

IDENTIFICATION AND MANAGEMENT OF AGRICULTURAL ZONES USING REMOTE SENSING AND GIS IN SHEIKH MASOUD VILLAGE, MINYA GOVERNORATE

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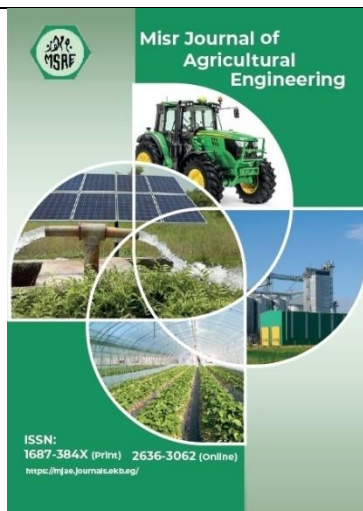
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ABSTRACT

This study was conducted in Sheikh Masoud village (28°39'15.3"N, 30°40'49.1"E) in the Western Desert, Minya Governorate, Egypt, the texture of the soil is sandy loam. Geographic Information Systems (GIS) and remote sensing were used to enhance precision agriculture by delineating soil management zones. Utilizing methodologies such as Inverse Distance Weighting (IDW) and Kriging, it combines various soil and micro-nutrient (Fe, Mn, Cu and Zn) data with GIS-based spatial interpolation models. Soil characteristics like texture, pH, and electrical conductivity (ECe) were analyzed, revealing significant spatial variability across a 3,260 Fed. area. ECe values ranged from 4 to 14.3 dS/m, and pH levels from 7.23 to 8.0, indicating diverse salinity and alkalinity conditions. Three samples were taken from each profile at different depths to estimate the various elements. The interpolation models, validated through Root Mean Square Error (RMSE) calculations, showed Kriging with a reliable RMSE of 1.5, producing accurate spatial soil property maps. Sixteen management zones were identified: good, moderate and low Nutrient Zones and for salinity from non- to strong salinity levels. According to the study's results, it can be recommended, tailored irrigation methods, such as drip and subsurface irrigation to manage water-sensitive and saline conditions. GIS and spatial modeling approach support sustainable agricultural practice.

INTRODUCTION

In recent decades, technological advancements have transformed agricultural practices, introducing innovative approaches that significantly enhance efficiency and productivity (Ratnaparkhi et al., 2020). The evolving field of precision agriculture is particularly noteworthy, as it leverages extensive data sets and data-driven insights to inform and optimize farm management practices. As data volumes increase exponentially, the need for advanced methods to manage, analyze, and interpret these data becomes critical (Rub, 2012). Technologies like the Global Positioning System (GPS), Geographic Information Systems

(GIS), and remote sensing have become instrumental in precision agriculture, facilitating site-specific management through high-resolution spatial data.

Precision agriculture enables farmers to adapt management practices to the specific needs of individual field areas, thereby maximizing resource use efficiency and improving crop productivity (**Chandra Pandey et al., 2021**). Remote sensing, as a central tool in this approach, involves acquiring and analyzing data from sensor systems that detect and measure energy patterns without physical contact. This technology provides valuable information about the physical characteristics of the environment and facilitates efficient data collection across large areas. Incorporating remote sensing data into crop modeling has proven effective for evaluating regional yields and supporting decision-making in farm management (**Kasampalis et al. 2018**).

One of the most critical outputs derived from remote sensing is vegetation indices, which are essential for tracking changes in vegetation cover and health over time (**Aparicio et al., 2002**). These indices, often calculated using spectral data, provide insights into crop conditions and land cover dynamics, supporting efforts to monitor growth stages, detect stress factors, and optimize management interventions. Effective farm management practices also influence crop yield and soil quality at various spatial and temporal scales (**Corwin et al., 2006**). Thus, the capacity to assess and manage spatial variability within fields, particularly in soil properties, is crucial for effective resource allocation and crop performance.

An important consideration in site-specific management is understanding and accurately characterizing soil variability. Farmers rely on GPS technology to gather spatial data, which is used to produce detailed maps of soil types, units, and properties. This mapping capability allows for precise adjustments in irrigation, fertilization, and other field practices to match the needs of specific soil zones. Selecting an optimal sampling plan is critical in this process, as it determines the reliability of soil variability assessments and supports informed decision-making (**Vašát et al., 2010**). A systematic sampling approach, often using grid-based methodologies, is advised when initial knowledge of soil variability is limited (**Elsharkawy et al., 2022**). Increasing sample density and reducing the spacing between

samples enhance the accuracy of soil variability maps by minimizing kriging variance, thereby providing a more reliable foundation for precision agriculture (**Corwin & Lesch, 2005**). The application of GIS in precision agriculture has expanded, enabling farmers and agronomists to integrate multi-level data and develop spatial decision-support systems (**Narayana & Rao, 1995**). This capability supports the detailed analysis of field variations, empowering farmers to understand where and why yields may differ across their land. Such insights facilitate targeted interventions that improve both yield consistency and resource efficiency (**Seelan, 2003**). This research aims to use GIS and mathematical models to delineate soil data into distinct management zones in Sheikh Masoud farms, providing insights into the spatial variability of soil properties. The delineation of these zones aims to facilitate more sustainable precision agriculture practices.

MATERIAL AND METHODS

Study Area and sampling:

The study area located in Sheikh Masoud village in the Western Desert (28°39'15.3"N 30°40'49.1"E), Minya Governorate, Egypt. The study area spans approximately 3,260 Fed.

(sandy soil). Satellite imagery of the area, which shows a digital elevation topographic variation and the location of studied soil profiles and the representative surface soil samples (**Fig. 1**). From 10 soil profiles, thirty-one soil samples were collected (3 samples from each profile) at depths of 0-30 cm, 30-60 cm and >60 cm, in addition to 13 representative surface samples, that were selected to represent physiographic diversity. The sampling distribution is illustrated in (**Fig. 1**). Most of the studied profiles and the surface soil samples are taken from uncultivated areas. Morphologically the studied soils are mostly sandy in the texture having medium to coarse gravels especially in the surface layer. The water source consists of shallow wells with depths ranging from 10 to 15 meters. Samples were prepared following standard laboratory procedures, including grinding and sieving through a 2 mm mesh. The analysis covered key soil properties: pH, measured with a calibrated pH meter according to method (**McLean, (1982).**); electrical conductivity (ECe), measured in past soil extract using a conductivity meter according to (**Rhoades, 1982**),exchangeable cations (Ca and Mg) were extracted with 1 M ammonium acetate, Chloride(Cl⁻) and Bicarbonate (HCO₃⁻) according (**Carter & Gregorich, 2007**). Available micro-nutrient elements (Fe, Mn, Cu and Zn) were extracted by DTPA and measured by atomic absorption spectrophotometry according to (**Thomas,1982**), (**Lindsay & Norvell, 1978**). Location of the soil samples are shown in Table (1).

-Climate data:

Some climate data of the study region area such as temperature, humidity, sunshine hours and precipitation are shown in Table (2)

Table 1: Location of the soil samples.

Profile			Profile		
No.	Long	Lat	No.	Long	Lat
1	30°37'10.6"E	28°41'30.3"N	6	30°34'39.0"E	28°40'43.6"N
2	30°36'43.5"E	28°41'34.6"N	7	30°35'10.9"E	28°40'36.7"N
3	30°36'07.4"E	28°41'37.6"N	8	30°35'40.1"E	28°40'46.7"N
4	30°35'31.7"E	28°41'36.1"N	9	30°35'52.4"E	28°40'45.7"N
5	30°34'53.9"E	28°41'07.5"N	10	30°36'25.1"E	28°40'38.6"N

Table 2: Climate data for the study region.

Month	Average Temperature (°C)	Precipitation (mm)	Sunshine Hours	Humidity (%)
January	21	0.5	8	30
February	23	0.7	9	28
March	26	1.7	10	25
April	30	0.3	11	22
May	35	0	12	20
June	39	0	12.8	18
July	39	0	12.8	18
August	38	0	12.5	18
September	35	0	11	20
October	31	0.2	10	22
November	26	0.5	9	25
December	22	0.4	8	30

Climate-Data.org and World Bank's

-Irrigation water source:

The source of irrigation water is shallow wells with depths ranging from 10 to 15 meters. Seven water samples were collected and analysis in the laboratory of Soil Department at Faculty of Agriculture, Ain Shams University, to measure some chemical properties (pH, Ec, Ca, Mg, HCO₃ and Cl) as shown in **Table (3)**.

