WORKING PAPER

Options for Digital Twin Application in Developing Country River Basin Management: A Review

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ABSTRACT

A Digital Twin (DT) is a digital representation of reality. This report explores the implementation of DT in the context of basin scale water management, with a particular focus on developing countries. The review begins with an examination of the background of DT and then delves into successful applications of DT particularly in developing nations. It also explores the potential of integrating Virtual Reality (VR) technologies as a part of DT, emphasizing the importance of stakeholder needs assessment for effective deployment. The review highlights the significance of data infrastructure architecture and data governance in the context of Digital Twins. The review concentrates on the published literature and the application of Digital Twins to river basins, emphasizing their role in decision-making at this level and outlining various use cases for water management. Furthermore, it assesses the expected impact of DT through the lens of the Sustainable Development Goals (SDGs). The review concludes by exploring the integration of Artificial Intelligence (AI) in the context of DT for river basins. Overall, this review summarizes the potential benefits and challenges of implementing DT for water management in developing countries.

1. Background

Natural systems are inherently complex webs of interconnected components that encompass environment, ecosystems, and numerous earth system processes operating at scales. Human activities and their iterations with these systems make them more complex leading to several intended and unintended consequences with dynamic feedback loops. While these complexities have always existed, these have increased due to the recent technological explosion (Sargut and McGrath, 2011). As averred by Sargut and McGrath (2011), the complexity has gone from something found in large confined systems, such as factories and cities, to remote environments such as entire river basins. The non-linear effects and dynamic feedback loops from the natural systems and their human interactions are making it harder to predict what will happen because they interact in unexpected ways and are difficult to manage. This is especially true where reliable data are not easily accessible.

River basins are complex natural systems where human activities imparted profound influence on water, land, ecosystems, and climate patterns. There is no doubt that the management of the water resources of a basin is a complex issue due to the inherent interplay of the changing environment (Bernhardt et al., 2006; Cosgrove and Loucks, 2015; Leb et al., 2018; Young and Harshadeep, 2020). River basin ecosystems provide water resources for agriculture, livestock, and fisheries, industry and for domestic use, sustaining the livelihoods of

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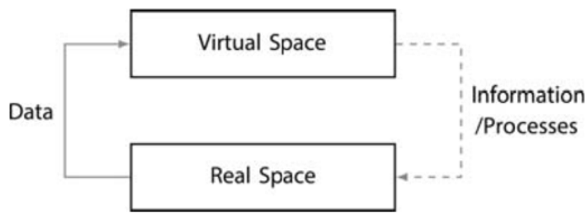

Figure 1 A simple representation of Digital Twin (Jones et al., 2020)

millions of people in the region. Nonetheless, these river basin ecosystems are also subject to hydroclimatic extremes, land degradation, poor water quality, urbanization and population growth. These environmental shifts not only pose a threat to the rich biodiversity in river basins but also weaken the resilience of local communities to climate change (Fazey et al., 2021; Carmen et al, 2022).

To effectively manage these complex natural systems impacted by human activities, there is a need to leverage technological advancements such as high-performance computing, Artificial Intelligence (AI), and real-time database management systems. The DT concept is an advanced version of traditional Decision Support Systems (DSS) used to manage water resources and environmental processes in river basin ecosystems. By utilizing new generation sensors, big data, cloud processing and AI, a digital representation of the river basin is created, providing a dynamic framework that offers comprehensive information for effective management.

A DT is a rapidly emerging concept that digitally depicts an object, a process, or a system (Grieves, 2014; Ademenko et al., 2020 and references therein). Grieves and Vickers (2004) pioneered the work of DT and presented a DT framework as comprising three components, a physical object, a digital representation of that object, and the bi-directional data connections that feed data from the physical to the digital representation, and information and processes from the digital representation to the physical (Figure 1). DT has the capability of accelerating innovation (e.g., improved modelling of system changes or optimized business supply chains) if coupled with the Internet of Things (IoT) or AI (Jones et al., 2020).

A review of DT literature by Jones et al. (2020) demonstrated increased interest in recent years across both academia and industry as seen in the growth in the number of related publications, processes, concepts, and envisaged benefits. In a bid to determine if DT could be used in the Nature-based Solutions (NbS) for stormwater and transboundary water security projects, the existing conceptual challenges and the DT definition as a framework were examined (Brasil et al., 2022). They identified how the mathematical modelling reported in the literature could improve the DT development, and evaluated the potential benefits associated with the application of DT in NbS. Noting the sparse presence of DT applications in water resource management and in particular river basin management, the present review aims to a) establish the role of AI techniques such as machine learning, deep learning, and data analytics in enhancing the predictive and decision-making capabilities of digital twins, b) compile information about existing DT applications in developing countries, c) assess the DT infrastructure, architecture and data governance frameworks, and d) characterize the relevant DT use cases for river basin management. This review contributes towards developing a robust conceptual framework for an operational Limpopo River Basin DT.

2. Literature Review

The era of digital technologies capable of transforming the livelihoods of developing country populace is now more obvious. Yet the inherent core pillars including the digital infrastructure, human capital and enabling environment, continue to act as impediments to these countries' massive digital ecosystem potential that is hugely needed for socio-economic equitable growth (Union, 2020). Juxtaposing the role that water sensitive sectors play in support of advancing economic growth, socio- and gender equity and creating jobs under changing climate, this underscores the value of digital innovation ecosystem in the context of water resource management (Shilin et al., 2021; Józefowicz et al., 2023).

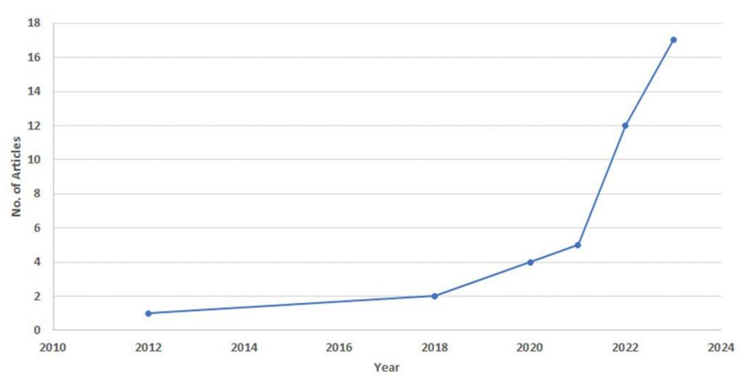

Figure 2 Annual publications of Digital Twin applications for river basin management globally. There are a total of 41 peer reviewed scientific publications between 2012 and 2023 (Source: Authors)

