Water quality and influence of interpolation procedure on visualization of selected parameters in a headwater stream, in Ayepe-Olode, southwestern Nigeria

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Abstract

Data interpolation – construction of new data points within range of a discrete set of known data point – is an important modeling activity in geographical studies. In this study, three commonly applied interpolation methods (nearest point, kriging and moving average) were examined in an assessment of the varying dispersion of selected physical and chemical parameters of stream-borne effluents from palm oil processing area in a growing commercial centre in Ife South local government area in Nigeria. Specific objectives were to examine selected physiochemical properties of a stream that receives palm oil effluent, and compare results of a kriging interpolation using derived variogram values with that which was based on the accepted parametric default in a popular geographical information system. The study also presents visualised results of interpolation of selected parameters based on ordinary kriging, moving average and nearest point interpolation. Analysis were achieved using PAST 3 and ILWIS GIS software. Result showed that although the stream is vulnerable to contamination by the palm oil processing activities around the area, it also receives contaminants from other non-source points that were not investigated in this study. It also indicated that the different point interpolation methods did not produce similar results. Whereas the values of conductivity were interpolated to vary as 120.1 – 219.5 μScm^{-1} with kriging interpolation, it varied as 105.6 – 220.0 μScm^{-1} and 135.0 – 173.9 μScm^{-1}, with nearest point and moving average interpolations, respectively. Also, whereas the computed variogram model produced the best fit lines with Gaussian model, the Spherical model was assumed default for all the distributions in selected GIS software, such that the value of Nugget was assumed as 0.00, when it actually varies with data locations distribution. Conclusively, procedure of estimating spatial variation always produce results that are influenced by data distribution and model assumptions, and as such the data characteristics rather than GIS software's defaults are appropriate for consideration in geospatial evaluation.

Keywords: *Palm oil mill effluent; Point-interpolation analysis; Geographical information system; Interpolation*

1. Introduction

Studies have revealed that water bodies are increasingly becoming threatened by urbanization, commercialization and industrialization [1 - 3]. A stream channel is typically subdivided into the up-, mid- and down-stream, such that the impact of landuse activities in the upstream and mid-stream are usually felt at the downstream, where deposition (rather than erosion) dominates. In geographical information systems, information is regarded as point based when it is characterised by 1-D values of northings, eastings and selected descriptive attributes [4, 5], and such that information at representative point-based locations can be generalized [5]. Point interpolation achieves estimation of defined surfaces from data collected at sample points [6]. The procedure is typically required because many scientific investigations are based on representative samples rather than the entire population [7-9]. The role of geographical information system is to provide decision support system, but it is not clear if the various methods of point interpolation available produce similar conclusion for policy making, especially when study such as Xie et al. [10] have reported that the effects of the choice of interpolation procedures can be profound in the visualisation and interpretation of the dispersion of chemical ions at the farm scale.

A number of point interpolation methods exist, and popular ones are kriging, moving averages and nearest point. Kriging, and its variants; ordinary, co-kriging disjunctive anisotropic and universal kriging, are known to interpolate and estimate errors of interpolated values over the area of interest, based on a concept of random functions, such that the surface or volume is assumed to be one realisation of a random function with a certain spatial covariance [11 - 13]. Kriging is a statistical method that is based on the theory of regionalized variables, capable of predicting in different dimensional space that enables incorporation of anisotropy (a random process which shows different degrees of autocorrelation in different directions) [11, 13, 14]. Moving average method performs a weighted averaging on point values of a point, such that the output value for a pixel is calculated as the sum of the products of weights and point values, divided by the sum of weights. Weight values are calculated in such a way that point close to an output pixel obtain large weights and points further away obtain small weights. Thus, the values of points close to an output pixel are of greater importance to the output pixel value, than the values of points that are further away. In moving average, a limiting distance must be specified, and points that are further away from an output pixel than the limiting distance, obtain weight zero and thus have no influence on the output value for that pixel. It also assumes a constant mean, seasonality and time variance [14, 15]. In addition, the nearest point interpolation technique is a deterministic method of interpolation where the value, identifier, or class name of the nearest point is assigned to the pixels according to the Euclidean distance. It is also known as Nearest Neighbour or Thiessen Polygons [13, 16], and it assumes that constant mean, considers values of nearest point (pixel) rather than neighboring point values, and appreciates evenly spaced data.

Furthermore, it is known that studies from developing countries, especially where the understanding of geographical information system is still budding, that uncertainties of software are rarely reported, probably because only the cheaply provided ones are used or for the fact that many users of the software often accept their default parametric values. Subsequently, it is rather scarce to find studies where default parametric values of software are compared with the ground-truthed values. Whereas Beven [17], among others advocated that models be tested for uncertainties for improved understanding of their applications, geographical information system (GIS) software have been applied using default parametric values. Also, data have been interpolated using approaches that do not conform to data distribution pattern. Many studies involving kriging interpolation of results have been performed with no concern for the semi-variogram parameters, that is; nugget, range and sill [18]. Nugget describes micro-scale variation while sill describes the variance of the random effect; range refers to the distance at which data are no longer auto-correlated [13, 19]. Gotway et al. [14] argued that the parameters (nugget, sill and range) are required to be fitted into procedures, including spherical, exponential and Gaussian models for assessment of data quality. Webster [20] noted that quality assured interpolation procedure requires that data be first examined with different semi-variogram models, and that the model which accounted for the highest percentage of variance in the distribution of data along with the positions (x, y) be selected for the spatial analysis of each variable.

