

Review

Recent Advances in Information and Communications Technology (ICT) and Sensor Technology for Monitoring Water Quality

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Abstract: Water quality control and management in water resources are important for providing clean and safe water to the public. Due to their large area, collection, analysis, and management of a large amount of water quality data are essential. Water quality data are collected mainly by manual field sampling, and recently real-time sensor monitoring has been increasingly applied for efficient data collection. However, real-time sensor monitoring still relies on only a few parameters, such as water level, velocity, temperature, conductivity, dissolved oxygen (DO), and pH. Although advanced sensing technologies, such as hyperspectral images (HSI), have been used for the areal monitoring of algal bloom, other water quality sensors for organic compounds, phosphorus (P), and nitrogen (N) still need to be further developed and improved for field applications. The utilization of information and communications technology (ICT) with sensor technology shows great potential for the monitoring, transmission, and management of field water-quality data and thus for developing effective water quality management. This paper presents a review of the recent advances in ICT and field applicable sensor technology for monitoring water quality, mainly focusing on water resources, such as rivers and lakes, and discusses the challenges and future directions.

Keywords: information and communications technology (ICT); machine learning; monitoring; sensor; water quality

1. Introduction

The introduction of various contaminants, such as organic matter, hazardous chemicals, and nutrients from domestic, industrial, and agricultural activities to natural water systems has caused harmful effects, such as harmful algal blooms (HAB) on drinking water supply systems like rivers or lakes [1]. Thus, appropriate water-quality-monitoring technologies are needed in order to develop an effective water-resource-management strategy and/or improve existing natural-water-system-management plans. Generally, water quality data is commonly collected on a regular basis by field/grab sampling and consecutive physicochemical analyses of the samples in a laboratory-based environment. Sometimes field-deployed analyzers or portable sensors are used to measure the water quality parameters. The water quality data include various physical, chemical, and microbial parameters [2]. The conventional method of field sampling (e.g., point sampling at a single location) and laboratory analyses requires considerable labor and time (several hours to weeks), and are

therefore labor-intensive, time-consuming, and costly, further hindering the ability to gather a synoptic view of the water source [3]. It also requires transportation of the samples, which may not represent the water quality at the time of sampling (e.g., an undesirable reaction may occur during the transportation). The data are often collected on a weekly, monthly, or seasonal basis, and this limits the applicability of the data in decision-making processes for effective water resource management or rapid operational responses to accidental events such as a toxic pollutant input. By developing monitoring capabilities, a simultaneous water quality database including spatial and temporal variations could allow for improved water quality management on a regional scale and for inaccessible topographic locations [4]. Advanced data collection could significantly benefit purposes such as continuous monitoring of water resources, assessments of flood areas, pollution management, and effects due to anthropogenic activities. Recently, automated sampling devices have been used to collect the water samples on a regular basis (e.g., few-hour interval) to estimate the pollutant load in designated field streams. Then associated pollutant concentrations (importantly, total nitrogen (TN) or phosphorous (TP) concentrations) are measured in a laboratory. One of the deficiencies in using automated sampling devices is the limited number of sampling bottles. It is known that the first flush may exhibit a higher pollutant load. Thus, the sampling time interval should be managed by considering the peak loading period (i.e., frequent sampling at the beginning of a flood event rather than at the end) [5,6]. However, regardless of these limitations, most monitoring programs are field-based, suggesting an urgent need for monitoring-methodology improvement [7].

The advanced monitoring techniques, such as in situ sensing and information and communications technology (ICT), enable effective water quality monitoring and are often called “smart water quality monitoring techniques”. A real-time water quality monitoring system can be applied for the management of drinking-water-supply processes, including raw water in lakes, rivers, and the sea [2]. In particular, drinking-water-supply systems require real-time monitoring to maintain the water quality standard and to prevent unexpected accidents, including the malfunctioning of water treatment processes and contamination of raw water. The natural water in lakes, rivers, and the sea can be effectively managed by an in situ real-time monitoring system where area-based monitoring with multi- or hyper-spectral imaging sensors are increasingly applied to collect data for wide-ranging areas [8–11]. The recent advances of ICT and sensing technologies in environmental engineering enable reliable measurements, and the transmission and management of massive environmental data at low costs [5,12,13], which can support decision-making processes (Figure 1). The technologies are already widely used in various fields, such as early warning systems for meteorological issues and public health protection [5,14,15]. The general function of real-time online water quality monitoring systems is to conduct data acquisition, transmission, and interpretation of the measured data [2]. The advanced data analysis technologies, such as machine learning, also provide valuable tools for effective water quality data management (e.g., prediction of water quality changes) [16–18]. Recently, deep-learning, a type of machine learning method, is increasingly used for the analysis of massive environmental data, to provide useful information for water quality management.

This review provides an overview of current and in-development technologies, processes, and parameters of water-quality-monitoring sensor technology for water resources, such as lakes and rivers. This paper also reviews recent advances of water-quality-monitoring systems based on ICT, including area-based monitoring systems using hyper- or multi-spectral imaging sensors and their integration with machine learning tools for the analyses of massive data.

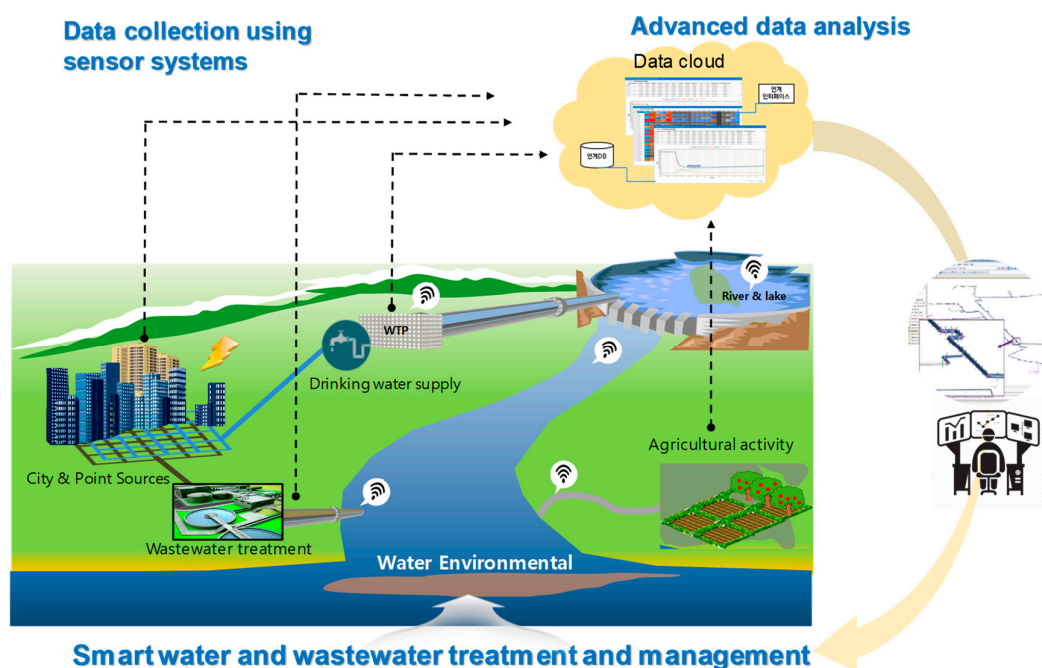


Figure 1. Schematic of the combination of real-time monitoring, transmission, and advanced data management system for smart water and wastewater treatment and management.