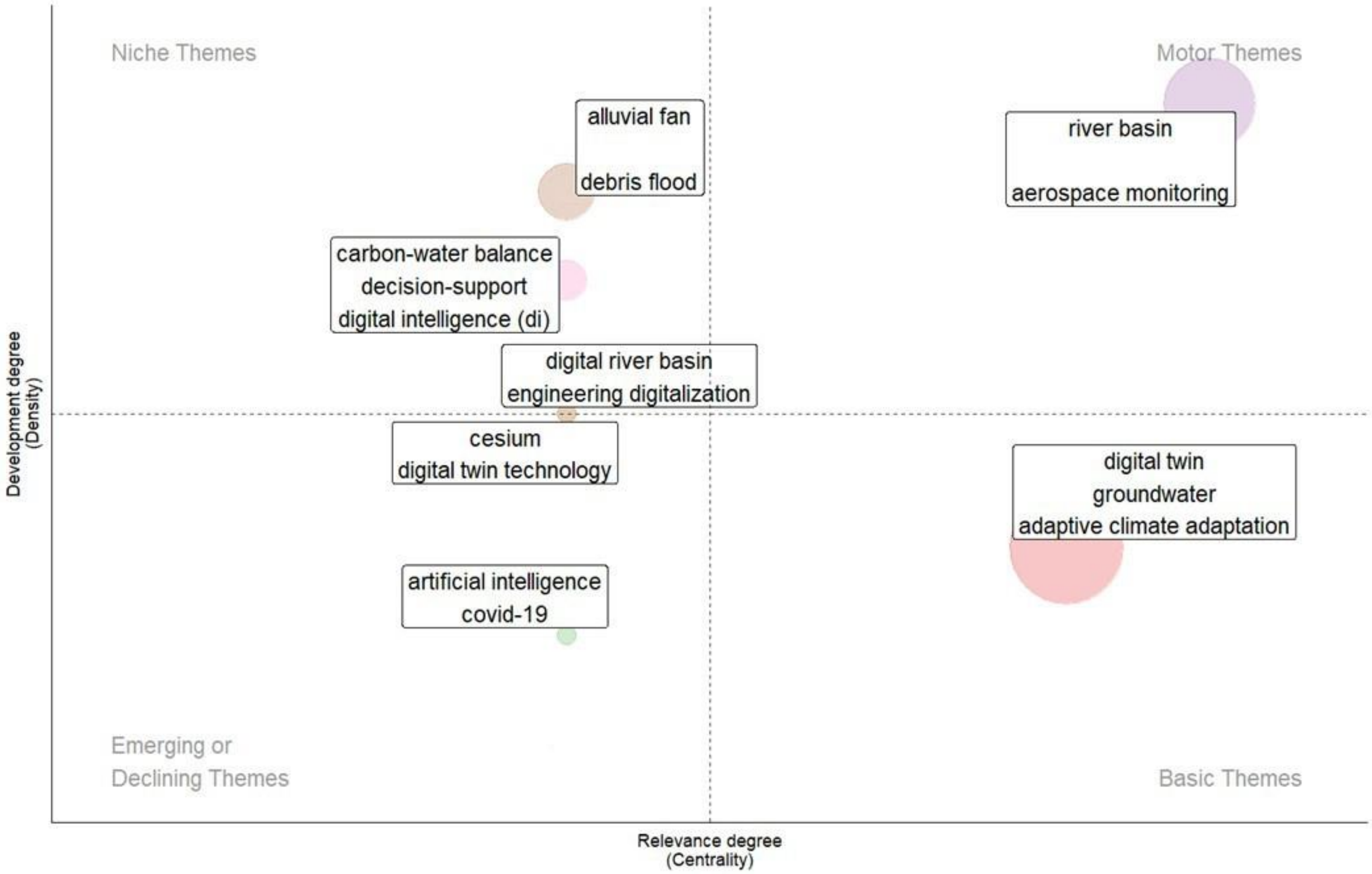

Figure 3 Trends of research themes. Upper-right quadrant are the motor themes (hot topics); themes appearing in the upper-left quadrant are considered very specialized topics-niche themes; the lower right are termed basic themes; emerging or declining themes are generally weakly developed, have low density, low centrality and are either emerging or disappearing.

Fortunately, our world is abuzz with disruptive technologies that are transforming the way we respond to the present and future challenges. The digital transformation strategy for Africa (2020-2030), avers that;

> *"Africa presents a sea of economic opportunities in virtually every sector, and the continent's youthful population structure is an enormous opportunity in this digital era and hence the need for Africa to make digitally enabled socio-economic development a high priority."*

Against the backdrop of the digital transformation strategy for Africa, there is need to ameliorate the unique challenges of adoption of digital technologies across Africa. There is no doubt that the new technologies and approaches for digitalizing and smartening water systems through Big Data, algorithm development and Artificial Intelligence (using Deep & Machine Learning) are increasingly being recognized globally. While Digital Agriculture & Digital Water Innovations (hereafter DA-DW-I) have a global footprint, arguments for their impact and developmental implications are generally subtle in the global South (e.g., Amankwa et al., 2021).

Table 1 Digital Twin Research interests across countries

Country articles	Single-country	Multi-country
China	11	0
South Africa	3	0
United Kingdom	1	1
USA	2	0
Argentina	1	0

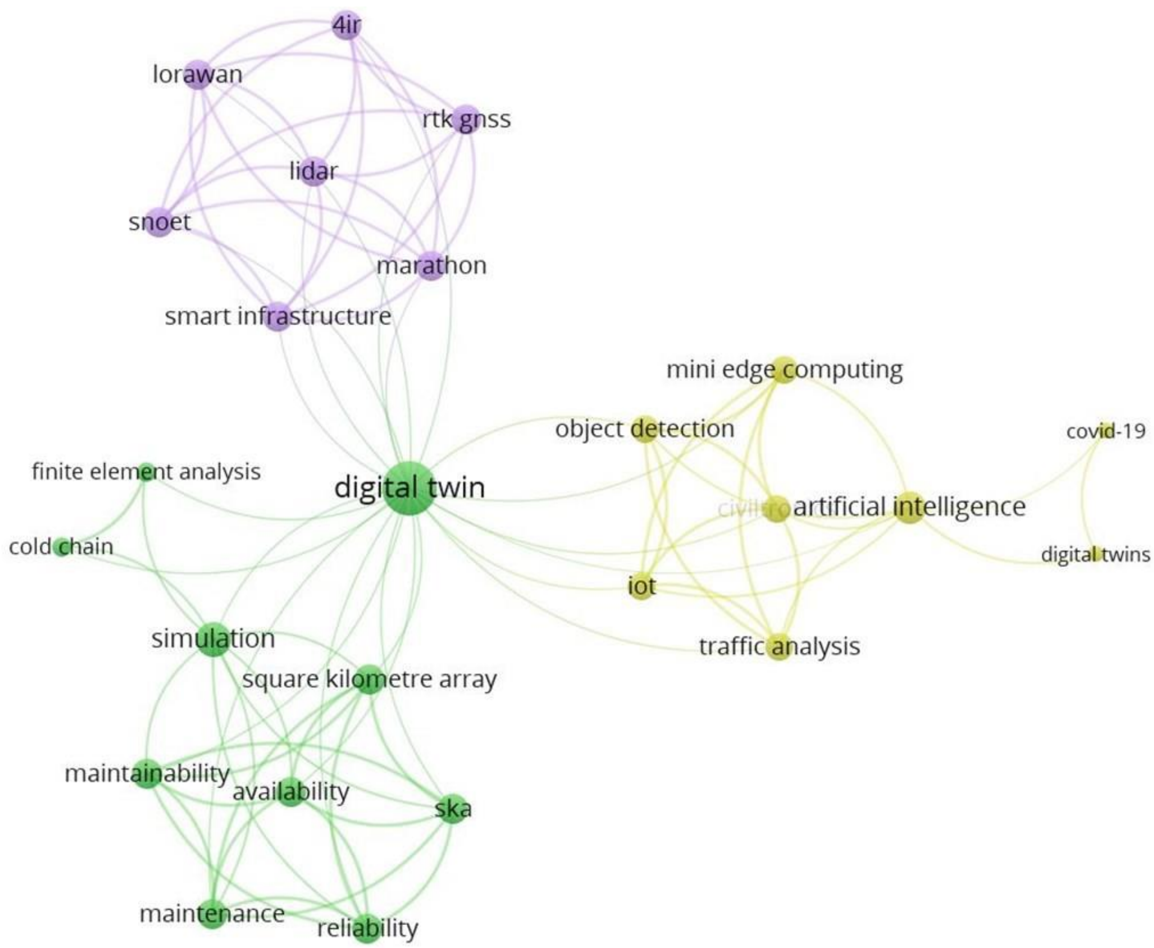

Figure 4 Content analysis of Digital Twin scholarship in Africa (Source: Authors)

Peer-reviewed published literature on DT and river basin management in scientific databases (e.g., Scopus and Web of Science (WoS)), illustrates that the global DT scholarship on river basin management is generally a nascent research agenda. This evidence is illustrated by more than 12 years of publications given in Figure 2, wherein the majority of the scientific articles focusing on DT only emerge in the past three years. There were 41 peer-reviewed scientific publications on DT with river basin references. In terms of the research interests across countries, the review analysis suggests that China and South African researchers are at the forefront, albeit surprisingly lacking collaboration as most publications focus on single country (Table 1). In terms of emerging themes in the DT research domain, the review established that there are subtle hot topics (upper right), very specialized (upper left) as well as basic (lower right) and emerging (lower left) research themes as depicted in Figure 3. The evolution of the research themes from a global perspective is expected to change as the direction of DT scholarship changes in future.

