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Spatial dependency of groundwater quality in Benin City, Edo State, Nigeria using semi-variogram models

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Abstract

Water quality is a worldwide concern especially water for human consumption. Regular monitoring and tools should be developed, to ensure continuous assessment of the level of concentration of chemical constituents prevalent in water. This will guide against health dangers and risks associated with water of low quality. The research focus on using semi-variogram models to measure the degree of spatial dependency of sampled boreholes for prediction of the concentration of water quality parameters at un-sampled locations because of the cumbersome nature of assessing the whole boreholes in Benin City. One hundred and ten (110) different domestic boreholes were systematically sampled and analyzed in laboratory for determination of the concentration of some chemical water quality parameters which include Electrical Conductivity (EC), Total Dissolve Solids (TDS), Bicarbonate (HCO3), Sodium (Na), Potassium (K), Calcium (Ca), Magnesium (Mg), etc. Laboratory examination of boreholes water quality parameters were carried out in wet and dry seasons. Geographical locations of sampled boreholes were also determined. The obtained experimental results were utilized in investigating the spatial structure of the boreholes using semi-variogram models which include spherical, exponential, Gaussian etc. Exponential model was the most fitted model. The borehole water quality parameters exhibited high degree of spatial dependency in EC, TDS, HCO3, Na, K, Ca. Mg, Cl, P, and NO3 in both seasons with $\frac{Cn}{C}$ ratio < 25% therefore, interpolation technique can be employed to produce spatial variation quality map of boreholes in Benin City as a monitoring technique to detect contamination or changes in water quality.

Keywords: Water quality; Semi variogram models; Spatial dependency; Prediction

1. Introduction

Utilization of water by humans cannot be stopped because water is an essential liquid for survival, so much desired in many spheres of lives and activities. The quantity and quality matter a lot in human developments and progress. Access to clean water and sanitation is one of the major goals of United Nation for sustainable developments. The shocking epitome of water quality lies on its impacts and health implications on humans when ingested or indirectly in contact with a contaminated water. There is need for assessment and continuous monitoring of water quality especially domestic boreholes which are the major sources of water supply in Benin City, due to the non-functioning of state water cooperation. It may be cumbersome to investigate water quality of all domestic boreholes in the city, therefore, it is important to employ some spatial interpolation techniques. Spatial interpolation is a technique utilized with observed values on earth surface to estimate and make prediction of values in un-sampled locations within the same area. This spatial interpolation assumes that there is a degree of similarities or attributes between points close to each other [1]. This degree of similarity is otherwise known as spatial dependency. Degree of spatial dependency that exists between observations are expected to be similar to each other, than to distant observations [2]. This investigation in boreholes

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water quality parameters employs the use of semi variogram models to provide model parameters that are used to measure spatial dependency. If the dependency is higher, an accurate variation map depicting boreholes water quality for the entire area can be produced. The concentration values of boreholes water quality parameters sampled within Benin City were investigated to determine its degree of spatial dependency for predicting values in un-sampled borehole points. The inhabitants of Benin-City, Nigeria depend on water from rivers and streams, rain water and boreholes to meet their domestic and industrial needs [3]. Groundwater is one of the most sources exploited for human consumption [4, 5]. In Benin City, water demand had increased as a result of increase in population, urbanization, industrial and agricultural activities, etc. Thus, the quest for alternative sources to satisfy water demand has led to the indiscriminate construction of boreholes by individuals as coping strategy without any concern on the quality of water abstracted. The quality of water suitable for drinking must be free of pathogenic organisms and dissolved contaminants. Some of the domestic borehole owners have no knowledge of water quality and have never engaged in laboratory determination of borehole water quality. Therefore, it is cumbersome to determine all the domestic borehole in Benin City to assess their quality. Semivariogram models were employed to ascertain the degree of spatial dependency of sampled boreholes quality for determination of un-sampled boreholes water quality within the study area. Semivariogram is one of the significant functions to indicate spatial correlation in observations, measured at sample locations [6]. Semivariograms can be fitted with many models which include circular, spherical, exponential, qaussian, power, rational quadratic, Sine hole effect, K-bessel, J-bessel and stable. The Fitted semivariogram model for each of the water quality parameter provide information referred to as model parameters which are used to measure the degree of spatial dependency of sampled borehole points as a result of distance between them. The model parameters are the range (a), nugget (Cn) and sill (C). The ratio of Nugget to Sill ($\frac{Cn}{C}$) measures the degree of spatial structure (dependency) of a water quality parameter [7]. If the ratio is less than 25%, the variable has strong spatial dependence; between 25% and 75%, the variable exhibit moderate spatial dependence, and greater than 75%, the variable shows only weak spatial dependence and cannot be relied upon to make prediction of concentration of other un-sampled location [6, 7]. The nugget, the range and the sill are shown in Figure 1.

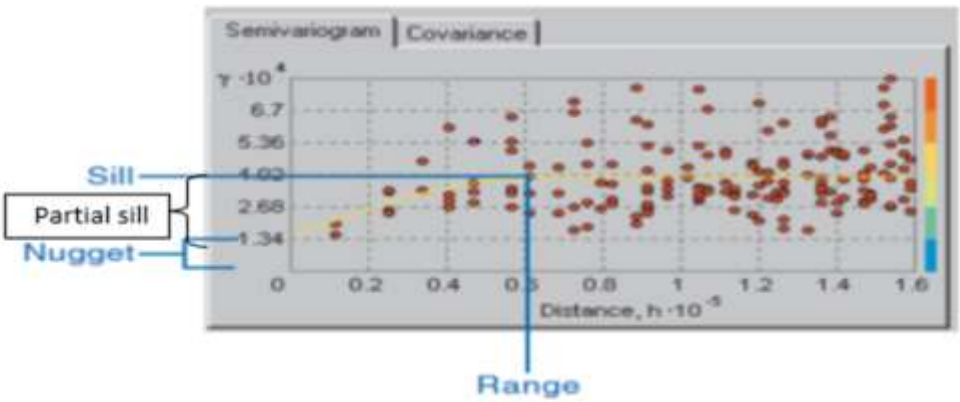

Figure 1 Modified Semivariogram depicting range, sill, and nugget effect [8].

