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OPTIMIZED GIS-BASED RISK MAPPING OF WATER WALLS IN KIRKUK CITY

Amel Nashat Shakir[1*], Omar Falah Mirdan[2], Arjan Sharfuldeen Omar[3]

[1]Lecturer, Researcher, Department of Mathematics, Northern Technical University, Kirkuk, Iraq. e-mail: umayaa75@ntu.edu.iq,*
orcid: https://orcid.org/0000-0001-7936-4576
[2]Assistant Lecturer, Researcher, Department Technical of Surveying, Northern Technical University, Kirkuk, Iraq. e-mail: omer-falah@ntu.edu.iq,
orcid: https://orcid.org/0000-0002-2456-1270
[3]Assistant Lecturer, Researcher, Surveying Engineering, Northern Technical University, Kirkuk, Iraq. e-mail: arjan.bazirgan@ntu.edu.iq,
orcid: https://orcid.org/0000-0001-5468-1786

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SUMMARY

In Kirkuk City, Iraq, groundwater pollution is increasingly a problem due to intense urbanization, population growth, and unregulated water well drilling. Although the systematic assessment of groundwater pollution is essential to domestic and agricultural applications, the systematic analysis of its contamination has not been conducted, and the currently available approaches are not able to determine the high-risk zones. This paper involves Geographic Information Systems (GIS) and Multi-Objective Particle Swarm Optimization (MOPSO) to develop optimization risk maps of groundwater contamination. Data on key water quality parameters pH (7.10–8.30), turbidity (5.30–190.50 NTU), electrical conductivity (EC) (681.40–4245.87 µS/cm), total dissolved solids (TDS) (476.78–2563.5 mg/l), calcium (Ca) (31.33–256.33 mg/l), and chloride (Cl) (10.3–192.4 mg/l) were collected from 43 wells in the city. Kriging and Inverse Distance Weighting (IDW) were used as spatial interpolation methods, and then MOPSO was used to optimize the weights of the parameters to produce a more accurate risk mapping. The findings revealed that the central and southern areas were more contaminated, with TDS reaching up to 1477 mg/L and chloride up to 192.4 mg/L. On the other hand, contamination was lower in the northern and eastern parts, with TDS values of approximately 264 mg/l. The incorporation of MOPSO improved the reliability of groundwater risk predictions, providing a superior decision-making aid. This paper outlines how MOPSO and GIS can be used to manage groundwater effectively, which shows more precise risk evaluation. To improve predictions of long-term groundwater contamination, future studies should incorporate real-time monitoring and account for seasonal changes.

Key words: *groundwater contamination, GIS (geographic information systems), MOPSO (multi-objective particle swarm optimization), risk mapping, water quality parameters, TDS (total dissolved solids), spatial interpolation, contamination prediction.*

INTRODUCTION

Given that humans require water for survival, several scientific approaches have been developed to enhance the efficiency and effectiveness of locating well water sources. Above all things, clean water is crucial because, as a species, to simply cannot survive without it. In addition to drinking it, humans have long used the many natural surface water bodies for a wide variety of activities. As a result of political unpredictability and shifting development paradigms, several Western Asian countries have instituted food self-sufficiency policies that have increased surface and groundwater extraction through subsidies and the centralization of both large- and small-scale agricultural production [15][18]. When it comes to managing and developing water resources, groundwater is crucial. Information on groundwater hydrology and the hydraulics of water flow in aquifers is thus in high demand. Consequently, surface water must be sought after, stored, and utilized as a substitute. Groundwater was extracted from the soil at different depths using this process, guided by the geology of the ground core and the water's chemical composition [10][19]. Many elements and concentrations are predicted in this study. Recently, GIS (Geographic Information System) has become a widely used computer application [1]. With GIS, data is constantly updated; data cannot be collected, but it can be evaluated and modelled [4]. Much research has been conducted on using GIS to prepare the area and the city core. Conducted hydrogeological research on the Adana city settlement using GIS, groundwater level maps, and water quality evaluation maps that were generated [17]. Research conducted on larger scales using the same methodology, including river basins and aquifers. For this study, an internet tool was used to convert the geographical locations of 64 wells in Kirkuk City to the UTM coordinate system [20]. The water levels, both static and dynamic, were then collected from these wells. After that, using what to know about the research region, to adjust the positions of a few wells. To employ the interpolation analyst in GIS using two distinct approaches, namely Kriging and Inverse Distance Weighting (IDW), to forecast the PH, turbidity, E.C., TDS, Ca, and CL concentration maps, and then combine them to generate a risk map in the water wells of Kirkuk City.

Problem Statement

The research paper addresses the pressing issue of water pollution in Kirkuk City, where inundated urbanization, population growth, and uncontrolled drilling of water wells have already become a major concern for water quality and people's health. Although people heavily use groundwater for domestic and agricultural purposes, systematic evaluation and spatial knowledge of contamination levels across various areas are lacking. Current methods tend to be weak at combining various water-quality parameters and cannot accurately predict risky areas. In addition, there is no smooth analysis model that combines GIS services and application of advanced optimization processes, which makes it impossible to make effective decisions in the management of water resources. Therefore, the following conditions are necessary: a comprehensive, data-intensive approach applied to groundwater quality to evaluate contamination risk and enable sustainable planning by identifying vulnerable areas more accurately and with greater confidence.

Objectives

1. Produce the risk map of underground water using GIS techniques.
2. Production of maps for many types of interpolation.
3. Statistical comparison between the methods.

Key Contributions

- Developed a risk mapping system with GIS, including water quality parameters (pH, turbidity, EC, TDS, Ca, Cl) and spatial interpolation algorithms (IDW and Kriging) to assess the groundwater contamination in Kirkuk City.
- Applied the multi-objective particle swarm optimization (MOPSO) to enhance the accuracy and reliability of the spatial prediction and decision making to ascertain high-risk groundwater locations.

- Prepared risk maps with overlay analysis, raster-based, which would help identify hotspots of contamination, and successfully manage the city's water resources.

The paper is structured in the following way: I present the research problem, objectives, and context with emphasis on groundwater contamination in Kirkuk City. Section II will consider current related literature on GIS-based methods and quality assessment of groundwater. Section III provides the methodology that includes the use of GIS to perform spatial interpolation and MOPSO to perform risk mapping. Section IV gives the description of the study area and then Section V gives the information of the used data. The results are presented in Section VI, discussed in Section VII, and conclusions are made about the findings and directions at the end of the paper in Section VIII.

LITERATURE REVIEW

Groundwater is a scarce resource for drinking and irrigation, and its management has become a major concern in recent years as its contamination and demand are on the rise. Risk analysis and optimization methods based on GIS have turned into important tools to evaluate the quality of groundwater and water resources management [5]. The combination of Geographic Information Systems (GIS) and remote sensing (RS) has emerged as an effective tool in evaluating the quality of groundwater, enabling better predictions that are more accurate and spatially explicit [2]. In recent times, there has been increased use of GIS and remote sensing methods to track and determine the quality of groundwater. As an illustration, GIS and Analytic Hierarchy Process (AHP) have been used to evaluate the potential of groundwater, and demonstrated the potential of GIS-based systems to combine various layers of data and provide valid forecasts of groundwater availability [6]. Equally, land resource management has been enhanced through remote sensing and GIS, which has shown the effectiveness of these technologies in groundwater resources management, and in the analysis of the land use effects on water quality [7]. Multi-objective optimization methods like MOPSO (Multi-Objective Particle Swarm Optimization) have been employed in risk mapping of groundwater. Groundwater contamination predictions have been optimized using optimization algorithms and combining GIS with multi-objective optimization to ensure the balance of different water quality parameters, and high-risk areas have been determined [13][16]. These developments enable a stronger and more accurate groundwater hazard assessment to make improved management choices. Water risk assessment. In water risk assessment, water erosion risk as a result of climate change has been investigated, showing the ability of state-of-the-art modeling methods to evaluate environmental risks in susceptible areas, such as groundwater [9]. In addition, flood hazard mapping has been done using remote sensing and GIS, which helps to emphasize the importance of spatial analysis in managing environmental risks in water systems [8]. A number of studies have examined the flood risk management and the performance of water treatment plants in urban areas as well [12]. A water balance method utilizing GIS has been implemented to aid surface water flood-risk management, which could be provided to groundwater risk mapping [11]. Performance of water treatment plants has also been assessed using GIS with a focus on using the spatial data to enhance the management of water quality [14].

