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RESEARCH ARTICLE

HEAVY METAL CONTAMINATION IN NWANIBA RIVER: A MACHINE LEARNING-DRIVEN ECOSYSTEM ANALYSIS

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ABSTRACT

The rapid industrialization and urbanization of the Uruan Local Government Area of Akwa Ibom State, Nigeria, have significantly contributed to heavy metal contamination in the Nwaniba River. This research assesses the ecological risks associated with contamination using advanced machine learning techniques. Water, sediment, and marine organism samples were analyzed using ICP-OES to quantify seven heavy metals: iron (Fe), copper (Cu), nickel (Ni), lead (Pb), zinc (Zn), chromium (Cr), and manganese (Mn). Three machine learning models—Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN)—were employed to predict heavy metal concentrations and evaluate ecological risks. Random Forest exhibited the highest predictive accuracy ($R^2 = 0.88$), followed by ANN ($R^2 = 0.83$) and SVM ($R^2 = 0.52$). Results indicated significant contamination levels in sediments and bioaccumulation in marine organisms, particularly for Cu, Zn, and Mn, posing risks to aquatic life and public health. Although water quality parameters such as dissolved oxygen and pH generally met WHO, EPA, and NSDWQ standards, the high levels of heavy metals in sediments and organisms underscore the need for continuous monitoring and remediation. The study highlights the critical role of machine learning in enhancing ecological risk assessment and informs strategies for the sustainable management of aquatic ecosystems.

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INTRODUCTION

Water is an essential resource for all living organisms. Approximately 97% of the earth's total water supply is made up of seas and oceans, with freshwater resources making up just 3%. On the poles, glaciers and ice caps contain about 68.7% of the freshwater, whereas groundwater contains 30.1%, surface water bodies contain 0.3%, and other forms contain 0.9% (Javed & Usmani, 2019). Water scarcity can significantly impact the distribution patterns of various organisms, including humans, and it has a lasting effect on the ecosystem. Insufficient water supply, its progressive depletion, and widespread contamination are major sources of ecosystem degradation. The growing issue of river water pollution has brought increased attention to water quality concerns in recent times (Hama Aziz *et al*., 2023; Javed & Usmani, 2019; Obadimu *et al.,* 2024a & 2024b; Shaibu *et al*., 2024). For instance, the introduction of heavy metals into water bodies, such as lakes and rivers, has led to pollution, which is evident in the case of the Nwaniba River in Uruan Local Government Area of Akwa Ibom State. The detrimental effects of water pollution underscore the urgent need for effective water management and conservation strategies to maintain healthy ecosystems and secure water resources for future generations. The ever-increasing industrialization and urbanization have led to a significant surge in heavy metal contamination in aquatic ecosystems, posing severe threats to environmental health and biodiversity (Hakeem *et al*., 2020; Mishra *et al*., 2019; Moses *et al*., 2022; Ubong *et al*., 2023). Heavy metals, such as mercury, lead, and cadmium, can enter rivers and oceans through various pathways, including industrial effluents, agricultural runoff, and atmospheric deposition (Shaibu *et al*., 2022; Sobti *et al*., 2019). Accurate assessment of ecological risks associated with heavy metal contamination is crucial for the development of effective management and conservation strategies (Väänänen *et al*., 2018; Zhang *et al*., 2017). However, traditional methods for ecological risk assessment have largely relied on laboratory experiments and field observations, which can be time-consuming, costly, and limited in their ability to capture the complex interplay between different environmental components (Abiona *et al*., 2019; Jin *et al*., 2020; Liu *et al*., 2018; Zamora-Ledezma *et al*., 2021). Recent advancements in machine learning (ML) can potentially revolutionize various fields, including environmental sciences and engineering. These innovative tools can help overcome existing limitations and enable more accurate predictions of environmental hazards under different pollution conditions (Yaseen, 2021). In this context, a novel machine learning-driven ecological risk assessment approach will be implemented to collect and analyze water, sediment, and fish samples from multiple locations along the Nwaniba River. Utilizing cutting-edge modeling techniques, the study aims to reveal the spatial and temporal distribution of heavy metal contamination and its potential impact on the river's fragile ecosystem. The primary objective of this research is to explore the application of machine learning techniques for evaluating the ecological risks associated with heavy metal contamination in the Nwanibariver. Specifically, it will focus on the complex interactions between water, sediment, and marine organisms. By combining environmental data with advanced modeling methods, the study seeks to uncover underlying patterns and dynamics of heavy metal contamination, thereby enhancing our understanding of its effects on the river's ecosystem and potential consequences for human health. The findings of this study will contribute significantly to the scientific understanding of heavy metal contamination in the Nwaniba River and provide crucial insights for developing efficient remediation and management strategies. Furthermore, this research will lay the foundation for future research on applying machine learning techniques in environmental risk assessment, ultimately fostering a more sustainable and resilient future for our planet.

