Artificial Intelligence for Sustainable Environmental Management: Integrating Stormwater and Wastewater Systems

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Abstract

Sustainable environmental management demands a holistic, systems-thinking approach that moves beyond the operational siloes separating stormwater and waxstewater governance. Urban water systems — encompassing stormwater conveyance, combined sewer networks, and centralised wastewater treatment — are intrinsically interconnected, yet historically managed by distinct engineering disciplines, institutional actors, and regulatory frameworks. This institutional fragmentation imposes substantial environmental, economic, and social costs: suboptimal infrastructure investment, missed opportunities for resource recovery, elevated receiving water pollution loads, and inequitable distribution of flood risk and service quality. Artificial intelligence (AI) offers the integrative analytical capacity to bridge these siloes, enabling holistic water system optimisation grounded in sustainability principles. This article presents a comprehensive review of 103 peer-reviewed studies published between 2018 and 2025, examining how machine learning, deep learning, reinforcement learning, multi-agent systems, life cycle assessment-informed AI, and circular economy-oriented decision support tools are transforming the integrated management of stormwater and wastewater systems. We evaluate AI applications across six sustainability dimensions: resource recovery maximisation, energy self-sufficiency, ecological quality protection, social equity and environmental justice, circular economy integration, and governance and institutional capacity. Key findings reveal that AI-optimised resource recovery — including nutrient recapture, biogas generation, water reuse, and heat recovery — can convert WWTPs from net energy consumers to net energy producers in 34–58% of case study contexts, while AI-driven green-grey infrastructure integration reduces combined sewer overflow volumes by 38–61% in reviewed deployments.

Keywords: *sustainable environmental management; artificial intelligence; stormwater integration; wastewater treatment; resource recovery; circular economy; SDGs; green infrastructure; environmental justice; life cycle assessment*

1. Introduction

The global urban water crisis is, at its core, a systems integration problem. Stormwater falling on an urban surface follows pathways determined by decades of piecemeal infrastructure decisions: it flows across impervious streets, through inlet grates into underground pipes, merges with sanitary sewage in combined systems, overflows when network capacity is exceeded, and eventually reaches receiving water bodies carrying a complex cocktail of pathogens, nutrients, heavy metals, microplastics, and emerging contaminants. At each step, decision-making has been fragmented across drainage engineers, wastewater operators, environmental regulators, urban planners, and public health authorities who rarely share data, models, or objectives [1]. The result is a water system that is simultaneously over-engineered for peak storm events, under-resourced for routine performance, and systemically misaligned with sustainability goals.

The case for integrated management of stormwater and wastewater systems is both environmental and economic. From an environmental perspective, the combined sewer overflow (CSO) events that are an almost universal feature of older combined sewer cities represent the single largest point-source threat to urban receiving water quality in high-income countries, discharging billions of litres of untreated sewage mixed with stormwater runoff annually [2]. From an economic perspective, the resource losses embedded in this fragmentation are staggering: the nitrogen, phosphorus, organic matter, and water contained in wastewater have recoverable value estimated at USD 100–200 per person per year in high-income countries, yet the vast majority is destroyed through energy-intensive treatment rather than captured through resource recovery [3]. Stormwater itself — a locally generated water resource of increasing value in drought-stressed urban environments — is similarly wasted, discharged to the sea rather than captured for non-potable reuse or managed through green infrastructure that generates co-benefits for biodiversity, urban cooling, and community well-being [4].

Artificial intelligence provides the data integration, pattern recognition, optimisation, and decision support capabilities required to operationalise sustainable integrated water management at the scale and complexity of modern urban systems. The past seven years have seen rapid maturation of AI applications across the stormwater–wastewater domain, driven by falling IoT sensor costs, proliferating open-source machine learning frameworks, and growing recognition among water utility managers that conventional rule-based approaches cannot navigate the multi-objective complexity of sustainable water system operation [5]. However, the sustainability dimension of these applications — their contribution to resource conservation, ecological protection, social equity, and circular economy transition — has received substantially less systematic attention than their operational performance characteristics.

This article addresses that gap by reviewing AI applications in stormwater and wastewater management through an explicit sustainability lens, structured around six sustainability dimensions derived from the United Nations Sustainable Development Goals and the Ellen MacArthur Foundation's circular economy principles. Following a methodology section describing the systematic literature review protocol, we examine AI contributions across each sustainability dimension, then synthesise findings into the Sustainable AI Water Integration (SAWI) framework and a forward-looking research agenda. The review is intended to serve researchers working at the AI-environment interface, water utility practitioners seeking to align operational AI investments with sustainability commitments, and policy-makers designing regulatory and incentive frameworks for sustainable urban water management.

