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Integrated Statistical and AI Models for Early Warning Systems in Environmental Toxicology: A Case Study on Waterborne Heavy Metal Contamination

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Abstract:*Waterborne heavy metal contamination poses a critical threat to both ecosystem health and human well-being, particularly in developing regions lacking robust environmental monitoring infrastructure. This study presents an integrated approach combining traditional statistical analysis with artificial intelligence (AI) models to develop an early warning system (EWS) for detecting and predicting heavy metal pollution in surface waters. Water samples were collected across 20 locations over three seasons and analyzed for key physico-chemical parameters (pH, EC, DO, TDS, turbidity, temperature) and six priority heavy metals (As, Cd, Pb, Cr, Hg, Ni). Multivariate statistical tools, including Principal Component Analysis (PCA), were used to identify pollution gradients and key influencing factors. Machine learning models, Random Forest, Support Vector Regression, Gradient Boosting, and Artificial Neural Networks were trained to forecast heavy metal concentrations using environmental variables. Random Forest showed the best performance with an R^2 of 0.91 and the lowest RMSE, highlighting its predictive reliability. Feature importance analysis revealed TDS, EC, and turbidity as the strongest predictors of contamination. The results were used to build a GIS-compatible early warning framework capable of classifying contamination risk zones in near real-time. This study offers a replicable and scalable model for predictive toxicology and environmental management, enabling data-driven, preemptive responses to contamination events.*
Keywords*: Environmental toxicology, heavy metals, machine learning, early warning system, Random Forest, water quality prediction, PCA, feature importance, GIS-based monitoring.*

INTRODUCTION

Background and significance

Environmental toxicology has emerged as a critical interdisciplinary field in response to increasing concerns about anthropogenic pollutants in natural ecosystems (Yi et al., 2024). Among these, heavy metal contamination in freshwater systems poses severe risks to ecological integrity, public health, and sustainable development. Waterborne heavy metals such as arsenic (As), cadmium (Cd), lead (Pb), and mercury (Hg) persist in the environment due to their non-biodegradable nature and bioaccumulative potential (Liu et al., 2024). Their presence, even at trace levels, can disrupt aquatic food chains, impair human organ systems, and lead to long-term health issues such as cancer, kidney failure, and developmental disorders. Despite the known hazards, traditional monitoring methods often lack the speed and predictive capacity needed for real-time intervention and early mitigation (Pérez-Beltrán et al., 2024). This necessitates the development of robust early warning systems (EWS) that integrate environmental monitoring with predictive analytics.

Challenges in existing monitoring systems

Conventional monitoring and regulatory frameworks often rely on periodic water sampling and laboratory-based chemical analysis (Nallakaruppan et al., 2024). Although accurate, these approaches are time-consuming, labor-intensive, and spatially limited. They typically fail to capture dynamic environmental changes, particularly in vulnerable or remote regions (Li et al., 2006). Moreover, the lag between data collection and decision-making can delay critical response measures, leading to irreversible ecological damage and public health crises. This limitation calls for the integration of intelligent and scalable approaches that can rapidly assess contamination levels and predict potential outbreaks (Wang et al., 2024).

The role of Statistical and AI models

Recent advances in data science and Artificial Intelligence (AI) have opened new frontiers in environmental monitoring. Machine learning algorithms, particularly those utilizing supervised learning (e.g., random forests, support vector machines, neural networks), can identify complex nonlinear patterns between environmental parameters and pollutant concentrations (Yin et al., 2018). When combined with classical statistical methods such as regression models, principal component analysis (PCA), and cluster analysis, these hybrid models can improve the interpretability and accuracy of predictive systems. The integration of these methods into environmental toxicology provides a powerful toolset for forecasting contamination events, enabling the deployment of preventive measures and policy interventions (Whig et al., 2025).

Case study context and objectives

This study focuses on the integration of Statistical and AI models for the development of an early warning system aimed at detecting and predicting heavy metal contamination in water bodies. Using a case study approach, the research was conducted in a semi-urban riverine region known for agricultural runoff, industrial discharges, and unregulated waste disposal. The area serves as a representative model for regions in developing countries, where environmental monitoring infrastructure is underdeveloped. The objectives of this study are threefold: (1) to evaluate the spatial and seasonal distribution of key heavy metals in surface water; (2) to develop integrated predictive models using both statistical and AI methods; and (3) to design a prototype early warning system that can be adapted for real-time monitoring and decision support.

