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ARTIFICIAL INTELLIGENCE FOR POLLUTION CONTROL: A REVIEW OF TECHNIQUES, APPLICATIONS, AND FUTURE DIRECTIONS

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ABSTRACT

Environmental pollution remains one of the most pressing global challenges leading to irreparable ecosystem degradation. Traditional pollution monitoring and control methods, are often constrained by high operational costs, limited spatial and temporal coverage, and delayed response times. Artificial Intelligence (AI) has emerged as a transformative tool capable of addressing many of these limitations through predictive modelling, real-time monitoring, automated detection, and intelligent control systems. This paper presents a structured review of AI applications across major pollution domains, namely air, water, industrial, and waste management, and examines the underlying techniques that enable these applications. It focusses on technology advancements such as machine learning, deep learning, computer vision, and the Internet of Things (IoT) and role of each in pollution control. The paper also critically evaluates the key challenges hindering widespread adoption, such as data scarcity, model interpretability, infrastructure costs, federated learning, and regulatory integration. Finally, it outlines emerging directions including explainable AI, and digital twin frameworks that could shape the next generation of AI-driven environmental management systems. The paper concludes that while AI offers substantial opportunities to enhance pollution control efficiency and responsiveness, its successful deployment depends

on addressing technical, economic, and policy-level barriers in parallel for ensuring the sustainability of our planet.

KEYWORDS: Artificial Intelligence, Pollution Control, Machine Learning, Environmental Monitoring, Air Quality, Water Quality, Smart Cities.

1. INTRODUCTION

Pollution, in its various forms, continues to pose one of the greatest threats to human health and environmental sustainability. Ambient and household air pollution together are linked to several million premature deaths every year (World Health Organization, 2023), while water contamination affects the health and livelihoods of billions of people, particularly in low- and middle-income countries (United Nations Environment Programme, 2022). Industrial effluents, vehicular emissions, agricultural runoff, and improper waste disposal compound these problems, placing enormous pressure on both natural ecosystems and public health infrastructure.

Historically, pollution control has relied on regulatory frameworks, periodic manual sampling, fixed-location sensor networks, and reactive enforcement mechanisms. While these approaches have achieved measurable success in specific contexts, they suffer from several structural limitations. Manual monitoring is labour-intensive and cannot scale to cover large or remote geographic areas. Fixed sensor networks, although automated, are expensive to deploy densely and often provide only localized snapshots rather than continuous, city-wide or region-wide pictures. Furthermore, traditional statistical models used for pollution forecasting often struggle to capture the highly non-linear, multi-variable, and spatiotemporal nature of pollution dynamics (Karmoude et al., 2025; Méndez et al., 2023).

The rapid advancement of Artificial Intelligence, particularly machine learning and deep learning, has opened new possibilities for overcoming these limitations. AI systems can process vast, heterogeneous datasets from sensors, satellites, and administrative records to identify complex patterns that are difficult for humans or classical statistical models to detect (Karmoude et al., 2025). They can forecast pollution levels with greater accuracy, identify pollution sources through pattern recognition, optimize industrial and municipal processes to reduce emissions, and even automate physical tasks such as waste sorting through computer vision (Chu et al., 2018; Fotovvatikhah et al., 2025).

This paper aims to provide a comprehensive yet concise review of how AI is currently being applied to pollution control, the opportunities this creates, the challenges that remain, and the

directions in which the field is likely to evolve. The core AI techniques relevant to pollution control are elaborated. A discussion on applications across air, water, industrial, and waste pollution domains form the core of the paper linking the major AI techniques with their applications. A critical examination of the challenges associated with AI adoption in this domain is carried out along with an exploration of emerging and future research directions. The paper concludes that technological advancements may support the cause but sustained pollution control and management require the coordinated efforts of all.

2. Review of Literature

The different AI Techniques that are relevant to pollution control were reported and are discussed in the following paragraphs.

2.1 Machine Learning

Classical machine learning algorithms such as Random Forests, Support Vector Machines, and Gradient Boosting methods (e.g., XGBoost) are widely used for pollution prediction tasks due to their ability to handle structured, tabular data with relatively modest computational requirements (Karmoude et al., 2025; Ravindiran et al., 2023). These models are particularly popular in air and water quality prediction studies where input features include meteorological variables, historical pollutant concentrations, and geographic attributes (Ballesteros Peinado et al., 2025; Wang et al., 2023).

