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STUDIES ON THE SPATIAL DEPENDENCE AND TEMPORAL VARIABILITY OF GROUNDWATER QUALITY PARAMETERS IN SOME PARTS OF BENIN CITY METROPOLIS USING KRIGING INTERPOLATION AND MULTIVARIATE ANALYSIS OF VARIANCE

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Abstract

In this study, geospatial modelling technique using kriging interpolation and multivariate analysis of variance were employed to evaluate and analyze the spatial dependence and temporal variability of groundwater quality in parts of Benin City Metropolis.

Various ground water quality parameters such as pH, turbidity, total suspended solids (TSS), Electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), phosphate, nitrate, sulphate, total solids (TS), sodium, potassium, calcium, magnesium, iron, lead, cadmium, zinc and chloride were investigated for fifteen (15) boreholes around Idunmwowina, Isiohor and Oluku communities. For the spatial dependence and multivariate analysis, six physico-chemical parameters, namely; pH, electrical conductivity (EC), alkalinity, dissolved oxygen (DO), concentration of zinc and iron were employed.

Results obtained revealed that the parameters tested possess very strong spatial dependence. The computed degree of spatial dependency was observed to be less than 25% for all the water quality test parameters. For the multivariate analysis of variance, the assumption of multivariate outliers was not violated which justify the use of multivariate analysis of variance. In addition, it was observed that more than 95% of the computed significant values (p-value) for all the dependent variables were less than 0.05; (p <0.05), hence the null hypothesis of covariance matrix was rejected and it was concluded that the covariance matrix assumption was not satisfied. This means that the covariance matrices of the dependent variables are not equal across group an indication that temporal variability exists. On the percent variability that is accounted for due to the different sampling locations, the partial Eta squared value of the Pillai's trace was employed. From the calculated partial Eta squared of the Pillai's trace, 86.70% temporal variability of the dependent variables was observed.

Keywords: MANOVA, Covariance Matrix, Mahalanobis Constant, Null Hypothesis and Normal Distribution

1.0 Introduction

The availability of water in adequate quality and quantity is essential for the existence of human life. Water is one of the basic elements that sustain life on earth. Man can survive for a considerable amount of time without food, but he will succumb within days without water. As reported in [1, 2, 3], where there is water, there is life; and that life exists around numerous uses of water which make it important for survival and luxury. The average daily intake of water per person, directly or as contained in other foods, is about four litres. For those who live in hot dry climate, this daily requirement is at least double [2, 3]. Whenever a number of people live together, a supply of water is always paramount. On this note, for all purposes for which water is required, the quality of water is of great importance [3]. As world population is constantly growing, the demand for water increases every day. According to the United Nations, every day, 4,400 children under the age of five die around the world, having fallen sick because of unclean water [3].

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Water is available in the three states of matter namely solid (as ice), liquid (as water) and gas (as vapour). However, the water that is available for civilization comes from two major sources viz; ground water and surface water [4]. The flow of ground water depends on the hydraulic gradient; solid type and soil porosity while its quality is determined by the type of underlying rocks through which the water flows or is extracted [5]. A review conducted in [6] on groundwater quality in Nigeria urban areas revealed that Nigerian urban groundwater quality is influenced by the geological condition of the soil through which it flows, geochemical and physical process of the environment, rate of urbanization, industrialization and seasonal variability [7]. An integral part of any environmental monitoring program is the reporting of results to both managers and the general public. This poses a particular problem in the case of groundwater quality monitoring because of the complexity associated with analyzing a large number of measured water quality variables [8].

A critical problem associated with ground water monitoring is the issue of mapping the spatial variability of the parameters that affects the water qualities [9]. In addition, understanding the temporal variability of groundwater quality parameters can be very difficult owing to the multivariate nature of water quality test parameters. Introduction of geographical information systems (GIS) and multivariate statistics in the modelling and analysis of groundwater quality parameters can help reduce the difficulties associated with ground water monitoring especially in developing countries.

2.0 Research Methodology

2.1 Description of study area

The study area was limited to some parts of Benin City preferably Ovia North East Local Government Area specifically Idunmwowina, Isiohor and Oluku communities. For this study, water samples were collected randomly from fifteen (15) boreholes around the study area. The rectangular coordinates of the boreholes including the elevation were also determined and recorded.

Benin City serves as the principal administrative and socio-economic center for both Oredo Local Government Area and Edo State in Nigeria. Benin City is a humid tropical urban settlement which comprises three Local Government Areas namely Egor, Ikpoba Okha and Oredo. It is located within latitudes $6^{0}20^{'}$N and $6^{0}58^{'}$N and longitudes $5^{0}35^{'}$E and $5^{0}41$'E. It broadly occupies an area of approximately 112.552 sq km. The Benin City hydrological basin is partitioned into two main units. The first unit consists of the Ikpoba River Basin which drains the whole eastern part of the city while the second unit covers the Ogba River Basin which drains the western part. The base map of the study area is presented in Figure 1