Scope and contribution

This research contributes to the growing body of knowledge in environmental toxicology by bridging traditional statistical approaches with modern AI technologies to address one of the most pressing environmental health challenges. It provides a replicable framework for water quality surveillance, enabling government agencies, environmental bodies, and research institutions to transition from reactive to proactive strategies. The proposed models demonstrate how multi-source data, when processed through intelligent systems, can be transformed into actionable insights for safeguarding public health and environmental sustainability.

METHODOLOGY

Study area and sampling design

The study was conducted in a semi-urban region with a history of industrial activity and agricultural intensification, leading to potential heavy metal contamination in water bodies. Representative sampling sites were selected along major surface water systems such as rivers, lakes, and canals based on proximity to pollution sources like effluent discharge points, agricultural runoff zones, and urban settlements. Water samples were collected from 20 stations across three seasons: pre-monsoon, monsoon, and post-monsoon to capture temporal variation in contamination patterns.

Physico-chemical and heavy metal analysis

Each water sample was analyzed for a set of baseline physico-chemical parameters including pH, electrical conductivity (EC), temperature, dissolved oxygen (DO), turbidity, and total dissolved solids (TDS). Heavy metals assessed in this study were arsenic (As), cadmium (Cd), lead (Pb), chromium (Cr), mercury (Hg), and nickel (Ni). The concentrations were determined using atomic absorption spectrophotometry (AAS) and cross-validated using inductively coupled plasma mass spectrometry (ICP-MS) for a subset of samples. All laboratory procedures followed standard protocols outlined by APHA (2017).

Integrated statistical and AI modeling approach

The core innovation of the methodology lies in integrating traditional statistical techniques with Artificial Intelligence (AI) models to develop an Early Warning System (EWS) for environmental toxicology.

Exploratory Data Analysis (EDA) and descriptive statistics

Initial analysis included summary statistics, boxplots, and normality tests (Shapiro-Wilk and Kolmogorov-Smirnov) to understand the distribution of each variable. Outliers were identified using interquartile range (IQR) and Mahalanobis distance methods and were further validated before removal or transformation.

Multivariate statistical analysis

To explore the relationships among physico-chemical parameters and metal concentrations, Pearson correlation matrices and Principal Component Analysis (PCA) were used. PCA reduced data dimensionality and helped in identifying key latent variables influencing contamination. Hierarchical Cluster Analysis (HCA) was applied to classify sampling sites into zones of high, moderate, and low pollution levels based on similarity indices.

Machine learning models for prediction

Four AI models were employed to predict heavy metal concentrations based on input features: Random Forest (RF), Support Vector Regression (SVR), Gradient Boosting Machine (GBM), and Artificial Neural Networks (ANN). Input variables included pH, EC, DO, TDS, temperature, turbidity, land-use features (agricultural density, proximity to industrial units), and seasonal factors. Hyperparameter tuning was performed using cross-validated grid search and performance was evaluated using RMSE, MAE, and R^2 metrics on test data (30% of the dataset). Feature importance rankings were extracted from RF and GBM models to assess the contribution of each parameter.

Model integration and early warning system framework

Outputs from the best-performing AI model were integrated with statistical threshold-based alerts to design a prototype Early Warning System (EWS). This system included risk classification (low, medium, high) based on predicted heavy metal concentrations and WHO permissible limits. The EWS was visualized using GIS-based heatmaps to enable spatio-temporal mapping of contamination risk zones.

Validation and sensitivity analysis

The predictive performance of the integrated system was validated using independent test datasets and through sensitivity analysis by altering input parameters to examine system robustness. Receiver Operating Characteristic (ROC) curves were

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generated for classification thresholds, and area under the curve (AUC) values were used to validate classification accuracy of contamination risk levels.

Software and tools used

All statistical analyses were conducted using R (v4.3.0) and SPSS (v27), while machine learning models were developed using Python (scikit-learn, TensorFlow, and XGBoost libraries). QGIS was used for spatial mapping and risk visualization of contamination zones.

