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Systematic Review

Internet of Things (IoT) Sensors for Water Quality Monitoring in Aquaculture Systems: A Systematic Review and Bibliometric Analysis

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Abstract: This review aims to study the applications of sensors for monitoring and controlling the physicochemical parameters of water in aquaculture systems such as Biofloc Technology (BFT), Recirculating Aquaculture Systems (RASs), and aquaponic systems using IoT technology, as well as identify potential knowledge gaps. A bibliometric analysis and systematic review were conducted using the Scopus database between 2020 and 2024. A total of 217 articles were reviewed and analyzed. Our findings indicated a significant increase (74.79%) in research between 2020 and 2024. pH was the most studied physicochemical parameter in aquaculture, analyzed in 98.2% of cases (sensors: SEN0169, HI-98107, pH-4502C, Grove-pH), followed by temperature (92.9%, sensor DS18B20) and dissolved oxygen (62.5%, sensors: SEN0237, MAX30102, OxyGuard DO model 420, ZTWL-SZO2-485, Lutron DO-5509). Overall, water monitoring through the implementation of IoT sensors improved growth rates, reduced culture mortality rates, and enabled the rapid prediction and detection of atypical Total Ammonia Nitrogen (TAN) levels. IoT sensors for water quality monitoring in aquaponics also facilitate the evaluation and prediction of seed and vegetable growth and germination. In conclusion, despite recent advancements, challenges remain in automating parameter control, ensuring effective sensor maintenance, and improving operability in rural areas, which need to be addressed.

Keywords: Biofloc technology (BFT); Recirculating Aquaculture System (RAS); aquaponic system; Internet of Things (IoT); real-time; water management; freshwater

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1. Introduction

Aquaculture is a key activity contributing to global food security [1]. Its expansion has generated worldwide growth in the consumption of aquaculture resources. It is currently one of the main suppliers of fishery inputs, a source of proteins, vitamins, and minerals of high nutritional value, significantly increasing the production of fishery products [2], with an impact of 87.5 million tons of aquatic animals valued at USD 264.8 billion [2,3]. This growth has promoted the implementation of new farming systems, such as Biofloc

Technology (BFT), Recirculating Aquaculture Systems (RASs), and Aquaponic Systems, to improve and increase production. However, the increased use of these systems brings several challenges that must be addressed to maintain cultural stability [4]. One of the main ones is water quality, a critical aspect that requires equilibrating different parameters to prevent the increase in pathogenic organisms [5,6].

One of the main challenges in aquaculture is the optimal maintenance of water quality since the balance of physicochemical parameters is essential to avoid the development of pathogenic organisms to ensure the sustainability of production [7,8]. Factors such as pH, temperature, dissolved oxygen, turbidity, and Total Dissolved Solids must be maintained within adequate ranges to prevent the growth of pathogenic microorganisms and reduce susceptibility to bacterial or fungal infections [8,9]. The instability of these parameters during the production phase can cause high mortality rates, directly affecting food safety and the profitability of the aquaculture sector [9]. Despite advances in water quality monitoring in aquaculture, conventional methods still present significant limitations. Although effective, manual sampling and laboratory analysis are laborious and costly processes and do not allow the immediate detection of changes in critical water parameters [10–12]. The lack of automation in these procedures makes it difficult to make timely decisions, increasing the risk of production losses due to unexpected fluctuations in factors such as dissolved oxygen, pH, and temperature. These shortcomings have prompted the search for more efficient technological alternatives, most notably using sensors based on the Internet of Things (IoT) [13–15].

IoT connects objects to real situations or environments through a wireless network. These objects are integrated by electronic components (sensors, actuators), transmitters, microcontrollers, and algorithms, which improve the recording, process automation, and visualization of data on devices such as phones, computers, and tablets [16,17]. Recently, IoT technology has been used in different productive sectors, especially in aquaculture, due to its capacity to optimize processes and improve the use of resources. This technology reduces operating costs by real-time data collection, where all the parameters are transmitted to virtual platforms. This allows the real-time monitoring of pond water quality from smart devices [8,18–20]. To summarize and show the knowledge or applications in a specific subject, methods such as Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) and bibliometric analysis are required to facilitate the understanding and interpretation of big databases [21,22].

Given the increasing use of IoT sensors in aquaculture, it is essential to analyze the current state of research in this field. For this purpose, PRISMA is a method widely used in diverse research fields, from health sciences to humanities [23]. The field of aquaculture and fisheries is no exception and is used in production [24] and the health of fish culture [20]. This method identifies patterns, trends, and impacts within a specific thematic area, providing a global and accurate view of research development in the field. To develop this approach, we mainly use VosViewer tools, which allow us to dynamically observe trends, collaborative networks, and scientific production over the years [25–27].

Previous studies have explored the use of IoT technology for water quality monitoring in aquaculture. However, the present study provides a comprehensive review of 56 scientific papers published between 2020 and 2024, being the first to comprehensively analyze the advantages and challenges associated with implementing IoT sensors in different aquaculture systems. In Biofloc (BFT) systems, real-time monitoring via IoT enables the optimal growth of cultured organisms and reduces their mortality [10,28]. In Recirculating Aquaculture Systems (RASs), this technology facilitates the evaluation of Total Ammonia Nitrogen (TAN) levels, whose prolonged exposure can cause intoxication and mortality in aquatic organisms [29,30]. Likewise, in aquaponic systems, the constant monitoring of water quality parameters contributes to predicting seed and plant growth and optimizing the production of aquatic organisms [11].

This article is distributed as follows. Section 2 provides a detailed explanation of the data collection using the PRISMA methodology, followed by a bibliometric analysis. Section 3 identifies the annual production by country and the contribution of authors and affiliations and shows a network of keywords and future trends to be addressed. After distinguishing topics such as real-time water quality monitoring sensors in aquaculture systems, Section 4 sets out how the IoT works to monitor aquaculture water quality and identifies specific cultures that use this technology. Section 5 focuses on applying IoT sensors as an effective, safe, and low-cost alternative for real-time water monitoring in various systems such as BFT, RAS, and aquaponics. Finally, the review article concludes with Sections 6 and 7, detailing the challenges and insights that need to be addressed.

2. Methodology

2.1. Data Collection

The present review applies the PRISMA method (Appendix A), which comprises four stages: Identification, Selection, Eligibility, and Inclusion (Figure 1).

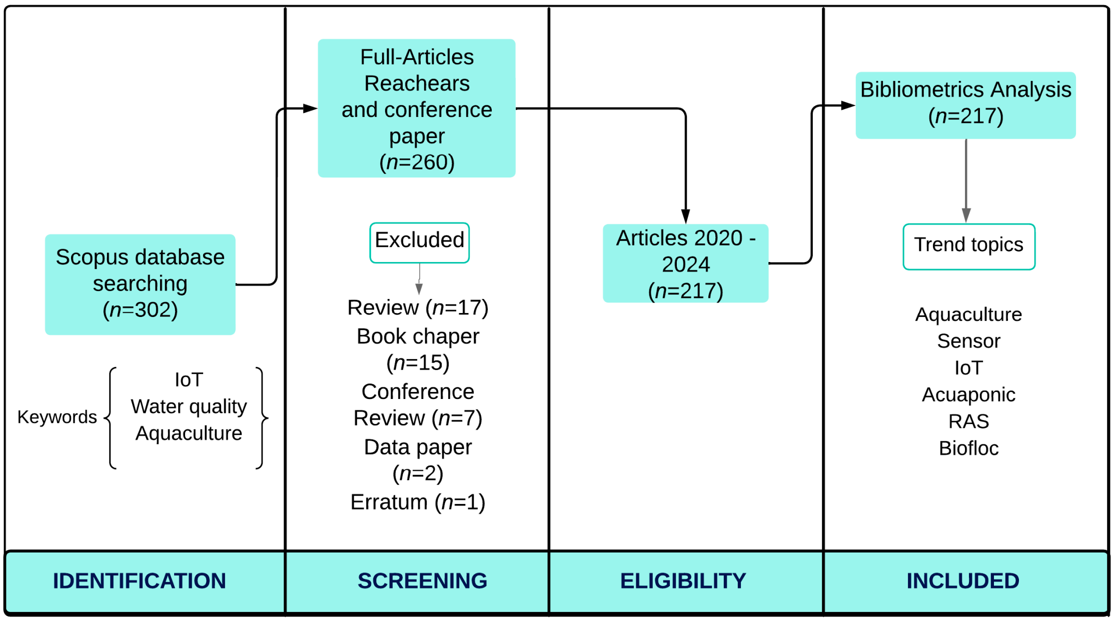

Figure 1. Schematic representation of the bibliographic search using the PRISMA method.

