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Groundwater Quality Prediction Using Water Quality Index and Multiple Regression Modelling in Trans Amadi Industrial Area, Port Harcourt, Nigeria

Braide, A. I., Nwoke H.U., Dike B.U., and Ukachukwu O.C.

Department of Civil Engineering, Federal University of Technology Owerri, Imo state, Nigeria.

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ABSTRACT

Groundwater quality assessment is essential for ensuring safe drinking water and mitigating contamination associated with industrialization and urbanization. This study developed a predictive model for groundwater quality assessment using the Water Quality Index (WQI) and Multiple Regression Modelling (MRM) within Trans Amadi Industrial Layout, Port Harcourt, Nigeria. Groundwater samples were collected from fifteen (15) boreholes and analyzed for selected physicochemical parameters following standard procedures. Results indicated considerable spatial variation in groundwater quality, with elevated concentrations of heavy metals such as lead (Pb) and cadmium (Cd) observed at several locations. WQI values revealed that most sampling points were unsuitable for drinking, indicating widespread groundwater deterioration. The developed regression model demonstrated excellent predictive performance (R^2 = 0.9998; Adjusted R^2 = 0.9989), with Pb, Cd, dissolved oxygen (DO), sulphate (SO_4), and zinc (Zn) identified as major predictors influencing WQI. The close agreement between observed and predicted WQI values confirms the model's reliability for groundwater quality prediction. The findings demonstrate that integrating WQI and MRM provides an effective and cost-efficient approach for groundwater monitoring, contamination assessment, and sustainable water resource management in industrial environments.

Key words: Groundwater quality; Water Quality Index (WQI); Multiple Regression Modelling (MRM); groundwater prediction; heavy metals; industrial pollution

INTRODUCTION

Access to safe and adequate drinking water remains a fundamental requirement for human health, socioeconomic development, and environmental sustainability. Groundwater constitutes one of the most important freshwater resources globally, supplying nearly half of the world's drinking water and supporting agricultural and industrial activities, particularly in developing regions where surface water infrastructure is limited (UNESCO, 2022). Rapid urbanization, industrialization, population growth, and climate variability have intensified pressure on groundwater resources, leading to increasing concerns regarding groundwater depletion and deterioration in water quality (UNESCO, 2022; WHO, 2022).

Groundwater is often perceived as a relatively protected source of potable water because of natural filtration processes occurring within geological formations. However, anthropogenic activities such as industrial discharge, improper waste disposal, agricultural runoff, sewage infiltration, and petroleum-related contamination significantly alter groundwater chemistry and increase the risk of contamination by nutrients, heavy metals, and other pollutants (Lapworth et al., 2017; Tirkey et al., 2017). These contaminants pose severe threats to public health through long-term exposure and may contribute to waterborne diseases, organ toxicity, and other chronic health conditions (WHO, 2022).

The degradation of groundwater quality is particularly concerning in rapidly developing urban and industrial regions of developing countries, including Nigeria, where regulatory enforcement and environmental monitoring may be inadequate. Industrial clusters often generate substantial quantities of untreated or poorly managed effluents capable of infiltrating aquifer systems and compromising groundwater suitability for domestic consumption (Egbueri & Unigwe, 2020). Consequently, continuous groundwater quality assessment has become essential for protecting public health and ensuring sustainable water resource management.

Conventionally, groundwater quality assessment relies on laboratory analyses involving extensive sampling, transportation, and physicochemical characterization of water samples. While effective, these approaches are often expensive, time-consuming, and unsuitable for rapid decision-making, especially in regions with limited monitoring infrastructure (Chen & Han, 2018). Therefore, predictive approaches capable of estimating groundwater quality efficiently have gained increasing attention in environmental studies.

Water Quality Index (WQI) has been widely adopted as an effective approach for summarizing multiple physicochemical parameters into a single numerical value that reflects the overall suitability of water for specific uses, particularly drinking purposes (Uddin et al., 2021). Although WQI simplifies interpretation of groundwater conditions, predictive models are required to anticipate future water quality variations and support proactive management strategies.

Among predictive techniques, Multiple Regression Modelling (MRM) has emerged as a robust statistical approach for evaluating relationships between dependent variables and multiple independent predictors simultaneously. In groundwater studies, MRM enables the identification of dominant water quality determinants and facilitates prediction of groundwater quality using measurable physicochemical parameters (Wang et al., 2020). The ability of MRM to model complex environmental interactions makes it useful for groundwater monitoring, contamination assessment, and environmental decision support systems.

