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Assessment and Modeling of Water Quality in the Niger River: A Comprehensive Study Using Water Quality Indices and Intelligent Techniques

Konare Mahamadou [a], Traore Adama [b], Abdourazakou Maman Hassan [c*], Dembele Abdramane [d], Cissoko Fatoumata [e] and Sissoko Diabélou [f]

[a] Laboratoire Sciences et Technologie (LaST), Unité de Formation et de Recherche en Sciences et Technique (UFR ST), Université Thomas SANKARA (UTS), 12 BP 417 Ouagadougou 12, Burkina Faso.
[b] Laboratoire Société Mobilité Environnement, Département de Sociologie, Université Joseph KI-ZERBO (UJKZ), Ouagadougou, Burkina Faso.
[c] Département de Géosciences, Ecole des Mines, de l'Industrie et de la Géologie de Niamey, Niger.
[d] Département de Topographie, Ecole Nationale d'Ingénieurs Abderrhamane Baba TOURE, Bamako, Mali.
[e] Direction Nationale de l'Hydraulique (DNH), Bamako, Mali.
[f] Institut de Pédagogie Universitaire (IPU), Bamako, Mali.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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**Corresponding author: E-mail: abdourazakoum@gmail.com;*

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ABSTRACT

The Niger River is essential to the livelihoods of those in Bamako and its neighboring areas, providing vital resources for drinking water, agriculture, livestock, industry, and fishing. Given its significance across these sectors, there is a pressing need to establish an effective water resource management strategy that incorporates a thorough qualitative assessment of the river's water quality. This research seeks to characterize the water quality of the Niger River by employing Water Quality Indices (WQI) and intelligent modeling techniques. To fulfil this objective, various physicochemical parameters, including pH, electrical conductivity (EC), nitrate (NO_3^-), nitrite (NO_2^-), and iron (Fe), were collected from 40 sampling points along the river during three distinct periods: December 2017, March 2018, and July 2018. The study utilized a weighted arithmetic approach to compute the WQIs, while the predictive models were developed using two of the most famous and effective modeling techniques namely Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN). In order to evaluate the predictive performance of the models, the dataset was partitioned into three distinct segments, allocating 60% for training purposes, 20% for validation, and the remaining 20% for testing, with the segments organized in a sequence from upstream to downstream. The performance of both models was evaluated using metrics such as the correlation coefficient (r^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The computed Water Quality Indices (WQIs) vary from 0.44 to 1887.40, indicating a diverse range of water quality across the samples analyzed. The classification of these samples reveals that 62.5% are considered excellent, while 15% are categorized as good, another 15% as poor, 2.5% as very poor, and 5% as unsuitable for consumption. Furthermore, the results derived from ANN with five inputs, one hidden layer (13 neurons) and one output (WQI) demonstrates superior efficiency in assessing water quality.

Keywords: Niger river; water quality index; multiple linear regression; artificial neural network.

1. INTRODUCTION

Throughout the world, the proximity of cities and countryside to water points (sources and rivers) undoubtedly makes it possible to measure the importance of water in daily life. consequently, water is at the heart of human numerous activities necessary of society development. Indeed, people in societies need water for their own consumption and to carry out their various activities (industrial, agricultural, livestock breeding, fishing, etc.). The use of water must take into account its quality requirements on population health. Thus, some human activities requiring water have their requirements in terms of quantity and quality. The quality of water, is evaluated through the conformity of its physicochemical and bacteriological parameters to pre-established standards (WHO, EU, EUA, etc.). Qualitatively, all the physicochemical and bacteriological parameters of a given water body do not play the same role. This is how, for a given activity, the same watercourse can have both essential parameters for defining its quality and other accessories [1].

Continuous water monitoring has a direct positive effect on the interpretation of its spatial and temporal variations [2]. The assessment of water quality and the frequency of monitoring have a positive impact on the control of surface water quality, thus facilitating its management [3,4]. Many techniques have been developed to evaluate the quality changes in water resources. Thus, water quality parameters such as precipitation, temperature, nitrate, DO, TDS, or flow are used as variables. Measurement of long-term quality and flow parameters, which are interpreted with appropriate methodology, are used in the planning and management of water resources. All water quality parameters are rarely within the permissible limits of the class in water quality classifications. Sometimes, surface water is included in several quality classes according to its different quality parameters. The Water Framework Directive (WFD) classifies the quality of water parameter by parameter through the result of the physicochemical analysis. In fact, according to WFD, each quality parameter is high, good, medium, bad, or poor. This type of classification is insufficient to provide an overview of water quality over time, as the quality can change over time through a single element and such classification does not reflect the overall water quality reality [1]. In that way, it is difficult to evaluate water quality from a large number of samples, each one containing many parameters [5]. To solve this situation, many researchers have used the Water Quality Index (WQI) to determine the quality of surface water for the last few decades [6,7,1].

[8] implemented the first technique to calculate WQI by considering ten water quality parameters. Later, other WQI calculating techniques like the National Sanitation Foundation WQI [9], Oregon WQI [10], and more recently the Canadian WQI [11] have been made. WQI method is a basic technique that helps by reducing large datasets to a unique value that considers the overall quality of the water [8]. Recently, WQI calculation methods have greatly facilitated the determination of water quality, and its monitoring and evaluation, temporarily and spatially. Therefore, it should be recognized that the WQI calculation techniques provide significant added value in decision-making in terms of water quality control and management [1]. [12] tested several WQI calculation techniques. Their study reveals that each of these techniques suffers from being linked to the context or the use of water. Thus, to compensate for these inadequacies, they developed Universal WQI. To make WQI, sampling and analysing several parameters is non-practical and very expensive [13]. [14] applied the PCA method to classify surface water quality parameters according to their importance, and the HCA technique to divide the sample points according to their degree of similarity to pollution. Later on, [1] used HCA by considering quality parameters and calculated WQI by Canadian WQI method. Further analysis allows to classify these parameters according to their contribution to WQI. HCA permitted to classify quality parameters as essential and non-essential. Thus, this technique has advantage of reducing the number of parameters to be analysed in the laboratory and saving money in long-term monitoring.

Alongside its undeniable socio-economic importance, the Niger River suffers the consequences of both climate change and human activities. In Bamako, for decades, the combined actions of the population explosion and artisanal, industrial, and agricultural activities around the Niger River has exerted unprecedented pressure on it [15]. With almost 40% of the entire country's urban population, this has resulted in an unprecedented deterioration in the quality of river water in the Malian capital [16]. Climate change has also contributed to a continuous decline in flow since the 1970s [17]. This situation has led several researchers to look into the physicochemical and bacteriological quality of the Niger River in this locality. This is why the conclusions of the work of [18] revealed that the physicochemical quality of the waters of the entire river basin is relatively good. A little later, [19] showed that the chemical quality of the Niger River on the Bamako-Koulikoro axis is acceptable because of its very high flow. [20] highlighted the chemical and bacteriological pollution of the Niger River in the city of Ségou, some 235 km downstream from Bamako.

