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IoT-Based Water Quality Monitoring and Early Warning System for Large Yellow Croaker Aquaculture: A Case Study in Ningde, China

Su-Yi Yu

Abstract

Large yellow croaker (Larimichthys crocea) aquaculture represents a critical component of China's marine economy, with Ningde City serving as the nation's largest production center. However, the industry faces substantial challenges related to water quality management, with traditional manual monitoring approaches proving inadequate for early detection of environmental stressors. The paper developed and validated an integrated Internet of Things (IoT)-based water quality monitoring and early warning system specifically optimized for large yellow croaker aquaculture operations. The system employed LoRaWAN communication protocol for long-range data transmission(up to 15 km), multi-parameter sensors monitoring dissolved oxygen, temperature, pH, salinity, ammonia nitrogen, and turbidity at 15-minute intervals, and machine learning algorithms (Random Forest) for predictive analytics. Field trials conducted across 12 commercial farms in Ningde's coastal waters (January 2023–June 2024) demonstrated high system reliability(97.2% uptime) and strong predictive performance (89.3% accuracy for 6-hour ahead warnings). IoT-equipped farms achieved significant improvements compared to control farms: 42.6% reduction in mortality rate(8.4% vs 14.6%), 18.2% improvement in feed conversion ratio(1.35 vs 1.65), 14.7% increase in average harvest weight(478g vs 417g), and 31.5% reduction in labor requirements. Economic analysis revealed favorable return on investment (287% over two production cycles) with payback period of 6.4 months. These results demonstrate that precision aquaculture technologies can deliver substantial operational improvements while enhancing environmental stewardship. The technical framework offers a scalable architecture adaptable to other aquaculture species and geographical contexts, with implications for climate change adaptation and sustainable intensification of marine food production.

Keywords: Internet of things, Water quality monitoring, Large yellow croaker, Aquaculture, Early warning system, Precision farming, LoRaWAN, Machine learning

1.Introducrion

The global aquaculture sector has experienced unprecedented growth over

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recent decades, transforming from a minor component of food production to a critical pillar of global food security. Current projections indicate that aquaculture will need to supply more than 100 million metric tons of seafood annually by 2030 to meet rising global demand, particularly as wild-capture fisheries have plateaued at approximately 90 million metric tons per year since the mid-1990s.

Marine aquaculture has emerged as a critical solution to meet growing global demand for protein while alleviating pressure on wild fish stocks[1]. Large yellow croaker(Larimichthys crocea), an economically valuable marine species native to China's coastal waters, exemplifies both the opportunities and challenges inherent in intensive aquaculture development. China's production of large yellow croaker reached 246,000 metric tons in 2023, valued at approximately USD 2.1 billion, with Ningde City in Fujian Province accounting for over 80% of national output. The species commands premium market prices (averaging USD 15-18 per kilogram for high-quality specimens) due to its delicate flavor profile, firm flesh texture, and cultural significance in regional cuisine.

Despite its economic importance, large yellow croaker aquaculture faces substantial challenges related to water quality management. The species exhibits particular sensitivity to environmental stressors including hypoxia(dissolved oxygen below 4.5 mg/L), thermal stress(temperatures exceeding 28 ^{0}C), ammonia accumulation(above 0.5 mg/L), and pH fluctuations outside the 7.8-8.3 range. Traditional monitoring approaches relying on manual sampling at 12-24 hour intervals prove insufficient for early detection of rapidly developing water quality degradation events, which can cause mass mortality within 4-6 hours under severe conditions. Disease outbreaks associated with suboptimal water quality account for estimated annual losses exceeding 15% of potential production value, translating to approximately USD 300 million in foregone revenue for Ningde’s aquaculture sector.