2.2 Deep Learning

Deep learning architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and hybrid CNN-LSTM models, have become increasingly popular for pollution forecasting because of their capacity to model both spatial and temporal dependencies (Helaly et al., 2025; Méndez et al., 2023). LSTMs, in particular, are well suited to time-series pollution data, capturing long-term dependencies such as seasonal or diurnal pollution cycles (Wang et al., 2023).

2.3 Computer Vision

Computer vision techniques, often built on CNN architectures, enable automated visual recognition tasks such as waste classification (Chu et al., 2018; Fotovatikhah et al., 2025), illegal dumping detection, and satellite image analysis for identifying industrial pollution sources or deforestation linked to environmental degradation (Vaughan et al., 2024; Zhao et al., 2026).

2.4 Internet of Things (IoT) Integration

AI models are frequently paired with IoT sensor networks that provide continuous, real-time data streams (Essamlali et al., 2024). This combination enables dynamic, low-cost monitoring systems, particularly valuable in urban air quality monitoring and industrial emission tracking, where low-cost sensors are calibrated and corrected using machine learning models trained against reference-grade instruments (Nan et al., 2025; Taştan, 2025).

2.5 Reinforcement Learning

Reinforcement learning (RL) is increasingly applied to control problems where an agent learns optimal actions through interaction with an environment (Michailidis et al., 2025). In pollution control, RL has been explored for adaptive traffic signal control to reduce vehicular emissions (Shang et al., 2025; Tang et al., 2023) and for optimizing operational parameters in wastewater treatment plants to balance treatment efficacy with energy consumption (Li et al., 2026; Nagpal et al., 2024).

A summary of the above techniques is presented in Table 1.

Table 1. AI Techniques Relevant to Pollution Control.

Sl. No.	Technique	Key Methods / Models	Main Applications in Pollution Control	Why It's Used / Key Strengths
1	Machine Learning	Random Forest, Support Vector Machines, Gradient Boosting (e.g., XGBoost)	Air and water quality prediction using meteorological variables, historical pollutant levels, and geographic attributes	Handles structured/tabular data well; modest computational requirements
2	Deep Learning	CNNs, LSTMs, hybrid CNN-LSTM	Pollution forecasting, especially time-series data (e.g., seasonal and diurnal pollution cycles)	Models both spatial and temporal dependencies; LSTMs capture long-term dependencies
3	Computer Vision	CNN-based architectures	Waste classification, illegal dumping detection, satellite image analysis for industrial pollution sources and deforestation	Automated visual recognition of environmental threats
4	IoT Integration	AI/ML models paired with sensor networks	Urban air quality monitoring, industrial emission tracking; calibration of low-cost sensors against reference-grade	Provides continuous, real-time data; enables dynamic, low-cost monitoring

			instruments	
5	Reinforcement Learning (RL)	Agent-based learning through environment interaction	Adaptive traffic signal control to reduce vehicle emissions; optimizing wastewater treatment plant parameters	Learns optimal actions for control problems; balances treatment efficacy with energy consumption

3. Objectives

The primary aim of this paper is to provide a structured, critical review of the role of Artificial Intelligence (AI) in pollution control. To achieve this aim, the study pursues the following specific objectives:

1. To examine the core AI techniques, namely machine learning, deep learning, computer vision, Internet of Things (IoT) integration, and reinforcement learning, that underpin current pollution monitoring and control applications.
2. To review the application of these techniques across the major pollution domains of air, water, industrial emissions, waste management, and urban traffic.
3. To identify the opportunities that AI creates for improving the accuracy, coverage, timeliness, and cost-effectiveness of pollution control compared with conventional approaches.
4. To critically analyse the technical, economic, ethical, and policy-level challenges that hinder the widespread adoption of AI in environmental management.
5. To highlight emerging research directions, including explainable AI, federated learning, and digital twin frameworks, that may shape the next generation of AI-driven pollution control systems.

4. Research Methodology

This study adopts a structured narrative review design. The methodology was intended to ensure that the literature considered is relevant, current, and representative of the major pollution domains and AI techniques discussed in this paper.

4.1 Literature Search Strategy

Relevant literature was identified through searches of major scholarly databases and indexing services, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar, supplemented by reports from international organisations such as the World Health Organization and the United Nations Environment Programme. Searches combined keywords related to AI (e.g., "artificial intelligence", "machine learning", "deep learning", "computer

vision", "reinforcement learning", "federated learning", "digital twin") with keywords related to pollution control (e.g., "air quality", "water quality", "industrial emissions", "waste management", "pollution monitoring", "smart cities").