Some of the semi-variogram mathematical models for investigation of spatial dependency of parameters [1,9] include the following:

$$Spherical: \quad \gamma(h) = \begin{cases} 0 & if \;\; h = 0 \\ c_n + \sigma\left(1.5\left(\frac{h}{a}\right) - 0.5\left(\frac{h}{a}\right)^3\right) & if 0 < \; h \; \leq a \\ c & if \; a < h \end{cases} \quad (1)$$

$$Circular: \quad \gamma(h) = \begin{cases} c_n + \sigma\left(1 - \frac{2}{\pi} cos^{-1}\left(\frac{h}{a}\right) + \sqrt{1 - \frac{h^2}{a^2}}\right) & if \; h \; \leq a \\ c & if \; h > a \end{cases} \quad (2)$$

$$Exponential: \quad \gamma(h) = c_n + \sigma\left(1 - exp\left(\frac{-h}{a}\right)\right) \quad (3)$$

$$Gaussian: \quad \gamma(h) = c_n + \sigma\left(1 - exp\left(\frac{-h^2}{a^2}\right)\right) \quad (4)$$

$$Sine\ hole\ effect: \quad \gamma(h) = c_n + \sigma\left(1 - \frac{\sin(\pi h/a)}{\pi h/a}\right) \quad (5)$$

Where, $\gamma(h)$ = semivariogram model
h = lag distance, c_n = nugget effect,
a = range (the distance at which the semivariogram reaches the sill)
σ = partial sill
c = sill (consists of the nugget effect and the partial sill) i.e., $c = c_n + \sigma$ (6)

Models provide information about the spatial structure. There is need for cross validation of models to choose the best that suits a particular chemical water quality data. The cross validation criterions for choosing the best model [6,10] are; the Mean Error (ME) and Mean Standardized Errors (MSE) should be close to 0 which indicate that the predictions were not biased but centred on the measured values; the Root Mean Square Error (RMSE) and Average Standard Error (ASE) should be as small as possible and close to each other. These indicate how closely the models predict the measured values and the variability in prediction are well assessed; the Root Mean Square Standardized Error (RMSE) should be close to one (1) indicating that the standard errors are accurate. The chemical parameters analyzed have relative importance in the overall quality of water for human consumption [11]. Their concentration in water indicates the degree of pollution or purity of the water source for drinking purposes.

2. Description of study area

Benin City is one of the ancient cities and the capital of Edo State in Nigeria. Erah et al., [12] reported that, it has an area coverage of 500km^2 bounded by 6° 06'N to 6° 30'N and 5° 3'E to 5° 45' E coordinates. It is about 40.2km North of the Benin river and 321.8km East of Lagos. The study area experiences wet season (March – October) and dry season (November – February). A base map of the study area is presented in Figure 2.

Figure 2 Location Map of the Study Area in Nigeria (Source: https://www.mapsofworld.com/).

3. Methodology

3.1. Laboratory Determination of Boreholes water quality parameters

One hundred and ten (110) boreholes were studied within the study area for the determination of the concentration of boreholes chemical parameters during wet and dry season respectively. The chemical parameters analyzed were EC, TDS, HCO_3, Na, K, Ca, Mg, Cl^-, P, NO_3, SO_4, Fe, Zn. They were determined using standard procedure of American Public

Health association [13] for determination of water quality parameters in the laboratory. EC and TDS were measured using Multi Portable Meter (HI 9813-6). Titrimetric method were carried out to analyze HCO_3, Ca, Mg and Cl^-. Ultraviolet visible spectrometer (Thermo Scientific Spectronic 20D$^+$) was utilized in investigating P, NO_3, SO_4. Iron and Zinc were determined using Atomic Absorption Spectrometer (Unicam 969 AA Model) which is dependent on wavelength and lamp current of the metals. Geographical locations of sampled boreholes were determined using Garmin GPS 72 receiver.

3.2. Method for Fitting of Semi-Variogram Models

The fitting of experimental results of boreholes water quality parameters into semi-variogram model were carried out using ARCGIS 10.1 software. The location points of the observed boreholes were tied with the results of water quality parameters for that point in microsoft excel sheet to form data base. Using geo-data base creation function of the software, the data in Microsoft excel was imported into the ArcMap 10.1 by clicking add data menu. From the file menu, the XY coordinates of the sampled points were added to create the surface for water quality parameters. Geostatistical analyst toolbar was used to first examine the distribution of observed borehole parameter data using histogram as shown in Figure 3 and transformation were applied where necessary for uniform distribution.

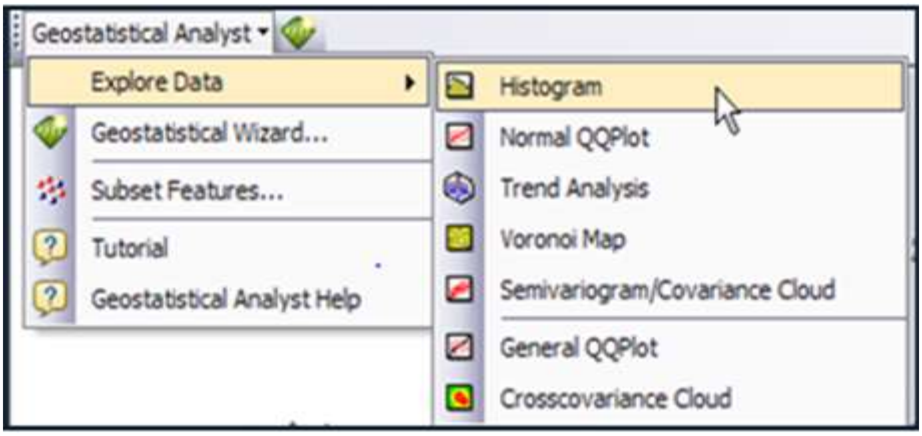

Figure 3 Geostatistical analyst toolbar and its features in the software.

