



A Geo-Statistical Analysis of the Impact of Ecological and Environmental Risks on Epidemiology in the South-west, Nigeria

Kehinde Adekunle Bashiru^{1*}, Taiwo Adetola Ojorongbe¹, Olusola Olayemi Fadipe², Onyedikachi Joshua Okeke³, Habeeb Abiodun Afolabi¹, Nureni Olawale Adeboye¹, Iwa Abiola Akanni⁴

¹ Department of Statistics, Osun State University, Osogbo, Nigeria.

² Department of Civil Engineering, Osun State University, Osogbo, Nigeria.

³ Department of Mathematical and Statistics, University of New Mexico, Albuquerque NMUSA.

⁴ Department of Physics, Osun State University, Osogbo, Nigeria.

ARTICLE INFO

ORIGINAL ARTICLE

Article History:

Received: 22 November 2022

Accepted: 20 January 2023

*Corresponding Author:

Kehinde Adekunle Bashiru

Email:

kehindebashiru@uniosun.edu.ng

Tel:

+23 48034997776

Keywords:

Sanitation,

Biological Factors,

Fuzzy Logic,

Epidemiology.

ABSTRACT

Introduction: The probability of contamination is frequently elevated in scenarios where a well and pit latrine coexist, or in situations where heavy rain causes the overflow of open excreta dumps, which in turn flush into wells and surface water. Many possible negative health effects might arise from exposure to various ecological and biological agents in the environment. Therefore, there is a need to examine the risk of disease transmission in Ife North Local Government Area (LGA) of Osun state, using epidemiological, environmental, and ecological factors.

Materials and Methods: Geostatistical analysis was used to examine the epidemiological risk, based on various environmental, biological, and ecological variables. The technique employed demonstrated the complexity and multiple parameters that raise the probability of an epidemic. The Shapiro-Wilk test was used to determine whether or not the data were normally distributed. Fuzzy logic, correlation, and spline surface interpolation analysis were conducted using ArcGIS 10.3 and ENVI 5.0 software. Three levels of epidemic risk were used to construct the disease surveillance and projection maps.

Results: According to the final susceptibility map, 8.08 km² of 460.12 km² of the research area were considered to be at very low risk for an epidemic, followed by 364.98km² of low risk and 87.06km² of moderate risk areas, with percentages of 1.75%, 79.32%, and 18.92%, respectively.

Conclusion: A very substantial correlation was observed between biological and ecological components and water-borne diseases. It is, therefore, advised that all water sources be treated before consumption, and community involvement be encouraged in environmental sanitation programs.

Citation: Bashiru KA, Ojorongbe TA, Fadipe OO, et al. *A Geo-Statistical Analysis of the Impact of Ecological and Environmental Risks on Epidemiology in Southwest, Nigeria*. J Environ Health Sustain Dev. 2023; 8(1): 1878-96.

Introduction

The study of diseases distribution and environmental determinants is known as environmental epidemiology¹. Numerous epidemiological studies have used geographic factors to predict diseases based on their environmental, biological, or ecological conditions¹. The information on the triggering factors and (intermediate) hosts is

typically combined with environmental and ecological data in this type of research, using a geographic information system (GIS), which also incorporates geostatistical modelling and exploratory analysis². Ecological studies can investigate the relationship between diseases and exposures in the community using data on diseases from historical hospital records and discharges, estimations of

exposure from proximity to exposure from the open dumpsite, or levels of water pollution. When pathogens and pollutants are discharged into the environment, complicated mechanisms that can be biological, physical, or chemical, mark the transmission across every environmental compartment. When humans and ecosystems are exposed to these pollutants, complex interactions and mixtures of stressors are created that may have an impact on ecosystem services³. The majority of environmental elements (physical, microbiological, chemical, and occupational exposures) control community's health status and disease manifestation. Up to 24% of all fatalities in 2016 could be attributed to the environment⁴, therefore, global health is improved when environmental health concerns are decreased. Measuring exposure to significant environmental dangers and assessing the health implications have become increasingly important⁵. It is observed that environmental and ecological diseases, particularly in underdeveloped countries with weak public health systems, are the cause of recurrent annual events with high fatality rates. Environmental health takes different forms in developing and industrialized nations; in the latter, attention is given to issues like basic sanitation, clean air, and clean water. Water, sanitation and hygiene, interior and outdoor air pollution, and other factors are indicators for assessing environmental risks^{5,6}. There are a number of environmental issues that can have an effect on health, including air and chemical pollution, climate change, disease-causing bacteria, a lack of access to health care, bad infrastructure, poor water quality, and global warming⁷.

Neurological disorders, reproductive problems, and gastrointestinal illnesses are just a few of the adverse health effects resulting from contaminated water⁸⁻¹¹. A high correlation has been reported between the physical condition of groundwater sources and their microbial purity.

Synergistic spaces are formed to address dynamic environmental concerns when environmental factors are properly assessed¹². As a result, a sensitive disease surveillance system is needed for case reporting, early case detection, and

case prediction¹³.

Due to the inherent nature of the phenomenon under consideration, Boolean logic occasionally fails to produce accurate and high-quality conclusions when modelling real geographical crisp sets. In such cases, it would be difficult or even impossible to interpret imprecise and ambiguous data using any other method, but fuzzy set theory and solutions offered by fuzzy logic. Water contamination and signs of water-borne infections were reported to occur often in the study area according to previous studies¹⁴. Hence, the study's goal is to create fuzzy logic-based illness surveillance and predictive maps.

Materials and Methods

The study area

In Nigeria's Osun State, the Ife North Local Government Area (LGA) is the subject of the study. The LGA is located in latitudes 7°33'59.201"N and 6°59'2.246"N, longitudes 4°21'42.436"E and 4°36'1.56"E, and has a land area of around 425.3 km². The LGA has its headquarters in Ipetumodu and consists of 35 towns and villages.

Study area mapping

ArcGIS version 10.1, ENVI version 4.7, Surfer 10, R-project, and SPSS are the software programs used for this investigation. The data-set used for this study includes secondary data of both spatial and non-spatial attributes. The National Airspace Research and Development Agency (NARSDA, Ile-Ife) provided the administrative map, demographic map, Shuttle Radar Topography Mission (SRTM), and mid-resolution NigeriaSAT-X to obtain the spatial data. The administrative map of the study area was geo-coded with a root mean square error (RMSE) of 0.00005 in order to delineate the study area. The subset output was digitized using the on-screen method and the digitized products were subsequently overlain on each other.

The region of interest with coordinates longitude 4°21'42.436"E and 4°36'1.56"E and latitude 7°33'59.201"N and 6°59'2.246"N is shown in Figure 1.