Despite growing applications of predictive modelling in groundwater assessment, studies integrating Water Quality Index and Multiple Regression Modelling within industrialized environments in the Niger Delta region remain limited. Trans Amadi Industrial Area in Port Harcourt hosts diverse industrial operations with potential impacts on groundwater quality arising from industrial effluents, waste disposal activities, and urban expansion. The potential contamination of groundwater within this area presents significant environmental and public health concerns due to dependence on borehole water for domestic purposes.

Therefore, this study evaluates groundwater quality within the Trans Amadi Industrial Area using physicochemical parameters and Water Quality Index, while developing a Multiple Regression Model for predicting groundwater quality. The study aims to provide a predictive framework capable of supporting groundwater monitoring, contamination mitigation, and sustainable water resource management in industrialized environments.

METHODOLOGY

2.1 Study Area

The study was conducted in Trans Amadi Industrial Area, Port Harcourt, Rivers State, Nigeria, located approximately between latitudes 4°47′N–4°48′N and longitudes 7°01′E–7°02′E. Trans Amadi is one of the largest industrial hubs in Port Harcourt, covering about 1,000 hectares, and hosts numerous manufacturing, petroleum-related, and commercial activities that potentially contribute to environmental pollution (Nwankwoala, Osayande, & Uboh, 2022). The area experiences a tropical monsoon climate, characterized by high temperatures, relative humidity, and annual rainfall generally ranging from 2,000–2,500 mm, conditions that promote groundwater recharge and contaminant transport (Nwankwoala et al., 2022). Geologically, the study area lies within the Niger Delta sedimentary basin, predominantly composed of coastal plain sands and alluvial deposits with relatively high permeability, increasing groundwater vulnerability to anthropogenic contamination (Ekwere et al., 2025). Rapid industrialization, urbanization, poor waste disposal practices, and untreated industrial effluent discharges have been reported as significant contributors to groundwater quality deterioration within the Trans Amadi environment (Nwankwoala et al., 2022).

2.2 Groundwater Sampling and Sample Collection

Fifteen groundwater sampling locations (B1–B15) were selected across Trans Amadi based on anthropogenic influences including industrial activities, population density, waste disposal sites, and proximity to river

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catchments. Groundwater samples were collected from existing boreholes.

Water samples were collected using sterile 1.5 L high-density polyethylene (HDPE) containers following standard procedures outlined by the American Public Health Association (APHA, 2017). Prior to sampling, containers were rinsed three times with distilled water and subsequently with groundwater from the sampling location. Bottles were filled to overflow, corked tightly and labelled to avoid mix ups. Samples were immediately preserved in ice chests and transported to the laboratory within three hours of collection before storage at approximately 4°C pending analysis.

2.3 Physicochemical Analysis

Physicochemical parameters analyzed included:

i. pH
ii. Dissolved Oxygen (DO)
iii. Total Dissolved Solids (TDS)
iv. Electrical Conductivity (EC)
v. Sulphate (SO_4^{2-})
vi. Chloride (Cl^-)
vii. Bicarbonate (HCO_3^-)
viii. Nitrate
ix. Iron (Fe)
x. Zinc (Zn)
xi. Copper (Cu)
xii. Lead (Pb)
xiii. Chromium (Cr)

Sensitive parameters including pH, DO, temperature, and EC were measured in situ using calibrated portable meters because of their susceptibility to temporal variation after collection. Laboratory analyses were performed according to APHA standard analytical procedures (APHA, 2017). Heavy metal concentrations were determined using Atomic Absorption Spectrophotometry (AAS), while titrimetric and instrumental methods were employed where appropriate.

Descriptive statistics including mean, standard deviation, minimum, maximum, and range were computed and compared against permissible limits established by the World Health Organization (WHO) and Nigerian standards for drinking water quality.

2.4 Water Quality Index (WQI) Computation

Groundwater quality was evaluated using the Weighted Arithmetic Water Quality Index method, which integrates multiple physicochemical parameters into a single index representing overall water suitability for drinking purposes (Tyagi et al., 2013).

