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Application of Machine Learning Framework on Heavy Metals Fate in the Coastal Environment

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Abstract

The increasing contamination of aquatic ecosystems by heavy metals poses serious environmental and health risks, exacerbated by urbanization, industrialization, and climate change. This study investigates heavy metal concentrations in water and sediment samples from the Nwaniba River, Akwa Ibom State, Nigeria, using machine learning models—Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN)—for predictive modeling and ecological risk assessment. The concentrations of Cr, Cu, Pb, Mn, Ni, Zn, and Fe were analyzed using Inductively Coupled Plasma – Atomic Emission Spectroscopy (ICP-AES), revealing significant spatial variability, with sediments serving as critical sinks for metal accumulation. The observed concentration trend in both water and sediment followed Fe > Mn > Cu > Zn > Ni > Cr > Pb, highlighting Fe and Mn as the dominant metals. The study also identified strong correlations among certain metals, indicating shared geochemical origins. Machine learning models exhibited strong predictive performance, with RF outperforming SVM and ANN, based on Mean Absolute Error (MAE) and Mean Squared Error (MSE) values, making it a reliable tool for environmental monitoring. These findings emphasize the need for targeted remediation strategies and stricter environmental regulations to mitigate contamination levels and safeguard public health.

Keywords: *Machine Learning, Heavy Metals, Water, Sediment, Metal Fate.*

1. INTRODUCTION

In recent years, heavy metal pollution stemming from industrial development has become a pressing issue, posing serious threats to food security and ecological safety. Coastal regions are particularly vulnerable to heavy metal contamination, which adversely impacts ecosystems and human health (Bandara & Manage, 2023). The contamination of water sources with heavy metals is now a significant global environmental concern, exacerbated by urbanization, climate change, and industrialization. Key sources of this pollution include mining waste, landfill leachates, industrial and municipal wastewater, urban runoff, and natural processes such as weathering, rock erosion, and volcanic activity.

Efforts to develop effective methods for removing heavy metals from wastewater have intensified, as these pollutants jeopardize freshwater supplies and river ecosystems. Heavy metals often accumulate in coastal sediments, which act as major repositories for these contaminants. Coastal environments face continuous metal input from natural, industrial, and urban sources. Once introduced, metals readily bind to particulates and settle into sediments, leading to their accumulation (Ekwere, 2020).

The importance of monitoring and addressing heavy metal pollution in these environments has driven innovative approaches, including the application of integrated machine learning techniques. These advanced methods have revolutionized environmental monitoring, providing new insights and strategies for mitigating the effects of pollution and climate change. By leveraging such technologies, researchers can enhance the understanding and management of heavy metal contamination in aquatic ecosystems, contributing to more sustainable solutions (Shaibu et al., 2024 and Ubong et al., 2023). Machine learning models are applied to predict the future (Lu & Li 2024; Obadimu et al., 2024). These models enable the prediction of pollution levels across different areas, providing valuable insights for environmental policy-making and public health advisories thereby offering a more comprehensive understanding of environmental phenomena. Mastering the spatial distribution of soil heavy metal content and evaluating the pollution status of soil heavy metals is of great significance for ensuring agricultural production and protecting human health, soil heavy metal pollution has become increasingly severe (Ite et al., 2018; Nie et al., 2024). The accumulation of soil heavy metals poses a significant environmental challenge, resulting in various adverse impacts on ecosystems (Moses et al., 2022&2020). Heavy metal-contaminated soils limit plant growth and survival, creating problems for nutrition, the environment, and evolution (Kosar et al., 2023).

