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Smart Water Management: Governance Innovation, Technological Integration, and Policy Pathways Toward Economic and Ecological Sustainability

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Abstract

Smart water management (SWM) represents a transformative shift in urban water governance, integrating advanced digital technologies—including the Internet of Things (IoT), Artificial Intelligence (AI), big data analytics, and digital twin modeling—to enable real-time monitoring, predictive analytics, and adaptive decision-making. While drawing extensively on a structured literature review to build its theoretical foundation, this manuscript is primarily presented as a research paper that combines conceptual analysis with empirical insights derived from comparative case studies, rather than a standalone comprehensive review. A five-layer system architecture—encompassing data sensing, transmission, processing, intelligent analysis, and decision support—is introduced to evaluate how technological components interact across operational layers. The model is applied to two representative cases: Singapore's Smart Water Grid and selected pilot programs in Chinese cities (Shenzhen, Hangzhou, Beijing). These cases are analyzed for their level of digital integration, policy alignment, and performance outcomes, offering insights into both mature and emerging smart water implementations. Findings indicate that the transition from manual to intelligent governance significantly enhances system performance and robustness, particularly in response to climate-induced disruptions. Despite benefits such as reduced non-revenue water and improved pollution control, challenges including high initial investment, data interoperability issues, and cybersecurity risks remain critical barriers to widespread adoption. Policy recommendations focus on establishing national standards, promoting cross-sectoral data sharing, encouraging public–private partnerships, and investing in workforce development to support the long-term sustainability and scalability of smart water initiatives.

Keywords: smart water management; IoT; digital twin; environmental carrying capacity; sustainable development; water governance

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Academic Editor: Jianjun Ni

Received: 27 May 2025
Revised: 23 June 2025
Accepted: 26 June 2025
Published: 27 June 2025

Citation: Dai, Y.; Huang, Z.; Khan, N.; Labbo, M.S. Smart Water Management: Governance Innovation, Technological Integration, and Policy Pathways Toward Economic and Ecological Sustainability. *Water* **2025**, *17*, 1932. https://doi.org/10.3390/w17131932

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1. Introduction

Water resources are under increasing pressure due to rapid urbanization, climate change, and growing demand across various sectors. According to recent global assessments, over four billion people face severe water scarcity at least one month per year [1], and this challenge is expected to intensify in the coming decades [2]. In response to these escalating pressures, traditional water management practices are proving insufficient to

ensure sustainable supply, equitable distribution, and environmental protection. SWM represents a paradigm shift in urban water governance, integrating advanced digital tools such as IoT, AI, cloud computing, and digital twins to improve robustness, performance, and long-term sustainability [3,4].

At its core, SWM leverages tools such as the IoT, AI, big data analytics, and digital twin modeling to enable real-time monitoring, predictive maintenance, and adaptive decision-making. One of the most promising innovations in SWM is the adoption of intelligent digital twins, which allow for the creation of virtual replicas of physical water systems. These models support simulation-based planning, optimization, and risk assessment, thereby enhancing operational agility and supporting strategic planning over time [5]. Furthermore, AI and big data have shown significant potential in enhancing water quality prediction, leak detection, and demand forecasting, offering scalable solutions for both developed and developing regions [6].

From a policy perspective, SWM are increasingly recognized as essential tools for achieving the United Nations Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation) and SDG 11 (Sustainable Cities and Communities) (UN, 2015). By enabling the more efficient use of limited water resources, reducing environmental degradation, and supporting data-driven governance, SWM contributes directly to the enhancement of environmental carrying capacity and sustainable economic development.

This paper examines the evolutionary path of SWM and highlights core technological elements that facilitate their adoption within contemporary water governance structures. Adopting a mixed-methods approach, the study integrates a structured literature review with qualitative comparative case analysis and technical architecture modeling. This methodological approach facilitates a dual focus: advancing theoretical understanding while enabling context-sensitive evaluation of smart water deployments in diverse governance environments.

2. Theoretical Background and Developmental Trajectory

2.1. Evolutionary Path of Smart Water Management

The evolution of water management systems reflects a broader transformation in urban infrastructure, shifting from reactive and manual operations to intelligent, data-driven governance [7]. This transition is driven by increasing urbanization, climate pressures, and the need for sustainable resource use. Scholars have identified several developmental phases that illustrate how water organizations have adapted to these changes, including:

- Manual Monitoring Stage
- Automated Control Stage
- Digital Water Stage
- Smart Water Stage

Each phase represents a step toward the greater integration of digital technologies and improved decision-making capabilities.

2.1.1. Manual Monitoring Stage

Historically, water utilities relied heavily on manual observation, paper-based records, and periodic inspections to manage distribution networks and detect issues such as leaks or contamination [8]. These methods were not only labor-intensive but also limited in their ability to provide timely insights or predictive capabilities. As a result, maintenance was often reactive rather than proactive, leading to inefficiencies, service disruptions, and increased operational costs. Moreover, the lack of real-time data significantly hindered decision-making processes. Operators had little visibility into system performance until problems manifested in the form of visible damage or service complaints. This approach

lacked scalability and could not meet the growing demands of urban populations or address emerging environmental challenges.

2.1.2. Automated Control Stage

In the late 20th century, many water agencies began adopting Supervisory Control and Data Acquisition (SCADA) systems. SCADA allowed for the remote monitoring of critical parameters such as pressure, flow rate, and tank levels, enabling more responsive control over infrastructure [9]. The introduction of these systems marked a significant improvement in operational efficiency, reducing reliance on manual labor and enabling centralized monitoring. However, despite its advantages, SCADA remained largely centralized and static. While it provided real-time data, its capacity for advanced analytics and adaptive decision-making was limited. Decision rules were often hardcoded, and system adjustments required manual intervention. Furthermore, the lack of interoperability between SCADA platforms restricted flexibility and scalability, making it difficult to integrate with newer technologies. This phase laid the groundwork for future digitalization efforts by demonstrating the value of real-time monitoring and automated control. Nevertheless, it became increasingly evident that more sophisticated tools would be needed to address the complexities of modern water management.

2.1.3. Digital Water Stage

With the rise of big data and IoT technologies in the early 21st century, water organizations entered the digital water era. This stage was characterized by the integration of IoT sensors, telemetry, and centralized data platforms, which enabled continuous monitoring and basic automation [10]. Utilities could now collect large volumes of operational data from distributed sources, supporting performance tracking, trend analysis, and predictive maintenance. Unlike earlier systems, digital water platforms facilitated data-driven decision-making by aggregating information from multiple subsystems into unified dashboards. Despite these advances, the digital water stage introduced new challenges. Data silos were common due to the use of disparate systems and protocols. Moreover, the sheer volume and heterogeneity of data required more advanced processing techniques, which many organizations were not yet equipped to handle. Still, this phase represented a major step forward in terms of transparency, responsiveness, and analytical capability.

2.1.4. Smart Water Stage

Today's water systems are increasingly defined by the adoption of AI, cloud computing, and digital twin modeling, enabling real-time decision-making, predictive analytics, and adaptive control [11,12]. These innovations support dynamic resource allocation, early leak detection, and scenario-based planning, significantly improving system functionality and ecological robustness.

Notably, the concept of smart water grids has emerged as a key component at this stage, integrating multiple technologies to improve transparency and responsiveness across the entire network [13]. Digital twins, serving as virtual replicas of physical infrastructure, are particularly valuable for simulating scenarios, assessing risks, and supporting emergency preparedness.

