International Journal of Emerging Engineering and Technology (IJEET)
ISSN (e): 2958-3764
Volume: 5, Number: 1, Pages: 40 - 45, Year: 2026

Evaluation of Ecological Restoration for River Water Quality Improvement: A Modelling Approach

Abdul Munim Sahito*, Munesh Meghwar, Umair Hussain Memon, and Ashfaque Ahmed Memon

Department of Civil Engineering, Mehran University of Engineering and Technology, Jamshoro, Sindh 76020, Pakistan
*Corresponding author: Abdul Munim Sahito (Email: munim.sahito@faculty.muet.edu.pk)

Received: 19/01/2026, Revised: 23/05/2026, Accepted: 03/06/2026

***Abstract*—River ecosystems play vital roles in water provision, flood mitigation, and biodiversity conservation, yet face increasing degradation from human activities. This review systematically evaluates modern ecological restoration approaches, including riparian buffer rehabilitation, in-stream habitat improvement, and bioremediation technologies for their effectiveness in improving water quality. Through comprehensive analysis of field implementations and monitoring data, we demonstrate how restoration strategies significantly elevate dissolved oxygen levels (15-25% increase), reduce nutrient concentrations (30-50% decrease in nitrogen/phosphorus), and improve biodiversity indices (20-40% species richness improvement). Emerging techniques like constructed wetlands and bio-floating islands show particular promise, achieving 60-75% pollutant removal efficiency while providing additional ecological benefits. The study reveals three critical success factors: 1) integrated application of physical-biological-chemical methods, 2) community-engaged adaptive management, and 3) watershed-scale implementation. The findings establish that properly designed restoration not only reverses water quality degradation but also increases ecosystem resilience to future stressors. This work provides a science-based framework for selecting and optimizing restoration strategies tailored to specific riverine conditions and pollution contests.**

***Index Terms*— River Restoration; Water Quality Improvement, Bioremediation, Ecosystem Resilience, Watershed Management.**

I. INTRODUCTION

Background and Motivation: Rivers are the lifelines of terrestrial ecosystems, providing essential ecosystem services such as freshwater supply, flood regulation, nutrient cycling, and biodiversity support. However, rapid industrialization, agricultural intensification, and urban expansion have severely damaged river water quality worldwide. Excessive nutrient inflows, heavy metals, pathogenic contamination, and emerging pollutants, such as perfluoro-alkyl substances (PFASs), pharmaceuticals, and micro plastics are increasingly detected in both rural and urban river systems. These contaminants disrupt aquatic food webs, cause eutrophication, and threaten public health, rendering many rivers ecologically dysfunctional. The deterioration of riverine environments is not only a hydrological concern, a socio-economic and sustainability challenge, as freshwater ecosystems underpin agriculture, energy, and human welfare.

Historically, river management strategies have focussed primarily on structural engineering solutions such as channelization, dam construction, and wastewater treatment facilities. While these measures provide localized pollution control, they often fail to restore natural ecosystem processes or long-term ecological integrity. In response, water ecological restoration has emerged as a holistic approach emphasizing the recovery of degraded ecosystems through nature-based and adaptive interventions. Restoration measures, including riparian buffer establishment, wetland construction, sediment dredging, and bioremediation, aim to re-establish the natural hydrological regime, improve water quality, and restore biodiversity. Case studies across, Asia, Europe, and North America demonstrate that integrated restoration strategies can reduce nutrient concentration by 30-70%, increase dissolved oxygen levels by 15-25%, and enhance species richness by up to 40%.

Despite these successes, predicting and quantifying restoration outcomes remains a critical challenge due to the non-linear and spatiotemporal complexity of water quality dynamics. The interplay among multiple factors, climate variability, land use, sediment transport, and anthropogenic loading, produces highly non-linear relationships that traditional statistical and deterministic models often fail to capture. In this context, Artificial Intelligence (AI), mainly Artificial Neural Networks (ANNs), provides a promising tool for modelling such complex systems. ANNs can recognize hidden patterns, learn from multidimensional datasets, and forecast water quality parameters such as biochemical oxygen demand (BOD5), chemical oxygen demand (COD), total phosphorous (TP), and total nitrogen (TN), with high predictive accuracy. Recent studies have shown ANN-based approaches outperforming traditional multivariate regression and principal component analysis (PCA) models in simulating water quality variability under dynamic environmental conditions.