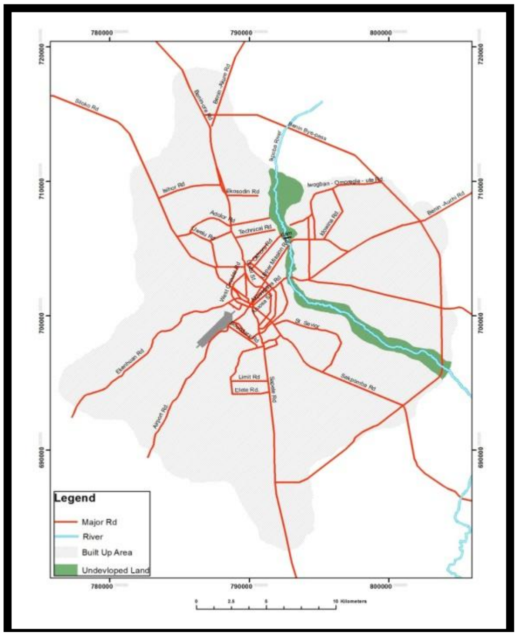


Figure 1: Base map of study area (Source: [10])

2.2 Sample collection/conditioning

Water samples were collected randomly from fifteen (15) boreholes around the study area. On the spot (in-situ) test such as pH, conductivity, total dissolved solids and dissolved oxygen were conducted immediately after sample collection. The water samples were then conditioned by storing them in clean dried sample bottles at room temperature before analysis. The need for conditioning was to allow the water to settle properly and give room for the microbial organisms to exhibit their full characteristics behaviour for ease of detection [11].

2.3 Physico-chemical analyses of water samples

The water samples were then subjected to full laboratory analysis in order to determine their physico-chemical properties. Some of the methods employed in the analysis are described below:

(a) Turbidity measurement

The amount of colloidal and residual suspended matter present in the water samples was determined using the Jenway 6035 Turbidimeter.

(b) Hydrogen Ion Concentration (pH)

The hydrogen ion concentration (pH) of the water samples was determined using a standard laboratory digital micro-processor pH meter; Hanna pH 210 model.

(c) Dissolved Oxygen Content (DO)

The dissolved oxygen content (DO) of the water samples was measured using a standard laboratory sized digital dissolved oxygen analyzer model: DO – 5509.

(d) Conductivity Measurement

The conductivity of the water samples was determined using a digital water/sand quality test kit model SN2209

(e) Total Dissolved Solids (TDS)

The amount of total dissolved solids (tds) present in the different water samples was determined using a digital water/sand quality test kit model SN2209

(f) Heavy Metal Determination

The concentration of heavy metals present in the different water samples was determined using Atomic Adsorption Spectrophotometer (AAS). (SOLAAR 969 UNICAM SERIES, using air acetylene flame).

3.0 Analysis of water quality data

Two methods were employed for the analysis of the water quality parameters and they include; geostatistical method using kriging interpolation and multivariate statistical technique multivariate analysis of variance

(a) Kriging interpolation

Kriging is a geostatistical interpolation technique that considers both the distance and the degree of variation between known data points when estimating values in unknown areas. It attempts to minimize the error variance and set the mean of the prediction errors to zero so that there is no over- or under-estimates. It is a robust interpolation tool which derives weights from surrounding measured values to predict values at unmeasured locations. The kriging weights are obtained from fitting of semi- variogram models, developed by viewing the spatial structure of the data. The following steps are involved in the use of kriging interpolation method for the geospatial analysis of selected ground water quality parameters [12]

i. Assessment of normality
ii. Global trend analysis
iii. Fitting and testing of semivariogram
iv. Estimation of cross validation statistics
v. Spatial Dependency determination
vi. Creation of spatial distribution maps

Spatial modeling works better when data are normally distributed hence the need for normality check. Data transformations are employed to convert the raw data to normally distributed data in case of non-normality. Such transformation methods include Box-Cox, arcsine and logarithm [13].

(b) Analysis of data using multivariate analysis of variance

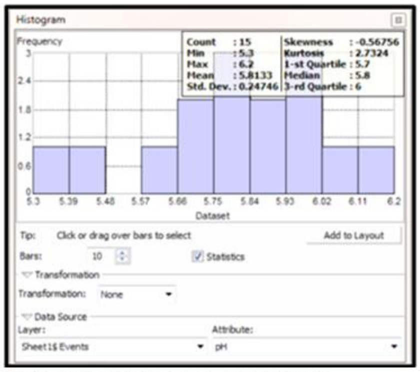
To study the seasonal and temporal variability of the water quality parameters using multivariate analysis of variance, the following steps were employed

i. Water samples were collected randomly from fifteen (15) boreholes around the study location, namely; Idunmwowina, Isiohor and Oluku communities.
ii. The physico-chemical properties of the collected water samples were determine to assess the groundwater qualities
iii. The dependent variables (water quality parameters) and independent variables (location) were thereafter defined
iv. Multivariate assumption such as assessment of the presence of multivariate outlier was adequately examined to justify the use of multivariate analysis of variance in assessing the temporal variability of groundwater quality parameters
v. Finally, multivariate syntax was generated and the syntax was ran to generate the results of the temporal variability
vi. The analysis was executed using statistical package for the social science (SPSS 22)

4.0 Results and discussion

4.1 Assessment of normality using frequency histogram

Frequency histogram was generated for the selected water quality parameters to ascertain if the measured parameters are normally distributed. It is expected for spatial dependence that the measured parameters be well distrubted (statistically normally distributed). The generated histogram for some selected water quality parameters are presented in figures 2a and 2b