2. Sensing Technology for Water Quality Monitoring

2.1. General Sensor-Based Water Quality Monitoring Systems

Natural and anthropogenic pressures on aquatic environments and resources have significantly increased in recent years. To conserve the integrity of water bodies and expedite the efficacy by which human systems can respond to ecologically critical situations, such as floods, eutrophication, and offshore oil spills, it is necessary to develop water quality monitoring systems that can provide real-time measurements for rapid data analysis [19]. Understanding water quality trends requires a detailed and wide coverage of water quality fluctuations over multiple timescales that is area-dependent [20]. For example, coastal fringes are subject to episodic delivery of sediments and nutrients that can affect reef ecosystems via nutrient and toxicant load delivery and resuspension, which may pose ecological threats during flood events [21]. Transitional waterways like rivers and streams are also subject to high pollution impacts [19]. Water quality monitoring by managing agencies is traditionally costly, labor-intensive, and time-consuming, with sample collection being variable over temporal and spatial scales. Vessels such as boats and ships are historically needed to reach monitoring sites of interest, containing bulky instruments that require manual handling to collect samples, which then must be transported back to land-based laboratories for analyses. This long and tedious process can be expensive and result in information that is not fully representative over changes in time, as delays between sampling and analyzing can compromise sample integrity [7].

The assessment of water quality comprises physical, chemical, and biological indicators. Common corresponding parameters include pH, electric conductivity (EC), dissolved oxygen (DO), turbidity, temperature, total organic content, total suspended solids (TSS), and nutrient concentrations such as nitrogen (N) and phosphorus (P), which represent the degree of contamination of water. In general, sensors detect stimuli from the environment, which are converted to signals (e.g., mV and pA) and stored in a data platform for further use [5]. A wireless water quality monitoring system comprises several steps: data collection; signal processing, such as noise control; data amplification and transmission; and data management, including a computing process [2,22]. Geetha and Gouthami (2016) specified the three steps as follows: First, the field water quality data is collected

by wireless sensors and transmitted to a controller by a wireless or wired system. Second, the data transmission system transmits the collected data from the controller to the data storage cloud. Finally, the stored data in the cloud is used for the analysis and operation of a system [2].

2.1.1. Physical Monitoring Sensors

In situ methods allow for measuring variables directly in the environmental medium in continuous or semi-continuous time intervals and for data to be sent to land-based facilities. In situ sensors have been used for years to measure physical-based parameters, such as oxygen, pH, and CO₂ in seawater; conductivity, depth, and temperature (CDT); and nephelometric turbidity units (NTU). Arrays of sensors are typically used together in automated systems, either deployed from a ship or on a mooring, as part of an observation system [23,24]. In situ sampling offers high-resolution and reliable measurements, with the added benefit of a vertical water column profile analysis. Low-cost sensors and commercially available sensors can predict total suspended solids (TSS) concentrations based on high-frequency time series of turbidity, conductivity, and water-level data. For example, Adamo et al. (2014) used a compliant seawater probe that can measure water temperature, salinity/conductivity, turbidity, and chlorophyll-*a* (Chl-*a*) concentration [19]. Vertical water column sampling (oceanographic) from ships at fixed coordinates is a long-time physical technique that provides continuous transect-based water data. Water clarity was observed by filtering suspended solids, using turbidity probes and beam attenuation probes to estimate particle concentrations in the water and to estimate light attenuation [21].

Spectrometers and water quality probes containing fluorescent detectors can be used to measure downwelling spectral irradiance, surface-water levels of dissolved nutrients, Chl-*a*, fluorescence, and turbidity at transects, while a towed body probe can be used in underway sampling; surface light sensors can also be used to monitor profile-based ambient fluctuations. For Chl-*a* measurement, it should be noted that fluorescent quenching to indicate Chl-*a* is dependent on light intensity [7,21,25]. In Leigh et al.'s (2018) study of river water quality during high-flow events, in situ automated water quality sensors that contained NTU and CDT sensors were placed at three study sites. Sensors were placed inside flow cells on monitoring stations on the riverbank sides, allowing water to pump through the flow cell and for pressure-induction sensors to record NTU and electrical conductivity [25].

2.1.2. Chemical Monitoring Sensors

The most common and widely available solute for chemical sensors is pH and nitrate (NO₃⁻). Traditionally, hydrochemistry monitoring has been conducted through automatic water-samplers, yet these are costly due to the need for regular sample collection and laboratory analysis, and such methods are limited by performance and reagent wastes. Spectrophotometers have enabled high-frequency sampling of riverine dynamics [23,24,26]. For other solutes, wet analytical chemistry remains the most viable method, with “lab-on-a-chip” sensor technology lowering power requirements, while reducing anomalies and interferences associated with optical absorbance measurements. There are also deployable optical sensors, such as fluorimeters, that are capable of measuring photosynthetic pigments and organic matters like Chl-*a* [20].

As an indicator of the water quality, the pH value is defined as the negative logarithm of the hydrogen-ion (H⁺) concentration, which expresses whether the water is acidic or basic. The pH range is 0–14, and the water sample is acidic or basic if the pH value is below or above 7, respectively. High and low pH values can cause harmful effects on human health [27]. Conventionally, the pH value is measured by measuring the potential difference between the working pH probe and the reference electrode. There is a direct correlation between the voltage output (mV) of the electrode and the pH value of the water sample [22,27].

According to Mills and Fones (2012), there are two main methods to measure pH in situ: (1) potentiometric, using a pressure-balanced glass electrode and Ag/AgCl reference probe, and (2) fiber optic, using an indicator dye added directly to the test solution or placed within a sensing cell/matrix [23]. However, while these techniques have excellent accuracy and precision, they are ideally suited

for flow-through systems and observed to work best on research ships. Additionally, they note that flow-injection analyzers (FIA), which comprise a pump, detector, and narrow tube manifold, can offer a spectroscopic method whose colored products post-reagent can be detected by visible wavelength spectroscopy or fluorimetry [23]. However, FIA methods are affected by large changes in bodies of water that can lead to significant bias in data collection. Therefore, FIA may be best suited for deeper environments, such as hydrothermal vent locations, or localized and contained bodies of water [23,24].

