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A Systematic Literature Review of Dissolved Oxygen and Turbidity Monitoring in Biofloc Aquaculture: IoT and Machine Learning for Water Quality Management

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Abstract. Various technologies have been developed to monitor dissolved oxygen (DO) and turbidity in aquaculture, yet integrated evaluations focusing on biofloc systems, particularly those involving IoT and Machine Learning (ML), remain limited. This review analyzed 32 studies published between 2020 and 2026 using the PRISMA 2020 framework to examine DO measurement, turbidity measurement, IoT integration, and ML applications in biofloc aquaculture. To support methodological discussion, several studies from broader aquaculture and water-quality monitoring contexts were also considered. The reviewed literatures shows that IoT-based and manual methods are the most commonly used approaches for DO and turbidity monitoring. IoT systems, mainly based on ESP32, ESP8266, and Arduino platforms, support real-time monitoring and automation. ML models such as Random Forest, LSTM, and CNN-LSTM are frequently applied for water-quality prediction, anomaly detection, and decision support. However, challenges related to sensor calibration, data availability, and model generalization remain. These findings suggest a growing shift toward more intelligent and integrated aquaculture monitoring systems.

Keywords: Biofloc Aquaculture, Dissolved Oxygen Monitoring, Turbidity Monitoring, Internet of Things, Machine Learning

1. INTRODUCTION

The aquaculture industry plays a vital role in strengthening national food security, especially in meeting the increasing demand for animal protein. As fish consumption continues to grow, there is a need for more efficient and sustainable farming systems. One of the main challenges in fish farming is the high demand for feed and nutrients, which often represents the largest part of operational costs [1]. To address this challenge, the biofloc system has emerged as an innovative solution widely adopted in aquaculture. The biofloc system utilizes microorganisms to convert organic waste into biomass that can be consumed again by the fish [2]. This system not only reduces the need for external feed but also offers greater resilience to environmental changes such as temperature fluctuations and water quality variations.

Although it offers distinct advantages over conventional fish farming techniques, the biofloc system requires intensive water quality monitoring and management to maintain high fish survival rates [3]. Two of the most critical parameters in this system are dissolved oxygen (DO) levels and water turbidity. Low DO levels are a major issue that can arise in biofloc systems. Insufficient DO can lead to hypoxia, hinder fish growth, and reduce feed conversion efficiency [4]. On the other hand, high turbidity caused by the accumulation of biofloc particles can disrupt the balance of microbial populations in the system, reduce light penetration, and negatively impact phytoplankton photosynthetic activity. These suggest that DO and turbidity are interrelated stressors that, if not properly managed, can undermine the overall resilience of biofloc systems.

Therefore, accurate and reliable measurement techniques for DO and turbidity are essential for ensuring optimal biofloc performance. Various sensor-based and analytical techniques have been developed to monitor these parameters, ranging from conventional methods to advanced sensor-based systems, each with differing levels of precision, cost-efficiency, and suitability for real-time application. In addition, technologies such as the Internet of Things (IoT) and Machine Learning (ML) have recently been introduced, which offer new opportunities for aquaculture. Specifically, IoT enables continuous and precise data collection and analysis in biofloc systems [5], while ML enhances these capabilities by predicting environmental changes and providing automated recommendations for preventive measures [6].

However, despite the availability of both conventional and modern approaches, studies rarely provide a systematic comparison of these methods, particularly in the context of biofloc aquaculture. Unlike previous studies that focus only on individual monitoring technologies or specific water-quality parameters, this review provides an integrated synthesis of dissolved oxygen monitoring, turbidity monitoring, IoT-based systems, and ML/AI applications within biofloc aquaculture contexts.

To address the limited systematic comparison of conventional and modern approaches for water quality measurement and monitoring in biofloc aquaculture, this review addresses the following research questions:

1) RQ1: What dissolved oxygen monitoring methods are commonly applied in aquaculture systems, including biofloc systems?
2) RQ2: What turbidity monitoring methods are commonly applied in aquaculture systems, including biofloc systems?
3) RQ3: How has IoT been integrated into water quality monitoring in biofloc aquaculture?
4) RQ4: How have ML and AI approaches been applied for water quality management in biofloc systems?

In this review, studies on dissolved oxygen and turbidity measurement methods also include broader aquaculture and water-quality monitoring literature, whereas IoT and ML/AI studies are predominantly focused on biofloc systems.

2. METHODS

This study adopts a Systematic Literature Review (SLR) approach based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 framework [7]. The process involves several sequential steps to ensure a transparent and replicable approach.

2.1. Search Strategy Execution

First, the research questions were defined to focus on four topics as already mentioned in the introduction. Thereafter, a comprehensive search was conducted in the Scopus database between March and May 2026. Scopus was selected because it provides broad coverage of peer-reviewed international journals and conference proceedings with strong indexing quality relevant to engineering, IoT, aquaculture, and interdisciplinary technology research. Separate search queries were constructed for each research question to maximize relevant coverage. Additionally, Boolean operators (AND, OR) were used appropriately to refine the search. The search terms included: for RQ1, (dissolved AND oxygen AND method AND measurement AND aquaculture); for RQ2, (turbidity AND method AND measurement AND aquaculture); for RQ3, ((iot OR "internet of things") AND biofloc); and for RQ4, (("artificial intelligence" OR "machine learning") AND biofloc). The search was limited to articles published from 2020 to 2026, in English, and available in full-text.

2.2. Screening and Eligibility Criteria

The literature search across the four research questions initially yielded 234 articles from the Scopus database. A two-stage screening process was then conducted by two reviewers. In the first stage, titles and abstracts were reviewed to exclude studies that did not meet the inclusion criteria, such as articles outside the publication year range, non-empirical studies, non-English publications, or studies unrelated to the review topics. In the second stage, the remaining full-text articles were evaluated for eligibility based on empirical relevance, alignment with the research questions, English-language publication, and accessible full-text content.

After removing duplicate and overlapping records, the final review corpus consisted of 32 unique articles included in the qualitative synthesis. In addition to the reviewed studies, several foundational references published outside the selected review period were cited in the Introduction sections to provide theoretical and contextual explanations related to biofloc systems, water quality monitoring, IoT, and machine learning concepts. These references were used solely to support the conceptual framework and background discussion and were not considered part of the systematic review dataset or qualitative synthesis. The article selection process is summarized in the PRISMA flow diagram (Figure 1).

