



Application of artificial neural network and multi-linear regression techniques in groundwater quality and health risk assessment around Egbema, Southeastern Nigeria

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Abstract

This paper examined the efficiency of artificial neural network (ANN) and multivariate linear regression (MLR) models in the prediction of groundwater quality parameters such as ecological risk index (ERI), pollution load index (PLI), metal pollution index (MPI), Nemerow pollution index (NPI), and geoaccumulation index (Igeo). 40 groundwater samples were collected systematically and analyzed for mainly heavy metals. Results revealed that adopting measured parameters is effective in modeling the parameters with high level of accuracy. Contamination factor results reveal that Ni, Zn, Pb, Cd, and Cu have relatively low values < 1 within the region while the Iron values ranged from low contamination to very high contamination (> 6). PLI, MPI, and ERI results indicated low pollution. NPI results indicated that the majority of the samples were heavily polluted. Quantification of Contamination results revealed that most of the sample's quality was geogenically influenced. Igeo results revealed that most of the samples had extreme pollution. The health risk assessment results revealed that children are substantially prone to more health risk more than adults. The ANN and MLR models showed a high effective tendency in the prediction of ERI, PLI, MPI, NPI and Igeo. Principal component analysis results showed appreciable variable loadings while the correlation matrix results reveal that there exists weak and positive correlation amongst elements. Based on the outcome of this study, this research recommends the use of ANN and MLR models in the prediction of groundwater quality parameters as they yielded positive, reliable, acceptable, and appropriate accuracy performances.

Keywords Artificial neural networks · Multi-linear regression · Health risk assessment · Quantification of contamination · Geoaccumulation index · Ecological risk index

Introduction

Groundwater is a significant asset extremely pivotal for the supportability of human existence and the climate. It is trusted that around 65–75% of the earth's assets are water, access to quality water for drinking, homegrown and modern objects is restricted particularly in non-industrial nations (Eyankware et al. 2022a; Akakuru et al. 2022). Groundwater has become a fundamental requirement of life as more than 1.5 billion people around the world rely on groundwater as their primary source of drinking water (He et al. 2019; Agidi et al. 2022). Unfortunately, groundwater resources have faced serious problems in recent years, especially in urban, industrial and commercial areas. Chemicals used in agriculture, such as pesticides, make the groundwater that comes into contact with them undrinkable (Obasi et al. 2020; Opara et al. 2021). The restricted accessibility of

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value water, both in rustic and metropolitan regions is, for the most part, brought about by anthropogenic exercises. The anthropogenic elements which are famous wellsprings of water pollution framework emerge from modern, farming, and homegrown exercises to unfortunate waste administration (Sakram and Adimalla 2018; Eyankware and Akakuru 2022). Then again, the nature of groundwater generally relies upon the substance creation that is available and the focus levels of these synthetic boundaries are significantly gotten from the anthropogenic and land exercises in a specific district or region (Akakuru and Akudinobi 2018; Yahaya et al. 2021). Many elements control the groundwater quality; they incorporate geology, precipitation, mineral structure and dissolvability, oxidization, ionic trade, poor sterile circumstances, poor and uncontrolled composts, and pesticide application with minimal comprehension of substance cosmetics soils (Akakuru et al. 2017; Sakram and Adimalla 2018). Regardless of the overflow of groundwater, it is as yet unusable when its quality is significantly debased by substance defilements with expanding human populace, industrialization, urbanization and the resulting increment for the interest of water for both homegrown and modern purposes, the orderly expansion in the ramifications of dirtied water on man and the climate have been severally contemplated (Egbueri 2019; Barzegar et al. 2019; Akakuru et al. 2021b, 2022; Eyankware et al. 2021). It is important to note that the concentration of heavy metals in groundwater resources has greatly increased due to anthropogenic activities and this poses threat worldwide. In the past 5–6 decades, there has been a high increase in the rate at which humans are exposed to heavy metals and this has been attributed to an exponential increase in heavy metals released from exploration, exploitation, mining, industrial, agricultural processes, technological advancement and her increase in the human population (Opara et al. 2021).

Yang et al. (2019) has reported that two incidences among the top ten (10) global environmental disasters are attributed to contamination by heavy metals. Consequently, the release of large volumes of untreated effluents which contain a high concentration of heavy metals by industries into soils, surface and groundwater resources has further worsened the problem (Tziritis et al. 2017; Akakuru et al. 2021b). The toxic impacts of heavy metals often result from the intake of heavy metals, contaminated food, and water absorption through dermal contact with humans and inhalation of contaminated air. Thus, it is necessary and imperative that the sources, concentration and spread patterns of the heavy metals in surface and groundwater mediums are known; as such will help in sustainable environmental management programmes globally (Zhu et al. 2020). Groundwater contamination has the characteristic of being difficult to find and control (Eyankware et al. 2020, 2021; Akakuru et al. 2021a). In

any case, as of late, with the quick improvement of the general public and the sped-up advancement of urbanization, industrialization, and rural modernization, the effect of human activities has made groundwater defilement a serious level (Sakram and Adimalla 2018; Barzegar et al. 2019; Yahaya et al. 2021).

Human health risk assessment has been utilized to decide whether openness to substance, at any portion, could cause an expansion in the frequency of unfavourable impacts on human wellbeing (Li et al. 2015; Akakuru et al. 2022). Subsequently, people are concerned more about the connection between human wellbeing risk and groundwater contamination than contamination itself, so wellbeing risk evaluation is vital (Akakuru et al. 2022; Eyankware et al. 2022c). Over the most recent couple of years, artificial neural networks (ANNs) have been generally applied in the space of water quality displaying. They are viewed as a forecasting device and have been generally utilized in different fields. They have additionally been utilized in hydrogeology to decide spring boundaries, assess the subjective attributes of groundwater (Hasda et al. 2020; Zhu et al. 2020; Mattas et al. 2019), and foresee groundwater levels (Ghorbanin et al. 2017; Nathan, et al. 2017; Singha et al. 2021). Regression models are best for laying out a relationship among dependent and independent variables, and they are thought of as the least difficult and generally direct type of model. They depend on the technique for least squares and are normally thought of as the main phase of an examination of the relationship among factors (Nathan et al. 2017; Zhu et al. 2020; Hasda et al. 2020).

Locally, several works have been done within the Egbema area in ascertaining the pollution level of groundwater but none has been done to integrate artificial neural networks and multi-linear regression models in the health risk assessment and quantification of contaminants in water resources around Egbema, Nigeria, hence this study which focuses on:

1. Integrating artificial neural networks and multi-linear regression models in the prediction of water quality parameters;
2. Assessing the groundwater quality using multivariate statistics such as principal component analysis (PCA) and correlation matrix;
3. Determining contamination and pollution status of groundwater resources using different models such as contamination factor (CF), pollution load index (PLI), Nemerow Pollution Index (NPI), metal pollution index (MPI), quantification of contamination (QoC), geoaccumulation index (Igeo) and ecological risk index (ERI);
4. To assess the health risk index of groundwater as it affects adults and children.

Materials and methods

The study area

The review area is in the southwestern part of Imo and features the usual boundaries of Owerri to the east, Oguta to the north and Ogbu/Egbema/Ndoni to the southwest of Rivers. In the 2006 assessment, the rating area was rated at 182,500. Occupants, however, as of late because of industrialization and urbanization, the review region has seen an extraordinary flood of populace deluge. The review region exists in Latitudes 4.9412 N to 4.9412 N and Longitudes 66.5382 E to 6.564 E. It covers an area of around 895 km². The review region is to a great extent depleted by Urashi, Oloshi and Nkesa waterways and other occasional streams like Ugbujiagu and Nwagbedokpe streams. There are places in the review area that have important physiographic areas. The undulating wetland plain has something to do with its terrain. The lower land region is to a great extent underlain by the more youthful and approximately combined Benin Formation (Ezeigbo 1987).

Geology

Egbema is located in the eastern part of the Niger Delta Basin and is described by the Niger Delta lithography unit. Units include the Akada, Agbada, and Benin layers of age reduction requirements (Opara et al. 2021). The total width of the Tertiary debris is about 10,000 m, and all drill holes in the test area have evolved into a young Benin layer. Miocene-late developments generally consist of medium to coarse-grained sand units, with rocks properly placed at adjacent focal points of poorly consolidated sand and mud. The collaboration of sand and Earth in space shows a multi-spring framework. These sources are separated by a ground bond and their thickness determines the thickness of the aquifer in a particular well. Heavy rains in this area give the spring ample new energy (Aniwetalu and Akakuru 2015). The Niger Delta Basin otherwise called the Niger Delta territory, is an augmentation at the right bowl situated in the Niger Delta and bay of guinea on the detached mainland area close to the western bank of Nigeria with the thought or demonstrated admittance to Cameroon, Equatorial Guiana and Sao Tome and Principe. The bowl is extremely perplexing, and it conveys high monetary worth as it contains an exceptionally useful oil framework. The Niger Delta is one of the biggest sub-areas with around 75,000 km², all-out areas of 300,000 km², and a silt fill of 500,000 km³ (Urom et al. 2021). The Niger Delta Basin was formed by crushed joints that were shocked during the division of the South American Plate,

and the African Plate of the South Atlantic began to open. This shell collapse began in the late Jurassic and ended in the middle Cretaceous. As breaking proceeded with a few issues framed large numbers of the push blames likewise of this time syn-fracture sands and afterwards shale were stored in the late cretaceous (Ezeigbo 1987; Aigbadon et al 2022a, b; Onyekuru et al 2021).