The identification stage was carried out in the Scopus database for its wide coverage in research, indexing quality, and advanced bibliometric analysis tools. Titles, abstracts, and keywords, including the following words, were selected in the search criteria: IoT, Water quality, and Aquaculture. A total of 302 documents were identified. We then selected publications of the "article" type, available in full text, published in English, and in the final publication stage. In the screening phase, reviews (n = 17), book chapters (n = 15), conference reviews (n = 7), data reviews (n = 2), and errata (n = 1) were excluded, leaving a total of 42 documents. In the eligibility phase, from the 260 papers, the publication years of 2020 and 2024 were selected (through 27 November 2024) [31]. Finally, 217 papers were included in the study (Appendix B).

2.2. Bibliometrics Analysis

The 217 documents were exported in .cvs format. The free software R (v 4.4.1), with the bibliometrix package and the biblioshiny function, was used for the bibliometric analysis. A network analysis was performed to identify the main connections and collaborations between authors, journals, affiliations, and scientific production in relation to topics on water quality monitoring using IoT technology [24,32], which can help to clarify the relationship between the selected keywords and the temporal evolution of critical points over time. Clusters were generated among the terms with the highest density of collaboration, which allowed for more clarity on the main themes underpinning the intellectual structure in the field of research. VosViewer software was used to visualize connections and clusters over time [33]. A factor analysis of concepts was also performed using a structure map that used multiple correspondence analysis (MCA) to determine the relationship between key terms and cluster groupings. In addition, the keywords were evaluated on a thematic map to observe the development and relevance of the themes through the keywords [27].

3. Performance and Network Analyses

The bibliometric analysis begins by describing the annual scientific production of the country and its contribution to research on monitoring water quality parameters using IoT sensors. This is followed by an analysis of the authors' contributions and affiliations. Finally, the trends of relevant keywords in the identified topics are addressed.

3.1. Annual Scientific Output

In the last four years, IoT-based research output has grown significantly. In 2020, 21 papers were reported, making up 9.6%. In 2021, 46 (21.1%) were reported. However, in 2023, this research had a slight decline, with 30 documents (13.8%). Nevertheless, between 2023 and 2024, 120 documents were registered, representing more than 55% of papers related to IoT technology's use in aquaculture water quality monitoring.

3.2. Scientific Production by Country

In terms of scientific production by country, India occupies the first place, with 33 documents; in second place is China with 19 documents, and it also stands out for having the highest number of collaborations in this type of research, 2 and 6, respectively. At the same time, countries such as Indonesia, Philippines, USA, Morocco, Algeria, Nigeria, and Peru register 19, 8, 4, 3, 1, and 1 research, respectively. It should be noted that, in countries such as Australia, Canada, Ireland, and Portugal, all the documents registered were carried out through international collaborations (Figure S1).

3.3. Authors Contribution

The h-index was analyzed to measure productivity and impact, citations per author, and total scientific production. Thus, Arepalli PG stands out with an h-index of 5, with nine documents (Figure S2) followed by 45 citations, being the most relevant author in this type of research. Among the topics addressed with the participation of Arepalli PG are the use of artificial intelligence to maintain water quality in optimal conditions and the evaluation of contaminants by computational analysis [34–36]. Authors such as Naik KJ and Ngon NC register an h-index of 5 and 3, with 25 and 89 citations in eight and three documents, respectively. Meanwhile, Ngon NC is the most cited author in the documents on water-quality-monitoring topics based on IoT systems and artificial intelligence [37–39], followed by Abdelouahid RA, Al Rasyid M, and Baccay M, who register an h-index of 2 with two documents submitted by each. Among the topics addressed by the authors is the design of monitoring water quality [40,41] in aquaponic systems using IoT [42,43].

3.4. Contribution of Affiliations

Among the most influential institutions employing IoT technology in aquaculture during 2020–2024 is The National Institute of Technology, Raipur, with 17 documents (Figure S3). Among the most prominent topics is the use of deep learning, such as long shortterm memory (LSTM) and neural convolution (CNN), to determine hypoxia conditions and efficient pond management [35,44]. At this institution, authors such as Arepalli and Naik stand out for their collaborative relevance. Meanwhile, De La Salle University (DLSU) is the second most relevant institution with the second largest contribution to the application of this technology, with a record of 14 documents. DLSU stands out mainly for its science and technology programs, which address design, digital signal processing, and computer architecture. For example, Paconit et al. [45] developed a water quality monitoring system using IoT, and Baldovino et al [46] implemented an automatic feeding system for *Cyprinus rubrofuscus* based on the same technology. The Department of Science and Technology (DST) from IND and Florida Atlantic University (FAU) from the USA registered 12 documents each. The DST is an institution that promotes the development of technologies with a sustainable approach [47], monitoring water quality in shrimp culture using the LoRaWAN connection and tilapia culture in a Recirculating Aquaculture System (RAS) [48]. FAU addresses automatic robot design that increases aeration on water surfaces in aquaculture ponds [49,50].

3.5. Keyword Analysis

The factor analysis (Figure 2), based on a structural map of concepts, distributes the key terms in four quadrants: the upper right quadrant associates concepts such as IoT, digital storage, deep learning, automation, and monitoring, focusing on technologies applied to water quality monitoring. The upper left quadrant groups terms related to water quality parameters such as pH, temperature, turbidity, dissolved oxygen, ammonium, and quality control. The lower quadrants are dominated by water management, water conservation, solar energy, and fish farming, highlighting a technological approach to improve the efficiency and management of water quality monitoring in aquaculture.

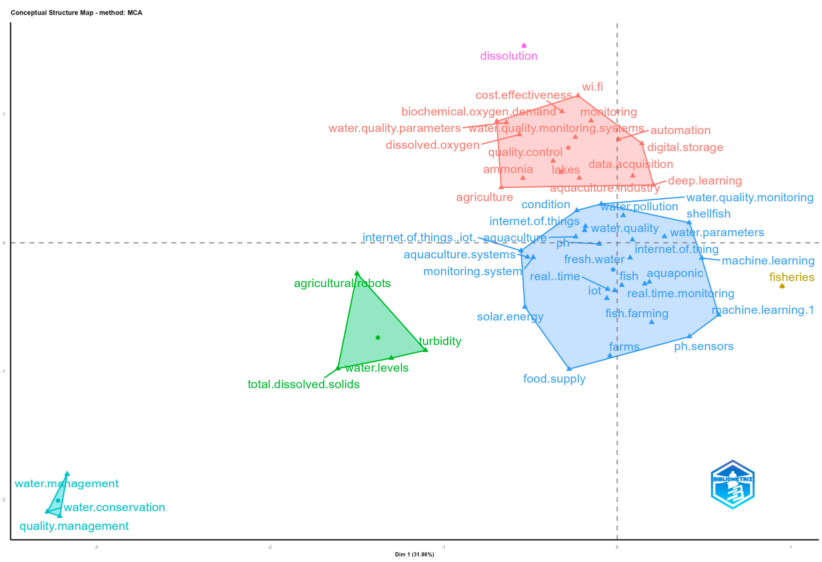

Figure 2. Factor analysis of concepts employing a structure map using multiple correspondence analysis (MCA).

Likewise, the thematic map (Figure 3) reveals the most addressed research topics (density) and with greater relevance (centrality); thus, themes such as water quality, IoT, and aquaculture make up the main topics, being the main keywords in this type of research. On the other hand, researchers highly address themes that are niche but of very low relevance, highlighting topics such as sensors, water parameters, and freshwater. While basic themes involve low research development, they are very relevant, with themes like real-time monitoring, machine learning, and deep learning predominating.

