The Evolution of Digital Twins in Hydrology and Environmental Science: From Physical Models to AI-Assisted Autonomous Systems

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Abstract
Digital Twin (DT) technologies have emerged as transformative framework in hydrology, enabling adaptive, real-time modeling of water systems through data-driven intelligence. This position paper proposes a five-level technological evolution model for hydrological digital twins, tracing field's progression over the last three decades (1995-2025) from physical models to autonomous & interconnected systems. Each level is anchored in technological milestones such as web systems, Geographical Information Systems (GIS), Internet of Things (IoT), Artificial Intelligence (AI), and immersive environments that collectively enhance the interactivity, intelligence, and integration capacity of DT systems. The study introduces a layered implementation framework that links enabling technologies to functional capabilities across the DT lifecycle. Drawing from this thirty-year synthesis and real-world applications, we illustrate how DTs are being used for flood prediction, watershed management, infrastructure resilience, and stakeholder engagement. A cross-level capability matrix is presented to analyze DT levels in terms of data requirements, visualization methods, computational demand, expertise, and cost. The study also identifies critical research challenges in data interoperability, AI ethics, cybersecurity, and institutional coordination. Recommendations are provided to guide future research, emphasizing open standards, modular architectures, participatory design, and public trust. This study presents a vision for hydrological digital twins as scalable, intelligent, and ethically grounded systems that support climate resilience, disaster mitigation, and sustainable water governance.

Keywords: Digital Twin (DT); Hydrological modeling; Water resources management; AI-assisted autonomous system; Decision-support

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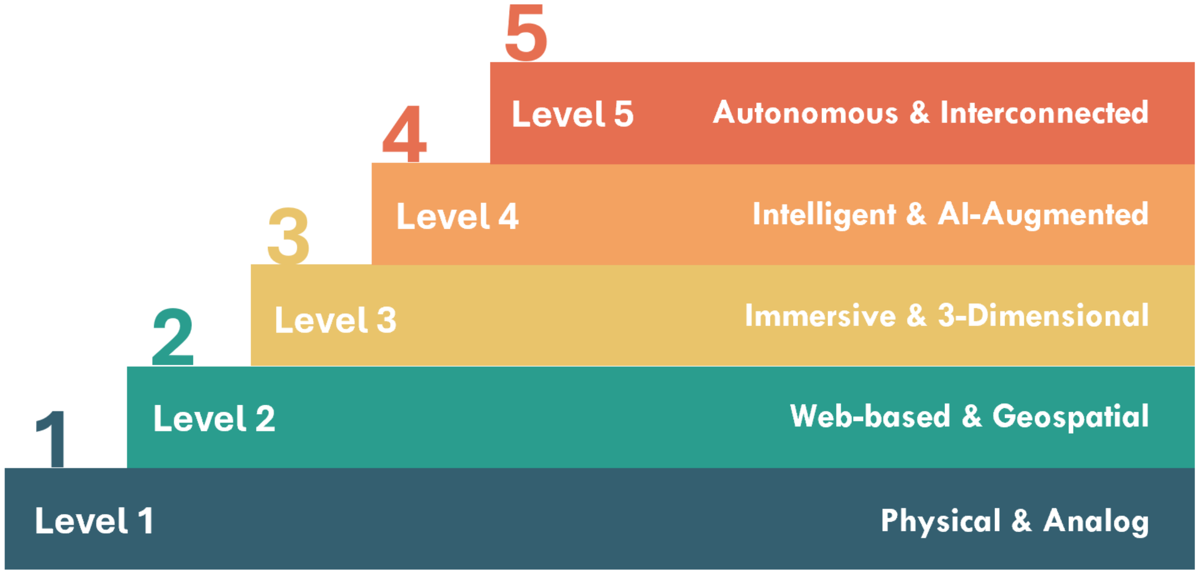
Highlights:

- Maps the 30-year technological evolution of hydrological Digital Twins from physical models to autonomous & interconnected systems.
- Proposes a dual-trajectory vision advancing vertical AI autonomy and horizontal cross-domain federation.
- Presents a layered implementation framework and capability matrix linking enabling technologies to functional maturity.
- Outlines a research agenda prioritizing agentic AI, interconnected systems, and ethical water governance.

Graphical Abstract:



Digital Twin Technological Evolution Framework

1. Introduction

Digital Twin (DT) technology has emerged as a transformative paradigm across multiple domains, enabling the creation of dynamic, real-time digital replicas of physical systems for enhanced monitoring, simulation, and decision-making (Qian et al., 2022). The conceptual foundation was originally introduced by Michael Grieves in 2002 during his presentation at the SME Management Forum, where he proposed it as the Conceptual Ideal for Product Lifecycle Management (Grieves, 2002). In 2005, Grieves further contextualized this paradigm within the broader scope of product lifecycle management (Grieves, 2005). This framework matured when the specific Digital Twin terminology was formally adopted within the NASA Technology Roadmap (NASA, 2010) and subsequently adapted in 2012 to model and monitor spacecraft systems (Glaessgen and Stargel, 2012). In 2016, Grieves and Vickers provided a formal definition of digital twins, conceptualizing them as composed of three dimensions: the physical entity, the virtual model, and the connection between them (Grieves and Vickers, 2016). El Saddik later expanded the DT framework to include multimedia systems, emphasizing data transmission and synchronization between the physical and virtual worlds (Saddik, 2018). Since then, DTs have evolved far beyond their manufacturing and aerospace origins, now playing pivotal roles in healthcare, transportation, energy, smart cities, and environmental sciences (Tao et al., 2018; Barricelli et al., 2019).

DTs can be developed through a series of implementation steps, each leveraging a set of enabling technologies (Jeong et al., 2022). Inspired by Grieves' general framework, numerous studies have extended DT framework to suit the unique demands of diverse application domains, including hydrology. For example, Liu et al. (2018) proposed a multi-layer DT modelling framework consisting of a data assurance layer, a modelling calculation layer, a functional layer, and an immersive experience layer. Korenhof et al. (2021) introduced an expanded structure that included predictive and prescriptive capabilities and allowed for bi-directional feedback. More recently, Pal et al. (2025) presented a six-dimensional framework tailored for river basin DTs, incorporating physical system, data infrastructure, modeling, services, and connectivity layer. Furthermore, Al-Obeidat et al. (2024) added a forecasting layer, integrating artificial intelligence (AI) models and big data analytics in the context of Earth Digital Twin (EDT) for environmental applications. Within hydrology, the adoption of DTs presents a critical opportunity to transform the monitoring, understanding, and management of water systems amidst growing uncertainty and climate-induced variability (Henriksen et al., 2022; Rigon et al., 2022).

Traditionally, hydrological modeling has relied on static or semi-dynamic tools such as physics-based simulations, GIS platforms, and scenario-based forecasting (Krajewski et al., 2021). These tools have been foundational for applications such as flood modeling, watershed planning, and groundwater analysis (Singh, 2016; 2018). However, conventional approaches and tools often lack the capacity for real-time responsiveness, integration of heterogeneous datasets, interoperability, and adaptive behavior under dynamic or extreme conditions (Henriksen et al., 2022; Ge and Qin, 2025). As hydrological events grow in frequency, intensity, and complexity, driven by climate change, urbanization, and land-use changes, there is an urgent need for more dynamic, intelligent modeling frameworks. These systems have to combine real-time data from IoT-based sensors, satellite observations, and cloud platforms with advanced simulation capabilities, immersive visualization, and AI-driven analytics (Park and You, 2023; Li and Demir, 2024; Manocha et al., 2024).

