Advanced Engineering Informatics 61 (2024) 102485

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Full length article

Application of artificial intelligence in digital twin models for stormwater infrastructure systems in smart cities

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ARTICLE INFO

Keywords:
Digital twins
Urban drainage systems
Smart stormwater management
Artificial intelligence
Sensor technology
Smart city

ABSTRACT

Digital twins provide insights into physical objects by serving as advanced virtual representations. Their sensors capture detailed information about an object's functionality through their use of various sensors. It is possible to gain a deep understanding of the object's performance and potential areas for improvement by collecting data, which includes metrics such as energy output, temperature, and weather conditions. Digital twins are becoming important in a variety of research and industrial application sectors as production lines and processes become more digitalized and as improved data analysis techniques such as machine learning and enhanced visualization techniques are used. There is no unified definition of the digital twin concept in scientific literature, which results in imprecise applications and the weakening of its terminology. However, this study demonstrates how digital twin models can be applied to urban drainage systems. As a result, this highlights the relatively novel use of digital twins within the field of urban water system engineering. Our review of the language, practices, and directions in smart stormwater management provides a framework to organize and comprehend the current research landscape while highlighting crucial areas for future research. Our results demonstrate that there is near-unanimous agreement within the literature that smart technology has been, or will be, advantageous for stormwater management. However, while some progress has been made in terms of quantity management, maturity in water quality management has not yet been achieved. This study examines the scientific literature on digital twins in the application of artificial intelligence for smart city stormwater infrastructure systems, specifically focusing on urban drainage systems. A demonstration of the workflow and features of current digital twin applications in urban drainage systems is also presented, providing valuable insights and guidance for future research and development in this field.

1. Introduction

The idea of the digital twin has been crucial in aiding engineers with the creation and oversight of complex systems as an outcome of model-based engineering [1]. In this method, physical twins are paired with virtual twins (digital representations of essential aspects and behaviors of the system, often implemented as software agents) as described in [2]. A digital twin facilitates the assessment of feasibility during the requirements analysis and initiation phase by enabling trade-off analysis and experimentation without requiring the actual operation of the system. The virtual twin aids in delineating specifications and removing ambiguity throughout the development process. Sensors connect the physical system to its virtual counterpart for real-time monitoring and enhancement of the physical system using the digital twin's data and longitudinal analysis [3]. More examples of digital twin applications in cities have been provided in recent review publications [4,5]. Numerous cases have been reported where single-metric solutions have been used to solve problems, such as streamlining production lines [6], managing wastewater [7], maintaining vehicles [8], and others. The digital twin technology has recently drawn attention for its potential in mass

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https://doi.org/10.1016/j.aei.2024.102485
Received 16 April 2023; Received in revised form 8 March 2024; Accepted 12 March 2024
Available online 26 March 2024
1474-0346/

personalization, particularly in relation to distinctive wetland habitats [9]. While most of the earlier research on the subject of the digital twin focused on manufacturing, recent studies have explored the relationship between the digital twin and mass individualization in order to develop a com- prehensive reference architecture for digital twin applications [10]. A Digital Twin as a Service (DTaaS) model demonstrated notable benefits in several industries, such as smart planned maintenance, real-time monitoring, remote control, and predictive functions [11]. New capabilities are set to be added to the AQUADVANCED® Water Networks "Distribution" software, which is essential for managing drinking water distribution systems. Thousands of users will benefit from these upgrades before the summer of 2022, not only in France but globally as well [12]. Using artificial intelligence (AI) in digital twin models for smart cities can enhance the efficiency and sustainability of stormwater systems. A digital twin model that incorporates AI techniques can provide valuable insights for decision- makers and stakeholders, enabling them to make informed decisions regarding infrastructure planning, design, and maintenance.

1. AI algorithms, such as machine learning (ML) and deep learning (DL), can process vast amounts of data from various sources, including sensors, weather forecasts, and historical data. This enables the digital twin to make accurate predictions about stormwater flow, system performance, and potential issues. Consequently, decision-makers can proactively address potential problems and optimize system operations.
2. AI-enhanced digital twin models can dynamically adjust the stormwater infrastructure's operation based on real-time data and predictions. This includes controlling retention basins, gates, and pumps, allowing for adaptive responses to changing weather conditions, and preventing flooding or damage to infrastructure.
3. AI-powered digital twins can analyze data to identify patterns and trends in system performance, enabling predictive maintenance. By identifying areas requiring attention before failure occurs, maintenance efforts can be focused where needed most, reducing costs, and minimizing disruptions to the system.
4. AI algorithms can help identify the best solutions for multiple, often conflicting, objectives within stormwater infrastructure systems. This includes balancing water quality, flood mitigation, and cost-effectiveness while considering environmental and social impacts. The digital twin model can analyze various scenarios and provide decision-makers with optimal solutions based on the desired outcomes.
5. Digital twin models enhanced with AI can provide visualizations and simu- lation, enabling stakeholders to better understand the system's performance and potential impacts. This promotes more effective communication, collab- oration, and decision-making among various parties involved in stormwater management.

Integrating AI into digital twin models for stormwater infrastructure systems, smart cities can better manage and optimize their resources, ultimately improv- ing urban resilience and sustainability. As AI technology continues to advance, digital twin models will likely play an increasingly important role in addressing complex urban challenges, such as stormwater management, in an increasingly interconnected world. This paper explores the integration of Artificial Intelli- gence into Digital Twin models to enhance stormwater infrastructure systems within smart cities. With a focus on urban drainage systems, it provides an analysis of the current state of digital twin technology. Reviewing and organizing existing literature on smart stormwater management, the study clarifies terminology and practices. Case studies from various cities demonstrate how digital twins can be used to manage urban water systems practically. As well as identifying key research areas, the paper emphasizes how AI can revolutionize stormwater management in smart urban environments. An overview of digital twins and their importance in smart cities is presented in the introduction, along with information on how AI can enhance stormwater systems. A description of the literature review process and the time frame of selected publications is presented in the methodology section. A detailed examination of the technologies fundamental to digital twin models follows a detailed examination of how digital twin models integrate with AI. After discussing characteristics, terminology, optimization of Smart Water Management (SWM), short-term forecasting, decentralized systems, and the role of AI in stormwater management, the paper explores the application of digital twins in smart cities. The subsequent sections analyze the implementation of digital twins and the role of AI in cities such as Helsinki, Zurich, and Vienna. An examination of digital twins' contributions to green infrastructure planning is included in one section, while another focuses on digital twin modeling and real-time data visualization. In a conclusion section, the paper examines the current state of digital twin technology, its potential limitations, and the implications for future research on AI-enhanced digital twin models for smart cities' stormwater infrastructure.

2. The literature review methodology

Considering the recent developments in AI applications within Digital Twin models for stormwater infrastructure in smart cities, our methodology incorporates a literature review and a case study analysis. It ensures a rigorous examination of both theoretical insights and practical applications by exploring the field. We reviewed the literature using prominent databases, including Google Scholar, Scopus, and Web of Science, chosen for their extensive coverage across interdisciplinary research areas relevant to our subject matter. As part of our search strategy, we used terms such as "digital twin," "AI in urban water management," "smart city infrastructure," and "stormwater system modeling" in combination with Boolean operators and specific filters (e.g., publication years 2015 to 2023) to identify the most relevant studies. A two-stage screening process - reviewing titles and abstracts, followed by a full-text review based on inclusion criteria such as relevance, contribution to the field, and citation impact - ensured that noteworthy works were included. Using a thematic analysis, key information was systematically gathered from the selected publications and synthesized. Through this process, core themes, challenges, and opportunities in leveraging AI for digital twins in managing stormwater systems were identified, bridging theoretical knowledge with practical insights. In addition, we highlighted the global application of digital twins in various geographic locations and urban environments because of our case study analysis. Academic journals, municipal reports, and project documents were consulted when selecting these case studies for their innovation, maturity, and depth of information. We examined how these practical applications addressed challenges and opportunities identified in the literature, providing a real-world perspective on theoretical findings. Based on insights from the literature re- view and observations from case studies, we were able to construct a nuanced understanding of the current state and future directions for AI in stormwater infrastructure digital twins. Besides providing an overview, this methodology also identified common challenges such as data integration issues and model accuracy, as well as opportunities such as enhanced decision-making capability and operational efficiency. Its strength lies in the systematic and rigorous examination it facilitates, combining the depth of literature review with the breadth of case study analysis. Despite this, we acknowledge that there may be limitations, such as database selection bias and publication bias inherent in the method. In order to address these concerns, future research could include additional databases and grey literature. As a result of using this structured, yet integrated methodology, we ensured an exploration of AI applications in digital twins for stormwater management, contributing valuable knowledge to the field and addressing the research question in its entirety.

3. Technologies that enable digital twin

A city is composed of several blocks or neighborhoods that are distinguished by their social and technical characteristics. In smart buildings, rooms may contain devices affected by the environment, with additional interconnections like those in smart cities where power consumption reduction is linked to device usage, competing with, or aligned with room controls. A planner is more concerned with the consequences of their execution than with offering smart equipment. The second problem is to build realistic representations of the city and its components after embracing the idea of a multi-scale, multi-attribute, multi-objective, complex, sociotechnical system. Fig. 1 illustrates the digital twins of urban physical assets. An image of the physical city is depicted on the left, along with its buildings, supporting infrastructure, and citizens, while organizations and corporations are represented on the right, along with technical sensors and their derived metrics. For planning and governance, the digital twin ensemble provides computational decision support. In the lower part of Fig. 1, you can see how the interaction of crucial standards, metrics, and methods is illustrated. These benchmarks, measures, and techniques, which may be used in both physical and virtual contexts, are developed from green best practices. In the sections that follow, these ideas in greater detail are examined, as well as the standards shown in Fig. 1. In the rapidly evolving economy of today, organizations must prioritize sustainability in order to maintain a competitive edge, as illustrated in Fig. 2. Sustainable practices can reduce costs, enhance safety and security, and improve employee well-being [14]. Moreover, being green enhances an organization's brand image, contributing to talent recruitment and employee retention [15,16]. Despite increased awareness and acceptability, firms' sustainability activities are not assessed using a single, widely accepted set of indicators. These metrics serve as the basis for creating rules and regulations in addition to being crucial for monitoring and evaluating businesses and their operations. Fig. 2 illustrates a preliminary definition of the structure of an urban digital twin by examining the physical city as the field in which finite quantities of resources flow among a wide range of agents, each with a different degree of influence over public policy decisions, with effects on each of these agents in terms of their quality of life. There is no doubt that the regulatory framework plays a important role in this matter.