Electrochemical sensors and biosensors are also potentially viable methods of water quality monitoring. Commercially available CDT instruments use conductometric electrodes to measure salinity, Ag_2S electrodes to measure sulfur, and potentiometric methods to detect oxygen and nitrous oxide. The phosphate ion electrode is one of the most important parts of the sensing system, and it has been proposed to use a cobalt (Co)-based phosphate microelectrode because Co is a phosphate-sensitive electrode material [28,29]. Micro-electro mechanical systems (MEMS) conjugated with microelectrode array sensors have been developed for the detection phosphate and showed robust and precise in situ measurements and multi-analyte detection with a small amount of sample volumes; but due to the configuration of the microelectrode array sensors, it may be fragile under high-flow or turbulent water environments [30]. The microfluidic devices can be integrated with electrochemical and optical sensors for water quality monitoring of heavy metals, nutrients, or pathogens in a microchannel system [31]. The advantage of using microfluidics includes the requirement of a small volume of samples, better processing control, reduced waste generation, and system compactness [31].

Biosensors are usually classified on the basis of the type of recognition unit or the transducer nature; DNA, enzymes, immunological systems, and receptor proteins can be supported by electrochemical, chemical, and piezoelectric mechanism-based transduction components. Both electrochemical sensors and biosensors are highly specific, sensitive, and can work in a variety of matrices, but the industrial production and long-term deployment are often complicated by calibration and validation difficulties. Biosensors are not widely used in the environment and less in in situ water monitoring, but have some potential when looking at drinking water purification or water treatment plants for the detection of live organisms, such as parasites and pathogens [23,24].

Despite the prominence and widespread use of in situ sensors, there are many disadvantages that stem from the manual handling and instrumentation required to collect the samples. Both filtered and unfiltered water samples are typically collected, frozen, and analyzed in the lab, using photochemical methods for total nitrogen (TN) and total phosphorus (TP) [21,24]. CDT probes and plug-in devices are expensive and bulky, limiting their roles in sensitive sensor networks. In situ sampling must be undertaken, usually on research vessels that require substantial time, effort, and financial support in order to reach the area of interest. In Adamo et al.'s (2014) study, a compliant seawater probe was used to indicate water eutrophication, but it was unable to identify the composition of the vertical water column, providing only information relative to a fixed depth [19]. Pressure-induction automated sensors require linear interpolation of data to provide quality time-matched observations, and the removal of anomalies can result in periods of missing data [25]. Precision calibration equipment (stable reagents and standards), supporting infrastructure, such as flow systems, and interval frequency consistency are among the major issues that affect in situ monitoring. Nitrate sensors particularly require consistent cleaning to remove biofilm or unwanted contaminants [20]. Additionally, it is difficult to maintain calibration parameters during long-term deployments [23,24].

2.1.3. Optical Remote Sensors

Satellite sensing works by direct solar radiation entering the water column and absorbing or scattering, depending on the types and constituents within the column. This radiation is reflected in the atmosphere; the ratio of outward radiance to the direct solar radiation on the sea surface is called reflectance, and this can be passively recorded by a sensor. Remote-sensing reflectance integrates the spectral absorption and backscattering properties of the materials that compose the column. Satellites then perceive spectral color change and quantify concentrations through validated algorithms [7,24].

Satellite ocean color technology has historically provided Chl-*a*, colored dissolved organic matter (CDOM), TSS, and light attenuation measurements. Chl-*a* is a proxy for phytoplankton biomass, CDOM is a nutrient source and vector for heavy metals in water, TSS provides information on phytoplankton and sediment particles, and light attenuation is critical to understand the growth and maintenance of suspended and benthic plant life [7]. Chl-*a* and turbidity can be observed and retrieved from combining the visible, mid-infrared, and infrared bands. Optical sensors can be used as a cost-effective technique to monitor water quality parameters at a basin-scale [26,32].

Remote observations provided by satellite sensors offer among the greatest spatial coverage at a specific time. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor was used to gain global coverage every 1–2 days, who notes that using ocean color to determine water turbidity and phytoplankton population (Chl-*a*) based on radiative transfer equations provides spatial coverage and an easy method to observe water quality patterns, but at the cost of limiting analyses of absolute concentrations and small-scale horizontal and vertical variability. In situ field sampling may be required to solve this issue [21]. Despite these advantages, MODIS is limited when it comes to broad, overlapping spectral features, as it can only read seven spectral bands at visible wavelengths and rough spatial resolution (e.g., 1.0 km). Satellite readings can also be disturbed by landforms' highly reflective quality compared to water, cloud masking, and turbid coastal waters [7]. Practical retrieval of water quality parameter concentration from shallow bodies of water using optical sensors is challenging because of background effects from sediment deposits, embankments, landmass features, and atmospheric conditions [23,32]. Overall, sensors based on colorimetric UV spectral measurements are widely used in commercially available systems but all suffer from various limitations: compound-to-compound concentration to absorbance linearity, the small compound spectrum that can absorb light with 190 nm to 850 nm wavelengths, and difficulty in application to real-time in situ processing [26].

2.2. Current Commercially Available Real-Time Monitoring Sensors

Real-time monitoring sensors are applied in various fields, such as drinking-water supply systems, river and lake management, and water resource distribution [27,33]. Table 1 lists exemplary water quality parameters measured with sensing technology. For proper management of water quality, pH value, DO concentration, electric conductivity (EC), and temperature are among the most common parameters that provide useful information. For example, abrupt changes in the pH value, EC, or DO concentration suggest an input of toxic chemicals, whereas abrupt changes in the temperature affect the aquatic ecosystem [34]. Furthermore, increasing turbidity increases the costs of the water-treatment processes and affects the freshwater ecosystem (e.g., fish life) [35,36]. These basic items are measured by commercial sensors at relatively low costs [2,27,34]. The DO concentration represents the soundness or self-purification ability of a water system. A high DO concentration generally indicates that organic contaminants are low in the water systems. The EC represents the ability of water to conduct an electric current. It is commonly measured with two platinum (Pt) electrodes based on Ohm's law ($\mu\text{S}/\text{cm}$) (i.e., conductance is the reciprocal of resistance) in water. There is a correlation between current and EC in the sample, and EC is measured by measuring the resistance between two parallel electrodes [27]. The easy-to-measure basic-water-quality parameters (e.g., DO concentration, pH, and EC) provide important information for water quality management. However, management of the water quality in water bodies, such as rivers, lakes, and oceans, requires massive datasets, including more complicated items, such as organic compounds, nutrients, and flow rate.

Table 1. Examples of water quality parameters monitored with sensing technology.