Count : 15
Min : 5.3
Max : 6.2
Mean : 5.8133
Std. Dev. : 0.24746
Skewness : -0.56756
Kurtosis : 2.7324
1-st Quartile : 5.7
Median : 5.8
3-rd Quartile : 6

Tip: Click or drag over bars to select
Bars: 10
☑ Statistics
Transformation: None
Layer: Sheet1$ Events
Attribute: pH

Figure 2a: Histogram plot of pH

Count : 15
Min : 4.8
Max : 8.1
Mean : 6.2867
Std. Dev. : 1.1179
Skewness : 0.033757
Kurtosis : 1.5824
1-st Quartile : 5.125
Median : 6.3
3-rd Quartile : 7.35

Tip: Click or drag over bars to select
Bars: 10
☑ Statistics
Transformation: None
Layer: Sheet1$ Events
Attribute: DO

Figure 2b: Histogram plot of DO

Result of figures 2a and 2b shows that the pH and dissolved oxygen data are well distributed and thus requires no transformation. The mean and median value for both the pH and dissolved oxygen were observed to be equal. The mean values for pH and DO was 5.8133 and 6.2867 while the median values is 5.80 and 6.30 respectively. The mean, median, skewness and kurtosis coupled with the transformation method for the selected water quality test parameters is presented in table 1.

Table 1: Descriptive statistics/transformation method

S/No	Parameters	Mean	Median	Skewness	Kurtosis	Transformation Method
1	pH	5.8133	5.80	-0.56756	2.724	Non
2	EC	14.333	10.00	1.372	4.5026	Log
3	Alkalinity	25.26	19.00	1.7185	4.6587	Log
4	DO	6.2867	6.30	0.03376	1.5824	Non
5	Zinc	0.2333	0.13	2.5341	8.436	Log
6	Iron	0.3889	0.053	0.7265	1.5909	Log
7	Sulphate	0.968	10.00	1.372	4.5026	Log

For normality, the skeweness value is closer to zero and the kurtosis approaches 3.0 with the mean and median value almost the same. Based on this criteria, it was observed that pH and dissolved oxygen are assumed to be normally distributed hence, do not require any transformation. Since EC, Alkalinity, Zinc, Iron and Sulphate violated the normality assumption, log transformation method was then applied to normalize the data.

4.2 Trend analysis

To exammine the presence of trend between sample points, 3D trend graph was generated for some selected water quality parameters as presented in figures 3a and 3b.

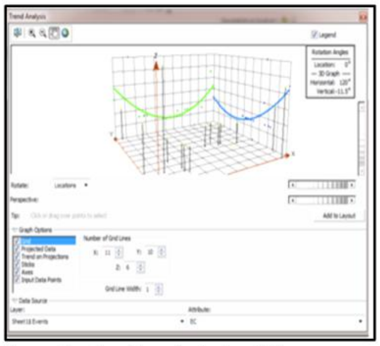


Figure 3a: trend analysis for EC

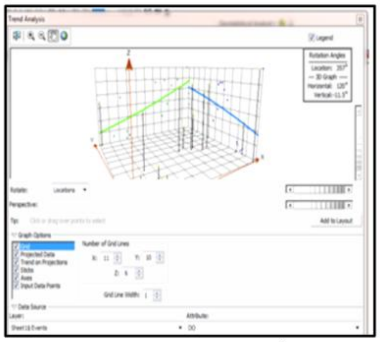
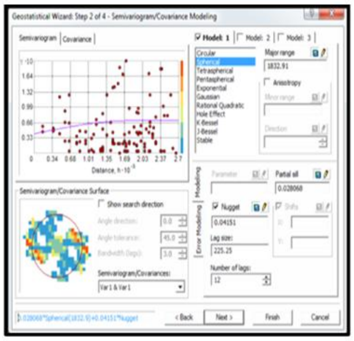


Figure 3b: trend analysis for DO

Result of figure 3a reveal the presence of trend in electrical conductivity data. The curved line in EC graph represented by (green and blue) indicate the presence of trend as against the flat line for dissolved oxygen which indicate no trend.

4.3 Fitting and testing of semivariogram

Semivariogram is one of the significant functions to indicate spatial correlation in observations measured at sample locations. It is commonly represented as a graph that shows the variance in measurement with distance between all pairs of sampled locations. Such a graph is helpful to build a mathematical model that describes the variability of the measurement with location. The Semivariogram/Covariance model for the selected water quality parameters are presented in figures 4a, 4b, 4c and 4d representing pH, electrical conductivity, alkalinity and iron



