A Study on Artificial Intelligence Applications in Environmental Pollution Monitoring and Control

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ABSTRACT

This study explores the use of artificial intelligence (AI) technologies in the field of environmental pollution monitoring and control. It offers a systematic discussion of the limitations of the existing monitoring approaches against the background of rising environmental pollution around the world, and the techniques behind deep learning and reinforcement learning in terms of monitoring, prediction, anomaly detection, pollution source tracking, and intelligent control. In addition, it offers insights into the development trends of multiple data source fusion technology, model generalization, and interpretability of AI applications in governance decision-making and ecology restoration. It is revealed that the introduction of AI greatly improves the timeliness of environmental monitoring and scientific, economical decision-making in governance solutions, thus paving the way for preventive governance. However, some limitations such as insufficient cross-region generalization ability, data leakage, and ethical bias still exist. Future studies should focus more on the combination of physics-based information neural network and digital twin as well as improving the mechanism of ethical evaluation.

Keywords: Artificial Intelligence, Environmental Pollution Monitoring and Control, Deep Learning and Reinforcement Learning, Multi-Source Data Fusion, Explainable Artificial Intelligence.

1. INTRODUCTION

1.1 Research Background and Significance

The environmental pollution problem constitutes an enormous threat to the sustainable development of human society. Against the backdrop of intensified economic activities characterized by rapid industrialization and urbanization, cases of PM2.5 exceedance, heavy metal contamination of natural water bodies, and persistent organic pollutants (POPs) contamination have been growing at an alarming rate. Millions of lives were lost prematurely, billions of dollars worth of economic loss occurred, and damage was inflicted on the environment. In conventional environmental pollution detection methods, field sampling and laboratory testing are carried out, but such approaches suffer from inherent limitations, such as limited coverage in both time and space, delayed transmission of collected data, and poor predictive capabilities, restricting their performance in precise environmental governance. On the other hand, through deep learning, reinforcement learning, and multi-source data fusion technology, artificial intelligence techniques are capable of leveraging satellite remote sensing data, Internet of Things sensors, and monitoring big data to conduct pollutant concentration inversion and diffusion simulation as well as anomaly early warning, leading to an appreciable increase in monitoring precision and speed [1]. Regarding governance, digital twin and optimization algorithms can simulate the pollution scenario, dynamically adjust emission reduction measures and remediation schemes, reduce the cost, and provide scientific decision-making support. The study will be conducted under the background of climate change, the implementation of “Dual Carbon” goals, and ecological civilization construction. It has important theoretical and practical value [2]. First, it provides data-driven decision-making tools for environmental pollution control departments, helping shift from passive emergency response to proactive prevention. Second, it helps decrease the expenditure on public health treatment and ecological restoration. Third, interdisciplinary integration is promoted, generating valuable insights into global environmental governance through the exploration of replicable Chinese solutions. Therefore, comprehensive and systematic research into its application has significant strategic importance in realizing a modern human-nature harmonious society.

1.2 Current Status of Research at Home and Abroad

Foreign research started earlier and has yielded fruitful results. In the field of air pollution monitoring, scholars have systematically reviewed the application of machine learning and deep learning in spatiotemporal prediction, emphasizing the advantages of hybrid models in handling nonlinear features and data sparsity problems [1]. American and European teams proposed a hybrid CNN-LSTM architecture, combined with feature engineering to achieve short-term air quality index prediction, with an F1-score of 91%, and assessed its potential impact on health [3]. In terms of water pollution control, reinforcement learning controllers have been used for electrochemical desalination and wastewater treatment process optimization, maintaining effluent quality and reducing energy consumption by more than 15% under dynamic conditions [4]. Digital twin technology combined with artificial intelligence has been applied to urban pollution diffusion simulation and intelligent decision support systems. Domestic research has developed rapidly in recent years, focusing on the application of artificial intelligence in water pollution control, exploring the integration of adaptive optimization control and real-time monitoring, and effectively solving the problems of low accuracy and high cost of traditional methods [5]. Researchers in China used a multi-mode fusion model in smart cities and watershed management to help accurately identify the source of the problem and make appropriate responses. However, there are still common problems in the research at home and abroad, such as the unclear model, poor performance in different places and ethical risks. In essence, artificial intelligence is changing from an auxiliary tool to a main governance mode, and it will need more cooperation with other disciplines and verification through experiments in the future.