Content	Parameter	Sensor Type	Ref.
Basic-item monitoring	pH value, DO concentration, EC, temperature, oxidation-reduction potential, and turbidity	In situ electrodes, colorimetry, conductivity cell, membrane electrode, optical sensor, potentiometric, thermistor, nephelometric, etc.	[2,34,37]
Organic-compound monitoring	COD	In situ electrochemical sensor	[38,39]
Nutrient monitoring	Nitrate	Using an optical sensor where nitrate concentration is determined from the relationship between UV light absorbance and nitrate concentration in a water sample	[40–42]
	Nitrate, Ammonium, Phosphate	Wet chemistry sensor where the nutrient concentration is measured based on a colorimetric reaction	[43]
	Chl- <i>a</i>	Using satellite images (Chl- <i>a</i> concentration is determined from the empirical relationship between satellite image and Chl- <i>a</i> concentration)	[44,45]
Harmful algal blooms (HABs) Monitoring		In situ optical sensor with wireless data transport network	[19]
	Phycocyanin	In situ fluorometric sensor	[46,47]
	Cyanobacteria biomass	Using satellite images (Cyanobacteria biomass concentration is determined from the empirical relationship between satellite image and cyanobacteria biomass)	[48,49]
HABs monitoring using hyperspectral image (HSI)	Chl- <i>a</i>	Chl- <i>a</i> concentration is determined from the empirical relationship between HSI and Chl- <i>a</i> concentration	[10,50]
	Phycocyanin	Phycocyanin concentration is determined from the empirical relationship between HSI and phycocyanin concentration	[8,50,51]
	Cyanobacteria biomass	Cyanobacteria biomass concentration is determined from the empirical relationship between HSI and cyanobacteria biomass	[8,10]
Physical status for water quantity monitoring	Water level	In situ acoustic sensor where the distance from the surface of the water to bottom is measured from the echoes of the acoustic waves	[52]
	Velocity	Velocity sensor (e.g., ADV)	[53,54]

The concentration of organic compounds is one of the most important parameters for estimating the pollution level of water. The organic contaminants have been expressed indirectly by a measurement of the oxygen required to decompose organic carbon in water, such as biological oxygen demand (BOD) or chemical oxygen demand (COD). The conventional method for measuring COD is the degradation of organic matter in water, using an oxidizing agent which is a labor- and time-consuming (about 2 h) process. As BOD has been used for regulation purposes, there have been continuous efforts to find alternative methods for measuring BOD (or COD) in a shorter time and with fewer requirements of toxic agents for oxidation treatment. In the late 1990s, a thin-layer electrochemical cell was suggested as an alternative method, as it has a faster detection time—although, it still requires about 20–30 min for detection of COD—and later, amperometric methods were suggested to further shorten the analysis [55,56]. This method requires a lower oxidation potential, in which several novel electrodes have been developed, such as the Rh₂O₃/Ti electrode [57] and copper nanoparticle electrode [56]. Although there are several electrochemical sensors developed in laboratory tests, more evaluation and validation are still required to be used for in situ monitoring of the COD in natural water (e.g., lakes and rivers) and the effluent of wastewater treatment plants [38,39]. Currently, there are no available BOD and COD sensors for field uses.

Nutrients, particularly nitrogen (N) and phosphorus (P), are one of the most important contaminants in freshwater systems [1,58,59]. Excessive nutrient input is often considered a major

cause of HABs, which affect drinking-water-supply systems and ecosystems [60–64]. Table 2 shows the advantages and disadvantages of commercially available nutrient-sensor technology. There are three types of sensors for nutrient measurements: ion-selective electrodes, wet-chemistry sensors, and optical (UV) sensors [43]. Ion-selective electrodes were the first type of sensors used for the analysis of nitrate concentrations in freshwater and wastewater effluents developed in the 1970s [43,65]. The ion-selective electrode measures nitrate ion activity related to its molar concentration, where the volts (mV) measured with the electrode are represented as the molar concentration of nitrate (NO_3^- -N) by empirical equation [65]. The ion-selective electrode has several benefits, e.g., it is relatively inexpensive and easy to use, yet it has a lower accuracy than wet-chemistry or UV optical sensors [65] and requires frequent maintenance (e.g., calibration). The wet-chemistry sensors have been increasingly used due to the development of wet-chemistry analyzing technology in the last 20 years, where the water sample is supplied to the analyzer by a pumping system, and the ammonium or orthophosphate concentration is measured by a colorimetric reaction [43,66]. Recently, researchers have estimated the nitrate loading in watersheds with in situ optical sensors for high-frequency observation of nitrate in river systems [40–42,67]. The optical nitrate sensor measures nitrate by detecting UV-light-attenuating properties of nitrate, which is composed of the UV light source, optically coupled sensing probe, and the high-frequency spectrometer [41].

Table 2. Advantages and disadvantages of commercially available nutrient sensor technology [43].

Type	Principle	Advantages	Disadvantages
Ion-selective electrodes (ISE)	Direct potential difference measurements between a working electrode and a reference electrode	• Inexpensive (<\$1,000) and easy to use • Fast response times • Not influenced by color or turbidity • Available for NO_3^- and NH_4^+	• Low resolution, accuracy, and precision • Subject to ionic interferences • High instrument drift • Limited shelf life (~months)
		• High resolution, accuracy, and precision • Chemical-free • Fast response time • Additional optical information in spectra	• Expensive (<\$15,000) • High power requirement and maintenance costs • Only available for NO_3^-
Optical (UV) sensors	Spectral absorption by a photometer	• High resolution, accuracy, and precision • Potential for in situ calibrations • Relatively fast response time • Available for NO_3^-, PO_4^{3-}, and NH_4^+	• Expensive (<\$10,000) • High power requirement and maintenance costs • High potential for fouling • Requires reagents and generates wastes
Wet chemical analyzers	Wet chemical colorimetric reaction with detection by photometry		

The direct counting of harmful algal cells is arduous and time-consuming. Thus, the Chl-*a* or phycocyanin concentration is widely used as an indicator of the algal bloom concentrations [47,68–70]. Area-based monitoring with imaging sensors, such as the medium-resolution imaging spectrometer (MERIS) on a satellite, is also increasingly used to monitor algal blooms [44,49,71]. The satellite images provide useful information on algal blooms (e.g., the cyanobacteria biomass or Chl-*a* concentration) of wide-ranging areas in a relatively short time, in which real-time monitoring is limited, owing to the long duration of data processing [45,48,49]. Furthermore, high-resolution airborne hyperspectral image (HSI) has been increasingly used for the areal monitoring of algal

blooms (e.g., the cyanobacteria or Chl-*a* concentrations), as it compensates for the limitation of medium-resolution satellite monitoring data [8–10]. The HSI sensor scan data of light spectrum (or reflectance) from target objects with various wavelengths (400 to 950 nm) and is known to be ideal for HAB identification in places where the light is diffracted for further analysis of the spectrum (Figure 2) [10]. The collected data are often referred to as apparent optical properties (AOP), which include reflection from atmospheric conditions (e.g., wind and cloud) between the sensor and the target object. Thus, the interference of atmospheric conditions needs to be compensated to obtain inherent optical properties (IOP), which are characteristic optical properties of the target object [72,73]. The Chl-*a* concentration can then be obtained from an empirical model, using the relationship between Chl-*a* concentration and IOP [73,74].