The timing for a hydrological DT revolution could not be more critical. Over the past five years, there have been significant breakthroughs in AI, immersive web technologies, edge computing, and the metaverse. AI approaches, including deep learning, generative modeling, and reinforcement learning, have matured to the point that predictive accuracy in hydrology, once limited by sparse data and rigid models, is now attainable with unprecedented precision (Kreuzer et al., 2024; Sajja et al., 2025). These AI tools provide powerful mechanisms for predictive modeling, anomaly detection, and decision support in complex water systems (Abdulameer et al., 2025; Demiray et al., 2024).

Concurrently, immersive visualization tools (AR/VR/XR), gaming engines, and web-based collaborative platforms have reshaped participatory environmental modeling and stakeholder engagement (Oyshi et al., 2022; Chandramouli et al., 2022). The rise of the metaverse, conversational AI, and Web 3.0 ecosystems indicates that hydrological DTs must also evolve, becoming more user-centric, adaptable and platform-interoperable. Meanwhile, scalable cloud architectures and IoT infrastructures continue to support real-time synchronization between digital and physical hydrological systems (Minerva et al., 2020; Kaynak et al., 2025). The convergence of these technological advancements marks a pivotal moment: DTs must transition from passive replicas to active, autonomous systems that can support real-time, cross-domain governance and long-term water sustainability strategies.

In this position paper, we argue that the trajectory of digital twin technology in hydrology must expand beyond traditional frameworks to embrace intelligent, autonomous, and federated capabilities. We propose that DTs must evolve along two simultaneous trajectories: (1) vertically, toward higher levels of intelligence, autonomy, and adaptability; and (2) horizontally, toward greater integration and federation across domains such as meteorology, infrastructure, policy, and ecology. Our proposed DT technological evolution model maps this progression, correlating enabling technologies with functional capabilities, including virtualization, real-time synchronization, advanced modeling, AI-based analytics, and autonomous operation.

Crucially, we advocate for viewing hydrological DTs not only as technical systems but as socio-technical infrastructures designed for participatory governance, transparency, and ethical AI integration. Key design considerations must include data governance, system transparency, interoperability, and equitable access. We envision a future in which digital twins of rivers, aquifers, and watersheds are co-managed by AI agents, public institutions, scientists, and community stakeholders—working together to enhance climate resilience, optimize water resource management, and foster inclusive governance.

This manuscript offers a vision-driven framework for the next generation of hydrological digital twins, synthesizing existing research and anticipating emerging trends to advocate for a more comprehensive and interdisciplinary approach. To structure this vision, we propose a five-stage DT technological evolution model tailored to hydrology, which provides a conceptual roadmap for the field's evolution from static replicas to autonomous, federated systems. To ground this model in practice, we articulate a multi-layer implementation framework that links enabling technologies to functional capabilities across the DT lifecycle. We then substantiate the model's relevance by synthesizing real-world use cases that illustrate the transformative impact of DTs on hydrological science and management. Finally, we examine the critical research challenges and ethical considerations that must be addressed, offering targeted recommendations to steer future development. Through this structured analysis, we aim to shift the DT discourse in hydrology from siloed experiments toward scalable, integrated, and ethically grounded platforms for future water systems management, resilience-building, and public engagement.

This paper is organized as follows: Section 2 provides background on digital twins in hydrology, including historical context, current applications, and the core components that define hydrological DT systems. Section 3 presents the proposed five-level digital twin evolution model, detailing how DTs progress in sophistication through the integration of enabling technologies. Section 4 highlights practical applications and use cases of DTs across various hydrological domains, demonstrating their transformative impact on flood forecasting, water quality monitoring, and stakeholder engagement. Section 5 discusses current research challenges and offers targeted recommendations to address key barriers related to data, interoperability, computational complexity, ethics, and institutional collaboration. Finally, Section 6 concludes the paper by summarizing the key findings and outlining future directions for the development of intelligent, federated, and ethically grounded DT ecosystems in hydrology.

2. Background on Digital Twin in Hydrology

2.1. Overview

A Digital Twin (DT) can be broadly defined as an intelligent, dynamic, and interactive digital representation of physical systems that continuously mirrors and evolves alongside its physical counterpart using real-time data, analytics, and simulation tools (Qian et al., 2022; Crespi et al., 2023). In the context of hydrology, DTs are applied to model and manage natural and engineered water systems, such as river basins, reservoirs, groundwater aquifers, urban drainage, and watershed-scale ecosystems (Henriksen et al., 2022; Rigon et al., 2022). By creating a digital replica of a watershed, river basin, or dam (Park and You, 2023; Shao et al., 2025), DTs enable continuous monitoring and proactive management of water-related events (Park et al., 2023).

For example, during extreme weather events, a DT can predict flood occurrences based on real-time data and historical trends, allowing authorities to implement timely mitigation strategies (Suquet et al., 2023; Ge and Qin, 2025). Furthermore, DTs enhance decision-making by integrating multiple data sources, including remote sensing imagery, weather forecasts, and satellite-derived precipitation data (Brahmbhatt et al., 2023). What if scenarios are developed to provide decision-makers with a digital modeling platform to visualize, monitor, and forecast hydrology related activity on the planet in support of sustainable development and the prediction and management of environmental disasters.

Unlike traditional hydrological models that rely on static data and predefined assumptions, DTs integrate real-time measurements from distributed sensor networks, crowdsourced citizen monitoring, remote sensing platforms, and hydrological databases (Sermet et al., 2020). These are then coupled with artificial intelligence (AI), immersive visualization, and user interaction components to support more accurate forecasting, scenario testing, and adaptive decision-making. DTs in hydrology serve both operational (e.g., monitoring, control) and strategic (e.g., planning, resilience analysis) functions. For example, flood risk assessment can be conducted using dynamic DTs that incorporate river discharge data and rainfall forecasts to simulate inundation in real time (Seo et al., 2019; Manocha et al., 2023). Similarly, long-term water quality management can be enhanced through DTs that integrate data from drones, satellites, and in-situ sensors (Chen et al., 2023; Adebayo et al., 2024). Hydrological DTs are now being used to simulate surface water flow through a river basin (Yang et al., 2024), wastewater treatment (Wang et al., 2024), drinking water networks (Conejos Fuertes et al., 2020), urban drainage (Bartos and Kerkez, 2021) or stormwater infrastructure (Sharifi et al., 2024).

The growing range of DT applications in hydrology demonstrates their transformative role across scientific, engineering, and policy domains. One of the most widespread applications of DTs is in flood prediction and emergency response. Open-source frameworks integrating hydrologic-hydrodynamic models are increasingly being developed to improve early warning capabilities and risk assessment in data-scarce regions (Rápalo et al., 2024). Decision-support platforms now simulate flood scenarios to aid mitigation planning, while web-based DT systems using height-above-drainage metrics enhance flood inundation predictions (Li et al., 2023a). Furthermore, recent AI-enhanced DTs improve both the lead time and spatial resolution of disaster response systems by leveraging graph neural networks and deep learning-based satellite analysis for flood extent extraction within cloud computing environments (Roudbari et al., 2024).