☑ Model: 1 ☐ Model: 2 ☐ Model: 3

Major range: 1832.91

☐ Anisotropy

Partial sill: 0.028068

☑ Nugget: 0.04151

Lag size: 225.25

Number of lags: 12

☐ Show search direction

Angle direction: 0.0

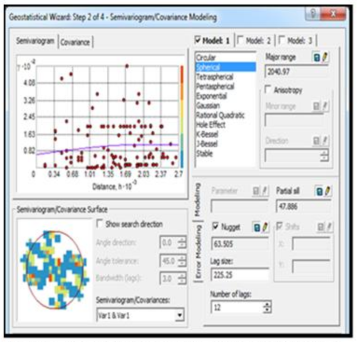
Angle tolerance: 45.0

Bandwidth (lags): 3.0

Semivariogram/Covariances: Var1 & Var1

0.028068*Spherical(1832.9)+0.04151*Nugget

Figure 4a: Semivariogram model for pH



☑ Model: 1 ☐ Model: 2 ☐ Model: 3

Major range: 2040.97

☐ Anisotropy

Partial sill: 47.886

☑ Nugget: 63.505

Lag size: 225.25

Number of lags: 12

☐ Show search direction

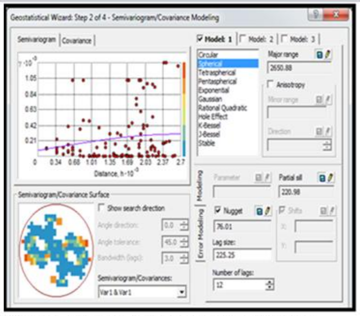
Angle direction: 0.0

Angle tolerance: 45.0

Bandwidth (lags): 3.0

Semivariogram/Covariances: Var1 & Var1

Figure 4b: Semivariogram model for EC



☑ Model: 1 ☐ Model: 2 ☐ Model: 3

Major range: 2650.88

☐ Anisotropy

Partial sill: 220.98

☑ Nugget: 76.01

Lag size: 225.25

Number of lags: 12

☐ Show search direction

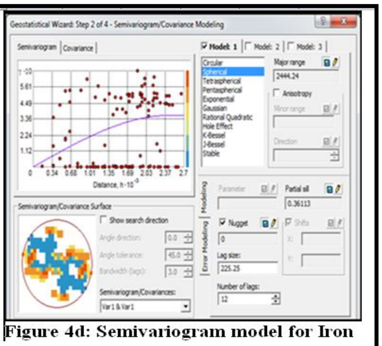
Angle direction: 0.0

Angle tolerance: 45.0

Bandwidth (lags): 3.0

Semivariogram/Covariances: Var1 & Var1

Figure 4c: Semivariogram model for Alkalinity



☑ Model: 1 ☐ Model: 2 ☐ Model: 3

Major range: 2444.24

☐ Anisotropy

Partial sill: 0.36113

☑ Nugget: 0

Lag size: 225.25

Number of lags: 12

☐ Show search direction

Angle direction: 0.0

Angle tolerance: 45.0

Bandwidth (lags): 3.0

Semivariogram/Covariances: Var1 & Var1

Figure 4d: Semivariogram model for Iron

Six (6) semivariogram models (Circular, Spherical, Stable, Hole Effect, K-Bessel and J-Bessel) were fitted for each selected water quality parameter used for geostatistical analysis. The selected water quality parameters include pH, electrical conductivity (EC), alkalinity, dissolved oxygen (DO), zinc, iron and sulphate). Fitted semivariogram can be used for estimating the semi-variance at any given distance and it is characterized by three measures, namely; the nugget, the range and the sill. Nugget refers to the variability in the field data that cannot be explained by distance between the observations. Range is the point at which the semi-variance stops increasing. It represents the distance at which two observations are independent. In other words, the range corresponds to the spatially correlated portion of the semivariogram. Sill is the semi-variance at which the leveling takes place. Result of the fitted semivariogram model for pH is presented in table 2

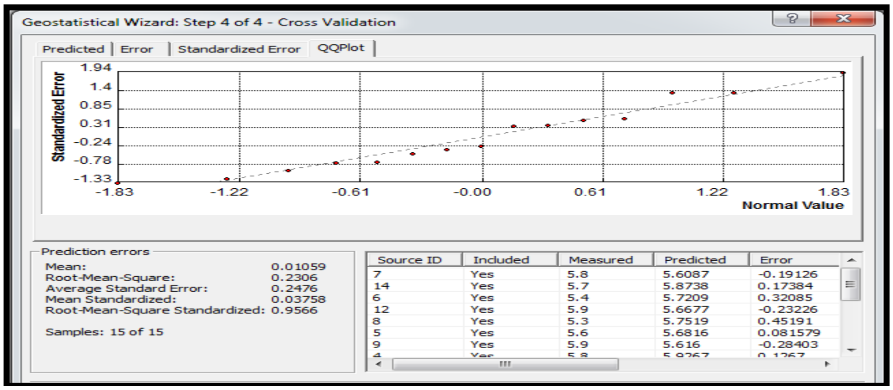
Table 2: Semivariogram models for pH

S/N	Model Type	Nugget	Major Range	Partial Sill
1.	Circular	0.023400	377.300	0.040302
2.	Spherical	0.04151	1832.91	0.028068
3.	Stable	0.035525	1634.50	0.092346
4.	Hole Effect	0.041346	1776.55	0.046220
5.	K-Bessel	0.387641	409.008	0.160302
6.	J-Bessel	0.023659	367.225	0.088745

Fitted Semivariogram models for each of the water quality parameters provided information about the range, nugget and partial sill (Model Parameters) which were employed to measure the degree of spatial dependency of sampled borehole points. It also provides the input parameters that were utilized for the kriging interpolation. To select the model that best described each water quality parameters, selected goodness of fit statistics generated from the cross validation step were employed.