2. APPLICATION OF ARTIFICIAL INTELLIGENCE IN POLLUTION MONITORING AND CONTROL

2.1 Monitoring, Prediction, and Anomaly Identification

Prediction and anomaly identification in environmental pollution monitoring are important technical links to realize early warning. Traditional methods use fixed critical values or simple statistical models, and it is difficult for them to capture the nonlinear fluctuations and sudden anomalies of pollutant concentration in time and space. Deep learning time series models, especially the MCN-LSTM architecture, can accurately process multivariate sensor network data through the fusion of multi-channel convolution and long short-term memory networks, and realize real-time detection and dynamic prediction of water quality and air pollution anomalies (Figure 1) [6]. Empirical studies have shown that the accuracy of this model is significantly better than traditional algorithms such as isolated forest in complex industrial and urban scenarios, and the false alarm rate is reduced by more than 30%, which wins valuable response time for emergency management. At the same time, the prediction framework, combined with historical monitoring and meteorological data, can predict pollution peak events several hours to several days in advance, and support the construction of a graded early warning mechanism. Similar applications in the field of air pollution show that the autoencoder and LSTM integrated system performs outstandingly in identifying fine particulate matter anomaly patterns, effectively improving the intelligence level of the monitoring network [7]. These technologies promote the transformation of environmental monitoring from passive data collection to active intelligent early warning, provide accurate data foundation for pollution control, and have important engineering application value.

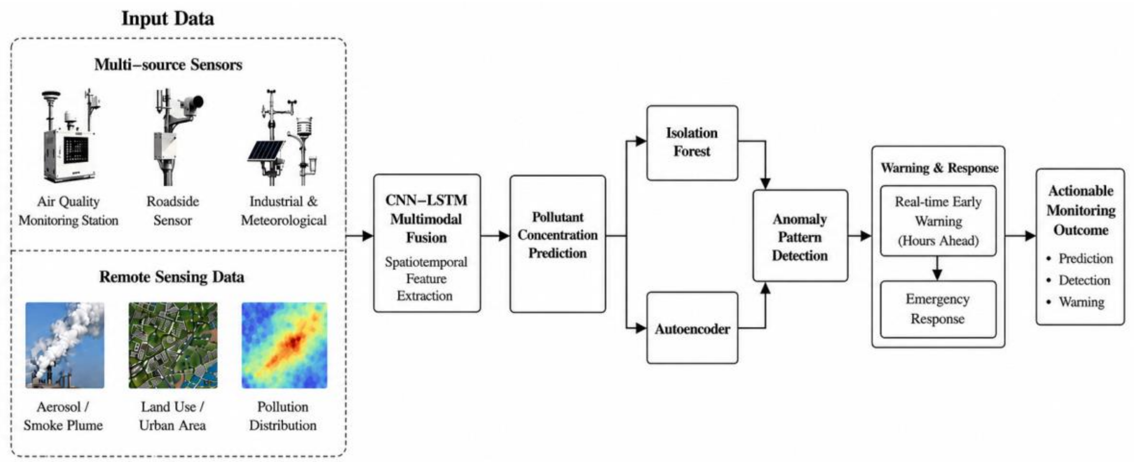

Figure 1. Deep learning-driven pollution concentration prediction and anomaly identification process.

2.2 Pollution Source Tracing and Intelligent Control

Accurate source tracing and intelligent control of pollution sources are the core challenges of environmental governance. Traditional inversion methods are computationally inefficient and greatly affected by data uncertainty. However, source tracing models based on deep learning can quickly identify industrial emissions and non-point source contributions by integrating remote sensing and ground monitoring data. The water quality early warning and pollution source tracing system constructed in this study successfully identified major polluting industries in a semi-arid watershed using deep learning technology and predicted water quality change trends in advance, with a source tracing accuracy of over 90% [8]. In the field of air pollution, the hybrid deep learning and fuzzy entropy method combined with remote sensing data can achieve classification and tracking of PM2.5 and PM10 pollution sources with a classification accuracy of 97.56%, which is significantly better than a single CNN or LSTM model [9]. In terms of intelligent control, the machine learning classifier was trained on a multi-dimensional pollutant dataset in the case of South Korea to achieve real-time tracking of emission sources and optimization of dynamic control strategies.