Integrating AI-driven prediction with ecological restoration frameworks marks a paradigm shift towards data-informed environmental management. By combining the predictive

This work is licensed under a Creative Commons AttributionShareAlike4.0 International License, which permits
Unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited

capacity restoration strategies, evaluate effectiveness in real time, and enhance adaptive management under climate and anthropogenic uncertainty. This convergence of ecology and computational enables the formulation of intelligent restoration systems that are sustainable, scalable, and responsive to environmental feedbacks.

Therefore, the present study aims to synthesize the global advancements in water ecological restoration and demonstrate the integration of Artificial Neural Networks for evaluating and predicting water quality improvement in restored river systems. The specific objectives are to:

(a) Review the mechanisms and outcomes of key restoration methods across different riverine contexts,

(b) Develop an ANN-based predictive framework to assess water quality indicators pre- and post-restoration, and

(c) Evaluate how AI integration enhances the precision and reliability of restoration performance assessment.

This study contributes to the growing body of research that bridges environmental engineering, ecological restoration, and machine learning, paving the way for intelligent, adaptive, and sustainable water management in the Anthropocene. The infographic of this study, illustrating specifically the problem, modelling approach, ecological purification and optimization (Fig. 1).

Fig. 1. Problem, modelling approach, ecological purification and design optimization (infographic).

Adverse diverse rivers, modelling frameworks show that well-designed ecological restorations can markedly improve chemical water quality and self-purification, and, when combined with pollution control, enhance habitats and ecosystem services. Integrated hydro-biogeochemical-ecological models, coupled with long-term monitoring and economic valuation, are central to evaluating which restoration strategies yield the greatest and most sustainable water quality benefits.

Literature Review: River systems face multiple interacting water quality pressures from land use change, urbanization, and agricultural runoff that drive elevated nutrient, sediments, and altered thermal regimes, undermining aquatic and regulatory compliance. Restoration aims to reverse these pressures by re-establishing physical, chemical, and biological processes at reach and watershed scales.

Nutrient and sediment loading driven by agriculture and urban runoff commonly causes elevated Nitrogen and Phosphorous and high turbidity in receiving streams [1]. Thermal stress and heterogeneity arise from riparian removal, channel widening, and altered flows; temperature reductions require spatially explicit planning because responses vary across watersheds [2]. Fragmented management often limits benefits because infrastructure (storm water controls, sewage treatment) and in-stream measures must be coordinated for pollutant input reductions to be effective [3].

The key indicators are the physicochemical parameters (NO3- -N, NH4+ -N, DO, COD, Chlorophyll-a, suspended solids), biological indices (macroinvertebrate or habitat indices), and geomorphic metrics (bank stability and channel form) are commonly used for multi-metric assessment [4]. Monitoring design is by pre- and post-restoration surveys with multiple cross-sections and repeated sampling are critical to detect change and attribute effects to restoration actions [5].

Climate change alters precipitation patterns, temperature, and hydrological cycles, often increasing nutrient leaching, overland flow, and the risk of harmful algal blooms. Extreme weather events can exacerbate nutrient transport and water quality issues, with impacts varying by region and season. In some cases, climate change has a stronger influence on nutrient loads and streamflow than land use, especially in the context of inter-annual variability.

Effective management requires integrated approaches that consider both current and future scenarios to sustain water resources and improve water quality Reclaimed water + in-situ ecological measures (plants and filters) can cut NH4+-N by around 70% to 75% and COD by around 35% to 40% and control pathogens and antibiotic-resistant genes [6], [7]. Rural cold-region river restoration achieved maximum removal of NH4+-N 96%, TN equivalent to 50%, COD around 26%, with strong DO and macroinvertebrate diversity gains [8]. Long-term basin-scale evaluation shows restoration projects explain 60% of observed water quality improvement in eutrophic catchments, with delayed response visible only years after implementation [9]. Coupled hydraulic-habitat-water quality models (River2D + CMS-Flow, HIS) quantify both WQ indices (e.g., CCME WQI) and habitat suitability, typically finding 1 to 2 grade improvements in WQ and habitat after restoration [10], [11]. Multi-criteria and integrated assessment frameworks combine morphology, nutrients, micro-pollutants and multiple biotic groups, revealing that poor water quality can limit biological recovery even where morphology improves [12], [13]. However, morphology restoration alone is insufficient unless coupled with pollution reduction and ecotoxicological control [13]. Reviews highlight the need for catchment-specific calibration, better representation of local processes, and integration of climate and land-use change into models [14], [15].