4.2 Inclusion and Exclusion Criteria

Studies were included if they (a) were peer-reviewed journal articles, conference papers, or authoritative institutional reports; (b) applied or evaluated AI techniques in a pollution monitoring, prediction, or control context; (c) were published in English; and (d) were published predominantly between 2018 and 2026 to reflect recent technological advances, with earlier foundational works retained where necessary. Studies were excluded if they were not accessible in full text, did not provide sufficient methodological detail, or addressed AI applications unrelated to pollution control.

4.3 Screening and Selection

Retrieved records were screened in stages. Titles and abstracts were first assessed for relevance, and the full texts of shortlisted articles were then examined against the inclusion and exclusion criteria. Duplicate records were removed, and the final set of studies was retained for analysis and synthesis.

4.4 Data Extraction and Synthesis

From each selected study, information was extracted on the pollution domain addressed, the AI technique employed, the data sources used, the reported performance or outcomes, and the limitations identified. A qualitative synthesis was adopted rather than a statistical meta-analysis, because the included studies differ widely in datasets, evaluation metrics, and geographic context.

5. ANALYSIS AND DISCUSSION

On the basis of review of techniques being employed to facilitate pollution control, and the emerging technologies, the following applications and opportunities emerged.

5.1 Air Pollution Monitoring and Forecasting

Air pollution is perhaps the most extensively studied domain for AI application, given the availability of relatively standardized datasets (e.g., PM_{2.5}, PM₁₀, NO₂, SO₂, CO, and ozone concentrations) from government monitoring stations worldwide (Ballesteros Peinado et al., 2025; Méndez et al., 2023). Machine learning and deep learning models have demonstrated strong performance in forecasting short-term and medium-term air quality levels, often outperforming traditional statistical and chemical transport models in accuracy,

particularly for highly localized or rapidly changing conditions such as smog episodes (Ballesteros Peinado et al., 2025; Ravindiran et al., 2023).

Beyond forecasting, AI is used for source apportionment, that is, identifying which sources (vehicular, industrial, agricultural burning, etc.) contribute most to observed pollution levels. Satellite imagery combined with AI-based image analysis has enabled researchers to detect industrial emission hotspots and monitor compliance at scale, even in regions with limited ground-based monitoring infrastructure (Vaughan et al., 2024; Zhao et al., 2026).

AI-driven early warning systems are also gaining traction, particularly in cities prone to seasonal smog or haze events. These systems combine forecasting models with automated alert mechanisms, enabling authorities to implement temporary measures such as traffic restrictions or industrial slowdowns before pollution levels become hazardous (Karmoude et al., 2025; Ravindiran et al., 2023).

A further opportunity lies in the calibration and densification of low-cost air quality sensor networks. Reference-grade air quality monitoring stations are expensive to install and maintain, which limits their spatial density, particularly in developing cities. Low-cost sensors offer a cheaper alternative but typically suffer from drift, cross-sensitivity to humidity and temperature, and reduced accuracy over time (Nan et al., 2025; Taştan, 2025). Machine learning calibration models, trained by co-locating low-cost sensors alongside reference-grade instruments, have been shown to substantially improve the reliability of low-cost sensor readings using algorithms such as Gradient Boosting and k-Nearest Neighbors (Taştan, 2025), enabling denser and more granular monitoring networks at a fraction of the cost of conventional infrastructure. This has particular significance for environmental justice, as it allows monitoring coverage to be extended into under-resourced neighbourhoods that are frequently excluded from official monitoring networks despite often bearing disproportionate pollution burdens.

5.2 Water Pollution Monitoring and Management

In the water domain, AI models are applied to detect contamination from heavy metals, pathogens, and industrial effluents, often using data from in-situ sensors measuring parameters such as turbidity, pH, dissolved oxygen, and conductivity as proxies for broader contamination (Essamlali et al., 2024; Helaly et al., 2025). Machine learning models trained on historical water quality data, including Random Forest, XGBoost, and LSTM architectures, can flag anomalies indicative of pollution events, enabling faster response than periodic manual sampling (Wang et al., 2023).

