On the Development of State-of-the-Art Computational Decision Support Systems for Efficient Water Quality Management: Prospects and Opportunities in a Climate Changing World

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ABSTRACT: The concept of water quality has often generally revolved around the all-round safety of water for human consumption. The quality of much of the 3% of the earth's humanly consumable water classed as freshwater is under threat of climate change, rising population numbers, indiscriminate land usage, detrimental agricultural practices and contamination from poor waste management. The need for optimal water quality enhancement has become more germane to sustainable socio-economic development. This paper examines the evolution of efforts made by the scientific community over the years to ensure water quality can be characterized and properly managed to ensure the global ever-growing demand for clean water for human consumption is continually met. The development of state-of-the-art computational decision support systems (DSS) should play a vital role. However, efforts in this regard are currently bedevilled by major challenges such as quantifying, measuring, processing and controlling the numerous metrics of water quality, as well as their adaptation and integration into a fully developed universal water quality model. In addressing these challenges, a shift towards simpler modelling approaches and the integration of uni-purpose models which can be cascaded into decision-making systems is being popularly proposed. However, with technological advancements already stimulating a water quality management revolution, there is a shift in paradigm to more universal modelling attempts with great optimism towards overcoming the challenges of developing universal water quality models and DSS. The prospects and opportunities of a water quality management renaissance offered by radical scientific innovations look promising, as the world races with time to provide support systems that can help deal better with the dynamics of sustainable water supply in increasingly contaminable environments and progressively unpredictable climates.

KEYWORDS: DSS, IOT, modelling, quality management, water quality, remote sensing

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Introduction

Climatic challenges resulting from the climate change phenomenon are currently impacting human livelihoods, triggering social disruptions and economic hardships. Its impacts on the quality, availability and use of water resources too, are not far-fetched, having both direct and indirect effects on the socioeconomic and biophysical environments (Arnell, 2004; Bates et al., 2008; Kundzewicz et al., 2008; Rutashobya, 2008; Warburnton et al., 2005), on agriculture (Crane et al., 2011; Pielke et al., 2007; Vermeulen et al., 2012), on health (Bunyavanich et al., 2003; Gage et al., 2008), on ecosystems and biodiversity and on energy generation (Fameso et al., 2020, 2022; Magadza, 2010; Magadza et al., 2020; Yamba et al., 2011). The rise in the rates of recurrence and degrees of intensity of extreme climatic and geographic events such as hurricanes, storms, droughts, volcanic eruptions and earthquakes – on both sides of the extremities, are interfering with the balance in quantum and quality of water available in the ecosystem, impacting on access, conservation, distribution and the overall sustainability of water resources.

Quinn et al. (2022) affirmed in their editorial that the sustainability of inland water resources is also suffering human-induced problems and maladministration, in addition to climatic and environmental challenges such as aquifer depletion and subsidence, water logging, contamination from household and agro-chemicals and seasonal drying of river flows. Several human activities produce by-products which when discharged into the environment without caution find their way into water bodies. This can be in the form of sediment due to wind and water erosion of soils; nutrients from fertilizer, animal wastes from livestock husbandry, pesticides including herbicides, insecticides and fungicides; salt mostly from winter road application; effluent discharge from sewage-treatment plants and septic systems or toxins from manufactured and refined products (Otterpohl et al., 1999; Biswas and Tortajada, 2019; Brown et al., 2020). These in no small measure have affected water quality in a manner which requires a pragmatic and vehement approach to the rethinking, re-evaluation and re-evolution of water resource management policies. This is even more expedient for industry and municipal sectors that place high premiums and are heavily reliant on the highest possible quality of water supply as a way to manage extra costs that need to be incurred in addressing treatment and pollution of their water stock.

Managing water quality through rigorous water resource analyses happens to be a crucial part of the water resource development process as illustrated in Figure 1. Water quality analysis and prediction ensure the safety and availability of consumable freshwater. This comes with the burden of

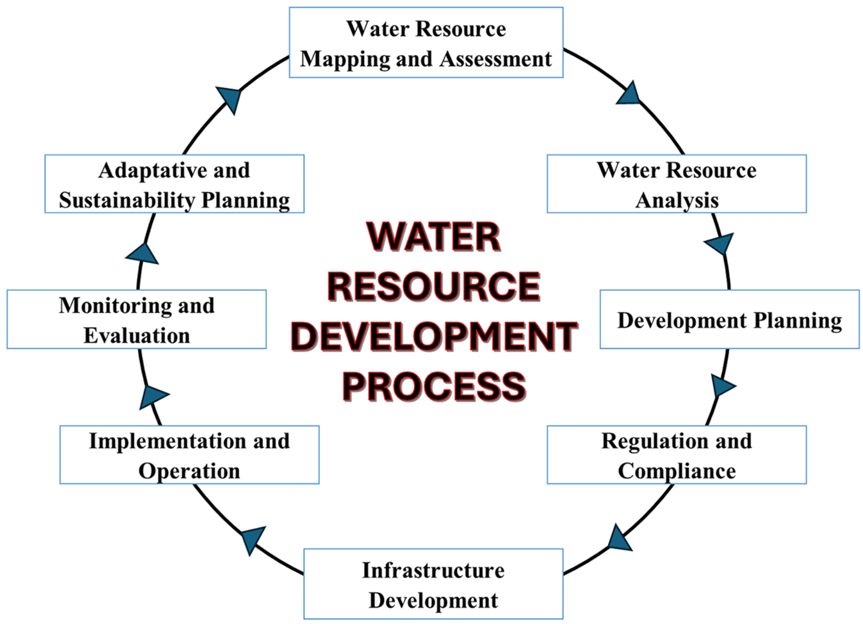

Figure 1. A flow graph of the water resource development process.

understanding the influences of factors, including but not limited to precipitation patterns, soil properties, watershed inundation and replenishment modes and man-made activities. Climatic conditions have been observed to also alter these factors, increasing the frequency and extremities of weather events and affecting water distribution, quantity and quality in the ecosystem.

The concept of water quality and what amounts to 'quality water' which will be further discussed in this paper is highly multidimensional. It has been observed to encompass various parameters within classifications of physical, chemical and biological characteristics. These numerous water quality parameters may interact in complex ways, posing challenges for modelling and prediction. The variability of natural water systems, technological limitations, consumption requirements and the transient nature of other driving factors over time and space also add convolutions to water quality metrics and characterization. On the one hand, obtaining accurate and reliably comprehensive water quality data poses a herculean task, on the other hand, the integration of these water quality metrics into a fully developed universal water quality model presents further hurdles. The complexity and interconnectedness of water quality parameters have made it difficult to develop a comprehensive model that can accurately represent a diverse range of water systems. The integration of data from different sources and disciplines, such as hydrology, ecology and environmental engineering, adds another layer of complexity to the development of decision support systems. Thus, the questions beg:

- Currently, are there established protocols that holistically govern and quantify water quality determinands?
- Are there any works of research that have successfully provided through parametric evaluation, a hierarchy of influence or a hierarchy of affectance of water quality parameters on the overall quantification of water quality?
- Can there be a possibility that one (or two) indicator(s) or property (ies) for example, Acoustic frequency, or electromagnetic resonance can be found to meter a significant majority (if not all) of water quality parameters and hence reduce the drudgery and analytical cost of wholesomely determining water quality across the three categories of water quality determinands – physical, chemical and biological.
- What does the future portend for water quality modelling in light of recent advancements in technology, changing global climate and yearnings for sustainability?
- What are the prospects and opportunities for developing reliable water quality models and decision support systems?

This study thus provides a review of the challenges impeding the development of DSS that are essential to improving the efficiency of water quality management. These challenges are viewed particularly from the perspectives of water quality quantification, characterization, measurement and integration into a robust universal water quality model. The prospects and opportunities provided by technological advancements in overcoming these challenges are also appraised. More specifically, this review:

i. Looks at challenges of, and efforts by the scientific community over the years to characterize, control, predict and properly manage water quality for the benefit of end-users, without starving any group of its required quantity and quality of supply.

ii. Presents an overview of how operators and scientists are leveraging the availability of full-phased digital technology, to provide support systems that will help to deal better with the dynamics of water quality in increasingly contaminable environments, progressively unpredictable climates, but ever-more insatiable demand for the highest possible quality of a fundamental resource utilized in virtually every part of the globe.

iii. Explores the prospects and opportunities of a fourth industrial revolution-backed water quality management renaissance offered by radical scientific innovations for water service supply operations are discussed.

To do justice to the key questions and objectives of this study, documented results of previous similar studies were collected from a wide range of publications with a view to obtaining compelling evidence and drawing the right conclusions. The search included scholarly articles, studies and other relevant literature obtainable from academic databases, journals, books and other sources. This was conducted using science citation indexing databases such as SCOPUS and the Web of Science with the words/phrases 'water quality', 'water quality management', 'water resources management', 'decision support systems in water quality management', 'water quality modelling' as some of the keywords used in the search. Of the hundreds of results generated, the search filter was further screened to output results that: (1) are clearly related to water quality modelling and (2) involved the development and application of decision systems for managing water resources. Consequently, As shown in Figure 2, a total of about 150 publications that identified with the key objectives of this study, spanning the last half a century and with a total of close to 40,000 citations were reviewed.

Majority of the reviewed literature was a product of research contributions to the body of knowledge through peer-reviewed articles published in research journals. This is followed by reports from industry experts published in serials and periodical report documents and proceedings of research outcomes presented at conferences and other science engagement and communication forums. Internet sources and books formed the rest of the body of literature which were all thoroughly read and analysed, and a distinct understanding their main arguments, methodologies, findings and conclusions were digested. The aim is to better understand the different challenges to the development of state-of-the-art decision support systems for water quality management systems – from the characterization of water quality, to the construction of a universal water quality model based on a highly condensed, minute, yet highly effable and reliable set of metrics, to the development of all-encompassing decision-making systems. This is important because the prospects and opportunities offered by these systems, from

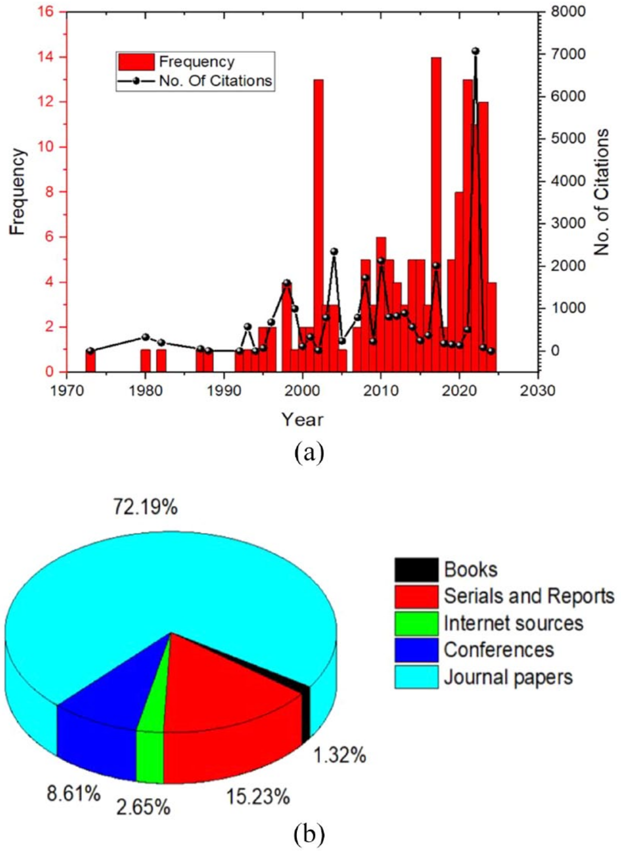

Figure 2. Graphical illustration of the literature review statistics showing distribution by (a) period (b) bibliographic sources.

early warning capabilities to support and management analytics, present a powerful toolkit for safeguarding water resources without losing cognisance of their ability to contribute to equitable, sustainable and resilient water quality management practices in the face of a dynamic and evolving climate.