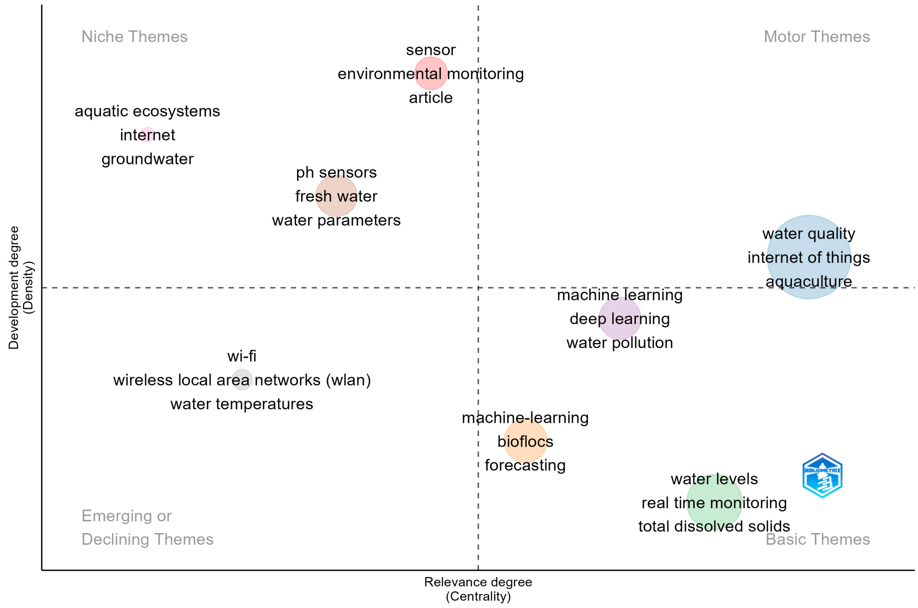

Figure 3. Thematic map on the density and relevance of water quality monitoring studies based on IoT technology.

However, emerging technologies such as wireless connectivity for data transmission have begun to capture interest in aquaculture research. In particular, Wi-Fi and WLAN (lower left quadrant, Figure 3), which allow wireless data transmission, is gaining relevance in this field. Furthermore, measuring parameters such as water temperature and its transmission through wireless connections could optimize water quality monitoring in aquaculture, improving the efficiency and accuracy of the process. For this reason, this review compiled 56 articles with relevant information on the use of IoT for monitoring and controlling water quality parameters in various aquaculture systems.

4. Internet of Things (IoT) in Aquaculture

The application of this technology is wide, from everyday (domestic) situations, such as the control of home electronic devices, to the development of complex activities, standing out in areas such as security, medicine, biology, and productive sectors such as agriculture and aquaculture [16,17]. The IoT is a tool that has increased its usefulness in aquaculture, as it facilitates the sending of information remotely for real-time decision-making [8,10].

The IoT architecture in aquaculture consists of four layers: sensing, processing, connectivity, and application. Sensors collect physicochemical data (pH, temperature), microcontrollers process them, and connectivity systems transmit them for real-time visualization. The Arduino UNO [10] is an inexpensive option for basic sensor integration among the most commonly used microcontrollers. ESP32 [51,52] offers greater capability with Wi-Fi and Bluetooth, which is ideal for advanced wireless applications. The Raspberry Pi [53,54] powers complex tasks such as AI and multisensor management. Other options include STM32F103 [55], PIC18F4550 (for aquaponics), and ATmega328 (used in Arduino Nano), each selected according to specific processing and power consumption needs. Regarding connectivity, Wi-Fi [56,57] is the most common choice because of its high speed and suitability for urban environments. LoRaWAN [47] stands out for its low power consumption and long range for remote areas. Bluetooth is used for short-range connections, while SMS (2G/3G/4G) [58,59] is useful in areas without internet access. Alternatively, NB-IoT [60], ZigBee [61], and LoRa [62] are used in low-power, low-bandwidth applications.

The inclusion of this technology is relevant in intensive culture due to the high stocking density, the large culture areas, and the high investment cost. This technology is ideal for automatic and continuous monitoring at a low cost in activities such as feeding and water quality control [10]. This last aspect is a substantial guideline for aquaculture management since the optimal management of the parameters that make up the water quality in a pond determines the productivity of the culture [63]; therefore, the present review identified 56 papers of the initial 217 that focus on the monitoring of water quality parameters using sensors using IoT technology in aquaculture.

4.1. Parameters Monitored Using IoT Sensors

Under the IoT concept applied to aquaculture, sensors are electronic devices used to obtain data in situ (perception layer); this information is transmitted via Wi-Fi, SMS, Bluetooth, or a LoRaWAN connection (network layer) to microcontrollers (processing layer) and then visualized by digital applications in smart devices (application layer) (Figure 4). The objective is to monitor the physicochemical parameters of the water and record their fluctuation over time [64–68].

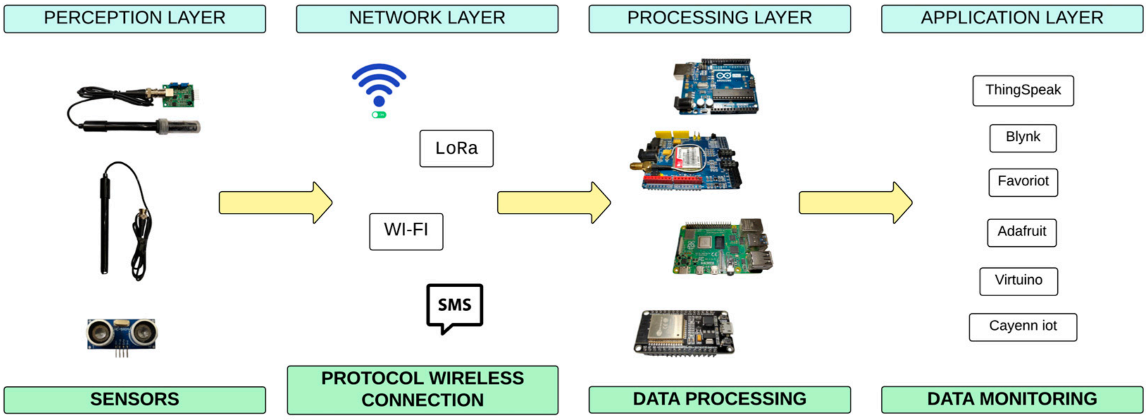

Figure 4. Graphical description of the technology operation using the Internet of Things to monitor water quality through sensors.

In this review, the documents collected use IoT technology to monitor the physicochemical parameters of water using sensors (Figure S4). The sensors with the highest incidence are pH in 55 papers (98.2%), temperature in 52 papers (92.9%), dissolved oxygen (DO) in 35 papers (62.5%), and Total Dissolved Solids (TDS) in 17 papers (30%). Meanwhile, turbidity, salinity, electrical conductivity (EC), ammonium, hardness, carbon monoxide (CO), carbon dioxide (CO_2), and water level were recorded in 16 (28.9%), 9 (16.1%), 8 (14.3%), 6 (10.7%), 1 (1.8%), 1 (1.8%), 1 (1.8%), and 1 (1.8%) documents, respectively. In addition, a water level sensor was used in 13 (23.3%) papers (Figure S4A). The following describes the most widely used sensors for water quality monitoring in aquaculture.

pH: Among the sensors used in this review, we have SEN0169, HI-98107, pH-4502C, and Grove-pH (Table 1). The SEN0169 has a glass electrode sensor that is widely used [58] for its compatibility with Arduino. It offers good accuracy (±0.1 pH) (Table S2) but requires frequent calibration (monthly) in high-biofilm environments like BFT. The pH-4502C is affordable and has an analog output, suitable for small-scale setups [69], though less precise (±0.2 pH) and sensitive to temperature fluctuations in RASs.

These sensors measure the hydrogen potential in water using an electrode inside a glass bead that, when in contact with the water, records information through portable display systems [70], except for the HI-98107 sensor. The other sensors can be connected to microcontrollers such as Arduino UNO and ESP32 or microprocessors such as Raspberry PI [71].

Temperature: In this review, several sensors for measuring temperature were recorded, including DS18B20 and DS18S20 (Table 1), dynamic sensors with low conversion rates ideal for aquaculture works [72,73]. This digital sensor provides high accuracy (±0.5 °C) (Table S2) and waterproofing, ideal for all systems. Its cost (USD ~2–5) is a strength, but long-term submersion can reduce lifespan in saline aquaponics [74].