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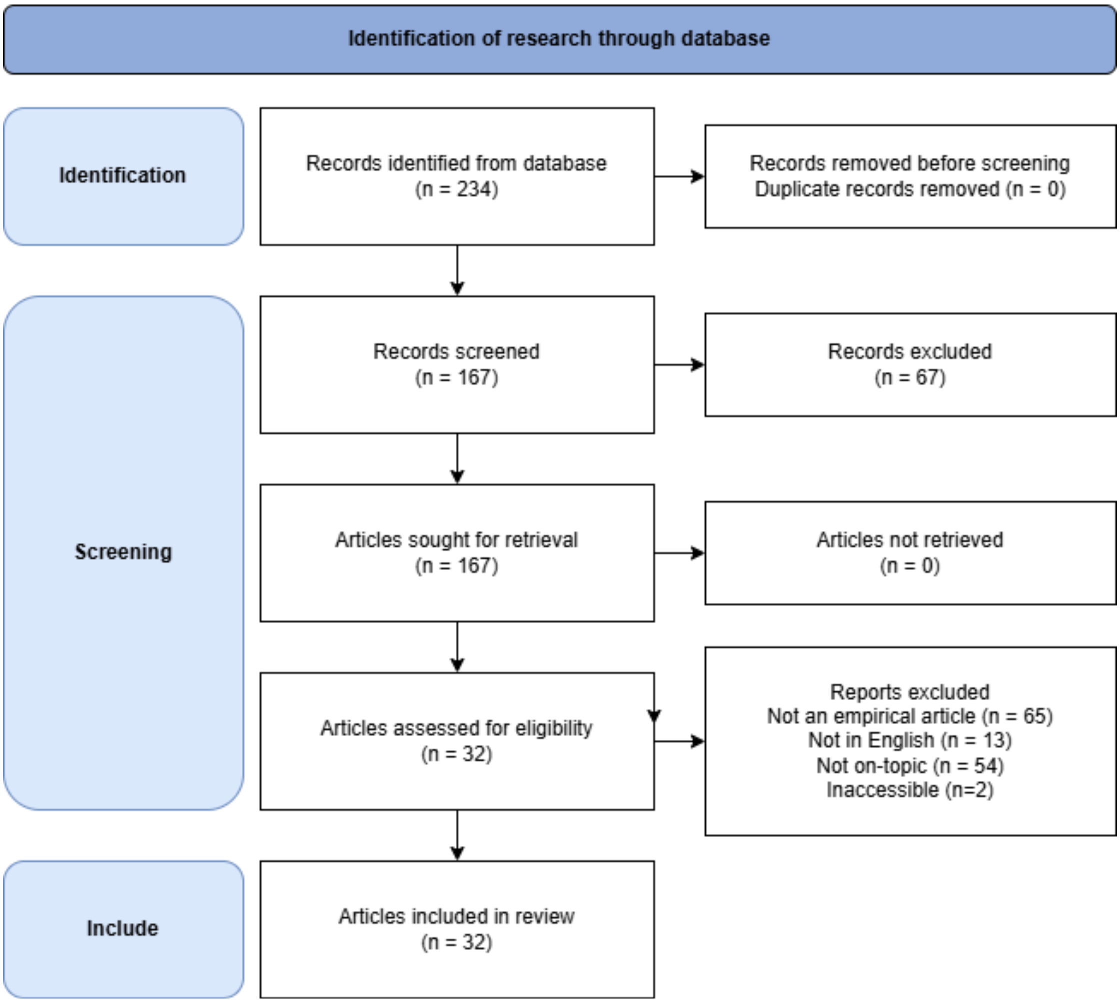

Figure 1. PRISMA flow diagram

2.3. Quality Assessment

Upon populating articles, two independent reviewers assesed the article corpus. the methodological quality of the included studies was assessed using a modified Critical Appraisal Skills Programme (CASP) checklist [8]. Due to the heterogeneous nature of the included studies, the checklist was adapted to evaluate general methodological transparency, relevance, and applicability across IoT, machine learning, and aquaculture-related research. The checklist consisted of five items:

1) Clarity of research objective
2) Appropriateness of methodology
3) Adequacy of data source description
4) Relevance to review objectives
5) Practical/scientific applicability

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Each item was rated as "Yes", "No", or "Unclear". Studies with ≥70% of applicable items rated "Yes" were categorized as high quality, studies with 50–69% rated "Yes" as moderate quality, and studies with <50% rated "Yes" as low quality. The quality assessment was used to evaluate the overall reliability and transparency of the reviewed studies, but it was not used as an exclusion criterion. The appraisal results are summarized in Table 1.

Table 1. Quality appraisal of the included studies (n=32)

Article	Q1	Q2	Q3	Q4	Q5	Quality Rating
[9]	Yes	Yes	Yes	Yes	Yes	High
[10]	Yes	Unclear	Yes	Yes	Unclear	Moderate
[11]	Yes	Yes	Yes	Yes	Yes	High
[12]	Yes	Yes	Yes	Unclear	Yes	High
[4]	Yes	Yes	Yes	Yes	Yes	High
[13]	Yes	Yes	Yes	Yes	Yes	High
[6]	Yes	Yes	Yes	Yes	Yes	High
[14]	Yes	Yes	Yes	Unclear	Yes	High
[15]	Yes	Yes	Yes	Unclear	Yes	High
[16]	Yes	Yes	Yes	Yes	Yes	High
[17]	Yes	Yes	Yes	Yes	Yes	High
[18]	Yes	Yes	Yes	Yes	Yes	High
[19]	Yes	Yes	Yes	Unclear	Yes	High
[20]	Yes	Yes	Yes	Yes	Yes	High
[21]	Yes	Yes	Yes	Yes	Yes	High
[22]	Yes	Yes	Yes	Yes	Yes	High
[23]	Yes	Yes	Yes	Yes	Yes	High
[24]	Yes	Yes	Yes	Unclear	Yes	High
[25]	Yes	Yes	Yes	Yes	Yes	High
[26]	Yes	Yes	Yes	Yes	Yes	High
[27]	Yes	Yes	Yes	Yes	Yes	High
[28]	Yes	Yes	Yes	Yes	Yes	High
[29]	Yes	Yes	Yes	Yes	Yes	High
[30]	Yes	Yes	Yes	Yes	Yes	High
[31]	Yes	Yes	Yes	Yes	Yes	High
[32]	Yes	Yes	Yes	Yes	Yes	High