1.1 Sustainability Dimensions in Urban Water Management

Drawing on the Brundtland Commission's foundational definition of sustainability as development that meets present needs without compromising the ability of future generations to meet their own needs [6], and on the three-pillar model of environmental, economic, and social sustainability, we identify six operational sustainability dimensions relevant to integrated stormwater–wastewater management. These are: (i) resource recovery maximisation — extracting energy, nutrients, water, and materials from waste streams; (ii) energy self-sufficiency — minimising net energy consumption and maximising renewable generation; (iii) ecological quality protection — maintaining receiving water body health and urban biodiversity; (iv) social equity and environmental justice — ensuring equitable distribution of service quality, flood risk, and pollution burden; (v) circular economy integration — replacing linear take-make-dispose flows with regenerative resource cycles; and (vi) governance and institutional capacity — building the organisational, regulatory, and community frameworks for sustained sustainability performance. These six dimensions organise the substantive review sections that follow.

1.2 Methodology

This review follows PRISMA 2020 guidelines for systematic scoping reviews. Database searches of Web of Science, Scopus, ASCE Library, and the EBSCO Environment Complete database used search strings combining ('artificial intelligence' OR 'machine learning' OR 'deep learning') AND ('sustainable' OR 'sustainability' OR 'resource recovery' OR 'circular economy' OR 'environmental justice') AND ('stormwater' OR 'wastewater' OR 'combined sewer' OR 'urban water'). The initial search returned 5,341 unique records after deduplication. Following title and abstract screening, full-text review of 1,402 candidate articles identified 103 studies meeting all inclusion criteria: application of at least one AI method, explicit sustainability performance reporting, and peer-reviewed publication between January 2018 and August 2025. The geographic distribution of included studies is tracked as a secondary analytical variable to assess equity in knowledge production.

2. AI for Resource Recovery Maximisation

2.1 Nutrient Recovery: Phosphorus and Nitrogen Recapture

Phosphorus is a finite, non-substitutable element essential for food production; global reserves of phosphate rock are projected to become economically marginal within 50–100 years under current extraction trajectories [7]. Urban wastewater is simultaneously the primary conduit for phosphorus loss from agricultural and food systems, and a potential secondary source of recovered phosphorus if treatment processes are designed and operated for recovery rather than destruction. Struvite (magnesium ammonium phosphate) precipitation from sidestream reject water is the most commercially advanced phosphorus recovery pathway, with operational recovery rates of 50–80% of influent phosphorus achievable under optimal process conditions [8].

AI optimisation of struvite precipitation — controlling the magnesium:ammonium:phosphate molar ratio, pH, temperature, and mixing intensity that determine crystal formation and growth — has demonstrated consistent improvements over manual operator control. A study by Zhou et al. [9] applied a Gaussian Process Regression (GPR) model to optimise struvite precipitation at a full-scale anaerobic digestion reject water treatment facility in Chengdu, China, achieving a 23% increase in phosphorus recovery rate and a 31% reduction in magnesium chloride chemical dosing costs. The GPR model's uncertainty quantification capability proved particularly valuable for operating safely during process upsets, providing operators with probabilistic bounds on expected crystal quality rather than point estimates that might encourage overconfident control decisions.

Nitrogen recovery — as ammonium sulphate, struvite, or biochar-based slow-release fertiliser — presents a parallel opportunity. Ammonia stripping and absorption from sidestream liquors, optimised using Long Short-Term Memory controllers trained on real-time pH, temperature, and ammonium concentration signals, has achieved nitrogen recovery efficiencies of 78–91% in pilot-scale demonstrations across four European countries [10]. The economic case for AI-optimised nutrient recovery strengthens substantially when global fertiliser prices are elevated, as during the 2022–2023 commodity price spike that increased synthetic nitrogen fertiliser costs by 240% and accelerated municipal interest in wastewater-derived nutrient products [11].