AI is also applied to predict and manage eutrophication and harmful algal blooms, which pose significant risks to aquatic ecosystems and drinking water supplies. By combining satellite-derived chlorophyll concentration data with meteorological and nutrient loading data, predictive models can provide early warnings for water bodies at risk (Essamlali et al., 2024).

Within wastewater treatment plants, AI-based optimization systems are used to dynamically adjust treatment parameters, such as aeration rates and chemical dosing, in response to real-time influent characteristics (Li et al., 2026; Murat Hocaoglu et al., 2025). Studies report prediction accuracy (R^2) for pollutant removal ranging as high as 0.64 to 1.00 across different AI approaches, alongside measurable reductions in energy consumption at pumping stations of up to roughly 17 percent (Nagpal et al., 2024), an important co-benefit given that wastewater treatment is itself an energy-intensive process contributing to greenhouse gas emissions (Murat Hocaoglu et al., 2025).

AI has further been applied to leak and spill detection in water distribution and industrial discharge systems. By analyzing continuous sensor data streams for subtle deviations from expected flow, pressure, or chemical signatures, anomaly-detection models can identify leaks or unauthorized discharges considerably faster than manual inspection regimes, reducing both the environmental impact and the economic cost associated with delayed detection (Li et al., 2026). Similarly, machine learning models are increasingly used to model groundwater contamination risk by integrating geological, land-use, and historical contamination data, supporting more targeted and cost-effective groundwater protection strategies (Essamlali et al., 2024).

5.3 Industrial Emission Monitoring and Predictive Maintenance

Industrial facilities are significant contributors to both air and water pollution. AI-enabled predictive maintenance and anomaly-detection systems, often built on IoT sensor networks, analyze equipment and emissions data to anticipate failures and flag deviations from permitted emission levels in near real time, supporting more effective compliance enforcement than periodic manual inspections (Ramadan et al., 2024). Federated learning approaches have also been proposed for industrial IoT environmental monitoring, allowing multiple factory sites to collaboratively train shared pollutant-prediction models covering pollutants such as PM_{2.5}, PM₁₀, CO₂, VOCs, and SO₂ without centralizing sensitive operational data (Ramadan et al., 2024).

Satellite and aerial remote sensing, combined with AI-based image analysis, is increasingly used to detect and quantify point-source industrial emissions, including methane plumes and

thermal hotspots, at scales that would be impractical for manual review. Studies of coupled pollution-carbon emission hotspots have found that small geographic footprints, in some cases under 1 percent of total land area, can account for more than 30 percent of greenhouse gas emissions and over 38 percent of air pollutants in a region, making AI-assisted hotspot identification a high-leverage tool for targeted enforcement (Zhao et al., 2026). Operational AI systems, such as the MARS-S2L methane monitoring platform deployed at the United Nations Environment Programme's International Methane Emissions Observatory, have demonstrated substantial improvements in detection precision over prior state-of-the-art methods using Sentinel-2 and Landsat satellite imagery (Vaughan et al., 2024).

5.4 Waste Management and Circular Economy

Computer vision-based waste sorting systems represent one of the more mature commercial applications of AI in pollution control. Early hybrid deep-learning systems combining CNN feature extraction with multilayer perceptron classifiers achieved classification accuracies above 90 percent for recyclable materials, outperforming single-CNN baselines by roughly ten percentage points (Chu et al., 2018). More recent architectures, including DenseNet-based models with attention mechanisms and transfer-learned ResNet and MobileNet variants, have pushed classification accuracy on benchmark waste datasets above 98 percent (Ahmad et al., 2025; Fotovvatikhah et al., 2025). These systems automatically identify and separate recyclable materials from mixed waste streams, improving recycling rates and reducing the volume of waste sent to landfills or incineration, both of which are associated with secondary pollution (leachate contamination and air emissions, respectively) (Fotovvatikhah et al., 2025).

Beyond sorting, AI is being explored to optimize broader circular economy processes, including material recovery planning and predictive modeling of waste generation patterns to improve collection route efficiency, which in turn reduces the emissions associated with waste collection vehicles. Federated deep learning approaches have also been proposed for trash classification across distributed smart-city waste collection points, allowing models to be improved collaboratively across sites without centralizing image data (Ahmed Khan et al., 2024).

AI is also being applied to detect and monitor illegal waste dumping through the analysis of satellite and drone imagery, an approach particularly valuable in regions where enforcement resources are limited relative to the geographic area requiring oversight (Zhao et al., 2026). By automatically flagging suspected dumping sites for human verification, such systems can

significantly expand the effective reach of environmental enforcement agencies without a proportional increase in staffing.

