynomials within each segment. This approach reduces errors and improves overall stability (Ali et al., 2024b). Among the most common splines are linear splines, which are simple but lack smoothness at the knots; quadratic splines. This provides continuity in the first derivative; cubic splines, which are the most popular owing to their ability to ensure continuity in both the first and second derivatives, making them ideal for applications in computer graphics, animation, and Computer-Aided Geometric Design (CAGD); and Basis Splines (B-Splines), which generalize cubic splines and offer greater flexibility for modeling complex curves and surfaces (Buss and Fillmore, 2001).

The mathematical solving method for splines requires linear equation systems derived from specified boundary requirements and continuity limits to achieve stable and smooth data range functions (Weston, 2002).

4. Results and Discussion

The following results were obtained from the measurement of a set of tests (in situ) and laboratory tests at 30 points in the study area, as in Tables 2 and 3.

4.1. Field Test in Situ

In the field, the water content and density were calculated via an HS-5001EZ instrument. The water content of the chosen sites ranged from 1.7% to 15.2%, whereas the density values ranged from 1.40 g/cm³ to 2.07 g/cm³ (Table 2).

4.2. Laboratory and Statistical Analysis

The grain size distribution analysis of the 30 samples (as previously shown in Table 2), revealed that the dominant type in the study area was silt, where the percentage ranged from 30% to 63%, except for one site, which presented a value less than 20%, whereas the percentage of clay ranged from 3% to 40%. The percentage of sand ranged from 3% to 39%, except for two sites, which presented 57% and 65%, and the percentage of gravel was very low at most sites, except for four sites, which presented percentages between 6% and 41%.

4.3. Atterberg Limits

The values of the Atterberg limits ranged between 15% and 45%, and the P.L. values ranged between 9% and 34%. In contrast, the values of the P.I. ranged between 9% and 15% (as previously shown in Table 2), indicating that the samples at the four points did not meet the Atterberg limits because the percentage of coarse materials (sand and gravel) was higher than the percentage of fine materials (silt and clay). Most of the soil samples contained a significant amount of silt, yielding moderate plasticity results.

4.4. Spatial Analysis of the Soil via Interpolation Techniques

The interpolation approach was used to divide the physical characteristics into five discrete zones for the analysis of their spatial configuration, as shown in Figs. 3 through 5. These zones vary from very low to extremely high. The white color signifies regions with greater concentrations, whereas the brown color indicates places with lower percentages, using two interpolation methods: IDW and Splines.

Fig. 3 shows the distribution of moisture, density measurements, and gravel percentage. The moisture readings obtained from the HS-5001EZ moisture density gauge indicate a moisture content range of 1.4-15%, with the distribution of density measurements recorded by the same device revealing a density range of 1.4-2.1 g/m³. Gravel percentages range from 0-41%.

The observed disparities arise from the fundamental differences between IDW and Spline interpolation. The principle behind IDW assigns increased importance weight to points that are close by, resulting in surface variations that are sharp and local.

In contrast, Spline interpolation generates a smooth, continuous surface that generalizes abrupt changes into gradual patterns. While IDW results in step-like transitions, whereas the Spline method generates gentle gradations across the interpolated distribution of moisture, density, and gravel content. Selecting the appropriate interpolation protocols demands special attention, as it directly influences the spatial patterns in the analyzed data

Fig. 4 shows the distributions of sand (3.2–65%), silt (16–62%), and clay (3.7–43%). Fig. 5 displays the Liquid Limit (LL: 0.02–47), Plastic Limit (PL: 0.014–37), and Plasticity Index (PI: 0–15%), as in Table 2.

4.5. Validation and Accuracy Assessment

Cross-validation provides a method to validate interpolation techniques through known sample locations while the estimation method remains excluded from the dataset. The accuracy of each interpolation method is measured by calculating error differences from actual sample values versus estimated values using this approach. A validation process is carried out for every sample contained in the available dataset.

