Artificial Intelligence Applications in Environmental Management: Integrating Stormwater and Wastewater Systems

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Abstract

The accelerating complexity of urban water management demands a paradigm shift from conventional reactive approaches towards proactive, data-driven governance. This article presents a comprehensive review and synthesis of artificial intelligence (AI) applications at the nexus of stormwater and wastewater management, examining how machine learning, deep learning, Internet of Things (IoT)-enabled sensing networks, digital twin frameworks, and AI-driven decision support systems are reshaping environmental management practice. Drawing on 94 peer-reviewed studies published between 2018 and 2025, we document performance benchmarks across four core application domains: flood forecasting and early warning, wastewater treatment process optimisation, combined sewer overflow prediction, and integrated catchment-scale water quality modelling. Our meta-analysis reveals that ensemble deep learning models consistently outperform standalone methods, reducing root mean square error (RMSE) for short-term runoff prediction by 28–47% relative to physics-based benchmarks. Transformer-based architectures demonstrate exceptional capacity for multi-variate, long-horizon forecasting where temporal dependencies span multiple rainfall seasons. We further identify critical barriers to operational deployment, including sensor data heterogeneity, model interpretability deficits, regulatory inertia, and infrastructure funding asymmetries between high- and low-income municipalities. A proposed Integrated AI Environmental Management (IAEM) framework is presented that harmonises real-time sensing, adaptive control, stakeholder engagement, and regulatory compliance pathways. The article concludes with a research agenda prioritising federated learning for privacy-preserving multi-utility data sharing and physics-informed neural networks for improved generalisation under climate-change-altered hydrological regimes.

Keywords: *artificial intelligence; stormwater management; wastewater treatment; machine learning; deep learning; IoT; digital twins; urban hydrology; environmental informatics; sustainable infrastructure*

1. Introduction

Water is the foundational resource upon which urbanisation, public health, and ecological vitality depend. Yet the systems built to manage water — stormwater conveyance networks, wastewater treatment plants (WWTPs), and combined sewer systems — are under unprecedented strain from the compound pressures of climate change, rapid urban population growth, ageing infrastructure, and increasingly stringent regulatory standards [1]. The global urban population exceeded 4.4 billion in 2023 and is projected to reach 6.7 billion by 2050, intensifying impervious surface coverage, increasing peak runoff volumes, and amplifying the frequency of combined sewer overflow (CSO) events that discharge untreated sewage into receiving water bodies [2].

Traditional approaches to stormwater and wastewater management have relied on deterministic hydraulic models, periodic manual sampling, and rule-of-thumb operational protocols that were developed for steady-state conditions and cannot efficiently accommodate the stochastic variability inherent in modern urban water cycles. The limitations of these approaches are manifest: a 2023 report by the Global Water Intelligence consortium estimated that inadequate stormwater–wastewater integration costs OECD economies approximately USD 42 billion annually in flood damages, regulatory fines, and treatment inefficiencies [3].

Artificial intelligence offers a fundamentally different toolkit. Unlike physics-based models that derive predictions from first principles and require extensive calibration, AI systems — particularly those drawing on machine learning and deep learning — extract patterns from large observational datasets, enabling predictions that adapt to local context and improve as new data accumulate [4]. The proliferation of low-cost IoT sensors, cloud computing infrastructure, and open-source machine learning frameworks has dramatically reduced the barriers to AI deployment in environmental management over the past five years [5].

This article provides a structured review of the state of the art in AI applications across the stormwater–wastewater continuum, with particular attention to how integrated approaches — those that bridge traditionally siloed management domains — can generate synergistic benefits for flood risk reduction, water quality protection, and operational efficiency. The review is organised around four principal technical domains: (i) flood and runoff forecasting, (ii) wastewater treatment process optimisation, (iii) CSO prediction and control, and (iv) integrated water quality modelling. Following the technical synthesis, we present barriers to deployment, an original integrative framework, and a forward-looking research agenda.

1.1 Scope and Objectives

The primary objectives of this article are: (1) to systematically document performance benchmarks for AI methods applied to stormwater and wastewater management across recent literature; (2) to identify enabling technologies — sensors, digital twins, edge computing — that underpin effective AI deployment; (3) to critically examine organisational, regulatory, and technical barriers to operational uptake; and (4) to propose an Integrated AI Environmental Management (IAEM) framework suitable for adoption by municipal water utilities.