Unlike previous stages, the smart water stage emphasizes not only data collection and monitoring but also autonomous adaptation and system-wide optimization. AI-powered algorithms process vast volumes of sensor data to detect anomalies, anticipate failures, and propose optimal interventions.

Cloud-based platforms further facilitate seamless information exchange among stakeholders. This stage represents a paradigm shift from rule-based control to intelligence-driven governance, where decisions are guided by forecasting rather than past practices. It

also introduces new pathways for citizen participation through mobile apps and open data initiatives, promoting greater accountability and stakeholder involvement.

Understanding this developmental path is essential for designing future-ready water management strategies that align with global sustainability goals and local implementation constraints. The transition from manual to intelligent governance reflects a continuous effort to improve operational effectiveness, environmental stewardship, and institutional adaptability. Each stage has built upon its predecessor, introducing novel technologies and methodologies to address evolving challenges.

To visually illustrate this progression, we present Figure 1, outlining the chronological evolution of SWM with an emphasis on real-time analytics and adaptive governance. Additionally, Table 1 summarizes the core features of each developmental phase, including data acquisition approaches, decision-making mechanisms, and major constraints.

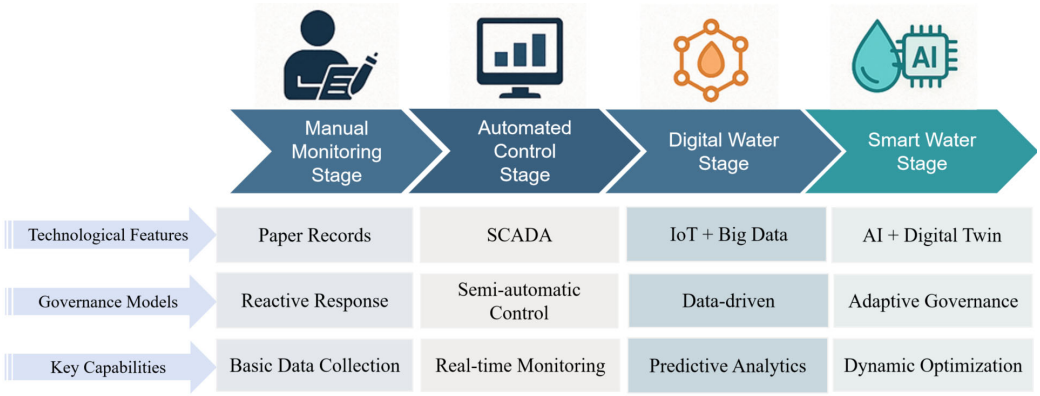

Figure 1. Technological Advancements in Smart Water Governance from Manual to Intelligent Systems.

Table 1. Comparative Summary of the Four Developmental Stages in Smart Water Governance.

Stage	Technology	Data Collection Method	Decision-Making Mode	System Response	Limitation
Manual Monitoring	Paper records, visual inspection	Infrequent, human-dependent	Reactive	Slow and error-prone	High labor cost, low accuracy
Automated Control	SCADA systems	Real-time but limited scope	Rule-based automation	Improved but rigid	Centralized, not scalable
Digital Water	IoT sensors, telemetry, big data platforms	Continuous, multi-source	Data-driven	Proactive within limits	Data silos, lack of integration
Smart Water	AI, digital twin, cloud computing	Real-time, integrated	Predictive and adaptive	Highly responsive	High investment, cybersecurity risks

However, despite these advancements, several challenges remain in achieving full interoperability, ensuring robust cybersecurity, and building institutional readiness for AI-integrated governance. Many utilities still struggle with outdated infrastructure, fragmented data ecosystems, and a shortage of technical expertise—all of which constrain the widespread adoption and long-term impact of smart water technologies. These limitations set the stage for further discussion on policy frameworks and implementation strategies that can address such barriers.

2.2. Intelligent Water Governance: From Predictive Analytics to Adaptive Control

The smart water stage marks a paradigm shift from rule-based control to intelligence-driven governance, where decisions are informed by predictive insights rather than historical patterns. Unlike earlier models focused on monitoring and basic automation, modern SWM emphasizes system-wide optimization, machine learning integration, and real-time adaptation. Recent advancements continue to push the boundaries of what is possible.

For instance, the integration of explainable AI (XAI) is becoming crucial for building trust and transparency in automated decision-making processes within water management [14]. Furthermore, edge computing solutions are increasingly deployed to enable faster real-time analytics to be closer to the data source, reducing latency and bandwidth requirements for smart water grids [15].

The rapid evolution of AI has significantly expanded its applicability in smart water systems. Recent studies highlight the growing integration of AI techniques—including machine learning, deep learning, and hybrid models—into real-world water governance frameworks [14]. For instance, ref. [15] provide a comprehensive review of deep learning applications in urban water management, emphasizing their advantages in demand forecasting, leak detection, and system optimization over traditional methods.

One notable application is the Bloom Sense project, which integrates AI with automated buoy systems to detect and predict harmful algal blooms [16]. This initiative demonstrates how AI can be applied not only for anomaly detection but also for predictive water quality monitoring in surface water environments. The authors of [17] further illustrate the potential of digital twins in climate change adaptation and disaster risk reduction through the HIP digital twin framework, showing how virtual modeling can support adaptive governance under extreme climatic conditions.

Moreover, the integration of explainable AI (XAI) is becoming crucial for building trust and transparency in automated decision-making processes within water management [18]. Furthermore, edge computing solutions are increasingly deployed to enable faster real-time analytics closer to the data source, reducing latency and bandwidth requirements for smart water grids [19].

These developments reflect a broader trend toward data-driven, adaptive water management practices supported by intelligent technologies. In addition to improving operational efficiency, such approaches contribute to long-term resilience and sustainability. As noted by [13] digital twin technologies enhance resource efficiency, reduce environmental impacts, and align urban water systems with the UN SDGs. The authors of [20] further demonstrate how digital twin-based strategies can improve emergency response and optimize resilience planning in smart urban water distribution networks.

The key features of this intelligent stage include:

1. Proactive Leak Detection: AI algorithms analyze sensor data to identify anomalies before they cause major losses. For example, in El Prat de Llobregat, a municipality in the Barcelona metropolitan area, AI-powered systems implemented by Adasa Sistemas successfully detected micro-leaks that were previously undetectable using conventional SCADA systems [21];
2. Demand Forecasting: Machine learning techniques predict consumption patterns, supporting optimized supply planning and energy use. These models enable utilities to anticipate peak demand periods and adjust operations accordingly;
3. Adaptive Distribution Strategies: Real-time adjustments to pumping schedules and valve settings improve system responsiveness and reduce waste, particularly during emergencies or extreme weather events.

Moreover, the integration of urban digital twins allows for comprehensive modeling under different scenarios, enabling robust planning and emergency preparedness [12]. These virtual models support what-if analyses, risk assessments, and long-term sustainability planning, offering a powerful tool for water managers.

The emergence of “Cognitive Digital Twins” reflects a new phase in smart water governance, where AI enables digital replicas to self-optimize based on real-time inputs [22].

This transition not only improves operational performance but also enhances long-term robustness against climate-induced disruptions such as droughts, floods, and extreme

weather events. Resilience in this context can be understood through metrics such as system recovery time, supply redundancy, and adaptive capacity—dimensions that are significantly strengthened through intelligent water governance.

