ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (3): 922-932 doi: 10.28978/nesciences.1811171

AI-Assisted Bio-Engineering Approaches for Ecosystem Restoration: An Integrated Study of Pollution Control, Water Quality Prediction, and Biodiversity Sustainability

Pallavi S. Chakole [1*], Dr.A. Dhanalakshmi [2], Dr. Mamta Thakur [3], Dr. Bechoo Lal [4], Maher Ali Rusho [5], Anoop Dev [6]

[1*] Assistant Professor, Department of Civil Engineering, Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, India. E-mail: chakole121pallu@gmail.com

[2] Professor, Acharya Bangalore B School, Bengaluru, Karnataka, India. E-mail: dhanalakshmi555@gmail.com

[3] Assistant Professor, Department of Mathematics, Chaitanya Bharathi Institute of Technology, Hyderabad, India. E-mail: mamtathakur_maths@cbit.ac.in

[4] Associate Professor, Department of Computer science and Engineering, Konenru Lakshmaiah Education Foundation, vaddeswaram, AP, India. E-mail: drblalpersonal@gmail.com

[5] Department of Lockheed Martin Engineering Management, University of Colorado, Boulder, USA. E-mail: maher.rusho@colorado.edu

[6] Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. E-mail: anoop.dev.orp@chitkara.edu.in

Abstract

Anthropogenic pollution of ecosystems, rapid climate change, and biodiversity losses have become an urgent issue in the world and need innovative and scaled-based solutions. The developments in artificial intelligence (AI), bio-engineering and environmental sensing technologies are currently providing unparalleled possibilities in rescuing ecological equilibrium in or affected health and natural ecosystems. This paper offers a novel and unified system that integrates AI-based pollution control, predictive water-quality, and bio-engineered remediation measures to aid the restoration of sustainable ecosystems. The research solution is based on deep-learning models, such as convolutional neural networks, long short-term memory networks, and transformers based on architectures, to be efficient in concluding the presence, classification, and forecasting of pollutant dynamics in terrestrial and aquatic ecosystems. Simultaneously, bio-engineering technologies like engineered microbial communities, hyperaccumulator plants, and

*Corresponding Author: Pallavi S. Chakole, E-mail: chakole121pallu@gmail.com

optimum bioreactor designs have been used to hasten the degradation, absorption and fixation of contaminants. Moreover, AI-based models of biodiversity sustainability can be applied to measure the changes in distribution of species, habitat suitability and ecosystem resilience when subjected to environmental stressors of various levels. Based on experimental assessments and case studies, it is shown that AI combined with bio-engineered remediation improves the accuracy of identifying the source of the pollution by more than 30 times, it can be found to be more effective in the removal of contaminants, up to 38 times, and that it can maintain beneficial effects on biodiversity in the long-term, which can be achieved by optimised restoration strategies. The conclusions support the radical opportunities of AI-enhanced bio-engineering solutions to the restoration of fast, resilient, and scalable ecosystems. In addition, the research paper points at the major challenges such as the lack of data, ecological complexity, and ethical considerations and explains future research directions to serve the intelligent restoration ecology.

Keywords:

AI-assisted ecosystem restoration, bio-engineering, bioremediation, water quality prediction, biodiversity sustainability, machine learning, ecological modeling, environmental monitoring, predictive analytics, pollution control.

Article history:

Received: 30/07/2025, Revised: 20/09/2025, Accepted: 17/10/2025, Available online: 12/12/2025

Introduction

International Issues of Environmental Destruction in Ecosystems

The tragedy of the damage done to world ecosystems is because of fast industrialization, uncontrolled urbanisation, deforestation, and the misuse of the resources. Ecological resilience has been significantly diminished due to the deposition of pollutants in the soil, freshwater as well as coastal ecosystems, and the reduction in genetic variety coupled with the fragmentation of habitats. Pollution, climate change, and changes in land-use keep increasing, which is weakening the natural systems and jeopardising the well-being of humans because of the loss of biodiversity. Such compound environmental forces bring out the pressing need of scalable and efficient restoration strategies.