Table 2 Nature of country collaboration on the DT publications in Africa

Country articles	Single-country	Multi-country
South Africa	2	1
United Kingdom	1	1
France	0	1
Germany	1	0
Morocco	1	0

In reviewing published literature on DT in Africa, few key words were used i.e., “Digital Twin” and “Africa” and the search kept to “within” abstracts only. Only nineteen articles (17 from Scopus and 2 from WoS) were extracted that had some content on DT. A quick analysis of the trends, and social

Figure 5 A computer-generated digital environment of the Hatfield Digital Twin City, Pretoria, South Africa (Source: https://www.up.ac.za/news/post_3008856-future-fit-african-cities-up-designs-digital-twin-city-to-improve-metro-management. Assessed on 11th October, 2023)

networks of the DT scholarship illustrated that the scientific discourse only emerged in databases considered from 2018 (only one article) with most articles published in 2023 (7 seven articles). Seven peer reviewed scientific publications on DT (where river basin management is also mentioned) were published between 2020 and 2022. The composition of the article types illustrated that most of the DT research has mostly appeared in scientific conferences, while five, two, and four appeared in Journals, Book Chapters and Reviews respectively. The nature of publication collaborations by country, Table 2, illustrates that DT scholars from South Africa and the United Kingdom exhibit both single and multiple country publications while France, Germany and Morocco have single country publications. To understand the research direction or applications of DT in Africa, Figure 4 shows the content analysis of abstracts of the 17 reviewed articles. Though research on DT in the African continent is still at it's infancy, content analysis results of the reviewed articles given in Figure 4 bring forth three main research directions, i.e., methodology, applications and use. It however important to note that these results are not exhaustive at this stage.

Smart City and Digital Twin City are new novel methods of city management being implemented worldwide, in response to the expansion of cities and megacities in the current era of technology disruption, rapid urbanization and climate change. For instance, in 2021, the University of Pretoria announced the creation of Hatfield Digital Twin City, a novel initiative that aims to boost service delivery with the help of smart technology (Figure 5).

A literature search of smart city applications of DT in the African continent resulted to only the following notable publications:

a) Nigerian Electricity Supply Industry (NESI): Aliyu et al. (2021) analyzed the NESI framework and concluded that the system uses a novel framework that is premised on a SoS and digital twins.

b) Broekman and Steyn (2022) reported on Digital Twinning of Lap-based Marathon Infrastructure: the digitization of the marathon route using Real-Time Kinematic Global Navigation Satellite Systems (RTK GNSS) and high-density Light Detection and Ranging (LiDAR) sensing capabilities to allow for the detailed geometry measurements and environmental analysis before and after such events. They concluded that the intersection of engineering and sports disciplines and technology illustrates the potential realization of smart cities and recreation in an evolutionary society.

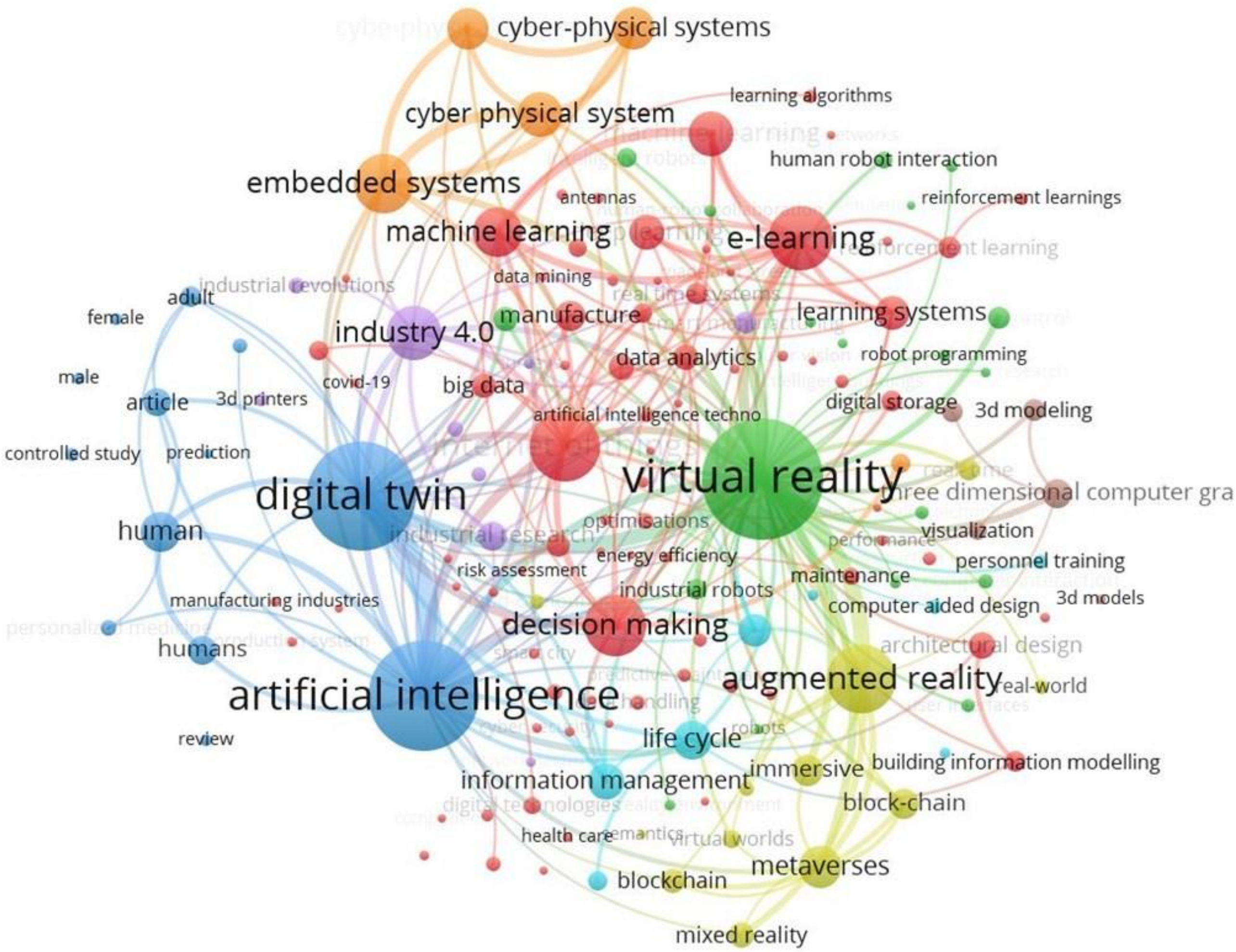

Figure 6 Digital Twin and the virtual reality-related research themes (Source: Authors)

c) Braekman et al. (2021) designed a real-time traffic quantization using a mini edge artificial intelligence platform as a proof of concept of a mini edge computing platform for real-time edge processing, which serves as a digital twin of a multi-lane freeway located in Pretoria, South Africa.

3. Digital Twins and Virtual Reality

In the rapidly advancing technological era we inhabit, it is advantageous to critically evaluate the functionalities and applicability of immersive and interactive digital technologies such as Virtual Reality (VR) to sectors which impact our well-being and quality of life in sectors such as agriculture and water management. Furthermore, it is important to explore how these emergent technologies like VR can shape and guide decision making in water resources management, aid in risk management and accelerate technology usage. This will result in the generation of innovative technology-based solutions toward solving river basin challenges to ameliorate humanity and the sustainability of food and water resources.

Gigante (1993) defines VR as being “characterized by the illusion of participation in a synthetic environment than external observation of such an environment. It relies on three-dimensional, stereoscopic, head-tracked displays, hand/body tracking, and binaural sound”. Additionally, VR may be delineated as an immersive, multisensory experience (Holuša, et al., 2023; Azarby, & Rice, 2022). It is also referred to as providing virtual environments, virtual worlds, or microworlds. A journal titled, Development of a Digital Twin for smart farming: Irrigation management system for water saving asserts that the "digital twin applied to agriculture is in its early stages of development". It further defines a digital twin as an entity where "data flows automatically and in both directions between a physical object and a virtual object" (Alves, Maia & Lima, 2023). It is imperative to note that the adoption of these technologies is in an experimental phase and the consolidation of two or more technologies such as DT and VR is an even more recently employed practice. A literature review on the linkages between VR and DT revealed an interesting pattern of these two concepts. The concepts of VR and DT seems to have appeared only in the last two decades (based on the Scopus and WoS databases). According to the two databases, 857 articles (comprising of largely journal articles-50%; and conference papers-25%). Most of the scholarship only emerged post-2018. In terms of the linkages between DT, VR and Artificial Intelligence (AI), Figure 6 illustrates detailed interconnections between the three concepts and other antecedent terminologies. As shown in Figure 6, there are intrinsic interlinkages between these three concepts and other concepts such as data analytics, augmented reality, machine learning – all related to advanced computational techniques.