Trends were also examined using trend analysis tool in the software to remove any trend pattern in the data set. Geostatistical wizard in the software was employed to fit semivariogram models and determine spatial dependency for prediction of concentration of other boreholes. Eleven (11) semivariogram models (circular, spherical, tetraspherical, pentaspherical, exponential, gaussian, rational quadratic, hole effect, K-bessel, J-bessel and stable) were fitted for each water quality parameter during dry and wet seasons to determine the best fitted model for the parameter through assessment of prediction errors using criterion already discussed earlier.

4. Results and discussions

4.1. Experimental Results of Boreholes water quality parameters.

The minimum and maximum concentration of laboratory results of the sampled boreholes are summarized in table 1 for wet and dry season.

Table 1 Statistics results of boreholes chemical water quality parameters.

Parameter(mg/l)	Wet season		Dry Season	
	Range			
	Min	Max	Min	Max
EC	45.58	711.23	42.0	660
TDS	22.88	369.91	20.1	329
HCO_3	3.19	92.24	3.15	85.6
Na	1.41	38.10	1.29	33.4
K	0.09	5.02	0.11	4.24
Ca	4.15	90.28	4.12	80.2
Mg	0.11	2.48	0.11	2.13
Cl	13.30	157.10	11.32	138.48
P	0.03	1.08	0.01	0.97
NO_3	0.01	4.78	0.02	3.59
SO_4	0.15	8.19	0.11	6.92
Fe	0.09	1.10	0.02	0.89

The chemical parameters are within the maximum permissible limit recommend by World Health Organization (WHO) therefore, the concentration in boreholes are satisfactory for human consumption. This is in line with study carried out and reported by Obahiagbon and Ilori [3] on physic chemical studies of groundwater in Benin City.

4.2. Fitted Semivariogram Models

Using the observed boreholes water quality values for both seasons, eleven (11) semivariogram models (circular, spherical, tetraspherical, pentaspherical, exponential, gaussian, rational quadratic, hole effect, K-bessel, J-bessel and stable) were fitted for each water quality parameter. The prediction errors were also captured for validation. Table 2 shows semi variogram models depicting the prediction errors for EC parameter in wet season.

Table 2 Semivariogram models for EC parameter during wet season.

S/N	Model Type	Mean Error (ME)	Root Mean Square error (RMSE)	Mean Standardized error (MSE)	Root mean Squared Standardized error (RMSSE)	Average Standard error (ASE)
1.	Circular	5.716	139.13	0.0092	0.9574	161.95
2.	Spherical	6.139	140.41	0.0021	0.9823	160.43
3.	Tetrapherical	6.093	141.30	0.0050	1.0021	159.05
4.	Pentaspherical	6.047	141.72	0.0080	1.0102	158.47
5.	Exponential	5.669	148.75	0.0061	1.1530	149.68
6.	Gaussian	6.500	134.53	0.0371	0.8772	168.53
7.	Rational Quadratic	6.835	147.19	0.0456	1.1322	154.19
8.	Hole effect	5.403	132.92	0.0517	0.8377	170.22
9.	K-bessel	6.953	144.34	0.0151	1.0282	159.84
10.	J-bessel	5.483	132.95	0.0511	0.8391	170.24
11.	Stable	7.298	140.96	0.0064	0.9726	163.79

From Table 2, exponential model is the best fitted model for EC parameter in wet season. The RMSSE is 1.1530 which is approximately 1(one) indicating that standard errors are accurate. RMSE and ASE values (146.75 and 149.68 respectively) are the closest when compared with RMSE and ASE values of other models in table 2, depicting that the variability in prediction with the measured values were well assessed. With this criteria, models were assessed and cross validated for the best fitted for all the remaining chemical parameters for both seasons. Tables 3 and 4 are the best fitted models selected for each water quality parameter in wet season and dry season respectively.

Table 3 Best Fitted models for Borehole parameters and prediction errors for Wet season.

Water parameter (mg/l)	**FITTED SEMI VARIOGRAM MODEL**	**PREDICTION ERRORS**				
		ME	RMSE	MSE	RMSSE	ASE
EC	Exponential	5.669	148.75	-0.061	1.1530	149.68
T.D.S	Exponential	3.1901	83.2654	-0.0597	1.1504	83.9477
HCO_3	Exponential	1.017	19.901	-0.073	1.148	22.599
Na	Exponential	0.347	7.337	-0.040	0.979	8.867
K	Exponential	0.092	1.040	-0.045	1.030	1.524
Ca	Rational Quadratic	1.017	19.184	-0.057	1.207	20.543
Mg	Exponential	0.017	0.443	-0.0077	1.198	0.492
Cl	Exponential	1.331	29.811	-0.040	1.128	30.937
P	Exponential	0.031	0.250	0.002	0.869	0.379
NO_3	Exponential	0.135	1.061	-0.100	1.149	1.706
SO_4	Hole effect	0.064	1.516	-0.012	1.239	2.057
Fe	J-Bessel	0.013	0.260	-0.07	0.926	0.308

In wet season, exponential model was the best fitted model for nine (9) water quality parameters namely EC, TDS, HCO_3, Na, K, Mg, Cl and P. Hole effect model gave the best fitted for SO_4; rational quadratic model is best fitted for Ca, and J-bessel model gave the best fit for Fe.

Table 4 Best Fitted model for Borehole parameters and prediction errors for Dry season.

Water parameter (mg/l)	**FITTED SEMI- VARIOGRAM MODEL**	**PREDICTION ERRORS**				
		ME	RMSE	MSE	RMSSE	ASE
EC	Exponential	4.304	131.82	-0.062	1.149	128.72
T.D.S	Exponential	2.38	73.84	-0.062	1.149	71.99
HCO_3	Exponential	0.781	18.24	-0.063	1.117	19.41
Na	Exponential	0.281	6.711	-0.044	1.000	7.824
K	Exponential	0.046	0.832	-0.035	1.039	1.050
Ca	Exponential	0.793	16.546	-0.037	1.084	17.735
Mg	Spherical	0.015	0.374	-0.064	1.087	0.418
Cl	Exponential	0.952	26.88	-0.032	1.076	27.41
P	Exponential	0.031	0.188	-0.029	1.065	0.331
NO_3	K-bessel	0.117	0.824	-0.105	1.162	1.290
SO_4	Hole Effect	0.049	1.126	-0.016	1.154	1.524
Fe	Hole effect	0.0029	0.251	0.007	1.015	0.248

In dry season, exponential model was the best model for eight (8) water quality parameters namely EC, TDS, HCO3, Na, K, Ca, Cl and P. The Hole effect model fitted best for Fe and SO4. Spherical model fitted best for Mg and k-bessel model for NO3.