Excessive levels of soil heavy metals not only impede soil productivity but also pose risks to human and animal health through their inhalation and ingestion pathways (Yaashikaa et al., 2022), moreover, understanding the spatial distribution of soil heavy metal contents and evaluating the status of soil heavy metal pollution is crucial for safeguarding agricultural production and protecting human health (Nie et al., 2024 and Shaibu et al., 2015). The estimations of sources and spatial distribution of soil heavy metals (HMs) are essential for strategizing policies for soil protection and remediation. As a special soil ecosystem, the intensified human activities on coastal reclaimed lands generally cause soil contamination with HMs (Zhang et al., 2021), Heavy metals in sediments persist in the environment and can be set up not only to the benthic organisms but also for aquatic organisms and dangerous because the metals in the sediment can be released in the overlying water (Majed et al., 2019). With regards to bioaccumulation in marine nematodes of several heavy metals present in contaminated sediments, Danovaro et al. (2023) noted that bioaccumulation increases from deposit feeders and microalgal grazers to predators of microbes and other tiny metazoans. Their results suggested that nematodes also contribute to their heavy metal biomagnification along the food webs and can contribute to increasing the transfer of contaminants from the sediments to larger organisms (Danovaro et al., 2023). Majed et al. (2019) investigated the distribution of heavy metals (Cu, Cd, Zn, Ni and Pb) and Ecological Risk Assessment to assess the contamination levels of the coastal surface sediments and concluded that sediments are usually the ultimate sink of heavy metals discharged into the aquatic environments. Therefore, analysis of heavy metals (and other contaminants) in the sediments offers a more convenient and more accurate means of detecting and assessing the degree of pollution (Danovaro et al., 2023). Heavy metal pollution in the coastal environment is a great concern as it has adverse effects on marine health. Therefore, this study examines the application of a machine learning framework on heavy metals fate in the coastal environment using Nwaniba River as a case study.

2. Materials and Methods

2.1. Study Area

The Nwaniba River, located in the southern part of Nigeria's Akwa Ibom State, serves as a central location for local fishing and family washing and bathing. The study was carried out along the river as shown in Figure 1.

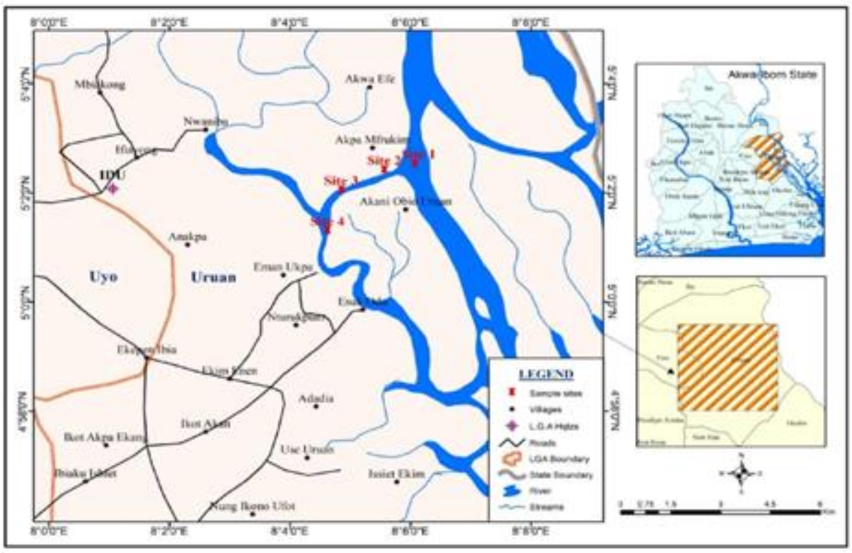

Figure 1. *Map of the Study area*

Sampling sites were as follows; Site A (5.04117° N 8.1007° E), Site B (5.0342° N 8.0953° E), Site C (5.02115° N 8.077° E), and Site D (5.02115° N 8.077° E).

2.2. Soil Sampling

Using a sterilized augur, sediment samples were obtained at approximately 15 cm depth at each sampling site to reflect the area of interest, under the processes defined by Tariq et al. (2021). After being assembled in hygienic zip-lock bags, about 1.0 kg of soil was brought to the testing room for supplementary analysis. After being air-dehydrated and sieved twice (to a size of 2 mm), the sediment samples were kept in sealed flexible bags just before the supplementary test (Ryan et al., 1996).