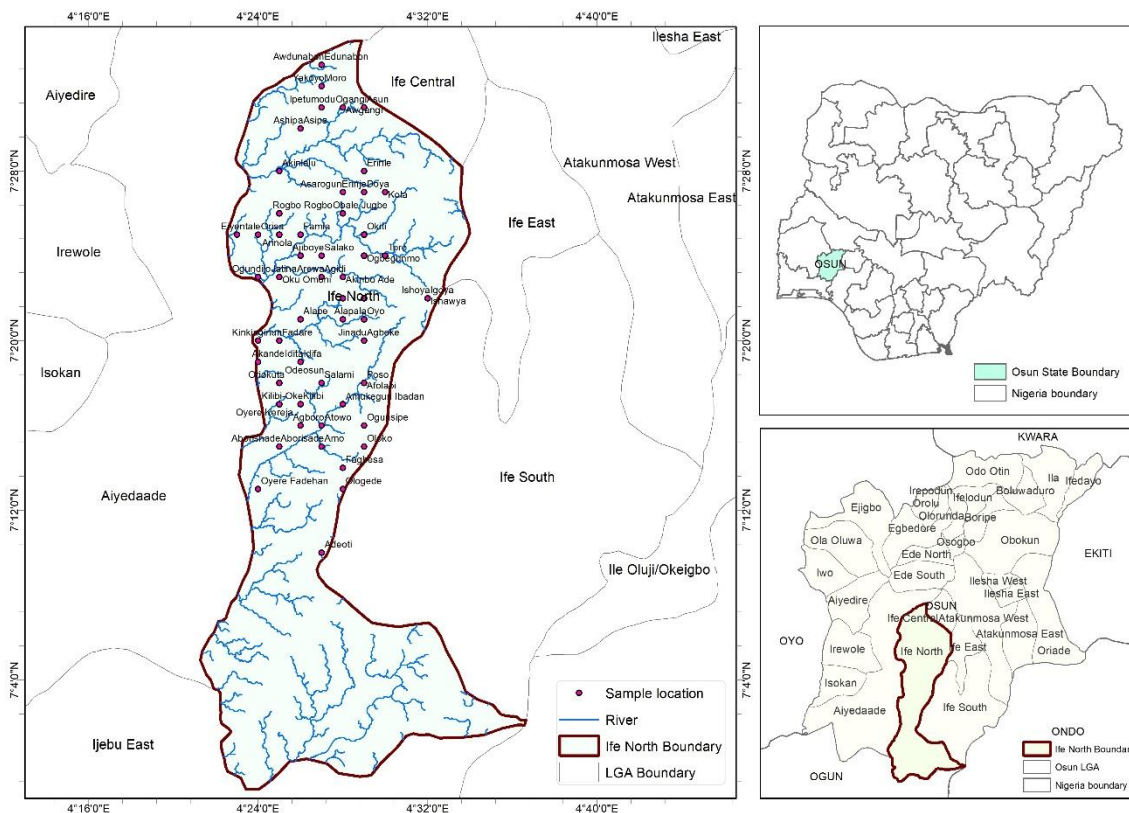


Figure 1: Map of the Study area

Spatial attributes such as contour, drainage network, settlements, utilities, and other spatial features were equally marked out. Using a portable Global Positioning System (GPS) GARMIN model, the coordinates of the chosen public boreholes and hand-dug wells were obtained.

Sampling method

Nine important cities and villages (Table 1) were chosen from among the 35 towns and villages under the local administration. Purposive sampling method was employed in the selection process to identify towns having healthcare facilities, reports of water-borne illnesses, accessible public and private water supply systems, and populations greater than 500. Using the fishnet tool in ArcGIS 10.1, the nine largest towns were griddled into a 2 km by 2 km area. In order to fairly reflect the entire study region, 52 water supply facilities in

total were chosen from the centers of each grid for the final assessment.

Hospital records

Ten primary health care centers and clinics within the Ife North LGA provided records of cases of water-borne diseases for the past 7 years (2005–2012) (Table 2). Diarrhea, typhoid fever, gastroenteritis, schistosomiasis, guinea worms, and cholera were among the ailments recorded.

Epidemic factors consideration

Ecological factors like surface waters, land use/cover, and relief, environmental factors like physico-chemical parameters of water samples from water sources, and biological factors like coliform concentration in water samples were taken into account when determining the epidemiology of the study area.

Table 1: Sample size distribution in this study

S/N	Sample location	Population figures	Sample size
1.	Akinlalu	3,479	3
2.	Ashipa	4,109	3
3.	Edunabon	11,246	8
4.	Famia	345	2
5.	Ipetumodu	31,995	24
6.	Moro	6,147	5
7.	Okuuomoni	624	1
8.	OyereAborishade	1,375	3
9.	Yakoyo	3,343	3
Total		60,559	52

Geostatistical method of analysis

The Shapiro–Wilk test for normality (descriptive statistics)

The Shapiro–Wilk test was used to check if the Ife North samples and parameters were normally distributed. The Shapiro-Wilk test applies the concept of the null hypothesis to determine if a given set of data, consisting of x_1, \dots, x_n , is derived from a population that follows a normal distribution.

The test statistics is; $W = \frac{\sum_{i=1}^n (a_i x_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$ (1)

Where,

$x_i = i$ th order of statistics i.e. i^{th} -smallest number in the sample;

$\bar{x} = \frac{(x_1 + \dots + x_n)}{n} = \text{sample mean};$

Table 2: Distribution of water borne diseases recorded at sampled hospital of Ife North LGA

Diseases	Diarrhoea	Typhoid	Cholera	Onchocerciasis	Schistosomiasis	Gastroemteritis	Guinea Worm	Total
Gen Hosp Ipetumodu	1241	0	0	25	30	0	0	1296
Health Centre Ipetumodu	1373	230	0	25	4	212	0	1844
PHCD Agency Eduabon	164	0	0	0	0	0	0	164
MHC Ilupeju Ipetu Modu	95	38	0	15	6	21	0	175
PHC Okoko Ipetumodu	426	55	5	26	9	19	0	540
OLL Hosp Ipetumodu	260	94	7	49	0	44	0	454
PHC Oyere Aborishade	96	0	17	0	0	0	0	113
PHC OkuuomoniI	114	57	2	0	0	0	0	173
PHC Famia	79	36	0	0	0	0	0	115
PHC Akinlalu	171	64	0	0	0	0	0	235
Total	4019	574	31	140	49	296	0	5109
%	78.66	11.2	0.6	2.7	0.95	5.79	0	100

The constants a_i are given by

$$(a_1, \dots, a_n) = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{\frac{1}{2}}}$$

$m = (m_1 + \dots + m_n)^T$ and $(m_1 + \dots + m_n)$ are the expected values of the order statistics derived from random variables, which are independently and identically distributed from a standard normal distribution, and the covariance matrix of these order statistics is represented as V.

The Spline tool was used as an interpolation method to minimize overall surface curvature, resulting in a smooth surface that passes exactly through the input points. The Spline function used Equation 2 for the surface interpolation:

$$S(x, y) = T(x, y) + \sum_{j=1}^N \lambda_j R(r_j) \tag{2}$$

Where,

$N =$ is the number of points $j = 1, 2, \dots, N$.

$\lambda_j =$ coefficients found by the solution of a system of linear equations.

$r_j =$ distance from the point (x, y)

to the j th point.

$T(x, y)$ and $R(r)$ are defined differently, depending on the selected option.

Using the ArcGIS 10.1 software, the regularized options (Equation 3) of spline surface interpolation were applied. The option adjusts the minimization criterion, so third-derivative terms were included in the minimization criteria. The weight associated with the third-derivative terms during minimization is specified by the weight parameter τ (tau).

$$T(x, y) = a_1 + a_2 x + a_3 y \tag{3}$$

Fuzzy set theory (mathematical model)

The fuzzy classification models used for environmental data are modifications of the functions¹⁰. The indicator variable's membership function generates a $\mu(x)$ value for each value of x , thus, the pair $(x, \mu(x))$ becomes the fuzzy set.

The standard union of two fuzzy sets A and B is fuzzy set with the membership function defined by Equation 8.

