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Leveraging Immersive Digital Twins and AI-Driven Decision Support Systems for Sustainable Water Reserves Management: A Conceptual Framework

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Abstract: Effective and sustainable water reserve management faces increasing challenges due to climate-induced variability, data fragmentation, and the limitations of traditional, static modeling systems. This study introduces a conceptual framework designed to address these challenges by integrating digital twins, IoT-driven real-time monitoring, game engine simulations, and AI-driven decision support systems (AI-DSS). The methodology involves constructing a digital twin ecosystem using IoT sensors, GIS layers, remote-sensing imagery, and game engines. This ecosystem simulates water dynamics and assesses policy interventions in real time. AI components, including machine-learning models and retrieval-augmented generation (RAG) chatbots, are embedded to synthesize real-time data into actionable insights. The framework enables the continuous assessment of hydrological dynamics, predictive risk analysis, and immersive, scenario-based decision-making to support long-term water sustainability. Simulated scenarios demonstrate accurate flood forecasting under variable rainfall intensities, early drought detection based on soil moisture and flow data, and real-time water-quality alerts. Digital elevation models from UAV photogrammetry enhance terrain realism, and AI models support dynamic predictions. Results show how the framework supports proactive mitigation planning, climate adaptation, and stakeholder communication in pursuit of resilient and sustainable water governance. By enabling early intervention, efficient resource allocation, and participatory decision-making, the proposed system fosters long-term, sustainable water security and environmental resilience. This conceptual framework suggests a pathway toward more transparent, data-informed, and resilient decision-making processes in water reserves management, particularly in regions facing climatic uncertainty and infrastructure limitations, aligning with global sustainability goals and adaptive water governance strategies.

Keywords: sustainability-centric metrics; smart water management; real-time analytics; interactive hydrological modeling; game engine; scenario planning

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1. Introduction

Water reserves management has long been a cornerstone of environmental stewardship, economic stability, and societal well-being [1]. For centuries, human societies have relied on a variety of traditional practices to manage freshwater resources, from the construction of reservoirs and dams to the establishment of irrigation systems [2–4]. However, in recent decades, these traditional methods have been challenged by the rapid pace of global change, which has altered precipitation patterns, increased demand on water supplies, and exacerbated the frequency and intensity of droughts, floods, and other climate-induced events [5,6]. Moreover, water systems are often mismanaged due to insufficient data, a lack of comprehensive forecasting tools, and limited coordination across sectors and regions [7]. Historically, water reserves management has operated in a relatively reactive manner, with decision-makers relying on static, periodic data that only provides a snapshot of water conditions at a particular time [8,9]. Early warning systems, typically employed for flood and drought prediction, have also followed a largely deterministic and limited approach, offering basic alerts without accounting for the full complexity of the water cycle [10,11]. For instance, most systems focus on monitoring water levels or predicting immediate hazards based on historical data and predefined models. While these systems provide useful alerts, they often fail to address longer-term trends, provide real-time feedback, or simulate the broader impacts of various factors such as urban development, land-use changes, or extreme weather events [6,12,13].

The advent of Digital Twins offers a transformative potential for overcoming these limitations [14–17]. A digital twin is a dynamic, real-time digital replica of a physical system—integrated with data from archives, sensors, satellite images, weather forecasts, and other monitoring technologies [18,19]. This allows for continuous tracking, predictive modeling, and scenario-based simulations that reflect the actual status of water reserves [20]. Unlike traditional methods that rely on static data or overly simplistic models, digital twins can adapt in real time to changing conditions, providing decision-makers with up-to-date information and the ability to simulate various future scenarios [21–23]. The potential for these technologies to address critical gaps in water management and enhance decision-making processes has sparked growing interest among researchers, policymakers, and water resource managers worldwide [24–26]. Despite the promising outlook of digital twins, the integration of this technology into water reserves management is still in its nascent stages [27]. Current implementations, while promising, often focus on individual aspects of water management, such as river flow, flood forecasting, or reservoir monitoring. However, they rarely incorporate a comprehensive, multi-layered approach that spans the entire water system and engages a wide array of stakeholders, from local communities to government agencies [28]. Furthermore, many existing models rely on oversimplified simulations that fail to account for complex interactions between physical, ecological, and social systems [29]. This gap limits their effectiveness in addressing the evolving challenges of sustainable water governance and climate adaptation. As such, there is a clear need for a new conceptual framework that rethinks water reserves management and incorporates cutting-edge technologies to provide a more holistic, adaptable, and dynamic approach [30].

This paper presents a conceptual framework that advances water reserves management by integrating digital twins and game engines into a cohesive system for real-time monitoring, predictive modeling, and scenario-based decision-making. The framework proposes leveraging digital twins as interactive, real-time models that simulate not only the physical dynamics of water systems (such as flow rates and water storage levels) but also the broader socio-environmental factors that influence water management decisions. This is achieved through the integration of land use and soil data, hydrological models, real-time water-quality sensors, and meteorological inputs, enabling simulations that reflect the interdependence between terrain, vegetation, water demand, and infrastructure. By incorporating such multi-dimensional data streams, the framework supports sustainability-aligned trade-offs among competing water uses, such as urban, agricultural, and ecological demands, within dynamic environmental contexts. Moreover, by using immersive game engine environments, the framework enables stakeholders to explore scenarios involving community-driven decisions, conservation policies, and land-use planning in real time. These interfaces empower both experts and non-experts to visualize complex system responses, increasing transparency, inclusiveness, and long-term sustainability orientation in water planning.

By integrating real-time data, predictive modeling, and immersive simulations, we aim to provide a more adaptive and resilient water management system that can support better decision-making, anticipate risks, and respond proactively to emerging challenges. While conceptual in nature, this study will showcase how digital twins can actively and significantly partake in water reserves management and early warning systems. These case studies will help illustrate the feasibility of the proposed framework, identify the potential challenges, and outline the benefits of adopting this technology on a broader scale. Additionally, this paper will address the innovative integration of game engines—platforms traditionally used for video game development—to create immersive and interactive models that allow stakeholders to explore and manipulate water management scenarios in an engaging, accessible way. By employing game engines, we aim to break down complex simulations into intuitive, visual experiences that promote a deeper understanding of the implications of water management decisions [31,32]. In examining the potential for digital twins to enhance water reserves management, this paper will also emphasize the interdisciplinary nature of the task. It will explore how these technologies can bridge the gap between scientific research, public policy, and community engagement. Crucially, the framework proposed here is not just a technical innovation; it is a call to rethink the entire approach to water reserves management, incorporating considerations of social resilience, environmental sustainability, and policy adaptability. We argue that the integration of digital twins and game engines can provide decision-makers with a powerful tool to manage water resources more efficiently, anticipate future challenges, and ultimately build more resilient and sustainable water systems in an increasingly uncertain world [33–37].

By providing a fresh perspective on water management through the lens of digital twins, this paper seeks to fill a gap in existing research and provide a blueprint for future advancements in this field. The proposed framework will highlight how digital twins can enable a more comprehensive, data-driven, and interactive approach to water reserves management, setting the stage for more effective strategies and solutions in the years to come. In particular, the objectives of the framework include improving real-time monitoring, providing immersive simulations, and fostering adaptive water management strategies that align with the core pillars of sustainability: equity, efficiency, and ecological balance.

2. Materials and Methods

2.1. Conceptual Framework Design and Theoretical Underpinnings

The integration of digital twins and game engines into water reserve management represents a paradigm shift that aims to integrate traditional methods with immersive, interactive, and real-time decision-making capabilities [15]. This conceptual framework seeks to bridge the gap between data-driven insights and community engagement, emphasizing the need for a more dynamic and adaptive approach to water resource management. By embedding advanced modeling techniques, real-time data, and immersive simulation technologies, the framework fosters more informed, proactive, and sustainable water management strategies.

The proposed framework combines two cutting-edge technologies—digital twins and game engines—to create an integrated system for real-time monitoring, predictive modeling, and decision support in water reserves management. Digital twins serve as virtual replicas of physical water systems, continuously updated with live data from IoT sensors, satellite imagery, and other monitoring technologies [38]. Game engines, such as Unreal Engine and Unity, are employed to visualize and simulate water dynamics, flood scenarios, and management strategies. Together, they offer a comprehensive solution that not only visualizes water systems in real-time but also enables the simulation of various water management scenarios, facilitating interactive, scenario-based decision-making. This framework addresses several challenges in traditional water management, including the need for better monitoring of complex water systems [39], predictive modeling of potential risks (such as droughts or floods), and enhanced public awareness and community engagement [40]. By providing immersive simulations of water systems and their behavior under different conditions, stakeholders, from water managers to local communities, can gain a deeper understanding of water dynamics and better prepare for future challenges.

At the core of this framework is the integration of digital twins and game engines, both of which offer powerful capabilities for enhancing decision-making and predictive modeling. From a theoretical perspective, digital twins provide real-time, data-driven insights that inform water management strategies, while game engines facilitate immersive, interactive simulations of water systems, allowing users to explore different scenarios and visualize outcomes. This combination enables more accurate predictions of water demand, flood and drought risks, and potential interventions. Moreover, it allows water managers to test a variety of strategies in a controlled virtual environment before implementing them in the real world. Predictive modeling is also enhanced by the continuous integration of real-time data, enabling better forecasts of water availability, demand, and potential risks. The ability to simulate future conditions, such as changing climate patterns or shifts in land use, further strengthens the predictive capabilities of the framework. Complementing these technologies is artificial intelligence (AI), the third foundational pillar of the framework. Techniques such as machine learning and deep learning are employed to analyze temporal trends, optimize scenario-based response strategies, and automate decision-support processes. These capabilities are essential for transforming data streams from digital twins into actionable insights, enabling adaptive water governance that evolves with both environmental dynamics and user behavior. One of the most innovative aspects of this framework is its potential to foster community engagement. By providing an interactive platform where users can visualize and manipulate water systems, the framework allows for greater public involvement in decision-making processes. Communities can directly engage with simulations, test different management strategies, and observe their potential impacts, fostering a more participatory approach to water management.

The primary objectives of the proposed framework are (Figure 1):

1. Improving Real-Time Monitoring: By leveraging digital twins and IoT-based sensors, the framework enables the continuous collection of data on water levels, quality, flow rates, and other key parameters. This real-time monitoring provides water managers with up-to-date insights into the health of water systems and the effectiveness of current management strategies [41,42].
2. Providing Immersive Simulations: Using game engines, the framework creates detailed, interactive simulations of water systems that allow users to explore how different variables (e.g., rainfall, temperature, human interventions) affect water resources [43]. These simulations offer an intuitive understanding of complex water dynamics, making it easier for stakeholders to visualize potential outcomes and make informed decisions.

3. Fostering Adaptive Water Management Strategies: The framework supports adaptive water management by enabling water managers and communities to test a variety of strategies in a virtual environment before implementing them in the real world. By simulating different scenarios (e.g., floods, droughts, and demand surges), the system allows users to understand the implications of different management approaches, enabling more flexible, responsive decision-making via artificial intelligence (AI).

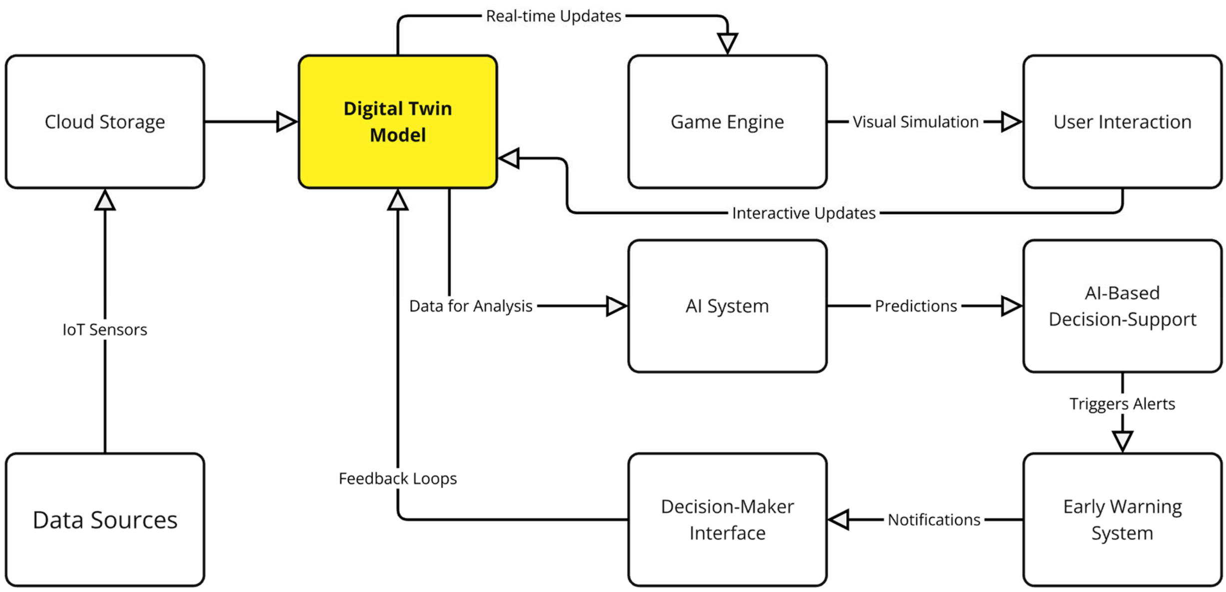


Figure 1. Conceptual framework for digital twin and AI-driven water reserves management.

The proposed integration of digital twins and AI-driven systems builds upon several well-established theoretical paradigms in both water resource management and computational sciences. At its core, the framework aligns with the principles of Integrated Water Resources Management (IWRM), which emphasizes adaptive, participatory, and system-oriented decision-making across spatial and temporal scales [1,9]. By leveraging real-time feedback, predictive modeling, and immersive simulation, the framework also reflects cyber–physical system architectures, where continuous interaction between physical processes and digital intelligence enhances responsiveness and resilience. In terms of computational logic, the use of machine-learning and deep-learning methods follows the trajectory of hybrid modeling approaches that combine data-driven insights with domain-specific knowledge, often used in hydrology to augment process-based simulations. Moreover, the framework's decision-support logic draws from control theory (e.g., model predictive control for reservoir regulation) [44], uncertainty quantification (e.g., Bayesian inference, ensemble forecasting) [45–47], and explainable AI [48], all of which are essential for maintaining stakeholder trust and system transparency. In this sense, the framework acts as a theoretical bridge between modern AI-based evaluation systems and the foundational methodologies of hydrological modeling, decision analysis, and participatory environmental planning.

The proposed framework introduces several methodological innovations that extend beyond existing digital twin paradigms in water resource management. First, it combines hybrid AI modeling—including the integration of deep learning (e.g., LSTM) and ensemble-based machine learning (e.g., Random Forests)—with real-time sensor data and process-based hydrological models to enable more adaptive, scalable predictions. Second, the use of game engine technology (e.g., Unreal Engine) for building immersive 3D visualizations and stakeholder interaction environments represents a novel application within the domain of early warning and water system planning. Third, the framework includes a modular and interoperable system architecture (i.e., plug-and-play) that allows the seamless integration of diverse data sources (e.g., legacy datasets, satellite inputs, and IoT sensor streams), simulation modules, and AI tools with minimal reconfiguration. Finally, the inclusion of explainable AI techniques (e.g., SHAP, LIME) embedded within the decision interface enhances model transparency and user trust, setting this system apart from traditional black-box models. In comparison to conventional hydrological modeling practices, such as lumped conceptual models or static threshold-based alert systems, the proposed system offers greater temporal resolution, scenario generalization, and operational responsiveness. While full empirical benchmarking remains a focus of future implementation phases, the modular design allows for comparative assessments against baseline methods such as lumped flood simulation, rule-based reservoir operations, or fixed early warning thresholds. These innovations collectively contribute to the framework's capacity for dynamic evaluation, participatory engagement, and scalable deployment in real-world settings.