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Article	Q1	Q2	Q3	Q4	Q5	Quality Rating
[33]	Yes	Yes	Yes	Yes	Yes	High
[34]	Yes	Yes	Yes	Yes	Yes	High
[35]	Yes	Yes	Yes	Yes	Yes	High
[36]	Yes	Yes	Yes	Yes	Yes	High
[37]	Yes	Yes	Yes	Yes	Yes	High
[38]	Yes	Yes	Yes	Yes	Yes	High

2.4. Data Extraction and Thematic Analysis

Data extraction and coding were conducted systematically by two reviewers to identify key characteristics of each study. The extracted information included research methods, sample size, algorithms, dissolved oxygen sensors, turbidity sensors, additional monitored parameters, IoT systems, outputs or actuators, application contexts, and main findings. Each study was coded according to its relevance to the research questions, implementation approach, monitoring objectives, and technological characteristics. The selected studies were then analyzed thematically following Braun and Clarke's reflexive thematic analysis framework [39], which emphasizes identifying recurring patterns and themes across the selected articles. Studies with similar characteristics and findings were grouped into broader thematic categories corresponding to the four research questions.

Several studies addressed multiple research questions simultaneously, particularly studies integrating IoT-based monitoring systems with machine learning and predictive analytics approaches. Therefore, thematic classification was refined during the data extraction and synthesis stages, allowing individual studies to contribute to more than one research question category when relevant. Rather than assigning each study exclusively to a single category, studies were interpreted according to their primary methodological and technological contributions across the review themes. This approach enabled a more integrated synthesis of sensing technologies, IoT systems, and ML/AI applications in aquaculture monitoring.

This review relied exclusively on the Scopus database for literature retrieval. Although Scopus provides broad coverage of peer-reviewed international publications, relevant studies indexed only in other databases such as Web of Science, IEEE Xplore,

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ScienceDirect, or Google Scholar may not have been captured. Therefore, some potentially relevant studies related to aquaculture monitoring, IoT systems, or ML applications may have been excluded from the review corpus.

3. RESULTS AND DISCUSSION

The findings of the reviewed studies are summarized in Table 2, which categorizes the literature based on the research questions (RQ1–RQ4), themes, and corresponding articles.

Table 2. Literature Synthesis Based on Research Questions and Themes

RQ	Theme	Article Example
RQ1	IoT-based	[9], [10], [4]
	Manual portable	[11], [23], [24], [40], [28], [30]
	Automatic	[20], [26], [27], [29]
RQ2	IoT-based	[9], [13], [17]
	Manual	[11], [5], [20], [23]
	Automatic	[20]
	Remote sensing	[15], [16]
RQ3	Real-time monitoring	[9], [13], [6][17], [18]
	Automations systems	[13], [18]
	Operational efficiency	[9]
RQ4	Predictive analytics	[6], [11], [12]
	Decision support systems	[10], [13], [6]
	Anomaly detection	[10]

Table 2 summarizes the 32 reviewed studies based on the four research questions (RQ1–RQ4), including measurement methods, IoT integration, and AI/ML applications in aquaculture water quality monitoring. For RQ1, the studies mainly reported IoT-based, manual portable, and automatic DO monitoring methods. For RQ2, turbidity monitoring approaches included IoT-based systems, manual measurements, automatic sensors, and remote sensing methods. For RQ3, the reviewed studies primarily focused on real-time monitoring, automation systems, and operational efficiency enabled by IoT platforms. For RQ4, the studies mainly explored predictive analytics, decision-support systems, and anomaly detection using AI/ML approaches.

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The distribution of studies suggests that dissolved oxygen monitoring technologies are more widely implemented in aquaculture, particularly through the adoption of IoT-based and continuous monitoring systems. Compared with dissolved oxygen monitoring, fewer reviewed studies focused on automated and remote-sensing-based turbidity monitoring approaches in aquaculture contexts. The reviewed literature also indicates a growing transition toward integrated IoT-based monitoring and ML-driven predictive analytics, although fully autonomous and adaptive biofloc management systems remain relatively limited.

3.1. RQ1 – Measurement Methods for Dissolved Oxygen in Biofloc Systems

The reviewed literature identified three major approaches for dissolved oxygen (DO) monitoring in aquaculture systems: IoT-based systems, manual portable instruments, and automatic/professional monitoring systems, as summarized in Table 2. IoT-based approaches were the most frequently reported methods, appearing in mulitple studies (e.g., [9], [13]). These systems commonly utilized low-cost sensors integrated with ESP32, ESP8266, or Arduino platforms for continuous data acquisition. Manual portable measurements were also commonly used, particularly in field-based monitoring studies. Commonly reported instruments included handheld dissolved oxygen meters and portable multiparameter probes. Several studies used these instruments for periodic sampling and calibration purposes in pond and biofloc environments [11], [28]. Automatic and professional monitoring systems were less frequently reported but provided continuous and high-precision measurements. These studies commonly employed multiparameter sondes, CTD profilers, and optical DO sensors capable of simultaneously monitoring multiple water quality parameters [20], [27], [26], [24]. Table 3 summarizes the distribution of DO monitoring methods and representative sensor examples identified in the reviewed literature.

Table 3. Dissolved oxygen monitoring approaches and representative sensors

Category	% Study	Model Example	Main Advantages
IoT-based	38%	SEN0237 (DFRobot)	Real-time, cheap
Manual Portable	43%	YSI Pro20i, Hanna HI9147	Accurate, flexible

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Category	% Study	Model Example	Main Advantages
Automatic / Professional	19%	YSI EXO2, SEABIRD-19, Sensorex Inc., DO1200/T	High accuracy, continuous monitoring

The reviewed studies also highlighted the importance of calibration and operational maintenance in maintaining measurement reliability. Monitoring frequency varied considerably across studies, ranging from periodic manual sampling to continuous real-time acquisition through IoT-based platforms. This variation reflects differences in monitoring objectives, operational scale, and technology availability across aquaculture applications.

