Original Research Article

Geostatistical Modelling of Groundwater Quality at Rumuola Community, Port Harcourt, Nigeria.

ABSTRACT

The groundwater quality of Rumuola community of Rivers State, Nigeria was investigated. This study was done to determine the pollution potential of a solid waste open dump in a borrow pit in the community. The leachate pollution index was calculated for the borrow pit at the centre of the community using weighted additive leachate pollution index. The result showed that the LPI value was 5.31 and has low pollution potential. It was discovered that the groundwater in the entire community was acidic with pH levels ranging from 3.6 to 4.2, which is below NSDWQ's permissible range of 6.5-8.5. Nickel and arsenic also showed concentrations that were above permissible limits with nickel values averaging 0.033mg/l which is slightly above the limit of 0.02mg/l. Arsenic had concentrations that ranged from 0.16 to 1.57mg/l which is above permissible limits of 0.01mg/l. WQI was determined using weighted arithmetic water quality index analysis. As a result of the high concentrations of arsenic, the WQI values were very high with values ranging from 144 to 1367 and this shows that the water in the study area is unsuitable for drinking. In modelling the water quality index of Rumuola community, geostatistical methods were applied. Ordinary kriging, Empirical Bayesian kriging (EBK), inverse distance weighting (IDW) and cokriging interpolations methods were used to produce surface maps showing the distribution of variables using ARCGIS software. The best interpolators were: EBK for pH, TDS, Sulphate and nitrate; Ordinary kriging for Nickel and Hardness; IDW for Iron and arsenic; Cokriging for WQI.

Keywords: water quality index, geostatistics, kriging, groundwater pollution, groundwater modelling, geostatistical modelling

1. INTRODUCTION

Groundwater is important to the entire world's population, in semi-arid and arid regions there is even more focus given to it because of the insufficiency of surface water [1]. In Nigeria, more than 57 million people do not have access to clean water [2]. Groundwater can become polluted by natural and anthropogenic activities, and the type of pollution depends on the activities performed in that region. These pollutants fall into these categories: nutrients, pesticides, pathogens, metals and dissolved minerals [3]. Groundwater quality is dependent on composition of recharge water, the reciprocal action of water and soil, the rock that it associates with in the unsaturated zone, the detention time and reactions that take place inside the water bearing aquifer [4]. There are many pollutants of groundwater but those of uttermost concern are naturally occurring arsenic, fluoride and nitrate [5]. Groundwater problems exist because there is no infrastructure to treat and distribute water to the populace [6].

Groundwater can be impeded by the use of fertilisers, pesticides and even from untreated effluent discharged into the environment [1]. Effluents from industrial sources are also a big problem especially in developed cities like Port Harcourt with a high presence of industries [7]. Groundwater can also be polluted by leachate from landfills practices [8]. The magnitude of the menace of leachate pollution depends on the quantity of the leachate from the landfill and the distance of the landfill from the groundwater [9]. Leachate contains multitudinous compounds which are mostly toxic, they penetrate the landfill bottom and pollute the groundwater posing serious health issues to the locals and the environment [10]. Heavy metal contamination is another area of concern especially in agricultural dominant areas

[11]. Heavy metals like iron, zinc, cadmium, chromium and mercury are a problem as ingestion of these chemicals causes serious health problems [12]. People living in warmer climates like Nigeria are at higher risk of exposure because of the need to take more water[11]. Some of the problems that may be experienced due to bioaccumulation and biomagnification of heavy metals in the environment are: Water quality and soil quality degradation, Low birth weight, Cancer, Neurological diseases, Congenital malformations and Mercury toxicity from eating fish with high concentrations of mercury [13]. Freshwater has continued to lose quality worldwide and the groundwater levels are being depleted. This has forced a lot of people to resort to consuming unhealthy water which often leads to chronic health challenges which are a major causative agent for the death of young people [14].

It is imperative that groundwater is assessed systematically and monitored continually applying proven scientific methods to determine its quality to ensure that it can be used for domestic purposes especially drinking and cooking, and that no adverse effects are experienced due to its use. [4]. Groundwater quality across regions are spatially related and geostatistical methods of evaluating spatial relationships are relevant to predict the values at areas where sampling may be impossible. Geostatistics does not only look at the incidence of a variable but also at the location, the Spatial association between values and the effect geographical factors have on the distribution of variables at a location [15]. Also, it gives information on the level of uncertainty of the model, increasing the overall accuracy of this method.

