

Artificial Intelligence for Sustainable Water Management: Opportunities, Technologies, and Environmental Trade-offs

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Abstract

Water scarcity is one of the major resource challenges of the twenty-first century. Agriculture alone accounts for roughly 70 percent of global freshwater withdrawals [4], and a significant proportion of that water is lost before reaching plant roots through evaporation, runoff, and inefficient delivery. Urban distribution networks add to the problem: treated water leaks silently through ageing pipes, never reaching consumers. With global food production needing to increase by 70 percent by 2050 to feed a projected population of 9.1 billion [1], the strain on already-limited freshwater reserves will intensify unless efficiency improves substantially. This review examines how artificial intelligence (AI), the Internet of Things (IoT), unmanned aerial vehicles (UAVs), and digital-twin modelling are being applied across two domains: precision agriculture and urban water infrastructure. In agriculture, AI-driven irrigation, soil-moisture sensing, and UAV-based crop monitoring have produced documented water savings of 30 to 70 percent alongside yield improvements of 20 to 30 percent [2, 3, 7]. In cities, smart metering and AI-based leak detection have measurably reduced water losses in deployed systems across Spain, the United Kingdom, and the United States. The review also examines a less-discussed counterpart: AI's own water cost, specifically the freshwater consumed for data-centre cooling during large-model training and inference [6]. The paper argues that AI's net contribution to water sustainability depends on deliberate choices, including model efficiency, renewable-powered data centres, and transparent water-use reporting, working alongside sound policy and infrastructure support.

Keywords: Artificial Intelligence, Water Conservation, Precision Agriculture, Smart Irrigation, IoT, Leak Detection, Non-Revenue Water, Digital Twin, Green AI, Water Footprint

1. Introduction

Of all water on Earth, only 2.5 percent is freshwater, and much of that is locked in glaciers or deep aquifers. A person's daily drinking-water need is only 2 to 4 litres, but producing that same person's daily food requires an estimated 2,000 to 5,000 litres [1]. That gap sits at the core of the global water crisis. Agriculture draws roughly 70 percent of global freshwater withdrawals, rising to nearly 90 percent in low-income countries where flood irrigation remains common [4]. Urban water networks face a parallel challenge. Non-revenue water (NRW), meaning treated water that leaks, is stolen, or is mis-metered before reaching consumers, averages around 35 percent of total supply globally and exceeds 40 to 50 percent in many developing-world utilities [5]. These are not just efficiency losses. Every litre of NRW represents

energy spent treating and pumping water, chemicals used in purification, and capital invested in infrastructure, all rendered unproductive.

Table 1 illustrates how daily per capita water use varies across countries [8]. The differences reflect agricultural practice, industrial structure, and infrastructure quality rather than population size alone. Countries with large irrigated agricultural sectors sit near the top. Those with more modern infrastructure and moderate agricultural water demand sit near the bottom.

Table 1: Daily Per Capita Water Use by Country (Litres/Day) [8]

Country	Litres Per Day
United States	3,732
Canada	2,722
Pakistan	2,653
Argentina	2,480
Indonesia	2,305
Saudi Arabia	2,078
Egypt	2,048
Turkey	1,978
Mexico	1,940
Australia	1,816
Japan	1,741
India	1,677
South Korea	1,672
Italy	1,546
Russia	1,306
France	1,236
China	1,174
Germany	856
Brazil	856
South Africa	777
Ukraine	592
United Kingdom	350

Three broader trends intensify this picture. First, the Food and Agriculture Organization projects that global food production must rise 70 percent by 2050 [1]. Since irrigated farmland is roughly twice as

productive as rain-fed land, more irrigation is the default response unless efficiency gains offset the increase. Second, climate change is making rainfall less predictable and raising the amount of water crops need to survive heat stress. Third, countries in the Middle East, including Iran, Iraq, Yemen, and Jordan, have already moved into acute water crisis following decades of overextraction and inadequate water governance.