4.3. Spatial dependency Results

Fitted semi-variogram models chart for each of the water quality parameter provide information about the range, nugget and partial sill (model parameters) which are used to measure the degree of spatial dependency of sampled borehole points.

The fitted semi-variogram charts for the parameters are given in Figures 4a – 15a for wet season (WS) and 4b – 15b for dry season (DS) revealing the model parameters, i.e., the nugget, sill and partial sill.

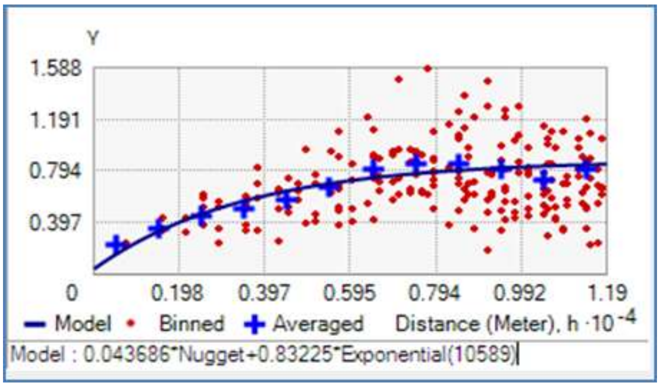

Figure 4a Electrical Conductivity (WS)

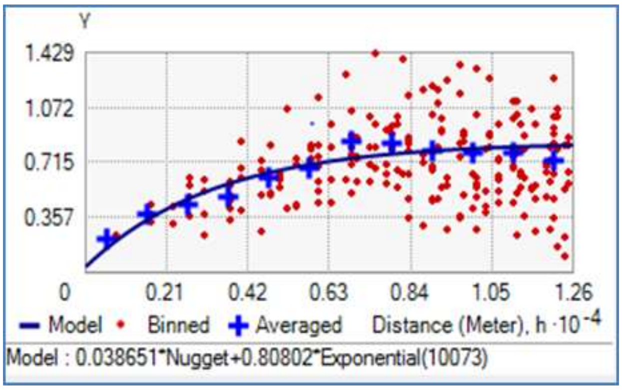

Figure 4b Electrical Conductivity (DS)

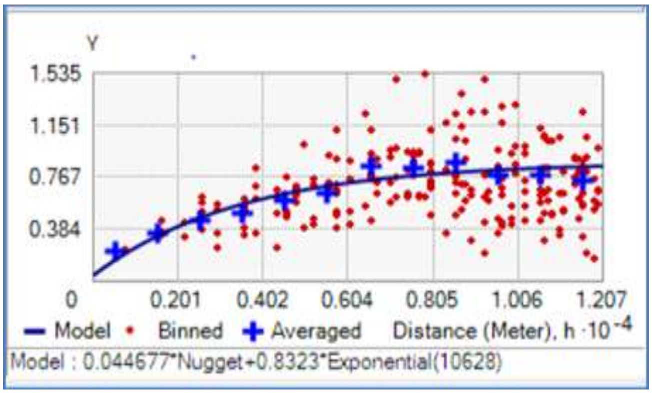

Figure 5a Total Dissolved Solid (WS)

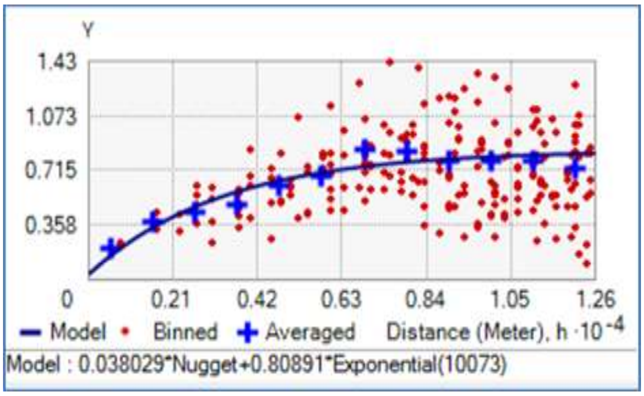

Figure 5b Total Dissolved Solid (DS)

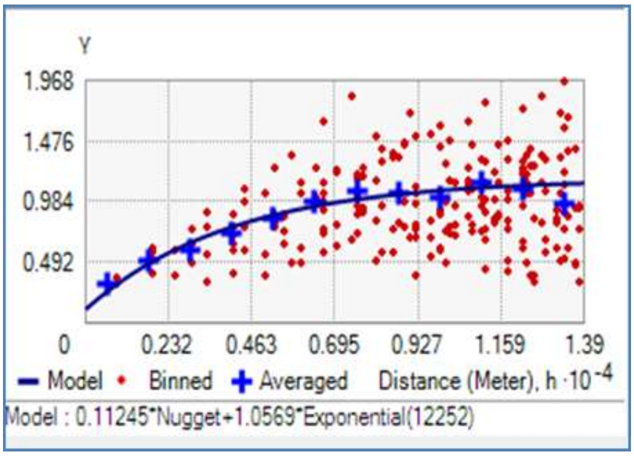

Figure 6a Bicarbonate (WS)

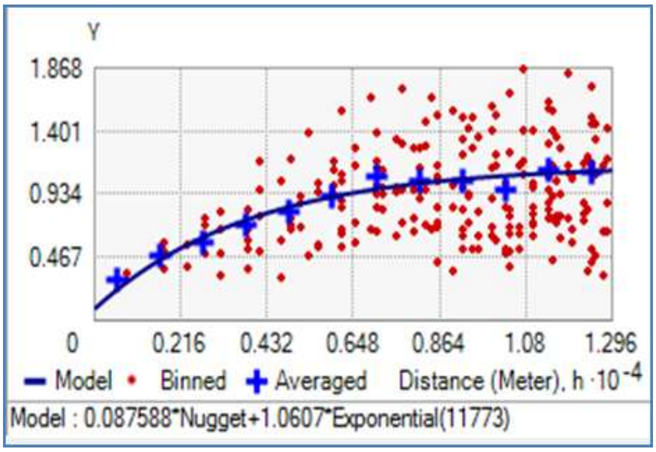

Figure 6b Bicarbonate (DS)