According to Hassan (2014) [5], The techniques of geostatistics are used to: forecast values at locations not sampled, evaluate the uncertainty affiliated with the forecasted values and model the spatial patterns of the parameter being considered. Geostatistics is applied in different industries, for example, petroleum geology, hydrogeology, forestry, environmental engineering, landscape ecology and agriculture. It is used in determining the spatial variation of events such as in geography, while considering the spread of diseases (epidemiology), in

Environmental Engineering to model the water quality distribution of a region and in reservoir engineering to build reservoir models. Therefore, it is an important tool in the decision-making processes in these fields [15]. There are different interpolation methods that can be applied in groundwater modelling for example: Ordinary kriging, Empirical Bayesian kriging, cokriging and inverse distance weighting. In this study, these methods are explored and the best method is selected after cross-validation.

Kriging is a spatial prediction mathematical technique developed for use in meteorological predictions. Kriging presupposes a statistical model and has standard errors that measure the level of uncertainty of the values that have been forecasted [16]. Kriging is a linear method of interpolation that generates probabilistic models for the value of attributes [17]. Classical kriging assumes that the variogram estimated initially is the correct variogram of the studied data but, this assumption is not always true in practice and this is why EBK was introduced [16]. It is advantageous to use kriging because it estimates interpolation error of the values in points where there was not initial sampling. It helps to assess the exactness and accuracy of the variable's distribution [18].

Empirical Bayesian Kriging (EBK) is different from classical kriging because it considers the error introduced by the semivariogram model. EBK does not use just one semivariogram as kriging does but applies many semivariograms [16]. The processes involved while applying EBK is highlighted below:

1. A semivariogram model is roughly calculated from the data
2. The software then uses this semivariogram to simulate new values at each input data location.
3. After this, a new semivariogram model is generated from the simulated data and weights for this is estimated to show how possible it is to generate the observed data from the semivariogram model.
4. Step 2 and 3 are repeated, variogram and sample data is generated. Weights also are estimated.

5. Predictions and prediction standard errors are then generated at unsampled locations using the weights. A number of semivariograms are created in this process. Observed processes could be generated from each semivariogram as it is an evaluation of the actual variogram.

Cokriging is a kriging method that estimates samples that were thought of as poorly collected with the aid of a sample that was collected more appropriately. For cokriging to be applied there has to be some very high correlation (positive or negative) between the two samples.

Inverse Distance Weighting is a deterministic method for interpolating spatial data. In this method, weights are given to points to be measured, and the amount of weight given to that point is dependent on the distance of that point to another unknown point. If the power of these weights is increased, the effect of points that are farther away will be undermined and keeping the power low will mean that the weights will be distributed more uniformly between points close by. if the points have the same distance between them, then the weights, in turn, are the same [19]. The weight factor is calculated using Equation 1:

$$\delta = \frac{D_i^{-\alpha}}{\sum_{i=1}^{n} D_i^{-\alpha}} \qquad (1)$$

Where: δ = weight of the point

D_i = distance between point i and unknown point.

α = the power ten of weight.

To decide which model best fits or predicts most accurately, cross-validation is done. The model is best fitted if the following conditions are met:

1. Mean prediction error should be closer to zero
2. It should have a lower root mean square prediction error
3. The root mean square standardized error should be closer to 1

N/B If RMSE < 1 then the prediction is underestimated.

If RMSE > 1 then the prediction is overestimated [5].

Hassan (2014) [5] mapped the groundwater of Tehsil Sheikhupura in Pakistan, applying geostatistical methods. The data in the GIS setting were therefore provided in order to better understand the spatial distribution of each parameter. In his study, ordinary kriging was applied. He tested four models (circular, Gaussian, exponential and spherical) for each groundwater parameter and the best was selected after cross examination. The values of the mean error, root mean square error and root mean square standard error were assessed by applying the four models mentioned above. The model best fits if the root mean square error (RMSE) values are closer to the average standard error (ASE) also, the mean error should be closer to zero for the model to fit best and perform best. Finally, surface maps showing pollutant concentration in different regions were created using ordinary kriging.