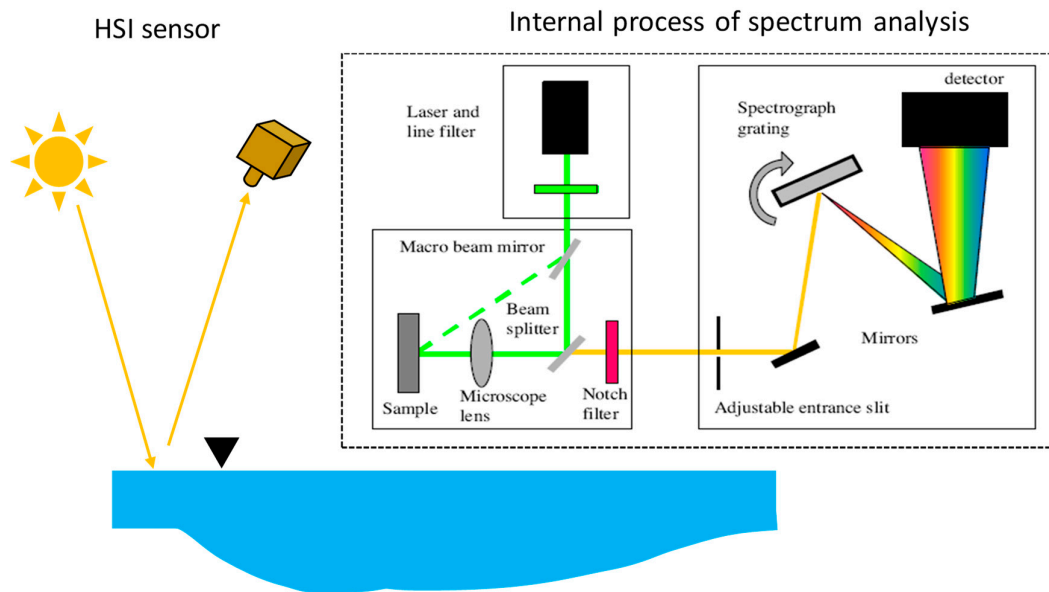


Figure 2. Schematic of a hyperspectral images (HSI) sensor system.

The water depth is an important parameter for the management of water quantity and quality. Researchers have used wireless sensors for the real-time monitoring of water levels in coastal areas and estuaries [52,75]. An acoustic sensor is the present standard for measurement of water level, where the distance is measured from the echoes of the acoustic waves return to the transducer [52]. Boon and Brubaker (2008) observed similar accuracies of water level monitoring for a newly developed microwave sensor with an acoustic water level sensor in an estuarine area [52]. A microwave water level sensor has several advantages over acoustic sensors, including a higher reflectivity and lower sensitivity to variations in the air temperature and humidity [52]. Recently, the use of a chipless radio-frequency identification sensor, which exhibits a reliable detection with relatively low cost for water level monitoring, was suggested [76].

Monitoring flow rate and contaminants in rivers and streams is also important to estimate the pollutant mass loads. The flow rate is often determined indirectly by measuring water depth, which is usually much easier to measure than flow rate. The relationship between water depth and the corresponding flow rate can be defined from multiple field measurements. Once the relationship is defined, the flow rate is estimated by multiplying the cross-sectional area with water velocity. The velocity sensors (e.g., acoustic Doppler velocimetry (ADV)) were widely used to measure velocity until recent years [53,54]. The ADV sensor consists of one transmitter and several receivers, where the velocity is measured based on the Doppler shift effect [77]. Wireless sensors are also combined with other related technologies (e.g., geological information systems (GIS)) for water loss management in urban water distribution systems [78]. A more advanced sampling technology that includes ICT and the development of a model algorithm adjusts the sampling interval according to the flood status. Thus, it provides more precise information on the pollutant load during flood events

[79,80]. This real-time flow-rate-sensing technology enables the proper management of water distribution systems during flood events in urban watersheds [81].

2.3. Electrochemical Detection of Algal Toxins

For the detection of algal toxins using biosensors, previous studies have demonstrated the efficiency of both antibody-coated surfaces, as well as an immobilized microcystin-LR (MC-LR) molecule coating, for the detection of MC-LR in various water samples [82–85], a technique heavily reliant upon the affinity between the antibody and microcystin-LR molecules. The first electrochemical immunosensor for MC-LR analysis using an antibody coating was designed in 2007, using a screen-printed graphite electrode as support for antibody adsorption [83]. It was previously discovered and is now well-known that MC-LR contains a unique structural feature, a β -amino acid (ADDA), which plays both an important role in its toxicity, as well as its recognition by ADDA-specific antibodies [86]. Additionally, there have been studies demonstrating microcystin detection, using numerous antibodies, such as AD4G2 [87,88], IgG1(mouse, goat, etc.) [89,90], and polyclonal antibodies [83]. The use of a monoclonal antibodies, specifically (clone (MC10E7)) (Enzo Life Sciences, Cat. ALX-804-320-C200, NY, US), is promising, as it is highly sensitive and selective for MC-LR [84], where MC10E7 demonstrated to be very stable, presenting low interferences by humic acid, salts, and surfactants/organic solvents present in solution. The detection mechanism of this type of sensor is solely based on the adsorption of MC-LR molecules onto the antibody-coated sensor surface. For the sensors to be coated with immobilized MC-LR molecules, the carbon working electrode is functionalized by electrochemical oxidation in an alkaline solution (e.g., 1.16 V vs. Ag/AgCl for 1 min in NaOH), to produce oxygen-containing functional groups on the carbon surface that are subsequently used as anchoring sites for the covalent immobilization of MC-LR to the surface via cross-linkers [82]. The functionalized sensor is to quantify MC-LR concentrations by utilizing the immobilized MC-LR molecules, which act as available bonding sites for the attachment of the free horseradish peroxidase (HRP) antibody molecules (i.e., those which do not bind to the MC-LR molecules in solution).

2.4. Consideration in Water Quality Monitoring Using Sensors

Udy et al. (2005) stated that water quality assessment is a compromise between practicality of measuring the various indicators of interest with the requirements to sample spatial and temporal dynamics at appropriate scales and that technology such as in situ probes can be used with remote sensing and higher-quality sensors, to provide an in-depth spatial and multitemporal coverage of an area [21]. According to Adamo et al. (2014), three major challenges of water quality monitoring using in situ probes are the manual labor and time required for sampling, finding optimal time intervals to go out to water bodies, and the availability of funds from agencies responsible for monitoring. Remote sensors and wireless communication systems can lead to real-time monitoring technologies by providing rapid hydrologic changes that can implicate alarm events, such as algal blooms and flooding [19,24].

The composition of the waters in question can also lead to difficulties in the analysis. For example, Chl-*a* has no homogenous distribution in water, but spatial disorganization can indicate events occurring on a scale of single-digit to tens of meters. Chl-*a* is an important indicator of waterbody trophic status, but analysis of spatial patterns can be complicated due to biological, physical, and chemical factors [32]. Thus, it is important to consider sensors that are tunable to ecological proxies (e.g., Chl-*a* sensitive sensors to detect signs of HAB development, or TSS-sensitive probes capable of monitoring resuspension events that can provide traceable steps for pathogen detection or anthropogenic disturbance) [7].