3.2. RQ2 – Measurement Methods for Turbidity in Biofloc Systems

The reviewed studies identified four main categories of turbidity monitoring approaches: IoT-based systems, manual methods, automatic instruments, and remote sensing approaches. IoT-based turbidity monitoring commonly used turbidity sensors connected to microcontrollers for automated and continuous measurements [9], [13]. Several systems integrated turbidity monitoring with other water quality parameters such as DO, pH, temperature, and TDS. Manual approaches included the use of Secchi disks and handheld turbidimeters [4], [11], [20], [23]. These methods were frequently applied because of their low operational cost and simplicity in field applications. Automatic turbidity monitoring systems were less frequently reported and generally appeared as part of integrated multiparameter monitoring platforms. Remote sensing approaches utilized satellite imagery, particularly Sentinel-2 data, combined with image-processing tools and machine learning models for turbidity estimation [15], [16]. These studies demonstrated the application of optical reflectance data for large-scale water quality monitoring. Figure 2 summarizes the main turbidity monitoring approaches identified in the reviewed studies.

The reviewed studies also showed considerable variation in monitoring frequency and operational scale. IoT-based systems generally supported continuous real-time monitoring, whereas manual approaches relied on periodic field observations. Remote sensing applications were primarily designed for large-scale spatial analysis rather than localized pond-scale monitoring, highlighting differences in monitoring objectives and technological capabilities across aquaculture contexts.

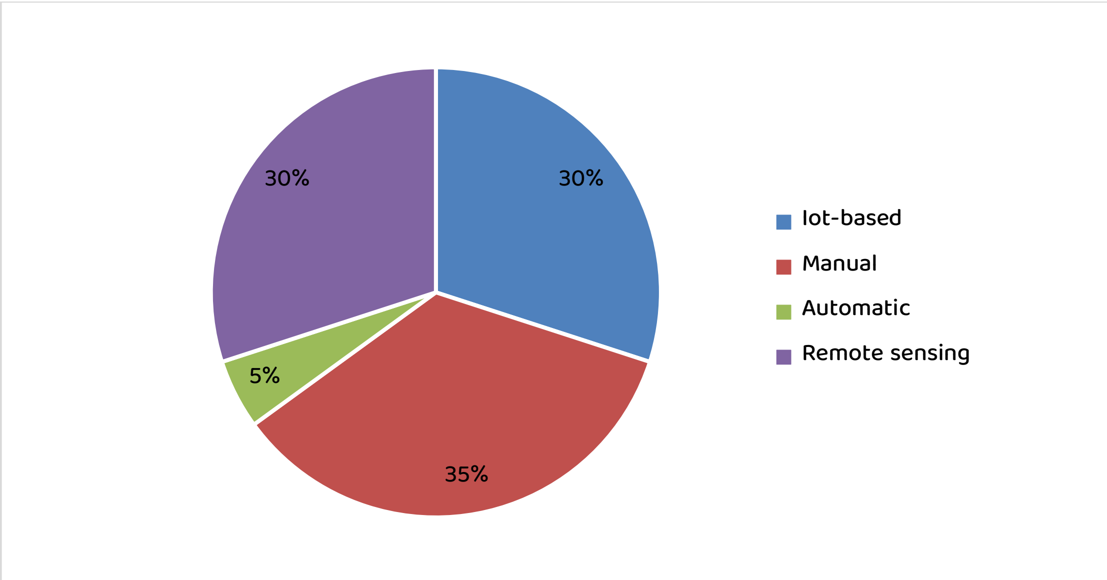

Figure 2. Classification of turbidity monitoring approaches identified in the studies

3.3. RQ3 – Potential of IoT Integration in Biofloc Water Quality Monitoring

The reviewed literature showed that IoT-based monitoring systems in aquaculture commonly integrated multiple water quality sensors with low-cost microcontroller platforms such as ESP8266, ESP32, Arduino UNO, and Raspberry Pi. The monitored parameters included dissolved oxygen, turbidity, pH, temperature, TDS, water level, and gas concentration sensors. Wireless communication protocols identified in the reviewed studies included Wi-Fi, MQTT, HTTP, Zigbee, GSM/GPRS, and LoRa. Several systems provided remote access through mobile applications, web dashboards, cloud databases, and IoT platforms such as Blynk and Thingspeak.

The reviewed studies showed that IoT systems were primarily applied for real-time monitoring, automation, historical data storage, warning systems, and actuator control. Several studies also integrated predictive functions and anomaly detection into IoT monitoring platforms.

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Table 4. Characteristics of IoT-based monitoring systems identified in the studies

Article	Sensor	Microcontroller	Protocol	User Access	Actuator	Output/Feature
[9]	DO, Turbidity, pH, Temperature, and Total Dissolved Solids (TDS)	ESP8266	MQTT	Mobile App, Web App, Google Sheet, OLED Display	-	Local Database, Real Time Monitoring, Sensor Value Prediction
[10]	DO	ESP32 and Arduino	LoRa/Wi-Fi, MQTT/HTTP	-	-	Anomaly Detection, Real Time Monitoring
[13]	DO, Turbidity, Temperature, TDS, pH, Water Level	ESP32	Wi-Fi	Blynk	Water Pump, Air Pump, Water Heater	Real Time Monitoring, Warning and Suggestion Message, Automatic and Manual Actuator Controller
[6]	Temperature, TDS, pH	Arduino UNO	Wi-Fi	Mobile App	-	Real Time DO Level Prediction, Warning and Suggestion Message
[17]	MQ-7, MQ-135, TDS, Turbidity, DHT11, Water Temperature, pH	ESP8266	Wi-Fi	Thingspeak	-	Real Time Monitoring, Mortality Prediction, Historical Data
[18]	pH, Water Temperature	Arduino, Raspberry Pi	Wi-Fi	Mobile App	Feeder, Heater, Fan, Motor	Real Time Monitoring, Automated Feeding, Automatic and Manual Actuator Controller
[21]	Satellite data	ATMEGA 328	GSM/GPRS	Mobile App	-	User Monitoring View and Historical Data
[25]	pH, DO, Temperature	CC2530	Zigbee	-	-	Periodic Monitoring

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3.4. RQ4 – Potential of AI/ML Integration in Biofloc Systems

The reviewed studies identified multiple machine learning and artificial intelligence approaches for water quality prediction, anomaly detection, classification, and decision support applications in aquaculture systems. Commonly reported models included Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN-LSTM), XGBoost, CatBoost, AdaBoost, and Deep Neural Networks (DNN). The input variables commonly used in the reviewed studies included dissolved oxygen, turbidity, pH, temperature, salinity, TDS, chlorophyll-a, transparency, and biofloc-related indicators. The outputs of these models included dissolved oxygen prediction, turbidity estimation, mortality prediction, anomaly detection, and water quality classification. Table 5 summarizes the AI/ML approaches identified in the reviewed studies.