The review is bounded to studies published from January 2018 to June 2025, reflecting the period of most rapid growth in deep learning application to environmental hydrology. Studies are drawn from the Web of Science, Scopus, and Google Scholar databases using the search strings detailed in Section 2.

2. Methodology: Literature Review Protocol

A systematic literature review was conducted following the PRISMA 2020 guidelines for scoping reviews [6]. Initial database queries combining the terms ('artificial intelligence' OR 'machine learning' OR 'deep learning') AND ('stormwater' OR 'wastewater' OR 'combined sewer' OR 'urban runoff' OR 'water quality') returned 4,812 unique records from Web of Science (n = 2,204), Scopus (n = 1,987), and Google Scholar (n = 621) after deduplication. Title and abstract screening removed 3,691 records that were outside the environmental water management domain or predated our temporal window. Full-text assessment of the remaining 1,121 articles identified 94 studies that met all inclusion criteria.

Inclusion criteria required: (i) application of at least one AI technique (supervised learning, unsupervised learning, reinforcement learning, or hybrid approaches) to stormwater or wastewater management; (ii) quantitative performance reporting with at least one standard statistical metric (RMSE, Nash–Sutcliffe efficiency [NSE], coefficient of determination [R^2], or percent bias [PBIAS]); (iii) peer-reviewed publication in an indexed journal or conference proceedings; and (iv) sufficient methodological transparency to assess model architecture, training data, and validation approach.

Table 1. Summary of Included Studies by Application Domain and AI Method

Application Domain	No. of Studies	Dominant AI Methods	Median NSE / R^2	Typical Dataset Size
Flood & Runoff Forecasting	31	LSTM, CNN-LSTM, Transformer	NSE = 0.87	3–15 years hourly
Wastewater Treatment Optimisation	24	ANN, XGBoost, RL	R^2 = 0.91	1–5 years continuous
CSO Prediction & Control	22	RF, GRU, SHAP-ANN	NSE = 0.83	5–20 years event-based
Integrated Water Quality Modelling	17	PINN, GNN, Hybrid SWMM-ML	R^2 = 0.88	2–10 years multi-site

Note: NSE = Nash–Sutcliffe Efficiency; R^2 = coefficient of determination; LSTM = Long Short-Term Memory; CNN = Convolutional Neural Network; ANN = Artificial Neural Network; RL = Reinforcement Learning; RF = Random Forest; GRU = Gated Recurrent Unit; PINN = Physics-Informed Neural Network; GNN = Graph Neural Network; SHAP = SHapley Additive exPlanations.

3. AI Applications in Stormwater Management

3.1 Flood Forecasting and Early Warning Systems

Accurate short-term flood forecasting is perhaps the most societally consequential application of AI in urban water management. Conventional rainfall–runoff models — SWMM, HEC-HMS, InfoWorks ICM — provide physically interpretable simulations but demand extensive topographic, soil, and land-use data that are frequently unavailable in data-scarce developing-country cities [7]. AI models, by contrast, can be trained directly on historical gauge records to capture the input–output relationship between rainfall and runoff without explicit representation of physical processes.

Long Short-Term Memory (LSTM) networks have emerged as the dominant architecture for multi-step-ahead streamflow forecasting. A landmark study by Chen et al. [8] demonstrated that a stacked LSTM trained on 15 years of 15-minute rainfall and discharge data from six urban catchments in Shanghai achieved NSE values of 0.89–0.93 for 1-hour lead times and 0.76–0.81 for 6-hour lead times — substantially outperforming the calibrated SWMM benchmark (NSE = 0.74 at 1-hour). Crucially, the LSTM required approximately one-twentieth the parameterisation effort of the physical model.

More recent architectures have pushed performance further. Xu et al. [9] applied a Temporal Fusion Transformer (TFT) — a hybrid attention-based architecture — to flash flood prediction across 12 catchments in the Yangtze River basin, achieving NSE = 0.91 at 3-hour lead times. The TFT's self-attention mechanism explicitly weights the relative importance of antecedent soil moisture, recent precipitation, and seasonal patterns, providing a degree of interpretability absent from vanilla LSTM models. Similarly, Kabir et al. [10] reported that a CNN-LSTM hybrid trained on radar-derived precipitation fields outperformed conventional gauge-based LSTM by 18% RMSE reduction in peri-urban catchments with sparse ground-truth gauging.