The urban digital twin as a model of physical objects and urban agents is shown in Fig. 2. The digital twin is developed and managed through a range of technological innovations that capture, process, and display data. Digital twins are supported by a set of fundamental elements already present in many organizations today, providing operational and data processing support. These digital twins are a class of emerging technologies typically implemented during an organization's digital transformation process, allowing them to reach their full potential as comprehensive, live data models spanning various resources. Key technologies that form the foundation of the digital twin system include the Internet of Things (IoT), 5G technology, AI and Big Data Analytics, Visualization Tools, Digital Platforms, Social Sensing, Participatory Sensing, Spatio-temporal fluctuation, Semantic Model Approach, ML Approach, and Energy Bench- marking Approach, among others. IoT, a network of interconnected devices equipped with sensors, software, and other technologies, enables interaction and information exchange with various systems and platforms over the Internet. Equipment monitoring via IoT helps construction firms track usage, manage costs, and make informed decisions. Cloud computing and real-time monitoring assist in reducing theft, enhancing efficiency, and controlling resource expenses. 5G technology serves as an integral digital twin accelerator, offering ultra-high speeds, rapid response times, and the capacity to support high device densities. With constantly changing construction site environments, teams can leverage 5G to monitor real-time activities and execute virtual or autonomous construction operations. This technology enables seamless access to data-intensive edge and cloud applications, facilitating real-time communication among users globally [19]. Digital twin technology relies heavily on AI and big data analytics. The use of AI aids city managers in making informed decisions and automating operational tasks when combined with analytical tools. An audio sensor within the city infrastructure, for example, could alert operations center personnel to an incident and suggest potential responses. Drones can also be automatically activated by such sensors. The emergence of automation in construction relies on AI and extensive data mining technology [20]. In addition to digital twins, visualization tools play an important role as well. The main components of digital twins are real-time operation centers with video walls and 3D simulation software like BIM. These tools can be enhanced with augmented reality and virtual reality technologies, enhancing their accuracy and utility. Additionally, these technologies have impactful implications for operations, training architecture, and simulation. The Digital Platform connects all previously

Fig. 1. Urban physical assets and digital twins.

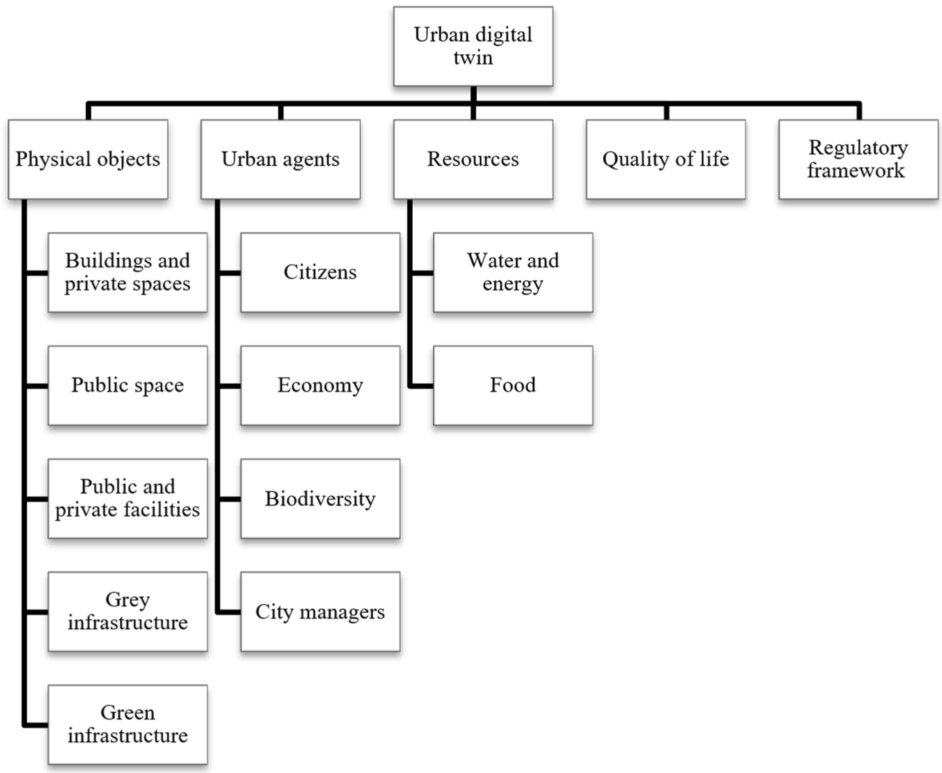

Fig. 2. The urban digital twin as model of physical objects and urban agents [17].

mentioned technologies, linking applications and data to eliminate the need for storage facilities. The platform also connects various businesses and socioeconomic and educational sectors, enabling an exploration of the ecosystem and surpassing individual system capabilities. Social sensing involves various sensing paradigms wherein data is collected on behalf of humans or computers. Mobile sensing devices are crucial in social sensing to monitor and sense mobile targets. Social sensing generally encompasses three types of data collection: participatory sensing, opportunistic sensing, and social data scavenging. Participatory sensing involves individuals actively participating in the sensing process and performing specific tasks essential for meeting application requirements [13,21]. Spatiotemporal fluctuation measures landscape changes based on change patterns. These metrics indicate landscape structure changes in various ways, while the direction and frequency of fluctuations reveal spatial variations. This helps identify physical vulnerabilities that may cause hazards and risks in construction [21].

The semantic data model is a conceptual data model containing semantic information that imparts significant meaning to data and relationships among them. A semantic approach to information processing and execution implicitly defines the purpose of represented knowledge using semantic settings and prior information [22]. The goal of ML is to enable computers to adapt and improve based on experience, rather than directly programmable instructions. Computer systems that are capable of acquiring and interpreting data for self-learning are being developed. As a method to assess the energy efficiency of buildings over time by comparing them to other similar structures or modeled simulation of a reference building designed to meet specific standards, benchmarking, a method that compares one or more aspects of products, services, and strategies against industry-leading organizations, is applied to building energy consumption. Benchmarking is an effective tool for gauging the energy efficiency of buildings and identifying areas for improvement when it is applied to their energy consumption. Therefore, the digital twin concept utilizes a combination of advanced technologies such as IoT, 5G, AI, Big Data Analytics, Visualization Tools, Digital Platforms, Social Sensing, spatial–temporal fluctuations, Semantic Model Approach, ML Approach, and Energy Benchmarking Approach to create a comprehensive, real-time data model.

The combination of these technologies enhances decision-making, optimizes resource utilization, and improves overall efficiency in the number of industries, including construction and urban planning. The use of digital twins will become increasingly important as organizations continue to adopt digital transformation processes and embrace emerging technologies. An explanation of modeling and visualization techniques is shown in Table 1.

4. Digital twins and smart city

A Digital Twin is a simulation technique that combines several disciplines, physical qualities, scales, and probabilities using physical models, sensors, and historical operational data. This simulation acts as a digital depiction of the product throughout its useful life. There are now many ways to understand the idea of a digital twin, and there is no agreed-upon definition. The physical things, virtual models, data, connections, and services make up the digital twin. A digital twin gives a two-way mapping between the real and virtual worlds, which is where it differs from a digital shadow. Digital twins, unlike digital shadows, enable physical entities to be controlled without human intervention [31], a feature not present in digital shadows. A virtual twin enables the representation of physical characteristics, structures, states, performance, functions, and behaviors of a system in a virtual environment [28], creating a dynamic model with high fidelity over a variety of dimensions, scales, and physical quantities. The model allows for effective observation, comprehension, control, and transformation of the physical world [28,29]. In cities embracing technological advancements and urbanization challenges, humans, infrastructure systems, and technologies are increasingly interdependent. As a result of these interdependencies, management decisions may be less than ideal, resulting in increased uncertainty and inaccurate predictions. To address this problem, city decision-makers must change the way they understand, influence, and manage urban infrastructure. A Smart City

Table 1
An explanation of the techniques involved in modeling and visualization.

Authors	Year	Concepts	Important tools and methods	Important role
Jaleel et al. [23]	(2023)	3-Danimation with virtual or augmented reality	Dynamic Models	Outlines how to use this taxonomy as a base for decision support to select the right visualization technique for specific target groups.
Soria et al. [24]	(2018)	AR, and CAD	Mapbox API, and Google Tango	Interacts with unidentified subsurface components by handling and manipulating (CRUD) spatial design data.
Napolitano et al. [25]	(2018)	VR, sensor networks, and SHM data	Data visualization and Kolor Panotour	Intuitive graphical VR based connections are made between SHM data and frameworks.
Li et al.. [26]	(2018)	AR, GIS	Mobile device, and Mapbox API	Present a client–server structure to create an AR system that locates subsurface pipes quickly and affordably.
Zhi et al. [27]	(2019)	3D visualization, GIS, and simulation models	Integrate a flooding simulation approach with the Unity 3D engine to accommodate heterogeneous data from multiple sources.	Implements a 3D dynamic method for simulating flooding that continuously replicates the appearance of an urban drainage system.
Fenais et al. [18]	(2020)	AR, GIS and cloud-based storage	Data management in the cloud, GNSS device, Unity3D, ARKit	Allows for immersive utility mapping, which is used to direct site development and protect subterranean pipelines from harm when digging is being done.
Tan et al. [28]	(2021)	Information systems, display, and OFDR	Analyzing SHM data with DFOS and MATLAB algorithm	Offers possible approaches to utilizing a DFOS for detecting, quantifying, and visualizing concrete cracks and pipe deterioration.