Mehrjard et al. (2008)[19] applied geostatistical approaches for groundwater quality interpolation in Ardakan-Yazd plain. In his research, IDW, kriging and cokriging methods were used to predict spatial distribution of groundwater parameters like TDS, TH, EC, SAR, Cl and sulphate. In this study, the data was normalized, experimental variograms were fitted and the best interpolation method was selected based on cross validation and Root mean square error. Kriging and cokriging showed superiority to IDW method in his results. Finally, surface maps of different groundwater parameters were created.

Karami et al., (2018) [18] mentioned that geostatistics is a vital instrument for establishing the subsurface non-uniformity in groundwater formations and that the results from geostatistics are vital for decision-makers to ensure groundwater quality is protected. Ordinary kriging was used and seven water quality parameters were modelled (Sodium absorption ration, TDS, EC, sodium, total hardness, chloride and sulphate). Surface interpolation maps, estimation variance maps and prediction error maps were created using WinGslib software to evaluate the quality estimation at each point.

Narany et al. (2014) [17] created a method to classify high-risk areas of nitrate pollution in Amol-Babol plain, Iran. Indicator kriging was applied and the USEPA DRASTIC method was used. Geostatistical methods for the optimum sampling locations were applied to assess the vulnerability of the groundwater in the region to nitrate contamination. A risk map was produced to show the areas of high and low vulnerability. It was discovered that 3% of the area had a high moderate risk of being polluted by nitrate.

In this study, the leachate from an open dump in the study area will be evaluated to check its constituents and to ascertain its pollution potential. Also, the water quality index from surrounding boreholes will be calculated using weighted arithmetic water quality index method and finally interpolation models will be created using ARCGIS software.

2. MATERIAL AND METHODS

This study was conducted in Rumuola community in Obio-Akpor local government area in Rivers state, Nigeria. Rivers state is found in the coastal plain of the eastern Niger Delta [20]. Temperature ranges from 21.2 - 23.2ºC to 28.7 - 33.4ºC. Annual rainfall is 4,700 mm/year [20]. Ngah et al., (2016) [21] studied this area extensively and came to understand that, the borrow pit at Rumuola community was born as a result of sand mining done many years ago to aid the construction of major roads in the state.

The Rumuola borrow pit lies longitudes E 007º 00’ 01.0’’ to E 007º 03’ 09.7’’ and latitudes N 04º 50’ 08.5’’ to N 04º 50’ 14.2’’. Although the region has evolved and houses have emerged, the enormous borrow pit still remains. A large pond has been formed covering an area of 135,000m^2 with a depth of 7.68m, the water table lies at 7.49m and this shows that the pit has cuts into the water-table [21]

The groundwater quality was determined using weighted arithmetic water quality index and the groundwater parameters were modelled using geostatistical methods. The leachate pollution index was calculated using weighted additive leachate pollution index and the leachate values were compared to effluent standards.

In Calculating WQI, the Weighted Arithmetic Water Quality Index (WAWQI) Method was used, and it is outlined as follows:

Step 1: Collect data of the water quality parameters that will be used to determine the WQI.

Step 2: calculate k using Equation 2

$$k = \left(\frac{1}{\sum_{i=1}^{n} \frac{1}{S_i}}\right) \quad (2)$$

Where k = proportionality constant

S_i = Standard permissible limit for the nth parameter

Step 3: Calculate the quality rating for the nth parameter qn.

$$qn = 100(((v\_n - v\_io\ ))/((s\_i - v\_io\ )\ )) \quad (3)$$

Where: V_n = estimated concentration of the nth parameter of the given sampling location.

V_{io} = ideal value of the nth parameter in pure water [22].

S_i = standard permissible limit of the nth parameter.

Step 4: Calculate the unit weight of the nth parameters using Equation 2.3

$$W_n = \left(\frac{k}{s_i}\right) \quad (4)$$

Step 5: Calculate the Water Quality Index using Equation 2.4

$$WQI = \left(\frac{(\sum w_n * q_n)}{\sum w_n}\right) \quad (5)$$

Table 1 shows the water quality status based on the WQI value for each water sample. 0-25 shows excellent water while anything above 100 is unsuitable for drinking purposes.