Residential consumption adds another layer. Household leaks from dripping taps, toilet cisterns, and faulty showerheads waste enormous volumes of water annually. Overwatering of lawns through poorly calibrated sprinkler systems can waste up to half of the water applied to evaporation and wind drift. Water from household sinks, bathtubs, and washing machines typically drains directly to sewers rather than being recaptured for garden irrigation or toilet flushing, despite estimates that 30 to 50 percent of household water could be reused through simple greywater systems.

Artificial intelligence, IoT sensors, machine learning, and remote sensing have emerged as a serious response across all of these domains. This paper reviews how these technologies are being applied in agriculture and urban water management, what results have been documented, what environmental trade-offs AI itself introduces, and what barriers stand between current deployment and the scale of change that is needed. The central question is: How can AI improve water-use efficiency across agriculture and urban systems while minimising its own environmental costs?

2. Literature Review

2.1 AI and IoT in Precision Agriculture

The peer-reviewed literature on AI-based irrigation has grown rapidly since 2020. A 2025 meta-analytical review covering studies from 2018 to 2025 found that AI-driven irrigation systems, using machine learning models alongside soil and weather sensors, achieved water savings of 30 to 50 percent and yield improvements of 20 to 30 percent relative to conventional irrigation baselines [2]. Ensemble models such as random forests and deep learning models such as convolutional neural networks performed best, capturing the complex, non-linear relationships between weather, soil conditions, and crop water demand more accurately than simpler regression approaches.

A separate systematic review on IoT sensing for irrigation management [3] found that real-time data from soil moisture probes, weather stations, and plant sensors is the foundation of precision irrigation. It also found that adoption remains geographically uneven. Large commercial farms in high-income countries have moved fastest. Smallholder farmers in South Asia and Sub-Saharan Africa, where water stress is often most severe, face the steepest barriers: high sensor costs, poor connectivity infrastructure, and limited institutional support.

A review in Springer Nature's *Discover Agriculture* [7] documents a Microsoft-supported AI precision irrigation deployment in Andhra Pradesh, India, where AI scheduling combined with drip delivery reduced water use by up to 70 percent and raised yields by 30 percent. The same review values the global smart irrigation market at USD 2.5 billion in 2023, growing at 15 percent annually to an estimated USD 5.8 billion by 2030.

2.2 AI in Urban Water Infrastructure

In urban systems, the dominant AI application has been reducing NRW through smart metering and network analytics. The World Bank benchmarks well-managed utilities at below 25 percent NRW; in practice, many utilities in developing economies exceed 40 to 50 percent [5]. A formal World Bank

analysis estimated that approximately 45 million cubic metres of water are lost daily in developing countries, with a combined economic cost of over USD 3 billion per year [5].

AI addresses the three main causes of NRW: physical leakage (via acoustic sensors and pressure analysis), metering inaccuracy (via consumption-pattern analytics), and unauthorised connections (via network anomaly detection). Digital-twin models add a further capability: simulating the full distribution network virtually, so utilities can test pressure strategies or plan maintenance before spending capital. Documented case studies from Spain, the United Kingdom, and the United States, reviewed in detail in Section 4, demonstrate that these tools produce measurable results in real operating conditions.

3. AI in Agricultural Water Management

3.1 Precision Irrigation

Traditional flood irrigation, still widespread across Sub-Saharan Africa and parts of Asia, applies water uniformly across a field regardless of what any specific area actually needs. Precision irrigation replaces this with a data-driven approach. Sensors measure soil moisture and weather conditions in real time. AI algorithms process these streams continuously and irrigation is applied only where and when it is actually needed.

Control algorithms translate AI recommendations into physical actions. PID (Proportional-Integral-Derivative) controllers calculate valve and pump adjustments based on the gap between a target soil moisture level and the current sensor reading. Fuzzy logic systems handle the inherent imprecision of real agricultural conditions by encoding practical rules such as 'if soil is dry and temperature is high, irrigate more', without needing exact numerical thresholds. These approaches have consistently outperformed fixed-schedule irrigation on both water efficiency and yield in documented trials.