Digital Twin (SCDT) integrates the real and digital worlds through iterative, data-driven feedback loops. Virtual reality, augmented reality, and mixed reality technologies combine IoT, analytics, and visualization capabilities to create a virtual representation of municipal infrastructure [31]. Decision-makers may be able to evaluate policies and projects that are driven by the community and stakeholder groups thanks to synergistic feedback loops between physical infrastructure and human systems. What-if scenarios and emergent behaviors may be used to predict how smart cities will function under various economic, environmental, and social circumstances. It is crucial to comprehend this idea in order to evaluate the success of smart growth initiatives and to close the gap between smart utopia and smart reality [32,33]. The development of such integrated cyber-physical city infrastructures requires new technological and methodological advances, as well as multidisciplinary collaboration. Digital twin cities will be a "new starting point" for innovation in urban management, planning, and services in the development of smart cities [34,35]. As a result, we will be able to visualize all aspects of city information and will be able to intelligently plan, manage, and deliver services within the city. As a key element of smart cities, digital twin cities are not only a goal of digital cities but also a critical component. To become smarter, cities must have these facilities and basic capabilities, marking a step in the transformation of urban information technology from qualitative to quantitative change, which creates greater opportunities for innovation in the development of smart cities [36].

4.1. Characteristics of smart cities based on digital twins

As a result of diverse perspectives, the concept of the digital twin has been interpreted in many ways. In their study, Tao et al. [29] explore various dimensions and analyze current understandings of digital twins. In Table 2, they describe the five dimensions of an ideal digital twin: model, data, connection, service/function, and physical. It has been noted by Tao et al. that digital twins exhibit unique characteristics at various stages, so it is important to understand and apply digital twins in the context of specific objects, applications, and requirements [29–31]. In real-world implementations, a digital twin need not exhibit all ideal traits; satisfying the users' particular requirements is enough [28,29]. The digital twin city concept, as a broader application of the digital twin idea in urban contexts, displays distinct features that originate from the ideal attributes of digital twins. Various industries, such as manufacturing, aerospace, healthcare, and transportation, have applied digital twin technology in recent years implementation of digital twins has led to improved efficiency, reduced costs, and enhanced decision-making in these sectors [32]. In the context of smart cities, digital twin cities can help with urban planning, resource management, traffic control, and environmental monitoring. By incorporating real-time data, digital twin cities can optimize infrastructure utilization and maintenance, leading to more sustainable urban development. The capabilities of digital twin cities can be bolstered by integrating cutting-edge technologies like AI, ML, and big data analytics. This enables improved forecasting, optimization, and adaptability in response to evolving circumstances [33–35]. To ensure the successful implementation of digital twin cities and to address the diverse needs of urban environments, collaboration among stakeholders such as governments, businesses, researchers, and citizens will be crucial.

Digital twin city consists of precise mapping, virtual-real interaction, software- driven representations, and intelligent feedback. Aerial, ground, subterranean, and river sensors are used to map urban infrastructure, such as roads, bridges, manhole covers, lamps, and buildings [37–41]. Through this, it is possible to gain a complete understanding of the city's operational status as well as a dynamic monitoring of it, which ultimately allows an accurate alignment of the virtual city with the physical city in terms of information. A virtual model of the physical city

Table 2
Varied interpretations of the term digital twin.

S. No.	Perspective	Understanding of Digital Twin
1.	Representation Aspect	A digital representation of a physical system or product that captures its geometry, composition, and structural behavior.
2.	Data Dimension	The integration of real-time and historical data, enabling continuous updating and synchronization of digital twins with its physical counterpart.
3.	Linkage Aspect	A digital twin's connection and communication with its physical counterpart, as well as with other digital twins are seamless.
4.	Functional Aspect	The digital twin's capacity to provide services and functions, such as predictive maintenance, performance optimization, and what-if scenario analysis.
5.	Physical Dimension	The ability of a digital twin to control and influence its physical counterpart, enabling real-world changes based on insights and decisions derived from the digital twin.

can be created by twin cities using software platforms that simulate the behavior of urban people, events, and objects in the virtual environment [42–45]. By planning, designing, and simulating the digital twin city and proposing reasonable and viable countermeasures, intelligent feedback can provide smart early warning of potential negative effects, conflicts, and threats within the city. By integrating next-generation technology into the basis of the digital twin city, such as Internet of Items, cloud computing, big data, and AI, it is feasible to direct and optimize the design and management of smart cities [46,47]. The provision of citizens' services will be enhanced, as well as the development of smart cities will be further assisted [48]. As part of the following discussion, five exemplary applications are presented for illustrating how digital twins support the operation of smart cities [49].

4.2. Clarifying the terminology

Despite its widespread use in everyday speech, science, government, and practice, smart technology is unlikely to be used as often in stormwater, hydrology, or hydraulics. The use of smart technology in a broader sense might pique the interest of decision-makers, legislators, and the public [50], but such expansive terminology can cause misunderstandings when discussing scientific advances. It is important to use consistent language so that the audience understands the nature, scope, and goal of the ideas being presented. To tie our discussion to the literature sources on which it is based [51–53], A variety of terminology is used to reflect similar yet noticeably different uses of smart technology. In this way, stormwater management will be improved along with related disciplines including green infrastructure, urban planning, and urban ecology. It refers to features and technologies that can be retrofitted to improve the capabilities of other devices, assets, or networks by enhancing their sensing, monitoring (data collection), communicating, managing, analyzing, integrating, controlling, or optimizing capabilities. Due to the inclusion of a variety of technologies with different degrees of "smartness" in this definition, current research uses smart technologies in a fragmented and uneven manner.

In everyday conversations, as well as in science, governance, and practice, the term smart technology is pervasive. However, it is arguably more prevalent in fields like energy, telecommunications, and HVAC than in stormwater, hydrology, and hydraulics. Using smart technology as a general descriptor can attract the interest of decision-makers, policymakers, and the public [50], but such broad terms can cause confusion when discussing scientific progress and needs. Consistent terminology usage is crucial for effectively disseminating knowledge, and ensuring that audiences understand the nature, scope, and intent of the proposed approaches. In this review, various terms are used to describe similar yet subtly different applications of smart technology, attempting to connect our discussion to the literature sources upon which it is based [51–53]. To prevent confusion, we will define the terms used in the following section. Authors should clearly define the terms they use in an evolving field like this to foster clear communication within the stormwater discipline and promote dialogue with related disciplines such as system optimization and control, green infrastructure, urban planning, and urban ecology. Smart technology refers to technologies capable of sensing, monitoring (data collection), communicating, managing, analyzing, integrating, controlling, or optimizing devices in a systematic manner. These integrated smart features and technologies can be retrofitted to enhance the capabilities of other devices, assets, or networks. This definition covers a wide range of technologies with varying levels of smartness, leading to fragmented and inconsistent application of smart technologies in current research. The development of a framework is reviewed within this paper to accommodate this array of technologies and capabilities, allowing for benchmarking and comparison.

Real-time control (RTC): In stormwater management, smart is an advancement from the established research field of RTC [54,55,56]. Parker et al. (2021) describes actuators, controllers, sensors, and telemetry in RTC systems [57].

Passive/active control: Passive control systems generally depend on hydraulic conditions to change the discharge rate from a specific asset, including orifices, vortex flow controls, and weirs. Passive systems may incorporate some degree of smartness if monitored (e.g., through telemetry reporting water levels) [58]. Typically, active control systems involve a device like an actuator which is driven by a local or global control system, and does not encompass assets controlling flow velocities using mechanical principles, such as vortex flow controls [59–61].

Internet of Things: The IoT refers to the interconnectivity of devices (both physical and virtual) to the Internet and other connected devices [62]. It encompasses both hardware and software in the context of smart stormwater.

Artificial Intelligence: AI has enabled stormwater management improvements such as optimization, prediction, and forecasting. By evaluating vast datasets, spotting trends, and generating predictions using AI approaches, stormwater systems can be managed more effectively [63–65]. AI can be used to optimize adaptive control strategies, enabling stormwater infrastructure to respond effectively to changing environmental factors such as rainfall intensity and duration. The result is a reduction in flooding risk and better management of water quality [66].

Geographic Information Systems (GIS): Stormwater infrastructure geo- graphical data may be managed, analyzed, and visualized using GIS [67]. It assists with flood risk assessment, the design of stormwater systems, their upkeep, and the identification of sensitive locations [68].

Remote Sensing: Remote sensing technology, which utilizes satellite imaging and aerial photography makes it possible to monitor vast regions and gather useful information on land cover, precipitation, and urban growth [69]. Stormwater management decisions can be guided this information current stormwater systems can be evaluated on the basis of this data [70].

Green Infrastructure: Green infrastructure consists of natural or constructed systems that mimic natural processes to manage stormwater [71]. Permeable pavement, bioswales, rain gardens, and green roofs are some examples. Further- more, these methods help to reduce stormwater runoff, enhance water quality, and mitigate urban heat islands [72,73].

Sensors and Telemetry: Stormwater infrastructure can be equipped with sensors and telemetry systems to measure water levels and flow rates in real-time. Proactive management of stormwater systems can be enabled by RTC systems [74].

Supervisory Control and Data Acquisition (SCADA) Systems: SCADA systems centrally monitor and control stormwater infrastructure, allowing operators to effectively manage numerous assets, spot problems, and adapt to changing conditions [75–77].

Modeling and Simulation: The behavior of stormwater systems may be predicted using sophisticated hydrologic and hydraulic models, which can also be used to evaluate the operation of current infrastructure and provide information for the creation of new stormwater management strategies [78].

Cloud Computing and Big Data Analytics: Data related to stormwater management can now be processed and stored in huge quantities using cloud computing [79,80]. By analyzing big data uncover trends and make better decisions [81].

4.3. Optimization of SWM

Due to the advancement of network-scale monitoring, several best-practice RTC methods are being created. These methods include fuzzy logic control, genetic algorithms, and neural networks. Making sure that water systems are used sustainably and independently is a key component of optimizing SWM [13,81]. As a result, it is possible to minimize leaks and losses, guarantee the quality of the water, enhance customer happiness, and increase operational effectiveness. Understanding water systems better, detecting leaks earlier, controlling water loss more effectively, and continuously monitoring water quality, and achieving economic gains from water and energy conservation, financial loss reductions (of up to 30 % on water bills), improved system efficiency, and customer service quality, among other things are additional benefits of the sophisticated information technology used in SWM systems [82]. Flood control, combined sewer overflows, and network capacity are a few of the optimization techniques that emphasize water quantity management over water quality management. A major reason for this discrepancy is the maturity of the components required for monitoring quantity, which includes sensors, actuators, and telecommunications. Due to reliability and scalability issues, water quality measurement technology, in particular sensors, hasn't yet reached the point where it can provide real-time feedback [83–86]. Table 3 summarizes relevant studies on optimizing SWM systems.