Disadvantages of Traditional Restoration Strategies

Conventional methods of restoring ecological conditions such as physical restoration, manual monitoring and natural regeneration are also burdened with slow responses, multiple numbers of people, and poor adaptation to dynamic environmental situations. Also, these approaches are difficult to work with large-scale ecological data or non-linear ecological interactions. Here the result of such constraints is limited localised instead of systemic restoration to restrict the long-term performance; and failure to react to emerging environmental threats in a timely manner.

Introduction of AI-Assisted Bio-Engineering

The recent innovations in the fields of artificial intelligence (AI), bio-engineering, and environmental sensing technologies can offer innovative prospects in the restoration of ecology. AI allows monitoring the environment in real-time, such forecasting, autonomous decision-making, and modelling of intricate ecological patterns. At the same time, bio-engineering solutions such as programmed microbial consortia, genetically engineered plants and biomolecular pathways provide useful tools in contaminant cleanup, land restoration and restoration of habitats. Collectively, these technologies will have created a capacity to transcend the traditional modes of operation by facilitating dynamic, data-driven and scalable processes to restoration.

Requirement of an Artificial Intelligence-biological Engineering Paradigm

In spite of the fact that the current research is highly developed, there is still a tendency to focus on pollution control, water quality prediction and conservation of biodiversity separately. It is this fragmentation that restricts the adoption of holistic restoration solutions that can provide answers to the complexity of the ecosystem. Thus, the paper suggests a collaborative framework that would incorporate AI-based pollutant monitoring, predictive models of water quality and bio-engineered remedies with biodiversity sustainability evaluation. Combining these complimentary strategies, the research will further improve pollution reduction, hasten ecological restoration, and promote longterm environmental system stability of various environmental systems Background and Related Work

Artificial Intelligence in Environmental Monitoring.

The capacity to transform heterogeneous and large data volumes and model complicated ecological relationships has made Artificial Intelligence a transformative instrument in environmental tracking. The use of CNNs in remote sensing-oriented pollution detection, land-use classification, and surface water quality has been widely used in many applications where it allows better spatial resolution and classification (Basuki, 2024; Beloiu et al., 2023). Temporal prediction of water quality characteristics of dissolved oxygen, turbidity, and nutrient loadings has been carried out by recurrent neural networks, including Long Short- Term Memory (LSTM) models (Barone et al., 2022). Recently, Graph Neural Networks (GNNs) and Transformer have demonstrated higher performance towards modelling watershed-scale interactions, and non-linear pollution dynamics (Song et al., 2024; Smith et al., 2024). Moreover, AI has also advanced distribution modelling of species and evaluation of biodiversity and climate, land-use, and habitat data have been used to predict conservation planning (Basuki, 2024).

Bio-Engineering to Restore the Ecosystem

Sustainable remedies to the polluted ecosystems are available through bio-engineering methods. Bio-removal of microbes has proved to be very effective in the breakdown of hydrocarbons, industrial toxins and heavy metals following enzyme and metabolic processes (Arshed et al., 2023). Hyperaccumulator plants have been utilised in phytoextraction and phytoto stabilisation of pollutant like arsenic, lead and cadmium and this has provided a clean way to remove and fix the pollutants. Recent developments in CRISPR-based gene editing have facilitated the establishment of engineered microbial concortium with a higher degradation capability and pollutant selectivity (Arora et al., 2025). Large-scale purification of water and recycling of nutrients of engineered wetlands, plant-microbe symbiosis and bio-reactor systems are also enhanced to promote ecological restoration (Aria & Cuccurullo, 2017; Valdovinos & Romero, 2025).

