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POLLUTION STATUS AND POLLUTION SOURCE IDENTIFICATION IN THE GROUNDWATER OF YAR-DALLA IN WUDIL, KANO, NIGERIA

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Abstract

The recent increase in population growth and industrialization has resulted in higher pollution loads in the environment including the groundwater, which is a vital freshwater resource. Water Quality Index (WQI) was used to assess the water quality of the study area, while multivariate statistical techniques, including Principal Component Analysis (PCA) and Cluster Analysis (CA), were used to identify possible sources of the pollutants. The results of the descriptive statistics show that pH, Chloride, Alkalinity, Nitrate, and Cu are within the WHO standard for drinking water in all the water samples, while Cl^-, Cd, Cr, and Pb exceeded the allowable standard in 20 %, 30 %, 10 %, and 40 % respectively of the water samples. CA group sample locations into three distinct clusters: C1 (A, B, E, G, F, and H), C2 (C, J, and I), and C3 (D). C1 has the highest anthropogenic influence followed by C2, while C3 has the least. WQI shows that C1 is in the extremely poor class (WQI>100), C2 is in the poor class (51<WQI<75), and C3 is in the good class (26<WQI<50). The PCA yielded 3 components which explained 72.98 % of the total variance in the data set. The first Component accounts for 38.85 %. Component 2 accounts for 19.76 % of the total variance while Component 3 accounts for 14.37 % of the total variance. The groundwater of the area is mainly impacted by anthropogenic factors such as agricultural activities, domestic waste, and vehicular/traffic input.

Keywords: groundwater, water quality index, PCA, cluster analysis, pollution source identification.

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1. Introduction

Groundwater provides the largest store of freshwater apart from the ice caps and represents 26 % of the total freshwater withdrawal globally [1]. It is used for agricultural, industrial, and domestic purposes. Globally, groundwater provides 98 % of domestic water use, and 43 % of irrigation water, while more than 20 % of the world's population depends on groundwater for drinking purposes [2]. In Nigeria, it is estimated that 59 % of the population depends on hand-dug wells for drinking water sources [3].

Although groundwater is less prone to contamination than surface water [1, 4] and provides the major source of drinking water globally, especially in developing nations, they are also vulnerable to contamination from different sources [5]. Groundwater can be polluted from anthropogenic sources (e.g. agricultural activities, industrial activities, waste dumps, urban runoff, cemeteries, etc.) or natural sources (e.g. seawater intrusion, rock-water interactions, radioactive decay, etc.) [6]. Anthropogenic activities can also increase natural sources of groundwater pollution. For instance, excessive aquifer abstraction can lead to saltwater intrusion, acid-mine drainage from the exploitation of mineral resources, and leaching of hazardous chemicals as a result of excessive irrigation [6, 7].

Groundwater pollution poses significant health risks for humans and other animals and also affects the general ecosystem [6, 8, 9]. Therefore, the protection of groundwater resources is necessary to protect human health, maintain food supplies, and conserve ecosystems [2]. Protective measures are simpler and less costly than corrective measures for groundwater pollution [10]. Identification of pollution sources is one of the major prerequisites for the effective protection and preservation of groundwater resources. Source identification helps in preventing the spread of pollutants in the aquifer, and developing an optimal pollution control strategy [11], and it is also important for the efficient management of groundwater resources [12].

The degree of accuracy of the pollution source identification processes increases with the number of water quality parameters [13]. This leads to the increased complexity of the data which can only be successfully analysed using multivariate statistical methods. The most widely used multivariate statistical techniques in pollution source identification include Principal Component Analysis (PCA) and Cluster Analysis (CA) [12, 14, 15]. The objective of this research is to use the above-mentioned multivariate statistical methods and Water Quality Index (WQI) to evaluate the groundwater quality and identify possible pollution sources in the groundwater of the study area.