Beyond immediate disaster response, DTs play a pivotal role in watershed-scale modeling and planning. Recent DT-based watershed information modeling frameworks emphasize real-time data visualization, scenario analysis, and multi-stakeholder collaboration for water allocation, hydrological cycle simulation, and sustainable planning (Liu et al., 2024; Qiu et al., 2022). Large-scale cyberinfrastructure systems demonstrate how DTs can enable multi-agency data sharing and joint decision-making across river basins such as the Upper Mississippi River (Mount et al., 2024). These applications highlight how DTs function as integrative platforms that unify environmental observation, data analytics, and collaborative governance.

In addition, DTs are revolutionizing aquatic ecosystem monitoring and water quality management. Drone-based DT systems now deliver high-resolution spatial and temporal data for nutrient tracking and pollution mapping, proving especially valuable in inaccessible regions (Hamzah et al., 2024). Urban DTs are being developed for hydrogeological risk assessment by integrating environmental monitoring with smart urban infrastructure such as adaptive lighting or traffic systems (Barrile et al., 2025; Kušić et al., 2023). Such DTs combine real-time sensing and AI-based analytics to monitor ecological dynamics and evaluate remediation strategies for environmental protection.

DTs also contribute to infrastructure risk modeling and logistics during floods, integrating hydrological modeling with transportation analytics to optimize road accessibility, emergency facility placement, and evacuation routes under flood conditions (Alabbad et al., 2024; Mitropoulos et al., 2025). These systems enhance real-time response strategies and infrastructure design for climate-resilient urban planning and management.

Another rapidly growing frontier is public engagement and education through DTs. Immersive simulations and serious games simplify complex hydrological phenomena for non-expert audiences, facilitating better understanding and trust in water management decisions (Demiray et al., 2025; Yin et al., 2024). Virtual labs and interactive 3D environments allow users to visualize flood wave dynamics, explore infrastructure behavior, and test mitigation strategies (Dunlop et al., 2024). Such immersive applications strengthen participatory learning, stakeholder communication, and community preparedness.

The integration of conversational AI into DT platforms represents the next stage of operational hydrology. Natural language assistants linked with multimodal DT data sources enhance user accessibility, allowing managers and policymakers to query systems intuitively for training and operational purposes (Pursnani et al., 2025). Immersive and AI-enhanced DT frameworks are now supporting sustainable water reserve management and participatory platforms that address nutrient pollution and water quality (Zhao et al., 2025; Shrestha et al., 2025).

At the cutting edge, federated DT systems link multiple environmental and infrastructural domains into unified decision-support ecosystems. Large-scale prototypes, such as NASA's Earth System Digital Twin (ESDT), demonstrate how AI, immersive visualization, and multi-source data integration can synchronize across global river basins, supporting comprehensive water governance and climate adaptation strategies (Le Moigne, 2025). These cross-agency, cross-domain DTs represent the future direction of hydrological digital twins, scalable, intelligent, and policy-relevant systems for sustainable and resilient water management.

In summary, hydrological DTs have evolved from basic digital monitoring tools into powerful decision-support and participatory platforms. They now span a spectrum of functions from flood prediction and water quality monitoring to infrastructure resilience, ecosystem health, and stakeholder engagement. By integrating AI, immersive visualization, and federated computing, DTs enable real-time insight, predictive foresight, and collaborative governance of complex hydrological systems.

2.2. Conceptual Components

The effectiveness and sophistication of hydrological digital twins (DTs) depend on several interlinked components. These components enable dynamic representation, simulation, and adaptive management of water systems. For hydrological DTs, four technological and foundational categories define the system architecture and functionality: Data and Synchronization, Visualization and Operations, Modeling and Analysis, and Governance and Operation (Figure 1).

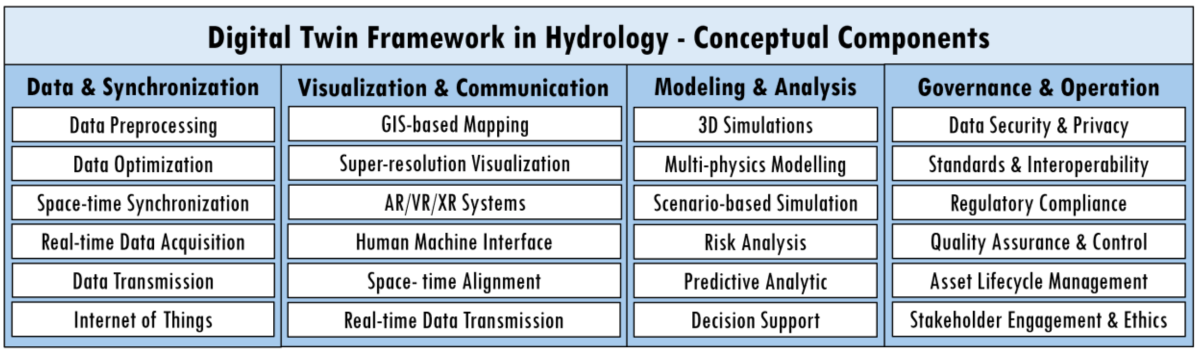


Figure 1. Conceptual components of digital twin framework in hydrology

Data and Synchronization: Reliable, high-resolution, and continuous data streams are the backbone of any digital twin. In hydrology, data are acquired from a combination of in-situ sensors, satellite observations, remote sensing platforms, and historical records, including precipitation, streamflow, water quality, soil moisture, and groundwater levels. IoT-enabled hydrological sensor networks and telemetry systems provide up-to-date measurements, which are transmitted using technologies like 5G, LPWAN, and satellite links (Kaynak et al., 2025; Zanella et al., 2023). Cloud-based data pipelines ensure temporal consistency and spatial alignment across distributed monitoring networks, while space-time synchronization algorithms maintain real-time coherence between the physical and digital domains (Placidi et al., 2020; Balaprakash et al., 2021). Robust integration tools manage raw input cleaning, standardization, fusion across heterogeneous data types, and real-time anomaly detection to ensure data reliability and model validity (Dos Reis et al., 2022; Demir et al., 2015).

Visualization and Communication: Effective visualization bridges technical analysis with decision-making and public understanding. Hydrological DTs employ interactive dashboards, GIS-based mapping tools, and 3D/4D visual analytics environments that allow users to explore scenarios, monitor performance, and simulate management strategies. Immersive visualization technologies such as AR, VR, and XR environments enable intuitive comprehension of flood propagation, aquifer recharge, and watershed dynamics (Mudiyanselage et al., 2025). These visualization layers also underpin stakeholder engagement, community outreach, and disaster preparedness, translating scientific complexity into accessible spatial narratives (Oyshi et al., 2022). Operational DTs can interface directly with physical infrastructures such as dams, pumps, and drainage systems allowing simulation of interventions before real-world deployment, optimizing management of flood control, irrigation, and water distribution.