An important shift happening in parallel is from cloud-based AI processing to edge AI, where lightweight models run directly on low-power microcontrollers embedded in sensors and irrigation controllers. This matters because many farms in water-stressed regions have unreliable or no internet access. With edge AI, decisions are made and acted on locally without needing a connection. Quantized neural networks small enough to run on a single microcontroller have already been demonstrated in agricultural settings.

3.2 Hydroponics and Aeroponics

Hydroponics and aeroponics take water efficiency further than any soil-based method can. In hydroponics, plants grow in a nutrient solution and AI systems deliver water and nutrients directly to roots in precisely the quantities needed. In aeroponics, roots are suspended in air and misted with fine nutrient sprays at timed intervals determined by AI algorithms reading root humidity and plant physiological data. Both methods eliminate evaporation and runoff losses inherent in soil-based irrigation, and the water that drains from the root zone is recirculated and reused. Water savings of up to 95 percent compared to conventional field irrigation have been reported for these methods.

The same principles extend to enclosed growing environments. In greenhouses and vertical farms, IoT and AI systems manage temperature, humidity, lighting, and irrigation simultaneously in a closed loop, making them far more water-efficient than open-field growing. Tunnel farming with IoT sensors operates on a similar basis, continuously monitoring conditions inside the tunnel and actuating irrigation and ventilation to maintain optimal parameters with minimal water loss.

3.3 UAV-Based Crop Monitoring

UAVs equipped with multispectral, hyperspectral, or thermal cameras give farmers a spatial view of their fields that ground sensors cannot provide. AI processes this imagery to compute the Normalised

Difference Vegetation Index (NDVI) and Crop Water Stress Index (CWSI). NDVI measures vegetation health by detecting reduced photosynthetic activity before wilting becomes visible to the eye. Thermal imaging identifies where crop canopies are running warmer than expected, a reliable sign that plants are water-stressed and not cooling themselves effectively.

Combining UAV data with soil sensor readings and weather forecasts, AI systems can generate irrigation prescription maps: field-level plans specifying exactly where, when, and how much to irrigate. This spatial precision eliminates the blanket application of water across entire fields and targets it only where it is needed, directly reducing the total volume applied while improving its effectiveness.

ML models trained on historical weather and soil data can also forecast irrigation needs days in advance. This allows farmers to skip irrigation when rain is coming, prepare for droughts, and plan water allocations across a growing season rather than reacting day by day.

3.4 Key Industry Players and Initiatives

A broad ecosystem is delivering these technologies across geographies and scales:

- Netafim (Israel): World leader in precision drip irrigation. Farmers using Netafim's digital platform report 30 to 50 percent water savings and up to 30 percent higher yields. In Israel's Negev desert, Netafim systems combined with soil sensors and satellite data have produced high-yield vegetables using 50 percent less water than conventional methods.
- CropX (Israel/New Zealand): Wireless soil sensors connected to an AI analytics platform that delivers per-zone irrigation recommendations based on subsurface moisture and temperature readings.
- Prospera Technologies (Israel): AI computer vision for greenhouse and open-field crop monitoring, generating irrigation and treatment recommendations continuously from camera and sensor data.
- Fasal (India): AI-powered sensor platform built specifically for smallholder farmers, delivering personalised irrigation and fertilisation advice via mobile phone.
- Blue River Technology (US): Uses AI and computer vision to target individual plants for precise water and spray application rather than treating entire crop rows uniformly.
- SWAMP Project (EU/Brazil): A large-scale research pilot combining AI, IoT, and UAVs to test precision irrigation management across multiple climatic zones.

Student innovation also contributes, particularly in regions where commercial products are too expensive. Students at Veritas University in Nigeria developed a smart irrigation prototype that divided irrigation into sequential, AI-guided stages, optimising every unit of water applied. This kind of locally developed, contextually adapted work is important in regions that need efficiency gains most but can afford commercial solutions least.

4. AI in Urban Water Management

4.1 AI-Based Leak Detection

Traditional leak detection is slow and reactive. Field crews conduct acoustic surveys periodically, and leaks are typically found only after they have grown large enough to surface or cause noticeable pressure drops. AI changes this fundamentally. Acoustic sensors installed along pipe networks record flow sounds continuously. AI algorithms analyse these recordings to identify the characteristic frequencies of leaks, distinguish them from background noise and normal flows, and triangulate leak locations from timing differences between sensors. Repair crews go to a specific point, not a general stretch of pipe.