WQI is a rating reflecting the composite influence of different water quality parameters [16]. It combines the concentrations of several water quality parameters with their respective regulatory standards and converts them into a single value that reflects the water quality status and can be used to effectively communicate information on the quality of water to the concerned citizens and policymakers.

2. Materials and methods

2. 1. Sample collection and preservation

Samples were collected at different locations (**Table 1**) from 10 different hand-dug wells distributed in Yar-Dalla, Wudil local government, Kano. All sampling points were far away and the interval is a good representative of the entire study area. Sample containers (polyethylene bottles) were thoroughly washed with detergent and rinsed with tap water before soaking in 2 % HNO_3 [17]. The containers were finally rinsed with distilled water before being used for sampling. The samples' pH was recorded at the point of collection using a pH meter. Thereafter the samples were preserved by acidifying to pH<2 (with 1–2 cm^3 (17 %w/w) of concentrated HNO_3). The water samples were stored in a refrigerator and kept cool at a temperature range of 0–4 °C (to reduce microbial activities) pending analysis [18].

Table 1
Sample area code and description

S/N	Sample Code	Description
1	A	Gidan Yan Ali
2	B	Gidan Liman
3	C	Gidan Shehu W.
4	D	Gidan Ubale
5	E	Gidan Garjago
6	F	Gidan Garba
7	G	Gidan Iro
8	H	Gidan Idi
9	I	Gidan Bala
10	J	Gidan Shehu B.

2. 2. Preparation of samples for metal analysis

Samples for the metal analysis were acidified at the time of collection with concentrated nitric acid in other to bring the pH below 2. Exactly 100 cm^3 of each water sample was then transferred into a 200 cm^3 beaker, 5 cm^3 of concentrated HNO_3 was added and digested on a hot plate at 90 °C to 95 °C until the volume was reduced to 15–20 cm^3 [19]. The digested samples were transferred into a 50 cm^3 volumetric flask. Distilled water was used to make up the solution to the mark. This was used for the determination of the elements Cr, Cd, Cu, Zn, and Pb using an Atomic Absorption Spectrophotometer (Unicom 969).

2. 3. Chemical parameters

The determination of physicochemical parameters such as pH, Nitrates, and Alkalinity, was carried out following the method described by AOAC [20].

2. 4. Water quality index

The pollution status of the groundwater in the area was evaluated using the water quality index. The water quality index was calculated using the weighted arithmetic index method as reported by [21]. WHO/Nigeria reference standards (**Table 2**) were adopted for assigning weights to the water quality parameters.

$$WQI = \frac{\sum_{i=1}^{n} W_i Q_i}{\sum_{i=1}^{n} W_i}, \quad (1)$$

$$W_i = \frac{K}{S_i}, \quad (2)$$

$$k = \frac{1}{\sum_{i=1}^{n} \frac{1}{S_i}}, \quad (3)$$

$$Q_i = \frac{C_n - C_i}{S_i - C_i} \cdot 100, \quad (4)$$

where W_i is the relative weight, K is a proportionality constant, Q_i is the quality rating for the i-th water quality parameter, n is the total number of the water quality parameters, C_n is the concentration of i-th water quality parameter, S_i is the standard value of the i-th water quality parameter, C_i is the ideal value of the i-th water quality parameter (C_i for pH=7, for other parameters, C_i=0) [22, 23]. WQI rating according to this method is as follows: WQI<25=excellent; 26–50=good; 51–75=poor; 76–100=very poor;>100=extremely poor.