Modeling and Analysis: The analytical core of DTs lies in their ability to simulate, predict, and optimize hydrological processes. Hydrological DTs incorporate both physics-based and AI-driven models for process simulation, pattern detection, forecasting, and uncertainty quantification. Machine learning (ML), deep learning (DL), and hybrid modeling frameworks simulate streamflow, flooding, water quality dynamics, and groundwater fluctuations (Bayar et al., 2009; Kreuzer et al., 2024) while supporting scenario-based optimization and early warning systems (Haq et al., 2024). Multi-objective optimization, sensitivity analysis, and "what-if" simulations strengthen the DT's decision-support capacity for water allocation, emergency response, and infrastructure design. Advanced DTs employ generative and reinforcement learning models to enhance predictive precision, particularly under data scarcity or nonstationary conditions (Keyes et al., 2013; Menzel et al., 2006; Ebrahimi et al., 2024).

Governance and Operation: As DTs transition from localized projects to national or transboundary infrastructures, establishing robust governance, ethics, and interoperability becomes fundamental to system success (Addor et al., 2020). This pillar integrates data security and privacy protocols, utilizing cybersecurity measures to protect sensitive hydrological data, critical infrastructure information, and user privacy from unauthorized threats. To facilitate cross-sector coordination, the framework emphasizes standards and interoperability by adopting standardized data formats, such as WaterML or OGC, ensuring the digital twin can communicate seamlessly with broader smart city and environmental monitoring networks

(Song et al., 2019; Zhang, 2024; Jeong et al., 2022). Operational integrity is maintained through regulatory and policy compliance, ensuring all data handling adheres to regional water rights, environmental protection laws, and government safety regulations. Furthermore, the system incorporates quality assurance and control (QA/QC) processes to monitor the accuracy of incoming sensor data and the reliability of predictive models, thereby safeguarding ground truth integrity. The practical utility of the digital twin is realized through asset lifecycle management, which applies the digital model to manage physical infrastructure, such as dams, pipes, and sensors, via predictive maintenance and long-term resource planning. Finally, a framework for stakeholder engagement and ethics manages the interactions between government agencies, private entities, and the public, ensuring transparency and ethically grounded decision-making in water management (Ebert-Uphoff et al., 2017; Ariyachandra and Wedawatta, 2023).

These core components enable DTs to function as integrated platforms across several key domains. Prominent applications include disaster risk reduction through dynamic flood forecasting and early warning systems. In watershed and river basin management, DTs are used to monitor large-scale hydrological processes and facilitate stakeholder coordination for water allocation. They also emerge as critical tools in urban water infrastructure for optimizing drinking water, stormwater, and wastewater systems. Other important areas include continuous water quality monitoring to detect pollution events, proactive climate change adaptation and resilience planning by simulating future scenarios and enhancing public engagement through immersive interfaces and interactive simulations.

3. Technological Evolution of Digital Twin

The general concept of a digital twin is well defined in many studies (Gartner, 2016). However, aspects related to the specific technology and implementation of the digital twin systems are unclear (Schroeder et al., 2020). More recently, various DT projects related to different aspects of hydrology are modelled on city scale or larger areas (Iluita et al., 2024; Henriksen et al., 2022; Ghaith et al., 2021). Autonomous, federated and intelligent technologies for many types of DTs are required to optimize the real world in a large-scale DT (city or larger area scale). However, most of the existing studies focus on abstract concepts about these technologies among many DTs. It is necessary to describe the essential technologies clearly, rather than abstract descriptions. As challenges in the hydrological domain grow, a conventional digital twin model cannot offer a fully comprehensive solution.

Digital twins in hydrology are not static products, but evolving systems shaped by advancements in a range of digital technologies. The sophistication of these systems, from basic visualizations to intelligent, federated infrastructures, reflects the technological readiness of the tools that enable them. To provide a structured roadmap for development and assessment, we propose a five-level technological evolution model for hydrological digital twins, as illustrated in Figure 2. This framework reflects the technological, analytical, and operational evolution of DTs from static physical representations to autonomous, federated ecosystems. Each level captures a distinct level of system intelligence, real-time responsiveness, user interactivity, and cross-domain integration, providing a roadmap for the future of DT-enabled hydrological modeling and decision support.

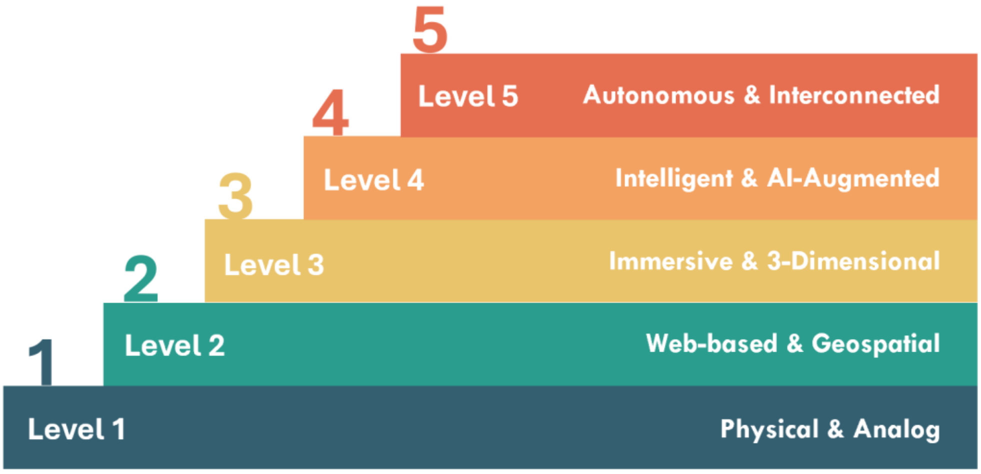


Figure 2. A five-level technological evolution model for DTs in hydrology.

The functional definition of each stage is as follows:

Level 1: Physical Digital Twins: representing hydrological events, phenomena or entity with physical prototypes

Level 2: Web & GIS-Powered Digital Twins: modelling hydrological concepts or entities with 2D web-based platforms

Level 3: Immersive & 3D Digital Twins: representing hydrological concepts or entities with 3D interactive environments

Level 4: Intelligent & AI-Assisted Digital Twins: enhancing hydrological concepts or models through advanced AI-driven predictive analytics

Level 5: Autonomous & Interconnected Digital Twins: autonomously recognizing and solving complex problems in interconnected digital twins and optimizing hydrological concepts or models according to the federated digital twin solution

The proposed evolution framework focuses on the technological trajectory of the last three decades (1995–2025), a period marked by the transition from standalone physical and static computational models to interconnected, autonomous systems. While the theoretical roots of hydrological modeling extend further back, this thirty-year window captures the critical convergence of web, GIS, VR, and AI systems that has made the modern Digital Twin possible. By mapping these specific technological milestones, we contextualize how current innovations in agentic AI and federated computing are built upon the foundational work of the late 1990s and early 2000s

The early 2000s marked the Web and Dot-Com Era, when the proliferation of web-based GIS and the rapid expansion of cloud computing reshaped data accessibility and visualization. Platforms developed during this period, often inspired by the digital transformation boom following the dot-com bubble, and laid the groundwork for web-enabled hydrological models. These systems enabled remote access to environmental datasets and geospatial visualization of water systems, setting the stage for Level 2. However, while they democratized access to spatial data, early web DTs lacked real-time synchronization and adaptive feedback mechanisms, functioning primarily as static visualization tools.