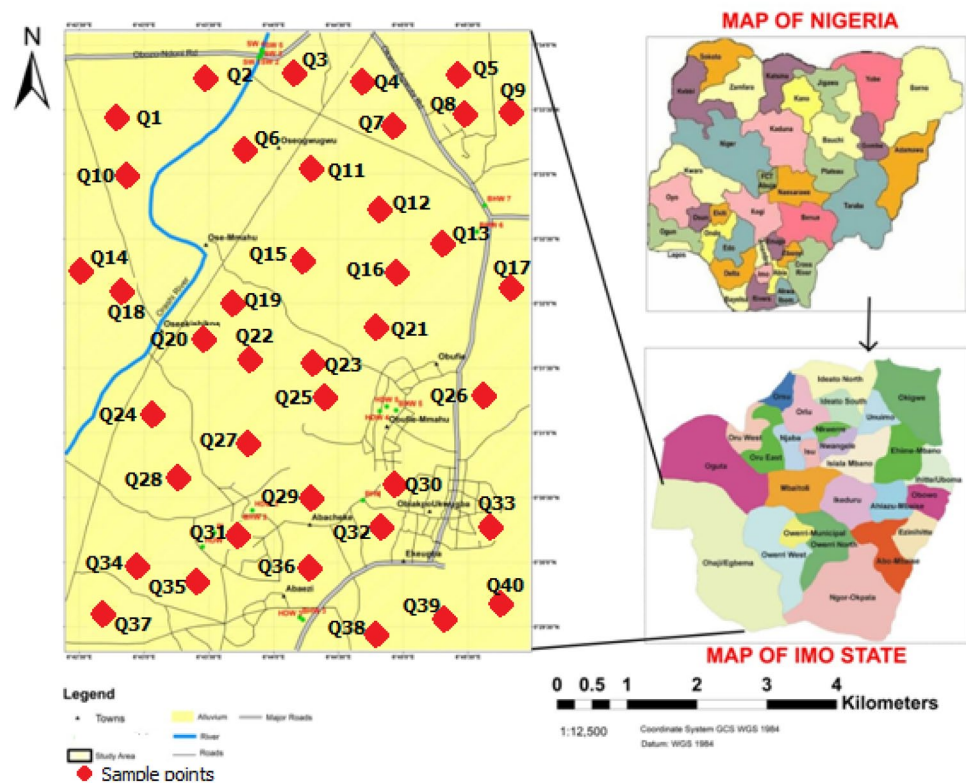
Water sample collection and analysis

After assortment, the examples were housed in polypropylene measuring utensils for assessment. The example measuring utensils/holders to be used were very much scrubbed and inundated in refined water fermented with 1.0 ml of HNO₃ for three (3) days before the field inspecting exercise. A sum of 40 water tests was accumulated efficiently from different water sources across the review region (see Fig. 1). To acquire a delegate test that truly addresses the water assets, borehole tests were gathered following 5–10 min of siphoning. After rinsing the container with aliquots, each sample was strained into a sample bottle using a 0.45 m gauge disposable channel to ensure that all floating contaminants were completely removed. Field samples were treated with 1.0 ml concentrate to limit heavy metal precipitation. HNO₃; Added 3 drops of HNO₃ using a new needle to avoid accretion. Purchased samples were properly stored at a temperature of 4° C in a tightly packed ice-filled container. On the way to the logic lab, the temperature was kept constant to prevent heat dissipation (Singh et al. 2005; Sehgal et al. 2012). Examples were synthetically analyzed for heavy metals Ni, Fe, Cu, Zn, Cd, and Pb using a fast continuous (FS) atomic absorption spectrophotometer (Varian 240 AA). All tests were performed according to the APHA specification (APHA 2012).

Artificial neural networks (ANNs)

ANN is used as a traditional insight-enhancing strategy and, as an extreme goal, contributes to the refinement and capacity of exploratory information and the transformation into structures of value that clients can process (Zhu et al. 2020; Mattas et al. 2019). A typical ANN consists of artificial processing elements called neurons or nodes connected by synapses. Neurons are collected in layers and data encoding is done in the most common way of preparation and learning. This structure is a widely involved model in hydrogeological applications with the ability to recognize designs between boundaries. The most capable exchange capabilities are the sigmoid logistic and hyperbolic tangent functions implemented in most ANN models (Hasda et al. 2020). Guided preparation depends on an "external educator" who gives objective value to each stage of preparation. The model

Fig. 1 Geological map of the region with sample locations



understands how to change the synaptic load by thinking about the goal. The goal is to limit the error by searching for the ideal load (Ghorbanin et al. 2017; Nathan, et al. 2017; Singha et al. 2021). The standard measurable criterion used to assess ANN performance is mean squared error (MSE). This combines the predicted and ideal outcomes, as well as the confidence level (R^2). The current review used a computational ANN model of feedforward, management, and back-generation learning to predict groundwater ERI. The ANN model consisted of a six-component information layer (Ni, Fe, Zn, Pb, Cd, and Cu), a three-hub secret layer, and a result layer for which an EC rating was determined. Of the complete examples, 70% were used for setup and 30% were used for testing. Certain fake brain network structures were chosen in the process of using "experimental" techniques by changing the boundaries of information (number of neurons pushed in, number of hubs, percentage of pretest sets, etc.). Because I got the best presentation at.

Multiple linear regression (MLR)

MLR is considered to be a very valuable and accurate tool for establishing connections between reliable variables

and various free factors considered indicators (Hasda et al. 2020). Various developers have effectively used this strategy in hydrogeology and hydrology to predict water quality and create factual models (Ghorbanin et al. 2017; Nathan et al. 2017). In this paper, a condition for assuming electrical conductivity using MLR have been created. Indicators were selected during the implementation of the Pearson relational coefficients because the selection of appropriate indicator coefficients is important for further developing the prediction level and narrowing down the required datasets (Singha et al. 2021). Connection factor (Pearson) is a fact-based tool commonly used to quantify and model the interrelationship and robustness design between two elements. MLR condition is introduced in condition 1.

$$Y = k + a(\text{Ni}) + b(\text{Fe}) + c(\text{Zn}) + d(\text{Pb}) + e(\text{Cd}) + f(\text{Cu}) + \epsilon \quad (1)$$

where $Y = \text{ERI, PLI, MPI, NPI, Igeo}$, $k = \text{regression constant}$, $\epsilon = \text{error}$, a, b, c, d, e, f , are coefficient of predictors in the model.

Ni, Fe, Zn, Pb, Cd, and Cu are input parameters.

Model performance

The performance of the model and the predictive power of the model were evaluated using R^2 . This emphasizes the magnitude of the percentage of variation in the y-axis variable explained by the x-axis variable. The range is 0 to 1. Mean Absolute Percentage (MAPE, %) is a measure of the prediction accuracy of the prediction method as defined in Eq. (2):

$$\text{MAPE} = \frac{100}{N} \sum \left| \frac{A_t - F_t}{A_t} \right|, \quad (2)$$

where A_t is the actual value, F_t is the predicted value, and n is the number of samples. The root mean square error (RMSE) is the root mean square of the total error (Eq. (3)):

$$\text{RMSE} = \sqrt{\frac{\sum (S_i - O_i)^2}{n}}, \quad (3)$$

where O_i is the observed value, S_i is the predicted value of the variable, and n is the number of observed values. Therefore, RMSE is a good measure of accuracy, but not between variables, but only to compare the prediction errors of different models or model configurations of a particular variable.

Water pollution indexes calculation

Contamination factor (CF)

CF in this study was determined by utilizing the Hakanson (1980) recipe

$$\text{CF} = \frac{C_k}{B_k}, \quad (4)$$

where C_k is the metal concentration and B_k is the background/target level (Eyankware and Akakuru 2022).

Pollution load index (PLI)

Hakanson's (1980), Eyankware and Akakuru (2022) equation was utilized to compute the PLI.

$$\text{PLI} = \sqrt[n]{\text{CF}_1 \times \text{CF}_2 \times \text{CF}_3 \times \dots \times \text{CF}_n} \quad (5)$$

Nemerow pollution index (NPI)

$\text{NPI} (PI_{\text{Nemerow}})$ assess the overall level of soil contamination and take into account the levels of all heavy metals tested (Gong et al. 2008). Calculated using the following formula:

$$PI_{\text{Nemerow}} = \sqrt{\frac{\left(\frac{1}{n} \sum_{i=1}^n PI \right)^2 + PI_{\text{max}}^2}{n}}. \quad (6)$$

Metal pollution index (MPI)

The integrated effects of individual heavy metals on water quality were determined by MPI (Horton 1965; Eyankware and Akakuru 2022; Caeiro et al. 2005). Equation 7:

$$\text{MPI} = \sqrt[4]{M_1 \times M_2 \times M_3 \times \dots \times M_n}. \quad (7)$$

Quantification of contamination (QoC)

QoC has since been adopted as a contamination appraisal procedure integrated to decide the wellspring of a toxin (geogenic or anthropogenic). QoC was determined by the use of using Eq. 8

$$\frac{C_n - B_n}{C_n} \times \frac{100}{1}. \quad (8)$$

Geoaccumulation index (Igeo)

This is the rating level that made it possible to determine toxic substances by the Geoaccumulation Index (Igeo). According to Eyankware and Akakuru (2022), it is calculated as follows.

$$\text{Igeo} = \log_2 \frac{C_n}{1.5B_n}. \quad (9)$$

C_n represents the content of toxic metal n , B_n represents the background of toxic metal n , with 1.5 being a possible factor.

Potential ecological risk index (ERI)

$$E_r^i = C_f^i * T_r^i = T_r^i * C_i / C_b. \quad (10)$$

ERI was first proposed by Hakanson (1980).

where E_r^i represents the ERI of metal i^{th} ; T_r^i is i^{th} metal response factor to toxic. T_r^i of Zn, Cr, Pb, Cu, Ni, and Cd are 1, 2, 5, 5, 5 and 30, respectively (Islam et al. 2015; Mgbenue and Egberi 2019). The C_f^i is the contamination factor.

$$\text{RI} = \sum_i^n E_r^i \quad (11)$$

Health risk assessment

Evaluation of exposure

An important route of exposure of dissected trace components (Ni, Fe, Zn, Pb, Cd, and Cu) is usually by ingestion (Mgbenu and Egbueri 2019). Thus, the openness of the human, two child, and adult populations to these factors was measured using the chronic daily intake (CDI) given in Eqs. (1)... (12) (USEPA 1989; Mgbenu and Egbueri 2019). Where CDI (mg/kg/day); Cw stands for trace element concentration in water (mg/l). IRW is the water intake rate (IRW = 2L for adults, 1L for children). EF is the frequency of exposure (EF is usually equal to 365 days). ED is the duration of exposure (adult ED = 70 years, child ED = 6 years). BW is weight (adult BW = 70 kg; child BW = 15 kg); AT is average exposure time (adult AT = 25,550 days, child AT = 2190 days) (USEPA 1989; Mgbenu and Egbueri 2019).