Despite its advantages, the implementation of intelligence-driven systems faces challenges such as high initial investment, data interoperability issues, and cybersecurity risks. The increasing connectivity also makes these systems potential targets for cyber-physical attacks, necessitating advanced security protocols and frameworks [23]. Furthermore, increasing reliance on complex algorithms raises concerns about transparency and potential biases in automated decision-making.

Given these advantages, the transition to intelligent water systems is increasingly seen as a strategic imperative for future-ready urban infrastructure. As cities face growing environmental and demographic pressures, adopting smart water technologies becomes essential for ensuring long-term sustainability and service reliability.

3. Research Framework and Methodological Approach

This section outlines the methodological framework, data sources, and system architecture used to support the analysis presented in this study. Given that this research focuses on the developmental trajectory and practical implementation of SWM, a mixed-methods approach was adopted. This approach combines a structured literature review to establish the conceptual framework with a qualitative comparative case analysis to explore practical implementations. The objective is to develop a comprehensive understanding of SWM by integrating theoretical foundations, practical implementations, and technological innovations.

3.1. Structured Literature Review

This study adopts a qualitative comparative case analysis approach, supported by a structured literature review to inform the conceptual framework and guide case selection. The research methodology is designed to align with the paper's objective of analyzing the developmental trajectory, technological integration, and policy implications of SWM.

A structured literature review was conducted using academic databases such as Scopus, Web of Science, and IEEE Xplore to identify key publications related to smart water technologies, governance models, and implementation challenges. Search terms included combinations of keywords such as "smart water management," "Internet of Things in water," "AI in water systems," and "digital twin water".

Following an iterative search process, a total of 156 peer-reviewed articles were initially identified. After applying inclusion criteria based on relevance, publication date (2010–2024), and methodological quality, 84 studies were retained for thematic synthesis.

Thematic insights were extracted using an inductive coding approach, categorizing findings into four domains: (1) enabling technologies; (2) governance frameworks; (3) implementation barriers; and (4) economic and environmental impacts. These categories informed the development of the five-layer architecture model and guided the identification of key performance indicators used in the case comparisons.

Building upon this conceptual foundation, two representative cases—Singapore's Smart Water Grid and selected Chinese pilot programs (Shenzhen, Hangzhou, Beijing)—were selected according to predefined criteria (see Section 3.3).

These cases provide contrasting yet complementary perspectives on smart water governance, offering valuable insights into localized implementation strategies and system maturity levels. Each case is mapped to the proposed five-layer architecture to evaluate the degree of digital integration and functional coordination across layers.

To further enhance the reliability and traceability of the findings, data were collected from official reports, technical briefs, and open-access publications issued by national and municipal water authorities.

3.2. Data Collection and Sources

Although this study does not rely on primary data collection through field experiments or surveys, it draws upon a variety of secondary data sources, including:

- Official reports from national water authorities, such as PUB Singapore and China's Ministry of Water Resources;
- Open-access datasets from international organizations including the World Bank, United Nations, and FAO;
- Peer-reviewed academic articles and conference proceedings focusing on smart water technologies;
- Technical white papers published by industry leaders such as IBM, Siemens, and ABB;
- Governmental and municipal publications describing smart city initiatives and infrastructure upgrades.

These sources collectively offer foundational insights into current practices, emerging trends, and performance indicators related to SWM.

3.3. Case Study Selection

Building upon the theoretical insights derived from the structured literature review, representative case studies were then selected based on predefined criteria to evaluate the practical implementations of SWM. To ensure relevance and comparability, case studies were selected based on the following criteria:

- Geographic diversity: Including both developed and developing regions to reflect varying contextual challenges;
- Level of technological integration: Preference was given to cases where IoT, AI, cloud computing, or digital twin technologies had been clearly implemented;
- Availability of public documentation: Only cases with sufficient publicly available information were considered to ensure transparency and reproducibility;
- Policy alignment: Priority was assigned to cases that demonstrated clear links between smart water strategies and broader sustainability or urban development goals.

3.4. Performance Indicators and Assessment Criteria

To assess the effectiveness of SWM across different dimensions, a set of evaluation metrics were defined, covering:

- Operational efficiency (e.g., reduction in non-revenue water, response time to leaks);
- Environmental impact (e.g., pollution control, ecosystem protection);
- Economic benefits (e.g., cost savings, return on investment);
- Social outcomes (e.g., user satisfaction, public participation).

These metrics were used to compare the performance of different smart water implementations and to derive policy recommendations.

3.5. Technical Architecture Overview

To illustrate the functional structure of SWM, this study proposes a five-layer system architecture that supports intelligent water governance. The model includes the following interconnected layers:

- Data Sensing Layer
- Data Transmission Layer

- Data Processing Layer
- Intelligent Analysis Layer
- Decision Support Layer

The five layers operate in coordination through real-time data exchange. This enables continuous monitoring, predictive modeling, and responsive decision-making within a closed-loop framework.

Table 2 provides an overview of each layer's core technologies and their respective functions within the SWM framework. A visual illustration of the architecture is presented in Figure 2, showing its hierarchical layout and interactive relationships between components.

Table 2. Technical Components and Functions in Smart Water Management (SWM).

Technology Layer	Key Technologies	Functions
Data Sensing	IoT sensors, Smart meters, Drones	Real-time monitoring of water quality, flow, pressure, leakage
Data Transmission	5G, LoRa, NB-IoT	High-speed, low-latency communication between devices and central systems
Data Processing	Cloud platforms, Big data analytics	Storage, integration, and processing of large-scale heterogeneous data
Intelligent Analysis	Machine learning, Deep learning, Digital twins	Predictive modeling, fault diagnosis, scenario simulation
Decision Support	GIS visualization, Emergency alert systems, Mobile apps	Facilitate informed decisions and public participation

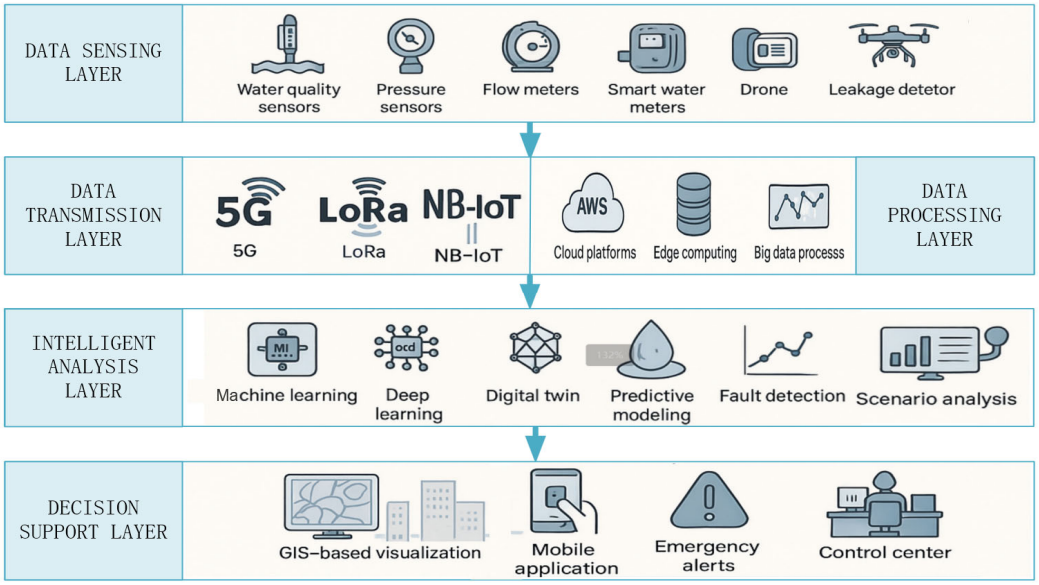

Figure 2. Hierarchical Architecture of a SWM Showing Layered Data Integration and Functional Coordination.