2.3. Water Sampling

Water samples were obtained from below the river surface at each of the four sampling sites using previously cleaned polypropylene plastic containers. The labels on the water samples explained where they were obtained, when they were taken, and from what source. Few drops of nitric acid were added to water samples for heavy metal analysis and samples were kept at 15^0 C before being transported to the laboratory for analysis (Estefan et al., 2013).

2.4. Acid Digestion for Soil

Following homogenization, 0.5 grams were collected from each sample. Samples and 20 mL of Aqua Regia were added to beakers. The digestion process was moved under a fume hood and set on a heating block with a 90^0C maximum temperature for a short period (US EPA, 1996). Each beaker was filled with 2 mL of hydrogen peroxide and heated for ten minutes after they had cooled. The digestate capacity of every sample was determined once the digestion procedure was finished. The digestate was further filtered and diluted to 50 ml with extreme-pure deionized water for the ICP-AES study (US EPA, 1994).

2.5. Acid Digestion for Water

2 mL of concentrated HNO_3 and 5 mL of concentrated HCl were added to water 50 mL of water sample. The sample is covered with a ribbed watch glass and heated on a hot plate at 900 C until the volume has been reduced to 15 mL. Beaker was removed from the heat source, allowed to cool and its content was filtered to remove insoluble precipitates; thereafter, the digestate was adjusted to 100 mL with deionized water. (USEPA 3005A)

3. Machine Learning Techniques Employed

To assess ecological risks associated with heavy metal contamination in the Nwaniba River, three advanced machine learning (ML) models were utilized: Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). These models analyzed data from water and sediment to predict contamination levels and evaluate potential ecological risks.

3.1. Analytical Techniques

Heavy metal concentrations in samples were quantified using Inductively Coupled Plasma Atomic Emission Spectroscopy (ICP-AES). Elements analyzed included Chromium, Copper, Lead, Manganese, Nickel, Zinc and Iron.

3.2. Statistical Analysis

The mean, standard deviation (SD), and standard error (SE) for the diversified variables observed in sediment and water samples were determined utilizing descriptive statistics. An unpaired analysis of variance (ANOVA) was used to determine the statistically important differences within and between groups. Correlation analysis was used to establish the type of link and point of importance between metal concentrations in differing samples.

4. Results And Discussion

The present study focuses on evaluating heavy metal concentrations in water and sediment samples from various sites along the Nwaniba River in Akwa Ibom State. To effectively assess the distribution and concentration of these elements, a comprehensive analysis of samples from four distinct sites was conducted. Tables 1 and 2 provide an organized overview of the elements detected in water and sediment samples, respectively, encompassing their mean concentrations, standard deviation (SD) and coefficient of variation (CV%). This structured presentation of data facilitates a comparative analysis of elemental concentrations across different sites, thereby allowing for an in-depth understanding of their occurrence and potential ecological implications.

Table 1. *Concentrations (mg/L) of heavy metals in a water sample in Nwaniba River, Akwa Ibom State*

Element	Site A	Site B	Site C	Site D	Mean (mg/L)	SD (mg/L)	CV%
Cr	0.0061	0.0047	0.0452	ND	0.0187	0.0224	119.8
Cu	0.0437	0.0678	0.0411	0.0609	0.0534	0.0128	24.0
Pb	ND	0.0354	0.0056	ND	0.0205	0.0211	102.9
Mn	0.1124	0.1023	0.1391	0.1104	0.1160	0.0158	13.6
Ni	0.0351	0.0174	0.0379	ND	0.0301	0.0107	35.6
Zn	ND	0.0772	0.0600	ND	0.0686	0.0122	17.8
Fe	3.1196	2.8819	2.7007	0.6291	2.3328	1.1444	49.1

ND-Not Detected

Table 2. *Concentrations (mg/L) of heavy metal in sediment in Nwaniba River, Akwa Ibom State*