The unit weight for each parameter was determined as:

$$Wn = \frac{K}{Sn} \qquad [1]$$

where:

W_n = unit weight of parameter (n)

S_n = permissible standard value

K = proportionality constant

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The quality rating scale was calculated as:

$$Qn = \frac{(V_n - V_0)}{(S_n - V_0)} \text{ x } 100 \qquad [2]$$

where:

V_n = observed concentration

V_0 = ideal value

S_n = standard permissible value

The overall Water Quality Index was computed as:

$$WQI = \frac{\sum W_n Q_n}{\sum W_n} \qquad [3]$$

Groundwater quality categories were classified as:

i. 0–25: Excellent

ii. 26–50: Good

iii. 51–75: Poor

iv. 76–100: Very Poor

v. 100: Unsuitable for drinking

2.5 Statistical Analysis and Multiple Regression Modelling

Descriptive statistics, correlation analysis, and multiple linear regression analyses were performed using Microsoft Excel to evaluate relationships between groundwater physicochemical parameters and the Water Quality Index (WQI). Multiple Regression Modelling (MRM) was applied to predict WQI using measured physicochemical parameters as independent variables, while WQI served as the dependent variable.

The regression model was expressed as:

$$WQI = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \epsilon \qquad [4]$$

where:

(WQI) = dependent variable

X_n = independent variables

β_n = regression coefficients

ϵ = random error

Pearson correlation analysis was conducted to examine relationships among groundwater quality parameters and WQI. Model performance and predictive accuracy were evaluated using the coefficient of determination (R^2), adjusted R^2, analysis of variance (ANOVA), standard error, residual analysis, and significance testing (p-values). The statistical significance of the regression model and individual predictors was assessed using ANOVA, with $p < 0.05$ considered statistically significant. Residual diagnostics, including predicted values and residual plots, were examined to evaluate model fit and verify assumptions of linearity and homoscedasticity. The developed

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regression model was subsequently used to predict groundwater WQI and compare predicted values with observed WQI measurements.

RESULTS AND DISCUSSIONS

3.1 Groundwater Quality Parameters and Comparison with Permissible Standards

The descriptive statistics of groundwater physicochemical parameters across the sampling locations, together with WHO and NAFDAC permissible limits, are presented in Table 1. Variations in water quality were observed across sampling points, with some parameters exceeding recommended drinking water standards, indicating potential contamination risks.

Table 1: Descriptive statistics of groundwater quality parameters and comparison with WHO and NAFDAC standards

Location	**DO (mg/L)**	**NO_3 (mg/L)**	**HCO_3 (mg/L)**	**pH**	**TDS (mg/L)**	**Cl (mg/L)**	**SO_4 (mg/L)**	**Fe (mg/L)**	**Zn (mg/L)**	**Cu (mg/L)**	**Pb (mg/L)**	**Cd (mg/L)**
B1	5.9	10.86	120	7.0	496	671	6.28	0.08	0.02	0.000	0.010	0.001
B2	6.2	40.01	12.5	4.0	220	710	7.50	2.40	0.13	0.002	0.060	0.000
B3	4.2	28.04	18.5	5.3	684	243	6.83	1.80	0.06	0.010	0.025	0.001
B4	5.8	32.47	35.0	6.3	346	566	8.20	7.15	0.14	0.000	0.220	0.000
B5	6.4	18.00	20.0	6.2	431	24	6.20	0.01	0.09	0.002	0.002	0.000
B6	6.1	17.27	365	7.1	450	86.8	6.74	0.00	0.02	0.001	0.150	0.001
B7	5.2	15.66	38.0	7.15	210	75.1	8.55	9.60	0.17	0.000	0.200	0.000
B8	5.4	10.86	110	7.0	530	71	6.16	0.02	0.01	0.020	0.200	1.000

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Location	DO (mg/L)	NO_3 (mg/L)	HCO_3 (mg/L)	pH	TDS (mg/L)	Cl (mg/L)	SO_4 (mg/L)	Fe (mg/L)	Zn (mg/L)	Cu (mg/L)	Pb (mg/L)	Cd (mg/L)
B9	6.2	14.00	29.5	6.2	410	399	9.40	2.25	0.18	0.030	0.050	0.000
B10	5.1	2.70	55.5	6.4	573	12.2	5.00	0.60	0.02	0.004	0.280	0.000
B11	6.2	40.01	13.6	5.3	320	419	7.50	2.20	0.09	0.002	0.075	0.001
B12	4.8	2.90	12.0	5.0	312	14.1	5.04	0.02	0.01	0.000	0.090	0.001
B13	4.7	3.30	13.0	5.0	341	21.3	5.00	0.02	0.04	0.010	0.006	0.000
B14	3.9	1.70	14.5	6.8	370	7.1	16.16	0.02	0.02	0.002	0.100	0.010
B15	1.1	2.70	14.5	6.6	369	9.1	17.16	0.03	0.03	0.001	0.100	0.000
WHO Standard	**6.0**	**50**	**500**	**7.0–8.5**	**1500**	**250**	**500**	**1.0**	**3.0**	**0.5**	**0.01**	**0.003**
NAFDAC Standard	**5.0**	**10**	**100**	**6.5–8.5**	**500**	**100**	**100**	**3.0**	**5.0**	**1.0**	**0.01**	**0.003**