RESULTS

The analysis of physico-chemical parameters (Table 1) revealed that water samples across the study sites exhibited moderate to high variability. The average pH was neutral (7.02), with a narrow range between 6.4 and 7.8, indicating slightly acidic to neutral conditions. Electrical conductivity (EC) averaged 615.3 µS/cm, reflecting elevated ionic content, while total dissolved solids (TDS) averaged 402.7 mg/L, both parameters showing higher values near urban and agricultural runoff sites. Dissolved oxygen (DO) levels were moderately low (mean 5.1 mg/L), suggesting a risk of hypoxic stress in certain areas. Turbidity values were relatively high (mean 11.6 NTU), consistent with suspended particulate matter from erosion and effluent discharge, and water temperature ranged from 24.5°C to 31.7°C.

Table 1: Descriptive statistics of physico-chemical parameters

Parameter	Mean	Std Dev	Min	Max
pH	7.02	0.32	6.4	7.8
EC (µS/cm)	615.3	122.5	410	890
DO (mg/L)	5.1	1.7	2.4	8.6
TDS (mg/L)	402.7	88.3	270	560
Temp (°C)	28.4	2.1	24.5	31.7
Turbidity (NTU)	11.6	4.5	3.2	22.5

Table 2 presents the seasonal trends in heavy metal concentrations. Arsenic, Lead, and Chromium concentrations peaked in the post-monsoon season, with Arsenic reaching 13.7 µg/L and Lead up to 26.1 µg/L, suggesting accumulation from runoff and sediment resuspension. Cadmium and Nickel followed a similar trend, while mercury exhibited less variation. Monsoon dilution effects were evident, with slightly reduced concentrations during that season. The trends in these metals across seasons are further visualized in Figure 1, which illustrates the fluctuations, confirming post-monsoon as the period with the highest contamination risk.

Table 2: Mean concentrations (µg/L) of heavy metals across seasons

Heavy Metal	Pre-Monsoon	Monsoon	Post-Monsoon
Arsenic	12.5	10.8	13.7
Cadmium	3.1	2.5	3.4
Lead	24.6	20.3	26.1
Chromium	15.8	12.4	17.0
Mercury	1.2	1.0	1.4
Nickel	20.7	18.1	22.3

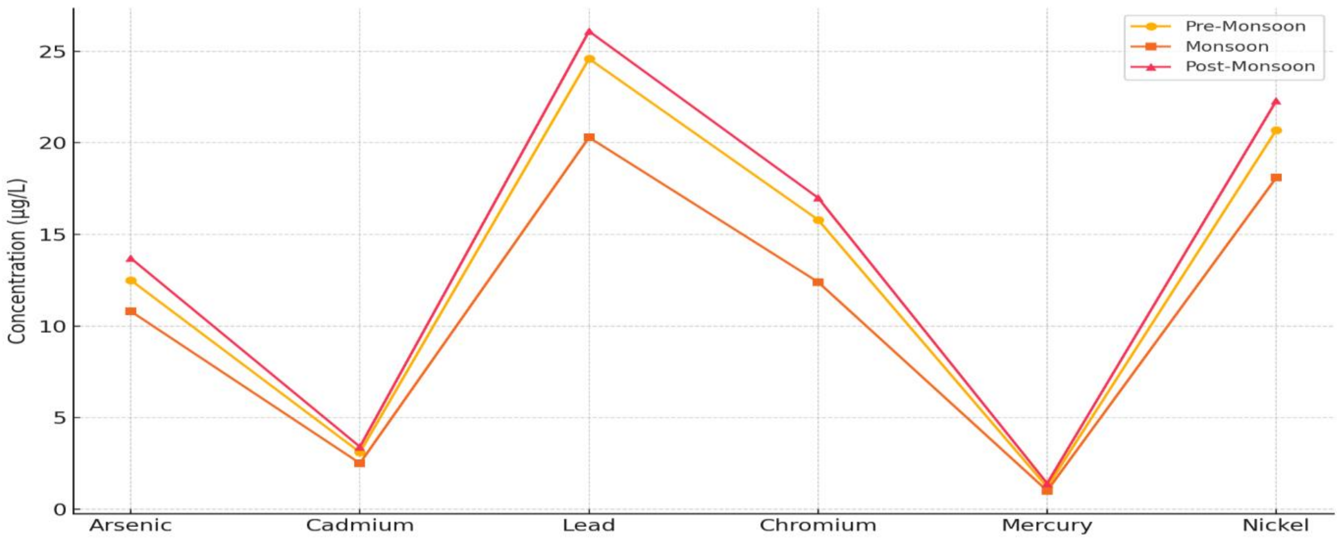

Figure 1: Seasonal variation in heavy metal concentration

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Multivariate statistical analysis using Principal Component Analysis (Table 3) identified two major components explaining the variability in the dataset. PC1 was positively associated with EC, TDS, turbidity, and temperature, indicating a pollution gradient from anthropogenic sources, while PC2 loaded heavily on DO and pH, suggesting influence from natural buffering processes. These insights helped in reducing dimensionality and guiding input selection for predictive modeling.