The implementation of the proposed framework follows a multi-layered methodology, beginning with the construction of the digital twin model, followed by comprehensive data collection and integration from diverse sources. This is supported by advanced modeling techniques, simulation design in game engines, and interactive visualization components. The following subsections outline (1) the construction of the digital twin, (2) the sources and processing of input data, (3) the modeling and simulation environment, and (4) the game engine-based interactive interface that enables real-time scenario testing.

2.2. Digital Twin Model Construction

The main constituents of a digital twin for water systems involve the integration of physical models, real-time sensor data, and high-fidelity 3D visualizations to create an interactive, dynamic representation of water reserves, rivers, reservoirs, dams, and groundwater systems. At the core of the digital twin is a hydrological model that simulates water flow, distribution, and quality under varying conditions, which is continuously updated with data from IoT sensors, satellite imagery, and meteorological inputs. This real-time data enables accurate, up-to-date simulations and predictive modeling. The integration of game engines, like Unreal Engine or Unity, enables immersive 3D visualizations of these water systems, facilitating scenario analysis and decision-making by providing stakeholders with a virtual, interactive environment to test and analyze different management strategies and forecast the impact of future events, such as floods or droughts. Together, these components create a robust and dynamic digital twin that offers detailed insights and allows for better-informed water resource management. These steps are:

- Real-Time Sensor Data Collection, Satellite Imagery, and Meteorological Data Integration
- Three-dimensional Visualization and Game Engine Integration
- Hydrological Model Integration
- Predictive Modeling and Scenario Analysis
- Continuous Data Updates and Simulation Refinement
- Stakeholder Interaction and Decision-Making Interface

2.3. Data Collection and Integration

This section explicitly outlines the procedures and technologies used for data collection, including the deployment of real-time IoT sensors, acquisition of satellite imagery, meteorological data retrieval, and field-based terrain modeling. Data from these diverse sources are systematically integrated into the framework using structured preprocessing pipelines and geospatial alignment protocols.

The success of the proposed digital twin framework relies heavily on efficient and accurate data collection. This section details the sources of data, integration methods, and tools employed to collect, process, and integrate data from diverse monitoring technologies, including IoT sensors, satellite imagery, and geospatial data.

2.3.1. Data Sources

To provide a comprehensive view of the water reserve systems, data are collected through several key sources. These include IoT sensors, satellite imagery, and meteorological data, each contributing to different facets of water monitoring and management.

1. IoT Sensors: Real-time data from water systems is gathered through a network of IoT sensors strategically placed across critical points of the water reserves. These sensors measure various parameters integral to water management, including:
    - Water levels are measured using ultrasonic and radar-based sensors to monitor the height of water in reservoirs, rivers, and dams.
    - Flow rates are monitored using electromagnetic flow meters or ultrasonic Doppler flow sensors, ensuring accurate data on the movement and distribution of water.
    - Water quality is assessed through sensors that track parameters such as pH, turbidity, dissolved oxygen, and conductivity. These sensors rely on technologies like optical sensors and ion-selective electrodes.
    - Temperature data are collected using RTD (resistance temperature detectors) or thermocouples, helping to monitor thermal variations within water bodies.

The sensors are interconnected through an IoT network, ensuring a continuous and reliable flow of data from remote locations, even in challenging environmental conditions. The deployment of LPWAN (Low Power Wide Area Network) technologies, such as LoRaWAN and NB-IoT, ensures low-power and long-range connectivity, which is essential for widespread sensor deployment in water management systems (Figure 2).

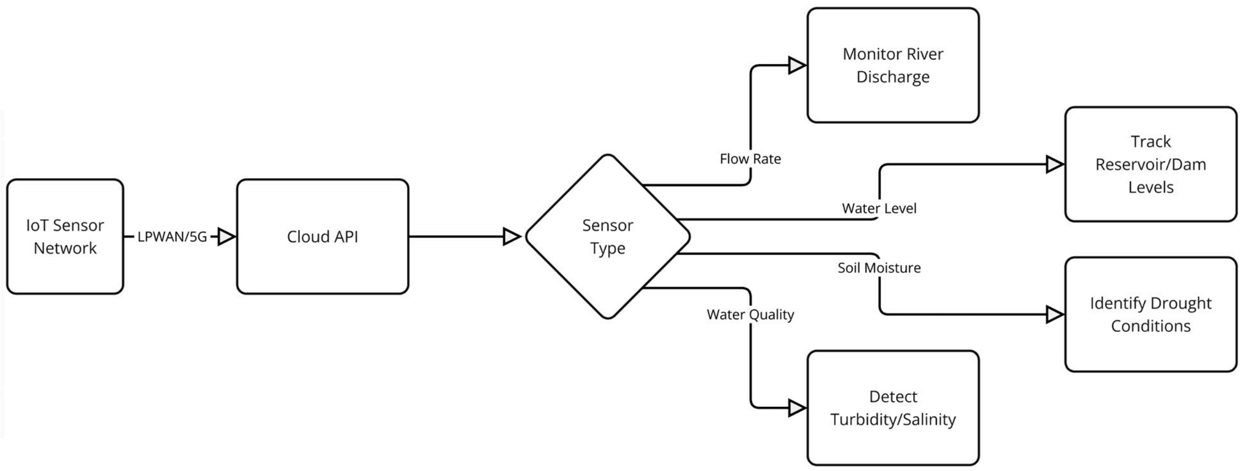


Figure 2. Setting up IoT sensor network for real-time monitoring.

2. Satellite Imagery: In addition to ground-based sensors, satellite imagery plays a pivotal role in obtaining large-scale spatial data for monitoring land cover, water body changes, vegetation health, and soil moisture [49,50]. Two primary types of satellite imagery are utilized:
    - Optical Satellites like Sentinel-2 provide high-resolution imagery (ranging from 10 to 60 m) and are valuable for observing vegetation and water surface changes.

The Copernicus Sentinel-2 mission offers a revisit cycle of 5 days, ensuring frequent monitoring of regions of interest.

- Radar Satellites such as Sentinel-1 are employed to monitor hydrological processes such as flooding, water levels, and soil moisture. These satellites utilize Synthetic Aperture Radar (SAR) technology, which operates regardless of weather conditions or time of day. The ability to collect radar data under all weather conditions makes it ideal for flood and drought monitoring.

The advantage of using free satellite data—like those from the Sentinel missions—lies in their accessibility, cost-effectiveness, and regular updates. Commercial satellite services, though offering higher spatial resolution and additional services, often involve significant costs, which makes free satellite data a preferable option for continuous monitoring over large geographic regions (Figure 3).

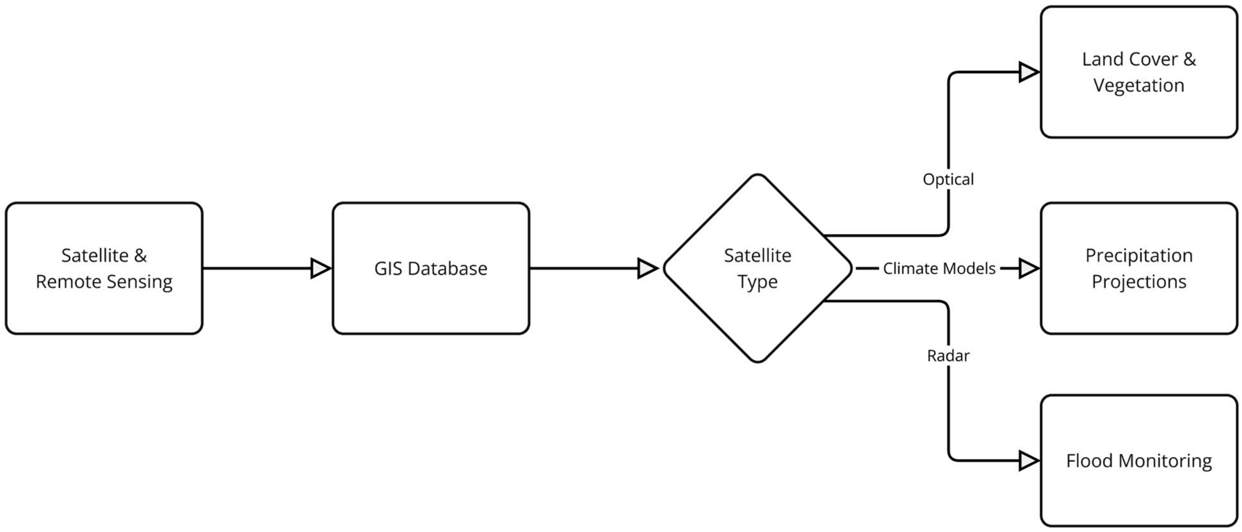


Figure 3. Collecting satellite and remote-sensing data.

3. Meteorological Data: To complement water-related data, meteorological data from local weather stations and global sources (e.g., NOAA and ECMWF) are also integrated into the framework. These data include:
   - Precipitation levels
   - Temperature
   - Wind speed and direction
   - Relative humidity

Meteorological data are critical for predicting future hydrological events, such as rainfall–runoff patterns, extreme weather events, and potential droughts or floods. This data helps in validating and calibrating hydrological models used in the digital twin.

4. Other Monitoring Technologies: In addition to sensors and satellites, other technologies, such as drones and ground-based monitoring stations, are used for specific tasks, such as capturing high-resolution images of reservoirs, performing terrain mapping, and monitoring groundwater levels. Drones are particularly valuable for rapid response monitoring and can be deployed quickly to areas that are difficult to access by traditional methods.

2.3.2. Integration of Geospatial Data

Geospatial data are an essential part of the framework, providing the spatial context needed to model and simulate water flows, terrain dynamics, and land-use changes. These data are integrated with real-time water flow data and environmental factors to create a highly accurate representation of water systems (Figure 4).

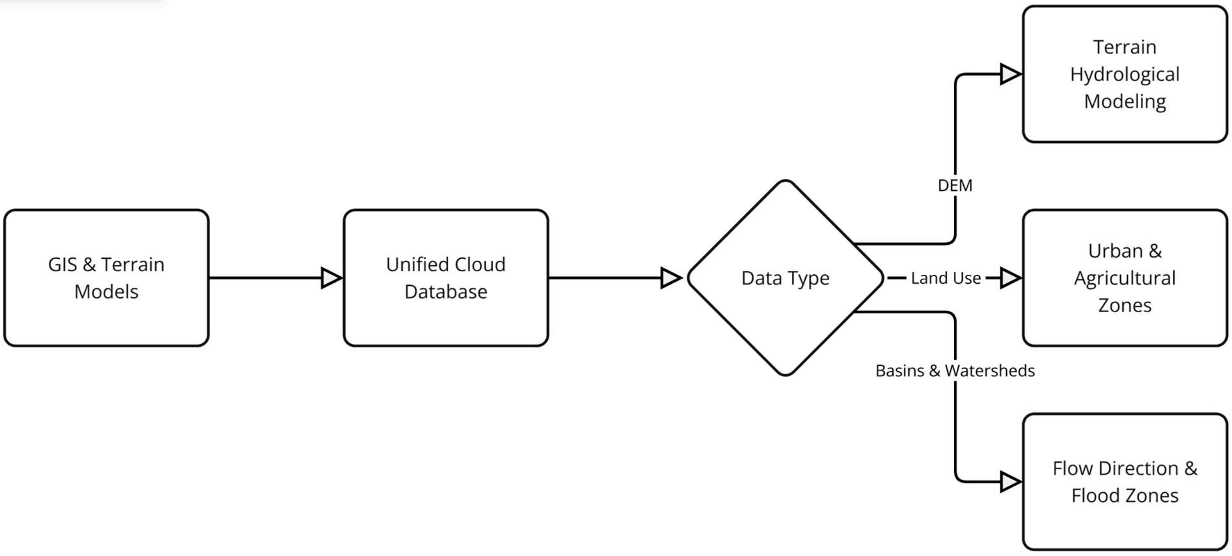


Figure 4. Geospatial data integration via GIS and terrain models.

1. High-Resolution Digital Elevation Models (DEMs)

Digital Elevation Models (DEMs) are foundational for the accurate simulation of water flow, flood dynamics, and watershed management. They provide detailed information on terrain structure and elevation, which is critical for understanding how water interacts with landscapes and how changes in topography influence water distribution across a given area. The integration of high-resolution DEMs with the digital twin framework plays a critical role in enhancing the realism and predictive capability of water reserve management. In the context of the digital twin, DEMs act as the foundational layer that supports the simulation of water flow, flooding events, and terrain changes over time. By accurately mapping the elevation and shape of the terrain, the DEMs allow the digital twin to simulate hydrological processes in a highly realistic manner. Furthermore, game engines (such as Unreal Engine and Unity) rely on accurate DEMs to create immersive 3D models of water systems and infrastructures, which are essential for visualization and scenario-based simulations. The integration of high-resolution DEMs into game engines facilitates the creation of interactive environments where users can manipulate water flow, test flood mitigation strategies, and analyze the impact of land-use changes. The real-time visualization of these terrains within the digital twin framework enables decision-makers to understand how various factors, such as rainfall, land cover changes, or infrastructure modifications, affect water reserves and flood risks. Additionally, DEMs play a significant role in enhancing real-time data updates that are core to the digital twin system. As IoT sensors provide live data on water levels and flow rates, the DEM can be dynamically updated to reflect changes in the terrain or water body, providing a continuous and accurate representation of the environment. This integration ensures that the model is always in sync with the real world, providing timely insights into potential risks such as flooding, drought, or water scarcity. By integrating high-resolution DEMs, the framework can precisely model water movement and terrain dynamics, providing a more accurate depiction of hydrological processes in the digital twin environment.