Recent progress in optimization methods, such as modified conjugate gradient algorithms and multi-objective arithmetic optimization, has presented new solutions to the management of groundwater resources. A new optimization algorithm is suggested to improve the performance of multi-objective problems in groundwater risk mapping [13].

This expanding literature shows that GIS, remote sensing, and high-order optimization methods are essential in enhancing the quality and efficiency of groundwater risk mapping, particularly in urban and semi-urban areas.

The literature notes that the use of GIS-based techniques, remote sensing, and optimization techniques in groundwater risk management, and specifically in mapping contamination, is becoming an increasingly important aspect of groundwater risk management. Recent research notes the efficiency of the combination of AHP and MOPSO with spatial information to improve the quality of groundwater vulnerability and contamination evaluation. The techniques enable optimization of a variety of water quality parameters and give more accurate risk maps, which can be used to make informed decisions in water resource management. Also, the effects of climate change and land use changes on the quality of groundwater are becoming more and more appreciated, and combined flood risk and erosion models provide a global strategy in managing the groundwater resources. Overall, these advancements in GIS, remote sensing, and multi-objective optimization are crucial for accurate risk prediction and sustainable groundwater management.

METHODOLOGY

In this project, in order to identify the risk map for water wells in Kirkuk City, a GIS-based interpolation process was used, and for this, MOPSO, or multi-objective particle swarm optimization, was employed. This chapter will explain the properties of the study area and the list of the data used for Produce a Risk map for Water Wells of Kirkuk City Using GIS Techniques. As shown in figure 1:

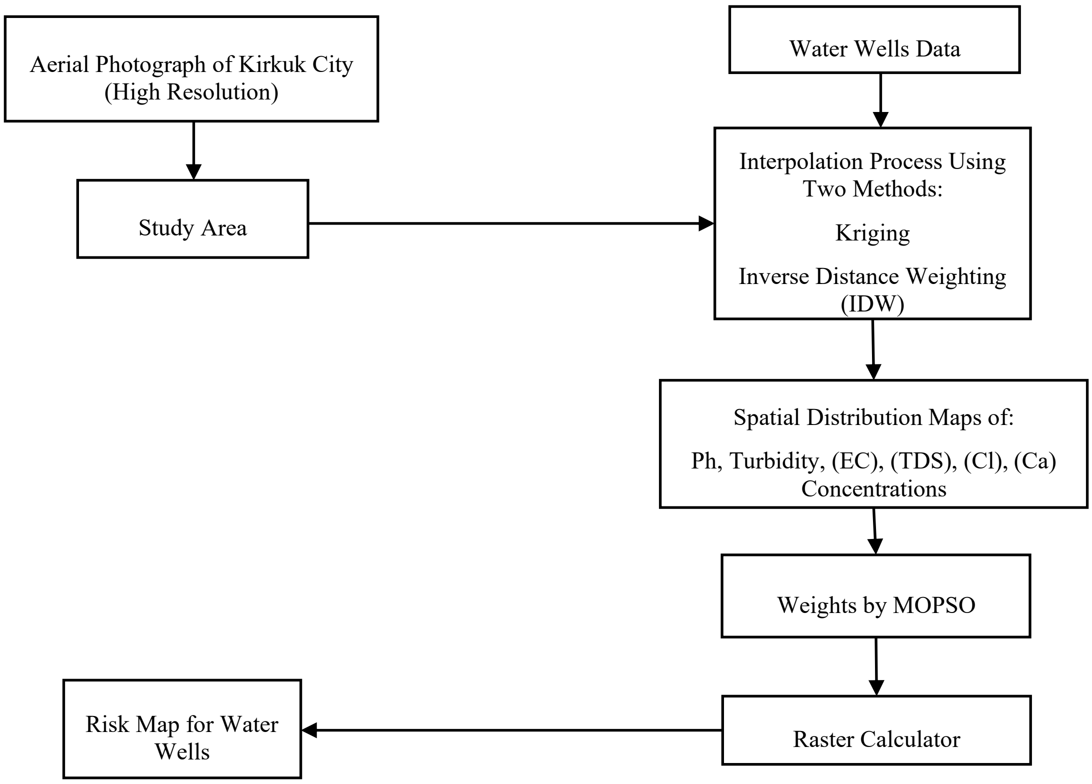


Figure 1. Flowchart of project methodology

Overview of MOPSO

Multi-Objective Particle Swarm Optimization (MOPSO) is a version of Particle Swarm Optimization (PSO) algorithm that is capable of solving multiple conflicting problems with multiple objectives all at the same time by generating a pool of the best trade-off solutions called the Pareto front. In this research, MOPSO is used to maximize the combination of different water quality variables and spatial interpolation products, which allows for the more precise delineation of risk zones of groundwater. The approach has been selected since it is able to effectively address complex, non-linear, multi-objective problems and strike a balance between exploration and exploitation. MOPSO is much faster to converge to an optimal solution than traditional methods of optimization, which include Genetic Algorithms (GA) and classical mathematical optimization, and is able to find more than one optimal solution in a single run, which makes it especially applicable to environmental modeling and space-based decision making.

Multi-Objective Optimization

When dealing with difficulties with more than one purpose, it is far more difficult to find a workable solution than when dealing with problems with a single objective. To find a collection of Pareto optimum solutions to these issues, which are not always better than one another. This set of solutions is optimal in that there is no better solution than them, taking into account all the objectives. It is very difficult to develop conventional optimization methods, such as gradient-based methods, simplex-based methods, and heuristic methods, such as simulated annealing, to solve a multi-objective problem accurately and completely. In general, in these methods, multi-objective problems must be transformed into a single-objective problem before optimization. One of the disadvantages of these methods is that a single solution is produced each time the optimization algorithm is run.

In multi-objective problems, instead of a single objective function, several objective functions are simultaneously optimized, and a compromise must be made between them. It is clear that the more the number of objective functions, the more complicated the compromise between them will be. The general form of a multi-objective problem can be represented by the following pseudo code:

Optimize: $Y = F(X) = [f1(X), f2(X), \dots, fk(X)]$

subject to: $g_{i(x)} \geq 0 \; i = 1,2, \dots, q$

$\mathrm{h}_{i(x)} = 0 \; i = q + 1, \dots, m$

Where $X = (x_1, x_2, \dots, x_n)$is an n-dimensional real vector in the set nE, which is called the decision vector, and $Y = (y_1, y_2, \dots, y_k)$ is the k-dimensional objective vector. As can be seen, a multi-objective optimization problem consists of k objective functions and m constraint functions in an n-dimensional x space. In these problems, are faced with a set of practical and impractical solutions. In these problems, are certainly looking for solutions that, while satisfying the existing constraints, are also the best compromise between the objectives. To say that the solution x is dominated by the solution x if x is worse than or equal to x in all objectives or if x is absolutely worse than x in at least one of the objectives. To show this partial order as follows. The solution x is dominated by:$x: x \prec x$. To consider all the undefeated solutions in a set like p. say that the solution x is undefeated if:$\forall x \in P: x \neq x \implies x \succ x$.

