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TOPICAL REVIEW

Surface Water Monitoring Systems–The Importance of Integrating Information Sources for Sustainable Watershed Management

YULI SUDRIANI[1], VIKTOR SEBESTYÉN[1,2], AND JÁNOS ABONYI[1], (Member, IEEE)

[1]ELKH-PE Complex Systems Monitoring Research Group, University of Pannonia, 8200 Veszprém, Hungary

[2]Sustainability Solutions Research Group, University of Pannonia, 8200 Veszprém, Hungary

Corresponding author: Viktor Sebestyén (sebestyen.viktor@mk.uni-pannon.hu)

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ABSTRACT The complex interactions from anthropogenic activities, climate change, sedimentation and the input of wastewater has significantly affected the aquatic environment and entire ecosystem. Over the years, the researchers have investigated water monitoring approaches in terms of traditional monitoring or even integrated systems to handle such an environmental assessment and predictions based on warning systems. However, research into the selection and optimization of water monitoring systems by the combination of parallel approach in terms of sampling techniques, process analysis and results is limited. The research objectives of the present study are to evaluate the existing water monitoring systems based on the latest approach and then provide insights into factors affecting sensor implementation at sampling locations. Here we summarize the advancement and trends of various water monitoring systems as well as the suitability of sensor placement in the area by reviewing more than 300 papers published between 2011 and 2022. The research highlights the urgency of an integrative approach with regard to water monitoring systems including water quality model and water quantity model. A framework is proposed to incorporate all water monitoring approaches, sampling techniques, and predictive models to provide comprehensive information about environmental assessment. It was observed that the urgency of model-based approaches as verification and fusion of data assemble has the ability to improve the performances of the systems. Furthermore, integrated systems with the inclusion of a separate modeling approach through integrated, semi-mechanistic models, data science and artificial intelligence are recommended in the future. Overall, this study provides guidelines for achieving standardized water management by implementing integrated water monitoring systems.

INDEX TERMS Infrastructure, integrated monitoring, water monitoring system, modelling, water quality.

I. INTRODUCTION

Water monitoring systems play such an important role in aquatic environmental systems and catchment areas, which have been applied to reduce water pollution in freshwater environments that is one of the priorities set by the United Nations [1]. Water monitoring systems have received far more attention because they offer a wide range of solutions in terms of the prevention, environmental assessment, management and mitigation of disasters [2]. For example, Harmful Algal Blooms (HAB) have highlighted the need for water quality monitoring systems to prevent the eutrophication of water bodies [3]. Water monitoring activities can reveal the answer to the problem by estimating water scarcity [4]. Various water quality monitoring programs around the world have analyzed a lot of environmental conditions in terms of water demand [5], monitoring microplastics [6], planning wastewater systems [7], monitoring pesticide [8], hydropower [9], surface melt rate [10], the impact of water pollution on human health [11] and biodiversity observations [12]. Furthermore, remote sensing technologies have advanced to assess the distribution of water hyacinth *(Eichhornia crassipes)* [13], dispersal of

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phycocyanin [14], spatial prediction of surface water quality [15], measure of nutrient cycles [4], hydrological parameters [16] and identify spatial coastal hazards [17].

Monitoring water dynamics in aquatic environments is challenging because it is influenced by various environmental phenomena such as internal load, hydrodynamic mixing, thermal stratification, vertical distribution, biogeochemical cycles, residual loads, and nutrient recycling. The complex driving force can be difficult to explain using limited amounts of data representing the state of the environment. There are some issue in water monitoring system such as optimization algorithm, design of sampling frequency, variables and indicators, stabilize the network under environmental uncertainty change and the detection of an unpredictable event [18]. The compilation of studies from different monitoring locations in Tables S5 and S6 shows that with regard to water pollution, more of an emphasis should be given to the anthropogenic activities, including soil leaching and discharges from wastewater treatment plants (WWTP) [11]. Initially, the obstacles of system implementation have considered with regard to the accuracy of data collection [19], data acquisition from different locations of point sampling [14], the selection of key parameters which influence changes in water dynamics [20]. The development of the real-time geographical distribution of the surface water quality monitoring [21] and the performances of various sensor algorithms [22]. The water monitoring system, which is based on an optimal monitoring network, as proposed as a powerful instrument for collecting measurement data and maximizing the detection of anomalies concerning water dynamics [20].

Therefore, the amount of research on water monitoring systems has dramatically increased (Fig.1.). Nowadays, water monitoring program obtained environmental data to represent the trend of phenomena of water pollution, water flow and hazard assessment based on automation tools [23]. Monitoring frequency and high-quality data are the key factors to produce the acceptable result and precision which should be reported [24]. Additionally, the effective of existing environmental monitoring of water availability and quality required a large amount of water monitoring points in relation to nutrient concentration [25]. However, the water monitoring system is at risk of vandalism, maintenance issue, sensor reading and system failures [26]. Overall, the current water monitoring system is in exploration stage which can be developed into integration system in a real-time [18].

The advancement of water monitoring has been applied in the system called NJU-EWS, which was used to explore the deployment of various sensors for the purpose of collecting data through automatic control from the monitoring centre [27]. Manfreda et al. summarized spatio-temporal Unmanned Aerial Systems (UAS) to improve environmental monitoring during limited time use [22]. The result of study Sumargo et al. acknowledged the potential of integrated measurements including hybrid networks, real-time weather monitoring, high-resolution images, and sampling measurements [28]. Moreover, the quantification of phycocyanin from satellite imagery has been assessed through bibliometric analysis [14]. Nevertheless, it was observed that different algorithms or methods did not compare including the data collection processes from different sampling points for oligotrophic to mesotrophic state [14].

Twelve parameters including Dissolved Oxygen (DO) [29], Total Suspended Solids (TSS) [30], Turbidity - Chlorophyll-a [31], Electrical Conductivity (EC) [32], pH [33], Total Chlorine [33], Organic pollution [34], Biochemical Oxygen Demand (BOD) [34] including Secchi depth, Total Phosphorus (TP), Total Nitrogen (TN) [35] were used to determine water quality that have frequently been applied in aquatic environments status. Other parameters proposed in this current research are hydromorphological, and biological as well as related to climate change, anthropogenic activities, and microplastics. The authors in another study concerning this issue addressed the challenge in terms of optimal monitoring networks to identify the most important variables of water quality [36] and how to optimize the survey sampling by managing the Total Maximum Daily Load (TMDL) [37]. Monitoring the spatial and temporal distribution of water quality and quantity is required to identify of sampling points from upstream data, while the optimal sampling frequency correlates with the topology of sampling points [38], pollutant concentrations [8], the availability of data [39], time periods [40], catchment behaviour [3].

Considering all the research published in previous studies between 2011 and 2022, the advancement of research on water monitoring is swift, moreover, the availability of existing water monitoring systems should be reviewed to propose an optimal approach for long-term water quality planning. Manfreda et al. show that the integrated system was proposed to overcome deficiencies in data collection [22]. Furthermore, the integrated system increased the accuracy of both systems significantly in terms of both spatial and temporal data [19] as well as improved the reliability of the water monitoring system [41].

However, the methods discussed in the literature mainly focus on solutions at specific sampling locations. The approaches have been used limited number of samples through sampling analysis and data models which influence decision-making. Rarely does the design and deployment of water monitoring systems involve the ideal selection, optimisation of various combination and parallel monitoring systems from the identification of sampling points to the availability of monitoring stations. In addition, the monitoring systems with a model validation approach, best selection of water parameters and the optimal sampling frequency as well as determining sensor placement in one system will increase the performance of systems. Under these circumstances, the need to expand a methodological analysis which takes into consideration the selection of all water quality sampling techniques is pressing. As a result, more alternatives to suit different requirements of the system must be proposed to answer the more complex problem concerning the implementation of water monitoring and provide high quality results from information decision system results.

While the water monitoring system was considerably reviewed, reviews of integrated different source in one monitoring system for freshwater have not published yet. There is a need for an overview display the stage of grow field. At present, we first review the implementation of water monitoring system of each integrated stage, then discuss how different information is connected to achieve much more result validation, and finally highlight the decision-making process for early warning system in water pollution and hydrological problem.

II. METHODS

In this topical review for water monitoring system development, aspects related to the integration of water quality and quantity are explored. The incorporation of monitoring systems on the basis of which a framework will be recommended in order to optimally implement the collection of information for the long-term sustainable management of surface water bodies. The last search was performed on 9 February 2022 using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. Figure 1 summarizes all the scientific papers reported in this study. This survey searched for literature in google scholar and Scopus considers four sets of keywords:

- Keywords 1: TITLE-ABS-KEY (water AND monitoring AND (lake OR river) AND (review OR overview)) AND (LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017) OR LIMIT-TO (PUBYEAR, 2016) OR LIMIT-TO (PUBYEAR, 2015) OR LIMIT-TO (PUBYEAR, 2014) OR LIMIT-TO (PUBYEAR, 2013)).
- Keywords 2: TITLE-ABS-KEY (water AND monitoring AND system AND (lake OR river) AND (review OR overview)) AND (LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017) OR LIMIT-TO (PUBYEAR, 2016) OR LIMIT-TO (PUBYEAR, 2015) OR LIMIT-TO (PUBYEAR, 2014) OR LIMIT-TO (PUBYEAR, 2013)).
- Keywords 3: TITLE-ABS-KEY (water AND forecast AND system AND forecasting AND method) AND (LIMIT-TO (EXACTKEYWORD, "Water Management") OR LIMIT-TO (EXACTKEYWORD, "Numerical Model") OR LIMIT-TO (EXACTKEYWORD, "Water Supply") OR LIMIT-TO (EXACTKEYWORD, "Data Assimilation") OR LIMIT-TO (EXACTKEYWORD, "Water Resources") OR LIMIT-TO (EXACTKEYWORD, "Computer Simulation")) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017) OR LIMIT-TO (PUBYEAR, 2016) OR LIMIT-TO (PUBYEAR, 2015) OR LIMIT-TO (PUBYEAR, 2014) OR LIMIT-TO (PUBYEAR, 2013)).
- Keywords 4: TITLE-ABS-KEY (water AND quality AND hydrology AND lake AND river AND freshwater) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020)).

The papers have been checked one by one manually, and the papers related to the proposed water monitoring development strategy applied the following rules to get the final paper sample set: inclusion of studies focusing on rivers, lakes, surface freshwater, monitoring system, and modelling. In Fig.1., a total of 1446 papers were covered by the retrieved search result while 953 papers are not related to the studies. The exclusion of the papers were covered on groundwater, socioeconomic environment, bio-indicator, and languages other than English. More details, 165 results are duplicate papers from different keywords. For the last screening, we categorized the papers into nine specific areas: water quality, remote sensing, monitoring, climate change, eutrophication, surface water, deep learning, cyanobacteria, sensor, hydrology. Three hundred-thirteen articles were selected, most of which were published in the last 10 years and discuss about water quality monitoring areas.

A. RESEARCH OBJECTIVES

The scope of water monitoring system development is related to the monitoring of hydrological change, good ecological status regarding to the water quality and quantity in the surface water bodies, especially in lakes and flowing waters (streams and rivers). The aims of this topical review are: (i) to evaluate the specific existing water monitoring systems regarding the water quality and water quantity of variables, stressors and threats in the aquatic ecosystem, (ii) to provide insights into factors affecting the implementation of sensors in terms of sampling locations. In this paper, several relevant issues have been investigated to answer the following research questions:

- How to integrate different water monitoring solutions into an integrated system?
- What are specific infrastructure and different sources of information to support integrated water monitoring system?
- How does data management influences the performance of water monitoring systems?
- How can the specific water quantity and water quality parameters be defined to support the water monitoring systems?
- How can the planning of system requirements and smart operation of monitoring solutions be supported with system integration?

