



Climate Smart Technologies: AI-Enhanced, IoT-Driven Environmental Sustainability for Aquaculture in Emerging Economies

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Abstract

Aquaculture is increasingly recognized as a critical pillar for food security and economic growth, especially in emerging economies where population growth and dietary transitions drive high demand for affordable protein. However, aquaculture faces significant environmental challenges such as fluctuating water quality, pollution, climate variability, and infrastructural constraints. Traditional monitoring systems often fail to provide timely insights, resulting in poor management practices and losses in productivity. This chapter explores the transformative potential of artificial intelligence (AI) integrated with the Internet of Things (IoT) for environmental monitoring in aquaculture. By enabling real-time sensing, predictive analytics, and intelligent decision-making, AI-enhanced IoT systems offer a resilient approach to water quality management, operational efficiency, and sustainability in resource-constrained settings. The chapter discusses critical parameters for monitoring, architectural designs, machine learning applications, governance and ethics, and practical implementation strategies, supported by illustrative case examples. It concludes with recommendations for future research and policy directions that emphasize inclusivity and sustainability.

Keywords: *Climate smart technologies, AI-Enhanced, IOT, Environmental suitability, Aquaculture, Emerging Economies*

1. Introduction

Aquaculture has become one of the fastest-growing food production sectors globally, now contributing more than half of the world's fish consumed, and it plays a particularly critical role in emerging economies (FAO, 2024). In many of these regions, aquaculture provides not only a vital source of affordable protein but also generates employment and income for millions of households, thereby reinforcing food and economic security. However, despite its growth and promise, aquaculture operations in developing contexts remain highly susceptible to

environmental shocks and infrastructural deficiencies. For example, fluctuations in dissolved oxygen levels, particularly during early morning hours when photosynthetic activity is minimal, often result in mass fish die-offs, leading to significant economic losses for farmers. Furthermore, contamination from anthropogenic activities, such as heavy metal pollution caused by mining and industrial runoff, not only impairs fish health but also raises serious food safety and public health concerns (Nguyen et al., 2023). These vulnerabilities underscore the limitations of traditional aquaculture practices, which rely heavily on manual sampling and laboratory analysis. Such approaches, while effective for periodic assessments, are costly, time-consuming, and incapable of providing the real-time insights needed to manage sudden or dynamic environmental changes. This gap has created a pressing demand for innovative monitoring and management solutions that are both technologically robust and economically feasible for adoption in resource-constrained settings.

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) has emerged as a transformative approach to overcoming these challenges. IoT technology, through the deployment of low-cost, interconnected sensors, allows for continuous, automated monitoring of key water quality parameters such as temperature, pH, turbidity, ammonia levels, and dissolved oxygen. These sensors generate vast amounts of data in real time, which can then be processed by AI algorithms to detect anomalies, predict potential risks, and recommend timely interventions. For example, AI models trained on historical and real-time data can forecast oxygen depletion events and trigger aeration systems before catastrophic losses occur. In emerging economies, where access to advanced laboratory facilities and trained personnel may be limited, the ability of IoT systems to provide consistent and reliable data streams becomes particularly advantageous. Moreover, the scalability of these systems makes them adaptable for both smallholder farmers and larger aquaculture enterprises, ensuring inclusivity across varying scales of production.

Beyond data collection, the real strength of AI-enhanced IoT systems lies in their ability to facilitate proactive rather than reactive aquaculture management (Sahu et al., 2021). By harnessing predictive analytics, these systems empower farmers to make evidence-based decisions that enhance productivity while reducing risks. For instance, predictive models can be used to optimize feeding regimes, thereby reducing waste, improving feed conversion ratios, and minimizing environmental impacts such as eutrophication. Similarly, real-time alerts on deteriorating water quality can guide immediate corrective measures, safeguarding both fish health and consumer safety. Importantly, these systems can also integrate with mobile platforms to provide user-friendly dashboards and alerts, enabling even farmers with limited technical expertise to make informed decisions. This convergence of AI and IoT aligns with broader sustainability goals, as it reduces reliance on reactive interventions, minimizes economic losses, and enhances resilience against environmental shocks. Ultimately, such innovations hold the potential to transform aquaculture into emerging economies, supporting not only food security but also long-term ecological and economic sustainability.