Thus section 1 has introduced the background to the study, the changing global climate and the multiple dimensions to which it has impacted the water quality question, as well as the aims, objectives and steps taken to gather the necessary information for this study. Section 2 thereafter, talks about the challenges to the characterization, quantification and measurement of water quality, especially from the purview of previous studies by researchers and its implications on decision-making in water quality management. Section 3 reviews the early advances in the development of decision support as inspired by mathematical modelling for predictive and pre-emptive actions on water quality management. Section 4 reviews the shift in paradigms in predictive analysis and sustainable water quality decision making at the turn of the millennium in the light of the shift in global attention and commitment towards achieving breakthrough in issues such as nutrition, human rights and sustainability and how the optimal utilization and management of water resources systems can play a key role in attaining such goals. Section 5 examines contemporary approaches of adaptive support applications towards model performance optimization, scalability and higher-level simulation applications, within the perspectives of the progress made in terms of a variety of methods, expansion in spatial resolution and advances in uncertainty and reliability evaluation. Section 6 presents a synthesis of the reviewed literature and the authors' points of view and proposed contributions as to how water quality modelling and decision support development should be approached in the light of the problems identified and the short comings of the current regime of problem solving and decision making. The paper concludes with Section 7 discussing the prospects and opportunities of operational solutions for water resource management offered by the acceptance of science and communication technology-based applications, emerging cyber-physical and artificial intelligent systems in management operations primed to transform day-by-day management of water and providing lasting solutions to quality water availability and supply challenges.

Challenges of Water Quality Characterization and Quantification

To the general public, the concept of water quality is a question of its safety for consumption, however, it gets more complex than that. According to Haarhoff (2023), water quality is defined by parameters grouped either by their potential risk or by analytical considerations. Potential risks include aesthetic risks such as colour, taste, odour or turbidity; Health risks which are characterized by the presence (or not) of chemical compounds or microbiological organisms; Operational risks such as the measure of corrosivity, alkalinity, acidity or temperature. Analytical considerations define water quality in terms of methods and expertise required for its analysis. These are classed under Microbiological, Physical, Chemical or Organic determinands. The World Health Organization (WHO) provides globally sanctioned and reliable protocols that guide the definition, management and policy direction of water quality, which is subjected to periodic revision and re-evaluation. Various countries and regions across the globe also have adopted local-specific and community-targeted regulations that guide the establishment and maintenance of water quality within their geophysical domains. For example, the South African Bureau of Standards administers the SANS 241 (Haarhoff, 2023), which is the country's version of protocols that guide the definition and prescription of water quality. Similarly, the United States Environmental Protection Agency also provides water quality standards which are enforced within the American territory. The Directorate of Water Inspectorate (DWI) sets the regulations in England and some other parts of the United Kingdom for public water supply, while the European Union also has water quality standards set for Europe as a region.

Private water supply companies also do have their water quality standards and parameters as an addendum to those set up by government agencies and global bodies like the WHO (World Health Organization, 2022). These may be in line with, or more stringent in measure, to those set by regulatory agencies empowered by law for such purposes. They are essentially designed in such manners as to ensure the safety and integrity of the water being supplied to consumers. Table 1 provides information on the parameters used in determining water quality according to the SANS 241 protocols. Though most of the various region-specific quality standards as well as the WHO standard share a general pattern, quantitative comparisons by researchers have shown large deviations and differences among them (Mamba et al., 2008). While some other researchers have tried to provide justifications for this, in the form of considerations such as locally specific problems and prevalence which require more attention, such as soil mineral profiles, economic activities or climatic conditions and so on, there begs the question as to the possibilities of having unified, probably, empirically motivated, generally acceptable metrics for the determination of water quality parameters suitable for consideration and application across board.

The quality conundrum: Navigating variability and shifts in water quality characterization and reporting

Amongst other things, monitoring and maintaining water quality is paramount to public health, hence the need to ensure water is available and safe for use and effectively managed, conserved and utilized. This task is however plagued by the complexity of the metrics associated with defining water quality as it spans scientific, technological and logistical domains. Being a multidimensional phenomenon, it is affected by several natural, ecologic, anthropometric and economic factors which are transient in their own right, escalating the difficulty in accounting for all the influential variables. This was affirmed by Fang et al. (2020), Teixeira et al. (2014) and C. Zhao and Chen (2014) in their investigations on driving force(s) of water quality, surmising that the change of water quality is often influenced by multiple factors, such as economy, population, land use, water resources, industry and so on. Exacerbating this challenge, according to Brunner et al. (2021) and Quan and Meon (2015) are other factors such as sampling issues and uncertainty related to limited data or unaccounted values. Hutley et al. (2020) asserted that despite advances inmodelling capability, field data remains a limiting factor in understanding these complex water quality systems, potentially resulting in misrepresentations across a broad spectrum by several orders of magnitude. Phenomena such as sediment transport, loading into downstream receptors, the ephemeral nature of streamflow and topography, limit water quality monitoring capacity and contribute in no small measure to the multiplicity of the spectrum of variables that requires description and characterization in defining water quality. J. Huang et al. (2021) demonstrated the dynamic nature of water quality in river systems, emphasizing

Table 1. Water Quality Parameters Grouped According to Potential Risk or Analytical Considerations.

DETERMINAND	RISK CATEGORY	SPECIFIC EFFECT
Microbiological water quality parameters		
E. coli or faecal coliforms	Acute health	Faecal pollution indicator
Cytopathogenic viruses	Acute health	Damage to cells
Protozoan parasites	Acute health	Gastro-enteritis and diarrhoea
Total coliforms	Operational	Faecal pollution indicator
Heterotrophic plate count	Operational	Microbiological activity indicator
Somatic coliphages	Operational	Faecal pollution indicator
Physical and aesthetic water quality parameters		
Free chlorine	Chronic health	Disinfectant
Monochloramine	Chronic health	Disinfectant
Colour	Colour aesthetic	Consumer resistance
Conductivity at 25°C	Aesthetic	Dissolved salts indicator
Odour or taste	Aesthetic	Consumer resistance
Total dissolved solids	Aesthetic	Unpleasant taste
Turbidity	Operational	Particle removal indicator
Turbidity	Aesthetic	Consumer resistance
pH at 25°C	Operational	Corrosivity, taste and dissolved metals
Chemical (macro-determinands) water quality parameters		
Nitrate as N	Acute health	Methemoglobinemia
Nitrite as N	Acute health	Methemoglobinemia
Sulphate as SO^{-}_{4}	Acute health	Diarrhoea
Sulphate as SO^{-}_{4}	Aesthetic	Bitter and salty taste
Fluoride as F^{-}	Chronic health	Tooth enamel and skeletal fluorosis
Ammonia as N	Aesthetic	Taste and odour
Chloride as Cl^{-}	Aesthetic	Salty taste
Sodium as Na	Aesthetic	Taste and hypertension
Zinc as Zn	Aesthetic	Taste and milky appearance
Chemical (macro-determinands) water quality parameters		
Antimony as Sb	Chronic health	Diarrhoea and liver damage
Arsenic as As	Chronic health	Skin lesions and skin cancer
Cadmium as Cd	Chronic health	Kidney damage
Total chromium as Cr	Chronic health	Gastro-intestinal cancer
Cobalt as Co	Chronic health	Heart damage and thyroid damage
Copper as Cu	Chronic health	Taste, staining and gastro-intestinal
Cyanide as CN–	Acute health	Nervous system and thyroid
Iron as Fe	Chronic health	Fatigue and joint pain
Iron as Fe	Aesthetic taste	Taste, stains and deposits

(continued)

Tabel 1. (continued)

DETERMINAND	RISK CATEGORY	SPECIFIC EFFECT
Lead as Pb	Chronic health	Neurological damage
Manganese as Mn	Chronic health	Neurological damage
Manganese as Mn	Aesthetic	Taste, staining
Mercury as Hg	Chronic health	Damage to nervous system and liver
Nickel as Ni	Chronic health	Skin irritation
Selenium as Se	Chronic health	Liver damage and slow growth of hair
Uranium as U	Chronic health	Radioactivity
Vanadium as V	Chronic health	Slow growth and respiratory symptoms
Aluminium as Al	Operational	Possible neurotoxic effects
Organic water quality parameters		
Total organic carbon as C	Chronic health	Indicator of organic pollution
Chloroform	Chronic health	Low risk of cancer
Bromoform	Chronic health	Low risk of cancer
Dibromochloromethane	Chronic health	Low risk of cancer
Bromodichloromethane	Chronic health	Low risk of cancer
Microcystin as LR	Chronic health	Skin irritation
Phenols	Phenols aesthetic odour	Odour

the need for continuous monitoring to grasp the complexity of pollutant transport and transformation.

More importantly, the transient variability of quality parameters with time, location and geography from day to day and season to season poses challenges to data sampling and monitoring efforts, constraining the budget, scope and resources needed to ensure data accuracy and reliability. Fan et al. (2010), Fan and Fang (2020), Y. Zhao et al. (2019), C. Liu et al. (2019), evaluated studies on water quality data and observed that these tend to cover periods of short duration, have small sample sizes or are restricted to a single sub-catchment. This has made the temporal accountability of an already complex spectrum and phenomena of water quality characterization one requiring a great deal of analytic and operational sophistication. Consequently, the unavailability of adequate spatiotemporal water quality data to build, calibrate and validate a model, has indirectly compounded the difficulties in water resource planning and management decisions due to a lack of accurate information on changes in water quality under different conditions. Manjakkal et al. (2021), reviewed the challenges associated with deploying sensor technologies for water quality monitoring, highlighting the importance of technological advancements in addressing measurement accuracy and reliability. Thus, the economic realities of the acquisition, operation and maintenance of high-quality sensors and instruments required to sustain the integrity of temporal and spatial variability and fluctuation in water constitutions ensures that ascertaining water quality is an exclusive preserve of institutions who have the financial wherewithal to implement such projects (Tsitsifli et al., 2019).

The wide range of objectives of these often citizen-based water quality monitoring projects according to Ramírez et al. (2023) means that they differ in focus, methods used and sampling frequency. This in turn, affects the spatial and temporal resolution of the data and its value for different hydrological studies, with possibilities of having extensive spatial coverage but data that has a lower precision, quality and reliability, by essence raising another question of data integration and standardization and the notification of assessment metrics and protocols. The likes Agustsson (2018), Kelly (2013), Pardo et al. (2012) and Josefsson and Baaner (2011), have also reported apparent misinterpretation due to a lack of clarity on some metrics, definitions and objectives. This is quite evident in the variability of metrics of water quality across recent water quality assessment studies as shown in Table 2.

The seeming lack of a unified characterization poses hindrances to efforts to integrate and leverage on information from different sources, especially in the face of emerging threats to water quality which traditional monitoring protocols have not accounted for. This has made it challenging to keep pace with adaptation to these evolving environmental threats. Santos

Table 2. Variability of Quality Definition Metrics in Recent Water Quality Assessment Studies.

AUTHORS	CASE STUDY AREA	QUALITY PARAMETERS	MAJOR DRAWBACKS
Ma et al. (2023)	Pearl River Basin, China	Ammonium ($NH4+-N$), chemical oxygen demand (COD) and dissolved oxygen (DO)	• The seeming insufficiencies of the assessment methods: i. The standard permissible concentrations of each parameter considered in the study were obtained from third party sources. ii. Rank correlation coefficient method was used to evaluate the changes of various pollutants over time. iii. Trend analysis needs to be performed
Qian et al. (2023)	Lower Neches River, Texas, USA	pH, alkalinity, ammonia–N, nitrate–nitrite, chloride, hardness, total phosphorus, sulphate, TSS, turbidity, DO, conductivity, Secchi depth, *E. coli*, temperature and water elevation	• Due to the large volume of data collected for a wide range of parameters Pearson correlation techniques were required to be applied to establish correlations that provide a proxy as a single alternative indicator for some of the quality factors/indicators, together with its associated computational and analysis costs.
Ramírez et al. (2023)	Mississippi River, Shale Sites in Pennsylvania, in the United States of America and Huangpu River in China	Clarity, temperature, conductivity, pH, dissolved oxygen, nitrate, Phosphate, macroinvertebrates and faecal coliform bacteria	• The diversity in quality parameters means different measurement techniques are often required, thus generating a hoard of data reliability and quality questions.
Ayele et al. (2023)	Dire Dawa City, Ethiopia	Nitrate, fluoride, hardness, TDS, total alkalinity, iron, pH, conductivity, iron, halides, temperature, turbidity, potassium and ammonia	• Relied majorly on secondary water quality data from third party sources raising questions as regards data reliability and uncertainty.
Fabian et al. (2023)	East and South Asia	Temperature, chlorophyll-a, nitrates, phosphates, pH, dissolved oxygen, biological oxygen demand (BOD), COD, total suspended solids, conductivity, ammonia, dissolved inorganic phosphates, algal bloom and transparency	• Inability to fully evaluate the model's performance with respect to water quality assessment • Lack of adequate flow and water quality data. • The hydrologic simulation programme Fortran (HSPF) model was found to be lacking in usefulness for temporal variations in WT, • Probabilistic approaches often failed to detect a significant trend from climate extremes due to sampling issues and limited data • Parametric approaches for finding linear trends analysis may fail to reveal underlying patterns in extremes, particularly indices of extremely unusual events. • Difficulties in defining the whole range of extremes due to a lack of water quality data, further complicating systematic analysis of the relationship between water quality and climate extremes.