WHO = World Health Organization; NAFDAC = National Agency for Food and Drug Administration and Control.

The physicochemical analysis revealed substantial spatial variations in groundwater quality across the sampling locations, reflecting heterogeneous contamination patterns likely associated with industrial and anthropogenic activities within the Trans Amadi area. Dissolved oxygen (DO) values ranged from 1.1–6.4 mg/L, with several locations below recommended thresholds, indicating possible organic pollution and reduced water quality. Similarly, pH values (4.0–7.15) showed acidic conditions at several sampling points, which may increase metal

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mobility and groundwater vulnerability to contamination (WHO, 2022). Nitrate concentrations remained within WHO limits (50 mg/L) but exceeded the NAFDAC permissible level (10 mg/L) at some locations, suggesting possible influence from industrial discharges, sewage infiltration, and waste disposal activities. Elevated chloride concentrations observed in some locations further indicate potential anthropogenic contamination sources (WHO, 2022).

Heavy metals constituted the most significant groundwater quality concern, with Pb (0.002–0.280 mg/L) and Cd (0–1.0 mg/L) exceeding WHO and NAFDAC permissible limits at several sampling points. Excessive exposure to these metals has been associated with neurological, renal, and developmental disorders, highlighting potential public health risks associated with untreated groundwater consumption (WHO, 2022; Teschke & Xuan, 2025). Iron concentrations also exceeded guideline values in some locations, whereas Zn, Cu, and SO_4^{2-} remained largely within acceptable limits. The widespread exceedance of Pb, Cd, Fe, acidity, and chloride levels suggests that groundwater quality in portions of the study area may be unsuitable for direct consumption without treatment and emphasizes the need for continuous monitoring and predictive groundwater management strategies (WHO, 2022).

3.2 Water Quality Index (WQI) of Groundwater Collected from Different Areas in the State.

Table 2 shows the WQI of groundwater collected from different areas in the state and their respective values.

Table 2: Water Quality Index (WQI), groundwater status, and dominant contributing parameters across sampling locations

Location	Sampling Point	Actual WQI	Water Status	Dominant Contributing Parameter(s)*
B1	Danjuma Road 1	48.40	Good	Cd, Pb
B2	Danjuma Road 2	137.92	Unsuitable	Pb, Fe
B3	Danjuma Road 3	83.11	Very Poor	Pb, Cd
B4	Rivoc Road	505.15	Unsuitable	Pb, Fe
B5	ITF Office by Rivoc Road	30.08	Good	Cd, Pb
B6	Elizade by Garrison Road	368.75	Unsuitable	Pb, Cd
B7	KingSo Global Maritime Ltd	459.94	Unsuitable	Pb, Fe
B8	Sea Food Products, Oco Dr Road	712.02	Unsuitable	Pb, Cd

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Location	Sampling Point	Actual WQI	Water Status	Dominant Contributing Parameter(s)*
B9	Trans Amadi Power Plant	115.03	Unsuitable	Pb, Fe
B10	Aosor Well PLC	640.93	Unsuitable	Pb
B11	Chief Nwuke Street	197.63	Unsuitable	Pb, Cd
B12	Onitcha Road	231.43	Unsuitable	Pb, Cd
B13	Championx Oilfield	13.80	Excellent	Pb
B14	Total Energies	483.16	Unsuitable	Pb, Cd
B15	The Nook Apartments	228.88	Unsuitable	Pb
Minimum	—	**13.80**	Excellent	—
Maximum	—	**712.02**	Unsuitable	—
Mean	—	**283.21**	Predominantly Unsuitable	Pb, Cd
Percentage unsuitable	—	**73.3%**	Unsuitable	—

*Dominant contributing parameters determined from highest WnQn contributions.