The Data Sensing Layer serves as the foundation of the system, where physical parameters such as water quality, pressure, flow rate, and leakage are continuously monitored using a variety of IoT sensors. These include water quality sensors, pressure sensors, flow meters, smart water meters, drones, and leakage detectors, which are strategically positioned across urban infrastructure or pipeline networks. These devices generate real-time data streams that form the basis for all subsequent processing and analysis.

In the Data Transmission Layer, wireless communication technologies such as 5G, LoRa, NB-IoT, and fiber optic links are employed to transmit raw sensor data from the field to centralized or edge computing systems. Arrows indicating bidirectional data

flows illustrate the seamless connectivity between sensing nodes and backend platforms, ensuring low-latency, high-reliability data transfer essential for timely decision-making.

The Data Processing Layer includes cloud platforms (e.g., AWS, Azure), edge computing devices, and big data processing modules responsible for storing, integrating, and preprocessing the heterogeneous data collected from lower layers. This stage ensures data quality, consistency, and readiness for advanced analytical tasks by filtering noise, normalizing formats, and structuring datasets for further use.

At the Intelligent Analysis Layer, machine learning algorithms, deep learning models, digital twin simulation engines, predictive modeling tools, fault detection systems, and scenario analysis modules process the structured data to extract actionable insights. This layer supports the dynamic optimization of supply–demand balances, early identification of anomalies, and simulation-based planning, significantly enhancing both system performance and resilience.

The Decision Support Layer combines tools such as GIS-based dashboards, mobile apps, emergency alerts, and control centers to enable data-driven decision-making. It enhances situational awareness and responsiveness while encouraging active stakeholder involvement in water management processes.

3.6. Model Differentiation and Practical Relevance

The five-layer architecture proposed in this study distinguishes itself from conventional smart water models by integrating novel features that enhance both its technical functionality and governance applicability. Unlike traditional IoT-centric frameworks, which primarily focus on data acquisition and transmission, this model emphasizes system-wide intelligence, adaptive decision-making, and stakeholder interaction—attributes that are essential for advancing smart water governance.

A key innovation of the framework is the integration of digital twin modeling and public engagement tools within a cohesive design. This dual focus supports not only operational efficiency but also participatory governance, reflecting the evolving understanding of SWM as socio-technical ecosystems rather than purely engineering constructs [24]. The inclusion of mobile applications and open-data platforms further promotes transparency and empowers citizens to play an active role in resource management and leak reporting.

Moreover, the architecture incorporates closed-loop feedback mechanisms—a fundamental feature for enabling real-time responsiveness and long-term robustness. Such capabilities are particularly valuable for cities facing climate-induced disruptions, where predictive analytics and flexible control strategies can significantly improve governance outcomes [12,25].

Unlike general-purpose smart city frameworks, this architecture is specifically tailored for water governance needs. While many smart city models emphasize connectivity and basic data aggregation, they often lack domain-specific integration of functionalities such as predictive maintenance, environmental monitoring, and resource optimization—all of which are central to SWM.

By incorporating these novel elements, the proposed framework provides a more comprehensive and application-oriented approach to smart water governance, distinguishing itself from both generic smart infrastructure models and earlier water-focused architectures that lacked full-scale intelligence and adaptability.

4. Case Studies and Implementation Pathways

Based on the predefined selection criteria—geographic diversity, level of technological integration, availability of public documentation, and policy alignment—this section examines two representative implementations: Singapore's Smart Water Grid and selected pilot

programs in China, including Shenzhen, Hangzhou, and Beijing. These cases were chosen for their contrasting yet complementary approaches to smart water governance.

Singapore exemplifies a highly centralized, technologically mature model driven by national water security imperatives. It has achieved full-scale integration of smart technologies, including advanced analytics, digital twins, and citizen engagement tools. In contrast, China's initiatives represent a decentralized, rapidly evolving approach shaped by municipal-level priorities such as pollution control, leakage reduction, and resource efficiency. The selected pilot cities demonstrate varying levels of technology adoption and offer insights into how SWM can be adapted to different governance structures and developmental stages.

Each implementation is mapped to the five defined layers—data sensing, transmission, processing, intelligent analysis, and decision support—to evaluate the degree of digital integration and system maturity. Particular attention is given to the deployment of enabling technologies such as IoT sensors, AI algorithms, and digital twins, as well as the presence of feedback mechanisms that support adaptive governance.

4.1. Singapore's Smart Water Grid

Singapore, a city-state with inherent water scarcity, has emerged as a global leader in SWM, driven by its strategic "Four National Taps" policy framework. The Public Utilities Board (PUB) has systematically integrated digital technologies into this governance model, positioning the Smart Water Grid as a core technological platform for optimizing resource use and ensuring national water security. A cornerstone of Singapore's success is its proactive approach to Non-Revenue Water (NRW) management, consistently achieving one of the lowest global rates. This is not merely a result of deploying IoT sensors for the real-time monitoring of pressure, flow, and water quality, but a multifaceted strategy encompassing high-fidelity sensor networks, advanced acoustic sensors, and AI-driven predictive analytics [13]. These tools allow PUB to anticipate and address potential leaks before they escalate, shifting from reactive to proactive maintenance—a hallmark of the Intelligent Analysis Layer within the SWM architecture.

The implementation of Singapore's Smart Water Grid follows a structured five-layer architecture, with each layer incorporating specific technologies and analytical methods:

1. Data Sensing Layer: Over 50,000 IoT sensors are deployed across reservoirs, pipelines, and treatment plants to monitor parameters such as pressure, flow rate, turbidity, and chlorine levels in real time.
2. Transmission Layer: Data is transmitted via secure SCADA systems and fiber-optic networks to centralized cloud platforms, ensuring low-latency communication and high data availability.
3. Processing Layer: Raw data undergoes cleaning, normalization, and integration through middleware platforms that unify inputs from heterogeneous sources (e.g., weather forecasts, historical records).
4. Intelligent Analysis Layer: Machine learning models, including ARIMA for time-series forecasting and Random Forest for anomaly detection, are used to predict leaks, optimize pump schedules, and assess system health.
5. Decision Support Layer: Insights generated by the intelligent analysis layer are visualized on dashboards accessible to PUB operators and city planners. These dashboards integrate GIS mapping, alarm systems, and scenario simulation tools to support both routine operations and emergency responses.

This technological prowess is complemented by active leakage control teams, a systematic pipe renewal program, and public engagement initiatives encouraging citizens to report leaks.

The integration of digital twin modeling in Singapore is particularly advanced, extending beyond predictive maintenance to encompass holistic system optimization. These digital replicas enable integrated scenario planning—for example, optimizing energy-intensive pumping schedules based on real-time water demand and electricity tariffs, as well as simulating responses to climate-induced events or security disruptions. These capabilities directly contribute to system resilience, a defining feature of Singapore's "Smart Water Stage" strategy. Moreover, digital twin models play a vital role in long-term infrastructure planning by assessing the impact of urban development and supporting the energy efficiency optimization of NEWater and desalination plants. For instance, Ref. [26] demonstrated that digital twin paradigms in water services can effectively integrate meteorological forecasts with operational data, thereby enabling the optimization of processes such as desalination and water distribution and achieving notable improvements in energy efficiency.