(continued)

Tabel 2. (continued)

AUTHORS	CASE STUDY AREA	QUALITY PARAMETERS	MAJOR DRAWBACKS
Perveen (2023)	Pakistan	pH, conductivity, TDS, temperature, hardness, faecal coliform, *E. coli*, COD, BOD and TSS	• Inadequate data on drinking water quality, especially in rural and remote locations • Difficult to regularly evaluate the quality of natural water in freezing glacier regions
J. Huang et al (2021)	China	Dissolved oxygen (DO), chemical oxygen demand (COD), total phosphorus (TP), ammonia nitrogen (NH3–N) and eight heavy metals including copper (Cu), zinc (Zn), selenium (Se), arsenic (As), mercury (Hg), cadmium (Cd), chromium (Cr) and lead (Pb)	• Complex interplay among instream physical, chemical and biological processes profoundly modulate the ambient variables data • Data aggregation in time and or space may not be reflective of the wide range of spatiotemporal dynamics typically experienced in any riverine ecosystem nor does it allow to evaluate progress with ecosystem services at the degree of granularity required to assess the public sentiment
Albert et al. (2021)	Karst landscapes of Guadalcanal, Solomon Islands	Turbidity, conductivity, pH and water depth	• Testing and identifying underground flow paths and interactions between surface water and groundwater

et al. (2021), stated, for example, that the paradigm of water management has shifted from an anthropocentric perspective of water (defining it as a resource for direct exploitation by humankind) to an ecocentric perspective (where water is seen as an ecosystem holder). This establishes ecological status as a new concept to consider and focusses on ecosystem integrity as the foundation of management decisions concerning water quality. The assessment of ecological status of a given water body has hence changed from a general chemical quality assessment to the integration of a range of descriptors concerning biological communities, hydromorphological and physico-chemical quality elements. Ramírez et al.'s (2023) review of water quality assessment studies showed serious divergence in the trends and objectives of quality parameters considered by the investigators as illustrated in Figure 3, with most studies covering different varieties and ranges of parameters. They later submitted that the diversity of approaches that were used in the studies is a strong indication of the complex challenge of a water quality assessment, with every method posing different questions concerning cost, logistical efforts, requirements for training and the type and quality of data that can be obtained. The diversity in quality parameters means different measurement techniques are often required, thus generating a hoard of data reliability and credence questions. This in itself remains a limiting factor in the development of decision support systems and present modelling challenges to water quality and its management. This has contributed in no small measure to the challenge of policymakers in developing and recommending broad-based effective regulations and interventions to address water quality issues.

Decision-making in water quality management

While amongst decision-makers, water resource managers, industry practitioners and other stakeholders, there is unanimity in the acceptance of science-based decision support in water quality determination and management, the design, application and administration of the support tools and systems requiring unified quality parameter definition have remained an open-ended question. Decision support systems (DSS) are meant to be pivots upon which socio-economic decision-making with regards to water quality is driven, to improve efficiency, attract investments, guide research and innovation, drive scientific regulatory practices and provide means for service delivery and feedback networking with the public. This pivotal role that a DSS can play in water quality management is illustrated in Figure 4 (Quinn et al., 2022). With the advancement in computing power in recent decades and the increasing acceptability and progress of mathematical modelling and simulation technologies in research and innovation, the computational analysis and development of water quality management have expanded the opportunities for improved prediction of time scales and patterns of variability of water quality parameters. DSS has since advanced the science of data-driven modelling and science-based decision support for water quality management. Structured, semi-structured and/or unstructured data can now be obtained and analysed in massive datasets running to exabytes in volume from real-time or quasi-real-time smart sensors and computed by supervised or unsupervised computational algorithms to provide forensic insights into what, how, when or which factors affect corresponding quality outcomes and how managers should address them.

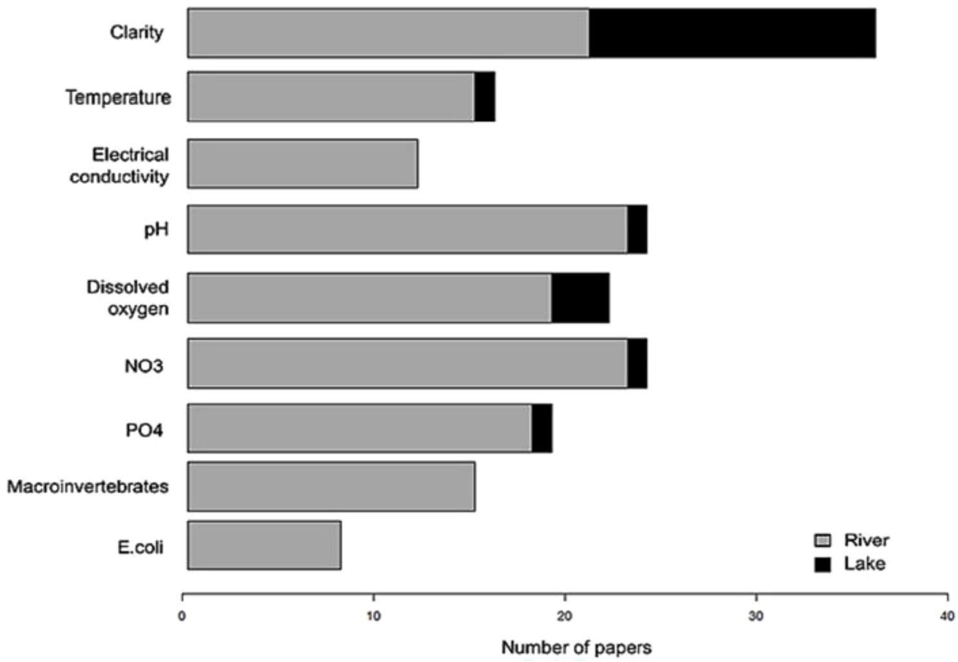

Figure 3. Frequency of the physical, chemical and biological water quality parameters measured in rivers and lakes for the reviewed studies.

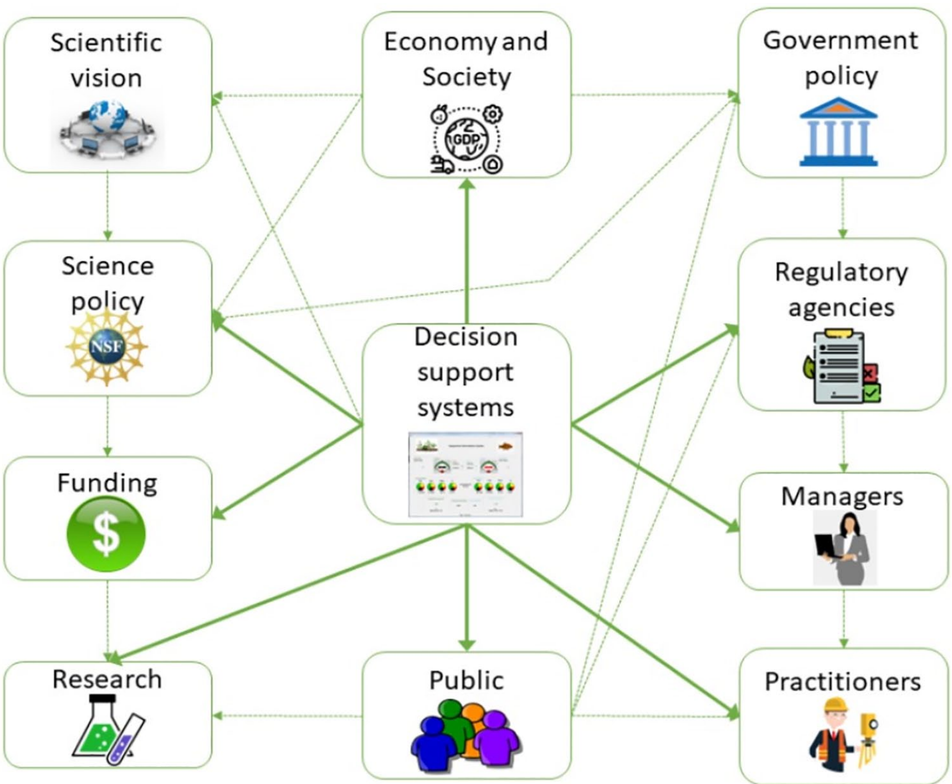

Figure 4. Decision support systems as a centrepiece of water quality management.

Izquierdo et al. (2004) in their review of mathematical models and methods in the water industry emphasized the necessity of having analysis tools which will enable reliable simulations of the different models by examining and being able to compute different configurations, operation modes and load conditions to study existing installations from their basic characteristic data. These could require the application of numerical techniques for coupled and possibly, typically non-linear systems of algebraic, ordinary differential and partial differential equations. Lately and due to advancements in available techniques and technologies, procedures based on neural networks, genetic algorithms, fuzzy theory and chaos theory are becoming indispensable, especially where experimental designs are necessary to turn design processes into real optimization problems.

Early Advances Inspired by Mathematical Modelling

Mathematical modelling efforts towards more efficient management of water resources and improved decision-making via the development of computational decision support systems predate well over half a century ago when Walker and Skogerboe (1973) applied mathematical modelling techniques to water management strategies and decision support. In evaluating and thereafter developing alternative strategies for controlling urban water quality and supply demands, his study investigated the feasibility of alternative water management strategies to alleviate mounting problems of water shortage and water quality deterioration. Special emphasis was placed on the levels of water quality control achievable in arid urbanizing areas and the optimal policies to accomplish such control. Mathematical and optimization formulations were proposed from an economics and cost-benefit perspective, utilizing the Jacobian Differential Algorithm (JDA), a differential approach to solving linear and non-linear resource optimization problems. According to Walker and Skogerboe (1973), water quality management revolves around or emphasizes pollution control, hence their focus on two (2) major quality parameters that is, the inorganic concentration of total dissolved solids (TDS) or Salinity as often referred to in concise terms, and the 5-day biochemical oxygen demand (BOD_5), to describe the effects of water quality or lack thereof. They proposed two models which apply to determining the optimal strategies for water management in arid urbanizing areas, especially in applications requiring increasingly stringent water quality standards as well as optimal management approaches.

Kitanidis (1980) formulated non-linear conceptual models for accurate real-time short-term forecasts of river flows and optimal control of watershed systems. This was done in an attempt to provide a generic water resource management model amenable and adaptable to the variability of water quality metrics, which will utilize real-time data to update system states and improve streamflow predictions. These data could be measured, guessed or even obtained from forecasts. But the goal was to conceptualize and create a system that will process incoming real-time discharge information and thereafter forecast flow and supply available, hours in advance over a stepwise time domain. Employing a highly numerical methodology based on the state space formulation of equations, flow at fixed spatial descriptions could be determined, as a nonlinear function of the state of the system. By building up the model to be amenable, they succeeded in developing a water quantity and quality management system that would combine information from various sources to report in real-time the hydrological profile of a location. Though their study treated water quality metrics as a lumped input vector and did not emphasize meeting up or not with prevailing quality standards, the model was however able to generate the resulting information on flow, interflow, runoff and free water storage forecasts given the required inputs and the time step required.

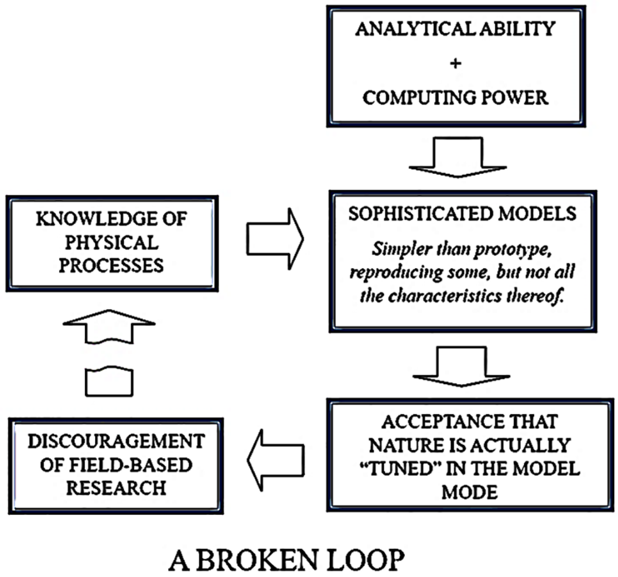

Figure 5. The field of Hydrological Science in general described as a broken loop.

