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INTEGRATED PHYSICOCHEMICAL, WATER QUALITY INDEX, AND ARTIFICIAL NEURAL NETWORK ASSESSMENT OF GROUNDWATER FROM BOREHOLES AND HAND-DUG WELLS IN NORTH BANK, MAKURDI, NIGERIA

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ABSTRACT

Groundwater remains the primary source of domestic water supply in North Bank, Makurdi, Nigeria, yet its quality varies with source type and exposure to contamination. This study assessed the physicochemical characteristics, Water Quality Index (WQI), and parameter influence on groundwater from boreholes (BHs) and hand-dug wells (HDWs) using multivariate analysis and Artificial Neural Network (ANN) modeling. Borehole water exhibited slightly alkaline conditions (pH 7.50 ± 0.79) with higher mineralization, reflected by Total Dissolved Solids (427.6 ± 176.2 mg/L) and Electrical Conductivity (747.2 ± 492.8 µS/cm), indicating prolonged water–rock interaction within deeper aquifers. In contrast, HDWs showed lower mineral content (TDS = 267.6 ± 181.8 mg/L; EC = 510.2 ± 321.2 µS/cm) but elevated indicators of organic and anthropogenic contamination, including Biochemical Oxygen Demand (48.6 ± 6.4 mg/L) and nitrate (41.4 ± 24.7 mg/L), alongside reduced dissolved oxygen (5.12 ± 0.19 mg/L). Water Quality Index values ranged from 28.6 to 45.9 for boreholes, classifying them predominantly as Good, while HDWs ranged from 32.1 to 51.4, spanning Good to Poor categories. The integrated mean WQI of 37.5 places groundwater in North Bank within the Good class overall; however, the presence of Poor-quality HDWs indicates localized deterioration linked to shallow aquifer vulnerability and surface contamination. ANN synaptic weight analysis identified nitrate (12.7%), total hardness (11.6%), electrical conductivity (11.1%), and calcium (10.4%) as dominant drivers of borehole water quality, reflecting geogenic control. Conversely, HDW quality was most influenced by chlorine (12.5%), electrical conductivity (11.5%), dissolved oxygen (11.1%), calcium (10.5%), and turbidity (10.4%), underscoring the role of anthropogenic inputs. The findings demonstrate that while boreholes in North Bank generally provide relatively safe groundwater, hand-dug wells pose significant quality concerns that lower overall water reliability. Targeted protection, routine monitoring, and appropriate treatment of shallow wells are therefore essential to safeguard public health and ensure sustainable groundwater use in Makurdi.

KEYWORDS: Groundwater quality, Water Quality Index (WQI), Artificial Neural Network (ANN), Boreholes and hand-dug wells, North Bank, Makurdi.

1. INTRODUCTION

Groundwater is a critical freshwater resource that supplies drinking water to nearly half of the global population and plays an especially vital role in developing countries where surface water treatment infrastructure is inadequate or unreliable (Foster & Chilton, 2018; Lapworth et al., 2017). In urban centers across sub-Saharan Africa, groundwater has increasingly become the primary source of domestic water due to rapid population growth, climate variability, and the progressive failure of centralized water supply systems (UNESCO, 2019; Adimalla & Qian, 2019).

The quality of groundwater is intrinsically linked to surface processes through recharge mechanisms such as rainfall infiltration, river seepage, floodplain inundation, and irrigation return flow. These surface-to-groundwater interactions create direct pathways through which contaminants introduced at the land surface or into surface water bodies can migrate into aquifers (Lapworth et al., 2018; Li et al., 2019). Shallow aquifers in urban floodplain environments are particularly vulnerable, as permeable soils, high water tables, and seasonal flooding facilitate rapid contaminant transport from surface water to groundwater systems (Bhaskar et al., 2020; Brunner et al., 2021).

Surface water bodies, especially rivers, exert a strong control on groundwater quality where hydraulic connectivity exists. Polluted rivers can act as persistent sources of groundwater contamination through bank infiltration and hyporheic exchange, particularly during high-flow events (Foster & Chilton, 2018; Lapworth et al., 2017). Under such conditions, dissolved solids, nutrients, pathogens, and heavy metals present in river water may infiltrate adjacent aquifers, leading to long-term degradation of groundwater quality (Briffa et al., 2020; Kumar et al., 2021).