This constraint, in contrast to the virtually immediate nature of water level monitoring, results from the lag between gathering water quality samples and lab analysis. Proxy measurements including color, turbidity, and dissolved oxygen content have been used in recent years to develop this field, frequently in combination with real-time management of downstream treatment alternatives [87].

4.4. The role of short-term forecasting in smart stormwater

Data management at catchment scale has been improved by the integration of weather data and short-term forecasts into RTC [93–95]. As a result, storm predictions and responses have become more accurate. A considerable period has passed since early flood warnings were developed for predicting future network states [96]. Meydani et al. [97] developed a real-time daily runoff forecast system by downscaling seasonal weather forecasts using Bayesian Belief Networks (BBN), particularly demonstrating BBN's effectiveness in improving the accuracy of probabilistic precipitation forecasts. Zamani et al. [98] recently studied water quality forecasting. Various DL models were evaluated for chlorophyll-a concentrations, including recurrent neural networks (RNNs), long short-term memories (LSTMs), gated recurrent units (GRUs), and temporal convolutional networks (TCN). According to their results, the GRU model performed better, and the integration of these models into ensemble models using genetic algorithms improved forecasting accuracy. Particularly, the Mult objective optimization algorithm NSGA-II outperformed standalone DL and ensemble models based on GA. Having the ability to predict such events has reduced flood-related damage and improved emergency response. As computational models have become more powerful and cost-effective, coupled with high-resolution input data like weather radar, rainfall radar has been incorporated into the management of large sewer systems [99–102]. Consequently, stormwater infrastructure has become more efficient and automated, enhancing urban communities' resilience. Table 4 shows a review of neurocomputer models for hydrology and hydraulics based on review studies.

Rainwater harvesting systems can benefit from RTC technology in terms of water provision, flood protection, and environmental flow. Predicting rainfall before storm events allows this system to release water before storms occur, preventing uncontrolled overflows. A more efficient management of water resources can be achieved due to this approach, thereby reducing flood risks. Many advanced applications have relied on 24-hour forecasts, while long-term forecasts remain largely unexplored. It is possible that the exploration of these longer-term forecasts may result in further benefits and improvements to the performance of the system. RTC systems harvest less rainwater than passive systems, but they deliver environmental water for streamflow restoration and flood mitigation [99,100]. It has been primarily the use of weather data for prediction rather than for actuating the operation of network features that have been the primary focus of the initial deployment. The accuracy and responsiveness of these systems can be further enhanced using auto-calibration feedback loops developed by some models using observed measurements within drainage catchments. Furthermore, several modeling studies have demonstrated that nowcasting approaches can be implemented to actuate and control detention ponds and drainage systems using rainfall radar [101]. As far as stormwater management is concerned, this is an important development. Recent reviews have demonstrated that nowcasting has significant potential, and a limited number of pilot studies have already been carried out on a commercial scale. Climate change also drives big changes in cities [109]. SWM and urban resilience will be impacted by this technology as it continues to evolve.

4.5. Decentralized smart stormwater systems

The majority of literature on smart stormwater management systems incorporates RTC primarily into large infrastructure systems. These trends have led to centralized systems for water supply, treatment, and sewerage, sometimes called gray systems [110,111]. In recent years, the emphasis has shifted from large assets to maximizing network capacity by utilizing multiple large assets across traditional sewer network components, including pipes, combined sewer overflows, and tanks. As such, RTC has been extensively demonstrated as a cost-effective method for increasing network capacity while maintaining options for future adaptation through retrofitting or updating control rules. There are some strategies for transforming existing urban areas into decentralized stormwater runoff management, but these are usually country- or city-specific [112,113,21]. The transition of urban areas towards decentralized management approaches, therefore, requires a systematic approach. Additionally, cities need assistance in assessing the practical potential for transforming their urban areas into decentralized solutions [114]. A framework for smart water systems is shown in Fig. 3 [118]. Coordinated catchment-scale networks are believed to be the most effective way of using rainwater harvesting and attenuation basins.

Table 3
A summary of relevant studies on the optimization of SWMsystems.

Reference	Year	Method	Result
Ramos et al. [89]	2022	Digital twin technology	A fast detection of leaks combined with a rapid configuration and optimization of pressure control valves can lead to a water saving of up to 28 %, increasing the overall system efficiency.
Siew et al. [90]	2012	Fuzzy-based constraint handling and a new entropy based mixed reliability index	In this study, a modified two-loop architecture was looked at. These examples showed that the fuzzy technique and the new dependability score were both only partially successful in creating the best water distribution networks.
Sangroula et al. [91]	2022	Genetic Algorithm based SOP-WDN program	The technique was applied to three benchmark water distribution network optimization issues, and the outcomes were consistently good. Engineers can use the SOP-WDN to help with water distribution pipeline design and restoration.
Xin et al. [92]	2022	Mult objective Optimization	Balancing water quality, energy, and cost factors in water distribution system design.
Shirajuddin et al. [88]	2022	Genetic Algorithm	As the problem of aging pipes worsens, NSGA-III should replace NSGA-II as the go-to technique for solving increasingly difficult WDS optimization issues, however, NSGA-II may still be used for easier optimization tasks.

Table 4
An overview of how neurocomputing models are used in the domains of hydrology and hydraulics, as determined by review studies.

Researcher(s)	Years	Application	Results
Zounemat-Kermani et al. [103]	2020	Hydrology of surface waters	Providing researchers and practitioners involved in data mining and ML within the fields of water engineering and hydrological science with a guide, this review assists them in selecting appropriate methods, network structures, and modeling strategies based on specific problems that they face.
Tao et al. [104]	2022	Groundwater level (GWL) forecasting	A review summarized the details of all the ML models used between 2008 and 2020, including the types, data ranges, timescales, inputs and outputs, and performance criteria. Furthermore, future research directions are suggested enhancing knowledge related to GWL prediction models and improve their accuracy.
Demir et al. [105]	2023	Lake water level (LWL) forecasting	The results of the study indicate that the forecasting models used are effective and reliable. Time series predictions are improved when the periodicity component is included. It may also be possible to enhance the outcomes of cross-station modeling by using data from nearby sites as a means of transferring learning.
Ahmadi et al. [106]	22,022	Groundwater Level	The progress in ML and DL algorithms, coupled with computational advancements that integrate them with physics-based models provide unparalleled opportunities to utilize new information sources, such as InSAR data, to enhance the spatiotemporal resolution and accuracy of groundwater monitoring and forecasting.
Zounemat-Kermani et al. [107]	2021	Surface water hydrology and hydraulics	According to the findings of this study, ensemble strategies are clearly superior to single-model learning in hydrology. Additionally, boosting techniques (such as boosting, AdaBoost, and extreme gradient boosting) are more commonly employed to solve hydrological problems than bagging, stacking
Antwi-Agyakwa et al. [108]	2023	Flood Risk Prediction	In the present study, they found that ML models have been extensively employed to predict floods, while probabilistic models such as Copula and Bayesian Networks (B.N.) play a crucial role in evaluating the uncertainty associated with flood risks, which warrants further study due to their inherent uncertainty. In addition, the advancement of remote sensing, GIS, and cloud computing creates an ideal platform for integrating data and tools for flood forecasting.

Offline optimization based on asset status, upstream conditions, or forecasting is currently the predominant method for coordinating assets. Despite equivalent volumes of distributed measures in individual tanks, distributed smart control systems offer some advantages [115,116]. The decentralized control is becoming more widely accepted as a reliable solution because it requires minimal communication and has been shown to perform better in managing assets, such as capturing water during high- magnitude events, compared to passive operation alone.

This is commonly referred to as "sweating the assets." However, most studies have only looked at the benefits at the individual asset level, ignoring the advantages of coordinated control across networks. Therefore, further research is needed to explore how these benefits can be optimized [117].

4.6. Modeling AI in stormwater

In many newly developed towns, stormwater retention ponds are a best manage- ment practice, but their widespread usage may be harmful to aquatic life. Many input parameters must be collected and calibrated for existing models, which are process-based. Researchers studied thermal modeling tool that incorporates readily available climatic data based on AI. AI-process-based models can often predict the temperature of shallow water bodies, such as small lakes and ponds [118–123]. These types of models use climatological information and empirical equations to study convection, advection, and evaporation heat transport before utilizing numerical techniques to solve the heat equation. The quality of the input variables, some of which are hard to collect or prone to mistakes, has an impact on the accuracy of the model. As well as ANN models, evolutionary computing algorithms are influenced by Darwinian processes of natural selection and biological operations. In [125], genetic programming (GP) was introduced as the first advancement of the genetic algorithm. Random numbers (also called chromosomes) are used to form populations in the GP model. By comparing the fitness of each chromosome to a target value, fitness is evaluated. According to Darwin's principle of survival of the fittest, computer programs are genetically reproduced through genetic crossover. GP models have been used to predict velocity in laboratory-scaled vegetated floodplains, develop rainfall-runoff relationships from synthetic data, assess salt intrusion in estuarine environments, simulate rainfall-runoff processes, and predict total organic carbon concentrations in lakes with flexible beds covered with vegetation.

There is not a perfect link between hydrological parameters, climatic circumstances, and flow behavior in complex hydraulic systems like man-made wetlands. Hydrodynamic equations including the Manning's roughness coefficient and the coefficient may be used to simulate the hydraulic behavior of these wetlands. Hydrodynamic models need a lot of data to be calibrated and validated in remote, biodiverse habitats like artificial wetlands. In comparison to hydrodynamic models, data- driven models may be better able to depict the nonlinear interactions between various hydraulic and hydrologic parameters connected to wetlands [118–125].

Table 5 is a new attempt to contrast the usage of AI models in a wetland system since no other studies have thoroughly studied the use of data-driven models for forecasting hydrological parameters. In addition to using AI techniques, wetland hydraulic characteristics were compared with the conventional stepwise regression model as a baseline. Even though there have been numerous research efforts on neurocomputing models for predicting sediment concentration, as well as evaluations of their accuracy, some of these models are still not accurate or are computationally expensive. In [126] features a comparison of four multivariate non-linear regression models, including FFNN, ARIMA, and Multivariate Non-Linear Regression. FFNN often provided better forecasts, according to the researchers (Table 5).