Ugo (1988) in his perspectives of water resources development at the time identified the amelioration of water quality as one of the major measures which would dictate innovation in water resources technology for the future, with decision analysis and support systems being integral in water resources analysis and planning. However, challenges such as the large volume of quantities required to define and describe the physical and chemical processes of diffusion and dispersion must be overcome to escape the encumbrances of a large number of mathematical models and poor available data, both in quantity and quality, let alone the difficulties encountered in obtaining reliable measurements. This was observed in the strong tendency of National and International Agencies to oppose the use of sophisticated models in the search for better knowledge of the dynamics of water quality evolution. Experimental and theoretical work was preferred to mathematical modelling and simulation, despite their attendant demerits and inflexibility. A general consequence was the disconnect between those producing the models and those who should make use of the models to make decisions, leading to the alienation between researchers and practitioners. Even in the field of research concerning water management at the time, only about 5% applied mathematical modelling methods, largely owing to inadequacy and cumulatively insufficient reliability of design parameters (Rogers & Fiering, 1986). Thus, clearly, there seemed to be a break in the loop, as illustrated in Figure 5, which made informed decision-making and the development of effective and efficient management systems impracticable.

The inadequacies of water quality modelling according to Somlyody (1995) remained a major reason for the seeming kneejerk reaction to water quality challenges at the time, usually driven by crises, accidents and interests. Countermeasures and corrections were made nearly exclusively when the problem manifested itself and action should be made immediately. Problems are accepted and treated, rather than prevented (Wetzel, 1992). Where progress has been made in the areas of nutrient removal and cycling in rivers and lakes, integration has been a challenge as there are hardly two such models, as elucidated by Rauch et al. (1998); Thomann and Mueller (1987), which would use the same water quality variables (and fractionation) and thus could be linked to each other.

In their attempt to develop models for application in software that can provide decision support during water resource management (WRM) planning and operations, Andreu (1996) also identified complexities in defining and capturing water quality characterization as a hindrance to developing DSS modules that can evaluate it. Reitsma (1996) in his study further discussed the necessity of looking beyond the usual role of decision support systems (DSS) as analytical tools for assisting the operational management of water resources systems, advocating for the inclusion of components capable of supporting the political, organizational and social dimensions of the decision-making process. The complexity of defining quality metrics and objectives under the prevalent ill-structured nature renders the number of feasible combinations virtually infinite according to Bosman (1983) and Fedra et al., (1987). Scepticisms thus arose as to the usefulness of the decision support models to host organizations, with questions arising as to if any discernible difference in their performance was being recorded. Consequently, the study avowed that traditional DSS approaches based on physical modelling alone are unlikely to represent the true and salient features of these problems. Instead, new modelling and DSS paradigms are needed.

Singh and Xu (1997) found a way around the complexity and ill-structured challenge in water resource management modelling with a proposition that they can also be resolved in a series of structured components. With progressive increases in experience gained in modelling over time through continuous upgrades and testing against practical requirements, the importance of different hydrologic parameters under varieties of hydrologic conditions came under scrutiny. In their review of hydrological models, it was noted that the approach of developing models at different time scales and to varying degrees of complexity found proclivity in exploring the impact of climatic change (Arnell, 1992; Schaake & Liu, 1989; Xu & Halldin, 1996) and long-range streamflow forecasting (Alley, 1985; Xu & Vandewiele, 1995). Applications were found along the lines of reconstruction of the hydrology of catchments, assessment of climatic impact changes and evaluation of the seasonal and geographical patterns of water quality demand. It appeared from the review that three to five parameters may be sufficient to reproduce most of the information in a hydrological record on a monthly scale in particular regions. This aligned with the submission of Dooge (1977) who surmised the need for brevity in the number of parameters used in defining quality objectives in hydrological modelling, since according to his study, 'keeping the number of parameters as low as possible increases the information content per parameter and therefore allows both a more accurate determination of the parameter and a more reliable corelation of the values obtained with catchment characteristics. A general comparison of the hydrological models developed at the time is presented in Table 3.

Table 3. General Comparison of the VariousEarly Models.

Common features	• Founded on based on continuity equation • Conceptually land-based hydrologic process or processes which are spatially averaged or lumped • Parameters estimated by fitting to observed hydrologic data • Specific-purpose models concerned primarily with streamflow simulation • Relatively simple structure • Small number of parameters compared with other short-period models
Different features	• Input data requirements • Variation in modes of accounting for soil moisture and aquifer recharge • Variation in the number of storages considered • Variation in the hydrological process considered; from evapotranspiration to streamflow to surface runoff, infiltration, evapotranspiration, deep percolation, base flow and ground water flow
Applications and limitations	• Models using precipitation as input cannot be recommended when other meteorological data besides precipitation are available • Monthly models using rainfall and temperature as input can be used in reproducing annual and seasonal flows, however the state variable simulated by these models may be unrealistic • Models using daily data of rainfall and evaporation as inputs are more reliable in the treatment of hydrologic processes

Water Resource Management Modelling at the Turn of the Millennium

By the turn of the millennium, global attention shifted towards issues such as nutrition, human rights and sustainability, producing commitments for combined international action on those matters, with the provision of portable drinking water forming a major cardinal point of interest of the 8-item development agenda of the international community (A/CONF.166/9: Copenhagen Declaration on Social Development (un.org). The Millennium Development Goals (MDGs) were eight international development goals for the year 2015 that had been established following the Millennium Summit of the

United Nations in 2000, following the adoption of the United Nations Millennium Declaration (United Nations Millennium Development Goals). Global water resource management and improvement initiatives, being very fundamental to the broad objectives of the SGDs, likewise, started to tilt toward overcoming challenges to innovation and exploration as those outlined in the gazette, especially in the upgrading of challenging areas in water systems. As envisioned from the onset, effective global water resource management and improvement initiatives are integral to addressing water-related challenges and contributing to sustainable development, which according to Heiba, Ibrahim, et al. (2023) and Heiba, Nasr, et al. (2023), entails practical approach to ensure the effective use of natural resources such as water, without jeopardizing the needs of future generations. Consequently, leveraging innovative technologies was one critical component of best practices needed to be adopted to tackle challenges associated to quantity, quality and access to water for equitable, resilient, water resource sustainability across the globe. Such best practices would effectively directly address at least 4 sustainable development goals relating to:

- Zero hunger (SDG 2) – which ensures that by making water plentifully available for agricultural purposes, especially in vulnerable regions, food production can experience a bountiful upturn.
- Good health and wellbeing (SDG 3) – which brings to the front burner the place of access to clean water in preventing waterborne diseases and the importance of sanitation in public health and well-being.
- Clean water and sanitation (SDG 6) – which addresses issues of water quality, availability and sanitation facilities, emphasizing the importance of sustainable water resource management.
- Life below water (SDG 14) – which focusses on conserving and sustainably using oceans, seas and marine resources.

One of these innovative technological best practices was the integration of modelling into predictive analysis and sustainable decision making as tools for assisting operational management of water resources systems, optimal utilization of water by consumers and preservation of ecosystems and the environment. As previously discussed, efforts had progressively been ongoing in the development of environmental and economic models for watershed management. A great deal of experience had been gained and there had been propositions as regards the need to continue to upgrade and test them against practical requirements. To enhance the sustainability of water-quality-management systems, in-depth research on the related barriers and the relevant mitigation approaches remain desirable (G. H. Huang & Xia, 2001). Concerns, as regards data availability and reliability, system complexity and methodology validity, limitations of computer techniques, the usefulness of research outputs, difficulties in policy implementation and necessity of training programmes, had dominated the list of items that constituted barriers to the development and integration of DSS into water quality management.

Integration of advanced computational techniques

The progress made in the areas of electronic, micro-electronic and computing technologies by the turn of the millennium opened up vistas by which different perspectives of sustainable water-quality management could be investigated. Cardwell and Ellis (1993) proposed stochastic dynamic programming models for water quality and quantity management. Huang (1996) and Huang (1998) similarly proposed inexact optimization models for watershed environmental planning and applied them to two real-world case studies. With these came challenges of uncertainties in system parameters and their interrelationships, complicated number of dependent factors, non-reflecting non-linearities as well as unavailable and/or unmeasurable parameters. With these in mind, G. H. Huang and Xia (2001) opined that low reliability in data systems could be worse than no data, as limited information on inputs inevitably led to the limited scope of applicability of the outputs, hence methods that improve reliability and certainty should be the cynosure of investigations bordering on water quality management for the immediate future. Lovejoy et al. (1997) also identified that less work is being undertaken to incorporate individual modelling components within a general framework, resulting in the generation of less efficient decision alternatives, with conflicting objectives, unrealistic independence assumptions and deviations from realistic regional objectives. Hence providing insights as to research direction in the coming years.

In recommending efforts for integration, G. H. Huang and Xia (2001), opined that the water pollution challenge does not just begin and end with water quality or contaminants at every given point and space, rather, the challenge has more to do with the pollution source as well as the effects on humans and the ecosystem and about the need to avoid these effects. Chapra (2003) thus took a wholesome look at water supply systems as a whole, in their effort to quantify, organize and process all sources of information necessary to adaptively manage the water supply system so that long-term plans can be adapted weekly to changing conditions and time-varying objectives. The study provided a sample DSS developed for real-time adaptive management of water reservoir systems that supplied the domestic needs of the Boston metropolitan region in the United States of America. Independent watershed models were developed to predict watershed runoff and yield and its attendant effects on water quality and flood control. They employed simplified quantification of water quality under two (2) parameters that is, Body of dissolved salts (BOD) and Total organic carbon (TOC) content. Backed by two-dimensional mass balance models, they succeeded in optimizing daily and weekly reservoir operations towards four objectives based on short-term climate forecasts. These objectives included maximum water quality, ideal flood control levels, optimum reservoir balancing, as well as maximum hydropower revenues. The success and applicability of their study to a metropolitan water supply system showed that simple tools, such as spreadsheet-based software and compact parameter definitions can be used to improve system efficiencies. This affirmed Loucks's (1995) position that the success of any real-time DSS model will be dependent on its ability to make predictions with an appreciable degree of accuracy using a minimum of input data. Westphal et al.'s (2003) segmented approach also showed that models could be applied in such a way as to select amongst different operating objectives for any given period as conditions may warrant. Such objectives may be singly optimized or simultaneously optimized and traded off to suit operational priorities.

Model development and quality assurance

The misperceptions of predictive modelling of climatology and hydrology, and decision support tools as a replacement rather than enhancements to water management operations used to be perceived as the key obstacles to the eventual acceptance and utility of the integrated support systems. For example, according to Refsgaard et al. (2005), the strengths and limitations of modelling applications are often difficult, if not impossible, for water managers to assess. Similarly, the transformation of objectives defined by the water manager to specific performance criteria can be very dificult for the model users to assess. Furthermore, re-creating or replicating the modelling process and its results can be challenging for non-technical experts. The inadequate use of guidelines and quality assurance procedures, and improper interaction between the manager (client) and the modeller (consultant), has also been fingered as the most prevalent reason for poor modelling results. For water quality modelling, description is usually based on the physical, chemical and biological components of water quality. However, the data to model all these are usually sparse, unavailable and still yet to be deeply understood.

Thus, as depicted in Figure 6, Refsgaard and Henriksen (2004) recommended committed efforts towards validation and calibration as necessities and priorities that must be undertaken to affirm the predictive capability of a model. Uncertainty and reliability analyses must accompany predictions achieved through simulations while continuous interactions between operator and modeller is also crucial for the success of the modelling process. In addition to multistage or multipurpose approach to modelling, as opposed to the development of one complex, all-encompassing model with a high degree of uncertainty and low-quality outcomes, Refsgaard et al. (2005) also recommended modelling according to specified technical guidelines as a way of ensuring quality is assured. Such quality assurance (QA) guidelines were classified according to:

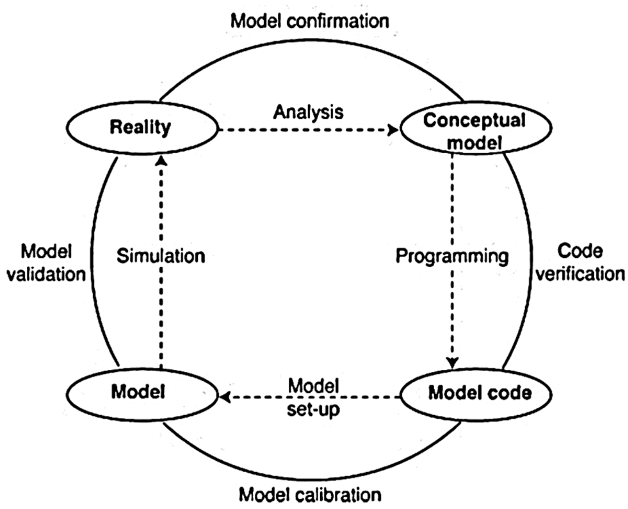

Figure 6. Computational model development cycle.