2. Aquaculture Environmental Monitoring Fundamentals

Environmental monitoring in aquaculture is a cornerstone for ensuring both the health of cultured species and the sustainability of production systems. It entails systematic tracking of physical, chemical, and biological parameters that interact dynamically within aquatic ecosystems. Among the most critical variables are temperature, dissolved oxygen (DO), pH, turbidity, ammonia, nitrite, nitrate, and heavy metals, all of which influence water quality and, consequently, fish physiology and growth (FAO, 2020). These parameters rarely act in isolation; rather, they form complex interdependencies where changes in one factor often trigger cascading effects across the system. For instance, elevated temperatures not only increase fish metabolic rates but also reduce oxygen solubility, compounding the risk of hypoxia a major cause of stress and mortality in fishponds. Similarly, fluctuations in pH alter the chemical equilibrium of nitrogenous compounds, increasing the likelihood of toxic ammonia accumulation that can damage gill function and suppress immune responses in aquatic organisms.

Chemical and physical conditions, biological indicators play a vital role in environmental monitoring for aquaculture. Algal biomass, for example, serves as both a food source and a potential stressor; while moderate phytoplankton densities support productivity, harmful algal blooms can deplete oxygen and release toxins harmful to fish health. Fish behavior, including feeding activity, swimming patterns, and surfacing frequency, provides further insights into water quality status, as subtle changes often precede measurable chemical fluctuations. The nitrogen cycle is especially important to monitor in intensive aquaculture systems, as it links feed input to the production of metabolites such as ammonia and nitrite, which at high concentrations become toxic. Without timely detection and mitigation, these imbalances can cause chronic stress, stunted growth, or mass mortality events, undermining farm performance and profitability.

Effective monitoring of these dynamics is therefore essential for optimizing farm management practices. When real-time information on water parameters is available, aquaculture managers can make data-driven decisions regarding feeding schedules, aeration, and water exchange. Such interventions directly improve feed conversion ratios (FCR), ensuring that the maximum proportion of feed is converted into fish biomass rather than wasted as pollutants (Zhang et al., 2020). Proactive monitoring reduces the likelihood of catastrophic system failures, thereby lowering operational risks and supporting long-term sustainability. In this way, environmental monitoring not only safeguards fish health but also enhances productivity and profitability, particularly in emerging economies where aquaculture contributes significantly to food security and livelihoods.

Reference Architecture for AI-IoT Aquaculture

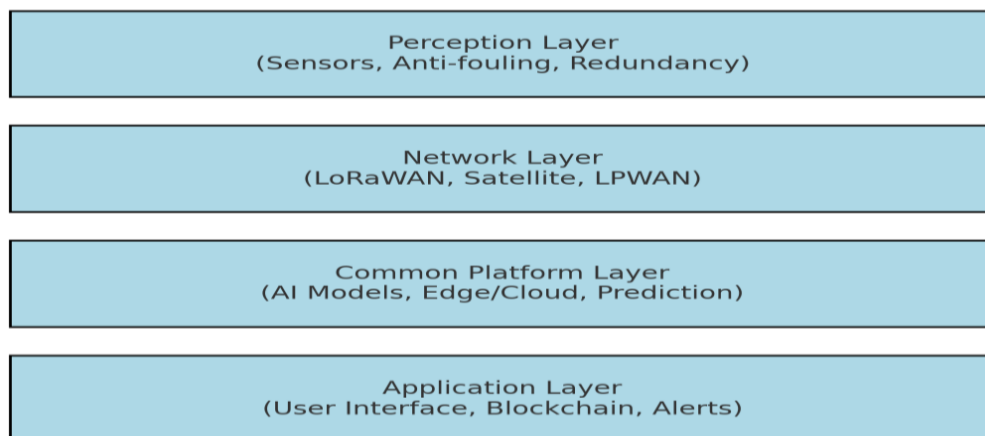
A robust AI-IoT architecture for aquaculture typically comprises sensors, edge nodes, communication infrastructure, cloud platforms, and AI-driven analytics. The architecture begins with the Perception Layer, which serves as the foundation for any AI-IoT aquaculture system. This layer consists of sensors deployed throughout the aquaculture environment to monitor key physical, chemical, and biological parameters such as temperature, dissolved oxygen, pH, turbidity, ammonia, and nitrate concentrations (Li et al., 2022). To ensure accurate and continuous data collection in aquatic conditions, the sensors incorporate anti-fouling measures and

redundancy mechanisms, such as multiple overlapping sensors or self-cleaning devices. By providing real-time, high-resolution data on water quality and fish health indicators, the perception layer establishes the primary source of information that drives all higher-level analytics and decision-making processes within the system. Without this foundational layer, the accuracy and reliability of predictive models and control interventions would be compromised.