Table 3: Irrigation water analysis

	ECe (dS/m)	pH	Ca meq/l	Mg meq/l	HCO ₃ ⁻ meq/l	Cl meq/l	Fe mg/l	Mn mg/l	Cu mg/l	Zn (mg/l)
1	9.81	6.34	0.26	4.68	0.48	4.46	0.29	0.49	0.03	0.20
2	4.73	6.37	0.84	1.18	0.28	2.4	0.13	0.22	0.01	0.09
3	3.24	6.37	0.44	1.40	0.24	1	0.10	0.16	0.01	0.07
4	3.36	6.36	1.02	1.00	0.20	1.04	0.10	0.17	0.01	0.07
5	5.57	6.36	0.80	2.10	0.38	2.04	0.17	0.28	0.02	0.11
6	5.62	6.39	0.68	2.22	0.16	2.08	0.17	0.28	0.02	0.12
7	4.87	6.39	0.58	2.36	0.24	1.68	0.14	0.24	0.02	0.10

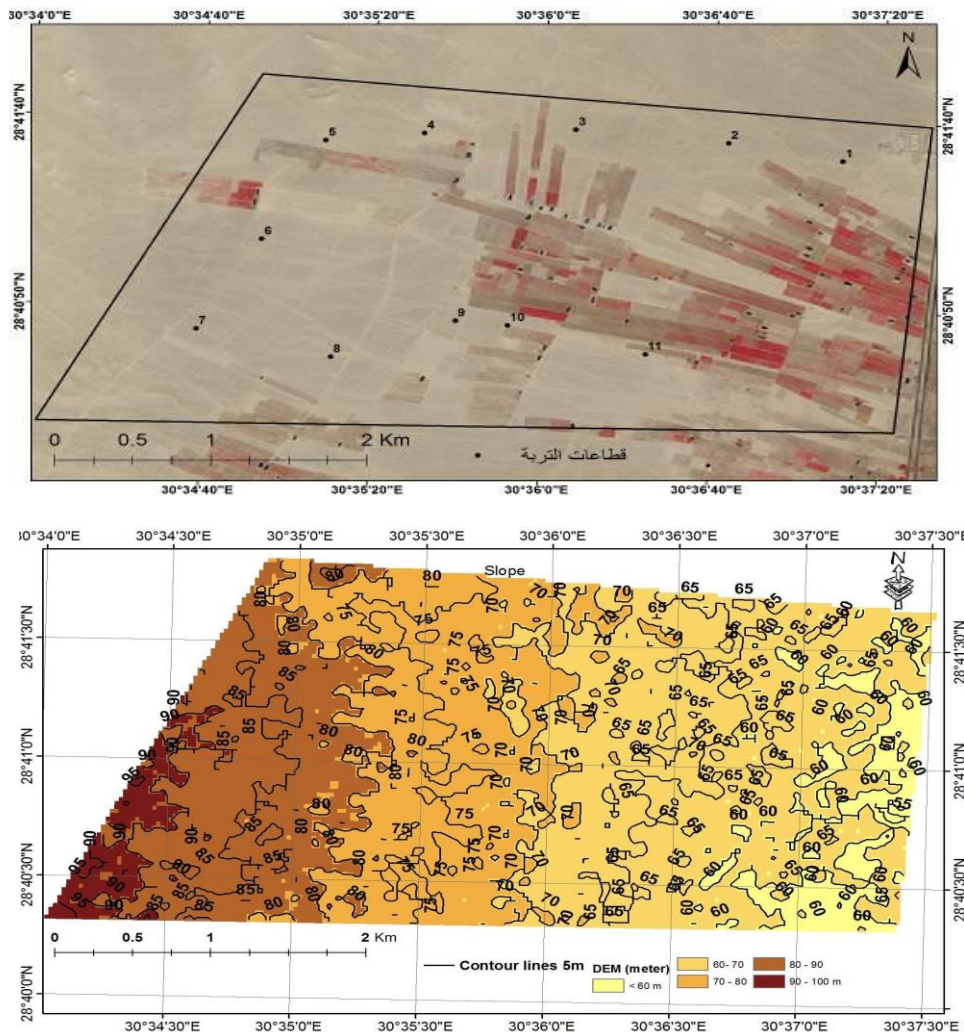


Fig. 1: Map of the study area with sampling points and profiles and Digital elevation model illustrating topographic variation in the studied area

GIS and mathematical model:

GIS and mathematical models were employed for spatial analysis of soil properties across the study area (**Webster and Oliver (2007)**). Spatial interpolation techniques, particularly IDW and Kriging, are fundamental methods for predicting values at unsampled locations in GIS applications. IDW posits that each measured point has a local influence that declines over distance, operating on the principle that closer samples carry more weight than distant ones. In contrast, Kriging is a geostatistical method that considers both the distance and spatial arrangement of measured points, incorporating spatial autocorrelation and statistical relationships among the measured points. While IDW is computationally simpler and works well with densely sampled data, Kriging often provides more accurate predictions and uncertainty estimates, especially when dealing with irregularly spaced samples and anisotropic spatial patterns (**Li & Heap, 2014**). Inverse Distance Weighting (IDW) Interpolation estimated unknown values based on sample proximity. For any target location x , the interpolated value $Z(x)$ is given by:

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

Where, $Z(x_i)$ is the observed value at point x_i , $d(x, x_i)$ is the distance to the target location x , and p is a power parameter, set to 2 for accuracy. The Kriging Model applied a spatial interpolation method accounting for spatial correlation among data points. The estimated value $Z(x)$ at x is calculated as:

$$z(x) = \sum_{i=1}^n \lambda_i Z(x_i)$$

Where, λ_i are weights assigned to each observed value $Z(x_i)$. These weights were derived from the semi variogram model, which characterizes spatial dependency and optimizes interpolation. Soil Salinity Calculation in each zone was determined by summing EC values across samples in the zone. Total salinity S was calculated as:

$$S = \sum_{i=1}^n CE_i$$

Where, EC_i is the salinity of each sample, and n is the number of samples in that zone. Classification of management zones based on EC and pH values divided the study area into four zones:

$$ones \left\{ \begin{array}{l} \text{Good Nutrient} \quad \text{if } EC \leq 5 \frac{dS}{m}, pH \ 6.5 - 7.6 \\ \text{Moderate} \quad \quad \text{if } 8 \leq EC < 12 \frac{dS}{m}, pH \geq 7.6 \\ \text{Low} \quad \quad \quad \text{if } EC \geq 12 \frac{dS}{m} \end{array} \right\}$$

RESULTS AND DISCUSSION

Soil chemical properties:

The Electrical conductivity (Ece): Distribution map shows elevated salinity in northeastern areas with E_{ce} levels up to 14.3 dS/m , indicating potential remediation needs, whereas western regions with E_{ce} values between 4 and 7 dS/m are more suitable for farming (**Fig. 2**).

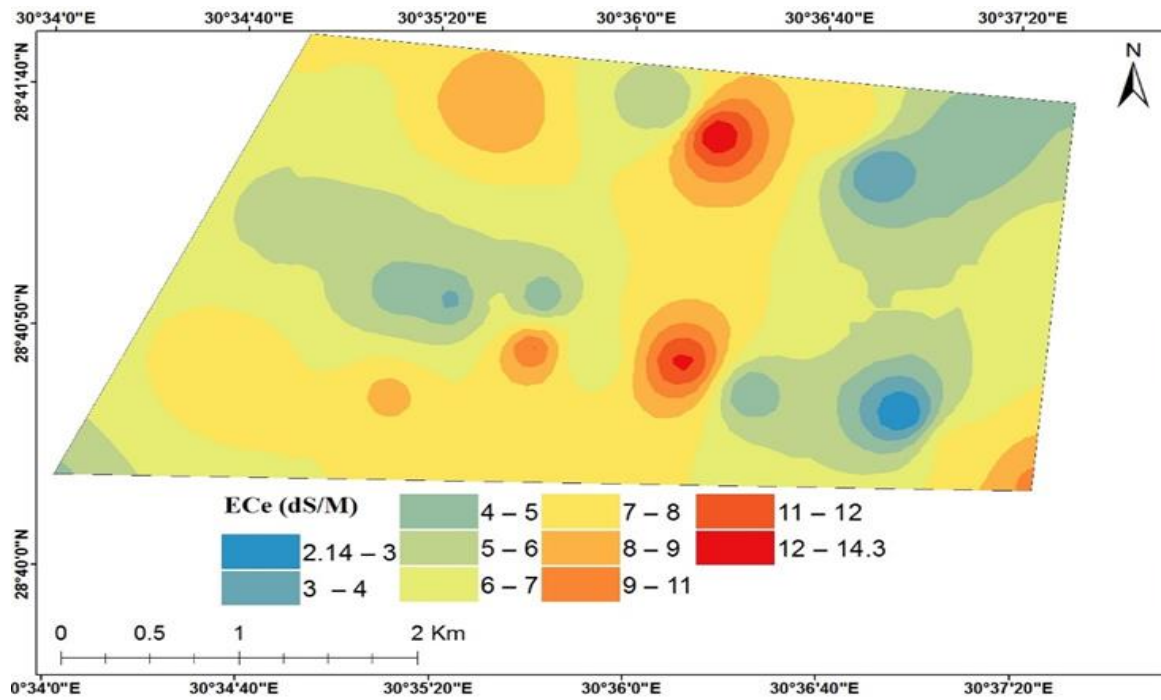


Fig. 2: Soil Salinity distribution map

Soil pH: Values of soil pH are shown in (Fig. 3), ranged from 7.23 to 8.0, indicating moderate to high alkalinity. Higher pH areas were associated with calcium carbonate deposits.