- Type 1 – Internal technical guidelines developed and used internally by the modeller's organization.
- Type 2 – Public technical guidelines developed in a public consensus-building process.
- Type 3 – Public interactive guidelines developed as public guidelines to promote and regulate the interaction between the modeller and the water manager throughout the modelling process.

These wares meant to assure technically and scientifically adequate parameters are catered for in the development and execution of the model, in addition to ensuring it is defensible and reproducible. This hypothesis was tested on existing model samples and from different countries and the summaries are presented in Tables 4 and 5, as well as Figures 7 and 8.

Thus summarily, initially, when models are developed, the key focus should be to set up for practical application, with internal technical guidelines (Type 1) originating from the research community applied. Transitioning from Type 1 to Type 2 guidelines should occur at the attainment of a certain degree of maturity, following continuous applications, calibration and validation within both the specific scientific discipline and the market. Process descriptions should be explicit and there should be common agreement about the scientifically sound procedures for solving the problems within the domain, driven by the demands of regulators and water managers. The transition from Type 2 to Type 3 will subsequently be dependent on a clear and conscious demand from regulators and water managers.

Big data application

Graduated quality assurance techniques have become helpful in big data modelling tasks such as in Ingleby and Huddleston's (2007) study on ocean temperature and salinity predictions where substantial checks were required, for both the historical data obtained from climatological and oceanographic archives

Table 4. Comparison of Hydrological Models According to Specified Technical Guidelines.

MODEL TYPE	APPLICATION	QA GUIDELINE	MATURITY LEVEL
Ground water modelling. (Refsgaard & Henriksen, 2002)	Modelling ground water flow, solute transport, geochemical modelling	Type 1 (geochemistry and underground water quality) Type 2 (solute transport) Type 3 (ground water flow)	Can oscillate between Immature and new/restricted fields of application to well developed and currently being applied in many areas and across many countries. Geochemical and ground water quality applications are still small and limited largely due to data availability, access and quality challenges Solute transport is emerging in the variety of application domains
Precipitation-runoff modelling (Perrin et al., 2002b)	Modelling runoff for flood forecasting and surface water quality. Integral parts of ground water and hydrodynamic models	Type 1/Type2	Currently being applied on a wide scale in a number of countries, especially as subroutines in the ground water modelling domain
Hydrodynamic modelling (Metelka & Krejcik, 2002a)	Surface water quality, flow, sediment transport and morphological transitions modelling in urban drainage and sewer systems, rivers, floodplains, estuaries and coastal waters	Type 1 (for sediment transport modelling) Type 2 for other applications	Hydrodynamic modelling of sediment transport is still on applied in new studies and not yet applied on a public commercial scale. Hydrodynamic modelling for surface quality and flow transition predictions already finds applications in many countries on a wide scale of scientific areas and has a competitive market
Flood forecasting modelling (Balint, 2002)	Surface flows, runoff and flood forecasting	Type 1	One of the oldest modelling fields, based on real-time operations. Applied widely in many countries
Surface water quality modelling (Da Silva et al., 2002)	Used to model water quality based on the description of physical, chemical and biological processes	Type 1	Still very new and finding applications in restricted areas of science and industry. The vast scope of what constitutes the definition of water quality and its parameters still remains a challenge to its maturity and emergence
Biota (ecological) modelling (Old et al., 2002)	Used to model biological processes, relations and interdependencies of flora and fauna to one another and to their physical environment	Type 1	Widely used, but in a very restricted domain. The general complexity of ecological systems and the general limited availability of relevant field data remains a restricting factor
Socio-economic modelling (Heinz and Eberle, 2002)	Modelling socio-economic impacts of water resources and management decisions undertaken by managers and governments	Type 2	Used in only a few countries. Still very restricted in application with respect to the water industry

and the real-time estimates transmitted from automated processing algorithms. The system was used to process archived data for 1956 to 2004, applying techniques such as Bayesian probability theory in the background check and the associated check against nearby observations. Versions of the system were used for near-real-time ocean analysis and for initializing both short-range ocean forecasts and seasonal atmosphere–ocean forecasts. The remote acquisition of data has thence become increasingly commonplace in water resources management and monitoring applications and driving new technology. The demands and usage of data for various management solutions have as a result increased in quantum leaps and hence, a spike in the level of quality of remotely monitored and obtained data for associated purposes.

Table 5. Comparison of Hydrological Modelling Guidelines in Different Modelling Environments.

MODEL TYPE	APPLICATIONS AND MARKET MATURITY	QA GUIDELINES
Dutch guidelines (Scholten and Groot, 2002)	Very generic and vast application in water management. A large market for modelling exists and technical expertise is vastly available at various levels of experience.	Type 3
Australian groundwater flow modelling guidelines (Henriksen, 2002a)	Though restricted to a small domain, the environment is technically comprehensive and has found consistent application over several years. Possess a very mature market for applying and integrating models into operations.	Type 3
Danish groundwater modelling guidelines (Henriksen, 2002b)	Though restricted to a small domain, the environment is technically comprehensive and has found consistent application over several years. Possess a very mature market for applying and integrating models into operations.	Type 3
Central and Eastern Europe (Metelka & Krejcik, 2002b; Van Gils & Groot, 2002)	New and unregulated market for modelling services. An immature market where the managers and their organizations often are technically too weak to adopt and integrate modelling into water management operations and decision support.	Type 1
French guidelines in flood forecasting (Perrin et al., 2002a)	Public or interactive guidelines do not exist in this area. The modelling market seems non-existent and technical capacity is limited to a few sectors.	Type 1
UK guidelines (Packman, 2002)	The use of models is generally described as routine and wide enough in areas of application. The market is agile and well-regulated, a sure characteristic of maturity. QA guidelines are well developed	Types 2 and 3
Bay-Delta Modelling Forum, California (BDMF, 2000)	Well mature with constant interactions between modellers, managers and even the public. Models find usage in virtually all spheres of water management as well as decision support.	Type 3
American Society for Testing and Materials (ASTM, 1992, 1994)	Very comprehensive, highly competitive and mature market for modelling services and applications. Technical support and expertise are readily available and the practice of the application of modelling into organizational systems has been in adaption for a while.	Type 2

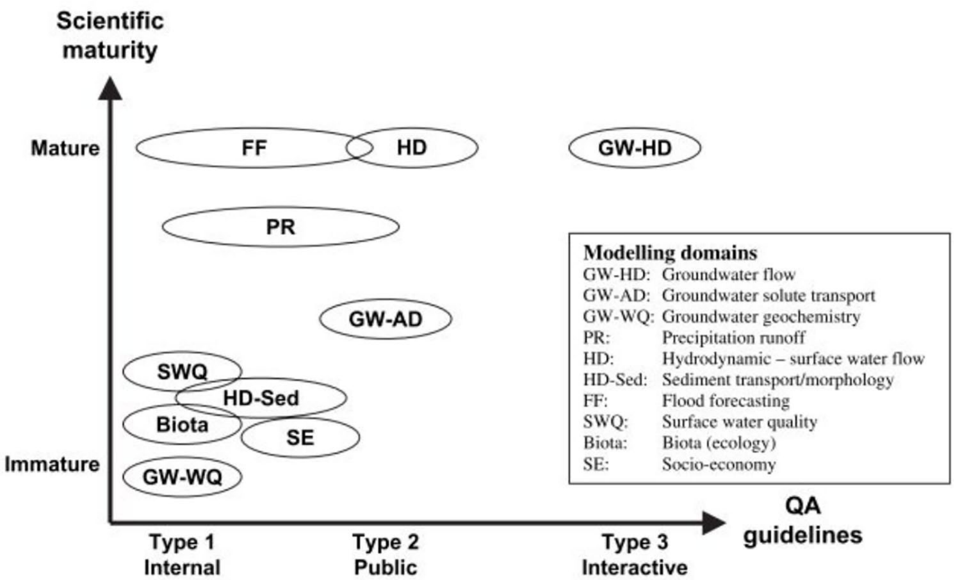

Figure 7. Hydrological models quality assurance as influenced by market maturity of its application domain.

The growth in the development of data management solutions according to Goasguen (2008) is buoyed by the overcoming of shortfalls of traditional methods such as the capacity to support real-time data access, dealing with the required data diversity needed to dictate specific technology choices at every level and the need to provide solutions that support high performance and scalability. Software solutions that address these needs without imposing strict requirements on the hardware or application side subsequently sprung up and have found applications in intelligent river basin management systems and water control operations. Gowdish (2009) applied partitioned data systems to the real-time water budgeting and

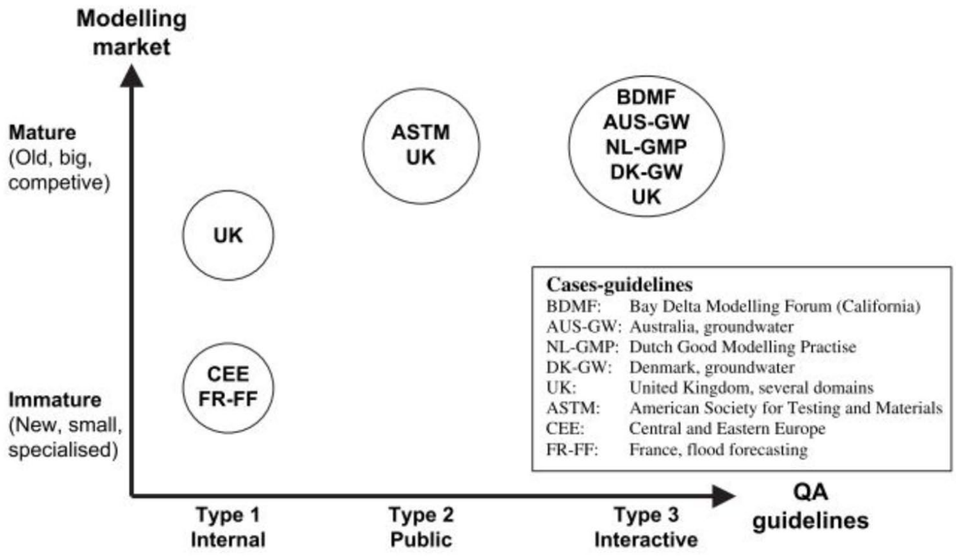

Figure 8. Prevailing modelling quality assurance patterns in selected domains.

efficient control and storage of water in the South Florida water management department in order to meet multiple water resource objectives. An operations decision support system was developed to receive rainfall, evaporation and flow/stage measurements from gauges, interpolate into regular time intervals and model the data into a water-budget equation to evaluate the storage of water in the control system. Quinn et al. (2010) in their study on the use of environmental sensors and sensor networks described the use of continuous surface flow and salinity monitoring as well as electromagnetic remote soil mapping techniques to develop water and salinity budgets for seasonal wetland real-time water quality management, and obtaining water and salinity mass balances for seasonally managed wetlands. More widespread applications recorded include weather station sensor arrays – used to estimate wetland pond evaporation and moist soil plant evapotranspiration; high-resolution multi-spectral imagery – used to differentiate between and estimate the area of wetland moist soil plant vegetation; and groundwater level sensors – used primarily to estimate seepage loses beneath a wetland pond during flood-up.