Non – carcinogenic risk assessment (CDI)

$$= \frac{(CW * IRW * EF * ED)}{BW * AT} \quad (12)$$

The element's CDI was evaluated in terms of the Health Hazard Index (HQ) and the Health Hazard Index (HI). These are given by Eqs. (1), (13) and (14), respectively.

$$HQ = \frac{CDI}{RFD}, \quad (13)$$

where RfD addresses the reference portion of a particular component (mg/kg/day). The RfD for the minor components is: 0.7 (Fe), 0.3 (Zn), 0.0035 (Pb), 0.04 (Cu), 0.02 (Ni) and 0.0005 (Cd) (Mgbenu and Egbueri 2019).

$$HI = \sum HQ. \quad (14)$$

Multivariate analysis

Pearson's correlation coefficient was calculated using the Social Science Statistics Package (SPSS) version 17.0 and the PCA. R-Studio version 1.1456 software was used to model the ANN and MLR.

Results and discussion

The results of CF, PLI, MPI, ERI, and NPI are presented in Table 1.

CF

The CF reflects the pollution caused by focusing on the area. It shows a history of unique impurities in certain metals in biological media. The degree of heavy metal fixation at the base convergence of heavy metals was evaluated as a pollutant factor (Ogundele et al. 2017). CF has been used in groundwater studies to obtain the focal ratio of heavy metals to foundation values. The included model is used to show the benefits of the fouling factor. $CF < 1$, less fouling. $1 \leq CF \leq 3$, moderate contamination; $3 \leq CF \leq 6$, severe contamination; $CF > 6$, very high contamination (Bhutan et al. 2017; Akakuru et al. 2021a, b). The CF shown in Table 1 of this review indicates that Ni, Zn, Pb, Cd, and Cu generally have a low fixation of less than 1 over the entire range. Fe concentrations range from low impurities to very high impurities (> 6). Iron in rustic groundwater supplies is a typical issue: its focus level reaches from 0 to 50 mg/l, while the WHO suggested level is < 0.3 mg/l. The iron happens normally in the aquifer, however, levels in groundwater can be expanded by the disintegration of ferrous borehole and hand pump parts. Iron-bearing groundwater is much of the time perceptibly orange in variety, causing staining of clothing, and has an upsetting taste, which is obvious in drinking and food arrangement. Fe broke up in groundwater is in the decreased iron II structure. This structure is solvent and ordinarily creates no issues without help from anyone else. Iron II is oxidized to press III in contact with oxygen in the air or by the activity of iron-related microscopic organisms. Iron III structures insoluble hydroxides in water. These are corroded red and cause staining and blockage of screens, siphons, pipes, reticulation frameworks and so forth. If the iron hydroxide stores are created by iron microorganisms, they are likewise tacky and the issues of stain and blockage are ordinarily more awful. This finding is like that of Bhutian et al. (2017) in India and Nigeria (Yahaya et al. 2021).

PLI

PLI is an important tool for determining the level of heavy metal contamination in samples (Akakuru, et al. 2021a; Yang et al. 2019). PLI is usually categorized as uncontaminated ($PLI < 1$), moderately contaminated ($PLI > 2$), severely contaminated ($2 < PLI < 3$), or very severely contaminated ($3 > PLI$). According to the results (Table 1), the groundwater concentration value in the survey area was $PLI < 1$. Therefore, there is no pollution. This study contradicts a review attempted in India (Gopinath et al. 2019; Bhutian

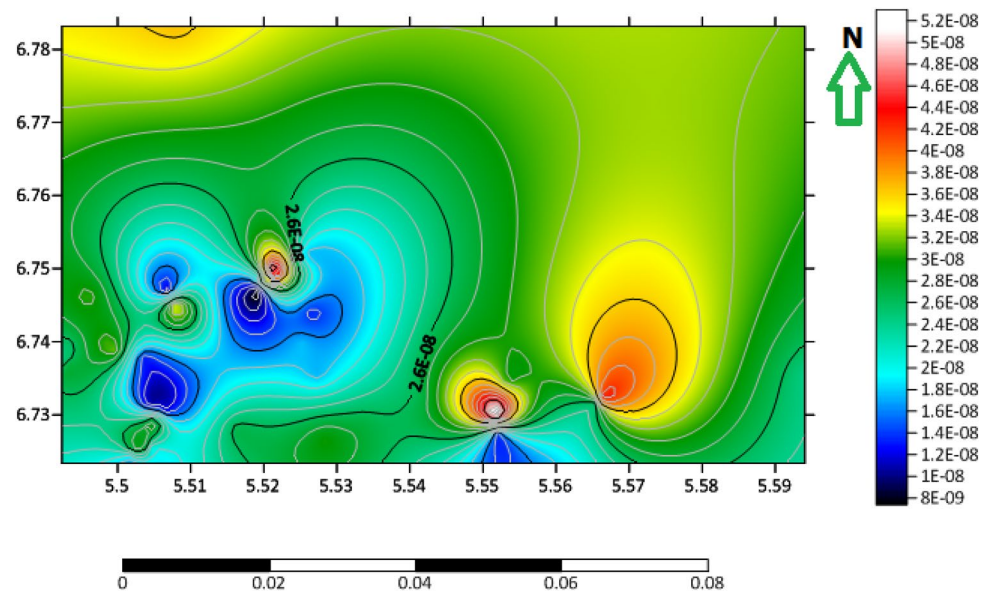
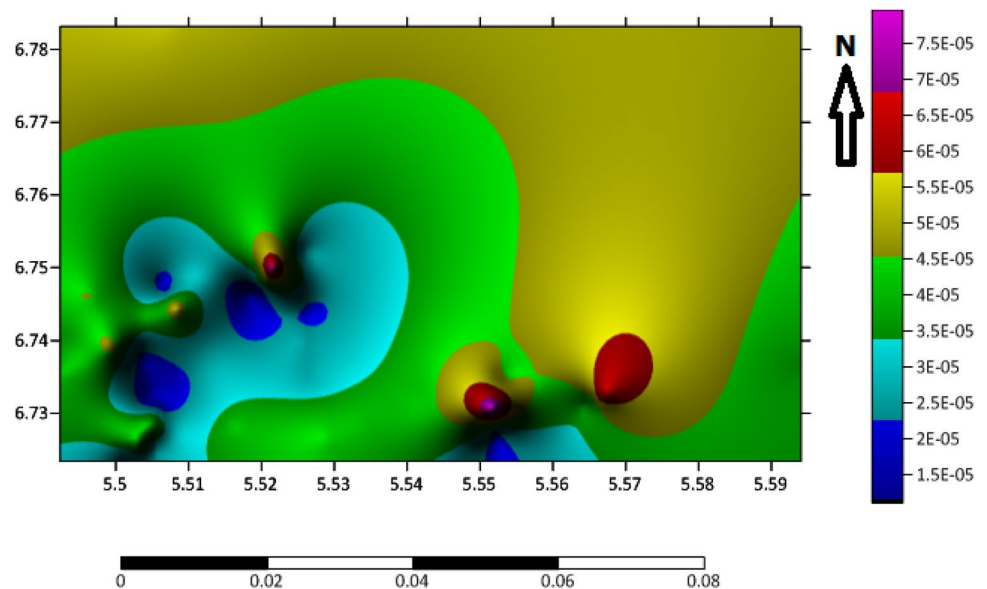
Table 1 CF, PLI, MPI, ERI and NPI of groundwater samples