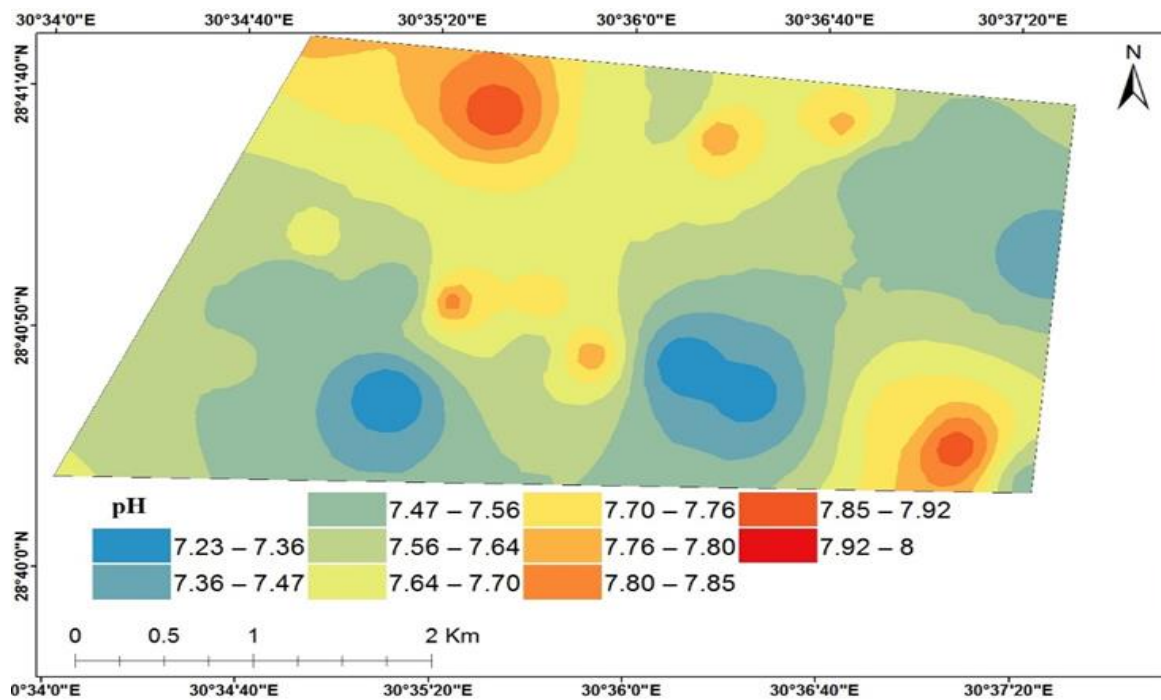


Fig. 3: Soil pH distribution map

Chloride: Its concentration, particularly high in the east (up to 1,142 meq/L), as seen in (Fig. 4).

Calcium: Levels of calcium peaked at 178 meq/L in eastern sections. (Fig. 5).

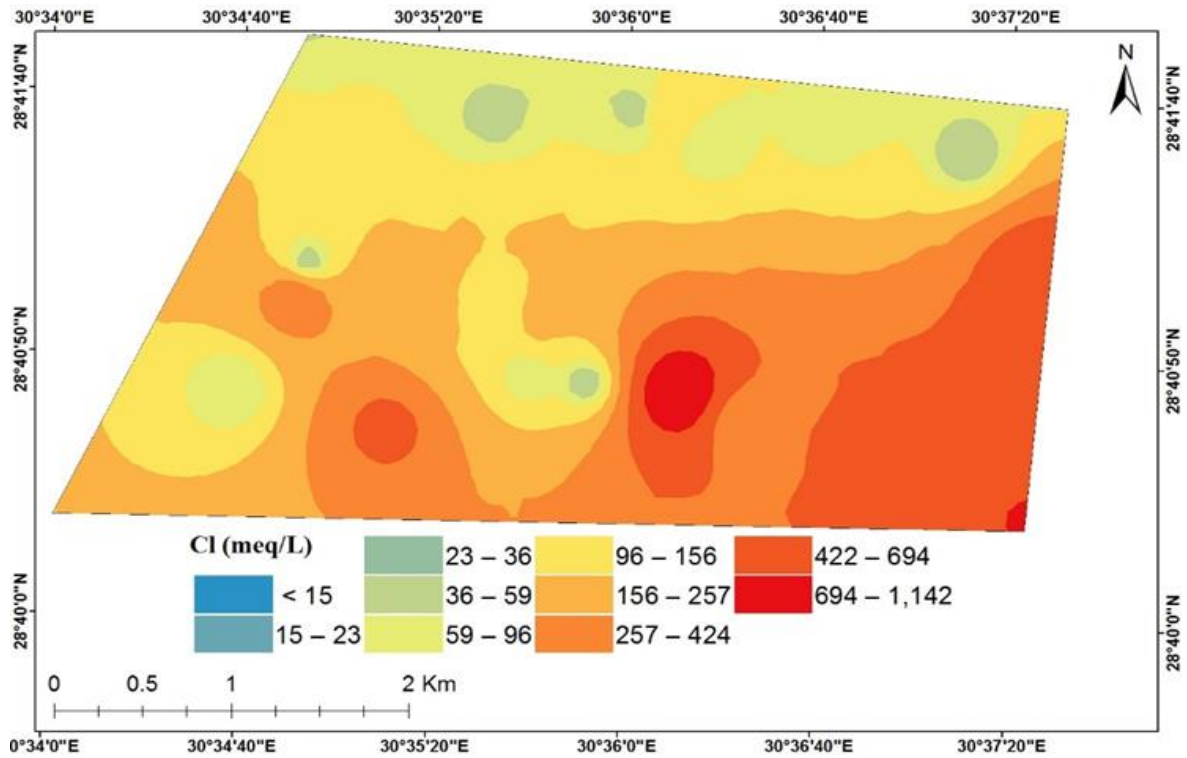


Fig.4: Chloride concentration map

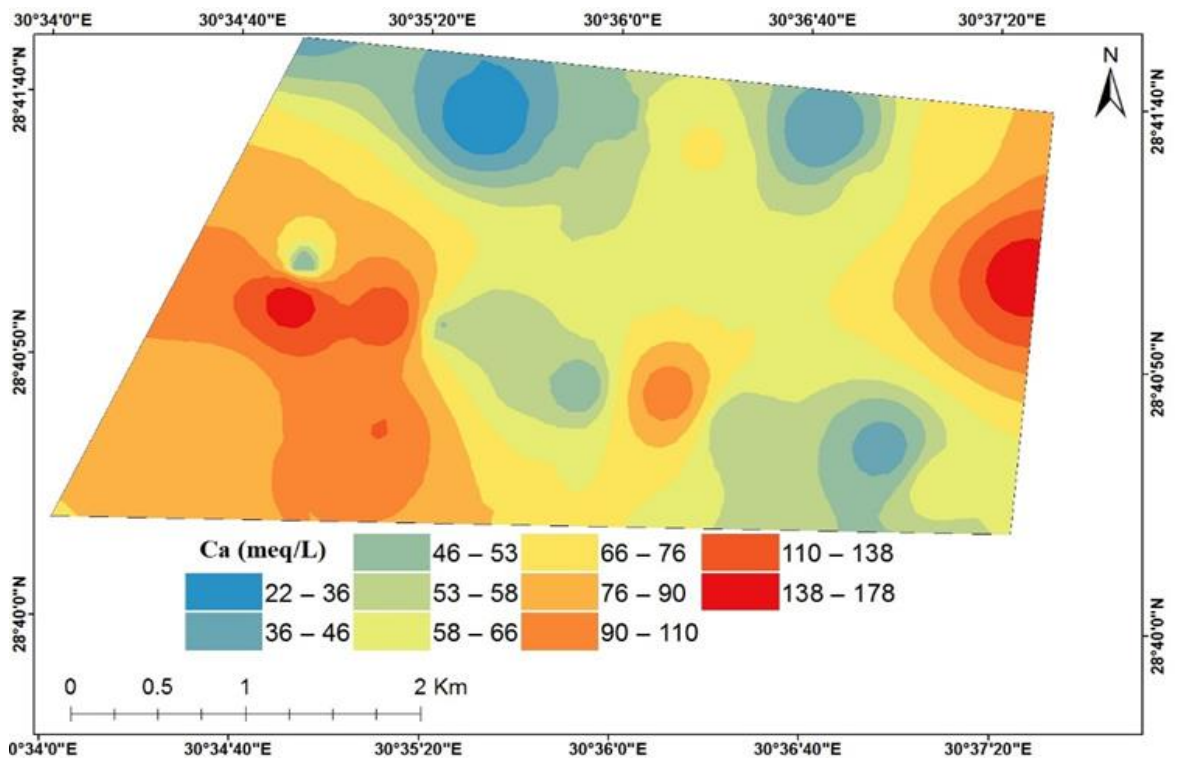


Fig.5: Calcium distribution map

Magnesium: It reached 432 meq/L in the southeast, as shown in (Fig. 6)

In (Fig.7) the highest level of bicarbonate is in the range of 16.8 - 18.4 meq/l, while the lowest level is in 4.0 - 5.6 meq/l. (Carter & Gregorich, 2020).