In Nigeria, groundwater dependence has intensified over the past two decades due to the declining functionality of public water supply infrastructure. Many state-owned waterworks operate far below installed capacity or have become completely non-functional because of poor maintenance, inadequate funding, erratic power supply, aging infrastructure, and weak institutional management (Akinwale, 2018; World Bank, 2020). As a result, urban residents increasingly rely on privately constructed boreholes and hand-dug wells, often without proper hydrogeological assessment or water quality monitoring (Ehirim & Maduka, 2019; Akoteyon et al., 2019).

Makurdi metropolis presents a clear example of this challenge. The Benue State Greater Waterworks, which once provided treated surface water from River Benue, has remained largely non-functional for extended periods, forcing households, institutions, and commercial establishments to depend almost entirely on groundwater sources for their daily water needs (Iwar et al. 2021; Eneji et al., 2017; Akaahan et al., 2015). This situation has led to a proliferation of shallow hand-dug wells and boreholes across the city, many of which are located in close proximity to pollution sources such as septic tanks, refuse dumps, drainage channels, and polluted surface waters.

The failure of centralized water supply has inadvertently increased pressure on groundwater resources and heightened the risk of contamination from surface-derived pollutants. In floodplain cities like Makurdi, where River Benue traverses densely populated areas, river water contributes significantly to groundwater recharge through bank infiltration and flood-induced percolation (Eneji et al., 2011; Ejembi et al., 2018). However, intensive anthropogenic activities along the riverbanks, including sand mining, indiscriminate waste disposal, agricultural runoff, and effluent discharge, have deteriorated river water quality, increasing the likelihood of contaminant transfer from surface water to groundwater (Iwar et al., 2020; Akaahan et al., 2015).

Studies conducted along the Makurdi stretch of River Benue have reported elevated concentrations of physicochemical pollutants and trace metals exceeding permissible limits, raising concerns about secondary groundwater contamination (Iwar et al., 2020; Ejembi et al., 2018). During seasonal flooding events, contaminated river water may infiltrate surrounding soils and shallow aquifers, facilitating the transport of dissolved solids, nutrients, and heavy metals into groundwater sources used for drinking and domestic purposes (Lapworth et al., 2018; Bhaskar et al., 2020).

The growing dependence on groundwater in Makurdi, combined with inadequate regulation of borehole construction and limited water quality surveillance, poses significant public health and environmental risks. Heavy metals and inorganic contaminants introduced at the surface are of particular concern due to their persistence and potential to accumulate within aquifer systems (Tchounwou et al., 2018; Briffa et al., 2020). Once groundwater is contaminated, remediation is technically complex and economically prohibitive, making prevention and early detection essential (Foster & Chilton, 2018; Kumar & Singh, 2021).

Effective groundwater quality management therefore requires analytical approaches capable of capturing the complex, nonlinear interactions between surface activities, recharge processes, and subsurface hydrochemistry. Conventional water quality indices and statistical methods provide valuable descriptive assessments but are limited in their predictive capability under dynamic surface-groundwater interaction scenarios (Rana et al., 2018; Vasistha & Ganguly, 2020). This limitation has driven increasing interest in data-driven modelling techniques.

Artificial Neural Networks (ANNs) have emerged as powerful tools for groundwater quality prediction due to their ability to model nonlinear relationships among multiple input variables without requiring prior assumptions about system behavior (Montgomery, 2018). Multilayer Perceptron ANN models have been successfully applied to groundwater quality assessment, water quality index prediction, and contamination risk evaluation in complex hydrogeological settings (Asadollahfardi et al., 2018; Khudair et al., 2018). Recent studies further demonstrate that ANN models are particularly effective in capturing the influence of surface-derived inputs and recharge dynamics on groundwater quality (Elhag et al., 2023; Akakuru et al., 2023).

Despite these advances, ANN-based predictive modelling of groundwater quality remains underutilized in Nigerian cities experiencing failure of centralized water supply systems. There is a clear need for integrated assessment frameworks that combine groundwater quality evaluation with predictive modelling to support proactive management. Therefore, this study applies an Artificial Neural Network approach to assess and predict groundwater quality in Makurdi metropolis, with specific consideration of surface-to-groundwater contamination pathways and the implications of non-functional public waterworks on groundwater reliance and vulnerability.

2. MATERIALS AND METHODS

2.1 Study Area

The groundwater sampling locations were georeferenced using representative geographic coordinates derived from satellite mapping and existing cartographic records of the North

Bank in Makurdi North area of Makurdi. The selected sites (Figure 1) are distributed between latitudes 7.786°N and 7.812°N and longitudes 8.531°E and 8.567°E, reflecting the spatial extent of residential and peri-urban groundwater abstraction points within the study area.