The Network Layer functions as the communication backbone of the architecture, enabling the seamless transfer of data from the perception layer to higher-level processing units. This layer employs a combination of connectivity technologies, including LoRaWAN for long-range, low-power wireless communication, satellite links for remote or offshore farms, and LPWAN protocols for wide-area data transmission (LoRa Alliance, 2020). By ensuring reliable connectivity, the network layer allows continuous monitoring even in geographically isolated locations where conventional internet infrastructure may be lacking. It also provides flexibility to handle both high-frequency local data transmissions and aggregated data streams sent to cloud or edge computing platforms for more sophisticated analysis. This layer is essential for bridging the physical sensors and the computational intelligence required to make sense of complex environmental data.

At the top of the architecture, the Common Platform Layer and Application Layer provide the analytical and operational intelligence for sustainable aquaculture management. The common platform layer hosts AI models, either on edge devices or cloud servers, capable of predictive analysis, anomaly detection, and optimization of environmental parameters (LoRa Alliance, 2020). By processing incoming sensor data, this layer generates actionable insights such as early warnings for hypoxia events or recommendations for aeration and feeding schedules. The application layer interfaces directly with end-users, delivering these insights through dashboards, alerts, or mobile applications. It may also integrate blockchain technology to ensure transparency and traceability of farm operations. Together, these top layers create a closed-loop system in which real-time monitoring, predictive analytics, and actionable interventions are tightly coupled, enabling proactive, data-driven management of aquaculture environments.

Figure 1: Architecture for AI-IoT Aquaculture



This reference architecture combines low-cost sensors, energy-aware edge computing, scalable cloud analytics, and AI-driven decision support to enable resilient, real-time monitoring and predictive aquaculture management.

As an example, Machine learning (ML) models enhance the predictive capabilities of aquaculture monitoring, enabling operators to anticipate water quality changes and optimize farm management. Time-series models such as ARIMA, gradient boosting, and deep learning architectures like LSTMs are commonly applied to forecast critical parameters like dissolved oxygen, ammonia, and pH (Zhang, Wang, & Chen, 2020). Hybrid approaches, integrating physical process models with data-driven ML methods, improve robustness and interpretability.

ML models also support operational optimization. Predictive insights can guide aeration schedules, feeding regimes, and energy usage. Early warning systems, driven by AI, allow detection of harmful events like hypoxia or algal blooms, providing critical lead time for interventions (Nguyen, Tran, & Le, 2023). Explainable AI (XAI) methods, such as SHAP values, help quantify feature importance and build trust among operators and regulators (Li, Smith, & Zhao, 2022).

Table 2. Machine Learning Models and Applications in Aquaculture

ML Model Type	Application Area	Benefits	Limitations
ARIMA	Time-series forecasting	Simple, interpretable	Limited nonlinear modeling
Gradient Boosting	Prediction of water quality	Handles nonlinearity, good accuracy	Computationally intensive
LSTM Networks	Long-term and short-term forecasting	Captures temporal dependencies	Requires large datasets, high complexity
Hybrid ML-Physical	Integrated water management	Improved interpretability and robustness	Complex model design and calibration

3. Data Engineering and Quality Management

The effectiveness of AI-driven aquaculture monitoring systems fundamentally relies on the quality and reliability of the data collected from various sensors. Regular calibration and rigorous validation of these sensors are essential to prevent measurement drift, which can compromise the accuracy of water quality assessments. Drift occurs naturally over time due to sensor aging or environmental factors, and if unchecked, it can lead to erroneous conclusions about the health of aquaculture systems. To complement calibration efforts, robust data preprocessing pipelines are employed to manage missing values, outliers, and random noise inherent in environmental sensor data. Techniques such as Kalman filters provide dynamic smoothing for time-series measurements, while Hampel identifiers detect and correct anomalous readings. Furthermore,

contextual annotation logging events such as rainfall, power outages, or maintenance interventions is critical for improving the interpretability of AI models, as these events often explain sudden deviations in sensor outputs that are not due to environmental changes alone (OpenAQ & WHO, 2021).