There are a host of possibilities for the application of technologies such as DT and VR to actively address water management concerns specific to river basins in developing African countries. The unique characteristics DT and VR offer respectively and when combined provide useful real-time data to allow for the continuous monitoring of river basins. Firstly, DT and VR offer accessible realistic digital visualizations which enable integrated river basin modelling. While DT establishes a real-time virtual representation of the river basin presenting water flow, dam operations, pollution sources and other environmental elements, VR allows for the visual navigation of the DT model and permits interactivity where users may directly impact the virtual environment they are visiting using their senses including sight, touch, smell and hearing to observe the real-time condition of river basins.

River basins play a pivotal role in supplying fresh water and regulating water flow and quality. A DT and VR collaboratively may be used to monitor the physical condition of the river basins. The DT will provide the data analytics required while VR will allow scientists and engineers to conduct virtual inspections and assessments eliminating the need for them to be physically present. Lastly, in the case of water crises such as droughts or floods the data extracted from the DT can be analysed to predict heavy rainfalls that may cause floods or increased evapotranspiration and the over-extraction of ground water that may cause droughts. Concurrently, VR can be employed to pre-visualize droughts and floods before they occur to implement prevention tactics or mitigate the impact if inevitable.

An exemplary case study where DT and VR has been utilized cooperatively to combat agricultural related challenges can be seen through AgroIT, a company that provides technological solutions for the agricultural sector, particularly focusing on precision agriculture. AgroIT's platform uses Digital Twin technology to create a virtual representation of farmlands, incorporating data like soil conditions, weather, and crop health. On the VR front, they have explored its use for visualizing these digital farms. This combination allows farmers to virtually 'walk' through their fields, visualize potential problem areas, and make informed decisions about irrigation, fertilization and other operations[1].

The ambitions of DT and VR for environmental application in developing countries based on its previous uses are to aid in water resource management systems. This one day may be as advanced as integrated user interfaces. Virtual reality is also known as an 'empathy machine' because of its unique ability to immerse users in emotionally charged perspectives, experiences, and environments which may prompt positive actions and behaviors in real life. Through the advancement of brain-computer interfaces users might control DT simulations or navigate VR environments using their thoughts. This could lead to more intuitive user experiences and might even allow for emotion-driven simulations, where users can "feel" the impacts of different river management decisions. DT and VR technologies strategically locate themselves at the heart of digital innovation as solution-based methods that directly address the need for visual representations to accurately measure the state of water, food and land conditions within various regions susceptible to food and water wastage, natural disasters and shortages. Researchers and scientists look forward to the progression of these technologies and the problems they will solve in the water management sector. A consideration of the manner we orient and define DT and VR as their operations evolve and their capacity expands will be essential to the integration and assimilation of these ever-changing digital innovations.

[1] Reference: https://cordis.europa.eu/article/id/202825-higher-quality-more-efficient-farming-through-open-standards

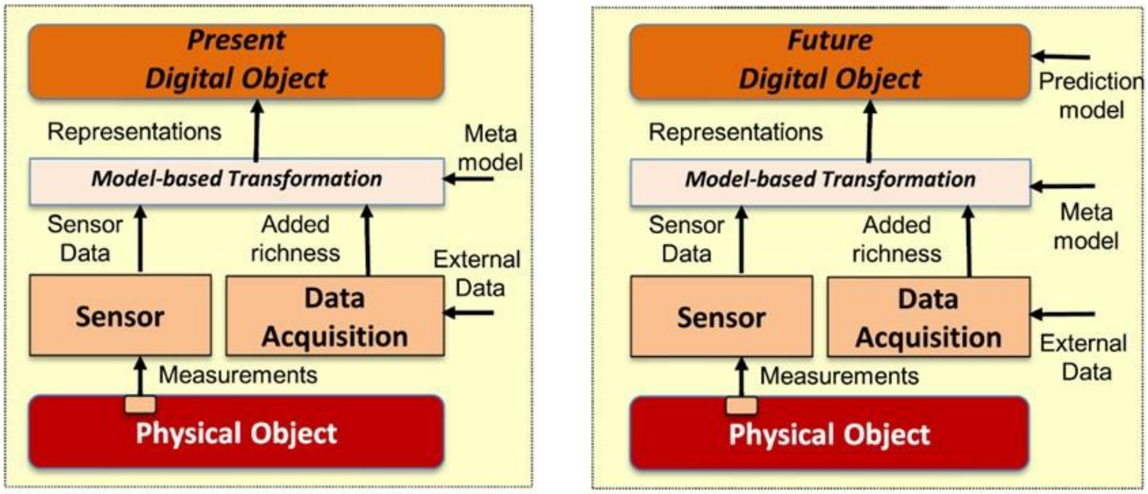

Figure 7 Digital Twin Typology (Source: Verdouw et al, 2021)

4. Stakeholder Needs Assessment

DT models are anchored on data from various life cycle phases that ought to be collected and analyzed to deliver services to a myriad of stakeholders. The utility of the DT services is dependent on the level of alignment with stakeholder needs. In order ensure uptake of the DT services, there is need to undertake stakeholder engagement through the development phases of the DT design and implementation. Stakeholders are defined as all groups and individuals who influence the aims of an organization, project or product and vice versa (Freeman and McVea, 2005). As part of stakeholder analysis, the stakeholders, their interests and their characteristics are identified. This is followed by clustering and prioritization of the stakeholders. After analysis, a strategy and recommended actions can be defined (Ramirez, 1999). From the DT design and implementation perspective, a stakeholder typology reported in Mitchael et al., (1997) as well as stakeholder identification based on the interest-influence matrix reported in e.g., Janssens de Bisthoven et al., (2022) should be considered. All the DT use cases relevant to river-based management presented in Section 7.2, undertook a well-designed iterative stakeholder engagement process during the design and implementation of the DT.

5. 3D Representation of a River Basin Digital Twin

The emergence of digital twin technology has revolutionized several fields, from manufacturing to urban planning (Tao et al., 2018). The application of this innovative concept to river basin management using the 3D Representation provides a compelling overview of the potential benefits and challenges faced. A river basin, being a complex system with a myriad of interrelated components such as water flow, sediment transport, vegetation, and human interventions, necessitates a robust modeling approach. The three-dimensional representation in the mentioned work provides a vivid and detailed visualization of these elements, making it an invaluable tool for stakeholders.

6. Data Infrastructure Architecture for a Digital Twin

The envisioned DT architecture is often characterized by two main typologies - monitoring and predictive DT as described in Figure 7. The monitoring typology represents the past and present dynamics of the physical and social-economic properties and interactions with the hydroclimatic environment, where a virtual representation is created using this data. From the perspective of predictive typology, predictive models will use past and present data to create a plausible future rendition of the present state of the environment.

As reported in Brasil et al. (2022) and Dhulipala (2021), a DT conceptual framework comprises the components briefly described below (also see Figure 8):

a) Data source layer: to accurately represent the LRB in a digital space, various data sets will be required. These data sets ought to represent not only the physical