Table 1: Water Quality Index (WQI) and Status of water quality

Water quality index level	**Water Quality status**
0-25	Excellent water
26-50	Good water
51-75	Poor water
76-100	Very poor water
>100	Unsuitable for drinking purpose

Source: [22]

The leachate pollution index can be calculated using the Equation 6 when all 18 leachate pollutions parameters are known:

$$LPI = \sum_{i=1}^{n} w_i p_i \qquad (6)$$

Where LPI= the weighed additive leachate pollution index

W_i = the weight of the i^th^ pollutant variable

P_i = the sub-index value of the i^th^ leachate pollutant variable

n = number of leachate pollutant variables used in calculating LPI and n=18.

Leachate parameters sum = 1 [23]. Nine (9) parameters were used in this study which summed up to 0.496. The sub-index values were determined from the sub-index curves of the respective parameters.

But when the data for all the 18 leachate pollutant variables required to calculate the LPI is not available, the LPI can be calculated with the available pollutants using Equation 7:

$$LPI = \frac{\sum_{i=1}^{m} w_i p_i}{\sum w_i} \qquad (7)$$

This method was applied in this report since all eighteen leachate parameters were not used in determining the LPI.

2.1 Sampling Technique

Leachate Samples were collected using sampling bottle that were thoroughly washed and dried. Leachate was collected from the base of the pit into One-litre polyethene bottles. The leachate had drained out by gravity. One leachate sample was collected and this was designated as Leachate Sample (LS). 10 Leachate parameters were analysed from the leachate sample collected from the open dump embedded in the borrow pit in the centre of the community. These parameters were chosen based on the method developed by Kumar and Alappat in 2003 [23]. The parameters used in this study are: Chromium, Iron, TDS, copper, nickel, lead, mercury, arsenic, chlorides and pH.

Groundwater samples were taken in one-litre polyethene bottles. Prior to collecting the samples, the water from the borehole was allowed to run for five minutes to ensure groundwater parameters were unchanged. Then, the sampling bottles were rinsed with the groundwater three times before collecting the samples. The water was taken from a point before the water enters the reservoirs (water tanks) used to store them. A plumber dismantled the piping works to enable water collection to be done directly from the source. This was done to prevent any form of contamination from the water storage reservoirs and to ensure the integrity of the samples. Borehole samples were designated by borehole 1 (BH1), borehole 2 (BH2) etc.

Eighteen (18) water samples were collected from boreholes in Rumuola community for this study. The sampling points were distributed around the community with the aid of the GIS software. The samples were collected and analysed using standard methods for TDS, pH, Nitrate, sulphate, nickel, arsenic, mercury, iron and total hardness.

To model, Arc map (ARCGIS 10.5) software was used. This software forecasted values at unsampled locations for each parameter investigated while also creating interpolated surface maps which shows the distribution of the pollutants across the study area and highlights areas with low and high concentrations. The methods that were explored in this project were Ordinary kriging, Cokriging, Empirical Bayesian Kriging and Inverse Distance Weighting and the best methods were chosen by cross-validation.

The secondary data that was used for the study is the Nigerian Standard for Drinking Water Quality(NSDWQ) and The Federal Environmental Protection Agency Act 1988 No. 58. This was used to determine the safe limits for the physicochemical parameters of drinking water and safe limits of effluent (leachate) discharge in ground and surface water.

3. RESULTS AND DISCUSSION

Table 2 shows how the LPI was determined. W_i is the weight and P_i is the sub index value as derived from the study done by Kumar and Alappat (2003) [23]. The determination of LPI was done using Equation 6. The leachate had a pH of 6.2. The concentration of arsenic in the leachate sample was 0.579mg/l, which is higher than the effluent discharge limit of 0.1mg/l. Every other leachate parameter had values that were below the effluent discharge limits specified by Nigeria's federal ministry of environment. LPI was determined using Allapat's method as outlined in Equations 6 and 7. The calculated LPI value was 5.31 and this shows that the pollution potential of the leachate is very low.