MATERIALS AND METHODS

Materials: Nitric Acid (Scharlau Spain) Purity: 99%, Whatman Filter paper (125mm), Ultra-pure reagent water (Merck US), MERCK Liquid Hydrogen Peroxide 30%, For Laboratory, Purity: 99%, Hydrochloric Acid (Merck US) Purity: 99%

Study Area: The Nwanibariver is located in the Uruan Local Government Area, which covers a substantial landmass of 449 km². Positioned at coordinates 6°40'N latitude and 7°20'E longitude (Figure 2), the river is bordered by several other Local Government Areas. The Odukpani Local Government Area of Cross River State lies to the east, while the Okobo Local Government Area is situated to the south. On the west, the river is flanked by the NsitAtai and IbesikpoAsutan Local Government Areas, and the Itu Local Government Area lies to the north. For this study, the area was divided into two distinct sampling stations - UfakEffiong in the Southern District, designated as Station I (ST1), and AkaniObio in the Uruan Central District, designated as Station II (ST2) (Moses *et al*., 2023).

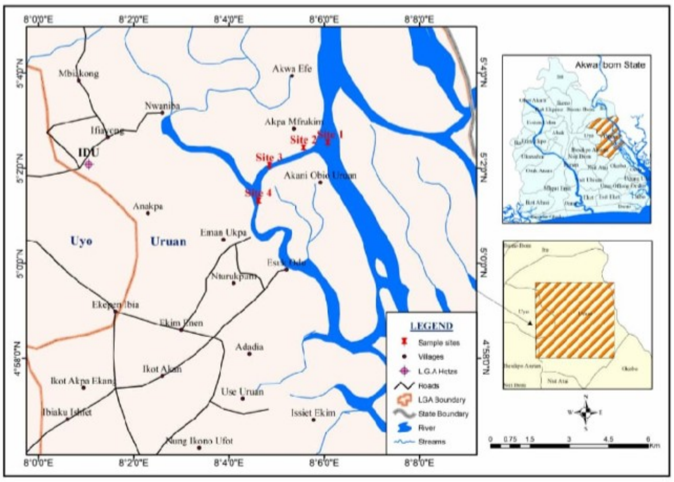

Figure 1. Map showing sample locations (insets of Uruan Local Government Area and Akwa Ibom State)

