Connected Sensors, Innovative Sensor Deployment, and Intelligent Data Analysis for Online Water Quality Monitoring

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***Abstract*—The sensor technology for water quality monitoring (WQM) has improved during recent years. The cost-effective sensorised tools that can autonomously measure the essential physical–chemical–biological (PCB) variables are now readily available and are being deployed on buoys, boats, and ships. Yet, there is a disconnect between the data quality, data gathering, and data analysis due to the lack of standardized approaches for data collection and processing, spatiotemporal variation of key parameters in water bodies and new contaminants. Such gaps can be bridged with a network of multiparametric sensor systems deployed in water bodies using autonomous vehicles, such as marine robots and aerial vehicles to broaden the data coverage in space and time. Furthermore, intelligent algorithms [e.g., artificial intelligence (AI)] could be employed for standardized data analysis and forecasting. This article presents a comprehensive review of the sensors, deployment, and analysis technologies for WQM. A network of networked water bodies could enhance the global data intercomparability and enable WQM at a global scale to address global challenges related to food (e.g., aqua/agriculture), drinking water, and health (e.g., water-borne diseases).**

***Index Terms*—Connected sensors, intelligent data analysis, Internet of Things (IoT), robotics, sensor deployment, water quality monitoring (WQM).**

I. Introduction

THE DETERIORATION of water quality (WQ), caused by drivers, such as climatic/seasonal changes, global warming, human activities, or industrial waste is a major global concern. Since WQ directly impacts public health and economy, monitoring and assessing the quality and the causes of its degradation in water bodies have been a priority for governments all over the world [1]–[4]. Traditionally, the WQ is monitored by collecting discrete samples at weekly or monthly intervals and analyzing in laboratory for physical–chemical–biological (PCB) parameters to reflect the changes in climatic, geochemical, and geomorphological conditions and the properties of underlying aquifers in riverine systems [5]–[8]. As the rivers and large water bodies exhibit highly dynamic and often nonlinear behavior in both time and space, such low-frequency data collection makes it difficult to establish linkages between the cause and effect and develop potential remedy or take timely decisions. Additionally, the outcomes of traditional "sample collection and lab analysis" methods could vary substantially due to the time gap between sampling and analysis.

Furthermore, due to climatic changes and human and industrial activities, new determinants are regularly added in the water system. As an example, in January 2014, the Elk River in Charleston, USA became contaminated by a leaking storage tank containing 4-Methylcyclohexanemethanol, a little-known coal-processing chemical, and the contaminated water drawn into the city's water supply system left over 300 000 people and area businesses without water for several weeks [9]. Researchers had little information on how the spilled chemicals moved through water, their stability or toxicity, or even how to measure them, because the published information was either limited or nonexistent. So, many more chemical compounds are continually added to the list of parameters needed to be monitored than the current capability allows. More recently, the pandemic has presented a similar situation due to the potential water-based transmission of coronavirus [10]. Robust strategies are required to bridge the knowledge gaps and to generate reliable estimates to develop appropriate mitigation measures.

Over the last decade, the WQ observing technology has risen to the challenge of scientists and has provided them with tools that identify poor WQ by autonomously measuring the essential PCB parameters [11]–[21]. Sensorised buoys and boats have been deployed for data collection and in-situ monitoring [22]–[28]. Likewise, the satellite imagery and time-averaged spatial analysis tools have been used for remote WQ monitoring (WQM) at regional levels [29]. Despite these options becoming more readily available, there is a gap

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between the technology and the end user and a disconnection between data quality, data gathering by autonomous sensors, and data analysis. The autonomous WQ observing technology could be advanced with a network of sensors and geographical information systems (GISs) and suitable analysis methods to obtain water-related information in real time [30]. With the impact of climate change, sole reliance on historical hydrologic patterns is no longer a viable route for forecast. Due to lack of standardized approaches for data analysis, and the gaps in the training of technicians and the approaches they use to analyze the data, it is also difficult to achieve the global data intercomparability. Such issues can be addressed by real-time WQM with suitable sensor networks [12], [19], [31]–[35].

Sensing in various water environments, particularly in large water bodies and underwater, is complex, expensive, and challenging for a number of reasons. The environment is unforgiving for many sensing technologies; many modalities readily available in the air cannot be used underwater and usually require specific packaging; or with a limited range and sensitivities, the communications are severely affected. For instance, electromagnetic (EM) waves do not propagate well in water, especially salt-water; corrosion is prevalent, and biofouling can present as real challenge in shallow waters. As a result, the real-time WQM remains a challenge and methods that allow holistic water management, also considering the catchment management or the WQM at the source, need greater attention. The catchment management or the WQM at the source are important as the proportion of nutrients and sediments could vary significantly (e.g., during stormy events).

The sensor technologies that enable accuracy, repeatability, reliability, and remote communication are vital to meet the growing challenges in the WQM. As new requirements for remote sensing emerge, there is a need to develop multisensory systems to simultaneously measure multiple parameters, as well their deployment strategies (e.g., using mobile robots) to capture the spatiotemporal variations. The comprehensive discussion in this review paper focusses on these challenges and their solutions based on smart sensing technologies. It may be noted that the sensor-based WQM has also been covered in some previous review articles [4], [36]–[45], where the discussion is restricted to measuring a limited set of parameters and the real-time monitoring using the connected sensor network is generally not covered. For example, review focussing on graphene-based sensors (pH, disinfectants, mercury, lead, chromium, etc.) for WQM [44], various electrochemical sensors and mechanisms for monitoring pH and chlorine have been reported [46]. Likewise, biosensors for pathogens or chemical water contaminants (i.e., faecal pathogens, arsenic, and fluoride) [47] and the information and communications technology (ICT) [14] have been reviewed. Complementing the previous reviews, the holistic discussion in this comprehensive review covers the key topics related to the connected sensors for real-time WQM, as summarized in Fig. 1. These include: 1) multiparametric sensory systems; 2) deployment of a network of multiparametric sensory systems in water bodies to broaden the data coverage in space and time (e.g., using autonomous marine robots and aerial vehicles); and 3) using intelligent algorithms [e.g., artificial intelligence (AI)] for standardized data analysis and forecasting. By structuring the paper on above lines, it is hoped that the reader will be able to identify the disconnect between data quality, data gathering, and data analysis and encouraged to explore innovative solutions. This is also a distinguishing feature of this review article.

This article is organized as follows: Section II focusses on the ways to improve the data quality. To this end, various sensors and materials have been discussed. The data quality can also be improved by using suitable form factors and, therefore, flexible and disposable sensors are also discussed in Section II. Various methods for sensor deployment in water bodies are discussed in Section III. These include sensor-instrumented buoys or moorings, as alternative to traditional sample collection and lab analysis methods, as well as advanced methods such as using underwater robots or autonomous aerial vehicles. These methods allow the high frequency collection of PCB properties of the water. Furthermore, sensors interface with onboard electronics of robots and communication between them and the control station are also discussed in Section III. The packaging methods employed for sensors and related components are also discussed in this section. Section IV briefly discusses the traditional methods, data analysis, as well as the potential use for AI in context with analysis and prediction of WQ. Future direction and perspectives are discussed in Section V, and this is followed by a summary of conclusions in Section VI.

II. Improving the Data Quality

The WQM is carried out through a range of sensors that measure the basic PCB parameters. The quality of data collected by these sensors can be influenced by several factors such as: 1) the type of sensors; 2) functional materials used for the development of sensors; 3) the number of sensors; etc. This section discusses these factors with a view to provide an insight into what it takes to improve the sensor data quality.

A. Water Quality Parameters

A large number of PCB parameters that need to be monitored to ascertain the WQ are summarized in Table I. The acceptable concentrations or range of theses parameters depend on the end use, for example, drinking water (DW), bathing, aquaculture (freshwater fish directive or salmonid water regulations), ground water, or surface water (SW) for other uses, etc. The most common parameters that are widely analyzed to ascertain the water quality are pH, dissolved oxygen (DO), Cl^-, Na^+, nitrate, and dissolved ions [4], [45], [48], [49]. Some of the parameters including pH, Cl^- ions and temperature are also used for monitoring health, food quality, or to monitor the quality of air [50]–[57]. For example, spatial variation can be expected in the values of pH and Cl^- in an area [52] and the sensors that offer wide operating range (e.g., pH sensors in the range of 1.5-12) could be employed.

The biological, organic, and inorganic toxic pollutants cause the variation of concentrations of various parameters in water or add new contaminants. For example, several human

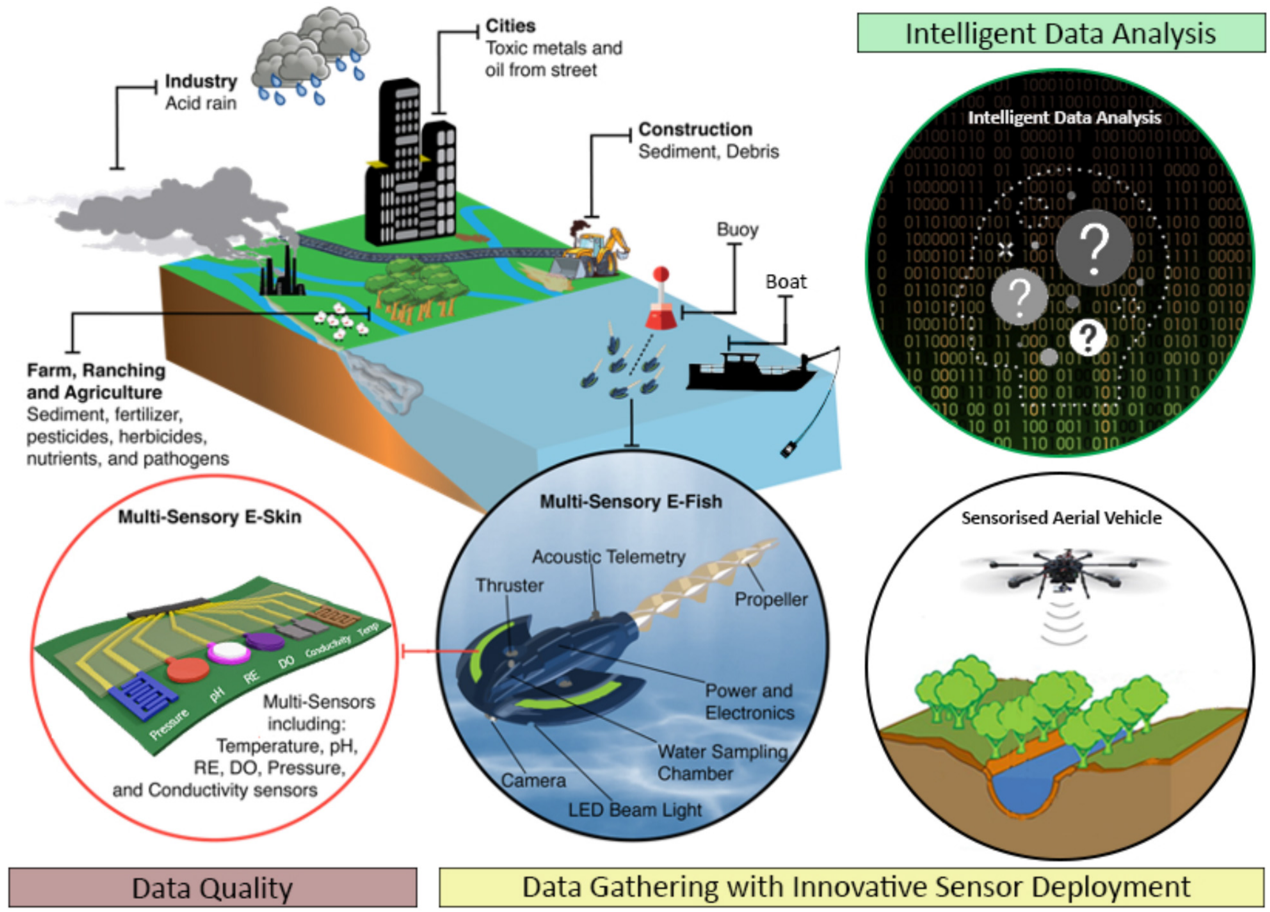

Fig. 1. (Left) Various human activities contributing to the deterioration of WQ and the ways for its monitoring, including using multiparametric sensor patches or electronic skin (e-Skin), traditional methods of sensor deployment such as using sensorized buoys, and advanced deployment using underwater robots or multisensory e-Fish. (Right) Key constituents of a holistic WQM system.

activities and products, such as pharmaceuticals (antibiotics, hormones, and nonsteroidal anti-inflammatory drugs), personal care products (preservatives, bactericides/disinfectants, and sunscreen UV filters), endocrine disruptors (pesticides, plasticizer, and antimicrobial) herbicides, artificial sweetener, etc., add new water pollutants [4], [58], [59]. As discussed in the previous section, there is always a possibility of the presence of new pollutants in water bodies [4], [60], [61]. As an example, micro plastics and pathogens need to be monitored to prevent loss of life or improve health and well-being [10], [61]–[66]. Few recent studies also indicate that presence of coronavirus in wastewater from the hospitals, quarantine centers, and domestic households with positive cases [64], [65], [67], [68]. The potential transmission of SARS-CoV-2 within faecal contaminated rivers has been highlighted recently and a similar transmission risk is likely to exist from untreated or partially treated wastewater and DW in regions or countries with poor sanitization, especially if they are experiencing high infection rates [69]. Transmission may also be possible to and from susceptible riparian animals, or some cetaceans, that have fed from, lived around or within, or ingested faecal contaminated water [69]. The timely detection of such new contaminants can offer an opportunity to develop an early warning system. For example, by monitoring the wastewater coming from an area, it is possible to identify the potential asymptomatic covid cases and prepare for the health requirements (e.g., readying the ventilators [70] or setting up temporary health center, etc.) in that area. The smart connected sensors-based approach is much needed for such cases. Furthermore, using multisensory patches could help establish the linkages or dependencies between the various parameters.

B. Materials for Sensors

The quality of data generated by the WQM sensors is evaluated through their sensitivity, response time, selectivity (interference to other ions), hysteresis, drift effect, lifetime, stability in various water conditions and biocompatibility, etc. For example, the ideal sensitivity of potentiometric pH sensors should be close to Nernstian response 59.12 mV/pH. Furthermore, these sensors have fast response (<1 min) and negligible hysteresis, drift, and interference effects. Few pH sensors that exhibit above-mentioned properties include RuO_2-based pH sensors [34], [71]–[74]. As an example, in our previous work, we observed the sensitivity of 56.11 mV/pH with a response time of <15 s [71]. A summary of the materials used for the fabrication of sensors, such as pH, DO, ammonia, nitrate, ions, etc., is included in Table II.