2.3 Governance Decisions and Remediation Optimization

The application of artificial intelligence in pollution control decision-making and remediation optimization has significantly improved the scientific and economic efficiency of the scheme. Traditional optimization methods are difficult to handle multi-objective conflicts and dynamic uncertainties, while reinforcement learning and multi-objective optimization algorithms can simulate complex environmental feedback and dynamically adjust remediation parameters. Research on the optimization of bioremediation strategies for river pollution shows that the artificial intelligence-driven framework adjusts the treatment intensity in real time through reinforcement learning, improving the remediation efficiency to 89.7% while ensuring ecological safety and reducing resource consumption [10]. The unified artificial intelligence framework integrates graph neural networks, generative adversarial networks and physical information neural networks, embeds pollutant transport equations, realizes virtual simulation of pollution scenarios and solves the optimal intervention strategy, and achieves a prediction accuracy of 89% in synthetic verification [11]. The decision support system combining digital twins and reinforcement learning can evaluate remediation costs and environmental benefits in multiple scenarios and support the government in formulating differentiated policies. These technologies promote the transformation of governance from experience-driven to data intelligence-driven, provide quantifiable and iterative optimization paths for large-scale ecological restoration projects, and have broad prospects for promotion.

3. TECHNOLOGICAL PATHS AND CHALLENGES OF ARTIFICIAL INTELLIGENCE APPLICATIONS

The overall technical framework for artificial intelligence in environmental pollution monitoring and control consists of an input layer, a core layer, an application layer, and an output layer (as shown in Figure 2). The input layer obtains information from multiple sensors, satellite images, Internet of Things data and traffic and weather information; Through deep learning (CNN-LSTM multimodal fusion) and reinforcement learning (multi-agent dynamic control), the central layer can predict, find the source and improve things. Then, the application layer detects the problem in real time, accurately controls the pollution source, and makes the repair decision. Finally, the output layer creates an intelligent alarm strategy and sends it back to the digital twin simulation system. Explanatory artificial intelligence and moral rules are everywhere in the whole process.

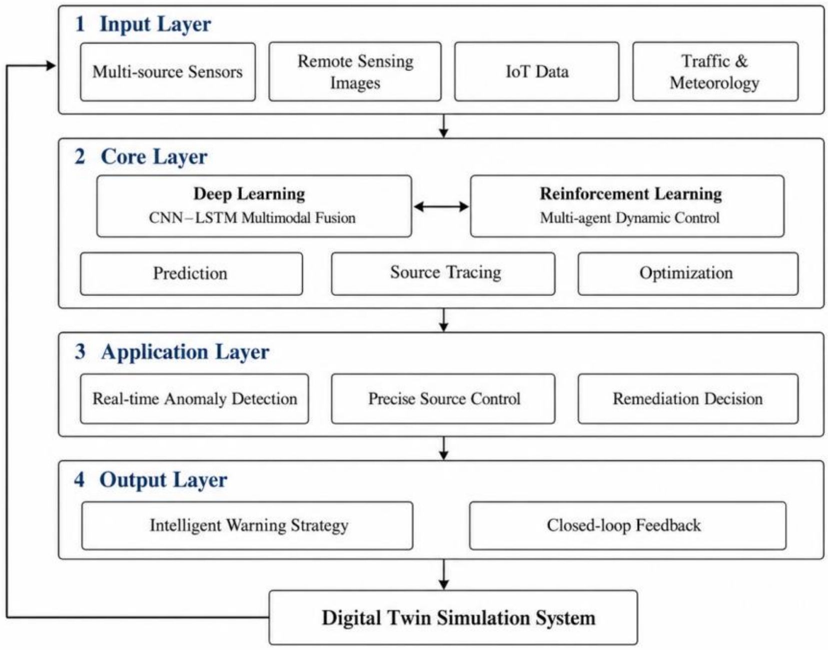

Figure 2. Technical framework of artificial intelligence in environmental pollution monitoring and control.