Beyond data quality, the process of feature engineering plays a central role in enhancing predictive modeling in aquaculture systems. Feature engineering involves transforming raw sensor readings into meaningful inputs that can reveal patterns or relationships that are not immediately evident. For example, temporal patterns such as diel cycles of temperature or dissolved oxygen fluctuations can provide insights into fish behaviour and metabolic processes. Interaction effects, like the combined influence of temperature and pH on ammonia toxicity, can also be quantified to inform more accurate predictions of water quality impacts on aquatic organisms. By incorporating these engineered features into predictive algorithms, AI models can more effectively capture the complexity of aquaculture environments and generate actionable insights for farm management.

A systematic approach to data management underpins the long-term sustainability and interoperability of AI-driven monitoring systems. Comprehensive metadata documentation, which details sensor specifications, calibration history, and deployment context, allows researchers and practitioners to understand the provenance and limitations of the data. Standardized data formats facilitate integration with other environmental monitoring platforms and enable seamless collaboration across organizations. This approach also ensures the reproducibility of analyses and supports the continuous refinement of AI models over time. By combining high-quality sensor data, advanced feature engineering, and meticulous data management practices, aquaculture monitoring systems can achieve reliable, real-time assessments that improve decision-making and enhance the resilience of aquaculture operations (OGC, 2016).

4. Machine Learning for Predictive Aquaculture

Machine learning (ML) models significantly enhance the predictive capabilities of aquaculture monitoring systems, allowing operators to anticipate changes in water quality and make informed management decisions. By analyzing historical sensor data, ML algorithms can identify complex temporal patterns and nonlinear relationships that are difficult to capture through traditional statistical approaches. Time-series models, including ARIMA and gradient boosting techniques, as well as deep learning architectures like Long Short-Term Memory (LSTM) networks, are particularly effective for forecasting critical water quality parameters such as dissolved oxygen, ammonia, and pH levels (Zhang et al., 2020). These models can capture both short-term fluctuations and long-term trends, enabling operators to plan interventions proactively rather than reactively. Furthermore, hybrid approaches that integrate physical process-based models with data-driven ML techniques improve the interpretability of

predictions while maintaining robustness, providing a more comprehensive understanding of the aquaculture environment.

Beyond predictive forecasting, machine learning models play a crucial role in operational optimization within aquaculture systems. Predictive insights can inform aeration schedules, ensuring that dissolved oxygen levels remain optimal for aquatic life while minimizing energy consumption at a significant operational cost for many farms. Similarly, ML-driven models can optimize feeding regimes by predicting metabolic demands and reducing waste, thereby improving growth efficiency and environmental sustainability. The integration of predictive analytics into early warning systems further extends the utility of these models, enabling timely detection of harmful events such as algal blooms, hypoxia, or sudden changes in water chemistry. By providing actionable lead times for intervention, these models help prevent fish mortality and maintain overall health system (Nguyen et al., 2023).

The reliability and adoption of AI-based aquaculture systems also depend on transparency and interpretability of the underlying models. Operators and regulators are more likely to trust decisions guided by ML if the rationale behind predictions is clear and understandable. Explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) values, are increasingly employed to quantify the contribution of each feature to model predictions, offering actionable insights while maintaining confidence in automated decisions (Li et al., 2022). By combining predictive accuracy with interpretability, ML-enhanced aquaculture monitoring systems not only improve operational efficiency and environmental management but also foster trust among stakeholders, ensuring wider adoption and long-term sustainability of AI-driven interventions.