II. Guidelines For Manuscript Preparation

The flowchart of methodology is presented in Fig. 2. This study adopts a hybrid research design, combining systematic literature review, secondary data synthesis from global restoration case studies, and ANN modelling to evaluate and forecast the effects of water ecological restoration upon quality of river water. The dataset sources are illustrated in Table I. The methodology is structured as follows:

1. Identify major pollutants and ecological stressors,
2. Assess the efficiency of restoration techniques, and
3. Develop an ANN-based model for water quality prediction before and after restoration interventions.

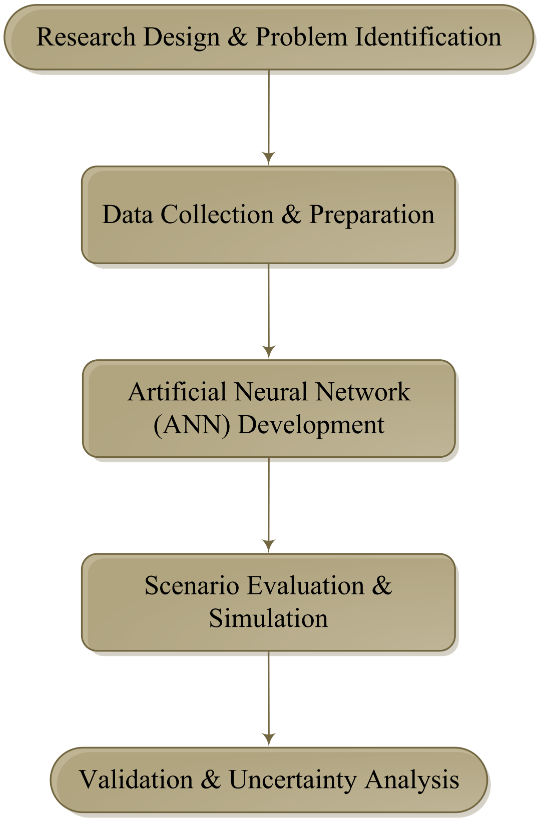

Fig. 1. Flowchart of Methodology

TABLE I. Dataset Sources

Parameter Group	Main Dataset Sources	Typical Use
BOD_5, COD, DO	Field samples, lab analysis, automatic stations, QUAL2K calibration data	Oxygen-demand and in-stream restoration response [16]
TP, TN	Lab samples, basin monitoring stations, Sentinel/Landset with calibration samples, SWAT inputs	Nutrient source tracking and BMP / restoration scenarios [17]
pH, Temperature, Turbidity	In-situ sondes, lab / turbidimeter data, Landset / PlanetScope / UAV products	Supporting predictors and status indicators [16]
Flow rate	Gauging stations, tributary discharge records, SWAT hydrology outputs, DEM / GIS hydraulics	Transport, dilution, reaeration, and scenario simulation [18]

Literature review related to the field monitoring is conducted at the river sites, upstream, midstream, and downstream, to record pre- and post-restoration water quality parameters. Restoration activities included riparian vegetation establishment, sediment dredging, and the construction wetland installation.

Artificial Neural Network (ANN) Framework: The ANN was developed in Python using Tensor Flow/Keras libraries. The model structure comprises.