Figure 1: Map of the Study Area

Specifically, the Nigeria Army School of Military Engineering (NASME) Barracks is located in the northeastern part of North Bank at approximately 7.801°N, 8.567°E, while the Federal Low-Cost Estate and Federal Housing Estate lie within the central residential corridor of the area, around 7.792°N, 8.558°E and 7.786°N, 8.552°E, respectively. Court-5 is situated in the south-central section of North Bank at approximately 7.799°N, 8.545°E, whereas Katungu, a peri-urban settlement characterized by intense surface–groundwater interaction, is located closer to the River Benue floodplain at about 7.812°N, 8.531°E.

The spatial distribution of these locations captures variations in land use, population density, and proximity to the River Benue, which collectively influence groundwater recharge dynamics and vulnerability to contamination. The coordinates provided represent approximate central points of each sampling area and are considered adequate for groundwater quality assessment studies where emphasis is placed on hydrochemical characterization and spatial trends rather than fine-scale geostatistical modeling.

2.2 Sampling and Laboratory Analysis

Groundwater samples were collected during the dry season from twenty water sources comprising boreholes and hand-dug wells across five locations: NASME Barracks, Federal Low-Cost Estate, Federal Housing Estate, Court-5, and Katungu. Standard sampling procedures were followed, and samples were collected in pre-cleaned 1 L polyethylene containers and transported to the laboratory for analysis. Physicochemical parameters analyzed included pH, turbidity, TDS, EC, DO, BOD, nitrate, chloride, phosphate, calcium, and total hardness. Analyses were conducted using standard methods recommended by the World Health Organization (WHO, 2022) and the American Public Health Association (APHA, 2017).

2.3 Water Quality Index Computation

The Weighted Arithmetic Water Quality Index was employed to assess groundwater suitability for drinking purposes. Quality ratings (q_n) for each parameter were computed relative to WHO guideline values, and unit weights (W_n) were assigned inversely proportional to the permissible standards. The overall WQI was obtained by aggregating the weighted quality ratings. Based on WQI values, groundwater quality was classified into five categories ranging from excellent to unsuitable for drinking.

2.4 Artificial Neural Network Modelling

2.4.1 ANN Architecture and Rationale

A Multilayer Perceptron (MLP) ANN with a feed-forward backpropagation learning algorithm was adopted for groundwater quality prediction. The choice of MLP was justified by its proven capability to approximate nonlinear functions and its widespread application in environmental modelling. Groundwater quality processes are inherently nonlinear due to complex interactions among physicochemical parameters, making MLP particularly suitable.

The ANN architecture comprised an input layer representing the measured physicochemical parameters, one hidden layer, and an output layer representing the Water Quality Index. A single hidden layer was selected to balance model complexity and generalization capability, as excessively deep networks may lead to overfitting given limited environmental datasets.

2.4.2 Data Preprocessing and Training Strategy

Input data were normalized using standardization to improve convergence and training stability. The dataset was randomly divided into training (70%), testing (15%), and validation (15%) subsets to ensure unbiased model evaluation. The hyperbolic tangent activation function was employed in the hidden layer due to its ability to capture nonlinear relationships, while a linear activation function was used in the output layer.

Model training was performed using backpropagation with error minimization based on mean squared error (MSE). Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). This multi-metric evaluation ensured robust assessment of predictive accuracy and generalization performance.

2.5 Statistical Analysis

Descriptive statistics and correlation analyses were conducted using SPSS software and Python script. The ANN modelling was implemented using the SPSS neural network module. Statistical significance was assessed at a 95% confidence level.

3. RESULTS

3.1 Physicochemical Characteristics of Groundwater

Table 1 presents the results of the physicochemical analysis of groundwater from both Boreholes and Hand-Dug Wells (HDWs). It revealed notable differences in physicochemical characteristics. The pH of Borehole water averaged 7.50, which is within the World Health Organization (WHO) recommended range of 6.5–8.5, indicating slightly alkaline but acceptable conditions. HDW water, however, had a lower average pH of 6.66, still within the safe range, but closer to neutral acidity.

Table 1. Physicochemical parameters of groundwater.