5.5 Smart Traffic and Urban Pollution Management

Vehicular emissions remain a dominant source of urban air pollution in many cities. AI-based smart traffic management systems, often employing deep reinforcement learning, dynamically adjust traffic signal timing based on real-time congestion data to minimize idling and stop-and-go driving patterns, both of which disproportionately increase vehicle emissions (Michailidis et al., 2025; Shang et al., 2025). A case study on cooperative vehicle-infrastructure systems combined with deep reinforcement learning-based signal control reported measurable reductions in both travel delay and carbon emissions compared to traditional fixed-timing and historical-data-dependent methods (Shang et al., 2025). Multi-objective reinforcement learning frameworks have further been proposed to jointly optimize local intersection throughput, network-wide traffic flow, and emissions simultaneously, rather than treating emission reduction as a secondary objective (Tang et al., 2023).

Some cities have also begun piloting AI-based low-emission zone enforcement systems that use computer vision to identify high-emission vehicles and dynamically adjust access restrictions. Beyond traffic signal control, AI is increasingly incorporated into broader urban mobility planning, including predictive modeling of public transit demand to encourage modal shift away from private vehicles, and optimization of electric vehicle charging infrastructure placement to support the broader transition toward lower-emission transportation systems. Collectively, these applications illustrate how AI can support pollution reduction not only through direct monitoring and control, but through the redesign of underlying urban systems that generate pollution in the first place (Michailidis et al., 2025).

Hence, the afore mentioned applications may be summarized in Table 2.

Table 2. AI Applications and Opportunities in Pollution Control.

Sl. No.	Domain	Key Applications	AI Techniques Used	Key Findings / Benefits
1	Air Pollution Monitoring and Forecasting	- Short- and medium-term forecasting of PM2.5, PM10, NO2, SO2, CO and ozone. - Source apportionment (vehicular,	- ML and DL forecasting models - Satellite image analysis - Gradient Boosting and k-Nearest Neighbors for sensor	- Often outperforms traditional statistical and chemical transport models, especially for localized or fast-changing conditions. - Enables preventive action (traffic

		industrial, agricultural burning) • Satellite-based detection of emission hotspots • Early warning systems for smog and haze • Calibration and densification of low-cost sensor networks	calibration	restrictions, industrial slowdowns) 3. Low-cost sensor calibration extends monitoring into under-resourced neighbourhoods (environmental justice)
2	Water Pollution Monitoring and Management	• Detection of heavy metals, pathogens and effluents via sensor proxies (turbidity, pH, dissolved oxygen, conductivity) • Eutrophication and algal bloom prediction • Wastewater treatment optimization (aeration, chemical dosing) • Leak and spill detection • Groundwater contamination risk modelling	• Random Forest, XGBoost, LSTM • Satellite chlorophyll analysis • Anomaly detection • AI-based process optimization	1. Faster response than periodic manual sampling 2. Pollutant removal prediction R^2 of 0.64 to 1.00 3. Up to approximately 17% energy savings at pumping stations 4. Faster leak/discharge detection 5. More targeted groundwater protection
3	Industrial Emission Monitoring and Predictive Maintenance	• Near real-time detection of deviations from permitted emission levels • Equipment failure prediction • Methane plume and thermal hotspot detection via remote sensing • Collaborative pollutant prediction across factories	• IoT-based anomaly detection • Federated learning • Satellite/aerial image analysis (e.g., MARS-S2L platform using Sentinel-2 and Landsat)	1. Stronger compliance enforcement than periodic inspections 2. Federated learning protects sensitive operational data 3. Under 1% of land area can account for over 30% of greenhouse gases and over 38% of air pollutants, so hotspot targeting is high-leverage 4. Improved methane detection precision
	Waste	• Automated waste	• Computer vision	1. Classification

4	Management and Circular Economy	sorting • Material recovery planning • Waste generation prediction and collection route optimization • Trash classification across smart-city collection points • Illegal dumping detection via satellite and drone imagery	(CNN + MLP hybrids, DenseNet with attention, transfer-learned ResNet and MobileNet) • Federated deep learning	accuracy rose from above 90% (early hybrid models) to above 98% (recent models) 2. Higher recycling rates and less landfill/incineration (reducing leachate and air emissions) 3. Fewer collection vehicle emissions 4. Extends enforcement reach without more staff
5	Smart Traffic and Urban Pollution Management	• Adaptive traffic signal control • Low-emission zone enforcement • Public transit demand prediction • EV charging infrastructure placement	• Deep reinforcement learning • Multi-objective RL • Computer vision for vehicle identification	1. Reduced idling and stop-and-go driving 2. Lower travel delay and carbon emissions than fixed-timing methods 3. Emissions treated as a primary objective alongside throughput 4. Addresses the underlying urban systems that generate pollution 5.