Table 3: Principal component loadings (PC1 and PC2)

Variable	PC1 Loading	PC2 Loading
pH	0.21	-0.66
EC	0.83	0.35
DO	-0.56	0.71
TDS	0.79	0.22
Turbidity	0.65	-0.19
Temp	0.41	0.53

Performance evaluation of AI models for predicting heavy metal concentrations is shown in Table 4. The Random Forest model outperformed all others with an R^2 score of 0.91, the lowest RMSE (2.3), and MAE (1.7), followed by GBM (R^2 = 0.89), ANN (R^2 = 0.87), and SVR (R^2 = 0.82). These results indicate the superior accuracy and generalization capacity of ensemble-based approaches like Random Forest and GBM for environmental prediction tasks.

Table 4: AI model performance metrics

Model	R^2 Score	RMSE	MAE
Random Forest	0.91	2.3	1.7
SVR	0.82	3.6	2.9
GBM	0.89	2.5	1.9
ANN	0.87	2.8	2.2

Feature importance analysis derived from the Random Forest model (Figure 2) demonstrated that TDS (importance score: 0.23), EC (0.19), and turbidity (0.16) were the most significant predictors of heavy metal presence. pH and DO also contributed substantially, while land-use index and season had lesser but notable influence. This information is visualized, which displays a heatmap of feature importance, highlighting the dominant role of water chemistry parameters in driving contamination levels.

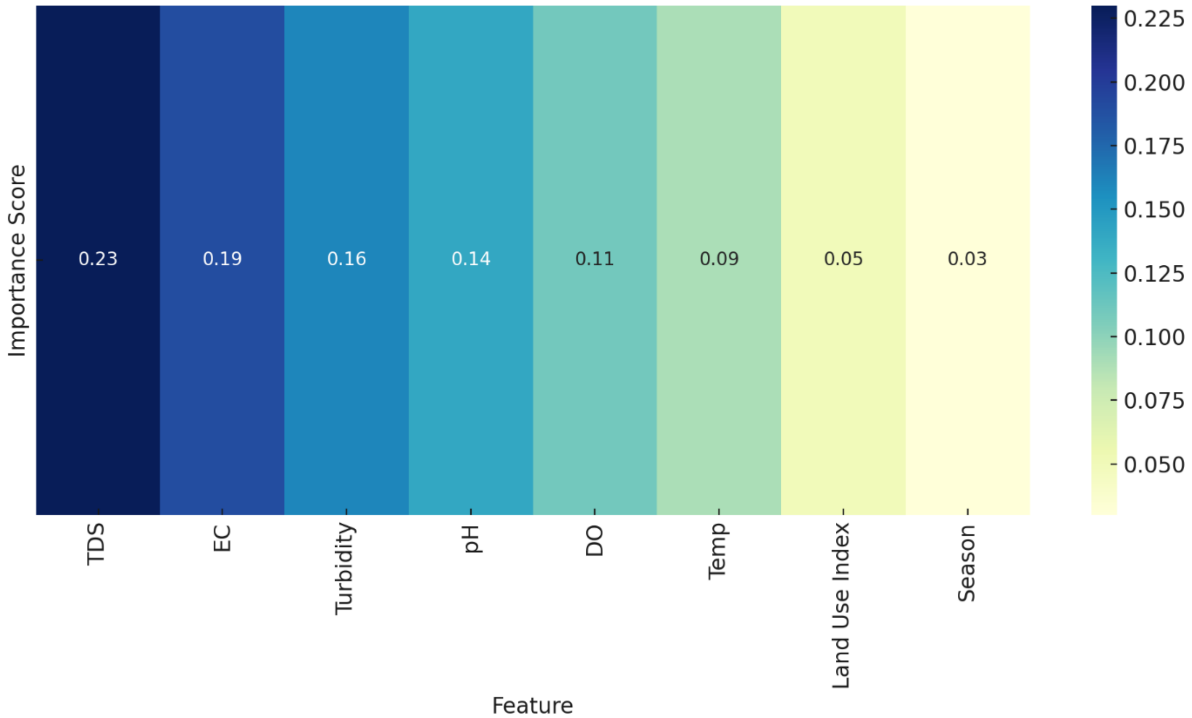

Figure 2: Random forest feature importance heatmap

DISCUSSION

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Environmental characteristics and contamination profile