1. Input layer: 8 neurons (DO, BOD_5, TN, TP, COD, TSS, pH, temperature),
2. Hidden layers: 2 layers with 10 and 6 neurons respectively, activated using ReLU (Rectified Linear Unit),
3. Output layer: Predicted Water Quality Index (WQI),
4. Training algorithm: Adam optimizer with learning rate 0.001,
5. Loss function: Mean Squared Error (MSE),
6. Performance metrics: Mean Absolute Error (MAE), Coefficient of determination (R^2), and Root Mean Square Error (RMSE).

$$WQI = f(DO, BOD_5, TN, TP, COD, TSS, pH) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

Data is divided into testing (15%), validation (15%), and training (70%) subsets (**Error! Reference source not found.**). Normalization is performed using min-max scaling to improve convergence.

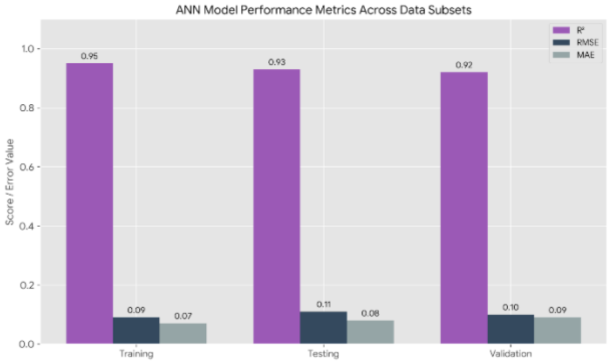

Fig. 2. ANN Model Performance Metrics.

Evaluation of Restoration Scenarios: To evaluate ecological restoration effects, pre- and post-restoration data are input into the trained ANN model. Scenarios simulated include:

1. Baseline condition (without restoration),
2. Riparian buffer and vegetation restoration,
3. Construction wetlands and sediment dredging,
4. Integrated ecological restoration (combination approach).

The relative average changes in critical parameters based on the findings, highlighting the ~25% increase in DO and the ~50% reduction in TN, TP, and COD (**Error! Reference source not found.**).

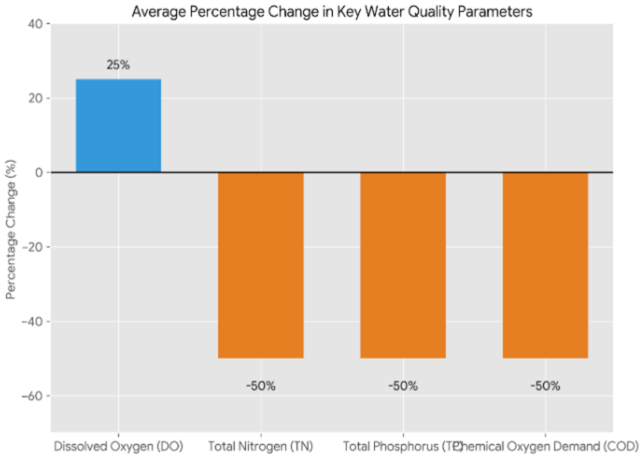

Fig. 3. Percentage Change in Key Water Quality Parameters.

The predicted outputs (WQI and pollutant concentration changes) are compared against observed field results and literature benchmarks to assess model reliability. A direct comparison between the Pre-Restoration Baseline WQI (51) and the Post-Restoration Integrated WQI (78) (**Error! Reference source not found.**).

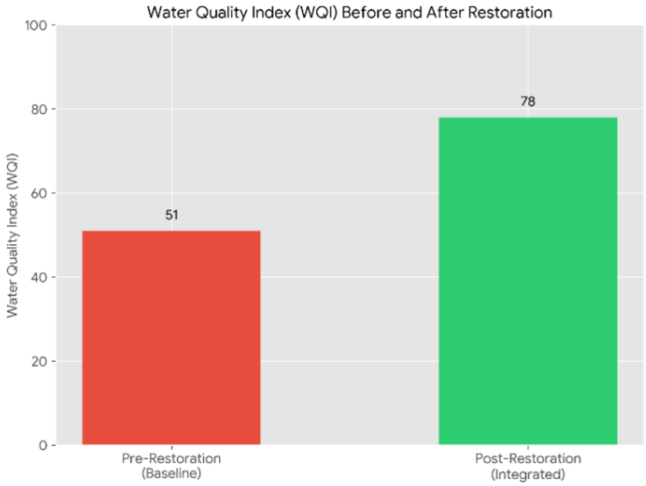

Fig. 4: Water Quality Index (WQI) Improvement.