Parameter	WHO Limit	Boreholes ($\bar{x}$ ± SD)	Hand-dug Wells ($\bar{x}$ ± SD)
pH	6.5–8.5	7.50 ± 0.79	6.66 ± 0.76
TDS (mg/L)	500	427.60 ± 176.17	267.60 ± 181.83
Turbidity (NTU)	5.0	4.04 ± 1.21	0.91 ± 0.53
EC (µS/cm)	1500	747.20 ± 492.80	510.20 ± 321.19
DO (mg/L)	8.0	6.14 ± 1.49	5.12 ± 0.19
BOD (mg/L)	10.0	31.51 ± 31.00	48.60 ± 6.39
NO_3^- (mg/L)	50	30.72 ± 10.88	41.43 ± 24.72
Cl^- (mg/L)	250	128.90 ± 68.06	89.17 ± 31.31
PO_4^{3-} (mg/L)	250	50.50 ± 111.53	0.21 ± 0.12
Total Hardness (mg/L)	500	387.20 ± 107.32	100.00 ± 37.42
Ca^{2+} (mg/L)	75	41.30 ± 19.19	23.34 ± 12.92

Total Dissolved Solids (TDS) were higher in Boreholes, with a mean of 427.6 mg/L, compared to 267.6 mg/L in HDWs. This suggests that deeper groundwater contains more dissolved minerals, which is consistent with natural leaching of soil and rock. Similarly, electrical conductivity (EC), a measure of the water's ionic content, was greater in Boreholes (747.2 µS/cm) than in HDWs (510.2 µS/cm), confirming the higher mineral content in deeper sources.

Turbidity, reflecting the presence of suspended particles, was slightly higher in Boreholes (4.04 NTU) than in HDWs (0.91 NTU), but both remained below the WHO limit of 5 NTU, indicating clear water overall. Dissolved Oxygen (DO) levels were moderate in both sources, averaging 6.14 mg/L in Boreholes and 5.12 mg/L in HDWs, suggesting adequate oxygenation to support aerobic processes.

Biochemical Oxygen Demand (BOD), which indicates the amount of organic matter present, was substantially higher in HDWs (48.60 mg/L) than in Boreholes (31.51 mg/L), reflecting greater organic contamination in shallow wells. Nitrate concentrations were also higher in HDWs (41.43 mg/L) than in Boreholes (30.72 mg/L), although both were below the WHO limit of 50 mg/L, suggesting some nutrient loading in the shallow water.

Chloride levels were higher in Boreholes (128.90 mg/L) compared to HDWs (89.17 mg/L), consistent with higher mineral dissolution in deeper aquifers. Phosphate concentrations were highly variable in Boreholes, with a mean of 50.50 mg/L, while HDWs had negligible phosphate levels (0.21 mg/L), reflecting minimal surface-derived phosphate contamination.

Hardness, largely determined by calcium and magnesium content, was significantly higher in Boreholes (387.2 mg/L) than in HDWs (100 mg/L), and calcium concentrations followed the same trend, 41.3 mg/L in Boreholes versus 23.3 mg/L in HDWs. These findings indicate that Borehole water is generally harder and richer in dissolved minerals than shallow well water, which is softer and less mineralized.

3.2 Water Quality Index (WQI) Assessment

The WQI assessment of groundwater sources revealed distinct differences between Boreholes and HDWs (Table 2). For Borehole water, 60% of the samples were classified as "Good," indicating generally acceptable water quality for domestic use, while 20% fell into the "Poor" category, suggesting some level of contamination or undesirable properties. An additional 20% of Borehole samples were considered "Unsuitable," highlighting pockets of groundwater that may pose health risks if consumed without treatment. Notably, no Borehole samples were rated as "Excellent" or "Very Poor," suggesting that while most deep groundwater is of adequate quality, certain locations experience localized degradation.

Table 2. Water quality index classification of groundwater samples.

Water Source	Excellent (%)	Good (%)	Poor (%)	Very Poor (%)	Unsuitable (%)
Boreholes	—	60	20	—	20
Hand-dug Wells	—	—	60	40	—

In contrast, the HDW samples showed a more concerning pattern. Sixty percent of the samples were classified as "Poor," reflecting moderate contamination, and 40% fell into the "Very Poor" category, indicating significant deterioration in water quality. No HDW samples were rated as "Good" or "Excellent," and none were deemed "Unsuitable," suggesting that while the water is not immediately hazardous, it generally fails to meet optimal standards for domestic consumption.

The WQI results corroborate the physicochemical findings: Boreholes generally provide higher-quality water due to their depth and reduced exposure to surface contamination, whereas HDWs, being shallow and more susceptible to anthropogenic and environmental inputs, display lower water quality. This trend is consistent with studies in similar hydrogeological settings, were shallow wells often present higher levels of microbial and chemical contamination, leading to poorer WQI classifications relative to deep boreholes (Adewale et al., 2017; Olajire & Ayodele, 2020).

Overall, the WQI classification highlights the need for targeted monitoring and possible treatment, especially for HDW sources, to ensure safe drinking water and mitigate health risks associated with suboptimal groundwater quality.