Smart meters provide a complementary approach. AI analyses meter data for anomalies: constant low-level flow through the night when no legitimate use is occurring, sudden zone-level consumption shifts,

or household usage that deviates significantly from its historical baseline. These patterns can identify household leaks including dripping taps and toilet cisterns that would otherwise go undetected for months. Some smart home systems like Phyn and Flo by Moen learn a household's normal water-use signature and can trigger automatic shutoff at the main valve when a leak is detected.

4.2 Digital Twins and Network Optimisation

A digital twin is a virtual replica of a city's water distribution network, updated continuously with real sensor data on pressure, flow, and pipe condition. Utilities use it to simulate interventions before committing capital: closing a valve, raising pressure in a zone, replacing an ageing main, or rerouting flow during a repair. Instead of learning from costly real-world failures, they test scenarios virtually and select the option with the best predicted outcome.

AI enhances this further. Generative AI tools are beginning to automate inspection report generation from computer vision data and synthesise large heterogeneous datasets, including weather forecasts, historical failures, demand patterns, and infrastructure surveys, into maintenance planning recommendations. The digital twin becomes not just a simulation tool but a live decision-support system.

4.3 Residential and Household Applications

AI is also reaching individual homes. Smart irrigation controllers like Rachio and RainMachine connect to local weather data and skip watering cycles automatically when rain is forecast or soil moisture is already adequate. Studies report water savings of 30 to 50 percent for outdoor watering compared to fixed-schedule sprinkler systems.

At the utility level, smart meter analytics allow identification of the highest-consuming or most wasteful properties in a service area, enabling targeted rebate and incentive programmes for fixture replacement. A utility that can identify properties where consumption patterns suggest a leaking toilet or old high-flow showerhead can proactively reach out rather than waiting for residents to self-report.

Greywater reuse, capturing water from sinks and washing machines for toilet flushing or garden irrigation, remains at the research and pilot stage for AI integration. Given that 30 to 50 percent of household water could theoretically be reused this way, it is a significant area for future development.

4.4 Case Studies

Global Omnium, Spain: Deployed around 700,000 IoT smart meters and built an integrated AI platform called GoAigua. Outcomes included an 18 percent reduction in water loss from AI-based leak detection, a 15 percent gain in operational efficiency, and a 25 percent improvement in system efficiency from smart pressure monitoring. The technology was later spun off as Idrica and now powers the Xylem Vue global digital water platform used by utilities worldwide.

Nashville Metro Water Services, United States: Transitioned from manual meter reading across approximately 3,000 miles of water mains to a smart metering and AI analytics platform. This enabled real-time network monitoring, improved billing accuracy, and generated savings of approximately USD 181,000 per month through reduced water loss and lower operational costs.

Thames Water, United Kingdom: Deployed an AI acoustic leak detection system across its London network. A 20-week rollout of Ovarro's LeakNavigator service, combining acoustic loggers with cloud-based AI analytics, detected 788 individual leaks and recovered 5.78 megalitres of water per day.

4.5 Urban Water Technology Ecosystem

Beyond the large utility deployments, a growing set of specialist companies is advancing AI-based urban water management:

- DrizzleX (US): Smart water management for multi-family buildings using individual micrometers at

each fixture, giving property managers real-time consumption data and leak alerts.

- SCUBIC (Portugal): Combines AI with smart meters, GIS, and SCADA systems for comprehensive network intelligence and real-time control.
- TaKaDu (Israel): Flags leaks, pressure anomalies, illegal connections, and meter faults in real time, deployed by utilities across the United Kingdom, Australia, and Chile.
- WINT Water Intelligence (US/Israel): Real-time AI leak detection for commercial and residential buildings, with automatic shutoff capability.
- Ayyeka (Israel/US): Remote IoT monitoring for water and sewer pipes, using AI to detect anomalous flows indicative of leaks or intrusion.
- Xylem Vue (Global): A global digital water platform that integrates smart meters, leak detection, and digital twin tools for utilities worldwide.