The descriptive statistics of physico-chemical parameters (Table 1) reflect a moderately impacted aquatic environment with variations across space and time. The observed neutral pH and elevated EC and TDS suggest increased ionic loading, likely due to runoff from agricultural zones and effluent discharge from industrial areas (Liao et al., 2005). Lower DO levels, especially in post-monsoon samples, hint at the onset of hypoxic conditions, a condition often triggered by eutrophication and organic pollution (Tariq et al., 2024). High turbidity values reinforce this, indicating active sediment resuspension or discharge of suspended solids. These baseline characteristics establish the physical environment in which toxicological risks from heavy metals are intensified, especially under anthropogenic stress (Barkat et al., 2023).

Seasonal trends and heavy metal dynamics

The seasonal analysis (Table 2) shows a distinct post-monsoon accumulation of heavy metals such as arsenic, lead, and chromium, which can be attributed to seasonal hydrological cycles. The monsoon season, known for dilution and high flow, temporarily reduces concentrations. However, post-monsoon stagnation promotes metal accumulation through sediment-water interactions and reduced flow velocity (Satyam & Patra, 2024). Arsenic and lead concentrations exceeding WHO limits during this season are particularly concerning given their carcinogenic and neurotoxic effects (Altowayti et al., 2022). The temporal dynamics illustrated in Figure 1 underscore the need for seasonal surveillance and intervention, especially during and after monsoon recession when concentrations spike due to desorption from sediments (Siddique et al., 2025).

Insights from multivariate statistical analysis

The Principal Component Analysis (Table 3) clarified the dominant environmental drivers of contamination. PC1, loaded heavily on EC, TDS, turbidity, and temperature, indicated pollution gradients influenced by anthropogenic discharge and evapoconcentration. PC2 emphasized pH and DO, parameters tied to natural buffering and oxygen dynamics (Wijayaweeraet al., 2024). Together, these findings highlight a dual influence: natural hydro-chemical variability coupled with strong anthropogenic pressure (Hossain et al., 2021). Cluster patterns from the PCA further allowed for pollution zoning and strategic site classification, which is essential for localized interventions and modeling accuracy (Wu et al., 2024).

Predictive model performance and implications

Among the tested AI models, Random Forest delivered superior performance (Table 4), followed closely by GBM. These ensemble-based methods proved more robust than SVR and ANN in handling non-linearity, interaction effects, and noise in environmental datasets. The high R^2 value (0.91) and low RMSE (2.3) from Random Forest validate its potential as a reliable tool for heavy metal prediction (Drogkoula et al., 2023). These results align with earlier environmental modeling studies, reaffirming that data-driven AI systems, when properly trained and validated, can offer decision-grade predictions essential for early warning frameworks (Arroyo-Ortega et al., 2024; Srivastava et al., 2024).

Variable importance and process understanding

Feature importance analysis (Figure 2) highlights the predictive influence of water chemistry, especially TDS, EC, and turbidity, on heavy metal dynamics. These indicators often correlate with anthropogenic inputs such as fertilizer residues, industrial discharges, and soil erosion (Jaskuła et al., 2021). Interestingly, DO and pH also played a significant role emphasizing that both redox-sensitive reactions and acid-base equilibrium influence the solubility and mobility of metals like cadmium and mercury (Wuet al., 2024). The relatively lower but notable importance of land-use and seasonal variables suggests that while spatial and temporal factors matter, real-time water chemistry is a more consistent predictor for contamination forecasting (Paul et al., 2019).

Early warning system and policy relevance

The successful integration of statistical and AI approaches supports the development of a functional early warning system (EWS). Such systems can provide preemptive signals based on model thresholds aligned with WHO water quality standards (Moldovan et al., 2022). Given the predictive accuracy and interpretability, this approach can inform targeted remediation, timely health advisories, and spatially guided monitoring (Egbueri et al., 2020). Moreover, the GIS-compatible outputs from this study can enable local authorities to visualize risk zones and prioritize interventions, especially in vulnerable communities with poor water infrastructure (Kumar et al., 2023).