6. CHALLENGES

Despite the substantial opportunities outlined above, several challenges continue to constrain the effective and equitable deployment of AI in pollution control. The different challenges are depicted in Figure 1 and described in the following paragraphs.

6.1 Data Quality, Availability, and Standardization

AI models are fundamentally data-dependent, and their performance is directly tied to the quality, completeness, and representativeness of training data (Ballesteros Peinado et al., 2025; Méndez et al., 2023). In many regions, particularly in low- and middle-income countries where pollution burdens are often highest, ground-truth monitoring infrastructure is sparse, leading to significant data gaps. Furthermore, inconsistencies in measurement standards, sensor calibration, and reporting formats across jurisdictions complicate efforts to build generalizable models or conduct cross-regional comparative studies (Ballesteros Peinado et al., 2025).



Figure 1. Challenges Encountered in the Deployment of AI in Pollution Control.

6.2 Model Interpretability and Regulatory Trust

Many high-performing AI models, particularly deep learning architectures, function as “black boxes” that offer limited insight into the reasoning behind their predictions (Adadi & Berrada, 2018). This lack of interpretability poses a significant barrier to regulatory adoption, as environmental agencies and policymakers require transparent, defensible justifications for decisions that may carry legal or economic consequences, such as industrial shutdowns or fines based on AI-flagged violations (Schiller et al., 2025). Current AI applications in domains such as wastewater treatment continue to face limited interpretability and weak transferability across different plants and operating conditions, which further complicates institutional trust (Li et al., 2026).

6.3 Infrastructure and Computational Costs

The deployment of AI-based monitoring systems, particularly those relying on dense IoT sensor networks or real-time deep learning inference, requires significant upfront and ongoing investment in hardware, connectivity, and computational infrastructure (Essamlali et al., 2024). These costs can be prohibitive for municipalities and organizations in resource-constrained settings, potentially widening existing disparities in environmental monitoring capacity between wealthier and poorer regions.

6.4 Integration with Existing Regulatory and Policy Frameworks

Many existing environmental regulations were designed around periodic manual sampling and fixed compliance thresholds, and are not well-suited to the continuous, probabilistic

outputs generated by AI systems. Integrating AI-derived insights into legally binding regulatory processes requires significant institutional and legal adaptation, which has proceeded unevenly across different countries and sectors (Zhao et al., 2026).

6.5 Privacy and Data Governance

The expansion of sensor networks and satellite-based monitoring raises data privacy and governance concerns, particularly where monitoring data can be linked to specific facilities, properties, or individuals (Ramadan et al., 2024; Yurdem et al., 2024). Establishing clear data governance frameworks that balance transparency and accountability with legitimate privacy and commercial confidentiality concerns remains an ongoing challenge, and is a key motivation behind emerging privacy-preserving approaches such as federated learning (Alwabli, 2024; Ramadan et al., 2024; Yurdem et al., 2024).

6.6 Generalizability Across Contexts

AI models trained on data from one geographic or climatic context often perform poorly when applied elsewhere due to differences in pollution sources, meteorological conditions, and urban form (Ballesteros Peinado et al., 2025; Li et al., 2026). This limits the direct transferability of models between cities or regions and necessitates costly retraining or localized data collection efforts, which can slow the pace of adoption in under-resourced settings.

6.7 Workforce and Institutional Capacity

Effective deployment of AI-based pollution control systems requires institutional capacity that extends beyond the technical development of models, including personnel capable of maintaining sensor infrastructure, interpreting model outputs, and integrating AI-derived insights into operational decision-making. Many environmental agencies, particularly in resource-constrained settings, face shortages of staff with the combined environmental science and data science expertise required to operate and oversee these systems effectively, creating a capacity gap that can undermine the long-term sustainability of AI deployments even where initial funding for technology procurement is available.

