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SPATIAL INVESTIGATION OF SULFATE IN GROUNDWATER OF ASMARA, ERITREA

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Abstract: This study examines the spatial distribution and prediction of sulfate levels in groundwater of Asmara, Eritrea. The research integrates data from wells and applies ordinary kriging and semi-variogram analysis. The study classifies the area into three zones based on standard categories: excellent, good, and poor quality. Data analysis indicates a skewed sulfate dataset requiring log transformation for normality. The semi-variogram analysis identifies hole effect as the best model for prediction, where the study's prediction map reveals that most of the areas meet the desired sulfate levels. The findings provide valuable insights for sustainable water management, guiding decision-making and highlighting the significance of geostatistics and GIS technology in predicting groundwater quality.

Keywords: *Sulfate, prediction, kriging, groundwater, Eritrea*

1. INTRODUCTION

Water is an essential resource that plays a vital role in sustaining human life and supporting the overall sustainability of individuals and communities. The best quality water supply plays a vital role in sustaining human health and ensuring overall well-being. Groundwater is one of the many different sources of water supply where many countries depend on it [1]. Due to improper disposal of waste and other materials nowadays the quality of groundwater has become a problem throughout the world. Managing and investigating problems before they occur is the best environmental protection policy. Therefore, it is crucial for decision-makers to understand the pollutant's spatial distribution for taking necessary pre-questions.

The point groundwater quality data conducted by water resource department shows that there are signs of increasing chemical contamination in Asmara in the study area. This is mainly due to agricultural, industrial and anthropogenic activities. Therefore, not all the aquifers are suitable for drinking water supply in terms of quality. In order to investigate the spatial variability of different chemicals a framework should be developed. To test this framework sulfate is taken as a base chemical for investigation. There are different causes of groundwater pollution due to sulfate, e.g., mining is one of them. Many researchers proved the presence of sulfate due to mining area [2–5]. Excess concentration of sulfate in water is one of the reasons for water quality deterioration [6], [7] and this leads to human health problems such as diarrhea and gastrointestinal disorders [4], [8]. Therefore, it is good to find a tool to avoid such scenarios before they occur. Geographical Information System (GIS) technology is one of the best tools to tackle such problems and many researchers did groundwater quality assessment using this technology [9–11]. Therefore, knowing the success of this tool, this work aimed to develop a framework for quality assessment using sulfate as a base chemical of investigation.

2. Study area

The research area is located in Asmara the capital city of Eritrea which is located on the geographic coordinate of Latitude 15° 19’ 12’’ N and Longitude 38° 56 ’16’’ E with a coverage area of 22.2 km^2 *(Figure 1)*. The boundary of the study area was delineated by using the location of the wells producing drinking water. This extent line was created to produce a framework for groundwater quality assessment considering sulfate as a test chemical in this research. The delineated area was applied for defining the extent of the interpolation.