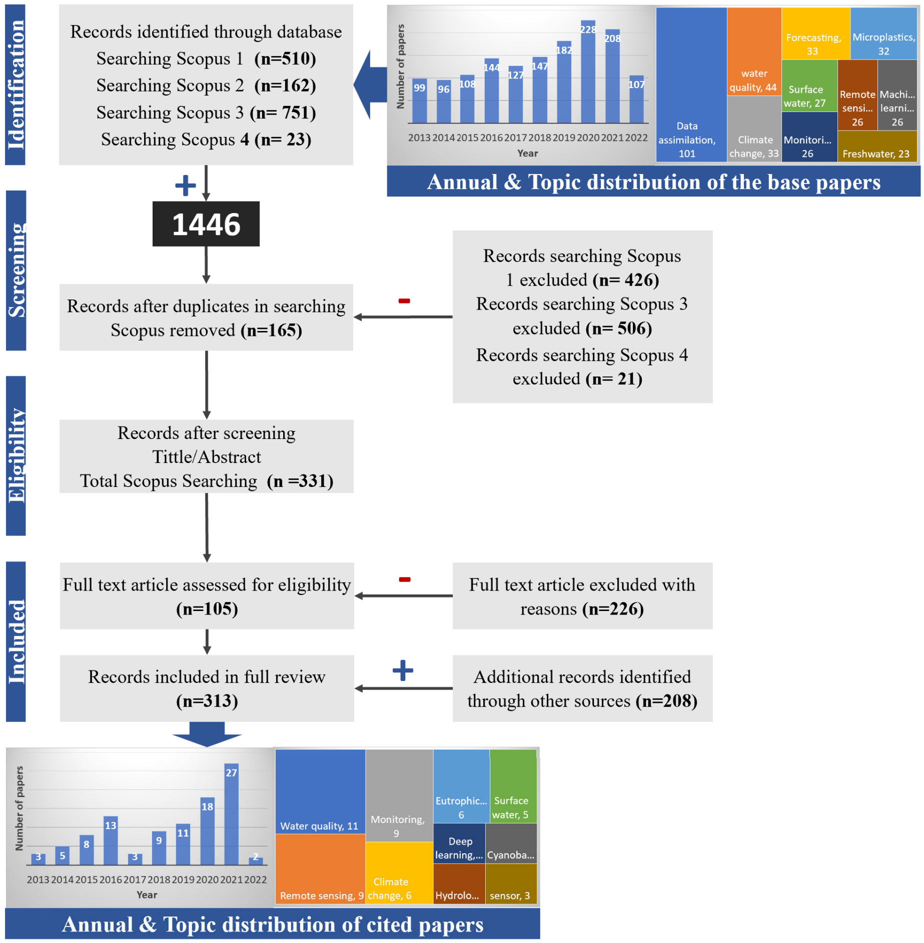

FIGURE 1. Exploring knowledge about water monitoring systems using PRISMA methodology.

- How can a higher level of decision support be achieved with integrated water monitoring systems?

The structure of the research is started from Section I to describe the research problem, status quo of water monitoring and research gap. The methodology for gaining knowledge incorporate research questions can be found in Section II. Our developed Framework for Integrating Monitoring Solutions (FIMS) is introduced in Section III. The FIMS process is split into six strongly interconnected stages, beginning with stage one, which correlated to Section IV. It consists of parts of computer hardware, including sensor boards, remote sensors, and laboratory measurements. The physical structure of the measurement in Stage I. has integrated different criteria sampling from laboratory and in-situ measurements to remote sensing. This process requires more frequent sampling and data collection to be acquired, improving the level of monitoring that can be carried out. The stages considered applicability of different information sources collection and recent implementation of infrastructure of water monitoring stations. The design and deployment of data acquisition in Stage II. which will be discussed in Section V are based on metadata quality, data transfer system, and power management. This section provided integrated data warehouse with support from citizen science application. Additionally, Section V discussed imagery mining, data outliers, data analysis and experiment, data correction had been designed in this section, also, the result was processed two stages before. In section VI, the selection of measurement variables and the use of modelling algorithms. In addition, model building used first principle model, data-driven model and semi-mechanistic models to analyze the data. In the case of analysis based on modelling, Stage V. about monitoring and management through water quality assessment, prediction, and threshold used these approaches to activate the warning system and to improve water quality measures which are discussed in Section VII. The problems associated with the identification of sampling points, each elements and related aspects including early warning system is explored. The last stage is decision support as the output of the water monitoring system, which will be discussed in Section VIII (Decision Support System (DSS). DSS is measured by operation support, R&D, academics, policy-making, local government and water directorates.

III. THE CONCEPT OF THE FRAMEWORK FOR INTEGRATING MONITORING SOLUTIONS (FIMS)

The environmental impacts of anthropogenic activities are increasing globally, which means monitoring systems is urgent in the scope of biodiversity, the dynamics of ecological connectivity, physiological processes and food networks. Effective monitoring systems are essential to inform people of management and public policy decisions. In addition, the balance of the ecosystem is a significant challenge in terms of understanding the roles that natural and water-quality changes play such as algal growth, microbial processes, as well as microbiological and genomics examinations. Keeping contaminants at low levels is a complex task requiring knowledge of the potentially toxic substances present in the freshwater and the calculation of hazard levels.

Currently, the discussion about integrated spatio-temporal water monitoring systems in terms of the water quantity and water quality in a single system is limited. Multiple integrated systems in a monitoring system leading to an integrated data platform are commonplace [42], for example, integrated technologies such as tiered frameworks and the Internet of Things (IoT) based on web-based data services [18]. It is also an integrated system related to data merging (data fusion) because it combines the algorithm in terms of spatio-temporal and spectral properties, as well as provides a uniform data set to end-users [43]. In addition, an integrated system will provide better information about dominant processes, reveal the patterns of biochemistry and contribute to the estimations of a quantitative model [44]. Nowadays, integrating spatio-temporal monitoring is popular when it comes to the monitoring of water temperature to collect long-term data (sub-hourly range) regarding temperature change dynamics, which supports large-scale monitoring networks [45]. Integrated monitoring technologies to facilitate process analytics and the absence of continuous monitoring have been real wireless sensor networks as well as in-situ and spaceborne satellites leading to the collection of real data from several distributed data points at a sampling site [18]. Moreover, the utilization of multisensor data fusion and virtual clusters from cloud computing has been developed [23] and the limitations of temporal sensors for Chlorophyll-a and Total Suspended Solids (TSS) discussed [19]. AquaWatch is an initiative within the Group on Earth Observations (GEO) that also uses integrated data to temporally and spatially forecast water quality over a short period of time following the participation of citizen science, drones, aircraft and in-situ sensors [46]. The hazard monitoring system has been developed by real-time in coastal areas through map sequence analysis to handle sedimentation, emergency situations, and pollution control [17]. In order to achieve the purpose of this study, we have developed the FIMS integrated conceptual framework by integrating different methodological design data flow while taking into consideration seven points related to each stages:

- Interconnect available data resources in various measuring instruments.
- Correlate water monitoring data acquisition covers power input, data distribution, and data integration including citizen science tools.
- The interlink from measurement tools (spatial-temporal data) and data incorporation (metadata) have an inflow into data warehouse.
- Data transmission stage consist of advance data analysis including spatial data. The collection of data is related to frequency of sampling.
- Identify the location of optimal sampling points and modelling tasks as fundamental functions of surface water management.
- Construct and use a multistage decision support framework. Define indicator threshold at the alert level as an input for early-warning and prediction systems to mitigate water-related disasters in inland water bodies through a water monitoring system.
- Deploy the method to enhance the prediction of robustness and define the event of an unpredictable outbreak of water dynamics through forecast system.

As can be seen from the Framework for Integrating Monitoring Solutions (FIMS) shown in Fig. 2., the monitoring activities of water management can be optimized by integrating different information sources so that more information can be obtained at a lower cost, while the cross-validation of data sources also supports the implementation of the FIMS.

Figure 2 shows the architectural design of the water monitoring system framework integrating different information sources (continuous in-situ monitoring, remote sensing, water sampling), several computations and the optimization of sampling points. The main stages of the proposed FIMS framework are presented in the following Sections (IV-VIII).

Overall, the fundamental motivation for proposing a truly integrated framework is to collect and process the data in a parallel system based on a cloud platform. We propose that each monitoring approach should be combined (e.g. sampling, in-situ measurements, models) to optimize the water management tasks and maximize the information content of sampling variables efficiently and effectively. The advantages and disadvantages of the proposed sources to be integrated in the FIMS are discussed in Section IV.

IV. INFRASTRUCTURE AND APPLICABILITY OF WATER MONITORING SYSTEMS

Currently, no coherent and integrated infrastructure for decision-making and analysis in the field of water management is available. Institutions involved in monitoring natural and anthropogenic factors affecting surface water bodies are in sufficiently coordinated. Coordinating measurements and modeling could provide more information, more cost-effectively than the current "business as usual" solutions. However, interoperability between the databases of institutions is generally not supported, moreover, uniform quality assurance and monitoring systems based on a common knowledge base are lacking. Therefore, service and information functions must be developed and strengthened to

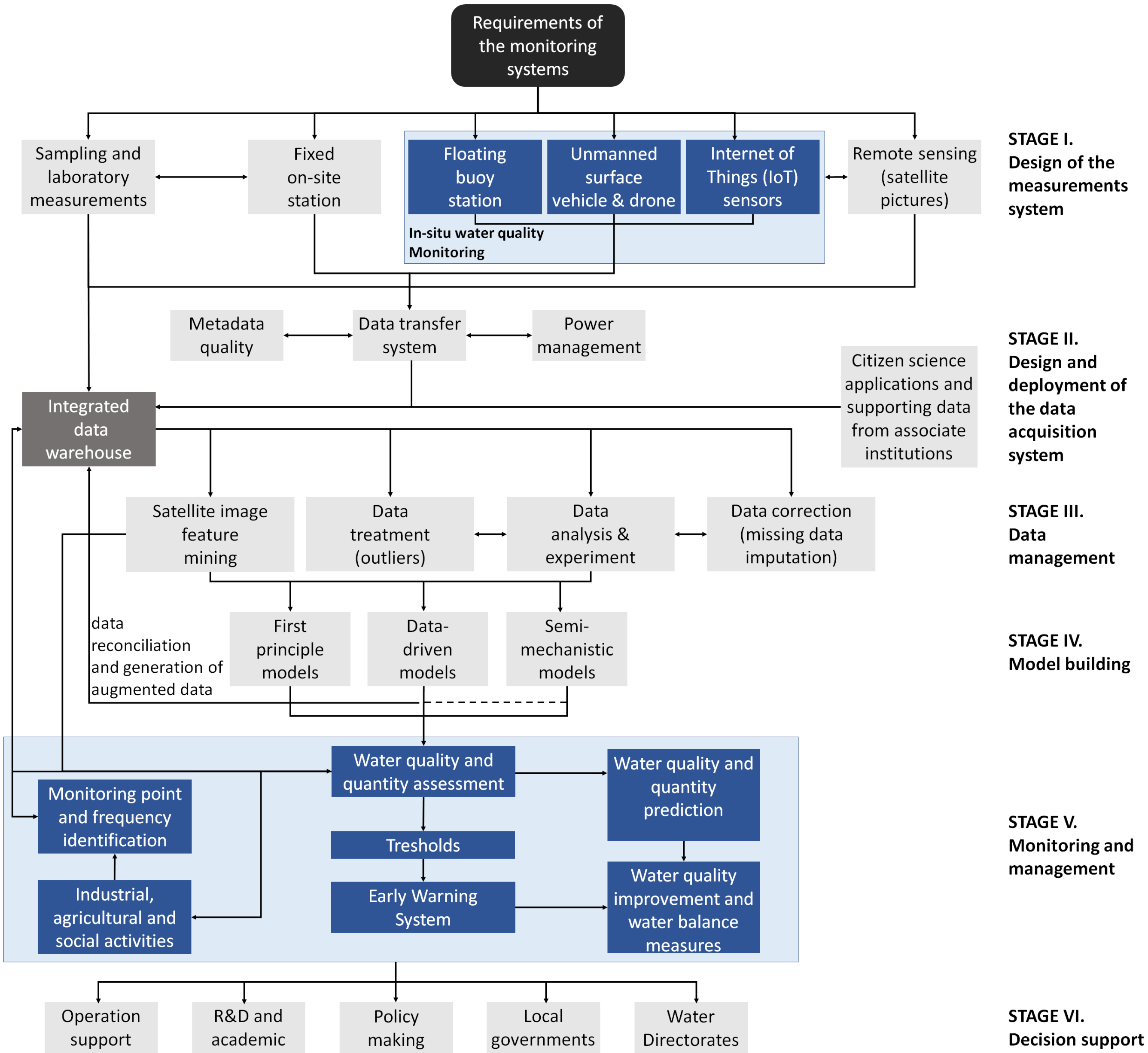

FIGURE 2. Framework for Integrating Monitoring Solutions (FIMS).

achieve the strategic goals of sustainable water management. No resources are available for integrated development activities and long-term operational monitoring systems. Due to anthropogenic activities and issues concerning water pollution, the need to assess the ecological status of water bodies and mitigate disasters using more informative monitoring activities is increasing.

A. APPLICABILITY OF WATER MONITORING SYSTEMS

Since the problem of inland water bodies becomes more complex and measuring using traditional monitoring is limited, it cannot describe how aquatic ecosystems respond to environmental changes. However, some parameters must be analyzed in the laboratory because they can not be measured by sensors, e.g. most biological parameters and some physicochemical ones. The development of monitoring technologies from traditional measurements to high-frequency technology and sensor data loggers offers a wide range of measurements of freshwater monitoring. However, the findings of this study are in line with Gholizadeh et al., namely that traditional monitoring is still needed to validate sensor parameters [47]. The most common solutions used to monitor water quality are summarized in Fig. 3, which was supplemented with modeling as one of the most promising sources of integration and further development of the existing monitoring systems.