2.2 Biogas Optimisation and Renewable Energy Recovery

Anaerobic digestion (AD) of primary and secondary sludge generates biogas — a mixture of approximately 60–65% methane and 35–40% carbon dioxide — that can be used for combined heat and power (CHP) generation, upgraded to biomethane for grid injection, or compressed for vehicle fuel. The theoretical energy content of UK wastewater alone is estimated at 3 times the energy consumed by all water industry operations, suggesting that WWTPs could become net energy exporters if digestion efficiency were fully optimised [12]. In practice, digester performance is highly variable, constrained by complex and poorly understood interactions between feedstock composition, microbial community dynamics, temperature, mixing, and loading rate.

AI models for biogas yield prediction have been intensively developed over the past decade, with Artificial Neural Networks, Random Forests, and gradient-boosted machines all demonstrating R^2 values of 0.88–0.95 for methane yield prediction from feedstock composition and operational variables in cross-validated studies [13]. More impactful are AI systems that use these predictions to drive proactive co-digestion scheduling — adjusting the blend of primary sludge, food waste, agricultural residues, and other organic substrates in real time to maximise methane yield from available feedstocks while respecting digester stability constraints. Deng et al. [14] demonstrated a Proximal Policy Optimisation RL agent managing co-digestion scheduling across three parallel digesters at a 450,000 PE plant in Guangzhou, achieving a 27% increase in average daily methane yield and a 19% reduction in biogas flaring over a 24-month evaluation period relative to the preceding human-managed scheduling regime.

The integration of AI-optimised anaerobic digestion with renewable energy procurement and grid electricity pricing creates additional value through energy arbitrage: producing and storing biogas during periods of high renewable electricity generation (and low grid electricity prices) and consuming it for CHP generation during high-price periods. A demonstration by Severn Trent Water in the UK coupled a Long Short-Term Memory electricity price forecaster with a digester loading optimisation model, achieving average energy cost reductions of £380,000 per year per WWTP across a portfolio of eight facilities without any capital investment in new biogas storage or generation capacity [15].

2.3 Water Reuse and Circular Water Flows

Treated wastewater reuse — for irrigation, industrial cooling, toilet flushing, groundwater recharge, and potable supply — represents the most direct pathway to circular water economy operation. Global treated wastewater reuse currently accounts for less than 4% of the technically recoverable volume, representing a massive untapped opportunity for freshwater conservation and drought resilience [16]. AI contributes to water reuse expansion through three mechanisms: real-time treatment quality assurance (ensuring reuse water meets end-use quality standards), demand-supply matching (optimising the allocation of treated water across competing reuse applications), and public acceptance enhancement through transparent, AI-generated water quality reporting.

A notable integrated deployment is the NEWater programme in Singapore, which produces high-purity reclaimed water from treated wastewater using membrane bioreactor, reverse osmosis, and UV disinfection processes. An AI quality assurance system combining online multi-parameter sensing with an LSTM predictive model provides real-time probability estimates that each batch of NEWater meets potable quality standards across 47 monitored parameters — enabling a 94%

reduction in laboratory confirmation testing while maintaining regulatory compliance assurance superior to that achievable through periodic batch sampling alone [17].

Stormwater harvesting — capturing urban runoff in surface storage, underground cisterns, or managed aquifer recharge — extends the circular water economy concept to the stormwater domain. AI optimisation of stormwater harvesting systems manages the competing objectives of flood attenuation (requiring available storage capacity before storms), water supply augmentation (requiring maximum stored volume), and ecological base flow maintenance (requiring controlled releases to receiving streams) through real-time forecast-guided storage management [18]. A deployment across 34 distributed stormwater harvesting systems in Melbourne, Australia, demonstrated that LSTM forecast-guided adaptive management delivered 38% more usable harvested water annually than rule-based fixed-threshold management while achieving equivalent or superior flood attenuation performance [19].

Table 1. AI-Driven Resource Recovery Performance Benchmarks

Resource Stream	AI Method	Performance Improvement	Economic Benefit	Key Study
Phosphorus (struvite)	Gaussian Process Regression	+23% recovery rate	−31% chemical costs	Zhou et al. [9]
Nitrogen (NH_3 stripping)	LSTM controller	78–91% recovery	Fertiliser product value	Hansen et al. [10]
Biogas (AD co-digestion)	PPO Reinforcement Learning	+27% methane yield	−19% flaring loss	Deng et al. [14]
Energy arbitrage (CHP)	LSTM + optimisation	£380K/yr/WWTP savings	No capex required	Severn Trent [15]
Water reuse (NEWater)	LSTM quality assurance	−94% lab testing	Compliance superior	PUB Singapore [17]
Stormwater harvesting	LSTM forecast-guided	+38% usable yield	Dual flood+supply benefit	Melbourne Water [19]

Note: PPO = Proximal Policy Optimisation; LSTM = Long Short-Term Memory; AD = Anaerobic Digestion; CHP = Combined Heat and Power; PE = Population Equivalent.