The extensive data requirements and the difficult tasks of building input parameter files, which had long been an obstacle to the development and application of such complex models for timely and effective decision support by resource managers now got to be addressed with object-oriented spatio-temporal data models. Such data models have the ability to restore, manage, query and visualize various historic and updated datasets and information concerning watershed hydrology, water resource management and water quality as well as compute and evaluate the watershed environmental conditions so as to provide online forecasting to police-makers and relevant authorities for supporting decision-making. Leveraging on the affirmations of Isakowitz et al. (1998) that with the rapid development of the Internet and maturity of database technology, management information systems will extend from Client/Server (C/S) architecture to Browser/Server (B/S) architecture, Y. M. Liu (2012) in their Huaihe basin water resource and water quality management platform project implemented a spatiotemporal data model to develop a WebGIS management platform. This water management data and decision support system combined spatial attribute and temporal information to update, query and analyse environmental information as well as manage historical data, and help the user interpret results so as to provide scientific support for decision-making. Ru's (2012) research on the management of water resources introducing GIS technology under the mode of water saving also laid emphasis on the positive impacts of the aid of modern advanced network technology, correspondence technology as well as GIS technology, in the realization of system integration of water resources monitoring, management and decision support. Their study demonstrated a real-time monitoring management system based on detailed network construction, hardware construction and the system assistance decision function. R. Harvey et al. (2013) described the development of a real-time water quality monitoring system based on the analyses of water quality data collected from watersheds using in-stream digital sensors with capabilities of recording a range of water quality indicators over long stretches of time. The evolution in remote sensing technology meant water quality on both spatial and temporal scales can possibly be continuously measured and collected using digital techniques. Their study highlighted the possibilities of concise definition and measurement of water quality by applying real-time measurements of variables like water temperature and specific conductance to predict the chemical concentrations of other water quality indicators. Just as Christensen et al. (2000), Christensen (2001) and Rasmussen et al. (2011) had similarly done previously, regression models were developed that employed real-time data parameters as surrogates for physical properties and chemical properties that define water quality. In a similar vein, measurements of air temperature were demonstrated as possible to be

Table 6. Predictive Models of Multiple Water Quality Metrics Developed Based on the Specific Conductance of Collected Samples.

VARIABLE	MEASURED RANGE	CCME GUIDELINES	REGRESSION MODEL (DEVELOPED BASED ON SPECIFIC CONDUCTANCE)	$R^2_{ADJUSTED}$
Alkalinity (mg/L_{CaCO3})	6–21	0–10	$Log_{Alkalinity} = 1.64 - 0.00037SC - 0.63ST$	.80
Dissolved Oxygen (mg/L)	7.1–24.7	>5.5	N/A	N/A
Hardness (mg/L_{CaCO3})	10–53	N/A	$Hardness = 4.18 + 0.61WT + 0.04SC$	.85
Total Dissolved Salts (mg/L)	107–959 142–625	N/A	$TDS = 0.66SC + 7.17$ $TDS = 0.56SC + 10.34$	.95 .90
pH	4.9–14	6.5–9.0	N/A	`N/A
Water Temperature (°C)	0.5–28.7	N/A	N/A	N/A
Turbidity	0.3–19.2	N/A	N/A	N/A
Zinc Content (mg/L)	0–0.03	0.03 mg/L	$Zn = 11.786/(1 + \exp(0.002 \times (4463.299 - SC)))$	.75

used in predicting water temperature and the concentration of dissolved oxygen at the real-time stations. This was backed by findings from previous works such as Crisp and Howson (1982), Webb (1987), Stefan and Preud'homme (1993), Pilgrim and Stefan (1995), Mohseni et al. (1998), Pilgrim et al. (1998) and Webb et al. (2003) in which historical data of air temperature were used for the prediction of important indicators of river health like water temperature and dissolved oxygen, both key metrics of water quality. The use of regression methods proved essential, as best-fitting models of unitary historical records mapped with real-time measurements, rather than multiple parameter datasets, were determined based on the computation of residuals, errors and probability values for the explanatory variables. The water quality datasets and variables considered are presented in Table 6.

These advances made during these years in real-time water resource management through improved and more reliable data engineering in no small way ensured more positive strides made in advancing the way managers and agencies implement protocols for operation and maintenance, quality assurance and control and data management and transmission around the world. The rapidly increasing number of sophisticated sensors available has thence expanded the innovation space of watershed monitoring and reporting networks. As these networks expand and more data become available both spatially and temporally, additional tools and techniques will need to be developed to make effective use of these data for river and human health protection.

Advancements in Adaptative Decision Support Applications Within the Last Decade

The data engineering era

The evolution of data-based solutions over the years paved the way for the development of tools and techniques to quantify and predict the function and response of aquatic systems (Montanari, 2013; Wagener et al., 2010), this has led to the widening of the scope of water quality management investigations and with that its peculiar challenges. However, even in the face of these challenges which include model performance optimization, scalability and higher-level simulation applications, appreciable progress has been made in terms of a variety of methods, expansion in spatial resolution and advances in uncertainty and reliability evaluation. According to Porter et al. (2009) and Read et al. (2014), successfully modelling aquatic environments across broad and heterogeneous landscapes, complexity and interdisciplinarity requires rich streams of data, hence the need for the establishment of flexible and interactive model libraries, data networks and learning frameworks. According to Hipsey et al.'s (2015) study of resilience and recovery predictions of aquatic systems, modelling efforts have historically been focussed on areas such as nutrient cycling, eutrophication and other drivers of water quality degradation. Advances in models are however required to provide more holistic predictions that capture system-level properties such as resilience and other emergent behaviours. Pahlow et al. (2015) demonstrated the use of Water Footprint Assessment (WFA) in the measure of appropriation of freshwater resources by source and polluted volumes by type of pollution in South Africa. Using indicators obtained from ratios of specific quality parameters, water pollution control was implemented from the additional information generated, contributing to the sustainability of freshwater use and allocation. The key water quality concerns as reflected by Department of Water Affairs and Sanitation (2015) include point and non-point sourced salination, eutrophication, micro and micro-biological pollution and erosion and sedimentation.

Probabilistic search algorithms

The trends in water resources management research and innovation in the last few years have seen an evolution into more numerical and intelligent computational methodologies usually utilized to define the optimum combination of parameters that will yield optimum outcomes either in dominating or non-dominating orders. Wang et al. (2018) presented a New Dynamic Firefly Algorithm (NDFA), an optimization technique based on swarm intelligence. The technique was developed to achieve an optimal and reasonable allocation of water resources which according to Davijani et al. (2016) is the key to sustainable utilization of water resources. With divergence in quality metrics for different water demand objectives, choosing what weighting parameters to rank quality and consumption purpose becomes a tough task. While some traditional methods such as the quota method (Assareh et al., 2010), regression analysis (Brentan et al., 2017), particle swarm and harmony searches (Bai et al., 2014; Oliveira et al., 2017) had been in use, swarm intelligence inspired algorithms proved to be promising in their performance (Cai et al., 2016, 2018; L. Z. Cui, Li, et al., 2017; Z. H. Cui, Sun, et al., 2017; Davijani et al., 2016; M. Q. Zhang et al., 2017). The NDFA show reduced dependency on its parameters in finding solutions to benchmark functions and real-world problems with its variable step factor that can be dynamically updated during the search process. In addition to swarm optimization searches, techniques such as the Kalman Filter modelling method have been demonstrated by Boukharouba and Harkat (2020) in the spatiotemporal modelling and prediction of hydrological principles that affect water quality such as precipitation and stream flow at different time scales. This technique supports the stochastic and nonlinear character of hydrological processes as well as the variability in the times in which they occur. This is essential for accurate water resource decision-making, management and regulation efforts. The obtained models provided predictions that respect the variables' stochastic character and also characterize the nonlinear nature of the hydrological system. Using data from annual stream flow records of ten gauging stations over a 25-year time frame, the state-space model formulation was used to generate multi-site annual predictions for the ten subsequent years from both temporal and spatial points of view.

Multi-decision optimization

Optimizing across multiple objectives has also been used to provide structures for decision-making, whereby trade-offs can be made across conflicting objectives. The economics of water quality management is an important aspect of water resource management, which requires as much attention as maintaining and ensuring water quality and security. This is even more essential in relation to water demand and supply quality, where the quality requirements for different applications also differ accordingly. Ullah and Nehring (2021) developed and applied a multi-objective constrained optimization model for optimal water allocation among irrigation and environmental sectors. The study adopted and improved upon the Lewis and Randall (2017) model, using a Non-dominating Sorting Genetic Algorithm (NSGA-II) of dominance and non-dominance sorting to maximize net returns while minimizing flow deficits under constrained groundwater pumping capacity and allocation. Similarly, Musa (2021) applied a multi-objective model in modelling optimal water allocation in three sectors named domestic, agricultural and industrial sectors, using a goal programming technique. Ikudayisi et al. (2018); Masood et al. (2021) also carried out demonstrations of simultaneous optimization of water allocation and crop distribution under constraints of water accessibility by implementing a combined Pareto multi-objective differential evolution algorithm. Zeinali et al. (2020) focussed on linking the NSGA II with a coupled surface water–groundwater model to achieve and sustain a balance between surface water and groundwater withdrawal by considering various constraints. This modelling approach provides a platform for decision-makers to simulate surface water–groundwater interaction in low-flow regions, especially for the simultaneous depletions in river flow and groundwater during dry seasons. Jalili et al. (2023) also successfully combined Support Vector Machine (SVM) method and NSGA-II algorithm for optimal real-time operation of water released volume from the reservoirs, leveraging on the low average error rate of optimality derived from both techniques. Fuzzy logic and genetic algorithm (GA) were also combined with computational neural network (CNN) in a hybridization concept and experimental benchmarks showed that the hybrid model outperforms the single CNN model. Romano and Kapelan combined evolutionary algorithms (EAs) and ANN to construct a smart estimation model. Boah and Twum (2020) study explicated, as shown in Table 7, the different applications by which stochastic techniques have been applied to water quality management and decision support.

Cyber intelligent systems

Web-based and intelligent systems have also found proclivity in water quality management and decision support. Despite the complexities earlier highlighted and the time-consuming computations of simulation models which have largely hindered application, the worldwide web has proven to be a useful resource for the development of a decision support system for watershed management (DSS-WM). D. Zhang et al. (2015), Syrmos et al. (2023) integrated open-source web-based GIS tool, soil-water modelling component, open-source libraries and a cloud computing platform do develop quasi-real-time decision-making systems to achieve the goal of distributing water resources and urban and rural water supply quality monitoring. Alshattnawi (2017), Feng (2020), R. Liu et al. (2022) also advanced the case of combining information technologies, the cyber-physical environment and hydrological theories and modelled their studies on smart water distribution management system architecture based on internet of things and cloud computing. In a physical world, according to Weiser et al.

Table 7. Stochastic Techniques in Water Quality Decision Support Modelling and Management.

MODEL CATEGORY	MODEL TYPE	PURPOSE AND APPLICATION
Mathematical programming	Linear programming	Optimizing water resource use in irrigation projects, economic water quality management and optimal water pollution management.
	Integer programming	Ground-water remediation
	Nonlinear programming	Stream water quality management, general water quality management, synthesis and optimization of water treatment processes
	Dynamic programming	General water quality management
	Stochastic programming	General water quality management
	Robust programming	Agricultural water quality management
	Multi-objective programming	For general water quality management, optimization of water quality pumps operation and storage sizing of water distribution systems
Meta-heuristic programming	Artificial neural networks	Optimize water distribution system designs and prediction of water quality parameters.
	Genetic algorithms	General water quality management, Minimizing the risk of low water quality along a river, developing water quality management of river systems and reservoirs and assisting water pollution control.
	Simulated annealing	Optimization of groundwater management

(1999), Talari et al. (2017), that is now richly and invisibly interwoven with sensors, actuators, displays and computational elements, embedded seamlessly and connected through a continuous network, developing systems that facilitate control and management of potable water characteristics such as quality, via remote monitoring of the most relevant parameters. Jothimani et al. (2017), Viswanathan (2017), Ahmed et al. (2021), C. Harvey et al. (2021), Jiang et al. (2022) also presented a smart water quality systems based on data from a system of sensors connected in a predefined network interface as shown in Figure 9. The system explored the use of models for data processing and analysis, visualizations using serial port terminal display functions, storage on a cloud facility and accessibility of detailed information about water quality via the Internet of Things (IoT) – which is a worldwide network of interconnected objects uniquely addressable based on standard communication protocols (Atzori et al., 2010). Its typical infrastructure setup is presented in Figure 10.

The common denominator in these systems was found in their technology architecture which primarily consisted of three layers; a layer which consists of wireless networks of sensors and readers (WSN) with the ability to collect data from source; a worldwide web interconnectivity layer through which data is shared via standard communication network protocols; a storage service to store and back up received data for future access. The Integrated hydrological modelling–information technology approach to real-time water resource management and decision support has since gone on to become a trend amongst hydrological scientists. With user-friendly interactive graphic interfaces, it has become even more convenient for operators and other users to access and apply.

Analogous approaches have also been recorded in several studies within the last half-decade. Kurtz, et al. (2017) integrated field data acquisition and stochastic physically based hydrological modelling in a data assimilation and optimization framework as a service to water resources management. The system which was developed to run in a cloud computing environment reported minimal computational costs associated with typical data assimilation platforms, making it more adaptable for practical application to solving water resources management challenges. Stochastic predictions are performed using the assimilated data as a first step, in the presence of invoked initial and boundary conditions. Subsequently, updated model predictions are used to perform real-time decision-making on the selected response parameters. Thereafter model and data resources are adapted to the cloud computing environment in compatible code structures.