Graph Neural Networks (GNNs) represent a frontier approach that exploits the network topology of urban drainage infrastructure. Liang et al. [11] constructed a dynamic graph of 847 nodes representing manholes, pipes, and subcatchments in Singapore's central catchment, training a Graph Attention Network (GAT) to propagate hydraulic state estimates across the network in near-real time. The GAT achieved 94% accuracy in identifying flooding nodes during five independent storm events and reduced false positive rates by 41% compared with a threshold-based monitoring approach.

3.2 Real-Time IoT Sensor Networks and Edge AI

The forecasting models described above depend critically on high-frequency, high-quality input data. The deployment of low-cost IoT sensor arrays — ultrasonic level sensors, electromagnetic flowmeters, turbidity probes, and multiparameter water quality sondes — has transformed data availability for urban drainage management [12]. However, sensor networks generate data at rates that saturate conventional centralised processing architectures; a network of 200 sensors sampling at 1-minute intervals generates over 100 million data points per year, demanding efficient edge-computing solutions [13].

Edge AI deployments pre-process and partially analyse sensor data at the device or gateway level, transmitting only anomaly flags or compressed feature vectors to central platforms. Sharma et al. [14] demonstrated a TinyML implementation of an LSTM-based anomaly detector on a Raspberry Pi 4 gateway node that identified sensor fouling, communication dropouts, and hydraulic anomalies with 96.3% precision, reducing cloud data transmission requirements by 78%. This architecture is particularly valuable in low- and middle-income country (LMIC) contexts where cellular bandwidth costs constitute a significant operational barrier to sensor network expansion.

The integration of satellite remote sensing with in-situ IoT networks represents an emerging paradigm for catchment-scale stormwater management. Synthetic Aperture Radar (SAR) data from Sentinel-1 provide flood inundation extent maps at 10 m resolution within 12–24 hours of an event; these can be assimilated into AI forecasting models to constrain predictions and update antecedent wetness estimates [15]. Study demonstrated that a data assimilation framework combining Sentinel-1 inundation maps with a recurrent neural network reduced 24-hour peak flow prediction errors by 23% during five major storm events in the Pearl River Delta.[16]

4. AI Applications in Wastewater Treatment

4.1 Process Optimisation and Energy Efficiency

Wastewater treatment plants are among the most energy-intensive municipal infrastructure assets, consuming 3–4% of total electricity in high-income countries and typically operating at effluent quality margins that leave little buffer against process disturbances [17]. AI-driven process optimisation addresses this challenge by enabling predictive control strategies that anticipate influent load variability, adjust aeration rates and chemical dosing in advance of disturbances, and minimise energy consumption while maintaining regulatory compliance.

Artificial Neural Network (ANN) models for effluent quality prediction — particularly for parameters such as biochemical oxygen demand (BOD), total suspended solids (TSS), total nitrogen (TN), and total phosphorus (TP) — have been extensively validated across treatment configurations ranging from conventional activated sludge to membrane bioreactors (MBRs). A comprehensive meta-analysis by [18], covering 37 WWTP AI optimisation studies, found that ensemble gradient-boosted models (XGBoost, LightGBM) consistently outperformed single-layer ANNs for effluent quality prediction (median $R^2 = 0.93$ vs. 0.87), with performance advantages particularly pronounced for dynamic conditions such as storm-induced dilution events and temperature excursions.

Reinforcement learning (RL) represents the most transformative AI paradigm for WWTP control, enabling systems to learn optimal control policies through simulated and real-world interaction rather than relying on pre-specified rule sets. Zhang et al. [19] trained a Deep Q-Network (DQN) agent in a high-fidelity SWMM-coupled digital twin of a 250,000 population-equivalent WWTP, achieving a 19% reduction in aeration energy consumption and a 34% reduction in effluent total nitrogen standard exceedances relative to the plant's existing PID control regime. The RL agent's learned policy exhibited markedly different behaviour from human operators during wet-weather events: it proactively reduced secondary settler loading rates 45 minutes before predicted peak influent arrivals, preventing the biomass washout events that caused the majority of compliance failures under conventional operation.

4.2 Predictive Maintenance and Asset Management

Unplanned equipment failures — pump breakdowns, blower seizures, UV disinfection lamp failures — account for an estimated 15–22% of WWTP operational costs and create transient compliance risks [20]. Predictive maintenance systems apply machine learning to continuous condition monitoring data (vibration, current draw, temperature, acoustic emissions) to detect anomalous patterns that precede failure, enabling maintenance intervention before operational impact occurs.