The computed WQI values ranged from 13.80 to 712.02, indicating substantial variation in groundwater quality across the study area. Only one sampling location (B13) exhibited excellent water quality, while two locations (B1 and B5) were classified as good, and one location (B3) was categorized as very poor. The majority of sampling locations (73.3%) fell within the unsuitable for drinking category, suggesting widespread groundwater deterioration within the industrial area. Elevated WQI values were largely influenced by increased concentrations of Pb, Cd, and Fe, which contributed significantly to overall water quality degradation. Similar studies have reported that high WQI values are commonly associated with heavy metal contamination and indicate groundwater unsuitable for domestic consumption without treatment.

The predominance of unsuitable groundwater quality may be attributed to intensive industrial activities, improper waste disposal, and urbanization, which are recognized drivers of groundwater contamination in industrialized environments. Elevated heavy metal concentrations in groundwater have been linked to increased risks of neurological, renal, and other chronic health effects following prolonged exposure through drinking water. Consequently, the observed WQI pattern emphasizes the need for continuous groundwater monitoring,

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contamination mitigation strategies, and predictive management approaches to safeguard public health and ensure sustainable groundwater use.

3.3 Multiple Regression Model Development for WQI Prediction

The following matrix, statistics and figures are the results gotten from having the physio-chemical parameters as independent variables and the calculated Water Quality Index (WQI) as the dependent variable as shown in Tables 1 to

3.3 Multiple Regression Modelling for WQI Prediction

A multiple linear regression model was developed using groundwater physicochemical parameters (DO, NO_3, HCO_3, pH, TDS, Cl, SO_4, Fe, Zn, Cu, Pb, and Cd) as predictor variables and Water Quality Index (WQI) as the response variable. The developed model demonstrated excellent predictive performance with a Multiple R of 0.9999, R^2 of 0.9998, and Adjusted R^2 of 0.9989, indicating that approximately 99.98% of the variability in WQI was explained by the selected physicochemical parameters. The result for this section is summarized in Table 3 to 6

Table 3: Performance statistics of the developed regression model for WQI prediction

Parameter	**Value**
Observations	15
Multiple R	0.9999
R^2	0.9998
Adjusted R^2	0.9989
Standard error	7.660
F-statistic	1041.899
Significance F	0.00096

The ANOVA result indicated that the regression model was statistically significant ($p < 0.05$), confirming the suitability of the model for predicting groundwater WQI.

Table 4: Analysis of variance (ANOVA) for the developed regression model

Source	**df**	**SS**	**MS**	**F**	**p-value**
Regression	12	733694.162	61141.180	1041.899	0.00096

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Source	df	SS	MS	F	p-value
Residual	2	117.365	58.682	—	—
Total	14	733811.527	—	—	—

The developed regression equation for predicting WQI is expressed as:

$$WQI = -346.48+100.93(DO)-3.456(NO3)-0.0264(HCO_3)+70.71(pH)+0.334(TDS)-0.097(Cl)+38.97(SO_4)+34.64(Fe)-1710.42(Zn)+327.7(Cu)+2007.65(Pb)+260(Cd)$$

Among the predictors, Pb ($\beta = 2007.65$; $p < 0.001$) exhibited the strongest positive influence on WQI, while Zn ($\beta = -1710.42$; $p = 0.008$) showed the strongest negative contribution. Significant positive effects were also observed for DO, SO_4, Fe, and Cd.

Table 5: Regression coefficients and significance of predictor variables

Variable	Coefficient	p-value	Significance
DO	100.932	0.0019	Significant
NO_3	-3.459	0.0233	Significant
HCO_3	-0.026	0.6091	Not significant
pH	-70.710	0.0113	Significant
TDS	0.334	0.0155	Significant
Cl	-0.098	0.0144	Significant
SO_4	38.970	0.0019	Significant
Fe	34.642	0.0046	Significant
Zn	-1710.425	0.0077	Significant
Cu	-327.705	0.6857	Not significant
Pb	2007.653	0.0003	Significant

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Variable	Coefficient	p-value	Significance
Cd	260.006	0.0054	Significant

Table 6: Comparison between actual and predicted WQI values

Location	Actual WQI	Predicted WQI	Residual
B1	48.398	47.273	1.125
B2	137.918	134.832	3.086
B3	83.109	83.251	-0.142
B4	505.145	510.111	-4.966
B5	30.077	31.450	-1.373
B6	368.751	369.298	-0.548
B7	459.936	457.022	2.914
B8	712.020	712.026	-0.006
B9	115.032	116.765	-1.733
B10	640.934	637.592	3.342
B11	197.626	196.597	1.029
B12	231.434	237.993	-6.559
B13	13.796	10.432	3.363
B14	483.157	482.042	1.114
B15	228.878	229.525	-0.647