The study validates that hybrid statistical-AI models are not only technically feasible but practically relevant in the context of environmental toxicology. The demonstrated seasonal sensitivity, pollutant predictability, and risk zonation potential underscore a shift toward proactive environmental governance. By integrating scientific rigor with technological innovation, this approach presents a replicable blueprint for other regions facing similar threats of waterborne contamination.

CONCLUSION

This study demonstrates the effectiveness of integrating Statistical and Artificial Intelligence (AI) models for developing an early warning system in environmental toxicology, with a specific focus on predicting waterborne heavy metal contamination. The results revealed significant spatial and seasonal variability in both physico-chemical parameters and heavy metal concentrations, with the post-monsoon season emerging as the most contamination-prone period. Principal Component Analysis highlighted the dominant environmental drivers, while machine learning models particularly Random Forest exhibited high predictive accuracy. The integration of these models into a prototype early warning system, supported by GIS-based visualization and feature importance mapping, offers a scalable and proactive framework for contamination risk assessment. By enabling timely predictions and targeted interventions, this approach enhances the capacity of environmental monitoring systems to safeguard public health and aquatic ecosystems. The findings advocate for broader adoption of hybrid statistical-AI methodologies in policy-driven water quality management, particularly in data-scarce, high-risk regions.

REFERENCES

1. Altowayti, W. A. H., Shahir, S., Othman, N., Eisa, T. A. E., Yafooz, W. M., Al-Dhaqm, A., ... & Ali, A. (2022). The role of conventional methods and artificial intelligence in the wastewater treatment: a comprehensive review. *Processes*, *10*(9), 1832.
2. Arroyo-Ortega, I., Chavarin-Pineda, Y., & Torres, E. (2024). Assessing contamination in transitional waters using geospatial technologies: A review. *ISPRS International Journal of Geo-Information*, *13*(6), 196.
3. Barkat, A., Bouaicha, F., Ziad, S., Mester, T., Sajtos, Z., Balla, D., ... & Szabó, G. (2023). The integrated use of heavy-metal pollution indices and the assessment of metallic health risks in the phreatic groundwater aquifer—The Case of the Oued Souf Valley in Algeria. *Hydrology*, *10*(10), 201.
4. Drogkoula, M., Kokkinos, K., & Samaras, N. (2023). A comprehensive survey of machine learning methodologies with emphasis in water resources management. *Applied Sciences*, *13*(22), 12147.
5. Egbueri, J. C., & Mgbenu, C. N. (2020). Chemometric analysis for pollution source identification and human health risk assessment of water resources in Ojoto Province, southeast Nigeria. *Applied Water Science*, *10*(4), 98.
6. Hossain, Z., Hossain, M. S., Ema, N. S., & Omri, A. (2021). Heavy metal toxicity in Buriganga river alters the immunology of Nile tilapia (Oreochromis niloticus L). *Heliyon*, *7*(11).
7. Jaskuła, J., Sojka, M., Fiedler, M., & Wróżyński, R. (2021). Analysis of spatial variability of river bottom sediment pollution with heavy metals and assessment of potential ecological hazard for the Warta river, Poland. *Minerals*, *11*(3), 327.
8. Kumar, L., Kumari, R., Kumar, A., Tunio, I. A., & Sassanelli, C. (2023). Water quality assessment and monitoring in Pakistan: A comprehensive review. *Sustainability*, *15*(7), 6246.
9. Li, N., Fu, Z., Wang, B., & Zhang, X. (2006, June). FDEWS 2.0: a Web-GIS-based early warning system for fish disease via water quality management. In *2006 6th World Congress on Intelligent Control and Automation* (Vol. 1, pp. 2570-2574). IEEE.
10. Liao, C. M., Jou, L. J., & Chen, B. C. (2005). Risk-based approach to appraise valve closure in the clam Corbicula fluminea in response to waterborne metals. *Environmental Pollution*, *135*(1), 41-52.