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \tag{8}$$

Zadeh's Union

The standard complement of two fuzzy sets A and B is fuzzy set with the membership function defined by Equation 9.

$$\mu_{-A}(x) = 1 - \mu_A(x) \tag{9}$$

Zadeh's Compliment

In the present study, the symmetric fuzzy models were defined as follows:

$$FP_x = \mu_A(x) = \frac{1}{1 + d(x - b)^2}; \quad \text{for } 0 \leq x \leq N \tag{10}$$

Where,

$FP_x =$ fuzzy membership function;

$A(x) =$ fuzzy membership level;

$d =$ parameter that is responsible for the function type; and

$b =$ parameter that defines the domain of X according to the central concept.

Following the process of applying membership functions to fuzzify each variable, fuzzy operators were implemented to combine distinct layers.

$y =$ chosen parameter in the interval $[0, 1]$

Given that the goal of the present study is the physical methods to examine the disease distribution level in Ife North using ecological, biological, and environmental factors, two values of the parameter y were used for the operator fuzzy gamma: $y = 0.2$ and $y = 0.95$.

Results

The Shapiro–Wilk test was used to check if Ife North samples and parameters were normally distributed. The Shapiro-Wilk test results in Table 3 show that the initial cluster centres before normalization were $1 = 2$, $2 = 24$, and $3 = 8$. The final cluster centres after normalization $1 = 2.5$ had a marginal difference of 0.5 from $1 = 2$; $2 = 24$ had a marginal difference of 0 from $1 = 24$, and $3 = 6.5$ had a marginal difference of -1.5, hence the samples size / data was normally distributed (Table 3). In addition, the mean (5.78) std. deviation (7.12) and descriptive statistics of the sample size were normally distributed as shown in Table 4 and Figure 2.

Table 3: Shapiro–Wilk test sample size distribution normalization clusters

	Initial cluster centres before normalization			Final cluster centres after normalization		
	1	2	3	1	2	3
Sample Size	2	24	8	2.5	24	6.5

Table 4: Descriptive statistics for sample size distribution

No.	N	Range	Min	Max	Sum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
Sample Size	9	23	1	24	52	5.78	7.12	50.694	2.588	7.023
Boreholes	9	3	0	3	9	1	1.118	1.25	0.69	-0.8
Wells	9	20	1	21	42	4.67	6.403	41	2.565	6.872
Streams	9	1	0	1	1	0.11	0.333	0.111	3	9
Sample Size	9	23	1	24	52	5.78	7.12	50.694	2.588	7.023

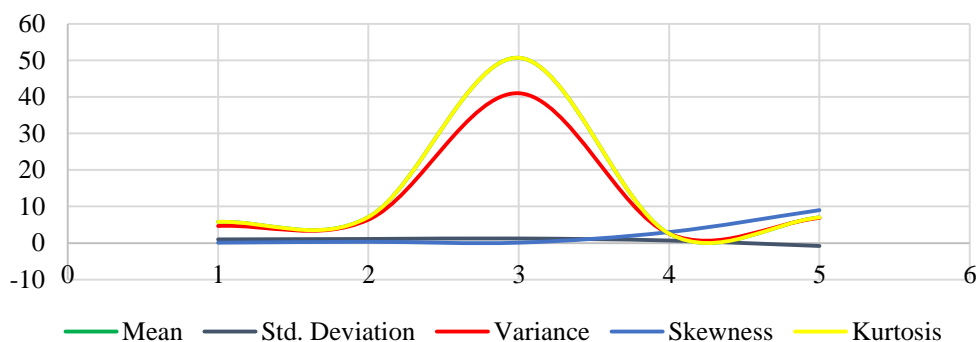


Figure 2: Descriptive statistics graph for sample size distribution

The ecological characteristics of the area can be divided into surface water (Figure 3a), Landuse/landcover (Figure 3b), and relief or elevation (Figure 3c). Vegetation had less contribution in increasing the epidemic risk. Well location is a crucial safety factor. Based on elevation and relief, a well located downhill of the source of bacterial contamination has a greater

risk of contamination than a well on the uphill of the contamination source. The highest elevated area is between 270 to 370m above mean sea level. In the study area, north eastern and southern sides are covered by structural hills greater than 270 m. While the south-western and southern parts of the area are characterised by low elevation.

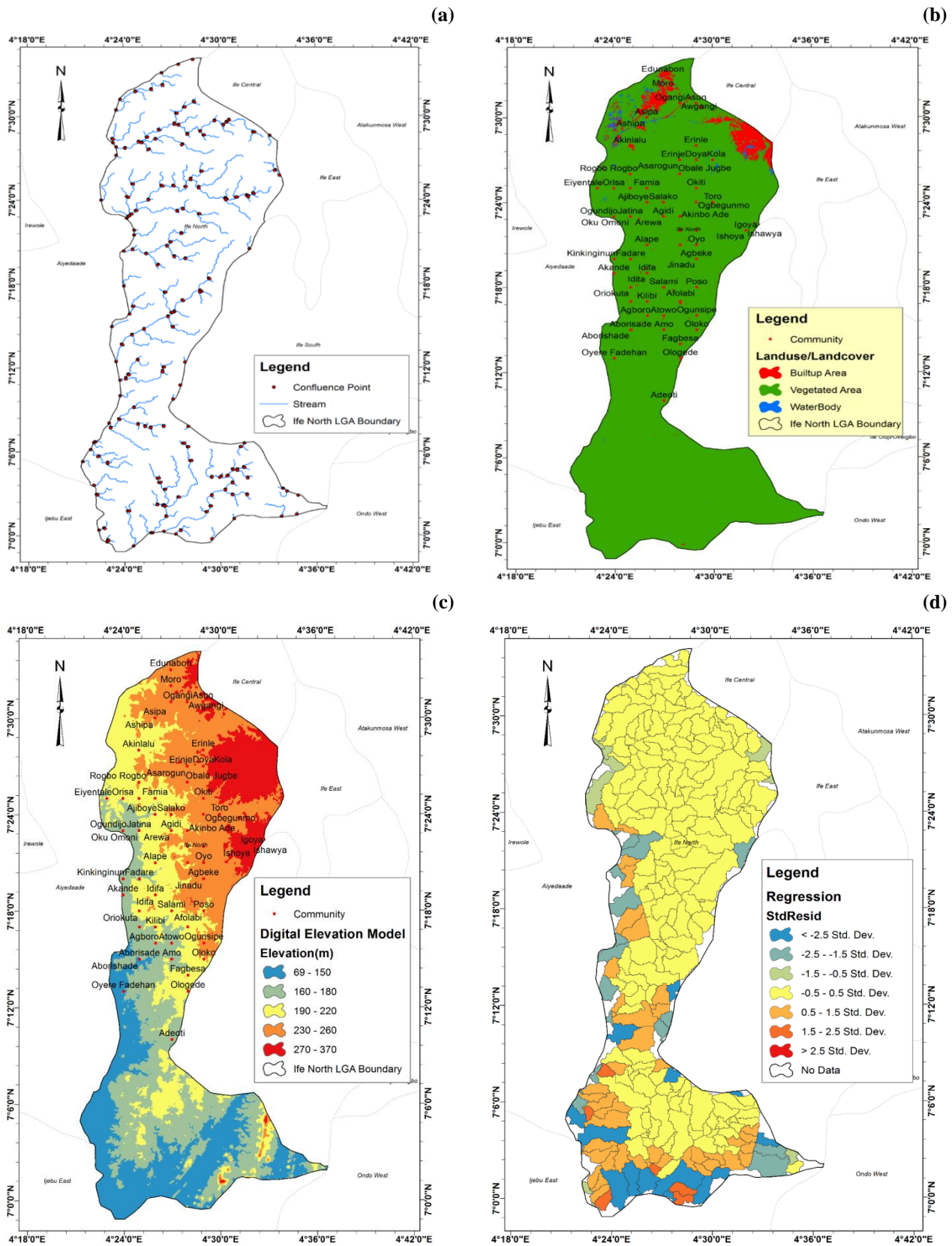


Figure 3: Maps of ecological factors: a) The map of surface water; b) The map of land-use and land-cover of the study area; c) The map of DEM of the study area; d) The map of geographically weighted regression model

Figure 4a and 4b display the mean result of the nearest neighbour analysis of the collected

boreholes and wells, showing that the distribution of the sample was random and thus dispersed.