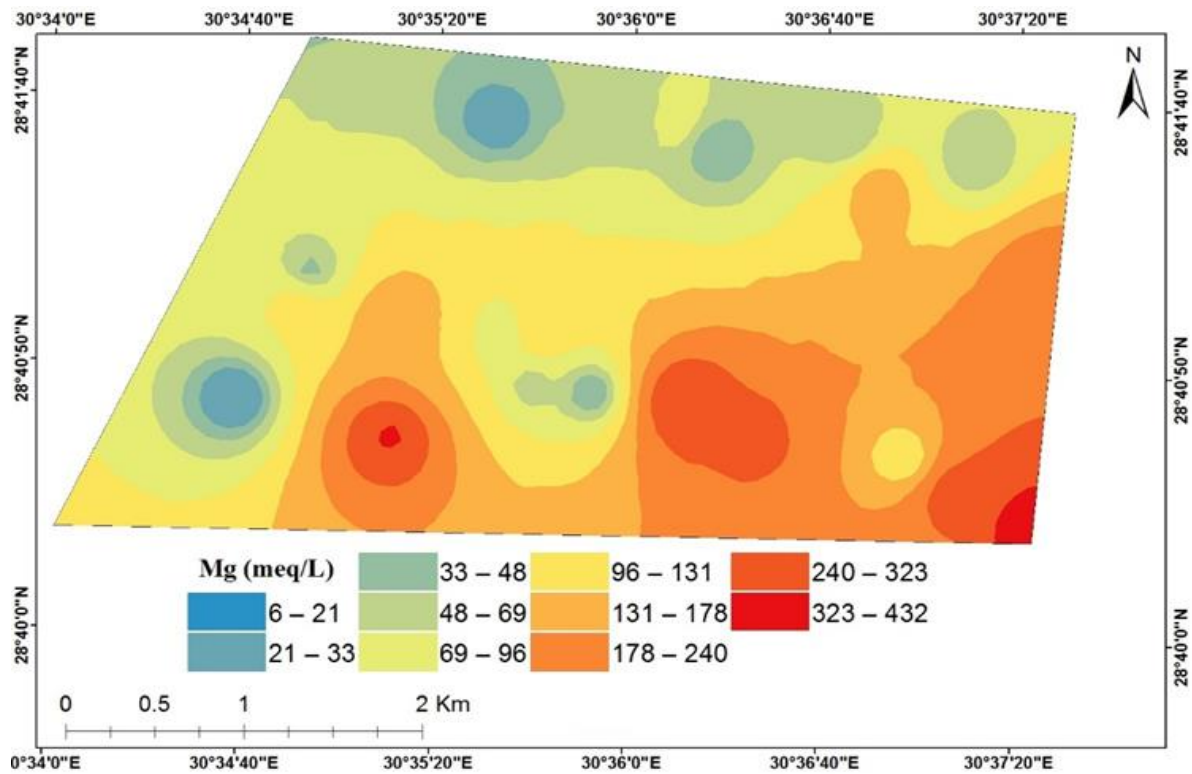


Fig.6: Magnesium distribution map

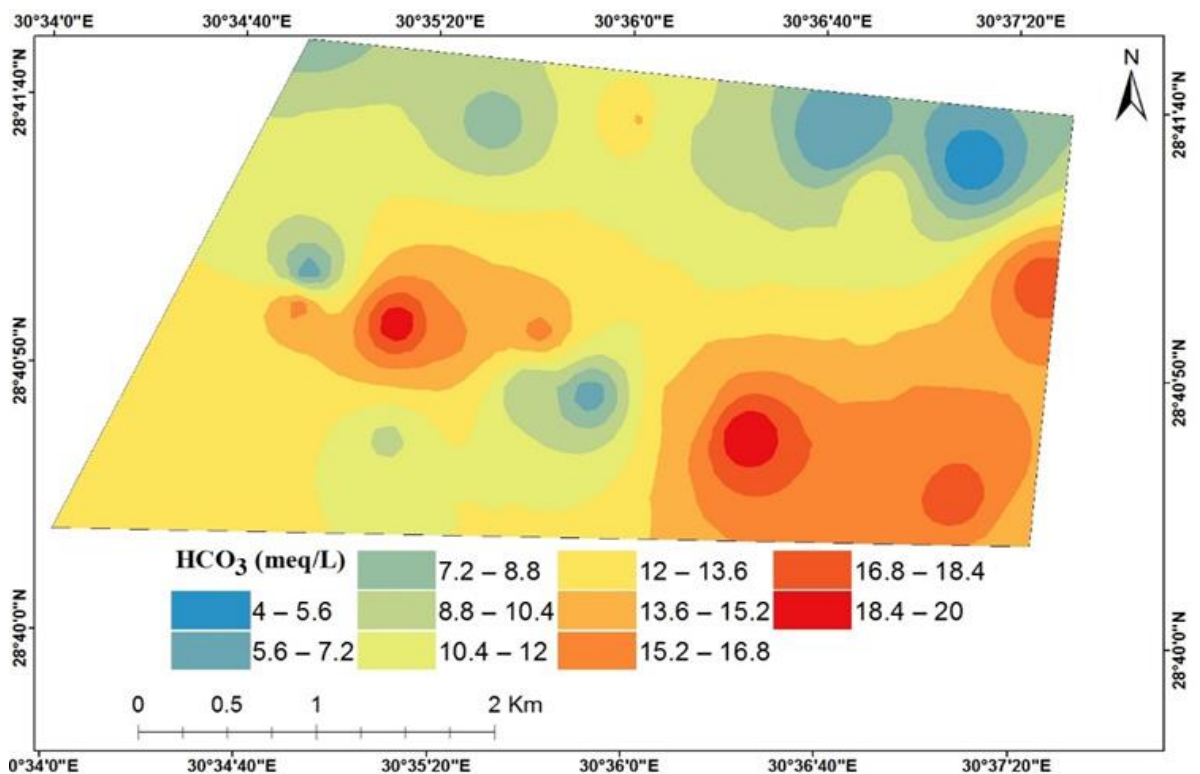


Fig.7: Bicarbonate distribution map

Micronutrient elements : Available micronutrient elements as shown in Table 3, the data indicates (Fig.8), that available iron range from 0.007 to 1.453 mg/L, with the highest level being 1.453 mg/L and the lowest level being 0.007 mg/L (Rohr, Brandenburg, & Brunner-La Rocca, 2023), it is evident (Fig.9) that the available copper concentration levels range from

0.0284 mg/L to 0.301 mg/L, with the highest level being 0.301 mg/L and the lowest level being 0.0284 mg/L (Fagnano et al., 2020), it is evident(Fig.10) that the available zinc levels range from 0.0189 mg/L to 0.605 mg/L, with the highest level being 0.605 mg/L and the lowest level being 0.0189 mg/L (Saleem et al.,2022) and it is evident (Fig.11) that the available manganese levels from 0.0083 mg/L to 4.811 mg/L, with the highest level being 4.811 mg/L and the lowest level being 0.0083mg/L(Khoshru et al., 2023), highest level being 4.811 mg/L and the lowest level being 0.0083mg/L(Khoshru et al., 2023).