The creation of high-resolution DEMs involves a combination of remote-sensing techniques and ground-based methods to capture elevation data at varying scales. Several tools and technologies are employed to ensure that the DEMs are both precise and comprehensive:

- Drones (UAVs): Drones are a valuable tool for creating high-resolution DEMs, especially in large, remote, or difficult-to-access areas. Equipped with LiDAR (Light Detection and Ranging) sensors or RGB cameras, drones can capture extremely detailed elevation data over vast areas with high accuracy. LiDAR technology, in particular, allows for the generation of point clouds, which are used to create precise 3D models of the landscape. The ability to fly low over the terrain ensures that even intricate topographic features, such as riverbanks, cliffs, and small water bodies, are captured in great detail. For large-scale areas, drones provide an efficient means of covering extensive regions while maintaining high resolution.
- Close-Range Photogrammetry: For more localized or small-scale elevation modeling, close-range photogrammetry offers another method for generating detailed DEMs. This technique involves capturing a series of overlapping images of the terrain from various angles, which are then processed through specialized software to create accurate 3D models. This method is particularly useful for generating fine-scale DEMs of specific features such as dams, embankments, or reservoirs. Structure-from-Motion (SfM) algorithms are commonly used in photogrammetry to reconstruct 3D surfaces from 2D images.
- Augmented DEM Refinement: To further enhance the resolution and detail of DEMs, particularly in areas that require fine-level adjustments (such as urban environments, water features, or intricate topographic structures), techniques like 3D Gaussian splatting, LiDAR Point Cloud Processing (Surface Reconstruction) using Poisson Surface Reconstruction or Alpha Shapes algorithms, Multi-View Stereo (MVS) Reconstruction using Semi-Global Matching (SGM) or PatchMatch Stereo methods, Volumetric Terrain Modeling using Octree-based voxelization techniques, Deep-Learning-based Surface Reconstruction techniques such as Convolutional Neural Networks (CNNs) or DeepLiDAR, Super-Resolution Algorithms such as Sparse Coding and Photogrammetric Dense Matching (e.g., Hierarchical Matching or Graph-Cuts) and Hybrid Point Cloud Processing can be applied. This method involves refining occlusions and gaps in the point cloud data by applying statistical models to the raw elevation data, effectively filling in missing or unclear areas. It also enhances the precision of DEMs, particularly in regions with dense vegetation or infrastructure, where traditional methods may struggle. This refinement process ensures that the resulting DEM is not only highly detailed but also accurate, providing the best possible representation of the terrain.

2. Land Use and Soil Types

Data on land use and soil types play a key role in understanding how various factors, such as land cover (e.g., urban, agricultural, forest), influence water retention, infiltration, and runoff. These datasets are typically sourced from publicly available geographic databases like the USGS National Land Cover Database (NLCD) or the European Space Agency (ESA) soil moisture products.

3. Real-Time Water Flow Data

The integration of real-time flow data from IoT sensors with DEMs and land-use data enables the framework to simulate and predict the behavior of water across different terrains. This combination of data allows for accurate modeling of hydrological processes, including river dynamics, flooding, and soil erosion.

2.3.3. Use of Existing Data Repositories

To further enrich the framework, various external data repositories are utilized to enhance the accuracy and depth of the model. These repositories provide valuable historical, regional, and global data that are essential for effective water reserves management.

- Hydrological Datasets: Data from Global Runoff Data Centre (GRDC), USGS National Water Information System (NWIS), and other regional hydrological monitoring systems are used to gather historical flow data, river discharge levels, and water storage data. These data support long-term trend analysis and improve the predictive capabilities of the model.
- Climate Projections: Future climate projections from sources such as the IPCC (Intergovernmental Panel on Climate Change) or CMIP (Coupled Model Intercomparison Project) provide insights into potential shifts in weather patterns that could impact water resources. These projections are integrated into the system to simulate future water availability and help plan for potential droughts or extreme weather events.

2.3.4. Specific Tools and Platforms for Data Aggregation and Integration

The preprocessing and integration of data from various sources is a crucial step (Figure 5). It requires the use of specialized tools and platforms that facilitate data aggregation, storage, and visualization, examples of which are explained below.

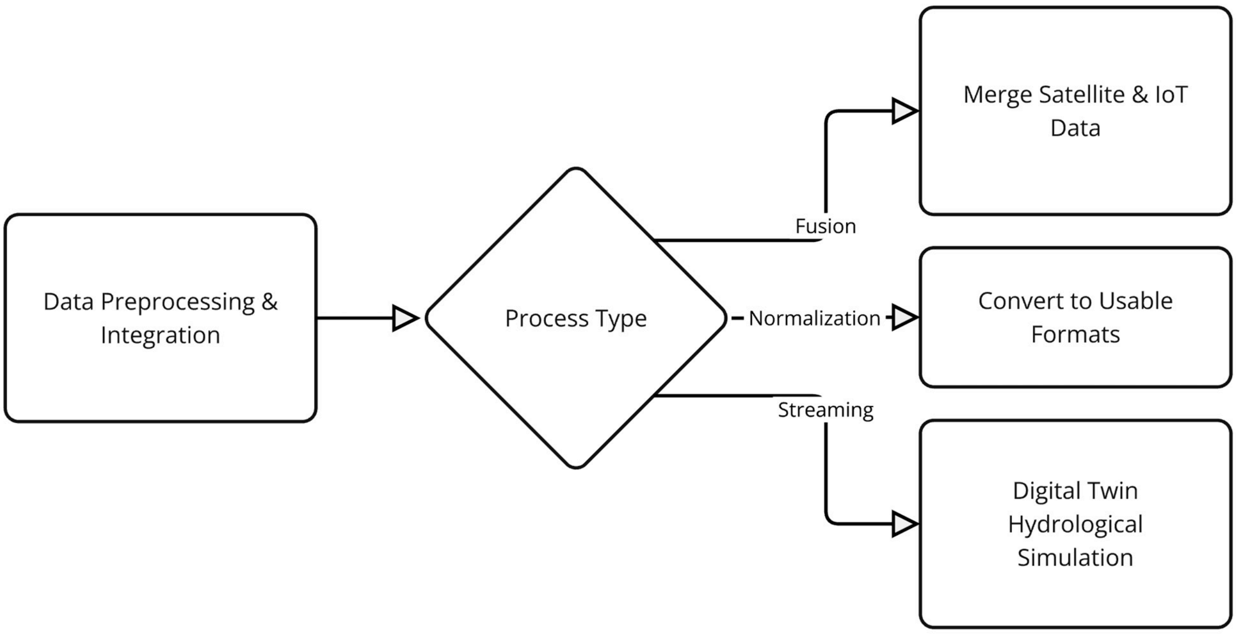


Figure 5. Multi-source data preprocessing and integration pipelines.

1. MQTT Protocol: The MQTT protocol is widely used for transmitting IoT sensor data to central systems due to its lightweight, low-bandwidth, and low-latency characteristics. It is particularly suitable for IoT networks in water reserves, where devices are often spread across large areas and require reliable, real-time data transmission.
2. Geographic Information Systems (GIS): GIS platforms such as ArcGIS and QGIS are critical for integrating, analyzing, and visualizing geospatial data [51]. These systems allow for the creation of accurate digital elevation models, land-use maps, and other spatial data products that are necessary for water flow simulation and management. GIS tools also allow for the visualization of satellite imagery and the overlay of real-time sensor data on maps.
3. Cloud-based Data Warehouses: Scalable cloud storage solutions like AWS Redshift, Google BigQuery, and Microsoft Azure are employed to store large amounts of data from various sources, including sensors, satellite imagery, and hydrological datasets. These platforms provide the infrastructure needed for real-time data processing, querying, and integration with the digital twin model.

4. Data Integration Platforms: Platforms such as Apache Kafka and Apache NiFi are used to ensure smooth data flow between various data sources and the central database. These tools allow for real-time streaming of data, as well as the processing and integration of large datasets from IoT devices, satellites, and external repositories.

2.4. Model Design and Simulation Environment

This section presents the modeling techniques used to integrate physical, hydrological, and behavioral components into a unified digital twin environment. The simulation design combines deterministic models (e.g., mass balance equations), spatial visualization tools (GIS), AI-based scenario prediction (machine learning models), and game engine-based immersive modeling. The foundation of the digital twin is the integration of hydrological models with physical representations of water systems such as rivers, reservoirs, and groundwater. These models are constructed within platforms like Unreal Engine, Unity, or Simulink, which allow for the creation of interactive 3D simulations. These platforms use data from various sources, such as sensor networks, satellite imagery, and meteorological inputs, to simulate real-time water flow, water quality, and environmental changes.

1. Physical Models Integration: Hydrological models and water balance equations are incorporated into the digital twin framework to simulate water distribution, quality, and behavior under various conditions. These models are calibrated and validated using historical data, real-time sensor readings, and satellite observations.
2. Real-Time Data Integration: The digital twin is continuously updated with real-time data collected through IoT sensors, satellite imagery, and weather stations. This allows for dynamic and accurate simulations, which can adapt to changing environmental conditions or management decisions in real time.

Once the data are integrated, the digital twin model allows for the simulation of various scenarios that can assist in decision-making processes related to water management. These capabilities include:

- Real-Time Data Updates: The digital twin continuously updates in response to new data, enabling up-to-date simulations of water systems.
- Predictive Modeling: The model includes predictive algorithms that can forecast future water system behaviors based on historical trends, climate projections, and real-time inputs. This is crucial for preparing for extreme weather events like floods or droughts.
- Scenario Analysis: Users can test different scenarios within the digital twin, such as the impact of a new dam, the effects of climate change on water reserves, or the potential for flooding during heavy rainfall. These simulations help stakeholders visualize the consequences of their decisions before implementing them in the real world.

2.5. Game Engine Integration and Simulation Design

The integration of game engines like Unreal Engine and Unity plays a pivotal role in enhancing the interactivity and visualization of water reserves management. These engines are utilized to build immersive, real-time 3D simulations that mimic real-world water systems and flood management scenarios. Game engines such as Unreal Engine and Unity are employed to create detailed and visually rich simulations of water reserves and flood management systems. These engines enable high-fidelity rendering, providing an engaging, interactive environment where users can manipulate water systems and visualize real-time changes based on various environmental factors. The ability of these engines to render large-scale terrains and water bodies with accuracy enhances the realism and applicability of the simulations.

The design of simulations focuses on user interface (UI) simplicity and interactivity, ensuring that users—whether stakeholders, decision-makers, or the general public—can easily engage with the system. The interface allows for intuitive interaction with complex data and water management systems. Key design features include:

- Water System Visualization: Realistic 3D renderings of water bodies, infrastructure (dams, reservoirs), and surrounding terrain.
- Real-Time Interaction: Users can change parameters such as rainfall levels, water demand, or flood mitigation measures and immediately see the resulting changes in water flow and management dynamics.
- Virtual Tour: Utilizing game engines for immersive digital twins is crucial for conducting virtual tours and providing a realistic water reserve management experience, as it allows policymakers and water managers to visualize and interact with hydrological data, flood scenarios, and reservoir dynamics in a highly engaging and informative manner.
- Simulating Various Water Management Scenarios: Visualizations include natural disaster scenarios like floods, droughts, rainfall-induced landslides, water conservation strategies, or infrastructure changes, allowing users to simulate and analyze different management approaches.

Several specialized tools and plugins are integrated within the game engines to simulate the complex dynamics of water systems. These tools enhance the realism of the simulations by modeling water behaviors and environmental factors in detail. FluidFlux is used for simulating tidal forces and water dynamics in coastal or river systems, and it allows for the accurate simulation of water movement and interaction with various topographies, providing insight into flood management and tidal behavior. Additionally, TerreSculptor is a terrain modeling tool used to generate realistic landscapes, terrain elevations, and water flow patterns. This plugin ensures that the simulation environment accurately reflects the real-world geographic features that impact water distribution and flow. Other custom plugins can be added for simulating specific hydrological processes like river currents, groundwater infiltration, or evapotranspiration, which are essential for modeling the behavior of water in different weather and environmental conditions. One of the most powerful features of the game engine-based simulation is the ability to conduct scenario-based simulations, enabling users to explore a wide range of potential water management scenarios. Users can test the effectiveness of various flood control measures, such as dam construction, levees, flood gates, or natural buffers (wetlands, forests). The system simulates water behavior under extreme conditions and shows how infrastructure or policy changes can mitigate or exacerbate flooding. The simulation allows for the exploration of water-saving strategies such as irrigation systems, water pricing, and land-use policies. By adjusting these factors, users can analyze their impact on water availability and distribution. Real-time, interactive simulations can show how water systems will respond to sudden events like heavy rainfall or system failures. Stakeholders can test preparedness strategies for both flood and drought events, enabling better risk management and response planning.

2.6. Evaluation Metrics and System Validation

Although this study introduces a conceptual and prototype-level framework, a series of preliminary validation procedures are proposed to assess the system's accuracy, usability, and responsiveness. The performance of predictive modeling components—such as AI algorithms for forecasting droughts or floods—can be evaluated using standard statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). In cases involving classification-based outputs, more complex metrics derived from the confusion matrix—such as Receiver Operating Characteristic (ROC) curves, accuracy, and precision—may also be employed by comparing predicted values with observed historical datasets. Calibration and validation of hydrological models will be conducted using long-term discharge and precipitation records sourced from local monitoring systems or global repositories such as the Global Runoff Data Centre (GRDC) and the U.S. National Water Information System (NWIS). To assess system usability and stakeholder interactivity, user-centered design principles can be implemented, drawing on evaluation criteria such as interface intuitiveness, system responsiveness, and realism of scenario simulations, which may be measured during expert walkthroughs or stakeholder workshops. In addition, the framework's adaptability can be tested through scenario-based stress testing under synthetic climate inputs (e.g., projected extreme rainfall or prolonged drought conditions). Collectively, these evaluation metrics validate the technical robustness, operational readiness, and potential for user engagement of the proposed digital twin framework.

Due to the high-stakes nature of water resource management—where decisions can directly impact public health, food security, disaster preparedness, and environmental sustainability—the framework places strong emphasis on model transparency and interpretability. While modern machine-learning and deep-learning algorithms often achieve superior accuracy compared to traditional models, their complexity can result in "black-box" behavior, making it difficult for decision-makers to trust or understand model outputs without additional interpretive scaffolding. To address this, the system incorporates explainable AI (XAI) techniques aimed at unpacking the decision logic behind each prediction. Methods such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) will be employed to attribute model outcomes to specific input features both globally (across the model) and locally (at the individual prediction level). These tools provide insight into how factors such as rainfall variability, reservoir capacity, or land use contribute to forecasted risks like flooding or water shortages. Additionally, complementary interpretability tools—such as partial dependence plots (PDPs), individual conditional expectation (ICE) curves, and permutation feature importance—can be incorporated within the decision-support interface to help users visualize model behavior over varying input conditions. These plots will be accompanied by natural language summaries and intuitive UI features (e.g., annotated graphs and color-coded feature contributions), enabling even non-technical stakeholders to understand what drives a particular forecast. This interpretability framework ensures that model predictions are not only accurate but also explainable, auditable, and trustworthy, fulfilling a crucial requirement in water governance where transparency and accountability are as important as predictive performance.

3. Results and Discussion

3.1. Implementation of a Digital Twin-Driven Early Warning System

Integrating early-warning capabilities into the digital twin framework is essential for proactive water management, especially in mitigating the risks of flooding, drought, and water-quality degradation [52]. By leveraging the power of IoT sensors, satellite data, and advanced modeling tools, the digital twin continuously monitors and predicts hydrological events. The framework processes incoming data through predictive algorithms, cross-referencing it with historical climate data and current water system conditions to provide accurate forecasts [53]. These predictions form the backbone of the early-warning system, ensuring stakeholders receive timely alerts on water-related hazards. The early-warning system's methodology relies on a combination of real-time data streaming, predictive analytics, and scenario-based simulations [54]. As environmental and hydrological conditions evolve, the system dynamically adjusts predictions and updates risk levels. For instance, changes in rainfall patterns, river flow rates, or water levels can trigger early warnings, while the system continuously recalibrates based on fresh data inputs. The integration of real-time data with predictive modeling enables a comprehensive understanding of the current state and potential future conditions, offering invaluable insights for timely decision-making.