Sampling: During the wet seasons, water samples and sediment (A, B, C, and D), and marine organisms (periwinkle flesh (PF), crab body (CB), and periwinkle shell (PS)) were taken from several points along the Nwaniba River to map the temporal and spatial distribution of heavy metal contamination. Standard procedures were followed during the sample collection to guarantee data consistency and accuracy (Moses *et al*., 2023). Sampling procedures adhered to established standards to maintain data consistency and precision (Moses *et al*., 2023). Sampling was conducted in the early hours before sunset, and the locations were chosen based on their geographical diversity and the potential impact of human activities on the environment.Water samples were obtained using amber glass cups, as outlined by (Moses *et al*., 2023), while sediment samples were taken from four distinct locations. Marine organisms were collected from one specific location (Location 3). The GPS coordinates and details of the sampling sites are provided in Table 1. At each location, in situ measurements of pH, Total Dissolved Solids (TDS), and conductivity were taken using standard water quality probes. Water and sediment samples were collected at a depth of 0.5 meters from the shoreline, while marine organisms were hand-collected from their natural habitats according to (Moses *et al*., 2023) and (Nor *et al*., 2022) All samples were stored in accordance with standard protocols and transported to the laboratory for further analysis. The soil sample was homogenized and 0.5g of each sample was weighed. Samples were transferred into beakers in addition to 20ml of Aqua Regia. The digestion was carried out on a heating block in a fume hood with a temperature not exceeding 90^0C for about an hour. The beakers were allowed to cool and 2ml of Hydrogen peroxide was added to each beaker and heated for 10mins. After the digestion was completed, the digestate volume of each sample was measured. It was then filtered and diluted to 50ml using ultra-pure deionized water for ICP-OES Perkin-Elmer; model Optima™ 2000 DV, using winLab32 software for the analysis. The acid digestion procedure for water samples followed report by (Nor et al., 2022) with little modification. A 20-mL aliquot of well-mixed sample was transferred to a beaker or conical flask. A 400 µL of concentrated HNO_3 and 1 mL of concentrated HCl. Were added to the beaker and heated at 90^0C to 95^0C for 1 hour (avoid boiling). The beaker was removed and allowed to cool. The digestate was filtered to remove particulates and the final volume was adjusted to 20 mL with deionized water.Collected samples were analyzed using ICP-OES Perkin-Elmer; model Optima™ 2000DV, using winLab32 software to quantify the concentrations of various heavy metals, including mercury, lead, cadmium, and chromium.

Table 1. Sample locations and their GPS coordinates

Samples /Sites	Location	GPS Coordinates (Latitude, Longitude)
Site 1	Ikoneto, Cross River, Nigeria	5.041174, 8.1007
Site 2	Central Uruan, Akwa Ibom, Nigeria	5.034249, 8.095301
Site 3	Central Uruan, Akwa Ibom, Nigeria	5.021154, 8.077039
Site 4	Central Uruan, Akwa Ibom, Nigeria	5.021154, 8.077039

Machine Learning Techniques: Three machine learning algorithms—Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN)—were employed to develop predictive models and assess the ecological risks associated with heavy metal contamination. The models were validated using statistical measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) (Han et al., 2018; Taoufik *et al*., 2022).

Data analysis: The test results were analyzed using both the descriptive and t-test methods. The variables analyzed were water quality parameters downstream with the recommendations in WHO, EPA, and NSDWQ, 2007 standards (Solihu & Bilewu, 2022). For the paired t-test part, rejection of the null hypothesis indicates a statistically significant difference while a non-rejection signifies that there is no statistically significant difference between these variables at a level of significance. The significance level was set at 0.05, indicating a 95% confidence interval. Analyses were computed with Python 3.12, Statistical Packages for the Social Sciences (IBM SPSS) Statistics software version 25.0, and Microsoft Excel version 2016 for Windows 10.

RESULTS AND DISCUSSION

The study employed machine learning techniques to evaluate the ecological risks of heavy metal contamination in the Nwaniba River. Random Forests, Support Vector Machines (SVM), and Artificial

Neural Networks (ANN) were utilized to analyze the concentrations of heavy metals in water, sediment, and marine organisms. Descriptive statistics and paired t-tests were used to validate the results by comparing water quality parameters with established standards from organizations like the WHO, EPA, and NSDWQ. Four sites were selected to measure water quality parameters, including Dissolved Oxygen (DO), pH, Total Dissolved Solids (TDS), and Conductivity. As shown in Figure 1, sites 4 and 3 exhibited higher levels of DO, indicating a more favorable environment for aquatic life. Site 1 had the highest pH, followed by sites 2 and 3, which could indicate potential alkalinity. TDS levels were most prominent at sites 1, 2, and 4, and conductivity was significantly higher at sites 1 and 2, suggesting variations in the water quality among these sites. The water samples collected from four different locations showed varying levels of dissolved oxygen, pH, TDS, and conductivity (Table 2). Dissolved oxygen concentrations ranged from 6.2 mg/L to 9.2 mg/L, indicating potential differences in water quality across the sites. The pH levels varied from 6.0 to 9.2, with higher pH levels observed at Ikoneto (Site 1), as illustrated in Figure 1. The presence of these parameters and their variations across the sites can have implications for the aquatic ecosystem (Nahhal et al., 2021). Dissolved oxygen is crucial for the survival of aquatic organisms, while pH levels can affect the solubility of heavy metals and other substances in the water. TDS and conductivity can impact water quality and the overall health of the ecosystem (Nahhal et al., 2021; Zhang et al., 2017). The observed differences in water quality parameters as shown in Table 2 align with findings from previous studies. Maity et al., (2022) and Ogwueleka, (2015) reported that disposing of solid waste in water bodies contributes to water pollution, leading to variations in TDS and conductivity between waste disposal and non-disposal areas. Moreover, Awomeso et al., (2019) and Ogwueleka, (2015) observed seasonal fluctuations in temperature and dissolved oxygen levels, further supporting the notion that water quality parameters can exhibit significant differences across various locations.