In other words, say that the solution is undefeated if no other solution has undefeated it. Given that evolutionary algorithms are inherently parallel, it has been recognized as a suitable tool for solving multi-objective problems. In these algorithms, a population of individuals (agents) can search for multiple solutions in parallel. Therefore, it has the potential to find multiple optimal solutions in a single execution of the algorithm.

Pareto Optimal Solutions

When solving optimization issues with many objectives, aim for a collection of solutions that are not mutually exclusive. This set of solutions is called Pareto optimal, named after the economist Vilfredo Pareto. the concept of Pareto optimality as follows: "For multi-objective problems, there is not a single solution, but rather a set of solutions called the Pareto set".

These sets of solutions are solutions that are not defeated by other solutions and are called non-defeatable. The set of solutions that are non-defeatable relative to other solutions to the problem are Pareto optimal solutions. Figure 2 shows Pareto optimal solutions. These solutions form a front in front of the other solutions, which is called the Pareto front.

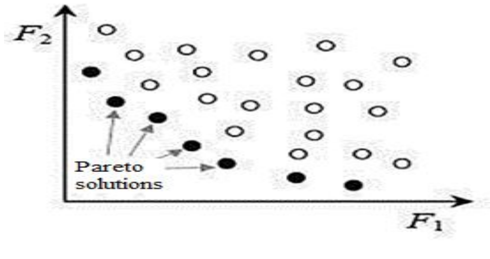


Figure 2. Pareto optimal responses

Evolutionary Algorithms

In recent decades, due to the increase in computer capabilities and their speed of iteration, the use of evolutionary algorithms has increased. Although these methods have their own shortcomings, to overcome some of the shortcomings of classical mathematical methods. The basis of these methods is trial and error.

Evolutionary algorithms are methods that are often based on the principles and laws of evolution, survival, life and progress in nature, living organisms or animals. In the natural process of evolution in the life of living organisms, a set of living organisms is evaluated based on specific characteristics and the best ones are identified and selected. Then, by reproducing or actually transferring the characteristics inherent in their existence between each other, these superior organisms are transferred from the present generation to the next generation, or the overall condition of their collection changes. Again, in the next generation, or in exchange for the new condition of the collection of organisms, the new organisms are evaluated according to specific goals and the best of them are selected for transfer to the next generation, or the condition of the existing collection changes again based on the condition of the best ones and to enter a new stage of life developments. In this way, successive future generations or different stages of life and growth of the collection are formed, and the general trend in question moves towards the evolution of organisms or improvement of the initial condition.

Among these methods, it can mention particle swarm algorithms, genetic algorithms, ant colony algorithms, forbidden search, simulated annealing, bee colony algorithms, colonial competition algorithms, etc.

Particle Swarm Algorithm

The particle swarm optimization algorithm is one of the methods of collective intelligence algorithms1, which was introduced. Bird population optimization is a heuristic method in particular. It has been widely used in recent years. This method has advantages over other methods, including that the optimal response is obtained independently of the initial values and after all particles participate in the algorithm, and in addition, the algorithm's less dependence and sensitivity to the objective function, its easy implementation, and its simple adjustment are advantage. The algorithm's simplicity and low implementation cost stem from the fact that it employs just a handful of fundamental computing operators. In addition, in some cases, it can overcome the problems that may be encountered when using the genetic algorithm.

This algorithm, like other algorithms that have a natural origin, is inspired by the behavior of birds and fish in nature. In nature, a group of birds or fish does not have much knowledge of their surroundings when are looking for food and adjust their movement according to the position of the birds around them so that can continue their movement and achieve their goal. In these movements, the creatures coordinate their speed with the other members of the group when are with other members of the group and do not collide with each other. In this group, each bird uses the experiences of other members of the group and improves its location each time compared to the previous time to find food.

In the problem context, searching and repeating form the basis of this method. Each solution is like a bird or particle exploring the issue space in this approach. Each particle's motion is affected by three distinct elements, which are:

1. The current position of the particle
2. The best position that the particle has had so far. (Pbest)
3. The best position that all particles have reached so far. (Gbest)

Particle swarm optimization (PSO) compares the population of replies to a group, and each answer to a particle, just as a bird in a flock. All particles possess a fitness value that must be optimized using the particle fitness function. The direction of movement of each particle is determined by its velocity vector. Each particle in this algorithm learns from its own and other particles' actions how to improve its social behavior so that it can reach its ultimate goal as efficiently as possible. Therefore, in this algorithm, a new answer is not created from the previous answers. The flowchart of this algorithm is given in figure 3.

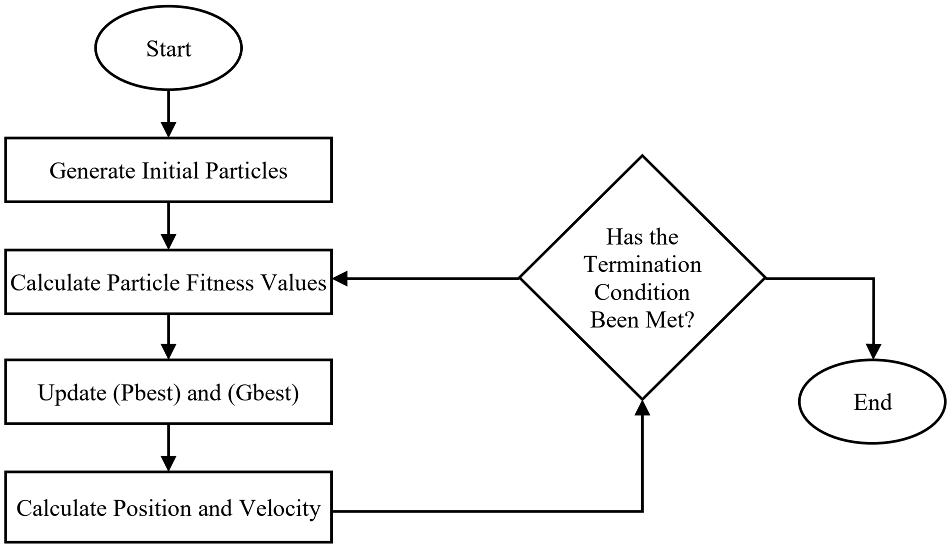


Figure 3. Flowchart of the PSO algorithm

In a D-dimensional issue:$Y_i = (x_{i1}, x_{i2}, \dots, x_{iD})^T$

represents the i-th particle's location in the population and $X_i = (a_{i1}, a_{i2}, \dots, a_{iD})^T$

represents the particle's velocity. To represent the iteration number by n.

$$V_{id}^{n+1} = V_{id}^{n} + c_1 r_1^n (pbest_{id}^n - X_{id}^n) + c_2 r_2^n (gbest_d^n - X_{id}^n)$$
$$V_{id}^{n+1} = V_{id}^{n} + V_{id}^{n+1} \quad (1)$$

$$V_{id}^{n+1} = x \cdot [w \cdot V_{id}^{n} + c_1 r_1^n (pbest_{id}^n - X_{id}^n) + c_2 r_2^n (gbest_d^n - X_{id}^n)] \quad (2)$$

$$X_{id}^{n+1} = X_{id}^{n} + V_{id}^{n+1} \quad (3)$$

The update rule of the velocity V_{id} of of the particle in PSO algorithm is explained in equations (1) and (2). The velocity is adjusted on the basis of the earlier velocity of the particle, the disparity among the current position and personal best position and the global best position. In equation (2), a weight of inertia w is included to balance between exploration and exploitation. Equation (3) changes the position of the particle X_{id} by the added velocity. All of these equations taken together can lead to best solutions because it takes into account both previous experiences and the overall swarm knowledge.