3. AI for Energy Self-Sufficiency

Wastewater treatment is among the most energy-intensive municipal service sectors, consuming 0.3–0.6 kWh per cubic metre of treated wastewater in conventional activated sludge configurations and accounting for 1–3% of national electricity consumption in high-income countries. The pathway to energy self-sufficient — and ultimately energy-positive — WWTPs requires simultaneous optimisation of energy consumption reduction (through aeration efficiency, pumping optimisation, and process intensification) and energy recovery maximisation (through biogas production, heat recovery, and photovoltaic generation). AI provides the integrative analytical capability to optimise across these twin objectives in real time.

Aeration control represents the largest single energy efficiency opportunity in activated sludge treatment. Conventional dissolved oxygen (DO) setpoint control — maintaining DO at a fixed target regardless of actual oxygen demand — systematically over-aerates during periods of low biological activity (night-time, dry weather), wasting 15–30% of aeration energy [21]. AI-based aeration control — using LSTM or CNN-LSTM predictors to forecast ammonia load arriving at the aerobic zone 30–90 minutes ahead, enabling proactive reduction of blower speed before demand falls — has demonstrated energy savings of 18–35% in full-scale WWTP deployments without any effluent quality degradation.

The benchmark for energy self-sufficiency — where WWTP electricity generation from biogas CHP and renewable sources equals or exceeds consumption — has been achieved operationally by a growing number of facilities. A global survey of energy-self-sufficient WWTPs found 47 confirmed cases across 14 countries as of 2024, with AI-optimised energy management identified as a contributing factor in 31 of these cases. The common features of successful energy self-sufficiency deployments include high organic loading enabling substantial biogas production, thermally efficient sludge management reducing heating demand, and AI-coordinated demand flexibility enabling peak consumption reduction during high-price grid periods.

4. AI for Ecological Quality Protection

4.1 Receiving Water Quality Modelling and CSO Impact Assessment

The ecological health of urban rivers, lakes, and estuaries that receive stormwater and treated wastewater discharges is the ultimate environmental performance indicator for integrated water management. Receiving water quality is determined by the complex interaction of point source discharges (WWTP effluents, CSO events), diffuse pollution (urban stormwater runoff, agricultural drainage), in-stream processes (dilution, reaeration, biological uptake, sedimentation), and flow conditions. Mechanistic water quality models — QUAL2K, WASP, EFDC — provide physically interpretable simulations but require extensive calibration data and are computationally too intensive for real-time operational decision support.

AI receiving water quality models trained on long-term monitoring datasets can predict dissolved oxygen, ammonia, E. coli, and phosphorus concentrations in receiving water bodies at sub-daily resolution, enabling operators to anticipate ecological impact from planned and unplanned discharges before they occur. Graph Neural Network models that represent the river network as a directed graph — with nodes at monitoring stations and edges representing hydraulic connections — have demonstrated NSE values of 0.84–0.91 for dissolved oxygen prediction at downstream monitoring stations during CSO events, outperforming conventional mass balance models by 0.08–0.14 NSE units.

The integration of receiving water quality AI models with CSO real-time control systems enables ecologically-informed discharge management — prioritising overflow prevention during ecologically sensitive periods (salmon spawning, bathing water season, low-flow drought periods) even when this conflicts with least-cost network management objectives. A deployment on the River Taff in Wales demonstrated that ecologically-informed CSO control, guided by an LSTM receiving water oxygen model, reduced the duration of dissolved oxygen depression below 4 mg/L (acutely toxic to salmonids) by 73% compared with hydraulically-optimised control that ignored in-stream ecological state.

4.2 Green-Grey Infrastructure Integration

Nature-based Solutions (NbS) — green roofs, bioretention cells, permeable pavements, constructed wetlands, urban forests — provide stormwater attenuation, pollutant removal, and ecological co-benefits that grey infrastructure cannot replicate. However, the spatial configuration, maintenance scheduling, and hydraulic integration of NbS with conventional grey drainage infrastructure presents a complex optimisation problem that conventional planning tools address inadequately. AI spatial optimisation models — combining genetic algorithms, multi-objective evolutionary computation, and machine learning-based performance prediction — have advanced substantially in capability for green-grey infrastructure integrated design.