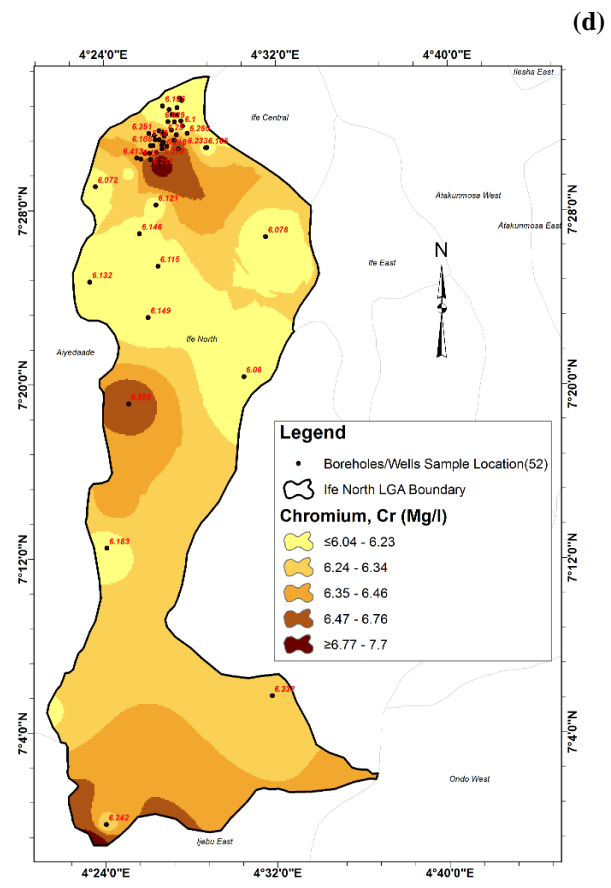
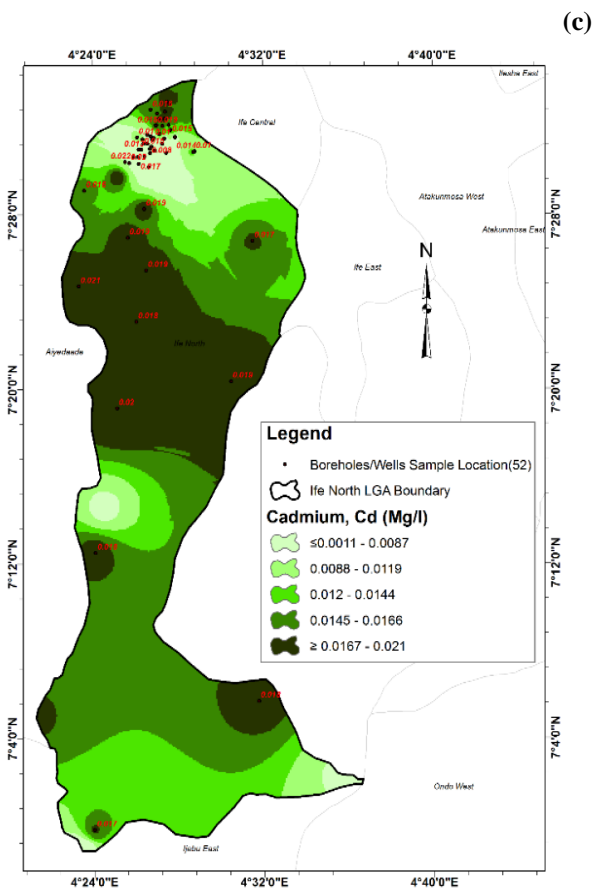
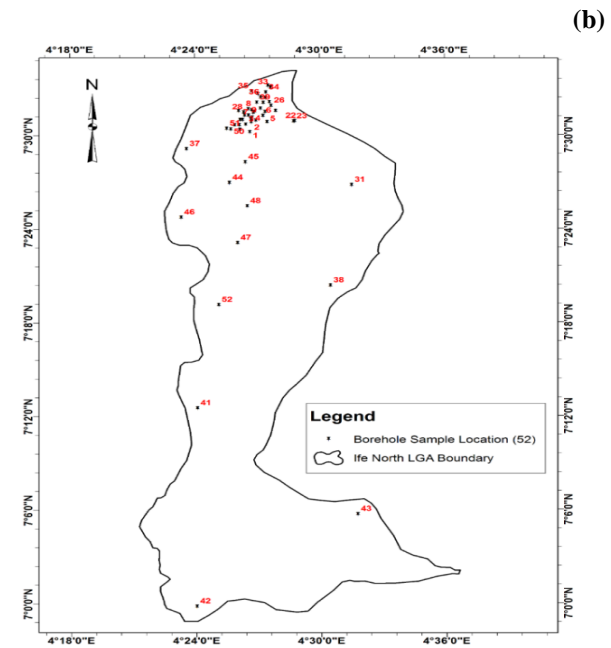
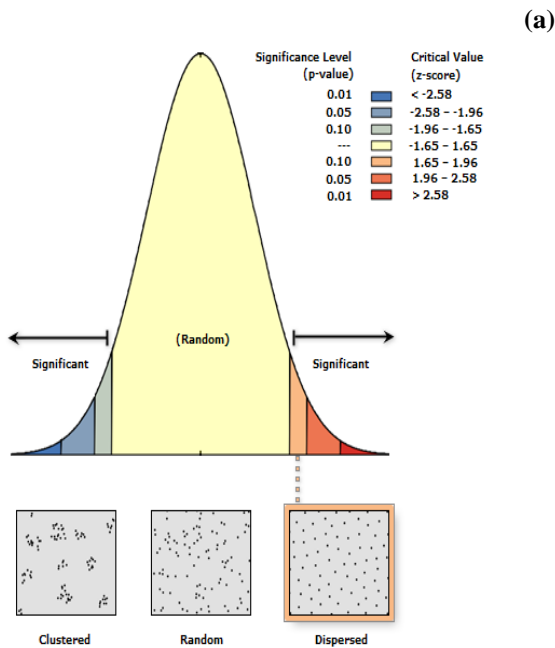


Figure 4: Mean nearest neighbour, boreholes/dug well and the maps of Cd and Cr: a) Mean nearest neighbour analysis of the 52 samples; b) Boreholes /hand-dug wells location; c) The map of cadmium (Cd) concentration; d) The map of chromium (Cr) concentration

Data on the physico-chemical parameters of water samples from the fifty-two (52) forty-three wells and nine boreholes (Figure 4, 5 and 6) show that pH of the water samples ranged between slightly acidic to slightly alkaline (near neutral) with a mean pH range of 8.2 ± 1.2 in Ipetumodu wells, to 11.1 ± 0.2 in Famia water sample (Figure 5). The acidic nature of the water samples has been attributed to the presence of tiny shale intercalations in the auriferous coastal plain sand¹³. The pH values were slightly above the maximum desirable limit of 8.5 set by the

World Health Organization (WHO) (WHO, 2006). The mean value of temperature was 26.52 ± 0.73 °C. Only the turbidity value (121.60 ± 1.20) Nephelometric Turbidity Units (NTU) was above the WHO guideline (Turbidity values less than 10 NTU are considered low, a value of 50 NTU would be considered moderately turbid, and very high turbidity values can be more than 100 NTU). This indicates that with the bare minimum of treatment, the water would be completely safe and suitable for human consumption.