The contraction constant X is used in the previous formulations, the constant and positive coefficients:c_1 and c_2 are often taken to be between 1.5 and 2, and the parameters f_1 and f_2 are uniformly distributed random integers between 0 and 1.$[-X_{\max}, X_{\min}]$ are used to restrict the ultimate value of the particle velocity in order to keep the algorithm from diverging. The inertia weight, or parameter w, controls how past velocities influence the algorithm's convergence. In fact, it establishes a balance between global and local explorations. The value of w in each iteration is defined according to the equation (4).

$$w = w_{\max} - \frac{(w_{\max} - w_{\min}) \times n}{tter_{\max}} \quad (4)$$

In the above formula, $w_{\max}$ is the inertia weight at the beginning of the search, $w_{\min}$ is the inertia weight at the end of the search, n is the current iteration number, and $tter_{\max}$ is the total number of parameters.

Multi-Objective Particle Swarm Optimization Algorithm

The multi-objective particle swarm optimization algorithm, is an extension of the particle swarm optimization technique designed to address multi-objective issues. The MOPSO method incorporates a notion known as the archive or repository, referred to as the Hall of Fame, into the PSO algorithm. Choosing the optimal overall solution and the most effective personal memory for each particle is a crucial and significant phase in the multi-objective optimization process. When particles intend to initiate movement, select a member of the repository as the leader. This leader must be a member of the repository and not subjugated. The repository members constitute the Pareto front and encompass the non-dominated particles. Consequently, a member from the pool is chosen instead of Gbest. Consequently, there is no pool in PSO, as it is characterized by a singular objective and a sole optimal particle. However, in MOPSO, several particles are not dominated and occupy a position inside the solution set. To evaluate the optimal personal memory vector, proceed as follows in equations (5) and (6):

1- In the event that the new location becomes more prominent inside the memory particle, it will supersede the best memory. When expressed mathematically:

$$\text{pbest}\,_{i}^{n+1} = X_{i}^{n+1} \tag{5}$$

Equation (5) will change the personal best position of the particle to its current position, in case the new position is superior to the previous position.

2- If the new position is dominated by the best memory, nothing is done. In mathematical terms:

$$\text{pbest}\,_{i}^{n} = \text{pbest}\,_{i}^{n+1} \tag{6}$$

Equation (6) $pbest_i^n = pbest_i^{(n+1)}$ means that the personal best of particle i is not changed unless the current position $X_i^{(n+1)}$ is superior to the previous personal best $pbest_i^n$.

3- One is chosen at random as the best position vector if do not dominate each other.

Proposed Algorithm

Algorithm: GIS–MOPSO-Based Groundwater Risk Mapping

Input: Groundwater quality parameters (pH, Turbidity, EC, TDS, Ca, Cl) and spatial well data

Output: Optimized groundwater risk map

Step 1: Import and preprocess groundwater quality data in a GIS environment

Step 2: Normalize all parameters to ensure uniform scaling

Step 3: Generate spatial distribution maps using IDW and Kriging interpolation

Step 4: Initialize MOPSO with a population of particles (random weights)

Step 5: Define objective functions to minimize contamination risk

Step 6: Evaluate fitness of each particle using weighted overlay of parameter maps

Step 7: Update particle velocity and position using Pbest and Gbest

Step 8: Store non-dominated solutions in Pareto repository

Step 9: Repeat evaluation and update steps until convergence is achieved

Step 10: Select optimal solution from Pareto front

Step 11: Generate final groundwater risk map using GIS raster calculator

The algorithm that is suggested combines GIS-based spatial analysis with MOPSO to optimize the groundwater risk assessment. First, the parameters of water quality are preprocessed and interpolated by IDW and Kriging to produce spatial maps. Optimal weights of the parameters are then obtained using MOPSO to reduce the risk of contamination by minimizing the risks associated with the parameters using a multi-objective method. The algorithm iteratively updates solutions and stores the best trade-offs in the Pareto front. Lastly, the best alternative is used in GIS in order to generate the ground water risk map which enhances the accuracy and decision making relative to the traditional approach.

Software and Tools Used

The combination of Geographic Information System (GIS) and computational tools has been used to perform the analysis in order to have effective spatial modeling and optimization. The ArcGIS software (ArcMap environment) was used to perform spatial data processing, visualization, interpolation (IDW and Kriging) and risk mapping based on raster techniques. The Raster Calculator tool was used to combine various water quality parameters and come up with the final risk maps. The Multi-Objective Particle Swarm Optimization (MOPSO) algorithm was coded in MATLAB, which simplified the work with the multi-objective optimization process and numerical calculations. Preliminary data organization, cleaning, and statistical preparations were also done with the assistance of Microsoft Excel. All of these tools allowed conducting an efficient data analysis, modeling, and visualization during the study.

Interpolation Methods for Spatial Analysis

In this research, the parameters on groundwater quality were estimated using two interpolation techniques, Inverse Distance weighting (IDW) and Kriging, in Kirkuk City. IDW is a deterministic algorithm that estimates the value of an unmeasured point by averaging the values of the known points that are close to it, giving the closer points larger weights. Its ease and speed of computation are well-suited to situations where the points that are closer to each other tend to be similar, like in groundwater research. However, IDW also presupposes homogeneity in local areas, which is not necessarily true, particularly in cities. Also, the results may depend on the selected power parameter. Kriging on the other hand is a geostatistical technique that uses a semi variogram to model the spatial correlation between data points. It is not only giving predictions but also estimates the error and it can be used in studies where it is necessary to know the prediction uncertainty. Kriging is especially applicable in the study of groundwater contamination as it can be used to explain spatial dependencies. Although it is more computationally intensive than IDW, Kriging has the capacity of minimizing errors in prediction as well as offering confidence intervals hence a useful tool. IDW and Kriging complement each other, providing efficiency and accuracy, respectively, to create a complete and reliable map of groundwater quality risk.

STUDY AREA

The study area is Kirkuk City, its geographical position is (44° 43' 00" N – 44° 32' 00" N) and (35° 50' 00" E – 35° 38'00" E) located in northern Iraq, at about (238 km) north of Baghdad. The altitude is (367 m) above mean sea level, and the area of Kirkuk government is around (9676 km2) and represents the ratio of about (2.2%) of Iraq. Figure 4. Shows the study area.

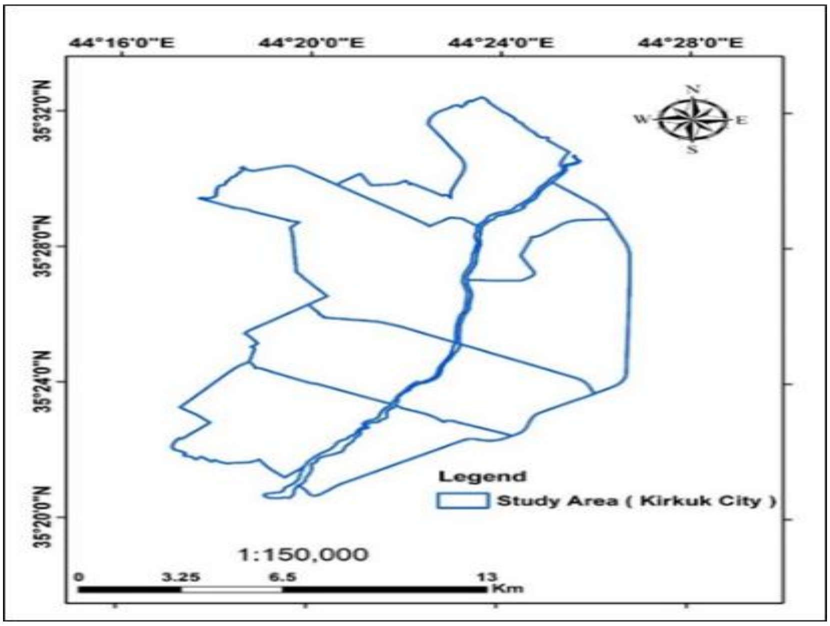


Figure 4. The study area of kirkuk city

DATA USED

The data of the project has been from the Water Drilling Department. The data represent the wells that distributed over Kirkuk City. The data contains 43 wells, and three of them were used as testing wells for the interpolation process. Table 1. Shows all points of wells. Furthermore, the correction process has been made for positions. Figure 5 shows the wells over Kirkuk City.