3.1 Deep Learning and Reinforcement Learning Methods

Deep learning and reinforcement learning are the main technical ways to control environmental pollution by using artificial intelligence. Deep learning models such as convolutional neural network and short-term memory network can obtain temporal and spatial information from multidimensional pollution data to make very accurate concentration prediction and identify patterns. In order to control, multi-agent reinforcement learning framework can adjust pollution load in real time by coordinating drainage system, sewage treatment plant and river, which can greatly improve urban water quality [12]. The research shows that this method is better than the traditional PID control strategy when there are complex pollution flows and loads, and it can use less energy while meeting the standards. Deep reinforcement learning is also used to reduce the pollution of smart cities. Through pointer network and multi-objective optimization, we changed our actions to improve the adaptability of the system [13]. These methods regard the environment as a markov decision processes, allow agents to learn the best strategy through simulation and actual feedback, change from fixed planning to self-improvement closed control, and provide a method that can be extended to control large-scale pollution.

3.2 Multi-source data fusion and model generalization

Multi-source data fusion and model generalization ability are important challenges and ways to improve the robustness of artificial intelligence application in the environment. It is difficult for single-mode data to fully describe pollution dynamics, while multi-mode fusion network integrates ground sensors, remote sensing images, traffic density and weather parameters to build a separation framework sharing specific modes, so as to obtain accurate short-, medium-and long-term air quality index predictions [14]. The framework uses the convolution module of hierarchical attention map to effectively separate the spatial-temporal characteristics of shared space and modal-specific information, and it can well predict the PM emission of urban construction sites. In order to solve the problem of cross-regional generalization, we introduce transfer learning and domain adaptation technology into environmental model training. By finely adjusting the pre-training weights, the data requirements of new scenes are reduced, and the model transmission performance under different climate and pollution sources is improved [15].

3.3 Explainability and Ethical Issues

Explanatory and ethical issues are the main obstacles to introducing AI into the environment. Very accurate black box models can make good predictions, but their decisions are not clear and it is difficult to gain the trust of the authorities and the public. The interpretable AI framework constructs an environmental management interpretation mechanism with three parts: input, model and output (Figure 3). Through feature importance analysis and counterfactual reasoning, it shows how key variables can help predict pollution and reduce emissions [16]. A systematic review pointed out that the method of XAI in water quality monitoring must balance accuracy and interpretability, and use causal inference and marginal calculation to gain more confidence [17]. At the ethical level, issues such as data privacy leakage, algorithmic bias, and attribution of responsibility are particularly prominent, especially when it comes to public health decisions, which may amplify regional inequalities. Studies emphasize the need to establish ethical review mechanisms and human oversight in the environment to ensure that AI-assisted governance complies with the principles of fairness, transparency, and sustainability. These challenges require the coordinated advancement of technology research and development and policy formulation to provide normative guidance for the application of responsible AI in the environmental field.

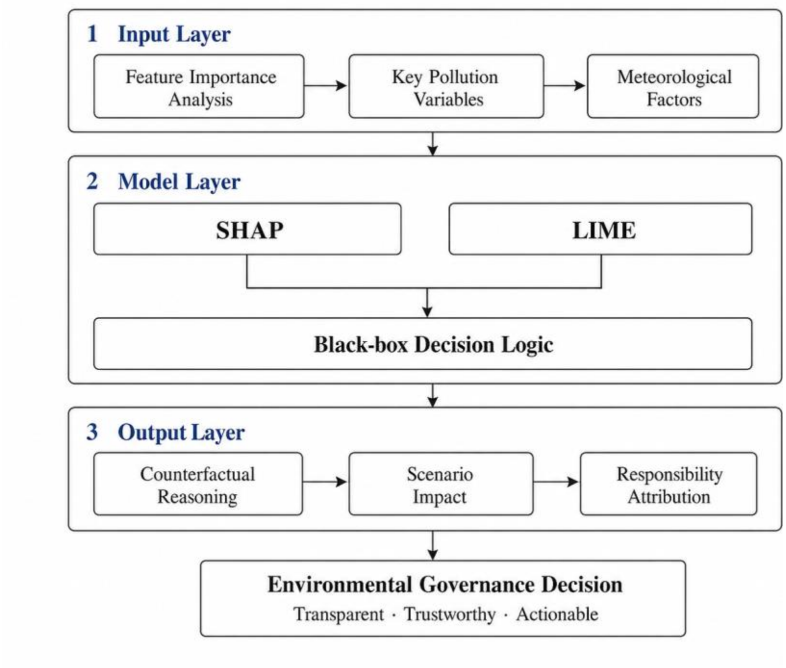

Figure 3. Explanatory mechanism of input-model-output for artificial intelligence in environmental governance decision-making.