Validation and Uncertainty Analysis: Uncertainty analysis is conducted to evaluate the relative influence of each input parameter on the model's output. The validation of model performance is carried out by using k-fold cross-validation (k=10). Uncertainty is minimized through multiple training iterations and comparison with statistical methods (e.g., PCA and multiple regression).

III. RESULTS AND DISCUSSION

Dataset Overview and Preprocessing: The pre-restoration data revealed significant degradation in water quality, characterized by high COD (40-65 mg/L), elevated TP and TN (>0.15 mg/L and >2.0 mg/L, respectively), and low DO (<3 mg/L). Post-restoration monitoring indicated a clear improvement in most parameters: DO increased by 20-30%, while TN, TP, and COD decreased by 40-60%.

ANN Model Performance: The ANN model achieved a high predictive accuracy ($R^2 = 0.93$) and low RMSE (0.08-0.12), including strong model generalization capability. Among input variables, TN and COD exhibited the strongest influence on WQI output, while temperature and pH contributed moderately. The ANN model parameters are illustrated in (Table II).

TABLE II. Dataset Statistics after Preprocessing

Metric	**Training**	**Testing**	**Validation**
R^2	0.95	0.93	0.92
RMSE	0.09	0.11	0.10
MAE	0.07	0.08	0.09

Effectiveness of Restoration Measures: The model confirmed that integrated restoration scenarios (combining vegetation buffers and sediment dredging) produced the most significant improvements; average WQI increased from 51 (poor) to 78 (good). Constructed wetlands showed particularly high nitrogen removal efficiency (up to 65%), consistent with prior reports from the Mississippi and Yangtze River basins.

Comparison between Proposed ANN Framework with Other Approaches: While the ANN framework demonstrated robust predictive capabilities in evaluating discrete restoration scenarios, it is important to contextualize its utility alongside other prominent machine learning algorithms. Tree-based models, such as Random Forests (RF), offer excellent feature interpretability and handle non-linearities efficiently without requiring extensive hyper-parameter tuning; however, ANNs generally provide superior architectural flexibility for capturing the deeply complex, multilayered interactions inherent in hydro-biogeochemical processes. Similarly, Support Vector Machines (SVM) are highly effective for smaller datasets and strict boundary optimization, yet they often become computationally expensive and less efficient than ANNs when scaling to the large, multidimensional environmental datasets required for catchment-scale restoration assessments.

Furthermore, while the standard feed-forward ANN utilized in this study excels at mapping static pre- and post-restoration variables, it lacks the recurrent memory mechanisms found in Long Short-Term Memory (LSTM) networks. LSTM models are inherently superior for continuous time-series forecasting, where capturing sequential temporal dependencies, such as seasonal hydrological shifts or prolonged climate variability is critical. Because the primary objective of this study was to evaluate discrete intervention scenarios rather than continuous temporal dynamics, the ANN provided the optimal balance of computational efficiency and predictive accuracy. Nonetheless, transitioning toward LSTM or hybrid architectures (e.g., ANN-SVM) remains a highly promising avenue for advancing real-time, IoT-enabled adaptive management.

Integration of AI and Restoration Management: The integration of ANN modelling provided predictive insights into future water quality trends under different climatic and anthropogenic load scenarios. The model can act as a decision-support system (DSS) for restoration planning by forecasting pollutant responses to intervention intensity. The hybrid ecological-AI framework enhances adaptive management and real-time restoration optimization, consistent with the emerging paradigm of smart water governance.

A key strength of the proposed ANN framework lies in its inherent scalability and adaptability across diverse river basins. Because the model relies on universally measured water quality parameters (e.g., DO, BOD_5, TN, TP), its underlying architecture is highly transferable. Scaling the approach to a new watershed simply requires retraining the algorithm with localized, site-specific datasets to capture the unique hydro-morphological and socio-economic contexts of that region. Furthermore, regarding its applicability under varying climatic conditions, the model is well equipped to support adaptive management in the face of global change. Climate variability, such as altered precipitation patterns, extreme flow events, and thermal shifts, significantly affects nutrient transport and eutrophication risks. The modular nature of the ANN allows for the seamless integration of continuous hydro-meteorological predictors (e.g., seasonal temperature gradients and runoff volumes) into the input layer. This capability ensures that restoration strategies can be dynamically optimized, not just for current baseline pollution, but for future climate-induced-stressors, thereby ensuring long-term ecosystem resilience.