TABLE I
GENERAL RANGE OF SOME IMPORTANT MARKERS WHICH NEEDS TO BE MONITORED FOR WQ (SW—SURFACE WATER; DW—DRINKING WATER) [3]

Parameters	SW	DW
Chemical Parameters		
pH	5.5 - 9	6.5 – 9.5
Dissolved Oxygen (DO) in ppm	0.5 -10	--
Sulphate (mg. l^{-1} SO_4)	200	250
Phosphates (mg. l^{-1} P_2O_5)	0.7	--
Sodium (mg. l^{-1} Na)	--	200
Ammonia (mg. l^{-1} NH_4)	0.005-4	
Fluoride (mg. l^{-1} F)	1.7	1.5
Iron (mg. l^{-1} Fe)	2	1.5
Chloride (mg. l^{-1} Cl)	250	250
Lead (mg. l^{-1} Pb)	0.05	0.01
Nitrate (mg. l^{-1} NO_3)	50	50
Manganese (mg. l^{-1} Mn)	2	0.05
Zinc (mg. l^{-1} Zn)	5	5
Nickel (mg. l^{-1} Ni)	--	0.02
Cyanide (mg. l^{-1} CN)	0.05	0.05
Chromium (mg. l^{-1} Cr)	0.05	0.05
Arsenic (mg. l^{-1} As)	0.10	0.01
Benzene (mg. l^{-1} compound)	--	0.01
Boron (mg. l^{-1} B)	2	1
Cadmium (mg. l^{-1} Cd)	0.005	0.05
Copper (mg. l^{-1} Cu)	1	2
Mercury (mg. l^{-1} Hg)	0.001	0.001
Selenium (mg. l^{-1} Se)	0.01	0.01
Vinyl Chloride (µg. l^{-1})	--	0.50
Biological Parameters		
ECH	--	0.0001
E-Coli (no./100 ml)	10000	0
Epichlorohydrin (µg. l^{-1})	--	0.10
Physical Parameters		
Temperature (ºC)	25	
Turbidity (ppm)	05-10	

TABLE II
PERFORMANCES OF WQM SENSORS

Sensor	Material	Sensitivity	Response time	Ref
pH	RuO_2	58 mV/pH (2-13)	1-2 s at 23°C	[107]
DO	RuO_2	41 mV/decade (0.6-8 ppm	8-10 min at 9°C	[107]
pH	$Bi_2Ru_2O_{7+x}$ + RuO_2	58 mV/pH (2-13)		[102]
DO	$Bi_2Ru_2O_{7+x}$ + RuO_2	30.57 mV/decade (0.5-8 ppm)		[102]
pH	RuO_2+SnO_2	56.5mV/pH(2-12)	5-9 s	[103]
Nitrite	Au	0.98 coefficient 0.5 - 8 mM range		[20]
Hg^{2+}	MoS_2	0.64 µA/ppb (0.1 - 100 ppb)	1.8 s	[21]

Recently, biocompatible and biodegradable materials have attracted a significant interest [75]–[77]. The choice of materials and, eventually, the sensor performance, depends on their structural properties. For example, nanostructured materials exhibit the high surface to volume ratio and, hence, the fast response and high sensitivity [20], [78]–[80]. In addition, the shape or morphology of the nanomaterial could influence the sensor performance [81], [82]. The porosity, pore size, and grain size of the crystals influence on the response time. For example, in a work involving the Cu_2O-doped RuO_2-based pH-sensitive electrode (SE), it has been shown that the pH sensitivity does not vary with the thickness of SE (from ∼2.0 to ∼5.0 µm) [78], but the response time does. The response time was found to improve from ∼80–120 s (for SE thickness of 2.0 µm) to ∼25 s (for SE thickness of 5.0 µm) as improved crystallization was possible for thicker SEs. Furthermore, the inner active site in the SE and developed porosity led to sensors with improved performances [78]. A comparison of various influencers of the bulk, microstructural, and nanostructural properties of the electrode is given in Fig. 2. Recently, molecule-based sensors have also received attention for the fabrication of electrochemical and biosensors [83]. The miniaturized sensors with fast response have been realized using materials with nano or molecular structures [83]. The cost (of both material and fabrication), lifetime, flexibility are other factors, which also need to consider in the SE design. As discussed in the following section, in a vast majority of the recently reported flexible sensors for WQM or other applications, such as wearables for health monitoring, the micro or nanostructured materials have been utilized. With the functionalization of nanomaterials and nanoparticles, they could be used in biosensors as the recognition elements or the transducers, especially for pathogen detection in WQM [84], [85]. The selection of the nanomaterials for the fabrication of a biosensor depends on the properties of the nanomaterials and their application and, as a result, several types of nanomaterials have been used in the design of microbial biosensors [85], as discussed in the following section.

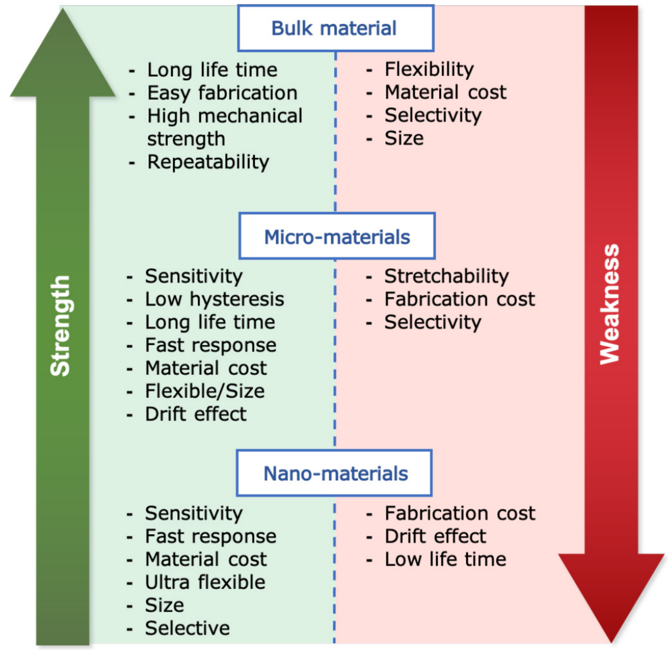

Fig. 2. Comparison (positive and negative) factors of materials for sensors fabrication.

C. Sensors for Water Quality Monitoring

The methodologies that have been employed for monitoring various PCB parameters in water include electrochemical, physical, and optical sensing. Among these, the electrochemical sensing is preferred [49], [54] due to several advantages as noted in Fig. 3(a). Electrochemical and biosensors offer cost-effective route for the simultaneous monitoring of PCB

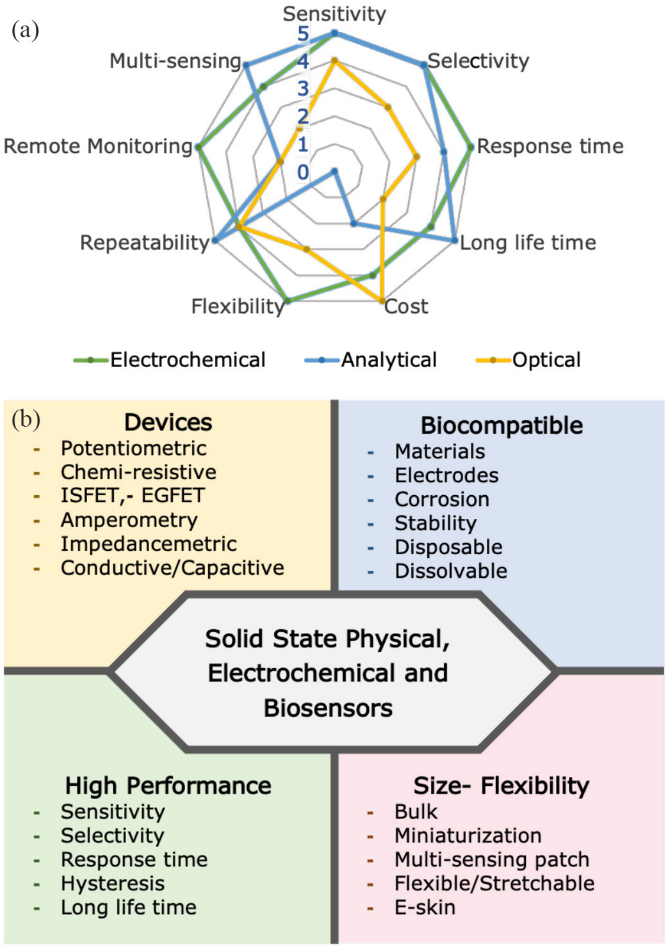

Fig. 3. (a) Comparison of electrochemical, analytical, and optical-based sensors. (b) General summary of solid-state sensors including various type of devices (sensors).

parameters using the multisensory patch and are suitable for online monitoring of large water bodies such as reservoirs. In electrochemical sensing, the conventional glass-based sensors are of limited use for online monitoring and their response could be influenced by the prevailing pressure and temperature conditions. In this regard, the electrochemical solid-state sensors based on metal–oxides (MO_x), polymers, or carbon-based materials (based on the thick/thin film) technology are better and suitable to be used as part of wireless sensor networks [54], [83], [86]–[89]. The qualitative analysis of the features and th1/8/22e advantages of the solid state-based physical, electrochemical, and biosensors are summarized in Fig. 3(b). This includes the type of sensors [potentiometric, voltammetry, chemiresistance, capacitive, ion-sensitive field effect transistors (ISFETs)] and materials used for the fabrication. The performance parameters, such as sensitivity, response time, and selectivity may depend on the type of fabrication adopted for the development of sensors, including screen printing, chemical deposition, physical deposition, sol gel methods [90], and type of sensors.

1) Potentiometric and Amperometric Sensors: It is essential to develop reliable sensors to measure individual parameters or multiparametric sensor systems for simultaneous detection of multiple analytes. Among different types of sensor configurations, the potentiometric sensors, as illustrated in Fig. 4(a) [54], are widely used for pH and DO monitoring. The potentiometric electrochemical sensors, consisting of sensitive and reference electrodes (REs), offer simple and attractive approach with their sensitivity measured by the Nernstian equations [18], [71]. Examples include sensors that use thick film Ag/AgCl/KCl-based RE, showing excellent long-term stability comparable with glass RE and, hence, suitable for applications requiring data collection over long periods [71], [91]–[97]. Due to high sensitivity, chemical stability, and long lifetime, the RuO_2 has been used as SE in many pH and DO sensors [54], [71], [97]. Using RuO_2, the pH sensor (2–13 range; sensitivity 58 mV/pH at 23°C) and DO sensor (0.6-8.0 ppm log $[O_2]$; -4.71 to -3.59 with sensitivity of -41 mV/decade at pH 8) have been developed with excellent performances [105, 117]. The response of these sensors is strongly influenced by the temperature of water. When the water temperature is low, the sensor shows slow responses. For example, at 9°C the pH sensor shows response time of 8–10 min as compared to 1–2 s at high temperature (23°C) [73], [98].

The silicon-based thin film sensor have been used in several applications [52]. Due excellent response consistency, they could offer excellent opportunity for WQM. However, one of the major issues with these sensors is the lack of compatible RE. A vast majority of reported works based on thin film-based Ag/AgCl REs show drift [99], [100]. To solve this issue, solid-state Ag/AgCl electrode could be placed in a mini tank of the KCl solution for better ion exchange, as done in the case of nitrite monitoring sensor [20], and the outcome was a stable potential with very small variation of 2 mV. The design of this sensor shows potential usefulness for monitoring of analytes, such as phosphates and ammonium. With further modification of the working electrode (WE), it may also be possible to use this design for urea and ammonia monitoring. The array of RuO_2-based SE has also been used for lower measurement errors in microfabricated sensors developed in ISFET technology [101]. These sensors show excellent performances with a sensitivity of 55.64 mV/pH and a low drift rate of 0.38 mV/h at pH 7 and the array of such sensors could be useful for monitoring parameters, such as free chlorine, DO, dissolved ions, and heavy metals.

There are many dissolved metal ions in water, which are also toxic and can cause health risks if their concentration is high, as listed in Table I. For example, toxic Hg^{2+} (as per WHO, it should be $<$1ppb) could cause acute poisoning, irreversible neurological damage, cancer, and motion disorders that can lead to death. Hg^{2+} could be detected using a molybdenum disulfide (MoS_2) functionalized AlGaN/GaN high electron mobility transistor (HEMT) sensor [21]. The sulphur atoms in MoS_2 attract the Hg^{2+}, leading to the adsorption of these ions on the surface of the MoS_2 to form Hg-S complexation. The formation of Hg-S reduces the electrons from MoS_2 surface and, hence, increases the drain-source current of the transistor. This type of sensor could also be used for other heavy metal ions, such as Cd^{2+}, Ni^{2+}, Cu^{2+}, Pb^{2+}, Zn^{2+}, and Cr^{3+} [21]. The heavy metal ions can also be monitored using the potentiometric or amperometric method.

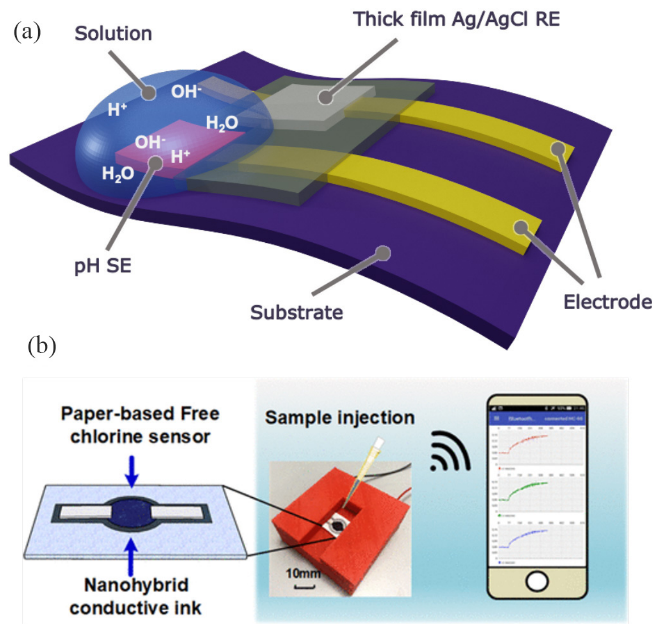

Fig. 4. (a) Schematic representation of a potentiometric pH sensors [54]. (b) Image of a nanohybrid paper-based free chlorine monitoring sensor with 3-D packing and readout Reprinted (adapted) with permission from [112]. Copyright (2020) Am. Chemical Soc.

2) Interdigitated and Chemiresistive-Based Sensor: To solve the RE-related issue with potentiometric sensors, the interdigitated electrode (IDE) design has been used in conductive/capacitive/impedance and chemiresistive (two electrodes)-based sensors. Several active electrode materials (metal–oxides, polymers and carbon) are suitable to be used with electrode of IDE-based sensors [104]–[106]. Such an IDE-based sensor is fabricated by using metal–oxides, polymers, and carbon-based material [79], [107]–[109]. One the best IDE-based sensors for WQM reported is the hydrogel (polymer), which shows biocompatibility and low cost for materials and fabrication. The electrical properties, including the conductivity of hydrogels, change during interaction with analytes [106], [110], [111]. The miniaturized pH sensor consists of an active electrode that is a hydrogel of polypyrole and polyaniline. The major drawbacks of the hydrogel-based sensor are their low mechanical strength and low lifetime.

The chemiresistive sensing is another class of sensors which does not require a RE. An example of the paper-based chemiresistive sensor for real-time monitoring of free chlorine is shown in Fig. 4(b) [112]. This sensor uses the nanohybrid ink based on graphene and PEDOT: PSS. The chemiresistive pH sensors, with nanocomposites of single-wall carbon nanotubes (SWCNTs) and nafion used for SE, have also been explored for WQM using drones with wireless communication capability [113]. The nafion layer enhances the performance of the flexible sensor by reducing the degradation of electrical properties due to the cracking (even breaking) of the SE while bending. Furthermore, the results from this type of sensor show that the sensitivity could be improved by increasing the number of printed layers of SE. Similar configuration could be used for online monitoring of conductivity, chloride ion detection, and temperature sensors. Furthermore, various

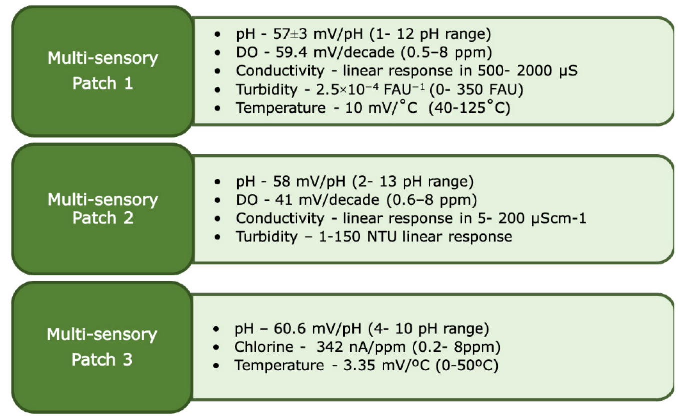

Fig. 5. Comparison of the performances of multisensory patches used for online WQM. Patch 1[72], Patch 2 [98], and Patch 3 [86].

forms of carbon nanotubes (CNTs) could be used for improved sensing performance [114].

3) Multisensors for WQM: As discussed in Section II-A, multiple parameters need to be monitored in water. In this regard, multiparametric sensors on the same substrate is advantageous. As an example, the multiparametric sensing platform (pH, DO, temperature, conductivity, and turbidity sensors) for online WQM [34], [74], [115]. The first printed multisensory patch (pH, DO, conductivity, and temperature) for WQM showed a continuous operation for several months in water with <5% and <10% errors for pH and DO sensors, respectively [116]. A multisensory patch by thick film technology for pH, DO, temperature, turbidity, and conductivity has also been developed with integrated data acquisition, and signal conditioning modules [72]. Another example highlighted the performances in Table II is the integrated online monitoring system with pH, free chlorine and temperature sensors [86]. In another work, emerging pharmaceutical contaminants, and heavy metal were also detected, along with pH, chlorine, and temperature, using multisensory patch [12]. A comparison of the performances of few multisensory patches reported for WQM is given in Fig. 5.