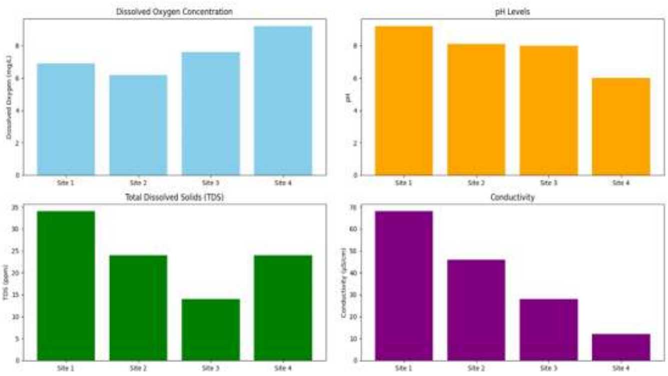

Figure 2. Selected Element Concentrations (mg/L) across Four Locations

Table 1. Physicochemical parameters of the water samples at different sites

Sample	Dissolve Oxygen Concentration (mg/L)	pH	TDS	Conductivity
Site 1	6.9	9.2	34	68
Site 2	6.2	8.1	24	46
Site 3	7.6	8	14	28
Site 4	9.2	6	24	12

The concentrations of various elements in the water samples are shown in Table 2, with key elements including iron (Fe), copper (Cu), nickel (Ni), lead (Pb), zinc (Zn), chromium (Cr), and manganese (Mn). Iron levels were highest at Site 1 (3.1196 mg/L), Site 2 (2.8819mg/L), Site 3 (2.7007mg/L) and lowest at Site 4 (0.6291 mg/L). Copper concentrations ranged from 0.0411 mg/L at Site 3 to 0.0678 mg/L at Site 2. Nickel was detected at Sites 1, 2, and 3, with the highest concentration at Site 3 (0.0379 mg/L). Lead was only detected at Sites 2 (0.0354 mg/L) and 3 (0.0056 mg/L). Zinc concentrations were observed at Sites 2 (0.0772 mg/L) and 3 (0.0600 mg/L). Chromium levels were highest at Site 3 (0.0452 mg/L) and lowest at Site 2 (0.0047 mg/L). Manganese concentrations ranged from 0.1124 mg/L at Site 1 to 0.1104 mg/L at Site 4. Figure 2 presents the concentrations of selected elements across the four locations, indicating potential contamination sources and varying environmental conditions. The presence of heavy metals in the water poses risks to aquatic life and public health, emphasizing the importance of monitoring these elements for effective environmental management. Figure 3 displays a heatmap visualization of all analyzed element concentrations in water samples from the four sites, corresponding to Table 3. This comprehensive overview facilitates a comparison of elemental levels between sites, enabling the identification of similarities and differences in the composition of each location's water sample. The heatmap highlights areas of high and low concentrations, offering valuable insights into varying degrees of contamination and overall water quality across the sites.

Table 3. Heavy Metal Concentrations (mg/L) in Water Samples

Element	Site 1	Site 2	Site 3	Site 4
Fe	3.1196	2.8819	2.7007	0.6291
Cu	0.0437	0.0678	0.0411	0.0609
Ni	0.0351	0.0174	0.0379	nd
Pb	nd	0.0354	0.0056	nd
Zn	nd	0.0772	0.0600	nd
Cr	0.0061	0.0047	0.0452	nd
Mn	0.1124	0.1023	0.1391	0.1104

Not detected (nd) levels of Pb and Zn in some locations suggest spatial variability in contamination sources.