	Contamination factor						PLI	MPI	ERI	NPI
	Ni	Fe	Zn	Pb	Cd	Cu				
Q1	0.000143	6.25	0.000143	0.0001	0.025	0.000833	1.63E-08	2.45E-05	7.005524	4.541524
Q2	7.14E-05	14	7.14E-05	0.0001	0.025	0.000833	1.22E-08	1.83E-05	14.7551	10.17176
Q3	7.14E-05	41.25	7.14E-05	0.0001	0.025	0.001111	2.42E-08	3.63E-05	42.00648	29.96844
Q4	7.14E-05	1.75	7.14E-05	0.0001	0.0375	0.001111	6.1E-09	9.17E-06	2.881484	1.272847
Q5	0.000143	31.5	0.000143	0.0001	0.025	0.000556	2.99E-08	4.49E-05	32.25413	22.88521
Q6	0.000143	39	7.14E-05	0.0001	0.025	0.000833	2.88E-08	4.33E-05	39.75545	28.33384
Q7	0.000143	17.25	7.14E-05	0.0001	0.0625	0.000833	3.03E-08	4.55E-05	19.13045	12.53427
Q8	0.000143	22.25	7.14E-05	0.0001	0.0625	0.000556	2.81E-08	4.22E-05	24.12906	16.16668
Q9	7.14E-05	42	7.14E-05	0.0002	0.0375	0.000833	3.66E-08	5.5E-05	43.1306	30.51377
Q10	7.14E-05	55	7.14E-05	0.0002	0.0125	0.000833	2.42E-08	3.63E-05	55.3806	39.9571
Q11	7.14E-05	43.5	7.14E-05	0.0002	0.0125	0.001111	2.48E-08	3.73E-05	43.88198	31.60255
Q12	0.000143	33.25	7.14E-05	0.0001	0.05	0.000556	3.07E-08	4.61E-05	34.75406	24.15751
Q13	0.000143	26.5	0.000143	0.0001	0.05	0.000833	4.75E-08	7.13E-05	28.00552	19.25376
Q14	0.000143	20.5	0.000143	0.0001	0.025	0.000833	2.95E-08	4.44E-05	21.25552	14.89391
Q15	0.000143	22	7.14E-05	0.0001	0.0375	0.001111	3.06E-08	4.6E-05	23.13184	15.98412
Q16	7.14E-05	11.75	7.14E-05	0.0001	0.025	0.000833	1.12E-08	1.68E-05	12.5051	8.537175
Q17	7.14E-05	8	0.000143	0.0001	0.025	0.000833	1.3E-08	1.96E-05	8.755167	5.812867
Q18	7.14E-05	22.25	0.000143	0.0001	0.025	0.000556	1.78E-08	2.67E-05	23.00378	16.16524
Q19	7.14E-05	15.25	7.14E-05	0.0001	0.025	0.000556	1.04E-08	1.56E-05	16.00371	11.07986
Q20	7.14E-05	40.25	7.14E-05	0.0001	0.0375	0.001111	2.93E-08	4.4E-05	41.38148	29.24243
Q21	7.14E-05	23.25	0.000143	0.0001	0.0375	0.000833	2.72E-08	4.09E-05	24.38017	16.89221
Q22	7.14E-05	15.25	7.14E-05	0.0001	0.025	0.000833	1.27E-08	1.91E-05	16.0051	11.07987
Q23	7.14E-05	23	0.000143	0.0001	0.0125	0.000556	1.28E-08	1.92E-05	23.37878	16.70962
Q24	7.14E-05	11.25	7.14E-05	0.0001	0.0625	0.000833	1.73E-08	2.6E-05	13.1301	8.175373
Q25	0.000143	47.5	7.14E-05	0.0002	0.0125	0.000833	3.18E-08	4.77E-05	47.88095	34.50848
Q26	7.14E-05	30.25	7.14E-05	0.0001	0.05	0.000833	2.54E-08	3.81E-05	31.7551	21.97807
Q27	7.14E-05	22.5	0.000143	0.0002	0.0625	0.001111	5.65E-08	8.49E-05	24.38206	16.34832
Q28	7.14E-05	32.75	0.000143	0.0001	0.025	0.000833	2.64E-08	3.96E-05	33.50517	23.79332
Q29	7.14E-05	55.5	7.14E-05	0.0001	0.025	0.000556	1.98E-08	2.98E-05	56.25371	40.3208
Q30	7.14E-05	37.25	7.14E-05	0.0001	0.0125	0.000833	1.41E-08	2.11E-05	37.6301	27.06202
Q31	7.14E-05	19	7.14E-05	0.0002	0.0375	0.001111	2.84E-08	4.27E-05	20.13198	13.80467
Q32	0.000143	19	7.14E-05	0.0001	0.0625	0.001111	3.67E-08	5.51E-05	20.88184	13.80563
Q33	7.14E-05	54	0.000143	0.0002	0.0125	0.000556	2.77E-08	4.16E-05	54.37928	39.23061
Q34	7.14E-05	21.75	0.000143	0.0002	0.0125	0.000556	1.76E-08	2.64E-05	22.12928	15.80152
Q35	0.000143	32.25	7.14E-05	0.0002	0.0375	0.001111	5.24E-08	7.87E-05	33.38234	23.43057
Q36	0.000143	29.25	7.14E-05	0.0001	0.05	0.000556	2.88E-08	4.33E-05	30.75406	21.25158
Q37	0.000143	8	0.000143	0.0001	0.05	0.001111	3.01E-08	4.53E-05	9.506913	5.81384
Q38	7.14E-05	13.75	0.000143	0.0001	0.05	0.000833	2.42E-08	3.63E-05	15.25517	9.991103
Q39	7.14E-05	41	0.000143	0.0001	0.025	0.000556	2.41E-08	3.62E-05	41.75378	29.7868
Q40	7.14E-05	17	0.000143	0.0001	0.0375	0.001111	2.69E-08	4.04E-05	18.13156	12.3517

et al. 2017), which found out elevated PLI values in groundwater sources, but it is reliable to the work done in Nigeria by Yahaya et al. (2021). Figure 2 shows the spatial distribution of PLI within the region.

MPI

MPI is an important tool for mapping groundwater. Water with an MPI of 0.3 or less is said to be very pure, while

Fig. 2 PLI distribution within the area**Fig. 3** MPI distribution within the area

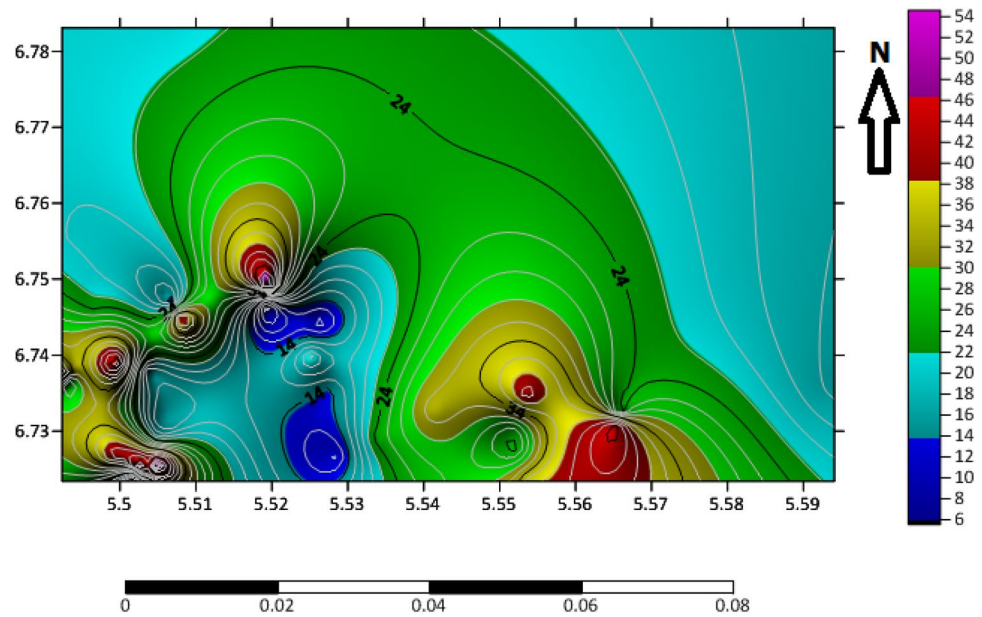
water with an MPI of 0.3–1.0 is said to be pure. Persons with an MPI of 1.0–2.0 are classified as Class III unrelated torture, and Class IV individuals are classified as truly affected. Appropriately affected by MPIs from 2.0 to 4.0. Water quality tests using MPIs ranging from 4.0 to 6.0 are said to be fully affected in Class V, and water quality tests with $MPI > 6.0$ are said to be truly affected in Class VI (Singovszka et al. 2017). According to MPI Table 1, groundwater tests at the site reached values below 0.3. This indicates that it is class I and is, therefore, particularly pure. This result commends PLI's follow-up in this study, where no contamination was detected. This work is similar to the review in Nigeria (Akakuru and Akudinobi 2018; Eyankware et al.

2020; Eyankware and Akakuru 2022). Figure 3 shows the distribution of MPI within the study area.

ERI

The ERI record was developed by Hakanson (1980), a Swedish researcher. It had been utilized to assess the antagonistic impacts of the impurities on the climate and humans and mirrors the harmfulness and natural awareness of the convergence of pollutants (Suresh et al. 2012). Initially, it was used as a tool for assessing silt pollution in oceanic climates. Used for soil, residue and air risk assessment (Qingjie et al. 2008; Suresh et al. 2012; Iqbal and Shah 2014; Ogunkunle

Fig. 4 ERI distribution within the area



et al. 2015; Riyad et al. 2015; Osipova et al. 2016). $ERI < 40$ means low ecological risk, $40 \leq ERI < 80$ means moderate ecological risk, $80 \leq ERI < 160$ means significant ecological risk, $160 \leq ERI < 600$ means very high ecological risk. The results in Table 1 show that 82.5% of all samples are within the range of low ecological risk and 17.5% have moderate ecological risk. The results are consistent with the CF, PLI, and MPI performed in this study, indicating minimal exposure to heavy metals. Heavy metal pollution in groundwater addresses the threat to climate and food security due to the rapid development of industry and agriculture and the disruption of normal biological systems due to human pressures associated with population growth (Sarwar et al. 2017;

Agidi et al. 2022; Akakuru et al. 2022). Ecological pollution and human openness to heavy metals stem from a variety of human practices, including mining, modern creation, and the use of metal-containing compounds in traditional and rural environments (Tchounwou et al. 2012). Figure 4 shows the spatial distribution of ERI in the region.

PNI

The Nemerow pollution index was used to understand the overall degree of pollution. This method provides a reasonable interpretation of the heavy metal load across each site, as different heavy metals can affect the site.

Fig. 5 PNI distribution within the area

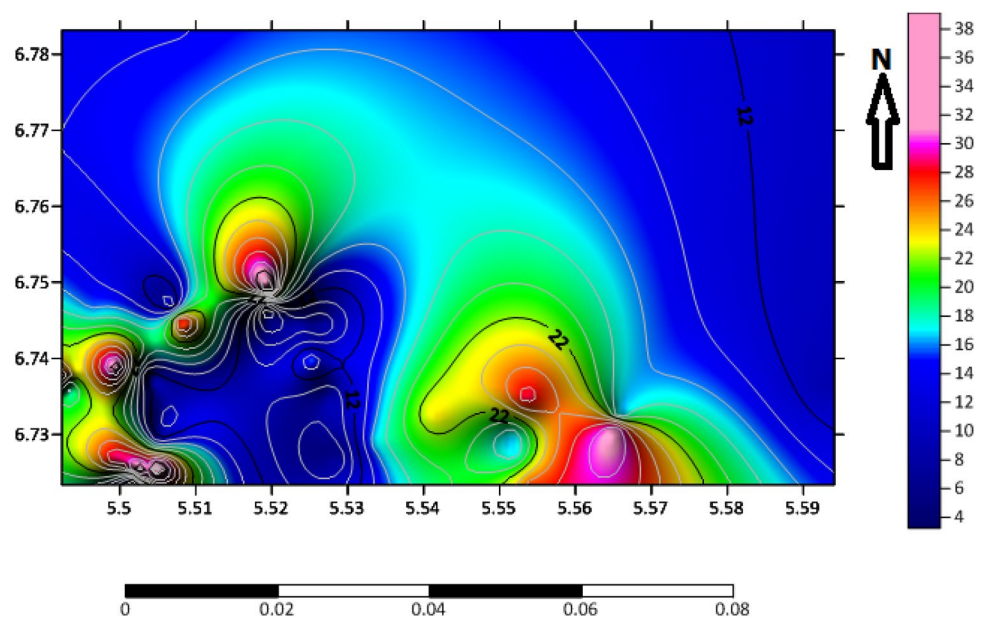


Table 2 Quantification of contamination (QoC)

