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Modeling Groundwater Quality and Prediction in a Highly Urbanised Coastal City of Lagos Using an Artificial Neural Network

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ABSTRACT
The quality of groundwater is a serious issue worldwide. The groundwater quality status was assessed by comparing it with World Health Organization (WHO) standards, and groundwater quality parameters were predicted using an Artificial Neural Network (ANN) model with the Levenberg-Marquardt algorithm. A total of 15 samples were collected from boreholes and wells and analyzed for Electrical Conductivity (EC), pH, temperature, salinity, and chloride, and predictions were made for Total Dissolved Solids (TDS), sodium (%Na), iron (Fe), and bicarbonate. The data were normalized and then divided into training, validation, and testing sets (70%, 15%, and 15%, respectively). The results indicated significant variations in the spatial distribution; Isheri had significantly higher EC (5860 µS/cm) and TDS (3180 mg/L), which are beyond WHO limits, likely due to industrial pollution. The salinity level on Tincan Island was high (2.24 ppt), and the water was undrinkable, whereas the salinity levels on Akodo and Akeusola were low (0.1 to 0.08 ppt), and the water was drinkable. The ANN had good predictive performance with Mean Square Error of 0.6908 (training), 0.5063 (test) and 1.11 (validation). The regression value of the 10-neuron hidden layer was 1.0 (training), 0.92601 (validation), and 0.95023 (testing). Absolute Error was minimal (TDS: 0.0 to 0.06; Fe: 0.0 to 0.001), and Mean Absolute Error (TDS: 0.84; Na: 0.17; Fe: 0.0019; bicarbonate: 0.5973), confirming the model's reliability. The study shows that ANN is a powerful tool for predicting groundwater quality and can support sustainable groundwater management in coastal urban areas. The disadvantages are a small sample size (15) and the use of fixed parameters that do not account for seasonal changes. Larger data sets and dynamic environmental factors should be included in future research.

Keywords:
Artificial Neural Network Model; Sustainable Management; Levenberg- Marquardt; World Health Organization

INTRODUCTION

Groundwater is an important source of drinking water worldwide. But it is being degraded by various human activities and natural processes, threatening its quality (Kayastha et al., 2022). With groundwater contamination from both natural and anthropogenic sources, groundwater quality has become a global concern. Groundwater is one of the most critical freshwater resources, particularly in highly urbanized areas such as Lagos, Nigeria, and needs to be properly protected for the sustainable management of groundwater. This resource has been overexploited due to population growth and industrial expansion, and has been a major factor in its degradation, especially in coastal areas such as Lagos,

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where pollution and saltwater intrusion from urbanization are issues for both shallow and deep aquifers (Mukate et al., 2019).

Groundwater quality status has been evaluated globally. According to Yusuf (2007), certain groundwater quality parameters exceeded the World Health Organization (WHO) drinking water standards, regardless of the pollution sources. Total dissolved solids (TDS) exceeded the recommended limit in 50% of the samples; electrical conductivity in 27.8%; lead in 38.9%; pH in 44.4%; and elevated sodium and calcium levels were observed in 11.1% of the samples. Sheu et al. (2025 investigated groundwater Salinity Levels using Physicochemical Analysis around the Gada-Mashegu Area, North Central Nigeria: Implications for drinking water and Irrigated Farms. The results of their findings from river, hand-dug well and borehole revealed that pH levels were (6.17, 6.60 and 7.53), SAR (0.07, 0.08, 7.35) ds/m EC (528, 12.51 and 4.19) *S*/cm Hardness (4554.1, 2831. 25) and that The Hand dug well and that of borehole water sample meet the standard set by WHO.

As a coastal megacity, Lagos faces increasingly complex hydro-environmental issues such as saltwater intrusion, groundwater contamination, and overexploitation. This environmental stress has led to a wide range of studies of groundwater systems in the region. Despite this, groundwater quality continues to deteriorate, and urgent, innovative interventions are needed. This study addresses remaining concerns about groundwater quality and uses Artificial Neural Networks (ANNs) to model and predict future groundwater quality trends, which will be helpful for informed decision-making and long-term groundwater management (Yusuf, 2007).

ANNs have been shown to be useful for groundwater quality modelling. For example, Maier and Dandy (1996) predicted salinity in the River Murray, Australia, using ANNs, demonstrating their usefulness in complex hydrological systems. Saltwater intrusion has been a major problem in the small freshwater lenses in the coastal plain sands of Lagos, leading to a decrease in safe drinking water availability. It is still important to assess the groundwater quality using suitable indicators and physicochemical parameters to estimate the Water Quality Index (WQI) (Abbasi & Abbasi, 2012; Nathan et al., 2017; Hossain & Patra, 2020; Islam et al., 2020).

Groundwater contamination is a serious environmental and public health hazard, especially in densely populated urban areas and industrialized regions. Nitrates, heavy metals, hydrocarbons, microbial pathogens, and other dissolved salts (e.g., sodium, chloride, TDS) are common pollutants from agricultural runoff, industrial discharges, leachate from landfills, and seawater intrusion. These pollutants affect water quality, pose health risks, impact crop yields, and damage water ecosystems (Li et al., 2022).

Soladoye and Ajibade (2014) reported significant variability in groundwater quality across Lagos State, with parameters such as TDS, iron, and magnesium frequently exceeding the Nigerian Standard for Drinking Water Quality (NSDWQ) and WHO limits, indicating that the water is not suitable for drinking. Akoteyon and Soladoye (2011) observed elevated concentrations of TDS, iron, and magnesium in Eti-Osa, revealing the uneven distribution of groundwater quality throughout the area.

Salami and Ayinde (2025) conducted a comprehensive investigation of groundwater quality at Lagos State University, EPE, Lagos State, Nigeria. Their study revealed that groundwater pH values ranged from 3.8 to 6.8, with a mean of 4.655 and a standard deviation of 0.659. Lead concentrations ranged from 0.003 to 0.15 mg/L, averaging 0.046 mg/L, while nickel concentrations varied from 0.0068 to 0.2 mg/L, with an average of 0.053 mg/L.

Pessu et al. (2022) analyzed groundwater quality in Ikorodu, Lagos, reporting mean values of pH (7.0 ± 0.59), TDS (176.0 ± 132.2 mg/L), salinity (0.14 ± 0.11 g/kg), turbidity (0.32 ± 0.05 NTU), hardness (59.58 ± 34.89 mg/L), BOD (11.59 ± 3.41 mg/L), COD (14.90 ± 4.18 mg/L), phosphate (0.97 ± 0.46 mg/L), nitrate (2.62 ± 1.27 mg/L), sulfate (9.44 ± 5.94 mg/L), and total bacterial count ($4.92 \pm 2.94 \times 10^2$ cfu/mL).

Traditional approaches for groundwater quality assessment, while reliable, are often time-consuming, costly, and spatially limited. With the increasing volume and complexity of environmental data, Artificial Intelligence (AI) has emerged as a powerful alternative for groundwater monitoring and prediction. AI techniques, particularly ANNs, Support Vector Machines (SVMs), Random Forests, and Deep Learning, have proven effective in capturing the complex, nonlinear relationships between hydrochemical variables (Gani et al., 2025).

These models can be used to predict groundwater quality parameters, identify sources of groundwater contamination, and simulate contamination scenarios based on historical and real-time data. They are well suited to large, heterogeneous, and incomplete datasets, which is important given the dynamic nature of groundwater systems (Adimalla & Venkatayogi, 2018). For example, the concentrations of TDS, sodium, iron, and bicarbonate have been estimated from variables such as pH, salinity, electrical conductivity, and temperature by using ANNs.

The use of AI-driven models is revolutionizing groundwater quality assessment by providing scalable, accurate, and timely solutions. They enable stakeholders and decision-makers to gain predictive insights to support proactive groundwater management, particularly in environmentally critical areas such as coastal Lagos (Gani et al., 2025). Additionally, AI-driven monitoring systems are more efficient and cost-effective (Tavakol et al., 2017; Tiwary et al., 2018; Gupta et al., 2016).

ANNs are widely used in water quality studies among the different AI techniques. They have been applied to predict groundwater table fluctuations (Zhu et al., 2020), water quality indicators (Ali et al., 2024; Mohammed et al., 2023), and heavy metal pollution (Singha et al., 2020). The ANN-NAR developed by Zhang and Stanley (1999) has been found to be more accurate in forecasting water quality than the models using ANN alone.

Groundwater quality studies have been carried out in the Lagos coastal area, but there is a lack of predictive modelling with AI. This study is essential for forecasting groundwater quality and for sustainable groundwater management, especially in the context of the challenges posed by urbanization, industrial waste, and seawater intrusion. Early prediction enables timely interventions, lowers health risks and aids future planning (Odjegba, 2023).

In recent times, the use of ANNs for WQI estimation has been extended and has shown good results in terms of predictive accuracy (Hameed et al., 2017; Aldhyani et al., 2020; Agrawal et al., 2021; Prasad et al., 2021; Ubah et al., 2021; Ali et al., 2024). Other AI methods, such as Gaussian Process Regression, Support Vector Machines, Fit Binary Trees, and Genetic Algorithms, have also been used in water quality modeling (Wang et al., 2008; Noori et al., 2013; Vahid et al., 2024). A total of 15 samples were collected from boreholes and wells, and analyzed for key groundwater parameters, including EC, TDS, pH, temperature, salinity, chloride, sodium, iron, and bicarbonate. Odjegba (2023) reported that the pH of water in 7 out of 10 boreholes in Lagos was acidic (pH less than 6.5). The two boreholes had high EC and TDS; six boreholes had lead levels above 0.01 mg/L; and five boreholes were above the WHO limit for iron (0.3 mg/L).

Groundwater quality in the coastal aquifers of Lagos has been widely studied, but recent studies have adopted mainly hydrochemical analysis, geophysical methods, hydrogeochemical modelling, and geospatial methods to characterize groundwater quality (Yusuf et al., 2021; Ezechinyere & Stanislaus, 2023; Oladele et al., 2023). The use of Artificial Neural Networks (ANNs) for predictive modelling of groundwater quality in saline-influenced coastal aquifers in Lagos is still limited. It is a methodological gap as the relationships between the hydrochemical variables in coastal aquifers are highly non-linear and cannot be described by conventional statistical methods.

Artificial Neural Networks (ANNs) were chosen because they can learn complex nonlinear relationships directly from observed data without making any assumptions about the hydrogeological processes. The ability to do this makes ANNs ideal for predicting groundwater quality in heterogeneous coastal aquifer systems where several physicochemical parameters may be acting at the same time (Maier & Dandy, 2000).

The Levenberg–Marquardt (LM) back propagation algorithm was chosen as it is one of the most efficient training methods for multilayer perceptron networks with small to medium-sized data sets, which is usually the size of data sets used in groundwater quality studies. The algorithm is a hybrid of the Gauss–Newton optimization method and the gradient descent method and has faster convergence, lower mean squared error and higher predictive accuracy than traditional back propagation algorithms (Hagan & Menhaj, 1994). LM is more memory intensive, but for the data set utilized in this study, it is a suitable option for groundwater quality prediction in the coastal aquifers of Lagos with accuracy.