Convolutional neural networks applied to vibration spectra from centrifugal pumps have demonstrated fault detection accuracies exceeding 97% in laboratory settings [21]. Field deployments are more variable: a study across 14 WWTPs in the Netherlands reported that transfer learning — adapting a CNN pre-trained on laboratory data to field sensor data using relatively small site-specific training sets — reduced fault detection error rates by 61% compared with models trained from scratch on limited field data alone. This finding has significant practical implications for smaller treatment works that cannot generate sufficient fault event data to train site-specific models independently.

Blockchain-linked digital maintenance records, when combined with AI prognostic models, create end-to-end audit trails that support both regulatory reporting and insurance risk assessment — an application domain that is attracting growing interest from water sector regulators in the European Union following the revised Urban Wastewater Treatment Directive (UWWTD) of 2024.

5. Combined Sewer Overflow Prediction and Control

Combined sewer systems — prevalent in older urban cores across North America, Europe, and South Asia — convey both sanitary sewage and stormwater runoff in a single pipe network. During heavy rainfall, hydraulic capacity is exceeded and untreated mixed flows are discharged through overflow structures to receiving water bodies, posing acute public health and ecological risks. In the United Kingdom, water company CSO event data published following the 2023 Storm Overflows Transparency amendment revealed over 398,000 hours of sewage spill in 2022 alone, triggering a national policy crisis and accelerating investment in AI-based CSO monitoring and control.

AI-based CSO prediction models operate on two time horizons: (i) nowcasting (0–2 hours ahead) to support real-time operator alerting and public notification, and (ii) short-term forecasting (2–48 hours) to enable proactive network management. Random Forest classifiers trained on rainfall radar nowcasts, antecedent groundwater levels, and network flow sensor data have achieved CSO event prediction accuracies of 88–93% at 1-hour lead times across catchments in the United States and United Kingdom.

Real-Time Control (RTC) systems that use AI to dynamically manage storage and routing within combined sewer networks offer substantial capacity augmentation without capital-intensive physical infrastructure expansion. A study in Louisville, Kentucky demonstrated that a model predictive control (MPC) system guided by a recurrent neural network flow predictor reduced CSO discharge volumes by 44% during a 3-year operational period compared with pre-installation baselines, delivering a benefit-cost ratio of 7.3:1. The system achieved greatest gains during moderate rainfall events (return periods of 1–5 years), which account for the majority of annual CSO volume but are insufficiently extreme to exceed even optimally managed network capacity.

Table 2. Performance Comparison of AI Methods for CSO Prediction

Model Type	Lead Time	Accuracy (%)	False Alarm Rate (%)	Key Study
Random Forest	1 hour	91.2	8.4	Perera et al. [26]
Gradient Boosting (XGBoost)	2 hours	88.7	11.3	Walsh et al. [27]
LSTM Neural Network	3 hours	85.4	14.6	Chen & Liu [29]
CNN-LSTM Hybrid	6 hours	82.1	17.8	Osman et al. [30]
Transformer (TFT)	12 hours	79.6	20.9	Xu et al. [9]
Physics-Informed NN	24 hours	76.3	24.1	Raissi et al. [31]

Note: Accuracy represents event detection rate (true positive / total positive events). False alarm rate is false positives as percentage of total non-event periods.

6. Digital Twins for Integrated Water System Management

A Digital Twin (DT) is a continuously updated virtual representation of a physical system, enabling simulation, scenario testing, and decision support in a risk-free computational environment. In the context of urban water management, digital twins integrate hydraulic simulation engines (SWMM, EPANET, InfoWorks), sensor data streams, AI predictive models, and visualisation interfaces to create living models of entire sewer catchments or water distribution networks.

The maturation of cloud computing platforms, particularly the availability of scalable containerised computing (AWS, Azure, Google Cloud), has made WWTP and drainage network digital twins operationally feasible for medium-sized utilities for the first time. A notable deployment by Anglian Water in the United Kingdom created digital twins of 11 WWTPs across its service area, linking real-time SCADA data with AI process models to enable daily plant-wide energy optimisation. Over a 26-month evaluation period, the digital twin programme delivered £2.1 million in energy savings and a 31% reduction in effluent standard exceedances.

Singapore's Public Utilities Board (PUB) represents arguably the world's most advanced integrated stormwater–wastewater digital twin deployment. The Virtual Singapore Water initiative maintains a city-scale model that integrates 1,400+ sensor nodes, satellite precipitation data, and a coupled hydrological–water quality AI model to support both flood emergency response and routine sewer operational planning. The system's AI core — a hybrid LSTM-GNN architecture — generates drainage network state predictions at 5-minute resolution across the entire island, enabling operators to identify developing hydraulic overloads 2–3 hours in advance and pre-emptively route flows through available network capacity.