Table 2: Leachate Pollution index calculation

Parameter	**Concentration(mg/l)**	**Weight (W_i)**	**Sub-Index (P_i)**	**Rating**	**W_iP_i**
Chromium	0.005	0.064	5		0.32
Iron	0.158	0.045	5		0.225
TDS	108	0.05	5		0.25
Copper	0.004	0.05	5		0.25
Nickel	0.114	0.052	5		0.26
Lead	0.012	0.063	5		0.315
Mercury	0.01	0.062	6		0.372
Arsenic	0.579	0.061	5		0.305
Chlorides	20.5	0.049	5		0.245
pH	6.2	0.055	7		0.385
TOTAL		0.551			2.927
			LPI		5.31216

Table 3, shows the distribution of the parameters through the selected sampling points. The lowest pH values were observed in BH 4, 8 and 20 with a value of 3.6. The range of values was from 3.6 to 4.2 across the region. The acceptable pH range as specified by the NDWQS is 6.5-8.5 but the water samples analysed were below that range, which is an indication of acidity. Arsenic concentrations were very high in all the boreholes sampled with values ranging from 0.16 to 1.57mg/l. Whereas, the acceptable level of arsenic in drinking water is

0.01mg/l. Nickel concentrations were also generally high in the region ranging from 0.013-0.144mg/l.

Table 3: Water quality input data for water quality index.

Parameter	**BH1**	**BH3**	**BH4**	**BH5**	**BH6**	**BH7**	**BH8**	**BH9**	**BH11**	**BH12**
pH	4.0	4.2	3.6	3.9	4.0	4.0	3.6	3.8	3.8	4.0
TDS	45	20	140	87	77	118	125	80	110	86
Nickel	0.016	0.013	0.024	0.027	0.028	0.026	0.03	0.028	0.03	0.035
Iron	0	0	0	0	0	0	0	0	0	0.061
Arsenic	0.394	0.375	0.779	0.433	0.76	0.16	0.885	0.615	1.29	0.981
Mercury	0	0	0	0	0	0	0	0	0	0
Sulphate	0.75	0.365	0.75	1.81	7.58	7.96	8.73	0.558	1.33	31.4
Nitrate	1	0.079	2.72	1.44	1.16	2.14	3.03	2.02	2.16	0.074
Hardness	6.2	3	13	12.8	6.4	16.6	24.8	8.4	15.2	2
WQI	345	327	680	381	664	144	773	539	1124	858

Parameter	**BH13**	**BH15**	**BH16**	**BH17**	**BH18**	**BH19**	**BH20**	**BH21**	**LCP**
pH	4.2	3.8	4.2	4.0	4.1	3.7	3.6	3.8	6.2
TDS	78	60	45	43	34	96	79	40	108
Nickel	0.027	0.028	0.031	0.031	0.027	0.027	0.029	0.028	0.144
Iron	0	0	0.036	0	0	0	0	0	0.158
Arsenic	1.01	1.17	1.38	1.15	1.25	1.57	1.57	1.48	0.579
Mercury	0	0	0	0	0	0	0	0	0
Sulphate	2.67	0.75	6.71	0.558	0.75	0.942	0.558	0.654	7
Nitrate	1.99	1.38	0.254	1.11	0.859	1.79	1.76	0.674	0.424
Hardness	7.2	8.2	5.4	7	4.2	8.4	13	5.8	66
WQI	881	1020	1203	1003	1089	1366	1367	1289	533

The WQI values were determined using Equation 5 and results presented as Table 4. When compared with Table 1, it is observed that the water in the entire region is unsuitable for drinking because they all had values greater 100.

Table 4: Water Quality index around Rumuola community.

Source	WQI Value	Interpretation
BH1	345	Unsuitable for drinking
BH3	328	Unsuitable for drinking
BH4	681	Unsuitable for drinking
BH5	381	Unsuitable for drinking
BH6	665	Unsuitable for drinking
BH7	144	Unsuitable for drinking
BH8	774	Unsuitable for drinking
BH9	539	Unsuitable for drinking
BH11	1125	Unsuitable for drinking
BH12	858	Unsuitable for drinking
BH13	881	Unsuitable for drinking
BH15	1020	Unsuitable for drinking
BH16	1203	Unsuitable for drinking
BH17	1004	Unsuitable for drinking
BH18	1090	Unsuitable for drinking
BH19	1367	Unsuitable for drinking
BH20	1367	Unsuitable for drinking
BH21	1289	Unsuitable for drinking

Hassan (2014)[5], outlined the conditions that need to be met for a prediction model to be selected over others. The mean error of the selected model should be nearest to zero, root mean square error should be lowest and root mean square standard error should be nearest to 1. Table 5 presents the best interpolators of the water quality parameters. The best method for modelling pH, sulphate, nitrate and TDS was EBK. This was probably because EBK does not use one variogram as kriging does in fitting the model but applies many variograms thereby reducing the error introduced by assuming the initial variogram is the right one [16]. For nickel and hardness ordinary kriging was observed to be the better modelling technique. IDW was best used to predict iron and arsenic While WQI was best modelled by cokriging. Cokriging models WQI better because it is a calculated parameter and it is determined with parameters that have the highest correlation with WQI values, thereby increasing the accuracy.