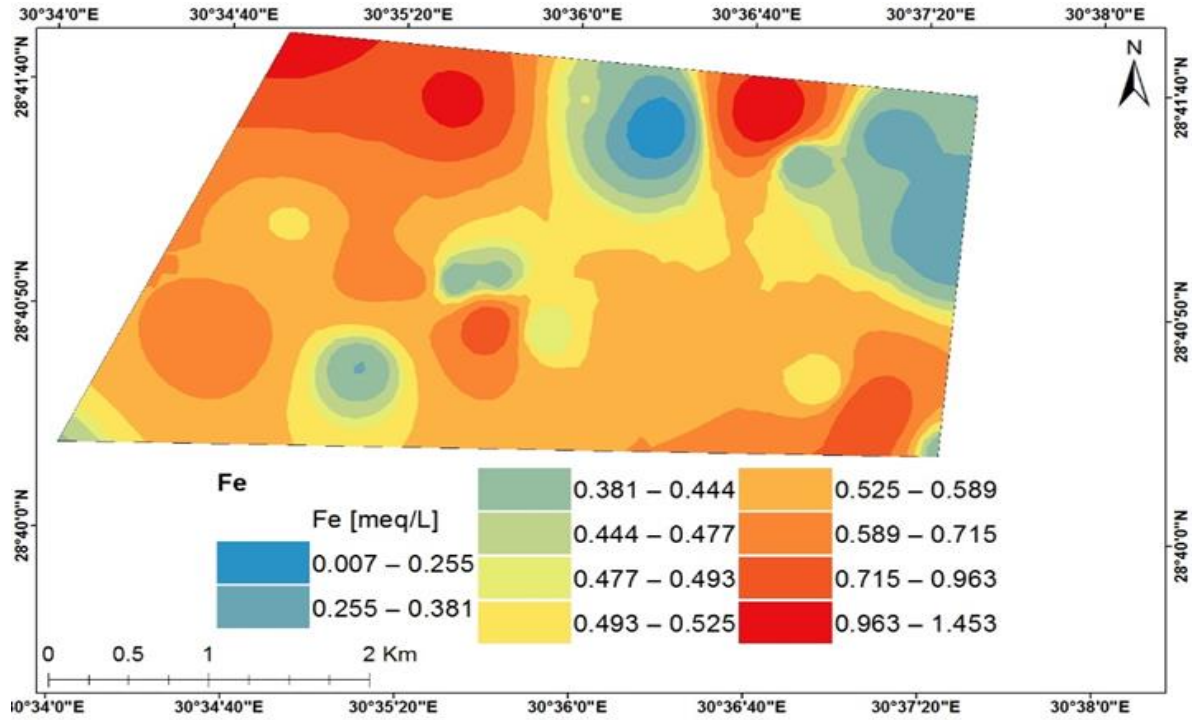


Fig.8: Iron distribution map

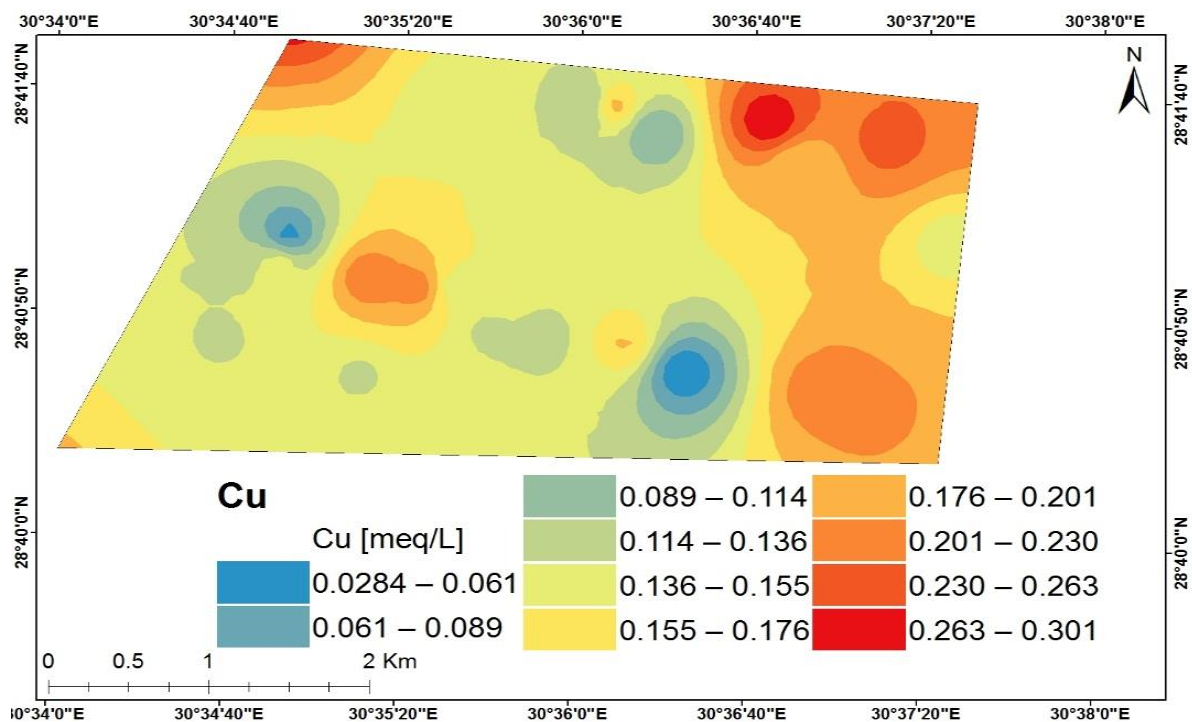


Fig.9: Copper distribution map

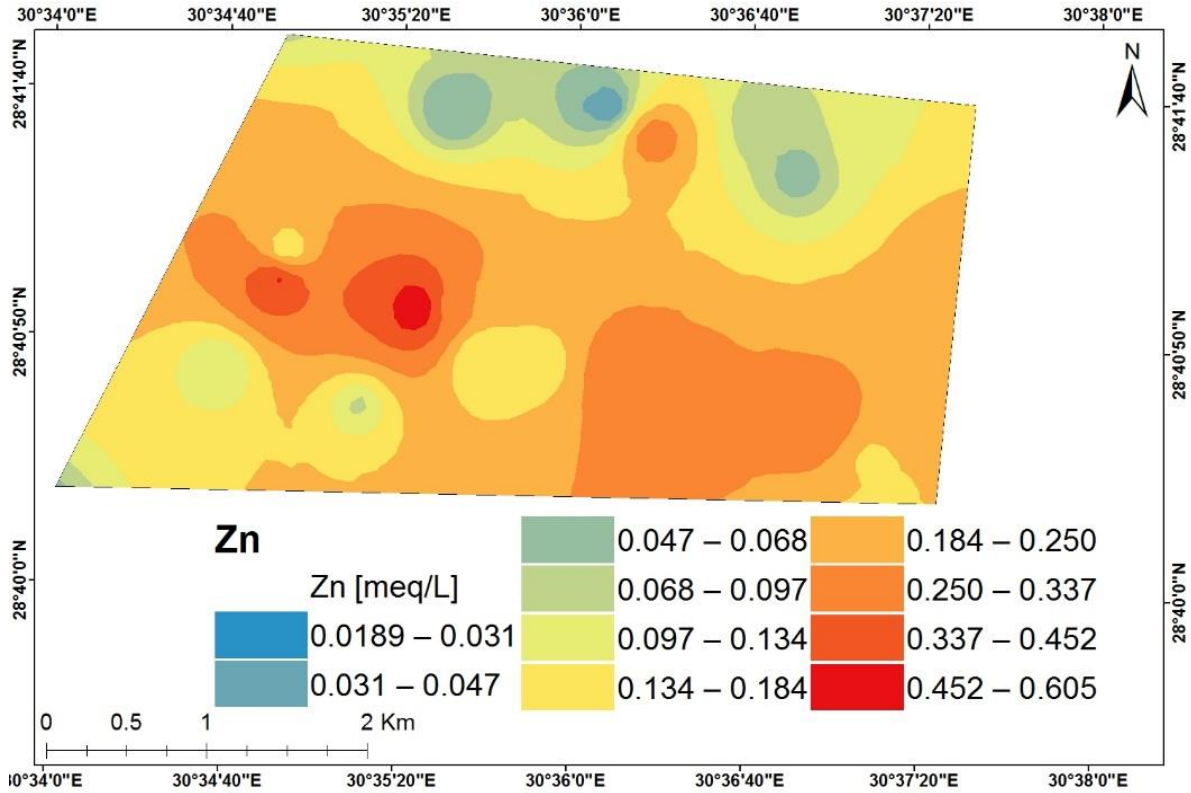


Fig.10: Zinc distribution map

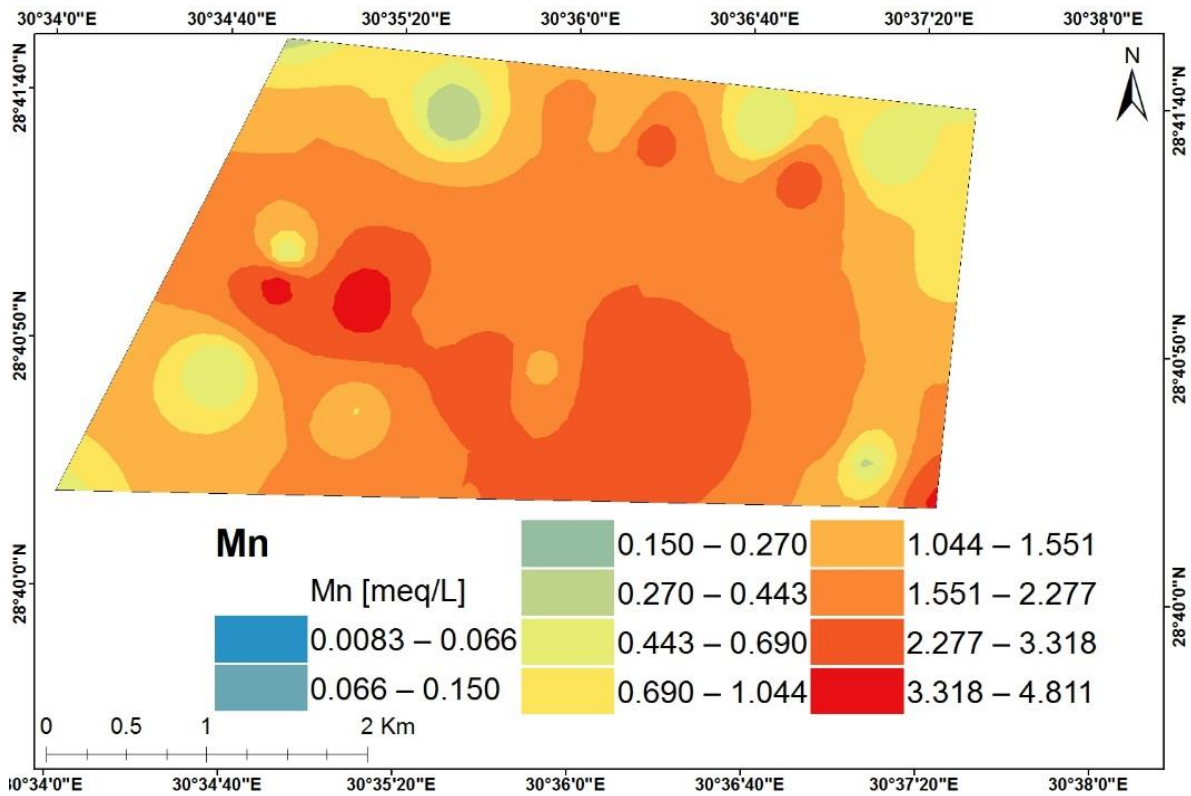


Fig.11: Manganese distribution map

Table 4: Some chemical properties and available micronutrients of soil samples.

Depth	ECe dS/m	pH	Ca meq/l	Mg meq/l	HCO ₃ ⁻ meq/l	Cl meq/l	Fe mg/l	Mn mg/l	Cu mg/l	Zn (mg/l)
0-30	4.04	7.5	72	46	4	14	0.327	0.388	0.246	0.134
30-60	4.92	7.6	54	80	8	10	0.469	0.078	0.333	0.179
>60	4.9	7.48	70	22	6	20	0.323	0.118	0.354	0.097
0-30	8.53	7.78	30	36	4	34	1.453	0.008	0.301	0.062
30--60	11.2	7.78	40	32	10	60	0.508	0.104	0.341	0.550
>60	14.7	7.92	42	30	10	84	0.660	2.462	0.331	0.016
0-30	4.04	7.5	64	108	10	170	0.398	0.080	0.194	0.019
30--60	4.92	7.6	8	212	10	292	0.467	0.058	0.093	0.030
>60	4.9	7.48	40	180	10	188	0.834	0.145	0.096	0.051
0-20	9.93	7.9	22	20	8	46	1.090	0.085	0.139	0.025
20--40	56.9	7.84	44	106	8	312	0.309	0.222	0.195	0.008
40-60	44	7.44	100	102	6	224	0.040	0.142	0.189	0.065
>60	42.2	7.66	50	110	10	238	0.373	0.316	0.131	0.110
0-30	4.99	7.7	40	40	6	16	0.493	0.233	0.048	0.125
30--60	2.9	7.66	48	10	4	10	0.356	0.203	0.098	0.025
>60	14.3	7.7	64	36	8	76	0.498	3.112	0.159	0.126
0-30	8.6	7.57	74	6	12	32	0.673	0.161	0.134	0.080
30--60	39	8.21	34	104	10	200	0.330	0.209	0.094	0.142
>60	39.8	8.17	50	68	6	204	0.354	0.164	0.105	0.032
0-30	87.6	7.23	112	338	10	532	0.371	1.000	0.131	0.086
30--60	81.4	7.4	70	400	16	500	0.478	0.389	0.015	0.058
>60	42.2	7.4	216	80	14	254	0.385	0.299	0.118	0.011
0-30	11.2	7.6	54	54	8	54	0.959	3.407	0.128	0.027
30--60	5.27	8	46	18	8	8	0.300	0.893	0.029	0.056
>60	5.38	7.69	50	30	6	12	0.310	0.918	0.007	0.232
0-30	5.64	7.8	46	22	6	10	0.422	1.183	0.125	0.140
30--60	14.8	7.96	52	34	4	78	3.188	4.034	0.105	0.667
>60	24.9	8	50	54	10	112	0.374	4.795	0.000	0.030
0-30	39.2	7.3	50	268	20	246	0.555	3.203	0.028	0.343
30--60	7.93	7.5	44	26	10	30	0.375	2.967	0.123	0.309
>60	7.41	7.3	44	64	8	30	0.640	0.554	0.009	0.353
1	5.63	7.69	48	32	14	20	0.484	2.260	0.092	0.045
2	14.3	7.8	70	24	10	64	0.007	2.698	0.078	0.317
3	26.5	7.48	60	158	12	138	0.347	2.812	0.159	0.049
4	68.2	7.4	164	236	18	672	0.243	0.928	0.138	0.252
5	62.8	7.47	178	112	16	398	0.563	3.999	0.150	0.468
6	42.7	7.47	138	194	20	260	0.644	4.811	0.236	0.355
7	35.6	7.84	52	128	16	176	0.629	2.227	0.226	0.605
8	6.16	7.71	46	50	14	16	0.356	1.657	0.138	0.286
9	38.6	7.74	58	134	16	196	0.404	1.939	0.156	0.211
10	131	7.25	106	340	14	1142	0.560	3.187	0.181	0.340
11	21.4	7.74	40	94	16	514	0.446	1.874	0.226	0.336
12	77.8	7.9	64	286	18	526	0.956	0.365	0.220	0.173
13	100	7.5	60	432	14	760	0.391	3.567	0.193	0.189

Interpolation models and validation:

The interpolation models provided distinct estimates of soil property distribution across Sheikh Masoud. The Kriging model produced smoother, more accurate surfaces due to its consideration of spatial correlations, validated by calculating Root Mean Square Error (RMSE). Defined as:

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