Sensor-derived high-frequency time series for multiple solutes can better allow for stoichiometric analysis of aquatic ecology. The hydrological interactions of the area of interest with its local landmasses and other artifacts must also be considered when optimizing systems; dynamic coastline environments require finer-scale monitoring that is durable and multi-temporal, providing localized and detailed water quality data. It may not always be economically or physically practical

to conduct experiments during high water flow events; a solution to these may be to use low-cost in situ automated sensors that can create multi-parameter time series, which can circumvent the need for manual sampling or laboratory analyses if optimized to catch the full range of water-quality conditions happening in transitional waterways [19,23]. However, temporal autocorrection used in most automated systems is not always efficient or wholly indicative of a water body's changes, especially in high- or low-flow events in transitional waterways [25]. Therefore, it is also preferable to design a water quality monitoring system that is tunable, such as enabling researchers to focus on the different spatial distribution of sensor probes, to assess the edges of a possible high-impact pollution area [19].

The management of the active surface of sensors (e.g., sensing area) is also important for the stable measurement of water quality in the longer term. For example, the formation of slimes or precipitations by the accumulation of biological or chemical materials on the surface of the sensor possibly reduces the accuracy of the sensor, as well as sensor's lifetime [91,92]. Thus, a practical management technology such as regeneration of sensing area by physical and/or chemical cleaning is another possible research area.

Mills and Fones (2012) explored the prospect of "lab-on-a-chip", showing that low-cost illumination and detected method integrated with a microfluidic system has been developed for nitrite (NO_2^-) but can equally be applied to other hydrochemical features via colorimetric methods [23]. Modern "lab-on-a-chip" offers the potential for combining conductimetric sensors, microelectrodes, and MEM arrays with microfluidics to act as portable monitoring laboratories that can be put in situ for real-time environmental monitoring, but current research on this topic is still in its early stages, especially for comprehensive hydrologic purposes [26]. Ideally, a robust, effective, and multiparameter technology with multi-temporal detection of real-time water qualities may require a multi-sensor system that is able to detect physical, chemical, and biological properties, operate on a long battery life or use sustainable energy sources such as solar or hydro-powered, and capable of consistent delivery of real-time data to central servers.

Regardless of the onward success in in situ sensor development, the main points of concern arise when spatial trends involving inaccessible locations or large-scale data requirements are of interest. Thus, integrating in situ measurements with recent developments in techniques, such as remote sensing, computer modeling, and other advanced information technology, illustrates the current direction of a more complete water quality monitoring methodology [93]. Remote sensing is a developing solution that utilizes reflected and emitted radiation to detect water quality parameters at a distance from the water body of interest, complementing large data requirements through efficient and comprehensive assessment capabilities [94]. Remote sensing has also been successful in data modeling predictions for use in best management strategies, such as exhibited in a study by He et al. [95]. This study utilized remotely sensed imagery, to estimate potential annual pollutant loads of 30 river basins in Japan. Remote sensors for water quality parameters may be classified into two main types, airborne and spaceborne. Airborne sensors are mounted on a platform within the Earth's atmosphere, at relatively low altitudes. In contrast, spaceborne sensors are carried outside of the Earth's atmosphere generally via satellites. Airborne sensors tend to retrieve data with greater accuracy and spatial resolution, suiting smaller waterbodies; however, in situations where monitoring a larger waterbody is required, spaceborne sensors provide broader observational feasibility [96]. The spatial coverage of most used spaceborne sensors ranges from tens to hundreds of kilometers [97].

Since remote sensing technology utilizes radiation, parameters signifying the presence of constituents that affect the optical quality of water, such as suspended solids, turbidity, chlorophyll concentrations, and temperature, can be measured. Other parameters that are important to assessing water quality yet exhibit weak optical properties, such as pH and certain nutrient concentrations, are a deterrent in implementation [98]. In general, one of the main limitations in remote sensing technology is due to spectral hindrances. A study done by Zielinski et al. (2009) on various water quality detection methodologies indicated a primary challenge in remote sensing is its constraint to surface layer measurements, which impedes vertical variation assessments [99]. A study on spatial

variations in water quality using airborne remote sensing completed by Olmanson et al. (2013) described small rivers and streams as limitations, as they may be so shallow that reflectance from the water is affected by bottom conditions, in addition to water quality characteristics [96]. Furthermore, implementation can be affected by the need for validation using in situ measurements, accuracy challenges due to spectrally competitive constituents, and weather conditions.

The current status of remote sensors for water quality measurement is not suited for all situations. For complete spatial and temporal, as well as accurate assessments, remote sensing is still to be integrated with other methodologies, such as field sampling and in situ sensor technology [100]. A study completed by Chen et al. (2018) recognizes these concerns and examples of the concept of water quality monitoring in a smart city [101]. This pilot project was developed to integrate Wireless Sensor Network (WSN)-based solutions with smart city infrastructure for improving monitoring methodology.

3. Technical Factors in Real-Time Monitoring

3.1. Data Transmission Systems

Recently, the applications of Information and Communication Technologies (ICTs) have become increasingly useful tools for managing water sectors. The ICTs for water quality monitoring include in situ sensing systems, data cloud, and machine learning components. Vijayakumar and Ramya (2015) emphasized the importance of ICT (e.g., ubiquitous computing and cloud computing) for the real-time monitoring and management of the water quality. Ubiquitous environments are already increasingly used in practical applications [15,102,103]. Cloud computing enables the storage and analysis of massive data, without using local computer hardware. The easy, remote assessment of the recorded data through a website is one of the important advantages [104]. In addition, wireless sensors are one of the most efficient methods for collecting field data [15,105]. Wong and Kerkez (2016) suggested several factors (e.g., the interoperability, power consumption, reliability, usability, and security) that should be considered for the widespread usage of in situ sensing technologies for water quality management [79]. First, they emphasize the importance of the interoperability between real-time data and hardware platforms of users to minimize additional adjustments. Second, a low power consumption rate of a sensing system is crucial for stable data transmission between in situ sensors and data platforms [79]. Third, the reliability and usability of data platforms are essential. The authors recommend a feature-rich commercial platform to minimize additional efforts in improving data system designs and to focus on the development of the sensing technology [79]. Finally, they emphasize the importance of proper security measures through encryption and authentication techniques to provide real-time data to the public [79]. The recent advances in low-cost wired or wireless technologies enable the easy transfer of real-time data to web-based data platforms and thus improve the usability of data for water quality management [5,106].

3.2. Wireless Sensor Technology

While multiple in situ online sensors are used for real-time monitoring in drinking-water treatment plants, for the monitoring of big natural-water systems, wired sensors are widely used [2,107]. However, a wireless sensor network has a clear advantage for the real-time detection of massive data with relatively low costs compared with those of traditional monitoring methods [107].