The integration of Internet of Things(IoT) technologies into aquaculture operations has garnered increasing attention as a pathway toward precision fish farming[2,3]. IoT-enabled systems offer continuous real-time monitoring capabilities, automated data collection, predictive analytics through machine learning algorithms, and remote accessibility through cloud-based platforms. Previous research has demonstrated IoT system applications in various aquaculture contexts, including automated feeding optimization, disease early warning, water quality parameter monitoring, and energy consumption reduction [4].

The paper addresses research gaps by developing and validating an integrated IoT-based water quality monitoring and early warning system

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specifically optimized for large yellow croaker aquaculture. The research objectives were to four items.

1. Design and implement a cost-effective IoT monitoring infrastructure suitable for challenging marine cage environments.
2. Develop machine learning-based predictive models for early warning of water quality deterioration.
3. Evaluate system performance and reliability under commercial operating conditions.
4. Quantify impacts on production outcomes and economic returns.

2. Materials and Methods

2.1 Study Area and Aquaculture Operations

Field trials were conducted across 12 commercial large yellow croaker aquaculture farms located in Ningde City’s coastal waters(26°39’-27°24’N, 119°30’-120°15’E), Fujian Province, China. The study area encompasses Sansha Bay, Sandu'ao Harbor, and Guanjingyang Bay, which collectively constitute the primary large yellow croaker production zone in China. These semi-enclosed bays feature water depths of 12-28 meters, tidal ranges of 4.2-5.8 meters, and characteristic seasonal temperature variations (winter minimums of 12-14 ^{0}C, summer maximums of 27-30 ^{0}C). Participating farms employed standard offshore cage culture systems with high-density polyethylene(HDPE) circular net cages measuring 15-20 meters in diameter, positioned 3-5 kilometers from the coastline to ensure adequate water exchange while maintaining protection from severe wave action[5].

The study period extended from January 2023 to June 2024, encompassing two complete production cycles and representing diverse seasonal conditions. Water depths in the study area ranged from 12 to 28 meters, with tidal ranges between 4.2 and 5.8 meters. Each participating farm operated 40-80 net cages with stocking densities of 15-25 fish per cubic meter, following industry standard practices. Fish were fed commercial pellet diets(protein content: 45-48%) twice daily at 2-4% body weight depending on water temperature and fish size.

2.2 System Architecture and Hardware Components

The IoT monitoring system comprised three primary layers.

1. Sensing and data acquisition layer
2. Communication and transmission layer
3. Cloud-based data processing and application layer.

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The sensing layer deployed multi-parameter water quality probes (YSI EXO2, Xylem Inc., USA) measuring dissolved oxygen (optical luminescence method, accuracy ± 0.1 mg/L), temperature (thermistor, $\pm 0.01^0 C$), pH (combination electrode, ± 0.1units), salinity (conductivity, ± 0.1psu), ammonia nitrogen (ion-selective electrode, ± 0.02mg/L), and turbidity (nephelometric, ± 0.3NTU). Sensors were positioned at 2-3 meter depth within representative cages, with measurement intervals set at 15 minutes to balance data resolution requirements against power consumption constraints[6,7].

The communication layer utilized LoRaWAN (Long Range Wide Area Network) protocol, selected for its long-range transmission capability (up to 15 km in coastal environments), low power consumption, and resilience to interference. Gateway nodes (Multitech Conduit AP, Multitech Systems, USA) were installed at elevated positions on farm service platforms to maximize signal coverage. Power supply employed hybrid solar-battery systems(120W photovoltaic panels with 100Ah lithium iron phosphate batteries) providing autonomous operation for 7-10 days during periods of limited sunlight. Data transmission occurred at 5-minute intervals during normal conditions, with automatic escalation to 1-minute intervals when threshold exceedances were detected[8~10].