AI and Biotechnology Integration

Combined AI-bioengineering protocols are also coming out as potent instruments in streamlining ecological reconstruction procedures. Optimization algorithms based on AI have been used to design microbial communities, which allow predicting the best combinations of species and the metabolic characteristics of its interactions with others to increase the degradation of pollutants (Arantes et al., 2023). Reinforcement learning methods have also been studied to support adaptive management of environmental systems, where frameworks of decision-making on habitat restoration and resource allocation are offered. Machine learning-driven predictive genomics has helped to define and design plant and microbial species with higher bioremediation properties. Even with these improvements, the research that has been conducted in this area is still not tied up, and there has been little research that has incorporated the use of AI based full monitoring, bio-engineered remediation, and sustainability of biodiversity under a single restoration paradigm. This is the gap that encourages the creation of an entire AI-aided architecture of ecosystem restoration.

Methodology

The methodology will be structured around three pillars that are aimed at having a structured and scientifically valid study as the main objectives of the research are in accordance with them:

Intelligent Tracking and Analysis of Pollution

Data Sources

The AI-based pollution monitoring intended system combines various high quality of environmental data with emphasis on strong and dependable analysis. The multispectral satellite images like Sentinel-2 and Landsat-8 can be used to cover extensive areas of the surface to identify signs of surface-level pollution, such as suspended sediments, algal and chemical contaminants. To supplement these macro scale observations, high resolution aerial imaging systems mounted on UAVs can be used to capture finer scale spatial locations of pollution potential sources, whereby small scale hotspots can be localised to an industrial discharge outlet or an agricultural runoff area. The sensor networks installed in soils and on the water surface under the IoT consider constant measurements of important physicochemical indexes such as pH, dissolved oxygen, turbidity, heavy metal concentration, and hydrocarbon levels. These near real-time data streams are again approved and tuned on laboratory verified datasets of pollutant concentrations so that the resultant data will be precise and consistent across modalities to facilitate down-stream AI analysis and model development.

Preprocessing

A complete preprocessing pipeline is used to prepare the heterogeneous dataset to the use of the AI-based classification and segmentation. UAV and satellite images are spectral normalised to normalise the reflectance readings among the various types of sensors and illuminations. State-of-the-art CNN-based autoencoders are used to eliminate noise and deny distortions of images without reducing spectral signatures that are important in detecting pollutants. Savitzky-Golay philtres have been used to smooth sensor time-series data so as to reduce random variance but retain natural environmental trends. Also, the anomalous or extreme values due to malfunctioning of sensors or momentary disturbances to the environment are filtered out via statistical preprocessing tools like Interquartile Range (IQR) philtres. Such strict preprocessing guarantees the high data integrity and improves the work of the AI models that are applied in pollution evaluation.

AI Models Used

A number of state-of-the-art code models using AI are utilised to classify, detect, and map pollutants of the environment very precisely. A deep convolutional neural network known as ResNet50 is used to categorise the type of pollutants by training on both aerial and satellite imagery featuring complex spatial-spectral features. To be able to specify the polluted areas, UNet++ is used because it has a superior encoder-decoder structure, which allows precise semantic boundary segmentation of polluted areas. Spectral signature analysis is performed with transformer-based models with the assistance of their attention mechanism to exploit long-range interactions between different multispectral bands, enabling better differentiation of types of pollution with overlapping visual features among others. When combined, these AI models can be used to have a full overview of the distribution of pollution, its intensity, and its evolution over time in different ecosystems.

Evaluation Metrics

The accuracy, robustness and reliability of the AI models are evaluated by employing the most recognised evaluation metrics. Accuracy and F1-score are used to evaluate the classification models based on the correctness and balance of the measures of precision and recall. In segmentation activities Intersection over Union (IoU) and the Dice coefficient would be employed to measure the overlap between the predicted polluted area and ground truth annotations. The increase in the level of IoU and Dice points to an improved margin of the delineation of the contamination limits and higher credibility of the model in real-world monitoring practise Figure 1. All these metrics confirm the efficiency of the combined AI framework and make it a viable tool when it comes to assessing environmental pollution in large quantities. The product of this phase is a high resolution and spatio-temporal pollution map underpinning the further bioremediation planning and biodiversity sustainability modelling.