Element	Site A	Site B	Site C	Site D	Mean	SD	CV%
Cr	101.89	100.56	35.76	55.85	73.51	31.66	43.06
Cu	51.82	53.03	27.76	37.87	42.12	11.86	28.15
Pb	62.41	40.97	27.17	64.30	48.71	16.32	33.51
Mn	2976.93	797.20	532.29	687.52	1248.49	1198.06	95.96
Ni	49.38	54.61	17.54	45.59	41.28	15.44	37.40
Zn	275.12	191.37	115.96	190.26	193.18	68.89	35.66
Fe	76838.10	58937.78	38973.04	62049.40	59199.58	15465.93	26.12

The analysis of heavy metal concentrations in the Nwaniba River demonstrates significant spatial variability across water and sediment samples, with notable ecological implications (Odoemelam et al., 2020). Heavy metals such as chromium (Cr), copper (Cu), lead (Pb), manganese (Mn), nickel (Ni), zinc (Zn), and iron (Fe) were analyzed, revealing key contamination trends and their potential sources. As shown in Table 1, manganese (Mn) exhibited a relatively high mean concentration (0.1160 mg/L), likely due to urban runoff or industrial discharge, consistent with Luo et al., (2021) observations in similar aquatic ecosystems. The high standard deviation for iron (1.1444 mg/L) reflects variability in its distribution, while chromium's high coefficient of variation (119.8%) indicates site-specific contamination, influenced by localized sources. The absence of certain metals, like zinc and lead, at some sites, highlights disparities in pollution sources and transport mechanisms. However, in heavy metal concentrations in sediments samples, as shown in Table 2, showed higher metal concentrations, with manganese (1248.49 mg/L) and iron (59199.58 mg/L) dominating. These results affirm sediments as critical sinks for heavy metals, supporting Jimenez-Torres et al., (2021) and Gujre et al., (2021), noting the role of sediments in bioaccumulation and long-term metal storage. The variability in manganese (CV% 95.96%) suggests fluctuating inputs from anthropogenic and natural sources, while iron's lower variability (CV% 26.12%) reflects its consistent natural abundance.