Dissolved oxygen (DO): Among the most widely used DO sensors in aquaculture are SEN0237, MAX30102, the OxyGuard DO 420 model, ZTWL-SZO2-485, and Lutron DO-5509 (Table 1). These allow the real-time monitoring and automation of actuators, such as aerators and feeders, which increases data collection's predictive and operational efficiency [75]. OxyGuard DO sensor, with accuracy (±0.2 mg/L) (Table S2) and Arduino compatibility, is suited for RAS and BFT. It requires regular calibration (every 3–6 months) and is costlier (USD ~100) than temperature sensors. On the other hand, MAX30102, an optical sensor [62], is less common, with high precision in controlled settings but impractical for continuous water submersion, limiting its use in experimental setups.

Total Dissolved Solids (TDSs): Among the most commonly used sensors are the SEN0244 and Grove-TDS. These are compatible with microcontrollers such as Arduino, which is key to issuing automatic alerts in the presence of critical values and analyzing the data collected (Table 1), both with ranges from 0 to 1000 parts per million (ppm) and analog output [76].

Turbidity: The most reported turbidity sensor is SEN0189. This sensor measures the amount of infrared light in a transistor, which captures the light waves and converts them into analog values. These values are expressed in nephelometric turbidity units (NTUs). In addition, it is characterized by easy integration with microcontrollers and microprocessors such as Arduino and Raspberry PI, respectively [77].

Ammonia: The review includes the MQ137 and MQ135 sensors, ranging from 10 to 300 and 10 to 1000 ppm, respectively. The MQ137 is used exclusively to measure dissolved ammonium and ammonia gas in water [78], while MQ135 is capable of detecting different gases in water, such as carbon monoxide (CO) and carbon dioxide (CO_2) [79]. Both sensors are compatible with microprocessors such as ESP32 and Arduino UNO and transmit information by Wi-Fi connection [80].

Electrical Conductivity (EC): Among the EC sensors used in aquaculture, we have ZT-SZEC-1001. This sensor provides a measurement range of 0–10,000 micro Siemens per centimeter (uS/cm), and it needs a voltage of 5 volts to transmit data in an analog format [61]. Grove-EC is a sensor with a range between 0 and 20 uS/cm, has analog and digital data output, and is compatible with microcontrollers such as Arduino and Grove [81] (Table 1).

Table 1. IoT sensors that are used in aquaculture for monitoring physicochemical water parameters.

Reference	Sensor	Data Analysis and Processing	Data Transmission	Network Technology	Findings
Nayoun et al. [56]	pH, T° (DS18B20), Water level	Arduino Nano (ATmega328P), NodeMcu Esp-12E (Based ESP8266)	Arduino IOT cloud	Wi-Fi	- Oxygen level prediction
M et al. [53]	T° (DS18B20), pH (SEN0169), DO (SEN0237), Salinity (SLP2000)	Raspberry Pi, Edge server	Smartphone	Wi-Fi	- Development of a real-time water monitoring system using sensors and deep learning.
Shaghaghi et al. [82]	DO (MAX30102), T° and Humidity (DHT11)	Wisen Whisper Node, Arduino Nano	EPIC IoT	LoRa	- Development of an optical sensor for dissolved oxygen measurement.
Arif et al. [58]	T° (DS18B20), pH (SEN0161), Turbidity (SEN0189)	Arduino UNO	GSM SIM 900A, Smartphone	SMS (2G)	- Real-time monitoring. - SMS alerts when parameters are critical.
Islam et al. [19]	pH, T° (DS18B20), Turbidity, Water level (HC-SR04), DBO	Arduino UNO	ThingSpeak (rest-API)	Wi-Fi	- Determination of survival in aquaculture ponds based on physicochemical water parameters.
Nabi & Kharaz [83]	DO (OxyGuard DO 420 model)	ARM Cortex-M3	N/R	SIM card (2G/3G).	- Development of early warning to oxygenate water.

Table 1. *Cont.*

Reference	Sensor	Data Analysis and Processing	Data Transmission	Network Technology	Findings
Dutta et al. [84]	pH, T° and Humidity (DHT11), Water level (HCSR04)	Arduino UNO (ATmeda328P), Node MCU	Blynk App and ThingSpeak—Smartphone	Wi-Fi	- Real-time pH evaluation. - Bicarbonate solution dispensing device.
Chen et al. [59]	pH, T°, DO (ZTWL-SZO2-485), EC (ZT-SZEC-1001)	STM32F103 chip	FreeCloud (Mobile App)	SMS 4G	- System design for real-time monitoring.
Xu et al. [85]	T°, pH, DO, Ammonia nitrogen	RS485, GD32F303 and ESP8266	OneNet cloud	Wi-Fi	- Development of a portable system to evaluate water quality parameters in aquaculture.
Singh et al. [86]	EC, pH, DO (ORP)	N/R	The Things Network	LoRaWAN	- Long-distance monitoring of water quality parameters.
Hawari & Hazwan [87]	T° (DS18820), Turbidity (SEN0189), pH (SEN0161)	Arduino, Orange Pi	Telegram notification/Google Drive	Wi-Fi	- Real-time monitoring.
Rohan et al. [88]	T° (DS18B20), Turbidity (SEN0189)	Raspberry Pi 3 Model B	ThingSpeakView App	Wi-Fi	- Increased productivity in aquaculture.
Uddin et al. [89]	Humidity, T°, Water level, Turbidity, pH, and DO	Arduino UNO R3	DWIFS and IoT cloud servers	Wi-Fi and SMS	- Water quality control in fish and rice farming.
Tsai et al. [51]	pH, DO, EC, T° (DS18B20)	ESP32	ThingSpeakView App	Wi-Fi	- Salinity prediction.
Lin et al. [68]	T° (DS18B20), pH. Dissolved Oxygen (DO), EC	Modulo SoC ESP-WROOM-32 (basado en ESP8266)	ThingSpeak IoT (MATLAB R2021b)	Wi-Fi and Bluetooth	- Real-time monitoring.
Q. Zhang et al. [60]	pH, Turbidity, DO	STM32F103ZT6	OneNet cloud	NB-IoT	- Aquaculture water quality monitoring in a UAV.
Boonsong et al. [61]	pH, DO (Kit-ATLAS SCIENTIFIC), T° (DS18B20)	ATmega328	Server Cloud	ZIGBEE	- Real-time monitoring.

Notes: N/R: No register. DO: Dissolved oxygen, T°: temperature, TDS: Total Dissolved Solids, EC: Electrical conductivity; Wi-Fi: Wireless Fidelity; LoRaWAN: Long-Range Wireless Area Network; SMS: Short Messages Service; NB-IoT: Narrowband Internet of Things; UAV: unmanned aerial vehicle.

4.2. Application in Aquaculture

Among the most outstanding research applying IoT sensors to water quality monitoring in aquaculture (Table 1) is the study reported by Nayoun et al. [56], who collected pH and temperature data to predict oxygen levels in real-time. Similarly, Shaghaghi et al. [82] and Nabi & Kharaz [83] developed an optical dissolved oxygen meter and an automated aerator system when oxygen levels showed anomalies in their measurements, respectively. Dutta et al. [84] evaluated the pH in a water pond to develop an automatic bicarbonate dispenser system, which was activated when pH levels were unstable; thus, the acidity levels in the water were controlled. Islam et al. [19] recorded real-time pH, temperature, turbidity, water level, and biochemical oxygen demand (BOD) data to evaluate the culture's survival. On the other hand, aquaculture farms are often located in geographically remote areas of cities, making communication lines difficult. However, Xu et al. [85] developed a portable water quality monitoring system using temperature, pH, DO, and ammonia sensors. Likewise, Singh et al. [86] used the LoRaWAN long-distance connection to transmit pH, EC, and DO data on The Thing Networks available under the online platform. Another alternative for monitoring water quality in aquaculture culture in rural areas is the development of unmanned vehicles; Q. Zhang et al. [60] developed a surface monitoring device for water quality parameters, which had pH, turbidity, and DO sensors, and the information was visualized in real time through the OneNet cloud online platform.