5. Digital twin implementation experience

In this paper, each city was chosen due to its unique contribution to the under- standing of digital twin technology in urban management. Helsinki's leadership in digital twin innovation, Zurich's focus on 3-D spatial data and open govern- ment data policies, Vienna's approach to 3-D city modeling, the University of Crete's application of IoT for sustainability, the UK's integration of digital twins in heritage conservation, Barcelona's use of supercomputing for urban planning, and Imola's emphasis on walkability and urban design all contribute to a rich collection of insights and experiences. These cities represent a cross-section of geographical locations, urban challenges, and technological advances, making them ideal case studies for exploring the diverse applications and impacts of digital twin technology in enhancing stormwater infrastructure systems and contributing to the development of smart, sustainable, and resilient cities. In addition to their individual achievements and challenges, their selection is based on the breadth of knowledge and experience they bring to the study of digital twins in urban infrastructure management.

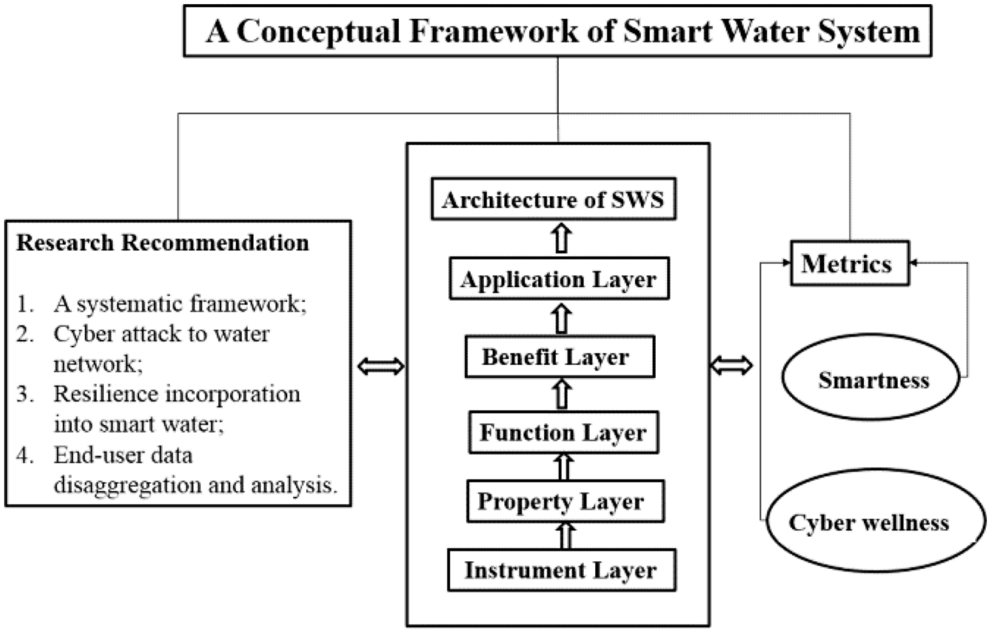

Fig. 3. A New Framework of Smart Water System [118].

5.1. Digital twin in Helsinki

The city of Helsinki, Finland is leading the way, spearheaded by Jarmo Suomisto, with its digital twin, which consists of both a Reality model and a semantic city GML model. As a benchmark for urban modeling, the city's approach to digital twinning includes both visual and semantic data. Helsinki's inclusion in this study is justified by its pioneering status in applying digital twin technology to urban planning and sustainability goals, particularly its ambitious carbon neutrality goals. Through the use of advanced software and open-data models, as well as its efforts to engage the public through digital twins on mobile devices, the city offers valuable lessons regarding the use of digital twins for improved urban simulation, public engagement, and data management. A reality model consists of two billion polygons and depicts the visual representation of the city, whereas a semantic model consists of layers of data that can be labeled, queried, modified, and expanded (see Fig. 4).

Challenge.

In less than eight years from now, the carbon neutrality goal of the city can be achieved through the models.

- Solar energy generation varies according to the season.
- Communicating the benefits, needs, and impacts of new developments to citizens and politicians.
- The ability to explore and validate new ideas, including the collection of data and calculation, with sufficient time and resources.
- Potential impacts of gentrification on various areas across the city.
- In order to achieve 2030 and 2050 goals, large-scale interventions are required.

Approach.

- Land, buildings, and infrastructure can be modeled using software such as Bentley OpenCities Map and CityGML.
- Using Bentley Context Capture4 for 3D laser scanning and reality mesh modeling.
- ANSYS Discovery Live and Bentley OpenCities Planner are used to simulate wind speed, air flows, air pressure, light, and shadow models.
- In semantic data modeling, objects and points within the model are associated with underlying and complementary data.
- Reality mesh and CityGML models are adopted on a free-and-open-data basis, giving construction, real estate, and government actors free access to them.

Impact.

- Improved capability for setting up urban simulation in an agile and rapid manner using a robust digital city model and data infrastructure.
- A digital twin on mobile devices can be used to communicate project information and gather crowd-sourced input, increasing public engagement.
- A federated source of truth that serves as an archive and hub for the city data, information, and spatial views and allows immersive VR headset exploration.

5.2. Digital twin in Zurich

Another facet of digital twin applications is Zurich's digital twin, which incorporates 3D spatial data, theme elements, and public participation. Its alignment with the Infrastructure for Spatial Information in the European Community“ (INSPIRE) Directive, despite not being a member of the EU, and its proactive Open Government Data policies since 2012 illustrate how digital twins can facilitate data accessibility and interoperability. As a result of its innovative use of digital twin technology in evaluating architectural designs and its commitment to improving spatial data visualization's visual and performative quality, Zurich illustrates the transformative potential of digital twins for urban planning and management. A focus on 3D spatial data is at the heart of Zurich's digital twin, which incorporates various thematic elements. It serves as a reference point for connecting spatial and other types of data. Cadastral and engineering surveying processes are adjusted to accommodate the third dimension during digitization and further processing of space. Blindflug Studios incorporated a 3D architectural component of the City of Zurich's digital twin in a dystopian cyberpunk recreation of Zurich that is focused on its Reformation. The objective is to pique the curiosity of those who are not generally drawn to the topic. A digital twin is shown in Fig. 5 in Zurich [130].

Table 5
Summary of the reviewed studies in modelling AI in stormwater.

References	Years	Model/ Motivation	Results
Alotaibi et al., [125]	2018	GCM and ANN/ Predictions of Rainfall and Temperature	ANFIS was found to be less effective than ANNs in accurately predicting long-term future temperature and rainfall. Nine GCM projections were considerably varied from one another, with three models and three emission scenarios accounting for each. A general pattern of temperature increase is expected to be observed in the Qassim region from 2011 to 2099, based on future projections.
Stajkowski et al. [119]	2022	GA/Optimized Sequential Model	It was shown that the hybrid GALSTM network outperformed the RNN in terms of performance, thus resolving the the fundamental challenge of determining the optimal memory cell number and time window for the GA-LSTM network. GA-LSTM can be used as a sophisticated DL method for time series analysis, according to the research.
Alsumaiei et al. [120]	2022	Modeling the fluctuation of groundwater levels using neural networks with exogenous inputs (NARX)	In comparison to previous statistical models applied in the same research region, the NARX models described in this work lowered the mean absolute error (MAE) of groundwater level projections by 50 %. These encouraging findings may be helpful to urban city planners in regulating short water tables in environments with comparable weather and aquifer systems.
Bayatvarkeshi et al. [122]	2021	Wavelet transformation combined with CANFIS/ predicts soil temperature using air temperature	This the study successfully developed new ML models that were enhanced by wavelet transform for effective feature extraction. These hybrid models were then demonstrated to be helpful for analyzing soil temperature based on air temperature inputs across a variety of climatic conditions. Researchers hope that their findings will help in making critical decisions in sustainable agriculture and other areas where changes in air temperature have an impact on soil health.
Fu et al. [123]	2020	ANFIS model with optimized wavelet de-noising / Prediction of wastewater discharge quality	As a result of the experiment, it was found that the proposed AI model outperformed existing ones. A total dissolved solids prediction, electro-conductivity prediction and chloride prediction were found to have R2 values of 0.976, 0.975, 0.988, and 0.986, respectively.
Thompson et al. [124]	2021	Adaboost model/predict urban runoff in water	Aside from maintenance, the Adaboost model achieved over 99 % accuracy on the test set and did not exhibit any false positives, with the exception of lag errors. There were a number of advantages to preprocessing data, but the optimal approaches varied from model to model. Most models included all nine variables related to water quality, but UVA254 and turbidity were the most significant.
Zubaidi et al. [126]	2020	Hybrid Artificial Neural Network Model / Urban stochastic water demand prediction	Local water managers can use this study to efficiently manage their existing water system and plan extensions to meet the increasing demand for water.
Hameed et al. [127]	2023	Review/ development of stormwater runoff management	The evolution of stormwater runoff management concepts was examined through reference emergence analysis, keyword clustering, and keyword emergence analysis. In addition to identifying hotspots, trends, and technological advancements, this approach also highlighted limitations.
Nyasulu et al. [128]	2023	Random Forest, Gradient Boosting and Ridge Regression / Providing daily rainfall forecasts for Matam, Senegal's northernmost city.	According to the Gradient Boosting model, its Mean Absolute Errors, Mean Squared Errors, and Root Mean Squared Errors are 0.1873, 0.1369, and 0.3671, respectively. With a Coefficient of Determination of 0.69, the Gradient Boosting model has a higher score. Rainfall is believed to be influenced by relative humidity.

The Federal Act on Geoinformation provides descriptions of spatial data, spatial data models, and spatial metadata, exceeding the INSPIRE Directive even though Switzerland is not an EU member state. Unlike other European countries, Switzerland already had a formal Spatial Data Infrastructure and a robust governance framework before implementing INSPIRE. In a digital city's infrastructure, Open Government Data (OGD) refers to administrative data that does not require specific protection. Since 2012, data from the city's public administration has been freely accessible, machine-readable, and available under an open license. OGD policies and guidelines have also been issued and implemented. The Office for Building Construction is utilizing digital technologies as part of a pilot project to facilitate the examination of submitted designs throughout the judging process. Through a web-based 3D map, the first tool enables users to review and submit 3D models of competition submissions (Fig. 6). The 3D map is projected onto a screen during the judgment process so that the jury may inspect the models, adjust viewpoints and sizes, compare designs simultaneously, and view spatial data like construction lines (Baulinien). Fig. 6 illustrates how 3D spatial data are becoming more prevalent as a spatial solution. There are more than a dozen cities worldwide that use Zurich's virtual city model in areas such as environmental studies (noise modeling, air pollution modeling, mobile phone radiation modeling), energy (solar potential modeling), and urban planning (shade analysis, visibility modeling), to name just a few.