2. Statement of Research Problem and Study Objectives

Spatial and temporal analysis of stream chemistry are case-specific, and waters from different sources have their respective distinct chemistry which is imbued upon them by the environment of the source. As water flows from one source area to another through various pathways, its chemistry may change; hence the need for better understanding of ways of modeling and predicting water pollution [21 - 23]. Application of geographical information techniques is relatively recent in many developing countries, including Nigeria, and typical practice often involves accepting software defaults, and with little or no consideration for sample distribution - which may be different from the one for which the default was representative. Spatial dependence (variogram) variables, such as nugget, sill and lag are assumed, and users accepting defaults may not report realistic results.

Examining changes in concentrations of solute loads in a catchment often requires interpolation of point-based values of concentration of selected organic parameters, and interpolating the point values for interpretation and decision may depend on the methods of interpolation used because of the different algorithms and purpose for which the methods have been created. The present study is in three perspectives; (a) to examine selected physicochemical properties of a stream that receives palm oil effluent; (b) to compare results of a kriging interpolation with derived (computed) nugget, sill and range values with that which was based on the accepted parametric default in the Integrated Land and Water Information System (ILWIS, 3.3 version); and (c) to visualise results of interpolation based on ordinary kriging, moving average and nearest point interpolation

3. Methods and Materials

3.1. Study area

'Ere' or 'Lucky' stream, as the headwater stream is known, is situated in Ayepe-Olode, a market town in Ife south local government area on latitude 4° 15'N - 4°20'N and longitude 7°35'E - 7°40'E, southwestern Nigeria (Figure 1). Ayepe-Olode is largely underlain by the migmatite-gneiss-quartzite complex of the metamorphic rocks of granite gneiss, quartzite and banded gneisses. Its population, with about 4.5% annual growth was 303,180 in 2015 and will be about 500,000 by 2022. The town provides a link to many other villages and as such, many of the residents are traders and farmers who cultivate perennial farm products such as cocoa, kola and palm produce. Farmers in the study area also engage in oil palm processing; an activity that often require a space with adequate water supply, and thereby often make encourage farmers to site the processing mills close to riverbanks [24 -25]. The stream, until recent time was a perennial stream; it has become seasonal because of blockage of its channel by waste from the palm processing activities. The oil processing activities within the catchment are characterized by storage of bunches of palm fruits, grinding and cooking of fresh palm fruits.

3.2. Data collection

Ere headwater segment was sectionalized into the upstream and downstream regions, with respect to location of the discharge of wastewaters from the palm oil processing unit; the points of discharge of the wastewaters are referred to as the effluent point (see Figure 1). Different points were identified to provide information about chemical gradation with a distance of approximately 4 m interval. In all, a total of 48 water samples (twice at a point in dry and wet) were sampled at 24 points, in a regular interval. Water samples were obtained using a 2-litre polyethylene plastic bottles at four stations, each at the upstream, effluent zone point (of the palm oil processing along the stream channel) and downstream in the study area. The water samples were obtained in the dry and wet seasons.

The wet season samples were taken during the peak of the rainy season (July-September) and the dry season water samples were collected at the mid-dry season (December, 2015-February, 2016). Water sampling was done using depth-integrated method for representativeness, such that the different stream depths were sampled in a composite mix. The bottles were rinsed before use and were filled to the brim to reduce oxygen reaction during transport of samples from site to the laboratory.