The reviewed studies reported various model performance metrics, including accuracy, coefficient of determination (R^2), and F1-score. Several studies reported high predictive performance for water quality prediction tasks using ensemble learning and deep learning approaches. In addition, some studies combined machine learning with remote sensing data for large-scale turbidity and water quality estimation. The reviewed literature also identified applications of AI/ML for biofloc-related parameter prediction, including biofloc volume estimation, dissolved oxygen dynamics, and microbial-related monitoring variables.

Table 5. AI/ML models and prediction outputs reported in the reviewed studies

Author	Input Parameter	ML/AI Model	Output
[9]	DO, Turbidity, pH, Water Temperature, Air Temperature, Air Humidity, and Total Dissolved Solids (TDS)	RNN, LSTM	pH forecasting; performance not reported
[10]	Temperature, pH, Turbidity	Random Forest, SVM, Neural Network, K-Means, Autoencoder.	DO prediction (Acc. 92%), anomaly detection
[11]	DO, pH, Temp, TAN, NO_2–N, ALK, Transparency	Random Forest, CNN-LSTM	Feature ranking; DO prediction (R^2=0.815), TAN (R^2=0.826), NO_2–N (R^2=0.831)

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Author	Input Parameter	ML/AI Model	Output
[12]	Chl-a, aCDOM(440), Turbidity	Ensemble Machine Learning (AdaBoost, LightGBM, XGBoost, CatBoost, RF, SVM)	Accurate prediction of Chl-a : R^2 = 0.958, aCDOM(440): R^2 = 0.928, and Turbidity: R^2 = 0.949
[4]	Daily Feed Amount (Kg), Days Of Culture (DOC), Biofloc Amount (ml/L), Secchi Disc Reading (cm), Carbon Essence (Kg), Surface Temperature (°C), Salinity (Ppt), Operated HP, Precipitation, Pressure, Relative Humidity	Random Forest	Predicted Avg DO (R^2=0.74, Acc. ~98%)
	Daily Feed, DOC, Water Temp, Surface Temp, SDR, Salinity, Operated HP, DO	Deep Neural Network (DNN)	Predicted Biofloc amount (Acc. ~90%)
[6]	pH, Temperature, TDS, Floc	Deep Learning	DO Level Prediction (Acc. 77.3%)
[15]	Sentinel 2 Red Band	Linear Regression	Water Turbidity Prediction (R^2 = 0.87)
[17]	CO, Amonia, Humidity, Turbidity, Air Temp, TDS, pH, Water Temp	Random Forest, Decision Tree, SVM, Logistic Regression, XGBoost, Gaussian Naïve Bayes, Ensemble Learning	Mortality prediction (best Acc. 97%, RF and XGBoost)
[22]	Temperature, Salinity, pH, DO	DiCNN-BiL-STM	Water quality prediction (Acc. 96.98%, F1=96.15%)
[25]	pH, DO, Temperature	Improved Bald Eagle Search algorithm (IBES)	Water grade judgment (Prob. 91%)
[28]	Calibrated Sentinel-2 Surface Reflectance Data	Decision Tree, Random Forest, Gradient Boosting Regression, Adaboost Regression	Water quality prediction (DO, COD, Chl-a, TSS), R^2 up to 0.90

3.5. Discussion

The reviewed studies demonstrate a clear transition from conventional manual monitoring toward continuous and sensor-based dissolved oxygen (DO) monitoring systems in aquaculture. The dominance of IoT-based and portable monitoring approaches suggests that real-time monitoring and operational flexibility have become primary considerations in modern aquaculture management. This trend appears particularly important in biofloc systems, where high microbial respiration and suspended organic matter may rapidly alter dissolved oxygen concentrations.

The findings also indicate a trade-off between affordability and measurement performance. Low-cost IoT platforms based on ESP32, ESP8266, and Arduino architectures provide scalable and accessible monitoring solutions for small- and medium-scale aquaculture operations. However, research-grade optical probes and multiparameter instruments continue to offer superior accuracy, calibration stability, and long-term reliability. This suggests that although low-cost monitoring technologies are increasingly adopted, precision and sensor robustness remain critical challenges for field implementation.

The reviewed studies further highlight the importance of calibration and monitoring frequency in maintaining data quality [18]. Manual fixed-interval sampling remains useful in low-resource settings; however, it may not adequately capture rapid DO fluctuations in intensive biofloc environments. In contrast, real-time monitoring systems provide higher temporal resolution and support faster operational responses to water quality deterioration. Overall, the distribution of studies suggests that DO monitoring research in aquaculture has reached a relatively mature stage in terms of sensor deployment and real-time monitoring architectures. Nevertheless, the integration of predictive and adaptive control systems remains comparatively limited in biofloc-specific applications.

The reviewed literature indicates that turbidity monitoring methods in aquaculture remain highly diverse, ranging from simple manual approaches to advanced remote sensing and IoT-based systems. The continued use of Secchi disks and handheld turbidimeters suggests that low-cost and operationally simple methods are still widely preferred, particularly in small-scale aquaculture operations. However, the increasing implementation of IoT-based turbidity sensors reflects a broader movement toward automated and continuous water quality monitoring. In biofloc systems, this shift appears especially relevant because suspended solids and microbial aggregates can fluctuate dynamically over short periods. Consequently, high-frequency monitoring may provide more reliable operational information than periodic manual measurements.