Cultures Employing IoT Sensors

Among the main techniques for monitoring water in aquaculture are manual methods of analysis, which consist of taking samples in situ and using labor and expensive equipment to measure parameters such as pH, dissolved oxygen (DO), and temperature [90–92]. Another method is colorimetric analysis, which uses chemical reagents to measure factors such as ammonium, nitrates, nitrites, alkalinity, and hardness. However, it lacks precision due to subjectivity in color interpretation and sensitivity to interferences such as organic matter and turbidity [93,94]. In addition, it is a manual and laborious method, which makes it difficult to use in frequent or real-time monitoring, generating chemical waste that requires proper handling and increasing operating costs [94]. Finally, the main limitation of laboratory sample analysis is the response time, since it requires sample collection, transport, and processing, which prevent real-time monitoring [95]. In addition, costs are high due to specialized equipment, reagents, and trained personnel [96,97]. There is also the risk of sample alterations due to contamination or parameter changes during transport [90].

In this context, sensors that use IoT technology to measure in real time the physico-chemical parameters critical for the efficient development of aquaculture are an alternative to improve efficiency, lower operating costs, and increase pond productivity; therefore, this review describes different cultures of cultured aquatic organisms that use IoT sensors to monitor water quality [98–100] (Figure 5).

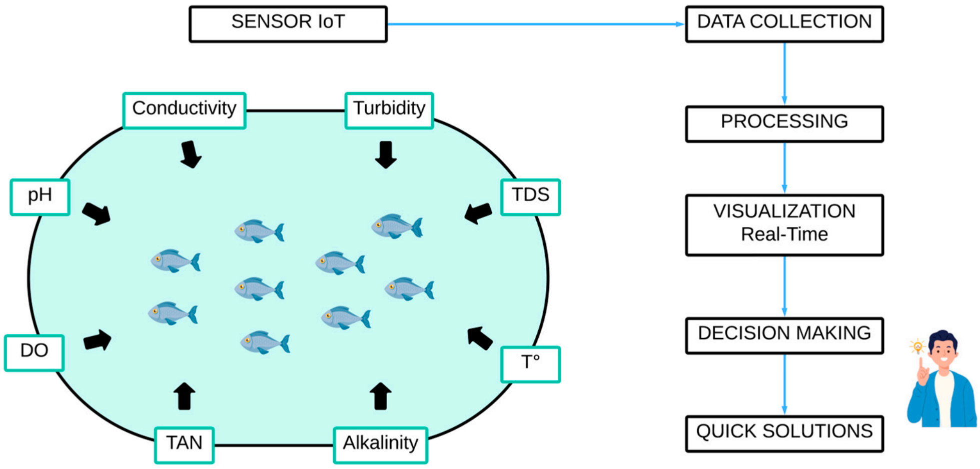

Figure 5. Schematic diagram of the technology IoT used for water quality monitoring in Aquaculture.

One of the critical points in shrimp (Malacostraca) farming is water quality monitoring [101,102]. IoT technology is presented as a more efficient alternative (Table 2), focusing mainly on developing early alerts when these parameters present anomalous ranges. Based on the above, Ahmed et al. [103] and Hasman et al. [104] established Wi-Fi connections for sending data to online platforms, while Espena et al. [47] used LoRaWAN and SMS protocols (Table S1). Similarly, E.B. Blancaflor & Baccay [41] evaluated the mortality and growth of *Litopenaeus vannamei* based on data from pH, temperature, and DO sensors, which were transmitted to an Arduino microcontroller via Wi-Fi to a mobile application.

Another Malacostraca that has experienced exponential growth in aquaculture culture is *Macrobrachium rosenbergii* (Giant Freshwater Prawn), a decapod widely cultivated in Asian countries such as China, Bangladesh, and Malaysia at more than 230,000 tons per year [112–114]. However, the main problems faced by this culture are mortality due to high stocking densities, reduced cultivation spaces, algal proliferation, and the imbalance of physicochemical water parameters, such as dissolved oxygen depletion and environmental temperature variations [115]. Based on this problem, Suhaili et al. [54] developed an intelligent and automated system for activating emergency lights, heaters, and feeders, based on the level of temperature, salinity, TDS, pH, and DO sensors (Table 2), using an ESP8266 microcontroller and a Raspberry PI microprocessor with Wi-Fi connection; these data were visualized in the Cayenne IoT platform (Table S1).

Table 2. Aquatic organism cultures employing IoT sensors.

Reference	Aquatic Organism	Sensor	Findings
Ahmed et al. [103]	Shrimp	pH, T°, TDS, EC, Salinity	- Early warning of atypical water quality ranges.
Espena et al. [47]		pH, Salinity, T°, DO	- Monitoring of water quality parameters in the culture.
Hasman et al. [104]		T° (DS18B20), pH, Turbidity, DO	- Increased productivity in aquaculture.
Abdullah et al. [105]		pH, DO, T°	- Reduction in operational costs.
E.B Blancaflor & Baccay [41]		DO, T°, pH	- Managing culture growth and mortality through water quality.
Brian Ganda Pratama et al. [106]	Tilapia	T°, pH, DO, EC	- Long-distance and real-time monitoring.
Libao et al. [48]		pH, Salinity, DO, T°	- Automated monitoring and comparison with human error.
Shete et al. [8]		pH, DO, T°	- Real-time monitoring.
Lopez et al. [57]		T° (DS18B20), pH, Turbidity	- Develop a prototype to dispense agricultural lime and aluminum sulfate and activate heaters and aerators based on temperature and pH values that are atypical.
Medrano et al. [107]		pH, DO, T° (DS18B20)	- Real-time monitoring.
Wibisono & Jayadi et al. [108]	Catfish	pH (SEN0169), T° (DS18B20), Water level (Ultrasonic)	- Disease prevention.
Joeng et al. [109]		T°, pH	- Automated monitoring.
Muhammad et al. [110]		pH	- Real-time pH monitoring.
Sari et al. [111]		DO (SEN0237), T° (DS18B20)	- Real-time monitoring of oxygen and temperature.
Mohd Jais et al. [20]	Asian seabass	T° (DS18B20), pH (SKU SEN0161), Ammonia (MQ137), DO, Salinity (DFR0300)	- Development of a real-time water quality monitoring system.
Suhaili et al. [54]	Giant Freshwater Prawn	T°, Salinity, TDS, pH, DO	- Activation of emergency lights, heaters, and troughs

Notes: N/R: No register. DO: Dissolved oxygen, T°: temperature, TDS: Total Dissolved Solids, EC: Electrical conductivity.

In the 1960s, tilapia was introduced to aquaculture by African countries such as Egypt, Malawi, and Zambia. It is the second most widely farmed freshwater fish worldwide, producing over 5 million tons annually [116]. Thus, it plays a key role in food security [116,117]. However, the physicochemical parameters of water in tilapia culture play a critical role, as an imbalance in these parameters can cause stress and increase susceptibility to disease outbreaks [118]. Currently, monitoring water parameters is manual, which increases the margin of error and costs in fish farms [118].

Therefore, IoT sensors have been integrated into water quality monitoring in tilapia farming to minimize this error and reduce costs. The most commonly used parameters are temperature, pH, DO, EC, and turbidity [8,48,106,107] (Table 2). On the other hand, Lopez et al. [57], based on the information transmitted to the Arduino UNO microcontroller via Wi-Fi and visualized in the Blynk mobile application (Table S1), designed a prototype capable of automatically dispensing calcium oxide, and aluminum sulfate, as well as activating heaters and aerators in the presence of anomalous temperature and pH values. Also, Brian Ganda Pratama [106] developed a system for the long-distance monitoring of water quality parameters (Table 2).

Similarly, Siluriadea (catfish) culture is an activity with significant relevance in African countries such as Kenya, Nigeria, and Mali [119,120]. The interaction with the environment is fundamental to its production, being an indispensable requirement to monitor the physicochemical parameters of water, which are determinants of minimizing mortality and controlling the health of the culture [120]. Therefore, Wibisono & Jayadi [109] evaluated temperature, pH, and water levels in real time to prevent the proliferation of pathogens in water. Muhammad et al. [110] evaluated pH using a WEMOS D1 R32 microcontroller via Wi-Fi to the MATLAB platform (Table S1) to monitor real-time water pH in *Clarias gariepinus* culture. Likewise, Sari et al. [111] designed a monitoring system based on IoT sensors to evaluate the levels of temperature and dissolved oxygen in the culture of *Pangasius* sp.; the data were obtained in real time using SD card memory and Wi-Fi connection, visualized on an LCD module and Adafruit.io online platform (Table S1).