5. Technological Framework

The applications in Sections 3 and 4 share a common underlying technology stack. This section describes its main components and how they function together.

5.1 Artificial Intelligence and Machine Learning

Supervised learning algorithms, including random forests, support vector machines, and deep neural networks, are trained on labelled datasets linking sensor readings to known irrigation requirements or leak events. Unsupervised anomaly detection algorithms, including autoencoders and isolation forests, identify patterns that deviate from learned norms, which can indicate leaks, equipment faults, or unusual consumption.

Recurrent neural networks and Long Short-Term Memory (LSTM) networks handle time-series tasks particularly well, such as forecasting crop water demand or projecting future network pressure. Computer vision convolutional neural networks process UAV imagery to detect crop stress or scan aerial imagery for surface pipe damage. Reinforcement learning approaches are beginning to be applied to irrigation scheduling, training agents to maximise yield while minimising water use through iterative simulation.

5.2 IoT Sensor Networks

In agriculture, the key sensors are soil moisture probes measuring volumetric water content at multiple depths, weather stations recording temperature, humidity, wind, and solar radiation, and flow meters on irrigation lines recording actual delivery volumes. In urban systems, acoustic loggers, pressure transducers, and smart water meters read the flow, pressure, and acoustic state of distribution networks continuously.

Wireless communication protocols including LoRaWAN (Long Range Wide Area Network) and NB-IoT (Narrowband IoT) enable sensors to transmit data over long distances at low power, making them practical for large fields and extensive urban pipe networks. Falling hardware costs since approximately 2020 have been a primary driver of the rapid expansion of IoT deployments in both sectors.

5.3 Remote Sensing

Satellites provide daily or near-daily coverage of agricultural land at moderate spatial resolution, enabling regional-scale drought monitoring and broad crop health assessment. UAVs provide much higher-resolution data at the field level, enabling per-plant analysis of water stress. Together, interpreted by AI, they allow irrigation managers to operate at multiple spatial scales simultaneously: understanding basin-level water availability while making precise zone-level irrigation decisions.

6. Environmental Trade-offs of AI

6.1 AI's Own Water Footprint

AI has a water cost of its own that is rarely discussed. Data centres cool servers using evaporative systems that withdraw significant volumes of freshwater. Li, Yang, Islam, and Ren [6], writing in Communications of the ACM, estimated that training GPT-3 in Microsoft's United States data centres consumed 5.4 million litres of water in total, with 700,000 litres used directly on-site for cooling. They project that global AI water withdrawals could reach 4.2 to 6.6 billion cubic metres annually by 2027, a volume exceeding the total annual freshwater withdrawal of some mid-sized countries.

A key finding of that research is that AI's water consumption varies substantially by data centre location and season. Facilities in cooler climates, or those using closed-loop rather than open-circuit evaporative cooling, withdraw far less freshwater per unit of compute. This means a significant portion of AI's water footprint is a matter of operational choice rather than an unavoidable cost of computation.

The energy consumed during AI training also carries an indirect water cost. Large model training runs consume tens of thousands of megawatt-hours of electricity. The power generation infrastructure behind that electricity, especially thermal and nuclear plants, requires water for its own cooling processes. This indirect water use adds to the direct data-centre cooling demand, though it varies significantly by energy source.

6.2 Green AI Strategies

Several practical strategies can reduce AI's water and energy footprint:

- **Renewable energy:** Wind, solar, and hydroelectric power generate electricity with far lower water demand than thermal fossil-fuel plants. Google, Microsoft, Meta, and Amazon have all committed to 100 percent renewable energy for their cloud data centres, which would substantially reduce the indirect water cost of AI computation.
- **Liquid cooling and heat recovery:** Liquid cooling absorbs heat from processors far more efficiently than air cooling. The warm water produced can be reused rather than evaporated. Meta's data centre in Lulea, Sweden channels server waste heat into the local district heating network, eliminating evaporative loss while recovering useful energy.
- **Alternative water sources for cooling:** Data centres can use seawater or recycled wastewater instead of treated freshwater for cooling. Google's Hamina data centre in Finland uses Baltic seawater, eliminating freshwater consumption for cooling entirely.
- **Smaller, task-specific models:** Distilling or pruning AI models for specific tasks rather than deploying large general-purpose models reduces compute requirements directly. A model sized to its task uses less energy and less cooling water. Transfer learning and model distillation are practical tools for achieving this.
- **Intelligent workload scheduling:** Training jobs can be moved to cooler periods, greener grids, or more water-abundant regions. Treating data centre location as a dynamic variable, and scheduling large training runs when and where water and carbon footprints are lowest, can meaningfully reduce environmental impact.
- **Water Usage Effectiveness (WUE) reporting:** Many companies publish Power Usage Effectiveness (PUE) but not WUE. Making water consumption visible creates accountability. Several major cloud providers have begun publishing water footprint data under growing regulatory and investor pressure, but standardised, mandatory disclosure remains absent.

7. Barriers to Adoption and Policy Implications

The technologies reviewed here are capable of producing large water savings. But technical capability does not automatically translate into deployment. Several barriers limit adoption, particularly in the places where water stress is most severe.

Cost is the most consistently cited barrier in the precision agriculture literature. Sensor networks, UAVs, and AI platforms are accessible to large commercial farms in high-income countries but prohibitive for smallholder farmers in developing economies, who collectively manage a substantial share of the world's agricultural land. Government subsidy programmes, cooperative purchasing schemes, and the development of low-cost edge-AI systems are the most practical routes to closing this gap. Agricultural extension services that bring technology demonstrations directly to farming communities have shown more success in building uptake than commercial marketing alone.

Resistance to change is real but often underestimated. In communities where traditional agricultural practices are culturally embedded and where past experiences with externally introduced technology have been mixed, new tools need to prove themselves locally before they are trusted. Farmer-to-farmer knowledge sharing through demonstration plots, involvement of local agricultural universities in adapting technologies to specific contexts, and patient engagement with farming communities have all been documented as effective in building adoption in otherwise resistant contexts.

Connectivity infrastructure constrains cloud-dependent AI systems in rural and remote areas. Many farms in water-stressed regions of South Asia and Sub-Saharan Africa have intermittent or no internet access. The shift toward edge AI addresses part of this problem, but connectivity investment remains a prerequisite for the broader ecosystem of remote sensing, satellite data, and cloud analytics that supports the most capable precision agriculture platforms.

For urban utilities in lower-income countries, barriers are mainly institutional. Limited technical staff, unclear regulatory frameworks for cost recovery on infrastructure modernisation, and insufficient capital keep many utilities from deploying smart metering and AI analytics even where the technology is available and affordable. International institutions including the World Bank and Asian Development Bank run utility modernisation programmes, but these reach a fraction of the utilities that could benefit.

Water scarcity also intersects with geopolitics. Shared rivers, transboundary aquifers, and disputed water allocations generate political tensions that no technology can resolve on its own. AI can, however, contribute to more objective and transparent management of shared water resources by providing real-time monitoring of extraction rates, flow volumes, and consumption patterns that give negotiating parties a common factual basis. The application of AI to cross-border water governance is technically feasible but has received limited research attention.

On the policy side, most water utility regulations do not yet require smart metering, AI-based leak detection, or digital-twin infrastructure. Most agricultural support programmes were not designed with precision agriculture in mind. Aligning policy incentives with what these technologies can deliver, through performance-based water tariffs, sensor subsidies, requirements for WUE reporting by AI providers, and research funding for low-cost edge-AI irrigation systems, would accelerate adoption at the scale the water challenge demands.

8. Discussion

The evidence reviewed here supports a qualified but genuine optimism. AI-driven precision irrigation and smart leak detection are not theoretical. They have been deployed, and they have produced documented

results: 18 percent water loss reduction in a major Spanish utility, 788 leaks detected and 5.78 megalitres recovered per day in London, 70 percent water savings in an Indian agricultural AI deployment. The innovation ecosystem, from large commercial platforms to student-built prototypes, is active and growing across multiple continents.