11. Liu, Z., Zhang, Z., Sang, J., Yin, Y., & Ding, X. (2024). Development and application of early warning system for heavy metal pollution accident in drinking water source area. *Process Safety and Environmental Protection*, *183*, 293-306.
12. Moldovan, A., Török, A. I., Kovacs, E., Cadar, O., Mirea, I. C., & Micle, V. (2022). Metal contents and pollution indices assessment of surface water, soil, and sediment from the Arieş River Basin Mining Area, Romania. *Sustainability*, *14*(13), 8024.
13. Nallakaruppan, M. K., Gangadevi, E., Shri, M. L., Balusamy, B., Bhattacharya, S., & Selvarajan, S. (2024). Reliable water quality prediction and parametric analysis using explainable AI models. *Scientific Reports*, *14*(1), 7520.
14. Paul, R., Brindha, K., Gowrisankar, G., Tan, M. L., & Singh, M. K. (2019). Identification of hydrogeochemical processes controlling groundwater quality in Tripura, Northeast India using evaluation indices, GIS, and multivariate statistical methods. *Environmental Earth Sciences*, *78*(15), 470.
15. Pérez-Beltrán, C. H., Robles, A. D., Rodríguez, N. A., Ortega-Gavilán, F., & Jiménez-Carvelo, A. M. (2024). Artificial intelligence and water quality: From drinking water to wastewater. *TrAC Trends in Analytical Chemistry*, *172*, 117597.
16. Satyam, S., & Patra, S. (2024). Innovations and challenges in adsorption-based wastewater remediation: A comprehensive review. *Heliyon*, *10*(9).
17. Siddique, A., Tan, Z., Rashid, W., & Ahmad, H. (2025). Sustainable Water-Related Hazards Assessment in Open Pit-to-Underground Mining Transitions: An IDRR and MCDM Approach at Sijiaying Iron Mine, China. *Water*, *17*(9), 1354.
18. Srivastava, S., Wang, W., Zhou, W., Jin, M., & Vikesland, P. J. (2024). Machine learning-assisted surface-enhanced Raman spectroscopy detection for environmental applications: a review. *Environmental Science & Technology*, *58*(47), 20830-20848.
19. Tariq, F., Ahrens, L., Alygizakis, N. A., Audouze, K., Benfenati, E., Carvalho, P. N., ... & Andersson, P. L. (2024). Computational tools to facilitate early warning of new emerging risk chemicals. *Toxics*, *12*(10), 736.
20. Wang, J., Huang, D., Zheng, D., Shen, F., & Zhang, Y. (2024). Selectively Quantify Toxic Pollutants in Water by Machine Learning Empowered Electrochemical Biosensors. *Environmental Science & Technology*, *59*(1), 616-627.
21. Whig, A., Gupta, V., & Whig, P. (2025). AI for Evaluation of the Impacts of Environmental Pollution on Human Health. *Artificial Intelligence-Driven Models for Environmental Management*, 225-251.
22. Wijayaweera, N., Gunawardhana, L., Bamunawala, J., Sirisena, J., Rajapakse, L., Patabendige, C. S., & Karunaweera, H. (2024). Use of Machine Learning and Indexing Techniques for Identifying Industrial Pollutant Sources: A Case Study of the Lower Kelani River Basin, Sri Lanka. *Water*, *16*(19), 2766.
23. Wu, Y., Xia, Y., Mu, L., Liu, W., Wang, Q., Su, T., ... & Zhang, Y. (2024). Health risk assessment of heavy metals in agricultural soils based on multi-receptor modeling combined with Monte Carlo simulation. *Toxics*, *12*(9), 643.

24. Wu, Y., Yu, J., Huang, Z., Jiang, Y., Zeng, Z., Han, L., ... & Yu, J. (2024). Migration of total petroleum hydrocarbon and heavy metal contaminants in the soil–groundwater interface of a petrochemical site using machine learning: impacts of convection and diffusion. *RSC advances*, *14*(44), 32304-32313.
25. Yi, Y., Wang, B., Yi, X., Zha, F., Lin, H., Zhou, Z., ... & Liu, H. (2024). Systematic and long-term technical validity of toxicity determination and early warning of heavy metal pollution based on an automatic water-toxicity-determination-system. *Frontiers of Environmental Science & Engineering*, *18*(8), 96.
26. Yin, J., Wang, A. P., Li, W. F., Shi, R., Jin, H. T., & Wei, J. F. (2018). Time-response characteristic and potential biomarker identification of heavy metal induced toxicity in zebrafish. *Fish & Shellfish Immunology*, *72*, 309-317.