Multi-objective optimisation of green infrastructure placement — simultaneously minimising CSO volume, maximising ecological habitat connectivity, reducing urban heat island intensity, and staying within capital budget constraints — has been demonstrated using NSGA-III (Non-dominated Sorting Genetic Algorithm) coupled with a surrogate LSTM-SWMM performance model across city-scale drainage networks with 500–2,000 potential green infrastructure placement sites. The AI-optimised green infrastructure configurations consistently delivered 15–28% greater CSO reduction per dollar invested than configurations identified through engineering professional judgment alone, while simultaneously improving habitat connectivity and heat island metrics that professional judgment tended to ignore.

Real-time green infrastructure performance monitoring using distributed IoT sensor arrays — soil moisture probes in bioretention cells, flow monitors on infiltration trenches, water level sensors in green roof drainage layers — provides the data foundation for AI models that can predict when individual NbS elements are approaching saturation and will revert to behaving as impervious surfaces during subsequent rainfall events. Pre-emptive drainage of partially saturated NbS elements before forecast rain events, guided by LSTM saturation prediction models, has been shown to increase effective NbS storage utilisation by 41–56% compared with passive management, particularly during the compound rainfall events that pose the greatest flood risk.

5. AI for Social Equity and Environmental Justice

5.1 Mapping Environmental Justice Dimensions of Stormwater Management

Flood risk and water service quality are not randomly distributed across urban populations. Decades of underinvestment in drainage infrastructure serving lower-income and minority communities — documented across the United States, United Kingdom, India, Nigeria, and Brazil — have created systematic environmental justice deficits in which the communities least responsible for generating urban water pollution bear the greatest burden of its consequences. AI spatial analysis tools are increasingly being deployed to map these justice dimensions quantitatively, providing an evidence base for equity-weighted infrastructure investment that conventional asset management frameworks — which prioritise hydraulic capacity rather than social vulnerability — systematically obscure.

The composite index revealed that informal settlements in the Ajegunle and Makoko districts experienced flood event frequencies 4.7 times higher than formal residential areas with equivalent hydrological exposure — a disparity attributable primarily to infrastructure investment shortfalls rather than topographic vulnerability. This quantitative evidence directly informed a World Bank-funded drainage investment programme that prioritised these underserved areas in a manner that conventional hydraulic capacity analysis would not have suggested.

5.2 AI-Enabled Community Engagement and Early Warning

Effective community engagement in stormwater and flood management requires communication tools that are accessible, timely, and culturally appropriate for diverse urban populations — including those with limited digital literacy or access to conventional media channels. AI-powered early warning systems that deliver flood risk notifications through WhatsApp, SMS, and community radio — in local languages, calibrated to the specific risk profile of individual neighbourhoods — represent a significant advance over the single-channel, English-language flood alerts that have characterised emergency communication in many LMIC cities.

Table 2. AI Applications Across Six Sustainability Dimensions: Summary of Evidence

Sustainability Dimension	Primary AI Methods	Studies (n)	Median Performance Gain	SDG Alignment
Resource Recovery	GPR, LSTM, PPO-RL, GBM	21	+27% recovery vs. baseline	SDG 12, 6
Energy Self-Sufficiency	LSTM, MARL, CNN-LSTM	18	−26% net energy cost	SDG 7, 13
Ecological Quality	GNN, LSTM, NSGA-III ML	24	NSE = 0.87 receiving water	SDG 14, 15, 6
Social Equity & EJ	GBM, NLG, LSTM	17	+47% early warning uptake	SDG 10, 11, 6
Circular Economy	RL, GAN, multi-objective	14	+34% resource circularity	SDG 12, 9
Governance & Capacity	XAI, federated ML, LLM	9	Qualitative gains	SDG 16, 17

Note: GPR = Gaussian Process Regression; LSTM = Long Short-Term Memory; PPO-RL = Proximal Policy Optimisation Reinforcement Learning; GBM = Gradient Boosted Machine; MARL = Multi-Agent Reinforcement Learning; GNN = Graph Neural Network; NLG = Natural Language Generation; XAI = Explainable AI; LLM = Large Language Model; EJ = Environmental Justice; SDG = Sustainable Development Goal.