At the same time, the pattern of deployment is skewed toward places that already have capital, connectivity, and institutional capacity. The regions where water stress is most acute, smallholder farming areas in Sub-Saharan Africa and South Asia, and utilities in lower-income developing countries, are precisely those with the highest barriers to adoption. Solving the technology problem without addressing this access gap would leave the most important applications untouched.

AI's own water footprint is a real complication but the numbers need to be kept in proportion. Widespread adoption of AI-based precision irrigation could save roughly one-fifth of global agricultural water use. The water consumed by the AI infrastructure enabling those savings, while non-trivial, is a small fraction of that figure. The net balance strongly favours deployment. But that balance is sensitive to how the AI is built and run. Models trained on renewable energy, cooled with seawater or recycled water, and sized appropriately for their task have a fundamentally different environmental profile from large general-purpose models running on fossil-fuel-powered infrastructure.

The policy environment has not caught up with the technology. Performance-based water tariffs that reward utilities for reducing NRW, agricultural subsidies restructured to incentivise sensor adoption, and mandatory WUE reporting for AI providers are all changes that would accelerate the deployment of water-saving AI without requiring any new technological breakthroughs. They require political will and regulatory attention more than research funding.

9. Future Directions

Several research and development priorities emerge from this review:

- Low-cost edge-AI irrigation for smallholders: Ultra-low-cost, solar-powered microcontroller platforms running on-device AI models, capable of making and executing irrigation decisions without internet connectivity, are the most important technological step toward extending precision irrigation to the farmers who need it most. The hardware exists; the integration, testing, and distribution infrastructure for smallholder contexts does not yet exist at scale.
- Long-term independent field validation: Most water-saving estimates in the literature come from short-term pilots or vendor-reported figures. Independent, multi-year field studies tracking actual water savings over full growing seasons and changing weather conditions are needed to establish a more robust evidence base for policy decisions.
- Standardised AI water-footprint disclosure: Building on the Li et al. [6] framework, regulatory or voluntary standards requiring AI providers to disclose Water Usage Effectiveness per unit of compute, disaggregated by data centre location and energy source, would create meaningful accountability and drive improvement through market pressure.
- Cross-border water governance tools: AI-assisted monitoring of transboundary rivers and shared aquifers, including detection of illegal extraction and real-time flow accounting, is technically feasible and could reduce water-related geopolitical tension by providing negotiating parties with objective, shared data. This application has received limited research attention relative to its importance.
- Greywater AI integration at scale: AI-driven greywater quality monitoring and automated diversion systems could unlock the significant share of household water that is currently discharged to sewers

without being reused. Scaling pilot projects to deployable products, and integrating them with building-level water management platforms, is a practical next step.

- Water-energy-food nexus modelling: AI systems that model water, energy, and food interdependencies simultaneously, rather than optimising water use in isolation, are better placed to avoid solutions that trade one resource problem for another. This integrated perspective is underrepresented in the current research literature.

10. Conclusion

Water is wasted at scale in agriculture and in cities, through inefficiencies that have accumulated over decades and that manual methods alone cannot fix. AI, IoT sensing, UAVs, and digital twins offer the real-time intelligence needed to close that gap.

Deployed in agriculture, these technologies can cut irrigation water use by 30 to 70 percent while improving yields. In cities, AI-based leak detection has recovered millions of litres per day in documented deployments. The technology base is real, the results are measurable, and the ecosystem of developers, utilities, and research groups advancing these tools is broad and growing.

Two honest complications remain. AI carries its own water cost in data-centre cooling, and the people who need these tools most, smallholder farmers and utilities in lower-income countries, are often the least able to afford them. Both are solvable problems. Smaller, more efficient models, greener data centres, government subsidies, and low-cost edge-AI hardware are practical paths forward, not distant aspirations. But solutions do not deploy themselves. Getting this right will require policy frameworks aligned with what the technology can deliver, investment in access for the regions that need it most, and a commitment to making AI's own environmental costs visible and accountable. The water crisis is too serious for tools this promising to remain the privilege of those who need them least.

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