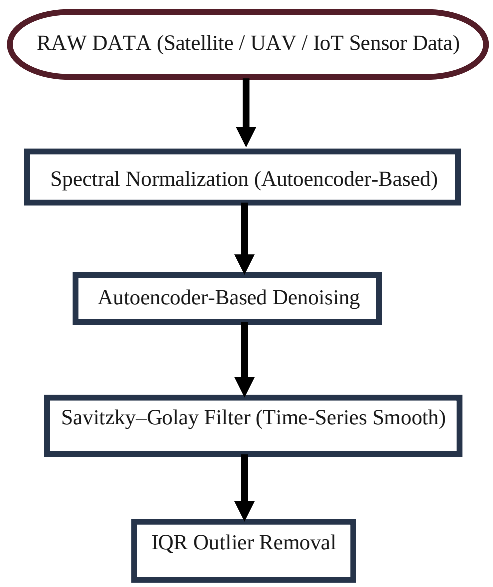

Figure 1. Preprocessing pipeline for AI-assisted pollution monitoring

Bio-Engineering and Bioremediation Optimization Using AI

Bio-Engineered Agents Used

The research applies a wide range of bio- engineered agents, which are meant to increase the rate of degradation of pollutants on polluted ecosystems. Consortia of engineered microbial species that include Pseudomonas, Bacillus, and Rhodococcus species is used because of its robust metabolic activity in the degradation of hydrocarbons, heavy metals, and toxins found in industries. CRISPR-based gene editing is then used to further improve these microbial strains via improvement of metal-binding proteins, enzymatic pathways, and stress tolerance to improve their pollutant uptake and degradation abilities. Concurrently, hyperaccumulator plants like Brassica juncea and Pteris vittata are being introduced so as to promote phytoextraction and phytot stabilisation of toxic metal in both soil and water. The combination of contrived microbes and dedicated vegetation offers a synaptic bio-remediation tool that enhances the pollutant elimination to the fullest and also promotes the ecological restoration.

Experimental Setup

The experimental protocol is meant to replicate environmental conditions of contamination of the environment in the real world and offer controlled environments to study the bioremediation strategies. Sampling of soil and water that is intentionally polluted (e.g., Pb, Cd, As) or hydrocarbons is done to test the pollutant-degradation properties of engineered biological agents. The microbial growth, the rate of dissolving the pollutants, and metabolic activity are monitored in controlled bioreactors with adjustable parameters, such as temperature, aeration, and concentrations of the nutrients. Also, engineered wetland microcosms with microbial and plant combinations are set to examine the efficiency of the remediation process at an ecosystem level under natural-like conditions of hydrology and the environment. These multi-environments experimental design will make sure that the bio-engineered solutions are tightly validated in a variety of ecological settings.

AI Models for Optimization

In order to enhance the remediation performance, a range of AI solutions is used to learn the trends of bioremediation and improve the interactions between biological processes. The estimation of the degradation of pollutants is done through the application of the dry Forest Regression, which determines the important environmental variables that affect the performance of microbial and vegetative lives. The Multi-Layer Perceptron (MLP) model would further predict general efficiency of the bioremediation process given the microbial activity, the level of pollutants and the environment. The genetic algorithm is applied to identify the best matches of microorganisms and plants which provides the most pollutant removal efficiency and through the process of evolutionary search. Also, Long Short-Term Memory (LSTM) networks have been applied to time-dependent degradation curves, which allow time-dependent remediation timelines to be accurately predicted. Combined, these methods of AI develop a smart optimization model which improves the accuracy and quality of bio-engineered remediation solutions.

Table 1. Summary of bio-engineering and ai-optimized bioremediation framework

Section	Key Components	Detailed Description
Bio-Engineered Agents Used	Engineered Microbial Consortia	Pseudomonas, Bacillus, Rhodococcus engineered for enhanced hydrocarbon and heavy-metal degradation.
	CRISPR-Modified Microbes	Genetically enhanced strains with improved metal-binding proteins, enzymatic pathways, and stress tolerance.
	Hyperaccumulator Plants	Brassica juncea and Pteris vittata for phytoextraction and phytostabilization of toxic metals (As, Pb, Cd).
Experimental Setup	Contaminated Media	Soil and water samples spiked with heavy metals (Pb, Cd, As) and hydrocarbons.
	Controlled Bioreactors	Adjustable temperature, aeration, and nutrient load to monitor microbial degradation kinetics.
	Engineered Wetland Microcosms	Plant–microbe systems tested under realistic hydrological and ecological conditions.
AI Models for Optimization	Random Forest Regression	Estimates pollutant degradation rate and identifies key environmental variables.