The developed multiple regression model exhibited excellent predictive performance with $R^2 = 0.9998$ and Adjusted $R^2 = 0.9989$, indicating that approximately 99.98% of the variation in groundwater WQI was explained by the selected physicochemical parameters. The statistically significant ANOVA result ($F = 1041.90$; $p = 0.00096$) further confirms the reliability of the model for predicting groundwater quality. Similar studies have reported that multiple linear regression (MLR) effectively captures relationships between physicochemical parameters and WQI, providing robust predictive capability for groundwater quality assessment and management (Jafar et al., 2023; Das et al., 2026). The minimal residual differences between actual and predicted WQI values observed across sampling locations indicate strong agreement between measured and estimated groundwater quality, suggesting high model accuracy. However, caution is required when interpreting extremely high predictive performance, particularly with relatively small datasets, as this may increase susceptibility to overfitting and reduce model generalizability.

Among the predictors, Pb ($\beta = 2007.65$; $p < 0.001$) emerged as the strongest positive contributor to WQI, indicating that lead contamination substantially influenced groundwater deterioration within the study area. Significant contributions from SO_4, Fe, Cd, and DO were also observed, whereas Zn and pH exhibited negative relationships with WQI. The dominance of heavy metals in influencing groundwater quality aligns with findings from groundwater studies in industrial regions, where elevated concentrations of Pb, Cd, and Fe were strongly associated with poor water quality and increased health risks (Akakuru et al., 2023). The results emphasize the importance of continuous monitoring and predictive modelling approaches for early identification of groundwater contamination and improved groundwater resource management.

CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

This study assessed the groundwater quality of selected locations within the Trans Amadi industrial area, Port Harcourt, using physicochemical parameters, Water Quality Index (WQI), and multiple regression modelling. The findings revealed substantial spatial variation in groundwater quality, with several sampling locations exceeding WHO and NAFDAC permissible limits for parameters such as Pb, Cd, Fe, chloride, and acidity (pH), indicating groundwater deterioration likely associated with industrial and anthropogenic activities. WQI classification showed that the majority of sampling locations were unsuitable for drinking purposes, while only a few locations exhibited good or excellent water quality, confirming widespread groundwater contamination within the study area.

The developed multiple regression model demonstrated excellent predictive performance ($R^2 = 0.9998$; Adjusted $R^2 = 0.9989$) and accurately predicted WQI using physicochemical variables. Among the predictors, lead (Pb) emerged as the strongest contributor to groundwater quality degradation, followed by cadmium (Cd), sulphate (SO_4), dissolved oxygen (DO), and iron (Fe). The strong predictive capability of the model suggests that multiple regression approaches can serve as cost-effective tools for groundwater quality assessment and reduce dependence on extensive laboratory analyses for routine monitoring. Similar studies have reported that multiple linear regression models effectively predict WQI with high accuracy and support groundwater quality management strategies (Jafar et al., 2023; Palabıyık et al., 2024). Overall, the study highlights the urgent need for improved groundwater monitoring and contamination control measures in industrial environments to protect public health and ensure sustainable groundwater utilization.

4.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

i. **Routine groundwater monitoring:** Continuous monitoring of groundwater quality should be implemented, particularly for heavy metals such as Pb and Cd, which showed significant contributions to groundwater deterioration and WQI variation.

ii. **Treatment before domestic use:** Groundwater from locations classified as unsuitable for drinking should undergo appropriate treatment prior to domestic consumption to minimize associated public health risks.

iii. **Strengthened environmental regulation:** Regulatory agencies should intensify surveillance and enforcement of industrial waste disposal practices within the Trans Amadi industrial area to reduce groundwater contamination resulting from anthropogenic activities.

iv. **Expansion of predictive modelling studies:** Future studies should incorporate larger datasets, seasonal variations, and additional sampling locations to improve model robustness and reduce potential overfitting associated with small sample sizes. Comparative evaluation of multiple regression with advanced machine learning approaches may further improve groundwater quality prediction accuracy (Palabıyık et al., 2024).

v. **Integrated groundwater management:** Groundwater quality prediction models should be integrated into environmental monitoring frameworks to support early contamination detection, informed decision-making, and sustainable groundwater resource management (Jafar et al., 2023).

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