The reviewed studies also demonstrate emerging interest in remote sensing approaches for turbidity estimation using satellite imagery and machine learning models. Although these approaches show promising predictive performance at broader spatial scales, their practical applicability in biofloc aquaculture remains limited. Small pond dimensions, shading effects, and dense floc conditions may reduce the effectiveness of satellite-based monitoring in intensive biofloc environments. These findings suggest that turbidity monitoring research is currently transitioning from traditional manual observation toward automated and data-driven approaches. Nevertheless, compared with dissolved oxygen monitoring, the adoption of advanced turbidity monitoring technologies in biofloc systems still appears relatively limited and less mature.

The reviewed studies indicate that IoT technologies have become central components of modern aquaculture monitoring systems. The widespread use of low-cost microcontrollers and wireless communication protocols demonstrates that IoT adoption is driven largely by affordability, accessibility, and ease of integration with commercially available sensors. In biofloc systems, IoT implementation appears particularly valuable because water quality conditions may change rapidly due to intensive microbial activity and organic accumulation. Continuous monitoring through IoT platforms allows farmers to observe water quality parameters in real time and supports faster responses to environmental changes. Several reviewed studies further demonstrate the integration of actuator systems, such as pumps, aerators, and feeders, indicating a gradual transition from monitoring-only systems toward semi-automated aquaculture management [18].

The findings also suggest that IoT platforms increasingly function not only as monitoring tools but also as data acquisition infrastructures for predictive analytics and intelligent decision-support systems. The integration of cloud storage, mobile applications, and historical databases provides a foundation for future AI/ML implementation in precision aquaculture. Despite these advantages, the reviewed literature highlights several persistent limitations. Low-cost IoT systems may experience reduced sensor stability, calibration drift, and operational durability under long-term field conditions. In addition, reliable internet connectivity and power supply remain practical constraints in some aquaculture environments. These limitations indicate that while IoT adoption has progressed rapidly, the long-term robustness and standardization of low-cost monitoring systems still require further development. Overall, the distribution of studies suggests that IoT-based monitoring has reached a relatively advanced stage of technological adoption in aquaculture. However, fully autonomous and adaptive biofloc management systems remain in an early developmental phase.

The reviewed studies demonstrate increasing adoption of AI and machine learning approaches for water quality prediction, anomaly detection, and decision-support applications in aquaculture. The dominance of Random Forest, XGBoost, and other ensemble learning approaches suggests that these models are widely preferred because of their robustness in handling nonlinear relationships and noisy environmental datasets. Deep learning models, particularly RNN-, LSTM-, and CNN-based architectures, were frequently applied for time-series prediction tasks. Their implementation indicates growing interest in modeling temporal dynamics of water quality variables such as dissolved oxygen and turbidity. In biofloc systems, where environmental conditions may fluctuate rapidly due to microbial interactions and organic loading, temporal predictive models appear particularly relevant.

The reviewed literature also indicates that ML applications are gradually expanding beyond conventional physicochemical monitoring toward biofloc-specific indicators such as floc volume, microbial activity, and mortality prediction. This trend suggests an increasing effort to represent the biological complexity of biofloc systems within predictive models. However, several limitations remain evident. Most supervised learning approaches require large and high-quality labeled datasets, which are still relatively scarce in aquaculture applications. In addition, many deep learning models operate as "black-box" systems, limiting interpretability and reducing user trust in operational decision-making. Remote sensing-based ML approaches also face practical limitations in small-scale biofloc ponds because of spatial resolution constraints and environmental interference. The reviewed studies further suggest that AI/ML research in aquaculture is currently more mature in prediction-oriented applications than in adaptive autonomous control systems. Predictive analytics dominates the literature, whereas anomaly detection and intelligent decision-support systems appear less frequently. This distribution indicates that AI/ML integration in biofloc aquaculture remains in an emerging developmental stage rather than a fully mature implementation phase.

Several important research gaps were identified from the reviewed studies. First, there is still limited availability of long-term and standardized datasets for biofloc systems, reducing the generalizability of predictive models across different environmental and operational conditions. Most studies also focused primarily on short-term experimental datasets rather than continuous field-scale monitoring. Second, although IoT-based monitoring systems are increasingly common, relatively few studies have implemented fully integrated IoT–AI architectures capable of autonomous and adaptive pond management. Most systems remain focused on monitoring and prediction rather than closed-loop decision-making and automatic optimization. Third, biofloc-specific monitoring variables remain underexplored. While most studies focus on conventional water quality parameters such as DO, pH, and turbidity, fewer studies incorporate microbial indicators, floc characteristics, and biological interaction variables that are central to biofloc system dynamics.

Future studies may benefit from developing hybrid frameworks that combine IoT monitoring, machine learning, and adaptive control mechanisms within integrated precision aquaculture systems. In addition, explainable AI approaches and lightweight edge-computing models may improve practical implementation and user trust in real-time operational environments. Overall, the reviewed literature indicates that aquaculture monitoring technologies are progressing toward more automated, predictive, and data-driven management systems. However, further advances are still required before intelligent and autonomous biofloc aquaculture systems can be implemented reliably at commercial scale.

4. CONCLUSION

This systematic review synthesizes current approaches for monitoring dissolved oxygen (DO) and turbidity in biofloc aquaculture systems. Four main findings emerge from the reviewed literature. First (RQ1), DO monitoring commonly employs IoT-based, manual portable, and automatic measurement systems, with IoT-based and portable approaches being the most widely applied. Second (RQ2), turbidity monitoring includes manual, IoT-

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based, automatic, and remote sensing methods, each offering different trade-offs between cost, scale, and reliability. Third (RQ3), IoT integration enables real-time monitoring, automation, and remote management, although challenges related to sensor calibration, data quality, and long-term reliability remain significant. Fourth (RQ4), ML and AI approaches show strong potential for predictive analytics, anomaly detection, and decision support, particularly through ensemble and deep learning models, but broader validation across diverse biofloc conditions is still required. Although this review focuses on biofloc aquaculture systems, studies on DO and turbidity measurement methods were also drawn from broader aquaculture and water-quality monitoring contexts to provide complementary methodological insights. In contrast, discussions regarding IoT and ML/AI integration were primarily derived from biofloc-oriented studies. Overall, IoT and ML/AI integration represent promising directions toward more adaptive and data-driven precision aquaculture systems.