The research, conducted in Lagos between June and November 2024, aims to: (i) assess the status of groundwater quality; (ii) compare the results with WHO standards; and (iii) model and predict future groundwater quality trends using ANN algorithms developed in MATLAB. This predictive modeling approach represents a novel contribution in the context of Lagos, where no prior ANN-based modeling has been documented. Ultimately, this study provides a cost-effective and proactive tool for forecasting groundwater quality, guiding urban planning, and informing decision-making. Its findings align with global efforts to ensure access to clean and safe water (SDG 6), and can serve as a model for other coastal cities confronting similar environmental challenges (Zhang & Stanley, 1999).

Concept of Artificial Neural Network

Artificial Neural Networks (ANNs) are powerful computational models inspired by the structure of the human brain and have shown great ability to identify complex, nonlinear relationships in environmental and hydrological systems (Junhao & Zhaocai, 2022; Mosavi et al., 2018). In the field of water resources management, ANNs have been extensively used for groundwater quality prediction, water level modeling, and hydrological forecasting, among other applications, where linear models are inadequate due to the complex and dynamic nature of groundwater systems.

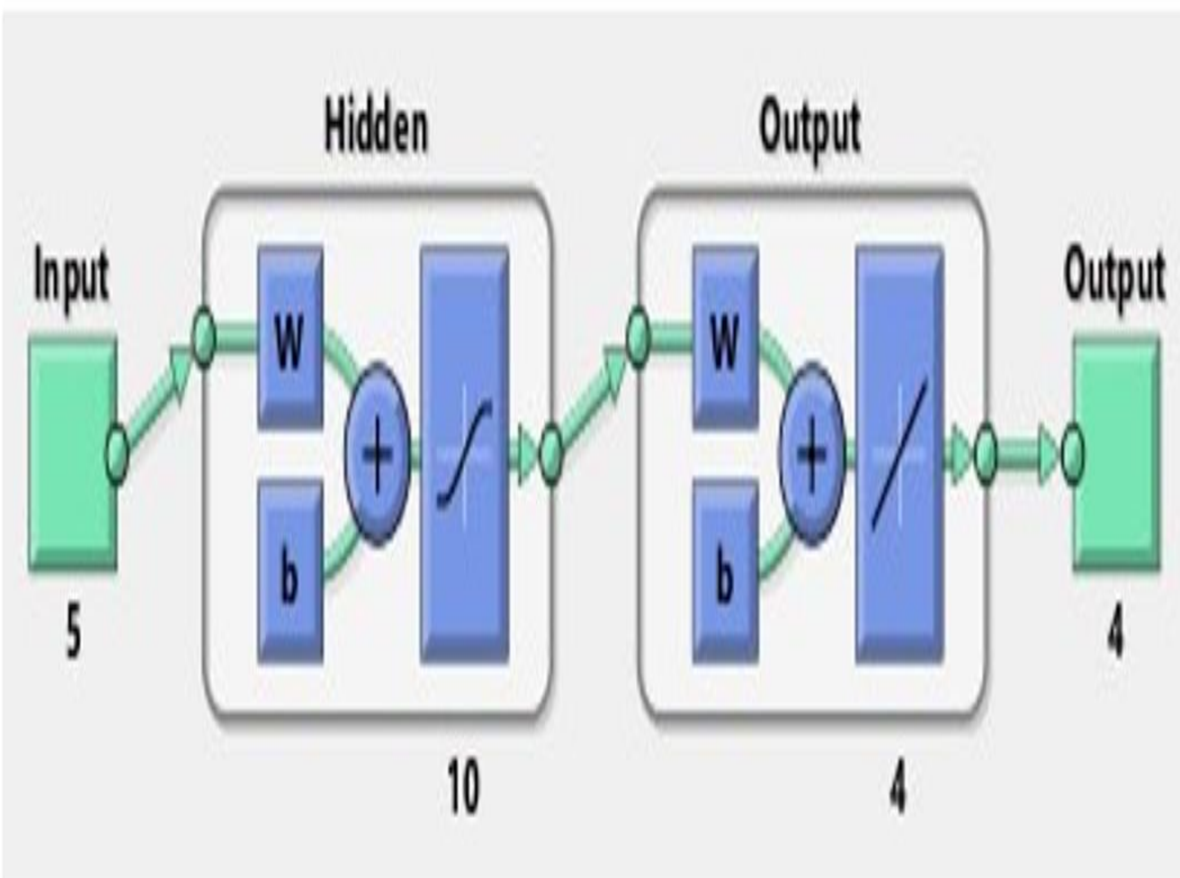
The ability to learn from historical data, adapt to new data, and find hidden patterns in multivariate datasets that may not be explicitly defined makes ANNs particularly well-suited for modeling groundwater. ANNs are also applied to classification, optimization, function approximation, and forecasting problems across various fields beyond hydrology. Their versatility stems from their architecture (Figure 2), which typically consists of interconnected layers: an input layer, one or more hidden layers, and an output layer (Hossain & Patra, 2020; Jixuan et al., 2024). The layers consist of artificial neurons (nodes) that compute a weighted sum and then apply activation functions (Figure 1). They enable the network to perform parallel computation and approximate nonlinear mappings between input parameters and output targets (Jixuan et al., 2024).

One of the most important characteristics of ANNs is their learning capability. In supervised learning, ANNs are trained using labeled datasets, where the inputs are variables such as pH, TDS, EC, etc., and the outputs are the desired results, such as the WQI or concentrations of contaminants. The learning process is based on the backpropagation algorithm, which includes a forward pass to make predictions (Figure 2) and a backward pass to update the weights using the error between the actual and predicted values (Mosavi et al., 2018; Hossain & Patra, 2020). A mechanism that allows the model to adjust its parameters during training to improve the accuracy of its predictions. Figure 2 shows the architecture of a feed-forward ANN with input, output, and hidden layers used in the study.

For optimal performance, ANNs use gradient-based optimization to update their weights and reduce error. These include batch, stochastic, and mini-batch variants, which differ in how the training data is used to update weights. The entire dataset is used per iteration in batch gradient descent, whereas stochastic gradient descent updates after each data point and mini-batch gradient descent uses small data subsets that balance speed and stability (Noor, 2020). This optimization allows ANNs to converge efficiently towards a solution, even when datasets are incomplete and noisy, as is often the case in groundwater monitoring.

However, with these capabilities, ANNs offer a powerful tool for forecasting groundwater quality in coastal and urban areas, where multiple physical, chemical, and anthropogenic factors interact, making the system dynamic and complex (Junhao & Zhaocai, 2022). They are highly adaptive and can learn from historical data to make predictions, detect new risks, and support sustainable groundwater management decisions (Junhao & Zhaocai, 2022; Jixuan et al., 2024; Mosavi et al., 2018).

Figure 1: A representative Neural Network structure showing 5 input parameters, a hidden layer of 10 neurons, and an output layer of 4 neurons used for the study



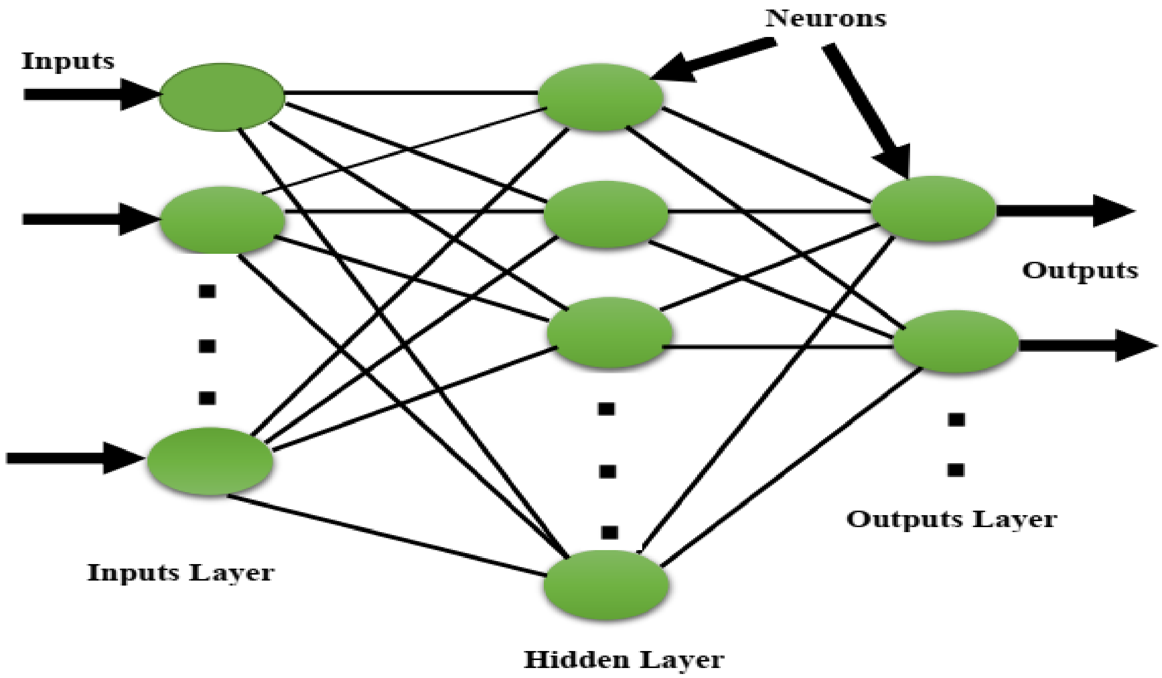


Figure 2: Architecture of the prototype feed-forward ANN with input, output and hidden layer used for the study

Levenberg–Marquardt Algorithm

Levenberg–Marquardt (LM) algorithm is a powerful optimization algorithm that combines the best features of gradient descent and the Gauss Newton method to efficiently solve non-linear least squares problems (Khan et al., 2021). Its ability to approximate complex non-linear relationships with high accuracy and its fast convergence rate make it a popular choice for training artificial neural networks (ANNs), which are widely used in applications such as environmental modeling and hydrology (Khan et al., 2021; Abiodun et al., 2019).

The LM algorithm is more effective for water quality prediction, groundwater modelling, and parameter optimisation, as it iteratively optimises model parameters to minimise the error between observed and predicted outputs (Yadav et al., 2020). The new rule in the LM algorithm can be mathematically stated as follows: where k is the iteration number, J is the Jacobian matrix, μ is the combination coefficient, I is the identity matrix, and e is the error vector. A key aspect of guiding the optimization process is the damping factor μ. If the error surface is curved in a complicated way, the algorithm will take the more conservative steepest descent path by increasing μ. On the other hand, if it is possible to reasonably model the error surface as quadratic, μ is reduced, and the algorithm can take advantage of the faster convergence of the Gauss-Newton method (Yadav et al., 2020).

The LM algorithm is generally superior to other optimization algorithms, with faster convergence, greater stability, and a lower tendency to fall into local minima (Toth et al., 2000).

The algorithm is frequently used in training neural networks, especially for nonlinear least-squares problems. For groundwater quality simulation, parameters are typically divided into two groups: inputs (Independent variables) and outputs (dependent variables). The input parameters include variables used by the model to predict groundwater quality (Hagan & Menhaj, 1994; Khan et al., 2021).

The Levenberg-Marquardt algorithm has a mixed training method. It is similar to the steepest descent method in regions of high curvature of the error surface, and is therefore stable. The algorithm switches to the more efficient Gauss-Newton method as the curvature of the local surface becomes better suited to a quadratic approximation, thereby speeding up the training process. In this context, the input data is utilized to train the neural network. The model's objective is to accurately predict the output parameters. During training, the model's predictions are compared with the observed values, and the Levenberg-Marquardt algorithm adjusts the model's internal parameters to minimize the difference between the predictions and the observed values. This iterative process ultimately optimizes the model's ability to accurately represent the relationship between inputs and outputs (Hagan & Menhaj, 1994; Khan et al., 2021).