Table 1. The wells and their information in kirkuk city

No.	Wel's Name in English	E	N	Excavation Year	PH	turbidity	E.C (Mmos/cm)
1	Al- Hamzaly Distrrict	442696	3923316	2012	7.1	40.1	1268
2	Al- Sayada Water Station / 2	441091	3915901	2011	8.06	70.17	1685
3	Al- Sayada Water Station / 3	441170	3916486	2011	7.36	9.98	1668
4	Al- Sayada Water Station / 4	440837	3915718	2012	8.1	40.88	2112
5	Antiquities Police Department	444683	3925483	2013	7.8	15.09	1267
6	Castle Houses / 1	444273	3916466	2013	7.98	15.73	2725
7	Castle Houses / 2	444649	3916002	2013	7.8	73.23	1287
8	Civil Defense Directorate - Wasity	440882	3918675	2012	8	35.15	1240
9	College of Education for Human Sciences	440219	3916924	2014	7.8	62.2	2310
10	Control point Wahid Huzairan	437680	3918882	2014	8.03	57.45	1744
11	Depatment of Ambulances immediate	442575.1	3919127	2011	8.3	9.63	800
12	Dumiz Police Office	443744	3916593	2014	7.9	13.46	2371
13	Emergency Kirkuk Regiment / 1	439692	3917975	2013	8.13	6.16	2265
14	Emergency Kirkuk Regiment / 2	442458	3924611	2013	7.8	67.75	1399
15	Emergency Kirkuk Regiment / 3	442661	3924702	2013	7.6	5.88	1343
16	Health Care Center / Al- askary District	444643	3919114	2011	7.94	19.09	3010
17	Health Care Center / Al- Nasir District	445887	3920133	2011	7.8	29.5	2870
18	Kirkuk police /3	440526	3922036	2013	7.8	135.8	1031

19	Kirkuk police training center - 2	440127	3922747	2013	7.8	33.4	1146
20	North Gas Company District / 4	440260	3920066	2011	8.07	4.68	1377
21	North Gas Company District / 5	440388	3920342	2011	8	10.21	1054
22	North Gas Company District / 6	440239	3920651	2011	7.31	190.1	1562
23	North Gas Company District / 7	439937	3920746	2011	7.95	83.01	1983
24	North Gas Company District / 8	439884	3920315	2011	8.22	59.98	1044
25	Old Tissen District / 1	442549	3922644	2011	8.1	32.68	1197
26	Old Tissen District / 2	439205	3920658	2011	8.15	32.51	1096
27	Sunni Waqf	443666	3924205	2011	7.85	17.37	1106
28	The presidency of kirkuk university	443662	3922753	2007	7.7	43.86	1992
29	The presidency of kirkuk university - Agriculture -1	440336	3916214	2013	8	28.47	1679
30	The presidency of kirkuk university - Agriculture -2	439705	3916157	2013	8	39.52	1962
31	Tissen overpass	443308	3923435	2013	7.4	19	1018
32	UN Mission office	442586.2	3924796	2014	7.8	69.35	1347
33	Wahid Huzairan Discrit	439291	3918378	2011	8.3	192.4	1500
34	Wahid Huzairan Discrit / 1	438515	3919246	2011	7.47	11.3	867
35	Wahid Huzairan Discrit / 2	438767	3919306	2011	8.14	12.8	677
36	Wahid Huzairan Discrit / 4	439818	3918005	2013	8.1	14.14	1135
37	Wahit Athar Discrit	442259.4	3917096	2012	8	46.8	1170
38	Wahit Huzairan - Assrya clinic	439542	3918161	2013	8.1	14.46	1376
39	Wahid Huzairan Discrit/3	440000.228	3918310	2011	8.3	192.4	1500
40	Planting Baghdad Road - baghdad 1	443288.386	3921031	2011	7.81	102.5	1369

No.	**Wel's Name in English**	**E**	**N**	**Excavation Year**	**T.D.S (mg/l)**	**Ca**	**CL**
1	Al- Hamzaly Distrrict	442696	3923316	2012	810	112	56.7
2	Al- Sayada Water Station / 2	441091	3915901	2011	1477	208	57
3	Al- Sayada Water Station / 3	441170	3916486	2011	1170	120	71
4	Al- Sayada Water Station / 4	440837	3915718	2012	1724	212	57
5	Antiquities Police Department	444683	3925483	2013	770	160.3	21.2
6	Castle Houses / 1	444273	3916466	2013	1477	22404	127.7
7	Castle Houses / 2	444649	3916002	2013	1201	256.5	87.5
8	Civil Defense Directorate - Wasity	440882	3918675	2012	974	160.3	42.5
9	College of Education for Human Sciences	440219	3916924	2014	2079	192.3	85.2
10	Control point Wahid Huzairan	437680	3918882	2014	1000	160.3	127.6
11	Depatment of Ambulances immediate	442575.1	3919127	2011	520	54	14
12	Dumiz Police Office	443744	3916593	2014	1300	208.4	148.9
13	Emergency Kirkuk Regiment / 1	439692	3917975	2013	1360	240.4	212.7
14	Emergency Kirkuk Regiment / 2	442458	3924611	2013	890	144.2	85.1
15	Emergency Kirkuk Regiment / 3	442661	3924702	2013	800	160.3	63.8
16	Health Care Center / Al- askary District	444643	3919114	2011	2428	116	128
17	Health Care Center / Al- Nasir District	445887	3920133	2011	1897	240	28
18	Kirkuk police /3	440526	3922036	2013	634	112.2	42.5
19	Kirkuk police training center - 2	440127	3922747	2013	720	99.7	78
20	North Gas Company District / 4	440260	3920066	2011	959	88	39
21	North Gas Company District / 5	440388	3920342	2011	738	35	60
22	North Gas Company District / 6	440239	3920651	2011	1093	98	99
23	North Gas Company District / 7	439937	3920746	2011	1500	92	64
24	North Gas Company District / 8	439884	3920315	2011	831	58	21
25	Old Tissen District / 1	442549	3922644	2011	839	68	21
26	Old Tissen District / 2	439205	3920658	2011	769	72	57
27	Sunni Waqf	443666	3924205	2011	915	35	36
28	The presidency of kirkuk university	443662	3922753	2007	1120	141	42.5