4.4: Estimation of cross validation statistics

The Cross Validation statistics gives you an idea of how well the model predicts the values at unsampled location. The cross validation plot generated for pH is presented in figure 5



Prediction errors
Mean: 0.01059
Root-Mean-Square: 0.2306
Average Standard Error: 0.2476
Mean Standardized: 0.03758
Root-Mean-Square Standardized: 0.9566

Samples: 15 of 15

Source ID	Included	Measured	Predicted	Error
7	Yes	5.8	5.6087	-0.19126
14	Yes	5.7	5.8738	0.17384
6	Yes	5.4	5.7209	0.32085
12	Yes	5.9	5.6677	-0.23226
8	Yes	5.3	5.7519	0.45191
5	Yes	5.6	5.6816	0.081579
9	Yes	5.9	5.616	-0.28403

Figure 5: Cross validation statistics for pH

The essence of cross validation is to examine closely the fitted models and select the model that gives the best result (prediction). To select the model that gives the best result, goodness of fit statistics, namely; Root mean square error (RMSE), Mean standardized error (MSE), Root mean square standardized error (RMSSE) and Average standard error (ASE) were employed. The computed goodness of fit statistics for pH is presented in table 3

Table 3: Cross validation statistics for pH

S/N	Model Type	RMSE	MSE	RMSSE	ASE
1.	Circular	2.3340	0.07600	2.1082	1.3054
2.	Spherical	**0.2306**	**0.03758**	**0.9566**	**0.2476**
3.	Stable	0.5607	0.52074	1.1183	0.4902
4.	Hole Effect	1.0045	0.40051	3.9004	0.8803
5.	K-Bessel	3.2210	0.24038	2.3005	1.2266
6.	J-Bessel	2.9034	1.03451	1.0332	2.3307

Following the application of different models on each water quality parameter, the errors were calculated using cross validation and the model that gives the best result was selected for each water quality test parameters. The criteria's for selecting the best model is as follows [12]:

i. The mean standardized error should be close to 0,
ii. The root mean square error and average standard error should be as small as possible and close to each other
iii. The root mean square standardized error should be close to one.

Based on the above criterion, the spherical model was selected as the best fit model for each selected water quality test parameters. The cross validation statistics for the selected water quality parameters including the best fit model is presented in table 4

Table 4: Best fitted model for groundwater quality parameters

S/N	Parameters	Best fit Model	RMSE	MSE	RMSSE	ASE
1.	pH	Spherical	**0.2306**	**0.03758**	**0.9566**	**0.2476**
2.	EC	Spherical	-0.8021	-0.0699	0.9793	9.3690
3.	Alkalinity	Spherical	13.580	0.0148	1.094	12.600
4.	DO	Spherical	0.3481	0.0562	1.3067	1.6034
5.	Zinc	Spherical	0.3384	0.0866	1.0160	0.3344
6.	Iron	Spherical	0.2770	0.0727	0.8995	1.0161

4.5: Investigation of spatial dependency

To investigate the spatial dependence of each of the selected water quality test parameters, the best fitted model for each water quality parameters was first determined as presented in table 4. Using the best fit model, the semivariogram parameters of each water quality test parameters, namely; nugget (C_n), major range and partial sill were then determined as presented in table 5.

Table 5: Computed semivariogram parameters based on best fit model

S/N	Parameters	Best fit Model	Nugget	Major Range	Partial Sill
1.	pH	Spherical	0.04151	1832.91	0.028068
2.	EC	Spherical	63.505	2040.97	47.886
3.	Alkalinity	Spherical	76.01	2650.88	220.98
4.	DO	Spherical	86.09	1056.91	34.67
5.	Zinc	Spherical	0.10112	2538.76	0.4815
6.	Iron	Spherical	0.4285	2444.24	0.36113

Using the results of table 5, the sill value (C_o) was then calculated. The sill is the summation of nugget and partial sill while the ratio of nugget to sill $\left(\frac{C_n}{C_o}\right)$ measured the degree of spatial structure (dependence) of a water quality parameter. If the ratio is less than 25%, the variable has strong spatial dependence; between 25% and 75%, the variable has moderate spatial dependence, and greater than 75%, the variable shows only weak spatial dependence. The computed spatial dependence for the selected water quality parameters using the selected best fit model is presented in table 6

Table 6: Computed semivariogram parameters based on best fit model

S/N	Parameters	Best fit Model	Nugget (C_n)	Partial Sill	Sill (C_o)	[C_n/C_0]	Degree of Spatial Dependency
1.	pH	Spherical	0.04151	0.02807	0.06958	0.59658	Strong
2.	EC	Spherical	63.505	47.886	111.391	0.57011	Strong
3.	Alkalinity	Spherical	76.01	220.98	296.99	0.25593	Strong
4.	DO	Spherical	86.09	34.67	120.76	0.71290	Strong
5.	Zinc	Spherical	0.10112	0.4815	0.58262	0.17356	Strong
6.	Iron	Spherical	0.4285	0.36113	0.78963	0.54266	Strong

Results of table 6 revealed that the water quality parameters showed relatively strong degree of spatial dependency which made it possible to generate the spatial distribution map for the selected water quality parameters as presented in figures 6a and 6b respectively.