By the early 2010s, advances in IoT networks, wireless telemetry, and remote sensing technologies enabled the transition from static or semi-static systems to dynamic, data-driven platforms. The widespread deployment of sensor networks for monitoring precipitation, streamflow, and groundwater levels bridged physical and virtual domains, forming the synchronization backbone of digital twin systems. This period marked a transition from Level 1 to Level 2, as real-time sensor data and cloud-based computation began to support continuous model updates and feedback loops between the physical and digital environments.

The mid-2010s witnessed a new leap with the advent of immersive and extended reality (XR) technologies, symbolized by breakthroughs such as Oculus Rift and similar virtual and augmented reality (VR/AR) platforms. These technologies introduced interactive, human-in-the-loop environments that transformed the way hydrological systems could be explored and communicated. The integration of real-time GIS data with 3D immersive visualization allowed scientists, policymakers, and citizens to simulate hydrological scenarios, visualize flood dynamics, and engage collaboratively in virtual decision environments. This era corresponds to Level 3, where user interactivity and experiential visualization became central to modeling, education, and stakeholder participation in water management.

The early 2020s were defined by the AI revolution, driven by the rise of deep learning, generative models, and large language models such as GPT-based systems. AI breakthroughs significantly enhanced pattern recognition, predictive analytics, and autonomous learning from large-scale, multimodal datasets. In hydrology, these technologies catalyzed the emergence of Level 4, capable of forecasting floods, identifying anomalies, optimizing infrastructure operations, and supporting complex decision-making. ML and AI transformed DTs from reactive systems into proactive tools that could anticipate hydrological dynamics and continuously refine their internal models through adaptive learning.

Most recently, the Agentic AI Era has begun to redefine the frontiers of digital twin evolution. The convergence of federated learning, edge computing, autonomous AI agents, and blockchain-based trust frameworks has enabled multi-domain systems that coordinate across distributed networks without central supervision. These developments underpin Level 5, which operate as self-organizing, cross-domain ecosystems. Such systems integrate hydrological, meteorological, and ecological domains; self-update based on continuous feedback; and negotiate trade-offs autonomously in real time. Emerging paradigms in agentic AI where AI systems act as collaborative agents capable of reasoning, planning, and communication, signal the next stage in hydrological DT development: a shift toward self-governing, ethically guided, and interoperable environmental intelligence networks.

Together, these technological milestones, spanning from the web revolution to immersive computing, artificial intelligence, and agentic autonomy, form the chronological backbone of our five-level digital twin evolution framework. Each level represents not merely an incremental improvement in modeling sophistication, but a fundamental paradigm shift in how hydrological systems is conceptualized, simulated, and managed. In the following sections, we detail each level's defining characteristics, technological enablers, and implementation challenges, outlining a roadmap for the continued evolution of hydrological digital twins.

3.1. Level 1: Physical Digital Twins

At the initial level of this evolution, representing the foundational period of the late 1990s and early 2000s, hydrological systems were primarily represented through physical prototypes or static digital models. These early representations provided the fundamental understanding of system dynamics but lacked real-time connectivity and adaptive synchronization that define modern digital twins. During this era, physical scale models of river basins, flumes and floodplains were widely used to study water movement, sediment transport, and morphological changes (Peakall et al., 1996; Green, 2014; Daniel et al., 2011).

Simultaneously, this period marked the consolidation of static computational modeling where hydrologists relied on physically based distributed codes, such as MIKE SHE (Refsgaard & Storm, 1995), and conceptual rainfall-runoff frameworks like the ARNO model (Todini, 1996) to simulate catchment behavior offline. These tools were instrumental for analyzing hydrological parameters, including watershed boundaries and potential flood risks under fixed conditions (Li et al., 2008; Papanicolaou et al., 2008).

The integration of early Geographic Information Systems (GIS) facilitated the spatial representation of these models, allowing for the mapping of environmental variables and land-use data (Tim, 1995; Maidment, 2002). While these systems enabled substantial advances in catchment analysis and flood forecasting (De Roo et al., 2000), they remained fundamentally static. NASA's early work with virtual models in aerospace hinted at the future potential of digital twins (Glaessgen and Stargel, 2012), but in hydrology, models were disconnected from real-time systems. They relied on manual data inputs, lacked interactivity, and could not dynamically reflect environmental changes, limiting their ability to support adaptive water management or immediate disaster response.

Despite these operational limitations, 3D physical prototypes have proven highly effective in STEM education and public outreach. Physical models, such as tabletop floodplain simulation systems, are visually engaging and ideal for demonstrating hydrological processes in a hands-on manner. For instance, models like WARD's Stormwater Floodplain Simulation System have been used in classrooms and science fairs to highlight floodplain dynamics, land-use impacts, and environmental stewardship. Their accessibility makes them valuable for outreach programs, where direct observation offers meaningful learning experiences.

While valuable for foundational studies and education, these static models were constrained by their disconnect from the living environment. This critical gap necessitated a shift toward the next stage of evolution: web-based digital models capable of integrating live data streams and providing dynamic visualization through remote platforms.

3.2. Level 2: Web & GIS-Powered Digital Twins

In second level, with the advent of web-based technologies, remote sensing, and cloud computing, hydrological models transitioned from static physical prototypes to digital platforms. Hydrological data became more accessible and dynamically visualized through 2D web platforms (Demir & Beck, 2009). GIS played a crucial role in this transformation by enabling large-scale mapping and data integration and facilitates spatial representation of hydrological elements, such as watersheds, river networks, and flood zones. Choi et al. (2005) presented a web-based framework integrating GIS technology and hydrologic modeling to support real-time watershed management. Valjarević (2024) used GIS technique to track 60 years of climate-driven changes in Serbia's river networks and basins. Cikmaz et al. (2023) developed GIS-based flood susceptibility maps for identifying high-risk flood zones and supporting mitigation planning.

The availability of high-resolution satellite imagery and remote sensing technologies enhanced data accuracy by providing high-resolution elevation models and land cover classifications and allowed for more precise and dynamic water management solutions. Li et al. (2023b) proposed MA-SARNet, a one-shot deep learning framework that uses physical drivers and historical SAR imagery to predict high-resolution SAR backscatter for flood nowcasting and mapping. Rogan and Chen (2004) highlighted remote sensing advancements and their integration with GIS for monitoring land-cover and land-use changes to support planning and management. Bühler et al. (2012) evaluated LiDAR and photogrammetry for high-alpine DEMs, finding optical methods accurate for moderate slopes and LiDAR better for steep terrain.

The rise of the Internet and cloud computing further enhanced DT capabilities by facilitating remote access to hydrological data. This level basically consists of three intermediate steps like mirroring, monitoring, and simulation. In mirroring (duplication of physical object into digital twin), the physical object simply replicated as digital object on the GIS-based mapping or web-based platform, and this step does not have additional processes such as simulation, testing, and optimization. In monitoring step, physical entities can be monitored and controlled based on analysis of the digital twin, which is started to incorporate real-time data streams from remote sensors, IoT devices, and high-resolution satellite imagery.