29	The presidency of kirkuk university - Agriculture -1	440336	3916214	2013	1000	97.2	21.2
30	The presidency of kirkuk university - Agriculture -2	439705	3916157	2013	1100	97.2	21.2
31	Tissen overpass	443308	3923435	2013	620	107	21.2
32	UN Mission office	442586.2	3924796	2014	800	63.2	170.2
33	Wahid Huzairan Discrit	439291	3918378	2011	975	78	43
34	Wahid Huzairan Discrit / 1	438515	3919246	2011	606	42	16
35	Wahid Huzairan Discrit / 2	438767	3919306	2011	474	31	16
36	Wahid Huzairan Discrit / 4	439818	3918005	2013	690	48.6	21.2
37	Wahit Athar Discrit	442259.4	3917096	2012	804	100	65.5
38	Wahit Huzairan - Assrya clinic	439542	3918161	2013	801	97.2	21.2
39	Wahid Huzairan Discrit/3	440000.228	3918310	2011	975	78	43
40	Planting Baghdad Road - baghdad 1	443288.386	3921031	2011	1050	107	21.2

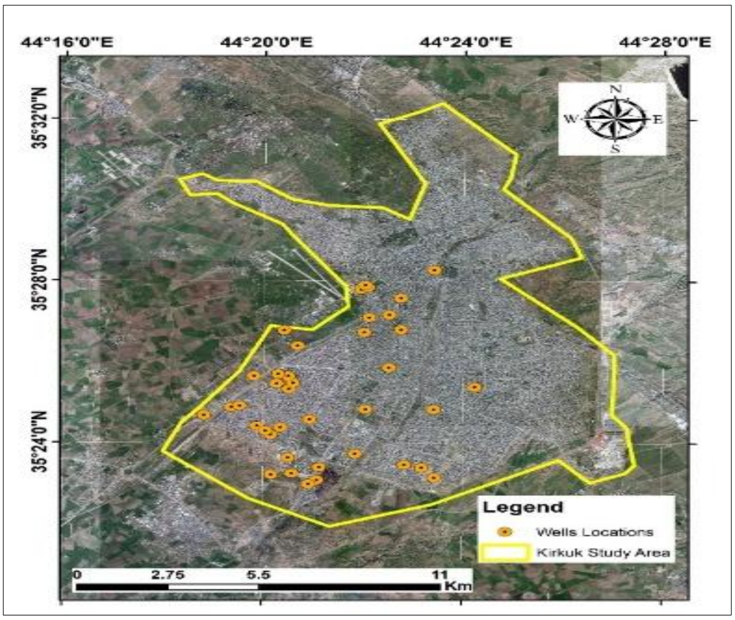


Figure 5. The distribution of wells over kirkuk city

Spatial Analysis and GIS Interpolation for Groundwater Risk Mapping

The GIS interpolation was used to conduct a spatial analysis of groundwater quality in order to estimate the water quality of Kirkuk City based on 43 wells. Continuous maps of pH, turbidity, EC, TDS, Ca, and Cl were created using the IDW and Kriging techniques to represent the local and global spatial variations. The accuracy of the interpolation was checked with the observed wells. The parameters maps were then superimposed with weighted overlay whereby the weight was optimized through MOPSO resulting in the final groundwater risk map which was categorized as low, medium, and high-risk zones. This will enable the hotspots of contamination to be identified clearly and will enable sustainable water management.

INTERPOLATION PROCESS

Recent years have seen a rise in geostatistics' focus on spatial dataset analysis and interpretation. People used to rely a lot on one another for this procedure, and as would all adopt somewhat different ways, the results were sometimes very varied. Each case was dependent on the judgment and experience of individuals to select the right interpolation or regression technique. However, the variety of spatial interpolation and regression technique, the increase availability of digital datasets, and with the increase software and hardware capabilities, the process of interpretation and analysis of spatial datasets became more machine dependent.

The analysis and interpolation of geographical data are crucial and significantly reliant on human expertise. It is widely recognized that various individuals use diverse methodologies, resulting in a multitude of unique solutions. The selection of spatial interpolation techniques for each instance is determined by the judgment and expertise of several experts. Geographic Information Systems (GIS) offer readily available spatial interpolation techniques that require examination through these models.

IDW (Inverse Distance Weight)

All interpolation methods are founded on the principle that proximate locations exhibit greater correlations and similarities than distant points. In the IDW approach, it is fundamentally assumed that the rate of correlations and similarities among neighbors is inversely proportional to the distance between them, which may be described as a distance inverse function for each point relative to its surrounding points. This method will be used by a state in which there are enough sample points with a suitable dispersion in local scale levels. One of the advantages of this method is that it is suitable for showing discontinuous lines such as fractures, quailings, faults, levees, and rivers, which create fractures and discontinuities on the surface.

$$Z_o = \frac{\sum_{i=1}^{N} z_i \, d_1^{-n}}{\sum_{i=1}^{N} d_1^{-n}} \tag{7}$$

In equation (7) Where, Z_o represents the estimated value of variable z at point i.

Z_i= sample value at point i.

d_1 represents the distance between the sample point and the estimated point.

N = A coefficient that establishes weight in relation to distance.

Ordinary Kriging

The idea of Kriging posits that the direction or distance between sample sites indicates a spatial relationship that may be utilized to demonstrate surface variation. This tool corresponds to the mathematical function for some spots or all points within a given radius to ascertain the output value for each site. Kriging tools use multi-stage processes. It encompasses the modeling of variables, exploratory statistical analysis of data, possibly investigating the variance surface, and constructing a surface. Kriging is the optimal method when there is directional bias in the data or a spatially correlated distance. These are frequently utilized in geology and soil science.

$$\breve{Z}\,(S_o) = \sum_{i=1}^{N} \lambda_i \, Z(S_i) \tag{8}$$

In equation (8), where:

$Z(S_i)$ = the value measured at the ith location

λ_i = an unknown weight for the value measured at the ith location

S_o = forecast site

N = the number of values measured

Methods Validation

Validation of analytical methods involves a thorough examination of the most pertinent processes for determining optimal parameters, utilizing various critical performance indicators such as selectivity, specificity, accuracy, precision, linearity, range, limit of detection (LOD), limit of quantification (LOQ), ruggedness, and robustness. This discussion aims to avert erroneous applications and to guarantee scientific integrity and uniformity across publications.

GIS-Based AHP

Data storage, integrated data management, and enhanced public engagement are all made feasible by the development of the Geographic Information System (GIS). Data in the 1960s, information in the 1970s, knowledge in the 1980s, and intelligence in the 1990s are the eras in which information technology has seen the most significant changes.

Since the 1970s, GIS technology has given the distinctive capability of automating and analyzing a variety of spatial data. It has also evolved into a mature research and application area concerning various fields, namely geography, civil engineering, computer science, land-use planning, and environmental science. At present, the GIS is a powerful tool in spatial modeling, which involves a large number of spatial decision problems, providing alternative scenarios in the context of maps.

Raster Calculator

The Raster Calculator is intended to perform a single-line algebraic statement utilizing several tools and operators through a user-friendly, calculator-style interface. The utilization of many tools or operators inside a single expression often enhances performance compared to running each operator or tool separately.

The Raster Calculator tool is not intended to be used in scripting environments and is not available in the standard Spatial Analyst Arc by module.

Risk Map

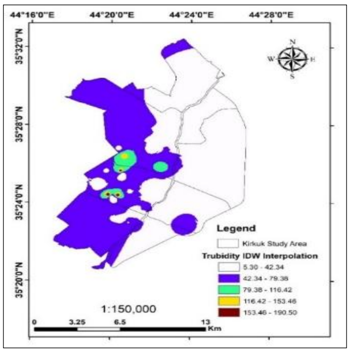
A risk assessment is a methodical analysis of possible hazards associated with an activity, project, or enterprise. Risks are recognized and prioritized for action according to their likelihood of occurrence and the severity of their potential effect. Risk assessment tasks are occasionally termed risk analysis or risk mapping. Risk assessments offer a means to identify and comprehend hazards, vulnerabilities, and threats that may adversely affect the business. With this information, a business may focus expenditures and efforts on risk mitigation and control techniques. In the work use raster calculator in ArcMap GIS to identify a risk map for concentrations of elements that harming human health. The overlay of raster layers will produce the risk map.