3.1.1. Flood and Drought Predictions

The core of flood and drought prediction lies in the digital twin's ability to simulate hydrological processes under different environmental and climatic conditions. The system uses real-time sensor data from water bodies, such as rivers, lakes, and reservoirs, along with high-resolution satellite imagery, to monitor key parameters like rainfall, soil moisture, water levels, and temperature. These inputs are integrated into a set of predictive models that simulate how water reserves will behave in the face of extreme weather events. Flood prediction is primarily based on simulations of river and reservoir dynamics, utilizing data on rainfall intensity, runoff rates, and existing water levels. The system can identify rising flood risks by predicting water accumulation patterns, potential dam overflows, and flash flood conditions. Similarly, drought prediction focuses on monitoring trends in precipitation, soil moisture, and groundwater levels. By identifying areas with persistent water shortages, the system can predict the onset of drought conditions and provide early warnings to facilitate water conservation efforts and drought management strategies.

3.1.2. Water Quality Monitoring and Disaster Preparedness

In addition to flood and drought predictions, the early-warning system incorporates continuous monitoring of water-quality parameters, which is essential for disaster preparedness [55]. Water-quality sensors measure indicators such as pH, turbidity, dissolved oxygen, and chemical pollutants to assess the health of water systems. By analyzing these parameters, the system can detect contamination events, potential algal blooms, or sudden changes in water chemistry that may compromise public health. The digital twin framework's integration of water-quality monitoring extends to disaster preparedness by enabling a proactive response to emerging threats. For example, if water-quality sensors detect abnormal pH levels or increased turbidity, the system can predict potential water contamination, alerting local authorities and enabling quick interventions. This proactive approach helps to prevent public health crises and ensures that water resources are safe for consumption and agricultural use. Additionally, by providing historical water-quality data alongside current monitoring, the system allows for more effective risk management and disaster response strategies.

3.1.3. Real-Time Decision Support and Risk Communication

The early-warning system's primary function is to ensure real-time decision support, particularly in responding to imminent or evolving threats. As the system continuously collects and processes data from IoT sensors, satellite imagery, and environmental models, it generates real-time alerts regarding potential flood, drought, or water-quality risks. These alerts are communicated to decision-makers through user-friendly interfaces, offering clear, actionable insights and visualizations that enable stakeholders to understand and assess the level of risk. In the case of an impending flood, for instance, the system can notify local authorities, emergency responders, and citizens about flood-prone areas, estimated water levels, and potential impacts. Similarly, in the case of drought conditions, the system will provide alerts about water shortages, areas at risk of water scarcity, and the potential for crop loss. The early-warning system also incorporates real-time water-quality monitoring, allowing stakeholders to track changes in water parameters and address incidents such as contamination or algal blooms. The communication of risk is crucial, and the system is designed to provide comprehensive risk assessments based on up-to-the-minute data. Through a combination of visualizations, maps, and predictive graphs, the decision support system ensures that users can fully comprehend the situation and make informed decisions. These alerts can be sent through multiple channels, including mobile apps, email notifications, and desktop dashboards, ensuring that the right stakeholders receive timely updates no matter their location.

3.1.4. Empirical Foundations, Research Gaps, and Framework Integration

The feasibility of a digital twin-based early-warning system for hydrological hazards is increasingly supported by recent applied research. For example, Song [56] developed a real-time river flood early-warning system for the Tartano River in Northern Italy, using digital terrain models and Unity game engine integration to simulate flood dynamics and generate threshold-based alerts. Similarly, Li [57] constructed a modular urban flood disaster prediction and dispatch system using digital twin technology in China, demonstrating the potential for dynamic interaction between sensor networks and predictive models in city-scale water systems. In a broader context, Riaz et al. [58] showcased how digital twins can improve climate resilience by integrating 3D city modeling with IoT data streams and forecast models. Their results showed improved warning lead times and system responsiveness when compared to conventional models. Thakur [59] proposed a digital twin-driven methodology for predicting urban waterlogging and sewer overflow conditions, with embedded sensors and predictive modeling frameworks for near-real-time alerts and decision support.

These studies confirm the viability of core components found in our proposed system, including hydrological simulation, real-time feedback loops, AI-enhanced alerts, and immersive visualization. However, none of these implementations offer a unified, modular, and immersive architecture that integrates decision-making interfaces, 3D stakeholder engagement tools, and scenario-based gamification into a single system. Most current systems remain application-specific (e.g., flood-only or sewer-only), lack participatory modules, or require extensive technical expertise for interpretation. The proposed framework in this paper builds upon these foundations by proposing an integrated, adaptive architecture that incorporates digital twins, IoT sensors, and game engines into a unified early-warning and decision-support environment. Furthermore, as shown in Section 3.5, various components of this framework have already been implemented in prototype form, demonstrating technical feasibility and the capacity for real-time terrain modeling, infrastructure reconstruction, and interactive simulation.

3.2. Where Data Meets Decisions: AI-Driven Decision Nexus as the Ultimate Solution

The integration of digital twins, real-time sensor networks, predictive analytics, and interactive simulations has laid the foundation for a transformative approach to water reserves management. However, the true potential of these technologies can only be realized when they converge into a unified, intelligent decision-support system (AI-DSS). This AI-driven nexus serves as the culmination of all discussed technologies, synthesizing vast streams of data into actionable insights that inform policy-making, emergency response, and long-term water conservation strategies. Through machine-learning and deep-learning models, the system continuously refines its predictions, learning from historical trends, real-time hydrological fluctuations, and external climate patterns. Advanced open-source large language models (LLMs) facilitate stakeholder engagement by transforming raw data into accessible, domain-specific insights. Additionally, Retrieval-Augmented Generation (RAG) chatbots provide an interactive interface, enabling users to query the system, receive instant risk assessments, and explore adaptive management strategies. Each preceding step—from the construction of digital twins to the integration of real-time monitoring systems, game engine simulations, and early-warning mechanisms—feeds into this AI-DSS, forming a cohesive intelligence-layered entity that optimizes water governance. The following sections explore how this decision-making nexus is designed, the algorithms that power it, and how it enables more adaptive, predictive, and interactive water management solutions.

3.2.1. Design of an AI-Driven System for Enhanced Water Management Decisions

The AI-based decision-support system is designed to continuously enhance water management decisions by leveraging advanced machine-learning and deep-learning techniques. By processing large volumes of real-time and historical data, the system provides intelligent insights that empower water managers to make more informed decisions regarding water reserves, flood management, drought response, and overall resource allocation. The system's core function is to adaptively optimize water management strategies by learning from incoming data, adjusting to changing conditions, and forecasting future events based on predictive models [60,61]. The AI-driven system integrates various data sources—such as sensor readings, satellite imagery, meteorological data, and historical water flow records—to provide a comprehensive understanding of water systems [62]. These diverse data streams are fed into the system to ensure that the AI continuously learns and updates its knowledge base. The system is designed to provide real-time recommendations for water usage, conservation practices, flood mitigation strategies, and drought management, with an emphasis on adaptability and efficiency.

3.2.2. Integration of Machine-Learning and Deep-Learning Algorithms

At the heart of the system's adaptability is the integration of machine-learning (ML) and deep-learning (DL) algorithms. These algorithms are essential for extracting patterns from complex, large-scale datasets and predicting future water system behavior based on historical trends. ML algorithms, such as decision trees, support vector machines and ensemble methods are employed to identify relationships within data, such as how changes in precipitation patterns may influence river flow or how temperature fluctuations impact water quality [63]. Deep-learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are utilized for more sophisticated tasks, including the analysis of time-series data, image recognition, and flood risk predictions. For instance, CNNs can process satellite imagery to detect changes in land cover, vegetation health, and water bodies, while RNNs are ideal for analyzing sequential data, such as water-level fluctuations over time. These algorithms enable the system to predict potential water shortages, flooding events, and the impacts of land-use changes, providing proactive decision-making support. Different ML and DL algorithms are described in Table 1.

The selection of machine-learning and deep-learning algorithms plays a critical role in water resource management, influencing the accuracy, efficiency, and interpretability of predictions. Supervised learning models, such as Linear Regression, Decision Trees, and Random Forests, offer transparency—meaning their decision-making process can be easily understood—and efficiency, as they require less computational power. These qualities make them suitable for tasks like predicting water demand based on historical usage patterns or classifying flood risk zones by analyzing past flood events and topographical data. However, they often struggle with capturing complex, nonlinear relationships, requiring feature engineering, where domain-specific knowledge is used to create relevant input variables. For example, when using Linear Regression to predict water consumption trends, engineers might need to introduce additional variables like seasonal variations or economic activity levels to improve accuracy. Deep-learning models, such as CNNs, RNNs, and LSTMs, provide powerful pattern recognition and time-series forecasting capabilities, making them well-suited for analyzing satellite imagery to detect water bodies, monitoring long-term hydrological trends, and providing real-time flood predictions. For instance, a

CNN can process satellite images to detect changes in river meanders, soil moisture levels, or deforestation, helping policymakers anticipate water resource challenges.

Table 1. Comparison of Machine-Learning and Deep-Learning Algorithms.

Algorithm Type	Model Type	Strengths	Limitations	Use Case in Water Management	Training Time	Data Requirements
Linear Regression	Supervised Learning	Simple, fast, interpretable	Assumes linear relationships; not suitable for complex patterns	Predicting water demand based on historical data	Short	Low
K-Nearest Neighbors (KNN)	Supervised Learning	Simple and intuitive	Computationally expensive for large datasets	Estimating regional water quality	Short	Medium
Decision Trees	Supervised Learning	Easy to interpret, good for classification	Can overfit; less accurate with complex data	Classifying flood risk zones	Medium	Medium
Random Forest	Supervised Learning	Robust to overfitting, handles large datasets	Computationally expensive	Predicting flood events and water quality	Medium	Medium to High
Support Vector Machines (SVM)	Supervised Learning	Effective in high-dimensional spaces	Computationally intensive, requires parameter tuning	Classification of water body conditions	Medium	High
Convolutional Neural Networks (CNN)	Deep Learning	Excellent for pattern recognition in images	Requires a large amount of data and computational power	Analyzing satellite imagery for land use changes	Long	High
Recurrent Neural Networks (RNN)	Deep Learning	Effective for time-series data	Can suffer from vanishing gradients, requires large datasets	Predicting water flow or rainfall patterns	Long	High
Long Short-Term Memory (LSTM)	Deep Learning	Handles long-term dependencies well	Requires significant training data, slow to train	Real-time water level predictions	Long	High

Recent advancements have demonstrated the efficacy of ML and DL techniques in water resource management. For instance, convolutional neural networks (CNNs) have been utilized for drought classification through vegetation indices like VHI and NDVI [64,65]. Long short-term memory (LSTM) networks have shown high temporal precision in river flow and flood forecasting [66,67], outperforming traditional hydrological models in capturing temporal dependencies in rainfall–runoff relationships [68]. Random Forest models have been applied to identify groundwater potential zones and predict agricultural water demand, offering higher spatial generalization than process-based models [69]. In the realm of water reserve management, transformer-based deep-reinforcement learning approaches have been employed to optimize multi-reservoir operations, balancing objectives like power generation, ecological protection, and residential water supply [70]. These methods have demonstrated superior performance compared to traditional techniques in terms of electricity generation and water supply revenue. Additionally, ML techniques have been applied for contamination detection in water distribution systems, urban water-quality prediction, and leakage detection, showcasing their versatility in various aspects of water resource management [71,72]. Compared to conventional hydrological models, ML and DL approaches offer enhanced capabilities in handling nonlinear relationships and large, diverse datasets. While traditional models rely on predefined equations and parameters, ML models can learn complex patterns directly from data, providing more accurate and adaptable predictions. However, they also require substantial amounts of high-quality data and may lack the interpretability of simpler models. Hybrid models that integrate physical-based knowledge with data-driven techniques have been developed to improve prediction performance, combining the strengths of both approaches [73,74]. In our proposed framework, these AI methods are not isolated prediction tools but are integrated into a real-time decision-support environment. For instance, a Random Forest model could classify risk zones based on dynamic sensor inputs, while an LSTM forecasts short-term reservoir inflows, both embedded within the digital twin for continuous adaptation and visualization. This approach bridges high-performance prediction with intuitive stakeholder communication, setting the foundation for adaptive, AI-driven water governance.

However, the trade-off between ML and DL lies in their high computational costs, large data requirements, and lack of interpretability compared to traditional models. Interpretability refers to how easily humans can understand a model's decision-making process, while a Decision Tree might explicitly show that a flood risk is high due to soil permeability and recent precipitation levels, and an LSTM flood model may not clearly indicate why it made a particular prediction. For real-time applications, LSTMs outperform traditional models due to their ability to capture long-term dependencies in sequential data, making them valuable for predicting water levels based on historical rainfall, river discharge, and groundwater fluctuations. For example, an LSTM trained in decades of river flow data can anticipate potential droughts or floods weeks in advance, providing critical early warnings. Conversely, Random Forests and Decision Trees remain valuable where interpretability and efficiency are critical, such as in policy decision-making and regional flood risk assessments. A Random Forest model can help government agencies assess which regions are most vulnerable to water shortages, combining factors like rainfall trends, population density, and agricultural water demand.

A key limitation across all models is data dependency—while simpler models require less data, deep-learning models demand vast, high-quality datasets for meaningful insights. For instance, a Linear Regression model might need just a few years of precipitation and water consumption records, whereas a CNN trained to detect drought-prone areas from satellite imagery may require decades of high-resolution images and labeled datasets to achieve reliable accuracy. This underscores the need for robust data-collection infrastructures, including remote sensing (e.g., satellite and aerial imagery), IoT-enabled water sensors (for real-time monitoring of water quality and levels), and hydrological databases that track long-term trends. Thus, selecting the appropriate algorithm hinges on the balance between computational feasibility (e.g., whether an agency has the processing power to run deep-learning models), data availability (whether sufficient historical or real-time data exists), interpretability (whether decision-makers need to understand the logic behind predictions), and prediction accuracy. Future advancements may see the hybridization of traditional and deep-learning models, such as combining a Decision Tree for interpretability with an LSTM for high-accuracy predictions, allowing for more precise, scalable, and actionable decision-support systems in water management.

3.2.3. Adaptive Decision-Making for Dynamic Recommendations

The AI-based decision-support system is designed to learn from past data and continuously update its models in response to new inputs and evolving environmental conditions. This adaptive decision-making process ensures that the system remains flexible and accurate over time. For example, if an unexpected weather event or environmental change alters water availability or quality, the system will automatically adjust its recommendations to reflect the new circumstances. The system's adaptability is enhanced by its ability to process real-time data streams, which allows it to respond to changes in water systems immediately. As data from IoT sensors, satellite observations, and meteorological reports are continuously fed into the system, machine-learning algorithms recalibrate the predictive models and adjust water management strategies accordingly. This ensures that the recommendations provided to water managers are always based on the most current information available, leading to more effective responses to emerging challenges, such as flood events, drought conditions, or contamination threats. By dynamically adjusting decision-making protocols, the AI system is able to provide highly accurate and context-specific guidance, facilitating optimal water management under diverse and changing environmental conditions. Whether it is adapting to shifting weather patterns, addressing new water quality concerns, or responding to changes in water demand, the AI system ensures that water reserves are managed efficiently and sustainably over time.