To explain the creation and tracking of spatial data, models, and metadata, 3D spatial data is used as a reference point for merging geographical and other types of data. Digital places can be created and maintained through metadata and lifecycle management. Real-time updates can be performed on the digital twin for some applications using sensors. Consequently, the third dimension is consistently captured and stored during the digitization of real space. The visualization of spatial data should be attractive and performant in order to enhance understanding and support for the digital twin. In order to encourage the dissemination of spatial data and the development of new applications, Open Government Data must be made available. There is a need for an automated mechanism for gaining access to and ordering data, as well as a simple and attractive method for searching and analyzing that data.

5.3. Digital twin in Vienna

A method for generating 3D city models and other geodata products was proposed by Lehner & Dorffner [131]. In order to create a virtual 3D replica of the city's elements, they used existing 3D surveying and mapping data to create a digital geoTwin. Besides developing photogrammetric roof models, they developed detailed building models based on construction plans and facade images. In order to create photorealistic models of buildings, generic textures were used. Furthermore, they developed models for two specific areas of landscape, vegetation, and city furniture. The 3D objects in these areas were not associated with

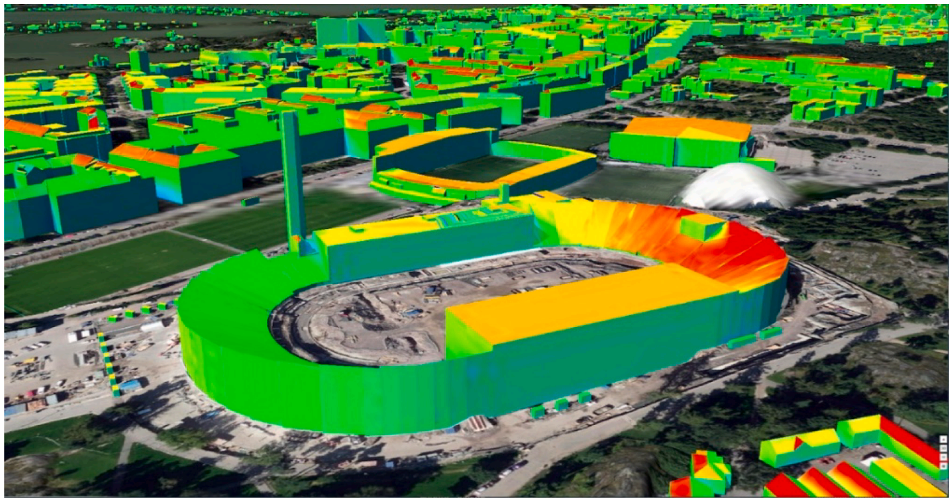

Fig. 4. Digital twin in Helsinki [129].

any semantic information, however.

The Digital geoTwin of Vienna is designed to develop a topological and semantic 3D model of the city based on raw measurements and other input sources. It is possible to create City Information Models (CIMs) by combining the Digital geoTwin with other datasets, such as census, socioeconomic, energy consumption, and maintenance management data. To capture smooth terrain forms and fill in missing information from terrestrial and photogrammetric surveys, both discrete surveying data and Airborne Laser Scanning (ALS) data are employed during the modeling process. For the Digital geoTwin, LOD2.4 F0 is selected as the preferred level of detail in order to address inconsistencies in footprints and to meet the requirements for generating lower levels of detail (LODs). An illustration of Schwedenplatz in 3D is shown in Fig. 7. Following is a summary of the process for measuring various building features for the Digital geoTwin:

- Rooftop: Stereo-photogrammetry is used to measure rooftops. The LOD2.4 takes into account roof overhangs, which require roof edge measurements, and captures the general roof shape and large superstructures.
- Overbuilt structures: Using terrestrial, mobile mapping data, or Terrestrial Laser Scanning (TLS), overbuilt structures must be measured from ground level if air space extends into the structure. On top portions of buildings with protruding parts, stereo-photogrammetry can be used, while on the bottom portions, terrestrial methods can be used.
- Footprint: In addition to terrestrial surveying, other methods are needed for building faces adjacent to public spaces. Data from mobile mapping can be used for facades facing streets but not adjacent public areas. ALS, oblique imagery, or stereo-photogrammetry can be used for facades that are not adjacent to public spaces and are orientated away from street areas. As a last resort, a fixed distance (Fd) can be employed if none of these datasets are available.

5.4. Improving sustainability at the University of Crete

The Technical University of Crete in Greece has integrated an IoT sensor system to improve its current building energy management system (BEMS). Between 2015 and 2020, OpenLink sensors were installed in three stages. On the TUC campus, more than 6,000 sensors have been put in more than 300 rooms spread over 16 student residential halls. The

Fig. 5. Digital twin in Zurich [130].

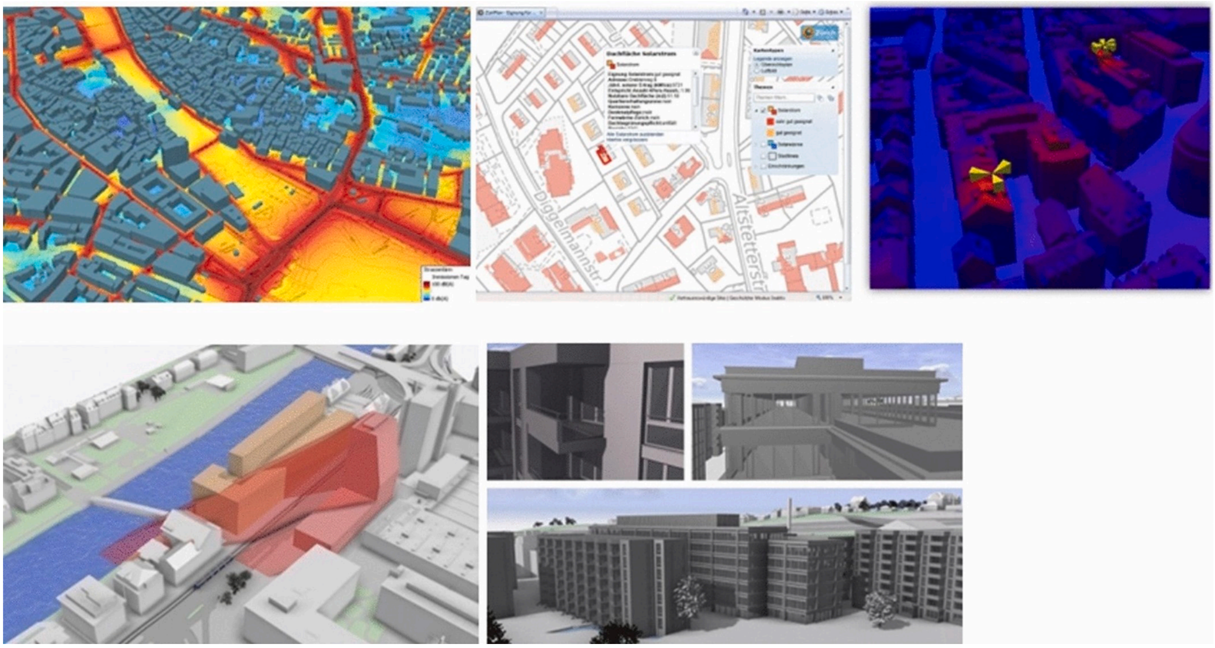

Fig. 6. 3D spatial data in Zurich [130].

sensors are managed via a web interface that continually tracks energy use, takes into account room occupancy, and collects data for system application analysis. The ultimate goal is to increase campus sustainability by lowering operating expenses by identifying utilization inefficiencies and spotting irregularities in energy use (Fig. 8).

Mavrokapnidis et al. [132] used the TUC building management system as a use case in their research, proposing a methodology for fusing static and dynamic building data from various sources. They tested this methodology using data from the OpenLink sensors. The high-level system architecture of the TUC building management system is depicted in Fig. 8. OpenLink sensors from different rooms wirelessly transmit data to their respective Remote Terminal Units (RTUs), which then forward the data to the system middleware via Modbus TCP/IP. The data is processed by the middleware and is kept in a database. A web-based server that centrally manages the building management system interprets the data using digital twins of campus structures. By merging data from the digital twin and the physical twin sensors, the front-end application creates graphical output, including building topology, electrical equipment, energy meters, and HVAC. Advanced analytics and calculations for optimum control may be done using this information (Fig. 9).

Devices for large-scale IoT sensor networks must be inexpensive and simple to maintain. Each sensor costs EUR 30 for hardware, installation, and setup is because of OpenLink's development of the hardware and software infrastructure that supports these sensing devices.

5.5. Digital twin in clifton suspension Bridge, UK

This digital twin provides a shared and open ecosystem of data and information from various collaborators and stakeholders to connect the real and digital worlds. Public and private organizations, both large and small, can benefit from its scale and delivery of meaningful output and services. Due to the municipal interest and complementary activities around regeneration in the area, East Birmingham and TEED were selected to provide a better understanding of previous influencing projects, initiatives, and strategic plans.

An illustration of Birmingham's ecosystem of activities is shown in Fig. 10. The snapshot captures a variety of local activities, and taking these activities into account will increase the value and relevance of the creation of a tangible digital twin. Each of the initiatives listed has been examined to determine its general focus and potential connections to the digital twin. Fig. 10 displays a color-coded overview of the outcomes.

5.6. Digital twin in Barcelona spain

An urban planning revolution was launched by Barcelona Supercomputing Centre (BSC), an entity that houses the MareNostrum supercomputer in a 19th-century chapel in Barcelona. This computing power allows urban planners to anticipate impacts and mitigate negative consequences by making decisions based on real data. A digital twin of the city has been created by BSC, allowing testing and validation of potential city planning scenarios before implementation. Over the next five years, the scheme will become a fundamental tool for urban planning, despite being still in its test phase. Across European cities, this technology-driven approach is expected to become standard practice in urban planning to benefit all citizens.

Challenge.