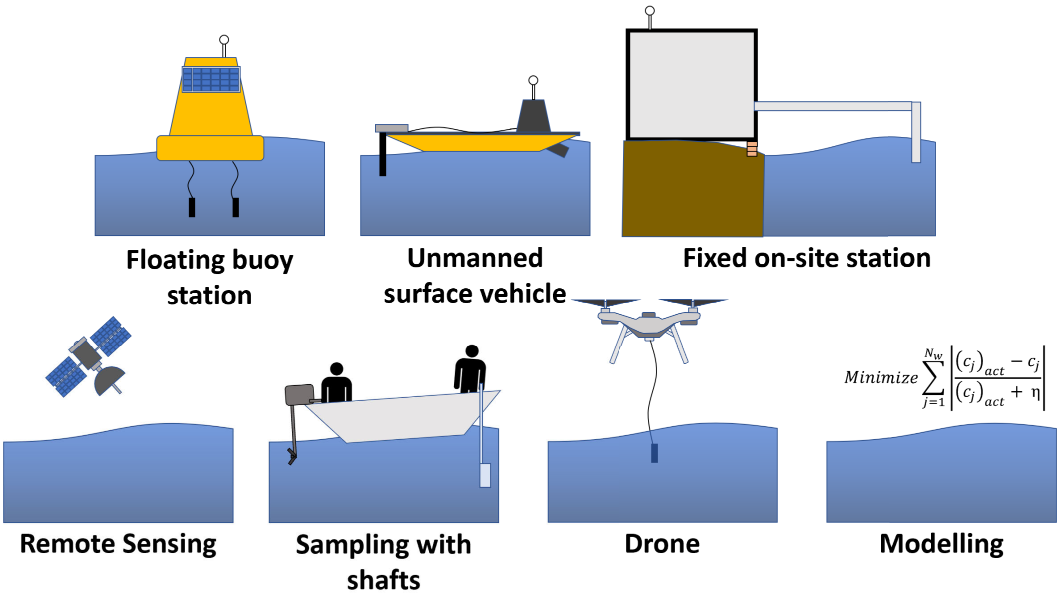

FIGURE 3. Water monitoring solutions and extended information sources in sustainable watershed management.

Figure 3 shows six different water monitoring solutions, which are suitable for data collection (water quality and water quantity parameters) in freshwater ecosystems, namely floating buoy stations, unmanned surface vehicles, fixed on-site stations, remote sensing, shaft sampling and Unmanned Aerial Systems (UAS). The demand of advance monitoring systems due to the increasing water pollution and hydrology disasters leads to the simultaneous measurement for better solutions in DSS. Moreover, high-quality data monitoring can be obtained with coherent and cross-validation in various monitoring data sources. The modelling approach can complement and verify the value of data monitoring. The discussion for the tools of water information source and validation can be found in Section VI.

The functionalities of these examined solutions which are suitable for ensuring water quality will also be summarized in Fig. 4. Floating buoy stations have been used to measure horizontal movement, moreover, the direction of flow can easily be measured anywhere in an inland water body and is easy to install [48]. Besides, the advantages of floating buoys are their fixed design [49], ability to continuously monitor data rapidly for in-situ measurements, the acquisition of long-term monitoring data, reduced costs [50] and fast measurements [51]. However, the unsteady nature of floating stations as a result of waves reduces the accuracy of their data [48]. Other reasons include the overestimation of the amount of cyanobacterial biomass [49], reduction in the accuracy of data measurements [50] and the minimization of data transmission [51].

A permanent station located at the sampling site can only monitor the coastal area, controls data measurements [52], and system maintenance due to time-frequency [53]. However, the parameter to measure capacity at the waterfront site, the ability to duplicate real-life environmental laboratories for experimental analysis [52] and the measurement of real-time data are some of the benefits of fixed on-site implementation [53].

In remote sensing methods, distribution analysis has provided detailed information about spatio-temporal water quality data [54], enabled the source for changes of water dynamic in freshwater to be identified [55], can analyze data at remote locations [56] and is capable of reinforcing spatial and temporal data [55]. On the other hand, the deficiencies of this spatial method are its accuracy [54], reduction in the quality of satellite images as a result of bad weather [56], as well as the limited range of water parameters and spectral bands [55]. Remote sensing provides data at a higher temporal frequency whereby spatial patterns can describe properties of the lake rather than in-situ measurements [57].

In addition, spatial analysis covers all areas of water measurements [58] based on moving functions [58] supported by GPS navigation [59], wave movement in the aquatic environments [60], the scope area [59] and the consistency of data in post-processing [61] are some concerns with regard to this sampling method.

The advantages of Remotely Piloted Aircraft Systems (RPAS) or, more known as, Unmanned Aircraft Systems, are their high spatial resolution as a support tool for conventional - manned airborne imagery applications, ability to reach difficult locations, capability to take high-quality images, additional data for monitoring systems and more comprehensive earth and environmental analyse based on the integration of platforms (traditional instruments, mobile camera surveys, satellite observations and geomorphological analyses) [22]. The drone can be implemented with other supplementary instruments [62] and enable water sampling of a specific volume [63]. UASs have weaknesses such as legislation, the volume of water samples collected by drones is restricted and their unreliability [63]. Other disadvantages of UASs are data repository [22], data interpretation [22], costly instruments [62] and the necessity of specialized training [62]. High-Frequency Measurements (HFM) provide huge amounts of data even by only using one set of sensors over a period of days or months. According to Meinson et al. have made use of HFMs in terms of lake ecologies, to obtain data about lakes, for hydrological processes, to evaluate the movement of water as well as gather vertical profiles of the lake, depth time series and depth measurements through transects [26]. HFM is recommended as an additional tool to support DSS and Early Warning Systems (EWS) [24].

The last monitoring measurement in this topical review is shafts sampling, commonly referred to as the traditional monitoring measurement. Until recently, monitoring activities have used traditional monitoring, e.q. in-situ water sampling to obtain physical, chemical and biogeochemical information, which is time-consuming as well as expensive [4]. Traditional monitoring yields extensive amounts of periodic data, which is inadequate to predict potential threat such as algal blooms or floods [24]. The traditional method used a Secchi - Disk, a sensor without a data logger, and other instruments to get momentary time sampling data. The advantage of this approach is the ability to select water parameters later on [64]. On the other hand, cons of traditional monitoring are the necessity of operators being present [65], instruments being calibrated and validated before taking measurements [66], momentary data results, higher quality control, as well as the parameters such as pH and dissolved oxygen to be analyzed at the sampling locations rather than in the laboratory because of differing results [64].

It is also important to examine which parameter group can be measured with which solutions (Fig. 3) in order to map the integratability of the different solutions, which is presented in detail in Fig. 4.

Figure 4 shows which of the physicochemical, biological and hydromorphological parameters can be measured by the previously described monitoring solutions as well as physically describes the amount of event space available for system integration. The online system architecture is essential to support real-time water data monitoring [47]. Long-term data collection is used to reveal information about event dynamics, change patterns, trends, as well as shifts and to understand the correlation between the processes that cause the disaster events [3]. The development of long-term-data measurement is used to reveal the trend and unpredicted events, for the purposes of testing hypotheses, supporting data in simulation software, and finding the main driver parameters in inland water bodies [67]. In particular, the development of sensors using fiber optics, laser technologies, biosensors, optical sensors, microsensors to continuously record data in sampling stations [19]. The three indicator parameters in traditional water quality monitoring are: (i). physical parameters (e.g. temperature, turbidity, conductivity), (ii). chemical parameters (e.g. pH, Dissolved Oxygen (DO), Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD), total organic carbon, heavy metal ions), and (iii). microbial factors (e.g. total bacteria, total coliforms) [4]. It has expanded from traditional monitoring to online monitoring supported with measurement sensors, including chemical sensor instruments.

The rapid development of water monitoring system concerning the uses of sensors to gain information on Dissolved Oxygen (DO), pH, turbidity [68], Water Temperature (WT), Chlorophyll-a ($Chl-a$), Electrical Conductivity (EC), ammoniacal nitrogen ($NH_3 - N$) [69], conductivity [26], NO_3 concentrations [44], salinity, temperature, depth, chlorophyll fluorescence (ARGO floats) [46], Dissolved Organic Matter (DOM) [3], nitrate concentration [24], water temperature [45], Total Dissolve Solids (TDS) [70], and plastic pollution [71] as well as with regard to water quantity measurements such as soil moisture and streamflow [28]. Freshwater has also been assessed by biological monitoring to gather data to support the rehabilitation of rivers [72].

Another category of sensors broadly used in water monitoring systems are remote sensing technologies. Remote sensing has been deployed to analyze some parameters such as in blue-green algae phycocyanin ($BGA - PC$), $Chl - a$, fluorescent dissolved organic matter ($fDOM$), turbidity, and TSS [23],TDS [73] and colored dissolved organic matter ($CDOM$) [3]. Compared with another spatial sensor, Landsat/TM sensors from Landsat 5 as well as Landsat 9 as well, which was launched on 27th September 2021 are commonly used to calculate the $Chl - a$ concentration, $CDOM$, Secchi Disk Depth (SDD), Total Phosphorus (TP), Biochemical Oxygen Demand (BOD), and Chemical Oxygen Demand (COD) [47].

In recent years, the implementation of the Internet of Things (IoT) presented a new approach to collecting, monitoring and analysing data from a sampling site based on an integrated network which connects various pieces of equipment on one platform [74]. For example, a web-based application based on IoT has been developed to increase cost-effectiveness and monitor water quality using a wireless module [74]. Another one is the implementation of an IoT system with a focus on consistency in terms of time measurements, that is as energy-efficient and effective as possible with minimal and installation costs [75]. Hernández-Alpizar et al. has deployed an embedded system that includes IoT instruments to take measurements over a range of time periods automatically and control devices to minimize energy consumption, maintenance costs, as well as ensure data quality control [76]. A smart water monitoring system has been developed based on a WiFi module with three parameters, namely pH, turbidity and temperature, as well as a Liquid Crystal Display (LCD) due to the urgent nature of obtaining automatic information based on a Wireless Sensor Network

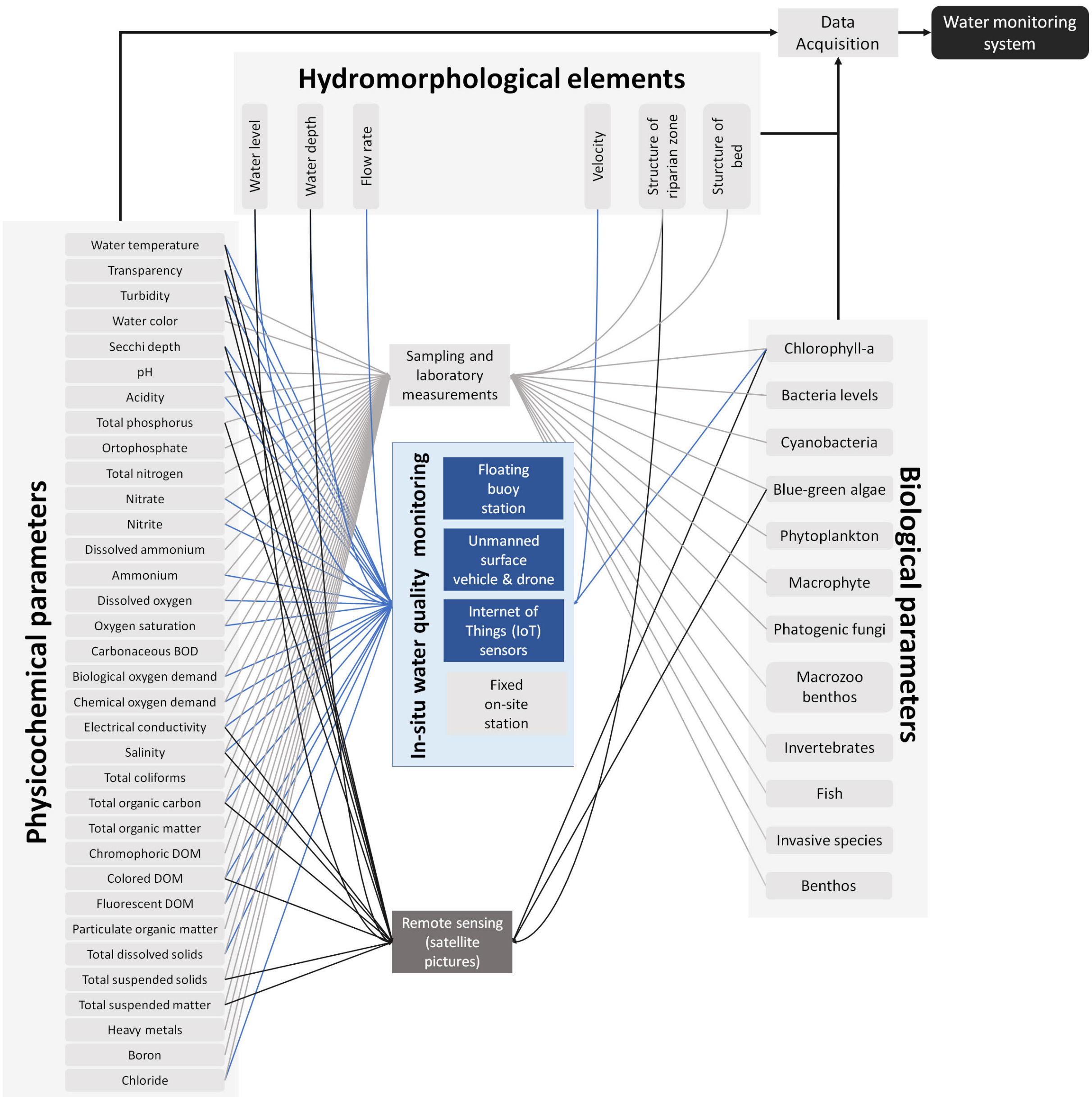

FIGURE 4. The applicability of different information sources in the monitoring of water bodies.