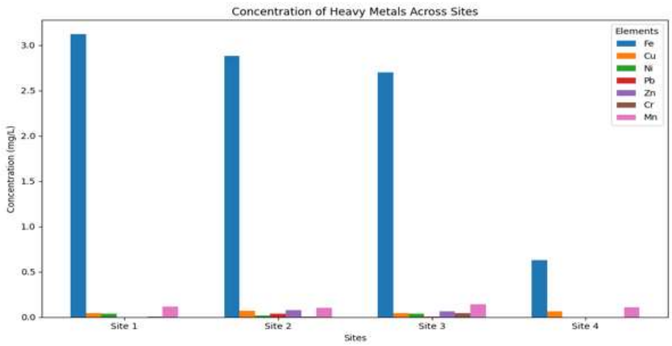

Figure 3. Heatmap of Element Concentrations in Water Samples from Four Sites

The variations in heavy metal concentrations align with findings from previous studies by Gwenzi et al., (2018) and Rind et al., (2024) which reported spatial variations in heavy metal concentrations due to factors such as industrial activities, waste disposal, and geochemical differences. These variations emphasize the importance of continuous monitoring and assessment of water quality parameters to maintain the health of aquatic ecosystems and protect public health. The Table 4 presents the statistical analysis of the physicochemical parameters of the Nwaniba River water across four sites. The mean values for each parameter were calculated to represent the average across all sites, while the standard deviation (SD) quantifies the variation from the mean. The coefficient of variation (CV%) was computed to assess the dispersion relative to the mean, and degrees of freedom (df) were included to support the analysis. These values provide insights into the water quality and variations in physicochemical parameters across the sampling locations along the Nwaniba River.

Several machine learning models were tested, including Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN). The flowchart diagram that illustrates the process of data analysis through the utilization of machine learning models is shown in Figure 4. These models were evaluated based on their performance, particularly using the coefficient of determination (R^2), which indicates how well the model explains variability in the data.

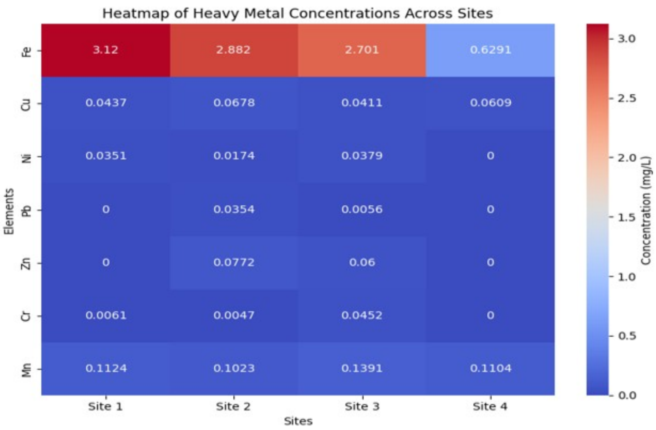

Figure 4: A flowchart to illustrate the process of data analysis through the utilization of machine learning models

Table 4. Statistical analysis of Nwaniba River water physicochemical parameters

Element	Site 1	Site 2	Site 3	Site 4	Mean	SD	CV%	df
Fe	3.1196	2.8819	2.7007	0.6291	2.332825	1.148696	0.492406	3
Cu	0.0437	0.0678	0.0411	0.0609	0.053375	0.013025	0.244037	3
Ni	0.0351	0.0174	0.0379	nd	0.030133	0.011116	0.368891	2
Pb	nd	0.0354	0.0056	nd	0.0205	0.021072	1.027892	1
Zn	nd	0.0772	0.0600	nd	0.0686	0.012162	0.177292	1
Cr	0.0061	0.0047	0.0452	nd	0.018667	0.022989	1.231564	2
Mn	0.1124	0.1023	0.1391	0.1104	0.11605	0.015975	0.137657	3