More recently, [21] showed that the methods previously used to assess the water quality of the Niger River were archaic. Indeed, they criticized these techniques based on the fact that researchers compared only physicochemical and bacteriological parameters to the quality standards. As a result, these techniques did not provide a better understanding of the spatiotemporal evolution of these parameters. To have better understanding on the water quality parameter evolution, [21] opted to implement the WQI taking into account the 2016-2020 analysis results of several physicochemical parameters (Turbidity, pH, Electrical Conductivity (EC), Dissolved Oxygen (DO), Total Dissolved Solids (TDS), Biochemical Oxygen Demand (BOD5), Chemical Oxygen Demand (COD), Nitrate, Nitrite, Ammonium, Phosphate, Sulphate, Chloride and Copper) at fifteen (30) sampling points. Thus, the calculated indices reflect the overall water quality for the considered sampling point and period. Based on the results, they concluded that the water of this river is polluted and cannot be used for human consumption or industrial uses without prior treatment. Through the calculated index, we can easily express ourselves about the quality of water sampled at a given point with much more serenity and clarity. It appears that this method of water quality evaluation has the merit of being synthetic. The most important thing regarding this evaluation method lies in the reading and understanding of the calculated indices which is not limited to researchers only. Thus, political decision-makers and all citizens anytime can easily read these results and understand their meaning.

While the methodologies for calculating Water Quality Index (WQI) using various parameters are scientifically validated, it is evident that these techniques are time-consuming. Thus, developing mathematical models able to skip this WQI calculation step will certainly save time and efficiency.

ANN (Artificial Neural Network) is a technique inspired by the human brain working system used to predict unknown data after passing the step of learning [22]. Through this technique, different layers are connected to determine the relationship between inputs and outputs [23]. ANN is used as a mathematical process to predict quickly and easily water quality parameters by saving both time and effort [24]. Nowadays, ANN as one of the branches of Artificial Intelligence (AI) is an inexpensive technic with a powerful tool. It's unavoidable in many fields for forecasting like finance, energy, medicine, and ecology [25]. Solutions made by this tool are diversified due to some characteristics like easy installation of hardware, high learning ability, and behavior adaptation to any change in the system [26].

ANN has been used specially to investigate the water quality of river systems, to plan and manage by forecasting water quality parameters [27,28], to determine the source of pollution according to microbiological water quality parameters [29,30]. This technic has also been used to model groundwater level [31,32], to determine the daily suspended sediment amount in wastewater [33], the rainfall-runoff models of rivers [34], the relationship between waste odour and biological oxygen demand [35], to evaluate water quality parameters in streams [36], to predict nitrate level on groundwater [26,37,38], surface water [26,39] or both ground and surface waters [40], to calculate nitrite level on groundwater [41], to estimate water salinity parameters levels [42,43], to predict SAR on groundwater [44,45] and surface water [46,47], or to forecast WQI on groundwater [48] and surface water [49,50].

This study aims to evaluate and model calculated WQI of Niger river in Bamako and neighboring areas using ANN and MLR methods. Therefore, it differs from other studies in the same area by modeling WQI and evaluation of the performance of models utilizing statistical tools (r^2, RMSE, MAE). To reach this goal, five parameters (pH, EC, NO_3^-, NO_2^-, Fe) were used for both WQI implementation and modeling in order to have better understanding about Niger River quality in Bamako and neighboring areas.

2. MATERIALS AND METHODS

2.1 Study Area

The District of Bamako, capital of Mali is located between 12°29'57'' and 12°42'17'' north latitude and 7°54'22'' and 8°4'6'' west longitude. The city was developed in the valley of the largest river in West Africa which divides it into right and left banks. It is divided into six municipalities; the first four of which are located on the left bank and the last two on the right bank of the Niger River (Fig. 1).

The rainy season begins in the end of the month of May and extends to September or even the beginning of October and the dry season begins just after and extends until the end of May. Bamako has seen its population increase rapidly since independence, going from 128,400 inhabitants to 2,703,588 in 2022, an increase of 2,575,188 inhabitants in 62 years [51]. While this population is growing very quickly, the liquid and solid waste management system suffers from enormous failures. Bamako does not have a sewer system for adequate wastewater collection. Raw wastewater of all types from the city of Bamako is therefore dumped directly or indirectly into the Niger River through diffuse runoff or through occasional discharges from rainwater collectors [52].

The Niger River, 4,200 km long with a basin estimated at 2,000,000 km², crosses Mali over a length of 1,750 km, or 42% of its total length. Its watershed, in Malian territory, covers 570,000 km², including an active basin of 300,000 km² which includes, in addition to the District of Bamako, most of the country's large cities [53]. This river crosses the city of Bamako for about twenty kilometers. The minor bed of Niger river has an average width of approximately 850 m, delimiting an aquatic area of nearly 17 km² (~7% of the district's surface area). The bottom of the minor bed is mainly made up of sandstone in place and fractured blocks [54].

2.2 Sampling and Analysis Methods

2.2.1 Sampling

In order to reach this purpose, 3 series of sampling (December 2017, March 2018 and July 2018) were carried out at 40 sampling points on the Niger river in the study area (Fig. 2). For each series, physical parameters: pH and EC were measured directly on the field using multiparameter HANNA HI 9828 and HANNA HI 2211 respectively. For chemical parameters (nitrate: NO_3^-, nitrite: NO_2^-, and total iron: Fe) measuring, samples were brought in the National Laboratory of Water (Laboratoire National des Eaux, LNE). The ionic chromatography method was used by Metrohm 881 Compact IC pro instrument to determine concentration of nitrate (NO_3^-), and nitrite (NO_2^-). Perkin Elmer ELAN 400 instrument was used to measure iron (Fe) concentration on the samples. Each sampling point was recorded using GPS (Global Positioning System) device.