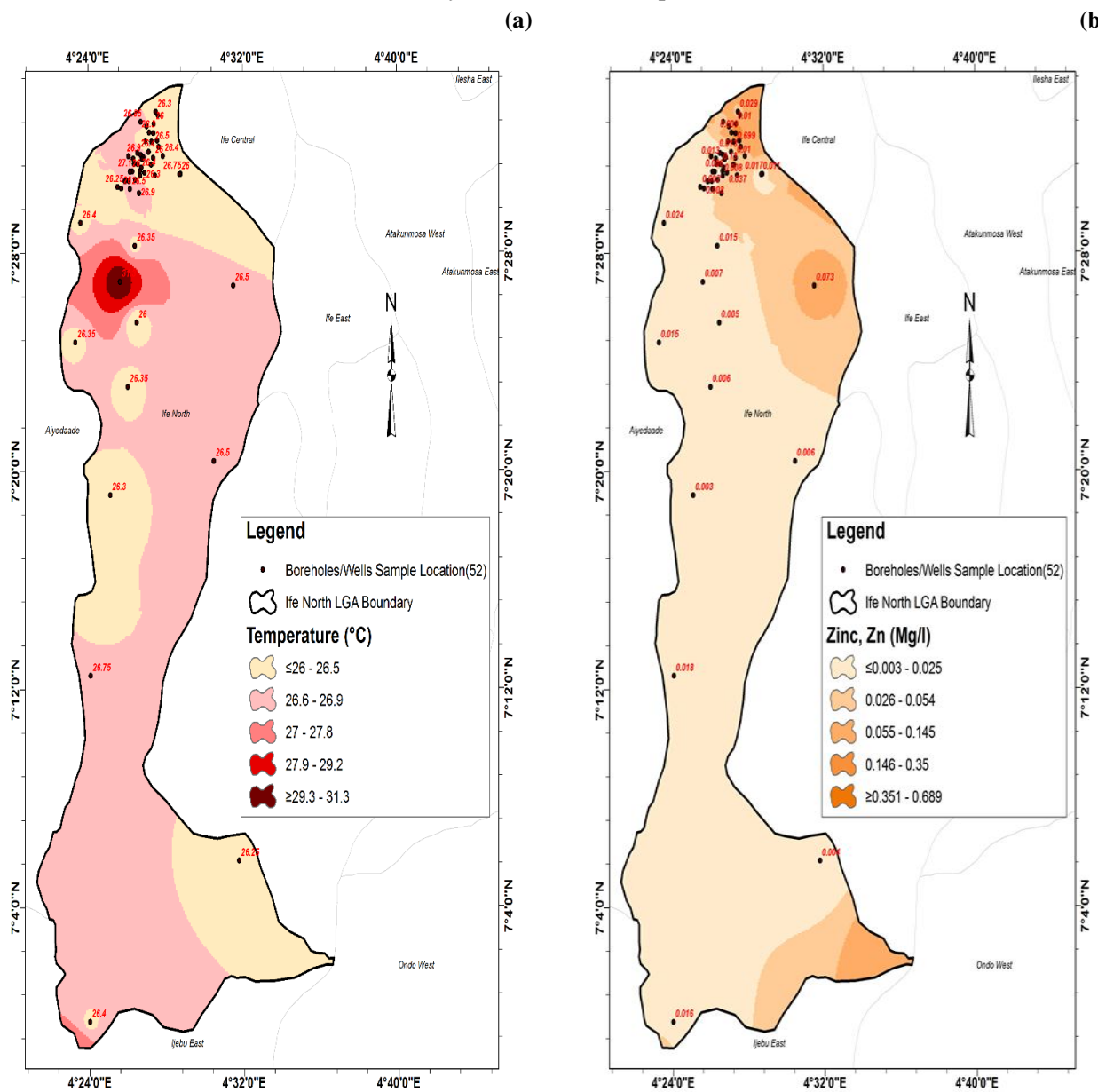


Figure 5: Concentration maps of temperature and Zn: a) Concentration map of temperature; b) Concentration map of Zinc (Zn)