Suciu et al. (2017)'s presentation of the Water-M project's new concepts such as water security, virtual water and integrated real-time data systems for the quality management of water resources, in a unified intelligent water management approach, using cyberinfrastructures based on cloud computing and IoT. No thanks to the rapid growth in urban areas, and ageing infrastructure, a lot of stressors are contributing to the complexity of water and wastewater management. Hence management decisions have to be taken, armed with the intelligence of support systems developed for the collection and analysis of even the most multifarious of data.

Sukaridhoto (2016) describes in Figure 11 the architecture of such cyberinfrastructure-reliant platforms capable of utilizing multi-variant data for monitoring water quality. The system would typically consist of a central measurement unit that

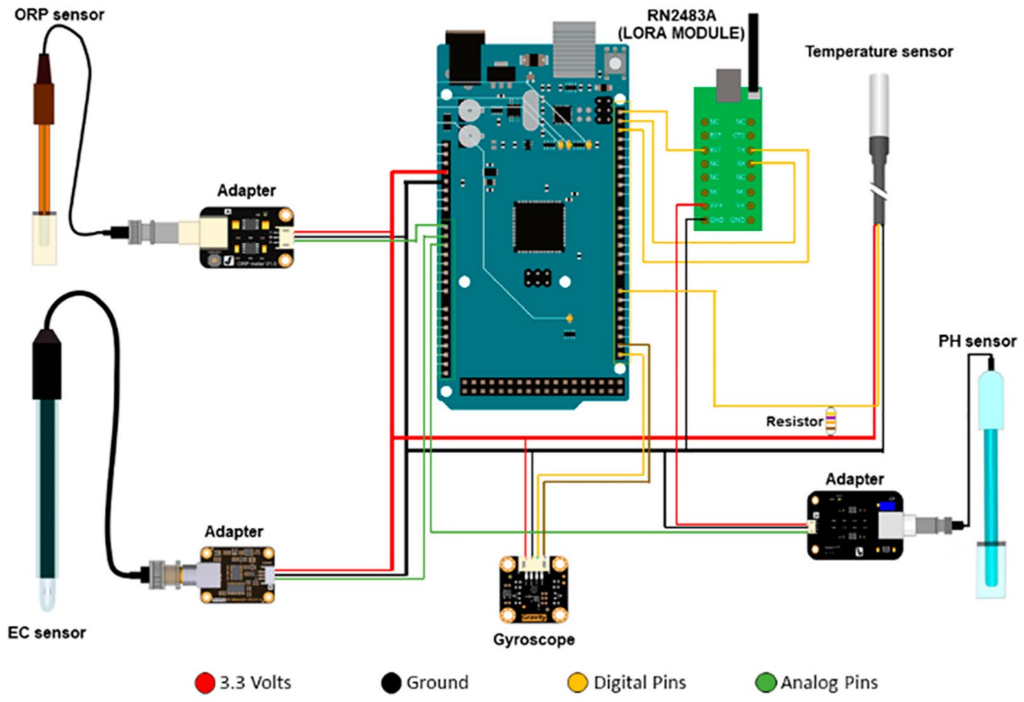

Figure 9. A schematic of a smart web-enabled water quality measurement unit showing four key measurement metrics – pH, temperature, electrical conductance and ORP.

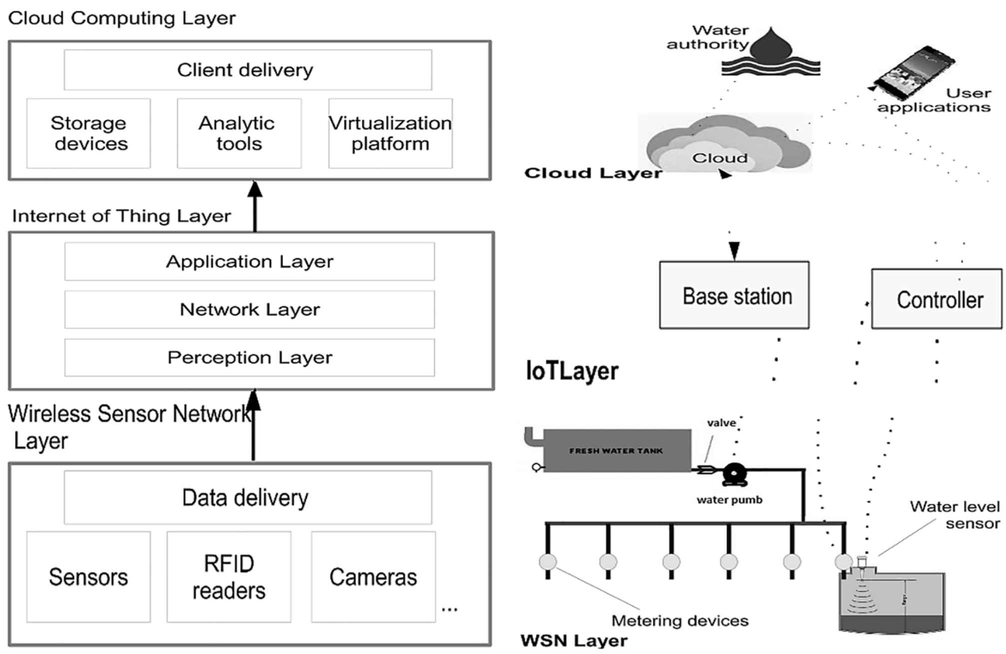

Figure 10. The integrated cyber-physical systems architecture.

collects water quality measurements from sensors, processes the collected data based on the model response algorithm and transmits the data to either control storage in a readable format (for operational, support, planning and management decision making) or a web server for access via internet protocols. Their identification of the need for the future introduction of artificial intelligence and data analysis techniques in water management would go on to become a recommendation that would shape the immediate future of research, application and innovation in the state of art on water management systems.

Syntheses From Reviewed Studies

The enthusiasm fuelled by advances in other fields of science, is creating a compulsion to create models which are as detailed, multifarious and as all-inclusive as they come. Hydrological systems on their own are already complex by nature, and

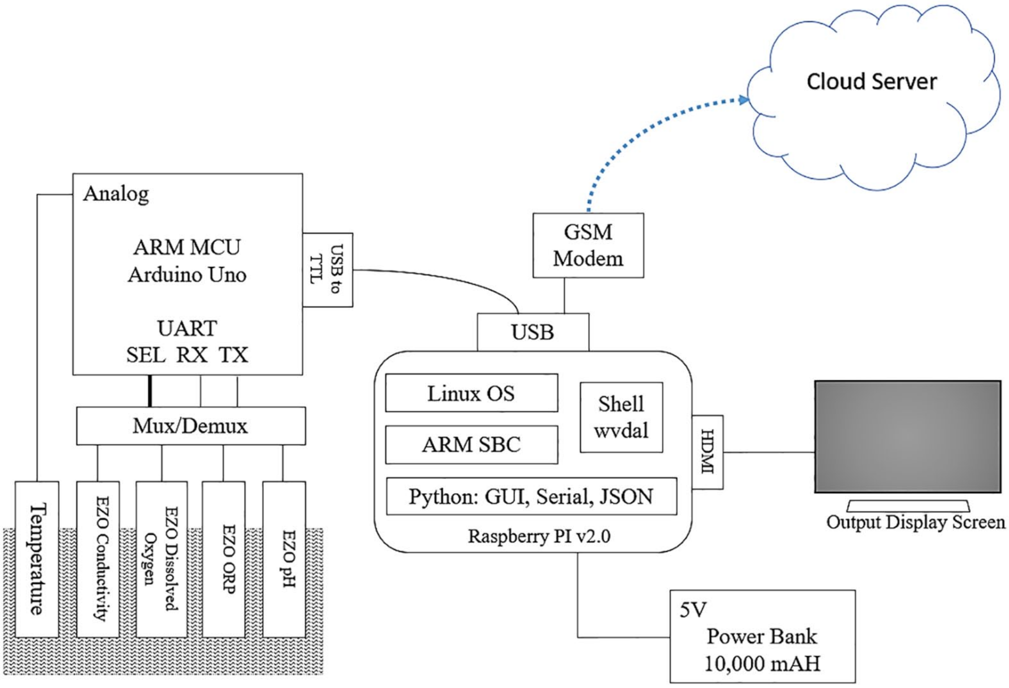

Figure 11. The general architecture of multi-variant data cyber-intelligent platforms.

undertaking scientific investigations on water resource systems is a complex endeavour involving immense details within its structure. The let-down of such efforts, if not facilitated appropriately may be a further be-clouding of the issues at hand and raising of more questions than answers. Some schools of thought believe it is rather more realistic to constrain modelling efforts more to answering specific questions and solving simple problems – Making each segment become well known to its operators and integrating them into a system of simple functions and subroutines – and by so doing, simple uni-purpose models can then be integrated into a matrix of decision-making systems to be managed by engineers and professionals.

While the general consensus seems to be in agreement that by adopting modelling approaches that progress from simple to advanced solutions, the development of DSS will be adaptable to the priorities of the users. However, to get this right, keeping the number of qualities determinands as low as practicable, say up to five parameters – with about two parameters aggregating multiple determinands from each of the physical, chemical and biological classifications of the water quality metrics – being sufficient enough to reproduce most of the information in a hydrological record, allows better accuracy and a more reliable correlation of values obtained. Validation of input data before usage is also highly desirable to maintain reliability and certainty and lend credence to whatever further analysis that would be carried out. Quite typically, it is not necessary to model with all detail the enormous variety of effects in a receiving stream but to emphasize the dominant aspects, hence, case studies can serve as very table tools for testing and benchmarking. These case studies can help planners and operators understand the potential value of the DSS being developed by addressing the uncertainty inherent in the predictive model elements, and by demonstrating whether or not the DSS could add value to the traditional operating methods while operating in full accordance with longstanding regulations and operating rules. Rigorous validation testing against independent data, uncertainty assessments and peer reviews of a model at various stages throughout its development is also essential to lend credibility to the modelling task. The success of the endeavour will eventually depend on an integrated approach that brings together scientific, education and training advances made across many individual disciplines and modified to fit the needs of the individuals and groups who must design, implement, monitor, evaluate and re-adjust their water quality management plans based on the results produced by the model. The improved prediction will contribute immensely to both exploring and better understanding the theory and supporting decision-making. Ultimately, integrating model predictions within observatory systems offers the advantage of increasing the worth of data to management agencies and encourages tight feedback between observation, understanding and on-the-ground actions.

Prospects and opportunities for water quality modelling

Literature reviewed thus far has revealed the growing desire for water quality models that incorporate various factors influencing water quality, such as hydrodynamics, pollutant transport and biogeochemical processes. However, there exist a plethora of challenges which have proven to be a drawback to endeavours aimed at developing generic integrated water quality models. The wide range of determinands required for consideration, coupled with their vulnerability to spatial, temporal and anthropogenic variabilities, makes the definition of water quality highly multi-faceted. Overcoming this entails extensive data collection, sophisticated data integration and accurate normalization and representation of hydrological and hydrodynamic processes. These challenges underscore the need for a comprehensive approach to water quality modelling, integrating robust data collection, adaptive modelling techniques and rigorous validation processes across different space and time divides.

These prevailing circumstances notwithstanding, advancements in technology, especially in areas such as High-powered Computing, Remote Sensing and Cloud-Internet of Things solutions have opened new avenues for more accurate and sophisticated modelling approaches. These advances are driving a revolution in data acquisition, correlational and sensitivity analyses and integration of complex computational algorithms and mathematical representations into single-model frameworks. Offering increased potential for a better understanding of water quality dynamics and development of decision support, contemporary scientific tools and evaluation approaches supported by Machine Learning and Artificial Intelligence techniques can process large datasets and changes across vast spatiotemporal domains, identify complex patterns and adapt to changing conditions. These developments are stimulating the evolution of integrated models that consider multiple determinands and their complex interactions to make predictions and enable real-time monitoring and decision-making strategies. This much has been revealed by the successes recorded and reported by various studies where the practical application of these contemporary methodologies has yielded appreciable results.