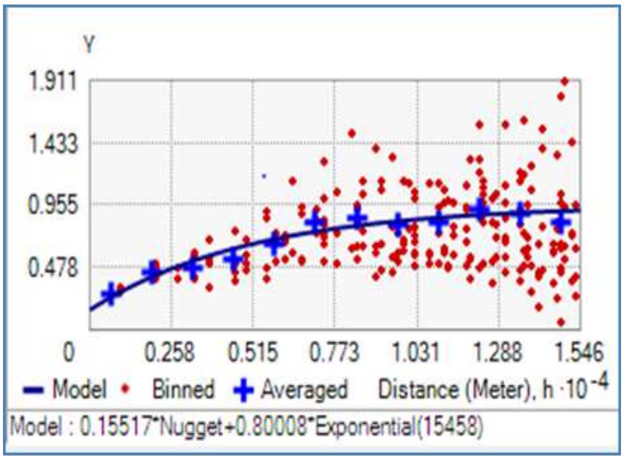

Figure 7a Sodium (WS)

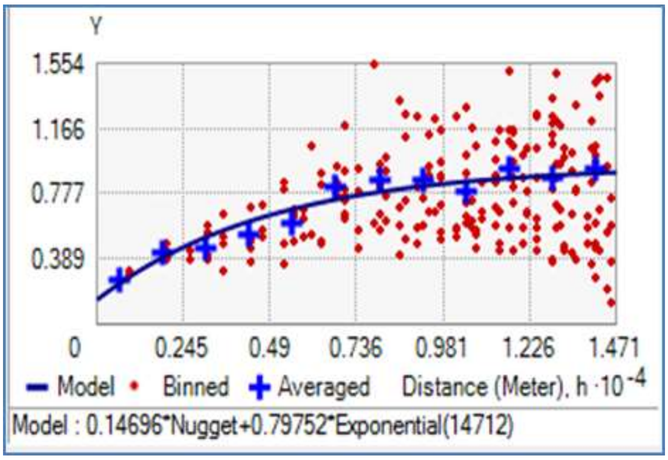

Figure 7b Sodium (DS)

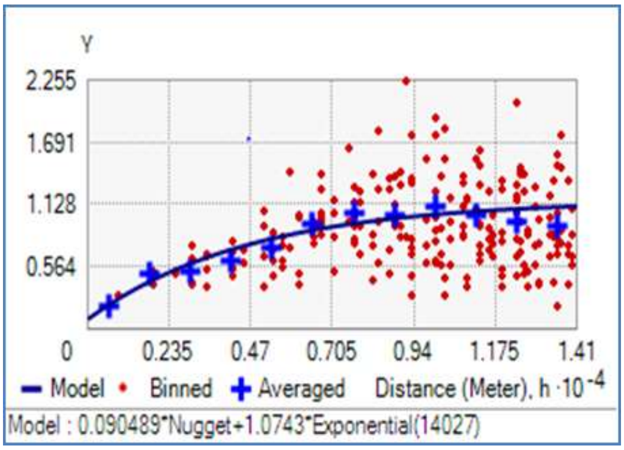

Figure 8a Potassium (WS)

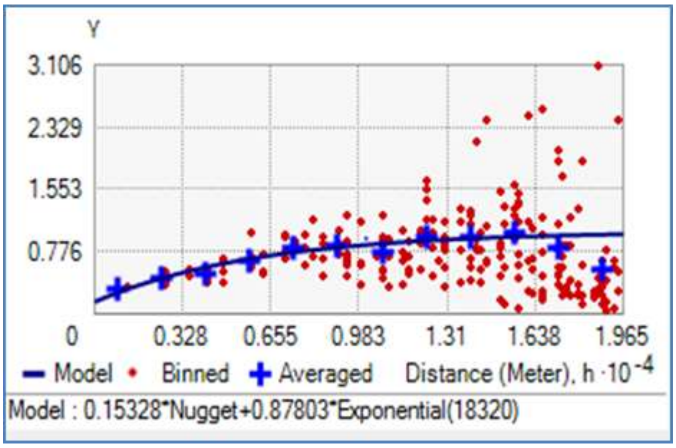

Figure 8b Potassium(DS)

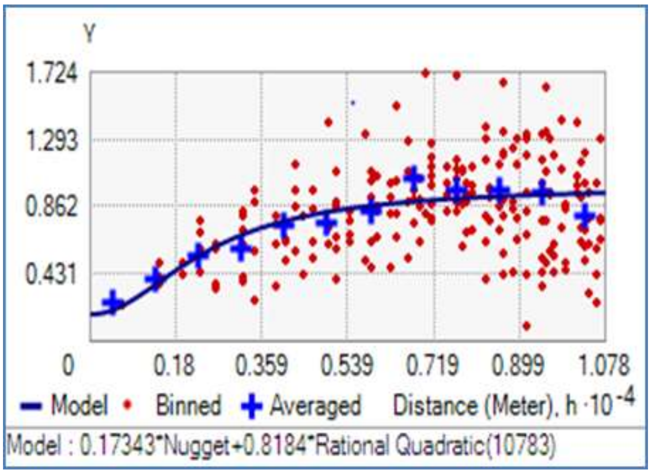

Figure 9a Calcium (WS)