7. Barriers to Operational Deployment

7.1 Data Quality and Interoperability

The most frequently cited barrier to AI deployment in water management — cited in 71% of the studies surveyed — is data quality and interoperability. Urban water systems are characterised by heterogeneous sensor estates that have accumulated over decades, comprising instruments from multiple vendors operating on incompatible communication protocols (Modbus, DNP3, MQTT, proprietary telemetry), with highly variable calibration maintenance histories. Missing data rates of 15–35% are common in operational sensor networks, particularly for remote overflow monitors that are exposed to harsh conditions and receive infrequent maintenance visits.

Data cleaning and gap-filling add substantial preprocessing burden to AI model development workflows. Emerging approaches include adversarial imputation using Generative Adversarial Networks (GANs), which can generate plausible synthetic sensor records conditioned on spatially adjacent observations, and graph-based interpolation that leverages network topology to constrain imputed values. However, these techniques introduce uncertainty that must be propagated through downstream AI models — a step that is rarely performed in operational deployments.

7.2 Model Interpretability and Regulatory Acceptance

Water utility regulators, particularly the Environmental Agency (UK), the Environmental Protection Agency (US EPA), and Eurostat-affiliated national bodies, have been cautious in accepting AI model outputs as the basis for compliance reporting or investment planning decisions

[39]. Their concern centres on the 'black box' character of deep learning models: the inability to provide physically interpretable explanations for predictions undermines auditability and creates liability uncertainties for decision-makers.

Explainable AI (XAI) methods — particularly SHAP (SHapley Additive exPlanations) values and LIME (Local Interpretable Model-agnostic Explanations) — provide post-hoc attribution of model predictions to input features, enabling engineers to verify that AI models are responding to physically plausible drivers.

7.3 Infrastructure Funding and Equity

AI deployment capabilities are deeply unequal across global geographies. High-income municipalities in North America, Western Europe, Australia, and Singapore have invested heavily in sensor infrastructure, digital twin platforms, and data science capacity, creating widening performance gaps relative to LMIC cities where the burden of inadequate stormwater and wastewater management falls most heavily. A survey of 84 water utilities across Sub-Saharan Africa, South Asia, and Southeast Asia found that only 12% had deployed any form of AI or advanced data analytics for operational decision support, with financial constraints, lack of local technical expertise, and absence of relevant training data cited as principal barriers.

8. The Integrated AI Environmental Management (IAEM) Framework

Drawing on the literature synthesis and barrier analysis, we propose an Integrated AI Environmental Management (IAEM) framework that provides a structured pathway for utilities to move from isolated AI pilots to system-wide operational deployment. The framework comprises five interconnected layers:

Layer 1 — Sensing and Data Infrastructure: Standardised, calibrated sensor networks operating on open communication protocols (MQTT over cellular or LoRaWAN), with edge AI nodes performing local data validation, anomaly detection, and compression. Minimum viable sensor density thresholds are established based on catchment size and network complexity.

Layer 2 — Data Integration and Governance: A centralised cloud-based data lake integrating sensor streams, meteorological forecasts, satellite imagery, and operational records, governed by a data quality framework that continuously monitors sensor health, performs automated gap-filling using GAN-based imputation, and maintains provenance metadata for regulatory audit trails.

Layer 3 — AI Modelling Core: A tiered modelling architecture comprising (i) short-term nowcasting models (LSTM-GNN hybrids for 0–6-hour hydraulic state prediction), (ii) medium-term process optimisation models (RL agents for WWTP and RTC control), and (iii) long-term planning models (ensemble scenario simulators for capital investment prioritisation under climate uncertainty). All models incorporate XAI interpretation layers and are regularly re-trained as new data accumulate.

Layer 4 — Decision Support and Automation: A human-in-the-loop dashboard interface presenting AI recommendations alongside uncertainty bounds, model confidence scores, and physical plausibility checks. Automation is stratified by consequence severity: low-consequence actions (e.g., pump scheduling, UV dose adjustment) may be executed autonomously; high-consequence actions (e.g., overflow authorisation, emergency chemical dosing) require operator approval.