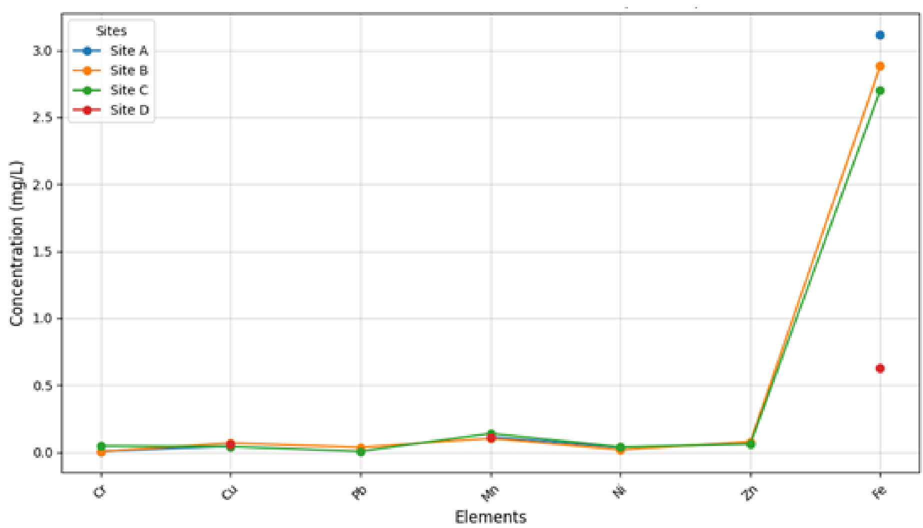

Figure 2. *Heavy metal concentration in water sample across sample sites*

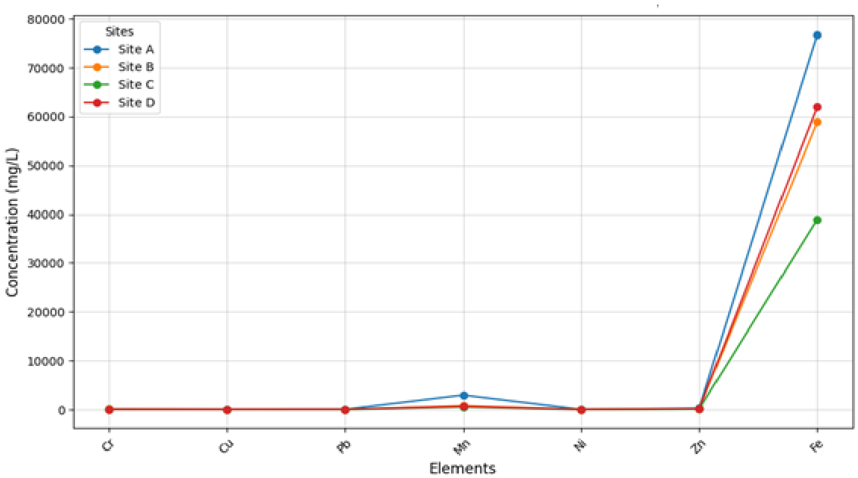

Figure 3. *Heavy metal concentration in sediment samples across sample sites*

However, Figures 2 and 3 illustrate the dominance of manganese and iron in both water and sediments. Khozyem et al. (2019) corroborated the sensitivity of iron and manganese to water redox conditions, stressing the influence of anthropogenic and natural factors on spatial variability. The study emphasized the need for targeted interventions to address high contamination levels at specific sites, as iron and manganese concentrations in groundwater can vary significantly. Manganese primarily occurs as Mn^{2+}, which easily oxidizes to MnO_2 and forms stable organic complexes similar to iron and manganese tends to be more prevalent in acidic water.