	Ni	Fe	Zn	Pb	Cd	Cu
Q1	– 700,000	– 15.75	– 700,000	– 1,000,000	– 3999.98	– 120,000
Q2	– 1,400,000	– 6.58286	– 1,400,000	– 1,000,000	– 3999.98	– 120,000
Q3	– 1,400,000	– 0.77424	– 1,400,000	– 1,000,000	– 3999.98	– 90,000
Q4	– 1,400,000	– 57.0729	– 1,400,000	– 1,000,000	– 2666.64	– 90,000
Q5	– 700,000	– 1.9146	– 700,000	– 1,000,000	– 3999.98	– 180,000
Q6	– 700,000	– 1.0041	– 1,400,000	– 1,000,000	– 3999.98	– 120,000
Q7	– 700,000	– 5.1071	– 1,400,000	– 1,000,000	– 1599.95	– 120,000
Q8	– 700,000	– 3.60438	– 1,400,000	– 1,000,000	– 1599.95	– 180,000
Q9	– 1,400,000	– 0.70095	– 1,400,000	– 500,000	– 2666.64	– 120,000
Q10	– 1,400,000	0.381818	– 1,400,000	– 500,000	– 7999.99	– 120,000
Q11	– 1,400,000	– 0.55885	– 1,400,000	– 500,000	– 7999.99	– 90,000
Q12	– 700,000	– 1.67752	– 1,400,000	– 1,000,000	– 1999.96	– 180,000
Q13	– 700,000	– 2.71358	– 700,000	– 1,000,000	– 1999.96	– 120,000
Q14	– 700,000	– 4.05805	– 700,000	– 1,000,000	– 3999.98	– 120,000
Q15	– 700,000	– 3.66545	– 1,400,000	– 1,000,000	– 2666.64	– 90,000
Q16	– 1,400,000	– 8.04064	– 1,400,000	– 1,000,000	– 3999.98	– 120,000
Q17	– 1,400,000	– 12.18	– 700,000	– 1,000,000	– 3999.98	– 120,000
Q18	– 1,400,000	– 3.60438	– 700,000	– 1,000,000	– 3999.98	– 180,000
Q19	– 1,400,000	– 5.94738	– 1,400,000	– 1,000,000	– 3999.98	– 180,000
Q20	– 1,400,000	– 0.87447	– 1,400,000	– 1,000,000	– 2666.64	– 90,000
Q21	– 1,400,000	– 3.37108	– 700,000	– 1,000,000	– 2666.64	– 120,000
Q22	– 1,400,000	– 5.94738	– 1,400,000	– 1,000,000	– 3999.98	– 120,000
Q23	– 1,400,000	– 3.42783	– 700,000	– 1,000,000	– 7999.99	– 180,000
Q24	– 1,400,000	– 8.43889	– 1,400,000	– 1,000,000	– 1599.95	– 120,000
Q25	– 700,000	– 0.20526	– 1,400,000	– 500,000	– 7999.99	– 120,000
Q26	– 1,400,000	– 2.09579	– 1,400,000	– 1,000,000	– 1999.96	– 120,000
Q27	– 1,400,000	– 3.54444	– 700,000	– 500,000	– 1599.95	– 90,000
Q28	– 1,400,000	– 1.74344	– 700,000	– 1,000,000	– 3999.98	– 120,000
Q29	– 1,400,000	0.418198	– 1,400,000	– 1,000,000	– 3999.98	– 180,000
Q30	– 1,400,000	– 1.19456	– 1,400,000	– 1,000,000	– 7999.99	– 120,000
Q31	– 1,400,000	– 4.50316	– 1,400,000	– 500,000	– 2666.64	– 90,000
Q32	– 700,000	– 4.50316	– 1,400,000	– 1,000,000	– 1599.95	– 90,000
Q33	– 1,400,000	0.308148	– 700,000	– 500,000	– 7999.99	– 180,000
Q34	– 1,400,000	– 3.7277	– 700,000	– 500,000	– 7999.99	– 180,000
Q35	– 700,000	– 1.81078	– 1,400,000	– 500,000	– 2666.64	– 90,000
Q36	– 700,000	– 2.2488	– 1,400,000	– 1,000,000	– 1999.96	– 180,000
Q37	– 700,000	– 12.18	– 700,000	– 1,000,000	– 1999.96	– 90,000
Q38	– 1,400,000	– 6.72273	– 700,000	– 1,000,000	– 1999.96	– 120,000
Q39	– 1,400,000	– 0.79902	– 700,000	– 1,000,000	– 3999.98	– 180,000
Q40	– 1,400,000	– 5.20235	– 700,000	– 1,000,000	– 2666.64	– 90,000

Bold values indicate positive values

PNI value of ≤ 0.7 signifies that the water is clean, PNI value of $0.7 < \text{PNI} \leq 1.0$ implies slightly clean, PNI value of $1.0 < \text{PNI} \leq 2.0$ implies slightly polluted, PNI value of $2.0 < \text{PNI} \leq 3.0$ implies moderately polluted, while PNI value of > 3.0 implies heavy pollution. From the results in Table 1, it shows that 2.5% of the entire sample had a value less than 0.7, implying clean water, while 97.5% of

the entire sample are > 3 , implying that the samples are heavily polluted. Anthropogenic factors could be responsible for the high levels of pollution seen in this study. This finding contradicts a study conducted in Nigeria (Agidi 2022; Eyankware et al. 2022a, b, c). The spatial distribution of PNI within the region is presented in Fig. 5.

Table 3 Geoaccumulation Index

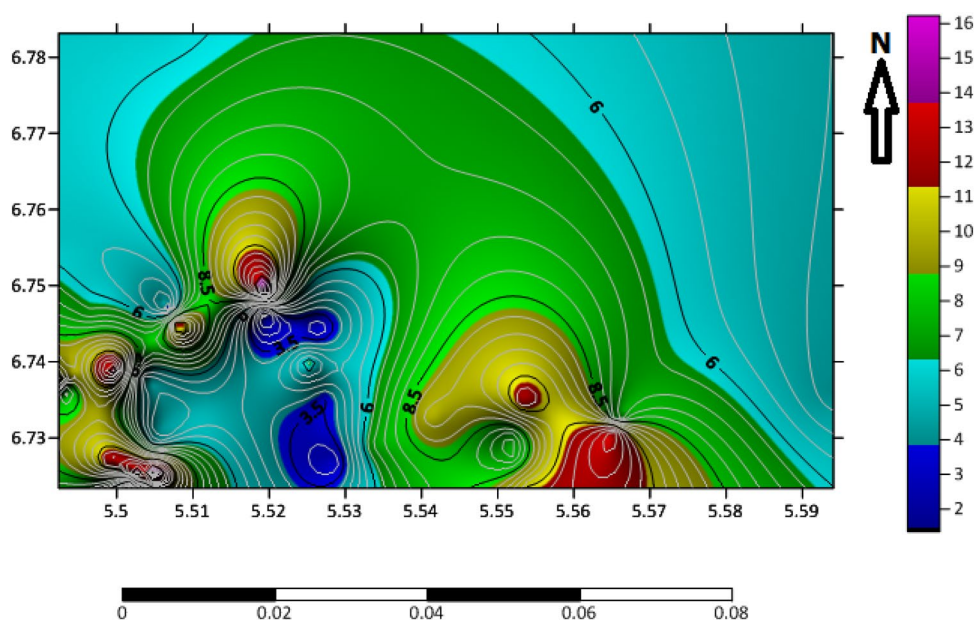
	Ni	Fe	Zn	Pb	Cd	Cu	Igeo
Q1	4.30043E-05	1.881437	4.3E-05	3.01E-05	0.007526	0.000251	1.88933
Q2	2.15021E-05	4.21442	2.15E-05	3.01E-05	0.007526	0.000251	4.22227
Q3	2.15021E-05	12.41749	2.15E-05	3.01E-05	0.007526	0.000334	12.42542
Q4	2.15021E-05	0.526802	2.15E-05	3.01E-05	0.011289	0.000334	0.538499
Q5	4.30043E-05	9.482445	4.3E-05	3.01E-05	0.007526	0.000167	9.490254
Q6	4.30043E-05	11.74017	2.15E-05	3.01E-05	0.007526	0.000251	11.74804
Q7	4.30043E-05	5.192767	2.15E-05	3.01E-05	0.018814	0.000251	5.211927
Q8	4.30043E-05	6.697917	2.15E-05	3.01E-05	0.018814	0.000167	6.716994
Q9	2.15021E-05	12.64326	2.15E-05	6.02E-05	0.011289	0.000251	12.6549
Q10	2.15021E-05	16.55665	2.15E-05	6.02E-05	0.003763	0.000251	16.56077
Q11	2.15021E-05	13.0948	2.15E-05	6.02E-05	0.003763	0.000334	13.09901
Q12	4.30043E-05	10.00925	2.15E-05	3.01E-05	0.015051	0.000167	10.02456
Q13	4.30043E-05	7.977295	4.3E-05	3.01E-05	0.015051	0.000251	7.992713
Q14	4.30043E-05	6.171115	4.3E-05	3.01E-05	0.007526	0.000251	6.179008
Q15	4.30043E-05	6.62266	2.15E-05	3.01E-05	0.011289	0.000334	6.634378
Q16	2.15021E-05	3.537102	2.15E-05	3.01E-05	0.007526	0.000251	3.544952
Q17	2.15021E-05	2.40824	4.3E-05	3.01E-05	0.007526	0.000251	2.416111
Q18	2.15021E-05	6.697917	4.3E-05	3.01E-05	0.007526	0.000167	6.705705
Q19	2.15021E-05	4.590707	2.15E-05	3.01E-05	0.007526	0.000167	4.598474
Q20	2.15021E-05	12.11646	2.15E-05	3.01E-05	0.011289	0.000334	12.12815
Q21	2.15021E-05	6.998947	4.3E-05	3.01E-05	0.011289	0.000251	7.010581
Q22	2.15021E-05	4.590707	2.15E-05	3.01E-05	0.007526	0.000251	4.598557
Q23	2.15021E-05	6.92369	4.3E-05	3.01E-05	0.003763	0.000167	6.927715
Q24	2.15021E-05	3.386587	2.15E-05	3.01E-05	0.018814	0.000251	3.405726
Q25	4.30043E-05	14.29892	2.15E-05	6.02E-05	0.003763	0.000251	14.30306
Q26	2.15021E-05	9.106157	2.15E-05	3.01E-05	0.015051	0.000251	9.121533
Q27	2.15021E-05	6.773175	4.3E-05	6.02E-05	0.018814	0.000334	6.792448
Q28	2.15021E-05	9.858732	4.3E-05	3.01E-05	0.007526	0.000251	9.866604
Q29	2.15021E-05	16.70716	2.15E-05	3.01E-05	0.007526	0.000167	16.71493
Q30	2.15021E-05	11.21337	2.15E-05	3.01E-05	0.003763	0.000251	11.21745
Q31	2.15021E-05	5.71957	2.15E-05	6.02E-05	0.011289	0.000334	5.731296
Q32	4.30043E-05	5.71957	2.15E-05	3.01E-05	0.018814	0.000334	5.738813
Q33	2.15021E-05	16.25562	4.3E-05	6.02E-05	0.003763	0.000167	16.25967
Q34	2.15021E-05	6.547402	4.3E-05	6.02E-05	0.003763	0.000167	6.551457
Q35	4.30043E-05	9.708217	2.15E-05	6.02E-05	0.011289	0.000334	9.719965
Q36	4.30043E-05	8.805127	2.15E-05	3.01E-05	0.015051	0.000167	8.820441
Q37	4.30043E-05	2.40824	4.3E-05	3.01E-05	0.015051	0.000334	2.423742
Q38	2.15021E-05	4.139162	4.3E-05	3.01E-05	0.015051	0.000251	4.154559
Q39	2.15021E-05	12.34223	4.3E-05	3.01E-05	0.007526	0.000167	12.35002
Q40	2.15021E-05	5.11751	4.3E-05	3.01E-05	0.011289	0.000334	5.129228