Table 2

Reference standards and relative weights of water quality parameters

Parameter	Unit	Standard (S_i)	$\frac{1}{S_i}$	Relative weight (W_i)
pH	–	6.5–8.5	0.143	0.118
Cl^-	mg/L	250.00	0.004	0.0000329
NO_3^-	mg/L	50.00	0.020	0.000165
Cr	mg/L	0.05	20.00	0.165
Cu	mg/L	1.00	1.00	0.00823
Zn	mg/L	3.00	0.333	0.00274
Pb	mg/L	0.01	100.00	0.823

2. 5. Statistical analysis

Multivariate statistical analysis was performed with the aid of Microsoft Excel and SPSS 20.0. Cluster analysis (CA) was performed to classify the pollutants. CA group data objects in such a way that objects within a group are similar to one another and different (unrelated) to the objects in other groups. The Hierarchical cluster analysis method was used in this study, and between-groups-linkage was chosen during the classifying procedure. The agglomerative hierarchical clustering approach refers to a collection of closely related clustering techniques that produce a hierarchical clustering by starting with each point as a singleton cluster and then repeatedly merging the two closest clusters until a single, all-encompassing cluster remains [24].

Factor analysis, using the principal component method was also carried out on the data. Principal Component Analysis (PCA) is a special case Factor Analysis that reduces the dimensionality of the data set by transforming the original variables to a new set of variables called principal components that are uncorrelated and ordered such as the first few components retain most of the variations present in the data [25].

3. Results and discussion

3. 1. The пroundwater quality

The descriptive statistics of the analysed water quality parameters in the groundwater of the area are presented in **Table 3**. The pH values ranged from 6.66–7.43, which falls within the WHO standard range of 6.50–8.50. The pH affects the solubility of metals and nutritive chemicals in water and is often used as an indicator of pollution in water [26, 27]. Alkalinity is also a measure of acidity. The values ranged from 0.00–73.00 mg/L, which is also below the maximum standard of 500 mg/L. The levels of Chlorides ranged from 39.98–454.84 mg/L. It shows that 20 % of the water samples exceeded the maximum limit for chloride in drinking water which is 250 mg/L. Chloride has no known health impact but is generally used as an indicator of water pollution [28]. High Chloride concentration in groundwater may indicate either seawater intrusion or the presence of other toxic pollutants [29, 30].

The levels of nitrates in the groundwater (0.724–0.744 mg/L) did not exceed the maximum allowable limit of 50 mg/L set by WHO. Nitrates in drinking water result in blue baby syndrome [31], cardiovascular damage [32], and congenital defects [33]. The values of Cd ranged from 0.001–0.056 mg/L, which shows that 30 % of the water samples exceeded the WHO standard. Health effects of exposure to Cd include nephrotoxicity [34], osteomalacia, and/or osteoporosis [35], cardiovascular effect, and neurological disorders [36]; liver damage, and retarded growth [37].

The results indicate that 10 % of the water samples exceeded the maximum limit for Cr in water. The values ranged from 0.015–0.056 mg/L. exposure to high a concentration of Cr (VI) causes tubular and glomerular damage, liver damage, chronic ulceration, and perforation of nasal septum and other skin surfaces, allergy/asthma [38].

Although Cu is a nutritional supplement and not considered a serious health concern, excess ingestion has been shown to result in gastrointestinal distress, nausea, and diarrhoea [39]. The values in this study ranged from 1.110–2.171 mg/kg. While the levels of Zn (1.020–2.493 mg/L) are all below the maximum limit (3.0 mg/L), 40 % of the samples exceeded the limit for Pb. Zn is a nutritional supplement with no WHO guidelines. However, exposure to an increased level of Zn has been linked to a decrease in high-density lipoprotein (HDL) and a decrease in iron stores [40]. Pb affects mostly infants. It impairs neurodevelopment, interferes with neurotransmitter function, and disrupts calcium metabolism [41].

Table 3

Descriptive statistics of water quality parameters

P	Range	Minimum	Maximum	Mean	Std. Dev.	Variance
pH	0.770	6.660	7.430	7.020	0.274	0.075
Alkal.	73.000	0.000	73.000	35.500	23.560	555.975
Cl^-	414.870	39.980	454.850	163.440	140.15	1964.98
NO_3^-	0.020	0.724	0.744	0.737	0.007	0.000
Cd	0.055	0.001	0.056	0.010	0.018	0.000
Cr	0.041	0.015	0.056	0.03	0.0129	0,000
Cu	1.061	1.110	2.171	1.615	0.486	0.236
Zn	1.473	1.020	2.493	1.643	0.438	0.192
Pb	0.043	0.001	0.044	0.014	0.0133	0.000