This step ensures that the virtual representation of hydrological systems remains accurate and reflective of real-time conditions. Real-time synchronizations are usually considered for digital twins because digital twins need to manage and synchronize various sensors to ensure consistency. Therefore, in this stage, the synchronization engine can manage many sensors and maintain consistency between the replicated twin world and the real world. IoT-enabled sensor technology plays a pivotal role in capturing real-time hydrological parameters such as river flow, rainfall, soil moisture, and groundwater levels (Kaynak et al., 2025).

These sensors transmit data using high-speed data transmission technologies, including 5G networks, LPWAN, and satellite communication, ensuring seamless and reliable data flow even from remote monitoring stations. Zanella et al. (2023) explored how sensor networks can address challenges in hydrological monitoring and modeling, emphasizing the need for adaptive sensing technologies. HydroLang, a modular, web-based framework enables real-time flood risk and mitigation assessment through interactive visualizations, geospatial analysis, and customizable modeling tools, aiming to support decision-making, public engagement, and community resilience across diverse flooding scenarios (Ramirez et al., 2022; Sufi et al., 2025). In the final step, the physical entities can be optimized by executing various simulations of the digital twin.

Multi-physics simulations integrate multiple physical processes such as atmospheric dynamics, water prediction, and hydraulic flow into a unified modeling framework (Keyes et al., 2013). These simulations leverage high-performance computing (HPC) or distributed volunteer computing infrastructures to process large-scale, high-resolution hydrological models efficiently (Agliamzanov et al., 2020). Scenario-based simulations also play a crucial role in evaluating various hydrological systems by running different "what-if" scenarios

(Menzel et al., 2006; Ebrahimi et al., 2024). These simulations help policymakers and engineers test the effectiveness of flood control infrastructure, water quality, and emergency response strategies under varying hydrological conditions and climate change.

This advancement enabled more accurate monitoring of hydrological variables such as precipitation, river flow, and groundwater levels (Xu et al., 2019a). Web-based models allowed several real-word applications such as flood monitoring systems, cloud-based watershed management platforms, and decision-support frameworks, providing stakeholders with up-to-date information on river levels, precipitation patterns, and watershed conditions (Qiu et al., 2022).

However, despite the ability to visualize real-time data, these web-based systems remained largely passive, offering limited interaction between the digital and physical counterparts. This limitation paved the way for the next advancement, where immersive technologies like Virtual Reality (VR) and Augmented Reality (AR) would transform these platforms into interactive, three-dimensional environments, enabling a more intuitive understanding of complex hydrological behaviors.

3.3. Level 3: Immersive & 3D Digital Twins

With improvements in computational capabilities and new immersive technologies like virtual reality (VR), augmented reality (AR) or mixed reality (XR), digital twins evolved into interactive and systems capable of real-time data processing, simulation, and visualization. In hydrology, this level introduced 3D simulations with AR/VR environments, which allow for high-fidelity modeling of river flows, groundwater movements, and precipitation-runoff interactions (Sermet and Demir, 2022). These tools enabled the creation of highly interactive, three-dimensional models that allowed for a more intuitive understanding of hydrological behaviors under different scenarios (Chandramouli et al., 2022). Some studies are related to decision support and disaster awareness and emergency response training (Sermet and Demir, 2022). These immersive platforms allow users to simulate and visualize extreme weather events and flooding in dynamic environments, thereby enhancing both technical preparedness and public communication. For example, researchers have used these tools to simulate flood projections, run flood models and demonstrate hydrometeorological extremes in virtual settings (Rink et al., 2021; Oyshi et al., 2022; Puertas et al., 2020).

A recent and notable extension of this immersive paradigm includes the use of gaming engines and metaverse platforms to host digital twin environments (Xu et al., 2019b; Uchimiya, 2024). Game development technologies such as Unity and Unreal Engine have been leveraged to create engaging, physics-based virtual hydrological worlds, enabling both scientific exploration and stakeholder participation. In parallel, the rise of the metaverse has opened the door for persistent, multi-user DT spaces, where planners, engineers, and citizens can collaboratively explore flood scenarios, co-design infrastructure, and test policies in shared digital ecosystems (Sermet et al., 2020; Xu et al., 2023). These developments have shown significant potential for participatory planning and education, particularly in urban water management contexts.

These interactive DTs allow hydrologists and policymakers to visualize flood scenarios, test mitigation strategies, and optimize water resource management in a virtual and interactive environment before implementing changes in the real world. These advancements have proven particularly valuable in urban water management, where policymakers can visualize the impacts of various infrastructure projects before implementation. Despite these advancements, interoperability and scalability remained key challenges, as integrating different hydrological models and data sources seamlessly remains complex. Additionally, immersive digital twin applications often require high computational power and specialized equipment such as headsets and motion controller, which may limit broader dissemination and accessibility, particularly in resource-constrained regions.

While these immersive systems offered unparalleled user interaction and intuitive visualization for scenario testing, they still relied on predefined models and lacked inherent intelligence. Their inability to learn from data or provide predictive analytics on their own marked a clear boundary, setting the stage for the next major leap: the integration of AI to create intelligent digital twins capable of forecasting, anomaly detection, and continuous learning

3.4. Level 4: Intelligent & AI-Assisted Digital Twins

In the fourth level, the Intelligent Digital Twin represents a major advancement in hydrological modeling by integrating AI and advanced ML algorithms. These DTs enable predictive analytics, allowing for more accurate forecasting of hydrological variables such as precipitation, river flow, groundwater levels, and flood risk assessment (Kreuzer et al., 2024). AI-driven predictive analytics in hydrology utilizes DL and ML models trained on both historical and real-time data (Ly and Xie, 2024). At the core of this layer is AI-driven analytics, which employs sophisticated algorithms to detect, learn, and predict complex hydrological patterns (Abdulameer et al., 2025).

These predictive tools support a range of operational goals, including streamflow prediction, disaster preparedness, water quality forecasting and water allocation optimization (Kumar et al., 2024; Sanikhani et al., 2025). In parallel, anomaly detection plays a crucial role in identifying irregularities in hydrological data, such as unexpected water level fluctuations, sensor malfunctions, or water quality dynamics (Haq et al., 2024; Leigh et al., 2019).

A key development within this level is the rise of AI agents, capable of simulating unseen hydrological conditions, filling gaps in sparse datasets, and generating synthetic training data to improve model robustness (Foroumandi et al., 2023; Kadiyala et al., 2024). These agents contribute to enhanced situational awareness and support more informed and timely interventions. They also reduce reliance on expert-driven calibration, allowing predictive systems to adapt more readily to emerging data (Kizilkaya et al., 2025). The integration of AI agents further enhances situational awareness, reduces human intervention, and enables more efficient resource allocation.

In recent years, foundation models, large-scale pre-trained AI models such as transformers, have begun to influence the development of intelligent digital twins. These models, trained on broad multimodal datasets, can be fine-tuned for hydrological applications including rainfall estimation, soil moisture prediction, or even semantic interpretation of environmental reports (Syed et al., 2024). Their adaptability makes them well-suited for tasks that require transfer learning across basins, regions, or variable data types.