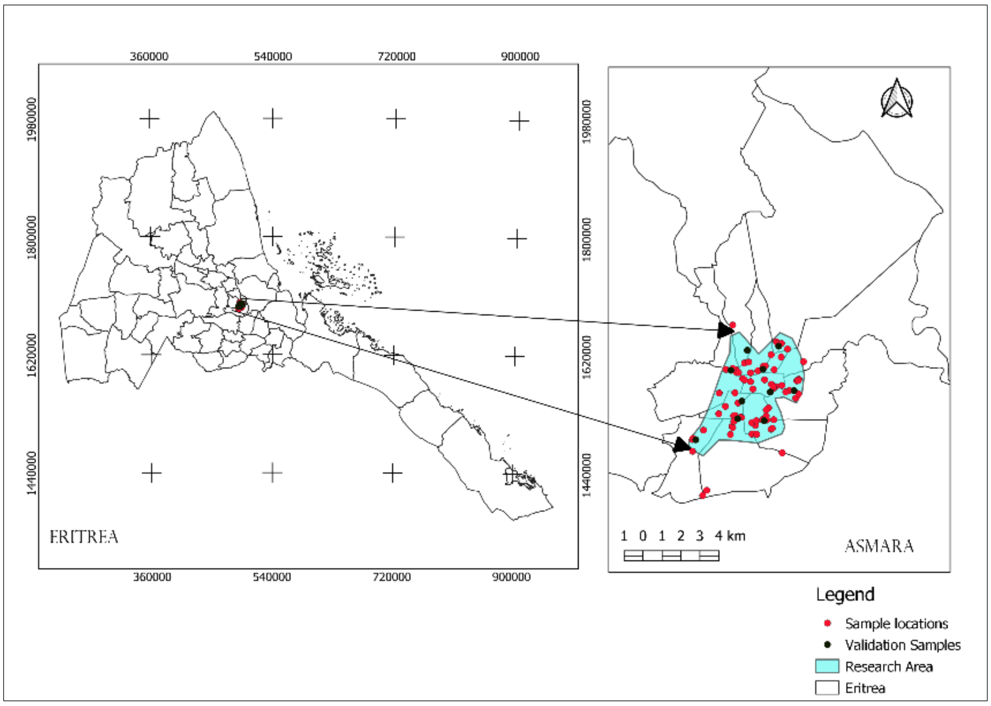


Figure 1
Location of the study area for sulfate distribution

The area is located on the Asmara plateau, is characterized by metamorphosed Precambrian basement and tertiary volcanic rocks. These geological formations can influence the chemistry of the groundwater. Asmara has almost uniform gradient, extending from an elevation of 2450 m at the eastern escarpment peaks, to the minimum elevation of 2290 m, around the West. The city is considered as situated in a semi-arid zone with temperature varying a little throughout the year. The mean temperature prevailing in the city is recorded as 17.1 °C, the annual rainfall is 859 mm [12]. The drainage network has a natural trend from east to west. The city has an estimated population of 600,000 which is expected to grow due to urbanization.

3. Materials and methods

3.1. Data collection

The raw data samples were collected and analyzed by Water Resource Department (WRD) in Eritrea. The total number of well samples is 82 which are located within the city's administrative boundary. Due to the temporal distribution of annual precipitation, the samples were gathered between October and November 2013 and analyzed in the department's laboratory. To provide predicted values of sulfate levels in unsampled locations, spatial interpolation was performed using the remaining dataset, while 10 samples were kept separate for validation purposes *(Table 5)*. The groundwater depth was not measured in this study due to the constructional properties of wells.

3.2. Methodology

The collected data from the wells were categorized as spatial and non-spatial, where the non-spatial data were tested in the water resource laboratory for finding the concentration of sulfate, and the spatial data was recorded using Global Positioning System (GPS) from the well location. These two data records are imported to the GIS database in CSV file format and converted to point shape file for further analysis. In this study, the prediction map was generated using the kriging interpolation method. The method was chosen due to its wide application and advantage in the water-related areas and other disciplines [13]. Moreover, it is a globally applicable method for spatial distribution of groundwater quality mapping [14].

Kriging is a geostatistical technique that applies autocorrelation within the data sets to predict the unknown values in unmeasured locations [15]. Each data has a weight which is optimized by the variogram [14], that finds out the best fit prediction model. If the datasets follow normal or Gaussian distribution the prediction is accurate. There are different techniques for checking normality, such as QQ-plot, histogram, skewness, and kurtosis (*Table 1* and *Figure 3*). Log transformation is one method of adjusting skewed dataset. Another important parameter for spatial dependency measurement is Nugget to Sill ratio [16]. To have strong dependency the ratio should be less than 25%, whereas moderate dependency ranges between 25% and 75%, ratio greater than 75% has weak spatial dependence [17], [18].

The cross-validation process ensures the accuracy of model predictions for the unknown values [1], [19]. These are Mean Square Error (MSE), Root Mean Square Error (RMSE), Average Standard Error (ASE), and Root Mean Square Standardized Error (RMSSE). For accurate prediction MSE and RMSSE should have a value closer to 0 and 1, respectively. In addition, closer value needs to be obtained for both RMSE and ASE. At last, the developed framework was validated using 10 measured samples. From the location of the 10 samples the generated predicted value was extracted to be used for comparison *(Table 5)*. A closer value between the two shows good prediction of the model.

4. RESULTS AND DISCUSSION

The log transformed dataset *(Figure 2)* has approximately the same mean and median values. In addition, the skewness becomes close to zero and kurtosis is close to three, which is a good indication of normal distribution (*Table 1* and *Figure 2*).

Table 1

Statistical evaluation of sulfate in groundwater in mg/l, (: after log transformation)*

Parameter	Min	Max	Mean	Median	Standard Deviation	Skewness	Kurtosis
SO_4	7	600	159.26	130	115.71	1.66	6.55
SO_4*	1.94	6.39	4.81	4.86	0.79	–0.79	4.38