3.3 ANN Model Performance

Figure 2 showed that the MLP-ANN analysis for Borehole groundwater employed seven hidden neurons, with

synaptic weights linking eleven physicochemical parameters to the hidden layer and subsequently to the output layer representing the Borehole Water Quality Index (AMWQI).

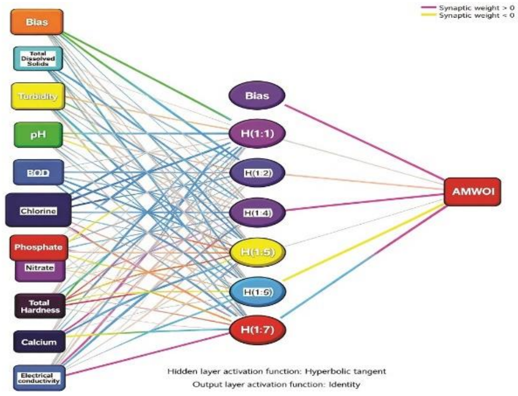

Figure 2: Multilayer perceptron network architecture for boreholes WQI.

Examination of the input-to-hidden weights (Table 3) shows that Nitrate had weights ranging from –0.489 to 0.394 across hidden neurons, Total Hardness ranged from –0.462 to 0.445, Calcium ranged from –0.429 to 0.493, and Electric Conductivity ranged from –0.436 to 0.436. Other significant contributors included Total Dissolved Solids (–0.479 to 0.378) and BOD (–0.377 to 0.481). Parameters such as Chlorine (–0.280 to 0.337) and Phosphate (–0.134 to 0.416) had relatively lower weights across neurons, indicating lesser direct influence.The hidden-to-output layer weights for Boreholes further modulated the influence of these neurons on the final AMWQI. H4 and H5 had strong negative contributions of –0.461 and –0.385, respectively, while H7 and H1 had positive contributions of 0.217 and 0.041. Combined through the network, these synaptic weight patterns indicate that Nitrate, Total Hardness, Calcium, and Electric Conductivity exerted the largest influence on Borehole WQI, reflecting the prominent role of mineral content and ionic composition in deeper aquifers.

Table 3. Synaptic weight ANN AMWQI for boreholes groundwater.

Predictor	**H1**	**H2**	**H3**	**H4**	**H5**	**H6**	**H7**
Bias	0.393	0.132	0.442	0.180	0.190	0.094	0.422
Nitrate	-0.231	-0.336	0.394	-0.424	-0.263	-0.489	-0.016
Total Hardness	0.407	0.445	-0.439	0.076	-0.438	0.042	-0.462
Calcium	-0.340	-0.280	-0.067	0.493	0.131	0.165	-0.429
Electric Conductivity	0.436	-0.106	0.311	0.296	-0.405	0.069	-0.436
Total Dissolved Solids	-0.311	-0.100	-0.479	0.272	-0.221	-0.360	0.378
Turbidity	0.489	-0.033	0.297	0.237	0.323	-0.069	0.189
pH	0.417	-0.487	0.124	-0.412	0.191	-0.123	0.082
Dissolved Oxygen	-0.470	-0.098	-0.399	0.144	-0.346	0.153	0.226
BOD	-0.364	0.453	-0.116	-0.377	-0.272	-0.234	0.481
Chlorine	0.135	0.189	-0.183	0.337	0.274	-0.269	-0.280
Phosphate	0.416	-0.390	-0.134	0.224	-0.084	-0.307	0.324

Hidden Neuron	Output Weight (BH-AMWQI)					
Bias	0.170					
H1	0.041					
H2	-0.322					
H3	-0.288					
H4	-0.461					
H5	-0.385					
H6	-0.264					
H7	0.217					

For Hand-Dug Wells (HDWs), the ANN employed five hidden neurons (Figure 3). Input-to-hidden weights (Table 4) show that Chlorine had large negative weights ranging from –1.034 to 0.688, Dissolved Oxygen ranged from –0.989 to 0.768, Turbidity ranged from –0.618 to 0.588, and Calcium ranged from –0.669 to 0.706. Parameters such as Phosphate (–0.506 to 0.060) and Total Hardness (–0.254 to 0.701) had smaller weights, indicating limited influence on the hidden layer activations.