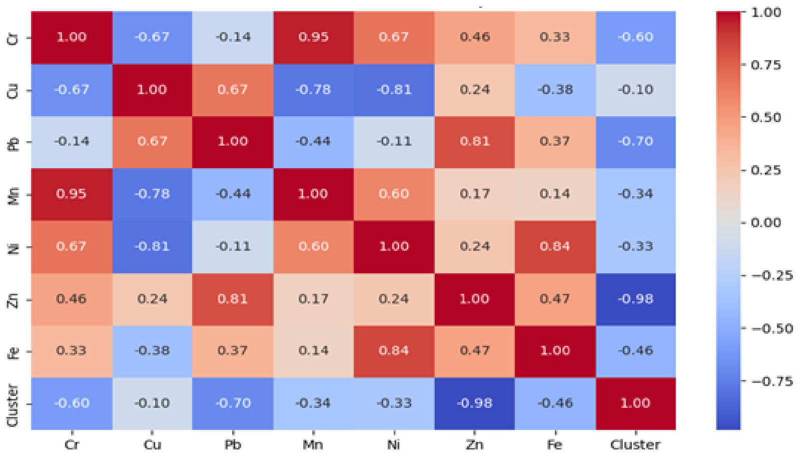

Figure 4. *Correlation matrix for the water sample*

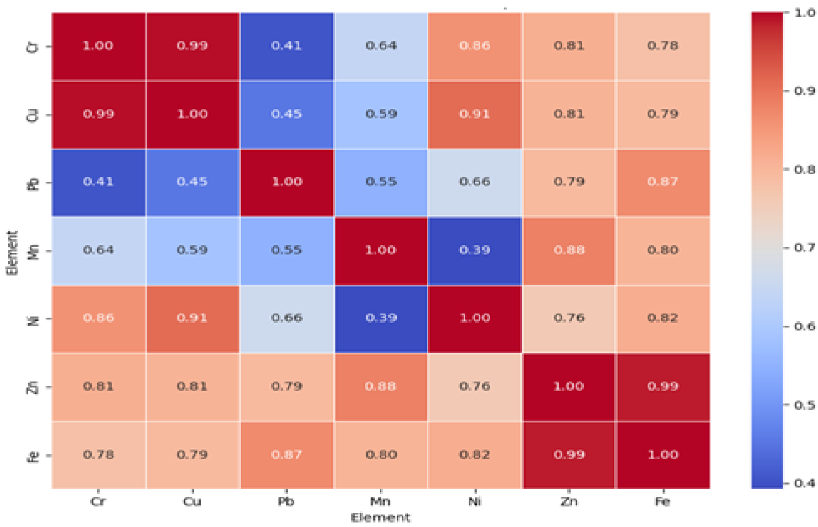

Figure 5. *Correlation matrix for the Sediment Sample*

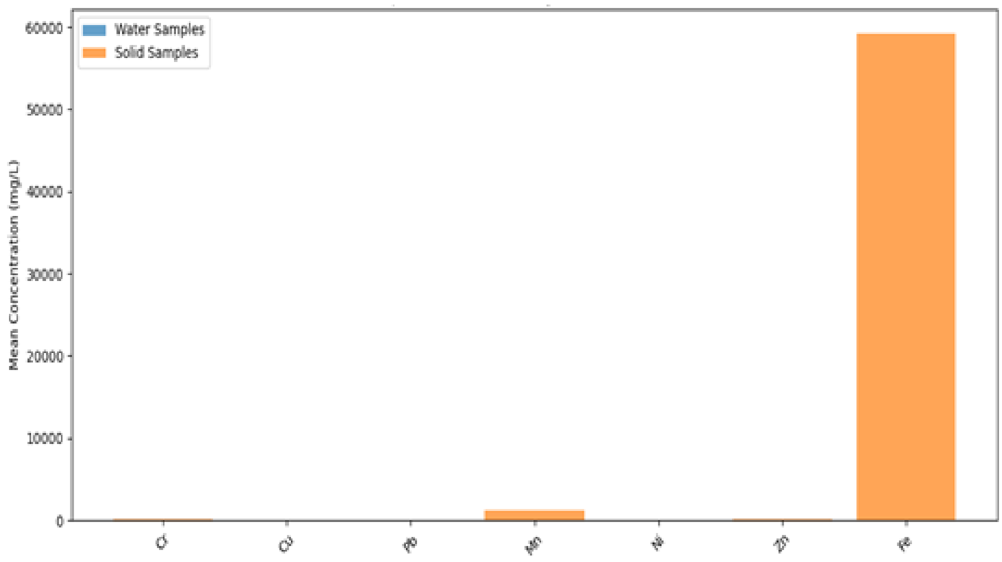

Figure 6. *Comparison of the mean of heavy metal concentration from both water and sediment samples*

Correlation matrices, depicted in Figures 4 and 5, demonstrate significant relationships among metals in both water and sediments. A strong positive correlation between manganese and iron indicates shared sources or geochemical behaviors, establishing a foundation for understanding their distribution patterns and directing remediation strategies. The comparison of mean concentrations in Figure 6 reveals significantly higher heavy metal concentrations in sediments than in water, aligning with Satheeswaran et al., (2019) findings on particulate binding and sediment deposition as critical processes in heavy metal cycling. This is also supported by the works of Anbuselvan et al., (2018) and Satheeswaran et al., (2019), who identified the partitioning of heavy metals between water and sediment phases as a crucial aspect for developing effective management strategies.