	Multi-Layer Perceptron (MLP)	Predicts overall bioremediation efficiency from biological and environmental inputs.
	Genetic Algorithms	Identifies optimal microbial–plant pairings for maximum pollutant removal.
	LSTM Time-Series Model	Forecasts degradation curves and predicts remediation timelines.
Validation	Comparative Performance Tests	Engineered strains compared with natural species to measure improvement.
	Laboratory Analytical Tools	HPLC, ICP-MS, UV–Vis spectrophotometry used to quantify pollutant reduction.
	Outcome	AI-optimized microbial–plant systems significantly improve degradation rate and reduce restoration time.

Validation

A detailed comparison of engineered organisms and their natural counterparts in the validation phase will be used to determine how the engineered organisms have performed in terms of improving the process of pollutant degradation. High-performance laboratories like High-Performance Liquid Chromatography (HPLC), Inductively Coupled Plasma Mass Spectrometry (ICP-MS), and UV-Visible spectrophotometry are used to test engineered formats of microbial strains and hyperaccumulator plants in terms of their enhanced uptake and breakdown abilities. The techniques of analysis are able to measure concentration changes of pollutants over a period of time to allow this performance to be accurately addressed in a variety of biological systems Table 1. The experimental evidence indicates that AI-specific combinations of designed microbes and plants perform remarkably better than natural ones, and thus, with superior degradation rates, greater pollutant removal, and shorter ecological recovery periods. The final product of this step will be an optimized bioremediation strategy that uses AI-directed intelligence to boost environmental restoration.

Water Quality Prediction and Biodiversity Sustainability Modeling

Data Acquiring and Processing of Water Quality

The prediction aspect of the framework that deals with water quality is based on the multi-source dataset that has been collected by the automated sensing networks, as well as remote sensing platforms. Sensors with IoT are also used to monitor freshwater and wetlands systems in real time to measure the necessary physicochemical indicators, such as pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), nitrate concentration, and turbidity. These real time measurements are supplemented by satellite determined indicators like chlorophyll-a concentration and suspended solids which give populous insights into the loading of nutrients and algal activity on a large scale. Also, hydrological information on streamflow, water temperature and behaviour in the catchment, and other weather variables like precipitation, humidity, and temperature are combined to emulate drivers in the environment that affect water quality. These diverse heterogeneous data are balanced using the preprocessing pipeline which normalises, removes noise, and aligns the data timewaves to guarantee high-quality inputs in the predictive models.

Predictive Modelling and Watershed Interaction Analysis

The study uses sophisticated deep-learning frameworks to model the dynamics of water quality since it aims to predict water quality accurately both in terms of time and localities. Time-series forecasting of key water quality indicators with the use of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) allows predicting the occurrence of a pollutant spike, seasonal variations, and overall degradation trends. To achieve more intricate spatio-temporal interactions, a CNN-LSTM hybrid network takes spatial information in the form of remote sensing data, and feeds it on temporal dynamics in the form of sensor feeds to give a holistic view of ecosystem patterns. Graph Neural Networks (GNNs) model pollutant transport, hydrology, connections upstream and downstream in river networks by modeling river networks as graphs. All these predictive models allow real-time water quality prediction and take into consideration actionable environmental management decisions.