4) Biosensor for Pathogens Monitoring: In addition to the chemical and dissolved metal ions, the detection of bacteria in water is another major challenge. The electrochemical transducer are most promising in this case also due to their selectivity, high sensitivity, measurability in complex and turbid samples, simple structure and miniaturization, rapid response, and low cost [137]. Electrochemical biosensors can be divided into major four categories: 1) impedimetric; 2) conductometric; 3) amperometric; and 4) potentiometric [10]. Table III summaries the different electrochemical sensors-based detection method for food and waterborne bacteria. The nanomaterial-based sensor approach is attractive in the case of bacteria detection due to rapid, inexpensive, and accurate measurement needed for food safety and environmental monitoring [138], [139]. The distinct physical, chemical, magnetic, sensing, catalytic, mechanical, and optical properties of nanomaterials due to the high surface to volume ratio, reactivity, and high penetrability allow the use of variety of advanced nanomaterials to develop sensors for microbial detection with

TABLE III
SUMMARY OF THE REPORTED ELECTROCHEMICAL-BASED BIOSENSORS FOR FOODBORNE AND WATERBORNE BACTERIA DETECTION

Transducer	Target	Material	Linear range	LOD	Ref.
Amperometric	*E. coli*	Au NPs	10–10^9 CFU/mL	10 CFU/mL	[117]
Amperometric	*E.coli* O157:H7	3-aminipropyl triethoxysilane (APTES)	1 fM–10 μM	0.8 fM	[118]
Amperometric	*E.coli* O157:H7	core–shell magnetic beads and Au NPs	10^2–10^6 CFU/mL	52 CFU/mL	[119]
Amperometric	*S. aureus*	SWCNT	10^2–10^5 CFU/mL	10^2 CFU/mL	[120]
Amperometric	*Listeria monocytogenes*	MWCNT Fibers	10^2 to 10^5 cfu/mL	1.7 ×10^2 cfu/mL	[121]
Amperometric	*E.coli* O157:H7	Nickel oxide	10^1 to 10^7 cells/mL	1 cell/mL	[122]
Conductometric	*Bacillus subtilis*	SWCNTs	10^2–10^{10} CFU/mL	10^2 CFU/mL	[123]
Conductometric	*Escherichia coli*	magnetic beads	2.5 × 10^3–2.5 × 10^8 CFU·mL^{-1}	2.3 × 10^4 CFU·mL^{-1}	[124]
Impedimetric	*E.coli* O157:H7	Gold nanofilm	50–500 CFU/mL	50 CFU/mL	[125]
Impedimetric	*E.coli*	Gold print	10–10^8 CFU/mL	3 × 10 CFU/mL	[126]
Impedimetric	*E.coli* O157:H7	Au NPs	300–10^5 CFU/mL	100 CFU/mL	[127]
Impedimetric	*E.coli*	Cu3(BTC)2/PANI	2-2 × 10^8 CFU/mL	2 CFU/mL	[128]
Impedimetric	*E.coli* O157:H7	polypyrrole (PPy)	10^3 -10^8 CFU/mL	10^3 CFU/mL	[129]
Impedimetric	Bacillus cereus	Au NPs	10^0 -10^7 CFU/mL	10^0 CFU/mL	[130]
Impedimetric	S. Typhimurium	Au NPs	10-10^5 CFU·mL^{-1}	10 CFU·mL^{-1}	[131]
Potentiometric	*Salmonella typhimurium*	PEDOT: PSS	1 - 1.28 × 10^5 cells mL $^{-1}$	5 cells mL^{-1}	[132]
Potentiometric	Vibrio alginolyticus	Magnetic Beads	10–100 CFU mL^{-1}	10 CFU mL^{-1}	[133]
Potentiometric	*Bacillus cereus*	Polypyrrole	10^2–10^5 CFU/mL	10^2 CFU/mL	[134]
Potentiometric	*E. coli*	carbon quantum dots	2.9 cfu/mL to 2.9 × 10^6 cfu/mL	0.66 cfu/mL	[135]
Potentiometric	*E. coli O157:H7*	ZnO Nanorod Arrays	10 CFU/mL to 10^5 CFU/mL	1.0 × 10^2 (CFUs)/mL	[136]

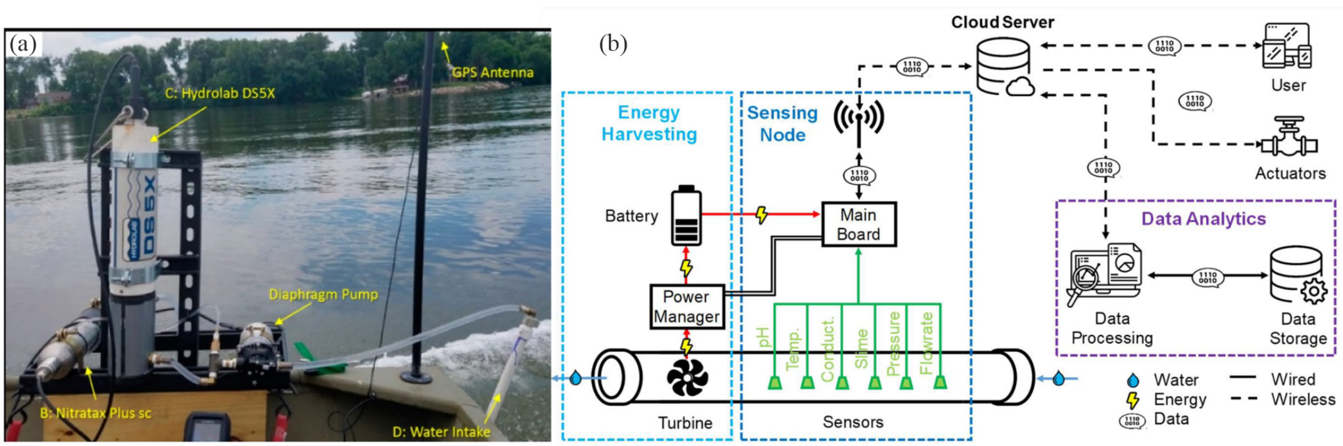

Fig. 6. (a) Nitrate monitoring sensors attached to the boat for real time monitoring in river [23]. (b) Architecture for monitoring physical–chemical parameters by kinetic energy harvesting and long-range radio links connection to a Cloud server, providing visualization, feedback control, and analytics [13].

improved specificity and sensitivity [139], [140]. The gold nanomaterials, also known as gold sol (colloid in which solid particles are dispersed in continuous liquid phase) are widely used for bacterial detection owing to their distinct physiochemical, optical, and electronic features. Additionally, they are biocompatible, easy to synthesise and control the physicochemical properties, and easy to functionalize with various biological recognition elements [141], [142]. Due to similar reasons, the magnetic nanoparticles (MNPs) have also attracted considerable interest for application in bacteria detection [143], [144]. Other category of materials employed in the fabrication of biosensors are the conducting polymers (e.g., PEDOT: PSS, polypyrrole) [84], [145]. Different recognition elements such as antibodies, enzymes, etc. have been used to improve the magnetic, optical, and electronic properties of conducting polymers with an aim to design inexpensive, simple, sensitive and selective biosensors [84]. Due to the mechanical and electrical properties, surface area, low-cost, stability over longer periods, and the possibility for real-time applications, the carbon-based nanomaterials are also widely used nanomaterials for biosensor. For example, graphene has received great attention via different variants, such as Graphene quantum dots (GQDs), reduced graphene oxide (rGO), graphene oxide, and graphene composites [146]. The CNTs (either multiple walls or single wall) and fullerenes, are other increasingly used nanomaterials for biosensors with enhanced performance due to their interesting catalytic, mechanical, and electrical properties [84], [147]. Taking the advantages of nontoxicity, biocompatibility, and high chemical and physical stability, the silica nanoparticles (SiNPS) have also been explored [148], [149]. For example, SiNPS with size range of 5–1000 nm have been used in electrochemical biosensors for microbial detection [141].

For rapid detection of WQ parameters, it is important to integrate the multiple sensors with readout electronics and wireless communication modules. An example of the reported architecture for monitoring physical and chemical parameters is given in Fig. 6 [13]. More details about the sensor deployment and communication are given in the following section.

III. Improving the Sensor Data Gathering

As discussed in Section I, the outcomes of traditional sample collection and lab analysis methods could vary substantially due to the time gap between sampling and analysis, as well as due to the gaps in the training of technicians and the approaches they use for the data analysis. As a result, robust strategies have been sought from time to time to bridge the knowledge gaps and to generate reliable estimates to develop appropriate mitigation measures. In this regard, the different methods for the deployment of autonomous sensors have been explored along with development of suitable interface electronics for real-time data transmission and communication. This section discusses these ways of placement of sensors in space and gathering their data at various times.

A. Sensor Deployment Methods

The deployment of autonomous sensors installed at select locations (based on experience) in the water body (e.g., using buoys) have been explored for in-situ analysis. In terms of technology, instruments such as sensor-instrumented buoys or moorings have been considered recently to overcome traditional bottlenecks related to WQM, as shown in Fig. 1. These methods allow the high frequency collection of PCB properties of the water. Sensor-instrumented buoys in a water column can also allow the temporal variations in WQ to be characterised and the drivers of these changes in the WQ to be better understood. For example, information on biological production (via DO measurements) and water column stratification (via temperature and salinity measurements) can be easily collected. However, the deployment and operation of permanent scientific monitoring buoys, as used by national and international agencies and harbour authorities, are typically expensive (e.g., capital cost of > £0.5–1 million) and, thus, few of them exist. While they provide excellent temporal coverage, the sparse spatial coverage in the heterogeneous coastal zones is challenging and also this approach is cost prohibitive for small-sized to medium-sized businesses to purchase and operate [150]–[153]. Cost-effective methods that allow capturing spatial and temporal variations in WQ are much needed. In this regard, sensor networks and advanced sensor deployment techniques, such as using surface or underwater robotic vehicle or autonomous aerial vehicle, namely, drones, could be useful. Such methods have already advanced the monitoring activities in areas such as agriculture and given many similarities there is no reason why they cannot be tried to WQM. When presented with the challenge of sensing in the underwater environment, one can envisage multiple requirements and scenarios, all requiring different approaches and deployment strategies: one end of the spectrum is large scale, long-term environment monitoring.

In this case, a large number of fixed sensors, able to measure environment parameters at regular intervals, when triggered by an external signal or based on changes in the environment is advisable [154]. For coastal WQM, compact and low-cost autonomous sensors are now being used within low-cost moorings [155], enabling the potential for widespread deployment of such sensors. Fig. 6 shows an example of nitrate monitoring sensors attached to the boat to collect data in every 15 s from Iowa and Cedar Rivers [23]. The addition of multisensory nodes on the number of traveling or fisheries boats could for a network to provide rich information about WQ. The deployment of such networks and their retrieval is often costly, and some nodes can be lost or damaged.

The low-cost lightweight autonomous airborne drones or unmanned aerial vehicles (UAVs) (<2 kg take-off weight) hold great potential for WQM via remote sensing, sensor deployment, and water sampling as shown in Figs. 1 and 7(a). Their potential for environmental and ecological monitoring has been identified [156] and they are already being used for coastal monitoring [157], while some advances have been made with water sampling [158]. However, their routine use for the remote sensing of the water and sensor deployment will require characterization of, and improvements in, the onboard geolocation accuracy and precision. This is needed to allow the drone to know its precise position (in all planes) for optical remote sensing and any deploy, return, and retrieve applications in water regions, where no-fixed points of reference exist. The relatively short flight times (e.g., due to battery and payloads limitations), and distances (often limited by country-specific flight rules) means that the use of the lightweight drones for WQM will likely be limited to inland waters and near-shore estuarine and coastal environments.

At the other end is the opportunistic or event-driven monitoring on-demand using a mobile asset, such as mobile robots, which offer the opportunity to gather data where and when required. The sensors modules attached on the string of buoy, as mentioned earlier, could provide WQM at various depths in a water body but still the information is from a fixed location. On the other hand, mobile assets such as autonomous underwater vehicles (AUVs) with sensory skin could provide frequent information from different areas. Getting the right data at the right time enables to respond quickly to emergency situation, adapt the sensing to the specific task at hand and complement environmental models requiring in-situ data to be calibrated and validated [159]. In this regard , the deployment of sensors by using AUVs, drifters, and autonomous surface vehicles (ASVs) illustrated in Figs. 1 and 7(b) leading to a heterogeneous system of fixed and mobile sensor nodes [160], is an interesting direction. In this setup, the fixed network can be used for environment sensing as well as acoustic localization of the mobile assets shown in Fig. 7(c). The mobile robot can be used to perform denser environmental sensing in specific areas of interest, track dynamics phenomena and fronts, and be used as a "data mule" to gather data from the fixed nodes using short-range, high-bandwidth acoustic, or optical channels.

Equipped with multiple sensors and the interfacing electronics, these autonomous robotic nodes could possibly connect to the Cloud for real-time WQM. However, the remote monitoring in this way can be challenging due to issues such as poor connectivity, large power requirements, and regular maintenance of large number of sensors nodes, as discussed

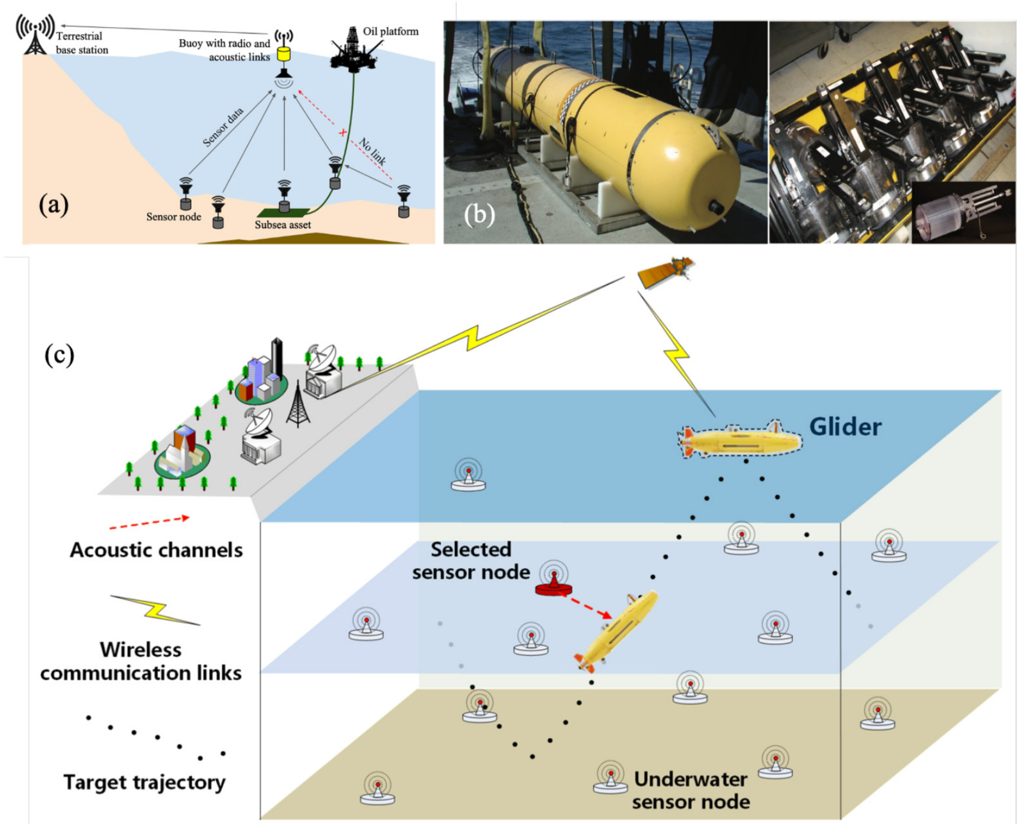

Fig. 7. (a) Sensor network deployment and data gathering. (b) Dorado AUV with an onboard water sample collection system consisting of 10 1.8 L "gulpers" that can be triggered by the onboard computer. Real-time measurements by the AUVs sensor suite can guide physical sample collection decisions. (c) Example of coordination between a fixed and mobile sensor network for data gathering and harvesting.

in Section III-C. Furthermore, the sensor nodes experience a wide variation of ambient conditions (e.g., pressure and temperature) as the sensors need to be deployed at different depth levels (surface, mid and bottom) to analyse in wide area and this often leads to calibration issues, as discussed in Section III-B. This requires designing sensors and electronics for wide operating ranges. Dedicated electronic circuit required for such sensors interface is discussed in the following.