(WSN) [77]. In the event of this, the monitoring system can be integrated into the citizen science platform, which is more useful to validate monitoring data and increase the amount of data collected in the database than the traditional sampling-based monitoring activities [78]. In addition, participation from the public to participate in scientific research is supported by the United Nations (UN) through the 2030 Agenda [79] because it helps to deepen understanding of sustainability-related issues. However, citizen science, as a new method in water monitoring systems, limited measurements such as data quality because of inexperienced system users in scientific research and cannot describe the trends of citizen participation [78].

Table 1 presents key aspects of design integration in a comparative maturity framework, e.g. system requirements, supporting technologies and smart operations. By considering the aspects in Table 1 and the assessment of the existing monitoring systems, the new type of truly integrated information collection system on surface water bodies proposed in this research can be implemented.

V. DESIGN, IMPLEMENTATION, AND MANAGEMENT OF THE DATA ACQUISITION SYSTEM

Stages II and III are prepared for the purpose of cloud-based spatio-temporal data acquisition, which is used to assess the sensor data quality. These stages are interlinked with

TABLE 1. comparison of the Maturity of the different monitoring solutions by considering aspects of system requirements, supporting technologies and smart operations.

Maturity groups	Aspects	Floating Buoy Station	Remote Sensing	Shaft Sampling	Unmanned Surface Vehicle	Fixed on-site station	Unmanned Aircraft System
Based on requirementsBased on requirements	Granuality/Distributed /Spatial	Points	Monitor in spatial Area	Points	Monitor in spatial Area	Points	Monitor in spatial Area
	Vertical	Available	Not Available	Available	Available	Not Available	Not Available
	Time frequency	Continuous	Continuous or Momentary	Momentary	Momentary	Continuous	Momentary
	Availability/Robustness	Low-High	Low-High	High	High	Low-High	High
	the Amount of Missing Data in database of online water monitoring	Low-High	Low-High	Low	Low	Low-High	Low
	Period Over Which is a Data Missing	Dependence on Time sampling period	High because of cost	Low	Low	Dependence on Time sampling period	Low-Middle
	Minimal set of parameters	Some hydromorphological and physicochemical parameters are covered	Some hydromorphological, and physicochemical parameters are covered	Some hydromorphological, physicochemical and Biological parameters are covered	Some hydromorphological, physicochemical	Parameters cover some hydromorphological, physicochemical	Parameters cover some hydromorphological, physicochemical
	Maintenance	Monthly	Monthly-Yearly	Weekly	Weekly to Monthly	Monthly	Weekly to Monthly
	Operation	Required to implement sensors	Required to get support from fast network system	Required for Physical Work	Required Instrument's Stabilizer due to Wave Influence	Required for Physical and Sensor Implementation	Highly skilled Operator required over a short time Period
	Total Cost	High	Low-Middle	High	Low-Middle	High	Low-Middle
Based on technologiesBased on technologies	Integrated	Available with spatio-temporal sensors	With drone	as validation data	Available with spatio-temporal sensors	Available with spatio-temporal sensors	Available with spatio-temporal sensors
	Models	Available	Available	Not Available	Not Available	Available	Not Available
	Data Processing	Available	Available	Not Available in an online system	Not Available in an online system	Available	Not Available in an online system
	IoT Implementation	Available	Available	Not Available	Available	Available	Available
Based on Smart OperationsBased on Smart Operations	Automated Sampling	Fully Automated Sampling	Combination Fully automated sampling and in-situ sampling	Not available	Fully Automated Sampling	Fully Automated Sampling	Fully Automated Sampling
	Automated Warning	Available	Available	Not Available	Not Available	Available	Not Available
	Data-Driven Services (Automated report)	Available	Available	Not Available	Not Available	Available	Not Available

Section VII through the selection of water parameters for monitoring systems. The devices can collect the water quality parameters defined in Table 3. Data cleaning and data correction are particularly important to define the outliers, noise in the satellite image and missing data points, including merging data, citizen science data, data transmission and extracting the data from different monitoring systems. The database of the water monitoring system will be complex, moreover, the need to combine information using the distribution of data processes and integrate the database (data warehouse, information system) between institutions will increase the amount of information efficiently based on essential data measurements.

The purpose of data management as shown in Stage III is to obtain information from an online monitoring system in a specific location to help water managers better understand the dynamic process of surface water bodies [18]. The integration of data incorporated different types of monitoring systems to support water quality policy with aggregation problem [80]. In Knowledge Discovery in Databases (KDD), information is extracted over five stages, namely selection, pre-processing, transformation, data mining, evaluation and knowledge [81]. The use of data quantity has been related to data quality to achieve high-level information from data monitoring with regard to site location [18]. The recent development of smart technologies and IoT has contributed to increasing the level of water quality parameters based on real-time applications as valuable tools for the purpose of measuring water quality in real time [18]. Marce et al. stated a trend related to the high amount of data which must be anticipated while transmitting data [24].

Data management included failure anticipation to retrieve the data, warning of the operational system and assessment of system performance [7]. Additionally, data management in Stage III considers sensors, cloud networking, and data security to collect and transmit data as monitor and control devices [76]. The applicability of sensors covers the spatial and temporal sensors, which have the capacity for real-time survey monitoring and land-based survey monitoring based on satellite-relay systems. The process of sensors starts with temporal sensors placement in in-situ measurement and spatial sensors obtained from imagery satellites. In the next step, temporal data is acquired from sensors and transmitted via cloud networking or satellite telemetry to a specific location where the data measurements are reviewed [82]. Next, the sensor deployed automatic data recording in the water column controlled by an internal computer. The next process, cloud networking, is required to get highly accurate data based on robust sensor connectivity devices. In addition, data are stored, and files can be used by policymakers. In contrast with conventional methods, the online monitoring system provides a large amount of data that can be accessed in real-time with less cost and effort. The metadata analysis mentioned in Stage 2 integrates different uniform data formats. The activity involved accessing data sources, the location of data collection, the parameters selection, and the procedures to download data from specific locations [80].

The development of aggregation algorithms and data processing has also been used to increase the results of the data management process with regard to the cluster [19]. More recently, the IoT data platform visualizes the data obtained based on the data management layer for end users [77]. Data management has operated, stored and processed big data based on distributed file systems.

Therefore, the advancement of the water monitoring system should be integrated into data quality assurance and efficient maintenance [7]. Data handling standards is one of the issues with a lake monitoring system, which should be a top priority for freshwater research [24]. This factor will lead to a high-quality standard of data handling and detect unusual measurements to assist the maintenance of the water monitoring system. The development of monitoring networks with an adequate level of redundancy is needed to reduce data losses and extend the water measuring period [7]. The approach to reduce the uncertainty of measurements can be explored in this stage to analyze data lost due to dynamic conditions.

VI. WATER QUALITY AND QUANTITY MODELING

Model selection for water monitoring systems involved high-accuracy performances. Hereof, the design and advance of hydrological monitoring can be integrated into water quality monitoring systems with close design of each other such as data collection, increase essential information, and decrease the uncertainty of sampling points. Most of the model results are useful for displaying the forward condition, current status, and past trends in the aquatic environment. Moreover, using the model in water monitoring can be categorized into support sensor implementation, design monitoring distribution point, threshold control, and warning system to utilize Decision Support System (DSS). For example, The use of fewer input data successfully improved the standard of sub-daily datasets and the efficiency of data-based mechanistic models [83]. The simulation of nutrients has been interpreted to control multi-temporal patterns in short-trend and long-term events [84]. Partial Least Squares Path Modeling (PLS-PM) revealed the contribution of changes in monitoring points for water level and salinity [85]. Generalized additive models (GAMs) and routine surrogate models examined the dynamics of nutrients in seasonal and annual trends to describe the state estimation [86]. In addition, the combination of satellite images and a linear model has analyzed the influence of air quality and vegetation to support algal bloom early warning systems [87].

The water quality of lakes is influenced by the adequacy of water level control. Multi-objective optimization, which is expected to have an impact on climate-change and societal needs, requires more accurate models for long-term planning of water resources management activities. This requires further refinement of evapotranspiration in terms of the water balance (as a key element of quantitative monitoring), accounting for measures to mitigate the drying of the catchment, and the development of additional measurement points to refine the projections and model development.

The challenge with regard to the analysis of water variables is to simulate the real behaviour of water dynamic by comparing observations and model results [88]. The water prediction models have been developed which can be categorized using any techniques ranging from statistical analysis to mechanistic models (dual - modelling approach). Models and simulations related to water management are commonly used to address this problem in terms of its environmental impact under various circumstances [89]. The combination of computational models, point sampling and data sampling yielded the main causes of the dynamic water system and revealed the complexity of the aquatic ecosystem [90]. The aim of water quality prediction models for the freshwater ecosystem is to reduce the risk of natural disasters and provide an early warning system for the purposes of public policy [91]. For this reason, early warning systems can be developed to enhance the prediction of cyanobacterial events based on temporal prediction, ANN-Multi Layer Perceptron−, and Self Organizing Maps (SOM) [92]. The integration of ANN with Adaptive Neuro-Fuzzy Inference System (ANFIS) approach has been used to estimate the water quality of the surface water [21]. In addition, Zhao et al. developed the streamflow forecast to maintain the level of robustness using a hybrid model predictive structure, namely sequential and monthly [93].

The acquired information fully decides the selection of models, which are described in Section VI. Following the different information deployed, the applied modelling approach can be divided into static and dynamic models. An advantage to selecting statistical models is that it requires resource implementation at selection time, while dynamic models predict based on performance at compile time. For example, the performance of a water monitoring system in water quality can be performed based on a statistical model to forecast water quality conditions in the San Joaquin River Basin [89]. In addition, the hydrodynamic model and water quality are used to decide whether land use, project operation and pollution inflow can contribute to the decrease of the aquatic environment in Hongze Lake [94].

In spatial analysis, the MODIS satellite data is capable of predicting algal blooms nine days in advance, the advantages of which are its controlling factors, provision of optimum solutions and variations in lag times [96]. Over recent years, the problem with long-term predictions was the time period, uncertainty factors, and computational error which have decreased the simulation accuracy [97].

Generally, the models can be divided into two categories, that is, deterministic models and stochastic models. It has been demonstrated that stochastic methods such as genetic algorithms [98], swarm intelligence - parallel computing [99], Deep Learning [100], integrated GRACE observations and the GLDAS - Noah Land Surface Model [91] or Extreme Gradient Boosting [101] can simulate the processes related to streamflow and flood forecasting. In meteorological time series, Autoregressive Integrated Moving Average (ARIMA) can be utilized to predict changes in the water resources [102]. Recently data assimilation has been implemented in shallow water models [103], in-situ remote sensing data surface water temperature [104], water temperature [105], spatio-temporal & real-time measurements [98], discharge forecasting [106] and the control of hydrometeorological variables [107]. The use of artificial neural network (ANN) ensemble models with their ability to combine data-driven models with one prediction rather than using a single model is gaining in popularity [108]. Hybrid models have some advantages over single models, namely their ability to predict measurement variables based on ANN ensemble models: (i). increase the forecasting accuracy and are more capable of capturing the monthly inflow prediction [109], (ii). decrease the uncertainty of long-term streamflow predictions [108], (iii). minimize computation time [110], and (iv). estimate total volume of forecast [111]. The model identification section will be explained based on the following classification [112]:

1) Dynamic models or deterministic models
2) Stochastic models or Learned pattern knowledge, which is categorized into three subtypes:
    - First principle models (white-box models)
    - Data-driven models (black-box models)
    - Semi-mechanistic models (gray-box models)

TABLE 2. The different methods of mathematical models (source: [95]).