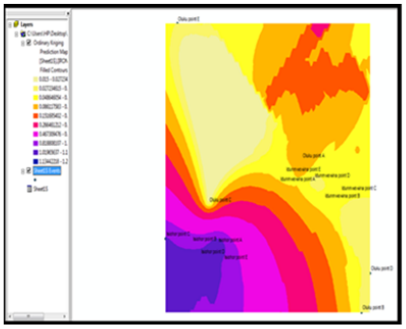


Figure 6a: Spatial distribution map for Iron

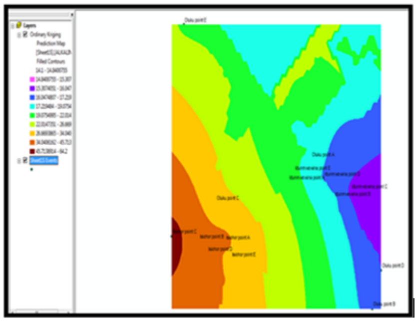


Figure 6b: Spatial distribution map for Alkalinity

In figure 6a, areas with dark blue colouration have high concentration of iron as against area with light yellow colouration with low concentration of iron. In figure 6b, areas with dark brown colouration have high alkaline concentration while areas with pink colouration have low alkaline concentration.

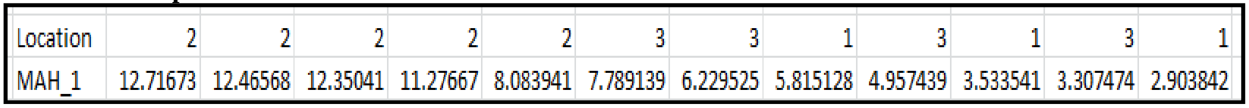
4.6 Investigation of temporal variability

To study the temporal variability of the groundwater quality parameters occasioned by the sampling locations, multivariate analysis of variance was employed as follows

(a) Assessing the suitability of MANOVA based on multivariate outliers

Multivariate alliance is usually calculated through a measure known as the Mahalanobis constant. If the maximum calculated value of the Mahalanobis constant is less than the critical value, then the assumption of multivariate outliers has not be violated. Therefore, if multivariate outliers has not been violated, then we can investigate the concept of temporal variability using multivariate analysis of variance (MANOVA) otherwise, we must think of another statistical concept to track the presence of temporal variability. Results of the calculated Mahalanobis constant using regression analysis is presented in table 7a

Table 7a: Computed Mahalanobis constant



Location	2	2	2	2	2	3	3	1	3	1	3	1
MAH_1	12.71673	12.46568	12.35041	11.27667	8.083941	7.789139	6.229525	5.815128	4.957439	3.533541	3.307474	2.903842

With a degree of freedom (df) = number of dependent variables = 6, the maximum value of Mahalanobis constant was observed to be 12.71673. The critical value of Mahalanobis constant at degree of freedom (df) equals 6 was observed to be 22.460. Since 12.71673 < 22.460, it was concluded that the assumptions of multivariate outliers has not been violated hence the use of multivariate analysis of variance to study the presence of temporal variability is justified.

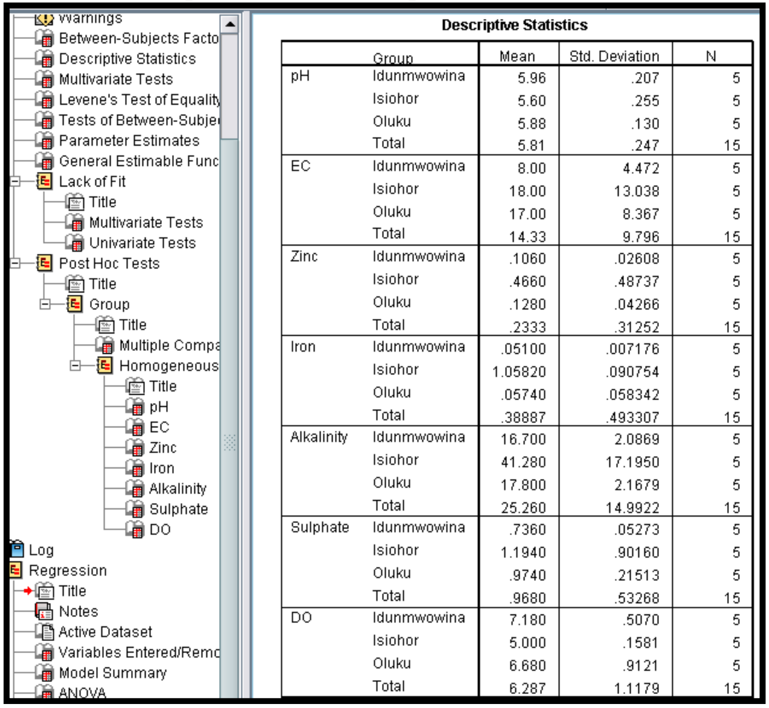
(b) Descriptive Statistics

Descriptive statistics was employed to check the difference in the mean and standard deviation of the sampling group. Tables 7b shows the descriptive statistics of the dependent variables

(c) Box Test or Covariance Matrix

In multivariate analysis of variance, we set out to test the null hypothesis that observed covariance matrix of all the dependent variables (water quality parameters) are equal across group (location 1, location 2 and location 3) that is there is no temporal variation in the water quality parameters. If the calculated p-value is less than 0.05 ($p < 0.05$) we reject the null hypothesis and conclude that the assumption of equal covariance matrices across group has not been satisfied; an indication that temporal variability exist among the group. The computed covariance matrix for the corrected model is presented in table 8