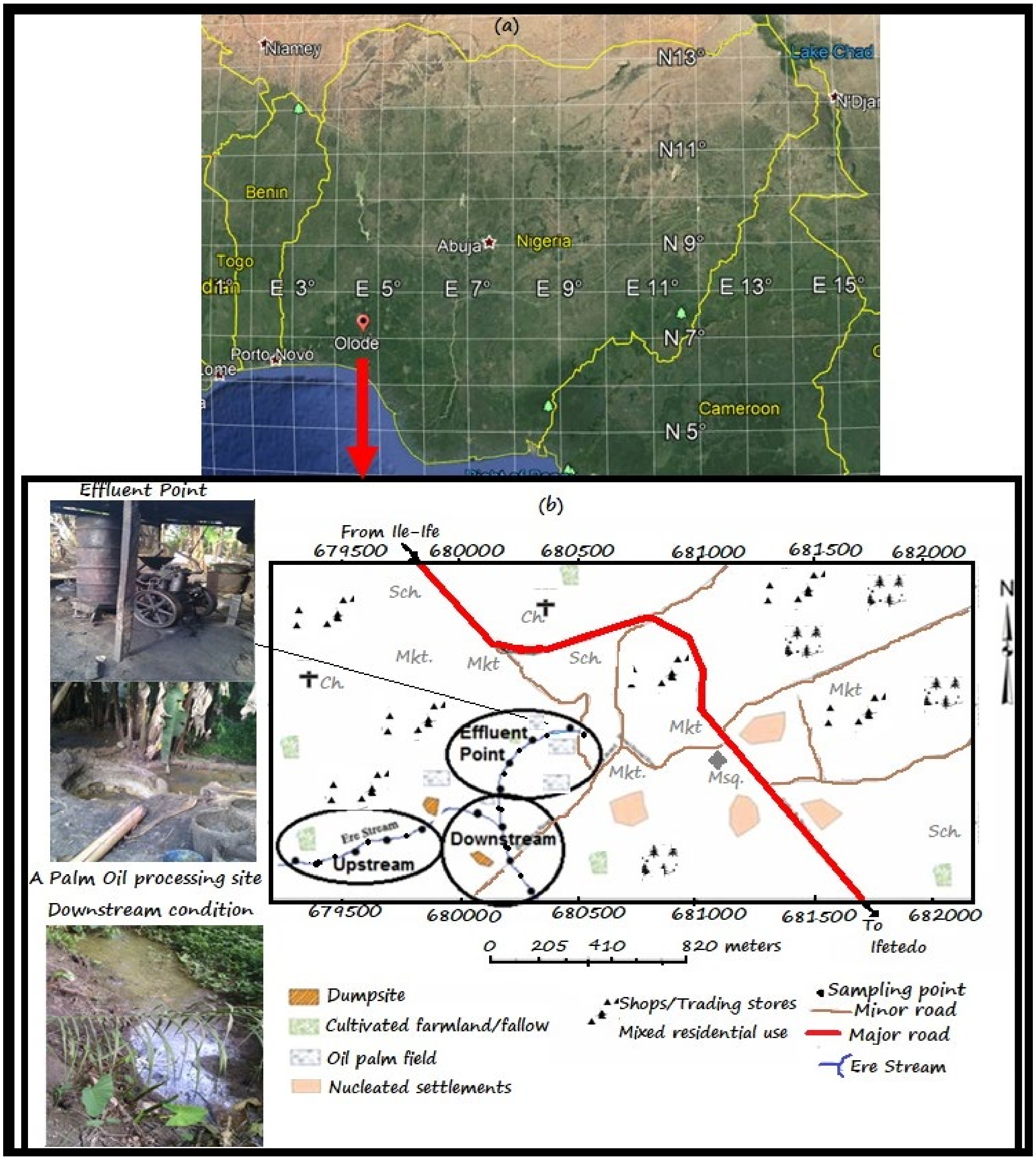

Figure 1. The study area, Ere stream catchment in (b) Ayepe-Olode, Southwest Nigeria (a)

Water temperature, pH, dissolved oxygen (DO) and electrical conductivity were determined on the field. Sample pH and electrical conductivity were measured *in situ* using the PCE-PHD 1pH meter. The pH probe was standardized from time to time using appropriate buffer solutions and the conductivity probe standardized using a set of potassium chloride (KCl) standard solutions. For DO and 5-day biochemical oxygen demand (BOD_5), glass reagent bottles and dark bottles were used, respectively, to collect water samples on the field. Dissolved oxygen was fixed on the field, immediately after collection with Winkler's reagent (manganous sulphate and alkaline iodide), and oxygen content later determined by iodiometric titration [26 - 27]. All the water samples were then taken to the Zoology laboratory, Obafemi Awolowo University, Ile-Ife, Nigeria for analysis of total solids (TS), nitrate (NO_3), sulphate (SO_4,), BOD_5 and chemical oxygen demand (COD) based on information from previous studies [24 - 25].

3.3. Laboratory analysis

Water samples were kept in the refrigerator in the laboratory when not analyzed immediately, to reduce bacterial activity that may significantly alter the water chemistry. Water samples were analyzed for solid contents (total solids, total dissolved solids; i.e. TS and TDS) and pollution-related chemical properties that have been indicated in studies to be relevant to effluent from palm oil processing activities (NO_3^-, $SO_4^{2-,}$ biochemical oxygen demand-BOD_5 and Chemical Oxygen Demand-COD) [24, 26]. The analytical determinations of the physico-chemical parameters of water quality analyzed were carried out within the holding time of each parameter, following applicable standard methods [26 -28]. The TS and TDS in the samples were determined gravimetrically after the samples were oven dried to constant weight at $105 \pm 2^{o}C$. TSS was calculated as the difference between TS and TDS [27].

The dark reagent bottles used for BOD_5 determination were then kept in a dark cupboard for five days, for subsequent analysis. SO_4^{2-} and NO_3^- were determined by spectrophotometric methods [33]; COD was determined by wet oxidation (Chromic-acid digestion) of 100 ml of samples with potassium dichromate, acidified with concentrated sulphuric acid (H_2SO_4) and then titrated with 0.1 N [$(NH_4)_2Fe\ (SO_4)_2.6H_2O$] Ferrous Ammonium Sulphate (FAS) with about 10 drops of Barium-Diphenylamine-Sulfonate (BDAS) solution as indicator.

3.4. Data analysis

Data obtained from both field and laboratory were analyzed in two ways. First, the chemical characteristics of the upstream, downstream and effluent source point of the Ere stream was descriptive and inferential (Analysis of Variance). Spatial variation in the chemical concentration of the examined variables was assessed with linear regression. Second, the influence of the different interpolation measures was determined using geographical information analysis. The dispersion of the chemical characteristics with selected interpolation methods was achieved using ILWIS (Version 3.3) GIS software. Value interpolation methods such as nearest point, moving average and kriging using point map created for each of the selected chemical variables. Descriptive mapping for visualisation was derived using basic GIS procedure in ILWIS, which was preferred because of their rich tessellation (raster)-compliant procedure and availability. The principle of ILWIS on interpolation is also not significantly different from those of the 'more popular software' such as Erdas Imagine and Envi that would have been preferred but for their unavailability for students and researchers in developing countries at low-cost or open source like ILWIS. Using the software, maps showing dispersion (output) based on nearest point, moving average and kriging techniques were produced.

For ordinary kriging, the Gaussian model was selected for its simplicity and error map was highlighted to be produced. The error map allows uncertainties attached to each sampling point to be produced. In doing so, values of the assumed spatial characteristics including sill, nugget effect and range were substituted with the calculated ones. Both the calculated and default values were used to produce maps for comparison of the effect of spatial dependence. The variogram characteristics (nugget, sill and range) and the acceptable optimizing model (Spherical, and Gaussian) were determined using the open-access Paleontological Statistics (PAST3) software of the University of Oslo, Norway. The optimizing model was selected by the software based on the distribution of the sampling points and values.