The feed-forward neural network architecture and the efficient Levenberg-Marquardt (LM) algorithm are used to train it. The LM algorithm is an extension of the least-mean-squares (LMS) algorithm (Abiodun et al., 2019) that is based on gradient descent and approximates the Hessian matrix by the Jacobian matrix. The original version of the LM algorithm was only applicable to layer-by-layer topologies, which may not be the most efficient, although it works well for smaller to medium-sized networks (Bogdan et al., 2007).

The Levenberg-Marquardt algorithm is replaced by layer-by-layer ANN training, which improves the scalability and generalization of the groundwater quality prediction model in Lagos. LM has a rapid convergence, suitable for smaller datasets, but layer-by-layer approaches better represent the complex non-linear patterns found in urban coastal aquifers, which are better suited to monitoring and managing groundwater in rapidly developing areas.

Artificial Neural Network application to groundwater quality modelling

Artificial Neural Networks (ANNs) are highly sophisticated computational models with wide applications in pattern recognition, predictive modelling, optimization, and content-addressable memory (Besaw, 2007; Jain et al., 1996). The algorithms in groundwater quality modeling that have been shown to achieve high accuracy are Levenberg-Marquardt Backpropagation (LMBP), Backpropagation Neural Networks (BPNNs), and Multilayer Perceptrons (MLPs). Many ANN applications are based on Feedforward Neural Networks (FFNNs), which can be described as networks in which information flows in one direction from the input to the output layers via hidden layers.

Besaw (2007) noted that backpropagation algorithms, such as the BPNN, are necessary to reduce prediction errors across different input sets and improve the model's accuracy. Groundwater quality assessment (GWA) has gained popularity in the use of ANN (Singh et al., 2004; Trichakis et al., 2010; Yu & Liu, 2012).

Sanchez et al. (2002) used Self-Organizing Maps (SOMs) to assess groundwater quality in a semi-arid area using hydrogeochemical parameters such as Cl^-, SO_4^{2-}, HCO_3^-, NO_3^-, Na^+, Mg^{2+}, Ca^{2+}, and TDS. In particular, saltwater intrusion in confined aquifers was modeled using Cl^- and SO_4^{2-} (Yamanaka & Kumagai, 2006). Kuo et al. (2004) were able to predict groundwater quality successfully in an affected area of Taiwan using BPNN. In a similar study, Sakizadeh (2016) studied the performance of standard ANN, Ensemble ANN (EANN), and Bayesian Regularized ANN (BRANN) for groundwater quality index (GWQI) prediction.

Nuret et al. (2021) gave a detailed overview of AI-based forecasting models in groundwater quality studies. Dar et al. (2012) used ANN to evaluate fluoride contamination in the Mamundiyar Basin, India, and Amini et al. (2009) combined classification trees, clustering, regression methods, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to predict fluoride content in groundwater worldwide. The review of different types of ANN Algorithms is presented in Table 1, with input parameters, desired outputs, and performance metrics.

S/N	Authors	ANN Type Used	Input Parameters	Desired Output	Performance Metrics
1	Nathan et al.,2017	MLP,BPNN,MLR	EC, TDS, TH, Cl^-, HCO_3^-, SO_4^{2-}, K^+, Na^+, Ca^{2+}, Mg^{2+}	CWQI	MAE, R^2, RMSE
2	Gholami et al.,2010	MLP	Es, GWTable, H, Lp, P, Tv,	PH, TDS, Cl^-, $SO_4 2^-$,Na^+,K^+,Ca^{2+}, Mg^2	MSE, R^2
3	Sakizadeh,2016	BPNN, BRANN, EANN, Early stopping	EC, pH, TDS, Turbidity, TH, F^-, NO_3^-, NO_2^-, SO_4^{2-},PO_4^{3-}, Ca^{2+}, Cu^{2+}, Mg^{2+}, $Mn2^+$, Fe^{3+},Cr^{6+}(VI)	WQI	MSE
4	Kheradpisheh et al.,2015	BPNN	Ev, EC, GWL, pH, Q-value, SAR, TDS, TH, %Na, Cl^-, HCO_3^-, NO_3^-, SO_4^{2-}, K^+, Ca^{2+}, Mg^{2+}	EC, Cl^-, NO_3^-, $SO_4 2^-$	COREL, Nash Sutcliffe coefficient, R^2, RMSE
5	Zhaoxian & Yuling (2011)	RBF, FFNN	TH, TDS, Cl^-, F^-, NO_3^-, NO_2^-, SO_4^{2-}, NH_4^+,Mn^{2+}, Fe^{3+}	Grade I, II, III, IV, V	MSE, REC
6	Sanchez-Martos (2002)	SOM	T, TDS, Cl^-, HCO_3^-, NO_3^-, SO_4^{2-}, Na^+, $Ca2^+$, $Mg2^+$	Salinity	Mean Concentration

Table 1: Synopsis of the review of different types of ANN Algorithms with the input parameters, desired Output and the performance metric

Feed-forward neural network (FFNN), Back-propagation neural network (BPNN), Levenberg Marquardt (LM), Radial basis function (RBF), Self-organizing map (SOM), Bayesian regulation artificial neural network (BRANN), Ensemble artificial neural network (EANN), Multilayer perceptron (MLP), Multi linear regression (MLR), Temperature (T), Groundwater level (GWL), Evaporation (Ev), Groundwater table (GWTable), Site elevation (Es), Number of household (H), Distance form pollution (Lp), Population (P), Transmissivity of aquifer formation (Tv), Coefficient of variation (CV), Correlation coefficient (R), Canadian water quality index (CWQI), Root mean squared error (RMSE), Mean squared error (MSE), Coefficient of determination (R^2), Mean absolute error (MAE)

Study area description, Geology and Hydrogeology

The study area includes selected locations in Lagos State (Figure 3), Nigeria's most industrialized region. This area has experienced rapid urbanization and is regarded as a hub of environmental hazards from various sources. It lies geographically between latitude 6° 23' 26.41 "N and 6° 40' 59". 88" N and between longitude 2º 49' 52.32" E and 3º 58' 28.31" E, with varied topography and elevations ranging from 5 to 35 meters. The topography is largely flat, particularly in coastal areas such as Akodo, Ibeju-Lekki, Victoria Island, Ilaje Bariga, and Tincan Island, with only slight undulations in regions like **Satellite Town and Ibeju-Lekki.** The flat terrain leads to slow, horizontal groundwater flow, especially in coastal zones, where proximity to the ocean increases the risk of **saltwater intrusion (Yusuf et al., 2021; Longe et al., 1987).**

Areas such as **Badagry, Epe,** and **Ikoyi** are particularly vulnerable due to high water tables and limited drainage, which reduce groundwater recharge. Urbanized regions such as **Mile 12, Tuluwalade (Oworonsoki),** and **Ijora Olopa** experience reduced natural infiltration, further hindering groundwater movement and quality (Adepelumi et al.,2009).

The overall flat terrain of Lagos reduces the vertical movement of groundwater, which has a greater potential to be contaminated (Longe et al., 1987). This area is highly vulnerable to contamination of its groundwater system because of several environmental factors (Adepelumi et al., 2009).

In addition, a concerning trend in groundwater quality is observed. The largest city in the region, Lagos State, stretches inland from the Gulf of Guinea through Lagos Lagoon. It is geographically enclosed by Ogun State to the north and east, the Bight of Benin to the south, and the Republic of Benin to the west. The topography is dominated by coastal creeks and lagoons, which are underlain by Coastal Plain Sands (Adepelumi et al., 2009) sedimentary deposits. The sands are part of the Dahomey Basin, one of the largest sedimentary basins in southwestern Nigeria, composed of sand, silt, and clay (Yusuf et al., 2021; Taiwo et al., 2020).

Geologically, the study area is underlain by post-Cretaceous sediments, including the Benin Formation (Miocene to Recent), recent littoral alluvium, and lagoon/coastal plain sand deposits (Longe et al., 1987; Taiwo et al., 2020). The alluvial deposits are mainly sand and are also dominated by littoral and lagoon sediments located between two barrier beaches (Adiat, 2018) and the Coastal Plain sands (Figure4). Geological investigations indicate that there are several aquifer systems present in the study area, from Cretaceous to Quaternary in age (Figure 4). The depth of these aquifers ranges from shallow to deep, some of which may not be feasible to extract groundwater from.

Hydrogeologically, four major aquifer units are identified within the Lagos region (Adiat, 2018; Yusuf et al., 2021; Adepelumi, 2009). The first unit, consisting of recent unconsolidated sediments, forms a shallow aquifer system that is highly vulnerable to contamination and saltwater intrusion, particularly in low-lying and densely populated coastal areas. The second and third aquifer units, which lie within the coastal plain sand formation, collectively serve as the primary groundwater reservoirs in Lagos. These aquifers are the most exploited, with approximately 90% of boreholes targeting them due to their relatively higher yield and accessibility. However, unsustainable abstraction and rising water demand have resulted in regional depletion of this formation, significantly affecting groundwater availability and quality (Yusuf et al., 2021). The fourth and deepest aquifer unit corresponds to the Abeokuta Formation, which is less accessed due to its greater depth and geological complexity (Figures 4 and 5).

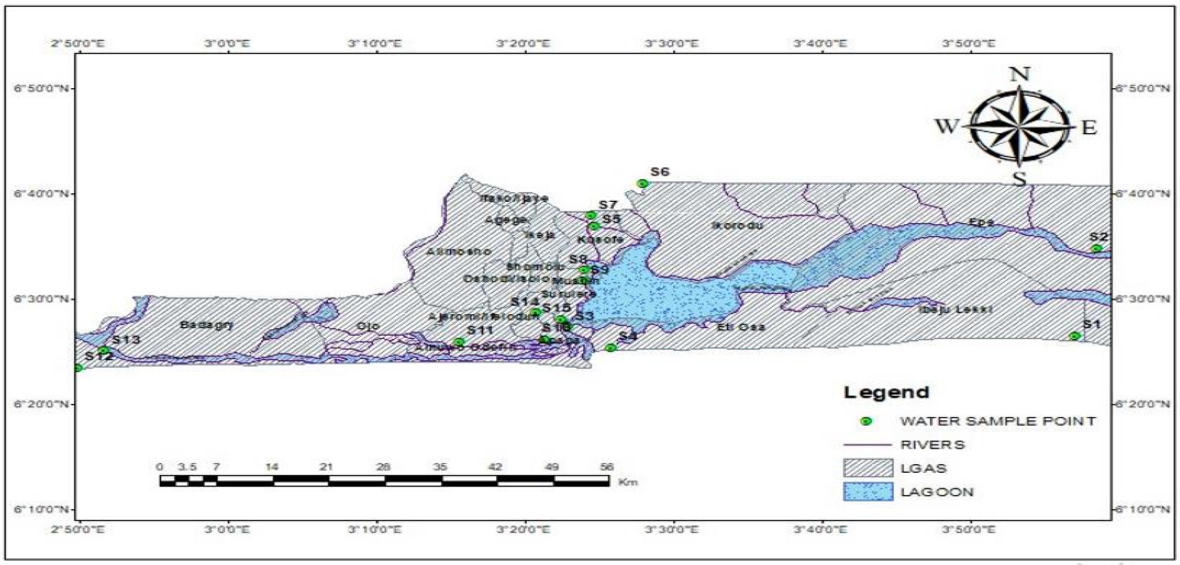
Saltwater intrusion remains a persistent threat to the aquifer systems in Lagos, primarily due to the region's coastal setting and excessive groundwater abstraction from the coastal plain sand aquifer. Rising sea levels, intensified by climate change, further exacerbate this phenomenon, allowing seawater to migrate inland and infiltrate freshwater aquifers, thereby compromising water quality and posing significant public health and environmental risks (Adiat, 2018; Yusuf et al., 2021).