Air quality and emissions issues have been inadvertently pushed to other areas by previous traffic and pollution management measures, necessitating additional measures. There are a number of key challenges to be addressed, including:

- Improving a community's access to facilities and services.
- Dealing with urban renewal and gentrification.
- Putting into action major climate change initiatives between 2030 and 2050.

Approach.

- Planning decisions, such as clean air measures, should be simulated prior to implementation, to identify and mitigate negative impacts, or to plan additional measures in advance.
- Monitoring gentrification trends based on indicative measures, such as homestays.
- Public transportation and services are underserved areas.
- The use of open-access technologies, including OpenstreetMap, to encourage citizen participation; allowing them to challenge and contribute to planning processes.

Fig. 7. Detailed 3D scene of Schwedenplatz [131].

Fig. 8. TU Creta campus buildings equipped with sensors on the Technical University [132].

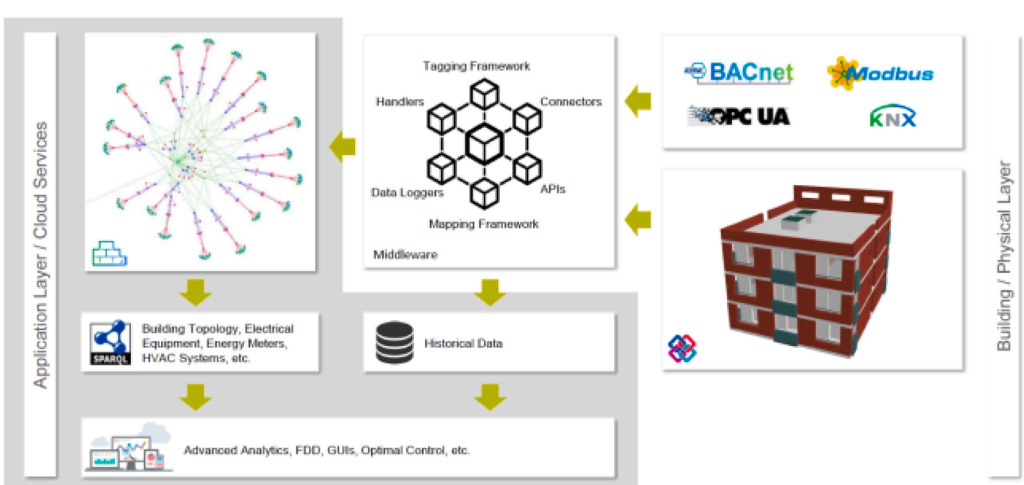

Fig. 9. The IoT-enabled building administration system's overall architecture [132].

Impact.

- To restructure cities so that people may live, work, and access all the services they require (such as shopping, health care, and education) within a 15-minute walk or bike ride.
- Decision-making based on evidence, data, and citizen accountability.

5.7. Digital twin in Imola Italy

Recently, urban design has made walkability a key consideration. The idea stresses the use of local transit, bicycles, or foot for the bulk of everyday requirements. Urban morphology, which encompasses the design of buildings, public areas, and roadway layouts, has an impact on walkability. In terms of urban morphology, connection and accessibility are crucial for walkability. A location is more likely to be frequented by pedestrians if it is geographically linked to other destinations. Contrarily, connectivity describes the availability and directness of paths connecting two sites. Using Rhino 6, the neighborhood's urban land use is imported to ensure accessibility and connectivity. Public green nodes, public transit nodes, and public urban space nodes are thought of as destinations as pedestrian paths originating from residential parcels. Within a small local region, the likelihood of walking far enough to fulfill health recommendations is frequently assessed. Every distance level between the starting nodes and the destinations, ranging from 0 to 3 km, is given a distinct score according to this model. The map will then be overlaid with the PET map to create a green pedestrian network. Imola, a historically big city in Italy with a humid subtropical climate, is the subject of the case study. The city, which has a population of 70,000, has a total area of 204 km^2. The city, which is part of the Bologna metropolitan area, has frigid winters and sweltering summers. The neighborhood in Imola that was chosen is in the city's historic district and is distinguished by its low-rise structures and scant street tree canopy coverage (Fig. 11).

The implementation of a digital twin in Imola, Italy, aims to enhance urban planning and address walkability challenges within the historical contextual 3D replica of Imola's urban elements and objects, enabling city planners and stakeholders to visualize, analyze, and optimize various urban planning scenarios. By incorporating multiple data sources such as cadastral data, aerial imagery, LiDAR, and socio-economic information, the digital twin offers a dynamic representation of the city's existing conditions. As a result of its low tree canopy cover and low-rise building structures, Imola's digital twin focuses on its historical core. This problem is addressed by incorporating data on public green nodes, public transportation nodes, and public urban spaces into the digital twin. Imola's city planners can identify potential improvements to the pedestrian network by analyzing the connectivity and accessibility of these nodes, leading to an increase in walkability and a greater quality of life for the city's residents. Additionally, planners can use the digital twin to evaluate the impact of various urban interventions, such as adding green spaces, expanding public transportation, or redesigning streets to prioritize pedestrians and cyclists. In order to create a more sustainable and livable city, stakeholders can simulate these interventions in a digital environment to better understand their potential outcomes and make more informed decisions.

As shown in Fig. 11, a three-dimensional model of the city has been developed, which includes connections, buildings, and urban vegetation [134]. The thermal comfort digital twin model presented in this study aims to effectively mirror the physical world through a three-step process: data collection, learning process and analysis, and post-implementation processes and decision-making. This innovative approach allows for an understanding of urban microclimates, walkability, and green pedestrian networks, ultimately supporting urban planners in making informed decisions. Data collection involves gathering a variety of data sources, such as meteorological data, GIS data, remote sensing imagery, and socio-economic information. These datasets are crucial for constructing a detailed and accurate digital twin that reflects the physical environment and its microclimatic conditions. After collecting the necessary data, ML algorithms and other analyt- ical tools are employed to process and analyze the information, allowing the model to learn patterns and relationships between various factors, such as urban morphology, vegetation, and thermal comfort. The outcome is an understanding of the factors influencing walkability and green pedestrian net- works within the urban context. confirming the digital twin and utilizing it to assist in decision-making for urban planning and design is the model's last stage. The digital twin may be improved to incorporate a wide range of data sources and simulations on many dimensions and themes by fusing offline microclimate models with real-time data sources.

6. Green infrastructure inventory

In order to create an inventory of local green infrastructure components in the research region, the first step in was to identify botanical species and their locations (Fig. 12). The location of the urban green infrastructure samples was established in the field using a GPS device. The measured points were saved as a KML file for Google Earth. In addition to registering the species of each specimen, a unique identification number for each item of urban infrastructure was documented in

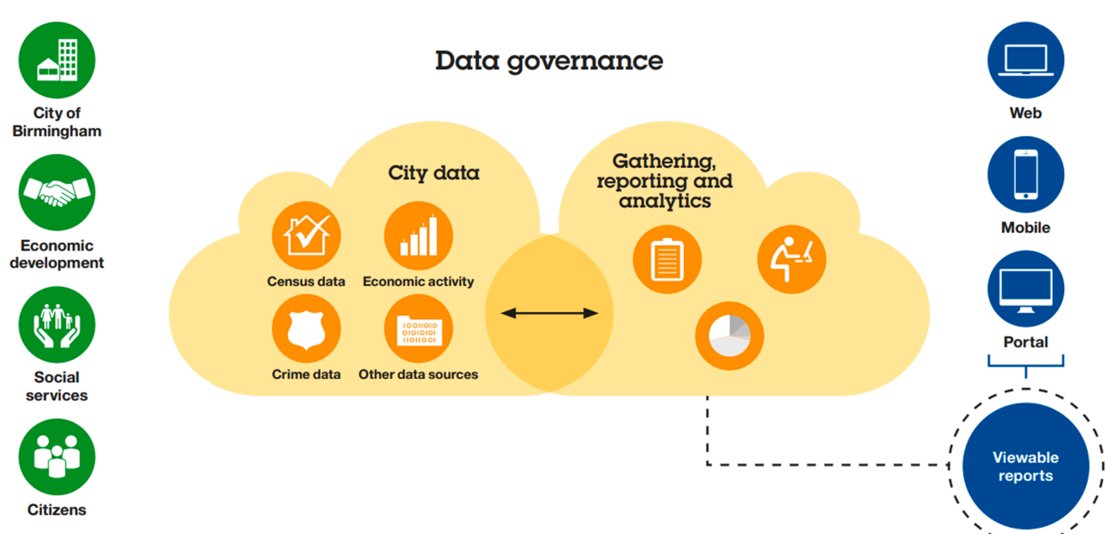

Fig. 10. Charting an ecosystem of activities throughout Birmingham [133].

an interoperable table using the KML format. The following phase entailed employing engineering and mapping techniques to determine the geometric dimensions of the specimens under study. By measuring the area (in square meters) of the crown projection over the orthophoto image with ArcMap GIS software, the surface area of each tree crown was documented (Fig. 12). Using Autodesk Recap software, the dimensions of each specimen from the LiDAR point cloud were measured in order to determine the specimens' height (Fig. 12). A list that was obtained had dimensions that were quite similar to those of genuine specimens. This 3-dimensional Green Pedestrian Network (GPN) digital twin's first section aims to estimate the Physiological Equivalent Temperature (PET). Based on Python 3.8.1 code, a hybrid model is developed which simulates each parameter in its own engine. The interrelationships of the parameters are programmed as an Python script in order to guarantee accuracy of input and output ordering in each phase, as well as the outcome of the model in the final step. There are three engines used in the model: EnergyPlus, Grasshopper, and OpenFOAM. Imola's historic center is shown in Fig. 12 [134].

Imola's historic center is shown in Fig. 12. The following steps are involved in the PET calculation:

1) Calculation of the body's thermal state for a specific set of meteorological variables using the Munich Energy-Balance Model for Individuals (MEMI);
2) Entering the computed mean skin and core temperatures into the MEMI

model and solving the energy balance equation system for air temperature with specific parameters ($v = 0.1$ m/s, vapor pressure (VP) = 12 hPa, and mean radiant temperature (T_{mrt}) = T_a) (Table 6).