4. Results and discussion

4.1. Physico-chemical characteristics of selected stream water

The headwater stream was characterized by mean temperature, pH and electrical conductivity of 26.3 – 26.5 °C, 5.5 – 8.7 units and 153.4-195.3 μscm^{-1}, respectively; downstream had mean temperature of 26.3 °C, little less than 26.5 °C at the upstream and effluent discharge, 6.4 unit of pH with total dissolved solids of 111.9 mg l^{-1}, 4.95 mg l^{-1} of DO, 1.9 mg l^{-1} of BOD_5. Conductivity, TDS, BOD_5 and COD values were unexpectedly significantly greater at the sampling point classified as upstream than either the effluent discharge point or downstream (Table 1). While NO_3^- and SO_4^{3-} peaked around the effluent discharge point the downstream contained higher concentrations of total suspended solids and dissolved oxygen than either the upstream or downstream. Whereas the lower concentration of most of the variables at the effluent discharge point can be attributed to their being flushed downstream, as the water level increased or during rainfall event, that of the increased concentrations of conductivity, total dissolved solids, $BOD_5$and COD suggest that the upstream was receiving organic and inorganic wastes that can be associated with the variables. The groundtruthing investigation conducted on the stream indicated that it is not considered drinkable, although a number of residents wash and bath in the upstream.

Table 1. Mean, Standard deviation, range (minimum – maximum) of the selected physical and chemical variables investigated at different sections of the Ere headwater stream in Ayepe-Olode, southwestern Nigeria

Variables	Upstream	Effluent Discharge Point	Downstream
Temperature(°C)	26.5±4.0^a (25.4-27.3)	26.5±4.3^a(25-27.3)	26.3±4.5^a (24.9-27.2)
pH (no unit)	7.8±0.5^a (6.4-8.5)	7.2±0.1^a(6.0-8.7)	6.4±0.1^a (5.5-7.1)
Conductivity (µScm^{-1})	195.3±95.6^a (105.6-377)	153.4±26.9^c (68.1-360)	169.6±66.2^b (82.5-220)
SO_4^{2-}(mg l^{-1})	2.1±2.5^b (0.8-6.4)	3.9±4.5^a (1.0-13.4)	3.7±0.2^a (0.7-9.9)
NO_3^-(mg l^{-1})	1.4±0.8^b (0.6-4.2)	8.2±2.8^a (0.6-6.6)	0.9±0.3^c (0.3-1.4)
TDS (mg l^{-1})	129.2±64.2^a (68-250)	102±4.9^c (45-250)	111.9±55.8^b (70-146)
Total Solids(mg l^{-1})	918±331.6^a (85-1817)	916.3±7.1^a (200-2050)	802±331.6^a (161-1170)
TSS (mg l^{-1})	789.3±575.1^c (3.0-1728)	814.5±93.3^b (100-1967)	924.5±189.2^a(15-1100)
DO (mg l^{-1})	3.4±1.2^b (0.0-8.8)	4.7±3.2^a (0.8-8.4)	4.9±2.3^a (2.0-8.0)
BOD_5 (mg l^{-1})	3.1±0.8^a (0.0-8.8)	2.5±1.4^b (0.4-5.2)	1.9±0.7^c (0.4-2.8)
COD (mg l^{-1})	19.9±7.2^a(9.0-33.8)	8.6±2.6^b(1.5-15)	8.4±3.3^b(2.0-16.5)

Note: Mean ± SD with same superscript (lower case alphabet; a, b or c) along same row are not significantly different for corresponding chemical variable.

4.2. Seasonal variations in the stream water characteristics

Evaluation of the seasonal variations showed relatively different patterns from the upstream, through the effluent discharge point, downstream (Table 2). Table 2 shows that SO_4^{2-}, conductivity, NO_3^-, TDS and BOD_5 were relatively more in the dry season at the upstream than in wet season. SO_4^{2-}, TDS, TS, DO, and BOD_5 also occurred in averagely higher concentrations in the dry than wet season at the effluent discharge point. Most of the investigated variables, except SO_4^{2-}, NO_3^- (wet season), BOD_5 and COD appeared to have decreased downstream as the water flows downstream. Furthermore, pH, SO_4^{2-} and NO_3^- appeared to peak at the discharge point while others mostly peaked downstream, except for conductivity, TS, and TDS that exhibited obvious influence of season (period of sampling) (Figure 2). In general, result of the analysis of variance using Scheffee multiple comparison showed significant difference at 95% confidence level in wet season values of conductivity and total dissolved solids; first between upstream and downstream, and between the discharge point and downstream (Table 3). There was however no significant difference among the three stream phases (upstream, effluent discharge point and downstream) in the dry season.

Table 2. Dry and wet seasons' means of selected variables at different section of the stream channel

Physico-chemical parameters	**Dry season**			**Dry season**		
	Upstream	Effluent Discharge Point	Down-stream	Upstream	Effluent Discharge Point	Down-stream
Temperature(°C)	27.2	27.2	27.1	25.8	25.7	25.5
pH	7.2	7.1	6.3	7.0	7.1	6.2
Conductivity (μScm^{-1})	266.4	177.6	148	124.1	129.1	184.0
SO_4^{2-}(mgl^{-1})	3.3	6.6	6.3	1.0	1.1	1.0
NO_3^-(mgl^{-1})	1.7	1.6	0.9	1.1	2.6	0.8
Total Dissolved Solids (mgl^{-1})	176	119.5	101.5	82.3	84	122.3
Total Solids (mgl^{-1})	782	917.5	978	1054.8	915	626
Total Suspended Solids (mgl^{-1})	606	798	876.5	972.5	831	503.8
Dissolved Oxygen (mgl^{-1})	3.3	5.7	6.3	3.5	3.6	3.5
BOD_5 (mgl^{-1})	4.0	3.5	2.1	2.2	1.6	1.6
Chemical Oxygen Demand (mgl^{-1})	17.6	7.8		18.6	9.4	12.1