6. AI for Circular Economy Integration

The circular economy concept — eliminating waste by keeping materials and energy in use at their highest value — provides a powerful reframing of urban water system purpose. In circular economy terms, stormwater and wastewater are not problems to be managed and disposed of; they are resource flows to be recovered, cycled, and regenerated. AI enables circular economy transition in urban water management through four principal pathways: closing the water loop (reuse and recycling), closing the nutrient loop (recovery and agricultural return), closing the energy loop (biogas generation, heat recovery, renewable integration), and closing the materials loop (biochar, struvite, recovered metals from sludge).

Life Cycle Assessment (LCA)-informed AI optimisation — which evaluates environmental impact across the full life cycle of water treatment alternatives, from raw material extraction through operation to end-of-life — represents the most sophisticated approach to circular economy-oriented water system design. Multi-objective RL agents that minimise both operational cost and LCA-quantified environmental impact simultaneously have been demonstrated in pilot-scale configurations, identifying treatment process combinations that reduce global warming potential by 18–34% relative to cost-optimised configurations by shifting from energy-intensive aerobic treatment to energy-recovering anaerobic pathways for appropriate wastewater fractions.

Source separation — collecting highly concentrated urine and faecal waste separately from grey water to enable more efficient nutrient and water recovery — is an emerging circular economy paradigm that challenges the conventional combined sewage collection model. AI models for optimising source separation collection logistics, treatment routing, and product market matching have been developed in Swedish and Dutch pilot contexts, demonstrating that source separation nutrient recovery can deliver 60–85% of the theoretical maximum phosphorus recovery at 40–55% of the treatment cost of conventional WWTP phosphorus removal, when AI-optimised logistics minimise collection and transport energy.

7. AI for Governance and Institutional Capacity

7.1 Explainable AI for Regulatory Compliance

The deployment of AI in environmental management decisions that affect public health, ecological integrity, and community well-being raises important questions of accountability, transparency, and democratic legitimacy. When an AI system recommends authorising a CSO discharge, adjusting a wastewater reuse quality standard, or prioritising one neighbourhood over another for drainage infrastructure investment, the basis for that recommendation must be explicable to regulators, elected officials, and affected communities — not merely to data scientists. Explainable AI (XAI) methods — SHAP value attribution, LIME local explanation, attention mechanism visualisation, and counterfactual explanation — are essential tools for building the regulatory acceptance and social licence that AI-enabled water management requires.

7.2 Capacity Building and Knowledge Transfer

The limiting factor for AI-enabled sustainable water management in most of the world is not technical capability but institutional and human capacity. Water utilities in LMIC settings — which serve the majority of the world's urban population — typically lack the data science expertise, computational infrastructure, and inter-departmental data sharing culture required to deploy and sustain AI water management systems independently. International capacity building programmes — including the IWA Digital Water Programme, the World Bank Water GPAi initiative, and the UN-Water Data and Innovation Lab — have collectively trained over 2,400 water sector professionals in AI fundamentals across 67 countries since 2020, but demand substantially exceeds supply in the most underserved regions.

8. The Sustainable AI Water Integration (SAWI) Framework

Drawing on the six-dimension sustainability review and the governance analysis, we propose the Sustainable AI Water Integration (SAWI) framework as an operational architecture for deploying AI across the stormwater–wastewater continuum in alignment with the Sustainable Development Goals. The SAWI framework is distinguished from existing AI water management frameworks by its explicit embedding of sustainability objectives — rather than purely operational performance targets — as the primary design criteria for AI system architecture, data governance, and performance evaluation.

The SAWI framework comprises four integrated layers. The Foundation Layer establishes the physical and data infrastructure prerequisites: a harmonised sensor estate covering both stormwater and wastewater network assets; a shared data platform integrating operational, environmental, meteorological, and socioeconomic data streams; and a sustainability data commons that makes performance data openly accessible to regulators, researchers, and community stakeholders. Open data standards — following the WaterML 2.0 and OGC SensorThings API specifications — ensure interoperability across utility, regulatory, and research contexts.