B. Electronic Interfaces to the Sensor

Distributed multisensory nodes/modules envisioned for WQM must be functional in an adverse environmental condition for a long period of time. They can be even more effective if they are able to communicate amongst themselves as well as a base station. However, the primary operating condition for a sensor node is the availability of enough power for front-end signal processing and data transmission (to the nearest node). The self-contained node is expected to contain active circuits that drive the transducer in contact with the environment. This drive circuitry is often called the analog front-end (AFE) and is critical in determining the quality of the data collected. Traditionally, the analog signal is digitized and processed in a digital backend before communicating to an external reader. There are multiple design considerations and challenges to designing these electronic modules. As explained earlier, the electrochemical sensors can be either voltametric, potentiometric, or conductometric. While both voltametric and potentiometric measurements can be 2 or 3 electrode based, conductometric measurement is either 2 or 4 electrode based. In all these options, there are some basic similarities in instrumentation techniques (e.g., the electrodes need to be excited with a voltage or a current) that results in the measurement of a current or a voltage, which is then amplified and filtered before being digitized. In the case of current measurement, the first stage is a trans-impedance amplifier that converts the current to a voltage, and then the same signal chain follows.

The signal-to-noise ratio (SNR) is a more obvious choice for describing the performance of an AFE circuit. Whereas, SNR describes what is actually achieved with a certain signal range in mind, dynamic range (DR) can be used to describe the performance that is possible to achieve with a system. The electrochemical sensors for WQM may have to detect harmful toxic concentrations as low as parts per billion (ppb) while some atmospheric gases of interest, such as O_2, are present in concentrations ten million times larger. Hence, the sensors discussed in Section II could generate a wide range of DC current outputs that the electronic interface should be able to measure. This varies from currents at sub-pA level (to achieve high sensitivity for scarce target) to μA level (for large concentrations) and all ranges in between [161]. Hence, AFEs for sensor interface need to have a very wide DR, along with sub-pA limit of detection.

Depending on how the WQM device is deployed and used, there could be a very stringent requirement for a power-management unit (PMU) that drives the AFE. In general, all wireless devices would require some sort of PMU to maintain a uniform power supply and create the necessary bias voltage/currents used in the analog domain. In WQM sensors, the need for a high-performance PMU is even more important since these devices, by definition, encounter a high degree of variation in their operating environment (temperature, pressure, humidity, vibration, radiation, etc.), which could be often quite harsh. The sensitivity of the AFE depends on the quality of the available supply and biases. Since the future of WQM devices are remote stand-alone modules that continuously monitor the surrounding environment, it is expected that these will be either battery powered or RF powered.

The classical calibration process consists of comparing a sensor in a controlled environment, for example, in a laboratory with high-cost instrumentation, where the sensor response is measured under different controlled conditions. Contrary to lab-based instruments, devices that are deployed in the field normally do not go through the user-initiated calibration cycle. In most cases, this is not practical and/or desirable. However, frequent (re-)calibration is an important requirement for any sensor to rule out the possibility of data errors, particularly when it is in direct contact with the environment. Ideally, the transducer and the interface electronics, both should be calibrated independently. The calibration of the electronics can be done by disconnecting it from the transducer and connecting it to a known signal, which is locally generated. This is also possible by using a dummy signal chain, which is expected to behave similarly to the main one. Though the quality of the known signal could be a matter of concern as well, the results can be extrapolated using some prior knowledge about the system. The complete AFE, ADCs, reference sources etc., can benefit from such calibrations. Similar to digital processors, analog built-in-self-test (BIST) technique has been adopted in complex mixed-signal chipset for some time [162]. Calibration including the transducer in the loop is however a much-complicated procedure. This could be rarely done using a single sensor module alone. A network of sensors is necessary for such a procedure [163]. The sensor parameters can be self-calibrated and adjusted in reference to another sensor of the network, whether calibrated with a ground-truth reference node, calibrated with respect to already calibrated sensor nodes (e.g., distributed calibration and group calibration), or with respect to not-calibrated sensor nodes (e.g., blind calibration) [164]. Consequently, calibration procedures suitable for sensor placed in field conditions have been widely investigated in the past two decades and continues to be an important future topic.

An important specification while designing the electronic interface to the transducer is power consumption. The energy budget of the sensor node determines several aspects of the overall system. In the case of battery-operated devices, it is often the primary determinant of the system form-factor (given by the battery volume) and lifetime. For energy harvesting devices, the power consumption determines the feasibility of the implementation itself. However, determining a uniform set of specifications for power consumption in WQ sensors is a complex task. It depends on a wide variety of topics roughly dependent on what is being measured, how often, and from how far [165]. One of the key problems in such sensor networks is the communication protocol being used. Table IV shows a comparison between different communication standards commonly used for such a distributed wireless sensor network. While the tradeoff between the data rate and power consumption is obvious, it should be noted that variables being monitored in a WQM sensor (e.g., pH, DO, conductivity) rarely change at a very fast rate. This factor has resulted in an interest in custom-integrated wireless sensor nodes that could work on a smaller battery or use harvested energy for environmental monitoring. Though the design process of such integrated circuits is more complex, they can provide a customized solution that consumes much lower power and has a miniaturized form factor that can be integrated into a wider variety of devices [166], [167]. However, these monolithic solutions must deal with many design tradeoffs depending on the application. Fig. 8. shows the power consumption tradeoffs in three major sections that can be used to determine the necessary design specifications.

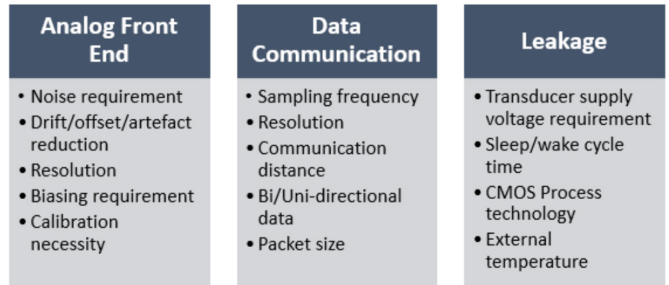

Fig. 8. Power consumption tradeoffs for custom integrated wireless sensor nodes.

TABLE IV
COMPARISON OF WIRELESS COMMUNICATION STANDARDS

Communication standard	Frequency Band	Speed	Range	Relative power consumption
Wi-Fi	2.4 & 5GHz	150Mbps	~200m	High
Zigbee	2.4 GHz	250 Kbps	~100m	Low
Bluetooth/BLE	2.4GHz	3Mbps	~100m	Very low
LoRa	Sub GHz	250 kbps	10 km	Very Low
SigFox	Sub GHz	1kbps	>20km	Very low

C. Communication Between Sensor Networks

Robust communication protocols are needed for live information extraction from the data generated by sensor networks. Unfortunately, standard communication based on EM waves are not an option in water, except at very short ranges and at a high energy cost. Optical communications are also limited in a range to a few meters to a few 10 s of meters depending on water visibility conditions. In practice, the most reliable and widely used communication systems is based on acoustics. In this case, the available transfer rate is often limited (a few bits/s to a few kbits/s), the acoustic bandwidth is narrow (10–20 kHz), and dispersion and multipath are prevalent. These limit the options for code-division multiple access (CDMA) and frequency-division multiple access (FDMA) protocols and promote the use of slower time-division multiple access (TDMA) approach. However, acoustic systems offer the advantage of combining communication and ranging, enabling joint localization of sensor nodes and communication network management [168], [169]. They enable in-situ monitoring of water parameters, such as plankton density, WQ, and pollutant detection, requiring the integration of multiple sensor modalities into a single package, including onboard processing to limit the requirements on transfer rate and energy. There is obviously a tradeoff between energy consumed in local processing and spent in transmission. However, low-power electronics have made significant progress and when integrated with modern batteries and energy harvesting, they can provide a solution to long-term deployment. An example of such a system developed in the EPSRC funded USMART project is depicted in Fig. 7(a).

IV. Spatiotemporal Data Analysis and Prediction

In depth analytical evaluation of quality assured, WQ data depend very much on the purposes of the monitoring programme from which the data have been extracted. There are many purposes labeled under tasks of operation and surveillance, including monitoring to report on status (e.g., reporting on WQ to national regulations such as the Water Framework Directive), evaluation of the effect of an intervention (e.g., upgrade to a wastewater treatment works), detection of a change (e.g., as a result of flow status), population surveillance (e.g., appearance of illegal drugs or covid), or some form of real time or near real-time decision making (e.g., water abstraction and reuse). Across these purposes, the data will have both temporal and spatial properties. Thus, the broadest definition of the current analytical tools, which are widely used, would be spatiotemporal models incorporating temporal modeling to evaluate trends over time and detect changes, and spatial modeling to evaluate trends over space and pinpoint hotspots.

For the spatial aspects of any catchment or basin network, we must consider the spatial/network dependence in the sensor locations and, hence, in the data generated. WQM networks will often be designed to provide spatially representative coverage but they are also connected sharing the same catchment area and linked through directed river flow. Spatial correlation may be related to Euclidean distance and river discharge but are more commonly connected through river distances and stream order. To achieve an understanding of the spatial patterns, spatial models must be developed taking into account the network structure and in the past decade, there has been considerable work to build models that have non-Euclidean spatial correlation structures [170]–[173].

For the temporal aspect of the network data, the fundamental design question concerns the temporal frequency of measurement, with many historical networks being dependent on physical sampling (often monthly), while newer networks have seen increased resolution to 15 mins and higher (determined by the temporal scale of the environmental processes). The classic analysis choice in time-series modeling remains whether to model in the time or frequency domain. In the time domain, classical time-series models of autoregressive or moving average (ARIMA models) have been used but as the temporal resolution of monitoring has increased, there has been more and more research using the frequency domain, where wavelets and other transforms have been used [174], [175]. Further developments in the modeling of environmental time series has come from the application of functional data analysis (FDA) methods [176]. In this context, the "data point" becomes the time-series curve [177], [178] this approach often is computationally efficient since it offers substantial data dimension reduction. Another important area of analytics frequently used in WQM concerns extreme value modeling (often using peak over threshold (POT) models). While used most commonly in flow modeling, this approach is also of use in quality modeling. Recent developments here have seen the extension of theory to spatiotemporal extremes [179], [180].

Increasingly, there has been much interest in the use of algorithmic learning and AI tools applied to network data as developed intelligent wireless systems routinely generate large volumes of data. Such volumes of data have required the adoption and development of new analytical methods including machine learning as artificial neural networks (with their many variations generally known as deep learning methods), as well as support vector machines, classification trees, adaptive neuro-fuzzy inference systems, etc. [181]–[183]. Many statistical models, such as decision trees, nonhierarchical classification methods, and the Bayesian networks have become the backbone of machine learning tools. More broadly termed as AI methods, these techniques, after being properly trained with large data sets, can extract information and detect patterns without use of network equations. They are computationally fast and efficient, are able to identify structures and dependencies automatically [184], [185] and can operate in near or real time. The fundamental principle of such methods is to learn from data with less human intervention (in the more classical analytical tools, the analyst must prescribe the structure and relationships parametrically). This is especially important since our knowledge about the ecological and environmental processes may be incomplete. Dealing with the data volume as well as the different data streams have also presented challenges [186]. In this space, there are new developments concerning methods to fuse and assimilate different data streams [187]–[189]. By harnessing the power of AI algorithms and big data analytics, water utilities can maximize information and data available to make better decisions while enhancing service delivery and reducing costs [190]. In addition, feeding the data generated by social media, mobile phones, and the Internet of Things (IoT) directly into AI could be new opportunity for WQM.

V. Discussion and Future Directions

New connected sensors, at local, regional, and global scales, offer tremendous environmental monitoring opportunities in delivering real-time data, which will allow our understanding of environmental processes to improve. The use of sensor networks and Internet communications combined with GIS tools will be having an important role in the future and can be very beneficial to stakeholders in not only efficiently managing the WQ but also in water distribution management, agriculture, and landscaping sectors, where it can reduce water consumption and wastage.

A. Sensor Integration

While the opportunities and potentials are great, there remain challenges [191]. The design of networks remains an area of scientific interest, developing quality assurance procedures to detect anomalous observations [192], performance issues (both on sensor and in data communications). The integration (and fusion) of data streams from different sensors is also an area of research. Extensive use of sensing and ICT devices comes with new environmental challenges such as increased electronic waste. To overcome these challenges, several research steps are required as summarized by the flowchart in Fig. 9. This starts from identifying the WQ parameters, materials for sensors, fabrication of sensors, their integration, deployment, and, finally, the analysis. Currently, a fragmented approach is taken with many of these steps carried out without strong linkages with the others. An integrated or holistic approach will go a long way in the direction toward effective WQM and could also offer new opportunities for monitoring in other areas, such as environment, agriculture, healthcare, etc.

B. Sustainable and Reusable Sensors

A large number of sensors and associated electronics are likely to add to the current issues such as electronic waste, which could be addressed by using biodegradable, natural, and biocompatible materials for sensing electrodes, conducting path, substrates, protective layers etc. [75], [193]. The current substrates for sensors, such as flexible PET, PVC etc., require long time to degrades and are potential source of new pollutants such as microplastics. The electrodes from costly, scarce, and highly purified materials, such as Pt, Ag, and Au also need to be replaced. In this regard, conducting polymers or degradable metals, and carbon-based electrodes are attractive alternatives. Currently, metal–oxides, such as RuO_2, are popular material for pH sensors as they lead to high performances. However, these materials are toxic, in addition being costly and, hence, alternative biocompatible metal–oxides need to be explored. To reduce the environmental impact of electronic waste, the WQM system should promote both disposable and reusable devices. For example, the sensors could be disposable and the electronics and communication modules would be designed for reusability [57], [194], [195]. In such a design, one of the options is to develop electrodes (for SE, RE, and conducting path) using biocompatible or dissolvable materials (e.g., operational life ~24 hr.) and reuse the substrate to develop new electrodes given in Fig. 10. Likewise, the interface electronics

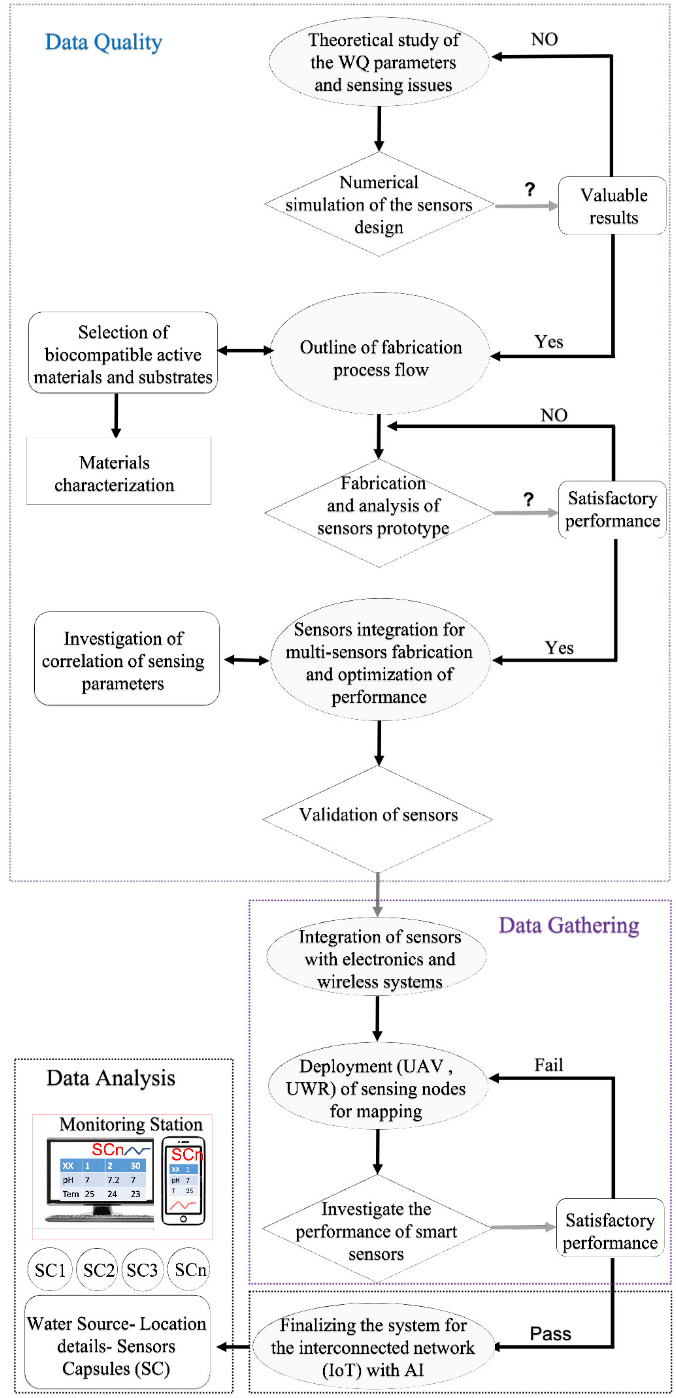

Fig. 9. Methodology for an advanced WQM system.

can be reused. The controlled degradability of these sensors can be achieved with suitable packaging. Such schemes could be easily implemented with mobile sensor nodes provided by the autonomous water and aerial vehicles, as discussed in Section III. For example, electronic skin like multisensory patches in flexible form factors could be attached to autonomous vehicle. Some options for SE fabrication include biodegradable conducting polymers including PEDOT: PSS or sustainable carbon-based electrodes [57], [196], [197]. Printed carbon-based electrodes could also be used for RE and CE fabrications, as reported for wearable biosensors [198].