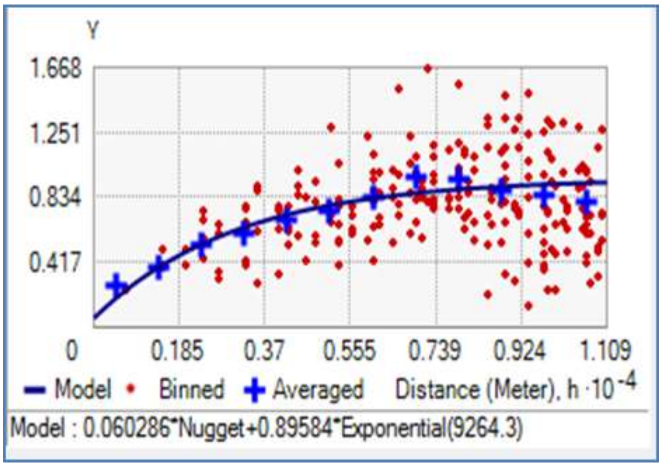

Figure 9b Calcium (DS)

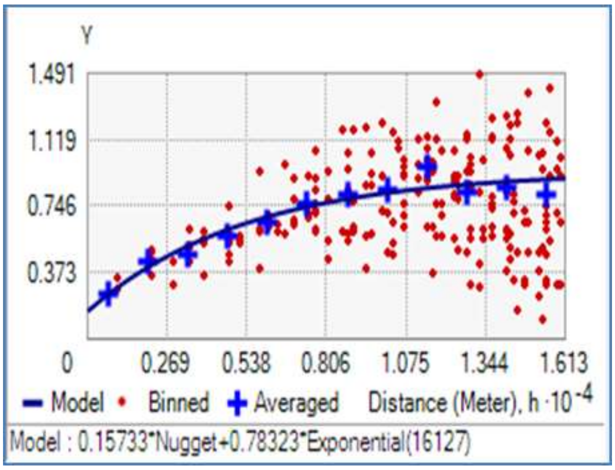

Figure 10a Magnesium (WS)

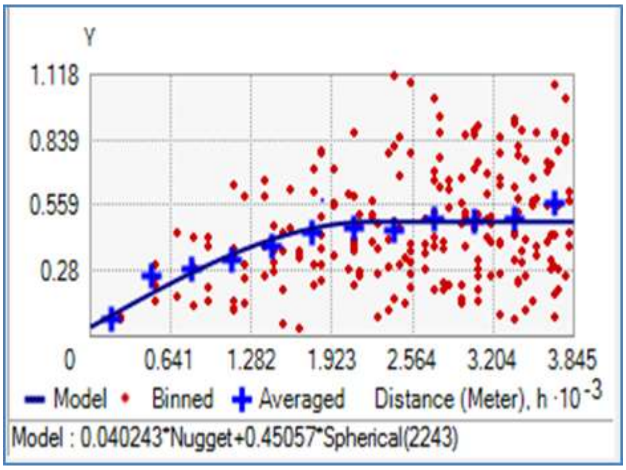

Figure 10b Magnesium (DS)

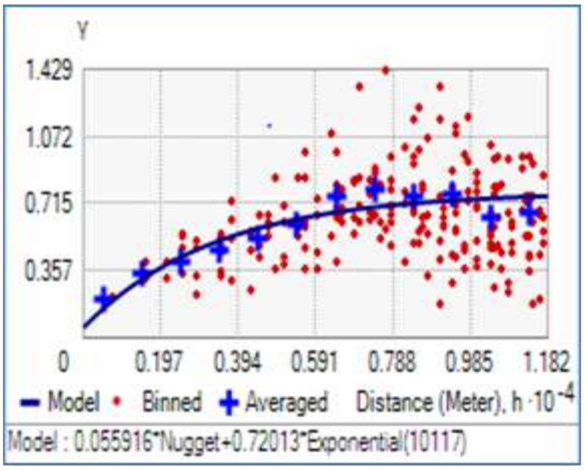

Figure 11a Chloride (WS)

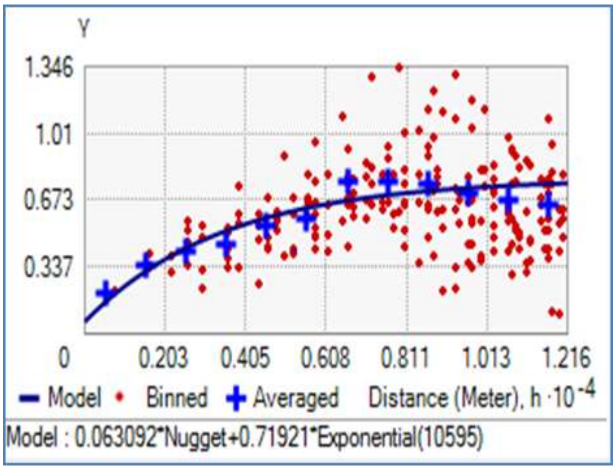

Figure 11b Chloride (DS)

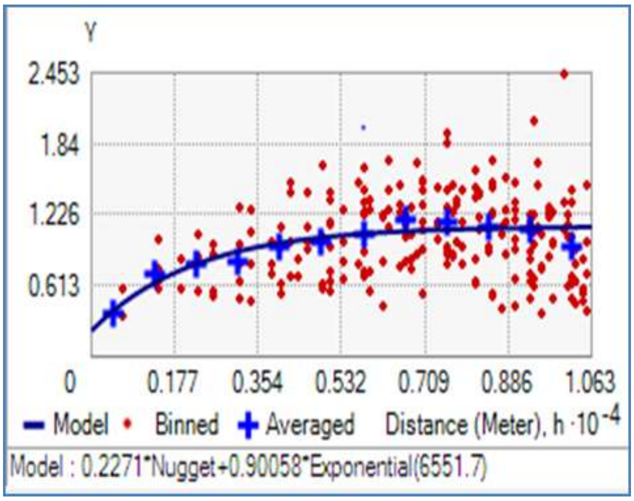

Figure 12a Phosphorus (WS)