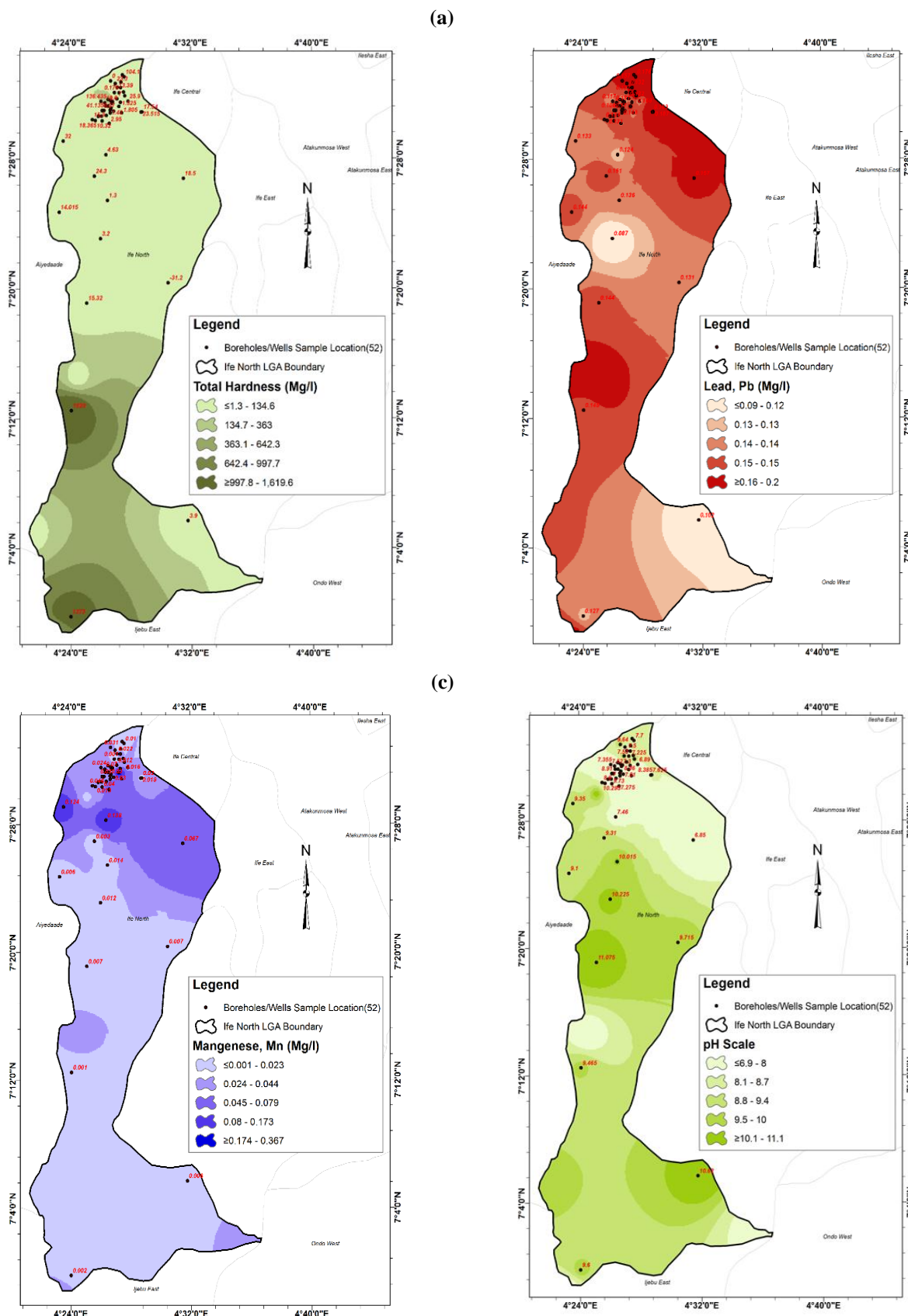


Figure 6: Concentration maps of total hardness, Pb, Mn, and pH: a) Concentration map of total hardness; b) Concentration map of Lead (Pb); c) Concentration map of manganese (Mn); d) Concentration map of pH

The spatial distribution of coliforms in the study area determined by the water sample test is depicted in Figure 7. The allocated fuzzy value was (0.2) and the total coliform load varied from $\leq 1.6e-001 - 2.1e + 005$ and $\geq 6.2e + 006 - 1.1e + 007$. Ilupeju in Ipetumodu, Oke Ola in Edunabon, and Ile-Arubiewe in Yakoyo had the highest $9.3E + 01$, $9.3E + 01$ and $9.3E + 01$ Cells/100ml, respectively.

Tables 5 and 6 and Figures 8 and 9 show the surveillance prediction and epidemic risk of the

study area, which were categorized as very low risk, low risk, and moderate risk. Figure 8 and Table 6 show that the majority of the community (such as Aborisade, Afolabi, Agbeke, Agboro, Agidi, Ajiboye, Akande, AkinboAde, Alapala, Alapata, Alape, Amo, Amukegun Ibadan, Amukegun Modakeke, etc.) in the study area was exposed to very low risk. However, communities such as Akinlalu and some part of Ashipa had moderate risk.

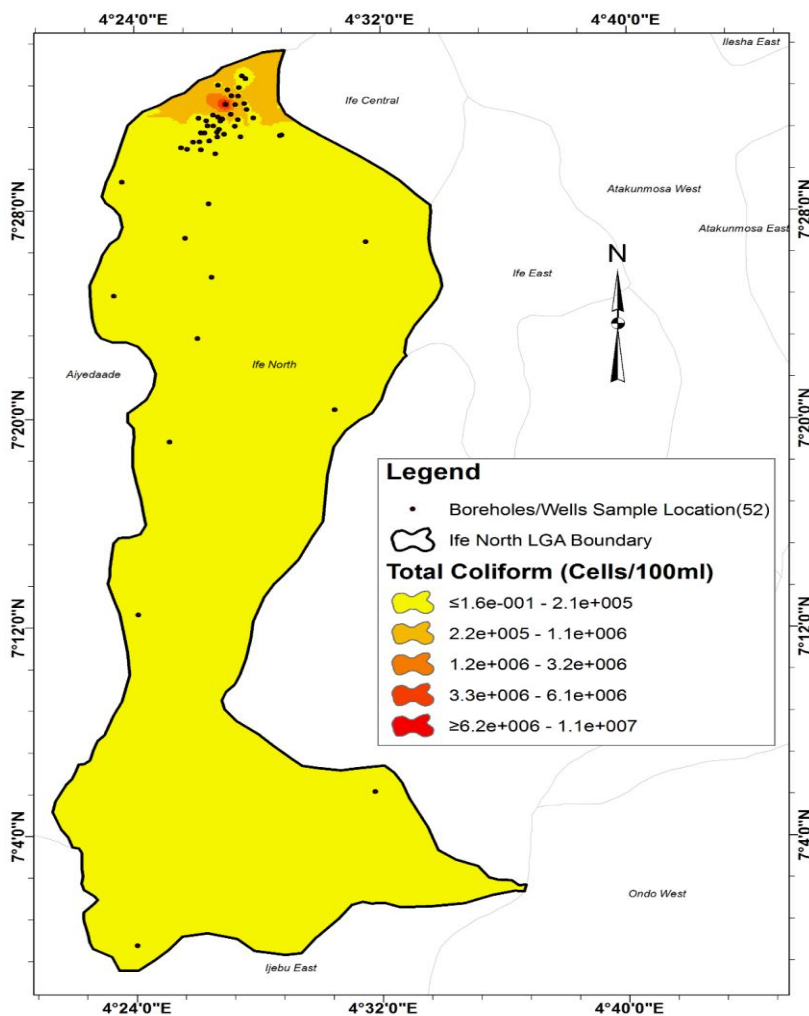


Figure 7: Spatial distribution of total coliform of the study area

Table 5: Fuzzification ranking combination of ecological, environmental, and biological factors

S/N	Factor	Feature	Fuzzy function	Weightage (%)	Subdivision	W.H.O	Fuzzy rank
1	Environmental	Cd	Gaussian/ Very	6.2	(Mg/l)	5.0mg/l	
					≤ 0.0011-0.0087	0.2	
					0.0088 - 0.0119	0.4	
					0.012 - 0.0144	0.6	
					0.0145 - 0.0166	0.8	
≥ 0.0167 - 0.021	0.98						
2	Environmental	Cr	Gaussian/ somewhat	5.2	(Mg/l)	0.05mg/l	
					≤ 6.04 - 6.23	0.2	
					6.24 - 6.34	0.4	
					6.35 - 6.46	0.6	
					6.47 - 6.76	0.8	
≥ 6.77 - 7.7	0.98						
3	Environmental	Pb	Linear /very	8.2	(Mg/l)		
					≤ 0.09 - 0.12	0.2	
					0.13 - 0.13	0.4	
					0.14 - 0.14	0.6	
					0.15 - 0.15	0.8	
≥ 0.16 - 0.2	0.98						
4	Environmental	Mangnese,(Mn)	MS small	9	(Mg/l)	0.05mg/l	
					≤ 0.001 - 0.023	0.2	
					0.024 - 0.044	0.4	
					0.045 - 0.079	0.6	
					0.08 - 0.173	0.8	
≥ 0.174 - 0.367	0.98						
5	Environmental	pH	Gaussian	12.2	Scale	6.5-8.5	
					≤ 6.9 – 8	0.2	
					8.1 - 8.7	0.4	
					8.8 - 9.4	0.6	
					9.5 – 10	0.8	
≥ 10.1 - 11.1	0.98						
6	Environmental	Temperature	Gaussian	6.3	(°C)		
					≤ 26 - 26.5	0.2	
					26.6 - 26.9	0.4	
					27 - 27.8	0.6	
					27.9 - 29.2	0.8	
≥ 29.3 - 31.3	0.98						
7	Environmental	Total hardness	MS Large	6.1	(Mg/l)	≤ 500mg/l	
					≤ 1.3 - 134.6	0.2	
					134.7 – 363	0.4	
					363.1 - 642.3	0.6	
					642.4 - 997.7	0.8	
≥ 997.8 - 1,619.6	0.98						
8	Environmental	Zn	MS Small	5.5	(Mg/l)	5mg/l	
					≤ 0.003 - 0.025	0.2	
					0.026 - 0.054	0.4	
					0.055 - 0.145	0.6	
					0.146 - 0.35	0.8	
≥ 0.351 - 0.689	0.98						