Lates Calcarifer (Asian seabass) is a widely cultivated perciform in China and Malaysia, characterized by its rapid adaptation to different environments. It also has high growth and great adaptability to reproduce in captivity on a large scale in a standardized way [20,121]. However, one of the main causes of mortality and increased disease proliferation depends on water quality management. This is why Mohd Jais et al. [20] (Table 2) developed a real-time water quality monitoring system based on temperature, pH, ammonia, DO, and salinity data. This information was sent by Wi-Fi to an Arduino UNO R3 microcontroller and displayed on the ThingSpeak and Virtuino platforms (Table S1).

The rice-crab system is the main culture model in integrated aquaculture [97]. This activity has been developed for over 30 years in countries such as China, including Eriocheir sinensis, a culture of great economic importance [97,98]. Due to the relevance of this culture, we decided to include the only report in 2018 employing IoT technology. Niswar et al. [122] evaluated a LoRaWAN connection to transmit data from temperature, salinity, and pH sensors to monitor culture water quality remotely.

5. Application of IoT Sensor in Cultivation Systems

For the Biofloc Technology System, the sensors are used to measure pH, TDS, and temperature with 10, 9, and 9 records, respectively, while ammonium, hardness, and salinity are reported with the lowest use (Figure S4B); on the other hand, in water quality monitoring in the Recirculating Aquaculture System, the sensors with the highest use are temperature, pH, and dissolved oxygen, while TDS and salinity sensors were the least used (Figure S4C). Finally, in the Aquaponic System, the sensors with the highest use were temperature and pH, with 11 and 9 records, respectively. On the other hand, electrical conductivity, hardness, and salinity were the least used (Figure S4D).

It should be noted that the country with the highest involvement in using sensors for aquaculture culture in the Biofloc system is Bangladesh, with four reported papers, followed by Malaysia with two, and countries such as India, Pakistan, Philippines, and South Korea with one paper each. On the other hand, the Recirculation Aquaculture System has four papers reported to date; countries like Brunei, Indonesia, the Philippines, and South Korea have one paper each. Likewise, the country with the highest scientific production using this technology in aquaponic systems is Indonesia, with three papers, while countries such as Algeria, Australia, Canada, India, Japan, Malaysia, Morocco, and Tunisia have 1 paper each. This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, and the experimental conclusions that can be drawn.

5.1. Biofloc Technology (BFT)

Biofloc Technology (BFT) integrates aquatic organisms with a consortium of microorganisms, consisting mainly of nitrifying and heterotrophic bacteria, as well as zooplankton and phytoplankton, known as Bioflocs [123,124]. Bioflocs play a crucial role by consuming dissolved ammonium in the water resulting from feces and food waste by cultured organisms, significantly reducing the toxicity of the water [125]. BFT has proven to be an environmentally friendly strategy, as it minimizes the waste produced by this activity and reduces pollution and eutrophication of natural systems. However, the main problems faced by this technology include stocking density, carbon sources, feeding regimes, carbon-to-nitrogen (C/N) ratios, and water physicochemical factors [124,125].

In the last 4 years, 10 papers have been recorded (Table 3) by Tasnim et al. [74], who designed an automated system to monitor water levels using pH, turbidity, TDS, and temperature sensors. Furthermore, Mozumder & Sharifuzzaman Sagar [126] built an automatic system to activate heaters and a water pump when the temperature and water level were below normal. In 2023, only one paper was reported, presented by Podder et al. [127], where they built an automated prototype to dispense acid-base solutions, in addition to activating heaters and a water pump when pH, temperature, and water levels were below the optimal values for the culture. However, in the last year, this type of research has increased in interest among the authors, registering three papers. The first is by Bakhit et al. [128], who designed a low-cost pH, TDS, EC, and DO sensor monitoring system connected to a Raspberry PI microprocessor and an analog-to-digital converter (ADS1115) via Wi-Fi to the Blynk mobile application (Table S3). Al Mamun et al. [52] had a similar paper, with the difference that the microcontroller used was ESP32 (Table S3).

Table 3. IoT sensors for water quality monitoring under Biofloc Technology (BFT).

Reference	Parameter	Findings
Abid et al. [129]	T°, pH, CO (MQ-7), TDS, Turbidity, Humidity (DHT11)	- Real-time monitoring and mortality prediction.
Al Mamun et al. [52]	T° (DS18B20), DO (DFRobot), Water level, TDS, Turbidity, pH (BNC)	- Real-time monitoring.
Bakhit et al. [128]	pH, DO, TDS, EC	- Real-time monitoring for temperature prediction by using ML.
Podder et al. [127]	T° (DS18B20), DO (Lutron DO-5509), pH (HANNA HI-98107), Water level, Turbidity, TDS (HM TDS-EZ)	- The heater and acid-basic solution dispenser are activated.
Bakhit et al. [130]	DO, pH, TDS, T°, Water level	- Real-time predictive analysis of water quality data.
E. B. Blancaflor & Baccay [41]	DO, T°, pH	- Mortality and growth management based on water quality monitoring.
Goswami et al. [131]	pH, T° (DS18B20), TDS, EC	- Real-time monitoring.
Mozumder & Sharifuzzaman Sagar [126]	pH, T° (DS18B20), Ammonia (MQ-135), TDS, EC	- Activation of heater and water pump.
Tasnim et al. [74]	pH, Turbidity, TDS, T° (DS18B20)	- Automated water level control.
Rashid et al. [7]	pH, T°, TDS	- Increase productivity based on water quality monitoring.

Notes: N/R: No register. DO: Dissolved oxygen, T°: temperature, TDS: Total Dissolved Solids, EC: Electrical conductivity, ML: Machine learning.

Finally, Abid et al. [129] designed an intelligent system for monitoring water quality parameters. This system includes temperature, pH, carbon monoxide (CO), TDS, turbidity, and humidity sensors to predict culture mortality.

5.2. Recirculating Aquaculture System (RAS)

RAS is a technology mainly used to intensify cultures sustainably. This system treats and reuses water, significantly reducing water consumption [132]. The RAS is composed of fundamental elements such as a mechanical filter that removes organic waste generated by feces and food not consumed by cultured aquatic organisms; a biofilter composed of nitrifying bacteria that break down nitrogenous compounds, transforming ammonium into nitrites and then to nitrates; an oxygenator that increases the capacity of dissolved oxygen in the water, benefiting the cultured organisms and the nitrification process of the bacteria; and, finally, a UV lamp that keeps the water free of microorganisms and contributes to the elimination of nitrates produced by the nitrification process through the biofilter [29,133,134].

The RAS is a closed and controlled system, which increases survival and decreases pathogen proliferation [135]. It should be noted that the constant monitoring of water quality is a crucial factor for the success of RAS systems. An alternative for assessing water quality is employing IoT sensors, a technology that has emerged as an efficient and innovative solution. Although this practice is relatively recent, some Asian countries such as Indonesia, the Philippines, Brunei, and South Korea have started implementing it in different aquaculture systems [32,136].

Lee et al. [137] used temperature, pH, and DO sensors to evaluate water treatment in a fish farm (Table 4). The collected data were processed by a Raspberry PI microprocessor connected to a Wi-Fi network (Table S3). Suhaili et al. [54] used the same microprocessor in conjunction with an ESP8266 to transmit information from temperature, salinity, TDS, pH, and DO sensors via Wi-Fi to the Cayenne IoT online platform (Table S3), allowing real-time data visualization and the activation of emergency lights, heaters, and automatic feeders. On the other hand, Libao et al. [48] compared automated monitoring based on IoT sensors for pH, salinity, DO, and temperature. The results showed that automated monitoring has a lower error rate, which allows greater control over the system, an increase in productive yield, and a reduction in the mortality of cultured organisms caused by pathogens.

Table 4. IoT sensors for water quality monitoring under RAS.

Reference	Sensor	Aquatic Organism	Filter		Findings
			Mechanical	Biofilter	
Libao et al. [48]	pH, Salinity, DO, T°	Tilapia	Mechanical filter	Bacterial	- Automated monitoring and comparison with human error.
Suriasni et al. [79]	DO (SEN0237), pH (SEN0161), TDS (SEN0244), T° (DS18B20), Water flow (YF-201)	Fish tanks	N/R	Nitrosobacter and Nitrosomonas	- Activation of aerators to oxygenate water for TAN removal.
Suhaili et al. [54]	T°, Salinity, TDS, pH, DO	Asian seabass and Giant Freshwater Prawn	Sponges and Aquarium wools	Bio-balls/K-1 and filters/ceramic	- Activation of emergency lights, heaters, and fish feeders.
Lee et al. [137]	T°, pH, DO, Water level	N/R	N/R	N/R	- Aquaculture water processing control.