In Table 6, the ranges of the Physiological Equivalent Temperature (PET) for different grades of thermal perception by human beings and physiological stress on human beings can be classified as follows (with internal heat production at 80W and heat transfer resistance of clothing at 0.9 [135]. Using the MEMI model. As a result of this method, the digital twin can accurately calculate the PET values across the urban environment, which will help to inform decisions related to improving walkability and establishing green pedestrian networks in urban planning and design.

7. Digital twin modeling and real-time visualization

A real-time link between the virtual digital twin and the real world was suggested by Wang et al. [136]. IoT sensors capture data, which is recorded in real-time in a database. By evaluating, modeling, and making decisions based on real-time data, users may build a virtual representation of the actual world. Gao et al. [137] introduced the idea of a digital twin production line based on simulation and modeling of the production line and digital twin. The production process for the digital twin is then in real-time modeled and simulated. The usefulness of the suggested approach is illustrated with an illustration of a product assembly line. As part of NASA's design, operation, and monitoring of airplanes, grieves initially put out digital twins in 2011. Scholars have created a large number of 3D models of Digital Twin technology. Digital twins were used by Sepasgozar et al., [138] to assess the feasibility of combining virtual and actual energy in industrial systems. A 3D representation of the digital twin utilizing the EnergyPlus, Honeybee, and Ladybug components from the grasshopper framework was recommended by Gholami et al. [134] for the Rhinoceros platform. Based on in situ datasets that demonstrate its dependability, a digital twin for the GPN is verified. Additionally, by giving urban planners and policymakers a precise and helpful approach for modeling pedestrian-level urban greenery impacts on human thermal comfort, it assures the effectiveness of policies in various urban contexts. Stakeholders can concentrate on their individual duties with the aid of the digital twin building system developed by Choi et al. [139]. The instances in this essay also concern Korean suppliers of car components. The system is simple to use for both major organizations and small and medium-sized businesses (SMEs). The digital twin may be utilized to easily manage the production site in addition to watching CCTV. According to Yang et al.'s [140] description, true 3D was achieved by transferring structural and semantic geographical elements that facilitate human- machine

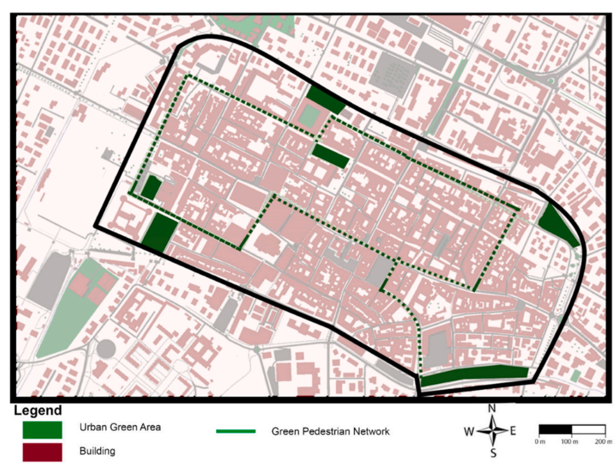

Fig. 12. The Green Pedestrian Route Network in Imola's historic center [134].

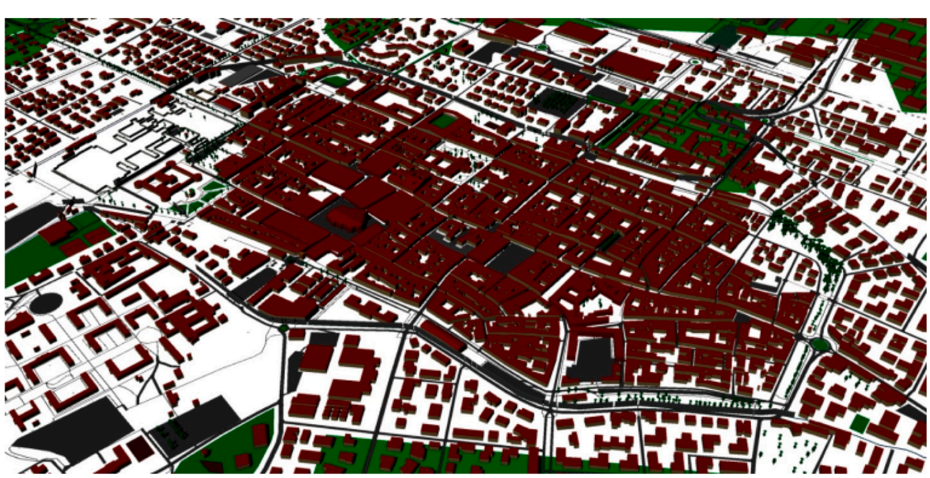

Fig. 11. The 3-dimensional model of the city includes connection routes, buildings, and urban vegetation [134].

compatibility and real-time perception of the IoT on 3D geographical sceneries. Digital elevation models, digital surface models, digital orthophotos, actual orthophotos, oblique 3D models, and laser point clouds are a few examples of digital representations of geographic scenes. The use of scanners to gather data presents a number of novel opportunities and difficulties, according to Perc and Topolek [141]. This analysis examines the digital development of smart green buildings to generate continuous ecological development regions in green ecological cities. The major points of Intelligent Green Buildings (IGB) are described in this part, along with the use and function of digital twins in intelligent buildings.

8. Discussion and potential limitations of digital twins

Digital twin modeling and real-time visualization as a powerful tool for modeling and simulating physical systems in real time, digital twins have gained attention in recent years. Through virtual representations of physical systems, data can be analyzed and manipulated in real-time, enabling more informed decisions and efficient management. There are, however, several limitations and challenges associated with digital twins that need to be considered, despite their potential benefits. The accuracy of digital twins is one of their potential limitations. A digital twin can only be as accurate as the data it is based on, so any errors or inaccuracies in the data will affect its accuracy. Any faults or malfunctions in the sensors or technologies used to collect data can also affect the accuracy of digital twins. Below is a summary of each application's limitations:

1. Data-driven vs. data science: In order to accurately represent complex systems being modeled, data science rather than a data-driven approach is needed.
2. Complexity of digital twins: Creating an exact digital twin of complex systems, such as life on Earth, weather, climate, and human health may be more challenging than creating a simple, static digital twin.
3. ML limitations: Modern ML models have impressive numbers of parameters, but they can't capture all the interactions and effects, leading to inaccurate predictions.
4. AI concerns: There is no universal AI, and AI systems are black boxes, which raises concerns about their potential harm and the need for meaningful human control.
5. Optimization challenges: Due to the lack of science to determine the right goal function, the concept of optimizing the world is problematic.
6. Data-driven society limitations: Intangible qualities are important to human life, but data-driven societies may struggle to achieve them.
7. Disruptive innovations: Digital twins can make pessimistic predictions that do not take into account disruptive innovations.
8. Humans vs. things: In a highly networked and complex world, managing people like things that pose ethical challenges.
9. Dual-use concerns: In order to prevent dual-use and improve transparency and accountability, digital twins, due to their powerful nature can cause large-scale damage.
10. Alternative uses of technology: The socio-ecological finance system promotes sustainable circular and sharing economies as an alternative to traditional technology-driven approaches.
11. Need for social innovation: The digital age can be fully tapped by promoting a multi-stakeholder approach to participatory resilience through social innovation.

Therefore, Complexity is an opportunity for new solutions and digital assistance can support flexible adaptation and co-evolution, but it is important to recognize that societies are not machines, and a narrow optimization approach is not sufficient to manage them.

Table 6
Thermal perception ranges of physiological equivalent temperatures (PET).

PET	Thermal Perception	Grade of Psychological Stress
$\leq 18\ ^\circ C$	Very cold	High
$18\ ^\circ C - 23\ ^\circ C$	Cold	Moderate
$23\ ^\circ C - 26\ ^\circ C$	Slightly cool	Slight
$26\ ^\circ C - 29\ ^\circ C$	Comfortable	None
$29\ ^\circ C - 32\ ^\circ C$	Slightly warm	Slight
$32\ ^\circ C - 38\ ^\circ C$	Hot	Moderate
$\geq 38\ ^\circ C$	Very hot	High

9. Conclusion

By building on the insights and contributions presented throughout the paper, our conclusion underscores the potential transformative impact of combining AI with digital twin models in the development of stormwater infrastructure systems within smart cities. Besides enabling more efficient resource management, this integration contributes to urban resilience and sustainability. Increasingly, AI technology is playing an increasingly pivotal role in augmenting digital twin models, providing sophisticated solutions to the multifaceted challenges of urban stormwater management. The present study reveals the current state and capabilities of digital twin technology in urban water systems management based on an review of existing literature and enriched by diverse case studies from cities such as Helsinki, Zurich, and Vienna. This paper lays a solid foundation for understanding how digital twins can be optimized through AI by clarifying terminology, practices, and fundamental technologies. The exploration of digital twins in managing smart water systems, from short-term forecasting to the enhancement of decentralized systems, underscores the critical role AI plays in revolutionizing stormwater management within smart urban environments.

In addition to demonstrating practical applications of digital twins in urban water management, the case studies also highlight key research areas where AI can further revolutionize these processes. In this study, we examine digital twins' contributions to green infrastructure planning and the pivotal role of real- time data visualization in the creation of more sustainable and resilient urban landscapes using AI-enhanced digital twins. The purpose of this paper is not only to examine the status of digital twin technology and its integration with AI, but also to project its trajectory in the future. In spite of the study's limitations, it identifies crucial implications for future research on AI-enhanced digital twin models, particularly in relation to the stormwater infrastructure of smart cities. With the development of digital twin technology, combined with advances in AI, complex urban challenges can be addressed more effectively. We must continue to explore and refine the integration of AI into digital twin models in the future to ensure that these technologies can fully realize their potential in contributing to smarter, more sustainable urban environments. In this endeavor, we can anticipate not only the enhancement of stormwater management systems, but also the improvement of urban living conditions in general, a step towards the realization of truly smart cities.

CRediT authorship contribution statement

Abbas Sharifi: Writing – original draft, Supervision, Software, Project administration, Methodology, Formal analysis. **Ali Tarlani Beris:** Writing – review & editing, Validation, Resources. **Amir Sharifzadeh Javidi:** Investigation, Data curation, Conceptualization. **Mohammadsadegh Nouri:** Writing – review & editing, Validation, Software. **Ahmad Gholizadeh Lonbar:** Methodology, Investigation, Data curation. **Mohsen Ahmadi:** Writing – original draft, Supervision, Methodology, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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