QoC

Heavy metals were identified as serious contaminants in the study area, so it was necessary to use the QoC model to investigate HM sources. As a result, this review introduced the QoC model and the source department completed the PLI model. Table 2 shows the QoC values obtained for each dissected heavy metal. Positive

QoC values often indicate anthropogenic effects, and negative QoC values indicate geological effects. Cu, Zn, Pb, Ni and Cd in the surveyed area are all 100% negative, according to the results shown in Table 2, whereas in Fe, 5% of the sample are positive indicating anthropogenic influence while 95% of the samples are negative implying geogenic influence. This means that the region's groundwater has been contaminated as

Fig. 6 Igeo distribution within the area



a result of geogenic activity with very minor intercalation of anthropogenic sources. In any capacity, little is had significant awareness of the potential geogenic processes that might impact the movement of these metals in water resources. Heavy metal harmfulness has been a well established and developing ecological issue. A few heavy metals have been troubled by the dirt by geogenic sources like draining and enduring of rocks, as well as anthropogenic exercises like extreme metal mining, purifying, consuming petroleum derivatives, pesticide use, and sewage slime (Agidi et al. 2022). Whenever these metals enter the natural pecking order, in addition to the fact that an unfavourable effect on the plant has improved physiology, however, they additionally represent a constant and pestilence wellbeing chance to people. The discoveries of this study go against the discoveries of Egbueri (2019) in Ojoto, Nigeria.

Geoaccumulation Index (Igeo)

The geoaccumulation (Igeo) record was developed by to check the magnitude of pollution at significant concentrations of waste, water, debris, and soil, and is widely used to study global pollution status. Used (Haris et al. 2017). The properties of Igeo and their individual translations are $I_{geo} \leq 0$ (essentially uncontaminated), 0 (uncontaminated), 1 (quite contaminated), 2 (moderately heavily contaminated), 3 (heavily contaminated), 4 (obviously heavily contaminated) and $I_{geo} \geq 5$ (clearly heavily contaminated) Very polluted), (Olujimi et al. 2014; Qing et al. 2015). From the aftereffects of the geoaccumulation file (Table 3), it revealed that 2.5% of the entire sample are unpolluted (< 1), 5% of the samples are within a moderate pollution area, 5% of the

samples had strong pollution, 10% of the samples had moderate pollution, 75% of the samples had extreme pollution. This result agrees with the Nemerow pollution results but it is contrary to the result of the CF, PLI and MPI. Anthropogenic inputs could be responsible for the high levels of pollution seen in this study (Akakuru et al. 2021a, b; Agidi 2022; Eyankware et al. 2022a, b). The spatial distribution of Igeo within the region is presented in Fig. 6.

Health risk assessment

USEPA characterizes human wellbeing risk appraisal as the method involved with surveying unfriendly wellbeing and the probability of human openness to synthetic substances in a tainted climate. There are three potential openness courses that direct admission of drinking water, air inward breath, and skin retention. Since groundwater nitrogen doesn't volatilize, and skin retention is short of one-thousandth of drinking water admission, this article just considers openness through the drinking water consumption course. The measurement is communicated in the accompanying detailing. There are no growth-based temperature rules, but high water temperatures have been shown to be harmful to the human body and promote the development of microorganisms that can cause problems related to taste, aroma, skin protection and use (WHO 2017; Mgbenu and Egbueri 2019; Oli et al 2022). The results of the HI in Table 4 reveal that Ni values of adults and children are very high ($HI \geq 4$), Fe, Cu and Pb values of adults are low and its considered negligible ($HI < 0.1$) but in children are very high ($HI \geq 4$), Zn values of adults and children are very high ($HI \geq 4$), Cd values of adults are low and it's considered negligible ($HI < 0.1$). Thusly, in light of this evaluation, the youngsters

Table 4 Non-carcinogenic risk of heavy metals in terms of hazard quotient (HQ) and hazard index (HI) for children and adults

	Ni(A)	Ni(C)	Fe (A)	Fe (C)	Zn(A)	Zn(C)	Pb(A)	Pb(C)	Cd (A)	Cd (C)	Cu (A)	Cu (C)
Q1	18,651,500	319,740	6,661,250	114,192.9	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q2	9,325,750	159,870	14,921,200	255,792	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q3	9,325,750	159,870	43,964,250	753,672.9	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	18,651,500	319,740
Q4	9,325,750	159,870	1,865,150	31,974	621,716.7	10,658	53,290,000	913,542.9	1.119E+09	19,184,400	18,651,500	319,740
Q5	18,651,500	319,740	33,572,700	575,532	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	9,325,750	159,870
Q6	18,651,500	319,740	41,566,200	712,563.4	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q7	18,651,500	319,740	18,385,050	315,172.3	621,716.7	10,658	53,290,000	913,542.9	1.865E+09	31,974,000	13,988,625	239,805
Q8	18,651,500	319,740	23,714,050	406,526.6	621,716.7	10,658	53,290,000	913,542.9	1.865E+09	31,974,000	9,325,750	159,870
Q9	9,325,750	159,870	44,763,600	767,376	621,716.7	10,658	1.07E+08	1,827,086	1.119E+09	19,184,400	13,988,625	239,805
Q10	9,325,750	159,870	58,619,000	1,004,897	621,716.7	10,658	1.07E+08	1,827,086	373,030,000	6,394,800	13,988,625	239,805
Q11	9,325,750	159,870	46,362,300	794,782.3	621,716.7	10,658	1.07E+08	1,827,086	373,030,000	6,394,800	18,651,500	319,740
Q12	18,651,500	319,740	35,437,850	607,506	621,716.7	10,658	53,290,000	913,542.9	1.492E+09	25,579,200	9,325,750	159,870
Q13	18,651,500	319,740	28,243,700	484,177.7	1,243,433	21,316	53,290,000	913,542.9	1.492E+09	25,579,200	13,988,625	239,805
Q14	18,651,500	319,740	21,848,900	374,552.6	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q15	18,651,500	319,740	23,447,600	401,958.9	621,716.7	10,658	53,290,000	913,542.9	1.119E+09	19,184,400	18,651,500	319,740
Q16	9,325,750	159,870	12,523,150	214,682.6	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q17	9,325,750	159,870	8,526,400	146,166.9	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q18	9,325,750	159,870	23,714,050	406,526.6	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	9,325,750	159,870
Q19	9,325,750	159,870	16,253,450	278,630.6	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	9,325,750	159,870
Q20	9,325,750	159,870	42,898,450	735,402	621,716.7	10,658	53,290,000	913,542.9	1.119E+09	19,184,400	18,651,500	319,740
Q21	9,325,750	159,870	24,779,850	424,797.4	1,243,433	21,316	53,290,000	913,542.9	1.119E+09	19,184,400	13,988,625	239,805
Q22	9,325,750	159,870	16,253,450	278,630.6	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q23	9,325,750	159,870	24,513,400	420,229.7	1,243,433	21,316	53,290,000	913,542.9	373,030,000	6,394,800	9,325,750	159,870
Q24	9,325,750	159,870	11,990,250	205,547.1	621,716.7	10,658	53,290,000	913,542.9	1.865E+09	31,974,000	13,988,625	239,805
Q25	18,651,500	319,740	50,625,500	867,865.7	621,716.7	10,658	1.07E+08	1,827,086	373,030,000	6,394,800	13,988,625	239,805
Q26	9,325,750	159,870	32,240,450	552,693.4	621,716.7	10,658	53,290,000	913,542.9	1.492E+09	25,579,200	13,988,625	239,805
Q27	9,325,750	159,870	23,980,500	411,094.3	1,243,433	21,316	1.07E+08	1,827,086	1.865E+09	31,974,000	18,651,500	319,740
Q28	9,325,750	159,870	34,904,950	598,370.6	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	13,988,625	239,805
Q29	9,325,750	159,870	59,151,900	1,014,033	621,716.7	10,658	53,290,000	913,542.9	746,060,000	12,789,600	9,325,750	159,870
Q30	9,325,750	159,870	39,701,050	680,589.4	621,716.7	10,658	53,290,000	913,542.9	373,030,000	6,394,800	13,988,625	239,805
Q31	9,325,750	159,870	20,250,200	347,146.3	621,716.7	10,658	1.07E+08	1,827,086	1.119E+09	19,184,400	18,651,500	319,740
Q32	18,651,500	319,740	20,250,200	347,146.3	621,716.7	10,658	53,290,000	913,542.9	1.865E+09	31,974,000	18,651,500	319,740
Q33	9,325,750	159,870	57,553,200	986,626.3	1,243,433	21,316	1.07E+08	1,827,086	373,030,000	6,394,800	9,325,750	159,870
Q34	9,325,750	159,870	23,181,150	397,391.1	1,243,433	21,316	1.07E+08	1,827,086	1.119E+09	19,184,400	18,651,500	319,740
Q35	18,651,500	319,740	34,372,050	589,235.1	621,716.7	10,658	1.07E+08	1,827,086	1.119E+09	25,579,200	9,325,750	159,870
Q36	18,651,500	319,740	31,174,650	534,422.6	621,716.7	10,658	53,290,000	913,542.9	1.492E+09	25,579,200	9,325,750	159,870
Q37	18,651,500	319,740	8,526,400	146,166.9	1,243,433	21,316	53,290,000	913,542.9	1.492E+09	25,579,200	18,651,500	319,740