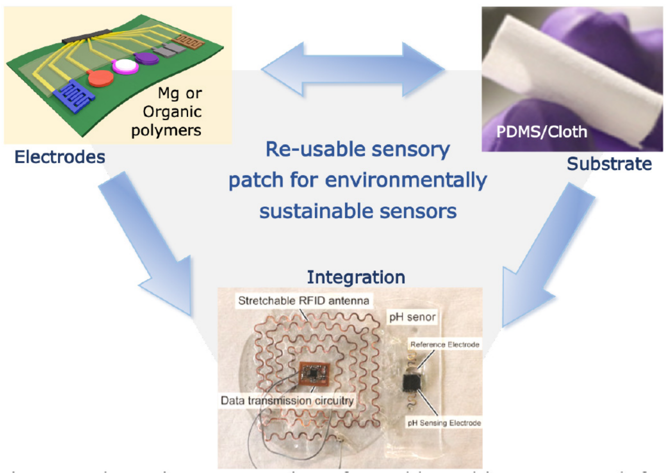

Fig. 10. Schematic representation of reusable multisensory patch for environment-friendly sustainable sensing.

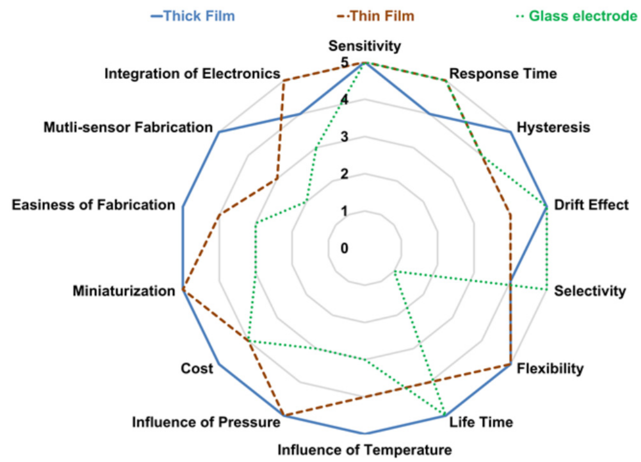

Fig. 11. Comparison of various types of electrodes for sensors fabrication [54].

C. Energy Autonomous Sensors

For remote quality monitoring the energy autonomy of sensor system or network and power management also need attention. The recent studies show that the energy autonomy in WQ sensors can be addressed by using the self-powered system, such as solar-powered sensors [33], [108], [199]–[201] or triboelectric/piezoelectric-based sensors. Furthermore, new renewable solutions, such as harnessing wave energy using triboelectric nanogenerators (TENGs) could be used to power the sensors as well as the autonomous vehicles [202]–[204]. Such energy autonomous sensing networks can also be useful for monitoring of WQ in fish farms, pollution in river water, and the DW in the pipelines (supply system in metropolitan areas) and open water bodies. For example, the smart networks could be deployed in pipelines using snake-like robots, even though it will be more challenging than using UAV or UWR in large water bodies. On the other hand, the water in metropolitan supply pipelines is likely to be treated already and, hence, much lower spatiotemporal variations is expected with respect to the open waters. Considering this, the use of sensor nodes at a fixed location may be sufficient.

D. Selective Sensing Material

The implementation of sensors for WQM need to consider many parameters such as: 1) selectivity; 2) lifetime; 3) low cost; 4) environmentally friendly materials; and 5) easy integration with smart connected network. In potentiometry or an amperometric type of sensors, the selectivity, stability, and lifetime purely depend on the type of SE. Moreover, in these two types of sensors, the stability and lifetime also depend on the RE. The typical thick or thin film Ag/AgCl-based REs show stability issues during long measurement time. One way to overcome the above issue is to use the other type of sensor. For example, using the chemiresistive sensor which do not use RE. But the selectivity and power requirement are the major challenges in chemiresistive sensor. Hence, there is a trade-off between the type of sensor, the material, the measurement method, sensitivity, and stability. The development of sensors with materials exhibiting excellent ionic and electronic conductivity could also offer attractive solution. For example, the selectivity of Pb free ceramic-based perovskite materials could be tuned by suitable doping. The thick film-based multisensing electrodes can also help in terms of selective sensing. The major advantage of this type of sensor the easy integration. A comparative analysis of the thick film-based sensors with other methods is shown in Fig. 11.

Despite the promising performances of individual sensors reported in literature, the stability and reliability issues, over a long time, could occur due to material degradation. In this regard, frequent calibration along with proper data analysis could be helpful. To understand the influence of material degradation, the long-term studies, involving electrochemical sensors in real condition, are required. Avoiding antifouling resistance during sensor deployment is another challenge. To this end, suitable packaging or frequent replacement of sensors or using sensors made from naturally degradable materials could help.

E. Data Handling and Cost Effectiveness

The increasing nutrients, chemical loads, and other sediments require networked WQM solutions at regional and global scale [205]–[209]. At such scales, the number of sensor and the data generated by them could require significant computing resources. The modeling or discrete observation routes and the sensor network with the satellite-based monitoring technique with data handling in the cloud or sending data packet with a suitable protocol can help overcome such challenges [210]–[215]. For commercial viability, the cost of the full sensor system also needs attention. The cost of connected sensors systems depends on the materials, fabrication method, sensor/electronic devices, integration strategy, and communication technology. If deployment using robotic vehicles is needed, then their addition costs related to robotic vehicles need to be considered too. The cost benefits of such deployments against the traditional sampling and laboratory analysis are an important factor. As an example, currently, the high cost of traditional sampling and laboratory analysis (e.g., in a low-income country, such as India, the marginal cost per test is ∼\$7.25 [216]) is a major factor that is hampering the monitoring of large supplies (e.g., in urban settings). Transport and labor together constitute half of this cost and as a result a limited number of monitoring centers exist. Such costs can be easily reduced by real-time monitoring with suitable sensor network. Likewise, a commercially available buoy could cost \$5K-6K [155]. On other hand, lightweight low-cost airborne drones (<5kg take-off weight) costs <£3.5K. This means, for the same cost of a commercial buoy (which are fixed in water bodies), it is possible to gather much richer data by deploying sensors using robotic vehicles. The lower costs could also improve the compliance with monitoring requirements.

In relation with the sensors, the cost is influence by the materials, fabrication method and integration technology [217]. For example, the higher cost of the RuO_2-based sensitive material in pH sensor is a major issue, which is being addressed through the use of binary oxides. The binary oxide-based pH sensors have been reported with excellent sensitivity. In terms of fabrication cost and easy integration, the methods, such as low temperature co-fired ceramic (LTCC)-based pH sensor or printed sensor, are some of the attractive routes. The pH measured by LTCC-based sensors is in good agreement with sensors using a conventional glass pH electrode. In another work based on IDE-based sensor, the authors observed that the total cost of the polymer-based sensors is low (\$1) as compared to commercial sensors (\$250-300) [54], but the pH measurement range is also low (6.5–9) [54]. The method of fabrication of such sensors has a significant influence on their cost. In this regard, printed electronics technology is attractive as it makes it easy to process various materials at low temperatures and enables the development of sensors in flexible-form factors [124]. Recently, 3-D printing technology for the pH sensor has also found application for WQM [108]–[110]. 3-D printing-based approaches have advantages in terms of low cost and packaging [218]–[221]. The multimaterial 3-D/4D printing is offering interesting opportunities for direct printing of conducting tracks and other functional devices on complex shapes [108]–[110].

VI. Conclusion

The connected sensor technologies for WQM could provide the bridging solution for current disconnect between data quality, data gathering, and data analysis and enhance the global data intercomparability. With this in view, this article has reviewed key sensing technologies, sensor deployment strategies and the emerging methods for data analysis. The review evaluated various sensing materials, substrates, and designs of sensors including multisensory patches. For data gathering, various components of sensor interface electronics and communication system have been discussed along with innovative deployment strategies using sensorized buoys, drones, and underwater robotic vehicles. Diverse techniques for data analysis of the sensors are briefly discussed along with the potential opportunities for real-time WQM with AI. Finally, the challenges related to discussed approaches, their solutions, and potential opportunities enabled by the holistic discussion about WQM have been discussed.

It is noted that ICT provides a unique opportunity for water stakeholders to obtain information in near real time about a number of physical and environmental variables such as temperature, soil moisture levels, rainfall, and others through Web enabled sensors and communication networks, and can thus have accurate information about the situation at hand (without physically being there) for their forecasts and decisions. The WQM sector will hugely benefit from the sensor networks and techniques that being developed for IoT. Such methods have already advanced the monitoring activities in areas such as healthcare, agriculture and environment monitoring etc. Given many similarities there is no reason why they cannot be tried to WQM. The opportunity to obtain real-time WQ parameters in a cost-effective manner is a huge gain that these new technological advances offer.

References

[1] R. Altenburger *et al.*, "Future water quality monitoring: Improving the balance between exposure and toxicity assessments of real-world pollutant mixtures," *Environ. Sci. Europe*, vol. 31, no. 1, p. 12, 2019.

[2] S. C. Mukhopadhyay and A. Mason, *Smart Sensors for Real-Time Water Quality Monitoring*. Heidelberg, Germany: Springer, 2013.

[3] Enviornmental Protection Agnecy. (2001). *Water Quaklity Parameters*. [Online]. Available: https://www.epa.ie/pubs/advice/water/quality/Water_Quality.pdf

[4] D. Pooja, P. Kumar, P. Singh, and S. Patil, *Sensors in Water Pollutants Monitoring: Role of Material*. Singapore: Springer, 2020.

[5] K. Acharya, A. Blackburn, J. Mohammed, A. T. Haile, A. M. Hiruy, and D. Werner, "Metagenomic water quality monitoring with a portable laboratory," *Water Res.*, vol. 184, Oct. 2020, Art. no. 116112.

[6] M. N. Byappanahalli, M. B. Nevers, D. A. Shively, A. Spoljaric, and C. Otto, "Real-time water quality monitoring at a great lakes national park," *J. Environ. Qual.*, vol. 47, no. 5, pp. 1086–1093, 2018.

[7] W. F. Directive, "Directive 2000/60/EC of the European parliament and of the council of 23 October 2000 establishing a framework for Community action in the field of water policy," *Official J. Eur. Commun.*, vol. 22, no. 12, p. 2000, 2000.

[8] "Water framework directive," *Open J. Leadership*, vol. 327, pp. 1–73, Dec. 2000.

[9] D. J. Paustenbach, B. Winans, R. M. Novick, and S. M. Green, "The toxicity of crude 4-methylcyclohexanemethanol (MCHM): Review of experimental data and results of predictive models for its constituents and a putative metabolite," *Crit. Rev. Toxicol.*, vol. 45, no. 2, pp. 1–55, 2015.

[10] A. Bogler *et al.*, "Rethinking wastewater risks and monitoring in light of the COVID 19 pandemic," *Nat. Sustain.*, vol. 3, pp. 981–990, Aug. 2020.

[11] K. Haldar, K. Kujawa-Roeleveld, P. Dey, S. Bosu, D. K. Datta, and H. H. M. Rijnaarts, "Spatio-temporal variations in chemical-physical water quality parameters influencing water reuse for irrigated agriculture in tropical urbanized deltas," *Sci. Total Environ.*, vol. 708, Mar. 2020, Art. no. 134559.

[12] A. U. Alam, D. Clyne, H. Jin, N.-X. Hu, and M. J. Deen, "Fully integrated, simple, and low-cost electrochemical sensor array for in situ water quality monitoring," *ACS Sens.*, vol. 5, no. 2, pp. 412–422, 2020.

[13] M. Carminati *et al.*, "A self-powered wireless water quality sensing network enabling smart monitoring of biological and chemical stability in supply systems," *Sensors*, vol. 20, no. 4, p. 1125, 2020.

[14] J. Park, K. T. Kim, and W. H. Lee, "Recent advances in information and communications technology (ICT) and sensor technology for monitoring water quality," *Water*, vol. 12, no. 2, p. 510, 2020.

[15] H. Cao, Z. Guo, S. Wang, H. Cheng, and C. Zhan, "Intelligent wide-area water quality monitoring and analysis system exploiting unmanned surface vehicles and ensemble learning," *Water*, vol. 12, no. 3, p. 681, 2020.

[16] R. Samavedam, J. Gunda, and R. Ziegler, "An affordable, autonomous, solar powered and modular robotic water monitoring system," *J. Undergraduate Res. Ohio State*, vol. 9, pp. 36–52, Feb. 2020.

[17] G. Medema, L. Heijnen, G. Elsinga, R. Italiaander, A. Brouwer, "Presence of SARS-coronavirus-2 RNA in sewage and correlation with reported COVID-19 prevalence in the early stage of the epidemic in The Netherlands," *Environ. Sci. Technol. Lett.*, vol. 7, no. 7, pp. 511–516, 2020.

[18] L. Manjakkal, B. Synkiewicz, K. Zaraska, K. Cvejin, J. Kulawik, and D. Szwagierczak, "Development and characterization of miniaturized LTCC pH sensors with RuO2 based sensing electrodes," *Sens. Actuators B, Chem.*, vol. 223, pp. 641–649, Feb. 2016.

[19] M. Simić, G. M. Stojanović, L. Manjakkal, and K. Zaraska, "Multi-sensor system for remote environmental (air and water) quality monitoring," in *Proc. 24th IEEE Telecommun. Forum*, 2016, pp. 1–4.

[20] J. Yin et al., "Batch microfabrication of highly integrated silicon-based electrochemical sensor and performance evaluation via nitrite water contaminant determination," *Electrochimica Acta*, vol. 335, Mar. 2020, Art. no. 135660.

[21] A. Nigam et al., "Real time detection of Hg^{2+} ions using MoS_2 functionalized AlGaN/GaN high electron mobility transistor for water quality monitoring," *Sens. Actuators B, Chem.*, vol. 309, Apr. 2020, Art. no. 127832.

[22] J. D. Chaffin, D. D. Kane, and A. Johnson, "Effectiveness of a fixed-depth sensor deployed from a buoy to estimate water-column cyanobacterial biomass depends on wind speed," *J. Environ. Sci.*, vol. 93, pp. 23–29, Jul. 2020.

[23] M. J. Meulemans, C. S. Jones, K. E. Schilling, N. C. Young, and L. J. Weber, "Assessment of spatial nitrate patterns in an eastern Iowa watershed using boat-deployed sensors," *Water*, vol. 12, no. 1, p. 146, 2020.