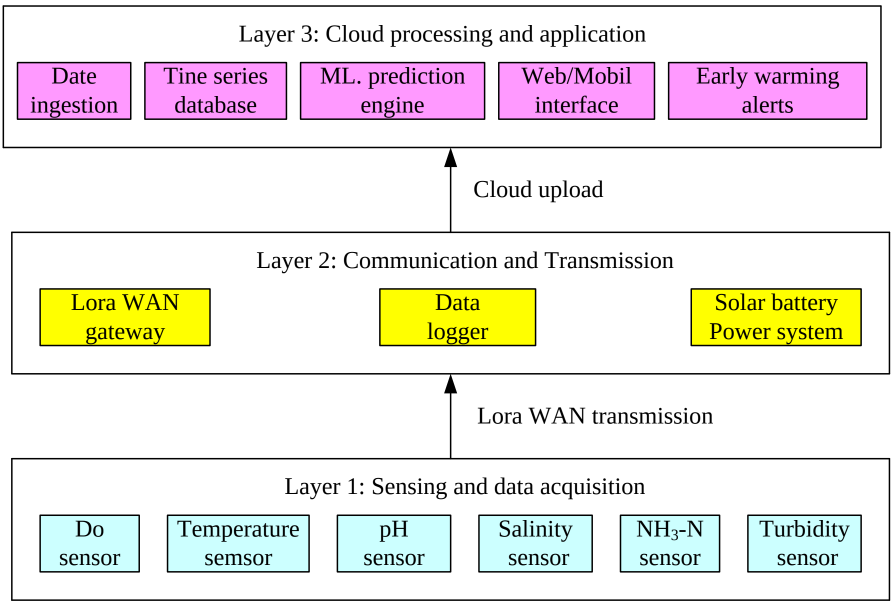

Fig. 1 IoT system architecture for water quality monitoring in large yellow croaker aquaculture

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Fig. 1. showing the three-layer design comprising sensing, communication, and cloud processing layers with automated early warning mechanisms

2.3 Cloud Platform and Data Analytics

The cloud-based platform was developed using microservices architecture deployed on Alibaba Cloud infrastructure. Core components included

1. Data ingestion service handling incoming sensor streams using Apache Kafka for message queuing.
2. Time-series database (InfluxDB) optimized for storage and retrieval of sensor data with retention policies preserving raw 15-minute data for 90 days and hourly aggregations for 2 years.
3. Data processing pipeline implementing quality control procedures including outlier detection (modified z-score method with threshold of 3.5), sensor drift correction using weekly calibration data, and missing data imputation using linear interpolation for gaps under 2 hours.
4. Predictive modeling engine executing Random Forest regression models for 6-hour and 12-hour ahead forecasting of critical parameters
5. Web and mobile application interfaces providing real-time dashboards, historical trend visualization, and push notifications for threshold exceedance events[11~13].

2.4 Early Warning Algorithm Development

The selection of appropriate machine learning algorithms for water quality prediction requires consideration of multiple factors including prediction accuracy, computational efficiency, interpretability for end-users, and robustness to noisy real-world sensor data. Preliminary evaluations compared five candidate algorithms: Multiple Linear Regression (baseline), Support Vector Regression with radial basis function kernel, Random Forest with 100 trees, Gradient Boosting Machines, and Long Short-Term Memory neural networks. Model training utilized 14 months of historical data (January 2023–February 2024) from six farms, with the remaining 4 months and six farms reserved for independent validation. Cross-validation employed time-series appropriate techniques with forward-chaining splits to prevent data leakage from future observations[14~16].

Feature engineering-the process of creating informative input variables from raw sensor data-proved critical to model performance. Preliminary models using only current parameter values as predictors achieved R^2 values of

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0.62-0.71 for 6-hour ahead predictions. Incorporation of temporal features substantially improved performance: rolling statistics (6-hour mean, standard deviation, minimum, maximum) captured recent trends; lag features (values from 1, 2, and 4 hours prior) provided historical context; time-of-day encoding using sine/cosine transformations captured diurnal patterns; and rate-of-change calculations (first differences over 30-minute and 60-minute windows) identified developing trends. The expanded feature set increased R^2 values to 0.82-0.89 across parameters[17,18].