SD= Standard Deviation CV= Coefficient of Variation

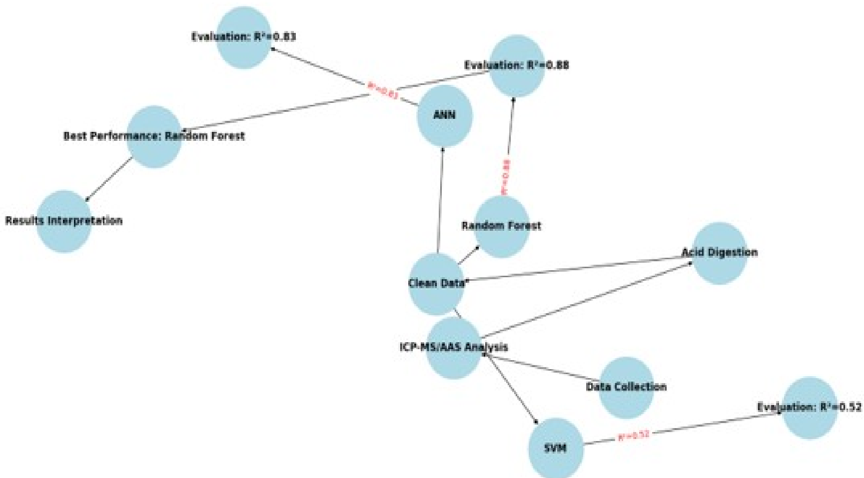

Figure 5. Evaluation of Random Forest, ANN and SVMMachine Learning Models for Predicting Heavy Metal Contamination in Sediments and Marine Organisms

Table 5: Heavy Metal Concentrations (mg/kg) in Sediment and Marine Organisms

Element	A	B	C	D	PF	CB	PS
Fe	76838.1016	58937.7813	38973.0352	62049.4023	3405.8621	5268.0986	1495.6705
Cu	51.8232	53.0319	27.7590	37.8672	433.3761	667.6241	80.5817
Ni	49.3766	54.6104	17.5351	45.5967	6.7698	5.6627	5.4470
Pb	62.4141	40.9736	27.1668	64.3024	49.2654	29.3082	5.5976
Zn	275.1165	191.3747	115.9560	190.2646	1111.1128	296.3757	119.7862
Cr	101.8957	100.5577	35.7551	55.8531	nd	2.4479	nd
Mn	2976.9326	797.2023	532.2999	687.5214	1549.4635	559.4444	522.0806

N D = Not Detected

The Figure 4 illustrates the use of Random Forest machine-learning techniques to compare actual and predicted element concentrations. This visualization helps uncover patterns and correlations between observed and predicted values, offering a deeper understanding of element distribution in the study area. Random Forest demonstrated superior performance with an R^2 of 0.88, accounting for 97% of the variance. It achieved a Root Mean Squared Error (RMSE) of 0.14 and a Mean Absolute Error (MAE) of 0.13, highlighting its high predictive accuracy for heavy metal concentrations in sediment and marine organisms.