3.2.4. Use of Open-Source Large Language Models (LLMs)

To enhance user engagement and provide interactive insights, the AI system incorporates open-source Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) chatbots. LLMs are used to process natural language inputs from users, enabling them to query the system, ask for recommendations, and receive detailed responses regarding water management strategies, flood risks, and drought. Different LLMs are summarized in Table 2 and Figure 6. The RAG chatbot integration allows the system to pull relevant data from multiple sources (such as IoT sensors, historical datasets, and real-time satellite imagery) and present this information in a conversational manner. This functionality encourages dynamic interaction, where users can request detailed analyses, run simulations, or explore different scenarios (e.g., assessing the effectiveness of a proposed flood mitigation measure). By leveraging RAG capabilities, the chatbot not only retrieves data but also generates responses that are contextually relevant, ensuring that users receive personalized, real-time insights [75]. These AI-powered interfaces enable water management professionals to access complex data and predictions in an intuitive and interactive manner. The integration of LLMs and RAG chatbots enhances the user experience, making it easier to interpret data and receive actionable recommendations without needing to interact directly with complex models or systems [76].

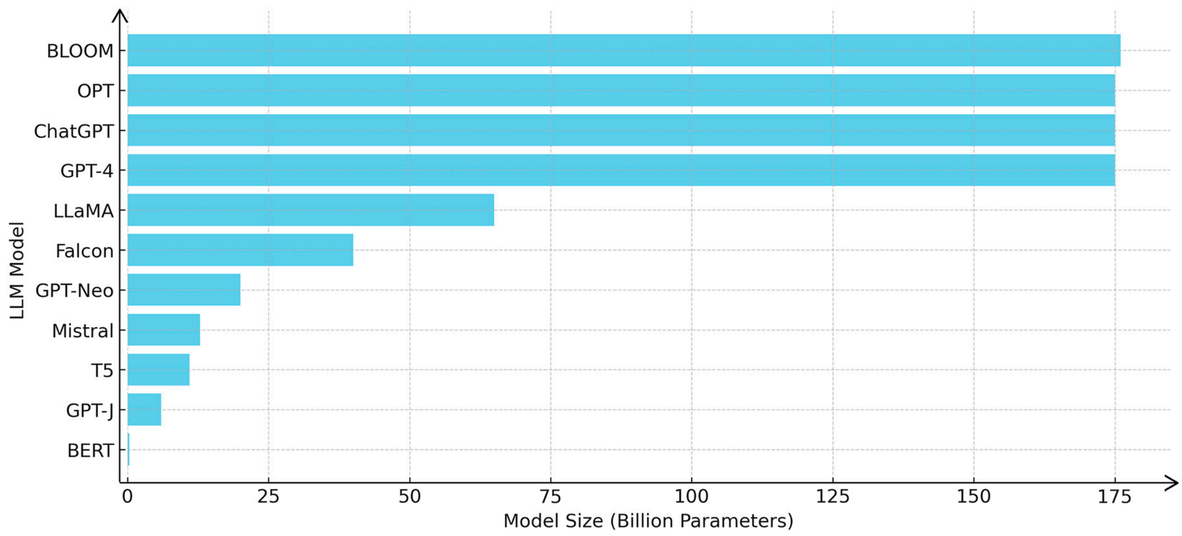


Figure 6. Comparison of Large Language Model Sizes.

Table 2. Comparison of Large Language Models (LLMs).

LLM Model	Developer	Strengths	Limitations	Use Case	Training Time	Open Source	Use Case in Water Management
GPT-4	OpenAI	Strong general language understanding, handles complex queries, computationally expensive and less easily fine-tuned for domain-specific tasks	Computationally expensive, lacks fine-tuned domain-specific knowledge	Conversational AI, text generation, decision support	Long	✘	Conversational insights on water management, predicting water stress
BERT	Google	Good at contextual language understanding, pre-trained on large corpora	Requires fine-tuning for specific tasks	NLP tasks, question answering, summarization	Medium	✓	Assisting with water reserve documentation, query handling
T5	Google	Strong in multiple NLP tasks, flexible with fine-tuning	Requires large datasets for training	Text-to-text generation, data extraction	Medium	✓	Generating insights and recommendations for water management policies
GPT-4-turbo	OpenAI	Specializes in conversational interfaces, handles long conversations	Limited by the pre-trained knowledge cutoff	Customer service, decision support	Medium	✘	Real-time user queries about flooding or water shortage conditions
LLaMA	Meta	Open-source, high performance for specific tasks	Requires fine-tuning for high accuracy	Text generation, summarization	Medium	✓	Generating reports or summaries on water system health
Falcon	Technology Innovation Institute	State-of-the-art performance with efficient use of resources	Smaller model sizes may not outperform larger models	Text generation, summarization, question answering	Moderate (due to optimizations)	✓	Localized water data analysis, simulation predictions, real-time monitoring
Mistral	Mistral AI	Efficient training, open architecture, cost-effective	May lack capabilities of larger models for complex tasks	Text generation, dialogue systems, question answering	Faster (optimized for deployment)	✓	Quick, accurate predictive insights for water systems, disaster risk assessment
GPT-Neo	EleutherAI	Open-source, high performance for various NLP tasks	Smaller model sizes might be less accurate	Text generation, summarization, question answering	Medium	✓	Assisting with decision support and system insights
GPT-J	EleutherAI	Open-source, strong language understanding for general purposes	Can be computationally demanding for real-time applications	Generating reports, conversational interfaces	Medium	✓	Providing on-demand decision insights for water system management
BLOOM	BigScience	Open-source, multilingual support, strong cross-lingual capabilities	Computationally expensive, not as fine-tuned for specific domains	Multilingual tasks, summarization, conversation	Long	✓	Multilingual flood management communication, cross-region collaboration
OPT	Meta	Open-source, high efficiency, optimized for conversational AI	Requires significant computational resources	Text generation, summarization, dialogue generation	Medium	✓	Supporting cross-departmental communication and action in water management
RAG (Retrieval-augmented generation)	Hugging Face	Supports retrieving documents and information to generate contextually aware responses	May require tuning to specific tasks	Real-time dynamic responses, knowledge retrieval	Medium	✓	Providing interactive decision support for flood management

Large Language Models (LLMs) play a crucial role in advancing decision-support systems for water management, particularly in predictive analytics, automated reporting, and real-time user engagement. One of the primary considerations in selecting an LLM for this purpose is whether the model is open source or proprietary. Open-source models such as BERT, Falcon, LLaMA, GPT-Neo, GPT-J, BLOOM, and OPT provide flexibility for customization, allowing researchers to fine-tune them using hydrological and environmental datasets. This adaptability enhances their applicability in domain-specific tasks like flood forecasting and water reserve analysis. In contrast, proprietary models like GPT-4 and ChatGPT offer superior general language understanding but lack transparency and fine-tuning capabilities. While they are well-suited for interactive decision support, their computational costs and closed nature limit their customization for specialized water management applications.

Computational efficiency is another key factor in determining an LLM's suitability for real-time water management. Larger models, such as GPT-4, BLOOM, and OPT (175 billion+ parameters), offer high accuracy in language comprehension but require substantial computational resources, making them less ideal for real-time deployment in resource-constrained environments. Meanwhile, more efficient models like Falcon (7–40 billion parameters) and Mistral (12.9 billion parameters) strike a balance between performance and deployment feasibility, enabling real-time monitoring of water reserves and flood risks. RAG model's size varies by implementation. Additionally, the multilingual capabilities of BLOOM make it particularly useful for cross-border water management initiatives, where collaboration and data sharing across different linguistic regions are essential. Selecting the right LLM for water management AI systems depends on the intended application. If interactive decision-making and conversational support are a priority, GPT-4 and ChatGPT are strong candidates. If customization and open-source accessibility are required, LlaMA, GPT-Neo, or OPT offers greater flexibility. Models like Falcon and Mistral are better suited for real-time analytics due to their efficient architecture, while BLOOM facilitates international collaboration through multilingual support. By strategically leveraging these models, water management systems can improve predictive capabilities, automate data interpretation, and provide timely insights to mitigate risks related to floods, droughts, and water scarcity.

3.2.5. Developing Retrieval-Augmented Generation (RAG) Chatbots

While LLMs excel at language comprehension and generating coherent responses, their knowledge is limited to pre-trained datasets and lacks real-time adaptability. Retrieval-Augmented Generation (RAG) chatbots, on the other hand, integrate dynamic document retrieval with generative AI, allowing them to pull up-to-date, domain-specific information from external knowledge bases [77]. This capability is particularly advantageous for water management, where real-time data on reservoir levels, flood risks, and drought conditions are critical. Unlike standard LLMs, which may generate responses based on outdated or generalized knowledge, RAG-based systems ensure that decision-makers receive the most current and contextually relevant insights. Furthermore, RAG frameworks like LangChain and Haystack enable fine-tuned responses based on structured hydrological reports, sensor data, and government advisories, reducing the risk of misinformation. By combining the generative power of LLMs with real-time retrieval, RAG chatbots offer a more reliable and adaptive solution for water resource management and disaster preparedness. Different RAG frameworks are described in Table 3.

Table 3. Comparison of Retrieval-Augmented Generation (RAG) Frameworks.

RAG Framework	Developer	Key Features	Strengths	Limitations	Integration	Supported Models	Use Case in Water Management
LangChain	Harrison Chase	End-to-end framework for RAG, supports LLM integration, chains together multiple tools (APIs, databases, etc.)	Highly flexible, great support for dynamic chains and task automation	Can require complex setup, might be too customizable for beginners	Easy integration with LLMs, APIs, and databases	GPT, OpenAI models, HuggingFace, etc.	Generating dynamic reports, offering real-time predictive insights
Haystack	deepset	Focus on building NLP pipelines, strong in document retrieval, supports vector search and dense retrieval	Scalable, robust search capabilities, well suited for large-scale document retrieval	May require tuning for specific workflows, complex setup for real-time applications	Elasticsearch, OpenSearch, FAISS, and others	BERT, T5, GPT, etc.	Search and retrieval of water management data from documents, helping users find specific risk mitigation strategies
Transformers (Hugging Face)	Hugging Face	Open-source platform for NLP, offers a wide variety of models, supports retrieval-augmented generation	Easy integration with other frameworks, large model hub, highly modular	High computational costs for large-scale models, slower for real-time applications	Can integrate with existing tools and platforms	GPT, BERT, T5, RAG models (Hugging Face)	Enabling query-based decision support for flood or drought predictions, retrieval of domain-specific knowledge
DeepPavlov	DeepPavlov	Multi-purpose conversational AI framework, supports retrieval-augmented generation	Simple to use, optimized for conversational agents, modular architecture	Focused more on chatbots, might need adjustments for complex RAG tasks	Supports integration with external data sources	BERT, T5, GPT, etc.	Assisting with AI-driven conversation for rapid responses to water crisis scenarios
RAG-TensorFlow	TensorFlow	End-to-end RAG framework for TensorFlow users, integrates document retrieval and text generation	Great for TensorFlow-based environments, robust integration with various NLP models	Requires TensorFlow knowledge, integration with non-TensorFlow tools can be challenging	TensorFlow, FAISS, ElasticSearch	TensorFlow-based models, OpenAI models	Real-time flood prediction insights, querying past water system performance

Among the leading RAG frameworks, LangChain stands out for its ability to integrate multiple tools, databases, and APIs into cohesive pipelines, making it particularly suitable for generating real-time predictive reports on water reserves and flood risks. However, its flexibility comes with a complexity that may require expertise to configure effectively. Haystack, developed by deepset, specializes in document retrieval and vector search, making it highly efficient for searching historical water management records and identifying past risk mitigation strategies. While it excels in large-scale document retrieval, its performance in real-time applications may require additional tuning. Vector search, also known as similarity search, is a technique used to find data points that are most similar to a particular query by representing them as mathematical vectors in a high-dimensional space. Unlike traditional keyword-based search, which relies on exact matches, vector search compares numerical embeddings of text, images, or other data types to determine relevance based on proximity in the vector space. In the context of RAG and water management applications, vector search allows AI models to efficiently retrieve relevant documents, reports, or historical data based on contextual meaning rather than just keyword presence.

This capability enhances decision-support systems by providing more accurate and context-aware responses, such as identifying patterns in past flood events, retrieving water-quality reports, or analyzing drought trends based on past climate data. For instance, a flood early-warning system integrated with a RAG model. A water management expert enters the query: "How did similar flood events in the past impact groundwater levels?" Instead of relying on keyword matching, the system converts this query into a numerical vector representation and searches a vector database of past flood reports, hydrological models, and research papers. It then retrieves documents with semantically similar content, even if they do not explicitly contain the exact words in the query. For example, the system might find:

- A 2012 flood study that analyzed groundwater depletion after extreme rainfall.
- A hydrological model report discussing aquifer recharge patterns post-flood.
- A research paper on soil-infiltration rates during high-precipitation events.

By retrieving and summarizing this information, the AI model provides a context-aware answer, helping decision-makers anticipate groundwater changes based on historical patterns. This method outperforms traditional keyword search, which might only return documents containing the exact phrase "groundwater levels" but miss relevant insights expressed differently.

Comparatively, Hugging Face's Transformers provide a vast ecosystem of pre-trained models with retrieval capabilities, making them a highly modular choice for integrating RAG-based insights into broader AI applications. However, their computational cost can be a limiting factor, especially for large-scale environmental simulations. DeepPavlov offers a more chatbot-centric approach, which can be advantageous for AI-driven conversational agents assisting policymakers in crisis scenarios, though it may lack the robustness of more complex RAG implementations. Lastly, RAG-TensorFlow integrates seamlessly with TensorFlow-based NLP models and excels in environments already built on this framework, making it a powerful tool for querying past water system performance and making real-time flood predictions. However, its reliance on TensorFlow can make cross-platform integrations challenging. Each of these frameworks provides distinct advantages depending on the specific needs of water management systems. Whether prioritizing scalability, real-time adaptability, or seamless integration with existing tools, selecting the right RAG framework can significantly enhance decision-making efficiency in addressing water-related challenges.

All the preceding steps form the core elements of an AI-driven decision-support system, as depicted in Figure 7.