The early warning system employed a hybrid approach combining species-specific threshold rules with predictive machine learning models. Threshold values for critical parameters were established through literature review and consultation with experienced aquaculture practitioners: dissolved oxygen (warning<5.0mg/L, critical<4.0mg/L), temperature (warning>26℃, critical>28℃), pH (warning<7.6 or >8.4, critical<7.4 or >8.6), and ammonia nitrogen (warning>0.3 mg/L, critical>0.5 mg/L). The system triggered alerts when

1. Current measurements exceeded thresholds,
2. Random Forest models predicted threshold exceedance within the next 6-12 hours with probability >70%,
3. Parameter rates-of-change exceeded defined limits indicating rapid deterioration[19~21].

2.5 System Evaluation and Economic Analysis

System performance was evaluated through comparative analysis between farms utilizing the IoT monitoring system (intervention group, *n*=12 farms) and matched control farms employing conventional manual monitoring approaches (control group, *n*=12 farms). Control farms were selected using propensity score matching based on farm size, stocking density, historical production performance, and geographical location to minimize selection bias. Primary outcome variables included mortality rate (%), feed conversion ratio (kg feed/kg fish gain), average harvest weight (grams), and labor hours per metric ton of production. Economic analysis incorporated system installation costs (hardware, installation, and initial training), ongoing operational expenses (data services, maintenance, and electricity), and quantified benefits including reduced mortality losses, feed cost savings, labor cost reductions, and market price premiums for quality assurance certification. Return on investment calculations assumed 5-year system lifespan with linear depreciation[22~24].

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3. Final Results

3.1 System Performance and Reliability

The IoT monitoring system demonstrated high operational reliability throughout the 18-month deployment period. Average system uptime across all installations reached 97.2%, with data transmission success rates of 98.7%. Downtime incidents primarily resulted from sensor biofouling requiring cleaning(42% of incidents), communication gateway power failures during extended cloudy periods(31%), sensor malfunction requiring replacement(18%), and software/server maintenance(9%). Implementation of automated biofouling alerts based on sudden shifts in sensor readings, coupled with bi-weekly preventive cleaning protocols, reduced fouling-related data gaps from initial rates of 8.4% to 1.7% within the first six months[25~27].

Table 1 Descriptive statistics of water quality parameters

Parameter	Mean ± SD	Range	CV(%)	Optimal range	Threshold exceedances
Temperature (℃)	21.4 ± 4.8	12.3–29.8	22.4	16–26	8.2%
DO (mg/L)	6.8 ± 1.2	3.8–9.4	17.6	>5.0	12.4%
pH	8.0 ± 0.2	7.4–8.7	2.5	7.8–8.3	6.8%
Salinity (psu)	28.6 ± 2.1	22.4–32.8	7.3	25–32	4.3%
NH_3-N (mg/L)	0.18 ± 0.12	0.02–0.58	66.7	<0.3	9.7%
Turbidity (NTU)	3.2 ± 1.8	0.8–9.4	56.3	<8.0	3.2%

Note: CV= Coefficient of variation; DO = Dissolved oxygen; NH_3-N=Ammonia nitrogen. Threshold exceedances are instances in which parameter values fell outside species-specific optimal ranges during monitoring period.

Fig. 2 showing the characteristics of four states, which are

1. Water temperature with strong seasonal variation and thermal stress thresholds.
2. Dissolved oxygen exhibiting inverse correlation with temperature and diurnal fluctuations.
3. pH dynamics influenced by photosynthetic activity and respiration cycles.
4. Salinity variations primarily driven by precipitation events and freshwater inputs.