where $Z(x_i)$ is the observed value, $\hat{Z}(x_i)$ is the interpolated value, and n is the number of points, the RMSE was 1.5 for Kriging, outperforming the 2.3 RMSE for IDW.

The data was collected from the analysis results and presented and analyzed using the Geographic Information System (GIS) program to show the different soil units (**Brevik et al., 2016; Pešić -Mikulec et al., 2019; and Sishodia et al., 2020**)

Delineation of Management Zones:

Based on the chemical analyses data of soil samples were shown in **Table (4)** and **Fig. (12)**. Sixteen management zones were identified: zone 1 (52.4% of the area) is classified as "Non-Salin (2.9-5.2 dS/m), good micro-nutrient and pH >7.6", indicating it has favorable soil conditions for agriculture, zone 2 (2.4%) is "Non-Saline, good micro-nutrient and pH >7.6", also suitable for agriculture, zone 3 (7.6%) is "Slightly Saline (5.3-20.0 dS/m), good micro-nutrient and pH >7.6", which may require some salinity management techniques, zone 4 (14.3%) is "Slightly Saline, good micro-nutrient and pH >7.6", similar to Zone 3., zone 5 (5.4%) is "Slightly Saline, Moderate micro-nutrient and pH >7.6", which may need more careful nutrient management, zone 6 (12.2%) is "Moderately Saline (20.1-60.0 dS/m), Low micro-nutrient and pH >7.6", indicating the need for salinity and nutrient amendments, zone 7 (1.9%) is "Moderately Saline, Good micro-nutrient and pH >7.6", a relatively better zone for agriculture, zone 8 (3.0%) is "Moderately Saline, Moderate micro-nutrient and pH >7.6", with similar requirements as Zone 6, zone 9 (5.9%) is "Moderately Saline, Moderate micro-nutrient and pH >7.6", also in need of salinity and nutrient management, zone 10 (2.1%) is "Moderately Saline, Low micro-nutrient and pH <7.6", the most challenging zone for agriculture, zone 11 (0.2%) is "Strongly Saline (>60.0 dS/m), good micro-nutrient and pH <7.6", requiring significant reclamation efforts, zone 12 (0.1%) is "Strongly Saline, good micro-nutrient and pH >7.6", also highly saline, zone 13 (0.3%) is "Strongly Saline, Moderate micro-nutrient and pH >7.6", with similar challenges as Zone 11 and 12, zone 14 (3.3%) is "Strongly Saline, Moderate micro-nutrient and pH >7.6", another highly saline zone, zone 15 (0.4%) is "Strongly Saline, Low micro-nutrient and pH <7.6", the most unfavorable zone for agriculture, zone 16 (0.3%) is "Strongly Saline, Low micro-nutrient and pH >7.6", also highly saline.

According to the study's results, and from **Fig. 12**, it could be recommended as follows:

-The most suitable zones for agriculture would be Zones 1, 2, and 7, which have good micro-nutrient levels and pH conditions. These zones could be suitable for various high-value crops: vegetable crops such as

tomatoes, peppers, and leafy greens according to (**Shahbaz and Ashraf, 2013**); fruit trees such as citrus, olives, and pomegranates consistent with (**Munns, R., & Tester, M., 2008**); cotton according to (**Ashraf, 2002**), potentially with the implementation of drip or sprinkler irrigation systems to manage salinity.