The hydrogeological dynamics of the region are further affected by the seasonality. An increase in rainfall during the wet season leads to greater recharge of groundwater resources, particularly in unconfined and semi-confined aquifers such as the coastal plain sands. This recharge can temporarily raise water table levels and reduce contaminant concentrations, which can improve water quality (Yusuf et al., 2021). During dry seasons, however, groundwater recharge decreases and extraction increases, resulting in declines in groundwater levels that stress aquifer systems and make freshwater aquifers more susceptible to saltwater intrusion. Seasonal variation of recharge and abstraction rates leads to variations in hydrochemical parameters such as salinity, electrical conductivity, total dissolved solids and chloride concentration, which are important in determining the progression of saltwater intrusion (Adepelumi, 2009; Yusuf et al., 2021).

In addition, seasonal fluctuations in hydraulic gradients can affect the direction and the velocity of groundwater flow. In inland regions, the hydraulic head rises during the wet season, which may cause saltwater to flow back towards the coast or to move more slowly. During the dry season, however, saline water may move landward because freshwater heads are depleted by over-abstraction and the hydraulic gradient is more favorable to its movement. Seasonal changes require ongoing monitoring of groundwater levels and quality to ensure the sustainable use of the aquifer (Yusuf et al., 2021).

Overall, the combination of aquifer properties, coastal location, overuse and seasonal hydrological variability all influence the ground water regime of Lagos. These factors are crucial for proper groundwater management, particularly to reduce the effects of saltwater intrusion and to guarantee long-term water security in this fast urbanizing coastal area (Adiat, 2018; Yusuf et al., 2021; Adepelumi, 2009).

Figure 3: Location Map showing the spatial distribution of the groundwater sample in the study area



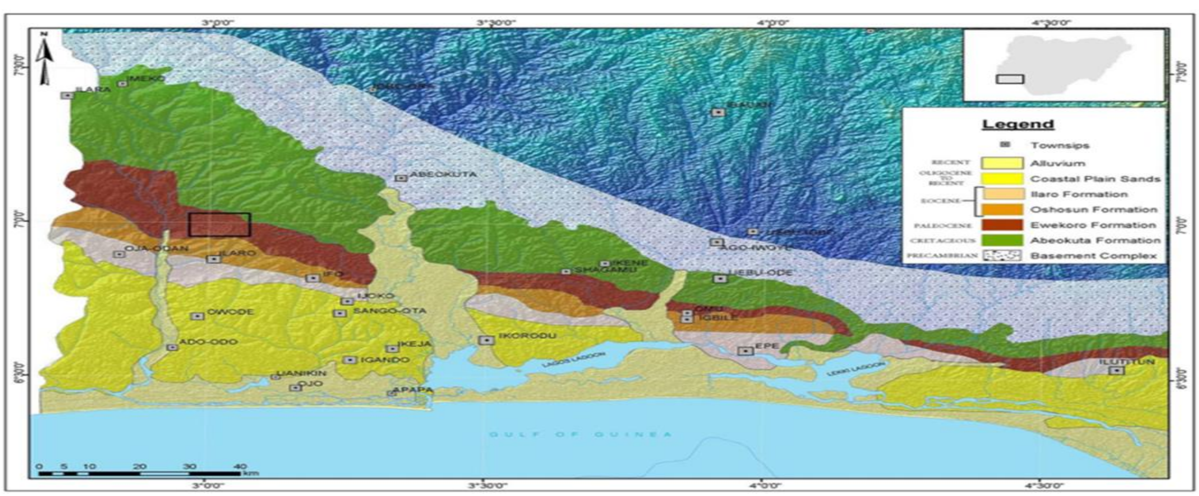


Figure 4: Geological Map of Eastern Dahomey Basin showing the study area State (Taiwo et al., 2020)

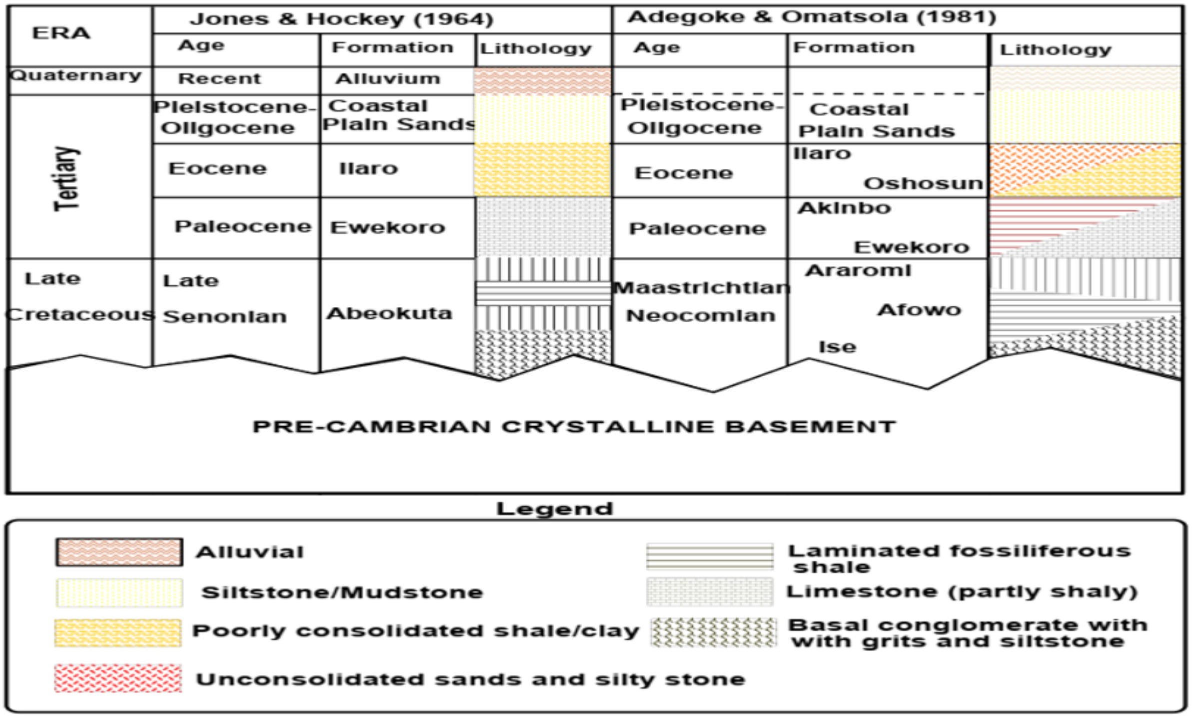


Figure 5: Generalized stratigraphy of the Dahomey Basin (Omotsola and Adegoke,1981).

MATERIALS AND METHODS

Fifteen (15) water samples were obtained from eight (8) boreholes and seven (7) wells in the coastal regions of Lagos State, Nigeria, for this study. The sampling sites were Lekki, Epe, Ikoyi, Victoria Island, Badagry, Ijora Olopa, Oniru, Oworonshoki, Apapa and Satellite Town (Figure 3 and Table 4). Samples were collected in the field and analyzed in the lab from June to November 2024. To precisely locate the sampling points, geographic coordinates were taken with a Garmin 72 Global Positioning System (GPS) device.

Fifteen groundwater samples were selected in a way that provides a good balance of methodological rigor and spatial representation across the study area. This sample size was deemed to be suitable for an exploratory study for the development and validation of analytical methods, not for a population-level statistical analysis. A special effort was made to capture the hydrogeological variability in the study area and to ensure that the data set would provide a representative basis for water quality patterns and for future, more extensive studies.

The collected water samples were preserved and transported under standard conditions to the Lagos State Water Corporation Laboratory for physicochemical analysis. Parameters measured included electrical conductivity (EC), pH, temperature, salinity, chloride, total dissolved solids (TDS), sodium, iron, and bicarbonate concentrations. Details on the preservation methods, container types, storage temperature, and holding time between sample collection and laboratory analysis are provided in Table 2. All laboratory analyses were conducted in accordance with established protocols described (Table 3) by the American Public Health Association (APHA) and the American Society for Testing and Materials (ASTM). The APHA Standard Methods for the Examination of Water and Wastewater served as the primary guideline, with an overview of the procedures illustrated in Table 3. The measured water quality parameters were compared with the permissible limits set by the World Health Organization (WHO) to evaluate the safety of the water for human consumption and other domestic or agricultural purposes.

A MATLAB R2021A software program was used for groundwater quality modeling to predict the output parameters based on selected input parameters for the Artificial Neural Network (ANN). The input variables included were EC, pH, temp, salinity, and chloride while the output variables were TDS, sodium, iron, and bicarbonate (Figure 6). The data was preprocessed before developing the model, such as normalization of input variables to ensure consistent scaling and improve the efficiency of the training process. The study concept is shown in Figure 7. The input parameters are included in the framework. Preprocessing, network training, validation and testing, evaluation and model prediction (EC, pH, temperature, salinity, chloride).

As there were not enough water samples, the data set was split into a training set (70%, 11 samples), a validation set (15%, 2 samples), and a testing set (15%, 2 samples).

The training and testing process was repeated twice for cross-validation to reduce the potential bias and prevent overfitting because of the small sample size. No missing or wrong values were specifically reported but standard quality control procedures were used. If data loss was suspected, methods like mean or regression imputation would have been used to maintain data integrity. Furthermore, statistical techniques, including Z-score and interquartile range (IQR) analyses, were employed to detect and control potential field or lab inconsistencies that could be due to abnormal values.

The ANN was a two-layer feed forward network trained with Levenberg-Marquardt back propagation algorithm. The network architecture included the definition of hidden layers, the number of neurons in each layer, the activation functions, the training algorithms, and the performance measures. The model's internal weights and biases were then adjusted in an iterative fashion in order to reduce the error between the predicted and actual output values during training.

The performance of the model was assessed by the statistical indicators such as Mean Square Error (MSE), Mean Absolute Error (MAE), Absolute Error, and regression coefficient (R) as shown in Equations 1 to 4 under ANN performance metric analysis. Various neuron configurations were tested to further optimize the model's accuracy. A flowchart of the ANN design process is shown in Figure 8. Even with the limited number of samples, the researchers took great care in handling the samples, verifying the data, preprocessing the data, and evaluating the performance of the model, which resulted in meaningful and reliable modeling outcomes within the study's limitations.