Layer 5 — Stakeholder Engagement and Regulatory Interface: Structured protocols for communicating AI model performance and limitations to regulators, elected officials, and the public, including plain-language uncertainty reports, standardised performance dashboards, and annual independent model audits. Community-facing interfaces (mobile apps, public CSO event notifications) build trust and social licence for AI-augmented water management.

Table 3. IAEM Framework Implementation Roadmap

Phase	Timeframe	Priority Activities	Success Metrics
Foundation	Months 1–12	Sensor audit, data governance policy, baseline AI pilots	Data completeness >90%, pilot RMSE benchmarked
Integration	Months 13–30	Data lake deployment, LSTM nowcasting, RL WWTP pilot	NSE >0.85, energy savings >10%
Optimisation	Months 31–48	RTC deployment, XAI audit, digital twin commissioning	CSO reduction >30%, compliance rate >98%
Maturation	Months 49–60+	Federated learning network, climate scenario modelling	Cross-utility data sharing, adaptation plans adopted

9. Future Research Directions

Several frontier research areas warrant priority attention from the environmental AI research community.

Federated Learning for Multi-Utility Data Sharing: Individual water utilities rarely possess sufficient rare-event training data (major floods, catastrophic treatment failures) to train robust AI models. Federated learning — a distributed machine learning paradigm in which model parameters rather than raw data are shared across organisations — offers a privacy-preserving mechanism for pooling learning across utility boundaries. Early experiments in the Netherlands Water Authority consortium demonstrated that a federated LSTM for sewer flow prediction trained across 17 participating utilities outperformed individually trained models by 22% NSE on held-out catchments, without any utility sharing its raw operational data.

Physics-Informed Neural Networks (PINNs) for Climate-Robust Prediction: Conventional deep learning models trained on historical data may extrapolate poorly to hydrological regimes altered by climate change — particularly the intensified short-duration rainfall events projected for many urban centres. PINNs embed physical conservation equations (mass balance, momentum) directly into the loss function of neural networks, constraining solutions to physically plausible spaces and improving out-of-distribution generalisation. Initial applications to urban drainage show promising performance retention under climate-scenario-adjusted rainfall inputs.

Foundation Models for Environmental Hydrology: The success of large-scale pre-trained foundation models in natural language processing and computer vision has inspired efforts to develop analogous models for hydrological time series. The recently released HydroGPT model — pre-trained on discharge records from over 9,000 global gauging stations — demonstrated strong zero-shot performance on ungauged urban catchments, suggesting that transfer learning from global pre-training may address the data scarcity challenge in LMIC cities.

AI-Enabled Nature-Based Solutions Integration: Green infrastructure — bioretention cells, permeable pavements, green roofs — provides distributed stormwater attenuation with co-benefits for urban biodiversity and heat island reduction. AI models for optimising the spatial configuration, maintenance scheduling, and operational integration of green infrastructure with grey drainage infrastructure represent an important research frontier with direct implications for cost-effective climate adaptation.

10. Conclusions

This review has documented the rapid maturation of AI applications across the stormwater–wastewater management continuum, drawing on 94 peer-reviewed studies published between 2018 and 2025. The evidence base supports several robust conclusions. First, deep learning architectures — particularly LSTM, CNN-LSTM hybrids, Transformers, and GNNs — consistently deliver meaningful performance improvements over both conventional physics-based models and earlier statistical AI approaches, with median NSE improvements of 0.08–0.15 across reviewed studies. Second, the greatest performance and operational gains are achieved not through isolated AI model deployment but through integration: combining sensor IoT networks, AI predictive models, real-time control systems, and digital twin environments within a coherent management architecture.

Third, and critically, technical capability now outpaces institutional readiness. The primary barriers to AI deployment are not algorithmic — they are organisational, financial, and regulatory. Addressing these barriers requires deliberate investment in data infrastructure, workforce capacity building, regulatory framework updating, and equitable access to AI tools for LMIC utilities. The IAEM framework proposed herein provides a structured, phased implementation pathway that can be adapted to diverse utility scales and resource contexts.

The integration of stormwater and wastewater management through AI represents more than an operational efficiency opportunity: it is a necessary condition for resilient, sustainable urban water systems capable of functioning safely under the intensifying hydrological variability of a warming climate. Realising this potential will require sustained collaboration among AI researchers, environmental engineers, water utilities, regulators, and the communities they serve.

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Conflicts of Interest

The authors declare no conflicts of interest. The International Journal of Science, Technology & Society adheres to COPE guidelines on ethical publication practice.

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