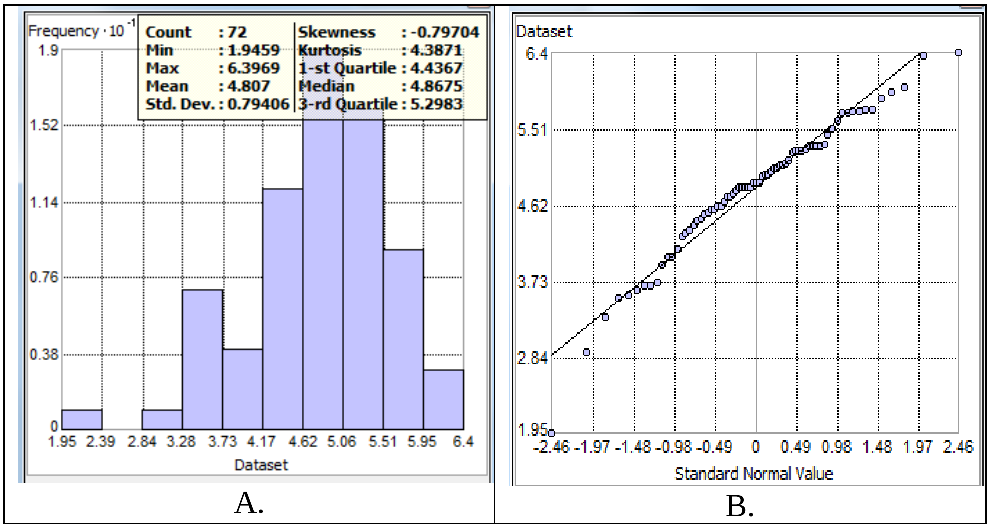


Figure 2

Checking for normality of the sulfate concentration dataset: (a) Histogram and (b) QQ plot after log transformation

The Hole Effect model, with Nugget and Sill values of 0.42 and 0.93, was chosen as the best fit model based on the semi-variogram analysis (*Table 2* and *Figure 3*). Since the Nugget to Sill ratio is 45.16%, which indicates the spatial dependence value of Sulfate is moderate. In addition, the cross-validation outcome demonstrates unbiased prediction with MSE of –0.56 and RMSSE of 0.78 *(Table 4)*.

Table 2

Spatial dependence parameters of variogram model

Para-meter	Model	Nug-get (Co)	Partial Sill (C)	Sill (Co + C)	(Nugget/Sill) %	Range (m)
Sulfate	Hole Effect	0.42	0.51	0.930	45.16	10949

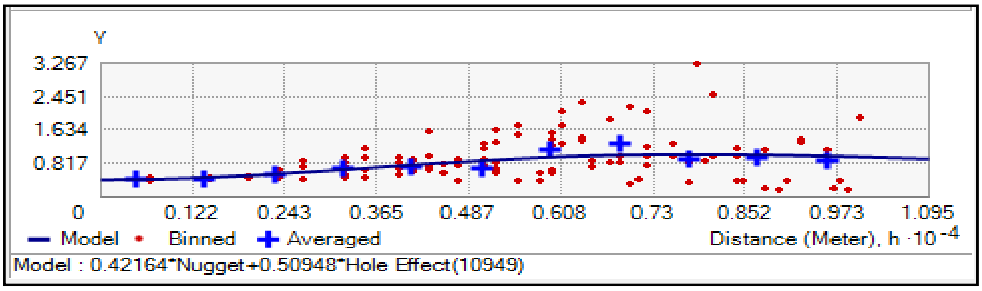


Figure 3

Sulfate variogram model (After log transformation)

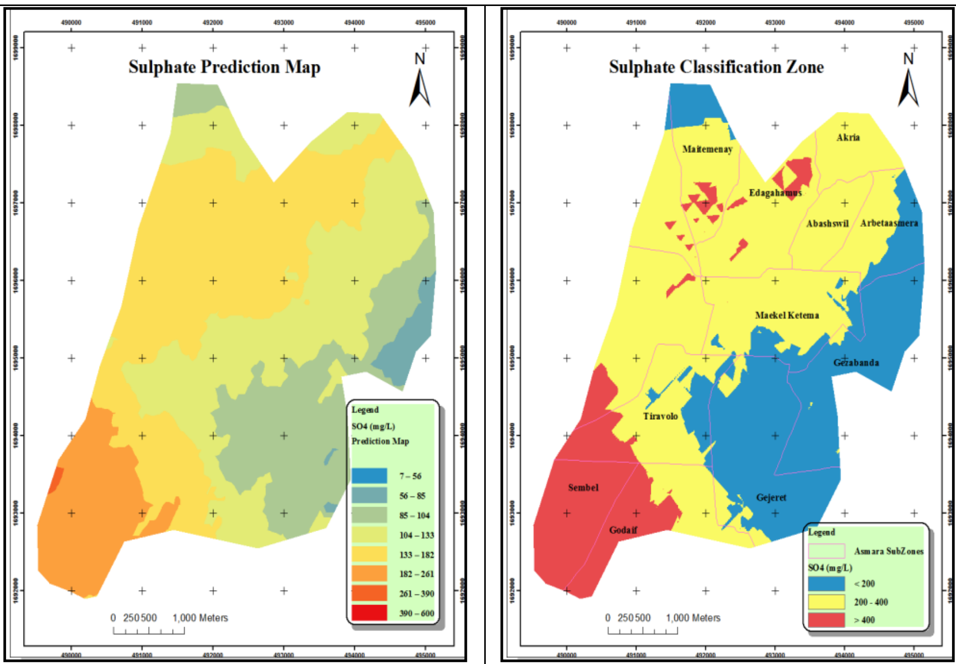
The Sulfate concentration of the study area is highly variable ranging from 7 to 600mg/L *(Figure 4a)*, where the mean and standard deviation are 159.26 and 115.26mg/L respectively *(Table 3)*. The prediction map reveals that the sulfate concentration falls within the desired/excellent range, except the South-West and some part of the North-West which exceeds the standard value of 400mg/l *(Figure 4b)*. It could be probably due to the presence of anthropogenic sources (e.g., agricultural activity) in the area, or the cause could be due to the east west sloping topography.