S/N	Factor	Feature	Fuzzy function	Weightage (%)	Subdivision	W.H.O	Fuzzy rank
9	Ecology	Elevation	Gaussian/somewhat	8.4	(Meters)	≥ 50m	
					≤ 69 – 150	0.2	
					160 – 180	0.4	
					190 – 220	0.6	
					230 – 260	0.8	
≥ 270 – 370	0.98						
10	Ecology	Flow accumulation	Gaussian/somewhat	4.6	Threshold	≤ 2,410.1	
					≤ 0 - 567.1	0.2	
					567.2 - 2,410	0.4	
					2,410.1 - 5,528.8	0.6	
					5,528.9 - 9,285.6	0.8	
≥ 9,285.7 - 18,075	0.98						
11	Ecology	Landuse/cover	Linear /Very	5.3	Type	Vegetation	
					Vegetation	0.4	
					Builtup Area	0.7	
					WaterBody	0.98	
12	Ecology	Stream	Linear	7.5	Order	≤ 3rd	
					1 st	0.2	
					2 nd	0.4	
					3 rd	0.6	
					4 th	0.8	
≥ 997.8 - 1,619.6	0.98						
13	Biological	Total coliform	MSLarge	15.5	(Cell/100ml)	0	
					≤ 1.6e-001 - 2.1e + 005	0.2	
					2.2e + 005 - 1.1e + 006	0.4	
					1.2e + 006 - 3.2e + 006	0.6	
					3.3e + 006 - 6.1e + 006	0.8	
≥ 6.2e + 006 - 1.1e + 007	0.98						
				100			

Table 6: Epidemic risk ranking of communities in Ife north LGA

Rating	Area (Km ²)	%	Community in Ife north LGA
Very low risk	8.08	1.75	Salako,Sagi,Aborisade,Afolabi,Agbeke,Agboro,Agidi,Ajiboye,Akande,Akinbo Ade, Alapala, Alapata, Alape, Amo, Amukegun Ibadan, AmukegunModakeke, Apamu Ife, Arewa, Arinola, Asun, Awdunabon,Awuro Oyo I,Ayakunle,Edunabon, Eiyentale, Ejesi II,Eleweran,Fadare,Famia,Idifa,Igoya,Ishawya,Jatina, Kinkinginun, Kola, OdanAsun, Odeosun,Ogundijo,Oku Omoni,Onibambu,Onikoko,Oriokuta,Orisa, Orisa, OyereAsujo, OyereFadehan,Oyo,Poso,RogboRogbo,Sagi,Salako andSalami (54)
Low risk	364.98	79.32	Yakoyo,Toro,OyereKereja,Olorunda,Oloko,Ologede,Okiti,Ogunsipe,Ogbegunmo, Ogangi, ObaleJugbe, Moro, Kilibi-Oke, Ipetumodu , Fagbesa, Erinle, Doya, Bolorunduro, Awgangi, Atowo,Asipa,Asarogun,Akinlalu and Adeoti (25)
Moderate risk	87.06	18.92	Akinlalu (1)
	460.12	100	

uphill from the pollution source.

The research area is between 270 and 370 m above mean sea level. Structural hills taller than 270 m are present in the north-eastern and southern sides of the study area. Low elevation is a feature of the south-western and southern portions of the territory, which may make them more susceptible to pandemic risk. Additionally, both human and animal contaminants may reach the low elevation areas' shallow aquifer. With a moderate to low slope and a rain forest covering about 70% of the land, there may be some modest runoff and minimal transmission of contaminants like coliforms. As presented in Figure 3d, the research area primarily consists of perennial rivers, which affects the overall drainage patterns of the rivers. Given that the river in the research area has a dendritic drainage pattern and a high drainage density, a significant amount of precipitation likely drains as surface runoff. On the other hand, a low drainage density means that less runoff is needed, since the majority of the rainwater will permeate the ground.

Environmental risk factors

The distribution of the sample was random and as a result dispersed, as shown in Figures 4a and 4b, according to the mean nearest neighbour analysis result of the collected boreholes and wells. The mean concentrations (Figures 4c and 4d) of Cd and Cr (0.012 ± 0.0065 mg/L and 6.31 ± 0.32 mg/L, respectively) were more than WHO desirable limits (0.003mg/L and 0.05mg/L). The Zn value (Figure 5b) is within the permitted limit of 3mg/L, and the mean temperature (26.520.73) (Figure 5a) is suitable for drinking water. The overall hardness of the water samples, ranging from 36 to 121.60 mg/L (Figure 6a), is the factor of their softness and foaminess¹⁷⁻²⁰. The WHO recommended limit exceeded by the mean Pb content (0.13 mg/L) in Figure 6b, while the Mn concentration (Figure 6c) was acceptable. The water samples pH values ranged from mildly alkaline to slightly acidic (near neutral). The water samples' acidic composition was due to the presence of minute shale intercalations in the

auriferous coastal plain sand¹⁴.

Biological risk factors

Figure 7 shows the coliforms' spatial spread. The major towns in the study area have a high concentration of coliforms ($9.3E + 01$ Cells/100mL), which must be caused by the area's high population and human activity, since the main causes of coliform contamination in water are human waste, animal waste, insects, rodents, and other animals getting into hand-dug wells, flooding, and older hand-dug wells. The spatial distribution of coliforms in the study area from the water sample test proved that Ilupeju in Ipetumodu, Oke Ola in Edunabon, and Ile-Arubiewe in Yakoyo had the highest $9.3E + 01$, $9.3E + 01$, and $9.3E + 01$ Cells/100ml, respectively. Ilupeju in Ipetumodu and Arubiewe in Yakoyo had excreta (ECN) and OkeOla in Edunabon had no excreta (ECNP). This must be due to the high population and human activities in the area, as human waste, animal waste, insects, rats, and other animals entering wells are the main sources of coliforms in water. Moreover, older wells and water sources are submerged with flood water. Figure 7 shows that the lowest coliform load was in OjuOla, in Famia $0.5E + 00$ Cells/100ml with no excreta (ECNP), this illness from coliform bacteria is unlikely. However, the fact that they are found in drinking water suggests that pathogenic organisms may be present in the water system^{16,18,19}.

Fuzzy logic model

The problem was identified as groundwater accumulation in the Ife north LGA using a multi-criteria analysis with a complete fuzzy overlay. The model was broken into sub-models, and input layers were identified as shown in Table 5. Weights factors from related papers¹⁴ were used to calibrate the produced maps. These weights were based on their estimated level impact to the epidemic risks of the study area on repeated procedures and on the comparison of the results to the observed factors up to the achievement of the desired accuracy. Thus, total coliform (15.50%) of biological factor assigned the most

weight in the research of epidemic, followed by pH (12.20%), temperature (6.30%), total hardness (6.10%), Zn (5.50%), Cd (6.20%), and Cr (5.20%). Table 5 reveals the ecological elements such as flow accumulation (4.60%), land use/cover (5.30%), and stream (7.50%). The weight factors of each were then added algebraically to the aforementioned thematic maps using fuzzy logic.