There are three levels of input-model-output explanation mechanism of explanatory AI for environmental governance decision-making. The input layer identifies key pollution variables and weather factors through the importance analysis of features; The model layer uses SHAP and LIME technology to reveal the black box decision logic; The output layer uses reverse reasoning to show the impact of emission reduction schemes and responsibility allocation, and finally forms transparent, credible and operable environmental governance decisions.

4. CONCLUSION

The research on monitoring and controlling environmental pollution by using artificial intelligence systematically studies important technologies such as deep learning, reinforcement learning and multi-mode integration. They have performed well in predicting air quality, finding anomalies in water, finding pollution sources and improving ecological restoration. With the help of multi-agent reinforcement learning and sharing specific modes to split the network, the monitoring has changed from simple registration to active alarm. This enables governance decisions to be improved on their own and at a lower cost. Interpretable artificial intelligence framework helps to better understand the model and build public trust, thus providing scientific support for the management environment. However, there are still problems: the model does not work in all regions, and there is a risk of privacy data and algorithm bias. In the future, we should better integrate physical information neural networks and digital twins, establish ethical rules and mechanisms for cooperation between human beings and the environment, help artificial intelligence and policy tools to better combine, achieve carbon balance and carbon neutrality, and build a beautiful China.

REFERENCES

[1] Agbehadji, IE, et al.: Systematic Review of Machine Learning and Deep Learning Techniques for Spatiotemporal Air Quality Prediction. Atmosphere, 15(11), 1352(2024).

[2] Madan, T., et al.: Hybrid deep learning model for air quality prediction and its impact on healthcare. Scientific Reports, 16(1), (2026).

[3] Campana, P., et al.: Artificial Intelligence and Digital Twins for Sustainable Development. Applied Sciences, 15(11), 6337(2025).

[4] Qiu, Z., et al.: Machine learning-driven advances in water treatment. Journal of Environmental Chemical Engineering, (2025).

[5] Wei, XS, Gao, HJ, Chen, YH, Chang, M.: Research progress of artificial intelligence technology in water pollution control. Journal of Environmental Engineering Technology, (2022).

[6] El-Shafeiy, E., et al.: Real-Time Anomaly Detection for Water Quality Sensor Networks Using MCN-LSTM. Sensors, 23(20), 8613(2023).

[7] Wang, J., et al.: Identification of pollution source and prediction of water quality based on deep learning techniques. Journal of Contaminant Hydrology, 261, 104287(2024).

[8] Choi, Y., et al.: Utilizing Machine Learning-based Classification Models for Tracking Air Pollution Sources: A Case Study in Korea. Aerosol and Air Quality Research, (2024).

[9] Murugesan, S., et al.: Air pollution source identification based on remote sensing and ground-level measurements with an optimized hybrid deep learning and fuzzy entropy approach. International Journal of Remote Sensing, (2026).

[10] Rabbi, MF, et al.: Unified artificial intelligence framework for modeling environmental pollution dynamics and remediation optimization. Scientific Reports, (2025).

[11] Blessing, AA, et al.: AI-driven optimization of bioremediation strategies for river pollution control. Environmental Science and Pollution Research, (2025).

[12] Huang, Z., et al.: Pollution-based integrated real-time control for urban drainage systems: a multi-agent deep reinforcement learning approach. npj Clean Water, (2025).

[13] Rajesh, K., et al.: Multi-Objective Optimization of Pollution Mitigation Booth Using Reinforcement Learning in Smart City. IEEE, (2025).

[14] Hameed, S., et al.: Deep learning based multimodal urban air quality prediction and traffic analytics. Scientific Reports, (2023).

[15] Chen, X., et al.: A multimodal feature fusion network based on shared-specific modal feature decoupling for air-quality prediction. Science of the Total Environment, (2025).

[16] Arashpour, M., et al.: AI explainability framework for environmental management: input, model and output perspectives. Journal of Environmental Management, (2023).

[17] Aderemi, IA, et al.: Explainable AI for Water Quality Monitoring: A Systematic Review of Transparency, Interpretability and Trust. IEEE, (2025).