Groundwater quality varies spatially in response to local geologic setup and anthropogenic factors [42]. Cluster analysis was used to classify areas with similar changes in groundwater quality and group similar sampling locations based on water quality characteristics. A dendogram in cluster analysis is a useful graphical tool that helps in deciding the number of clusters [43]. The dendogram of the hierarchical cluster analysis presented in **Fig. 1** identified three (3) distinct clusters: Cluster 1 (C1) (A, B, E, G, F, and H), Cluster 2 (C2) (C, J, and I), and Cluster 3 (C3) (D).

C1 is the largest group of sample locations and has the highest level of Cl^-, NO_3^-, Cd, Cr, and Pb (**Table 4**). The sampling locations of C1 has also the highest anthropogenic influence (agricultural and domestic activities). Nitrate is the most important parameter indicating that groundwater is affected by human activities (anthropogenic pollutant is the only source of nitrate in groundwater) [14]. Sources of nitrate in groundwater include agricultural activities such as nitrate-based fertilizers, manure, sewages, landfills, domestic runoff, etc. [11, 29, 44].

Chloride in groundwater occurs as a result of saline intrusion, sewage discharge, irrigation, and refuse leachate [29]. Since there was no possible saltwater intrusion in the area, human activities are the only source of Cl^- in the groundwater of the area. Also predominant in this cluster are the heavy metals Cd, Cr, and Pb which further suggests the impact of anthropogenic activities of this group.

On C2 are sample locations that received less anthropogenic impact than the first cluster. This cluster has the highest average value of Cu and Zn. Cu is mostly a marker for traffic pollutants or industrial pollution [11], while Zn can also be linked to vehicular origin like the tear and wear of tyres [45].

C3 has only one sample location and may be said to be closest to the natural groundwater quality of the area. The acidity values, which are more predominant in this cluster are still within the normal range, hence, there is less anthropogenic impact in this area.