Model Type	Characteristics	Consists of
White-Box	Required to know Physical Laws Parameters are defined	- Non-Linear Differential Equations
Light-Gray-Box	Required to know Physical Governing Laws in some areas Parameters Unknown	- Non-Linear Differential Equations using the estimation of parameters
Dark-Gray-Box	Required to know Model Structure Required to know Physical Governing Laws in some areas	- Transfer function with the estimation of parameters - State-space model with the estimation of parameters - Neuro-Fuzzy models with the estimation of parameters
Black-Box	Model structure unknown Parameters unknown	- Artificial Neural Networks (ANNs)

A comparison of the model structures with their content elements is provided in Table 2. Four categorised methods describe the dynamic of water quantity and quality in freshwater: White-box model provided an understandable and interpretable model which used physical formula. Light-gray-box model is a state space model with physical rules and model structure in its model. Dark-gray-box model involved the Neuro-fuzzy model and physical law. Finally, the black-box model can be classified into hyperplanes, and probabilistic-combinatory logic [113]. However, the black-box model does not contain the model structure and parameters commonly used in ANN as tool analysis.

A. DYNAMIC MODELS

The advancement of statistical and deterministic models (simple regression models) was used to analyze the total maximum daily load (TMDL) as a guideline on the concentrations of pollutants in the inflow of a river [89]. The dynamic model has been used to analyze the changing characteristics of water bodies [114], and interconnected distribution networks to describe the morphodynamics of rivers [115]. Furthermore, the coupling model between the Moving Particle Semi-implicit (MPS) and Discrete Element Method (DEM) to describe the morphological dynamics will be a promising solution to water surface elevation [116]. The simulation based on a dynamic model (model of stock and flow) divided into the (i). continuous linear model and (ii). discrete model (activity diagram). One of the advantages of dynamic forecast modelling is that it reduces the error result from multi-site systems using a copula function leading to hybrid spatio-temporal forecast improvements [117]. To analyze the nitrogen cycle on an hourly basis, Cui et al. has used a hybrid of the Nitrogen Dynamic Polder (NDP) model to simulate water and nitrogen dynamics [118].

B. APPLIED KNOWLEDGE MODELS

The further development of existing monitoring systems and the methodology of model integration depends on the existing infrastructural aspects and the available data set. The contribution options for the three main categories in water monitoring are described in the following subsections.

1) FIRST PRINCIPLE MODELS (WHITE-BOX MODELS)

The deployment of hydrodynamic models in water quality and hydrological model has been applied in a one-dimensional model (1D model), two-dimensional model (2D model) and three-dimensional model (3D model). It was eventually realized that the indication of the optimal flow release under flood controls should be obtained by jointly considering the composition of flows and water quality response in rivers [119]. This can be achieved by using integrated into various models to forecast the daily discharge [120]. The integration within 3D model water quality data, machine learning and related environmental models have capability to analyze physical and biogeochemical processes [121]. Data assimilation as an optimal state and parameters of the system has been considered to describe the inconsistency between sampling and modelling both vertical and sideward [122]. In addition, ensemble data assimilation (Kalman Filter, Dud-EnKF, EnKF-GS) provide the improvement of computation time in real-time forecasting [123]. One of platform, namely MeteoLakes, a 3D model can reveal the lake hydrodynamics based on unified approach [124]. Hybrid method in physical model were selected to predict water quality which chose COD as main pollution in Songhua River Basin [125]. In addition, physical - empirical model has been developed to support decision-making process to predict inflows into the lake [126]. Moreover, the lake's dynamic behaviour in terms of water quality is slower than in rivers because of the differentiation between the inflow and outflow [94]. Therefore, the calculation of hydrodynamics in the lake is different from its computational equivalent in the river.

The development of a two-dimensional (2D) hydrodynamic model with integrated pollutant diffusion and ecodynamic model has been utilized for the spatio-temporal of a coupled eutrophication model in a shallow lake [127]. The water quality was measured by considering transport, diffusion and pollutant inflow into the lake [94]. The Ensemble

Kalman Filter (EnKF) has been implemented into a two dimensional hydrodynamic model as well as a water quality model based on the assimilation of state variables and model parameters to improve the accuracy of results from models [128].

The 3D model has been applied to scientifically represent the impact of thermal changes in lakes. The 3D models used Reynolds-Averaged Navier-Stokes (RANS) Equations, mass balance, hydrodynamic processes and momentum which is divided into hydrostatic and time momentum [129]. For example, the model has been applied to determine the dynamic water quality in rivers [130].

However, since the hydrodynamic model required physical parameters and good quality data measurements (Table 2). The availability of limited physical data is the main cause for the reduction in the accuracy of the hydrodynamic model.

2) SEMI-MECHANISTIC MODELS (GRAY-BOX MODELS)

One of the challenges of implementing of white - and black box models is the scaling problem. The black-box model consists of a definite (exact) process that is incapable of describing dynamic process of the white-box model. To overcome this problem, a gray-box model, commonly known as a semi-mechanistic model, has been used. The process of semi-mechanistic modelling begins with a white-box modelling structure where the unspecified parts are modelled by a black-box model. The semi-mechanistic model based on transit time was formulated to extract the process from water flow and hydrology parameters [131]. Calculation of the transit time supposes that the compositions of the input and output flow are equal.

Besides the workflow of the transport time, a semi-mechanistic seasonal temperature profile was successfully tested in the stratified layer of the lake [132]. The semi-mechanistic model outperforms the two models (mechanistic and strictly empirical model) to define the phosphorus retention time in the lake [133]. The result showed that semi-mechanistic model produce better output result based on inflow of total phosphorus concentration, lake average depth and water retention time. However, according to Narasimha et al. research into semi-mechanistic studies with in the scope of the water dynamics in inland waters is limited [134]. Therefore, to evaluate the best performing semi-mechanistic models, the study recommends the use of a broader data set and various experiments covering different combinations of parameter [135].

3) DATA-DRIVEN MODELS (BLACK-BOX MODELS)

The comparison with the deep learning method has been used to predict the streamflow as far as two days in advance using Feed - Forward Neural Network (FFNN), Convolutional Neural Network (CNN), Stacked LSTM, LSTM - Gated Recurrent Unit (GRU) and Bidirectional LSTM (BiLSTM). However, the LSTM and GRU models are sufficient to produce highly reliable forecasts while minimizing the computation time because less memory is required. The water temperature in the river has been modelled using the LSTM method, Random Forest (RF) and BackPropagation Neural Network (BPNN) [136]. However, the GRU Model (simplified version of LSTM) utilized logistic regression neurons as the gate and has 2 gates correlated with weights: the update gate and the reset gate.

Implementing a hydrological model into a water monitoring design system has contributed to monitoring, modelling, and analyzing water usage and water consumption [5]. The combination of Sentinel-1 radar data and Sentinel-2 multispectral data as a hydrological model to calculate water quantity [137]. The monitoring of sustainable development of water resources has been shifted to geophysical satellites through global hydrological cycle components water [16]. The hydrological model has been an input into the monitoring system by analyzing flow dynamics [22], flood monitoring [28], water level and temperature periodic [53].

Comparison between The San Joaquin River (SJR) - Watershed Analysis Risk Management Framework (WARMF) model and Regression Model which contributed regression-based forecasting model performance better in daily [89]. Moreover, hydrological model using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANN) are the most used water quality monitoring and assessment in ten years. In addition, ANFIS, Wavelet-ANN (W-ANN) and Wavelet-ANFIS (W-ANFIS) were most precise to predict surface freshwater quality [21]. The water quality model is divided into three models: feed-forward, hybrid, recurrent, emerging methods. In Dissolved Oxygen (DO) prediction, Radial Basis Function neural networks (RBNN) model contributed higher accuracy than Multilayer Perceptron (MLP) [69]. The model's result in water quality and water quantity can be overfitting or underfitting which deteriorate model's capacity to forecast data or select trend of data based on details parameters [138]. However, with additional method from the Complete Ensemble Empirical Mode Decomposition Algorithm with Adaptive Noise (CEEMDAN) decomposition, the convolutional neural network (CNN), long short-term memory neural network (LSTM), and hybrid CNN-LSTM with different input data is analyzed. The combination from various method can effectively improve the forecasting for water quality prediction [139]. XGBoost has better performance than Random Forest (RF) and Support Vector Machine (SVM) to predict harmful algal bloom between 5-9 days [96]. Genetic algorithm and Pattern Search (PS) optimization methods have been compared to forecast optimal flow hydrological model for flood control [98]. In addition, Bootstrap, wavelet and neural network (BWNN) method and data resampling provided daily streamflow time series forecasting [140].

VII. MONITORING OF WATER QUALITY

Long-term water quality management strategic planning requires continuous monitoring, while current infrastructures and methodologies need to be improved in order to handle the new challenges (e.g. micropollutants, microplastics, climate change, etc.) generated by environmental changes. The prevention of algal blooms is a complex task because it requires operational and public policy decisions based on systematic measurements and accurate model-based predictions. Building models and producing decisions require events to be identified and parameters affecting water quality to be monitored. It requires systematic measurements of the sources as well as an understanding of the impacts of internal and external nutrient loads. The monitoring of internal nutrient loads is an important issue, while management options need to be optimized based on this information. The monitoring of external sources needs to be improved, e.g. comprehensive and regular water quality monitoring of inflows and rainfalls has yet to be addressed. Systematic detection, sediment transport, and flow conditions have a significant impact on water quality and the spread of contaminants. There is an urgency to reduce dimensions in order to develop forecasting models for data availability, reliability, cost, and data acquisition [97]. It has been analyzed among systematically reviewed that Principal Component Analysis (PCA) and Canonical Correspondence Analysis (CC) is one of the frequent approaches to reduce 50 % of dimension input including temporal dimension. For example, 10 variables were analyzed from 18 groups data and the use of single-parameter is helpful to predict harmful algal bloom [97]. In this section, the selection and classification of water quality parameters [141] will be discussed based on the number of input variables, which will increase the computational efficiency of our proposed FIMS framework. The water quality can be characterized by a different set of parameters, which could result in different assessment standards [142].

The applicability of water monitoring systems has been used to interpret the actual condition of the aquatic environment. In a concurrent surface water monitoring development, three phases have been presented to support Multi-Criteria Decision Making (MCDM) [142]. The process of decision starts with dimension reduction from water quality indicators and then developed Probabilistic Linguistic Term Set (PLTS) technique and weight interrelationship. Further form using fuzzy has been offered to generate the result. The performance of the monitoring system provided a 95 % of confidence level. The optimal design of water quality monitoring networks is employed using Bayesian Maximum Entropy (BME) framework through Value of Information (VOI) and Transformation Entropy (TE). These approaches are used to gain the optimal information using the lowest sampling station [143]. With five sampling stations in this study, the approaches provided 76 % of information represented the availability of 45 sampling stations. In addition, ensemble data assimilation through twin experiments improved the performance of water monitoring systems by more than 50 % [123]. For spatial imagery, empirical band ratios through MODIS provided an accuracy 40 % to calculate the water column for Suspended Particulate Matter (SPM) [57]. To reveal the Chl-a dynamics, linear empirical models based on Landsat imagery have been developed with 7.58 % accuracy. Water quality monitoring system is applied prediction based on artificial intelligence [2]. Some of the procedures obtained clustering techniques through ANN- PCA- Hierarchical Agglomerative cluster (HAC) and Improved Genetic Algorithm (IGA) - Backpropagation Neural Network (BPNN) for turbidity with Root Mean Square Error (RMSE) error is 0.159 and 0.0024, respectively.

Currently, the water monitoring system starts with designing representative sampling points and the contribution of pollutants from each sampling area. With the CA-Markov approach, the land-use data has been generated, and the potential pollution for non-point sources has been identified using the scoring method. The results demonstrate that different scores to select water quality monitoring are identified with high certainty result [144]. One of the major considerations of spectral indices is whether the spatial sensors can provide adequate spectral bands to calculate the quantity of algal mass in the freshwater [145]. The majority of Wireless Sensor Network (WSN) based Water Quality Monitoring (WQM) has temperature and pH sensors [19]. The other sensors applied in WSN are turbidity, water level, and humidity [74]. In addition, the WSN system has an automated warning SMS alert to the decision maker [77]. Moreover, the design structure of WQM to select the number and location of monitoring stations can be categorized into five methods: topology methods, multivariate analysis, information entropy, optimization framework, and geostatistic [20]. Aquatic environmental monitoring was designed to design a robust system accomplish of functioning remotely for expanded time intervals [75]. Streamflow influences pollutant loading as it is a flow release and absorption. Therefore, it is recommended to install discharge sensors into water quality monitoring systems [146].