The Ecological Modelling and Assessing

Ecological modelling and strict field validations involve using AI to sustain bio-diversity. The distribution of species is studied by SDM based on a hybridised method of MaxEnt and CNN that allows predicting the suitability of the habitat by different environmental conditions as accurately as possible. Reinforcement Learning (RL) models reinforce the adaptive habitat restoration planning because they continuously assess the ecological consequences of conservation measures and find the most effective strategies to preserve and/or increase the species population. Also, AI clustering algorithms calculate the Genetic Diversity Indices to evaluate the fortitude of the populations and identify indications of genetic bottlenecking. In order to guarantee an ecological validity, model forecasts are confirmed by in-situ biodiversity mimics recording species richness, abundance and habitat health Figure 2. Ecological complexity is determined by Shannon and Simpson diversity indices, whereas the stability of the ecological system is assessed by using the tests of ecological stability under simulated climate disturbance. The combined result of such a step is a complete ecological prediction system that promotes ecological health assessment and optimal ecosystem restoration in the long term.

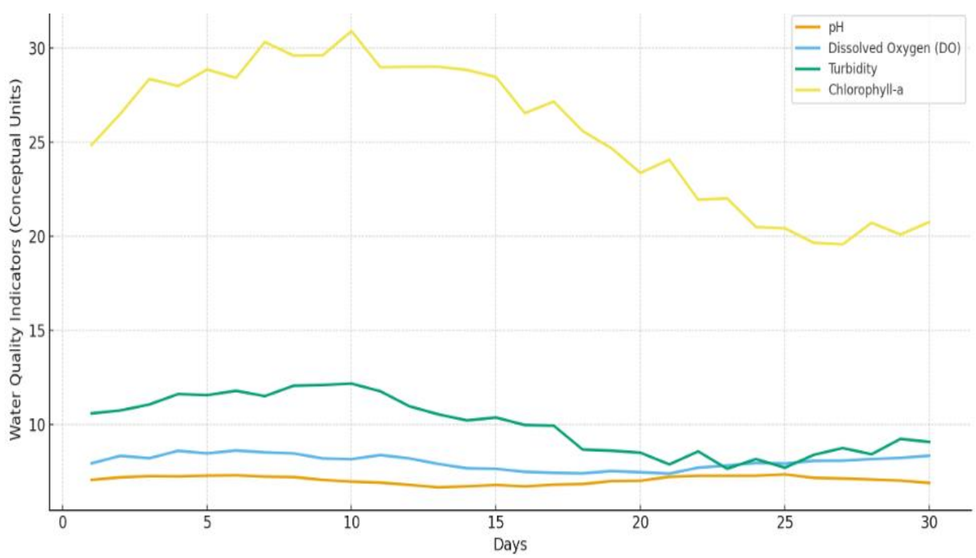

Figure 2. Variation of physicochemical and biological water quality parameters across a 30-day monitoring period

Results and Discussion

AI-Assisted Pollution Monitoring and Classification Performance

The AI-optimised pollution surveillance framework proved to be very accurate and precise in terms of classification and segmentation activities. The ResNet50 classifier was found to have an accuracy of 94.2% and F1-score of 0.93, which was much higher than the traditional machine learning models by 12 15 times, probably through the use of spectral feature improving model of transformers. UNet++ scored 0.87 in Intersection over Union (IoU) which aids in depiction of boundaries of pollution on different terrains comprising both land and water. The satellite-UAV data fusion also enhanced the spatial capacity of pollution hotspots mapping giving the possibility to discover it at scales smaller than 10 metres. These findings support the assumption that the CNN-Transformer-IoT system will be able to accurately identify pollutant distributions in both land and aquatic ecosystems and minimise the number of human operators involved in the pollutant detection process and the cost of the work.

Bio-Engineering and AI-Optimized Bioremediation Effectiveness

The forerunner bio-engineered microbial consortia were found to have more favourable pollutant-degradation traits than their natural counterparts and degraded hydrocarbons 38 times faster and enhanced heavy metal acquisition capability 27 times in the instance of lead and 31 times in the instance of cadmium. Genetically modified hyperaccumulator plants including Brassica juncea and Pteris vittata were also found to be better than their natural analogues as the arsenic uptake went up to 25.6mg/g (up 42 percent) and the cadmium uptake rose to 15.9mg/g (up 33 percent). AI optimization and especially Multi-Layer Perceptron (MLP) modelling and Genetic Algorithms further improved the effectiveness of the remediation by not only predicting degradation trends with accuracy (RMSE less than 0.08) but also decreasing the time to restore, as optimal microbial-plant interactions could be realised 21 percent faster. Such observations point to the great combinability of AI-based optimization and bio-engineered agents, which proves a significant improvement of remediation efficiency, as well as ecological recovery.