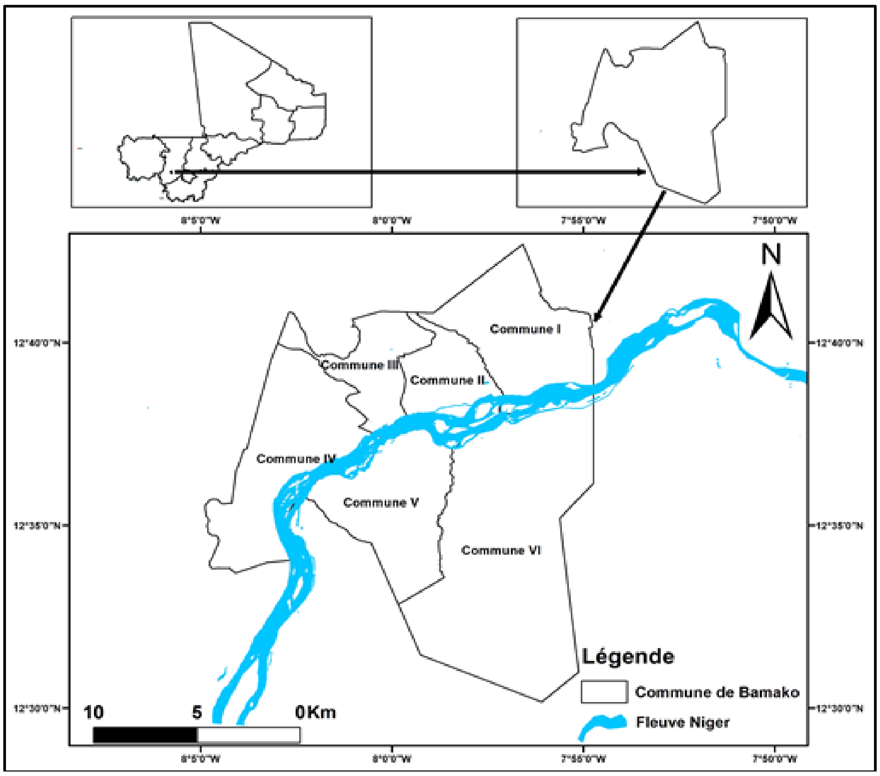

Fig. 1. Localization map of the study area

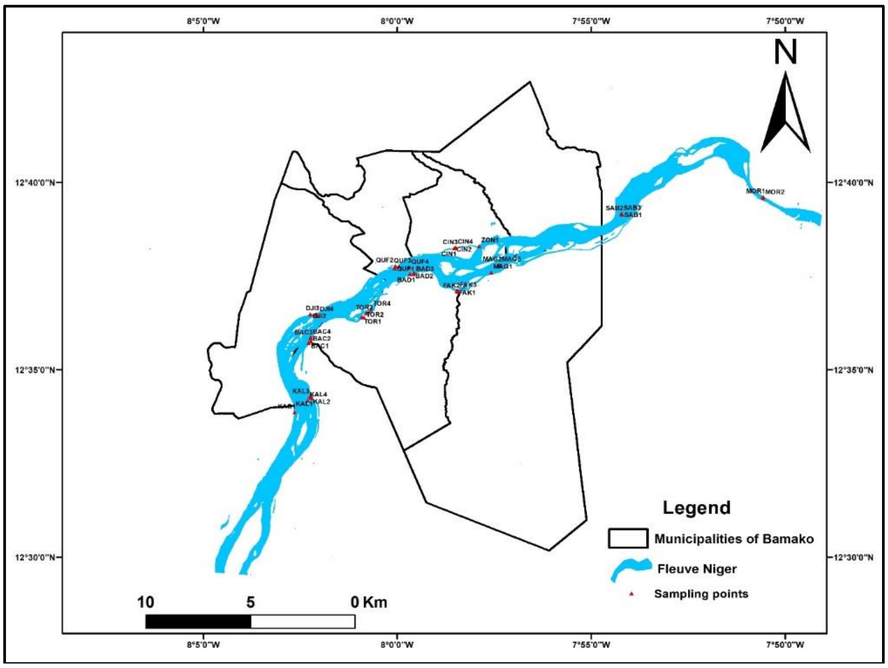

Fig. 2. Positions of sampling point in the study area

2.2.2 Water quality index technic

In this study, the Weighted Arithmetic Water Quality Index method based on the standards guideline values recommended by the WHO (World Health Organization) for drinking water was used to calculate and evaluate Water Quality Index of Niger river water. This technic, because of the fact that it reduces complex data into a single and simple value, is widely used worldwide to verify the suitability of water for different usages [1,13,14]. In this work, the weighted arithmetic WQI values were determined based on the following procedure:

In the first step, physicochemical parameters such as PH, EC, NO_3^-, NO_2^- and Fe (Table 1) which will be used for WQI calculation and their standard guideline values (WHO) were selected. In the second step, a weighted value (wi) is allocated for each selected parameter according to its influences on health and its relative importance in terms of drinking water quality following WHO requirements. The values of different assigned weights vary between 1 and 5 depending on the importance of each considered parameter in determining of the water quality for drinking (Table 1).

In the third step, the relative weight of each parameter was calculated (Table 1) using Equation 1.

$$W_i = \frac{w_i}{\sum_{i=1}^{n} (w_i)} \qquad \text{Equation 1}$$

Where wi represents the assigned weight value for each parameter, Wi indicates the relative weight and n corresponds to the total number of considered parameters (5). Considering this context, Table 1 gives standard value according to the WHO guideline value, assigned weight value and relative weight value of each parameter which is used to calculate the WQI. The weighted value 5 was given to NO_3^-, NO_2^- and EC, 4 to pH [55,56] and 3 to Fe according to their importance (Table 1).

In the fourth step, the quality-rating scale (Qi) value of each parameter was determined using Equation 2.

$$Q_i = \frac{(C_i - V_i)}{(S_i - V_i)} \times 100 \qquad \text{Equation 2}$$

Where Ci represents the estimated concentration value of each parameter, Si represents the recommended value according to the WHO standards for the quality of drinking water. Except for pH where it is equal to 7, the value of Vi is considered as zero for all other parameters [57,55].

In the fifth step, the sub-index value of each parameter is determined according to the following Equation 3.

$$SI_i = Q_i \times W_i \qquad \text{Equation 3}$$

Finally, the Water Quality Index (WQI) for each station is calculated according to Equation 4.

$$WQI = \sum_{i=1}^{n} (SI_i) \qquad \text{Equation 4}$$

So, the calculated WQIs made it possible to assess the quality of surface water of Niger River in the study area based on the table below (Table 2), but above all, to be aware of the variability of this quality over time and space.