Table 3: Seasonal and spatial variations

	Variables	**Overall ANOVA**		**Upstream *compared with***		**Discharge point *compared with***
		F-value	**F-probability**	**Discharge point**	**Down-stream**	**Downstream**
Wet Season	Temperature(°C)	0.91	0.44	0.97	0.68	0.83
	pH	1.21	0.34	0.90	0.15	0.08
	Conductivity (μScm^{-1})	1.60	0.25	0.97	*0.03*	*0.05*
	$SO_4^{2-}mgl^{-1}$	0.64	0.55	0.39	0.75	0.79
	NO_3^-(mgl^{-1})	0.41	0.67	0.47	0.99	0.39
	TDS (mgl^{-1})	6.34	0.02	0.99	*0.04*	*0.04*
	Total Solids (mgl^{-1})	0.11	0.89	0.93	0.54	0.75
	TSS (mgl^{-1})	0.82	0.47	0.93	0.49	0.69
	Dissolved Oxygen (mgl^{-1})	0.00	0.99	0.99	1.00	0.99
	BOD_5 (mgl^{-1})	0.90	0.44	0.70	0.74	0.99
	COD (mgl^{-1})	1.95	1.98	0.47	0.27	0.90
Dry Season	Temperature(°C)	0.91	0.44	0.99	0.93	0.95
	pH	1.21	0.34	0.99	0.73	0.07
	Conductivity (μScm^{-1})	1.60	0.25	0.59	0.78	0.95
	$SO_4^{2-}mgl^{-1}$	0.64	0.55	0.67	0.73	0.99
	NO_3^-(mgl^{-1})	0.41	0.67	0.66	0.78	0.29
	TDS (mgl^{-1})	6.34	0.02	0.62	0.82	0.94
	Total Solids (mgl^{-1})	0.11	0.89	1.00	0.91	0.91
	TSS (mgl^{-1})	0.82	0.47	0.99	0.94	0.91
	Dissolved Oxygen (mgl^{-1})	0.00	0.99	0.69	0.59	0.99
	BOD_5 (mgl^{-1})	0.90	0.44	0.81	0.38	0.75
	COD (mgl^{-1})	1.95	1.98	0.05	0.11	0.92

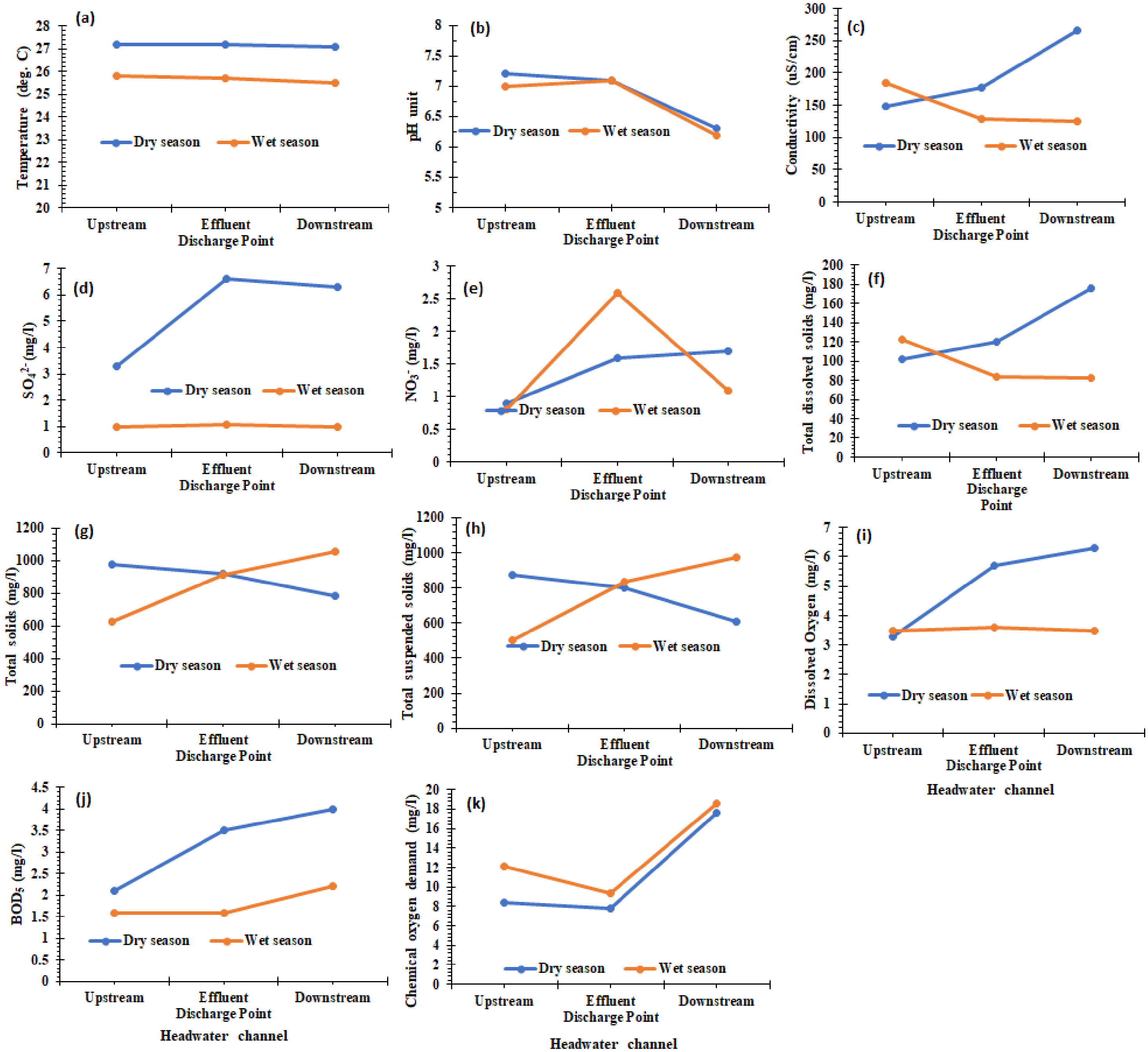

Figure 2. Seasonal distribution of selected physiochemical variables in Ere headwater stream in Ayepe-Olode, southwest Nigeria