Singapore's SWM strategy also strongly emphasizes demand management and public engagement, recognizing that technology alone is insufficient [8]. Mobile applications provide consumers with real-time feedback on their water usage, fostering water conservation consciousness and enabling informed decision-making. Some applications incorporate behavioral nudges, such as gamification or comparative consumption data, to further encourage savings. This approach directly links to the "Decision Support and Application Layer" of SWM, extending its reach to empower end-users. The overall success of Singapore's model is underpinned by robust political will, clear regulatory frameworks, sustained investment in research and development, and a culture of continuous improvement within PUB. While the high initial investment presented a challenge, it was justified by a long-term vision for water security and operational efficiencies. Ongoing focus areas include data security and the seamless integration of diverse technological systems [25].

These outcomes demonstrate the effectiveness of integrated smart water solutions in improving system performance, reducing waste, and promoting user engagement. As detailed in Table 3, Singapore has made significant strides across several key performance indicators (KPIs), including a 54.4% reduction in NRW rates since 2010, a 91.7% improvement in leak detection response times, and an impressive 750% increase in smart meter coverage since 2015. These findings align with recent scholarly work emphasizing the role of digitalization in improving system performance and reducing non-revenue water through predictive analytics and automated leak detection [27,28].

Table 3. Key Performance Indicators of Singapore's Smart Water Initiatives.

Indicator	Baseline (Year)	Latest Data (2023)	Change (%)	Source
Non-Revenue Water (NRW) Rate	9% (2010)	4.1%	↓ 54.4%	PUB Annual Report, 2023
Leak Detection Response Time	72 h (pre-2010)	<6 h	↑ ~91.7%	PUB Technical Brief on Leak Management, 2022
Smart Meter Coverage	10% (2015)	~85%	↑ 750%	PUB Smart Metering Rollout Update, 2023
Mobile App Adoption Rate	—	~35% household users	New feature	PUB Digital Services Report, 2023
Energy Consumption Reduction in Pumping	—	~15% since 2020	Estimated	PUB Energy Efficiency Roadmap, 2021

Note: ↑ indicates an increase; ↓ indicates a decrease.

To visually illustrate the deployment of smart water technologies in Singapore, Figure 3 presents a schematic overview of the city-state's SWM system. The diagram highlights the integration of IoT sensors, digital twins, cloud computing platforms, and citizen engagement tools across the entire water supply chain. Drawing on PUB's digital

transformation strategy [29], it reflects how these technologies are interconnected to enable real-time monitoring, predictive analytics, and adaptive governance.

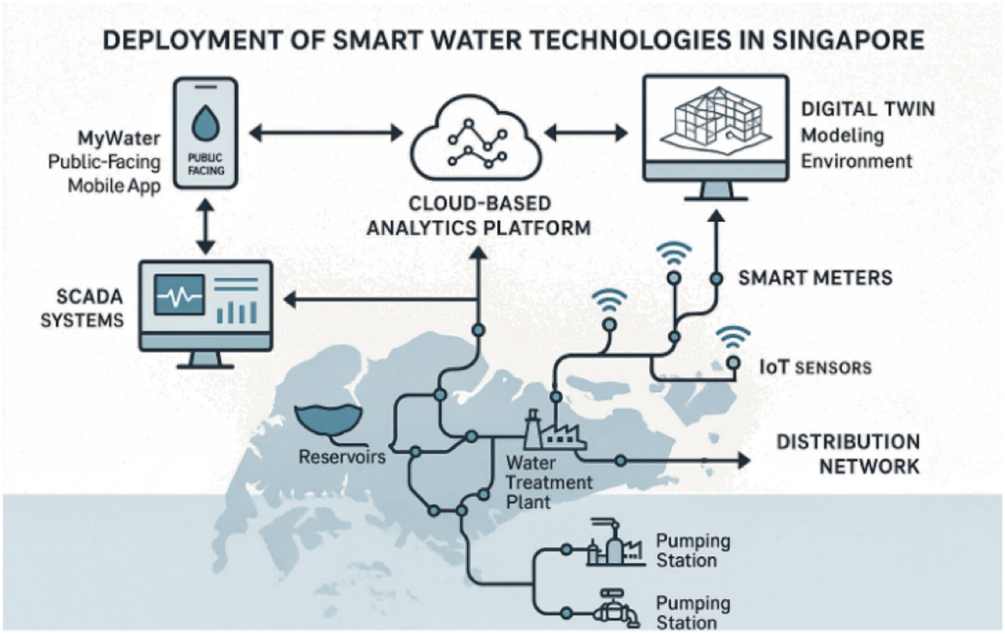

Figure 3. Integrated Digital Twin Process for Scenario-Based Planning and Real-Time Control.

Overall, Singapore's smart water initiatives have demonstrated how integrated technologies can support urban water security while maintaining high service standards. Its experience offers valuable lessons for other water-stressed regions seeking to adopt intelligent water governance models. Key takeaways include:

- Strong policy alignment between water management and national digital strategies;
- Strategic investment in IoT, AI, and digital twin technologies;
- Integration of public engagement tools to foster sustainable behavior;
- Emphasis on data interoperability, cybersecurity, and long-term capacity building.

By adopting a holistic approach to smart water governance, cities worldwide can build resilient and sustainable water systems capable of meeting future challenges.

4.2. China's Smart Water Pilot Projects

In recent years, several Chinese cities have launched smart water pilot projects aimed at modernizing aging infrastructure and improving resource efficiency. This trend aligns with global advancements in intelligent water governance, particularly in the adoption of IoT-enabled metering, GIS-based asset monitoring, and digital twin modeling [9,11]. National-level strategies such as the Guidance on Promoting Smart Water Management and the Urban Infrastructure Upgrade Action Plan have further facilitated these developments by providing strategic direction for digital transformation.

Shenzhen has implemented a city-wide smart metering system based on IoT-enabled devices to collect detailed consumption data in real time. This initiative demonstrates the effectiveness of sensor-based monitoring in improving demand forecasting and reducing non-revenue water, consistent with findings from peer-reviewed studies [4,30,31]. According to the Shenzhen Water Group Annual Report (2023), over 80% of residential households are now equipped with smart meters, and NRW rates have dropped to approximately 6.2%. The deployment is part of the Shenzhen Smart Water Grid Construction Plan (2021–2025), which emphasizes AI-powered analytics and cloud-based platforms for real-time monitoring and adaptive control [30].

Hangzhou has integrated geospatial analytics into its utility operations, significantly enhancing the planning and maintenance of underground pipelines [10]. By leveraging GIS technology and remote sensing, Hangzhou has achieved more precise mapping of pipeline networks, supported predictive maintenance and reduced the frequency of burst-related disruptions. This approach has been incorporated into the Hangzhou Smart City Development White Paper (2022), highlighting how spatial intelligence contributes to urban sustainability and resilience.

One of the most advanced applications of smart water technology in China is the use of the digital twin in Beijing. A flood risk assessment model has been developed to simulate urban drainage during extreme weather events [12,25]. This project, led by the Beijing Drainage Group, demonstrates how simulation-based planning can enhance climate resilience and operational efficiency.

As illustrated in Figure 4, the digital twin implementation process follows a six-stage workflow:

- Physical Data Acquisition
- Data Transmission and Preprocessing
- Digital Twin Model Initialization
- Scenario Simulation and Predictive Analytics
- Feedback-Based Optimization
- Adaptive Control and Continuous Learning

The arrows in the figure represent the direction of data flow and logical connections between different components of the system.