Table 2: Measurement Methods and Preservation Techniques (Sadeghi & Khademi, 2023)

Parameters	Specific Method / Instrument	Recommended Container	Storage Temp.	Max. Holding Time	Preservation
Electrical Conductivity (EC)	Conductivity Meter (e.g., HACH HQ40d)	Clean plastic or glass bottle (500 mL)	≤ 4°C	24 hours	No preservation required
pH	Portable Digital pH Meter (e.g., HANNA HI98191)	Clean plastic or glass bottle (500 mL)	≤ 4°C	15 minutes (immediate)	Field measurement recommended; no chemical preservation
Temperature	Digital Thermometer or Multiparameter Probe (e.g., YSI ProDSS)	Not applicable	Not applicable	Immediate	Must be measured on-site
Salinity	Multiparameter Probe with salinity function (e.g., HACH HQ40d)	Clean plastic or glass bottle (500 mL)	≤ 4°C	7 days	No preservation required
Chloride (Cl^-)	Mohr's Titration Method (Argentometric, using $AgNO_3$)	Clean polyethylene bottle (250–500 mL)	≤ 4°C	28 days	No preservation required
Total Dissolved Solids (TDS)	Gravimetric Method (evaporation and weighing)	Clean plastic or glass bottle (500 mL)	≤ 4°C	7 days	No preservation required
Sodium (Na^+)	Flame Photometry (e.g., Elico CL-361 Flame Photometer)	Polyethylene or borosilicate glass bottle (250–500 mL)	≤ 4°C	6 months	Preserve with nitric acid (HNO_3) to pH < 2
Iron (Fe)	Atomic Absorption Spectrophotometry (AAS) (e.g., PerkinElmer AAnalyst 400)	Acid-washed polyethylene or glass bottle (250 mL)	≤ 4°C	6 months	Preserve with nitric acid (HNO_3) to pH < 2
Bicarbonate (HCO_3^-)	Acid Titration Method (using H_2SO_4 and methyl orange indicator)	Clean plastic bottle (250–500 mL)	≤ 4°C	24–48 hours	No preservation; analyze as soon as possible

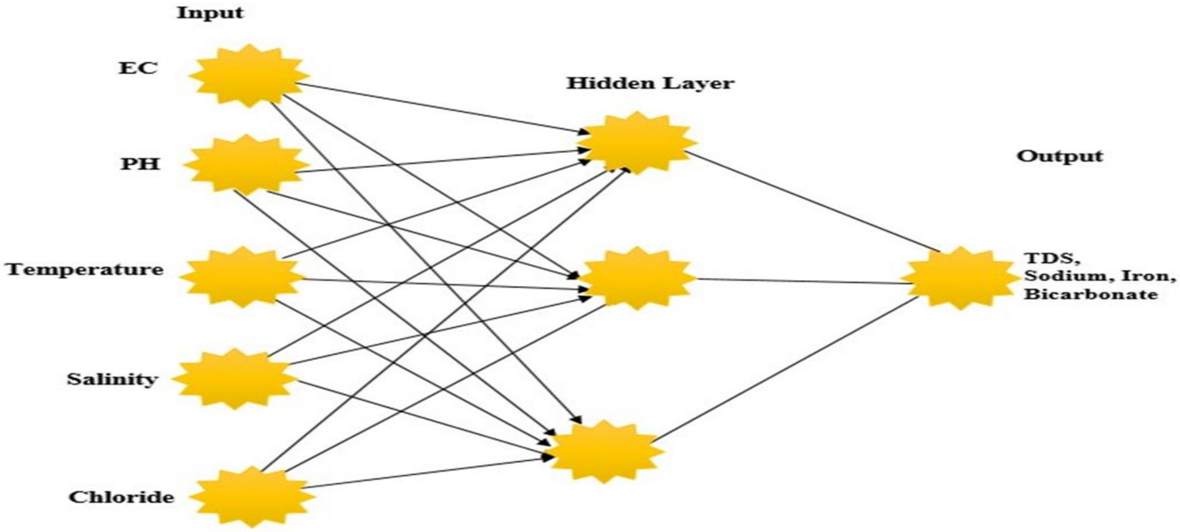


Table 3: Standard Analytical Methods Used for Physicochemical Parameter Determination (APHA, 2017 & ASTM, 2023)

Parameter	Unit	Analytical Method (APHA)	Equivalent Standard	Method Description
Electrical Conductivity (EC)	µS/cm or S/cm	APHA 2510 B	ASTM D1125	Measured using a calibrated conductivity meter at 25°C to assess ionic concentration.
pH	—	APHA 4500-H^+ B	ASTM D1293	Determined using an electrometric method with a standard pH electrode and reference cell.
Temperature	°C	APHA 2550 B	—	Recorded in situ using a calibrated digital or mercury thermometer.
Salinity	ppt	APHA 2520 B or calculated from EC	—	Estimated from electrical conductivity or measured directly using a salinometer or refractometer.
Chloride (Cl^-)	mg/L	APHA 4500-Cl^- B (Argentometric) or 4500-Cl^- C (Potentiometric)	ASTM D512	Quantified via titration with silver nitrate; detection via color change or potentiometry.
Total Dissolved Solids (TDS)	mg/L	APHA 2540 C	ASTM D5907	Determined gravimetrically by evaporation of filtrate and weighing the residual solids.
Sodium (Na^+)	mg/L	APHA 3500-Na B (Flame Photometry) or 3120 B (ICP-OES)	ASTM D4191	Measured using flame photometry or inductively coupled plasma optical emission spectrometry.
Iron (Fe)	mg/L	APHA 3500-Fe B (Phenanthroline) or 3111 B (AAS)	ASTM D1068	Determined colorimetrically using phenanthroline or via atomic absorption spectroscopy.
Bicarbonate (HCO_3^-)	mg/L	APHA 2320 B	ASTM D1067	Calculated from total alkalinity determined by acid titration to pH 4.5.

Figure 6: Artificial neural network architecture used for the study (Author)

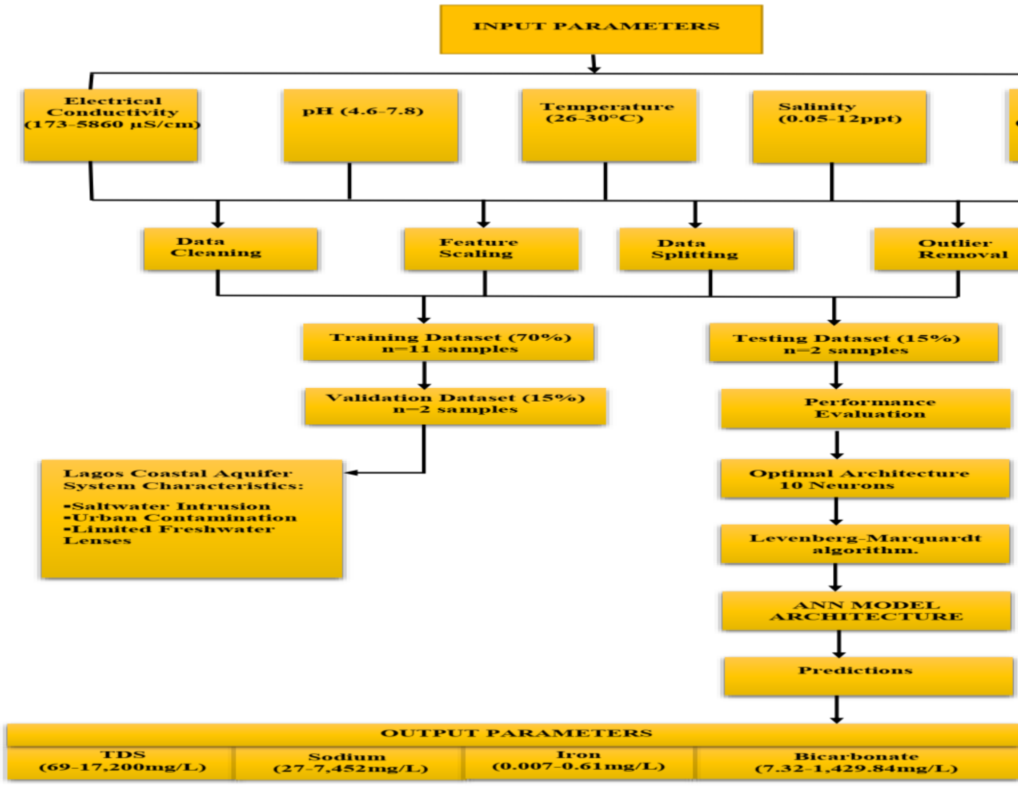


Figure 7: Conceptual framework diagram illustrating how ANN is applied to groundwater quality prediction adopted for the study.

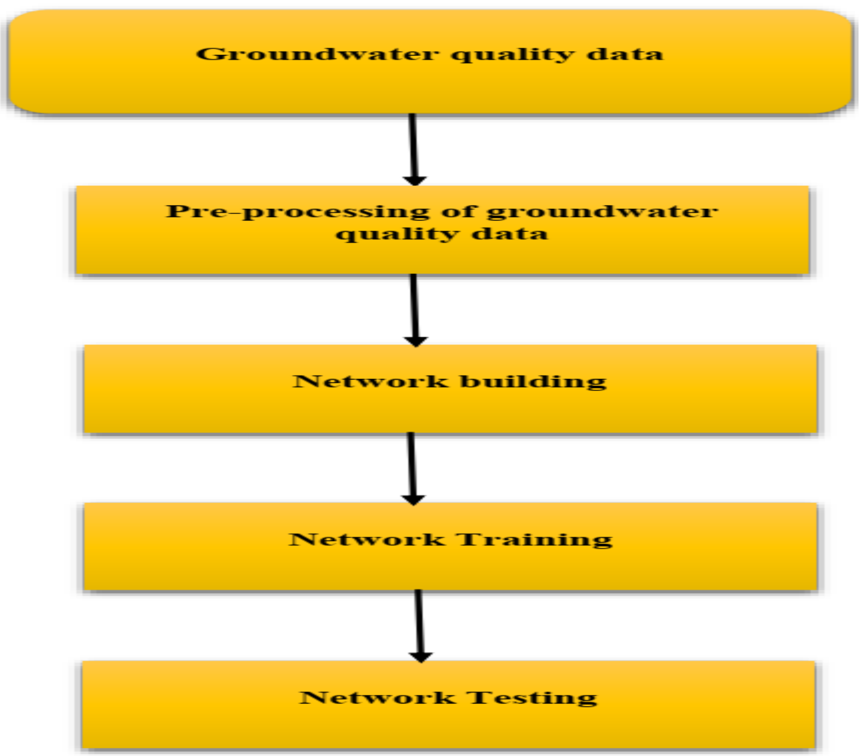


Figure 8: Flowchart used for the design of the groundwater quality artificial neural network model

RESULTS AND DISCUSSION

The results encompassed several key aspects: analysis of groundwater quality parameters; optimization of Artificial Neural Network (ANN) training parameters; validation and testing procedures; and evaluation of the developed ANN model's performance.

Groundwater quality Result

Spatially, the analysis showed significant variation in water quality among the study areas. Tincan Island in Apapa was a critical hotspot with very high values of electrical conductivity (5860 µS/cm) and total dissolved solids (3180 mg/L), which are higher than the WHO guidelines (Table 4 and 5). This suggests that there is substantial mineralization, possibly caused by marine intrusion or industry in this highly industrialized port area. By contrast, the EC and TDS levels in Akodo, Ibeju-Lekki, and Akeusola Street, Epe were satisfactory, indicating good groundwater quality, possibly due to distance from the coast and industry. The high salinity and TDS in the water are typically unsuitable for drinking, as they can cause digestive upset, electrolyte imbalances, and health risks for people with kidney disease or high blood pressure.