4.3. Quality assessment of the streamwater

Comparison of the mean and range values with the maximum permissible limits as shown in Table 4 indicated that the stream contained total suspended solids, COD and BOD_5 in concentrations that were more than the maximum permissible limits for either use as portable water or safe living fishes and aquatic life. The above-the-limit concentrations of BOD_5 and COD indicate that the stream water is biologically and chemically polluted. The high concentration of total suspended solids also indicates turbidity flow in the stream.

Table 4. Result comparison with the maximum permissible limits of WHO and EU for water and aquatic life

Variable	WHO [29] Standard for portable water	EU standards for fisheries and aquatic life (Chiaudani and Premazzi [30])	Ere Stream (This study)
Temperature (^oC)	32	32	26.4 (24.9-27.3)
pH (Unit)	<8.0	6-9	6.85 (5.5-8.7)
Conductivity (μScm^{-1})	<250	250	171.5 (68.1-377)
SO_4^{2-} ($mg\ l^{-1}$)	250	100	3.2 (0.7-13.4)
NO_3^-($mg\ l^{-1}$)	1.0	50	1.4 (0.3-6.6)
TDS ($mg\ l^{-1}$)	1000	Not provided	114.3 (45.0-250.0)
TS ($mg\ l^{-1}$)	1000	Not provided	878.9 (85.0-2050.0)
TSS($mg\ l^{-1}$)	1000	1000	764.6 (3.0-1967.0)
DO ($mg\ l^{-1}$)	>5	5-9	4.3 (0.0-8.8)
BOD_5 ($mg\ l^{-1}$)	<2	3-6	2.5 (0.4-8.0)
COD ($mg\ l^{-1}$)	<20	20	12.3 (1.5-33.8)

4.4. Comparison of default and estimated variogram models for interpolation

Whereas the ILWIS default suggested 'spherical' interpolation procedure, the optimization procedure used to maximize the distribution of the sample points indicated that the Gaussian model was more appropriate for most of the parameters (sample of conductivity, temperature and nitrate are presented in Figure 3). In addition, whereas the software default assumed nil (*0*) nugget, the result of the computed variogram did not return nil (*0*) for any of the parameters, indicating that accepting default will be an error. Except for pH, the values of the standard error estimate (*Sserror*) was relatively lower with computed variogram than the default. In terms of spatial dependence, the nugget to sill ratio in all the investigated parameters ranged from 60 % (pH) to 237.1 % (nitrate), indicating strong spatial dependence in the distribution of the variables over the stream channel, and as such accepting the default values will be wrong.

Further, the interpolation based on the default values shows that variables were generally overestimated. For instance, whereas the values of BOD_5 varied between 2.2 and 2.6 mgl^{-1}, the default kriging interpolation showed a maximum of 3.4 mgl^{-1}, which is 0.8 mgl^{-1} (30.8%) overestimation of the actual maximum values. Also, the TS, conductivity, COD, water temperature, were overestimated by 375 mgl^{-1} (3.5 %), 41.75 mgl^{-1} (20.1 %), 4.25 mgl^{-1} (22.6 %), 0.25 $mg\ l^{-1}$ (0.8 %) respectively, while nitrate show underestimation of 1.45 $mg\ l^{-1}$ in the default interpolation from the computed value and the pH and sulphate shows the same values. The results for pH, conductivity, BOD_5, COD and nitrate were over estimated by 0.35 mgl^{-1} (4.2 %), 34.15 mgl^{-1} (12.8 %), 1.05 mgl^{-1} (25 %), 0.65 mgl^{-1} (3.4 %), and 0.15 mgl^{-1} (5.9 %) respectively while sulphate has default underestimation of 1.05 mgl^{-1} (15.2 %) from the computed value.