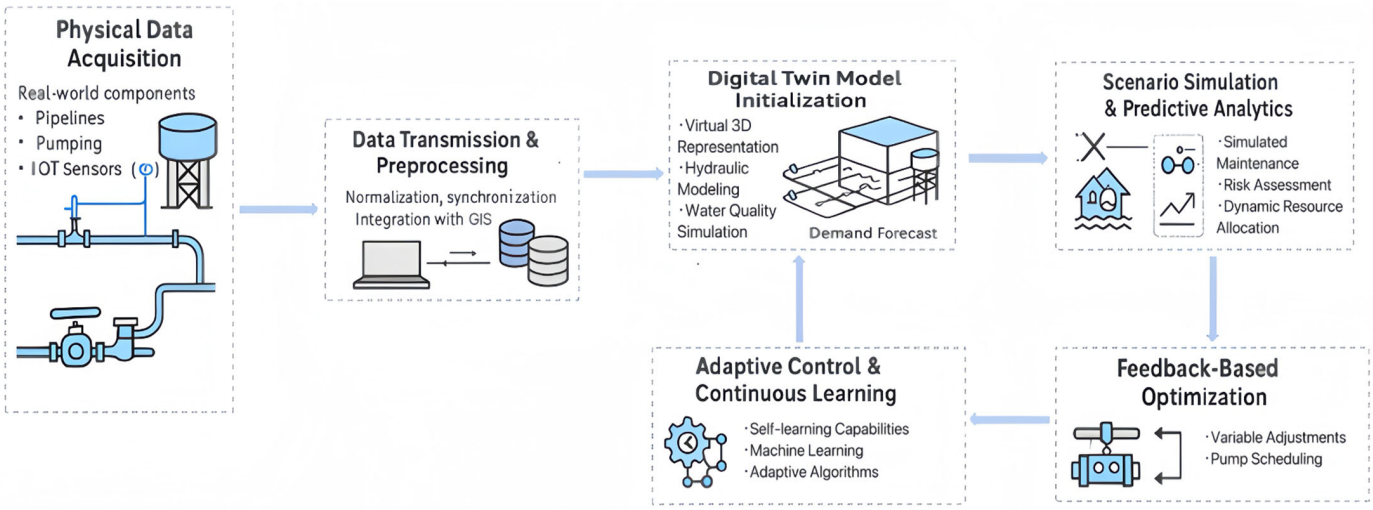

Figure 4. Implementation Framework of Smart Water Technologies in Singapore's National Digitalization Strategy.

The physical water network provides real-time sensor data to initialize and update the virtual model. Simulations are conducted under various scenarios (e.g., rainfall intensity, peak consumption), allowing operators to test emergency response strategies and optimize system performance without disrupting actual services [11].

This closed-loop interaction between the physical and virtual layers enables proactive decision-making, scenario testing, and adaptive control—capabilities that are essential for enhancing urban water resilience and efficiency.

These initiatives demonstrate how SWM can be tailored to local conditions while aligning with broader objectives of urban sustainability and resource conservation. Table 4 summarizes key performance indicators from selected pilot projects:

Table 4. Key Performance Indicators of Smart Water Pilot Projects in Chinese Cities.

City	Smart Meter Coverage	Non-Revenue Water (NRW) Rate	Leak Detection Accuracy	Digital Twin Application	Source
Shenzhen	~80%	~6.2%	High	Partially deployed	Shenzhen Water Group Annual Report, 2023
Hangzhou	~70%	~7.5%	Medium	GIS-based pipeline management	Hangzhou Urban Development White Paper, 2022
Beijing	~65%	~8.1%	High	Flood risk digital twin in major districts	Beijing Drainage Group Technical Brief, 2023

Despite these achievements, several challenges remain. As noted by [7], interoperability across heterogeneous systems continues to hinder large-scale integration. In addition, cybersecurity concerns and the lack of standardized data protocols pose significant barriers to long-term operational consistency.

To provide a more granular understanding of how smart water technologies are implemented across operational layers, we outline the technical deployment framework used in each city:

Shenzhen: The sensing layer consists of IoT-enabled smart meters installed at residential and commercial endpoints to monitor consumption patterns in real time. Data is transmitted via NB-IoT (Narrowband IoT) networks to cloud-based platforms where it undergoes preprocessing and anomaly detection using rule-based algorithms. Leak detection models are based on statistical thresholds derived from historical data. These insights are visualized on a centralized dashboard accessible to utility managers, enabling proactive leak response and demand-side management.

Hangzhou: In the sensing and processing layers, GIS-integrated sensors and remote sensing imagery are employed to map underground pipeline networks with high spatial resolution. Pipeline condition assessments are conducted using predictive maintenance models that analyze vibration and pressure data. Edge computing devices are used to run these predictive maintenance models located near critical infrastructure nodes, reducing latency and improving system responsiveness. Visualization tools include interactive maps and risk heatmaps for prioritizing repair activities.

Beijing: The digital twin system incorporates multi-source data (including rainfall forecasts, drainage network topology, and real-time sensor readings) into a unified simulation environment. Hydrological models (e.g., Storm Water Management Model) are used to simulate flood scenarios under different climate conditions. Predictive analytics are powered by deep learning algorithms trained on historical flood events. The results are integrated into municipal emergency response systems, allowing authorities to issue early warnings and optimize resource allocation during extreme weather events.

These implementation strategies highlight both the diversity and adaptability of smart water solutions in rapidly urbanizing contexts. While varying in scope and technological maturity, all three cities demonstrate how intelligent systems can enhance efficiency, resilience, and service delivery in water governance.

Moreover, the technical complexity and high initial investment required for digital transformation may limit widespread adoption, particularly in smaller municipalities or less economically developed regions [27].

To support the continued development of SWM in China, policymakers should focus on:

1. Establishing unified technical standards for data exchange and device compatibility;
2. Encouraging public–private partnerships (PPPs) to share financial and technical burdens;

3. Promoting open data platforms and cross-sectoral collaboration;
4. Investing in workforce training and interdisciplinary education programs to address the talent gap.

By addressing these issues, Chinese cities can build resilient and sustainable water systems capable of adapting to growing environmental and demographic pressures.

4.3. Comparative Analysis: Singapore vs. China Pilots

The approaches to SWM in Singapore and China reflect distinct governance models and implementation strategies shaped by their unique socio-institutional contexts. While both leverage digital technologies to enhance system efficiency and resilience, differences arise in terms of driving forces, integration scope, technological focus, and pace of adoption.

Singapore's Smart Water Grid is driven by a national imperative for water security, supported by a centralized governance structure under the PUB. This has enabled long-term planning, unified standards, and comprehensive digital twin utilization across the entire water cycle. In contrast, China's smart water initiatives are often launched at the municipal level to address pressing urban challenges such as pollution control, leakage reduction, and resource efficiency. These pilot projects demonstrate rapid deployment but also highlight the need for stronger inter-agency coordination and data standardization to ensure nationwide coherence.

As shown in Table 5, these differences provide valuable insights into how SWM can be adapted to various institutional settings. While Singapore exemplifies a top-down, integrated model, China's approach illustrates a bottom-up, localized strategy that gradually moves toward system-wide integration.

Table 5. Comparative Analysis: Singapore vs. China Pilots.