Hai et al. (2022) offered a robust practical approach to the prediction of the longitudinal dispersion of pollution in natural waters, improving on the previous efforts of Azamathulla and Ghani (2011) and Kargar et al. (2020). Their study highlighted the potential of machine learning techniques in providing accurate and reliable insights into pollution spread and control, especially in highly prone areas such as industrial and mining catchment areas. The paper's inclusion of a sensitivity analysis to assess the impact of various input parameters on model performance was a noteworthy contribution which helped to identify significant factors in pollution spread and hence scale down the number of model parameters to manageable limits. Abdalrahman et al. (2022) similarly made significant contributions to pollution estimation prediction in river basins, employing a backward stepwise sensitivity analysis to identify the most significant parameters required to predict infiltration rate and machine learning architecture to predict pollutant infiltration rates with high quality and accuracy. This was validated by a robust benchmarking of the model's predictive power with data obtained from 50 different rivers. Li et al. (2024) demonstrated the effectiveness of machine learning-based models for the prediction of water quality by employing a detailed correlation analysis and additive explanations methodology to identify the most relevant input variables for the prediction of water quality of Tualantin River. Deng et al. (2022) through their work on eutrophication prediction and its impacts on water quality demonstrates the effectiveness of ML models in handling non-linear problems and providing accurate predictions. Their integration of Environmental Kuznets Curve (EKC) models for future water quality forecasting in the semi-enclosed Tolo Harbour is an innovative approach, offering insights into potential trends and guiding decision-makers in managing coastal ecosystems.

Adaptative cross-disciplinary methodologies towards improved water quality decision support

Cross-disciplinary methodology integration refers to the combination of approaches, concepts and tools from multiple disciplines to create a more comprehensive and holistic solutions problems. More often than not, this allows for the assimilation of diverse perspectives and expertise, leading to more wide-ranging and universal understanding of prevailing complex phenomena. Potentials and opportunities have been identified from insights and techniques across diverse related domains such as public health, social and ecological sciences, which when adopted and adapted offer significant improvements to water quality modelling and the development of decision support systems. The complex, multifaceted nature of water quality issues, which often spans technical, environmental and social domains is one which yearns for such integrated interventions as efforts continue to be geared towards developing more robust and versatile models and improving the general strength of modelling endeavours with time.

Adoptive methodologies emphasize iterative learning, and continuous feedback and adjustments based on real-time monitoring and evaluation, enabling the development of models that dynamically adapt to changing conditions. The application of Explainable Artificial Intelligence (XAI) models adapted from other domains to water quality modelling are playing a vital role in helping the course of development of universal water quality models with their capacity to identify key variables amidst the stack of water quality determinands available and their interactions and influences on water quality outcomes. Generally, machine learning (ML) and artificial intelligence (AI) techniques are viewed to be black-box in nature, in that their decision-making processes are not open and often difficult to understand or explain, operating through complex layers of interconnected neurons and making deciphering how predictions and outcomes arrived at a challenging task. XAI techniques addresses identification of biases and errors and help in the refinement of models which when integrated into water quality models increase the possibilities of identifying critical quality determinands, detecting anomalies and understanding the factors driving water quality problems.

Nallakaruppan et al. (2024) demonstrated the burgeoning potentials offered by cross-disciplinary adaptation of XAI models when they used it to provide transparent and interpretable predictions to water quality by parametric analysis of potability of water based on key parameters. The proposed approach employs model-based and model-agnostic interpretations to provide a deeper understanding of feature importance and their relationship with water quality. The study presented case studies in river pollution and urban water contamination to validate and demonstrate the potential impact of XAI in addressing water quality issues using performance metrics like accuracy, precision, recall and *f*1-score to emphasize the reliability and credibility of the water quality predications. Natarajan et al. (2024) have also demonstrated the practical applicability of optimized machine learning models to air quality predition, a discipline which is analogous to water quality prediction in many ways than one. The study employed benchmark air quality data from 26 major cities in India to evaluate the proposed model. This comprehensive dataset allows for detailed analysis and validation of the model's accuracy and reliability, demonstrating pristine robustness and effectivness in predicting air quality. Kshirsagar et al. (2022) similarly emphasized the benefits of machine learning and deep learning techniques in tackling complexities that challenge and limit the prediction of air quality. Using a hybrid approach which combines different ML algorithms, their study overcame the limitations of individual models to enhance predictions accuracy and reliability of air quality forecasts. The likes of He et al. (2024) and Shitharth et al. (2023) and also put forward opportunities in adapting novel approaches of artificial intelligence-backed time series analysis and satellite imagery to benchmark baseline water quality models, indicating its effectiveness and feasibility for complex water environments. Ablation experiments showed substantial performance improvements with the inclusion of the coordinate attention (CA) module, efficient channel attention (ECA) module and varifocal loss function into the prediction algorithms. These components enhance detection accuracy by improving the ability to extract features from complex backgrounds and varying scales of floating objects. The inclusion of various optimization techniques and experimental verification through case studies further strengthen the validity of the proposed approach.

Attaining sustainability in water quality modelling in the face of climate change

While developing a truly generic and all-encompassing water quality model may be challenging as previously discussed, focussing on model flexibility, adaptability and modularity can help create frameworks that can be tailored to broad-based contexts and provide valuable insights for water quality management and decision support as buttressed by Strokal et al. (2019) and Van Vliet et al. (2021). This is very essential in response to the climate change phenomenon which is much of a reality in our contemporary world. Its potential to impact future generations has been reported to be far-reaching, with possible consequences on losses and alterations in biodiversity and ecosystems, degradation of water quality and availability with its attendant health risks and disruptions in food production as a result of shifts in weather patterns and season and lots more. This then calls for the alignment of the management of resources such as water, in ways that meet the needs of the current generation and without compromising those of future generations. Judging by how important water in general (potable water in particular) is to life, there are no indications yet that future generations will not be as reliant on water resources as the current. There will continue to be the need for access to clean and adequate volumes of water, efficient usage of available water, recycling of used water, improvement of water-supported agricultural practices and preservation of the environment. Thus, there is a need for the development and implementation of frameworks and strategies that ensure long-term protection, efficient management and equitable distribution.

As affirmed by Li et al. (2014), water quality modelling is a fundamental approach to ensure sustainable water resource management in line with sustainable development goals (SDGs). Since water quality is influenced by a series of determining factors and parameters, it must be taken into account in whatever strategies and frameworks to be developed for the preservation of future generations. According to Alcamo (2019), the challenges of the complex interactions of influential factors have to be overcome for the holistic understanding and development of adequate support systems. Reports from various studies reviewed so far have shown appreciable progress made in these regards while prospects and opportunities are promising. The integration of advanced data-driven computational techniques in water quality modelling is enabling the analysis of large datasets and enhancing the quality of forecasting and interpretation of complex patterns which can be used to develop early warning systems for future occurrences (Dawood et al., 2020; Sperotto et al., 2019). Given the uncertainty of future environmental conditions, adaptive and modular frameworks are essential. The potential of adaptative cross-disciplinary methodologies towards improved water quality decision support accommodates changing conditions, allowing for flexibility in response to environmental shifts, climate change and human activities. Interdisciplinary frameworks enable the integration of new components or methodologies without requiring a complete overhaul of existing models. The focus for stakeholders therefore has to remain geared towards aligning all arms of water quality management, which includes qualitative and quantitative forecasting, with sustainable development goals particularly those focussed on clean water and sanitation, good health and well-being, climate action and sustainable cities and communities. Efficient water quality modelling can help achieve these sustainability targets through:

- prediction and monitoring of water quality parameters and the effects of climate change on water quality.
- assessing pollution sources, spread and identification of areas at risk of contamination.
- evaluating the effectiveness of water treatment processes.
- developing interventions to prevent waterborne diseases and guide investments in associated infrastructure.
- supporting decision-making for water resource management and guiding policies for sustainable water management.

The associated challenges notwithstanding, these alignments with SDGs are crucial for developing sustainable practices that account for the uncertainty and variability associated with climate change and safeguard future generations' well-being. Accordingly, an adaptive water resource planning method should be based on ensembles and multi-model probabilistic approaches rather than on an individual scenario and a single-value projection for the future.

Conclusion

This review study has explored the development of water quality models and their application in decision support systems in a climate-changing world, highlighting the challenges, advancements and future opportunities in this field. It discusses the complexities of water quality characterization, universal modelling and the evolution of decision support systems that can improve water quality management. The development, implementation, integration and acceptance of model-based DSS in water quality management has come a long way since it evolved from an object of academic curiosity to a concept for possible practical implementation. Like many emerging methodologies, nascent challenges associated with the integration of science in the description and prediction of real-life phenomena initially proved to be a stumbling block, with a wide gap of distrust created between modeller and operator. This has left finding solutions to water quality challenges more of a reactionary endeavour rather than being pre-emptive, predictive and precautionary. However, as the realities of climate change, increasing populations and the endangerment of the environment began to dawn, the pressing need to bridge the gap between science and applications came. As observed, the biggest challenge to water quality modelling was the sheer number of parameters that define or serve as determinands of quality water, together with the means by which each of these determinands could be detected and measured. Nevertheless, continuous experimentation, testing and upgrades helped increase the experience gained in modelling over time. Departure from lumped descriptions to descriptions based on spatial, temporal and sensitivity analyses helped in scaling down quality metrics to be domain-specific. This meant that keeping the number of parameters as low as possible as a first breakthrough, increased the information content per parameter and therefore allows both a more accurate determination of the parameter and a more reliable correlation of the values obtained with catchment characteristics.

Limitations of the study

While this study has tried to be as extensive as possible in covering a wide range of sub-topics, focussing mainly on providing broad overviews without overshooting the scope of water quality modelling and development of associated decision support systems, the breadth of coverage has come at the expense of depth. With the hindsight that knowledge is inexhaustible and also the constraints of publishing costs, some aspects of water quality decision support systems such as the challenges of standardization and validation across different regions of the world have not been elaborated upon, potentially limiting the depth of insights into these subdomains of the overall scope of the review study. Furthermore, climatic contexts and their impacts on model variability have not been adequately enumerated, hence it is still unclear if the transferability of certain modelling outcomes can be guaranteed. Lastly, while mention has been made about the integration of methods and techniques across different levels of modelling and application, the pathway and frameworks for clear and seamless integration of these methodologies and collaborative efforts were not explored in this study.

Possible improvements

As highlighted in the limitations of the study, the vast horizon of the knowledge base associated with water quality and resource management makes it difficult to discuss in detail at the first time of asking. Broader focus for further research can be centred around more nuanced insights into the different contexts in which factors that influence water quality can be viewed, such as groundwater remediation, soil decontamination and strategies for minimization of water consumption. Exploring these domains has the potential to significantly enrich the water quality management discussion. This can be boosted by exploring innovative methods for collecting, standardizing and validating water quality data to ensure accuracy and reliability across diverse regions and ecosystems. Cross-disciplinary collaboration is key in this regard.

Future possible directions

The emerging fields of Machine Learning (ML) and Explainable Artificial Intelligence (XAI) are yet to be fully tapped into in terms of application to water quality decision support systems and management. Continued exploration of these techniques can provide valuable insights, transparency and interpretability into complex water quality patterns. The success rate of such will depend on the quality of data and models emanating from algorithms built on it. With such innovations coming through for water quality monitoring and evaluation, proactive actions can be taken by water supply mangers and operators to ensure consumers are not put at risk or compromised by water consumed. Already, digital technologies are revolutionizing and improving the quality of products, services and decision-making in many spheres. The rapidly increasing number and degree of sophistication of sensors available have expanded the innovation space for watershed monitoring and reporting networks with the capacity to gather data quickly and in real-time. Leveraging remote sensing and Internet of Things (IoT) technologies can enhance real-time monitoring and data collection for water quality management. This integration can improve the accuracy and scalability of water quality models. While efforts are ongoing in bridging the innovation gap between conceptualization and modelling by water scientists and managers in municipalities and industries, for more acceptance of science and communication technology-based applications in management operations, emerging cyber-physical and artificial intelligent systems have been primed to transform day-by-day management of water and provide lasting solutions to quality water availability and supply challenges. The prevailing challenges notwithstanding, there remains a vast landscape of possibilities and markets for exploration in developing tools, techniques and products that will help in ensuring quality water is sustainably available for all in line with the development goals of many nations of the world.

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Festus Fameso: Conceptualization and Writing (original draft). Julius Musyoka Ndambuki: Conceptualization and review (original draft). Williams Kehinde Kupolati: Review and Editing (second draft). Jacques Snyman: Review Synthesis.

Informed Consent/Patient Consent

The authors did not make use of any human or animal species as specimens in this study, hence, violated no rights to privacy from informed consent nor institutional and national standards for the care and use of laboratory animals.

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Data Availability Statement

The authors hereby affirm that this study consists of a review and synthesis of previous similar studies, hence, the references cited provide extensive library of indexed data from publicly available sources that can be accessed by intending readers. No new datasets were collected, generated or created by the authors while preparing this paper beyond the ones used in the cited references.

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