- The more saline and nutrient-deficient zones (6, 8, 9, 10, 11, 12, 13, 14, 15, and 16) would require special soil management practices, such as the application of micro-nutrient fertilization and leaching, as well as the implementation of advanced irrigation techniques like subsurface drip systems to leach salts and improve the soil profile, and for these zones, start with salt-tolerant forage crops and halophytic plants like *Hordeum*, *Atriplex*, and *Medicago* to help improve the soil, as suggested by (Qadir et al. 2001); grow salt-resistant shrubs and trees to gradually reclaim the land according to (Flowers and Colmer, 2008) and (Rengasamy 2006).

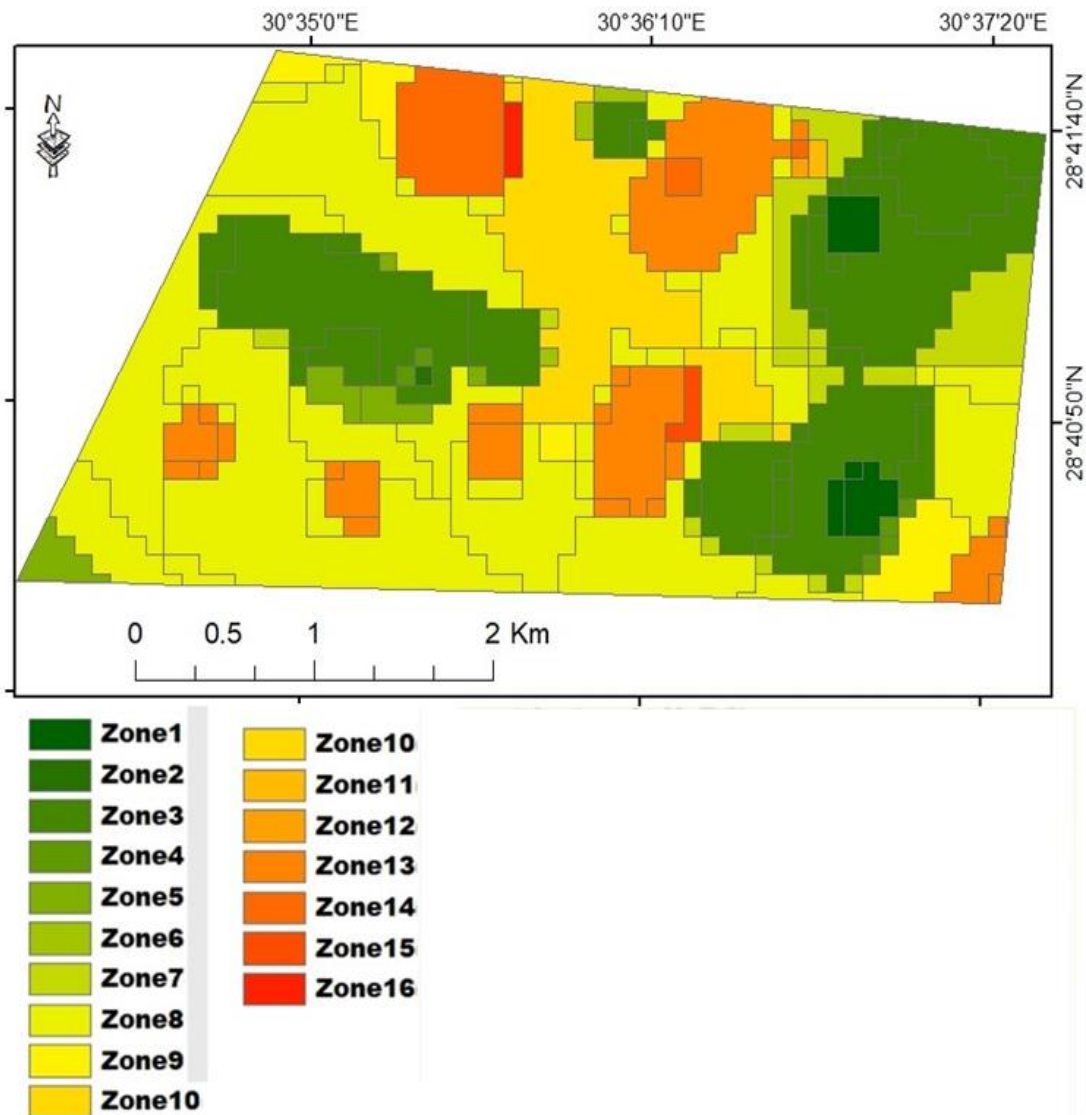


Fig. 12: Distribution of soil management zones in Sheikh Masoud village.

CONCLUSION

From this study, the following can be summarized: the study has demonstrated that GIS and mathematical modeling are highly effective for delineating soil management zones, allowing for precision agricultural practices tailored to the unique characteristics of Sheikh Masoud’s soil. The spatial variability of electrical conductivity (E_c) and pH, with E_c ranging from 4 to 14.3 dS/m and pH between 7.23 and 8.0, provided a basis for classifying the study area into

sixteen management zones. These zones were linked to specific crop recommendations and irrigation, enhancing water-use efficiency and productivity. Good Nutrient Zones, with low ECe and optimal pH, were found suitable for high-value, while Moderate and Poor Zones, characterized by higher salinity, were recommended for salt-tolerant crops or soil amendments to address saline conditions. The use of both IDW and Kriging models, validated by RMSE calculations, enabled accurate interpolation of soil properties, with Kriging proving especially reliable due to its spatial correlation, achieving an RMSE of 1.5.

REFERENCES

- Aparicio N, Villegas, D, Araus J.L, and Casadesus (2002). Relationship between growth traits and spectral vegetation indices in durum wheat. *Crop Science*;42: 1547-1555. <https://doi.org/10.2135/cropsci2002.1547>
- Ashraf, M. (2002). "Salt tolerance of cotton: some new advances." *Critical Reviews in Plant Sciences*, 21(1), 1-30. [https://doi.org/10.1016/S0735-2689\(02\)80036-3](https://doi.org/10.1016/S0735-2689(02)80036-3)
- Brevik, E. C., et al. (2016). Soil mapping, classification, and pedologic modeling: History and future directions. *Geoderma*, 264, 256-274. <https://doi.org/10.1016/j.geoderma.2015.05.017>
- Carter, M. R., & Gregorich, E. G. (2020). *Soil sampling and methods of analysis* (2nd ed.). CRC Press. <https://doi.org/10.1201/9781420005271>
- Chandra Pandey, P., Tripathi, A.K., and Sharma, J.K. (2021). An evaluation of GPS opportunity in market for precision agriculture. In *GPS and GNSS Technology in Geosciences*; Petropoulos, G.P., Srivastava, P.K., Eds.; Chapter 16; Elsevier: Oxford, UK,; pp. 337–349 <https://doi.org/10.1016/B978-0-12-818617-6.00016-0>
- Corwin, D. L., et al. (2006). Monitoring management-induced spatio-temporal changes in soil quality through soil sampling directed by apparent electrical conductivity. *Geoderma*, 131(3-4), 369-387.. <https://doi.org/10.1016/j.geoderma.2005.03.014>
- Corwin, D. L., & Lesch, S. M. (2005). Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture*, 46(1-3), 11-43. <https://doi.org/10.1016/j.compag.2004.10.005>
- Corwin, D. L., & Lesch, S. M. (2005). Characterizing soil spatial variability with apparent soil electrical conductivity. Part II. Case study. *Computers and Electronics in Agriculture*, 46(1-3), 135-152. <https://doi.org/10.1016/j.compag.2004.11.003>
- Elbasiouny, H., et al. (2014). Spatial variation of soil carbon and nitrogen pools by using ordinary Kriging method in an area of north Nile Delta, Egypt. *Catena*, 150, 291-301. <https://doi.org/10.1016/j.catena.2013.09.008>
- Elsharkawy, M. M., et al. (2022). Tool for the establishment of agro-management zones using GIS techniques for precision farming in Egypt. *Sustainability*, 14(9), 5437. <https://doi.org/10.3390/su14095437>