The Artificial Neural Network (ANN) performed slightly less effectively, with an R^2 of 0.83, an RMSE of 0.24, and an MAE of 0.23, yet it still captured a substantial portion of the data variance. In contrast, Support Vector Machine (SVM) had the lowest performance, with an R^2 of 0.52, explaining only 66% of the variance, alongside an RMSE and MAE of 0.50 each, indicating relatively poor predictive accuracy compared to Random Forest and ANN, as depicted in Figure 5. Based on the R^2 values, Random Forest was identified as the best-performing model for ecological risk assessment, followed by ANN, and lastly, SVM. Elemental analysis revealed substantial contamination by heavy metals such as aluminum, barium, manganese, and copper in both sediment and marine organism samples.Additionally, elemental concentrations (mg/L) from the four locations (as shown in Table 4) indicate significant bioaccumulation of heavy metals, which poses potential risks to human health (Khan et al., 2018). Heavy metals can have detrimental effects on various organ systems, making their presence in water a significant public health concern. Furthermore, the statistical analysis of physicochemical parameters in the Nwaniba River water reveals variations in water quality across the sampling sites, which may be attributed to both natural factors and human activities in the surrounding areas (Bawuro et al., 2018; Fu & Xi, 2020). The analysis of heavy metals (Fe, Cu, Ni, Pb, Zn, Cr, Mn) in sediment samples (A, B, C, D) and marine organisms (PF, CB, PS) reveals significant insights into contamination levels and their implications as shown in Table 5. Iron (Fe) concentrations were notably high in sediments, especially in samples A (76,838.10 mg/kg) and D (62,049.40 mg/kg), suggesting natural geochemical processes or anthropogenic sources such as industrial runoff. In marine organisms, Fe levels were significantly lower, with CB recording 5,268.10 mg/kg, indicating limited bioavailability or effective excretion mechanisms. Copper (Cu) showed high levels in organisms, particularly CB (667.62 mg/kg) and PF (433.38 mg/kg), reflecting bioaccumulation. While Cu is essential for biological processes, excessive concentrations pose toxicological risks.Nickel (Ni) concentrations were highest in sediment sample B (54.61 mg/kg) and relatively low in marine organisms, with PF containing 6.77 mg/kg. This suggests limited bioaccumulation and potential contamination from industrial discharges. (1,111.11 mg/kg) and relatively lower in sediments, suggesting significant bioaccumulation. While Zn is essential, elevated levels can disrupt metabolic functions in aquatic life. Chromium (Cr) concentrations were more pronounced in sediments, with sample A recording 101.90 mg/kg, but were minimal in marine organisms, with CB showing only 2.45 mg/kg. This indicates limited bioavailability or efficient detoxification mechanisms in organisms. Manganese (Mn) was notably high in sediment sample A (2,976.93 mg/kg) and PF (1,549.46 mg/kg), suggesting its bioavailability and possible leaching from sources like fertilizers or mining operations. While Mn is an essential nutrient, its elevated levels raise concerns about potential toxicity. The Figure 6 presents an analysis of the test results using descriptive and paired t-test methods. The water quality parameters downstream were compared with the guidelines set by the WHO, EPA, and NSDWQ (2007) standards. The Paired T-Test Analysis for Observed vs. Standard Values of Dissolved Oxygen (DO), pH, Total Dissolved Solids (TDS), and Conductivity is displayed in Figure 6. A significance level of 0.05 (95% confidence interval) was selected to assess whether statistically significant differences existed between the observed values and the established standards. For each water quality parameter, the p-values were greater than 0.05, indicating no statistically significant difference between the observed and standard values from the WHO, EPA, or NSDWQ. In the case of Dissolved Oxygen (DO), the t-statistic was -0.8176, and the p-value was 0.4735 (> 0.05), suggesting no significant difference between the observed and standard values (Awomeso et al., 2019; Vaage & Myrick, 2022). However, the lower DO levels observed downstream indicate potential pollution, likely caused by discharges of domestic, agricultural, and industrial effluents into the river (Ameta et al., 2023; Ling et al., 2016; Onisogen Simeon et al., 2019).

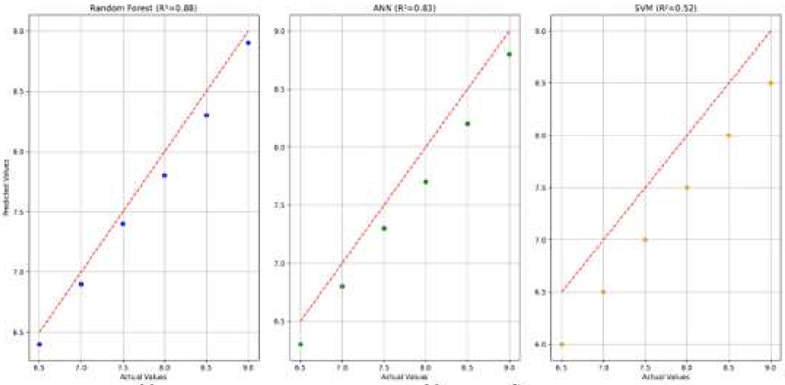

Figure 6. Paired T-Test Analysis: Observed vs. Standard Values for Dissolved Oxygen, pH, TDS, and Conductivity