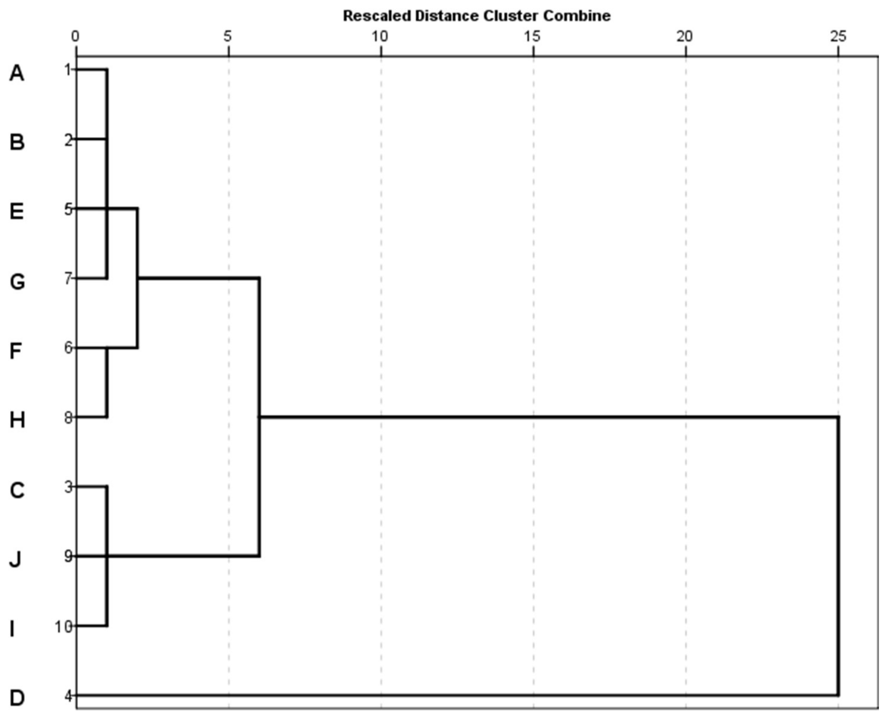

Fig. 1. Dendogram of the hierarchical cluster analysis of the sample locations

To identify the specific water quality class of the various clusters, Water Quality Index (WQI) was calculated, and the results are summarized in **Fig. 2**. The results show that C1 is in the extremely poor class (WQI>100), C2 is in the poor class (51<WQI<75), and C3 is in the good class (26<WQI<50). These results further demonstrate that the order of anthropogenic impact of the clusters is: C1>C2>C1. The parameter that recorded the highest quality rating in all the clusters is Pb. This shows that Pb contributed most to the deterioration of the water quality of the area. This is followed by Cr.

Table 4

Average values of the water quality parameters for each cluster

Parameters	Cluster 1 (A, B, E, G, F, H)	Cluster 2 (C, J, I)	Cluster 3 (D)
pH	6.980	7.060	7.140
Alkal.	20.000	54.000	73.000
Cl^-	219.090	93.300	39.98
NO_3^-	0.739	0.735	0.728
Cd	0.011	0.008	0.004
Cr	0.034	0.022	0.030
Cu	1.641	1.700	1.206
Zn	1.652	1.692	1.441
Pb	0.019	0.007	0.005

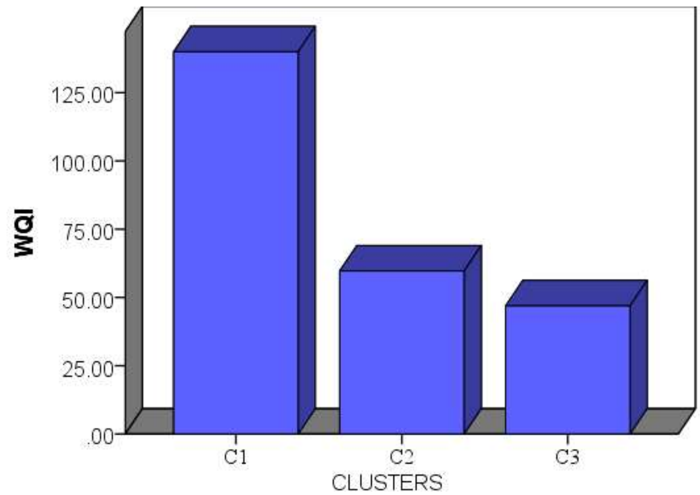

Fig. 2. WQI of the clusters of sampling locations

3. 2. Principal component analysis

Principal components are extracted by the scree plot method considering the eigenvalues greater than 1. Eigenvalues and eigenvectors provide the Eigen decomposition of a matrix, which analyses the structure of this matrix [46]. The calculated component loadings, cumulative percentage, and percentages of variance explained by each component are listed in **Table 5**, while the component plot and scree plot is shown in **Fig. 3**.

The PCA yielded 3 components that explained 72.98 % of the total variance in the data set, indicating that the remaining 27.02 % were not explained by these axes. The first component accounts for 38.85 % of the total variance and has strong positive loadings for pH, Cl^-, Cd, Pb, Cu, and NO_3^-. It also has strong negative loading for Alkalinity. Component two accounts for 19.76 % of the total variance with strong positive loadings for Zn and strong negative loading for Cr, while component 3 accounts for 14.37 % of the total variance and has strong positive loading for Alkalinity and strong negative loading for nitrate.

Component 1 correlates fairly well with C1, which also has the poorest water quality rating. The impact of more anthropogenic pollutants also explains why the component has the least water quality rating. This component embodies agricultural activities, domestic waste, and vehicular/traffic input. It is the highest source of pollutants in the groundwater of the area. Component 2, which can be attributed to vehicular contribution contributed 19.76 % of the total variance. The major contributor to this component is Zn.