Table 1. WHO guideline values, assigned weight and relative weight of physicochemical parameters

Parameters	WHO	Weight (w)	Relative weight (W)
EC (µS/cm)	2500	5	0.2273
pH	6.5-8.5	4	0.1818
Nitrate (mg/l)	50	5	0.2273
Nitrite (mg/l)	0.01	5	0.2273
Fer (mg/l)	0.03	3	0.1364
		∑(wi) = 24	∑(Wi) = 1

Table 2. Classification of water according to the WQI

WQI level	Water class
< 50	Excellent
50-100	Good
100-200	Poor
200-300	Very poor
> 300	Inadequate for drinking

2.3 Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN)

In addition to the calculations of the Water Quality Index (WQI) employing conventional methods, the physicochemical parameters were also utilized in two alternative models, namely Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN). This approach allows for a comprehensive analysis of water quality by integrating various modeling techniques. In this research, Niger river quality parameters and WQIs data are organized from upstream to downstream in order to evaluate the capacity of modeling methods (MLR and ANN) to predict downstream events based on upstream ones. In the study, 60% of the input data was allocated for training purposes, enabling the models to effectively predict the target, specifically the Water Quality Index (WQI). Additionally, 20% of the data was reserved for validation, while the final 20% was designated for testing. Each technique was utilized to develop a singular model. Multiple Linear Regression is a statistical method employed to assess the relationship between a dependent variable, referred to as the output, and two or more independent variables, known as inputs. This technique allows researchers to understand how changes in the independent variables can influence the dependent variable, thereby providing insights into the dynamics of the data being analyzed. It's an extension of Simple Linear Regression in which there is one input for one output ($Y = \beta_0 + \beta_0 X_1$). This methodology is applied across various disciplines, including economics, finance, and social sciences, to facilitate predictions and enhance the comprehension of the relationships among different variables. The multiple linear regression (MLR) technique formulates a linear equation that allows independent variables to collectively account for the dependent variable in the most effective manner. The analysis was conducted utilizing SPSS software (2017, Version 25). For MLR, the training dataset, which consists of input data corresponding to various parameters (EC, pH, NO_3^-, NO_2^- and Fe), was utilized alongside target data during the development of the MLR model. This approach facilitated the establishment of a predictive framework which allow the use of testing and validation input parameters to predict WQI values.

The general form of MLR is written in Equation 5:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots + \beta_{n-2} X_{n-2} + \beta_{n-1} X_{n-1} + \beta_n X_n \qquad \text{Equation 5}$$

Where Y is the output or dependent variable; X_1, X_2, X_3, …, X_{n-2}, X_{n-1} and X_n are input or independent variables and β_0, β_1, β_2, β_3, …, β_{n-2}, β_{n-1} and β_n are the coefficient for the independent variables. These coefficients are generated in order to minimize errors.

This technic by the fact that it gives a clear mathematical formula to calculate output parameter (WQI) is different to ANN in which there is no formula to obtain directly output parameter. this is why ANN is also called black box technique.

The application of Artificial Neural Network (ANN) modeling was conducted using MATLAB R2016b. The input parameters employed for modeling the Water Quality Index (WQI) were consistent with those utilized in the Multiple Linear Regression (MLR) technique. As previously mentioned, ANNs find utility across various domains, and numerous architectural configurations exist for predicting output data. In this study, the Multi-Layer Perceptron (MLP) architecture was selected, characterized by three distinct layers: input, hidden, and output, alongside the Feed Forward Back Propagation (FFBP) algorithm for the purpose of modeling the output parameter, specifically the WQI.

The algorithm operates in two distinct phases. Initially, it facilitates the flow of data from the input layer to the output layer, traversing through the hidden layer. This process involves calculating the weights assigned to the connections between each node in the input layer and those in the hidden layer.

Subsequently, the values of the nodes in the hidden layer are determined, along with the weights that connect these nodes to the output layer. Ultimately, the aggregation of the node values and the corresponding weights between the hidden and output layers enables the derivation of the final output values, characterizing the forward propagation aspect of the algorithm. After that and in order to reduce errors between calculated WQI and modelled one, weights between hidden-output and input-hidden layers are modified in the opposed sense: Back Propagation (BP) passing of the algorithm prosses (Fig. 3). This technic is widely used because of its BP process which contributes to reduce enormously errors between measured and modelled parameters [19,58,59]. Each neuron within a neural network possesses a distinct value that is treated as input by the subsequent layer, along with a specific weight that connects it to each neuron in that layer. For the hidden input layers, these weights are denoted as Wi, while for the hidden output layers, they are referred to as Wj, as illustrated in Fig 3. In the case of the input layer neurons, the values correspond to empirical measurements obtained from either field studies or laboratory experiments. The weight assigned between any two nodes is contingent upon the significance of the input parameter in relation to the output parameter being predicted. To derive the values for a node in either a hidden layer or an output layer, the values from all preceding nodes are multiplied by their respective weights, and the results are summed. This summation is then subjected to a nonlinear transformation through the application of an activation function, which may be linear, sigmoid, hyperbolic tangent, among others. In constructing the model, the number of input and output parameters is predetermined, while the number of nodes in the hidden layer is adjusted iteratively to identify the optimal configuration. Notably, there is no universally accepted formula for determining this ideal arrangement. During this work, in order to find optimal number of hidden layer nodes, we carry out trial-and-error method [60, 19] and the different results are compared themselves to choose the best one.