City	Singapore (PUB)	China (Pilot Cities)	Insights
Driving Force	National water security, long-term strategic vision	Urbanization pressures, pollution control, efficiency gains	Singapore's approach is holistic and deeply integrated; China's pilots are often responses to specific pressing urban issues, with a growing trend towards broader integration.
Scope and Integration	Fully integrated Smart Water Grid	Often specific project-based pilots (metering, DT for floods)	Singapore showcases mature, system-wide integration. China is moving from component-specific solutions towards more integrated systems, learning from these pilots.
Governance	Highly centralized, single national utility (PUB)	Decentralized (municipal-led) with central policy guidance	Centralization in Singapore facilitates standardization and rapid, unified deployment. China's model allows for local innovation but requires strong inter-agency coordination for national coherence.
Technological Focus	Advanced analytics, holistic digital twin, demand mgmt.	Smart metering, GIS, specific DT applications (e.g., flood)	Both leverage core SWM technologies, but Singapore exhibits a higher degree of sophistication in AI-driven optimization and integrated digital twin utilization across the entire water cycle.
Pace of Adoption	Gradual, strategic, long-term evolution	Rapid, large-scale deployment in pilot zones	Different paces reflect differing national contexts and urgency. China's rapid piloting offers opportunities for quick learning and iteration.

Beyond institutional and strategic differences, notable distinctions also exist in the technical implementation of smart water technologies across both regions. In Singapore, digital twin models are applied holistically to simulate the entire water cycle—from supply to wastewater treatment—enabling scenario-based planning and energy optimization. In contrast, China's pilots often deploy digital twins selectively, focusing on specific subsystems such as urban drainage or leakage detection.

Similarly, while both regions leverage AI for predictive analytics, the depth and integration differ. Singapore utilizes deep learning algorithms embedded within centralized control systems for long-term forecasting and adaptive decision-making. Chinese cities, by comparison, tend to apply rule-based or shallow machine learning models at the local level for real-time alerts and operational adjustments.

These variations highlight how technological adoption is shaped not only by infrastructure maturity but also by institutional capacity, data governance frameworks, and system interoperability requirements.

4.4. Synthesized Practical Insights from Case Studies

The case studies of Singapore and China's pilot programs offer synthesized insights into the practical implementation of SWM. It is evident that there is no one-size-fits-all solution; successful deployments must be tailored to local water challenges, economic conditions, technological readiness, and governance structures.

SWM success depends not only on technical capabilities but also on:

- Strong institutional frameworks
- Clear policy direction
- Sustained financial investment
- Availability of skilled professionals
- Effective public engagement

In this paradigm, data transforms from operational output to strategic asset. The ability to collect, manage, analyze, and act upon data becomes central to system effectiveness. This underscores the importance of dismantling data silos, ensuring high-quality data governance, and continuously investing in advanced analytical tools.

Furthermore, the most significant benefits of SWM are realized when individual components and solutions are integrated into a cohesive, system-wide architecture. Such integration enables a holistic view of the entire water cycle and facilitates coordinated control, leading to greater efficiency and resilience. As water systems become increasingly digitized and interconnected, it becomes non-negotiable to embed cybersecurity and resilience-by-design principles into every layer of the SWM architecture. The authors of [17] emphasize that digital twins—such as the HIP framework—play a crucial role in enhancing climate resilience by enabling real-time scenario modeling and adaptive planning under extreme weather conditions. These models not only improve operational performance but also support long-term risk mitigation and emergency preparedness.

Based on the case studies, several practical strategies can be derived to support effective implementation:

1. For Integrated Digital Twin Deployment: Cities aiming for full-cycle simulation should begin with modular development, starting with high-priority subsystems (e.g., flood management or leak detection), as seen in Beijing. Interoperability standards should be established early to ensure seamless integration with existing SCADA and GIS systems.
2. For AI-Based Predictive Analytics: The choice between centralized deep learning systems (as in Singapore) and localized rule-based models (as in China) depends on available resources and institutional capacity. A hybrid approach—combining cloud-based AI with edge computing for real-time responsiveness—may offer a scalable solution for mid-sized cities.
3. For Data Governance and Cybersecurity: Both cases emphasize the importance of secure data flows across sensing, transmission, and decision layers. Frameworks like ISO/IEC 27001 provide actionable guidelines for risk assessment and mitigation.

Additionally, adopting open data platforms with controlled access can facilitate inter-agency collaboration without compromising security.

4. For Policy and Institutional Coordination: In decentralized settings like China, central guidance should focus on harmonizing standards and promoting cross-city knowledge sharing. In more centralized systems like Singapore, continuous investment in workforce training and public engagement ensures long-term sustainability and adaptability.

Finally, particularly for large-scale deployments, an iterative development pathway—characterized by initial pilot projects, continuous performance monitoring, and adaptive management strategies—allows for crucial learning, refinement, and risk mitigation. These diverse global experiences offer valuable, albeit context-dependent, roadmaps for how urban centers can harness smart technologies to address pressing water challenges, highlighting both the transformative potential and the practical complexities inherent in the transition toward.

Notably, ref. [20] emphasize that digital twin-based resilience evaluation plays a key role in supporting emergency response and system recovery. Their study demonstrates how real-time simulation and scenario-based planning enable utilities to identify vulnerabilities, optimize resource allocation, and improve preparedness for high-impact events.

5. Contributions to Economic Development and Environmental Sustainability

The deployment of smart water technologies has demonstrated significant potential in advancing both economic development and environmental sustainability. By integrating advanced information and communication technologies (ICT), these systems not only improve operational efficiency and resource allocation but also foster sustainable urban and rural development. This section explores the dual contributions of SWM from both economic and environmental perspectives, supported by newly introduced scholarly sources.

5.1. Supporting Economic Growth

SWM enhances economic productivity by improving the reliability and efficiency of water supply across multiple sectors, particularly industry and agriculture. One of the most tangible benefits is the reduction in NRW—water that is produced but not billed due to leakage, theft, or metering inaccuracies. This highlights that reducing NRW can significantly lower operational costs for utilities while increasing revenue streams. Ref. [32] provides a systematic review of strategies to reduce NRW, emphasizing the role of real-time monitoring, pressure management, and intelligent metering as essential components of modern water governance.

In the agricultural sector, smart irrigation systems based on IoT technologies have been shown to optimize water use while increasing crop yields. Ref. [33] presents an overview of such systems, showing how sensor-based automation enables precise water delivery according to soil moisture levels and weather conditions. Ref. [28] further illustrates how IoT-enabled irrigation platforms reduce water waste and improve farm-level profitability, especially in arid and semi-arid regions facing water scarcity.

Moreover, the integration of ICT fosters greater public participation and transparency in water governance, which indirectly supports economic stability. Ref. [24] emphasizes that digital tools such as mobile apps and web dashboards allow citizens to monitor usage, report issues, and engage in decision-making processes. This participatory approach enhances trust between utility providers and consumers, ultimately contributing to more efficient resource allocation and service delivery.

5.2. Enhancing Environmental Carrying Capacity

From an environmental perspective, SWM plays a crucial role in protecting ecosystems, reducing pollution, and enhancing resilience to climate change. A major advancement lies in its ability to identify and localize pollution sources in real time. Studies such as [34] highlight how sensor networks integrated into wastewater systems enable rapid detection of contamination points, allowing for targeted remediation actions.