Component 3 indicates the natural water quality of the area. It is the component least affected by anthropogenic pollutants and correlates well with C3 with only one sample location. The location is farthest from the city, hence with the least anthropogenic impact. This also explains why it has negative loading for nitrate.

It is pertinent to state that this study is limited by the number and nature of water quality parameters selected for analysis. The degree of accuracy of the pollution source identification processes increases with the number of water quality parameters. Good water quality also does not always translate to no hazard as the result depends on the selected quality parameters. However, the WQI values can be used as a reference or base line for future monitoring of pollution to the groundwater of the area. Source identification on the other hand helps in preventing the spread of pollutants in the aquifer, developing an optimal pollution control strategy, and it is also important for the efficient management of groundwater resources.

Table 5
Principal component loadings for the water quality parameters

Parameters	Component 1	Component 2	Component 3
pH	0.617	–0.047	0.420
Alkalinity	–0.545	0.214	0.683
Chloride	0.933	–0.129	–0.141
Cd	0.780	0.229	0.290
Pb	0.754	0.321	–0.010
Cu	0.744	0.041	0.254
Cr	0.042	–0.925	–0.146
Zn	–0.213	0.833	–0.373
Nitrate	0.416	0.075	–0.568
% of variance	38.85	19.76	14.37
Cumulative %	38.85	58.61	72.97

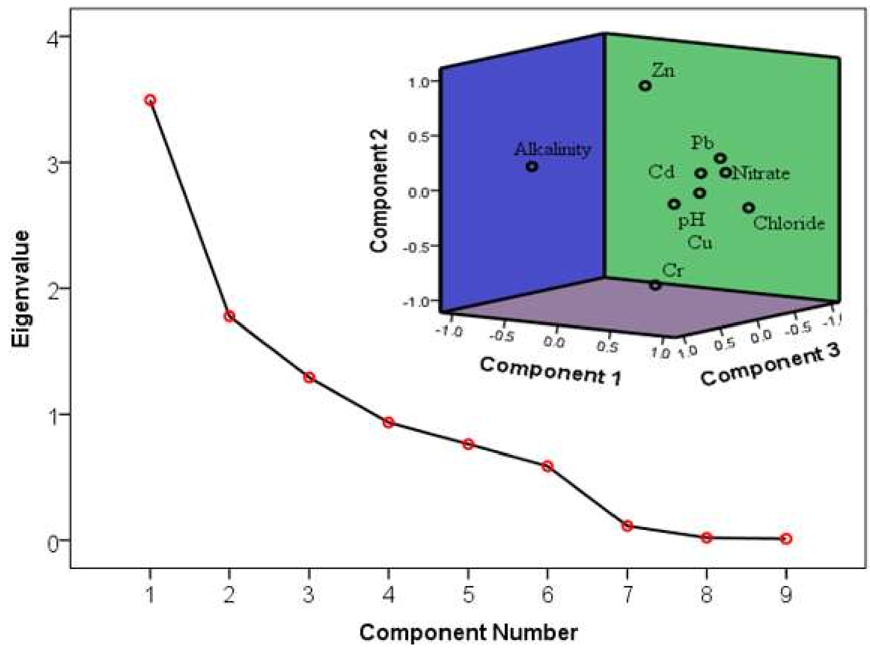

Fig. 3. Component plot and scree plot

4. Conclusions

The dendogram of the hierarchical cluster analysis identified three (3) distinct clusters of sampling locations. C1 is in the extremely poor class (WQI>100), C2 is in the poor class (51<WQI<75), and C3 is in the good class (26<WQI<50).

PCA also identified 3 components. Component 1 accounts for 38.85 % of the total variance, and indicates agricultural activities, domestic waste, and vehicular/traffic input. It is the highest source of pollutants in the groundwater of the area. Component 2, which can be attributed to vehicular contribution contributed 19.76 %, while Component 3, which accounts for 14.37 % of the total variance, indicates the natural water quality of the area.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

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