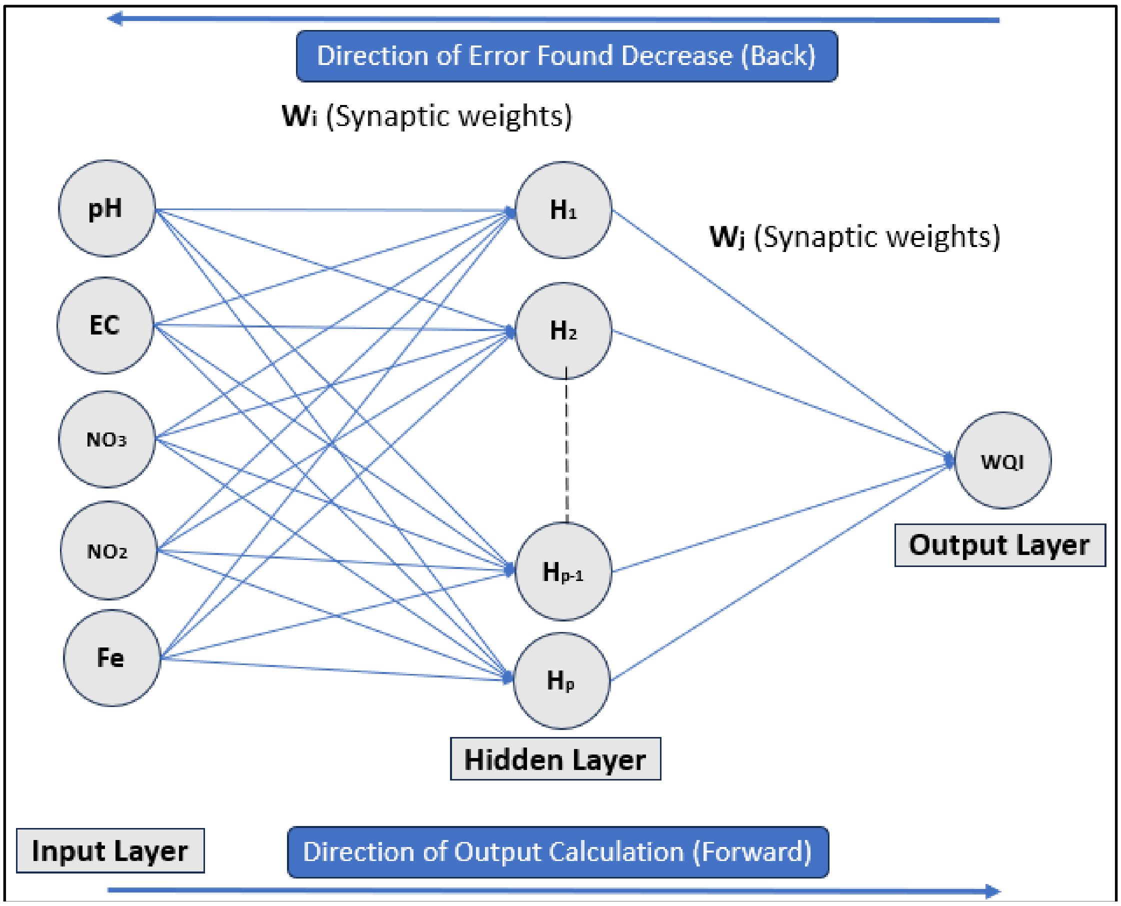

Fig. 3. Feed forward back propagation neural network representation

The optimization of the number of nodes in the hidden layer is directly influenced by the number of input features, aiming to identify the optimal configuration that maximizes the coefficient of determination (R^2), ideally approaching unity. This optimal configuration is also characterized by minimal values of root mean square error (RMSE) and mean absolute error (MAE). As the number of neurons in the hidden layer deviates from this optimal point, a corresponding decline in r^2 is observed, alongside an increase in both RMSE and MAE, prompting the cessation of testing under such conditions. Concurrently, various activation functions, including linear, sigmoid, and hyperbolic tangent, are assessed through multiple combinations of input-hidden and hidden-output layers to determine the most effective arrangement. In addition to the aforementioned parameters that were varied throughout the optimization process, several constants were maintained to streamline implementation. Specifically, the activation function employed between the input and hidden layers was fixed at the sigmoid function, while a linear activation function was utilized for the hidden-output layers. Other constants included a learning coefficient set at λ = 0.50, a momentum coefficient of α = 0.50, a maximum iteration limit of 10,000, and a single output neuron representing the Water Quality Index (WQI). These controlled parameters were essential for ensuring a consistent framework within which the optimization could be effectively evaluated [19].

W_i and W_j represent weights linked respectively input-hidden and hidden-output layers neurons themselves. So, each neuron of input layer (pH, EC, NO_3^-, NO_2^- and Fe) has "p" weights (corresponding to hidden layer nodes number). In this study, each hidden layer neuron has only one weight because there's only one node in output layer Fig. 2). In order to reduce difference between maximal and minimal measured data and to facilitate efficiency of ANN to work, data of input and output layers were normalized between 0.1-0.9 as first work through formula given in Equation 6 [19]:

$$X_{ni} = \frac{0.8(X_i - X_{min})}{(X_{max} - X_{min})} + 0.2 \qquad \text{Equation 6}$$

Here X_{ni} represents normalized data number i;

X_{min} and X_{max} are respectively minimum and maximum of the whole data.

The results obtained by modeling are denormalized taking into account X_{min} and X_{max} to obtain X_i coming from the model by transforming the formula above.

The results obtained through modeling are denormalized taking into account X_{min} and X_{max} in order to obtain X_i from the model by transformation of the formula above.

2.3.1 Evaluation of modeling results

The performance of predictions made by MLR and ANN models have been evaluated using coefficient of determination (R^2), RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) between network output (models) and network target output (measures) in training, validation and test sets through the Equations 7, 8 and 9.

$$R^2 = \left[\frac{\left[\sum_{i=1}^{n}(Y_{\text{Measured i}} - \overline{Y}_{\text{Measured}})(Y_{\text{Modelled i}} - \overline{Y}_{\text{Modelled}})\right]^2}{\left[\sum_{i=1}^{n}(Y_{\text{Measured i}} - \overline{Y}_{\text{Measured}})^2\right]\left[\sum_{i=1}^{n}(Y_{\text{Modelled i}} - \overline{Y}_{\text{Modelled}})^2\right]}\right] \qquad \text{Equation 7}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(Y_{\text{Measured i}} - Y_{\text{Modelled i}})^2\right)} \qquad \text{Equation 8}$$

$$\text{MAE} = \frac{1}{n}\left(\sum_{i=1}^{n}|Y_{\text{Measured i}} - Y_{\text{Modelled i}}|\right) \qquad \text{Equation 9}$$

Where, $Y_{\text{Measured i}}$ corresponds to the ith calculated WQI based on measured physicochemical parameters (field and laboratory); $\overline{Y}_{\text{Measured}}$ is the average of the calculated WQI's, $Y_{\text{Modelled i}}$ is the ith modelled WQI; $\overline{Y}_{\text{Modelled}}$ correspond to the average of modelled WQI's.

The closer R^2 value is to 1, the closer the values of RMSE and MAE are to 0, the more the model implemented is efficient. The statistical parameters derived from the calculations were employed to facilitate a comparison of the models across the training, validation, and test datasets, as well as between MLR and ANN. In the context of the MLR technique, the optimal and singular outcome, based on the input parameters of electrical conductivity (EC), pH, nitrate (NO_3^-), nitrite (NO_2^-), and iron (Fe), is readily identifiable As to ANN technic, several tests were carried out and, on the criteria mentioned above to find the best models.

3. RESULTS AND DISCUSSION

3.1 River Drinkability and Water Quality Index

The results of the descriptive statistical analysis concerning the physicochemical parameters of surface water from the study area are detailed in Table 3.

The pH levels observed in the study area range from 4.00 to 9.00, with an average value of 6.62, indicating that the waters are slightly acidic. In contrast, the EC values exhibit significant variability, with minimum, maximum, and average values recorded at 5.50 µS/cm, 1747.00 µS/cm, and 188.25 µS/cm, respectively. Nitrate concentrations fluctuate between 0.00 mg/L and 8.00 mg/L with average value of 2.04 mg/L, while nitrite levels range from 0.00 mg/L to 0.20 mg/L, with an average of 0.003 mg/L. Iron concentrations also show variability, spanning from 0.00 to 4.10 mg/L, with an average of 0.13 mg/L.

Notably, with the exception of electrical conductivity, the standard deviation for the other parameters measured is relatively low, suggesting minimal fluctuations in these values over time and across different locations. The variability in EC can likely be attributed to sporadic industrial or domestic discharges into the river, which occur without prior treatment. Conversely, the limited variation in the other parameters indicates that these discharges contribute only marginal amounts of these substances, reflecting a more stable environmental condition for those specific metrics.