[24] Z. Shareef and S. Reddy, "Deployment of sensor nodes for aquaculture in western Godavari delta: Results, challenges and issues," *J. Rel. Intell. Environ.*, vol. 6, no. 3, pp. 153–167, 2020.

[25] R. L. P. de Lima, F. C. Boogaard, and R. E. de Graaf-van Dinther, "Innovative water quality and ecology monitoring using underwater unmanned vehicles: Field applications, challenges and feedback from water managers," *Water*, vol. 12, no. 4, p. 1196, 2020.

[26] E. Q. Shahra and W. Wu, "Water contaminants detection using sensor placement approach in smart water networks," *J. Ambient Intell. Humanized Comput.*, vol 11, pp. 1–16, Jun. 2020.

[27] B. M. Zoss et al., "Distributed system of autonomous buoys for scalable deployment and monitoring of large waterbodies," *Auton. Robot.*, vol. 42, no. 8, pp. 1669–1689, 2018.

[28] M. Melo, F. Mota, V. Albuquerque, and A. Alexandria, "Development of a robotic airboat for online water quality monitoring in lakes," *Robotics*, vol. 8, no. 1, p. 19, 2019.

[29] M. Bonansea, M. C. Rodriguez, L. Pinotti, and S. Ferrero, "Using multi-temporal Landsat imagery and linear mixed models for assessing water quality parameters in Río Tercero reservoir (Argentina)," *Remote Sens. Environ.*, vol. 158, pp. 28–41, Mar. 2015.

[30] B. Arabi, M. S. Salama, J. Pitarch, and W. Verhoef, "Integration of in-situ and multi-sensor satellite observations for long-term water quality monitoring in coastal areas," *Remote Sens. Environ.*, vol. 239, Mar. 2020, Art. no. 111632.

[31] B. O'Flynn et al., "SmartCoast: A wireless sensor network for water quality monitoring," in *Proc. 32nd IEEE Conf. Local Comput. Netw.*, 2007, pp. 815–816.

[32] J. Huang, W. Wang, S. Jiang, D. Sun, G. Ou, and K. Lu, "Development and test of aquacultural water quality monitoring system based on wireless sensor network," *Trans. Chin. Soc. Agricul. Eng.*, vol. 29, no. 4, pp. 183–190, 2013.

[33] R. Yue and T. Ying, "A water quality monitoring system based on wireless sensor network & solar power supply," in *Proc. IEEE Int. Conf. Cyber Technol. Autom. Control Intell. Syst.*, 2011, pp. 126–129.

[34] S. Zhuiykov, "Solid-state sensors monitoring parameters of water quality for the next generation of wireless sensor networks," *Sens. Actuators B, Chem.*, vol. 161, no. 1, pp. 1–20, 2012.

[35] Y. H. Kim, J. Im, H. K. Ha, J.-K. Choi, and S. Ha, "Machine learning approaches to coastal water quality monitoring using GOCI satellite data," *GIScі. Remote Sens.*, vol. 51, no. 2, pp. 158–174, 2014.

[36] G. Xu, Y. Shi, X. Sun, and W. Shen, "Internet of Things in marine environment monitoring: A review," *Sensors*, vol. 19, no. 7, p. 1711, 2019.

[37] S. Behmel, M. Damour, R. Ludwig, and M. J. Rodriguez, "Water quality monitoring strategies—A review and future perspectives," *Sci. Total Environ.*, vol. 571, pp. 1312–1329, Nov. 2016.

[38] M. Karydis and D. Kitsiou, "Marine water quality monitoring: A review," *Mar. Pollut. Bull.*, vol. 77, nos. 1–2, pp. 23–36, 2013.

[39] R. O. Strobl and P. D. Robillard, "Network design for water quality monitoring of surface freshwaters: A review," *J. Environ. Manag.*, vol. 87, no. 4, pp. 639–648, 2008.

[40] J. O. Ighalo, A. G. Adeniyi, and G. Marques, "Internet of Things for water quality monitoring and assessment: A comprehensive review," *Artificial Intelligence for Sustainable Development: Theory, Practice and Future Applications*. Cham, Switzerland: Springer, 2020, pp. 245–259.

[41] X. Wen et al., "Microbial indicators and their use for monitoring drinking water quality—A Review," *Sustainability*, vol. 12, no. 6, p. 2249, 2020.

[42] T. Rajaee, S. Khani, and M. Ravansalar, "Artificial intelligence-based single and hybrid models for prediction of water quality in rivers: A review," *Chemometr. Intell. Lab. Syst.*, vol. 200, May 2020, Art. no. 103978.

[43] J. Li, X. Yang, and R. Sitzenfrei, "Rethinking the framework of smart water system: A review," *Water*, vol. 12, no. 2, p. 412, 2020.

[44] A. Zubiarrain-Laserna and P. Kruse, "Graphene-based water quality sensors," *J. Electrochem. Soc.*, vol. 167, no. 3, 2020, Art. no. 037539.

[45] E. Hanhauser, M. S. Bono, Jr., C. Vaishnav, A. J. Hart, and R. Karnik, "Solid-phase extraction, preservation, storage, transport, and analysis of trace contaminants for water quality monitoring of heavy metals," *Environ. Sci. Technol.*, vol. 54, no. 5, pp. 2646–2657, 2020.

[46] Y. Qin, H.-J. Kwon, M. M. R. Howlader, and M. J. Deen, "Microfabricated electrochemical pH and free chlorine sensors for water quality monitoring: Recent advances and research challenges," *RSC Adv.*, vol. 5, no. 85, pp. 69086–69109, 2015.

[47] W. Thavarajah et al., "A primer on emerging field-deployable synthetic biology tools for global water quality monitoring," *NPJ Clean Water*, vol. 3, no. 1, pp. 1–10, 2020.

[48] M. H. Banna, H. Najjaran, R. Sadiq, S. A. Imran, M. J. Rodriguez, and M. Hoorfar, "Miniaturized water quality monitoring pH and conductivity sensors," *Sens. Actuators B, Chem.*, vol. 193, pp. 434–441, Mar. 2014.

[49] I. Seymour, B. O'sullivan, P. Lovera, J. Rohan, and A. O'Riordan, "Electrochemical detection of free-chlorine in water samples facilitated by in-situ pH control using interdigitated microelectrodes," *Sens. Actuators B, Chem.*, vol. 325, Dec. 2020, Art. no. 128774.

[50] S. Dhar, P. Yadav, S. Pramanik, K. Sarkar, and A. P. Chattopadhayay, "Green synthesized silver NPs: Fluorescence sensor for Cl− ions in aqueous solution in biological pH and cell viability study," *SN Appl. Sci.*, vol. 2, no. 4, pp. 1–13, 2020.

[51] X. Jiang, Y. Xie, D. Wan, F. Zheng, and J. Wang, "Simultaneously detecting ethyl carbamate and its precursors in rice wine based on a pH-responsive electrochemical impedance sensor," *Analytica Chimica Acta*, vol. 1126, pp. 124–132, Aug. 2020.

[52] X. Ke, "Micro-fabricated electrochemical chloride ion sensors: From the present to the future," *Talanta*, vol. 211, May 2020, Art. no. 120734.

[53] R. Wang et al., "Stretchable gold fiber-based wearable electrochemical sensor toward pH monitoring," *J. Mater. Chem. B*, vol. 8, no. 16, pp. 3655–3660, 2020.

[54] L. Manjakkal, D. Szwagierczak, and R. Dahiya, "Metal oxides based electrochemical pH sensors: Current progress and future perspectives," *Prog. Mater. Sci.*, vol. 109, Apr. 2020, Art. no. 100635.

[55] Z. Wang, J. Shin, J. H. Park, H. Lee, D. H. Kim, and H. Liu, "Engineering materials for electrochemical sweat sensing," *Adv. Funct. Mater.*, vol. 31, no. 12, 2020, Art. no. 2008130.

[56] Z. Wu, J. Wang, C. Bian, J. Tong, and S. Xia, "A MEMS-based multi-parameter integrated chip and its portable system for water quality detection," *Micromachines*, vol. 11, no. 1, p. 63, 2020.

[57] W. Dang, L. Manjakkal, W. T. Navaraj, L. Lorenzelli, V. Vinciguerra, and R. Dahiya, "Stretchable wireless system for sweat pH monitoring," *Biosens. Bioelectron.*, vol. 107, pp. 192–202, Jun. 2018.

[58] S. A. Kraemer, A. Ramachandran, and G. G. Perron, "Antibiotic pollution in the environment: From microbial ecology to public policy," *Microorganisms*, vol. 7, no. 6, p. 180, 2019.

[59] A. R. Mahmood, H. H. Al-Haideri, and F. M. Hassan, "Detection of antibiotics in drinking water treatment plants in Baghdad City, Iraq," *Adv. Pub. Health*, vol. 2019, no. 4, 2019, Art. no. 7851354.

[60] L. Lvova et al., "Potentiometric E-tongue system for geosmin/isoborneol presence monitoring in drinkable water," *Sensors*, vol. 20, no. 3, p. 821, 2020.

[61] J. C. Prata, J. P. da Costa, A. C. Duarte, and T. Rocha-Santos, "Methods for sampling and detection of microplastics in water and sediment: a critical review," *TrAC Trends Anal. Chem.*, vol. 110, pp. 150–159, Jan. 2019.

[62] M. Enfrin, L. F. Dumée, and J. Lee, "Nano/microplastics in water and wastewater treatment processes–origin, impact and potential solutions," *Water Res.*, vol. 161, pp. 621–638, Sep. 2019.

[63] D. A. Larsen and K. R. Wigginton, "Tracking COVID-19 with wastewater," *Nat. Biotechnol.*, vol. 38, no. 10, pp. 1151–1153, 2020.

[64] C. G. Daughton, "Wastewater surveillance for population-wide COVID-19: The present and future," *Sci. Total Environ.*, vol. 736, Sep. 2020, Art. no. 139631.

[65] J. Wang *et al.*, "Disinfection technology of hospital wastes and wastewater: Suggestions for disinfection strategy during coronavirus disease 2019 (COVID-19) pandemic in China," *Environ. Pollut.*, vol. 262, Jul. 2020, Art. no. 114665.

[66] P. Foladori *et al.*, "SARS-CoV-2 from faeces to wastewater treatment: What do we know? A review," *Sci. Total Environ.*, vol. 743, Nov. 2020, Art. no. 140444.

[67] G. D. Bhowmick *et al.*, "Coronavirus disease 2019 (COVID-19) outbreak: Some serious consequences with urban and rural water cycle," *NPJ Clean Water*, vol. 3, no. 1, p. 32, 2020.

[68] W. Ahmed *et al.*, "First confirmed detection of SARS-CoV-2 in untreated wastewater in Australia: A proof of concept for the wastewater surveillance of COVID-19 in the community," *Sci. Total Environ.*, vol. 728, Aug. 2020, Art. no. 138764.

[69] J. D. Shutler *et al.*, "Rapid assessment of SARS-CoV-2 transmission risk for fecally contaminated river water," *ACS EST Water*, vol. 1, no. 4, pp. 949–957, 2021.

[70] A. Christou, M. Ntagios, A. Hart, and R. Dahiya, "GlasVent—The rapidly deployable emergency ventilator," *Global Challenges*, vol. 4, no. 12, 2020, Art. no. 2000046.

[71] L. Manjakkal, K. Cvejin, J. Kulawik, K. Zaraska, D. Szwagierczak, and R. P. Socha, "Fabrication of thick film sensitive RuO_2-TiO_2 and Ag/AgCl/KCl reference electrodes and their application for pH measurements," *Sensor. Actuators B, Chem.*, vol. 204, pp. 57–67, Dec. 2014.

[72] R. Martínez-Máñez, J. Soto, E. García-Breijo, L. Gil, J. Ibáñez, and E. Gadea, "A multisensor in thick-film technology for water quality control," *Sensor. Actuators A, Phys.*, vol. 120, no. 2, pp. 589–595, 2005.

[73] S. Zhuiykov, "Morphology of Pt-doped nanofabricated RuO_2 sensing electrodes and their properties in water quality monitoring sensors," *Sensor. Actuators B, Chem.*, vol. 136, no. 1, pp. 248–256, 2009.

[74] S. Zhuiykov, D. O'Brien, and M. Best, "Water quality assessment by an integrated multi-sensor based on semiconductor RuO_2 nanostructures," *Meas. Sci. Technol.*, vol. 20, no. 9, 2009, Art. no. 095201.

[75] E. S. Hosseini, S. Dervin, P. Ganguly, and R. Dahiya, "Biodegradable materials for sustainable health monitoring devices," *ACS Appl. Bio Mater.*, vol. 4, no. 1, pp. 163–194, 2021.

[76] N. Yogeswaran, E. S. Hosseini, and R. Dahiya, "Graphene based low voltage field effect transistor coupled with biodegradable piezoelectric material based dynamic pressure sensor," *ACS Appl. Mater. Interfaces*, vol. 12, no. 48, pp. 54035–54040, 2020.

[77] E. S. Hosseini, L. Manjakkal, D. Shakthivel, and R. Dahiya, "Glycine–Chitosan-based flexible biodegradable piezoelectric pressure sensor," *ACS Appl. Mater. Interfaces*, vol. 12, no. 8, pp. 9008–9016, 2020.

[78] S. Zhuiykov, E. Kats, K. Kalantar-zadeh, M. Breedon, and N. Miura, "Influence of thickness of sub-micron Cu_2JO-doped RuO_2 electrode on sensing performance of planar electrochemical pH sensors," *Mater. Lett.*, vol. 75, pp. 165–168, May 2012.

[79] L. Manjakkal, B. Sakthivel, N. Gopalakrishnan, and R. Dahiya, "Printed flexible electrochemical pH sensors based on CuO nanorods," *Sensor. Actuators. B, Chem.*, vol. 263, pp. 50–58, Jun. 2018.

[80] A. Fulati, S. M. U. Ali, M. Riaz, G. Amin, O. Nur, and M. Willander, "Miniaturized pH sensors based on zinc oxide nanotubes/nanorods," *Sensors*, vol. 9, no. 11, pp. 8911–8923, 2009.

[81] A. Ejaz, J. H. Han, and R. Dahiya, "Influence of solvent molecular geometry on the growth of nanostructures," *J. Colloid Interface Sci.*, vol. 570, pp. 322–331, Jun. 2020.

[82] D. Shakthivel, W. Navaraj, S. Champet, D. H. Gregory, and R. S. Dahiya, "Propagation of amorphous oxide nanowires via the VLS mechanism: Growth kinetics," *Nanoscale Adv.*, vol. 1, no. 9, pp. 3568–3578, 2019.

[83] I. Yaroshenko *et al.*, "Real-time wáter quality monitoring with chemical sensors," *Sensors*, vol. 20, no. 12, p. 3432, 2020.

[84] K. V. Ragavan and S. Neethirajan, "Nanoparticles as biosensors for food quality and safety assessment," in *Nanomaterials for Food Applications*. Amsterdam, the Netherlands: Elsevier, 2019, pp. 147–202.

[85] P. J. Vikesland, "Nanosensors for water quality monitoring," *Nat. Nanotechnol.*, vol. 13, no. 8, pp. 651–660, 2018.

[86] Y. Qin *et al.*, "Integrated water quality monitoring system with pH, free chlorine, and temperature sensors," *Sensor. Actuators B, Chem.*, vol. 255, pp. 781–790, Feb. 2018.

[87] P. Marsh *et al.*, "Flexible iridium oxide based pH sensor integrated with inductively coupled wireless transmission system for wearable applications," *IEEE Sensors J.*, vol. 20, no. 10, pp. 5130–5138, May 2020.

[88] M. Wang, F. Wang, Y. Wang, W. Zhang, and X. Chen, "Polydiacetylene-based sensor for highly sensitive and selective Pb^{2+} detection," *Dyes Pigments*, vol. 120, pp. 307–313, Sep. 2015.

[89] V. S. Palaparthy, M. S. Baghini, and D. N. Singh, "Review of polymer-based sensors for agriculture-related applications," *Emerg. Mater. Res.*, vol. 2, no. 4, pp. 166–180, 2013.