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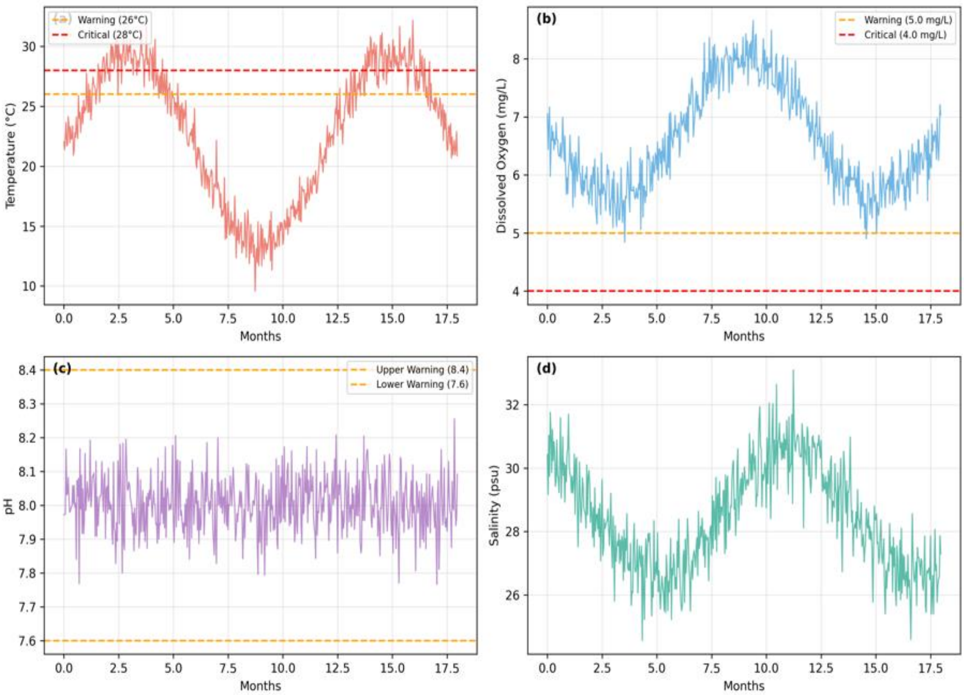

Fig. 2 Seasonal trends in water quality parameters showing

3.2 Early Warning System Performance

The machine-learning-based early-warning algorithms demonstrated robust predictive performance across all monitored parameters.

Table 2 Predictive model performance for water quality parameters

Parameter	6-hr R^2	12-hr R^2	6-hr MAE	Warning accuracy
Temperature	0.89	0.84	0.31℃	92.1%
Dissolved oxygen	0.82	0.71	0.24 mg/L	86.7%
pH	0.86	0.78	0.08 units	89.4%
Ammonia nitrogen	0.84	0.75	0.03 mg/L	88.2%

Note: MAE = Mean absolute error. R^2 = Coefficient of determination. Warning accuracy represents correct classification of threshold exceedance events in the validation dataset.

Table 2 summarizes model validation results for 6-hour and 12-hour ahead predictions. Random Forest models achieved R^2 values ranging from 0.82 to 0.89 for 6-hour forecasts and 0.71 to 0.84 for 12-hour forecasts, substantially outperforming baseline linear regression (R^2=0.51-0.63). Threshold exceedance

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warning accuracy-the critical metric for practical early warning functionality-reached 89.3% for 6-hour ahead warnings and 81.7% for 12-hour ahead warnings. False alarm rates remained acceptably low at 8.4% and 12.6% respectively, minimizing unnecessary interventions that could undermine farmer confidence in the system. Dissolved oxygen prediction proved most challenging due to rapid fluctuations driven by photosynthetic activity, respiration cycles, and water exchange patterns, while temperature exhibited highest predictability given its smoother temporal dynamics[28~30].