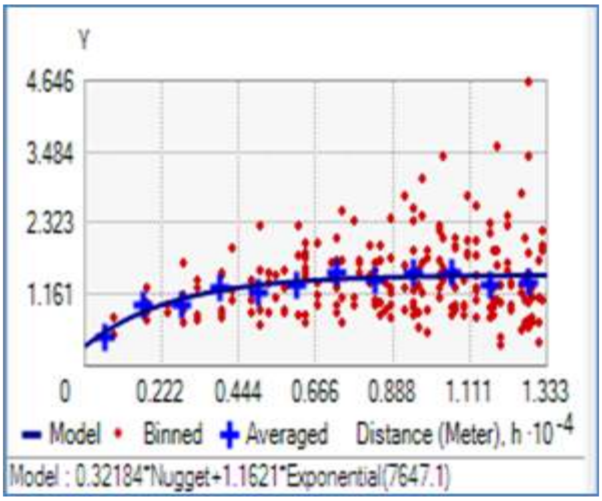

Figure 12b Phosphorus (DS)

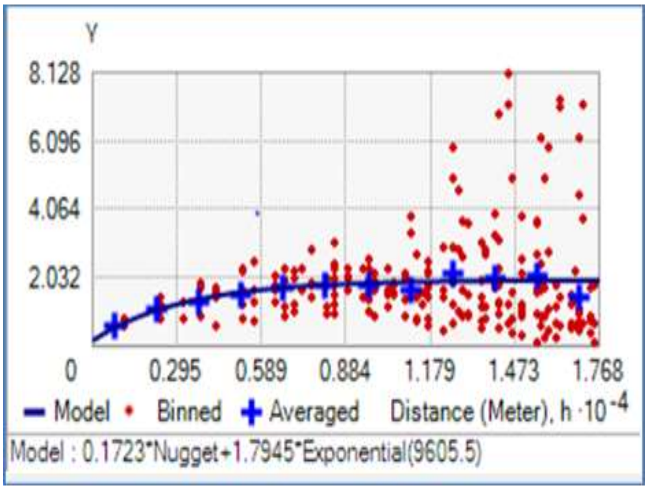

Figure 13a Nitrate (WS)

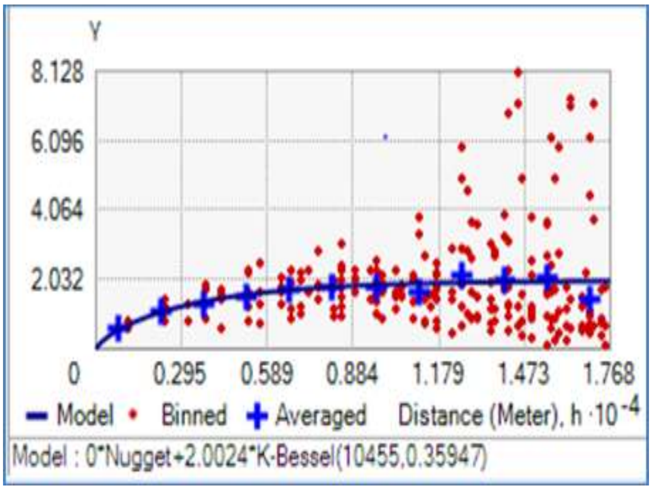

Figure 13b Nitrate (DS)

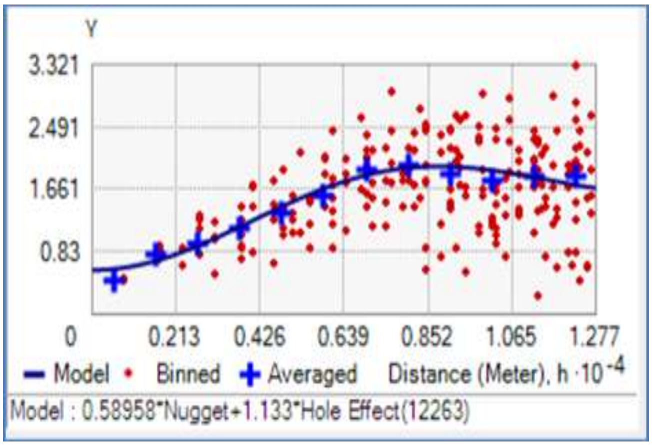

Figure 14b Sulphate (WS)

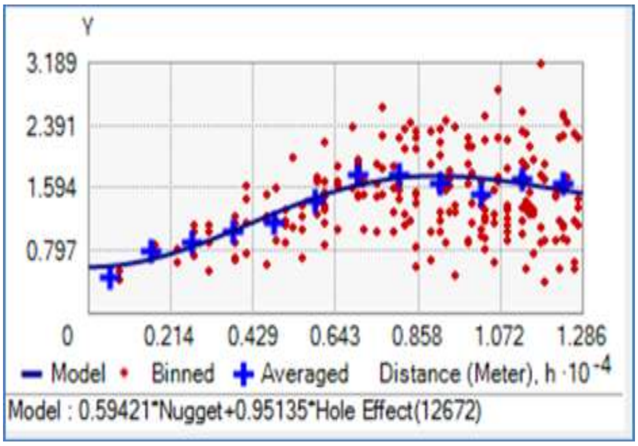

Figure 14b Sulphate (DS)

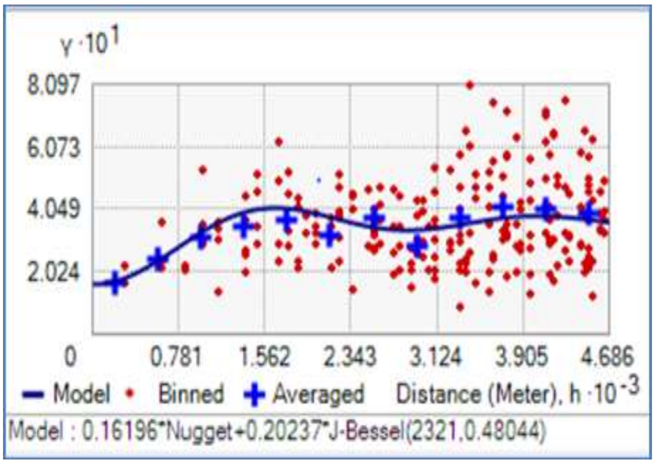

Figure 15a Iron (WS)