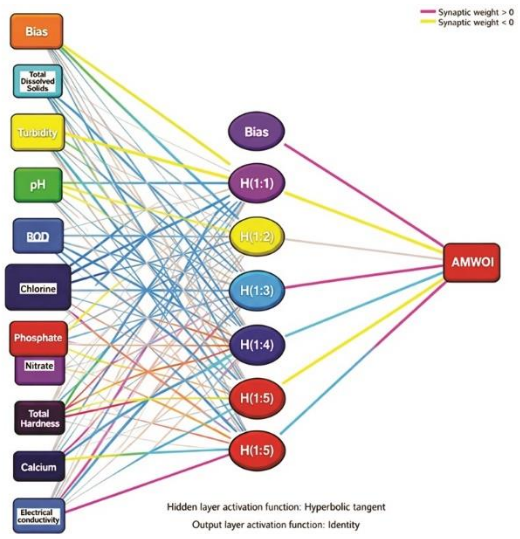

Figure 3: Multilayer perceptron network architecture for hand dug well WQI.

The hidden-to-output weights further highlighted the relative impact of each neuron: H3 had a strong negative weight of –0.578, H5 a strong positive weight of 0.882, while H1, H2, and H4 contributed 0.369, 0.213, and –0.007, respectively. This distribution of weights suggests that Chlorine, Dissolved Oxygen, Turbidity, and Calcium were the primary drivers of HDW WQI, highlighting the vulnerability of shallow wells to surface contamination and water quality deterioration.

Table 4: Synaptic weight ANN AMWQI for hand dug well groundwater.

Predictor	H1	H2	H3	H4	H5
Bias	-0.173	-0.123	-0.174	0.389	-0.249
Total Dissolved Solids	-0.318	-0.477	0.476	-0.285	0.199
Turbidity	-0.136	-0.345	-0.506	-0.618	0.588
pH	-0.429	0.451	-0.199	-0.088	0.386
Dissolved Oxygen	-0.989	-0.185	0.768	0.388	-0.258
BOD	-0.030	0.415	0.193	-0.640	-0.667
Chlorine	-1.034	-0.384	0.688	-0.135	-0.022
Phosphate	0.060	0.186	-0.506	0.256	-0.045
Nitrate	-0.129	0.126	0.473	-0.645	0.127
Total Hardness	-0.254	0.073	0.701	-0.249	0.054
Calcium	0.706	0.521	-0.669	-0.130	-0.368
Electric Conductivity	0.662	0.044	0.399	-0.666	0.463
Hidden Neuron	**Output Weight (AMWQI)**				
Bias	-0.165				
H1	0.369				
H2	0.213				
H3	-0.578				
H4	-0.007				
H5	0.882				

Comparison of the two groundwater sources demonstrates a clear distinction: Borehole water quality is predominantly influenced by parameters associated with geogenic mineral content such as Nitrate, Hardness, and EC, whereas HDW water quality is strongly affected by surface-derived contamination indicators including Chlorine, Turbidity, and Dissolved Oxygen. These numeric weight patterns provide a quantitative explanation for the differential sensitivity of Borehole and HDW water quality to physicochemical parameters and can inform targeted monitoring strategies.

Sensitivity Analysis of ANN Models

The Garson sensitivity analysis of the ANN models provides insight into the relative contribution of each physicochemical parameter to the WQI of Boreholes and HDWs (Table 5). For Borehole water, Nitrate emerged as the most influential parameter, contributing 12.7% to the overall WQI, followed closely by Total Hardness at 11.6%, Electric Conductivity at 11.1%, and Calcium at 10.4%.

Table 5: Side-by-Side Garson Sensitivity Table

Parameter	Borehole WQI (%)	HDW WQI (%)
Nitrate	12.7%	7.3%
Total Hardness	11.6%	6.8%
Calcium	10.4%	10.5%
Electric Conductivity	11.1%	11.5%
Total Dissolved Solids	9.4%	8.8%
Turbidity	7.3%	10.4%
pH	8.4%	6.7%
Dissolved Oxygen	8.1%	11.1%
BOD	9.0%	9.3%
Chlorine	5.2%	12.5%
Phosphate	7.0%	5.0%

These results indicate that the quality of Borehole water is largely determined by the mineral content and ionic composition, consistent with the characteristics of deeper aquifers where water-rock interactions dominate. Parameters such as Total Dissolved Solids (9.4%), BOD (9.0%), and pH (8.4%) had moderate influence, whereas Chlorine (5.2%) and Phosphate (7.0%) contributed the least, suggesting that surface-derived contaminants exert minimal effect on Borehole water quality.