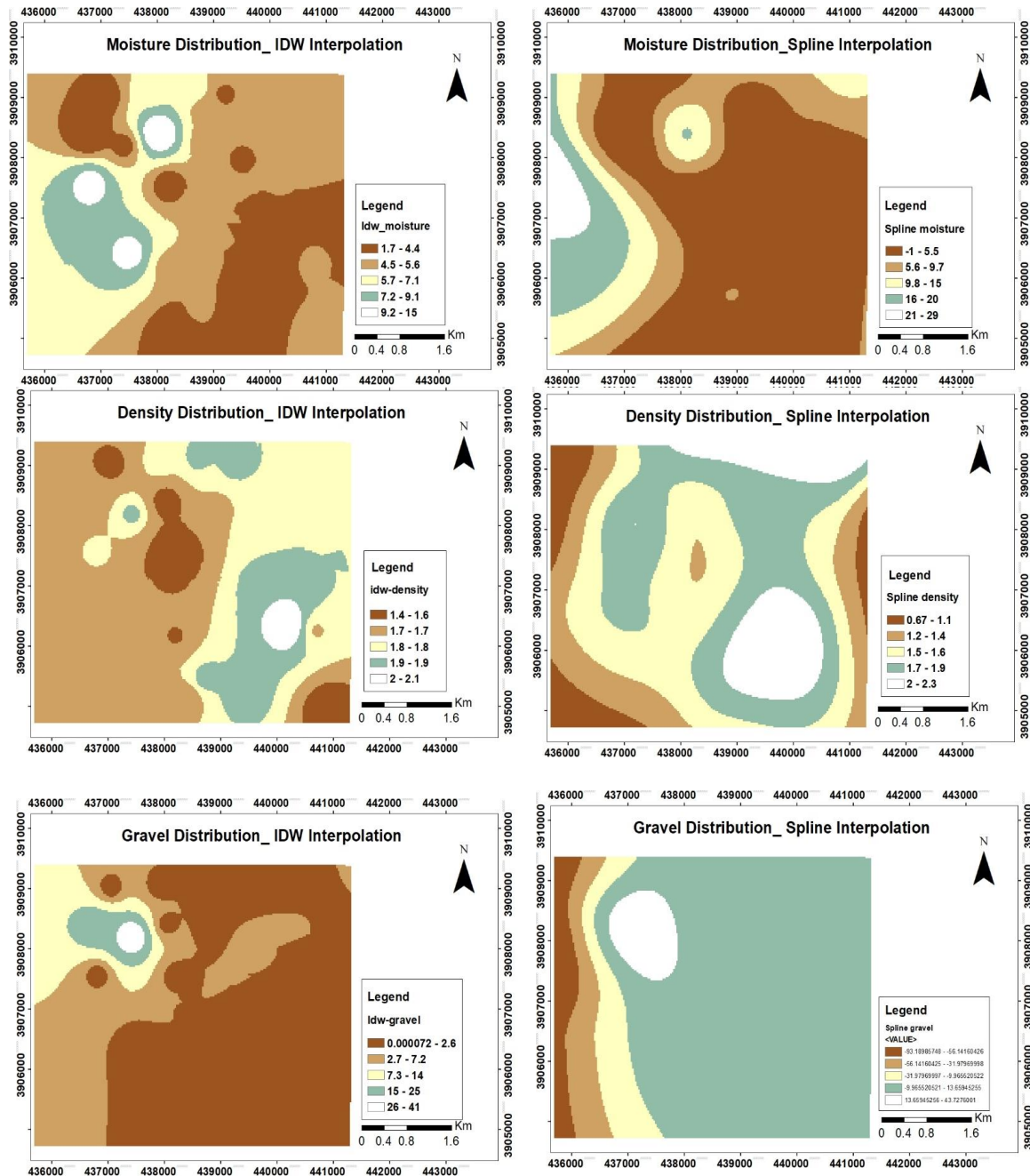


Fig. 3. Moisture contents, density, and gravel ratio maps of the study area

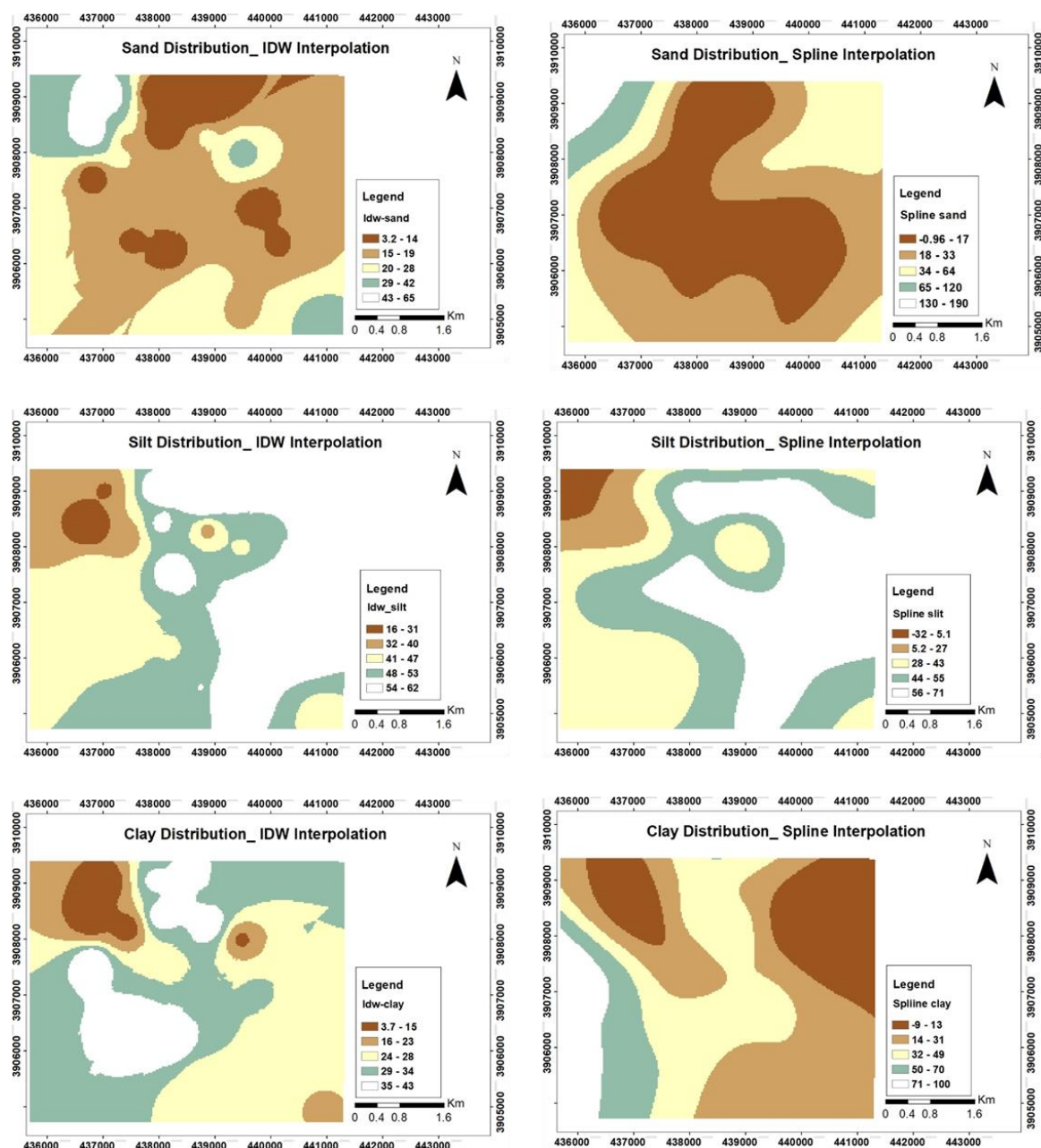


Fig. 4. Representation of sand, silt, and clay contents in the study region

For the IDW-based soil property maps of Kirkuk City, the validation process utilized 30% of the collected soil samples (Yao et al., 2013). Field values were compared against IDW-generated values as part of the validation. The evaluation employed RMSE, MAE, and R^2 metrics to compare observed and IDW-derived estimates (Table 3).

Spatial interpolation through IDW is highly valuable in areas with few data points because it generates smooth representations of spatial patterns. However, the distance-based weighting approach used by IDW may produce errors in landscapes that present strong variations in data values (Cameron and Windmeijer, 1997). A combination of IDW and other interpolation methods is recommended for more accurate prediction models (Table 3).

The selection of an interpolation method depends on the amount of data within a study area. Multiple interpolation techniques were employed to construct soil physical characteristic maps of Kirkuk city to determine the most suitable interpolation method.