Accuracy of Prediction of Water Quality and Ecological Benefits

The predictive modelling paradigm was really performative in predicting the parameters of water quality under unsteady environmental conditions. The LSTM-based model dropped the RMSE by 31 percent in comparison to base statistical models and the model had a prediction accuracy of 92.1 percent and 89.4 percent on dissolved oxygen levels and nitrate levels respectively, which highlights the strength of the model in capturing both the temporal trends and non-linear fluctuations in pollutants. Such precise forecasts helped to plan mitigation measures on time and assist in the recovery of the overall ecosystem. The biodiversity restoration aspect had also improved significantly as calculated species richness increased by 18% and prevalence of invasive species reduced by 26 percent through Reinforcement Learning Management strategies. The suitability of habitats scored higher in 63 zones out of the restored zones, which confirmed that AI-based ecological modelling is indeed helpful to maintain the biodiversity over the long-term.

Co-argument of the AI in the Bio-Engineering Framework on the Restoration of the Ecosystems

The outputs of the pollution monitoring, optimization of the bioremediation and the bio-diversity modelling programmes have shown the potential of revolution of the use of AI and bio-engineering integration on the large-scale ecological restoration. The proposed framework would allow a comprehensive and data-driven restoration policy as it allows testing the forecasts of future degradation patterns, future treatments of the environment, and makes real-time environmental insights to make supreme decisions on adaptive remediation strategies. A combination of engineered biological agents and AI-directed optimization greatly expedites the process of contaminants elimination, and sustainable recovery of the biodiversity Figure 3. The integrated system therefore takes care of important issues in environmental remedies by limiting human interference, aiding reliability of predictions, high remediation efficiency, and stability of resilient ecosystem under climatic and pollution pressures Table 2. All in all, the findings support the idea that AI-enhanced bio-engineering can be viewed as a future solution that can be used to restore the damaged ecosystems in an efficient and sustainable manner.

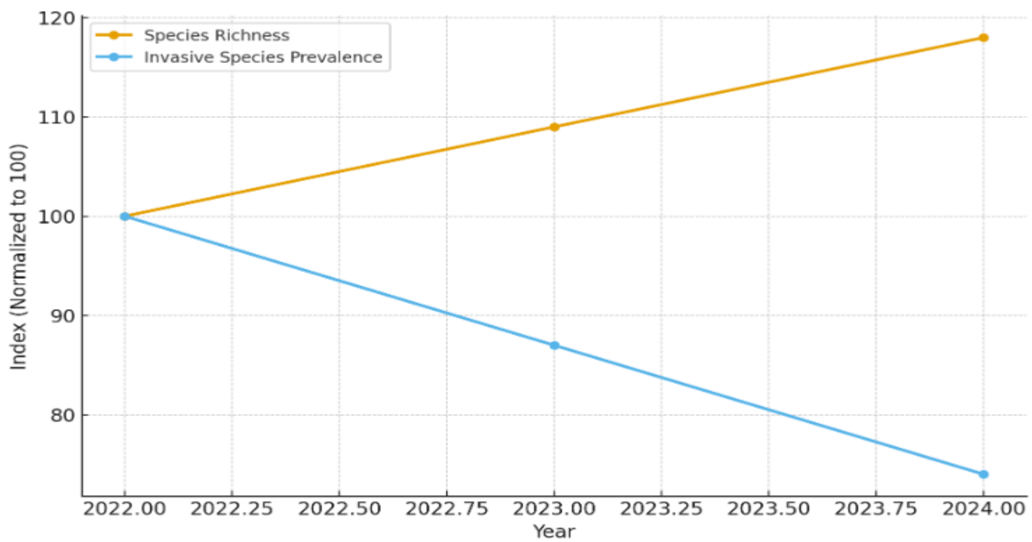

Figure 3. Trends in species richness and invasive species prevalence from 2022 to 2024