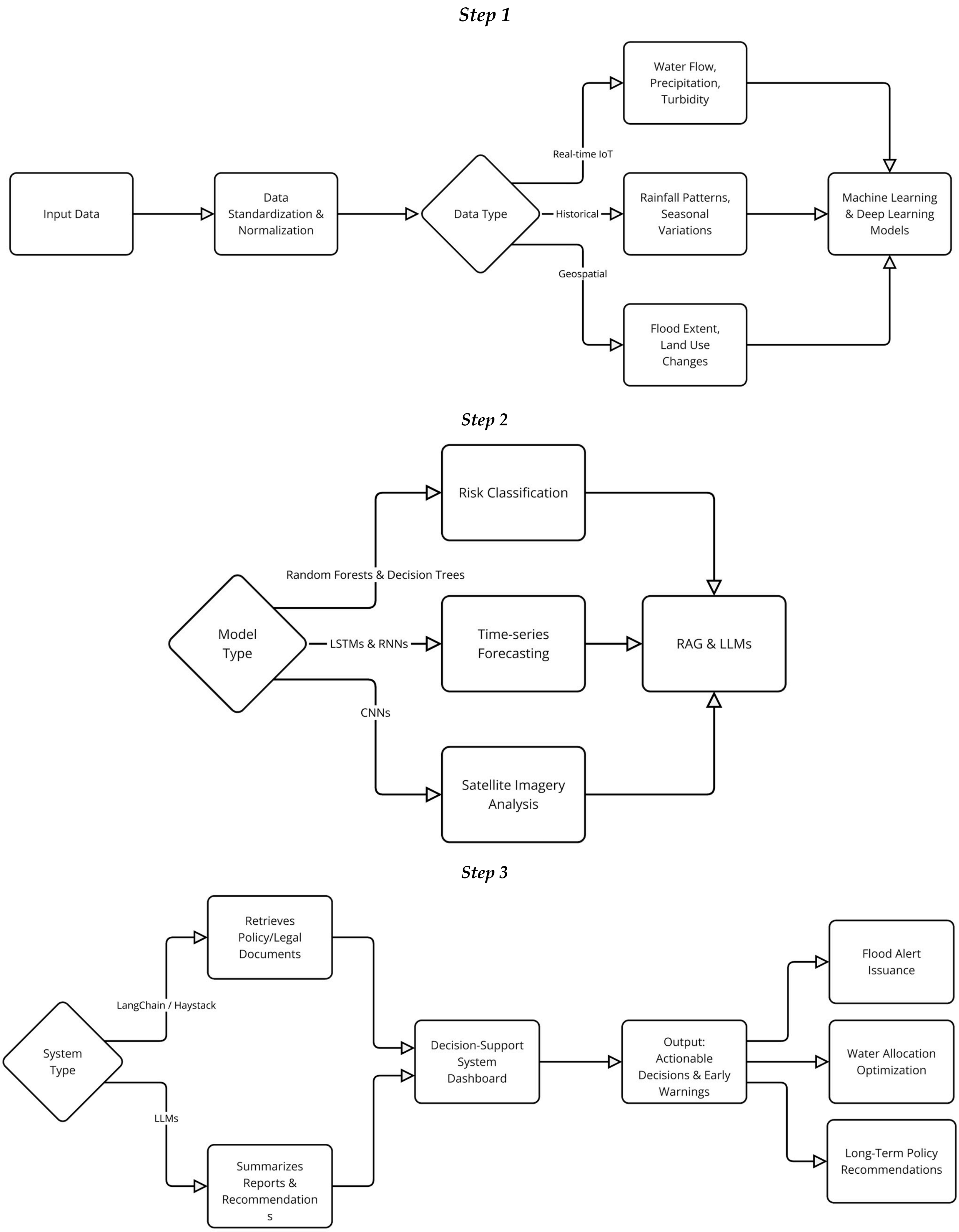


Figure 7. AI-Powered Decision-Support System implementation steps for adaptive water management.

3.3. Implications for Water Reserves Management and Policy

Digital twins enable continuously updated virtual replicas of water systems. This, combined with immersive simulations via game engines, allows for a dynamic analysis of future water demand and flood risks. The following sections explore how this framework enhances flood-control strategies, informs long-term water conservation policies, and integrates with smart water grids and climate models to drive data-driven decision-making in water management.

3.3.1. Transforming Water Reserves Management Through Digital Twins and Game Engines

The integration of digital twins and game engines marks a significant shift in water reserves management, offering dynamic, real-time, and interactive capabilities that surpass conventional water management practices. Traditional water management strategies rely on static, periodic data collection, deterministic hydrological models, and reactive decision-making processes. These limitations often result in delayed responses to water crises, inefficient allocation of resources, and inadequate predictive capabilities. By contrast, digital twins create continuously updated virtual replicas of water systems that integrate real-time data streams from IoT sensors, satellite imagery, and climate models. The inclusion of game engines enables enhanced visualization, scenario testing, and immersive stakeholder engagement, fostering a more informed and proactive approach to water reserves management. This transformative approach allows policymakers, engineers, and environmental agencies to simulate future water demand, assess flood risks dynamically, and evaluate the long-term sustainability of water conservation policies with unprecedented accuracy.

3.3.2. Enhancing Flood Control Strategies and Disaster Response

One of the most pressing challenges in water reserves management is mitigating the risks associated with flooding. Conventional flood models often lack the resolution and adaptability required to account for rapid environmental changes, urbanization, and evolving climate conditions. The proposed framework enhances flood control by integrating high-resolution Digital Elevation Models (DEMs) with real-time hydrological simulations in digital twins. These digital models incorporate rainfall data, soil moisture levels, and river discharge patterns, allowing decision-makers to visualize potential flood scenarios and implement mitigation measures such as controlled reservoir releases, embankment reinforcements, and green infrastructure solutions. Furthermore, game engine-based simulations enable real-time stakeholder training and decision support during extreme weather events. For instance, emergency response teams can use virtual reality (VR) environments to practice flood-evacuation procedures from a safe and remote area, analyze real-time water flow data, and assess the effectiveness of intervention strategies before implementation. This integration facilitates improved coordination among governmental agencies, urban planners, and local communities, ensuring a data-driven, collaborative approach to flood-risk reduction.

3.3.3. Advancing Long-Term Water Conservation and Sustainability Policies

Sustainable water use is paramount in the face of increasing water scarcity, climate change, and competing demands from agricultural, industrial, and domestic sectors. Traditional water conservation policies are often reactive, relying on historical consumption patterns and regulatory enforcement rather than predictive analytics. The digital twin framework, integrated with AI-based decision-support systems, enables adaptive water conservation strategies that evolve in response to real-time environmental and socio-economic changes. By continuously monitoring reservoir levels, groundwater recharge rates, and precipitation trends, policymakers can use digital twins to design demand-responsive water allocation policies. For instance, AI-driven simulations can assess the impact of agricultural irrigation schedules, urban water restrictions, and industrial usage policies under different climate scenarios. These insights allow for the optimization of water distribution while ensuring equitable access and long-term resource sustainability. Additionally, the integration of game engines allows for intuitive public engagement and education. Interactive simulations can demonstrate the consequences of over-extraction, the benefits of rainwater harvesting, and the potential of water-efficient infrastructure. By involving citizens, farmers, and industries in decision-making through immersive platforms, authorities can foster a culture of water conservation and collective responsibility.

3.3.4. Integration with Smart Water Grids and Climate Models

The effectiveness of digital twins in water management is further amplified when integrated with smart water grids and climate models. Smart water grids use IoT-enabled sensors to monitor water consumption, detect leaks, and automate water distribution across urban and rural networks. The incorporation of digital twins into these grids enables real-time optimization of water supply and demand, reducing wastage and enhancing efficiency [23,78–80]. Furthermore, coupling digital twins with climate projection models enables policymakers to anticipate long-term hydrological changes. For example, climate-driven simulations can predict shifts in rainfall patterns, glacial melt contributions to river basins, and extreme drought probabilities. These forecasts allow authorities to implement adaptive water management policies that mitigate the effects of climate variability and ensure resilient water infrastructure.

3.3.5. Policy Recommendations and Implementation Challenges at Institutional Level

While the adoption of digital twins and game engines presents significant advantages, successful implementation requires addressing several policy and operational challenges:

- Data Standardization and Interoperability: Water management agencies must establish standardized data formats and integration protocols to ensure seamless communication between digital twins, smart grids, and climate models.
- Investment in Digital Infrastructure: The deployment of IoT sensors, high-performance computing, and game engine-based simulations necessitates substantial investments in digital infrastructure and technical expertise.
- Regulatory and Institutional Adaptation: Existing water governance frameworks must be updated to incorporate digital twin-based decision-making, ensuring that insights from real-time simulations inform policy development.
- Stakeholder Engagement and Capacity Building: Training programs for policymakers, water managers, and emergency responders should be established to enhance the practical application of digital twin technologies.
- Cybersecurity and Data Privacy: As water management systems become increasingly digitalized, robust cybersecurity measures must be implemented to safeguard sensitive data and prevent cyber threats.

3.4. Real-World Applications of Digital Twins in Water Management

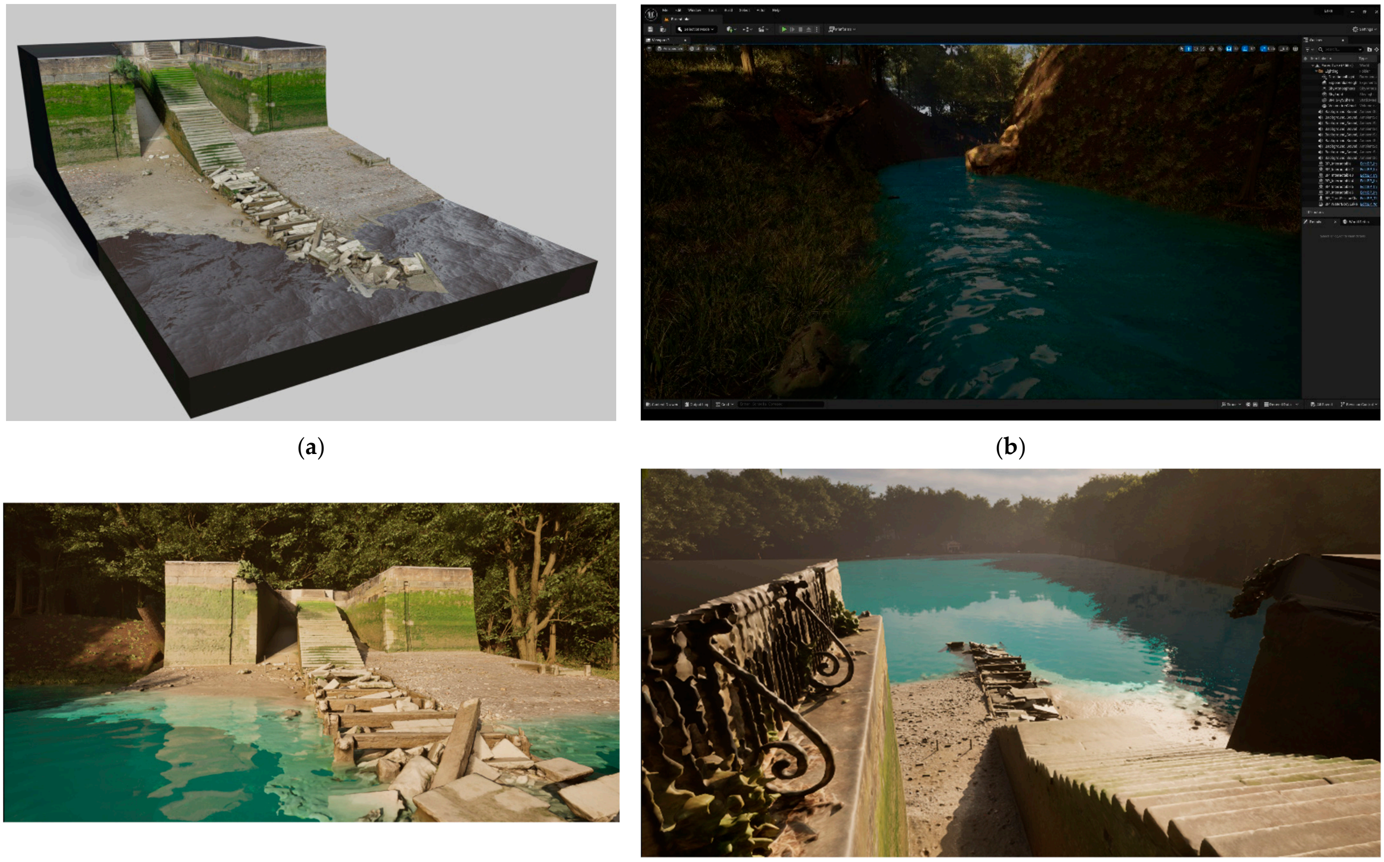
The integration of digital twins into water reserves management is evolving rapidly from theoretical constructs to operational systems across several countries. These real-world examples demonstrate the practical viability and growing momentum behind the adoption of digital twin frameworks for sustainable and resilient water governance. In Singapore, the Public Utilities Board (PUB), in collaboration with Jacobs Engineering, has implemented a high-fidelity digital twin of the Changi Water Reclamation Plant (CWRP) [81]. This system integrates approximately 1200 live data tags to model hydraulics and process control and operations under a unified platform, enabling real-time performance diagnostics, simulation of planned or unexpected scenarios, and short-term forecasting of wastewater system behavior, termed a "wastewater weather forecast". In China, digital twins are being scaled through both basin-wide and urban applications. In the Yangtze River Basin, a twin-based evaluation system has been used to assess ecological progress under the DP-SIRM model, incorporating real-time monitoring of hydrological and socio-environmental indicators [82]. At the city level, platforms such as the one developed in Nanyang model water-quality dynamics using Kriging interpolation, sensor-based pollution monitoring, and 3D visualization to support early-warning systems and river governance [83].

In Europe, the NEXTGEN project in the United Kingdom applies serious gaming environments and digital twins to model urban water circularity. By simulating closed-loop water cycles within digital environments, the system facilitates the interactive planning of wastewater reuse, stormwater harvesting, and decentralized treatment solutions [32,84]. In the Netherlands, the "Digital Twin Noord–Holland" initiative employs a layered hydrological modeling approach incorporating GIS data, climate projections, and stakeholder feedback to simulate long-term impacts of climate adaptation policies, including flood risk and groundwater salinization [85]. In Sweden, digital twins have been implemented at the municipal level to support real-time wastewater system control and sustainable urban drainage planning. For instance, in Gothenburg, a digital twin enables predictive control of the regional sewage network, integrating AI models with sensor telemetry in a cloud-based architecture [86], while cities like Lund and Uppsala have adopted automated data-transfer systems to feed live data into digital monitoring tools [87]. National-level research emphasizes open data sharing and cross-platform integration to promote scalable twin development [88]. Recent academic work has further advanced the field. For instance, Ramos et al. [78] developed digital twin prototypes for smart water grids, enabling efficiency management in water distribution systems through anomaly detection, AI-based predictive maintenance, and leak localization. Similarly, Wu et al. [79] showcased a high-fidelity digital twin system for fault detection and localized anomaly response in urban pipelines, using hybrid models and real-time telemetry data. Additional reviews, such as those by Ford and Wolf [89] and Zekri et al. [62], emphasize the increasing relevance of digital twins in integrated water infrastructure monitoring and disaster management.

While these implementations demonstrate the growing maturity and adaptability of digital twin technologies, they also reflect certain limitations that this study aimed to address. Most existing systems focus on specific operational components—such as drainage, flood control, or distribution efficiency—but do not offer an end-to-end framework that unifies physical, ecological, and social variables in an interactive and extensible platform. Furthermore, many projects lack immersive visualization layers, participatory interfaces, or modular AI decision-support systems capable of adapting to local contexts. The conceptual framework proposed in this study responds directly to these gaps by integrating game engine environments, retrieval-augmented AI models, and layered real-time simulations into a unified, stakeholder-oriented system. Section 3.6 outlines a detailed roadmap for implementing this framework, along with potential deployment challenges and mitigation strategies.

3.5. Framework Implementation Demonstrations and Prototype Applications

To demonstrate the technical feasibility of the proposed framework, several key components were implemented and tested as proof-of-concept simulations using real-world spatial datasets and hydrologically relevant terrain features. These demonstrations utilize a combination of UAV-based digital elevation models, close-range photogrammetry, and game engine-based 3D visualization environments to replicate conditions and infrastructure related to water reserves. As shown in Figure 8, a terrain model of a riverine setting was created by integrating UAV-derived elevation data and an open-source 3D model into Unreal Engine, enabling navigable simulations of a hypothetical river system and a water infrastructure. Figure 9 presents a digitally reconstructed check dam, built from photogrammetric scans and enriched with static arbitrary metadata, allowing immersive interaction within the simulation. Figure 10 showcases a virtual tour interface that enables users to interactively explore watershed landscapes and engage with hydrological features. Finally, Figure 11 illustrates a simulation of a rainfall-induced landslide near an open water storage structure, representing a hydro-geomorphic multi-hazard module that complements terrain and infrastructure-based modeling. Collectively, these examples serve as functional demonstrations of the terrain modeling, structure digitization, simulation design, and interactive visualization elements embedded in the proposed digital twin framework.