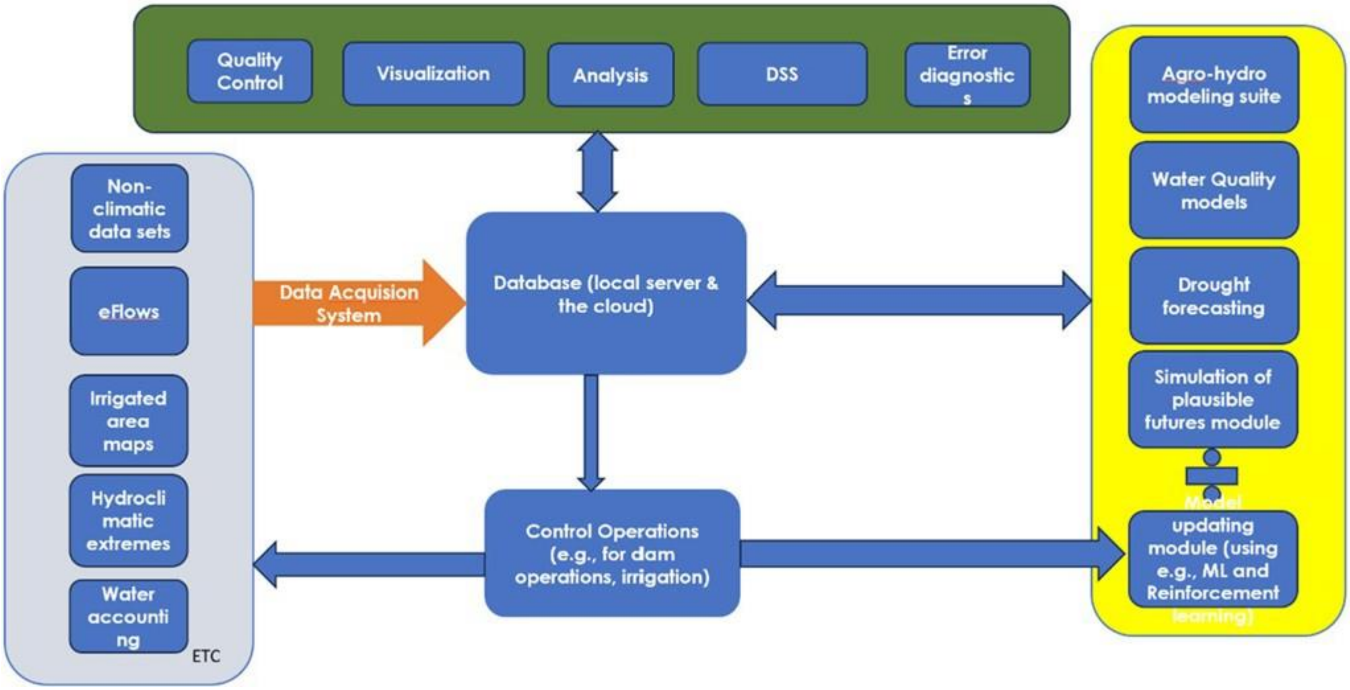

Figure 8 The physical environment, data storage, digital environment and applications services of the Digital Twin (Adapted from Brasil et al., 2022)

environment but also the biological and chemical conditions of the basin. Some of the data sources may include, remotely sensed data-from satellites and/or drones, hydrological process model data, ground observations (e.g., water quality/proxy measurements, weather data, mobile app captured data sets), and thirty party datasets which are often analysis ready (e.g., climatic data from the Digital Earth Africa platform or non-climatic datasets from the National Department of Statistics).

b) Data processing layer: One of the key functions of this layer is to pre-process and format the various data sets to ensure inter-operability among the various strands of the data. In addition, this layer executes a set of data modelling functions including hydrological process modelling, climate data downscaling and bias correction, satellite image classing to derive various product including hydroclimatic extremes and irrigated area maps.

c) Data visualization and analytic layer: Based on the outputs in b), this layer comprises GIS-enabled analytic tools embedded with dashboards to display various user selected features. Some of the key outputs from this layer would be the early warning messages that denote hydroclimatic extremes, risk areas and the general state of the river basin.

d) Advisory and dissemination layer: this layer is a rule engine embedded decision support rule system that helps provide intelligent management options suited for the present and future physical state of the river basin. These decisions are often disseminated using channels such as SMS/USSD, web and mobile applications, and even tower broadcasts once the system is implemented.

7. Digital Twin Data Governance Framework

At the heart of the DT, is the data collection, curation, management, analysis as well as output of data (Figure 8). Since DT information can be viewed as the high-end utility of all the data sets, a strong data foundation is necessary. To this end, a robust data foundation is underpinned by a strong data governance[2] and data management[3] strategy (see Plotkin,

[2] Data governance is the formal oversight, execution and enforcement of authority over the management of data.
[3] Data management is the effective management of data to achieve goals i.e. it ensures that an organization gets value out of its data while minimizing operating risk.

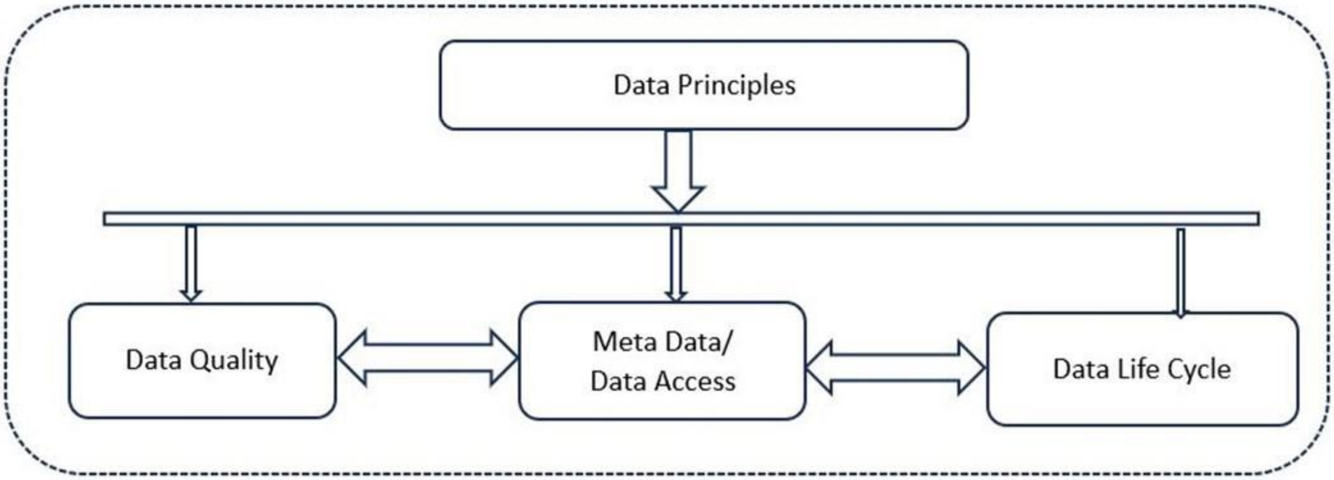

Figure 9 Data domains (Source: Khatri and Brown, 2010)

2020; Conarado, 2014). In the context of DT, the four decision domains of data governance reported in Khatri and Brown, (2010) are appropriate. Thus, a data governance framework could comprise; a) data principles (at the top) which are intended to establish the direction for all other decision domains, and set the boundary requirements for uses of data assets, thereby addressing standards for data quality; b) the data quality then determines how data are interpreted (metadata) as well as accessed (data access) by users; and c) the data life-cycle decision which defines the production, retention and retirement of data assets (Alhassan et al., 2016).

The aim of the DT for river basin management could be seen as the exhaustive capture of all physical environment parameters which are often intrinsically linked to aspects of people's lives, and intellectual property. Determining how this information is shared between organizations and individuals will naturally require some data sharing policy (Jones et al., 2020). This even more so when referring to both physical and virtual entities- to what extent does DT data ownership go? As a result, the question of ownership encompasses who accesses the data and for what purpose. As reported in Jones et. al., (2020), there are social and cultural implications associated with the large-scale collection, storage, and sharing of data through the Digital Twin that need to be fully addressed through a data governance framework.

While co-designed data governance framework could accelerate access and use of data and services of the DT, the following key challenges ought to be overcome;

a) Cataloguing for all the available data collected by separate and distinct scientists and/or institutions,

b) Understanding the data in the proper context and the need to link similar data sets together,

c) Akin to many sectors such as financial services, retail, and healthcare companies, there may be a lack of resources (e.g., data stewards) to curate and maintain the quality of the data.