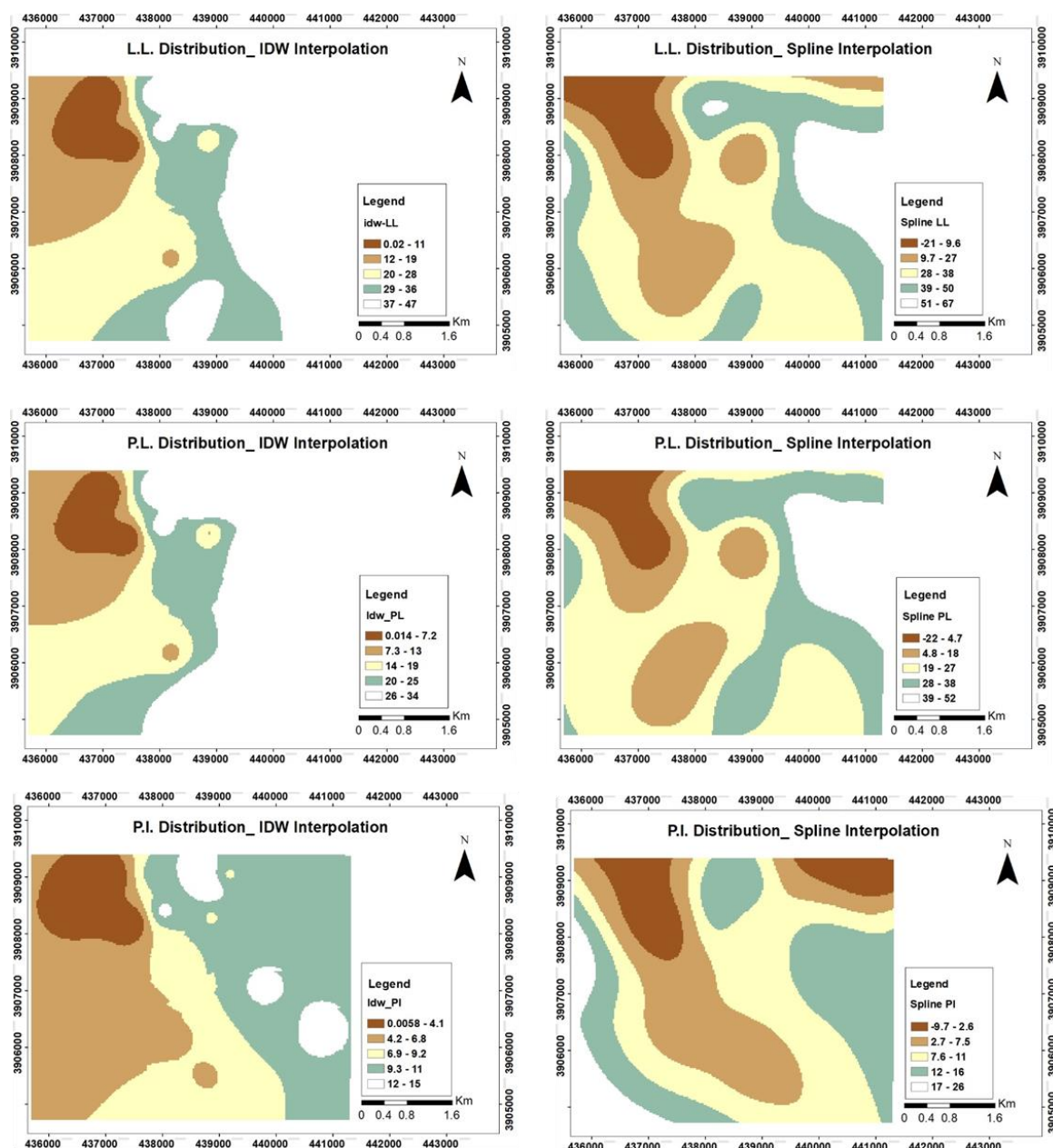


Fig. 5. Representations of the LL., PL, and PI

Table 3. Root mean squared error (RMSE) and R^2 for the interpolation methods

Physical Properties	IDW			Spline		
	RMSE	MAE	R^2	RMSE	MAE	R^2
Dry Density	0.21	0.16	0.87	0.33	0.25	0.77
Water content	3.39	2.42	0.72	2.68	2.00	0.82
LL (Liquid Limit)	8.91	7.40	0.85	7.94	7.23	0.76
PL(Plastic Limit)	7.35	6.19	0.75	6.40	6.01	0.79
PI(Plastic Index)	2.83	2.29	0.76	2.34	1.83	0.88
Gravel	2.12	1.54	0.90	4.31	3.27	0.76
Sand	7.42	6.30	0.70	8.80	6.08	0.71
Silt	4.31	3.62	0.74	21.82	17.79	0.70
Clay	7.76	6.77	0.77	6.69	4.56	0.74