The input criteria layers, which are ecological, biological, and environmental factors and are depicted in Figures 3-7 have different number systems with different ranges. To combine them in a single analysis, they were converted to grid raster, and each cell for each criterion was reclassified into a common preference scale between 0 and 1 in 5 ranges (0, 0.2, 0.4, 0.6, 0.8, and 1) (Table 5). The phenomenon's preference for the criterion was indicated by an assigned preference on the common scale. There was a relative scale for the preference values. When compared to a preference of 0.4, a preference of 0.2 was twice as high as the epidemic. The preference values had the same meaning across all factor subdivisions in addition to being assigned in relation to one another within a given factor subdivision. If a factor's subdivision range is given a preference of 0.8, it will have the same impact on the phenomena as a factor with a preference of 0.8.

The epidemic risk factors were selected based on the WHO desired limits as shown on Table 5.

Total hardness of 500 mg/L, Zn 3 mg/L, Cd 0.003 mg/L, and Cr should not be greater than 0.05mg/l as shown in Table 5. After converting the factors to grid raster, they were re-classified on a scale of 0.2 to 0.98. The input criteria were multiplied by the weights and then integrated based on uncertainty of fuzzy model. The fuzzy overlay analysis model was validated to make sure what the model indicates at a site is actually present, and the epidemic surveillance predictive map and graphs (Figures 8 and 9) of the study area were generated. The areas were categorised into very low risk, low risk, and moderate risk to epidemic as shown in Table 6.

The susceptibility map, which was created using fuzzy logic, indicates that a small portion of the study area, approximately 1.75%, has a very low risk of epidemic, while a vast majority of the area, about 79.32%, is considered to have a low risk. Moderate risk is identified in 18.92% of the area, which corresponds to 87.06 km². These findings are clearly represented in Figures 8 and 9.

Conclusions

The study demonstrated the association between water-borne diseases, ecological, biological and environmental factors, and it has provided information on risk level of disease epidemics. The surveillance map has provided a tool for monitoring and maintenance of environmental factors and quality of water sources. Increased precipitation is known to have a significant impact on vector and water-borne diseases, particularly in response to changes in climate variability. The study area experiences both benefits and drawbacks from rainfall, as it is a frequent trigger for natural disasters such as floods, which have a range of negative effects. Persistent inadequate management of floodwaters, both on the surface and underground, creates a breeding ground for vectors that carry diseases.

The health officials can use the zones determined by this study to emphasize improvement of water supply and carry out routine basic microbiological analysis of drinking water.

Abbreviations

WHO: World Health Organization

LGA: Local Government Area

Std: Standard Deviation

Gen. Hosp: General Hospital

PHC: Primary Health Centre

MHC: Maternity Health Centre

PHCD: Primary Health Care Development

GPS: Global Positioning System

RMSE: Root Mean Square Error

SRTM: Shuttle Radar Topography Mission

GIS: Geographic Information System.

Acknowledgements

The author would like to thank the researchers in the National Airspace Research and

Development Agency (NARSDA, Ile-Ife), Department of Civil Engineering both in Osun State University, Osogbo and Obafemi Awolowo University, Ile Ife., that equipped us with the require data and other necessary materials during the study.

Funding

None

Conflict of interest

There is no conflict of interest to declare.

This is an Open-Access article distributed in accordance with the terms of the Creative Commons Attribution (CC BY 4.0) license, which permits others to distribute, remix, adapt, and build upon this work for commercial use.

Referencics

- 1.Nriagu JO. Encyclopedia of Environmental Health. 2nd Edition. Elsevier; 2019.
- 2.Mesgari MS. Using a fuzzy logic and Gis-A case study of tiruchirappalli city-India. World Appl Sci J. 2008;31:60-5.
- 3.Reis S, Voigt K, Oxley T. Thematic issues on modelling human and ecologic health risks. Environmental Modelling & Software. 2017;93:106-8.
- 4.World Health Organization. Guidelines for drinking water quality. Geneva: Switzerland; 2009.
- 5.Ezzati M, Utzinger J, Cairncross S, et al. Environmental risks in the developing world: exposure indicators for evaluating, inventions, programmes and policies. Journal of Epidermal community Health. 2005;59(1):15-22.
- 6.Abdolabadi H, Ardestani M, Hasanlou H. Evaluation of water quality parameters using multivariate statistical analysis (Case study: Atrak River). Journal of Water and Wastewater; Ab va Fazilab. 2014;25(3):110-7.
- 7.Correl R. How environmental health impacts our quality of life and health. Available from:<https://www.verywellhealth.com/what-is-environmental-health-4158207>. [Cited 24 September 2020]
- 8.Darabi M, Jahani Zadeh SH, Chegeny M. Chemical and physical indicators in drinking water and water sources of Boroujerd using principal components analysis. J Med Lab. 2014;8(2):76-82.
- 9.Faryadi S, Shahedi K, Nabatpoor M. Investigation of water quality parameters in tadjan river using multivariate statistical techniques. Journal of Watershed Management Research. 2012;3:75-92.
10. Kolisko P. Examples of the Implementation of Fuzzy Models in Tourism in the South Moravian Region. Geoinformatics for Intelligent Transportation. 2014:161-85.
11. Samson M, Swaminathan G, Kumar NV. Assessing groundwater quality for portability using a Fuzzy logic and GIS—a case study of Tiruchirappalli city–India. Computer Modeling and New Technologies. 2010;14(2):58-68.
12. Ardoin NM, Bowers AW, Gallard E, et al. Environmental education outcomes for conservation: A systematic review. Conserv Biol. 2020;241:108224.
13. Jeje JO, Oladepo KT. Assessment of heavy metals of boreholes and hand dug wells in ife north local government area of osun state, Nigeria. International Journal of Science and Technology. 2014;3(4):209-14.
14. Nwaogu C, Okeke OJ, Fadipe OO, et al. Is Nigeria losing its natural vegetation and landscape? Assessing the landuse-landcover change trajectories and effects in Onitsha using remote sensing and GIS. Open Geosciences. 2017;9(1):707-18
15. Falola TO, Adetoro IO, Idowu OA, et al. Assessment of groundwater quality in Abekuta North, Nigeria. J Am Water Resour. 2021;9(2):41-8.
16. Varol S, Davraz A, Şener Ş, et al. Assessment of groundwater quality and usability of Salda Lake Basin (Burdur/Turkey) and health risk related to arsenic pollution. J Environ Health Sci Eng. 2021;19(1):681-706.
17. Oladeji AM, Adeleye AO, Bate GB, et al. Groundwater quality assessment: Physicochemical and bacteriological evidences from Hand – Dug wells in Gaya Town Nigeria.

- SLU Journal of Science and Technology. 2021;2(2):16-24.
18. Hamad JR, Yaacob WZ, Omran A. Quality assessment of groundwater resources in the city of Al-Marj Libya. *Processes*. 2021;9(1):154.
 19. Ephraim BE, Ajayi IO. Geoenvironmental assessments of heavy metals in surface sediments from some creeks of the great kwa river, Southeastern Nigeria. *J Environ Earth Sci*. 2014;4(21):2224-3216.
 20. Bassey BO, Allimba CG, Chukwu OL. Current metal pollution status and ecological risk impacts on ologe and badagry lagoon in Lagos, Nigeria. *J Toxicol Risk Assess*. 2019;5:23.