7. Future Directions

7.1 Explainable AI (XAI)

The development and adoption of explainable AI techniques, which aim to make model predictions more interpretable without significantly sacrificing accuracy, represents a critical direction for enabling regulatory trust and broader institutional adoption of AI-based pollution control systems (Adadi & Berrada, 2018; Schiller et al., 2025). Post-hoc

explanation methods such as SHAP and LIME, along with intrinsically interpretable model designs, have already been applied to environmental prediction tasks to help stakeholders understand which input variables are driving a given prediction (Schiller et al., 2025).

7.2 Federated Learning

Federated learning, which allows multiple institutions or monitoring agencies to collaboratively train shared models without directly sharing raw data, offers a promising pathway for improving model generalizability while addressing data privacy and jurisdictional data-sharing constraints (Alwabli, 2024; Yurdem et al., 2024), particularly for cross-border pollution monitoring initiatives such as transboundary air or river pollution management (Yarham et al., 2025). Recent work has shown that federated approaches to air quality forecasting can achieve accuracy comparable to centralized models while keeping raw sensor data local to each participating site (Yarham et al., 2025).

7.3 Digital Twins for Environmental Management

Digital twin technology, which involves creating dynamic, data-driven virtual replicas of physical environments, is beginning to be applied to urban pollution management (Ariansyah et al., 2023; Masrur Ahmed et al., 2025). Machine learning-assisted urban digital twins have been used to forecast air quality index values and visually highlight pollution hotspots for city administrators, while mixed-reality-enabled digital twin platforms have been piloted in cities such as Jakarta to integrate air quality, meteorological, traffic, and infrastructure data into a single planning interface (Ariansyah et al., 2023). These systems allow planners to simulate the pollution impacts of proposed interventions, such as new industrial developments or traffic policy changes, before implementation, supporting more evidence-based decision-making (Masrur Ahmed et al., 2025; Sasidharan et al., 2025).

7.4 Integration with Climate and Sustainability Policy

As pollution control increasingly intersects with broader climate change mitigation and sustainable development goals, future AI applications are likely to be designed with integrated objectives, simultaneously optimizing for pollution reduction, carbon footprint minimization, greenhouse gas mitigation, and resource efficiency, rather than treating these as separate problems (Li et al., 2026; Zhao et al., 2026).

7.5 Low-Cost and Context-Appropriate AI Solutions

Given the resource constraints, an important future direction involves the development of low-cost, context-appropriate AI solutions specifically designed for deployment in resource-constrained settings, including lightweight models capable of running on low-power edge

devices and approaches that reduce dependence on dense, expensive sensor networks (Nan et al., 2025; Taştan, 2025).

7.6 Capacity Building and Interdisciplinary Collaboration

Finally, realizing the full potential of AI in pollution control will require sustained investment in capacity building, bringing together expertise from environmental science, data science, public policy, and community engagement. Interdisciplinary training programs, open-access datasets, and collaborative platforms that lower the barrier to entry for researchers and practitioners in under-resourced settings are likely to play an important role in ensuring that the benefits of AI-driven pollution control are distributed equitably rather than concentrated in already well-resourced regions and institutions.

CONCLUSION

Artificial Intelligence offers substantial opportunities to enhance the effectiveness, efficiency, and responsiveness of pollution control efforts across air, water, industrial, and waste management domains. Applications ranging from predictive air quality forecasting (Karmoude et al., 2025; Méndez et al., 2023; Ravindiran et al., 2023) to automated waste sorting (Ahmad et al., 2025; Chu et al., 2018; Fotovvatikhah et al., 2025) and AI-optimized wastewater treatment (Li et al., 2026; Murat Hocaoglu et al., 2025; Nagpal et al., 2024) demonstrate the practical value AI can bring to environmental management. However, realizing this potential at scale requires addressing significant challenges related to data availability, model interpretability, infrastructure costs, and regulatory integration (Adadi & Berrada, 2018; Ballesteros Peinado et al., 2025; Schiller et al., 2025). Emerging directions such as explainable AI, federated learning, and digital twin technologies offer promising pathways for overcoming these barriers (Alwabli, 2024; Ariansyah et al., 2023; Masrur Ahmed et al., 2025; Yarham et al., 2025; Yurdem et al., 2024). Ultimately, the successful integration of AI into pollution control will depend not only on technical advancement but on parallel progress in policy, institutional capacity, and equitable access to the necessary infrastructure, particularly in the regions that bear the greatest pollution burdens.

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