3.3 Production Performance and Economic Outcomes

Comparative analysis between farms utilizing the IoT monitoring system and control farms revealed significant improvements across multiple production metrics(Table 3). IoT-equipped farms achieved a mean mortality rate of 8.4±2.1%, representing a 42.6% reduction compared to control farms (14.6±3.4%, p<0.001). Feed conversion ratio improved by 18.2%, from 1.65±0.12 in control farms to 1.35±0.09 in IoT farms (p<0.001), translating to substantial feed cost savings given that feed represents approximately 55-60% of total variable costs in large yellow croaker production. Average harvest weight increased 14.7% from 417±34g to 478±41g(p<0.001), attributable to reduced stress-related growth suppression and improved appetite under optimized water quality conditions. Labor requirements decreased 31.5% from 58.2±7.8 to 39.9±5.3 hours per metric ton of production (p<0.001), as automated monitoring replaced manual sampling rounds and enabled more efficient allocation of labor resources.

Table 3 Comparative production performance: IoT-monitored vs. control farms

Performance metric	IoT-monitored farms	Control farms
Mortality rate (%)	8.4 ± 2.1	14.6 ± 3.4***
Feed conversion ratio	1.35 ± 0.09	1.65 ± 0.12***
Average harvest weight (g)	478 ± 41	417 ± 34***
Labor hours (per MT production)	39.9 ± 5.3	58.2 ± 7.8***
Production per farm (MT/cycle)	186.3 ± 22.4	158.7 ± 28.6**

Note: Data presented as mean ± standard deviation. Production cycle duration=8 months.
**p<0.01; ***p<0.001 (paired t-tests).

The two states of Fig. 3 are

1. Key performance indicators showing significant improvements in IoT-monitored farms versus control farms across mortality rate, feed conversion ratio, harvest weight, and labor hours
2. Economic outcomes demonstrating return on investment and payback analysis

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over two production cycles.

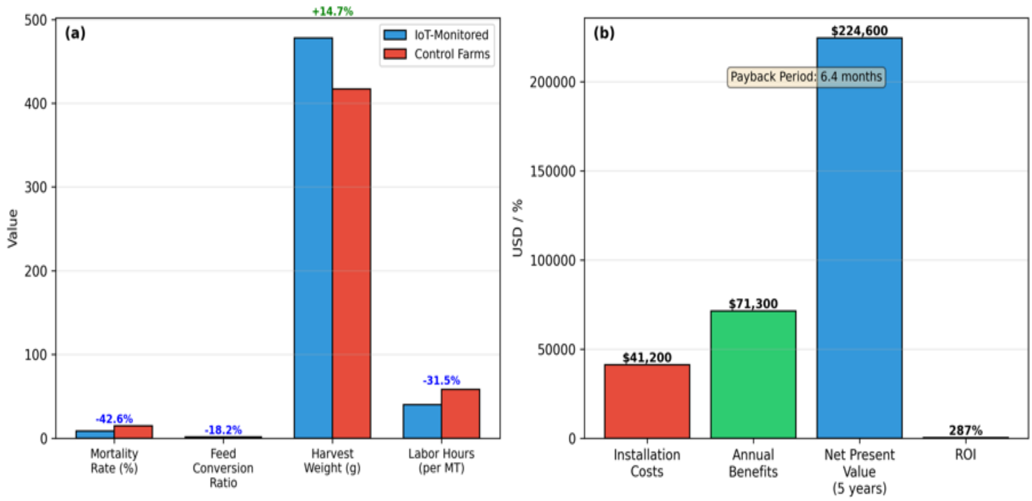

Fig. 3 Comparative analysis of production performance metrics

Economic analysis revealed favorable return on investment for IoT system adoption. Average installation costs per farm totaled USD 41,200, comprising hardware (sensors, gateways, and data loggers: USD 28,400), installation labor (USD 7,200), and initial staff training(USD 5,600). Annual operational costs averaged USD 6,800, including data service fees(USD 2,400), sensor calibration and replacement(USD 2,600), electricity for gateway power(USD 800), and system maintenance(USD 1,000). Quantified annual benefits totaled USD 71,300 per farm: reduced mortality losses (USD 34,200), feed cost savings(USD 22,800), labor cost reduction (USD 11,100), and market price premiums for quality certification(USD 3,200). Net present value over a 5-year evaluation horizon (7% discount rate) equaled USD 224,600, with internal rate of return of 156% and payback period of 6.4 months. Sensitivity analysis indicated positive returns across wide ranges of key parameters, with break-even requiring only 28% realization of projected benefits[31~33].