In terms of adherence to the WHO standards for physicochemical parameters, only the electrical EC and nitrate concentrations met the established criteria across all three sampling periods, as indicated in Table 3. This suggests that the values recorded for these specific parameters fall within the acceptable limits set by WHO for drinking water quality. The situation of the sampling points based on analysis results which are not comply with the WHO standards is described below:

In the initial sampling round, several points were found to be non-compliant with WHO standards. Specifically, the sampling points BAD1, BAD3, DJI4, KAB1, MAG2, MAG3, QUF1, SAB3, FAK1, MOR2, TOR1, TOR2, TOR3, and TOR4 were assessed for pH levels, while DJI2 was evaluated for nitrite. Additionally, the points BAD2, CIN2, CIN3, DJI1, DJI3, KAL2, KAL3, KAL4, MAG1, SAB1, MOR1, MOR2, TOR1, TOR2, TOR3, and TOR4 were examined for iron content. In total, 31 out of 40 sampling points exceeded the established standards.

During the second round of assessments, a significant number of sampling points again failed to meet the required standards. The points BAC1, BAC2, BAC3, BAC4, BAD1, BAD2, DJI1, DJI3, DJI4, KAL1, KAL3, KAL4, QUF1, QUF4, ZON1, TOR2, TOR3, and TOR4 were tested for pH, while DJI3 and QUF2 were analyzed for nitrite levels. Furthermore, the sampling points BAC3, CIN1, CIN2, CIN3, CIN4, DJI1, DJI2, DJI3, KAB1, KAL3, KAL4, SAB2, FAK2, FAK3, TOR2, and TOR3 were evaluated for iron. This round revealed that 36 out of 40 sampling points exceeded the acceptable limits.

Table 3. Descriptive statistics of the physicochemical parameters of surface waters

Parameters	pH	EC (µS/cm)	Nitrate (mg/l)	Nitrite (mg/l)	Fer (mg/l)
Maximum	9.00	1747.00	8.00	0.20	4.10
Minimum	4.00	5.50	0.00	0.00	0.00
Average	6.62	188.25	2.04	0.003	0.13
Std. deviation	1.09	378.00	2.29	0.02	0.48
WHO	6.50-8.50	2500	50	0.01	0.03

Std. deviation means Standard deviation.

In the final round of sampling, numerous points were again found to be non-compliant with the established standards. The points BAD1, BAD2, BAD3, DJI3, DJI4, KAB1, MAG1, MAG2, QUF1, QUF2, QUF4, SAB1, SAB2, SAB3, ZON1, FAK1, FAK2, FAK3, TOR1, TOR3, and TOR4 were assessed for pH, while DJI3 was specifically evaluated for nitrite. Additionally, the points DJI3, DJI4, QUF1, QUF2, QUF3, and QUF4 were tested for iron content. In this round, 28 out of 40 sampling points were found to exceed the prescribed. Throughout the three phases of sampling and analysis, pH levels were found to exceed acceptable standards at several locations, specifically BAD1, BAD3, QUF1, TOR3, and TOR4. Additionally, the iron concentration surpassed the permissible limits at the DJI3 sampling point. In contrast, other sampling locations exhibited varying degrees of compliance with the standards, with some exceeding the limits infrequently and others doing so on one or two occasions. This variability complicates the assessment of water quality, as certain parameters at the same sampling site may meet regulatory standards while others do not, highlighting the necessity for a comprehensive index that incorporates all physicochemical parameters. The inconsistencies observed in the water quality parameters necessitate a more holistic approach to evaluating the overall health of the water bodies in question. By developing an index that aggregates the results of all relevant physicochemical parameters, stakeholders can gain a clearer understanding of water quality trends and make informed decisions regarding water management and public health. This approach not only facilitates better regulatory compliance but also enhances the capacity for effective environmental monitoring and protection. Table 4 presents the maximum, minimum, average, and standard deviation of the WQI calculated for the 40 sampling points along the Niger River within the study area. The statistical parameters derived from these calculations demonstrate significant fluctuations across different sampling periods.

During the initial sampling phase, the WQI values ranged from 3.48 to 254.82, yielding an average of 58.41 and a standard deviation of 61.03, as presented in Table 4. According to the classification in Table 2, the water quality varied from very poor to excellent across the 40 sampling locations. The distribution of water quality in this round was characterized by 62.50% of samples falling into the excellent category, 17.50% classified as good, another 17.50% as poor, and a mere 2.50% deemed very poor. 2. In the subsequent sampling round, the WQI values exhibited a broader range, spanning from 3.42 to 1887.40, with an average of 183.73 and a standard deviation of 380.46. As indicated in Table 2, the water quality in this round was assessed as varying from inadequate for drinking to excellent. Among the 40 sampling points, the distribution of water quality was as follows: 55.00% of samples were rated excellent, 20.00% good, 5.00% poor, 5.00% very poor, and 15.00% classified as inadequate for drinking. Notably, all seven samples with the lowest WQI scores were recorded during this round across the three sampling campaigns. These samples were measured at points CIN1 (WQI = 1887.40), CIN3 (WQI = 1340.86), DJI3 (WQI = 813.92), TOR2 (WQI = 662.67), DJI2 (WQI = 406.81), FAK2 (WQI = 345.85) and SAB2 (WQI = 276.96).

In the last sampling round, the WQI ranged from 0.44 to 173.71, with an average value of 46.13 and a standard deviation of 46.35. According to the data presented in Table 2, the water quality classifications vary from poor to excellent. Among the 40 sampling points analyzed, the water samples exhibited excellent, good, and poor quality in proportions of 70.00%, 7.50%, and 22.50%, respectively. This sampling period is characterized by the most favorable WQI results observed. Fig. 4 illustrates the fluctuations in WQI across different sampling events and periods. It is noteworthy that the data does not indicate a consistent trend from upstream to downstream. Across all three sampling periods, the lowest WQI values were consistently found in the central region of the waterway. This area, located in the heart of Bamako, is likely the source of the pollutants. The observed improvement in water quality as one moves downstream can be attributed to various interactions and processes occurring along the water's path.