RESULTS

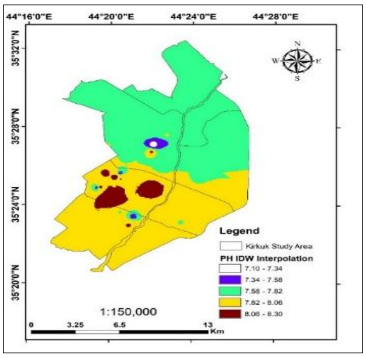
IDW Interpolation Outcomes

Figure 6 (a) illustrates the IDW interpolation for pH concentration in Kirkuk City's wells, classified into five classes: very low (7.10–7.34), low (7.34–7.58), moderate (7.58–7.82), high (7.82–8.06), and very high (8.06–8.30). The middle-south has very high concentrations of pH, whereas high PH levels are in the middle south to the south. Moderate PHs are distributed between the middle and north, with low PHs in small regions in the middle, and very low PHs in the north. Figure 6(b) shows the turbidity concentration map, classified into five classes: very low (5.30–42.34), low (42.34–79.38), moderate (79.38–116.42), high (116.42–153.46), and very high (153.46–190.50). Very high and high concentrations are found in small areas in the middle-south, while moderate levels are more spread across the middle and middle-south. The distribution of low turbidity is in the western parts, and a portion of the east, and very low turbidity is concentrated in the eastern parts of the city.

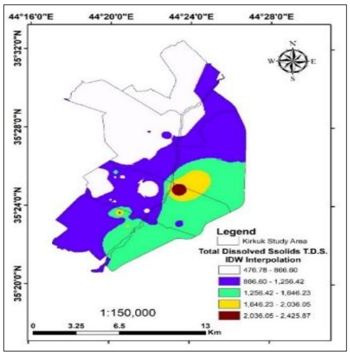
Figures 6 illustrates interpolation maps of different water quality parameters in Kirkuk City through IDW with the level of concentrations falling in five categories. Turbidity (5.30 190.50 NTU) is also exhibited in figure 6(a) and very high in the middle-south. At figure 6(b), the pH (7.108.30) is high, and in the middle south, it is very high. Figure 6(c) presents T.D.S. (476.78–2563.5 mg/l), with high levels in the southern areas. Figure 6(d) depicts EC (681.40–4245.87 µS/cm), with high concentrations in the south. Calcium figure (6(e)) is depicted to be 31.33-256.33 mg/l, wherein it is high in the south and the center. Figure 6(f) is chloride (10.33192.4mg/l), and the levels are very low in the eastern and northern parts of the city.



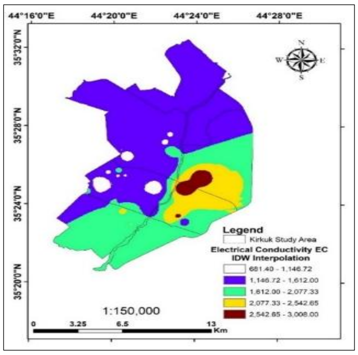
6(a)



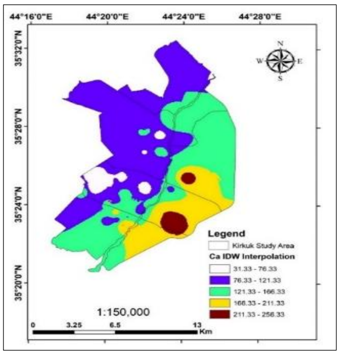
6 (b)



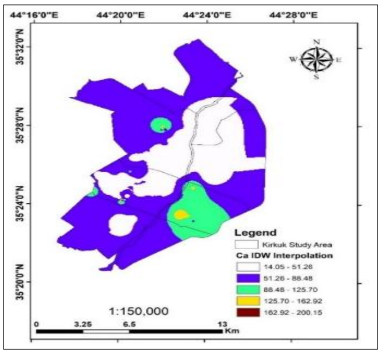
6(c)



6(d)

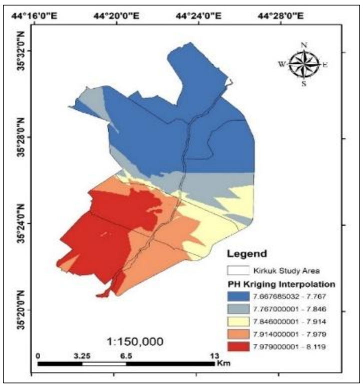


6(e)

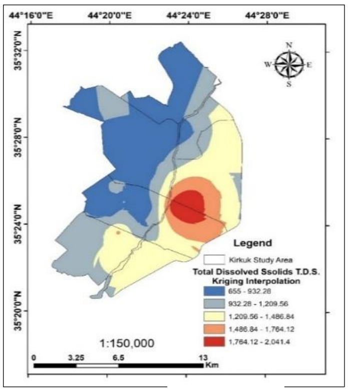


6(f)

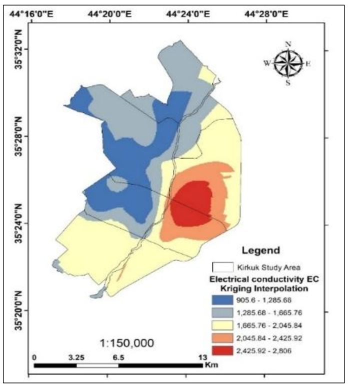
Figure 6 (a): IDW interpolation for turbidity concentration, 6(b): IDW interpolation for PH concentration, 6(c): IDW interpolation for total dissolved solids T.D.S, 6(d): IDW interpolation for electrical conductivity EC, 6 (e): IDW interpolation for Ca concentration, 6(f): IDW interpolation for Cl concentration



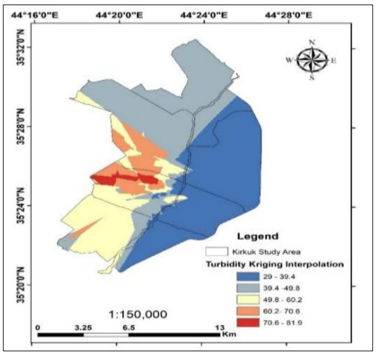
7(a)



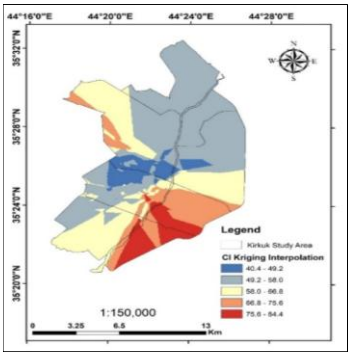
7(b)



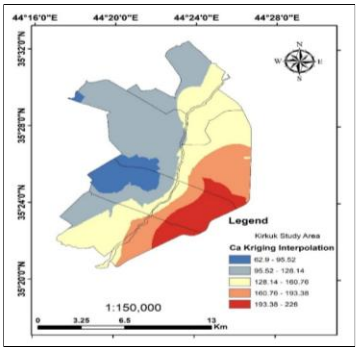
7(c)



7(d)



7(e)



7(f)

Figure 7(a). Kriking interpolation for PH concentration, 7(b). kriking interpolation for total dissolved solids T.D.S,7(c). kriking interpolation for electrical conductivity EC,7(d). kriking interpolation for turbidity concentration, 7(e). kriking interpolation for Cl concentration,7(f). kriking interpolation for Ca concentration

In figures 7, a sequence of Kriging interpolation maps of different water quality parameters in the wells of Kirkuk City is presented. The pH levels in figure 7(a) vary between 7.10 and 8.30, with the higher PH levels being centered in the middle-south. Figure 7(b) shows that the 476.78-2563.5 mg/l is Total Dissolved Solids (T.D.S.) and is high in the southern regions. Figure 7(c) shows Electrical Conductivity (EC) values ranging between 681.40 and 4245.87 µS/cm with high EC in the south. Figure 7(d) indicates turbidity levels (5.30190.50 NTU), and the levels are very high in the middle-south. In figure 7(e) chloride (Cl) concentrations range between 10.3 and 192.4mg/l with low concentrations in the east and north. Calcium (Ca) concentrations (31.33256.33 mg/l) are shown in figure 7(f), and are higher in the south and middle of the city. These maps can be used to determine regions of interest with different water quality problems, which are significant in water treatment and management.