8. Digital Twin for River Basins Applications

8.1. Digital Twin for decision making at the river basin-level

The utility of DT applications at basin level lies in the inherent adaptive capability wherein the near-real time river basin processes will be captured. As a result, any reactive measures (including plausible futures) lead to improved efficiency of the basin operations, optimized uncertainty measures, early warning detection and generally good emergency management (Pal et al., 2023). These salient features are supported by embedding AI algorithms with the DT architecture. The AI has the capability of providing additional insights beyond what the sensors provide through e.g., making future predictions of the state of the basin as well dynamically self-adjusting to independently determine optimal pathways towards a set of outcomes. Overall, DTs provide context to the data. As reported in de Koning et al. (2023), DTs will likely increase in popularity over the next decades, and this calls for greater attention focusing on how to capitalize on the strengths

Table 3 Examples of DT use cases for river basin management (Source: Authors' review)

Use-case name	Region/Country	Key problems	Architecture design	Selected data sources/inputs	Stakeholder engagement
Smart Lagoon (Cecilia et al., 2021)	Multi-country (Norway, Sweden, Italy, Denmark), Location: Murcia, Spain	Develop a DT to build a systemic understanding of the socio-environmental interrelationships affecting coastal lagoons and their ecosystem due to intensive agriculture and extensive urbanisation	Cloud-based system	Photrack: Discharge platform (web-based, mobile app); Geoserver map-based interactive interface (Geoserver map-based interactive interface); Social Sensing Tools (the front-end communicates with the web API, based on Google's Firebase; Apache Kafka cluster platform: publish; store and process these streams in real-time, distributes the information received from social media sources); WaterITech: ASAP Platform for real-time sensor data and short-term	Iterative stakeholder engagement undertaken
Innovative digital twin dam and watershed management platform (Park and You,	South Korea	Flooding damage and optimal dam operations	A GIS-based geospatial AI	Rainfall, dam and river; Water levels, flow rate; Closed-circuit television (CCTV); Three hydraulic and hydrological simulation models; Drones	Iterative stakeholder engagement undertaken
Digital Twin Ocean (https://op.europa.eu/en/publication-detail/-/publication/4902607b-e541-11ec-a534-01aa75ed71a1)	Multi-country	Restoring marine and coastal habitats, support a sustainable blue economy and mitigate and adapt to climate change	Block 1: Access to data, integrating existing data and new data flows, combined in a DataLake; Block 2: HPC: operational live model and additional capabilities, enabling the on-demand modelling powering; Block 3: front-end interactive simulation layer for user applications.	-Satellite & marine data, advanced models, AI and citizen science -A multi-variable and multi-dimensional description of the marine environment and biodiversity, from the coast to open ocean, from ocean physics to ice to biogeochemistry, from the surface to the seabed, allowing a digital exploration in time and space of the ocean according to different scenarios	
Smart river basin (https://www.freshwatercompetencecentre.com/digital-twin)	Vantaanjoki, Oulankajoki and Tenojoki catchements: Finland	Link the physical, chemical, biological and socio economic components	Data fusion tool (operational system for multi-sensor data fusion); Vemala river basin model: cost-efficient and participatory operations model for the monitoring, modelling and management of lakes and river basins	Chlorophyll-a data and turbidity from routine monitoring stations, ferrybox measurements, and data derived from Medium Resolution Imaging Spectrometer (MERIS) instrument on board the ENVISAT satellite	

of digital twinning for smart river basin management. While the popularity of DT is expected to grow, there is need to guard against the four key misconceptions about DTs elucidated in de Koning et al. (2023). These fallacies include the following:

DTs are not just

- AI/ML but they also require a good understanding of the domain of knowledge they represent,
- A large database of integrated data sets, but the context is only realized if modelling and simulations are embedded in order to give the data a meaning,
- Another word for a model, rather they are dynamic and unique from other forms of modelling. The users ought not be glued to the input data but are allowed to interactively explore system dynamics for decision-making, and
- A bid model for everything but are rather a simplified representation of a specific part of reality – either an entity, a system or a process.

Table 4 Impact of the Digital Twin based on the Sustainable Development Goal lens. Adapted from UN (2023). Accessed in October 2023.

SDG #	Description	Outcomes
6	Enable more sustainable management of water resources	• Satellite Data and Digital Twin Models incorporated into integrated water resources and river basin management at all levels, including through transboundary cooperation • International cooperation is expanded and capacity-building is supported through River Twinning frameworks
13	Improved actions to combat climate change and its impacts	• All countries' resilience and adaptive capacity to climate-related hazards and natural disasters are strengthened • Satellite Data and DT models are to optimise climate change measures into national policies, strategies and planning
15	Enable sustainable use of terrestrial ecosystems, combat desertification as well as halt land degradation and biodiversity loss	• Desertification, drought and floods are combated, and strive to minimize/eliminate land degradation • Conservation of ecosystems, including their biodiversity is ensured
17	Strengthen Global Partnership for Sustainable Development	• International scientific and technological cooperation is enhanced through Twinning of Rivers initiative for sharing knowledge and best management practices • Dissemination of environmentally sound technologies to developing countries on favourable terms is attained

8.2. Water Management Digital Twin Use Cases

Results of the literature review of DT for river basin management revealed that this area of research is still nascent and that many of the DT for river basins are on-going or are at conceptualization phases. The African region is worst hit given that many of the published literature on DT dwell on other sectors like construction, mining, energy and manufacturing. The only notable use cases relevant for smart river basin management are presented in Table 3.

8.3. Expected impact of Digital Twin through a lens of the Sustainable Development Goals

As outlined in UN (2023), Wu et al. (2023) and Pigola et al. (2021), the impacts summarized in Table 4 could be attained if the DT model for river basin eco-system is operationalized optimally.

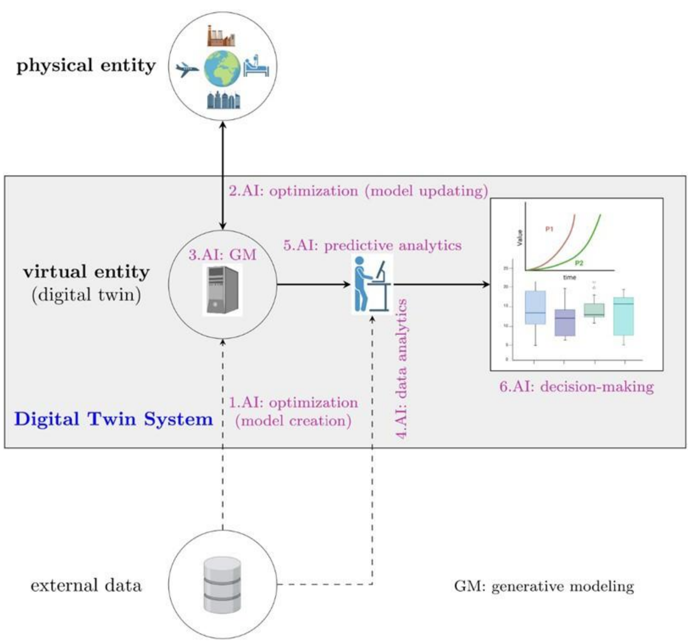

Figure 10 A Digital Twin System with depiction of the various contributions that AI can offer for optimizing the outcomes (Source: Emmert-Streib, 2023)