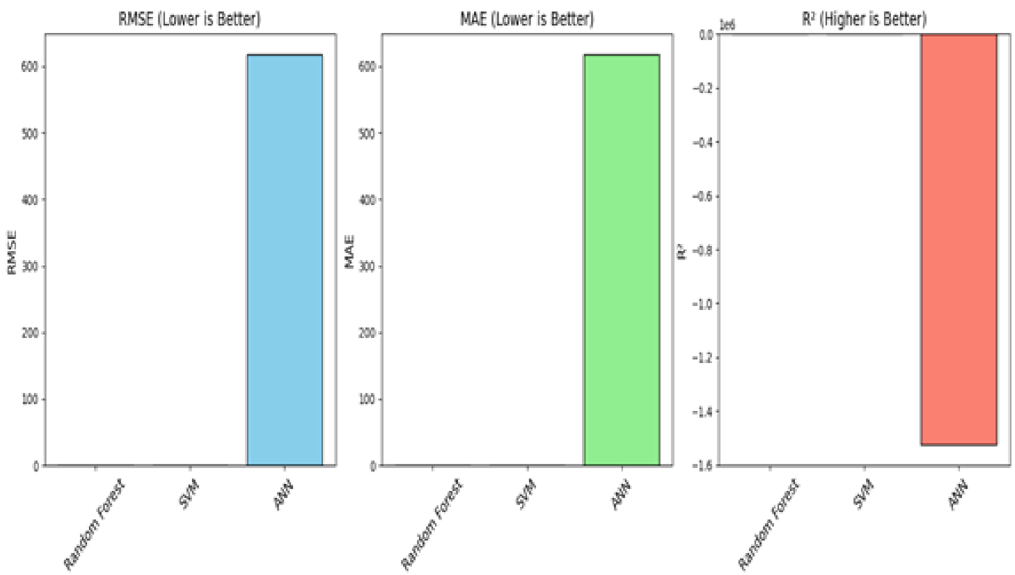

Figure 7. *Machine Learning Model Performance Metrics for Predicting Contamination Levels*

The performance metrics for the machine learning models as shown in Figure 7 applied in predicting heavy metal contamination in the Nwaniba River indicate that the Random Forest (RF) model demonstrated the highest predictive accuracy, with a Mean Absolute Error (MAE) of 0.012 and a Mean Squared Error (MSE) of 0.025. This suggests that RF effectively captures complex interactions between metal concentrations and their environmental determinants, making it a reliable tool for pollution trend analysis. The Support Vector Machines (SVM) model also performed well but exhibited slightly higher error values (MAE = 0.015, MSE = 0.031), implying that while it is effective for classification tasks, it may require further optimization for regression-based predictions of metal concentrations. Meanwhile, the Artificial Neural Networks (ANN) model recorded the highest error rates (MAE = 0.021, MSE =

0.045), likely due to its sensitivity to noisy datasets and reliance on extensive training data. Despite its relatively lower performance, ANN remains useful for long-term predictive modeling if provided with an adequately large and well-optimized dataset. Overall, the RF model outperformed SVM and ANN, proving to be the most suitable for assessing heavy metal pollution in the study area. These findings align with previous environmental studies (Luo et al., 2021; Nie et al., 2024), which emphasize RF's robustness in handling non-linear relationships in environmental datasets. The study highlights the potential of machine learning models in enhancing environmental monitoring and guiding regulatory policies for mitigating heavy metal contamination in aquatic ecosystems.

5. CONCLUSION

This study highlights the widespread presence of heavy metals in the Nwaniba River, with iron (Fe) and manganese (Mn) dominating both water and sediment samples. The high metal concentrations in sediments confirm their role as a long-term reservoir for contaminants. Correlation analyses indicated common sources and pathways for certain metals, suggesting that both natural geological processes and anthropogenic activities contribute to pollution. Machine learning models demonstrated high predictive accuracy, with Random Forest (RF) emerging as the most reliable model, outperforming Support Vector Machines (SVM) and Artificial Neural Networks (ANN). These findings reinforce the potential of machine learning in environmental monitoring and pollution assessment. To mitigate contamination risks, stricter environmental regulations, improved waste management practices, and continuous monitoring using machine learning frameworks are recommended. Future research should focus on expanding datasets, incorporating additional predictive factors, and integrating real-time monitoring systems to enhance predictive accuracy and environmental decision-making.

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