Acidity was also found to be different among the locations. The water samples from Akeusola Street, Epe (pH 4.6) and Ijora Olopa (pH 5.6) were more acidic and could cause issues with water taste and potability as well as corrosion of plumbing (Table 3 and 4). In the meantime, the pH values of Akodo (pH 6.8), Ibeju-Lekki (pH 6.8) and Tincan Island, Apapa (pH 6.35) were closer to neutral but still slightly outside the optimum range, indicating that the groundwater in these areas might need mild treatment to bring it into the optimum range for human consumption (Table 4 and 5).

The salinity data were consistent with the coastal influence at Tincan Island, with a salinity reading of 2.24 ppt, which is not potable as per WHO standards. Other areas, such as Akodo and Akeusola Street, however, had low salinity levels and were more suited to potable use. The chloride concentration at Tincan Island (1813.27 mg/L) further supports the saline intrusion, well above the WHO limit of 250 mg/L (Tables 4 and 5). The pattern indicates that groundwater salinity is strongly influenced by proximity to the coast and/or industry, with relatively good quality (chloride concentrations within safe limits) in more inland and less industrialised areas such as Epe and Ibeju-Lekki, reflecting the nature of the geology (Tables 3 and 4). The prolonged use of saline water can lead to dehydration and high sodium levels, especially for susceptible groups.

A similar spatial gradient was observed for sodium concentrations. Tincan Island indicated an alarming value of 1318.4 mg/L, severely exceeding the WHO limit of 200 mg/L. This reinforces the indication of saline water intrusion due to the proximity to the seashore and due to the nature of groundwater occurrence in this area. Meanwhile, Akodo and Akeusola Street once again showed sodium levels within acceptable boundaries, highlighting them as potentially safer sources for freshwater supply due to presence of freshwater aquifers in this area (Tables 3 and 4).

The concentration of iron was also found at Tincan Island at 0.074 mg/L, which is below the WHO recommended limit of 0.3 mg/L (Tables 4 and 5), but may be a result of small amounts of industrial discharge or infrastructure corrosion. Other samples sites had lower levels of Fe, which indicated lower contamination and better natural filtration (Tables 3 and 4).

The bicarbonate concentration was significant at Tincan Island, with a level of 1429.84 mg/L (Tables 4 and 5). Such concentrations are still within acceptable limits, but can impact the palatability of drinking water and lead to scaling in plumbing systems and water infrastructure. Elevated bicarbonate can change the soil pH over time, which can affect the uptake of nutrients and crop productivity for irrigation. The relatively lower bicarbonate concentration in other areas indicate relatively chemically balanced water, which may be attributed to less interaction with carbonate rich geological formations or anthropogenic input.

The spatial distribution of groundwater quality in the study area indicates good and poor water quality in the study area with highly urbanized and industrial coastal areas such as Apapa (Tincan Island) exhibiting strong signs of seawater intrusion and pollution while more residential or peri-urban areas like Akodo and Akeusola Street exhibited favourable water quality in several parameters. These insights emphasize the importance of location-specific monitoring and management strategies for sustainable groundwater use in Lagos' coastal belt.

Table 3: Water Quality analysis results from the Laboratory

Sample Location	Water Sample	Latitude	Longitude	Elevation	EC (S/cm)	PH	Temp (^{0}C)	Salinity (ppt)	Chloride (mg/L)	TDS (mg/L)	Sodium (mg/L)	Iron (mg/L)	Bicarbonate (mg/L)
Akodo, Ibeju Lekki	Borehole	6.441395	3.951238	15	320	6.8	27	0.1	12.4	136	51.8	0.011	98.82
Akeusola Street, Epe	Borehole	6.580363	3.974532	7.6	281	4.6	28.2	0.08	15.95	120	46.8	0.007	9.76
Leventis, Marina Road Ikoyi	well	6.455238	3.380707	6.6	5700	7.3	26.8	2.12	2082.68	3070	1269.4	0.008	253.76
Adetokunbo Ademola, Victoria Island	well	6.422948	3.430002	14.1	444	7.3	27.1	0.13	23.04	187	63.7	0.051	173.24
Weight Bridge, Owode Onirin	Well	6.615725	3.410668	11	1197	6.1	29	0.43	407.68	608	218.5	0.01	136.64
BRT, Mile 12	Borehole	6.68333	3.4659	30	173	6.25	29	0.05	26.59	69	27.8	0.053	17.08
Isheri North GRA	Borehole	6.631515	3.408258	10.5	5860	6.35	29.2	2.24	1813.27	3180	1318.4	0.074	1429.84
Tuluwalade, Oworosoki	well	6.545153	3.399453	17.4	694	6.05	29	0.33	304.87	470	174	0.015	7.32
Ilaje Bariga	well	6.528545	3.398456	35	594	5.6	29	0.07	33.6	94.4	34.8	0.01	14.64
Tincan Island, Apapa	Borehole	6.435968	3.355838	31.2	1433	7	29.1	0.55	299.5	789	291.4	0.013	268.4
Marwa Rd, Satellite Town	well	6.432078	3.259093	13.5	3200	7.17	30.9	1.28	900.43	1820	168.1	0.61	614.88
Badagry1	Borehole	6.390673	2.831203	3.7	-	7.8	29.2	12.1	21234.55	17200	7452.8	0.018	106.14
Gbaji, Badagry2	Borehole	6.418005	2.860763	5.1	1287	7.1	28	0.44	164.84	622	232.2	0.02	197.64
Iganmu Rd, Orile	well	6.47786	3.34597	6	868	5.8	29.1	0.27	145.35	386	162.4	0.018	51.24
Ijora Olopa	Borehole	6.468255	3.37345	11.5	402	6.12	29	0.2	42.54	285	103.8	0.01	183

Table 5: World Health Organization (WHO) Guidelines

Parameters	WHO Standard
Electrical Conductivity (EC)	<1000 µS/cm
PH	6.5–8.5
Salinity	<1 ppt (desirable)
Chloride(mg/L)	<250mg/L
Sodium(mg/L)	<200 mg/L
Iron(mg/L)	<0.3 mg/L
Bicarbonate(mg/L)	<500 mg/L

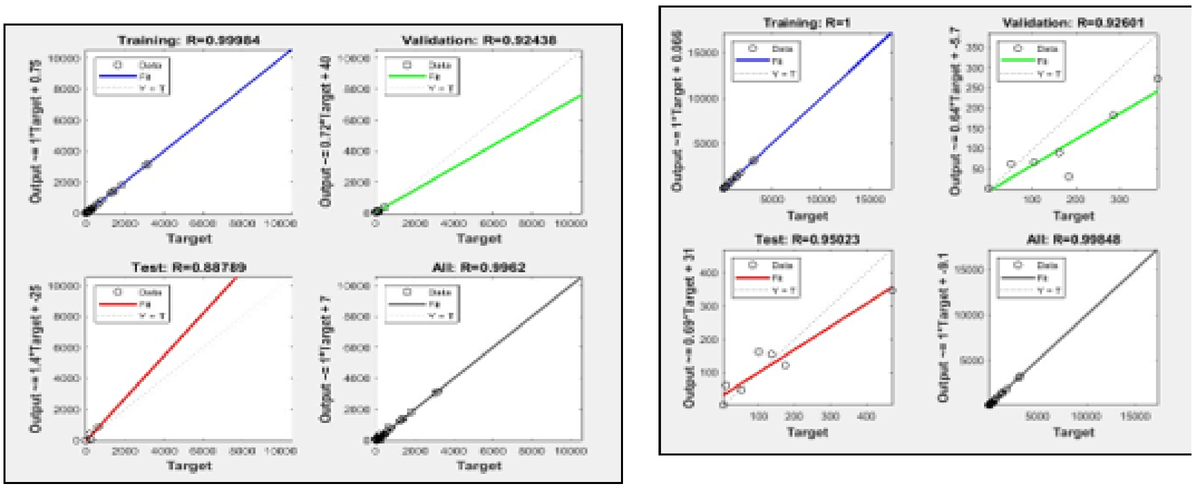
Artificial Neural Network (ANN) Results

MATLAB R2021a was used to run the ANN analysis and simulate groundwater quality based on the laboratory analysis. The structure of the artificial neural network (ANN) used in this study is shown in figure 6. Details of the characteristics of water samples and associated water quality parameters are given in Table 4. Graphical comparisons of observed and predicted values from the ANN model for the training, validation, testing, and complete datasets are shown in Figures 9 and 10.

As shown in Table 6, the selected input parameters for the ANN modeling are Electrical conductivity (EC), pH, Temperature, Salinity, and Chloride concentration, and the selected output parameters are Total Dissolved Solids (TDS), Sodium, iron, and Bicarbonate concentration. The feed-forward neural network architecture was trained using the Levenberg-Marquardt algorithm. The actual observed values and the predicted outputs from the ANN model were compared (Tables 6 and 7).

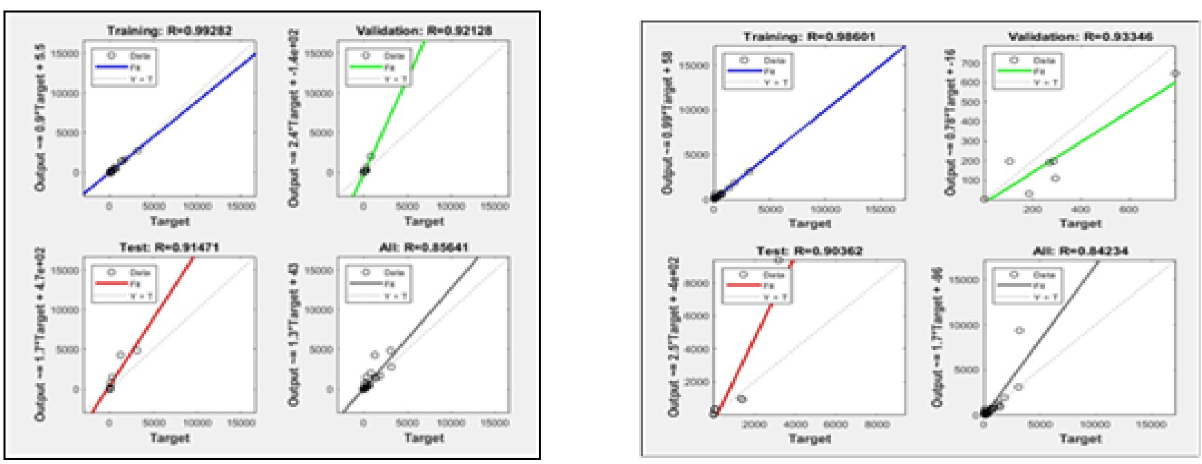
The absolute error (AE) was calculated by subtracting the predicted values from the observed values (Table 8), and the mean absolute error (MAE) was also determined (Table 9) to evaluate the model's performance. The absolute error indicates how much the model's predictions deviated at each sample location. TDS exhibited AE of 0.0- 0.06, Sodium 0.2- 3.8, Iron 0.001 (constant) and Bicarbonate 0.1- 2.84 (Table 8). The small deviations indicate that the model made good predictions for the parameters.