The representative wireless network technologies applicable to water quality monitoring are Wi-Fi, ZigBee, and Bluetooth. Wi-Fi is one of the most commonly used technologies [108] for the data transmission between devices based on wireless local area networks, according to the Institute of Electrical and Electronics Engineers 802.11 Standard [109]. ZigBee consumes less power and costs less than Wi-Fi. However, it exhibits a shorter transmission area and is thus suitable for closed networks such as home networks. The low power consumption of Bluetooth approaches that of ZigBee, and its transmission area is relatively wide; therefore, its use has recently been increased [108]. There are two steps for the transmission of real-time monitoring data between sensor nodes and data clouds: (1) from sensor nodes to controllers and (2) from controllers to data clouds. ZigBee or Bluetooth are used

for the transmission of data between sensor nodes and controllers [2]. Wi-Fi is rather used for the transmission of data between controllers and data clouds and not for data transmission between sensor nodes and controllers because of the excessively high power consumption [2,110].

Recently, the low-power wide-area networks (LPWA), such as LoRa and SigFox, are increasingly used for water quality monitoring, as they have wider communication range (over a few to tens of kilometers) than the traditional wireless technologies, such as Zig-Bee, Z-Wave, and Bluetooth (< a few hundred meters of communication range) [111,112]. Saravanan et al. (2017) used the LoRa network for a pilot project of smart water grid management in Mori, a village near to Bay of Bengal in India [113]. More recently, Di Gennaro et al. (2019) suggested a prototype water quality monitoring system using SigFox that includes units of pH, turbidity and temperature sensors, and a global positioning system (GPS) module, which also has the advantage of being low-cost and having a low power consumption [114]. These prototype LPWA studies suggest a possible advance of water quality monitoring paradigm with low cost and wide range in the near future.

4. Advanced Data Analysis with Machine Learning for Water Quality Analysis

The use of web-based data storing and processing with the Internet has recently increased with the usage of sensor data [5,115]. Various technologies related to the Internet of Things (IoTs) are applied for remote sensing and the management of measured data [116,117]. The easy accessibility and use of open-source programming languages (e.g., R or Python) enable advanced analysis of data with high data processing technologies, such as machine learning [5,118]. Multiple linear regression is one of the commonly used methods for water quality data analysis [119,120]. For example, Chang (2008) investigated the spatial distribution of water quality and analyzed the relationship between water quality and other parameters, such as urban development and soil properties. The Kriging, a spatial data analysis method, may provide the best linear unbiased prediction of intermediate values by interpolation and is often used for the estimation of groundwater quality [121–123]. For example, Hooshmand et al. (2011) estimated chloride concentration and sodium adsorption ratio in groundwater for irrigation using the Kriging method. The locally weighted scatter smoothing (LOWESS) is another data analysis method which is used for data analysis with the nonlinear relationship by repeating linear regression with regular intervals, to obtain smooth line fitted for nonlinear data [124]. LOWESS is often used for the estimation of the suspended sediment concentration from observed discharge data in rivers [125,126]. However, the linear regression method is unsuitable for complicated nonlinear problems, such as the effects of non-point sources (NPS) and self-purification processes in water systems [127,128].

Various machine learning techniques including deep-learning methods have widely been used for the analysis of massive water quality data and for the improvement of the prediction of water quality changes in water systems by utilizing advanced data analysis libraries, such as TensorFlow. Due to the increased accessibility to the data analysis library, the models could supplement the ICT and associated decision-making processes for various water quality challenges. These techniques are suitable for complicated nonlinear water quality management problems [127–132]. The class of machine learning models, examples of application cases, and water quality parameters measured at various time intervals are summarized in Table 3. Artificial neural networks (ANNs) are one of the most conventional and widely used machine learning techniques for water quality management [133–136]. The conventional ANN structure consists of input, hidden, and output layers; the hidden layer contains two or more layers of nodes [128,137]. In the hidden layer, the input value at each node is computed with weight and bias, and then consequently used as an input for the activation function where a sigmoid function is commonly used. The weight and bias are adjusted in the learning process of ANN to produce optimal output.

In the 1990s, the application of ANNs in flow forecasting and for water quality management was limited, owing to the lack of good-quality and long-term data [136]. Nevertheless, they have been increasingly employed for the analyses of water quality data such as for the modeling of water quality parameters (e.g., phosphorous, nitrogen, and DO concentrations) until the early 2010s [127,138,139].

Table 3. Examples of machine-learning application cases for water quality monitoring.

Type	Frequency	Estimation	Item	Data Collection	Ref.
ANN	Daily	Chl- <i>a</i>	Air temperature, average daily discharge, Cl ⁻ , daily precipitation, dissolved inorganic nitrogen, NO ₃ ⁻ -N, NH ₄ ⁺ -N, NO ₂ ⁻ -N, orthophosphate-phosphorus, sulfate, TP	Daily sampling with an automatic device and analyzed in a laboratory once a week	[133]
	Monthly	Chl- <i>a</i>	Monthly–seasonally: water temperature, TP, TN	Field sampling	[134]
			Daily monitoring of precipitation, sunshine hours, discharge, water level	Daily monitoring in weather stations	
	Weekly	Chl- <i>a</i>	Water quality data: Chl- <i>a</i> , PO ₄ ³⁻ -P, NO ₃ ⁻ -N, NH ₄ ⁺ -N, water temperature	Weekly field sampling	[137]
			Meteorological data: solar radiation, wind speed	Daily monitoring in a weather station	
	Real-time (6 min)	Turbidity, DO, Chl- <i>a</i> , specific conductance	Chl- <i>a</i> , specific conductance, DO concentration, turbidity Predicting future water quality based on past data for each item	In situ real-time monitoring data of USGS	[135]
SVM	Daily	Chl- <i>a</i>	Daily meteorological data: for instance, precipitation, sunshine hours Daily hydrological data: for instance, discharge, water level Monthly–seasonal water quality data: Chl- <i>a</i> , water temperature, TP, and TN	Water samples collected from the field and meteorological data collected in a weather station	[140]
	Monthly	TN, TP	Flow velocity, DO, water temperature, EC, pH value, turbidity	Used in situ monitoring sensors at the time of water sample collection	[127]
			Monthly–trimonthly: COD, TN, TP, NO ₃ ⁻ -N, NH ₄ ⁺ -N	Water samples collected in the field and analyzed in a laboratory	
	Monthly	BOD	Total alkalinity, pH value, total hardness, total solids, NO ₃ ⁻ -N, NH ₄ ⁺ -N, Cl ⁻ , PO ₄ ³⁻ -P, K ⁺ , Na ⁺ , DO, COD, BOD	Water samples collected in the field and analyzed in a laboratory	[141]
	Weekly	Chl- <i>a</i>	Water quality data: Chl- <i>a</i> , PO ₄ ³⁻ -P, NO ₃ ⁻ -N, NH ₄ ⁺ -N, water temperature Meteorological data: solar radiation, wind speed	Water samples collected in the field and analyzed in a laboratory	[137]
	Two weeks–monthly	DO	For instance, TN, TP, NH ₄ ⁺ -N, water temperature, DO, pH value	Water samples collected in the field	[16]
LSTM	10 min	DO	Water quality data: DO, water temperature, NH ₄ ⁺ -N, pH value Meteorological data: atmospheric temperature, air humidity, atmospheric pressure, wind speed	In situ real-time monitoring data	[17]
	1 min	Anomaly detection of water quality	Chlorine dioxide, pH value, redox potential, EC, turbidity, flow rate, water temperature	In situ real-time monitoring data using sensors	[142]