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REFERENCES

[1] R. Marnis, Jamalludin, and H. Mashadi, "Analisis usaha budidaya ikan nila (Oreochromis niloticus) di Desa Titian Modang Kecamatan Kuantan Singingi," *Jurnal Pengembangan Ilmu Pertanian*, vol. 12, no. 1, 2023.

[2] N. K. Yadav *et al.*, "The role of biofloc technology in sustainable aquaculture: nutritional insights and system efficiency," *Blue Biotechnology*, vol. 2, no. 1, p. 7, May 2025, doi: 10.1186/s44315-025-00025-x.

[3] M. G. C. Emerenciano, L. R. Martínez-Córdova, M. Martínez-Porchas, and A. Miranda-Baeza, "Biofloc Technology (BFT): A Tool for Water Quality Management in Aquaculture," in *Water Quality*, InTech, 2017. doi: 10.5772/66416.

[4] S. Ayesha Jasmin, P. Ramesh, and M. Tanveer, "An intelligent framework for prediction and forecasting of dissolved oxygen level and biofloc amount in a shrimp culture system using machine learning techniques," *Expert Syst. Appl.*, vol. 199, Aug. 2022, doi: 10.1016/j.eswa.2022.117160.

[5] H. Rastegari *et al.*, "Internet of Things in aquaculture: A review of the challenges and potential solutions based on current and future trends," *Smart Agricultural Technology*, vol. 4, p. 100187, Aug. 2023, doi: 10.1016/j.atech.2023.100187.

[6] Md. M. Rashid, A.-A. Nayan, S. A. Simi, J. Saha, Md. O. Rahman, and M. G. Kibria, "IoT based Smart Water Quality Prediction for Biofloc Aquaculture," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, 2021, doi: 10.14569/IJACSA.2021.0120608.

[7] M. J. Page *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *BMJ*, vol. 372, p. n71, Mar. 2021, doi: 10.1136/bmj.n71.

[8] H. A. Long, D. P. French, and J. M. Brooks, "Optimising the value of the critical appraisal skills programme (CASP) tool for quality appraisal in qualitative evidence synthesis," *Research Methods in Medicine & Health Sciences*, vol. 1, no. 1, pp. 31–42, Sep. 2020, doi: 10.1177/2632084320947559.

[9] V. Sowmiya and G. R. Kanagachidambaresan, "Brackish water parameters monitoring dashboard using Internet of Things and Industry 4.0," *EAI Endorsed Transactions on Internet of Things*, vol. 11, Nov. 2025, doi: 10.4108/eetiot.6860.

[10] K. Rama Krishna, D. Prasanna Anjaneyulu, A. Naikr, D. Samhitha, and S. Bhukya, "Dissolved Oxygen Level measurement in water using IoT and Machine Learning," *J. Theor. Appl. Inf. Technol.*, vol. 28, no. 4, 2025, doi: 10.5281/zenodo.16949104.

[11] R. Jongjaraunsuk, W. Taparhudee, and P. Suwannasing, "Comparison of Water Quality Prediction for Red Tilapia Aquaculture in an Outdoor Recirculation System Using Deep Learning and a Hybrid Model," *Water (Switzerland)*, vol. 16, no. 6, Mar. 2024, doi: 10.3390/w16060907.

[12] M. Karthick, P. Shanmugam, and G. Saravana Kumar, "Long-term water quality assessment in coastal and inland waters: An ensemble machine-learning approach using satellite data," *Mar. Pollut. Bull.*, vol. 209, Dec. 2024, doi: 10.1016/j.marpolbul.2024.117036.

[13] M. R. Al Mamun, M. Ashik-E-Rabbani, M. M. Haque, and S. M. Upoma, "IoT-based real-time biofloc monitoring and controlling system," *Smart Agricultural Technology*, vol. 9, Dec. 2024, doi: 10.1016/j.atech.2024.100598.

[14] M. M. Overrein, P. Tinn, D. Aldridge, G. Johnsen, and G. M. Fragoso, "Biomass estimations of cultivated kelp using underwater RGB images from a mini-ROV and computer vision approaches," *Front. Mar. Sci.*, vol. 11, 2024, doi: 10.3389/fmars.2024.1324075.

[15] S. Maimouni, A. A. Moufkari, L. Daghor, A. Fekri, S. Oubraim, and R. Lhissou, "Spatiotemporal monitoring of low water turbidity in Moroccan coastal lagoon using Sentinel-2 data," *Remote Sens. Appl.*, vol. 26, Apr. 2022, doi: 10.1016/j.rsase.2022.100772.

[16] W. García-Tuñon *et al.*, "Spatio-temporal variability of turbidity derived from Sentinel-2 in Reloncaví sound, Northern Patagonia, Chile," *Ecol. Inform.*, vol. 83, Nov. 2024, doi: 10.1016/j.ecoinf.2024.102814.

[17] M. A. Abid, M. Amjad, K. Munir, H. U. R. Siddique, and A. D. Jurcut, "IoT-Based Smart Biofloc Monitoring System for Fish Farming Using Machine Learning," *IEEE Access*, vol. 12, pp. 86333–86345, 2024, doi: 10.1109/ACCESS.2024.3384263.

[18] E. B. Blancaflor and M. Baccay, "Assessment of an automated IoT-biofloc water quality management system in the Litopenaeus vannamei's mortality and growth rate," *Automatika*, vol. 63, no. 2, pp. 259–274, 2022, doi: 10.1080/00051144.2022.2031540.

[19] K. Wu, G. Xu, Y. Tian, G. Li, Z. Yi, and X. Tang, "Synthesis and Evaluation of Aquatic Antimicrobial Peptides Derived from Marine Metagenomes Using a High-Throughput Screening Approach," *Mar. Drugs*, vol. 23, no. 4, Apr. 2025, doi: 10.3390/md23040178.

[20] F. G. Sampaio *et al.*, "Unveiling low-to-high-frequency data sampling caveats for aquaculture environmental monitoring and management," *Aquac. Rep.*, vol. 20, Jul. 2021, doi: 10.1016/j.aqrep.2021.100764.