The mean absolute error also provides a summary of how well the model predicts the values in the entire set of data. Table 9 shows that the accuracy of the TDS is very high and the error is minimal, with an MAE of 0.84. The MAE for sodium was 1.17, indicating good model performance with slightly higher variability. The MAE for Iron was very small at 0.0019, indicating very accurate predictions, whereas Bicarbonate had an MAE of 0.5973, indicating reliable predictions and that the model was working well (Table 9).



(a) Neuron 6 (b) Neuron 10

Figure 9: Graphical plots of the observed values and ANN model predicted values using the training, validation, test, and all dataset for neuron 6 and 10



(c) Neuron 20 (d) Neuron 22

Figure 10: Graphical plots of the observed values and ANN model predicted values using the training, validation, test, and all dataset for neuron 20, and 22

Table 6: The synopsis of the groundwater water quality parameters used as input and Output parameters

Sample Location	**ANN input parameters**					**ANN output parameters**			
	EC	**PH**	**Temperature**	**Salinity**	**Chloride**	TDS	Sodium	Iron	Bicarbonate
Akodo, Ibeju Lekki	320	6.8	27	0.1	12.4	136	51.8	0.011	98.82
Akeusola Street, Epe	281	4.6	28.2	0.08	15.95	120	46.8	0.007	9.76
Leventis, Marina Rd,Ikoyi	5700	7.3	26.8	2.12	2082.68	3070	1269.4	0.008	253.76
Adetokunbo Ademola, Victoria Island	444	7.3	27.1	0.13	23.04	187	63.7	0.051	173.24
Weight Bridge, Owode Onirin	1197	6.1	29	0.43	407.68	608	218.5	0.01	136.64
BRT, Mile 12	173	6.25	29	0.05	26.59	69	27.8	0.053	17.08
Isheri North GRA	5860	6.35	29.2	2.24	1813.27	3180	1318.4	0.074	1429.84
Tuluwalade, Oworosoki	694	6.05	29	0.33	304.87	470	174	0.015	7.32
Ilaje Bariga	594	5.6	29	0.07	33.6	94.4	34.8	0.01	14.64
Tincan Island, Apapa	1433	7	29.1	0.55	299.5	789	291.4	0.013	268.4
Marwa Rd, Satellite Town	3200	7.17	30.9	1.28	900.43	1820	168.1	0.61	614.88
Badagry1		7.8	29.2	12.1	21234.55	17200	7452.8	0.018	106.14
Gbaji, Badagry2	1287	7.1	28	0.44	164.84	622	232.2	0.02	197.64
Iganmu Rd, Orile	868	5.8	29.1	0.27	145.35	386	162.4	0.018	51.24
Ijora Olopa	402	6.12	29	0.2	42.54	285	103.8	0.01	183

Table 7: Comparison of the ANN output parameters with the Desired Results from ANN model

Sample Location	**ANN output parameters**				**Predicted Results from ANN model**			
	TDS	**Sodium**	**Iron**	**Bicarbonate**	**TDS**	**Sodium**	**Iron**	**Bicarbonate**
Akodo, Ibeju Lekki	136	51.8	0.011	98.82	135.2	51.41	0.015	99.6
Akeusola Street, Epe	120	46.8	0.007	9.76	120	46.66	0.006	9.952
Leventis, Marina Rd,Ikoyi	3070	1269.4	0.008	253.76	3071	1267	0.008	252.8
Adetokunbo Ademola, Victoria Island	187	63.7	0.051	173.24	187.3	63.81	0.051	172.9
Weight Bridge, Owode Onirin	608	218.5	0.01	136.64	608.3	218.9	0.01	136.8
BRT, Mile 12	69	27.8	0.053	17.08	69.06	28.1	0.053	17.2
Isheri North GRA	3180	1318.4	0.074	1429.84	3181	1319	0.073	1427
Tuluwalade, Oworosoki	470	174	0.015	7.32	468.6	172.3	0.016	7.23
Ilaje Bariga	94.4	34.8	0.01	14.64	93.99	35.08	0.01	14.77
Tincan Island, Apapa	789	291.4	0.013	268.4	790.4	292.1	0.013	268.5
Marwa Rd, Satellite Town	1820	168.1	0.61	614.88	1819	169.2	0.61	614.7
Badagry1	17200	7452.8	0.018	106.14	17198	7449	0.017	105.9
Gbaji, Badagry2	622	232.2	0.02	197.64	622.4	232.4	0.02	197.7
Iganmu Rd, Orile	386	162.4	0.018	51.24	384.7	160.99	0.011	52.46
Ijora Olopa	285	103.8	0.01	183	284.9	102.28	0.02	181.69

Table 8: Computed Absolute Error for each parameter

Sample Location	TDS	Sodium	Iron	Bicarbonate
Akodo, Ibeju Lekki	0.8	0.39	0.004	0.78
Akeusola Street, Epe	0	0.14	0.001	0.192
Leventis, Marina Road,Ikoyi	1	2.4	0	0.96
Adetokunbo Ademola, Victoria Island	0.3	0.11	0	0.34
Weight Bridge, Owode Onirin	0.3	0.4	0	0.16
BRT, Mile 12	0.06	0.3	0	0.12
Isheri North GRA	1	0.6	0.001	2.84
Tuluwalade, Oworosoki	1.4	1.7	0.001	0.09
Ilaje Bariga	0.41	0.28	0	0.13
Tincan Island, Apapa	1.4	0.7	0	0.1
Marwa Road, Satellite Town	1	1.1	0	0.18
Badagry1	2	3.8	0.001	0.24
Gbaji, Badagry2	0.4	0.2	0	0.06
Iganmu Rd, Orile	1.3	1.41	0.007	1.22
Ijora Olopa	0.1	1.52	0.01	1.31

Table 9: Mean Absolute Error (MAE)

Parameter	MAE	Interpretation
TDS	0.84	Very accurate – minimal error overall.
Sodium	1.17	Still very good – slightly higher variation.
Iron	0.0019	Extremely accurate – nearly perfect match.
Bicarbonate	0.5973	Very reliable predictions

The developed ANN in this study has a good accuracy as evidenced by the regression coefficient values that are close to one and the consistently low values of AE, MAE, and MSE. The results are similar to those obtained in the previous groundwater quality studies using ANN models, where R^2 values are generally in the range of 0.85 to 0.99 depending on the groundwater characteristics, input variables, network architecture, and size of the dataset (Maier & Dandy, 2000; Coulibaly et al., 2001; Mohanty et al., 2015). The excellent predictive performance achieved in this study suggests that the Levenberg–Marquardt algorithm can be used effectively to model non-linear hydrochemical relationships in moderately sized groundwater datasets. The present study shows that ANN modelling is applicable to saline-influenced coastal aquifers in Lagos and offers a framework which can be incorporated into the groundwater monitoring and spatial decision-support systems.

The ANN model simulated groundwater quality during the sampling period. Predicted TDS values (69.06–17,198 mg/L) closely matched the measured range (69–17,200 mg/L)(Figure 11), while predicted sodium (28.1–7,449 mg/L), iron (0.006–0.610 mg/L), and bicarbonate (7.23–1,427 mg/L) also showed close agreement with the observed values(Table 7). The model consistently predicted low mineralised groundwater at Akodo, Akeusola Street (Epe), BRT, Mile 12, and highly mineralised groundwater at Leventis (Marina Road, Ikoyi), Isheri North GRA, and Badagry1, indicating the model's ability to capture the spatial variation in groundwater quality in the Lagos coastal aquifer.

Predictions are based on the hydrochemical conditions at the time the sample was taken. Groundwater quality can be affected by seasonal changes in recharge and abstraction, either diluting dissolved constituents in the wet season or increasing groundwater mineralization in the dry season. Therefore, incorporating groundwater quality data from both wet and dry seasons would improve the model's ability to capture seasonal variability and enhance its application for long-term groundwater monitoring and management. Figure 11 shows the spatial distribution of ANN-Predicted Total Dissolved Solids (TDS) in the Study Area.

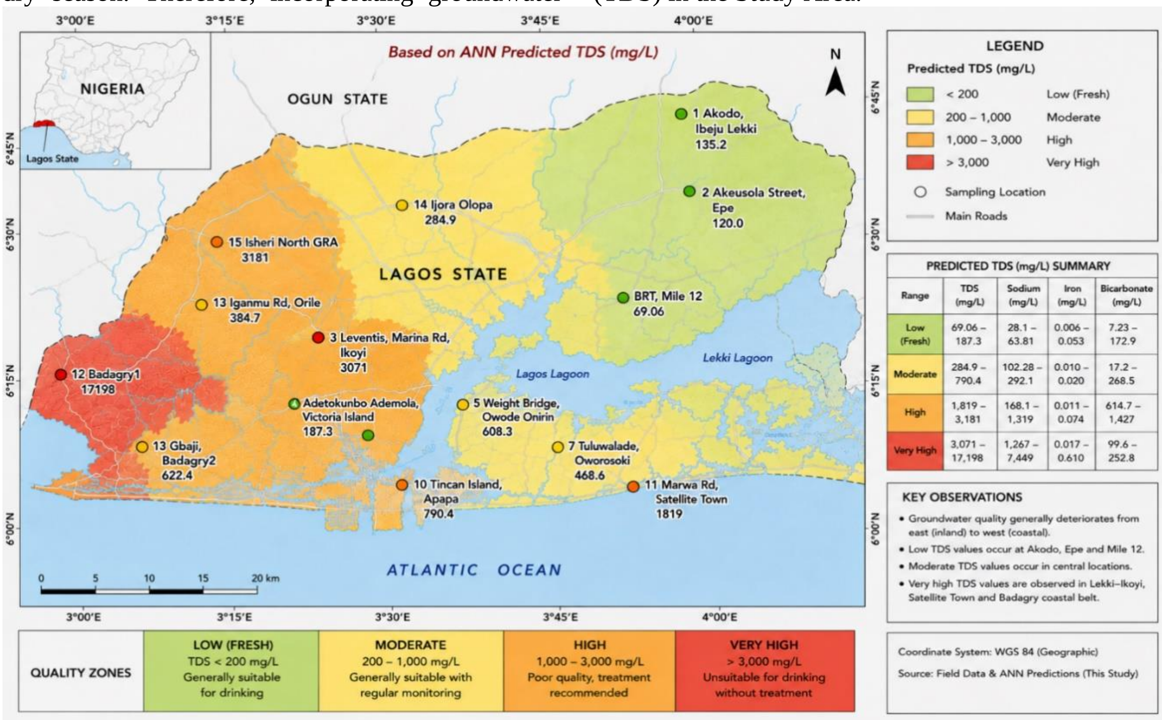


Figure 11: Spatial Distribution of ANN-Predicted Total Dissolved Solids (TDS) in the Study Area

processing and Architecture development of ANN

The input and output parameters utilized in the ANN model (**Table 6)** were randomly divided into three subsets in a 70:15:15 ratio, corresponding to the training, validation, and testing datasets. Alternative partitioning schemes, such as 80:10:10 and 70:20:10, did not yield satisfactory results, primarily due to suboptimal neuron configuration and poor network learning efficiency. Consequently, the 70%, 15%, and 15% split was adopted, comprising 11 samples for training and 2 samples each for validation and testing.