Support vector machines (SVMs) are another machine learning algorithm type often used for the analysis of water quality data [127,141,143,144]. Both ANNs and SVMs enable the prediction of the spatial distribution of nutrients in river systems [127]. An ANN determines the optimal solution by minimizing the training error, whereas an SVM determines a solution by minimizing the upper bound of the generalization error. Thus, an SVM encounters less overfitting [127]. Park et al. (2015) compared ANN and SVM for the prediction of the Chl-*a* concentration in a freshwater system and found that the SVM exhibited a better performance [137].

Deep-learning is one of the most advanced ANNs, with multiple hidden layers. It reduces the overfitting problem often found in conventional ANNs by employing the dropout technique and a rectified linear unit (ReLU) as an alternative activation function [145–147]. The drop-out technique selects nodes in the computational process of an ANN, in which the choice of nodes is random [145].

Deep-learning overcomes the vanishing-gradient problem found in conventional ANNs by using the ReLU as an activation function, as it computes negative input values as zero and leaves positive values unchanged [147].

Advanced deep-learning algorithms are increasingly used for the analysis of water quality data [18,130,131]. For example, Solanki et al. (2015) used a deep-belief network (DBN), a class of deep neural networks with multiple hidden layers, for the prediction of the DO concentration, pH value, and turbidity in a watershed [130,148]. More recently, Lee and Lee (2018) predicted the Chl-*a* concentration in rivers with a long- and short-term memory (LSTM) (a deep-learning algorithm) [131]. In a recurrent neural network (RNN), the output in the hidden layer is recurrently used as input data in the recurrent loops. Thus, RNNs exhibit good performance in data sequencing. The LSTM belongs to the RNNs. However, this type possesses a more complex structure than RNNs for controlling the use of the previous memory in recurrent loops [149]. The LSTMs are increasingly employed in the analysis of water quality data sequencing [16,18,150]. Muharemi et al. (2019) used various machine learning models (e.g., ANNs, SVMs, and LSTMs) for the analysis of time series data and suggested machine learning for the detection of anomalies in the water quality [142].

5. Future of ICT Research for Water Quality Monitoring

The advanced ICT has increasingly been used for water quality monitoring and provides useful information for the proper management of water resources. There are possible future research fields to improve the applicability of ICT for water quality monitoring of a wide range of areas.

Firstly, the compatibility of measurement frequencies between different water quality parameters in in situ real-time data collection is essential for effective management of water quality for future cities. There is often the absence of high-frequency (15 s to 1 day) data of a certain water quality parameter which is less-frequently measured that prohibits the further development of machine learning for water quality data analysis or prediction. The practical use of data with multiple items in various observation frequencies can be limited by the low-frequency items, deteriorating the benefits of using advanced data analysis technologies. Thus, observation of higher frequency data and proper pretreatment of the massive data (e.g., interpolation) to minimize internal error or missing points of data are essential for improving the practicability of the advanced data analysis technologies. Recently, real-time data measured with in situ sensors is increasingly used for the analyses and prediction of water quality; however, the information on the sensor types, measuring parameters, and their frequency of the measurement has not been clearly reported [17,135,142]. Normally, high-frequency real-time data includes errors (e.g., missing data or abnormal values) and thus require a proper pretreatment (e.g., consideration of missing data or removal of data errors) to obtain a reliable model performance [142,151]. The recent rapid development of high data processing technologies suggests that the combination of advanced data computing and analyzing technologies, including machine learning, sensing technologies for real-time data measurements, and data storage and transfer with ICT, is a feasible method for the effective management of the water quality in water systems. The Low-Power Wide-Area (LPWA) is one of the possible technologies that can improve the efficiency of data collection in the field where wide transmission distance needs to be secured. The extended battery life using LPWA is also one of the important advantages for practical application in fields.

Secondly, areal-based monitoring technology, such as HSI sensor, can be further developed for the collection of representative data in a remote and wide watershed, overcoming the limitation of point-based monitoring. For example, algal concentrations are often unevenly distributed within the surface of the water body, and thus point-based monitoring may not be able to provide accurate data for the degree of algal blooms. The areal-based monitoring using an HSI sensor can provide a more accurate distribution of algal concentrations [152,153]. The relatively high cost for the collection of data using aircraft and finding the proper relationship between HSI and algal concentrations are current issues to be challenged for improving the practical applicability of HSI in fields. Proper visualization of massive data is essential for the management of water resources in lakes, rivers, and

oceans, and GIS data combined with ICTs can provide an effective tool for the monitoring, management, and visualization of data [115,154].

6. Conclusions

The objectives of water quality management strategies using ICT are to perform efficient and real-time monitoring of water quality, predict future trends of water quality, and provide rapid responses to toxic events (e.g., HABs) in water resources. The recent development of high data processing technology in data analysis, such as deep learning, enables efficient analysis of a large amount of data with given time frames [145–147]. A large amount of data collected from in situ field monitoring using sensing technology can be more efficiently used for the management of water quality when it is combined with advanced data analysis techniques, such as deep learning. Thus, the recent development of these high technologies regarding field monitoring, data transmission, and analyses promotes the optimization of water quality management. However, many parts of water quality monitoring systems still rely on regular-basis manual sample collection and monitoring even though the collected data are analyzed by novel machine learning techniques [16,134,137,140]. Thus, it is essential to develop and apply in situ real-time monitoring systems using sensor technologies, along with high-tech data analysis techniques, such as deep learning, to find better solutions in water quality management.

There are also various strategies suggested for the future management of the water quality in water supply systems, including raw-water sources. First, the development of monitoring systems for emerging contaminants is essential. The global-scale circulation of emerging contaminants (e.g., microplastic, Per-and polyfluoroalkyl substances [PFASs], and microcystins) has become a huge concern [155]. To determine the distribution and circulation of these emerging contaminants between countries and continents and through rivers and oceans, the development of a proper in situ monitoring system is necessary. Second, a proper strategy for water quality management must consider the circulation of water resources within watersheds between raw-water and water supply systems, to optimize the distribution of limited water sources. This includes the reduction in physical water quantity losses and the optimization of the water distribution between domestic, industrial, and agricultural systems requiring the integration of advanced ICT [156]. In the future, the integration of ICT into environmental technologies is inevitable and would provide promising solutions for the advanced management of water resources.

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