Table 3. SAWI Framework: SDG Alignment and Implementation Indicators

SAWI Layer	Primary AI Tools	SDG Targets	Key Performance Indicators	Review Frequency
Foundation (Data)	IoT integration, GAN imputation	SDG 6.5, 9.1	Data completeness >92%, latency <5 min	Monthly
Intelligence (Models)	LSTM-GNN, PPO-RL, NSGA-III	SDG 6.3, 6.4, 11.5	NSE >0.85, energy self-suff. >80%	Quarterly
Governance (Accountability)	SHAP XAI, LLM reporting	SDG 16.6, 10.2	Equity index, audit compliance rate	Annual
Learning (Improvement)	Federated ML, AutoML	SDG 17.6, 4.7	Model accuracy trend, knowledge transfer	Biannual

Note: SDG = Sustainable Development Goal; GAN = Generative Adversarial Network; NSE = Nash–Sutcliffe Efficiency; SHAP = SHapley Additive exPlanations; LLM = Large Language Model; XAI = Explainable AI; AutoML = Automated Machine Learning.

9. Barriers to Sustainability-Oriented AI Deployment

9.1 Perverse Financial Incentives

Perhaps the most fundamental barrier to AI-enabled sustainable water management is the misalignment between prevailing water sector financial incentive structures and sustainability objectives. Water utilities in most jurisdictions recover costs primarily through volumetric water tariffs — a structure that creates financial incentives to sell water rather than conserve it, and to maximise treatment throughput rather than minimise resource consumption. Regulatory capital expenditure allowance frameworks that reward investment in new physical infrastructure over operational efficiency improvements further distort incentives against AI-driven optimisation that delivers sustainability gains without creating depreciable assets.

9.2 Regulatory Fragmentation

The institutional separation between stormwater and wastewater regulation — which mirrors the operational separation between the management systems this article seeks to integrate

— creates regulatory barriers to integrated AI deployment. In most jurisdictions, stormwater management is regulated under surface water or municipal planning codes administered by local government, while wastewater treatment is regulated under environmental permits administered by national or regional environmental agencies. Different data standards, reporting formats, performance metrics, and oversight relationships make it difficult for AI systems that span both domains to satisfy all regulatory requirements simultaneously.

10. Research Agenda

Seven priority areas are identified for advancing AI-enabled sustainable integrated water management over the 2025–2035 decade.

Priority 1 — Sustainability-Integrated AI Benchmarks: The water AI research community should establish standardised sustainability performance benchmarks — encompassing all six dimensions reviewed here — as required reporting elements in AI water management publications, enabling systematic cross-study comparison of sustainability performance rather than purely operational metrics.

Priority 2 — LCA-AI Integration: The integration of dynamic, real-time-updated Life Cycle Assessment with AI operational optimisation represents a frontier capability that would enable genuinely sustainability-optimised water system operation. Standardised LCA inventory databases for water treatment unit processes, updated through automated integration with real-time operational sensor data, are a prerequisite for this integration.

Priority 3 — Source Separation AI Economics: The economics of AI-optimised source separation systems — including nutrient recovery, collection logistics, and product market development — require systematic evaluation across diverse geographic and institutional contexts to identify the conditions under which source separation represents a more sustainable alternative to conventional sewerage.

Priority 4 — Environmental Justice AI Metrics: Standard methodologies for quantifying the environmental justice dimensions of AI water management decisions — measuring distributional impacts across income, ethnicity, and geographic vulnerability strata — are urgently required to enable accountability for equity objectives alongside environmental and economic performance.

Priority 5 — LMIC-Optimised AI Architectures: AI model architectures specifically designed for low-data, low-bandwidth, intermittent-connectivity LMIC deployment contexts — including lightweight edge AI models, transfer learning from data-rich contexts, and federated learning across sparse utility networks — require dedicated research investment.

11. Conclusions

This review has examined AI applications in stormwater and wastewater management through an explicit sustainability lens, finding compelling evidence that AI can contribute meaningfully to all six sustainability dimensions reviewed: resource recovery, energy self-sufficiency, ecological quality, social equity, circular economy integration, and governance capacity. The weight of evidence supports a reframing of urban water infrastructure — from a linear, pollution-control-oriented system to a circular, resource-generating, ecologically integrated, and equitably managed service — in which AI is the enabling analytical and operational technology.

Three overarching conclusions emerge from this review. First, sustainability and operational performance are not in tension in AI-enabled water management — they are mutually reinforcing. The case studies reviewed consistently find that AI optimisation for sustainability objectives (resource recovery, energy efficiency, ecological protection) delivers operational performance at least equivalent to, and frequently superior to, purely cost-minimising operational approaches. The framing of sustainability as a constraint on performance is contradicted by the evidence.

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