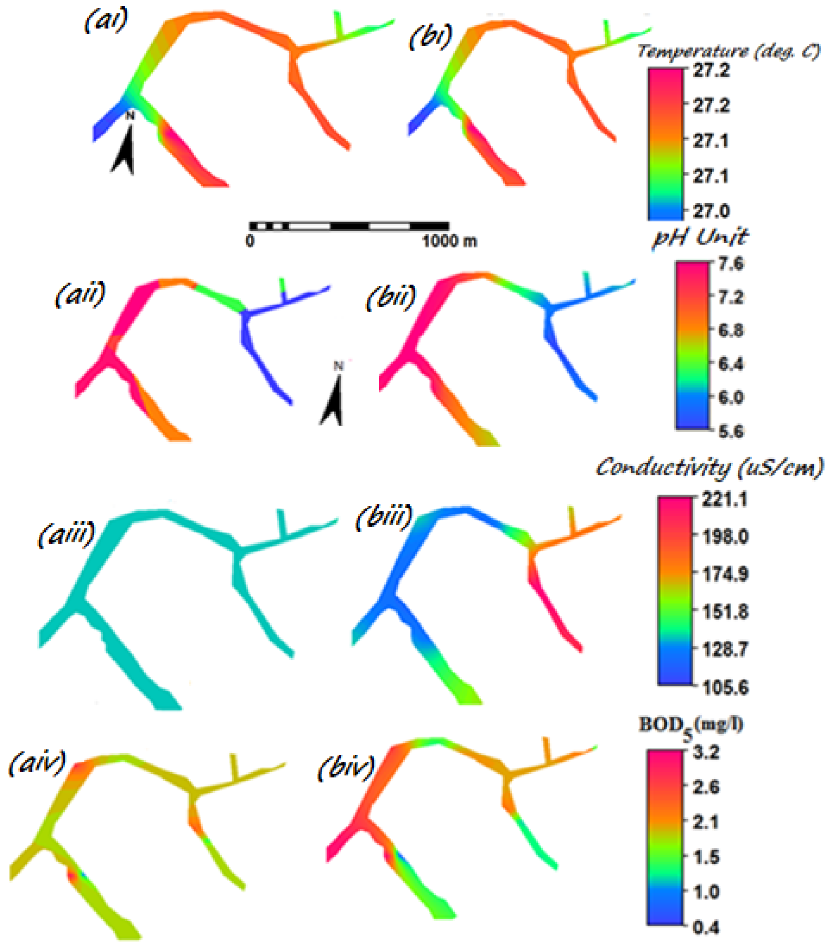

Figure 3. Samples of visualized results of computed (ai - iv, represent interpolated pH (unit), conductivity (µS/cm), water temperature (ºC), and biological oxygen demand, BOD_5 (mg/l) with computed variogram (nugget, sill and range) and default (bi - iv) variogram parameters after kriging interpolation

Comparison of selected interpolation methods

Samples of the comparison of the interpolation by ordinary kriging, nearest point and moving averages for each of the selected variables are presented in Figure 4. Values produced by the interpolation varied with procedure. For example, the mean values of the moving average interpolation ranged between 1.6 and 2 mgl^{-1} for BOD_5 were lower than values obtained with ordinary kriging or the nearest point interpolation (0.4-3.2 mgl^{-1} for BOD_5). The moving average value showed that the BOD_5 values was not more than 2 mgl^{-1}, but this was lower than that indicated by the nearest point (whose values was as high as 3.2 $mgl^{-1)}$.