Table 4 (continued)

	Ni(A)	Ni(C)	Fe (A)	Fe (C)	Zn(A)	Zn(C)	Pb(A)	Pb(C)	Cd (A)	Cd (C)	Cu (A)	Cu (C)
Q38	9,325,750	159,870	14,654,750	251,224.3	1,243,433	21,316	53,290,000	913,542.9	1.492E+09	25,579,200	13,988,625	239,805
Q39	9,325,750	159,870	43,697,800	749,105.1	1,243,433	21,316	53,290,000	913,542.9	746,060,000	12,789,600	9,325,750	159,870
Q40	9,325,750	159,870	18,118,600	310,604.6	1,243,433	21,316	53,290,000	913,542.9	1.119E+09	19,184,400	18,651,500	319,740
MIN	9,325,750	159,870	1,865,150	31,974	621,716.7	10,658	53,290,000	913,542.9	373,030,000	6,394,800	9,325,750	159,870
MAX	18,651,500	319,740	59,151,900	1,014,033	1,243,433	21,316	1.07E+08	1,827,086	1.865E+09	31,974,000	18,651,500	319,740
STDV	4,504,765.2	77,224.55	14,880,910	255,101.3	308,457.8	5287.849	22,536,451	386,339.2	479,351.831	8,217,460	3,502,134	60,036.59
HI	503,590,500	8,632,980	1.14E+09	19,495,005	34,816,133	596,848	2.61E+09	44,763,600	4.029E+10	6.91E+08	5.6E+08	9,592,200

Bold values indicate minimum, maximum, standard deviation, hazard index

are substantially more presented with the constant exposure than the grown-ups (Akakuru et al. 2022; Eyankware et al 2022c; Agidi et al. 2022).

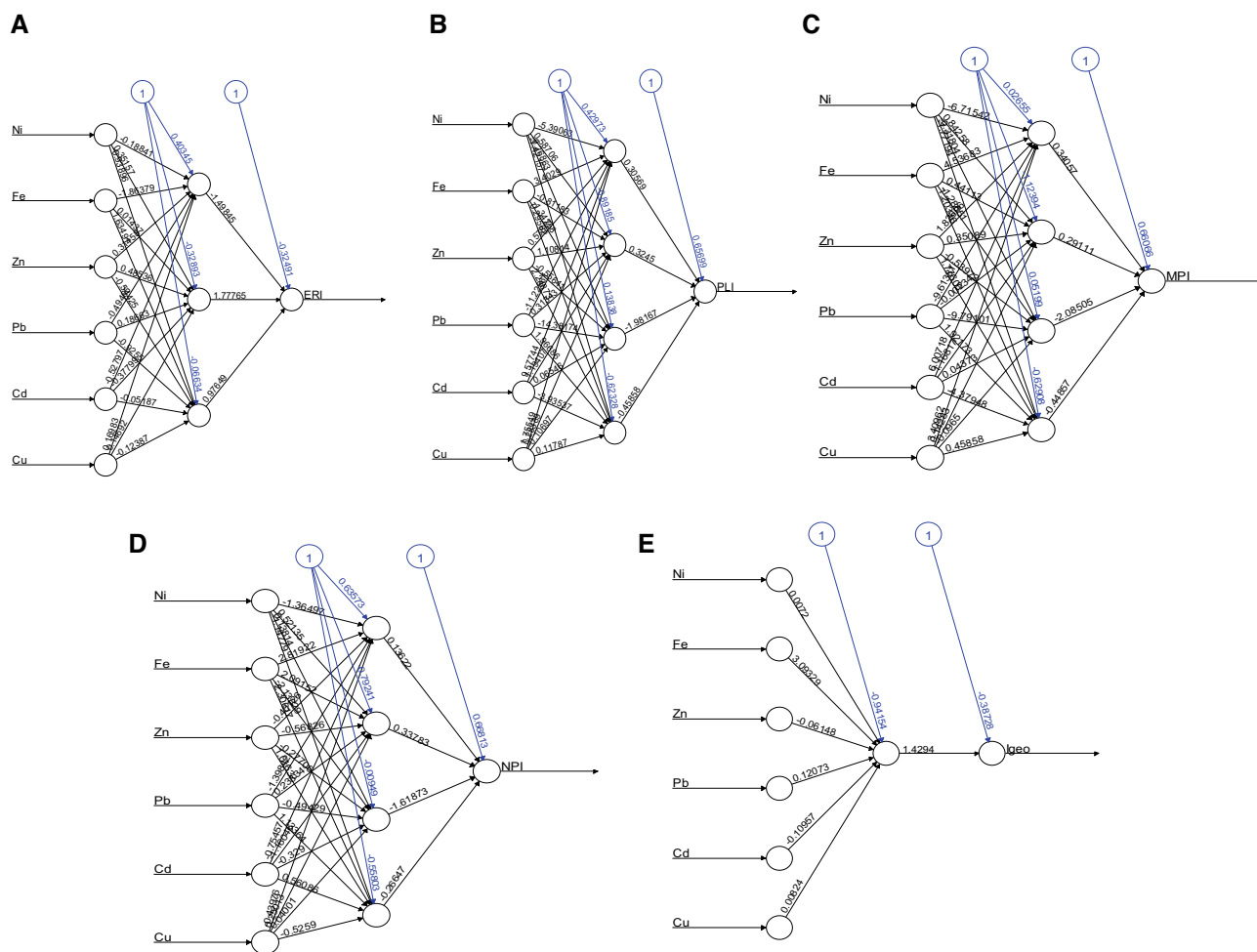
Groundwater quality prediction by the ANN and MLR models

Having an accurate model that can predict the boundaries of interest is the key to saving the cost of verifying and assessing groundwater quality. This review demonstrates that both the MLR and ANN strategies are solid devices for calculating and expecting ERI, PLI, MPI, NPI, and Igeo. During the training and testing phase, 40 samples of chemical composition were used. Sensitivity analysis was performed on the ANN and MLR models to determine the relative weights of each input variable in making rational predictions. In the ANN foreseeing model, the determination of information factors is a critical stage, as it influences the model exhibition. In this unique situation, chose every one of the heavy metal boundaries was utilized as information factors for the forecast of ERI, PLI, MPI, NPI and Igeo. The predicted performance of the five ANN models was compared to the corresponding MLR models using R^2 , RMSE, and MAPE (quantitative indicators) (see Table 5). The results of this comparison are also shown in Table 5, and the optimized ANN model is shown in Fig. 7. Models with high R^2 values and significantly lower MAPE and RMSE values are considered optimal simulation models and are suitable for further analysis. Table 5 shows the five ANN models, these models reveal that ERI has an R^2 value of 0.9966 with the quantitative indicators (RMSE and MAPE) for the train and test of 0.7534911 (RMSE), 0.104233 (MAPE), the test of 0.03391673 (RMSE), 0.05431428 (MAPE). PLI has an R^2 value 0.9828 with the quantitative indicators for the train and test of 1.446125e-09 (RMSE), 0.1639405(MAPE), test 2.678497e-09 (RMSE), 0.222993(MAPE). MPI has an R^2 value 0.9891 with the quantitative indicators for the train and test of 1.726522e-06 (RMSE), 0.1322456 (MAPE), test 2.979866e-06 (RMSE), 0.1924979 (MAPE). NPI has an R^2 value of 0.9946 with the quantitative indicators for the train and test of 0.7050911 (RMSE), 0.1214507 (MAPE), and test 0.1951383 (RMSE), 0.0818501 (MAPE). Igeo has an R^2 value of 0.9932 with the quantitative indicators for the train and test of 0.3261526 (RMSE), 0.078624 (MAPE), and test 0.1307295 (RMSE), 0.089026 (MAPE).

In the same vein, from the MLR modeling (Table 5), the ERI quantitative indicators (RMSE and MAPE) for the train and test shows that train is 2.224384e-06 (RMSE) and 1.167913e-07 (MAPE), while test has 2.381788e-06 (RMSE) and 1.3819e-07 (MAPE), with an R^2 value

Table 5 Performance of ANN and MLR models using RMSE, MAPE and R^2

	TRAIN		TEST		R^2
	RMSE	MAPE	RMSE	MAPE	
ANN					
ERI	0.7534911	0.104233	0.03391673	0.054314	0.9966
PLI	1.446125e-09	0.1639405	2.678497e-09	0.222993	0.9828
MP1	1.726522e-06	0.1322456	2.979866e-06	0.1924979	0.9891
NPI	0.7050911	0.1214507	0.1951383	0.0818501	0.9946
Igeo	0.3261526	0.078624	0.1307295	0.089026	0.9932
	TRAIN		TEST		R^2
	RMSE	MAPE	RMSE	MAPE	
MLR					
ERI	2.224384e-06	1.167913e-07	2.381788e-06	1.3819e-07	1.0
PLI	3.4193e-09	0.1671017	3.4982e-09	0	0.9043
MP1	5.13618e-06	0.1672727	5.242879e-06	0.1422162	0.9043
NPI	2.924335e-06	3.649546e-07	3.444335e-06	2.510343e-07	1.0
Igeo	1.450445e-06	1.108861e-07	1.437932e-06	1.62333e-07	1.0

**Fig. 7** Optimized ANN models for ERI (A), PLI (B), MPI (C), NPI (D), and Igeo (E)

of 1.0. PLI train and test values are train 3.4193e-09 (RMSE) and 0.1671017 (MAPE), while test has 3.4982e-09 (RMSE) and 0.0 (MAPE), with an R^2 value of 0.9043. MPI train and test values are train 5.13618e-06 (RMSE) and 0.1672727 (MAPE), while test has 5.242879e-06 (RMSE) and 0.1422162 (MAPE), with an R^2 value of 0.9043. NPI train and test values are train 2.924335e-06 (RMSE) and 3.649546e-07 (MAPE), while test has 3.444335e-06 (RMSE) and 2.510343e-07 (MAPE), with an R^2 value of 1.0. Igeo train and test values are train 1.450445e-06 (RMSE) and 1.108861e-07 (MAPE), while test has 1.437932e-06 (RMSE) and 1.62333e-07 (MAPE), with an R^2 value of 1.0.