Table 3

Statistical moment and area coverage of the predicted sulfate concentration

General overview of the Sulfate concentration in the study area						
Mini-mum	Maxi-mum	Mean	STD	<200 mg/L	200–400 mg/L	>400 mg/L
				Area Coverage		
7.0 mg/L	600 mg/L	159.26 mg/L	115.71 mg/L	11.11 km^2 (50.1%)	8.62 km^2 (38.86%)	2.46 km^2 (11.09%)

Generally, the desired sulfate level covers about 50.1% (11.11 km^2) of the study area, while the good quality level covers about 38.86% (8.62 km^2) of the study area. Whereas the rest of the study area falls under the poor-quality zone with an area coverage of about 11.09% (2.46 km^2).



A. **Spatial distribution of sulfate concentration in the study area**

B. **Standard classification zone of sulfate in the study area**

Figure 4

Spatial distribution of Sulfate concentration in the study area

Table 4

Cross-validation result from kriging interpolation for sulfate

Models	**Mean**	**Root Mean Square**	**Average Standard Error**	**Mean Standardized**	**Root Mean Square Standardized**
Circular	2.23	102.39	132.93	0.002	0.76
Spherical	2.53	102.17	133.3	0.003	0.76
Tetraspherical	2.81	101.98	133.7	0.005	0.76
Pentaspherical	3.07	101.83	134.11	0.006	0.75
Exponential	4.71	101.79	138.6	0.014	0.74
Gaussian	–0.92	106.8	130.42	–0.019	0.78
Rational Quadratic	4.95	99.9	135.73	0.027	0.74

Hole Effect	**–0.56**	**106.12**	**130.15**	**–0.016**	**0.78**
K-Bessel	–0.79	106.6	130.49	–0.017	0.78
J-Bessel	–0.58	106.15	130.13	–0.016	0.78
Stable	–0.58	106.15	130.13	–0.016	0.78

As a final step, the validation outcome using the 10 measured samples shows good results *(Table 5)*. But still, some variations are observed in the final comparison result, this could be due to measurement error or other uncertainties. To increase the prediction accuracy of the framework, a test should be carried out with more evenly distributed dataset in different parts of the country.

Table 5

Validation result of measured values against predicted values for sulfate

FID	EASTING	NORTHING	Measured (SO_4)	Included	Predicted
1	493115	1696340	19.80	Yes	156.19
2	492003	1694603	52.00	Yes	104.15
3	493182	1693548	105.00	Yes	93.15
4	493501	1695108	110.00	Yes	108.52
5	491778	1693653	130.00	Yes	138.70
6	493946	1697593	155.00	Yes	151.22
7	494758	1695175	155.00	Yes	83.65
8	491420	1696283	280.00	Yes	157.68
9	489573	1692517	300.00	Yes	233.76
10	492287	1697372	360.00	Yes	128.30

5. CONCLUSIONS

This study investigates the spatial variability of sulfate concentrations in the groundwater of Asmara using GIS and geostatistical approaches. Cross-validation and variogram analysis were used in selecting the best fit model for prediction. Based on the results, the Hole Effect model was chosen, and the resulting prediction map indicated most of the area falls within the World Health Organization's standards. The verification result from the 10 measured samples justifies this fact, even though there are some variations in the result, which may come from the location of the wells used for the interpolation. Generally, with the limitation of more datasets and the variable nature of the groundwater concentration, the model estimates good prediction. As a recommendation, increasing the number of samples and testing the framework in other parts of the country will increase the robustness of the model. Finally, the outcome of this research will assist the water resource policymakers and interested groups for further investigation and management in the study area.

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