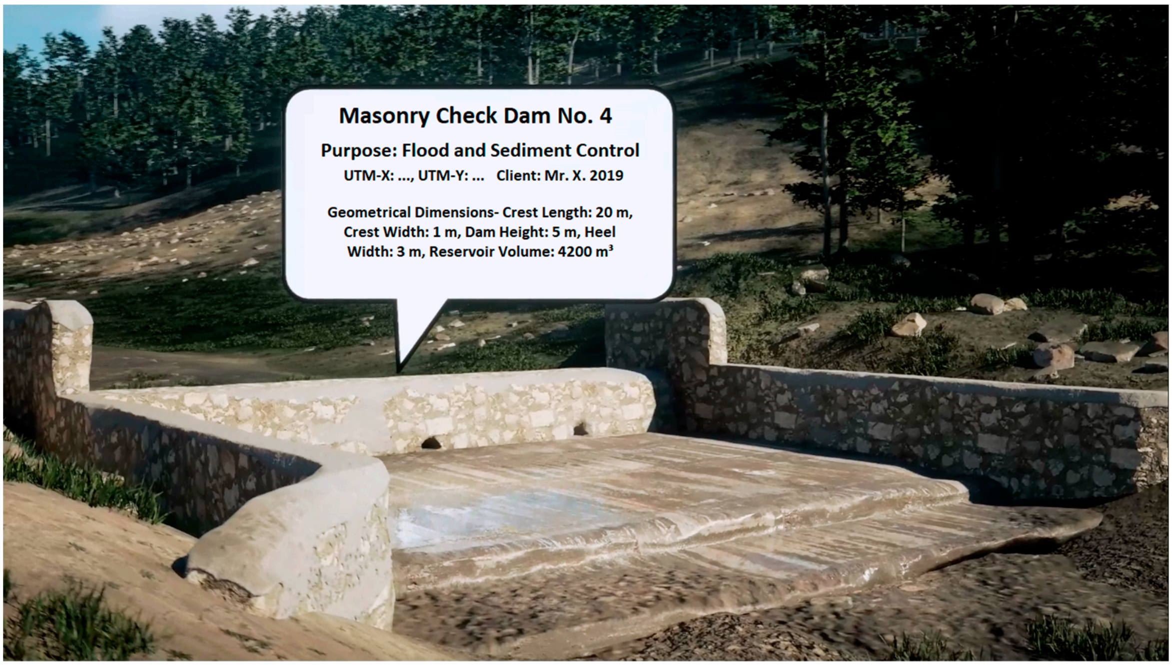
(**a**) (**b**) (**c**) (**d**)

Figure 8. A 3D terrain model, representing the UAV-derived topography of Kanas Lake and forests in Xinjiang Kanas National Geopark, integrated into Unreal Engine 4.5. This environment supports virtual navigation for watershed-scale exploration and water infrastructure impoundment: (**a**) A freely available 3D model of the stairs and causeway at Deptford Wharf known as Drake's Steps (artfletch. Drake's Steps. Available online: https://sketchfab.com/3d-models/drakes-steps-6f20ca3ead094e75ae059781d220ba03; accessed on 23 February 2025), (**b**) A river system created in Unreal Engine 5.3, (**c**) A bottom-up view of the 3D model of Drake's Steps integrated into the river system and a customized environment, entirely interactable and measurable as part of a river simulation, and (**d**) A top-down view of the causeway.

(a)

(b)

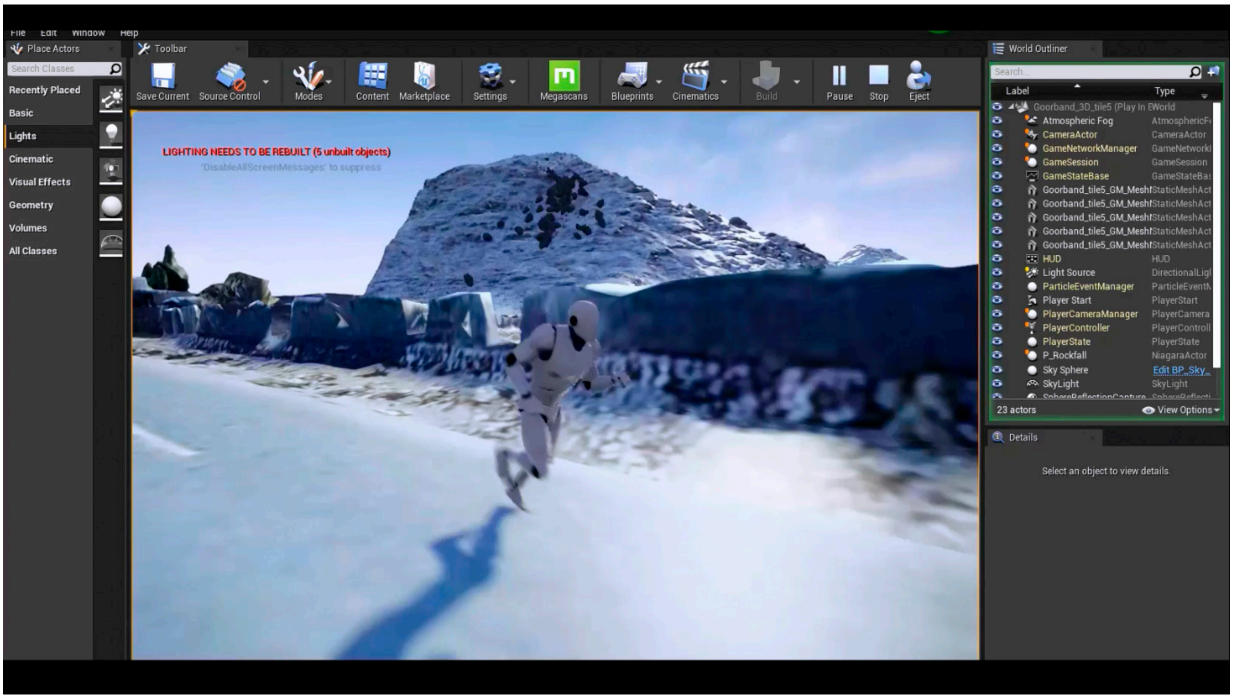
Figure 9. *Cont*.



(**c**)

Figure 9. A digitally reconstructed check dam on the streams of Kanas River (Xinjiang Region), representing a close-range photogrammetry-derived topography, annotated with static arbitrary metadata (e.g., geometry, purpose, construction year), displayed in Unreal Engine for immersive interaction and simulation: (**a**) A 3D-scanned masonry check dam and river using close-range photogrammetry displayed in Unreal Engine 5.3 (downstream perspective), (**b**) Dense point cloud of the dam created in photogrammetry software, (**c**) augmented with arbitrary descriptive information on the dam type, coordinates, client, construction year, primary function, and geometrical dimensions, entirely interactable and stimulable by the end-user through a virtual character during a virtual tour (upstream perspective).

Figure 10. Virtual tour interface built in Unreal Engine, set in a mountainous area resembling the Altai Mountains (Xinjiang Region), enabling interactive exploration of watershed terrains, hydrological infrastructure, and management scenarios from a user-centered perspective.



(**a**)

(**b**)

Figure 11. Simulated rainfall-induced landslide, resembling the Altai Mountains (Xinjiang Region), ((**a**) hydro-geomorphic multi-hazard component of water reserves management) scenario near an open water storage facility within a digital twin environment, allowing to assess the application of various mitigation scenarios and the comparison of outcomes. (**b**) A closer view of the simulated phenomenon for enhanced visualization).

3.6. Roadmap for Pilot Implementation, Deployment Challenges, and Mitigation Solutions

These emerging examples demonstrate both the scalability and adaptability of digital twins in diverse limatic, socio-political, and hydrological contexts. Building on these foundations, the implementation of the proposed conceptual framework in this study can follow a structured three-stage roadmap designed to ensure operational success while maintaining stakeholder engagement and technical flexibility.

Stage 1: Data Infrastructure and System Design

This foundational phase focuses on collecting, organizing, and integrating key data sources necessary to build the digital twin. These include digital elevation models (DEMs) derived from UAV-based photogrammetry, land-use and land-cover maps, soil and hydrological models, weather forecasts, and live data streams from field sensors. These sensors—measuring parameters such as water level, streamflow, and water quality—are installed at strategic points across the selected watershed. To ensure efficient and cost-effective transmission of data over long distances, low-power wide-area network (LPWAN) technologies like LoRaWAN are recommended. The modular architecture supports the integration of various software components—such as artificial intelligence engines, predictive simulation tools, or chatbots—without major reconfiguration. This modularity enables future upgrades, technology integration, or scaling without system-wide disruption.

Stage 2: Digital Twin and Game Engine Integration

In this phase, the collected data are used to develop a dynamic, interactive simulation of the real-world water system using advanced 3D modeling platforms. Game engines such as Unreal Engine or Unity serve as the visualization environment, allowing for the creation of lifelike virtual terrains and infrastructure elements. Specialized hydrological and terrain modeling plugins (e.g., FluidFlux, TerraSculptor) help simulate water flow, surface runoff, and reservoir behavior in response to various conditions. Simultaneously, the AI-based decision-support system (AI-DSS) is developed and trained using historical data, satellite imagery, and synthetic datasets to improve prediction accuracy and scenario analysis. Real-time data from sensors is fed directly into the simulation, enabling a continuously updated digital replica of the water system. This stage also incorporates interactive tools such as user-friendly dashboards, visual analytics, and stakeholder role-playing features. These components allow decision-makers and community members to explore hypothetical scenarios—such as extreme rainfall events, drought response, or land-use change—and understand their consequences in a visual, intuitive, and participatory way.

Stage 3: Scenario Testing, Feedback Loops, and Operational Deployment

The third stage involves testing the system's capacity to simulate various real-world scenarios under dynamic environmental, urban, and policy conditions. For example, simulations may explore the effects of prolonged drought, deforestation, or changes in water extraction policy. These scenarios are assessed not only for technical accuracy, but also for how effectively they communicate risks and trade-offs to stakeholders. Advanced AI tools—such as retrieval-augmented generation (RAG) agents—are integrated with explainable interfaces to answer questions and guide users through scenario outcomes. Importantly, feedback from diverse user groups—including local communities, technical experts, and decision-making authorities—is collected to refine the system's performance, interface design, and data parameters. After iterative testing and validation, the system is transitioned from a prototype into a semi-operational or fully operational platform. At this stage, it can support continuous monitoring, early warning, and policy evaluation in real time, serving as a living decision-support tool for sustainable and adaptive water management.

Scalability of the framework is made feasible by its modular design and reliance on widely adopted open-source and cross-platform technologies. By using containerized components and cloud-based services, the system can be replicated across multiple watersheds with minimal reconfiguration. Furthermore, the use of game engines and web-based dashboards makes it accessible to both technical and non-technical users, enhancing the potential for widespread adoption in diverse environmental and policy settings. While the proposed digital twin framework introduces a high level of integration and innovation, its successful implementation hinges on the early identification and mitigation of key technical risks:

- To address data heterogeneity and interoperability—the challenge of merging datasets from various sources and formats—the framework should prioritize the use of open-data standards such as GeoJSON for spatial vector data and NetCDF for gridded scientific data. These formats enable easier communication between systems and promote long-term compatibility. Additionally, adopting middleware solutions—software layers that act as translators between different data systems—can facilitate real-time synchronization between older, often static legacy datasets (e.g., institutional records, archival GIS layers) and high-frequency IoT-based sensor streams that provide continuous environmental measurements. A preliminary data audit is essential to identify inconsistencies, standardize schemas, and harmonize time-series formats, ensuring that all components feed into the digital twin seamlessly.
- To manage the computational demands of model calibration and AI algorithm retraining, the use of a hybrid infrastructure is recommended. In such a setup, edge devices (compact computing units installed near sensors or data sources) perform low-latency inference tasks—such as detecting anomalies or issuing alerts—while more complex, data-intensive operations such as periodic model retraining are handled in the cloud, where computing resources are virtually unlimited. The framework's efficiency can further be enhanced by applying transfer-learning techniques, which allow pre-trained models to be fine-tuned for specific tasks with relatively small datasets, and by designing modular AI model updates that isolate components needing revision without affecting the entire pipeline.
- To enhance transparency and stakeholder trust during deployment, the system will integrate explainable AI (XAI) tools such as SHAP and LIME to clarify the contribution of each input variable to the model's output. These explanations will be visualized through intuitive user interface elements such as annotated graphs or heatmaps. Coupled with uncertainty quantification (e.g., confidence intervals, probabilistic thresholds), these tools will help operational staff and decision-makers interpret forecasts and make informed, accountable decisions.
- Lastly, ensuring the cybersecurity and privacy of real-time data systems is vital, particularly when dealing with critical infrastructure. This requires the adoption of secure communication protocols such as TLS (Transport Layer Security) or SSL (Secure Sockets Layer) to encrypt data in transit and prevent interception. Implementing fine-grained user access control—defining who can view, modify, or manage different system components—is also essential to protect sensitive layers of information. In parallel, the system should apply data-anonymization techniques, especially for geospatial metadata that might reveal the exact locations of infrastructure or water assets, reducing the risk of surveillance, tampering, or misuse.

Embedding these strategies during the early stages of system design can significantly enhance the robustness, interoperability, and resilience of the digital twin framework. At the same time, it fosters stakeholder confidence, simplifies maintenance and scalability, and lays the foundation for broader institutional adoption and public acceptance.

3.7. Feasibility Assessment of the Proposed Framework

While the proposed framework is conceptual in structure, its implementation feasibility is grounded in the availability of robust technological ecosystems that support each stage—from real-time data collection and AI model training to immersive visualization and decision support. This section provides a detailed breakdown of how each component of the system can be operationalized using existing tools, protocols, and development environments, thereby reinforcing the practical viability of the roadmap presented in Section 3.6.

3.7.1. Data Collection and Communication Protocols

The initial stage of implementation involves collecting real-time environmental and hydrological data using IoT-enabled sensors and remote-sensing technologies. Industry-standard communication protocols such as MQTT (Message Queuing Telemetry Transport) are widely adopted for transmitting low-bandwidth, real-time data from distributed sensor nodes to a centralized data lake. These protocols are already in use in smart agriculture and environmental monitoring systems and are well-suited to scalable deployment in watershed-scale settings. Complementary technologies such as LoRaWAN and NB-IoT provide energy-efficient, long-range connectivity, ensuring that data can be transmitted from remote or hard-to-reach areas.

3.7.2. Data Integration and Preprocessing Tools

To manage the high heterogeneity of sensor data, satellite imagery, and GIS inputs, integration platforms such as Apache NiFi, Apache Kafka, or Google Cloud Dataflow can be employed to structure, synchronize, and filter incoming datasets before feeding them into the digital twin engine. These platforms enable real-time ingestion pipelines that are both modular and scalable, ensuring interoperability across data layers, formats (e.g., GeoJSON, NetCDF), and temporal resolutions.