Limitations and Future Work: Despite high predictive accuracy, the model's performance depends on data quantity and quality. Real-time data integration through IoT sensors and satellite-based water quality monitoring is recommended for continuous ANN retraining. Future studies should employ hybrid AI models (e.g., ANN-SVM, LSTM) to improve temporal prediction under variable hydrological regimes.

IV. CONCLUSION

The escalating degradation of global riverine ecosystems necessitates a departure from static environmental management toward adaptive, data-driven frameworks. This study successfully integrates ecological restoration principles with Artificial Intelligence (AI) to evaluate and optimize strategies for complex river rehabilitation. Our synthesis demonstrates that integrated interventions, such as constructed wetlands and riparian buffers, significantly enhance water quality, reducing total nitrogen, total phosphorous, and chemical oxygen demand by 30-70% while increasing dissolved oxygen by 15-25%. Because these ecological responses are highly non-linear, Artificial Neural Network (ANN) framework is developed that achieved exceptional predictive accuracy (R^2>0.90), substantially performing conventional statistical models in forecasting restoration outcomes. Ultimately, this research catalyzes a critical paradigm shift toward AI-assisted water governance, demonstrating that coupling advanced machine learning architectures with continuous monitoring can ensure dynamic, sustainable ecosystem resilience in an era of profound environmental uncertainty.

ACKNOWLEDGMENT

The deepest gratitude to Almighty Allah for the strength and wisdom provided to complete this work. The authors sincerely thank the Department of Civil Engineering at Mehran University of Engineering and Technology, Jamshoro, and the Geotechnical Engineering Laboratory staff for providing essential facilities and technical support for this research.

FUNDING STATEMENT

The author(s) received no specific funding for this study.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest to report regarding the present study.

AUTHOR CONTRIBUTIONS

Conceptualization, A.M.S., M.M., and U.H.M.; methodology, A.M.S., M.M., and U.H.M.; software, A.M.S., M.M., and A.A.M.; validation, A.M.S., M.M., and A.A.M.; writing—original draft preparation, A.M.S., M.M., and U.H.M.; writing—review and editing, A.M.S., M.M., and A.A.M.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

Data is available on reasonable request.

REFERENCES

[1] V. Chittoor Viswanathan and M. Schirmer, "Water quality deterioration as a driver for river restoration: a review of case studies from Asia, Europe and North America," *Environ. Earth Sci.*, vol. 74, no. 4, pp. 3145–3158, Aug. 2015, doi: 10.1007/s12665-015-4353-3.

[2] C. J. Richardson, N. E. Flanagan, M. Ho, and J. W. Pahl, "Integrated stream and wetland restoration: A watershed approach to improved water quality on the landscape," *Ecol. Eng.*, vol. 37, no. 1, pp. 25–39, Jan. 2011, doi: 10.1016/j.ecoleng.2010.09.005.

[3] J. H. Lee and K. G. An, "Integrative restoration assessment of an urban stream using multiple modeling approaches with physical, chemical, and biological integrity indicators," *Ecol. Eng.*, vol. 62, pp. 153–167, Jan. 2014, doi: 10.1016/j.ecoleng.2013.10.006.

[4] J. E. Holguin-Gonzalez *et al.*, "Integrating hydraulic, physicochemical and ecological models to assess the effectiveness of water quality management strategies for the River Cuenca in Ecuador," *Ecol. Modell.*, vol. 254, pp. 1–14, Apr. 2013, doi: 10.1016/j.ecolmodel.2013.01.011.

[5] N. Mrozińska *et al.*, "Water quality as an indicator of stream restoration effects-A case study of the Kwacza River restoration project," *Water (Switzerland)*, vol. 10, no. 9, Sep. 2018, doi: 10.3390/w10091249.