5. Energy-Aware and Resilient Design

Energy limitations represent a significant barrier to the widespread adoption of IoT-enabled aquaculture monitoring systems in emerging economies, where reliable electricity is often scarce. To overcome this challenge, solar-powered platforms, often integrated with lithium-iron-phosphate (LiFePO₄) batteries, provide sustainable and low-maintenance energy solutions. These systems can operate autonomously for extended periods, reducing dependence on grid electricity while maintaining consistent monitoring capabilities. Energy-efficient strategies such as duty-cycling where sensors are periodically powered on and off—and adaptive sampling where measurement frequency adjusts according to environmental variability significantly reduce overall power consumption. For example, during periods of elevated risk, such as nighttime when dissolved oxygen levels tend to drop, sensors may temporarily increase their sampling frequency to capture critical changes, ensuring accurate monitoring without unnecessary energy expenditure (Rizzo et al., 2020).

Resilience is another essential consideration for IoT aquaculture systems, as sensors and devices must endure challenging environmental conditions. Fouling of sensors, extreme weather events, and intermittent communication failures can compromise data integrity and system performance. To address these risks, robust design practices incorporate redundancy in communication pathways and local data storage at edge devices. This ensures that even if cloud connectivity is temporarily lost, data continues to be captured and stored for later transmission, maintaining the continuity of monitoring efforts. By anticipating potential points of failure, system designers can minimize downtime and prevent gaps in critical environmental data, which is vital for predictive modeling and operational decision-making.

User-friendly design and fault-tolerant architectures further enhance the reliability and adoption of IoT systems in aquaculture. Intuitive interfaces allow farm operators to interact with monitoring platforms without extensive technical training, promoting effective and timely responses to alerts or system recommendations. Fault-tolerant features, such as automatic error detection and recovery protocols, help maintain operational stability even under adverse conditions. By combining energy-efficient hardware, resilient communication networks, and operator-focused design, IoT-enabled aquaculture systems can achieve both sustainable deployment and dependable performance. These considerations are particularly crucial in resource-constrained environments, where maximizing system uptime directly translates to improved water quality management, fish health, and overall farm productivity.

Energy limitations are a major barrier to IoT adoption in resource-constrained aquaculture systems. Solar-powered platforms combined with lithium-iron-phosphate (LiFePO₄) batteries provide sustainable, low-maintenance solutions. Duty-cycling and adaptive sampling conserve energy by adjusting sensor activity based on environmental variability. For example, higher sampling rates may be triggered at night when dissolved oxygen levels drop (Rizzo, Rossi, & Bianchi, 2020).

Resilient system design is equally critical. Sensors must withstand fouling, harsh weather, and communication breakdowns. Redundant communication pathways and edge data storage ensure continuity, while user-friendly interfaces enhance adoption as shown in the table below:

Table 2. Energy and Resilience Strategies for IoT Aquaculture Systems

Challenge	Strategy	Example
Limited electricity supply	Solar-powered sensors + LiFePO ₄ batteries	Shrimp farms in India
High energy consumption	Duty-cycling & adaptive sampling	Adjusting sampling frequency at night
Sensor fouling and degradation	Anti-fouling coatings, regular maintenance	Copper tape or automatic cleaning systems
Communication failures	Redundant pathways, local edge storage	Edge nodes buffer data during outages

6. Cybersecurity, Ethics, and Governance

Cybersecurity is a critical concern in AI- and IoT-driven aquaculture systems, where sensitive operational and environmental data are continuously collected, transmitted, and analyzed. Unauthorized access or manipulation of sensor data, predictive models, or control systems can lead to severe consequences, including inaccurate water quality assessments, mismanaged feeding, or even mass fish mortality. Implementing robust security protocols, such as end-to-end encryption, multi-factor authentication, and secure firmware updates, is essential to safeguard both local and cloud-based infrastructures. Network segmentation and intrusion detection systems can further mitigate risks, ensuring that even if one component is compromised, the overall system remains protected. Given the distributed nature of IoT deployments in remote aquaculture sites, cybersecurity measures must balance rigorous protection with operational feasibility and resource constraints.

Ethical considerations are equally important in the deployment of AI and IoT in aquaculture, as decisions informed by automated systems can directly impact livelihoods, environmental sustainability, and food safety. Operators and stakeholders must ensure that AI models are developed and used responsibly, avoiding biases in predictive analytics that could disproportionately affect certain farms or regions. Transparency in data collection, usage, and decision-making is critical, as it fosters accountability and trust among stakeholders, including farm owners, regulators, and local communities. Furthermore, privacy considerations must be addressed, particularly when monitoring systems capture data on human operators or adjacent land use, ensuring compliance with data protection regulations and ethical best practices.