Moreover, generative AI techniques are increasingly used to simulate hydrological scenarios in data-scarce environments. Generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models have been applied to generate synthetic hydrographs, climate inputs, and land use scenarios, thus addressing data sparsity, uncertainty, and extreme-event modeling challenges (Sun et al., 2024; Ji et al., 2024). These capabilities enhance the resilience and adaptability of hydrological DTs, especially under nonstationary conditions driven by climate change and urbanization.

Although these intelligent digital twins represented a major advancement in predictive analytics, they still largely functioned as sophisticated decision-support tools, requiring human oversight for high-stakes decisions and operating as siloed systems. This reliance on human intervention and the lack of cross-domain integration defined their primary limitation, paving the way for the ultimate level of maturity: autonomous and federated digital twins capable of independent decision-making and seamless collaboration within a larger digital ecosystem.

3.5. Level 5: Autonomous & Interconnected Digital Twins

At the highest level of technological advancement, DTs operate autonomously and are interconnected across domains. These systems are capable of making independent decisions and integrating multiple DTs across hydrological, meteorological, ecological, and infrastructural networks. Such advanced DTs go beyond reactive monitoring; they function as intelligent agents that manage, predict, and optimize system behavior in real time using integrated data streams and machine intelligence.

These autonomous systems leverage real-time sensor data, DL algorithms, and adaptive control mechanisms to dynamically manage hydrological processes. AI-powered self-learning capabilities enable DTs to autonomously adjust flood mitigation strategies, simulate rainfall scenarios, optimize irrigation schedules, and regulate reservoir operations with minimal or no human intervention (Redel-Macías, et al., 2021; Yoon and Ahn, 2024). These systems continuously learn from historical and real-time data, improving their operational foresight and decision quality, and thereby contributing to more resilient and adaptive water management practices.

In many implementations, intelligent DTs are not only reactive or predictive but actively assist stakeholders in complex decision-making. They synthesize simulations, real-time data, and policy constraints to generate actionable recommendations for water management, flood response, infrastructure planning, and investment decisions (Nie and Liu, 2025). Such functionality enhances both the speed and quality of governance decisions, while also expanding stakeholder trust in digital systems.

As the number and scale of DTs grow, the concept of Interconnected (Federated) Digital Twins emerges as a critical architectural innovation. These systems enable cooperation between multiple domain-specific DTs, e.g., river basin models, urban flood control systems, and climate forecast engines, within an integrated digital ecosystem. This paradigm shift leverages cloud infrastructure, big data analytics, and high-bandwidth networking technologies to represent complex water systems holistically, supporting cross-sector coordination for water distribution, disaster risk reduction, and environmental stewardship.

Federated DTs allow for multi-agency collaboration, connecting stakeholders such as government bodies, utilities, researchers, and NGOs into a shared information and decision-making space. Several studies have conceptualized city-scale or regional-scale federated DTs where multiple models interoperate through standardized protocols and data exchanges, what has been termed a "practical form of digital twin federation" (Dembski et al., 2020; Lehtola et al., 2022; Ivanov et al., 2020). These systems support layered decision hierarchies and distributed operational control, offering enhanced responsiveness to dynamic environmental conditions.

The implementation of autonomous and federated DTs is further enhanced by edge intelligence, which brings computational power closer to data sources such as field sensors, unmanned arial vehicles (UAVs), and smart infrastructure. This reduces latency, increases robustness against network interruptions, and enables localized decision-making for time-critical applications like flood control operations or water resource management (Wang et al., 2022). Edge intelligence reduces reliance on centralized cloud infrastructure, paving the way for more resilient, scalable DT deployments across remote and decentralized settings. Moreover, federated learning plays a vital role in enabling privacy-preserving AI model training across distributed DTs.

In this framework, machine learning models are trained collaboratively across different datasets and nodes without requiring raw data to be shared or centralized (Akbulut et al., 2023). This approach addresses concerns around data ownership, confidentiality, and regulatory compliance while still enabling cross-regional model generalization and performance enhancement (Farooq et al., 2023). Federated learning also facilitates knowledge sharing across institutional boundaries, enabling, for instance, a regional flood model to benefit from patterns learned in adjacent basins without direct data transfer.

Despite their transformative potential, autonomous and federated DTs introduce significant challenges. Key concerns include data governance, model transparency, interoperability, and computational scalability. Implementing such systems requires robust legal frameworks, interoperable data standards, strong cybersecurity measures, and ethical oversight mechanisms to ensure their safe, equitable, and accountable use in public and environmental decision-making.

While Level 5 represents the current conceptual horizon, DT technologies will likely continue evolving. Future hydrological DTs may incorporate quantum simulation, neuromorphic AI, and self-evolving model architectures. The trajectory may not be linear but iterative, guided by regulatory shifts, ecological priorities, and the emergence of global water governance challenges.

4. Key Considerations and Recommendations

The evolution of Digital Twin (DT) technologies in hydrology and environmental science presents a complex interplay of opportunities and constraints. Effective implementation requires balancing several interdependent factors, data availability, computational infrastructure, technical expertise, and sustainable maintenance. Each of these dimensions influences the scalability, reliability, and longevity of DT systems. The following considerations outline these key aspects and provide targeted recommendations for advancing hydrological DT design and deployment.

Data Availability and Interoperability: Reliable, high-quality, and continuously updated data form the foundation of every hydrological digital twin. DTs depend on diverse sources, including in-situ sensors, satellites, IoT networks, and historical databases. However, data heterogeneity, inconsistent standards, and limited coverage in many regions undermine system reliability and scalability. Datasets are often fragmented across institutions, subject to proprietary restrictions, and poorly documented, leading to integration challenges and reduced confidence in model outputs. Addressing these issues requires coordinated efforts to improve data infrastructure and governance.

The adoption of open data standards that follow FAIR (Findable, Accessible, Interoperable, and Reusable) principles is essential for ensuring compatibility across platforms. Establishing federated data-sharing frameworks can facilitate collaboration among institutions while maintaining control over sensitive datasets. Expanding sensor networks, especially in data-scarce regions through IoT or crowdsourced citizen sensors, will enhance spatial and temporal resolution, while automated data validation and anomaly detection algorithms can safeguard data quality. Policy mechanisms should support transparent data sharing while balancing security and privacy, thereby building trust among agencies and stakeholders. A well-structured, interoperable data ecosystem is critical to the reliability and adaptability of hydrological DTs.

<u>Computational Infrastructure and Scalability:</u> The computational demands of DTs increase rapidly as systems evolve from static visualization platforms to intelligent, federated networks. High-resolution hydrological simulations, real-time analytics, and AI-driven forecasting require significant processing power, data throughput, and storage capacity. Reliance on centralized computing environments may lead to bottlenecks, latency issues, and high energy consumption. Scalable architectures that distribute computational workloads are essential for maintaining real-time responsiveness. A hybrid approach that combines cloud computing for large-scale simulations with edge intelligence for local processing near data sources can significantly enhance efficiency. High-performance computing (HPC) should be leveraged for multi-physics modeling and data assimilation, while modular, open-source software frameworks can reduce dependence on proprietary systems. Investments in energy-efficient infrastructure and sustainable computing practices will also minimize the environmental footprint of large-scale DT deployments. Shared regional or national DT infrastructure hubs can provide equitable access to computational resources, ensuring that smaller institutions and developing regions can participate in and benefit from DT technology.