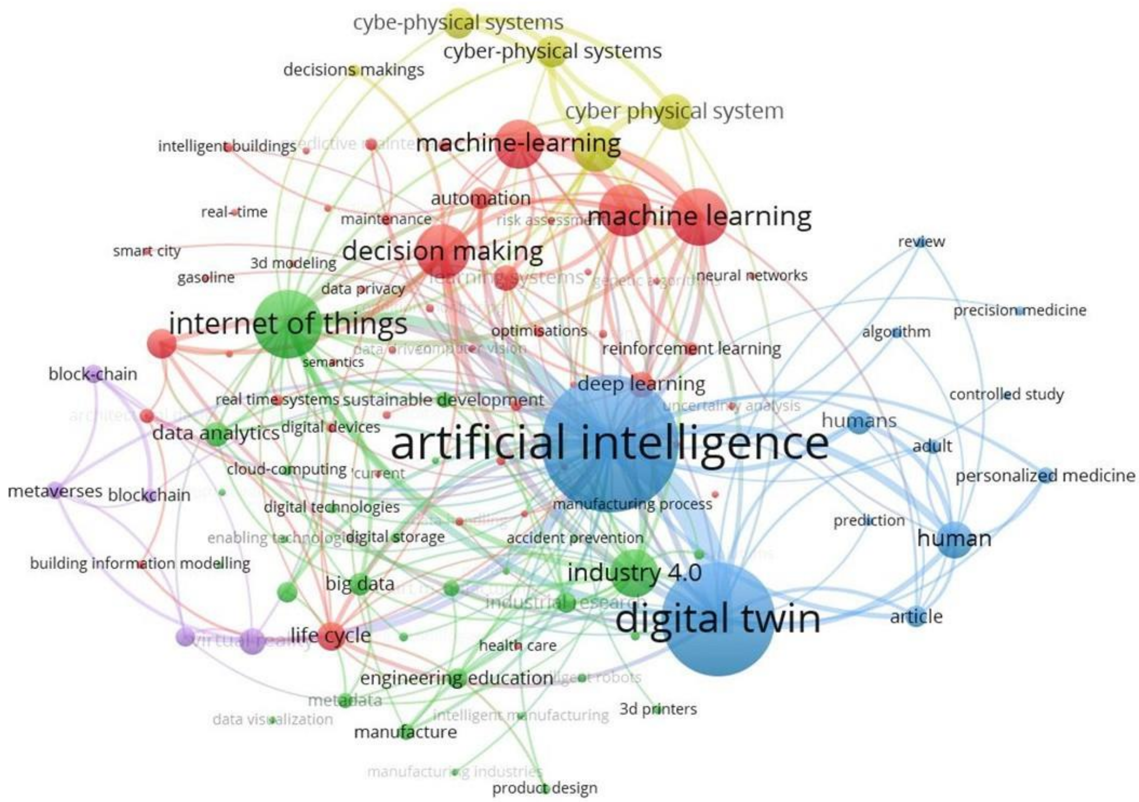

Figure 11 The linkages between DT and AI based on Scopus and Web of Science databases (Source: Authors)

9. Artificial Intelligence applications for River Basin Digital Twin

9.1. Status of AI integration with DT at river basin level

In addition to mechanistic models about the river basin ecology, DTs often contain elements of machine learning and AI to process a continuous stream of data (de Koning et al., 2023). Like a DT framework that utilises the lens of AI and Industry 4.0 reported in Kaklis et al., (2023), smart river basin management could be aided by an architecture that includes such components. From the perspective of Digital Twins Systems (hereafter DTS), it is important to underscore river basin management is better represented by not just a single DT but rather interconnected DT systems. In Emmert-Streib, (2023) and refences therein, the importance of AI and ML for digital twin research has been underscored. In part, Emmert-Streib, (2023) identifies six areas (Figure 10) of AI and ML integration in support of DT applications, i.e.,

a) AI: optimization (model creation)
b) AI: optimization (model updating)
c) AI: generative modelling
d) AI: data analytics
e) AI: predictive analytics
f) AI: decision making

Additionally, our own literature search from the Scopus and WoS given in Figure 11 depicts clear linkages between the DT and AI scholarship between 2007 and 2023. It is important to note that higher publication rate of the DT/AI scholarship only emerged from 2017 onwards- comprising largely journal articles (50%) and conference proceedings (18%).

9.2. Computational models and the AI Models of river basins

Recent advances in technology have led to the emergence of advanced analytic tools that have applications in natural resource management in general and water resource management in particular. Fuelled by the unprecedent amounts of environmental data, there has been a flurry of data science techniques and AI algorithms that have applications in making sense of the inherently complex and heterogeneous

Table 5 Examples of integration of AI in process models

Computational Models	AI Add on/contribution
Floods & Droughts monitoring& prediction	Use of fuzzy rule-based forecasts, Artificial Neural network, wavelet methods and Copulas (Kikon & Deka, 2022).
Hydrological /Hydraulic models	Exemplified by Gonzales-Inca et al. (2022) and the articles published in the MDPI Special Issue "Artificial Intelligence Techniques in Hydrology and Water Resources Management" (Chang et al., 2023).
Optimization	In Ezzat et al., (2023), five-phased approach premised on deep neural networks (DNN), artificial hummingbird algorithm (AHA), and explainable artificial intelligence was used to accurately and confidently predict water quality.
Early warning & decision making	Reported in Lamsal and Kumar (2020) and Gao et al. (2020).

data sets. Inevitably, the resultant data models and AI now work alongside process models (Babovic and Minns, 2022). Additional examples of these linkages are depicted in Table 5.

9.2.1. AI for floods & drought models

The implementation of AI in hydrology and climate modeling has revolutionized our understanding and prediction of extreme water-related events, notably floods and droughts. Traditionally, hydrological models are based on physical equations representing water movement in the environment. However, these models often require extensive calibration and may not capture non-linear and complex interactions in large systems (Kratzert et al., 2018). AI, particularly Machine Learning (ML) techniques such as Neural Networks (NNs) and Support Vector Machines (SVMs), offer a data-driven approach. By processing vast datasets from satellite imagery, river gauge readings, soil moisture content, and meteorological inputs, AI models can learn intricate patterns and predict potential flood or drought events with increased accuracy. Furthermore, AI integrates multiple data sources, capturing the dynamic interactions between atmospheric conditions, land use changes, and anthropogenic factors. This holistic view enhances our capacity to foresee, prepare for, and respond to water-related disasters. Especially with the imminent threats posed by climate change, AI's adaptability and continuous learning capabilities provide a cutting-edge tool for sustainable water management and disaster risk reduction.

9.2.2. AI for E- flows

Environmental flows (e-flows) are those river flows or discharges that "sustain aquatic ecosystems which, in turn, support human cultures, economies, sustainable livelihoods, and well-being. The goal of environmental flow management is to protect and restore the socially valued benefits of healthy, resilient, biodiverse aquatic ecosystems and the vital

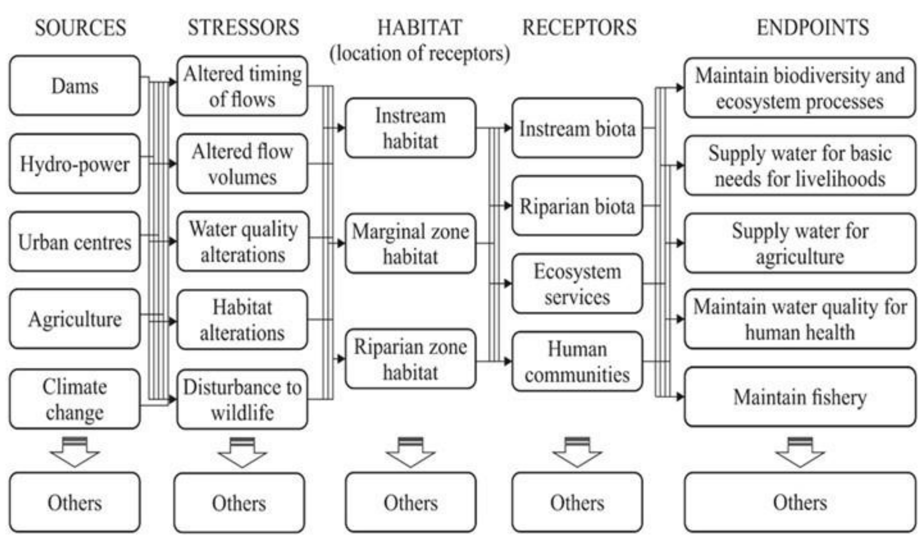

Figure 12 Basic conceptual model of the socio-ecological system for the Limpopo e-flow study (Source: O'Brien et al, 2022)

ecological services, economies, sustainable livelihoods, and wellbeing they provide for people of all cultures (Arthington, pers. Com. 2022). Thus e-flows are not just about protection of the natural environment, but they do so for the express purpose of supporting society.

There are now several hundred methods used to determine the e-flows for a river, most of which do not embrace in any comprehensive way, the interaction with society. No approach could be found that was more than a single or combination of statistical and mathematical models without any form of machine learning or AI input. Perhaps the most sophisticated e-flow model is PROBFLO (O'Brien et al, 2018) which incorporates establishing the probabilities of different relationships between the drivers of change in a river ecosystem and the biological responses. It uses this information to estimate the water flows that would protect the river ecosystem as well as the risks that several endpoints would be satisfied, which it achieves by the organization of large amounts of data using Bayesian Networks and Relative Risk Assessment. The relationships that are modelled are shown in Figure 12. The endpoints are included in the assessment to evaluate the socio-ecological effects of altered flows in the study to support the implementation of e-flows and to consider the trade-offs between the use and protection of water resources in the basin.

The options for future development of such models with AI revolve around the ability of AI techniques to process and run multiple layers of data using different models. Such a demonstration was done with the hydrological model MODFLOW which is used for predicting groundwater conditions and interactions between groundwater and surface water (Miro et al, 2021). The authors discovered that using machine learning techniques significantly reduced the time required for modelling and enabled greater exploration of the uncertainty space. The same should be the next step in development of e-flow models such as PROBFLO.