The risk maps in the present study are the spatial mapping of the different parameters of the groundwater quality in the Kirkuk study area, such as turbidity, pH, T.D.S., EC, calcium, and chloride levels. Such maps will offer important information as to the regions where the water quality is below normal levels, and where health risks in the use of groundwater are possible.

Cooler colors (purple and light blue) in each map correspond to lower concentrations, which is appropriate to indicate superior water quality and can be used without much treatment. Conversely, regions with greater concentrations, which are associated with warmer hues (yellow, red, and orange), denote areas of contamination that are more dangerous to human health and the utility of water sources. As an example, turbidity or EC can be high, which can be a sign of suspended particles, dissolved salts, and can influence the taste, quality, and applicability of the water to agricultural or domestic purposes.

Such maps enable the stakeholders to know the high-risk areas that need urgent solutions, either by treating water, policy action, or additional environmental investigations. It also assists in the management of water resources by maximizing its distribution in areas that are the most vulnerable, such that the groundwater consumption in the area is sustainable. The elaborate explanation of these maps helps make quality decisions regarding the water quality monitoring and improvement tactics.

Table 2. Comparison of water quality parameters between the current and previous studies in kirkuk city

Parameter	Current Study	Previous Study
Turbidity (NTU)	Very Low: 5.30–42.34 NTU Low: 42.34–79.38 NTU Moderate: 79.38–116.42 NTU High: 116.42–153.46 NTU Very High: 153.46–190.50 NTU	2020: 2.00–14.20 NTU 2022: 2.00–21.07 NTU
pH	7.10–8.30	2020:7.20–7.50 2022: 7.50–8.20
Total Dissolved Solids (TDS, mg/l)	476.78–2563.5 mg/l	2020: 264–268 mg/l 2022: 210–229.998 mg/l
Electrical Conductivity (EC, µS/cm)	681.40–4245.87 µS/cm	2020: 369–378 µS/cm 2022: 356–375.998 µS/cm
Calcium (Ca, mg/l)	31.33–256.33 mg/l	2020: 47.00–52.00 mg/l 2022: 45.00–49.998 mg/l
Chloride (Cl, mg/l)	10.3–192.4 mg/l	2020: 12.00–16.67 mg/l 2022: 12.00–17.99 mg/l

The comparison of the current study with the previous one presented in table 2 shows the most important differences in the water quality parameters that are observed in Kirkuk City. The current research had a level of turbidity between 5.30 and 190.50 NTU and therefore had high fluctuations in the water clarity, whereas the former study had lower levels of 2.00 to 21.07 NTU. Both studies were consistent in pH, with the current study having a pH of 7.10 to 8.30 and the previous study having 7.20 to 8.20, which represents slightly alkaline water. The current study had Total Dissolved Solids (TDS) between 476.78 and 2563.5mg/l which indicates that the mineral content was higher as compared to the previous study, which had a range of 210 to 268mg/l. The current study measured Electrical Conductivity (EC) between 681.40 and 4245.87 µS/cm, which indicated more variant water quality, whereas the previous research found the values between 356 and 378 µS/cm in 2020 and 45.00 to 49.9 Lastly, the concentration of

Chloride (Cl) in the current study was between 10.3 and 192.4 mg/l whereas the former study had a range of 12.00 to 17.99 mg/l, which showed that there was a relatively consistent level of chloride in both studies. According to this comparison, the alterations in water quality through time are noted, where the previous research indicated the advancement of water purity and reduced contaminant levels, especially in TDS and EC. [3]

Discussion

The paper gives an optimized method of groundwater risk mapping in Kirkuk City through GIS-based interpolation (Inverse Distance Weighting (IDW) and Kriging) and Multi-Objective Particle Swarm Optimization (MOPSO). The findings suggest that the central and southern parts of the city are highly contaminated with the TDS values and chloride concentration being the highest with 1477 mg/l and 192.4 mg/l, respectively, indicating that the contamination is related to the industrial and agricultural activities. On the other hand, the eastern and northern regions are less contaminated, and the values of TDS are as low as 264 mg/l, and chloride is about 12 mg/l, which means cleaner groundwater. These results support the current literature that indicates that there are similar relationships between industrial operations and groundwater pollution. As an example, risk analysis, which uses GIS and was applied to other cities, including Adana City, has found urbanization to be a significant factor in deteriorating the quality of groundwater. The innovative use of MOPSO in this research is a significant improvement on the conventional optimization methods, such as Genetic Algorithms (GA). MOPSO produces an array of Pareto optimal solutions as opposed to GA, which only offers one solution, optimizing many conflicting objectives at the same time. This aspect increases the accuracy and reliability of the groundwater risk maps since it balances the different water quality parameters like pH, EC, TDS, etc. MOPSO gives a more robust analysis that can provide decision-makers with a variety of the best solutions to manage water quality risks.

The study has its limitations, however. The effectiveness of the interpolation techniques is very sensitive to the spacing and location of the monitoring wells, and poor data might result in misleading risk maps. Additionally, while MOPSO improves the optimization process, it is still reliant on the quality of input data. Any further research may also include the real-time monitoring data and include the seasonal changes in the groundwater quality to increase the robustness of the model. Nevertheless, the research indicates that MOPSO and GIS integration have potential in groundwater management and prediction of contamination risk in urban areas despite these shortcomings.

CONCLUSION

This paper has come up with an efficient groundwater risk mapping methodology in Kirkuk City, a combination of GIS-based interpolation methods (IDW and Kriging) and Multi-Objective Particle Swarm Optimization (MOPSO). The results indicated that the central and southern parts of the city are more polluted, with TDS (maximum 1477 mg/l) and chloride (maximum 192.4 mg/l) being high, probably because of industrial and agricultural activities. Conversely, better water quality was observed in the north and east regions, whereby TDS was approximately 264 mg/l and chloride levels were approximately 12 mg/l. MOPSO usage offered a great benefit compared to the older techniques, such as Genetic Algorithms (GA), by producing multiple Pareto optimal solutions, as well as maximizing multiple conflicting goals at the same time. This enabled the risk to be assessed better and offered decision-makers a variety of possible solutions concerning the management of groundwater contamination. Nevertheless, the study also has its limitations, such as the interpolation of data on the basis of a few monitoring wells and the absence of real-time monitoring data. Moreover, the seasonal changes in water quality had not been considered, and this can influence long-term forecasts. Increased density of monitoring wells, the integration of real-time data, and seasonal variation in groundwater quality should be considered in future studies. These would increase the accuracy and applicability of the model in sustainable ground water management. This approach can be utilized to tackle these constraints in other cities with similar water pollution issues, leading to more informed and effective water management approaches.

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