Table 4. Descriptive statistic of the calculated WQI in the three rounds of sampling

Period of sampling	Maximum	Minimum	Average	Standard deviation
Round 1 (December 2017)	254.82	3.48	58.41	61.03
Round 2 (March 2018)	1887.40	3.42	183.73	380.46
Round 3 (July 2018)	173.71	0.44	46.13	46.35

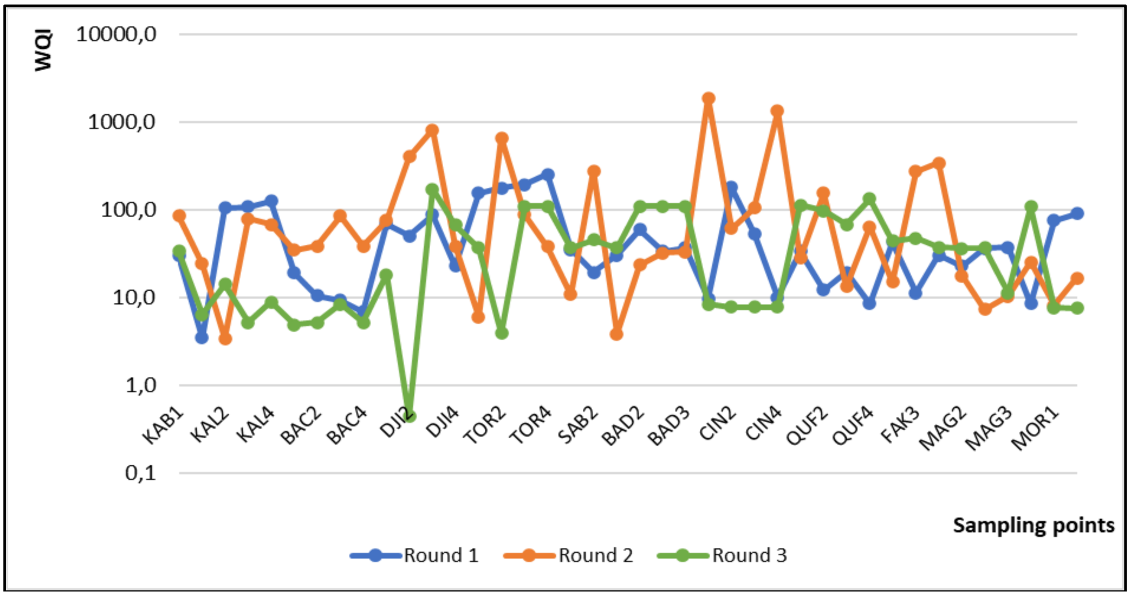

Fig. 4. Variation of WQI through sampling points and periods

Following the rainy season in December, the Niger River experiences elevated water levels and increased discharge rates. In contrast, March marks the onset of the dry season, during which both the water level and flow rates decline significantly. July, on the other hand, returns to the rainy season, characterized by substantial rainfall and heightened flow rates. The climatic conditions of the study area elucidate the fluctuations in Water Quality Index (WQI). The considerable influx of rainwater, along with the accompanying high flows, plays a crucial role in diluting pollutants from domestic and industrial sources present in the river, resulting in an acceptable water quality during the first and third sampling rounds. However, as the rainy season recedes, flow rates diminish, leading to reduced dilution and a subsequent decline in water quality due to the accumulation of pollutants from various origins. Consequently, the standard deviation of the WQI is notably greater during the March sampling period, which is marked by low flow conditions, compared to the other two periods. The relationship between reduced river levels and flow rates correlates with diminished dilution capacity, causing significant variability in physicochemical parameters from one sampling point to another. The pronounced standard deviation observed in the second round of sampling, as indicated in Table 4, underscores the extent of variation in these physicochemical parameters.

Throughout the three sampling periods, the second round yielded the least favorable results regarding water quality. This round recorded the lowest WQI at 1887.40, which is significantly higher than the maximum WQI observed in the first round (254.82) and the third round (173.71). As previously discussed, the observed variations in WQI across the sampling intervals can be attributed to the declining levels and flow rates of the Niger River, which are influenced by a lack of rainfall and considerable evaporation, alongside the continuous discharge of pollutants. Furthermore, the central area of the capital is identified as the primary source of pollution within the study region, as illustrated in Fig. 4.

3.2 Water Quality Indices Modelling

The data pertaining to the measured physicochemical parameters and the calculated Water Quality Indices (WQIs) from three sampling rounds have been categorized into three distinct sets: training, validation, and test sets, comprising 60%, 20%, and 20% of the data, respectively, arranged from upstream to downstream. This classification aims to assess the models' ability to predict downstream WQIs. A summary of the maximum, minimum, average, and standard deviation for the five input parameters and the output parameter (WQI) across the training, validation, and testing sets is presented in Table 5. In the training set, the WQIs range from 0.44 to 1887.40, with an average of 105.39 and a standard deviation of 251.44. The validation set shows WQIs fluctuating between 7.75 and 1340.86, yielding an average of 109.44 and a standard deviation of

267.13. Conversely, the test set is characterized by WQIs ranging from 7.32 to 345.85, with an average of 54.84 and a standard deviation of 83.95. Notably, the average WQI in the test set surpasses that of both the training and validation sets, while the standard deviation in the test set (83.95) is significantly lower than the closely aligned values of the training and validation sets (251.44 and 267.13, respectively). Among the five input parameters, only pH exhibits result that are somewhat comparable to this trend.

The objective of employing Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN) is to assess the predictive capabilities of these methodologies in modeling the Water Quality Index (WQI) of the Niger River within the designated study area. This assessment is based on data gathered from December 2017 to July 2018 across 40 sampling locations. To evaluate the efficacy of each model developed through training, validation, and testing datasets, statistical metrics such as the correlation coefficient (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were utilized for comparative analysis of the performance of the various techniques implemented.

- **MLR Model**

In the process of developing the multiple linear regression (MLR) model for predicting the Water Quality Index (WQI), the independent variables selected included electrical conductivity (EC), pH, nitrate (NO_3^-), nitrite (NO_2^-), and iron (Fe). The MLR model was constructed utilizing a training dataset, which comprised both input and output values, to determine an appropriate fitting structure. The fitting model obtained is shown in equation (10).

The variable WQIMLR represents the anticipated Water Quality Index (WQI) for the Niger River, derived through multiple linear regression (MLR) techniques. In this context, EC denotes the electrical conductivity measured in millisiemens per centimeter ($mS.cm^{-1}$), while pH indicates the water's potential. Additionally, the concentrations of nitrate, nitrite, and iron are expressed in milligrams per liter ($mg.L^{-1}$). This equation was employed to calculate the modelled WQIs across the training, validation, and testing datasets.