Governance frameworks provide the structure for integrating cybersecurity and ethical practices into operational protocols, regulatory compliance, and strategic decision-making. Clear policies on data ownership, access rights, and system accountability are necessary to establish responsibilities across different stakeholders, including technology providers, farm operators, and regulatory bodies. Standardized guidelines and best international practices, such as ISO/IEC standards for information security and IoT governance, support consistent implementation and interoperability across systems. Strong governance not only mitigates technical and ethical risks but also enhances system resilience, stakeholder confidence, and long-term sustainability, enabling AI- and IoT-enabled aquaculture to scale responsibly while contributing to food security and environmental stewardship.

Cybersecurity ensures the integrity of AI- and IoT-enabled aquaculture systems. End-to-end encryption, multi-factor authentication, network segmentation, and intrusion detection systems protect both local and cloud infrastructure. Ethical practices ensure transparency, fairness, and responsible AI use, protecting livelihoods, environmental health, and food safety. Governance frameworks define data ownership, access rights, and accountability, supporting policy alignment and system interoperability (ISO/IEC, 2021).

Table 3. Cybersecurity and Governance Considerations in IoT Aquaculture

Aspect	Key Measures	Benefits
Data security	Encryption, MFA, intrusion detection	Protects against unauthorized access
Ethical AI use	Bias checks, transparency, privacy compliance	Builds trust with operators and regulators
Governance	Policies on ownership and access	Ensures accountability and standardization
System reliability	Fault-tolerant design, redundancy	Maintains operational continuity

7. Implementation of Strategies for Emerging Economies

Phased implementation is a critical strategy for successfully adopting AI- and IoT-enabled monitoring systems in resource-constrained aquaculture settings. Launching pilot projects with a limited set of core sensors and simple dashboards allows operators to familiarize themselves with the technology while minimizing initial financial risk. These pilots provide valuable opportunities to assess the functionality of sensors, the reliability of data transmission, and the usability of visualization tools under real operational conditions. Gradually, more sophisticated components such as advanced machine learning models for predictive analytics, automated actuators for aeration or feeding, and edge computing devices for local processing can be introduced. This incremental deployment strategy not only mitigates potential system failures but also helps build confidence among operators and stakeholders before full-scale implementation, ensuring a smoother transition to fully integrated smart aquaculture systems (FAO, 2020).

Cost-effective deployment models are essential to improve accessibility and adoption in emerging economies. Cooperative ownership arrangements, in which multiple farms jointly invest in and share monitoring infrastructure, provide a practical solution to reduce upfront capital requirements. Subscription-based or “Monitoring-as-a-Service” models allow smaller operators to access real-time monitoring capabilities without the burden of large initial investments, while still benefiting from predictive analytics and automated control. These models also encourage data sharing across participating farms, which can enhance predictive accuracy and facilitate regional-level monitoring and decision-making. By lowering financial barriers and promoting collective participation, these approaches increase the scalability and sustainability of AI- and IoT-enabled aquaculture solutions.

Capacity building is equally crucial for the long-term sustainability of monitoring systems. Training local technicians and operators in sensor calibration, preventive maintenance,

troubleshooting, and data interpretation ensures that communities can manage and maintain systems independently, reducing reliance on external expertise. Collaboration between academia, government, and private sector stakeholders can foster knowledge transfer, support policy alignment, and enable ongoing technological innovation. Embedding these monitoring systems within broader frameworks for sustainability and food security allows emerging economies to leverage AI and IoT not only to increase productivity and operational efficiency but also to enhance resilience against climate variability, environmental challenges, and economic shocks. This holistic approach ensures that technological investments yield both short-term benefits and long-term societal impact.