Table 5: Best-fit model for interpolating groundwater parameters.

Parameter	**Method**	**Mean error**	**Root Mean Square error**	**Root mean square standard error**	**status**
pH	Ordinary Kriging	0.019	0.583	1.007	
	IDW	0.056	0.616		
	EBK	0.017	0.572	0.978	best fit

TDS	Ordinary Kriging	0.490	23.405	0.803	
	IDW	2.262	24.974		
	EBK	-0.505	22.987	0.958	best fit
Nickel	Ordinary Kriging	0.001	0.028	1.014	best fit
	IDW	0.003	0.030		
	EBK	0.002	0.029	0.995	
Iron	Ordinary Kriging	0.005	0.043	1.011	
	IDW	0.002	0.040		best fit
	EBK	0.002	0.040	0.976	
Arsenic	Ordinary Kriging	0.022	0.444	1.052	
	IDW	0.005	0.043		best fit
	EBK	0.022	0.459	1.016	
Sulphate	Ordinary Kriging	0.185	8.130	1.090	
	IDW	0.278	7.737		
	EBK	0.123	7.654	0.992	best fit
Nitrate	Ordinary Kriging	0.019	0.701	0.992	
Nitrate	IDW	-0.004	0.640		
Hardness					
Nitrate	EBK	0.000	0.634	0.951	best fit
Hardness	Ordinary Kriging	-0.047	14.067	1.335	best fit
Hardness	IDW	1.493	15.912		
WQI					
Hardness	EBK	0.433	15.288	1.023	
WQI	Ordinary Kriging	15.242	399.699	1.094	
WQI	IDW	-10.220	411.896		
WQI	EBK	16.070	398.469	1.004	
	Cokriging	-2.012	382.270	1.062	best fit

The best fit models were used to produce surface interpolation plots for the various water quality parameters measured. Figures 1-9 shows the spatial distribution of the water quality parameters over the region. The colors where chosen to symbolize a cold to hot effect. The blue color represents a cold region or a region of mild effects, while the red color represents a hot region or a region of adverse effects.

Figure 1: pH distribution in the study area

Figure 2: TDS distribution in the study area

Figure 3: Nickel distribution in the study area.

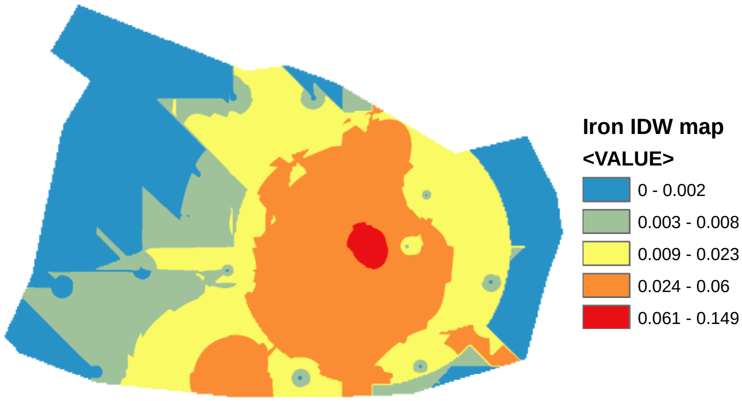

Figure 4: Iron distribution in the study area.