3.7.3. Game Engine Integration and Environmental Fusion

Game engines like Unreal Engine 5.3 and Unity offer powerful APIs and plugins for importing terrain models, simulation logic, and interactive data visualization. UAV-derived DEM point clouds, raster maps, and 3D photogrammetry models can be imported into Unreal Engine using Datasmith or Cesium for Unreal, while real-time data overlays can be built through MQTT plugin in UE5, custom C++ plugins, Blueprint scripting, or Python bindings. Environmental fusion with dynamic hydrological elements (e.g., water bodies, terrain deformation, erosion) can be enhanced using Chaos Physics, Fluid Flux, or OpenFOAM-Unreal Engine bridges. Moreover, interoperability with web-based dashboards can be facilitated via RESTful APIs, GraphQL endpoints, or gRPC, allowing simulation data to be accessed and manipulated externally by AI components and user interfaces.

3.7.4. AI-DSS, Chatbot Interaction, and Text-Based Scenarios

For decision support and stakeholder engagement, the framework integrates AI-based Digital Decision Support Systems (AI-DSS) and natural language chatbot interfaces within the 3D environment. Several proof-of-concept studies have already demonstrated this capability. For instance, Gould [90] implemented a 3D management simulation with embedded DSS logic in entrepreneurship training; Ellul et al. [91] showcased progress monitoring digital twins in construction using Unreal Engine; and Jiménez del Castillo [92] successfully linked a chatbot and text-to-speech API to a Metahuman avatar inside Unreal Engine for real-time conversational feedback. Our system leverages similar strategies by linking retrieval-augmented generation (RAG) chatbots or text-to-text AI models (e.g., GPT, T5) to a spatial simulation layer. These bots are embedded as virtual assistants in the digital twin environment, capable of interpreting real-time water scenarios, suggesting mitigation actions, and facilitating role-playing interactions among multiple user types (e.g., policymakers, emergency planners, and utility operators).

The AI-DSS is designed to support a range of critical decisions in water reserves management, including (1) reservoir operation scheduling under varying hydrometeorological forecasts; (2) prioritization of water allocation between sectors (e.g., agriculture, domestic, and industrial) during scarcity; (3) real-time adjustments to flood mitigation strategies such as gate operation or emergency releases; (4) early detection and containment of water quality anomalies; and (5) long-term planning decisions such as infrastructure investments, zoning restrictions in flood-prone areas, or ecosystem-based adaptation measures. These decision pathways are modeled as interactive workflows within the game engine, allowing users to simulate policy trade-offs, visualize cascading effects, and receive AI-generated suggestions in a transparent and explainable manner.

3.7.5. Use-Case Scenarios and Translation to Real-World Decision-Making

Scenarios modeled in the virtual environment include flood management under extreme rainfall, drought-driven reservoir reallocation, and land-use change simulations that affect urban runoff. For example, using sensor data and historical weather patterns, the system simulates flash flood propagation in mountainous terrain, enabling real-time interventions such as virtual dam release or evacuation alerts. Similarly, users can simulate the downstream effects of irrigation scheduling or reservoir operation based on short-term LSTM-based forecasts. These scenarios are not abstract—each reflects a real decision node in water reserves management. Through immersive interaction, game mechanics (e.g., scoring, thresholds), and real-time feedback, decision-makers are able to experiment with policies, visualize consequences, and co-create adaptive strategies with stakeholders in a controlled, safe, and fully interactive setting.

Ultimately, each module of the framework has a corresponding set of tools and technologies already in existence and tested in adjacent domains. These include:

- Sensor-to-engine integration via MQTT, Apache NiFi, Open3D, or RESTful APIs
- Simulation and terrain modeling via Unreal Engine with plugins like Cesium, Fluid Flux, and Chaos
- AI integration using TensorFlow, PyTorch, and ONNX models embedded via Python APIs or DLLs
- Decision support interactions facilitated through chatbots, voice interfaces, and gamified role-play using Metahumans

Together, these implementations form a plug-and-play architecture, where each component is modular, interoperable, and capable of being iteratively deployed within a pilot watershed. The proof-of-concept visualizations (Figures 8–11) developed by the authors further reinforce the framework's readiness beyond the conceptual level and into the domain of applied innovation.

3.8. Future Directions and Research Opportunities

As digital twins and game engines continue to evolve, their applications in environmental management and infrastructure monitoring are expanding. Future research should focus on enhancing predictive capabilities, integrating diverse data sources, and refining user interfaces to make these systems more accessible and impactful. Moreover, the vision of a fully connected digital twin ecosystem—where AI-powered digital twins across sectors collaborate to optimize decision-making—presents exciting possibilities for the future of water management. The following subsections explore these advancements, detailing how digital twins can be expanded into new domains, how prediction algorithms and data integration can be improved, and how an interconnected network of digital twins could revolutionize global resource management.

3.8.1. Expanding Digital Twin Applications in Environmental and Infrastructure Management

Building on the success of digital twins in water reserves management, future research should explore their application in other environmental domains. By integrating game engines with digital twins, new frontiers in climate resilience, disaster mitigation, and sustainable urban planning can be unlocked. For instance, digital twins can enhance wildfire risk assessments by simulating forest conditions or model air-quality dynamics in urban environments, providing policymakers with real-time, interactive insights. Similarly, digital twins could be used in wastewater treatment optimization, predicting treatment plant efficiencies based on incoming waste levels and environmental conditions. Additionally, infrastructure monitoring can benefit from digital twin integration. Dams, levees, and water distribution networks could be monitored in real time using IoT-connected digital twins, reducing failure risks by identifying structural weaknesses before they escalate. Game engines can make these insights more accessible, allowing decision-makers to interact with virtualized infrastructure scenarios, simulate emergency responses, and test potential interventions before implementing them in the real world.

3.8.2. Enhancing Predictive Capabilities and Data Integration

A key area for future refinement lies in improving prediction algorithms and integrating more diverse data sources. Current hydrological models rely heavily on precipitation records, satellite imagery, and in situ sensor data, but future digital twins should incorporate non-traditional datasets, such as social media reports on water crises, citizen science contributions, and even financial market indicators that reflect economic stress on water supply chains. Machine-learning models trained on these heterogeneous datasets could significantly enhance drought forecasting, flood-response coordination, and water conservation policy development. User interface improvements will also be essential. The accessibility of digital twins must extend beyond specialized hydrologists and policymakers to farmers, local water authorities, and community planners. Future research should focus on making these interfaces more intuitive and interactive, with voice-command AI assistants, VR-based scenario training, and mobile-friendly digital twin dashboards ensuring broader adoption.

3.8.3. Bridging the Gap Between Research and Implementation

While the potential for interconnected digital twins is vast, several research challenges must be addressed to make this vision a reality. These include:

- Standardizing data-exchange protocols across different digital twin platforms to ensure seamless communication.
- Developing AI models capable of handling cross-sectoral interactions, balancing environmental sustainability with economic and social priorities.
- Ensuring cybersecurity and data privacy, as an interconnected system could be vulnerable to malicious attacks or misinformation.

Future collaborations between environmental scientists, AI researchers, urban planners, and policymakers will be essential in shaping this next-generation digital twin network. By expanding the scope, predictive power, and interconnectedness of digital twins, water reserves management can evolve from a localized, siloed operation into a fully integrated, AI-driven global decision-making system.

3.8.4. The Utopia of a Fully Interconnected Digital Twin Ecosystem

A transformative vision for the future of digital twins is their interconnectivity across multiple sectors, forming a global AI-powered decision-making entity [93–96]. In this utopian framework, digital twins of water systems, transportation networks, energy grids, agricultural fields, and even economic markets would interact seamlessly. This would allow water reserves management to account for external socio-economic and political variables, such as regional trade policies affecting water demand or geopolitical tensions impacting upstream river flows. For example, a connected digital twin system could automatically adjust water distribution policies during an energy crisis by balancing hydropower production with municipal water needs [97]. It could also anticipate political disruptions—such as international disputes over shared river basins—and recommend diplomatic strategies before conflicts arise. This level of integration would create an intelligent, self-optimizing environmental management system, where AI continuously learns and refines policies based on evolving conditions across multiple domains.

3.8.5. From Utopia to Dystopia: Risks and Challenges of a Hyper-Connected Digital Twin Network in Water Management

While this vision promises efficiency and precision, it also introduces significant risks if not managed properly. A primary concern is data sovereignty—if control is monopolized, decision-making may become undemocratic, leading to inequitable water distribution, biased policy enforcement, or even water resource manipulation for economic or political gains. Moreover, an overreliance on AI-driven decision-making in water reserves management introduces the risk of algorithmic failures and cascading system-wide disruptions. A miscalculation in predictive water allocation—exacerbated by flawed or biased training data—could trigger widespread droughts or water shortages, especially in regions dependent on automated water distribution. To address these threats, the system must embed safeguards at both the architectural and algorithmic levels. This includes secure communication protocols (e.g., TLS/SSL), zero-trust network models, role-based access control, blockchain-based validation, and intrusion detection systems designed specifically for critical water infrastructure.

Additionally, cybersecurity vulnerabilities present a substantial threat; if hackers were to infiltrate a connected water management digital twin, they could manipulate dam operations, contaminate water supplies, or disable flood control measures, causing catastrophic consequences. To ensure model robustness and public trust, algorithmic bias-detection tools—such as fairness indicators and residual error analysis—should be implemented during both model training and live operation phases. Regular audits of training datasets, especially those involving socio-spatial variables, are critical to prevent discriminatory outcomes. Another key concern is the loss of human oversight in crisis response. As AI becomes the central decision-maker, there is a risk that automated systems prioritize efficiency over ethical and humanitarian concerns. For example, if an AI-powered digital twin determines that redirecting water from agricultural zones to industrial hubs is the most "optimal" decision, it could severely impact food security without considering broader societal implications. A hybrid decision-making architecture—where final decisions are mediated by human actors based on AI recommendations—offers a practical compromise between speed and accountability.

Furthermore, the complexity of a multi-sectoral AI-driven digital twin ecosystem could make troubleshooting failures extremely difficult, leading to blind reliance on opaque decision-making processes that stakeholders struggle to interpret or contest. To prevent these dystopian outcomes, safeguards must be established, including robust regulatory frameworks, transparent AI models, and hybrid decision-making approaches that combine AI precision with human ethical oversight. Explainable AI techniques (e.g., SHAP and LIME) and real-time dashboards showing contributing factors to each prediction must be implemented as standard tools to demystify AI logic and support informed oversight. A decentralized governance model, where regional water authorities retain decision-making autonomy while benefiting from AI-powered insights, could strike a balance between technological advancement and democratic control. Finally, the incorporation of federated learning and privacy-preserving data-exchange mechanisms ensures that sensitive regional data never leave their origin node, thus enhancing both privacy and cross-jurisdictional collaboration. Ultimately, while the future of connected digital twins holds immense promise, proactive risk mitigation strategies must be in place to ensure that water management remains fair, secure, and resilient against potential systemic failures.

4. Conclusions

This study presents a comprehensive, modular framework for intelligent water reserves management. It integrates digital twins, IoT-based real-time monitoring, game engine simulations, and AI-driven decision-support systems to enable adaptive and sustainable water governance. Unlike conventional static models, the proposed framework establishes a real-time, continuously updating AI-DSS that consolidates multi-source data into actionable insights for both operational and strategic water governance. A central contribution of this work lies in the prototyping of multiple key components across the data integration, simulation, and interface layers, demonstrating that such a system is not purely conceptual but partially implemented using real-world spatial datasets. The incorporation of UAV-based photogrammetry, 3D scanning, game engine visualization (Unreal Engine), and interactive scenario simulation illustrates how digital twins can be instantiated for real terrain and infrastructure conditions. In parallel, the integration of machine-learning models such as LSTM and Random Forest for flood forecasting and groundwater potential estimation was conceptually embedded within the architecture and aligned with recent successful implementations. These models are not merely theoretical; they are drawn from documented use cases in real hydrological applications, further validating the framework's feasibility and relevance. The study also proposes a plug-and-play system architecture supporting modular expansion, data stream fusion via MQTT, terrain modeling with high-resolution DEMs, and decision interfaces through LLM-powered chatbots. This architecture is supported by recent tools such as Open3D-UE bridges and Blueprint-based scenario scripting, offering a practical pathway for multi-sensor fusion, AI training, and immersive interaction within a unified system. From a sustainability perspective, this architecture fosters anticipatory planning, resource equity, and adaptive governance by enabling simulations that are transparent, interactive, and policy-relevant for evaluating competing water uses and stress-response strategies. Key achievements and contributions are summarized below:

- Prototype Implementation: Several core modules—including terrain modeling, scenario simulation, and stakeholder interface—have been implemented and tested in real spatial environments, validating system feasibility.
- Data-Driven Hydrological Monitoring: Real-time IoT data, satellite remote sensing, and GIS inputs enable continuous observation of floods, droughts, and water quality.
- AI Integration with Model Interpretability: Predictive components rely on LSTM, Random Forests, and CNNs, with built-in interpretability via SHAP, LIME, and uncertainty quantification, ensuring transparent and justifiable decision-making.
- Game Engine-Enabled Immersive Planning: Unreal Engine-based environments allow scenario testing for water management interventions, including dam construction, land-use shifts, or emergency response.
- Stakeholder-Centered Decision Interface: Open-source LLMs and retrieval-augmented agents enable interactive querying, translation of complex forecasts, and dynamic feedback loops for participatory governance.

- Security and Ethics by Design: The framework incorporates decentralized governance, explainable AI, privacy-preserving data handling, and hybrid human–AI decision layers to reduce systemic risks.
- Sustainability Alignment: The system promotes equitable access to water insights, empowers adaptive management under climate variability, and supports long-term resilience planning across ecological, economic, and social dimensions.

Future work will proceed through three parallel streams to operationalize and validate the proposed system. First, pilot implementations will be conducted in small watershed areas using UAV-derived terrain data, IoT sensors for real-time water level and quality monitoring, and local meteorological stations. These pilots will serve as testbeds for the integrated digital twin environment built within Unreal Engine and Python-based AI modules. Data pipelines will use MQTT and NiFi for ingestion, and predictive models will be stress-tested under synthetic flood and drought scenarios derived from CMIP6 climate projections and GRDC historical runoff records. Second, formal benchmarking protocols will be developed to evaluate system performance across four dimensions: (1) predictive accuracy (e.g., RMSE, MAE, R^2), (2) scenario realism and responsiveness (latency, FPS in game engine environments), (3) stakeholder usability (based on interface task success rate and time-on-task), and (4) interpretability (evaluated via user feedback on SHAP/LIME outputs). These benchmarks will be aligned with standards from WMO hydrological model evaluation guidelines and ISO/IEC usability metrics. Evaluation efforts will explicitly consider sustainability indicators such as reliability of supply, user inclusivity, and responsiveness under socio-environmental stressors. Third, the framework will be enhanced to include policy simulation tools such as dynamic water allocation under competing user demands, automated response recommendation modules, and chatbot-supported regulatory compliance prompts. Fairness auditing will be incorporated using subgroup testing for bias detection across geographical and demographic layers. Chatbot-to-dashboard workflows will also be redesigned using MetaHuman-LLM integration pipelines and feedback-capturing UI elements to support iterative learning and adaptation. These steps collectively aim to ensure that the system contributes not only to technological innovation but also to the advancement of sustainable, participatory, and ethically governed water resource management.

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