8. Case Studies in Emerging Economies including Zambia

Aquaculture in Zambia faces unique environmental challenges, particularly in regions adjacent to mining operations. Heavy metal contamination, including copper and cadmium, is a significant concern, as these pollutants can accumulate in water bodies and adversely affect fish health, growth, and survival. Traditional water quality monitoring methods, which often rely on periodic sampling and laboratory analysis, are slow and labor-intensive, limiting the ability to detect sudden contamination events. To address this challenge, farms have begun integrating IoT sensors with AI-driven forecasting systems. These systems continuously monitor water parameters, detect spikes in heavy metal concentrations, and provide real-time alerts to farm operators. Prompt interventions, such as adjusting water flow, aeration, or partial water replacement, can prevent mass fish mortality and protect human health by reducing the risk of contaminated fish entering the food chain (Nguyen, Tran, & Le, 2023).

The deployment of IoT and AI technologies in Zambian aquaculture illustrates the potential of digital solutions to enhance environmental monitoring and operational management. By using predictive models, operators can anticipate periods of elevated contamination risk based on historical data, seasonal trends, and mining activity reports. This predictive capability enables proactive decision-making, reducing reliance on reactive measures that are often too late to prevent losses. Additionally, continuous monitoring provides a rich dataset for research and regulatory purposes, allowing authorities and farm managers to understand the dynamics of water quality in mining-affected zones. Such data-driven approaches improve not only operational efficiency but also compliance with environmental regulations and sustainability standards.

In India, aquaculture farmers have faced similar challenges related to water quality management, particularly in shrimp farming operations that are sensitive to dissolved oxygen fluctuations. Pilot projects have introduced low-cost, solar-powered IoT monitoring systems that continuously measure critical water quality parameters such as dissolved oxygen, temperature, and salinity. These systems are coupled with AI-based models that predict oxygen depletion and suggest optimal aeration schedules. By automating alerts and providing actionable recommendations, farmers can maintain water quality within safe limits, reduce fish stress, and optimize feeding

schedules, which in turn improves growth rates and reduces operational costs. The use of solar power ensures energy reliability in off-grid or low-resource settings, demonstrating how sustainable energy solutions can support technology adoption in emerging economies.

These case studies underscore the broader impact of AI- and IoT-enabled aquaculture monitoring across different socio-economic and environmental contexts. In both Zambia and India, the integration of real-time monitoring, predictive analytics, and energy-efficient technologies has transformed traditional aquaculture practices, enabling more precise and proactive management. They also highlight the importance of designing systems that are contextually appropriate, considering local infrastructure, environmental conditions, and economic constraints. The adaptability of these technologies allows smaller-scale farms and resource-limited communities to benefit from advanced monitoring systems that were previously accessible only to larger commercial operations.

Lessons learned from these implementations provide a roadmap for other emerging economies seeking to enhance aquaculture sustainability, resilience, and food security. Critical success factors include phased deployment strategies, training and capacity building for local operators, and collaborative partnerships among governments, academia, and private stakeholders. By combining technological innovation with institutional support and knowledge transfer, emerging economies can leverage AI and IoT solutions not only to improve farm productivity and reduce environmental risks but also to build long-term resilience against climate variability, contamination events, and economic shocks. These experiences demonstrate that even in resource-constrained contexts, digital aquaculture solutions can create tangible benefits for both producers and consumers.

9. Conclusion

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) into aquaculture presents transformative opportunities for sustainable food production, particularly in emerging economies where environmental and economic challenges are pronounced. By enabling real-time monitoring of water quality parameters and predictive modeling of aquaculture conditions, these technologies enhance early detection of risks such as heavy metal contamination, oxygen depletion, and disease outbreaks. This ensures not only improved fish survival rates but also contributes to food safety and public health. Furthermore, adaptive sampling strategies, edge computing, and renewable energy solutions such as solar power address the infrastructural and energy limitations common in resource-constrained contexts. These innovations collectively demonstrate that AI- and IoT-driven aquaculture can improve productivity while ensuring resilience against environmental shocks and climate variability.

Equally important, successful implementation of these technologies requires holistic approaches that extend beyond technical deployment. Capacity building through training of local technicians, fostering public-private partnerships, and aligning initiatives with national policies

and food security goals are critical for long-term sustainability. Case studies from countries like Zambia and India demonstrate that phased deployment, cooperative ownership, and subscription-based models can reduce financial barriers and enhance accessibility. As emerging economies embrace AI- and IoT-enabled aquaculture systems, they position themselves not only to achieve sustainable production but also to strengthen resilience, promote inclusive economic growth, and contribute to global food security.

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