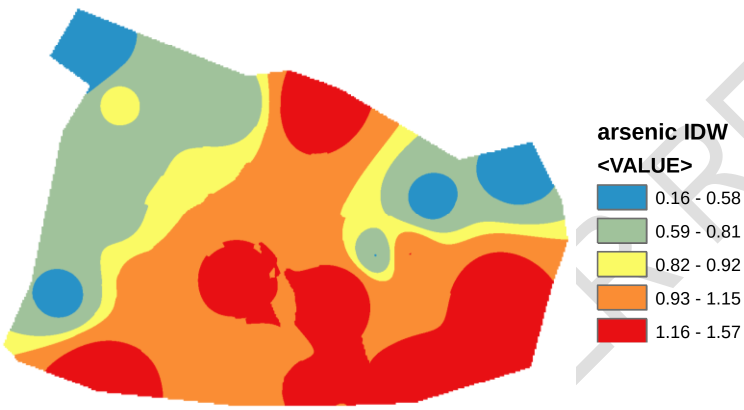

Figure 5: Arsenic interpolation in the study area.

Figure 6: Sulphate distribution in the study area.

Figure 7: Nitrate distribution in the study area.

Figure 8: Hardness distribution in the study area.

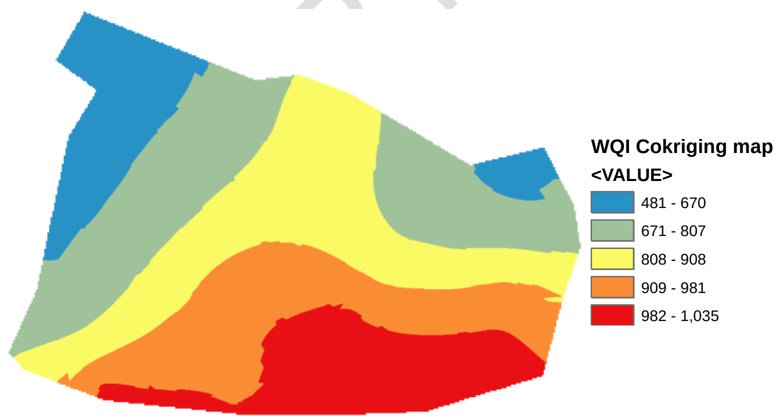

Figure 9: WQI distribution in the study area.

Based on the interpolation maps, areas near the western part of Rumuola community had very acidic groundwater with a pH of about 3.6. TDS increased steadily from east to the west although all values were below critical concentration. Nickel values were high at western and eastern boundaries. Arsenic concentrations across the community were above 0.01mg/l which is the permissible concentration. Sulphate and nitrate concentrations were within permissible limits and did not pose any threat to the groundwater of the community. Hardness increases from the south-east up to the northwest region but all concentrations are below the standard value of 150mg/l. WQI values are all above safe limits with values peaking at 1367. The southern region of the map displayed the worst water quality index values while the "best" water quality is seen in the northwest areas.

4. CONCLUSION

Findings showed that the LPI with a value of 5.31 has low pollution potential in line with the study done by Kumar & Alappat (2003)[23]. Arsenic was the only leachate parameter to exceed the standard limit of 0.1mg/l with a concentration of 0.579mg/l in the leachate sample. Arsenic is considered carcinogenic and is termed by some as the world's most hazardous chemical [24]. Other leachate parameters like pH, nickel, nitrate, sulphate, TDS, chloride, chromium, magnesium and lead were all within limits specified by The Federal Environmental Protection Agency Act 1988 No. 58.

The groundwater across Rumuola was generally acidic with values from 3.6-4.2. There was a high positive correlation between pH/nickel and pH/hardness. TDS, Iron, mercury, sulphate, nitrate and hardness levels were all below maximum limits. Nickel and arsenic values were above the acceptable limits for drinking water. The lowest concentration of arsenic that is allowable in drinking water is about 0.01mg/l but the maximum concentration in the groundwater around Rumuola was 1.57mg/l. The lowest arsenic concentration in the boreholes being 0.16mg/l was still above drinking water limits. Nickel was observed to have a value of 0.033mg/l and is above the limits of 0.02mg/l in drinking water. According to [25], nickel is a carcinogenic element. The water quality index ranged 144 and 1367 which are all greater than 100. This means that the groundwater across Rumuola community is unsuitable for drinking.

The best interpolation models for the groundwater quality parameters are as follows: EBK for pH, TDS, Sulphate and nitrate; Ordinary kriging for Nickel and Hardness; IDW for Iron and arsenic; Cokriging for WQI. .

Advanced treatment methods should be explored to reduce the concentration of the toxic metals and to reduce acidity of the water to levels where they do not cause any harm to the residents who rely on this water for cooking and drinking.

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