In contrast, the HDW WQI was most strongly influenced by parameters associated with surface contamination and chemical inputs. Chlorine had the highest contribution at 12.5%, followed by Electric Conductivity at 11.5%, Dissolved Oxygen at 11.1%, Calcium at 10.5%, and Turbidity at 10.4%. These findings reflect the shallow nature of HDWs, which makes them more vulnerable to anthropogenic inputs such as domestic effluents and agricultural runoff. Other parameters, including BOD (9.3%) and Total Dissolved Solids (8.8%), had moderate effects, while Phosphate (5.0%), Nitrate (7.3%), and pH (6.7%) were less influential.

Comparison between the two groundwater sources highlights a clear distinction in controlling factors. Borehole water quality is largely governed by geogenic parameters such as Nitrate, Hardness, and Conductivity, reflecting natural mineralization processes in deeper aquifers. HDW water quality, however, is primarily influenced by parameters indicative of surface contamination, particularly Chlorine, Turbidity, and Dissolved Oxygen, demonstrating the higher susceptibility of shallow wells to environmental and anthropogenic impacts. These numeric contributions from the Garson analysis provide a quantitative framework to identify priority parameters for monitoring and management for each water source, reinforcing the importance of source-specific water quality assessment strategies.

4. DISCUSSION

The physicochemical assessment of groundwater from Boreholes and Hand-Dug Wells (HDWs) in North Bank, Makurdi, revealed clear differences in water quality that are largely attributable to source depth, aquifer composition, and exposure to surface contamination. Borehole water exhibited a slightly alkaline pH (7.50 ± 0.79), higher Total Dissolved Solids (427.6 ± 176.2 mg/L), and higher electrical conductivity (747.2 ± 492.8 µS/cm), indicating greater mineralization resulting from prolonged water–rock interaction within deeper aquifers. In contrast, HDWs were less mineralized, with lower pH (6.66 ± 0.76), TDS (267.6 ± 181.8 mg/L), and EC (510.2 ± 321.2 µS/cm), reflecting the limited residence time and weaker geochemical buffering typical of shallow groundwater systems. Similar depth-controlled variations in groundwater chemistry have been reported across Makurdi by Iwar et al. (2021), Eneji et al. (2017), and more recently by Tongu et al. (2024), all of whom attributed higher mineral content in boreholes to enhanced geogenic influence.

Organic and nutrient contamination was more pronounced in HDWs, as reflected by higher biochemical oxygen demand (48.6 ± 6.4 mg/L) and nitrate concentrations (41.4 ± 24.7 mg/L) compared to boreholes (31.5 ± 31.0 mg/L and 30.7 ± 10.9 mg/L, respectively). The comparatively lower dissolved oxygen observed in HDWs (5.12 ± 0.19 mg/L) relative to boreholes (6.14 ± 1.49 mg/L) likely reflects increased microbial activity and organic matter decomposition in shallow aquifers. This pattern is consistent with the findings of Akaahan et al. (2015) and Tongu et al. (2024), who reported elevated BOD and nitrate levels in shallow wells within Makurdi due to their susceptibility to surface runoff, on-site sanitation systems, and improper waste disposal.

Water Quality Index (WQI) classification further emphasized these contrasts. Borehole samples were predominantly classified as “Good” (60%), with 20% rated as “Poor” and 20% as “Unsuitable.” In contrast, HDWs showed generally degraded quality, with 60% classified as “Poor” and 40% as “Very Poor.” When both sources were integrated, the overall WQI for North Bank was estimated at 37.5, corresponding to a “Poor” water quality classification. This indicates that, although boreholes generally provide better-quality water, the widespread deterioration of HDWs significantly lowers the average groundwater quality in the area. Similar WQI patterns, where shallow wells downgrade the overall groundwater status, have been documented in Makurdi by Vangeryina et al. (2025), particularly during dry seasons when dilution effects are minimal.

Artificial Neural Network (ANN) modeling further quantified the relative importance of individual parameters influencing groundwater quality. For boreholes, Garson sensitivity analysis identified nitrate (12.7%), total hardness (11.6%), electrical conductivity (11.1%), and calcium (10.4%) as the most influential parameters, confirming that geogenic mineral composition is the dominant control on deep groundwater quality. In contrast, HDW water quality was most strongly influenced by chlorine (12.5%), electrical conductivity (11.5%), dissolved oxygen (11.1%), calcium (10.5%), and turbidity (10.4%), highlighting the dominant role of surface contamination and anthropogenic inputs. These ANN-derived insights are consistent with recent multivariate and WQI-based assessments in Makurdi, which reported stronger anthropogenic signals in shallow wells compared to boreholes (Eneji et al., 2017; Tongu et al., 2024; Vangeryina et al., 2025).