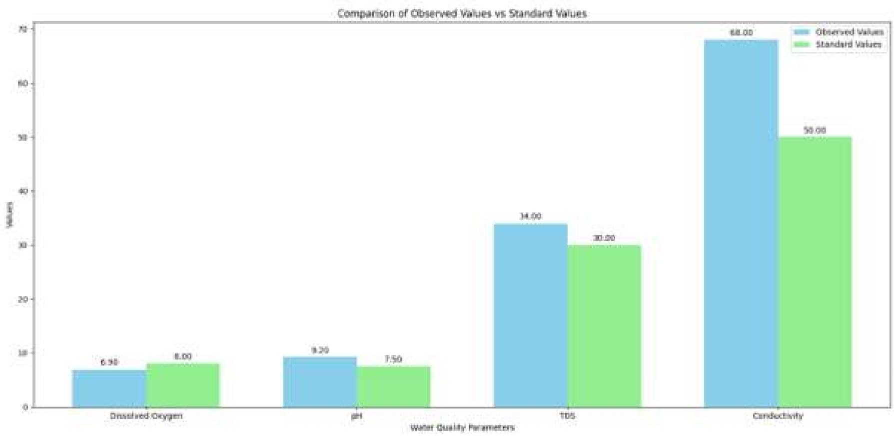

Figure 7. Paired T-Test Analysis: Observed vs. Standard Values for Dissolved Oxygen, pH, TDS, and Conductivity

However, Lead (Pb) was prominent in sediments, with the highest concentration in sample D (64.30 mg/kg), while marine organisms like PF and CB contained 49.27 mg/kg and 29.31 mg/kg, respectively. Pb's presence highlights potential biomagnification risks and contamination from anthropogenic activities such as vehicle emissions or industrial waste. Zinc (Zn) levels were highest in PF

Similarly, for pH, the t-statistic was 0.4878, and the p-value was 0.6591 (> 0.05), indicating no significant difference between the observed and standard values. Variations in pH can often be attributed to the dissolution of minerals and the influence of anthropogenic activities in the surrounding environment (Awomeso et al., 2019; Chibsa et al., 2023; Komonweeraket et al., 2015). For TDS, the t-statistic was -1.4697, and the p-value was 0.2380 (> 0.05), while for conductivity, the t-statistic was -0.9553, and the p-value was 0.4099 (> 0.05), both indicating no significant differences between the observed and standard values. As none of the p-values were below the 0.05 significance level, the null hypothesis (H_0) could not be rejected for any of the water quality parameters, implying that the observed water quality parameters did not significantly differ from the recommended standards. Although some variations were observed, such as DO levels ranging from 6.2 mg/L to 9.2 mg/L, indicating differences in water quality across sites, and slightly elevated pH values at Ikoneto (Site 1), TDS and conductivity remained within acceptable limits. Additionally, the paired t-test analysis showed no significant difference between the observed water quality parameters and the recommended values by WHO, EPA, and NSDWQ, suggesting that the water quality of the Nwaniba River, based on these parameters, is generally within the acceptable range set by international standards. However, potential heavy metal contamination detected in sediment and organisms remains a concern. Additionally, variations in TDS and conductivity across the sampling sites, as well as seasonal fluctuations in temperature and DO levels, align with findings by Maity et al., (2022) and Ogwueleka, (2015), which suggest that solid waste disposal contributes to water pollution and influences these parameters.

CONCLUSION

The integration of machine learning models with traditional environmental assessments has proven effective in evaluating heavy metal contamination in the Nwaniba River. The study identified significant levels of Fe, Cu, Ni, Pb, Zn, Cr, and Mn in sediments and organisms, with bioaccumulation posing risks to the aquatic ecosystem and public health. Random Forest emerged as the best-performing model, capturing 97% of the variance in the data and providing robust predictive capabilities for assessing contamination. Variations in water quality parameters and metal concentrations across the sampling sites reflect both natural geochemical processes and anthropogenic activities. While water quality parameters were generally within acceptable limits, the detection of toxic heavy metals in sediments and organisms underscores the urgency of implementing remediation measures. This research highlights the value of combining machine learning with environmental monitoring to enhance the understanding of pollution dynamics and support the development of targeted conservation strategies for fragile ecosystems like the Nwaniba River.

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