- **ANN Model**

In the construction of the artificial neural network (ANN) model, the same input variables utilized in the regression analysis were employed. To streamline the development of the ANN model, certain parameters were held constant, including the activation functions applied between the input and hidden layers (Sigmoid) and between the hidden and output layers (linear), as well as the learning coefficient set at λ=0.50, the momentum coefficient at α=0.50, a maximum iteration limit of 10,000, and a single output neuron corresponding to the Water Quality Index (WQI). The determination of the optimal number of neurons in the hidden layer was achieved through a trial-and-error methodology, where the ideal configuration was identified based on the model's high coefficient of determination (R^2) and minimal error rates, specifically root mean square error (RMSE) and mean absolute error (MAE), across various datasets. Ultimately, the most effective ANN model was established with 13 neurons in the hidden layer.1. Table 6 presents

Table 5. Descriptive statistics of training, validation and testing sets data

Sets	Parameters	pH	EC	NO_3^-	NO_2^-	Fe	WQI
Training	Maximum	9	1747	7,5	0,2	4,1	1887.40
	Minimum	4	5,5	0	0	0	0.44
	Average	6,45	171,78	1,94	0	0,14	105.39
	Std dev.	391,03	1,23	2,06	0,02	0,52	251,44
Validation	Maximum	8,6	1474,6	8	0,06	2,9	1340.86
	Minimum	5,3	12,5	0	0	0	7.75
	Average	6,97	292,41	2,13	0	0,18	109.44
	Std dev.	452,85	0,8	2,41	0,01	0,59	267,13
Test	Maximum	8,1	890,4	7,5	0,01	0,72	345.85
	Minimum	4	20,8	0	0	0	7.32
	Average	6,8	133,48	2,25	0	0,07	54.84
	Std dev.	217,84	0,93	2,86	0	0,18	83,95

Std dev. means standard deviation

Table 6. Performance of models derived from MLR and ANN techniques

Set	Method	Evaluation criteria		
		R^2	RMSE	MAE
Training	MLR	0.998	9.961	7.398
	ANN	0.999	0.8380	0.5396
Validation	MLR	0.997	14.071	10.618
	ANN	0.999	8.1905	4.2113
Test	MLR	0.976	13.009	10.332
	ANN	0.998	5.2615	2.8969

the outcomes of the Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models. The Water Quality Index (WQI) values derived from both methodologies were individually assessed against the calculated WQI (Equation 4). This evaluation was conducted in accordance with the statistical parameters outlined in Table 5.

The WQI serves as a crucial instrument for assessing the potability of water. A model utilizing this water quality assessment tool is essential for safeguarding the health of communities residing along the Niger River in Bamako, thereby protecting them from waterborne diseases. The performance of WQI models based on MLR and ANN was evaluated using statistical metrics such as R^2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), as presented in Table 6. The MLR model yielded R^2, RMSE, and MAE values of 0.998, 9.961, and 7.398 for the training set, 0.997, 14.071, and 10.618 for the validation set, and 0.976, 13.009, and 10.332 for the test set. In contrast, the ANN model demonstrated R^2, RMSE, and MAE values of 0.999, 0.838, and 0.5396 in the training set, 0.999, 8.1905, and 4.2113 in the validation set, and 0.998, 5.2615, and 2.8969 in the test set, respectively. Both methodologies produced R^2 values approaching 1 across all datasets, with error rates remaining within acceptable limits. Consequently, these findings indicate that both MLR and ANN techniques are effective in modeling the WQI of surface water in the study area.

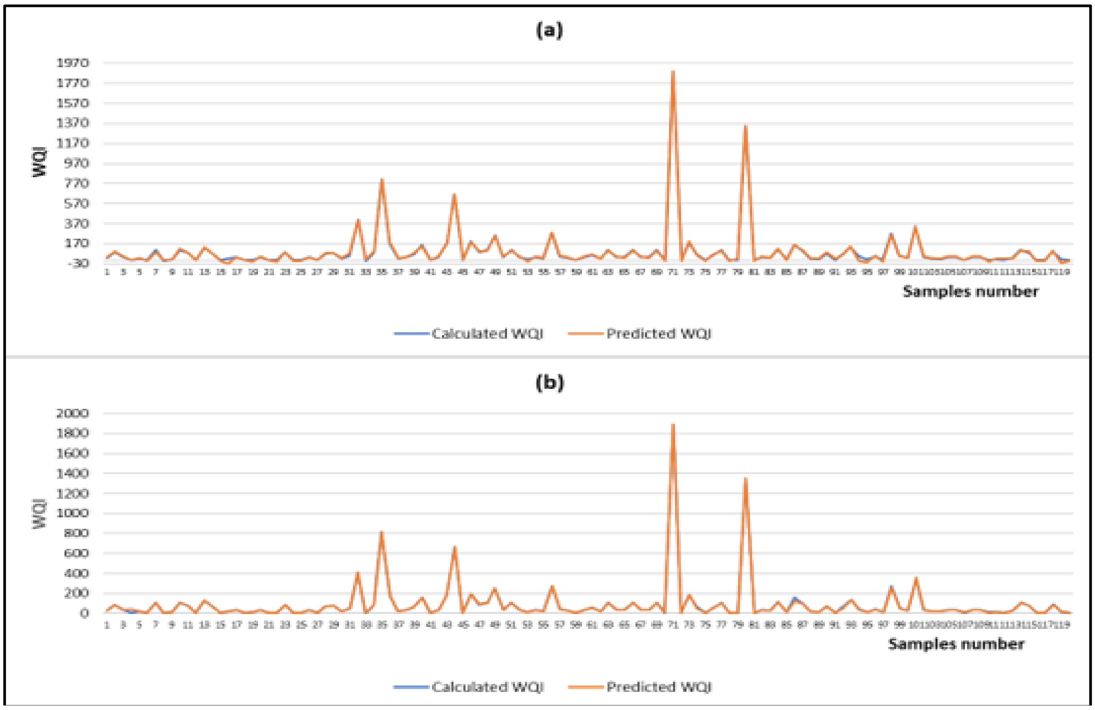

Fig. 5. Data profiles of calculated WQI and predicted WQI by MLR (a) and ANN (b) models from upstream to downstream respectively training, validation and test sets

The figure above illustrates the accuracy of the predicted WQI derived from both MLR and ANN methodologies, alongside the actual WQI values for the training, validation, and test datasets, as depicted in Figs 4a and 4b. The proximity between the predicted and actual WQI values indicates that both techniques have effectively learned from the data. However, a comparative analysis of the error rates reveals that the RMSE and MAE are significantly lower in the ANN approach compared to the MLR. Conversely, the R^2 is closer to 1 for the ANN model across all datasets, suggesting superior predictive performance. Consequently, it can be concluded that the ANN model demonstrates greater accuracy in predicting the WQI of the Niger River than the MLR approach.

It appears that the parameters used make it possible to model WQIs. Although the climatic parameters (rainfall, water flow speed or wind) do not participate in the construction of the models, their role in the river quality variation means that it would be wise to use them like inputs like used in [43] work. These additions would certainly have positive effects on the quality of the futures models. Moreover, [46, 48, 50] have shown the importance of climatic parameters in the quality of river water.

4. CONCLUSION

This research enabled an evaluation of the water quality of the Niger River, which is crucial for the growth and development of Bamako, the capital city of Mali. Consequently, it facilitated the identification of regions where the highest concentrations of pollutants are introduced into the river, while also emphasizing the influence of climatic factors, especially rainfall, on the fluctuations of the Water Quality Index (WQI) within the examined region. The mathematical models developed for the WQI of the Niger River in Bamako, along with their averages, serve as valuable instruments that will enhance river management and inform decision-making processes, thereby preparing stakeholders for potential future challenges. Finally, this study reveals that ANN is better than MLR technic.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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