- Fagnano, M., et al. (2020). Copper accumulation in agricultural soils: Risks for the food chain and soil microbial populations. *Science of The Total Environment*, 734, 139434. <https://doi.org/10.1016/j.scitotenv.2020.139434>
- Flowers, T. J., & Colmer, T. D. (2008). "Salinity tolerance in halophytes." *New Phytologist*, 179(4), 945-963. <https://doi.org/10.1111/j.1469-8137.2008.02531.x>
- Kasampalis, D. A., Alexandridis, T. K., Deva, C., Challinor, A., Moshou, D., & Zalidis, G. (2018). Contribution of remote sensing on crop models: A review. *J. Imaging*, 4(4), 52.. <https://doi.org/10.3390/jimaging4040052>
- Khoshru, B., et al. (2023). Enhancing manganese availability for plants through microbial potential: A sustainable approach for improving soil health and food security. *Bacteria*, 2(3), 129-141. <https://doi.org/10.3390/bacteria2030010>
- Li, J., & Heap, A. D. (2014). Spatial interpolation methods applied in the environmental sciences: A review. *Environmental Modelling & Software*, 53, 173-189. <https://doi.org/10.1016/j.envsoft.2013.12.008>
- Lindsay, W. L., & Norvell, W. A. (1978). Development of a DTPA soil test for zinc, iron, manganese, and copper. *Soil Science Society of America Journal*, 42(3), 421-428. <https://doi.org/10.2136/sssaj1978.03615995004200030009x>
- McLean, E. O. (1982). Soil pH and lime requirement. In A. L. Page, R. H. Miller, & D. R. Keeney (Eds.), *Methods of soil analysis, Part 2: Chemical and microbiological properties* (2nd ed., pp. 199-224). American Society of Agronomy, Soil Science Society of America. <https://doi.org/10.2134/agronmonogr9.2.2ed.c12>
- Munns, R., & Tester, M. (2008). "Mechanisms of salinity tolerance." *Annual Review of Plant Biology*, 59, 651-681. <https://doi.org/10.1146/annurev.arplant.59.032607.092911>
- Munns, R., James, R. A., & Läuchli, A. (2006). "Approaches to increasing the salt tolerance of wheat and other cereals." *Journal of Experimental Botany*, 57(5), 1025-1043. <https://doi.org/10.1093/jxb/erj100>
- Narayana, M.R, and Rao, N. H. (1995). GIS based decision support systems in agriculture. National Academy of Agricultural Research Management. Ragendranagar, Hyderabad. https://www.researchgate.net/publication/240617973_GIS_Based_Decision_Support_Systems_in_Agriculture
- Pešić-Mikulec, D., Stojanović, D., and Joksimović, D. (2019). Application of GIS in studying land use and soil properties. *Applied Engineering Letters*, 4(3), 93-97. <https://doi.org/10.18485/aeletters.2019.4.3.3>
- Qadir, M., et al. (2001). Amelioration strategies for saline soils: a review. *Land Degradation & Development*, 12(4), 357-386. <https://doi.org/10.1002/ldr.458>

- Ratnaparkhi, S., et al. (2020). Smart agriculture sensors in IOT: A review. *Materials Today: Proceedings*.. <https://doi.org/10.1016/j.matpr.2020.11.138>
- Rengasamy, P. (2006). World salinization with emphasis on Australia. *Journal of Experimental Botany*, 57(5), 1017-1023. <https://doi.org/10.1093/jxb/erj108>
- Rhoades, J. D. (1982). Soluble salts. In A. L. Page, R. H. Miller, & D. R. Keeney (Eds.), *Methods of soil analysis. Part 2: Chemical and microbiological properties* (2nd ed., pp. 167-179). American Society of Agronomy, Soil Science Society of America. <https://doi.org/10.2134/agronmonogr9.2.2ed.c11>
- Rohr, M., Brandenburg, V., & Brunner-La Rocca, H.-P. (2023). How to diagnose iron deficiency in chronic disease: A review of current methods and potential markers for the outcome. *European Journal of Medical Research*, 28, Article number: 15. <https://doi.org/10.1186/s40001-022-00922-6>
- Saleem, M. H., et al. (2022). Functions and strategies for enhancing zinc availability in plants for sustainable agriculture. *Frontiers in Plant Science*, 13, 1033092.. <https://doi.org/10.3389/fpls.2022.1033092>
- Seelan, S. K. (2003). Remote sensing application for precision agriculture: A learning community approach. *Remote Sensing of Environment*.,88:157-169. <https://doi.org/10.1016/j.rse.2003.04.007>
- Shahbaz, M., & Ashraf, M. (2013). "Improving salinity tolerance in cereals." *Critical Reviews in Plant Sciences*, 32(4), 237-249. <https://doi.org/10.1080/07352689.2013.758544>
- Sishodia, R. P., Ray, R. L., and Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing*, 12(19), 3136. <https://doi.org/10.3390/rs12193136>
- Thomas, G. W. (1982). Exchangeable cations. In A. L. Page, R. H. Miller, & D. R. Keeney (Eds.), *Methods of soil analysis. Part 2: Chemical and microbiological properties* (2nd ed., pp. 159-165). American Society of Agronomy, Soil Science Society of America. <https://doi.org/10.2134/agronmonogr9.2.2ed.c9>
- Vašát, R., Heuvelink, G.B.M., and Borůvka, L. (2010). Sampling design optimization for multivariate soil mapping. *Geoderma*, 155, 147–153. <https://doi.org/10.1016/j.geoderma.2009.07.005>
- Webster, R., and Oliver, M. A. (2007). *Geostatistics for Environmental Scientists* (2nd ed), John Wiley & Sons, USA. <https://doi.org/10.1002/9780470517277>
- ISBN-13: 978-0-470-02858-2 (HB).
- Zia, M. H., et al. (2007). Effectiveness of sulphuric acid and gypsum for the reclamation of a calcareous saline-sodic soil under four crop rotations. *Journal of Agronomy and Crop Science*, 193(4), 262-269. <https://doi.org/10.1111/j.1439-037X.2007.00262.x>

Zivotic, L. (2018). Effect of irrigation regime on yield, harvest index and water productivity of soybean grown under different precipitation conditions in a temperate environment. *Agricultural Water Management*, 213, 1-10 <https://doi.org/10.1016/j.agwat.2018.08.002>

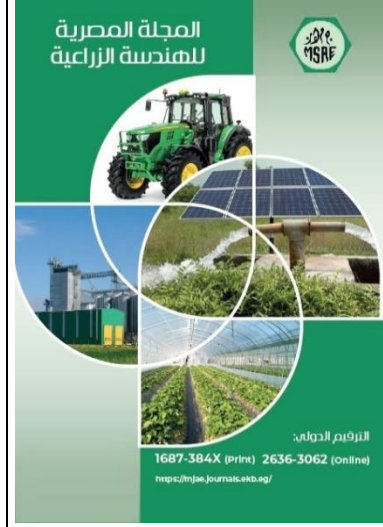
تحديد وإدارة المناطق الزراعية باستخدام الاستشعار عن بعد ونظم المعلومات الجغرافية في قرية الشيخ مسعود بمحافظة المنيا

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الملخص العربي

أجريت الدراسة في قرية الشيخ مسعود بالمنطقة الصحراوية غرب محافظة المنيا (28°39'15.3"N, 30°40'49.1"E) وكانت التربة ذات قوام رملي طمي بهدف تحديد النطاقات الزراعية باستخدام نظم المعلومات الجغرافية (GIS) والاستشعار عن بعد لتعزيز الزراعة الدقيقة من خلال تحديد نطاقات التربة وإدارتها باستخدام منهجيات مثل طريقة الوزن العكسي للمسافة (IDW) والتقدير الإحصائي (Kriging). ويتم دمج بيانات التربة المختلفة (الملوحة، درجة الحموضة) والعناصر الدقيقة (الحديد، المنجنيز، النحاس، والزنك) مع نماذج الاستيفاء المكاني القائمة على نظم المعلومات الجغرافية. وتم تحليل خصائص التربة مثل القوام، درجة الحموضة، والتوصيل الكهربائي (ECe)، وأوضحت النتائج عن وجود تنوع مكاني كبير في منطقة تبلغ مساحتها ٣٢٦٠ فدانا، حيث تراوحت قيم ECe من ٤ إلى ١٤,٣ ديسي سيمنز/متر، ومستويات درجة الحموضة من ٧,٢٣ إلى ٨,٠، مما يشير إلى ظروف مختلفة من الملوحة والقلوية. تم أخذ ٣ عينات على أعماق مختلفة من كل قطاع لتقدير العناصر المختلفة وقد أظهرت نماذج الاستيفاء المكاني التي تم التحقق منها باستخدام الجذر التربيعي لمتوسط الخطأ (RMSE)، وأن طريقة التقدير الإحصائي (Kriging) دقيقة وموثوقة مع قيمة RMSE وقيمتها ١,٥، مما أدى إلى إنتاج خرائط دقيقة لخصائص التربة المكانية. وتم تقسيم التربة لستة عشر نطاق: مناطق مغذية (جيدة ومتوسطة ومنخفضة)، ومن حيث الملوحة من مستويات ليس بها ملوحة إلى مستويات ملوحة قوية. ومما سبق يمكن التوصية باستخدام طرق ري مناسبة، مثل الري بالتنقيط والري تحت السطحي، لإدارة الأراضي تحت الظروف الحساسة للمياه والملوحة. وهذا النهج القائم على نظم المعلومات الجغرافية والنمذجة المكانية يدعم الممارسات الزراعية المستدامة.



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الكلمات المفتاحية:

مناطق إدارة التربة؛ نظم المعلومات الجغرافية؛ الاستشعار عن بعد في الزراعة؛ طريقة الوزن العكسي للمسافة (IDW)؛ درجة الملوحة (Ece).