This capability is especially relevant in rapidly urbanizing regions, where industrial discharges and stormwater runoff pose significant threats to water quality. Recent spatio-temporal analyses conducted along the Yangtze River Economic Belt have further demonstrated the importance of integrating digital monitoring into regional water sustainability planning [35]. Such studies emphasize the need for intelligent systems that not only detect pollution but also support long-term ecological protection through data-driven governance strategies.

Additionally, real-time water quality monitoring using chemical sensors improves environmental protection efforts. Ref. [34] explores the application of sensor technologies in continuous water quality assessment, highlighting their advantages over traditional sampling methods, which often miss transient pollution events. Real-time data facilitates early warning systems and timely interventions, preserving aquatic ecosystems and public health.

Scenario-based modeling and planning also contribute to long-term environmental sustainability. Ref. [36] introduces a multi-criteria decision support system for water resources planning, demonstrating how simulations can guide policy decisions under uncertainty. Ref. [37] expands on this by proposing a combined system dynamics and compromise programming framework for managing water supply systems under changing climatic and socio-economic conditions. These approaches enable proactive adaptation strategies that align with SDGs.

By leveraging smart technologies, water governance can shift from reactive to predictive models, ensuring both resource efficiency and ecological balance. As cities continue to grow and face mounting environmental pressures, the integration of intelligent water systems becomes essential for maintaining environmental carrying capacity.

To summarize the dual contributions of smart water technologies to economic development and environmental sustainability, a comparative overview is provided in Table 6, which outlines key benefits across different sectors and geographical contexts.

Table 6. Economic and Environmental Benefits of Smart Water Systems.

Technology	Economic Benefits	Environmental Benefits	Application City/Country	Source
Smart Metering	Reduces non-revenue water (NRW), improves billing accuracy	Reduces leakage and water waste	Shenzhen; Singapore	[27,28,30]
Digital Twin	Enhances emergency response efficiency, lowers maintenance costs	Supports flood risk assessment and resource optimization	Beijing; Singapore	[5,12,25,38]
Real-time Water Quality Monitoring	Lowers pollution control costs	Improves ecosystem protection	Beijing; Singapore	[34,39]
GIS + Telemetry	Optimizes pipeline planning, reduces labor costs	Enables accurate underground infrastructure management	Beijing; Singapore	[9,10]
AI-based Forecasting	Balances supply–demand dynamics, saves energy	Reduces over-extraction and ecological damage	Global (Case-based)	[28,33,40]

6. Challenges and Policy Recommendations

The implementation of SWM offers substantial benefits in terms of operational efficiency, sustainability, and resilience. However, the transition from traditional to intelligent water governance is not without its challenges. Addressing these barriers requires a comprehensive understanding of the technical, organizational, and institutional constraints currently limiting widespread adoption.

6.1. Main Challenges

The implementation of SWM offers substantial benefits in terms of operational efficiency, sustainability, and resilience. However, several challenges hinder their widespread adoption, particularly when scaling up or transferring solutions across institutional contexts.

One of the most pressing issues is data interoperability. Water-related data are often collected and stored by multiple agencies—such as municipal governments, environmental departments, and utility providers—using incompatible formats and platforms [25]. This lack of integration limits the ability to create a unified view of water resources and hampers real-time decision-making.

Another major obstacle is the lack of standardized protocols across regions and sectors. Without consistent frameworks for data exchange, device compatibility, and system integration, scaling smart water solutions becomes difficult [41]. This issue is particularly evident in developing countries, where regulatory frameworks may be underdeveloped or inconsistently applied.

In addition to structural and technical issues, cybersecurity risks and privacy concerns have emerged as critical challenges. As water systems become more connected and reliant on digital infrastructure, they also become more vulnerable to cyberattacks that could disrupt service or compromise sensitive data [42]. The potential consequences—ranging from operational failures to public health threats—highlight the need for robust cybersecurity measures and clear data protection policies.

Furthermore, the high initial investment required for smart water technologies can deter both public and private sector participation. Although long-term savings and operational efficiencies are well-documented, many stakeholders remain hesitant due to uncertainty surrounding return on investment (ROI) and the long payback periods associated with such projects.

Lastly, there is a notable shortage of skilled professionals who possess the interdisciplinary knowledge needed to design, implement, and maintain SWM. This includes expertise in hydrology, information technology, data analytics, and policy development [18]. Without sufficient human capital, even the most advanced technologies cannot be effectively deployed or sustained.

6.2. Policy Recommendations

To enhance the clarity and practicality of policy formulation, this section presents a structured set of policy recommendations, categorized into short-term (0–3 years) and long-term (>3 years) actions, as shown in Table 7. This classification aims to guide decision-makers in prioritizing interventions based on urgency, resource availability, and implementation timelines.

Table 7. Policy Recommendations: Short-Term vs. Long-Term Actions.

Recommendation Area	Short-Term Actions (0–3 Years)	Long-Term Actions (>3 Years)
Standardization and Interoperability	Establish national working groups to develop minimum data exchange standards for SWM	Implement unified national or regional digital water infrastructure protocols
Data Sharing and Open Platforms	Launch pilot open-data platforms for municipal-level water utilities	Develop cross-sectoral data integration frameworks involving agriculture, energy, and environment sectors
Public–Private Partnerships (PPPs)	Introduce incentive-based PPP models for pilot smart metering and leak detection projects	Scale up successful PPP initiatives nationwide with regulatory oversight and performance benchmarks
Workforce Development	Provide targeted training programs for utility staff on digital tools and data analytics	Integrate SWM into university curricula and professional certification programs
Cybersecurity and Data Protection	Adopt basic cybersecurity guidelines aligned with ISO/IEC 27001 standards	Build dedicated cyber-resilience units within water agencies with continuous monitoring and incident response capabilities
Incentive Mechanisms	Offer subsidies or tax breaks for early adopters of smart water technologies	Design performance-based funding mechanisms linked to water efficiency and service quality improvements

7. Conclusions

SWM represents a paradigm shift in how societies approach the planning, operation, and governance of water systems. Unlike traditional approaches that rely on reactive maintenance and manual monitoring, modern SWM leverages digital technologies to enable proactive, data-driven decision-making, significantly enhancing both efficiency and sustainability.

Through global case studies and theoretical analysis, this paper has demonstrated how SWM can substantially improve resource utilization, reduce environmental impact, and support economic growth. From Singapore's integrated smart grid to China's pilot programs in intelligent metering and digital twin modeling, successful implementations highlight the transformative power of digitalization in water governance.

However, realizing the full potential of SWM requires coordinated action across multiple dimensions. Technological advancements must be supported by institutional reforms, policy alignment, and capacity-building efforts. Only through such an integrated approach can cities and communities build resilient water infrastructures capable of meeting future challenges.

Looking ahead, future research should focus on developing integrated assessment models that capture the complex interactions between water, energy, and food systems. Additionally, long-term impact evaluations are necessary to better understand the socio-economic and ecological outcomes of smart water interventions. Finally, fostering international collaboration and knowledge exchange will be key to accelerating the global adoption of smart water practices.

By embracing innovation and aligning it with SDGs, SWM can serve as a cornerstone of future-ready urban and rural environments.

Author Contributions: Conceptualization, Y.D.; methodology, Y.D. and N.K.; formal analysis, Y.D. and N.K.; supervision, Z.H.; writing—original draft preparation, Y.D. and N.K.; writing—review and editing, Y.D., N.K., and M.S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available in all the references listed.

Conflicts of Interest: The authors declare no conflicts of interest.

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