9.2.3. AI for Water Quality

AI has emerged as a pivotal tool in monitoring, assessing, and predicting water quality, enabling more precise and timely interventions to protect aquatic ecosystems and human health (Zhang e al., 2020). Machine Learning (ML) algorithms, especially deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are capable of processing vast datasets from sources such as remote sensing satellites, underwater sensors, and IoT-equipped monitoring stations (Asfaw et al., 2021). By analyzing these data, AI can detect patterns and anomalies associated with various water quality parameters, including pH levels, turbidity, dissolved oxygen, and concentrations of contaminants like heavy metals or harmful microbes. Furthermore, AI-driven predictive models utilize historical data to forecast potential water quality deteriorations, allowing pre-emptive measures. Integrating AI with GIS facilitates spatial and temporal visualizations of water quality trends, pinpointing sources of contamination, and identifying vulnerable regions. As global challenges like industrial pollution, agricultural runoff, and climate change threaten water sources, the adaptability, and efficiency of AI in water quality management are becoming indispensable for sustainable water resource management.

9.2.4. AI for Crop Mapping

AI-driven crop mapping leverages machine learning techniques to detect, classify, and predict the distribution and types of crops in each region, providing an enhanced understanding of agricultural landscapes (Zhong et al., 2020). With the increasing availability of satellite imagery and remote sensing data, Convolutional Neural Networks (CNNs) have emerged as an instrumental tool in analyzing these large datasets (Liakos et al., 2018). Specifically, CNNs can be trained to recognize the spectral signatures and patterns associated with various crops, enabling accurate classification even when fields are closely packed or intercropped. Additionally, temporal analysis of imagery captures the growth stages of crops, facilitating identification based on phenological changes over time. AI crop mapping also plays a pivotal role in assessing crop health, predicting yields, and monitoring the impacts of pests, diseases, and climatic variations. By integrating AI-driven insights with Geographic Information Systems (GIS), stakeholders can visualize the spatial distribution of different crops, enabling efficient land-use planning, resource allocation, and timely interventions. As the demands on agriculture intensify due to global population growth and environmental challenges, the precision and scalability of AI-assisted crop mapping will be increasingly crucial for ensuring food security.

9.2.5. AI for Water Body Mapping

AI has shown significant potential in improving the mapping of water bodies, especially in vast and remote areas. Utilizing convolutional neural networks (CNNs) and other machine learning techniques, AI models can be trained to recognize patterns, shades, and textures associated with water bodies in satellite images. This ability is paramount in efficiently tracking changes in water body extents, such as those caused by climate change, human activities, or natural phenomena.

Such mapping offers valuable insights for urban planning, water management, and environmental conservation. Advanced AI models can differentiate between permanent and temporary water bodies, account for the shadows cast by nearby features, and correct for atmospheric distortions. These capabilities ensure a high level of accuracy and provide more comprehensive insights than traditional mapping methods. By leveraging AI in water body mapping, stakeholders can achieve better decision-making, predictive analysis, and even real-time monitoring of critical water resources.

9.2.6. AI for Optimization with Applications in River Basin Management

The application of AI in the realm of water resource management is rapidly transforming the ways in which we understand, allocate, and optimize the utilization of freshwater resources (Ruano et al., 2019; Moeini et al., 2020). As water scarcity becomes an increasingly pertinent global issue due to population growth, urbanization, and climate change, the need for efficient water management strategies has never been greater. AI provides tools that can analyze vast and diverse datasets, from satellite-based remote sensing data to on-ground sensor networks, offering insights into the temporal and spatial variability of water availability. Machine Learning (ML) models, including Neural Networks (NNs), Genetic Algorithms (GAs), and Reinforcement Learning (RL), have been particularly effective in forecasting demand, simulating groundwater flow, and predicting surface water availability (Abouali et al., 2019). Moreover, these AI techniques can be employed to devise optimal irrigation strategies, reduce water wastage in urban settings, and ensure equitable distribution across sectors. Importantly, AI-driven models can account for the multifaceted interactions between hydrological, meteorological, and anthropogenic factors, providing an integrated solution to the complexities of water resource optimization.

9.2.7 AI for Rainfall-Runoff Modelling

Predicting river discharge using empirical and physically based rainfall-runoff model has a long history (Beven, 2001). Advancements in computing resources and the availability of publicly available remote sensing datasets enabled the detailed representation of spatial catchment physical properties in a model to simulate various hydrological processes at high temporal resolution (Peel and McMahon, 2020). While techniques like regression models, Artificial Neural Networks (ANN) have historically found widespread application in rainfall-runoff modelling, their adoption by country stakeholders for operational applications remain limited owing to their complexity. In recent years, the prevalence of AI techniques and user-friendly programming packages has led to the creation of numerous machine learning models that can estimate river discharge. The purpose of incorporating ML into rainfall-runoff modelling is to facilitate the adoption of data-driven models and overcome past challenges.

Mohammadi (2021) identified three widely used machine learning models in rainfall-runoff modelling: adaptive neuro-fuzzy inference system, artificial neural networks, and support vector machine. However, most of the ML applications for this purpose are concentrated in data-rich regions across the globe. Among developing countries, ML-based rainfall-runoff models have started to be applied to major basins in Africa and Asia. Some of the ML-based rainfall-runoff applications to major river basins in developing countries includes the Mekong (Lee et al., 2020; Van et al., 2020; Nguyen et al., 2023), Ganges (Dayal et al., 2021; Singh et al., 2023), Indus (Rauf and Ghumman, 2018; Ammad et al., 2021), Congo (Kulimushi et al., 2023), Volta (Kwakye and Bardossy, 2020), Niger (Adounkpe et al., 2021), and Zambezi (Hughes et al., 2023).

Beyond conventional ML models, DL as a sub-set of ML approaches are gaining prominence in rainfall-runoff modelling. A comprehensive review on DL applications for water resources management identified CNN and Long-Short-Term Memory (LSTM) as two dominant techniques applied widely (Sit et al., 2020). The LSTM was applied on a large scale for 241 selected catchments in the US Catchment Attributes for Large-Sample Studies (CAMELS) database in which discharge predictions were comparable to other well-established models (Karpatne et al., 2018). This approach is now extended across different basins around the world for flood predictions (Kratzert et al., 2022). The use and adoption of machine learning (ML) in rainfall-runoff modelling is expected to become more widespread among stakeholders, especially in developing countries. This is due to the emergence and accessibility of user-friendly software and cloud-based platforms, which will simplify the process of applying ML to rainfall-runoff modelling. As a result, even those without a strong technical background can effectively use data-driven models.

10. Concluding Remarks

The present and future pressures that climate change and development options impose on the natural environment coupled with the unprecedented availability of a suite of data sets have provided opportunities for scholars and practitioners to co-develop new tools to advance environmental research domains in an integrative, collaborative and cross-disciplinary manner. River basins make inherently vital ecological and socio-economic contributions to the sustainable livelihoods of inhabitants, yet they are affected by frequent hydroclimatic extremes, land degradation, poor water quality, urbanization and population growth. These impacts often lead to unfavorable competition for the scarce resources in the basin. To better understand and manage these environmental shifts, there is a need to utilize the evolution of technological trends. Technological advances have led to the emergence of DT, which is a digital/virtual representation of a physical artifact that is constantly updated to reflect its current/future structure or behavior. In this regard, a river basin DT can be envisioned from the perspective of weather, floods, droughts, water quality, water use (across different values chains: domestic, industrial, agriculture), urbanization and population growth. The present review is aimed at assessing the DT scholarship, particularly in Africa, from the perspective of DT and VR, the role of stakeholder engagement in the design and operationalization of DT, DT data infrastructure architecture and governance, DT applications in river basin management, and the integration of AI in the DT framework. Results of the literature review point to the following;

a. Research on DTs for river-basin management remains nascent and the concept has not found adoption in the African river basins,

b. The DT research domain has inherent association with VR and AI,

c. Stakeholder engagement throughout the design and operationalization of the DT ought to be apparent,

d. DT for river basin management requires two-way linkages between a data repository, data models and process models,

e. Embedding AI into a DT framework has the potential to enhance river basin management.

While the present review had an African focus, a global lens of DT application in river basin management is likely to provide a different perspective.

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