[90] S. Khan, L. Lorenzelli, and R. S. Dahiya, "Technologies for printing sensors and electronics over large flexible substrates: A review," *IEEE Sensors J.*, vol. 15, no. 6, pp. 3164–3185, Jun. 2015.

[91] L. Manjakkal, D. Shakthivel, and R. Dahiya, "Flexible printed reference electrodes for electrochemical applications," *Adv. Mater. Technol.*, vol. 3, no. 12, 2018, Art. no. 1800252.

[92] L. Manjakkal, A. Vilouras, and R. Dahiya, "Screen printed thick film reference electrodes for electrochemical sensing," *IEEE Sensors J.*, vol. 18, no. 19, pp. 7779–7785, Oct. 2018.

[93] L. Manjakkal, C. L. Pascual, and R. Dahiya, "Electrochemical sensors with screen printed Ag|AgCl|KCl reference electrodes," in *Proc. IEEE SENSORS*, 2017, pp. 1–3.

[94] A. W. J. Cranny and J. K. Atkinson, "Thick film silver-silver chloride reference electrodes," *Meas. Sci. Technol.*, vol. vol. 9, no. 9, pp. 1557–1565, 1998.

[95] J. Atkinson, M. Glanc, P. Boltryk, M. Sophocleous, and E. Garcia-Breijo, "An investigation into the effect of fabrication parameter variation on the characteristics of screen-printed thick-film silver/silver chloride reference electrodes," *Microelectron. Int.*, vol. 28, no. 2, pp. 49–52, 2011.

[96] M. Sophocleous and J. K. Atkinson, "A review of screen-printed silver/silver chloride (Ag/AgCl) reference electrodes potentially suitable for environmental potentiometric sensors," *Sensor. Actuators A, Phys.*, vol. 267, pp. 106–120, Nov. 2017.

[97] P. Kurzweil, "Metal oxides and ion-exchanging surfaces as pH sensors in liquids: State-of-the-art and outlook," *Sensors*, vol. 9, no. 6, pp. 4955–4985, 2009.

[98] S. Zhuiykov, "Morphology and sensing characteristics of nanostructured RuO_2 electrodes for integrated water quality monitoring sensors," *Electrochem. Commun.*, vol. 10, no. 6, pp. 839–843, 2008.

[99] H. Suzuki, A. Hiratsuka, S. Sasaki, and I. Karube, "Problems associated with the thin-film Ag/AgCl reference electrode and a novel structure with improved durability," *Sensor. Actuators B, Chem.*, vol. 46, no. 2, pp. 104–113, 1998.

[100] A. Vilouras, A. Christou, L. Manjakkal, and R. Dahiya, "Ultrathin ion-sensitive field-effect transistor chips with bending-induced performance enhancement," *ACS Appl. Electron. Mater.*, vol. 2, no. 8, pp. 2601–2610, 2020.

[101] Y.-H. Liao and J.-C. Chou, "Preparation and characteristics of ruthenium dioxide for pH array sensors with real-time measurement system," *Sensor. Actuators B, Chem.*, vol. 128, no. 2, pp. 603–612, 2008.

[102] S. Zhuiykov, "Development of ceramic electrochemical sensor based on Bi2Ru2O7+ x− RuO2 sub-micron oxide sensing electrode for water quality monitoring," *Ceram. Int.*, vol. 36, no. 8, pp. 2407–2413, 2010.

[103] L. Manjakkal, K. Cvejin, J. Kulawik, K. Zaraska, D. Szwagierczak, and G. Stojanovic, "Sensing mechanism of RuO2–SnO2 thick film pH sensors studied by potentiometric method and electrochemical impedance spectroscopy," *J. Electroanal. Chem.*, vol. 759, pp. 82–90, Dec. 2015.

[104] L. Manjakkal, E. Djurdjic, K. Cvejin, J. Kulawik, K. Zaraska, and D. Szwagierczak, "Electrochemical impedance spectroscopic analysis of RuO_2J based thick film pH sensors," *Electrochimica Acta*, vol. 168, pp. 246–255, Jun. 2015.

[105] K. Arshak, E. Gill, A. Arshak, and O. Korostynska, "Investigation of tin oxides as sensing layers in conductimetric interdigitated pH sensors," *Sensor. Actuators B: Chem.*, vol. 127, no. 1, pp. 42–53, 2007.

[106] O. Korostynska, A. Mason, and A. I. Al-Shamma'a, "Flexible microwave sensors for real-time analysis of water contaminants," *J. Lectromagn. Waves Appl.*, vol. 27, no. 16, pp. 2075–2089, 2013.

[107] M. Simić, L. Manjakkal, K. Zaraska, G. M. Stojanović, and R. Dahiya, "TiO2-based thick film pH sensor," *IEEE Sensors J.*, vol. 17, no. 2, pp. 248–255, Jan. 2017.

[108] L. Manjakkal, F. Nikbakhtnasrabadi, and R. Dahiya, "Energy autonomous sensors for water quality monitoring," in *Proc. IEEE SENSORS*, 2018, pp. 1–4.

[109] L. Manjakkal, K. Cvejin, J. Kulawik, K. Zaraska, R. P. Socha, and D. Szwagierczak, "X-ray photoelectron spectroscopic and electrochemical impedance spectroscopic analysis of RuO2-Ta2O5 thick film pH sensors," *Analytica Chimica Acta*, vol. 931, pp. 47–56, Aug. 2016.

[110] Y. Li, Y. Mao, C. Xiao, X. Xu, and X. Li, "Flexible pH sensor based on a conductive PANI membrane for pH monitoring," *RSC Adv.*, vol. 10, no. 1, pp. 21–28, 2020.

[111] E. Gill, A. Arshak, K. Arshak, and O. Korostynska, "Response mechanism of novel polyaniline composite conductimetric pH sensors and

the effects of polymer binder, surfactant and film thickness on sensor sensitivity," *Eur. Polymer J.*, vol. 46, no. 10, pp. 2042–2050, 2010.

[112] Y.-K. Yen, K.-Y. Lee, C.-Y. Lin, S.-T. Zhang, C.-W. Wang, and T.-Y. Liu, "Portable nanohybrid paper-based chemiresistive sensor for free chlorine detection," *ACS Omega*, vol. 5, no. 39, pp. 25209–25215, 2020.

[113] J.-Y. Jeon, B.-C. Kang, and T.-J. Ha, "Flexible pH sensors based on printed nanocomposites of single-wall carbon nanotubes and Nafion," *Appl. Surface Sci.*, vol. 514, Jun. 2020, Art. no. 145956.

[114] H. Qi, J. Liu, Y. Deng, S. Gao, and E. Mäder, "Cellulose fibres with carbon nanotube networks for water sensing," *J. Mater. Chem. A*, vol. 2, no. 15, pp. 5541–5547, 2014.

[115] S. Zhuiykov, "Potentiometric DO detection in water by ceramic sensor based on sub-micron RuO2 sensing electrode," *Ionics*, vol. 15, no. 6, p. 693, 2009.

[116] J. K. Atkinson, A. W. J. Cranny, W. V. Glasspool, and J. A. Mihell, "An investigation of the performance characteristics and operational lifetimes of multi-element thick film sensor arrays used in the determination of water quality parameters," *Sensor. Actuators B, Chem.*, vol. 54, no. 3, pp. 215–231, 1999.

[117] R. Das, B. Chaterjee, A. Kapil, and T. K. Sharma, "Aptamer-NanoZyme mediated sensing platform for the rapid detection of Escherichia coli in fruit juice," *Sens. Bio-Sens. Res.*, vol. 27, Art. no. 100313, Feb. 2020.

[118] R. Rajapaksha, U. Hashim, M. A. Uda, C. A. Fernando, and S. De Silva, "Target ssDNA detection of E.coli O157: H7 through electrical based DNA biosensor," *Microsys. Technol.*, vol. 23, no. 12, pp. 5771–5780, 2017.

[119] M. Xu, R. Wang, and Y. Li, "An electrochemical biosensor for rapid detection of E.coli O157: H7 with highly efficient bi-functional glucose oxidase-polydopamine nanocomposites and Prussian blue modified screen-printed interdigitated electrodes," *Analyst*, vol. 141, no. 18, pp. 5441–5449, 2016.

[120] K. Yamada, W. Choi, I. Lee, B.-K. Cho, and S. Jun, "Rapid detection of multiple foodborne pathogens using a nanoparticle-functionalized multi-junction biosensor," *Biosensor. Bioelectron.*, vol. 77, pp. 137–143, Mar. 2016.

[121] Y. Lu, Y. Liu, Y. Zhao, W. Li, L. Qiu, and L. Li, "A novel and disposable enzyme-labeled amperometric immunosensor based on MWCNT fibers for Listeria monocytogenes detection," *J. Nanomater.*, vol. 2016, Jun. 2016, Art. no. 3895920.

[122] N. Dhull *et al.*, "Label-free amperometric biosensor for Escherichia coli O157: H7 detection," *Appl. Surface Sci.*, vol. 495, Nov. 2019, Art. no. 143548.

[123] M.-S. Yoo *et al.*, "Development of electrochemical biosensor for detection of pathogenic microorganism in Asian dust events," *Chemosphere*, vol. 175, pp. 269–274, May 2017.

[124] X. Zhang *et al.*, "Conductometric sensor for viable Escherichia coli and Staphylococcus aureus based on magnetic analyte separation via aptamer," *Microchimica Acta*, vol. 187, no. 1, p. 43, 2020.

[125] Z. Yang, Y. Liu, C. Lei, X.-C. Sun, and Y. Zhou, "Ultrasensitive detection and quantification of E.coli O157: H7 using a giant magnetoimpedance sensor in an open-surface microfluidic cavity covered with an antibody-modified gold surface," *Microchimica Acta*, vol. 183, no. 6, pp. 1831–1837, 2016.

[126] M. Cimafonte *et al.*, "Screen printed based impedimetric immunosensor for rapid detection of Escherichia coli in drinking water," *Sensors*, vol. 20, no. 1, p. 274, 2020.

[127] J. Wan, J. Ai, Y. Zhang, X. Geng, Q. Gao, and Z. Cheng, "Signal-off impedimetric immunosensor for the detection of Escherichia coli O157: H7," *Sci. Rep.*, vol. 6, Jan. 2016, Art. no. 19806.

[128] A. Gupta, S. K. Bhardwaj, A. L. Sharma, K.-H. Kim, and A. Deep, "Development of an advanced electrochemical biosensing platform for E. coli using hybrid metal-organic framework/polyaniline composite," *Environ. Res.*, vol. 171, pp. 395–402, Apr. 2019.

[129] J. Wu, R. Wang, Y. Lu, M. Jia, J. Yan, and X. Bian, "Facile preparation of a bacteria imprinted artificial receptor for highly selective bacterial recognition and label-free impedimetric detection," *Anal. Chem.*, vol. 91, no. 1, pp. 1027–1033, 2018.

[130] Z. Izadi, M. Sheikh-Zeinoddin, A. A. Ensafi, and S. Soleimanian-Zad, "Fabrication of an electrochemical DNA-based biosensor for Bacillus cereus detection in milk and infant formula," *Biosensor. Bioelectron.*, vol. 80, pp. 582–589, Jun. 2016.

[131] P. Pathania, A. Sharma, B. Kumar, P. Rishi, and C. R. Suri, "Selective identification of specific aptamers for the detection of non-typhoidal salmonellosis in an apta-impedimetric sensing format," *Microchimica Acta*, vol. 184, no. 5, pp. 1499–1508, 2017.

[132] N. F. Silva, C. M. R. Almeida, J. M. C. S. Magalhães, M. P. Gonçalves, C. Freire, and C. Delerue-Matos, "Development of a disposable paper-based potentiometric immunosensor for real-time detection of a foodborne pathogen," *Biosens. Bioelectron.*, vol. 141, Sep. 2019, Art. no. 111317.

[133] G. Zhao, J. Ding, H. Yu, T. Yin, and W. Qin, "Potentiometric aptasensing of Vibrio alginolyticus based on DNA nanostructure-modified magnetic beads," *Sensors*, vol. 16, no. 12, p. 2052, 2016.

[134] A. A. Lahcen, F. Arduini, F. Lista, and A. Amine, "Label-free electrochemical sensor based on spore-imprinted polymer for Bacillus cereus spore detection," *Sens. Actuators B, Chem.*, vol. 276, pp. 114–120, Dec. 2018.

[135] R. Hua *et al.*, "A sensitive Potentiometric resolved ratiometric photoelectrochemical aptasensor for Escherichia coli detection fabricated with non-metallic nanomaterials," *Biosens. Bioelectron.*, vol. 106, pp. 57–63, May 2018.

[136] Y. Tian *et al.*, "Label-free detection of E. coli O157: H7 DNA using light-addressable potentiometric sensors with highly oriented ZnO nanorod arrays," *Sensors*, vol. 19, no. 24, p. 5473, 2019.

[137] Y. Chen *et al.*, "Recent advances in rapid pathogen detection method based on biosensors," *Eur. J. Clin. Microbiol. Infect. Dis.*, vol. 37, no. 6, pp. 1021–1037, 2018.

[138] G. Sai-Anand *et al.*, "Recent progress on the sensing of pathogenic bacteria using advanced nanostructures," *Bull. Chem. Soc. Japan*, vol. 92, no. 1, pp. 216–244, 2019.

[139] H. Kumar *et al.*, "Applications of nanotechnology in biosensor-based detection of foodborne pathogens," *Sensors*, vol. 20, no. 7, p. 1966, 2020.

[140] P. J. Vikesland and K. R. Wigginton, "Nanomaterial enabled biosensors for pathogen monitoring—A review," *Environ. Sci. Technol.*, vol. 44, no. 10, pp. 3656–3669, 2010.

[141] S. Sharifi *et al.*, "Detection of pathogenic bacteria via nanomaterials-modified aptasensors," *Biosens. Bioelectron.*, vol. 150, Feb. 2020, Art. no. 111933.

[142] N. Elahi, M. Kamali, and M. H. Baghersad, "Recent biomedical applications of gold nanoparticles: A review," *Talanta*, vol. 184, pp. 537–556, Jul. 2018.

[143] M. Pastucha, Z. Farka, K. Lacina, Z. Mikušová, and P. Skládal, "Magnetic nanoparticles for smart electrochemical immunoassays: A review on recent developments," *Microchimica Acta*, vol. 186, no. 5, p. 312, 2019.

[144] F. Zhu, G. Zhao, and W. Dou, "Electrochemical sandwich immunoassay for Escherichia coli O157: H7 based on the use of magnetic nanoparticles and graphene functionalized with electrocatalytically active Au@ Pt core/shell nanoparticles," *Microchimica Acta*, vol. 185, no. 10, p. 455, 2018.

[145] J. Han, M. Wang, Y. Hu, C. Zhou, and R. Guo, "Conducting polymer-noble metal nanoparticle hybrids: Synthesis mechanism application," *Progr. Polym. Sci.*, vol. 70, pp. 52–91, Jul. 2017.

[146] E. Morales-Narváez, L. Baptista-Pires, A. Zamora-Gálvez, and A. Merkoçi, "Graphene-based biosensors: Going simple," *Adv. Mater.*, vol. 29, no. 7, 2017, Art. no. 1604905.

[147] M. R. Hasan *et al.*, "Carbon nanotube-based aptasensor for sensitive electrochemical detection of whole-cell Salmonella," *Anal. Biochem.*, vol. 554, pp. 34–43, Aug. 2018.

[148] Y. Luo, W. Dou, and G. Zhao, "Rapid electrochemical quantification of Salmonella Pullorum and Salmonella Gallinarum based on glucose oxidase and antibody-modified silica nanoparticles," *Anal. Bioanal. Chem.*, vol. 409, no. 17, pp. 4139–4147, 2017.

[149] F. Huang *et al.*, "An acid-responsive microfluidic salmonella biosensor using curcumin as signal reporter and ZnO-capped mesoporous silica nanoparticles for signal amplification," *Sensor. Actuators B, Chem.*, vol. 312, Jun. 2020, Art. no. 127958.

[150] T. J. Smyth *et al.*, "A broad spatio-temporal view of the Western English Channel observatory," *J. Plankton Res.*, vol. 32, no. 5, pp. 585–601, 2010.