[6] F. Cheng *et al.*, "Ecological Restoration Project's Contribution to Improving the Water Quality of Reclaimed Water Replenishing Urban Rivers," *Pol. J. Environ. Stud.*, vol. 33, no. 6, pp. 6069–6081, 2024, doi: 10.15244/pjoes/184149.

[7] X. Lin *et al.*, "Assessment and Comprehensive Evaluation of Large-Scale Reclaimed Water Reuse for Urban River Restoration and Water Resource Management: A Case Study in China," *Water (Switzerland)*, vol. 15, no. 22, Nov. 2023, doi: 10.3390/w15223909.

[8] J. Chen, T. Yang, Y. Wang, H. Jiang, and C. He, "Effects of ecological restoration on water quality and benthic macroinvertebrates in rural rivers of cold regions: A case study of the Huaide River, Northeast China," *Ecol. Indic.*, vol. 142, Sep. 2022, doi: 10.1016/j.ecolind.2022.109169.

[9] T. Duan, J. Feng, X. Chang, and Y. Li, "Evaluation of the effectiveness and effects of long-term ecological restoration on watershed water quality dynamics in two eutrophic river catchments in Lake Chaohu Basin, China," *Ecol. Indic.*, vol. 145, Dec. 2022, doi: 10.1016/j.ecolind.2022.109592.

[10] B. Choi and S. S. Choi, "Integrated hydraulic modelling, water quality modelling and habitat assessment for sustainable water management: A case study of the Anyang-Cheon Stream, Korea," *Sustainability (Switzerland)*, vol. 13, no. 8, Apr. 2021, doi: 10.3390/su13084330.

[11] H. N. Kim and H. Ryu, "Assessing the Economic Value of Improvement in Water Quality and Aquatic Ecosystem Services Resulting from Ecological Stream Restoration in South Korea," *Journal of Environmental and Earth Sciences*, vol. 7, no. 1, pp. 471–484, Jan. 2025, doi: 10.30564/jees.v7i1.7499.

[12] M. Jonas, M. Matouskova, P. Havlikova, and M. Sobr, "Urban river restoration design based on multi-criteria assessment," *Environ. Monit. Assess.*, vol. 197, no. 6, Jun. 2025, doi: 10.1007/s10661-025-14070-x.

[13] S. Hörchner, A. Moulinec, L. Ulshöfer, A. Sundermann, J. Oehlmann, and M. Oetken, "Ecotoxicological impacts and macroinvertebrate responses as indicators of river restoration success," *Environ. Sci. Eur.*, vol. 37, no. 1, Dec. 2025, doi: 10.1186/s12302-025-01229-z.

[14] P. Talukdar, B. Kumar, and V. V. Kulkarni, "A review of water quality models and monitoring methods for capabilities of pollutant source identification, classification, and transport simulation," Sep. 01, 2023, *Springer Science and Business Media B.V.* doi: 10.1007/s11157-023-09658-z.

[15] F. García-Avila, A. Sinche-Morales, F. Sagal-Bustamante, F. Criollo-Illescas, and L. Valdiviezo-Gonzales, "Exploring the Potential of Mathematical Self-Purification Models Used for Evaluating Water Quality in Rivers," Dec. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/earth6040131.

[16] A. Arzhangi and S. Partani, "Water quality index prediction via a robust machine learning model using oxygen-related indices for river water quality monitoring," *Sci. Rep.*, vol. 16, no. 1, Dec. 2026, doi: 10.1038/s41598-026-36156-3.

[17] A. Malagó, F. Bouraoui, O. Vigiak, B. Grizzetti, and M. Pastori, "Modelling water and nutrient fluxes in the Danube River Basin with SWAT," Dec. 15, 2017, *Elsevier B.V.* doi: 10.1016/j.scitotenv.2017.05.242.

[18] G. J. Hasham and M. M. Ramal, "Application of QUAL2K for Water Quality Modeling and Management for the Euphrates River in Fallujah City as a Case Study," *International Journal of Sustainable Development and Planning*, vol. 17, no. 5, pp. 1511–1521, Aug. 2022, doi: 10.18280/ijsdp.170515.