<u>Technical Expertise and Capacity Building:</u> The successful implementation of hydrological DTs depends not only on technology but also on human expertise. Developing and maintaining DTs requires interdisciplinary collaboration among hydrologists, data scientists, engineers, software developers, and policy experts. Many organizations, however, lack the integrated skill sets needed to design, operate, and interpret DT systems effectively. Bridging this gap requires sustained investment in training and capacity development. Universities and research institutions should establish cross-disciplinary curricula that combine environmental modeling, data analytics, and AI methodologies. Open-access training materials, workshops, and online platforms can expand participation and lower entry barriers. International collaborations and joint testbeds can accelerate learning and promote knowledge transfer between institutions. Capacity-building initiatives should also prioritize inclusiveness by supporting participation from regions with limited technical infrastructure. Long-term sustainability will depend on cultivating communities of practice that continuously exchange expertise and best practices across hydrological DT networks.

Cost, Maintenance, and Sustainability: Digital Twin projects often face challenges in sustaining operations beyond their initial development phase. High upfront costs for sensors, computing infrastructure, and software deployment are compounded by recurring expenses for data acquisition, model updating, and maintenance. Without clear financial planning, many DT systems risk becoming short-lived pilot projects. Achieving financial and operational sustainability requires both modular design and collaborative funding strategies. Modular architecture allows incremental scaling and targeted upgrades rather than large, one-time investments. Cost-sharing mechanisms among governmental agencies, research organizations, and private stakeholders can distribute maintenance responsibilities more equitably. The use of open-source software and shared digital infrastructure can reduce licensing costs and promote transparency. Long-term funding programs should be established to support data infrastructure upkeep, hardware replacement, and system modernization. Sustainability assessments must also evaluate the environmental and economic impacts of DT operation, promoting efficient use of computational and material resources. Building DT as living, adaptable system rather than static project ensures that they remain valuable assets for long-term water governance and climate resilience.

Table 1. A comprehensive comparison of various factors affecting the success of digital twins across all five technological evolution levels

DT Level / Factor	Physical DT	Web & GIS DT	Immersive DT	Intelligent DT	Autonomous DT
Data Sources	Historical records, manual measurements	IoT, remote sensing, sensor feeds	IoT, spatial sensors, 3D spatial data	Real-time and historical data, AI-enhanced inputs	Multi-domain, real-time AI-integrated systems
Visualization Approach	Physical models, static GIS maps	2D web dashboards, GIS overlays	AR/VR, 3D immersive environments	AI-powered dashboards, predictive visualizations	Integrated dashboards with autonomous control
Computational Demand	Low	Moderate	High	Very High	Extremely High
Technical Expertise	Basic hydrological knowledge	Web/GIS tools, basic analytics	3D modeling, immersive UX design	Data science, ML/AI modeling	AI, system integration, policy, governance
Cost & Maintenance	Low	Moderate	High	Very High	Very High
Typical Applications	Education, outreach, concept prototyping	Real-time monitoring, early warnings	Planning, stakeholder engagement, training	Flood forecasting, anomaly detection, resource optimization	National water systems, disaster coordination, autonomous decision support

Integrated Perspective and Strategic Planning: The interplay among data quality, computational power, expertise, and financial resources defines the feasibility and maturity of hydrological Digital Twins. As systems progress from simple static representations to intelligent, federated, and autonomous ecosystems, their benefits grow, but so do the associated costs and technical demands. Table 1 summarizes this continuum, highlighting how data, computation, expertise, and cost evolve across the five technological evolution levels. The matrix reveals a clear trade-off: greater analytical and decision-making capability comes with increasing resource intensity. For sustainable implementation, institutions must align their DT ambitions with available infrastructure, workforce, and funding capacity. Strategic planning that integrates these considerations from the outset will ensure that DT development remains both achievable and enduring.

The long-term success of hydrological Digital Twins depends on viewing them as evolving socio-technical ecosystems rather than standalone software projects. Open standards, modular architectures, and sustained collaboration across institutions will be vital for creating robust, adaptive, and trustworthy DT frameworks. By integrating these considerations such as data, computation, expertise, and sustainability, hydrological DTs can mature into resilient platforms that enable climate-informed water management, disaster mitigation, and inclusive environmental governance.

5. Conclusion and Future Directions

Digital Twin (DT) technologies are poised to revolutionize the field of hydrology by enabling real-time, data-driven, and collaborative management of water systems. By synthesizing technological milestones into a structured five-level model, this paper provides both a roadmap and a research agenda for hydrological DT evolution, from basic data visualization and simulation to fully autonomous system coordination. The integration of web systems, Geographic Information Systems (GIS), Internet of Things (IoT) sensors, cloud computing, artificial intelligence (AI), and immersive technologies have transformed DTs into sophisticated, interactive, and predictive platforms. These platforms are now central to diverse hydrological applications, including flood risk assessment, watershed monitoring, water quality forecasting, and infrastructure resilience planning.

The development of DTs in hydrology follows a clear and accelerating evolutionary trajectory. Beginning with static physical and conceptual models, DTs have progressively incorporated real-time sensing, immersive environments, and AI-driven intelligence, culminating in the vision of federated and autonomous systems. This progression reflects key technological milestones, such as the rise of web-based systems, the adoption of AR/VR tools for visualization and training, and the growing reliability and availability of machine learning for predictive modeling. By organizing these developments within a structured implementation and maturity framework, this manuscript offers a flexible conceptual guide for navigating the current state and envisioning the future potential of hydrological DTs.

Looking ahead, several transformative directions will define the next generation of DTs in hydrology. The integration of conversational AI and natural language interfaces is expected to make DT systems significantly more accessible to non-expert users, enabling broader participation in environmental decision-making. AI agents powered by large-scale foundation models and generative techniques will enhance forecasting accuracy, generate synthetic data for data-scarce regions, and simulate unobserved hydrological scenarios, greatly expanding the predictive capacity and robustness of DTs. Quantum computing, while still emerging, promises to revolutionize computational hydrology by enabling real-time, high-resolution, and multi-physics simulations that are beyond the reach of current technologies.

At a systems level, federated Digital Twin networks, such as NASA's Earth System Digital Twins (ESDT), will play a crucial role in enabling cross-domain coordination and global-scale water governance. These platforms will combine Earth observation data, cloud infrastructures, immersive visualization, and AI analytics to monitor and manage water systems across political and ecological boundaries. As user interfaces evolve with augmented and extended reality (AR/XR) technologies, citizen engagement will become more immersive and dynamic, fostering participatory science, real-time education, and hyperlocal policy feedback loops. Emerging technologies such as edge intelligence and 6G networks will further reduce latency and enhance system responsiveness especially critical for applications like disaster risk reduction and emergency response.

Beyond technical advancements, the convergence of DTs with global digital public goods, such as open-source platforms, shared ontologies, and open-access hydrological datasets, offers a pathway toward democratizing access to environmental intelligence. International collaboration will be essential for addressing shared water challenges, including transboundary river basin governance, global flood monitoring, and long-term climate adaptation planning. By embracing principles of open science, ethical and transparent AI, and inclusive design, the hydrological community can ensure that DT technologies evolve not only as powerful technical solutions but also as enablers of sustainability, equity, and resilience in a rapidly changing world.

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