Therefore, we will describe the most important water quality-related parameters based on the referenced papers in order to highlight the relevant variables for future water monitoring systems. Water quality parameters are grouped and explained according to the EU Water Framework Directive (WFD), as a systems approach is a prerequisite for this [95].

A. PHYSICOCHEMICAL ELEMENTS

Eutrophication is divided into two sources: (i). cultural eutrophication which originates from agriculture (farmland, forests, grassland), fish aquaculture (livestock farming, fish farming) and domestic-industrial wastewater; (ii). natural eutrophication such as climate factors, the nitrogen and phosphorus cycles, discharge levels (upstream water) as well as aquatic plants and fish [157]. The combination of chlorophyll-a, nitrogen, and phosphorus is helpful to monitor as well as evaluate the trophic and categorize the freshwater ecosystem, including measuring the accumulation of algal biomass [187]. Eutrophication has had an impact on the food chain of the aquatic ecosystem, algal bloom events, and

TABLE 3. The most commonly examined water quality-related parameters.

Parameters	References
Physicochemical	
Water Temperature	[147]
Transparency	[148]
Turbidity	[149]
Water color	[150]
Secchi depth	[151]
pH	[152]
Acidity	[153]
Total phosphorus	[154]
Orthophosphate	[155]
Total nitrogen	[156]
Nitrate	[157]
Nitrite	[158]
Dissolved ammonium	[157]
Ammonium	[7]
Dissolved oxygen	[159]
Oxygen saturation	[158]
Carbonaceous BOD	[25]
Biological Oxygen Demand	[160]
Chemical Oxygen Demand	[161]
Electrical Conductivity	[162]
Salinity	[79]
Total coliforms	[11]
Total organic carbon	[163]
Dissolved organic carbon	[163]
Dissolved organic matter	[163]
Cchromophoric DOM	[164]
Colored DOM	[165]
Fluorescent DOM	[166]
Particulate organic matter	[25]
Total dissolved solids	[11]
Total suspended solids	[30]
Total suspended matter	[167]
Heavy Metals	[168]
Boron	[11]
Chloride	[169]
Hydromorphological	
Water Level	[97]
Water depth	[170]
Flow Rate	[171]
Velocity	[172]
Structure of riparian zone	[173]
Structure of the lakebed	[174]
Structure of the riverbed	[175]
Biological elements	
Chlorophyll-a	[176]
Bacteria levels	[177]
Cyanobacteria	[178]
Blue-green algae	[179]
Phytoplankton	[151]
Macrophytes	[180]
Invasive species	[181]
Pathogenic fungi	[182]
Macrozoobenthos	[183]
Invertebrates	[184]
Fish	[185]
Benthos	[186]

the population of species which disrupt the function of the ecosystem [188]. Study from Othman et al. have shown that the *DO* is the most important variable, while the pH has the least influence on predicting the water quality index [34]. The average degree of transparency decreases as well as the level of eutrophication increases, rendering water transparency a significant indicator of aquatic assessment [148]. Sodium (*Na*) and chlorine (*Cl*) were identified as the most influential factors on total dissolved solids (*TDS*) [33]. Furthermore, total phosphorus and water clarity are most likely to lead to a dynamic phytoplankton community [35]. Nutrient and phosphorus inputs are related to the increase in effluent from WWTP that is not treated properly, leading to an increase in the growth of algal biomass and vascular plants [11]. In addition to samples of surface water data, data monitoring is measured from the influent or effluent of WWTPs [189]. From all the variables of environmental monitoring, the water temperature and total dissolved nitrogen are the critical variables to predict algal bloom events three weeks in advance [92].

Table 3 shows the list of parameters (physicochemical parameters, hydromorphological factors and biological elements according to the WFD) for the purpose of detecting anomalous events identified by using different mixtures of solutions from water monitoring systems with regard to the FIMS framework.

B. HYDROMORPHOLOGICAL ELEMENTS

Since Wetzel divided lakes into three types [190], namely (i). temperate lakes, (ii). tropical lakes, and (iii). polar lakes, the water temperature and dissolved oxygen of every lake is different depending on the its type. The Water Framework Directive investigated the ecology and environment as a hydromorphological assessment [191]. The morphology of a lake or river is generally described by a bathymetric map to obtain depth contour details and increase the detail of the analysis [190]. Water pollution has been an issue with regard to the restoration of water storage [192]. Fukushima et al. assumed that the phosphorus concentration increases during high flow dynamics in shallow eutrophic lakes [193]. Furthermore, rainfall influences sedimentation and pollution transport into freshwater [194]. Inflow discharges and waves are influenced by rainfall as well as wind speed and its direction. Specifically, changes in wind direction are a significant factor influencing lake hydrodynamics [195]. The distribution of algal blooms with lower nutrient concentrations is influenced by water depth, water temperature and turbidity [196]. The result observation from Mei et al. revealed that the temperature difference with 1.7 % average higher increased the nutrient concentrations [197]. Moreover, The development of empirical modeling approaches found that the range difference of temperature 3.3° has affected the growth of nutrients [198]. Variables of land use for agricultural, fertilizers are significant factors with regard to predicting the concentration of nitrate [199]. Additionally, the most prevalent elements in dissolved nutrients are the structure of water bodies and landscape characteristics [200].

The study related to most influence factors on water temperature has been collected between 1992-2019 to reveal the heat fluctuation in surface water [201]. Their findings indicate that solar radiation is the most significant factor contributing to the surface-water temperature during the spring [201]. The discharge level also influences the dynamics of nutrient loading [202]. A floating station was developed to obtain data over six years of ten solutes every two weeks as well as seven years of climatic-hydrological data monitoring and temperature data recorded on a daily basis to get information about evapotranspiration [203]. Based on Bayesian modelling results, the key driving variables for water quality dynamics are catchment runoff, rainfall and soil moisture [204]. During flood events, water quality dynamics depends on fluctuations in water levels, population growth, and the atmospheric temperature [205]. The indication of polynomial events between river network flow velocity and water diversions occurred when the water quality dynamics is higher in the wet season than the dry season [206]. As mentioned by Wetzel et al. the characteristics and structure of water bodies resulted in the different dynamics of water exchange and mixing processes in freshwater. Therefore, a combined assessment to cover anything from specific types of water bodies to specific responses would provide a comprehensive solution for evaluating the status of ecological quality and the environment [207], this topical review answers exactly this type of further development opportunities.

C. BIOLOGICAL ELEMENTS

The correlation between species and environmental stressors has increased to assess and monitor ecological environment [208]. For example, bacteria are one of the biological indicators by which the quality of an aquatic environment is assessed. By following the traditional approach, the analysis of indicator bacteria can achieve results after 18-24 hours, however using modern analysis tools, results can be achieved in 3-4 hours. To achieve faster results using different approaches, a predictive model is used with parameters such as temperature and turbidity [177]. The combination of geomatics, in-situ and satellite-derived variables is used to analyze fungi bacteria [182]. Another kind of bacteria in freshwater is cyanobacteria. The patterns of cyanobacteria events have been evaluated to assess the annual frequency of surface cyanobacteria blooms by spatial and temporal monitoring [178]. The use of cyanobacterial strains for biological monitoring has led to the construction of an environmental assessment through the response to water pollution dynamics [209]. Another bioindicator is the *E. coli* concentration as a pollutant in terms of environmental sanitation for the prevention and mitigation of pollution sources [210]. Furthermore, Ma et al. revealed that algal blooms favored higher temperatures and light rain while wind is the most influential factor in the growth of algal blooms [211].

In addition, algal blooms contain chlorophyll-a which was identified using satellite imagery to explore the spatial distribution of the pollutants [176]. The latest sensor to be applied in the analysis of water quality dynamics is a blue-green algae indicator [179]. The other biological indicator is phytoplankton [151]. Regarding biological oxygen, the most common parameter to measure the respiration of fish and bacteria is the oxygen uptake rate [212]. However, changes in habitat areas have influenced the habitats of biota with regard to the restoration project [160]. To prevent the impact of the degradation of the aquatic environment because of restoration, the water quality index should be evaluated and changes in habitat areas investigated [160]. The biological assessment in freshwater included macrophytes which used to respond to the bioavailable nitrogen [180]. In the other study, the assessment of ecological quality in freshwater was selected using Indices of Biological Integrity (IBIs). Therefore, a fish species were categorized based on functional groups and analyzed using a threshold to evaluate the environmental stressor [185]. Furthermore, a fish-based index (FBI) and IBIs were used to develop an ecological index and identify environmental conditions [213]. The distribution of fish was analyzed to assess the suitability of the water quality with regard to the heart and respiratory rates as a bioindicator [214]. Altenritter et al. proposed invasive species management to combat their rapid spread and potential to harm the endemic species in freshwater [181].

To analyze the heavy metals in surface sediments, the parameters of benthic toxicity is a common method to determine the biological effects of water pollution [186]. Based on the analysis of the results using benthos as a biological indicator, the study revealed that the heavy metals in the research originate from industrial and agricultural activities [215]. The study indicated that benthic macroinvertebrates contributed towards eutrophication in response to environmental changes and anthropogenic pressures [216]. In addition, macroinvertebrates play a key role as biomonitoring tools [217]. A zooplankton model has been developed by considering zooplankton biomass. The scenario of the model was created using two parameters, namely atmospheric temperature and nutrient input [183]. A multimetric index (HeLLBI) is used to analyze the effects of eutrophication and morphology on macroinvertebrates [184]. The use of biological indicators is advantageous in terms of its cost-effectiveness and combined approach to evaluate the pollution in the ecosystem [208].

D. OTHER WATER QUALITY RELATED ASPECTS

The impact of climate change on water quality are expected with regard to the linked process to simulate future climate-water quality scenarios. Moreover, the analysis of the impact of climate change has been developed from the GCM (Global Climate Model) and RCM (Regional Climate Model) on water quantity [218]. One of the impacts of climate change on water quality is the increase in cyanobacteria [219]. Minaudo et al. suggested that the increase in temperature and decrease in streamflow rate have the potential to increase the quantity of cyanobacteria and phytoplankton [220]. By projecting future water quality-climate simulation results, a study revealed that during wetter conditions, *TP* loading is increased [221]. A study stated that the parameters to be included in the related aspect with regard to water quality-climate change are flow rate, *TP* concentration, and *DO* [222]. Specifically, the parameters are influenced by residence time factors included in the mixing process [223]. Climate change is affecting lakes and rivers as water resources [224], wetland systems [225] and watershed systems [226]. An additional factor related to the deterioration in water quality are anthropogenic activities as a result of influents from agricultural, domestic and industrial wastewater [227]. The long-term impact of climatic conditions on catchment areas has influenced the increase in temperature predicted by the climate scenario and ecological model [228]. The highlight some impacts of climate change: (i). eutrophication, salinization, nutrients release; (ii). reduction in endemic species; (iii). increasing nutrient loads; and (iv). decreasing biodiversity [229]. Generally, the change in status of the lake from a mesotrophic to an eutrophic state is influenced by climate change [230]. Anthropogenic activities are divided into agricultural, domestic and industrial. Pesticides are one of the parameters to assess the water quality of surface water through long-term monitoring [8]. The use of pesticides in the agricultural area influences contamination in freshwater through surface runoff, soil leaching and coincidental runoff [11]. The excessive use of fertilizers in agriculture contributes to the increase in phosphor concentration [175]. Water pollution resulting from fertilizers is considered from point sources and diffuse sources [231]. Specifically, influents in the form of nutrients from industry are one of the primary sources of pollution resulting from eutrophication. However, nutrient loss has implications on cyanobacteria dominance, fish kill and water hyacinth as well as leads to a reduction in the health of the aquatic system [188]. With the selection of correlating aspects concerning parameters of water quality, the investigation determines which factor contributing towards trends in water quality is the most influential.

One of the most affected factors on water quality are microplastics concerning samples that are smaller than 5*mm* which are increasingly pervasive due to the growth in anthropogenic production [232]. Some microplastics are transported by runoff, wastewater treatment plant effluent and atmospheric deposition before being released into freshwater bodies, which can put the health of living organisms at risk [232]. Therefore, the distribution of microplastics is one important parameter to identify the specific point, estimate the total number of microplastics in surface-bottom water and soil as well as determine the controlling factor which affects the ecological process.