Notes: N/R: No register. DO: Dissolved oxygen, T°: temperature, TDS: Total Dissolved Solids. TAN: Total Ammonia Nitrogen.

5.3. Aquaponic System

The cultivation of organisms within the aquaponic system integrates two technologies: hydroponics, characterized by the cultivation of plants using a liquid substrate, and a water recirculation system that provides the ideal environment for the cultivation of aquatic organisms [138,139]. The fundamental principle is that waste excreted by the organism is recirculated into the hydroponic system. Initially, the water passes a sedimentation tank where nitrogenous compounds are oxidized, followed by biofilters that denitrify this compound from nitrite to nitrate [140]. This nitrogenous compound generates a surface nutrient biofilm, providing essential nutrients for plant growth. Once these nutrients are absorbed, the water returns to the culture tank, and the process starts again [138,141]. Aquaponics is an emerging system that proposes an ecosystemic balance, reducing pollution and promoting the sustainability of aquaculture and agricultural activity. However, it is essential to control and monitor water quality.

Therefore, the use of IoT technology for monitoring the physicochemical parameters of water using sensors is showing significant relevance since, in recent years, up to 11 papers have been produced using IoT sensor technology (Table 5), among which the one reported by Haruo et al. [69] evaluated temperature, pH, DO, TDS, and ammonia to determine the growth performance of cabbage with catfish. Rahayu et al. [142] designed an automatic system to dispense acid–base solutions to balance pH and increase the water level utilizing an automatic pump. This used data provided by pH and turbidity sensors, and the information was transmitted in real-time using an Arduino Uno microcontroller via Wi-Fi (Table S3). Similarly, Pramono et al. [143] evaluated temperature, pH, DO, and ammonia parameters using sensors connected to an Arduino microcontroller in tilapia culture to determine the growth of spinach. Mansor et al. [144] monitored, in real time, the pH, temperature, and humidity values in an aquarium fish culture to evaluate the germination and growth of mustard seeds. Kok et al. [145] designed an automated water quality control system using pH, temperature, turbidity, and TDS sensors, employing a Proportional Integrative Derivative (PID) algorithm and a PIC 18F4550 microcontroller connected to an LCD for information visualization (Table S3).

Table 5. IoT sensors used to monitor water quality under aquaponics systems.

Reference	Parameter	Plants	Aquatic Organism	Findings
Kok et al. [145]	pH (SEN0161), T°, Water level, Turbidity, TDS (SEN0244)	Vegetables	Catfish	- Automated control.
Asma et al. [146]	pH, T°, Humidity (DHTH)	N/R	N/R	- Real-time monitoring.
Chandana et al. [147]	pH, Humidity (DHT11), Water level	N/R	N/R	- Feed system control.
Ghobrini et al. [148]	pH, T°, TDS, Turbidity	N/R	Tilapia	- Real-time monitoring and automatic sensor calibration.
Mansor et al. [144]	pH, T° and humidity (DHT22)	Mustard	Aquarium fish	- Real-time monitoring.
Pramono et al. [143]	pH (pH-4502C), T° (DS18B20), DO (Gravity Analog), Ammonia (MQ-135)	Spinach	Tilapia	- Real-time monitoring and evaluation of spinach growth.
Abbasi et al. [149]	pH (pH-4502C), T° (DS18B20), DO (Gravity Analog), Humidity (DHT22)	Romaine lettuce	Aquarium fish	- Prediction of romaine lettuce growth by monitoring water quality.
Khaoula et al. [81]	pH (Grove-pH), Water level. T° (DS18B20), EC (Grove-EC), TDS (Grove-TDS), Humidity (SCD30) CO2, Taux Ammonia Nitrogen (TAN)	Vegetables	Aquarium fish	- Algorithm-based plant growth assessment (AI) and water quality monitoring.
Rahayu et al. [142]	pH (pH4502C), Turbidity	N/R	N/R	- Automatic water flow increase. - Dispensing of acid-basic solutions for automatic pH control.
Haruo et al. [69]	T°, pH, DO	N/R	N/R	- Plant growth monitoring through correlation of water quality data.
Rozie et al. [42]	T° (DS18S20), Turbidity, pH (pH-4502C), DO, TDS, Ammonia (MQ-135), Water level (HC-SR04)	Cabbage	Tilapia	- Ammonium level control.

Notes: N/R: No register. DO: Dissolved oxygen, T°: temperature, TDS: Total Dissolved Solids, EC: Electrical conductivity, AI: Artificial intelligence.

6. Challenges and Prospects

The significant increase in the world population makes aquaculture an alternative to meet the population's protein, vitamin, and mineral needs. This review describes several systems, such as Biofloc technology (BFT), Recirculating Aquaculture Systems (RASs), and aquaponic systems, which are alternatives to intensify cultures, reduce negative impacts on the ecosystem, and increase production. However, this implies the need to implement efficient, cost-effective, and easy-to-use technologies to improve the efficiency of this activity. The presence of sensors coupled with the Internet of Things (IoT) technology for water quality monitoring registers an important growth in aquaculture in different cultures and aquaculture systems as they provide the real-time control and monitoring of physicochemical parameters of water of interest in aquaculture. However, parameters such as TAN are crucial to maintain the development of these systems. Nevertheless, many reports do not have sensors to measure ammonium, nitrites, or nitrates, which are key factors for plant growth in aquaponic systems and toxic agents for aquatic organisms in RAS or BFT systems.

6.1. Challenges

The following describes points of view to complement and increase the effectiveness of using this technology.

Unmanned aerial vehicles (UAVs) can be used with sustainable energy. Intensive aquaculture employs thousands of hectares worldwide, which implies using constant human resources for water quality monitoring [150]. An alternative to reduce operational costs in aquaculture is to design and build prototypes that integrate sensors for water monitoring. For example, Setiawan et al. [151] created a prototype to estimate TDS, and Ngwenya et al. [152] implemented chlorophyll-a sensors in a remote-controlled UAV device to detect this compound in water bodies. In addition, integrating solar charging technology and employing self-charging panels with solar radiation will allow 24 h water quality monitoring and constant crop information.

Automatic maintenance can be used to extend sensor lifetime. Initially, IoT technology for water quality monitoring in aquaculture establishes connections between low-cost sensors. It is essential to ensure the durability of these sensors as they are in constant contact with water, which favors the formation of films that can obstruct their readings [20,130,153,154]. Implementing a sensor cleaning and calibration mechanism is essential in the construction of remote systems or devices. This will decrease data recording errors and prolong the device's lifetime.

Connectivity can be implemented in rural areas. The implementation of connectivity systems such as LoRa (Long Range), SMS (Short Message Service), and Sigfox, a Low-Power Wide-Area Network (LPWAN) connection protocol, is ideal in low-power and wide-range conditions [155,156]. These technologies would allow establishing connections at remote locations and maintaining the continuous monitoring of aquaculture ponds.

Artificial intelligence (AI) can be integrated. In aquaculture, the application of machine learning (part of AI) and deep learning (part of machine learning) is used to perform activities such as feeding, disease detection, and observation of atypical behaviors. However, water quality monitoring under the concept of AI integrates various mathematical algorithms that help to predict outliers of water quality parameters in aquaculture [103,157,158]. Incorporating these algorithms, such as Linear Regression, Decision Tree, Random Forest, and Adaboost [103], in the data processing stage can be a strategy to anticipate the occurrence of deviations outside the optimal ranges of water quality, thus avoiding factors that alter the environment of cultured organisms.

Finally, implement actuators. While it is true that digital platforms record the information collected by sensors, few works are reported to date that describe systems capable of making real-time decisions in an automated way to control the parameters encompassing water quality in an aquaculture pond. Actuators complement sensors and devices that allow the environment to be modified [10,16]. In this context, they can activate alarms and lights, dispense solutions, and activate aerators and heaters, being an alternative to fully automated aquaculture systems.