[151] R. J. Brewin, L. de Mora, T. Jackson, T. G. Brewin, and J. Shutler, "On the potential of surfers to monitor environmental indicators in the coastal zone," *PLoS One*, vol. 10, no. 7, 2015, Art. no. e0127706.

[152] O. Defeo *et al.*, "Threats to sandy beach ecosystems: A review," *Estuarine Coastal Shelf Sci.*, vol. 81, no. 1, pp. 1–12, 2009.

[153] H. B. Glasgow, J. M. Burkholder, R. E. Reed, A. J. Lewitus, and J. E. Kleinman, "Real-time remote monitoring of water quality: A review of current applications, and advancements in sensor, telemetry, and computing technologies," *J. Exp. Mar. Biol. Ecol.*, vol. 300, nos. 1–2, pp. 409–448, 2004.

[154] R. Mourya, W. Saafin, M. Dragone, and Y. Petillot, "Ocean monitoring framework based on compressive sensing using acoustic sensor networks," in *Proc. MTS/IEEE OCEANS Charleston*, 2018, pp. 1–10.

[155] W. Schmidt *et al.*, "Design and operation of a low-cost and compact autonomous buoy system for use in coastal aquaculture and water quality monitoring," *Aquacul. Eng.*, vol. 80, pp. 28–36, Jan. 2018.

[156] K. Anderson and K. J. Gaston, "Lightweight unmanned aerial vehicles will revolutionize spatial ecology," *Front. Ecol. Environ.*, vol. 11, no. 3, pp. 138–146, 2013.

[157] J. P. Duffy, L. Pratt, K. Anderson, P. E. Land, and J. D. Shutler, "Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone," *Estuarine Coastal Shelf Sci.*, vol. 200, pp. 169–180, Jan. 2018.

[158] C. Koparan, A. B. Koc, C. V. Privette, and C. B. Sawyer, "In situ water quality measurements using an unmanned aerial vehicle (UAV) system," *Water*, vol. 10, no. 3, p. 264, 2018.

[159] J. Das *et al.*, "Data-driven robotic sampling for marine ecosystem monitoring," *Int. J. Robot. Res.*, vol. 34, no. 12, pp. 1435–1452, 2015.

[160] X. Li, X. Xu, L. Yan, H. Zhao, and T. Zhang, "Energy-efficient data collection using autonomous underwater glider: A reinforcement learning formulation," *Sensors*, vol. 20, no. 13, p. 3758, 2020.

[161] H. Li, X. Liu, L. Li, X. Mu, R. Genov, and A. J. Mason, "CMOS electrochemical instrumentation for biosensor microsystems: A review," *Sensors*, vol. vol. 17, no. 1, p. 74, 2017.

[162] Z. Czaja, "Using a square-wave signal for fault diagnosis of analog parts of mixed-signal electronic embedded systems," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 8, pp. 1589–1595, Aug. 2008.

[163] J. M. Barcelo-Ordinas, M. Doudou, J. Garcia-Vidal, and N. Badache, "Self-calibration methods for uncontrolled environments in sensor networks: A reference survey," *Ad Hoc Netw.*, vol. 88, pp. 142–159, May 2019.

[164] F. Delaine, B. Lebental, and H. Rivano, "In situ calibration algorithms for environmental sensor networks: A review," *IEEE Sensors J.*, vol. 19, no. 15, pp. 5968–5978, Aug. 2019.

[165] S. O. Olatinwo and T. Joubert, "Energy efficient solutions in wireless sensor systems for water quality monitoring: A review," *IEEE Sensors J.*, vol. 19, no. 5, pp. 1596–1625, Mar. 2019.

[166] L. X. Chuo *et al.*, "7.4 A 915MHz asymmetric radio using Q-enhanced amplifier for a fully integrated $3\times3\times3\text{mm}^3$ wireless sensor node with 20m non-line-of-sight communication," in *Proc. IEEE Int. Solid-State Circuits Conf. (ISSCC)*, 2017, pp. 132–133.

[167] Y. Lee, D. Blaauw, and D. Sylvester, "Ultralow power circuit design for wireless sensor nodes for structural health monitoring," *IEEE Proc.*, vol. 104, no. 8, pp. 1529–1546, Aug. 2016.

[168] N. Morozs, P. D. Mitchell, and Y. Zakharov, "Dual-hop TDA-MAC and routing for underwater acoustic sensor networks," *IEEE J. Ocean. Eng.*, vol. 44, no. 4, pp. 865–880, Oct. 2019.

[169] N. Morozs *et al.*, "Robust TDA-MAC for practical underwater sensor network deployment: Lessons from USMART sea trials," in *Proc. 13th ACM Int. Conf. Underwater Netw. Syst.*, 2018, pp. 1–8.

[170] E. E. Peterson and J. M. V. Hoef, "A mixed-model moving-average approach to geostatistical modeling in stream networks," *Ecology*, vol. 91, no. 3, pp. 644–651, 2010.

[171] J. M. Ver Hoef and E. E. Peterson, "A moving average approach for spatial statistical models of stream networks," *J. Amer. Stat. Assoc.*, vol. 105, no. 489, pp. 6–18, 2010.

[172] K. Gallacher, C. Miller, E. Scott, R. Willows, L. Pope, and J. Douglass, "Flow-directed PCA for monitoring networks," *Environmetrics*, vol. 28, no. 2, 2017, Art. no. e2434.

[173] A. J. Neill *et al.*, "Using spatial-stream-network models and long-term data to understand and predict dynamics of faecal contamination in a mixed land-use catchment," *Sci. Total Environ.*, vol. 612, pp. 840–852, Jan. 2018.

[174] A. Gao, S. Wu, S. Zhu, and Z. Xu, "Wavelet and statistical analyses of river water quality parameters: A case study in the Lower Minnesota River," *Water Pract. Technol.*, vol. 13, no. 4, pp. 922–931, 2018.

[175] E. A. Mimouni, J. J. Ridal, J. D. Skufca, and M. R. Twiss, "A multiscale approach to water quality variables in a river ecosystem," *Ecosphere*, vol. 11, no. 2, 2020, Art. no. e03014.

[176] J. Ramsay and B. Silverman, *Applied Functional Data Analysis* (Springer Series in Statistics). New York, NY, USA: Springer, 2002.

[177] A. Elayouty, M. Scott, C. Miller, and S. Waldron, "Functional principal component analysis for non-stationary dynamic time series," in *33rd Int. Workshop Stat. Model. (IWSM)*, Bristol, U.K., pp. 84–89, Jul. 2018.

[178] R. Haggarty, C. Miller, and E. Scott, "Spatially weighted functional clustering of river network data," *J. Royal Stat. Soc. C, Appl. Stat.*, vol. 64, no. 3, p. 491, 2015.

[179] M. Franco-Villoria, M. Scott, and T. Hoey, "Spatiotemporal modeling of hydrological return levels: A quantile regression approach," *Environmetrics*, vol. 30, no. 2, 2019, Art. no. e2522.

[180] J. Tawn, R. Shooter, R. Towe, and R. Lamb, "Modelling spatial extreme events with environmental applications," *Spat. Stat.*, vol. 28, pp. 39–58, Dec. 2018.

[181] S. Decherchi, P. Gastaldo, R. S. Dahiya, M. Valle, and R. Zunino, "Tactile sensing data classification by computational intelligence," *IEEE Trans. Robot.*, vol. 27, no. 3, pp635–639, Jun. 2011.

[182] S. Mounce, C. Pedraza, T. Jackson, P. Linford, and J. Boxall, "Cloud based machine learning approaches for leakage assessment and management in smart water networks," *Procedia Eng.*, vol. 119, no. 1, pp. 43–52, 2015.

[183] W. P. Cantos, I. Juran, and S. Tinelli, "Machine-learning–based risk assessment method for leak detection and geolocation in a water distribution system," *J. Infrastruct. Syst.*, vol. 26, no. 1, 2020, Art. no. 04019039.

[184] A. Y. Sun and B. R. Scanlon, "How can Big Data and machine learning benefit environment and water management: A survey of methods, applications, and future directions," *Environ. Res. Lett.*, vol. 14, no. 7, 2019, Art. no. 073001.

[185] P. Tahmasebi, S. Kamrava, T. Bai, and M. Sahimi, "Machine learning in geo-and environmental sciences: From small to large scale," *Adv. Water Res.*, vol. 142, Aug. 2020, Art. no. 103619.

[186] G. Blair *et al.*, "Data science of the natural environment: A research roadmap," *Front. Environ. Sci.*, vol. 7, p. 121, Aug. 2019.

[187] N.-B. Chang and K. Bai, *Multisensor Data Fusion and Machine Learning for Environmental Remote Sensing*. Boca Raton, FL, USA: CRC Press, 2018.

[188] C. J. Wilkie *et al.*, "Nonparametric statistical downscaling for the fusion of data of different spatiotemporal support," *Environmetrics*, vol. 30, no. 3, 2019, Art. no. e2549.

[189] T. Meng, X. Jing, Z. Yan, and W. Pedrycz, "A survey on machine learning for data fusion," *Informat. Fusion*, vol. 57, pp. 115–129, May 2020.

[190] H. Jenny, E. G. Alonso, Y. Wang, and R. Minguez, *Using Artificial Intelligence for Smart Water Management Systems* (ADB Briefs). Metro Manila, Philippines: Asian Develop. Bank, 2020.

[191] E. M. Scott, "The role of Statistics in the era of big data: Crucial, critical and under-valued," *Stat. Probab. Lett.*, vol. 136, pp. 20–24, May 2018.

[192] J. L. Campbell *et al.*, "Quantity is nothing without quality: Automated QA/QC for streaming environmental sensor data," *BioScience*, vol. 63, no. 7, pp. 574–585, 2013.

[193] L. Manjakkal, I. P. Selvam, S. Potty, and R. Shinde, "Electrical and optical properties of aluminium doped zinc oxide transparent conducting oxide films prepared by dip coating technique," *Microelectron. Int.*, vol. 34, no. 1, pp. 1–8, 2017.

[194] R. Dahiya, "E-Skin: From humanoids to humans," *Proc. IEEE*, vol. 107, no. 2, pp. 247–252, Feb. 2019.

[195] M. Bhattacharjee, S. Middya, P. Escobedo, J. Chaudhuri, D. Bandyopadhyay, R. Dahiya, "Microdroplet based disposable sensor patch for detection of α-amylase in human blood serum," *Biosens. Bioelectron.*, vol. 165, Oct. 2020, Art. no. 112333.

[196] L. Manjakkal, F. F. Franco, A. Pullanchiyodan, M. G.-Jiménez, R. Dahiya, "Natural jute fibre-based supercapacitors and sensors for eco-friendly energy autonomous systems," *Adv. Sust. Syst.*, vol. 5, no. 3, 2021, Art. no. 2000286.

[197] L. Manjakkal, W. Dang, N. Yogeswaran, and R. Dahiya, "Textile-based potentiometric electrochemical pH sensor for wearable applications," *Biosensors*, vol. 9, no. 1, p. 14, 2019.

[198] L. Manjakkal, S. Dervin, and R. Dahiya, "Flexible potentiometric pH sensors for wearable systems," *RSC Adv.*, vol. 10, no. 15, pp. 8594–8617, 2020.

[199] M. K. Amruta and M. T. Satish, "Solar powered water quality monitoring system using wireless sensor network," in *Proc. IEEE Int. Mutli-Conf. Autom. Comput. Commun. Control Compressed Sens. (iMac4s)*, 2013, pp. 281–285.

[200] M. Dunbabin, A. Grinham, and J. Udy, "An autonomous surface vehicle for water quality monitoring," in *Proc. Aust. Conf. Robot. Autom. (ACRA)*, 2009, pp. 2–4.

[201] G. Pasternak, J. Greenman, and I. Ieropoulos, "Self-powered, autonomous Biological Oxygen Demand biosensor for online water quality monitoring," *Sens. Actuators B, Chem.*, vol. 244, pp. 815–822, Jun. 2017.

[202] Y. Xu, G. Min, N. Gadegaard, R. Dahiya, and D. M. Mulvihill, "A unified contact force-dependent model for triboelectric nanogenerators accounting for surface roughness," *Nano Energy*, vol. 76, 2020, Art. no. 105067.

[203] G. Min, L. Manjakkal, D. M. Mulvihill, R. S. Dahiya, "Triboelectric nanogenerator with enhanced performance via an optimized low permittivity substrate," *IEEE Sensors J.*, vol. 20, no. 13, pp. 6856–6862, Jul. 2020.

[204] G. Min, Y. Xu, P. Cochran, N. Gadegaard, D. M. Mulvihill, and R. Dahiya, "Origin of the contact force-dependent response of triboelectric nanogenerators," *Nano Energy*, vol. 83, 2021, Art. no. 105829.

[205] A. V. Kontrick, "Microplastics and human health: Our great future to think about now," *J. Med. Toxicol.*, vol. 14, pp. 117–119, Apr. 2018.

[206] R. Street, S. Malema, N. Mahlangeni, and A. Mathee, "COVID-19 wastewater surveillance: An African perspective," *Sci. Total Environ.*, vol. 743, Nov. 2020, Art. no. 140719.

[207] D. Garcia, V. Puig, and J. Quevedo, "Prognosis of water quality sensors using advanced data analytics: Application to the Barcelona drinking water network," *Sensors*, vol. 20, no. 5, p. 1342, 2020.

[208] X. Su, L. Sutarlie, and X. J. Loh, "Sensors, biosensors, and analytical technologies for aquaculture water quality," *Research*, vol. 2020, Feb. 2020, Art. no. 8272705.

[209] A. I. Flores-Anderson *et al.*, "Hyperspectral satellite remote sensing of water quality in Lake Atitlan, Guatemala," *Front. Environ. Sci.*, vol. 8, p. 7, Feb. 2020.

[210] V. Sagan *et al.*, "Monitoring inland water quality using remote sensing: Potential and limitations of spectral indices, bio-optical simulations, machine learning, and cloud computing," *Earth-Sci. Rev.*, vol. 205, Jun. 2020, Art. no. 103187.

[211] A. Salam, "Internet of Things in water management and treatment," in *Internet of Things for Sustainable Community Development*, Cham, Switzerland: Springer, 2020, pp. 273–298.

[212] Y. Chebud, G. M. Naja, R. G. Rivero, and A. M. Melesse, "Water quality monitoring using remote sensing and an artificial neural network," *Water Air Soil Pollut.*, vol. 223, no. 8, pp. 4875–4887, 2012.

[213] T. Kageyama, M. Miura, A. Maeda, A. Mori, and S.-S. Lee, "A wireless sensor network platform for water quality monitoring," in *Proc. IEEE SENSORS*, 2016, pp. 1–3.

[214] S. Geetha and S. Gouthami, "Internet of Things enabled real time water quality monitoring system," *Smart Water*, vol. 2, no. 1, pp. 1–19, 2016.

[215] L. Manjakkal, L. Lorenzelli, M. Willander, R. Dahiya, *Sensing Technologies for Real Time Monitoring of Water Quality*. Hoboken, NJ, USA: Wiley, 2021.

[216] J. Crocker and J. Bartram, "Comparison and cost analysis of drinking water quality monitoring requirements versus practice in seven developing countries," *Int. J. Environ. Res. Public Health*, vol. 11, no. 7, pp. 7333–7346, 2014

[217] A. Paul, M. Bhattacharya, and R. Dahiya, *Solid-State Sensors*, Hoboken, NJ, USA: Wiley, 2021.

[218] M. Banna *et al.*, "3D printing-based integrated water quality sensing system," *Sensors*, vol. 17, no. 6, p. 1336, 2017.

[219] M. Ntagios, H. Nassar, A. Pullanchiyodan, W. T. Navaraj, and R. Dahiya, "Robotic hands with intrinsic tactile sensing via 3D printed soft pressure sensors," *Adv. Intell. Syst.*, vol. 2, no. 6, 2020, Art. no. 1900080.

[220] Y. Ni, R. Ji, K. Long, T. Bu, K. Chen, and S. Zhuang, "A review of 3D printed sensors," *Appl. Spectrosc. Rev.*, vol. 52, no. 7, pp. 623–652, 2017.

[221] S. A. Jaywant and K. M. Arif, "A comprehensive review of microfluidic water quality monitoring sensors," *Sensors*, vol. 19, no. 21, p. 4781, 2019.

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