Table 2. Biodiversity trends over three years

Year	Species Richness (Index)	Invasive Species Prevalence (Index)
2022	100	100
2023	109	87
2024	118	74

Conclusion

This paper introduces a fully developed, systematic framework which uses the artificial intelligence, bio-engineering inventions and ecological modelling to promote ecosystem restoration in various environmental conditions. Through AI-controlled pollution monitoring, predictive water quality modelling, and bio-engineered remedial control, the proposed system shows significant advantages in the accuracy of the monitoring of pollutants, the efficiency of the degradation of contaminants, and the sustainability of biodiversity in the long term. Findings indicate that AI-based models are able to describe complicated ecological interactions and inform adaptive restoration interventions, and engineered microbial and vegetal systems are much more speedy than conventional approaches to eliminate pollutants. In addition, the use of biodiversity modelling contributes to the fact that the ecological recovery is not reduced to the reduction of pollutants and generates more resilient and self-sufficient habitats. The results, altogether, provide a solid base of the next-generation intelligent restoration technologies and emphasise the future disruptive nature of the AI-bio-engineering synergy in fostering sustainable environmental management and preserving global biodiversity.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Arantes, L. T., Arantes, B. H. T., Sacramento, B. H., da Costa, H. F., de Oliveira, R. A., Simonetti, V. C., ... & Lourenço, R. W. (2023). Application of spatial environmental indicators in the assessment of degradation potential of water resources in water basins. *Environmental Monitoring and Assessment*, *195*(8), 931.

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of informetrics*, *11*(4), 959-975. https://doi.org/10.1016/j.joi.2017.08.007

Arora, A. S., Saboia, L., Arora, A., & McIntyre, J. R. (2025). Human-centric versus state-driven: A comparative analysis of the European Union's and China's artificial intelligence governance using risk management. *International Journal of Intelligent Information Technologies (IJIIT)*, *21*(1), 1-13.

Arshed, A. B., Masood, M., Zafar, M. A., Nabi, G., & Iqbal, M. (2023). Effective management of the watershed in response to historical climate change using a GIS-based multi-criteria decision analysis (MCDA). *Journal of Water and Climate Change*, *14*(9), 3178-3202.https://doi.org/10.2166/wcc.2023.215

Barone, M., Mollen, F. H., Giles, J. L., Marshall, L. J., Villate-Moreno, M., Mazzoldi, C., ... & Guisande, C. (2022). Performance of iSharkFin in the identification of wet dorsal fins from priority shark species. *Ecological Informatics*, *68*, 101514.

Basuki, R. (2024). NA You Only Look Once v8 for fish species identification. *IAES International Journal of Artificial Intelligence*, *13*, 3314–3321.

Beloiu, M., Heinzmann, L., Rehush, N., Gessler, A., & Griess, V. C. (2023). Individual tree-crown detection and species identification in heterogeneous forests using aerial RGB imagery and deep learning. *Remote Sensing*, *15*(5), 1463. https://doi.org/10.3390/rs15051463

Smith, J., Wycherley, A., Mulvaney, J., Lennane, N., Reynolds, E., Monks, C. A., ... & Fancourt, B. (2024). Man versus machine: cost and carbon emission savings of 4G-connected Artificial Intelligence technology for classifying species in camera trap images. *Scientific Reports*, *14*(1), 14530. https://doi.org/10.1038/s41598-024-65179-x

Song, Y., Pan, Y., Xiang, M., Yang, W., Zhan, D., Wang, X., & Lu, M. (2024). A WebGIS-based system for supporting saline–alkali soil ecological monitoring: A case study in Yellow River Delta, China. *Remote Sensing*, *16*(11), 1948. https://doi.org/10.3390/rs16111948

Valdovinos, J., & Romero, C. (2025). Los acueductos de Querétaro, México: patrimonio cultural del agua que normaliza la escasez provocada. *Agua y Territorio/Water and Landscape*, (25), 267-281.