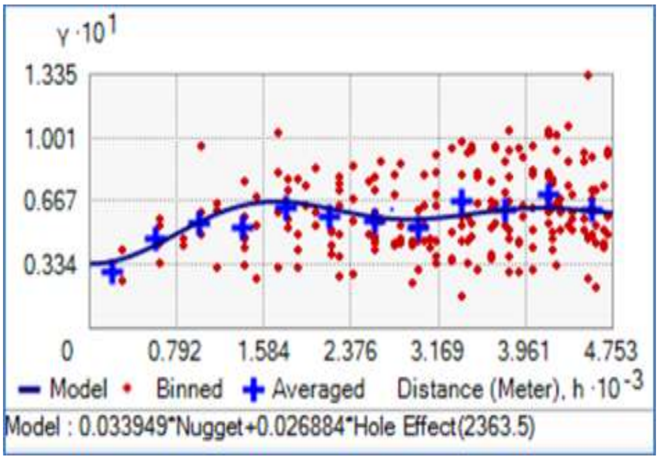

Figure 15b Iron (DS)

Figure 4a and 4b showed semi-variogram exponential model chart for EC in wet season (WS) and dry season (DS) revealing the model parameters i.e., the nugget, sill and partial sill. The range value is 10589, nugget (Cn) is 0.043686 and partial sill(σ) is 0.83225. The sill (C) is the summation of nugget and partial sill depicted in equation 6 which equals 0.87594. Therefore, the ratio of Nugget to Sill (Cn/c) for EC in wet season is 4.99% which is less than 25%, thus signifying strong dependency [14]. If the ratio is between 25% and 75%, the variable has moderate spatial dependence, and greater than 75%, denotes weak spatial dependency [6,7] .

The model parameters from the charts were utilized to calculate degree of spatial dependency summarized in Table 5 and 6 for wet and dry seasons respectively.

Table 5 Model Parameters and Degree of spatial dependency for wet season.

Water parameter (mg/l)	Fitted Model	Range (a)	Nugget (C_n)	Partial Sill (σ)	Sill (C) = C_n + σ	$\left(\frac{C_n}{C}\right)\%$	Degree of spatial Dependency
EC	Exponential	10589	0.043686	0.83225	0.87594	4.99	Strong
T.D.S	Exponential	10628	0.044677	0.8323	0.87698	5.09	Strong
HCO_3	Exponential	12252	0.11245	1.0569	1.16935	9.62	Strong
Na	Exponential	15458	0.15517	0.80008	0.95525	16.24	Strong
K	Exponential	14027	0.090489	1.0743	1.16479	7.77	Strong
Ca	Rational Quadratic	10783	0.17343	0.8184	0.99183	17.49	Strong
Mg	Exponential	16127	0.15733	0.78323	0.94056	16.73	Strong
Cl	Exponential	10117	0.055916	0.72013	0.77605	7.21	Strong
P	Exponential	6551.7	0.2271	0.90058	1.12768	20.14	Strong
NO_3	Exponential	9605	0.1723	1.7945	1.9668	8.76	Strong
SO_4	Hole effect	12263	0.58958	1.133	1.72258	34.23	Moderate
Fe	J-Bessel	2321.0	0.16196	0.20237	0.36433	44.45	Moderate

Table 6 Model Parameters and Degree of spatial dependency for dry season.

Water parameter (mg/l)	Fitted Model	Range (a)	Nugget (C_n)	Partial Sill (σ)	Sill (C) = C_n + σ	$\left(\frac{C_n}{C}\right)\%$	Degree of spatial Dependency
EC	Exponential	10073	0.038651	0.80802	0.84667	4.57	strong
T.D.S	Exponential	10073	0.038029	0.80891	0.84694	4.49	strong
HCO_3	Exponential	11773	0.087588	1.0607	1.14829	7.63	strong
Na	Exponential	14712	0.14696	0.79752	0.94448	15.56	strong
K	Exponential	18320	0.15328	0.87803	1.03131	14.86	strong
Ca	Exponential	9264	0.060286	0.89584	0.95613	6.31	strong
Mg	Spherical	2243	0.040243	0.45057	0.49081	8.20	strong
Cl	Exponential	10595	0.063092	0.71921	0.7823	8.06	strong
P	Exponential	7647.1	0.32184	1.1621	1.48394	21.68	strong
NO_3	K-bessel	10455	0.1000	2.0024	2.1024	4.76	strong
SO_4	Hole effect	12672	0.59421	0.95135	1.54556	38.45	Moderate
Fe	Hole effect	2363	0.033949	0.02688	0.06083	55.81	Moderate

From Table 5 and 6 summarily, EC, TDS, HCO3, Na, K, Ca. Mg, Cl, P, and NO3 showed strong spatial dependency in both seasons with Cn/C ratio < 25% while SO4, and Fe exhibited moderate dependency between 25% - 75% in both seasons as well. In the study conducted by Karami et al, [15] on groundwater modelling, EC and TDS indicated moderate spatial dependence while Cl, Na+, SO42-, Total hardness revealed strong spatial dependency. However, it revealed that groundwater quality are spatially dependent.

5. Conclusion

Laboratory results of boreholes water quality parameters investigated revealed the conformity of the level of concentration of parameters within the recommended limits set for human consumption by World Health Organization. Semi-variogram models are an efficient geostatistical tools and have been utilized to evaluate spatial structure of boreholes water quality parameters in Benin City for the purpose of determining boreholes water quality of unmeasured locations within the area. Exponential model was mostly used for eight water quality parameters in both seasons. EC, TDS, HCO3, Na, K, Ca. Mg, Cl, P, and NO3 showed strong spatial dependency in wet and dry seasons indicating the strength of spatial correlation of the boreholes water quality parameters as a function of distance for accurate predictions of unmeasured locations. However, Fe and SO4 exhibited moderate spatial dependency. Constant monitoring of the boreholes water quality can be gingered through this technique that reduced the bottlenecks and cumbersome procedure of sampling the entire boreholes within the study area. This will ensure continuous protection from health risks of consuming contaminated water and directly will also save money, time and resources. Application of other interpolation techniques and Geographic Information System (GIS) can confidently be employed to create a continuous surface and produced spatial distributions map of boreholes water quality parameters in Benin City.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors wish to state that there is no conflict of interest in this work.

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