E. SENSOR PLACEMENT AND SAMPLING POINT IDENTIFICATION

The monitoring frequency and sampling points have obtained more data that represents the condition of a freshwater ecosystem and recognizes the long-term dynamics of a freshwater ecosystem [24]. Continuous monitoring from observational sampling improved the reliability of the system and provided a long-term collection of data points [18]. In this research, several studies about optimal sampling points and the monitoring frequency to improve the performance of water monitoring systems have been reviewed (Tables 5 and 6). Furthermore, examining the related factors such as biological indicators in basin areas is recommended [38]. The optimal key sensor of the monitoring network was determined to reduce the number of locations where sensors are implemented to four. The process steps to identify an appropriate sensor for the monitoring locations are defined below [36]:

1) Define the normal distribution and missing values in the water quality parameters of the data set.
2) Sampling points of pollutants and non-pollutants have been analyzed to detect patterns in the data through spatio-temporal including weather parameters.
3) From the previous process, the measurements of significant water quality parameters in the lake or waterflow have been taken and classified. CA and DA techniques used standardized values from different units of measurement.
4) Spearman's rank correlation coefficient is used to measure the correlation between the most significant variables in water quality measurements.
5) The significant parameters have been interpolated using Inverse Distance Weighting (IDW) to search for the optimal sampling point and predict the values of the non-point source locations.
6) The fuzzy overlay can be used to identify the sampling point with the highest concentrations using multi-criteria analysis.

The placement of sensors in aquatic environments is affected by the discharge level. For streamflow and coastal areas, the optimisation of sensor placement has contributed towards minimizing costs and identifying the main drivers of water pollution at critical outlets [39]. Furthermore, the optimal placement of sensors will optimize simulations, improving performance in the light of low computational costs [233]. In streamflows, the efficiency of distributed computing has been used to enhance the monitoring system by optimizing adaptive design [234]. However, some obstacles of water bodies change over time and their remote location has determined the monitoring efficiency of the network from different sensor locations [235]. Optimal sensor placement at different points has increased the response action resulting from a monitoring system to observe the flow and velocity of water in a river [236]. In addition, the optimal placement of sensors has provided a solution to higher model errors and boundary condition errors [91]. Sensor placement in lakes can reduce

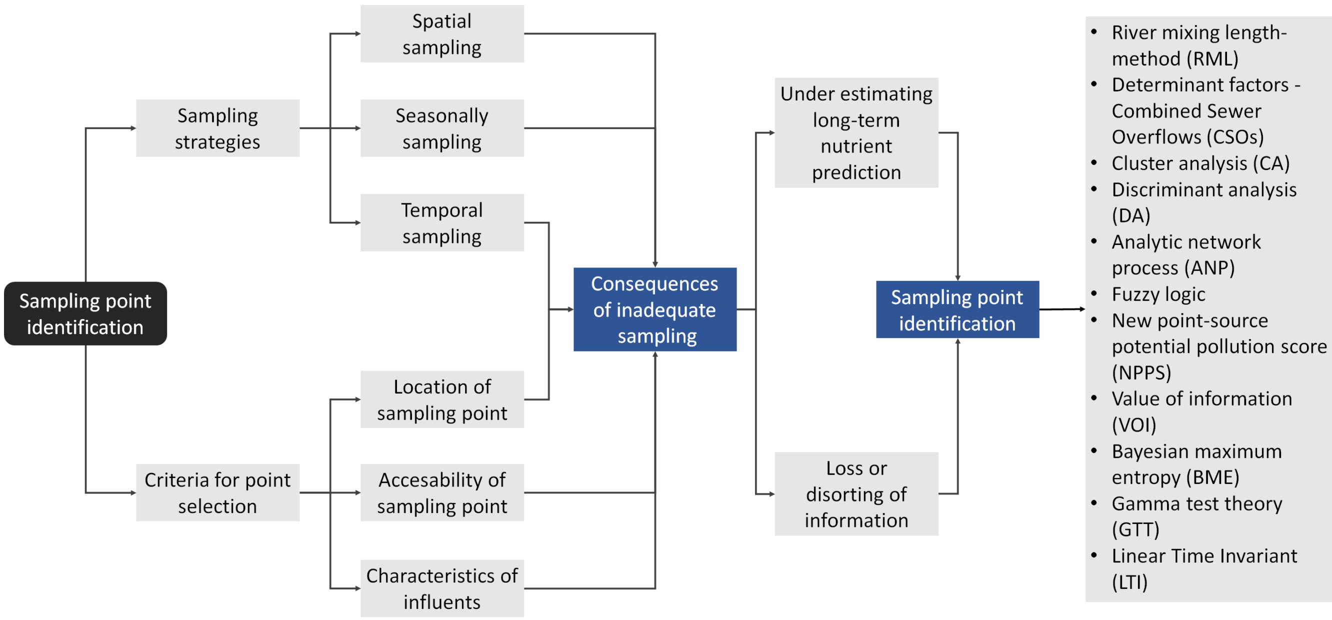

FIGURE 5. **Sampling Point Identification Process According to the FIMS Framework.**

costs as a result of optimisation and make the process less time-consuming [237]. For coastal areas, since sensor placement is easy to monitor, real-time data has provided feedback allowed to a sensor's performance [238]. However, Xu et al. have determined that the implementation of a large number of sensors is not operationally feasible. Therefore, the application of remote sensing is recommended to monitor large coastal areas on spatial and temporal scales [239], with further development of existing monitoring systems according to the proposed FIMS methodology. The potential placement of sensors in coastal areas contributes to minimizing the uncertainty of data, especially in terms of salinity data [240]. The other reason for the selection of optimal monitoring points is to examine flood hazards in coastal urban areas [241]. In the river monitoring network, since the water flow contributed towards pollution dynamics, it is crucial to minimize the river network and maximize the performance of the monitoring system by taking into consideration various factors such as hydrodynamics, contaminant fate, and transport simulation [37]. Furthermore, the optimal monitoring sampling point was determined by information from spatial analysis on the status of the entire reservoir and the reduction in the cost of monitoring network development [242].

The sampling point identification criteria and sampling strategies including the impact of insufficient of sampling activity were shown in Fig. 5. A study identified three criteria to choose the sampling points: (i). the location (source of pollution and the water resource), (ii). accessibility and (iii). number of influents (water inflow) [38]. Computation has been integrated based on the River Mixing Length Method (RML), land-use change modeling, multi-criteria evaluation, anthropogenic activities, sampling data including New point-source potential pollution score (NPPS) to identify the relevant river sampling point [144]. Based on the analysis results, the statistical approach is commonly used to design the sampling monitoring network in the water bodies. Other methods, e.g. quantitative techniques, can be used to select sampling points such as Cluster Analysis (CA), and Discriminant Analysis (DA) [36]. Furthermore, VoI has been applied together with Bayesian Maximum Entropy (BME) to determine the optimal sampling points and highest value of information related to healthy rivers and ecosystems [143]. The optimal sampling point is defined as increasing or reducing the existing sampling point depending on the calculation from available data and conditions. Using calculations from Gamma Test Theory (GTT), the results showed that the optimization of the Water Quality Monitoring Network (WQMN) sampling point is reduced to 23 percent in comparison with the original empirical network [243]. The other calculation concept to identify the optimal sampling point networks of reservoirs and lakes is Value of Information (VoI), which is used to mitigate the weakness of the existing approach in one dimension. Besides using VoI, the study is also supposed to use an evidential reasoning method to calculate the optimal sampling point and sampling frequency [40]. The combination of Wavelet-ANN and a high-frequency online monitoring sensor-based surrogate model is proposed to detect anomalies in aquatic environments [244]. The output result of contaminant loads along with the rank of the Linear Time Invariant (LTI) model are used to determine the optimal sensor placement in a water monitoring application. This approach has enabled the system to identify the contaminant which is a non-point source of river network [245]. Alilou et al. drew up a design for monitoring points by following a multi-criteria analysis approach, including the Analytic Network Process (ANP) and fuzzy logic integrated with the RML process [246]. A combination of Sewer Overflows (CSOs) - Determinant factors were used as a method for sensor placement based on three scenario (simulation data, expert data, and spatial data) [39].

Figure 5 shows three types of sampling techniques: (i). seasonal sampling (wet and dry season), (ii). temporal sampling (one sampling point in selected years) and (iii). spatial sampling (different locations) [247]. Differences in time sampling over short periods of time can potentially yield biased results that cannot be used for model validation [97]. Inadequate sampling frequencies lead to the underestimation of long-term nutrients [3] and loss or distortion of information or data [24]. Therefore, the sampling frequency to capture such dynamic behaviour is important to investigate the short-term dynamics of the $Chl - a$ concentration [18]. The different approaches should be integrated to standardize adequate measurements for the purpose of sample collection [247]. In addition, the main components methodology from Alilou et al. were a numerical model, which was used due to limited water quality data. First, the cross-sectional area and different size of the river are measured from satellite imagery before their accuracy is checked using field measurements. The rivers and branches are divided into small segments expected to be water monitoring points. The total number of segments for one river or one branch is defined before the results of potential sampling points along the full length of the river are identified. The process to choose the number of sampling stations is analyzed using the hierarchy of sampling points. The result of RML identified the potential of sampling points before a new non-point source Potential Pollution Score (NPPS) method was chosen to analyze the most critical sampling points under the conditions at the present and future locations [144].

The accuracy of the monitoring system is one of the key points to protect the ecosystem [8]. Therefore, sensors must be calibrated over a time range to avoid data losses (drift) during data transmitting while the sensor is undergoing maintenance [7]. The following problems are related to data gathered by hydrological and water quality sensors [248]: (i). there is no data or data gap in the database, (ii). the sensor reading has been decreasing because of the time frequency, (iii). the sensor failed to collect the data because it was defective (iv). data measurements fall outside the sensitivity range of the sensor, (v). the database contains an error because of a constant value, (vi). the data logger contains repeated data from the last record, (vii). power failure, and (viii). natural causes, such as the sensor being covered by snow. The combination of multiple sensors to reduce the error of data measurements has been recommended to develop an early warning threshold [27]. The utilization of sensors with different temporal, spatial and spectral resolutions may reduce the problems resulting from single systems [57]. Multiple signals from high-frequency sensors at sampling sites are used to develop a quantitative approach and understand the process [27]. The other reason is to minimize the multiplication of errors from in-situ data compared to measurements from satellite imagery [22]. In order to achieve optimal data accuracy, a Data-Driven Adaptive Sampling Algorithm (DDASA) based on a hybrid approach has been proposed, especially to deal with data fluctuations [42]. Monte Carlo permutations can be used to check measurements and test the availability of configuration data [41]. The latest study developed a calibration method to analyze low-cost water level sensors using seven parameters, namely stability, accuracy, repeatability, resolution, reproducibility, response time and environmental sensitivity [249].

F. EARLY WARNING SYSTEMS

Since Early Warning Systems (EWS) are needed to prevent irreversible damage to wildlife, one has been integrated into our FIMS framework as one of the measures to bring about water quality improvement planning (Figure 2 Stage V.). This process can be formulated based on the details explained in Section VII. The optimal placement of sensors (monitoring points) and fine-tuning will be implemented in addition to the traditional point sampling techniques, including information sources concerning models and remote sensing. In the proposed EWS, a warning message is processed to describe the status of the aquatic ecosystem both over time and spatially. The threshold process is critical in water monitoring systems as an input to the EWS. In Fig. 2., the threshold process for differentiating between normal and emergency modes differs depending on aspects of the water quality of the water bodies. This implies that the water monitoring system cannot be applicable at all freshwater locations, it must be specified based on the implementation of the FIMS framework. Therefore, to increase the reliability of the early warning systems, general threshold, an upscaling threshold that applies to all freshwater locations (lakes, rivers) or a minimum threshold applicable in one category of freshwater (lakes, rivers) must be set. The correction error for the formulation, data handling, categorization details, optimization modelling, utilization and processing of data from satellite imagery is needed to increase the accuracy of the threshold computation system, which is a good indication of how interconnected the FIMS stages are (Fig. 2). Correction is used to identify the time intervals of a disaster event as well as to reduce the number of false alarms produced by the warning system using this robust approach.