Table 7b: Descriptive statistics of dependent variables

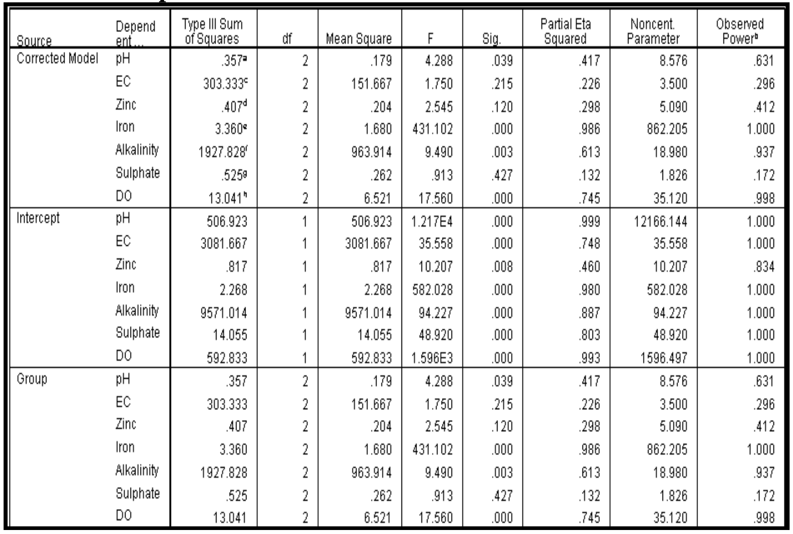


Descriptive Statistics

	Group	Mean	Std. Deviation	N
pH	Idunmwowina	5.96	.207	5
	Isiohor	5.60	.255	5
	Oluku	5.88	.130	5
	Total	5.81	.247	15
EC	Idunmwowina	8.00	4.472	5
	Isiohor	18.00	13.038	5
	Oluku	17.00	8.367	5
	Total	14.33	9.796	15
Zinc	Idunmwowina	.1060	.02608	5
	Isiohor	.4660	.48737	5
	Oluku	.1280	.04266	5
	Total	.2333	.31252	15
Iron	Idunmwowina	.05100	.007176	5
	Isiohor	1.05820	.090754	5
	Oluku	.05740	.058342	5
	Total	.38887	.493307	15
Alkalinity	Idunmwowina	16.700	2.0869	5
	Isiohor	41.280	17.1950	5
	Oluku	17.800	2.1679	5
	Total	25.260	14.9922	15
Sulphate	Idunmwowina	.7360	.05273	5
	Isiohor	1.1940	.90160	5
	Oluku	.9740	.21513	5
	Total	.9680	.53268	15
DO	Idunmwowina	7.180	.5070	5
	Isiohor	5.000	.1581	5
	Oluku	6.680	.9121	5
	Total	6.287	1.1179	15

From the results of table 7b, it was observed that there is a significant difference in the mean and standard deviation of all the dependent variables as a function of sampling locations. The difference in the mean and standard deviation suggest the presence of imaginative variance which is temporal variation occasioned by change in location.

Table 8: Computed covariance matrix for model



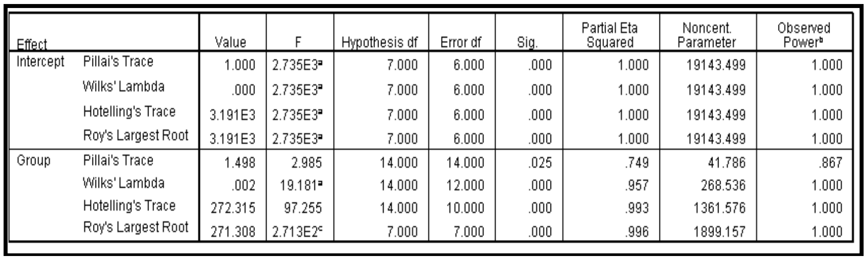
Source	Dependent...	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power^{b}
Corrected Model	pH	.357^{a}	2	.179	4.288	.039	.417	8.576	.631
	EC	303.333^{c}	2	151.667	1.750	.215	.226	3.500	.296
	Zinc	.407^{d}	2	.204	2.545	.120	.298	5.090	.412
	Iron	3.360^{e}	2	1.680	431.102	.000	.986	862.205	1.000
	Alkalinity	1927.828^{f}	2	963.914	9.490	.003	.613	18.980	.937
	Sulphate	.525^{g}	2	.262	.913	.427	.132	1.826	.172
	DO	13.041^{h}	2	6.521	17.560	.000	.745	35.120	.998
Intercept	pH	506.923	1	506.923	1.217E4	.000	.999	12166.144	1.000
	EC	3081.667	1	3081.667	35.558	.000	.748	35.558	1.000
	Zinc	.817	1	.817	10.207	.008	.460	10.207	.834
	Iron	2.268	1	2.268	582.028	.000	.980	582.028	1.000
	Alkalinity	9571.014	1	9571.014	94.227	.000	.887	94.227	1.000
	Sulphate	14.055	1	14.055	48.920	.000	.803	48.920	1.000
	DO	592.833	1	592.833	1.596E3	.000	.993	1596.497	1.000
Group	pH	.357	2	.179	4.288	.039	.417	8.576	.631
	EC	303.333	2	151.667	1.750	.215	.226	3.500	.296
	Zinc	.407	2	.204	2.545	.120	.298	5.090	.412
	Iron	3.360	2	1.680	431.102	.000	.986	862.205	1.000
	Alkalinity	1927.828	2	963.914	9.490	.003	.613	18.980	.937
	Sulphate	.525	2	.262	.913	.427	.132	1.826	.172
	DO	13.041	2	6.521	17.560	.000	.745	35.120	.998

From the results of tables 8, it was observed that more than 90% of the computed significant values (p-value) were less than 0.05; ($p < 0.05$), hence the null hypothesis was rejected and it was concluded that the covariance matrix assumption was not satisfied. This means that the covariance matrices of the dependent variables are not equal across group an indication that temporal variability exists. It was concluded based on the covariance matrix that the variation in the dependent variables is due to the different aquifer formation that constitutes the different locations from where the samples were collected.