[21] R. P. Shete, A. M. Bongale, and D. Dharrao, "IoT-enabled effective real-time water quality monitoring method for aquaculture," *MethodsX*, vol. 13, Dec. 2024, doi: 10.1016/j.mex.2024.102906.

[22] I. A. M., S. R. S., T. K., and A. A., "AQUASENSE: aquaculture water quality monitoring framework using autonomous sensors," *Aquaculture International*, vol. 32, no. 7, pp. 9119–9135, Dec. 2024, doi: 10.1007/s10499-024-01606-0.

[23] Z. A. Ariadji, G. Suantika, and P. Aditiawati, "Trophic state assessment of marine ecosystems used for floating net cage aquaculture: a case study in Pegametan Bay, North Bali, Indonesia," *Aquaculture International*, vol. 32, no. 5, pp. 6611–6647, Oct. 2024, doi: 10.1007/s10499-024-01481-9.

[24] W. Qi, P. V. Skov, K. J. de Jesus Gregersen, and L. F. Pedersen, "A novel method to estimate biofilm activity based on enzymatic oxygen release from hydrogen peroxide decomposition," *Biofilm*, vol. 5, Dec. 2023, doi: 10.1016/j.bioflm.2023.100121.

[25] D. Junfeng and F. Li-hui, "Water grade judgment of aquaculture based on IBES and evidence fusion," *Comput. Electron. Agric.*, vol. 212, Sep. 2023, doi: 10.1016/j.compag.2023.108173.

[26] A. Dimoudi *et al.*, "A spatial interpolation approach for environmental assessment of aquaculture effects on water quality of Pagasitikos Gulf (Eastern Mediterranean)," *Mar. Environ. Res.*, vol. 188, Jun. 2023, doi: 10.1016/j.marenvres.2023.106036.

[27] E. Royer and R. Pastres, "Data assimilation as a key step towards the implementation of an efficient management of dissolved oxygen in land-based aquaculture," *Aquaculture International*, vol. 31, no. 3, pp. 1287–1301, Jun. 2023, doi: 10.1007/s10499-022-01028-w.

[28] N. H. Quang, N. T. Dinh, N. T. Dien, and L. T. Son, "Calibration of Sentinel-2 Surface Reflectance for Water Quality Modelling in Binh Dinh's Coastal Zone of Vietnam," *Sustainability (Switzerland)* , vol. 15, no. 2, Jan. 2023, doi: 10.3390/su15021410.

[29] M. A. Dayıoğlu, "Experimental study on design and operational performance of solar-powered venturi aeration system developed for aquaculture – A semi-floating prototype," *Aquac. Eng.*, vol. 98, Aug. 2022, doi: 10.1016/j.aquaeng.2022.102255.

[30] G. Yin, M. C. Ong, J. Lee, and T. Kim, "Numerical simulation of oxygen transport in land-based aquaculture tank," *Aquaculture*, vol. 543, Oct. 2021, doi: 10.1016/j.aquaculture.2021.736973.

[31] E. T. Akange *et al.*, "Optimising the control factors of a smart biofloc aquaculture system for the sustainable production of Pacific whiteleg shrimp, Litopenaeus vannamei," *Aquaculture International*, vol. 33, no. 6, p. 617, Nov. 2025, doi: 10.1007/s10499-025-02324-x.

[32] R. P. Shete, A. Shekhar C., Y. V. Mahajan, A. M. Bongale, and D. Dharrao, "IoT-driven ensemble machine learning model for accurate dissolved oxygen prediction in aquaculture," *Discover Internet of Things*, vol. 5, no. 1, p. 94, Sep. 2025, doi: 10.1007/s43926-025-00201-w.

[33] Yaddarabullah, I. H. Sumiasih, and M. D. Puspitawati, "A Context-Aware Temporal Convolutional Network for Water Replacement Prediction in Catfish Biofloc Ponds With Imbalanced Event Handling," *Journal of Computer Science*, vol. 22, no. 3, pp. 747–765, Mar. 2026, doi: 10.3844/jcssp.2026.747.765.

[34] K. Song, Y. Yang, and H. Luo, "A hybrid ISFOA-AGCN-ILSTM model for short-term prediction of dissolved oxygen in aquaculture systems," *Aquaculture International*, vol. 34, no. 2, p. 53, Jan. 2026, doi: 10.1007/s10499-026-02462-w.

[35] J. Kim, H. Hwang, Y. Ko, C.-H. Lee, B. G. Lee, and J. Bae, "Digital twin-based smart aquafarm monitoring system with multi-instance learning based on autoencoder model," *Aquac. Eng.*, vol. 112, p. 102656, Jan. 2026, doi: 10.1016/j.aquaeng.2025.102656.

[36] M. Yu *et al.*, "Physics-Guided Transfer Learning for Predicting Dissolved Oxygen in Smart Aquaculture Farms," *IET Cyber-systems and Robotics*, vol. 8, no. 1, Jan. 2026, doi: 10.1049/csy2.70053.

[37] B. Xu, J. Yan, H. Tang, Y. Zhang, M. Wang, and J. Gao, "An efficient compressive CNN and transformer hybrid framework for long-term dissolved oxygen prediction in aquaculture," *Information Processing in Agriculture*, Jan. 2026, doi: 10.1016/j.inpa.2026.01.011.

[38] M. SHARMA, T. VERMA, and A. SHARMA, "Aquaponic innovations: Optimizing carp growth in polyculture tank with plant diversity in Himachal Pradesh," *Indian J. Anim. Sci.*, vol. 95, no. 4, pp. 344–347, Jul. 2025, doi: 10.56093/ijans.v95i4.156339.

[39] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qual. Res. Psychol.*, vol. 3, no. 2, pp. 77–101, 2006, doi: 10.1191/1478088706qp063oa.

[40] C. Sun *et al.*, "Fabrication and optimization of paper chips from calcinated Fe-MOFs for rapid and in situ visual detection of tetracyclines in water environments," *J. Hazard. Mater.*, vol. 458, Sep. 2023, doi: 10.1016/j.jhazmat.2023.131946.