VIII. DECISION SUPPORT SYSTEM (DSS)

The last stage of the FIMS framework (Fig. 2.) is the Decision Support System (DSS), which yields the output of the threshold computation by considering by how far and for how long the parameters are predicted and forecast to exceed the threshold line [250]. A DSS is used to process, assess, evaluate, propose decision options and rank the alternatives to

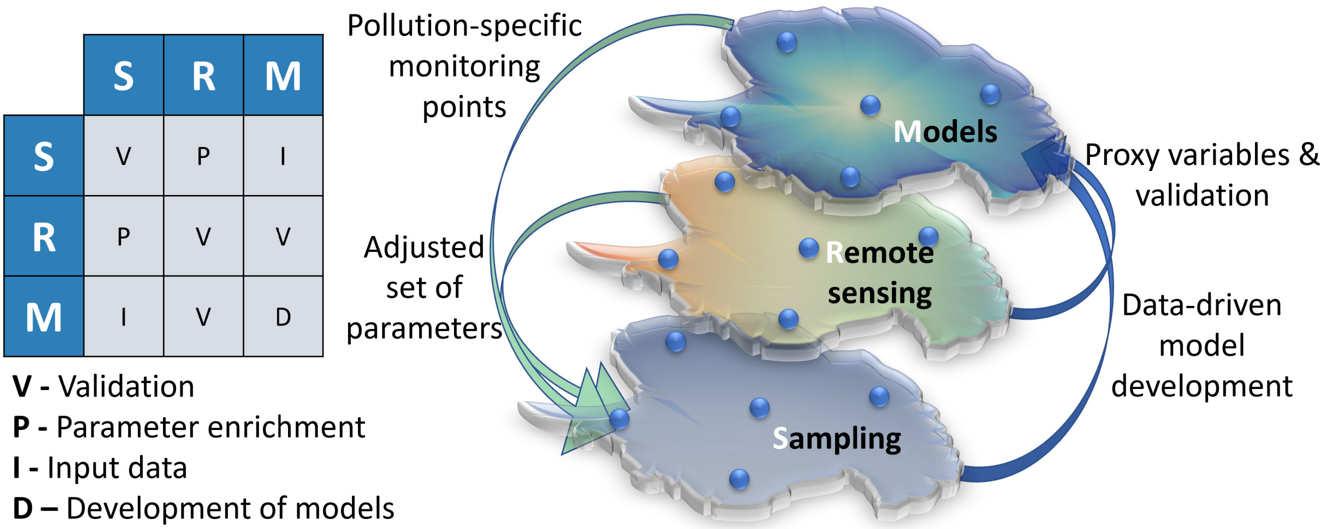

FIGURE 6. The use of the different information sources to support the water management activities.

determine the threshold in the event of outbreaks (risk level) in the form of spatial maps and temporal result [251]. The performance of the water monitoring system will be assessed under different conditions of the dynamic ecosystem and with regard to how the threshold can detect the event anomalies in freshwater to support decisions concerning water management. In addition to our proposed FIMS framework, the system describes the sources of pollution at an exact location and seasonal frequency to select the location of the continuous water monitoring system. Therefore, much more and better quality information is available to support decision-making by the implementation of the proposed FIMS methodology (Fig. 2.), as is the case in "business as usual" practice-driven water monitoring. Figure 6. shows the advantages of the integrated use of different information sources for decision-making support.

Further development of the existing water monitoring systems is necessary for the sake of long-term sustainable water resource management, so the reliability of decision support and cost optimization can be planned together based on the presented FIMS framework using different data sources since the ideal solution for monitoring water quantity, and quality parameters can be selected. Furthermore, with the cross-effects (Fig. 6), the validation procedures can be supported so that more well-founded development strategies can be established.

IX. CONCLUSION

The development of water monitoring system research has been increasing over many years. The results of specific scale overview from the existing citations emphasizes the importance of integrating efficient and effective water monitoring systems for making measurements from monitoring stations, optimizing sampling points, selecting relevant water quality-related variables, yielding precise model results, data handling and ensuring accuracy. Hence, a new Framework for Integrating Monitoring Solutions (FIMS) has proven to be a powerful tool that supports various fields of water quality management. The review was compiled from more than 300 papers that reveal changes in freshwater dynamics using the recent application, monitoring framework, and technology.

In this paper, the proposed integrated spatio-temporal water monitoring systems are interfaced with several support systems, as shown in Fig. 2. Several relevant questions regarding the implementation of the system were investigated. The key conclusion was included in this study based on the answer to research questions. It was analyzed that an efficient water modeling approach combined with a data acquisition system, cross-validation information measurement, and data management are discussed. It was shown that different cross-validation of modeling systems provided better performance in predicting the early warning system for changing environmental conditions (e.g. algal blooms events or water disasters). Additionally, the combination of in-situ measurement can be enhanced the implementation of different information sources. The metadata and information transfer through a monitoring network that can support high-quality data collection to make the system acceptable. Moreover, data processing, including data treatment, analysis, experiment, and correction, should be developed to ensure data accuracy from the sampling point. Finally, as highlighted in this article, the specific threshold detection that leads to higher accuracy in early warning systems should be implemented.

TABLE 4. Recent implementation of hybrid models in freshwaterbodies.

Models	Process	Application	Study Area	References
Random Forest-Deep Auto-Encoder	complex hydrological process	Streamflow Prediction	Bookan dam	[108]
Hybrid Bayesian Vine	Dynamic Model, Copula model	Water level Prediction	Dongjiang River	[252]
HMM, SVM-GA, ANFIS-GA	Hydrological data	Reservoir Inflow	King Fahad Dam	[91]
WRF	Coastal Model, 3D Hydrodynamic Model, Ecosystem Model	Hypoxic Condition Model	Ise Bay	[253]
CNN-GRU-ACO	Integral soil-plant-atmospheric water balance	Evapotranspiration Prediction	Murray-Darling Basin	[254]
WRF-Hydro-DART	dynamic change of flows	Flood prediction	North Carolina	[255]
Multimodal DL	Wastewater Influent Loads	Wastewater forecasting	North America	[256]
WT-LSTM	optimization algorithm, the improved ISSA-Cauchy mutation-OBL	Dissolved oxygen prediction	China	[257]
Bayesian-LSTM	the information flow of the cell	Streamflow prediction	Colorado, California-Nevada, Middle Atlantic, West Gulf	[258]
GR4J	lumped daily hydrological and rainfall-runoff models	Ensemble streamflow prediction	Ireland	[259]
Estuary-Shelf model	Ensemble Optimal Interpolation and data assimilation	Forecasting coastal water	HongKong	[260]
Ensemble AI	Autonomous Multi-model Machine Learning	Water Supply forecasting	Colorado, Missouri, Columbia, Rio Grande, Klamath	[261]
FoGSS error model	data transformation, bias-correction, Autoregressive Error Model, statistical distribution	Streamflow forecasting	Australia	[111]

Multidisciplinary research reviews on water monitoring systems have been analyzed, this research has been restricted to the latest findings and specific classifications of water measurement technology, water quality monitoring, bioindicator technology, water quantity monitoring and water models. The contributions of the present review article are summarised as follows: (i) this study summarises more than 300 reference papers based on the trends, modules, applications and advancement of technology implemented in water monitoring systems over the past 11 years (2011-2022) - most reference papers were analyzed in terms of sampling points, area, performance and results; (ii) this study reveals the advantages and weaknesses of the various requirements of monitoring stations in maturity models, integrated technologies, smart operations, and data-driven services; (iii) this review has highlighted the most influential variables which increase the efficiency of the water monitoring system; (iv) the study emphasizes the neglect of single measurements that integrate the availability of different measurements and monitoring stations to collect four elements of data measurements; (v) this study provides a practical recommendation for policymakers and water resource managers to improve water monitoring systems. Furthermore, this research presents a compilation of the development of water monitoring systems over the years.

The limitation of this study is that it does not include the socioeconomic aspects of environmental assessment. In future research, water monitoring systems will be rapidly used to assess the condition of aquatic environments over the years. Therefore, it is recommended that the performance of integrated water monitoring systems should be

TABLE 5. Patterns of recent water quality monitoring activities in lakes.

No.	Lake	Country	Average depth (m)	Surface Area (km^2)	Number of Stations	Number of Parameters	References
1	Lake Balaton	Hungary	3	-	10	13	[158]
2	Lake Erie	USA	8	3000	25	57	[262]
3	Dongjianghu Lake	China	60	160	8	14	[263]
4	Lake Garda	Italy	133	2260	1	5	[264]
5	Dongting Lake	China	6	2740	1	1	[265]
6	Lake Lanier	USA	18	150	18	9	[266]
7	Lake Baiyangdian	China	2	-	8	12	[267]
8	Donghu Lake	China	2	32	3	11	[268]
9	Lake Maninjau	Indonesia	105	97	7	1	[269]
10	Lake Maggiore	Italy		213	1	15	[248]
11	Pulicat Lagoon	India	1	450	27	8	[270]
12	Lake Kummerow	Germany	8	32	8	5	[271]
13	Lake Hawassa	Ethiopia	11	113	19	21	[272]
14	Lake Habbaniyah	Iraq	-	426	5	11	[273]
15	Lake Geneva	Switzerland	-	-	1	6	[274]
16	Lake Matano	Indonesia	-	-	1	8	[275]
17	Lake Occhito	Italy	-	14	3	12	[276]
18	Lake Tai	China	1	2338	5	2	[277]
19	Catahoula Lake	USA	11	119	3	10	[278]
20	Lake Madison	USA	3	3.4	1	6	[279]
21	Lake Chivero	Zimbabwe	9	2136	9	1	[280]
22	Lake Geneva (Small Lake)	Switzerland	41	580	2	1	[281]
23	Nanhu Lake	China	3	1	10	19	[282]
24	Lake Naplas	Hungary	3	-	3	4	[283]
25	Lake Madison	USA	3	5	1	6	[279]
26	Lake Chivero	Zimbabwe	9	2136	28	5	[284]
27	Lake Vaeng	Denmark	1	-	4	12	[285]
28	Lake Constance	Switzerland	100	476	1	4	[286]

TABLE 6. Patterns of recent water quality monitoring activities in rivers.

No.	River	Country	Length (km)	Catchment Area (km^2)	Number of Stations	Number of Parameters	References
1	Min River	China	-	-	8	14	[287]
2	Sinos River	Brazil	190	4000	3	13	[288]
3	Charles River	UK	128	-	4	6	[289]
4	Maumee River	USA	-	-	1	1	[290]
5	Citarum River	Indonesia	270	11,500	10	15	[291]
6	Ciliwung River	Indonesia	76	15,079	2	10	[292]
7	Jeziorka River	Poland	7	989	8	4	[293]
8	Karnaphuli River	Bangladesh	270	-	15	5	[294]
9	Sedim River	Malaysia	178	4219	3	6	[295]
10	Water of Leith	UK	-	54	1	9	[296]
11	Santee River	USA	170	-	2	21	[29]
12	Chassahowitzka River	Mexico	8	-	2	5	[297]
13	Upper Paraná River	Brazil	4	788	3	7	[298]
14	Sembrong River	Malaysia	22	200	3	5	[299]
15	River Ganges	India	-	65	3	8	[300]
16	Tigris River	Iraq	1850	253,000	3	5	[301]
17	Yautepec River	Mexico	95	-	34	14	[302]
18	Wabash River	USA	90	-	7	10	[303]
19	Odense River	Denmark	-	0.01	3	2	[304]
20	Rhine River	Germany	1250	-	8	4	[305]
21	Laspias River	Greece	-	160	5	20	[306]
22	Provo River	USA	50	675	3	2	[307]
23	Evros River	Greece	528	53,000	8	2	[31]
24	Teusacá River	Columbia	-	358	17	2	[308]
25	Cocagne River	Canada	70	345	5	4	[309]
26	Danube River	Hungary	2857	-	3	1	[310]
27	Huangpu River	China	113	-	16	29	[311]
28	Grand Morin River	France	120	1200	6	16	[312]
29	Narmada River	India	1	-	4	10	[313]

assessed through the implementation of real-world freshwater conditions. Further, the integration of different information sources, high quality data, spatio-temporal sensors, and different non-parametric water modeling approaches should be thoroughly considered in future water monitoring systems and decision making processes.

APPENDIX A RECENT IMPLEMENTATION OF HYBRID MODELS IN FRESHWATERBODIES

See Table 4.

APPENDIX B PATTERNS OF RECENT WATER QUALITY MONITORING ACTIVITIES IN LAKES AND RIVER

See Tables 5 and 6.

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YULI SUDRIANI received the bachelor's degree in informatics engineering and the master's degree in information systems from Binus University. She is currently pursuing the Ph.D. degree with the Chemical Engineering and Material Sciences Doctoral School, Department of Process Engineering, University of Pannonia, Hungary. Since 2014, she has been a Junior Researcher with the Deputy of Engineering and Earth Sciences, LIPI, which transformed into the National Research and Innovation Agency (BRIN). Her research interests include surface freshwater analysis, hydroinformatics, and water-monitoring systems.

VIKTOR SEBESTYÉN is currently the Head of the Sustainability Solutions Research Laboratory. He is a Senior Researcher with the University of Pannonia, Hungary. He is also an Expert in environmental modeling and data-driven model identification. His research interests include methodological developments for climate change, sustainable development goals, water quality assessment, and environmental impact assessment.

JÁNOS ABONYI (Member, IEEE) received the M.Eng. and Ph.D. degrees in chemical engineering from the University of Pannonia, Veszprém, Hungary, in 1997 and 2000, respectively, the Habilitation degree in process engineering, in 2008, and the D.Sc. degree from the Hungarian Academy of Sciences, in 2011. From 1999 to 2000, he was with the Control Laboratory, Delft University of Technology, The Netherlands. He is currently a Full Professor of computer science and chemical engineering with the Department of Process Engineering, University of Pannonia. He has coauthored more than 250 journal articles and chapters in books and has published five research monographs and one Hungarian textbook about data mining. His research interests include complexity, process engineering, quality engineering, data mining, and business process redesign.