The results confirmed that this configuration produced a robust and reliable model. Various neural network architectures with different neuron counts were evaluated to identify the optimal setup for groundwater quality prediction. Neuron configurations were tested up to 28; however, only the architecture with 10 hidden neurons provided consistent and acceptable performance **(Table 10).** This indicates that computational efficiency and model performance vary across neuron settings, which explains the variation in optimization results, as illustrated in **Table 10.**

Model performance varied across the tested architectures, and no significant improvement was observed beyond 28 neurons, indicating that 28 neurons is the upper limit for effective training. The configuration with 10 hidden neurons produced the best results, with regression coefficients (R-values) of 1.0 for training, 0.92601 for validation, 0.95023 for testing, and an overall R of 0.99848 **(Table 10),** indicating high predictive capability. Furthermore, the regression plots generated in MATLAB confirm a strong correlation between predicted and actual outputs, demonstrating that the Levenberg-Marquardt algorithm is well-suited for modeling groundwater quality in the study area.

As presented in **Table 11,** the training set mean squared error (MSE) values were generally low, signifying effective learning and good model accuracy. The MSE values for TDS and Sodium were 1.0 and 0.3 respectively, suggesting reliable predictions. The iron parameter achieved a remarkably low MSE of 0.0000005, indicating exceptional model accuracy. The bicarbonate parameter also exhibited a low MSE of 0.045, reflecting strong generalization capability (Table 11).

In the testing phase, the MSE for TDS (1.39) and Sodium (1.4487) were comparatively higher, suggesting moderate difficulty in generalizing to new data for these parameters. The Iron parameter achieved better accuracy during the test phase, with an MSE of 0.5049. Bicarbonate performed well with a test MSE of 0.045, reinforcing the model's robustness (Table 11).

During validation, the MSE for bicarbonate increased to 1.0962, higher than its test MSE, indicating slightly reduced prediction accuracy in the validation dataset. Nevertheless, the overall results affirm the efficacy of the ANN model, confirming its reliability in simulating groundwater quality parameters using the selected inputs and training strategy (Table 11).

Table 10: Synopsis of the Regression Performance evaluations of the Artificial Neural Network (ANN) Architectures from MATLAB Simulation

Network Architecture	Best Validation Performance	Training set Regression (R) values	Validation set Regression (R) values	Testing set Regression(R) values	Regression for All	Number of Iteration	Number of Iteration at best Validation performance
Neuron 6	3641.618	0.99984	0.92438	0.88789	0.9962	27	21
Neuron 10	6651.831	1	0.92601	0.95023	0.99848	13	7
Neuron 12	70934.4	0.9818	0.90085	0.87722	0.79897	10	4
Neuron 14	3456.9	0.99965	0.82131	0.98474	0.99759	10	5
Neuron 16	4715.0	0.99997	0.9476	0.60734	0.99912	12	6
Neuron 18	11366.68	0.99965	0.82131	0.98474	0.99759	10	4
Neuron 20	221353.02	0.99282	0.92128	0.91471	0.85641	12	6
Neuron 22	12355.56	0.98601	0.93346	0.90362	0.84234	10	4
Neuron 24	23531.7	1	0.91988	0.71269	0.99508	15	15
Neuron 26	685808.018	0.99965	0.89524	0.98488	0.73884	10	4
Neuron 28	23663.0	0.99038	0.92809	0.86085	0.97706	9	3

Table 11: Synopsis of the Mean Square Error (MSE) model performance

Parameters	Training MSE	Testing MSE	Validation MSE
TDS	0.7913	1.39	1
Sodium	1.0022	1.4487	0.98
Iron	0.0000019	0.5049	0.0000005
Bicarbonate	0.9698	1.0962	0.045

ANN Performance Metrics Analysis

To evaluate the performance of the developed ANN model, four key statistical indicators were utilized: Mean Squared Error (MSE), regression coefficient (R), absolute error (AE), and mean absolute error (MAE). These metrics provide a comprehensive understanding of the model's predictive accuracy by comparing the predicted outputs with the actual measured values across the training, validation, and testing datasets. The corresponding results are presented as follows: **Table 10** and **Figure 12 for** MSE; Figures **9 and 10, as well as Table 10, for** regression coefficient; **Table 8** and **Figure 12** for AE; and **Table 9** for MAE.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} \quad (ytrue - ypred)^{2} \qquad (1)$$

Where: $y$true, $_i$ is the true value (desired result), ypred, i is the predicted value (ANN output), and *n* is the number of samples (15)

$$R = \sqrt{1 - \frac{\sum_{i=}^{n} (Zi - Z^{I})^{2}}{\sum_{i=1}^{n} (z^{I})^{2}}} \qquad (2)$$

Zi and Z^i are the parameters and calculated value; n is the number of values used in the model.

The performance of the ANN was evaluated based on mean square error (MSE), coefficient of correlation (r), Absolute error and Mean Absolute error. The results include the error histogram for the ANN models, as shown in Figure 10. Additionally, Figure 13 depicts the variation of MSE against epochs, highlighting the deviations observed during the training and testing phases of the ANN models. However, the model fit into the best regression coefficient (R) values of 1.0, 0.92601, 0.95023 and 0.99848 for the training, validation, testing and regression coefficient (R) for all. These values correspond to the best neuron 10 in the network architecture. The Absolute Errors (AE) used as part of the model performance evaluation is given by equation 3 and Table 8.

AE= Predicted Value - Actual Value (3)

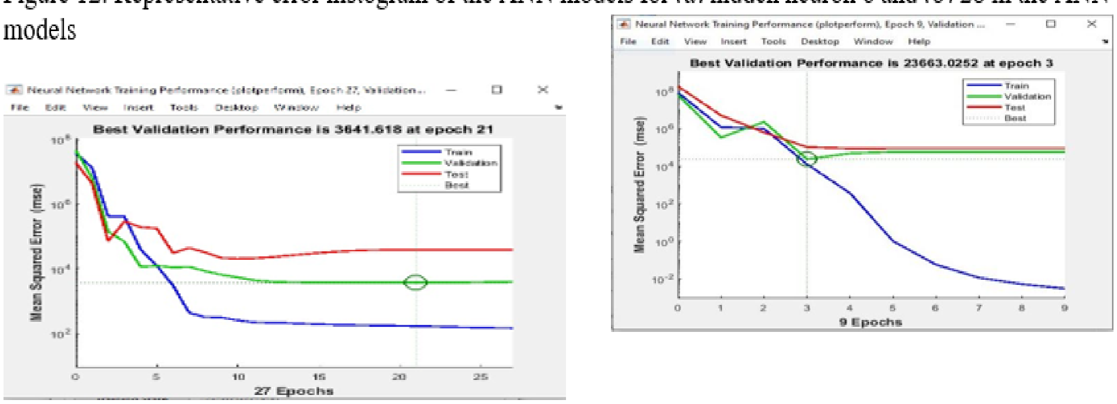
A small AE values were generated from the model signifying accurate prediction of the model for future groundwater prediction. The Absolute error yielded a value between 0 to 0.06 for the TDS, 0.0 to 0.001 for Iron, 0.2 to 3.8 for Sodium and 0.1 to 2.84 for bicarbonate (Table 9). These values are diagnostic feature of an accurate predictive model for future groundwater quality modeling. However, the Mean absolute errors (MAE) was also used as a predictive instrument for the model performance and it is given mathematically as (Equation 4 and Table 9).

MAE = $\frac{1}{n}\sum\ [Predicted\ values - actual\ values]$ (4)

The results showed that the mean absolute error ranged between 0.0019 to 1.17 where TDS has a mean absolute error of 0.84, Sodium with 1.17, Iron with 0.0019 and bicarbonate with 0.5973(Table 11).These values signifies model's performance from very accurate to very reliable predictions for sustainable groundwater quality optimization and modeling (Table 11)

(a) (b)

Figure 12: Representative error histogram of the ANN models for (a) hidden neuron 6 and (b) 28 in the ANN models



(C) (d)

Figure 13: Representative MSE against epoch variation of the deviation for (c) hidden neuron 6 and (d) 28 in

CONCLUSION

Groundwater quality varied considerably across the study area. Akodo and Ibeju-Lekki recorded low electrical conductivity (EC), total dissolved solids (TDS), and chloride concentrations, indicating low-salinity groundwater suitable for domestic use. Leventis, Marina Road, and Ikoyi, on the other hand, had high EC, TDS, and chloride levels, indicating that the groundwater quality in these areas is poor and requires treatment before use. Intermediate groundwater quality conditions were observed on Tincan Island and in Apapa, implying that treatment may be required to attain potable water quality. To enhance groundwater quality prediction in these heterogeneous coastal aquifers, an Artificial Neural Network (ANN) model was developed using the Levenberg–Marquardt algorithm. The optimum network architecture, consisting of 10 hidden neurons, resulted in high regression coefficients (R-values) of 1.000 for training, 0.9260 for validation, 0.9502 for testing, and 0.9985 for the overall data set, suggesting a high level of agreement between observed and predicted groundwater quality parameters. The model also yielded consistently small prediction errors with AE values of 0.00–0.06 for TDS, 0.20–3.80 for sodium, ~0.001 for iron, and 0.10–2.84 for bicarbonate. Likewise, the low MAE and MSE values indicated that the model accurately predicted groundwater quality and generalized to independent data sets. The model's ability to predict groundwater levels highlights its potential as a practical decision-support tool for groundwater management in the saline-influenced coastal aquifers of Lagos. Predictions of reliable groundwater quality can inform early-warning monitoring to detect areas vulnerable to water quality degradation before adverse impacts become widespread. The model can be used in conjunction with Geographic Information Systems (GIS) to aid in identifying groundwater quality hotspots and prioritizing vulnerable coastal communities for groundwater monitoring, protection, and water resource planning. The framework also lays the groundwork for future connectivity with the existing routine and real-time groundwater monitoring networks, which will enhance evidence-based groundwater management and policy development in Lagos. The model showed good predictive performance but could be further improved by adding more sampling locations and additional temporal data to better represent seasonal and spatial variations in groundwater quality. Increasing the data set would also minimize the risk of overfitting and increase the model's ability to be expanded to the wider area of the Lagos coastal aquifer.

Future studies should evaluate additional machine learning techniques, including Support Vector Machines (SVMs), Random Forests (RFs), Gradient Boosting Machines (GBMs), and Deep Neural Networks (DNNs), to compare predictive performance and develop more robust groundwater quality prediction models. The proposed ANN framework is not only technically significant but also has implications in the fields of environmental, public health, and socio-economic. Early detection of groundwater quality degradation can facilitate timely action, minimize exposure to contaminated groundwater, protect sensitive populations and enhance access to safe groundwater supplies. The results can help lower water treatment and health care expenses and facilitate sustainable groundwater management in the rapidly urbanizing coastal region of Lagos. In summary, the ANN model is a good tool to assess and predict the quality of the coastal aquifers of Lagos. The model can precisely identify areas where groundwater treatment is needed, such as Leventis, Marina Road, and Ikoyi, providing a scientifically sound foundation for groundwater monitoring, planning, and sustainable water management.

Author Contributions

The conception and design of the study were collaboratively carried out by all authors. OSO, JRA, and AEA were responsible for the methodology; the data collection and investigation were done by VOO and OOA. Data analysis was conducted by OSO, JRA, and YOA. OSO and KAS prepared the initial manuscript draft, with all authors providing critical feedback on earlier versions. All authors reviewed and approved the final manuscript.

Availability of Data and Material

The datasets used in this study are accessible from the corresponding author upon request.

Conflict of Interest

The authors declare that there are no conflicts of interest related to this publication.

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