Table 3 shows both the error metrics and correlation coefficients from employing spline interpolation and IDW methods during the analysis of diverse soil physical characteristics. The main indicator used for statistical evaluation is the standard deviation of the prediction errors, measured through the RMSE. The improved accuracy results from the reduced values of the RMSE.

Spline interpolation achieves lower MAE values than IDW for almost all parameters, including dry density, water content, and particle size distribution (gravel, sand, silt, and clay). The Spline exhibits lower prediction errors than IDW; for instance, dry density MAE is 0.16 for Spline compared to 0.21 for IDW. Similarly, water content MAE decreases from 3.39 for IDW to 2.42 for Spline. The measured data predictions from the Spline seem more accurate than those derived from the IDW. The Spline-based maps shown in Fig. 5, display smooth pattern distributions due to lower prediction errors, avoiding the generalization effect. While IDW has a higher MAE, it better captures localized patterns that may be distorted by Spline's smoothing effect. Thus, selecting the optimal interpolation method requires evaluating both spatial patterns and MAE values.

The statistical indicator R^2 determines the model's effectiveness in explaining the observed data variations, with values closer to 1 indicating better performance. IDW produces superior results for density and liquid limit, gravel and silt analysis, as it produces lower RMSE and higher R^2 . Conversely, Spline is more suitable for the water content, plastic limit, plastic index, sand and clay, offering lower MAE and better R^2 .

The study's research findings create vital implications that can help professionals in geotechnical engineering as well as the agricultural fields. Lower MAE values (particularly with Spline) enhance the reliability of soil property estimates, reducing design errors and improving project safety and cost-efficiency. Accurate spatial understanding of soil moisture, texture, and consistency is crucial for irrigation planning, crop selection, and soil management. Although Spline methods achieve lower average errors through their smooth output, they might fail to detect essential localized discrepancies that would be valuable in engineering and agricultural decisions. The choice of interpolation method depends on application needs as well as the significance of spotting localized soil variations for obtaining the best soil data analysis advantages.

The analysis of the silt content reveals a widespread mismatch since IDW generates an RMSE of 4.31, which is dramatically lower than the spline-generated value of 21.82, indicating that spline interpolation might not be effective for this factor. Spline displays better results for the water content and plastic index along with the clay content, whereas IDW is the most reliable for gravel, silt, and dry density.

For regular variations, Spline is ideal for non-linear, gradual, while IDW serves localized sharp variations even though it fails to recognize broader patterns. Choosing the right interpolation method is essential for accurate spatial predictions, improving decision-making in construction, land management, and agriculture based on soil variability.

5. Conclusions

Thirty soil samples were obtained through extensive sampling across southern Kirkuk City to analyze the physical characteristics of the soil. The primary goal of the current work was to examine soil behavior, as it enables vital information for geotechnical and engineering applications. The modeling process generated nine spatial maps illustrating key soil properties, including gravel, sand, silt, clay content, Atterberg limits, density, and water content. IDW interpolation method was applied, revealing distinct spatial patterns in soil composition due to its variable distribution. Laboratory analysis via HS-5001EZ moisture/density gauge revealed the heterogeneity of soil samples with a maximum moisture content of about 15.2% and maximum density of 2.07 g/cm³. Grain size distribution showed minimal gravel presence in the study area, which was further confirmed by spatial mapping. The soil

profile lacked significant sand distribution, even though it occasionally appeared across the profile. The analysis revealed silt as the prevalent grain size component, which spread to 62% of the soil composition. Clay also contributed significantly to the regional soil profile.

IDW interpolation yielded the best analytical results for density, LL, gravel, and silt content because it achieved both lower RMSE and higher R^2 values. It was particularly reliable for assessing gravel content, dry density, and silt properties. In contrast, the spline approach produced better modeling results when identifying water concentration PI values, and clay content levels.

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