It is also important to point out that based on the R^2 values, the MLR appears to perform better as 60% of the values had an R^2 value of 1.0 (ERI, NPI, and Igeo), implying that it is highly accurate in the prediction. The contribution level of the input parameters showing the predictor importance (Fig. 8) are in this order: Fe > Pb > Cd > Ni > Cu > Zn (ERI), Pb > Cd > Fe > Cu > Zn > Ni (PLI and MPI), Fe > Pb > Cu > Ni > Zn > Cd (NPI and Igeo). This result indicates that the ANN and MLR models could be considered for further analysis since they showed a high effective tendency in the prediction of ERI, PLI, MPI, NPI and Igeo based on their respective performances.

Table 6 Communalities and PCA

Communalities		Components			
		PC1	PC2	PC3	PC4
Ni	0.821	-0.463	0.585	-0.251	-0.135
Fe	0.736	0.64	0.612	-0.254	-0.006
Zn	0.78	0.082	-0.634	-0.36	0.534
Pb	0.771	0.6	0.389	0.365	0.354
Cd	0.736	-0.835	0.171	0.106	0.078
Cu	0.793	-0.277	0.182	0.767	0.398
Eigenvalues		-0.25	1.31	0.37	1.22
Variance (%)		0.35	0.21	0.19	0.07
Cumulative var. (%)		0.35	0.56	0.75	0.82

Bold values indicate loadings

PCA

PCA is a based arrangement technique that tries to make sense of the variety of countless interconnected factors (Eyankware, and Akakuru 2022; Akakuru et al. 2021a, b). It exhibits how factors are connected, which decreases the dataset's intricacy. PCA removes eigenvalues and eigenvectors from the first information's covariance framework. Head parts

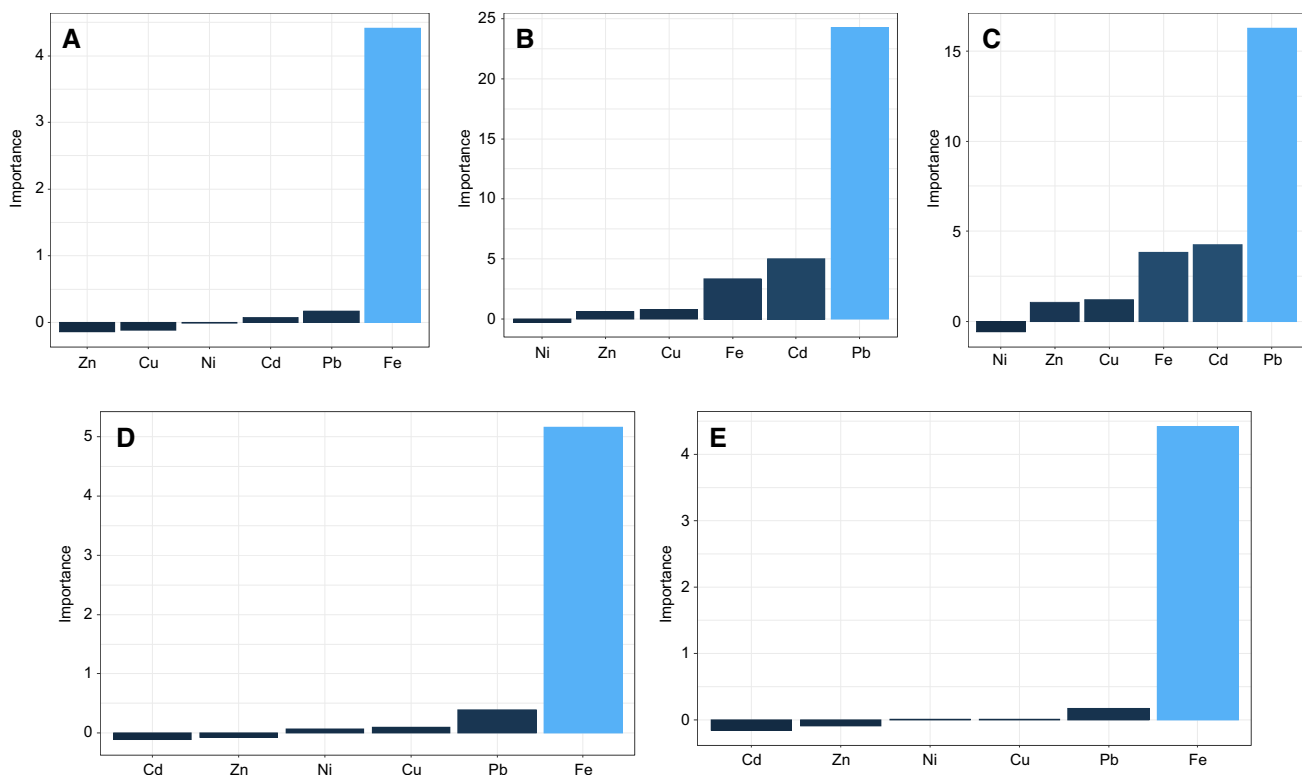


Fig. 8 Predictor importance of the input parameters for ERI (A), PLI (B), MPI (C), NPI (D), and Igeo (E)

Table 7 Correlation matrix

	Ni	Fe	Zn	Pb	Cd	Cu
Ni	1.000					
Fe	0.078	1.000				
Zn	− 0.180	− 0.203	1.000			
Pb	− 0.082	0.423	− 0.073	1.000		
Cd	0.371	− 0.390	− 0.129	− 0.250	1.000	
Cu	0.000	− 0.202	− 0.206	0.161	0.239	1.000

Bold values indicate significant values

(PCs) are the uncorrelated (symmetrical) factors acquired by duplicating the first connected factors with the eigenvectors (loadings). The Eigen upsides of the PCs evaluate their related difference, the loadings show the first factors' cooperation in the PCs, and the changed perceptions are alluded to as scores. In PC1, 66.7% of the variables in the components have loadings, they include Ni (− 0.463), Fe (0.64), Pb (0.6), and Cd (− 0.835). PC2 has a loading of 50% among variables Ni (0.585), Fe (0.612), and Zn (− 0.634) (see Table 6). For PC3, there was no variable loading while PC4 has a loading of 16.7% among variables Zn (0.573). The aftereffect of this PCA affirms past outcomes and it further uncovers that the proceeded with anthropogenic exercises inside the territory has enormously impacted the dirt nearby groundwater tainting with heavy metals attracts a certified concern perspective on their unfortunate results for the living biota. The steady and non-biodegradable nature of profound metals works with their assortment in the environment. Provincial soils are getting a huge proportion of poisons from various sources. Past fundamental limits, heavy metals give a dangerous impact on human prosperity as they ruin the customary working of the living structures. The gigantic measure of waste made ought to be managed properly keeping into thought the normal assessments related to land treatment (Eyankware et al. 2021; Agidi et al. 2022; Akakuru et al. 2022).

Correlation Matrix

Connection grids are an important strategy used when evaluating connections between two elements. The relation coefficient is usually between − 1 and + 1. Assuming the r-value is close to -1, the relationship is said to have a negative bias or vice versa. Whenever the value of r is close to + 1 the relationship is said to have a positive bias or is considered connected. If the value is zero, the centroid must be uncorrelated (Srivastava et al. 2014). The connection grid (Table 7) shows that there is a positive relationship between Pb and Fe (0.423). This result suggests a helpless and positive relationship between the components. This further means that salt water was not the main reactivated groundwater hotspot in the study area (Eyankware

et al. 2021; Agidi et al. 2022; Akakuru et al. 2022). Lead and iron can enter drinking water when synthetic reactions occur in lead-containing plumbing materials. This is called consumption-melting or erosion of pipes and metal from pipes.

Conclusion

The artificial neural networks and multi-linear regression modelling of groundwater quality parameters and health risk assessment around Egbema, Southeastern Nigeria has been done. Contamination factor results reveal that Ni, Zn, Pb, Cd, and Cu have relatively low concentrations < 1 in the entire region while the Fe concentration range from low contamination to extremely high pollution (> 6). Pollution Load Index results showed no contamination exists. Metal Pollution Index results show that the groundwater is safe. Potential ecological risks assessment indicated the majority of the entire samples are within the low ecological risk area. Nemerow pollution results indicated that the majority of the samples were heavily polluted. Quantification of Contamination shows that majority of the sample's quality was geogenically influenced. Geoaccumulation index results showed that most of the samples had extreme pollution. The health risk assessment results revealed that children are substantially prone to health risks more than adults. The modelling results indicated that the ANN and MLR models could be considered for further analysis since they showed a highly effective and accurate tendency in the prediction of ERI, PLI, MPI, NPI and Igeo, based on their respective performances. Principal Component Analysis (PCA) results showed considerable variable loadings, while the correlation matrix results revealed that there exists weak and positive correlation amongst elements. This further implies that saltwater was not the major re-energised hotspot for the groundwater in the survey area. In light of the result of this study, it suggests the utilization of ANN and MLR modelling approaches in the prediction of groundwater quality parameters as they yielded positive and reliable performances.

Author contributions A.B.C.D and E. wrote the main manuscript text and E.F, G and H. prepared the figures. All authors reviewed the manuscript.

Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Compliance with ethical standards This research work is carried out in compliance with transparency, moral values, honesty, and hard work. No human participation or animals are involved in this research work.

Ethical approval As per the literature review, this is neither a repetition of any work nor copied key data from other's work. The methodology, findings, and conclusions made here belong to original research work as per our knowledge and belief.

Informed consent Every step of processing for publication informed to all co-authors of this paper at the earliest, and everything is carried out with collective decision and consent.

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