(d) The Multivariate Test

Different statistical method for computing the F-value for multivariate analysis of variance exits in literature. One of them is the Roy's largest root which is probably the most acceptable and also the most susceptible to deviation in the covariance matrix. The next is the Pillai's Trace followed by Wilk's Lambda. Pillai's Trace is the least sensitive to the violation of the assumption of covariance matrix. If the p-value of the Pillai's Trace is less than 0.05 then we reject the null hypothesis that the water quality parameters are the same for the three groups and conclude that temporal variability actually exist. The computed multivariate test statistics are presented in table 9

Table 9: Multivariate statistical table



Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Intercept	Pillai's Trace	1.000	2.735E3[a]	7.000	6.000	.000	1.000	19143.499	1.000
	Wilks' Lambda	.000	2.735E3[a]	7.000	6.000	.000	1.000	19143.499	1.000
	Hotelling's Trace	3.191E3	2.735E3[a]	7.000	6.000	.000	1.000	19143.499	1.000
	Roy's Largest Root	3.191E3	2.735E3[a]	7.000	6.000	.000	1.000	19143.499	1.000
Group	Pillai's Trace	1.498	2.985	14.000	14.000	.025	.749	41.786	.867
	Wilks' Lambda	.002	19.181[a]	14.000	12.000	.000	.957	268.536	1.000
	Hotelling's Trace	272.315	97.255	14.000	10.000	.000	.993	1361.576	1.000
	Roy's Largest Root	271.308	2.713E2[c]	7.000	7.000	.000	.996	1899.157	1.000

From the result of table 9, it was observed that the computed p-value for the Pillai's Trace statistics is 0.000 for intercept and 0.025 for group, which is less than 0.05. Since (p-value < 0.05) we rejected the null hypothesis and concluded that there is the existence of temporal variability among the dependent variables occasioned by sampling locations

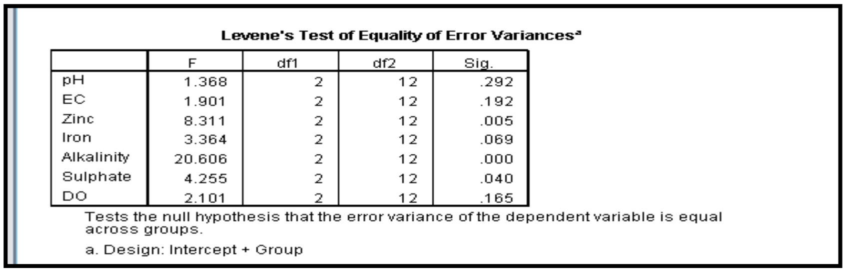
To calculate the percent variability that is accounted for due to the different sampling locations, the partial Eta squared value of the Pillai's trace was employed. From the result of table 9, the calculated partial Eta squared of the Pillai's trace was observed to be 0.867 which indicates an 86.70% temporal variability of the dependent variables occasioned by change in borehole location.

In addition, when the null hypothesis of equal variance assumption is rejected, then the observed power function based on Pillai's trace must be between 0.9-1.00. From the result of table 9, it was observed that the calculated power function based on Pillai's trace is 1.000 for intercept and 0.867 for group. This validates the initial claim that temporal variability exist between the dependent variables.

(e) Levene's Test of Equality of Error Variance

If temporal variability exists, then the calculated error variance for all the dependent variables for the different sampling location must not be the same. To test the null hypothesis that the error variance of the dependent variables is equal across groups, levene's test of equality of error variance was computed as presented in table 10

Table 10: Levene's Test Statistics



Levene's Test of Equality of Error Variances[a]

	F	df1	df2	Sig.
pH	1.368	2	12	.292
EC	1.901	2	12	.192
Zinc	8.311	2	12	.005
Iron	3.364	2	12	.069
Alkalinity	20.606	2	12	.000
Sulphate	4.255	2	12	.040
DO	2.101	2	12	.165

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Group

From the result of table 10, it was observed that the calculated p-value for most of the dependent variables is greater than 0.05; an indication that temporal variability exist among the group. The presence of temporal variability as observed in the analysis may be due to variation in the sampling locations. Knowledge of temporal variability of groundwater quality parameters is relevant in siting of boreholes especially for domestic and commercial purposes. It is also useful in urban planning and water resources management.

5.0 Conclusion

This study illustrates the usefulness of geospatial modelling in investigating the spatial dependency of water quality test parameters. It has also provided relevant information on the application of multivariate statistical techniques for the analysis and interpretation of complex water quality data sets. Although, the content of this study is not completely assuasive of the subject matter, It is has provided a bird eye information on water quality assessment and understanding of the temporal variability and spatial dependency of groundwater quality parameters using kriging interpolation and multivariate analysis of variance.

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