6.2. Future Trending

- Flexible sensors, such as the nonplanar multi-chamber array dissolved oxygen sensor developed by Xu et al. [159], enable real-time monitoring in aquaculture systems such as Biofloc. These soft sensors improve efficiency by adapting to dynamic aquatic environments and overcoming the limitations of traditional rigid sensors, but they still present challenges in scalability and cost.
- AI-driven digital twins, such as the model integrated by Ubina et al. [160], use big data and cloud computing to predict fish growth in real time. This approach, applicable to RAS or aquaponics systems, improves decision support and productivity but requires robust infrastructure and data integration, areas that continue to evolve.
- Nanosensors, developed by Abdelaziz et al. [161], such as an optical ammonia detection probe using dendritic nanoparticles, improve sensitivity in monitoring nitrogenous compounds, which is crucial for aquaponics and BFT. Despite their high sensitivity, their scalability and large-scale deployment remain a challenge.
- High-speed connectivity powered by 5G enables real-time monitoring in large-scale aquaculture farms, as reviewed in the study by Li et al. [162]. This improves data transmission compared to technologies such as LoRaWAN or Wi-Fi, but it requires a large infrastructure investment, limiting its immediate adoption in rural areas.

These advances address key challenges such as durability (flexible sensors) and data latency (5G connectivity) while opening new perspectives on precision and sustainability.

For example, combining nanosensors and digital twins could optimize nutrient cycles in aquaponics, improving the performance of both fish and plants.

7. Conclusions

The use of IoT sensors for monitoring water quality in aquaculture has grown significantly between 2020 and 2024, enabling improved efficiency in resource management and optimizing the growth of aquatic organisms. The most widely used sensors include pH, temperature, and dissolved oxygen, with applications in emerging technologies such as Biofloc (BFT), Recirculating Aquaculture Systems (RASs), and aquaponics, allowing increased growth and significantly reduced culture mortality in the case of BFT. Meanwhile, RASs allow the monitoring of parameters such as TAN, a nitrogen compound crucial in the growth of aquatic organisms; however, it is still deficient since not all the analyzed researchers evaluate this compound as crucial for developing this culture technology. On the other hand, the aquaponic system is an efficient alternative to predict the growth and germination of seeds and vegetables.

Despite its benefits, there are limitations, such as the lack of connectivity in rural areas, the maintenance of sensors, and the absence of the continuous measurement of key nitrogen compounds in RAS and aquaponic systems. Future research should focus on improving sensor durability, integrating artificial intelligence for predictive analytics, and extending connectivity through long-range networks. Furthermore, the implementation of IoT in aquaculture represents a move toward more sustainable and automated systems. Overcoming technological challenges will consolidate its role in optimizing aquaculture production, ensuring a positive impact on food safety and environmental management.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/agriengineering7030078/s1, Figure S1: Scientific production and collaborations between countries; Figure S2: Graphical description of document production by authors; Figure S3: Graphical description of document production by affiliations; Figure S4: Number of sensors used for water quality monitoring in aquaculture; Table S1: Networking, processing, and data transmission technology using IoT sensors for water quality monitoring in aquaculture; Table S2: Performance metrics and Suitability of key IoT sensors in aquaculture; Table S3: Layers in the operation of IoT in different aquaculture systems.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Appendix A

Table A1. PRISMA Checklist.

Section and Topic	Item #	Checklist Item	Location Where Item Is Reported
TITLE			
Title	1	Identify the report as a systematic review.	L.3
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	L.21
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	L.60
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	L.85
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	L.117
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	L.112
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	L.120
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	L.117-119
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	L.112-121
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	
	10b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results.	
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, meta-regression).	
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	

Table A1. *Cont.*

Section and Topic	Item #	Checklist Item	Location Where Item Is Reported
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	L. 248
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	
Study characteristics	17	Cite each included study and present its characteristics.	L.356
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g., confidence/credible interval), ideally using structured tables or plots.	
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	L.429
	23b	Discuss any limitations of the evidence included in the review.	L.547
	23c	Discuss any limitations of the review processes used.	L.553
	23d	Discuss implications of the results for practice, policy, and future research.	L.595
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	L.241
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	L.108
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	L.109
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	L.650
Competing interests	26	Declare any competing interests of review authors.	L.657
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	L.655

Appendix B

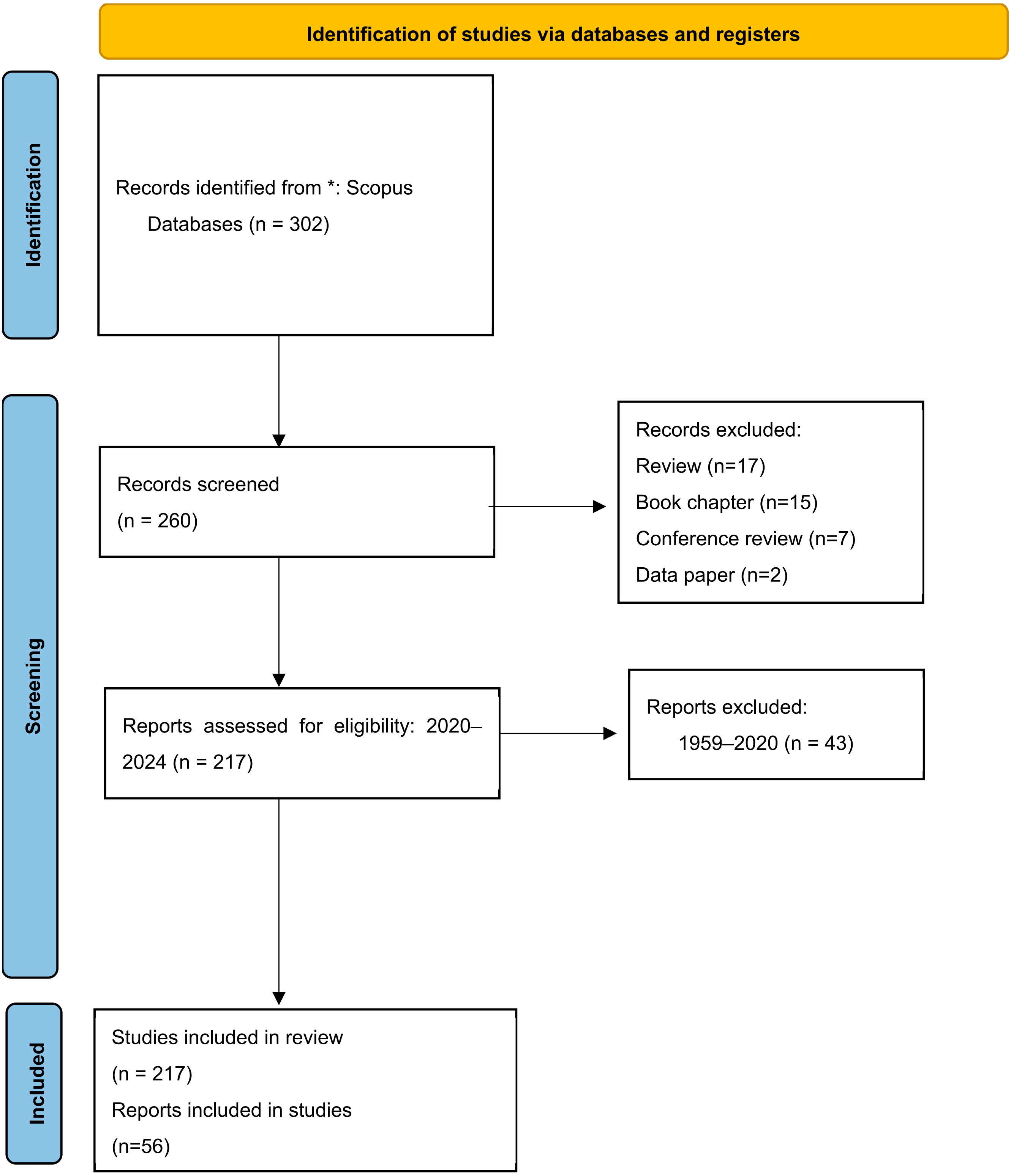

Figure A1. PRISMA Flow Diagram. * Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers). If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools. Source: Page MJ, et al. [163]. This work is licensed under CC BY 4.0. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/, (accessed on 12 January 2025).

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