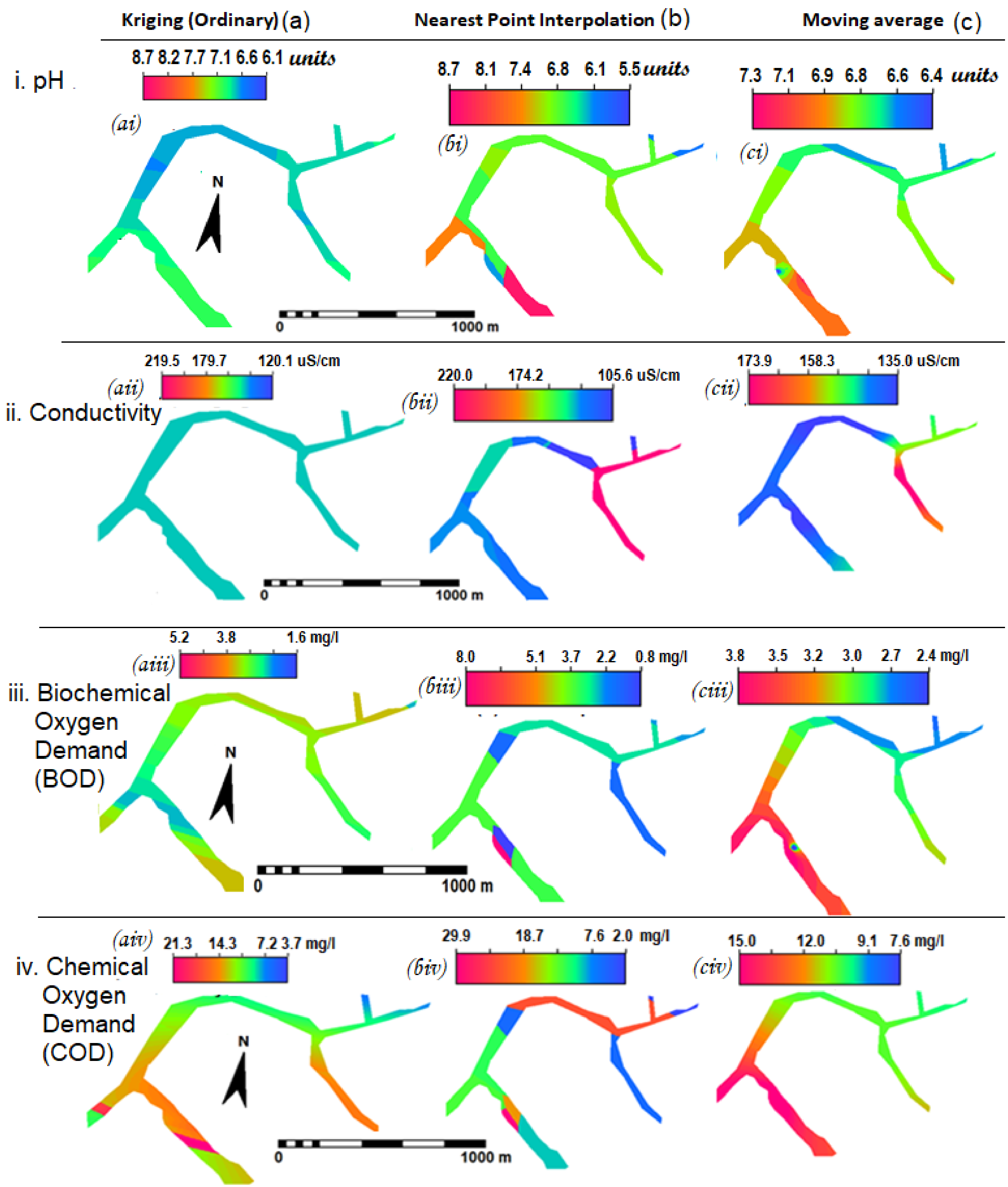

Figure 4: Samples of patterns of interpolation with kriging, nearest point and moving average methods; ai–iv, bi-iv and ci-iv, represent interpolated values of pH, conductivity, biochemical oxygen demand (BOD_5) and chemical oxygen demand (COD) using ordinary kriging (a) nearest point (b) and moving average (c) methods, respectively

Also, while the moving average suggested that the stream water varied from slightly acidic to neutral (pH value = 6.3-7.0 mgl^{-1}), kriging and nearest point showed that it could be more acidic or close to alkaline (pH= 5.7-7.6 mgl^{-1}). Although this study does not provide reasons for the differences, Maleika [31] argued that the models used different algorithms whose application vary with the spatial distribution of data, and that moving average could yield less precise results compared to other interpolation methods. In terms of COD, moving average produced 11.0-12.1 mgl^{-1} while the nearest point and kriging showed 2.1-22.1 mgl^{-1}, values that can make significant interpretation problems with the results. In general, ordinary kriging, moving average and nearest point analysis in this study have produced contrasting results.

Given the simple technology-based procedure of many rural regions, wastes generated are often not well treated and disposed [33 - 34]. In the study area, wastes from palm oil processing activities are often discharged into the adjacent stream, the Ere stream. The stream is one of those whose channel has been influenced by the increase in built-up areas over the years in the area. This study showed that the Ere stream was characterized by an average of 26.4 ºC water temperature, 6.8 pH unit, and about 878.9 mgL^{-1} of total solids. The BOD_5 and COD concentration indicated high organic and chemical concentration of the stream (when compared with the World Health Organization's concentration limit of potable water, and aquatic life respectively [29]. Analysis of variance of the concentration of selected parameters between the upstream, downstream and the effluent discharge section of the Ere stream showed that there is no significant variation in some of the selected variables. This implies that different section of the stream is similarly anthropogenically impaired. Results from many existing studies suggest that the upstream should be less contaminated than the downstream or effluent discharge section of a stream [3, 33 - 35]. The situation at the Ere upstream suggests the possibility of other sources of pollution, which cannot be confirmed until research is conducted in that line. The study also showed that the investigated variables, except the TS, COD and electrical conductivity occurred in higher concentrations in wet sampling period at either the upstream, effluent discharge point and downstream than in the dry period; a condition that may be accounted for by dilution effect [36].

Comparison of the different dispersion methods employed in this study (ordinary kriging, nearest point and moving average) showed that they do not produce similar results. Representation of dispersion of variables of water quality could vary with adopted approach. Burrough et al. [5] encourage that error estimates and uncertainties of models be presented since different methods of abstraction are characterized by different levels of uncertainty and accuracy. Based on the view of uncertainty, the algorithms for ordinary kriging in ILWIS also produces error maps that can be used to evaluate the level of uncertainties associated with each sampling point.

Furthermore, values of the spatial characteristics for the distribution of the sample values and location (semi-variogram) indicated that the default algorithms of software for geographical information analysis often assumes a spherical modelling of point value dispersion whereas it was the Gaussian model that produces less error for most variables. Consequently, it can be argued that dispersion interpolation using the default algorithm of standard GIS software does not produce accurate interpolation procedure, as inferred from the larger values of their standard errors when compared with the results of the interpolation whose values of nuggets, sills and range (typically assumed by standard GIS software) are substituted with the calculated values. Studies [37, 38] have indicated that accuracy of modelled (interpolated) results can vary with distribution of sampling location, as well as the method of interpolation. This variance in the modelled data also impact the interpretation of model results.

5. Conclusion

Studies have argued that open water systems are like open sewers that receive wastes from landuse activities. This study has therefore examined the concentrations of certain physio-chemical variables in a stream that receives effluent from locally processed palm oil processing areas in the southwestern Nigeria. The study also examined the procedure for modeling dispersion, using different interpolation methods: nearest point, kriging and moving average. The results of the study showed that although the stream is vulnerable to contamination by the palm oil processing activities around the area, it also receives contaminants from other sources which were not investigated in this study. Evidence from this study revealed that the general consensus as reflected in the Kyoto agreement that environmental pollution in the less developed nations, such as Nigeria is rather minimal probably underestimates the effects of biodegradable wastes on the biological and chemical pollution of the aquatic environment. One attribute of underdeveloped societies is poor solid and liquid wastes disposal, and the river system is often considered a disposal unit in many rural areas.

Furthermore, the study also showed that modelling of chemical variables in stream channel is influenced by method of interpolation, as well as the distribution of samples. Results from the study showed that it is important to consider the attribute information of spatial data and appropriateness of relevant spatial analysis method before conclusion is made. In general, the error estimates that are derived from kriging and nearest point interpolation methods appear to make them preferred to moving average method. The study concluded that the geographical information system's procedure of estimating spatial variation in the chemical properties of a stream produced results that are influenced by data distribution and model assumptions, and as such users in developing countries should determine their data characteristics rather than accepting the software defaults. Further studies are recommended on management of palm oil mill effluents and ensuring more predictive data modelling in the GIS environment.

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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