Importantly, our ANN-based Garson sensitivity results help explain why some sources deviate from compliance: for Boreholes, nitrate, Hardness, EC, and calcium were the dominant influences on water quality, consistent with deeper aquifer geochemistry and studies that report mineral dominance in these systems. For HDWs, parameters like Chlorine, EC, DO, and Turbidity were most influential, pointing to surface contamination pathways such as runoff and waste leachate, which are also implicated in heavy metal and turbidity concerns in River Benue and groundwater contexts around Makurdi.

When integrated into the Water Quality Index framework, these patterns reinforce prior conclusions: while much of Makurdi's groundwater remains within NSDWQ and WHO limits, a significant proportion, especially in shallow wells and during dry seasons, displays degraded quality that may not meet domestic use standards without treatment. This is reflected in studies where substantial seasonal shifts in WQI occur, with poorer classifications expanding in the dry season as dilution effects diminish (Iwar et al., 2021)

Overall, the findings demonstrate that deep boreholes in North Bank generally provide relatively safe, mineral-rich water, whereas shallow hand-dug wells are highly vulnerable to contamination, resulting in an overall groundwater quality classified as Poor. The study highlights the need for protection, routine monitoring, and treatment of HDWs, while reinforcing the role of boreholes as more reliable domestic water sources. These conclusions are critical for public health protection, groundwater sustainability, and urban water management planning in Makurdi.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study assessed the physicochemical characteristics, Water Quality Index (WQI), and Artificial Neural Network (ANN)–based sensitivity of groundwater from boreholes and hand-dug wells (HDWs) in North Bank, Makurdi, Benue State. The results revealed clear contrasts in groundwater quality between the two sources, largely controlled by aquifer depth, geogenic processes, and exposure to surface contamination.

Borehole water generally exhibited better quality, with slightly alkaline pH, higher mineral content, and improved WQI ratings, reflecting dominant geogenic influence and natural filtration in deeper aquifers. In contrast, HDWs showed elevated levels of organic and nutrient contamination, including higher BOD and nitrate concentrations, reduced dissolved oxygen, and poorer WQI classifications. When both sources were integrated, the overall groundwater quality for North Bank was classified as Poor (WQI = 37.5), indicating that the widespread degradation of shallow wells significantly lowers the average water quality in the area.

ANN modeling and Garson sensitivity analysis further demonstrated that borehole water quality is primarily controlled by mineral-related parameters such as nitrate, hardness, electrical conductivity, and calcium, whereas HDW quality is strongly influenced by surface-derived contaminants including chlorine, turbidity, and dissolved oxygen. These findings are consistent with previous studies in Makurdi and confirm the heightened vulnerability of shallow groundwater systems to anthropogenic activities.

Overall, the study concludes that while boreholes remain relatively reliable sources of domestic water in North Bank, hand-dug wells pose potential health risks if used without treatment, underscoring the need for improved groundwater management and protection strategies.

5.2 RECOMMENDATIONS

Drawing from the results of this study, it is advised that increased focus be placed on safeguarding and managing shallow groundwater sources in North Bank, Makurdi. Hand-dug wells should be properly secured by ensuring they are well-lined, covered, and situated at safe distances from potential contamination sources such as pit latrines, refuse sites, and drainage systems. Implementing these precautions will help limit the infiltration of surface pollutants into shallow aquifers. It is also important to establish routine groundwater quality monitoring, especially for hand-dug wells and boreholes previously identified as having poor or unsuitable water quality. Regular testing for both physicochemical and microbiological parameters will facilitate early detection of contamination and enable prompt action, particularly during the dry season when pollutant levels may rise.

Water from hand-dug wells should undergo treatment before being used for household purposes to reduce health risks. The community should be encouraged to adopt simple water treatment methods at home, such as filtration, boiling, and controlled chlorination. While boreholes typically yield better quality water, they too require periodic treatment and maintenance to consistently meet drinking water standards. Efforts to raise public awareness should be intensified to educate residents about safe water handling, improved sanitation, and the consequences of improper waste disposal on groundwater quality. Increasing community knowledge about the vulnerability of groundwater will help promote behaviors that minimize contamination.

For future groundwater development, urban water supply planning in Makurdi should emphasize the construction and regulation of boreholes rather than shallow wells, alongside strict enforcement of environmental and groundwater protection measures. Additionally, future research should include microbiological assessments, heavy metal testing, and long-term seasonal monitoring to gain a more thorough understanding of groundwater quality trends and to support sustainable management of water resources in the region.

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