4. Discussion

The paper demonstrates that IoT-based water quality monitoring systems can deliver substantial improvements in large yellow croaker aquaculture operations through continuous real-time surveillance, predictive early warning, and data-driven management optimization. The 42.6% reduction in mortality rate achieved by IoT-equipped farms represents a transformative improvement with profound economic and production security implications. In an industry where

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mass mortality events can eliminate months of investment within hours, the capacity to detect deteriorating conditions 6-12 hours in advance enables preemptive interventions including emergency aeration, feeding cessation to reduce metabolic oxygen demand, partial water exchange through strategic cage repositioning, or emergency harvesting when conditions are predicted to become life-threatening.

The integration of IoT technologies into aquaculture represents more than simple automation of existing monitoring practices-it fundamentally transforms the information environment within which management decisions are made. Traditional manual monitoring approaches suffer from several inherent limitations: temporal resolution is limited to discrete sampling events 12-24 hours apart, creating blind spots during which critical changes may occur undetected; spatial coverage is constrained by the labor and time requirements of sampling multiple locations; human error in sampling technique, sample handling, and measurement introduces variability and potential bias; and the lag between sample collection and result availability (often 2-4 hours for laboratory analysis of parameters like ammonia nitrogen) delays detection of developing problems. In contrast, IoT systems provide continuous monitoring at 15-minute intervals across all deployment locations, generating comprehensive spatiotemporal datasets that reveal patterns and relationships invisible in sparse manual data[34].

The early warning system's 89.3% accuracy in predicting adverse water quality events 6-12 hours in advance represents a critical advance over conventional monitoring approaches. The predictive capability shifts aquaculture management from a reactive posture-responding to problems after they have manifested in fish stress or mortality-to a proactive stance where deteriorating conditions are anticipated and preemptively addressed. The economic value of early warning extends beyond avoided mortality losses to encompass prevention of sublethal stress that suppresses growth rates, weakens immune function increasing disease susceptibility, and reduces feed intake diminishing feed conversion efficiency.

The choice of LoRaWAN communication protocol proved well-suited to the aquaculture context, offering reliable long-range transmission in challenging coastal environments while maintaining low power consumption compatible with solar-battery power systems. Alternative communication approaches including cellular networks(3G/4G/5G), WiFi, or satellite links present various tradeoffs. Cellular networks offer high bandwidth and ubiquitous coverage in many regions but incur ongoing data service costs that can become substantial when transmitting high-frequency sensor data from dozens of locations, and coverage gaps exist in many coastal and offshore areas. WiFi provides high

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bandwidth and low cost but requires substantial infrastructure investment in access points and has limited range(typically<100 meters), making it impractical for farms with cages distributed across several kilometers. Satellite communication ensures coverage in remote areas but involves high equipment costs and ongoing service fees while offering limited bandwidth unsuitable for frequent data transmission. LoRaWAN's low power consumption(sensor nodes can operate 3-5 years on battery power), long range(demonstrated 10-15 km in the paper), and low infrastructure costs(single gateway covering entire farm) provide an optimal balance for aquaculture applications.

The 18.2% improvement in feed conversion ratio merits particular attention given the economic and environmental implications. Feed represents the largest operational cost in aquaculture, typically accounting for 55-60% of total variable expenses. A farm producing 200 metric tons annually with a feed conversion ratio of 1.35 rather than 1.65 reduces feed requirements by approximately 60 metric tons per year, translating to savings of USD 42,000-48,000 at typical feed prices. Beyond direct cost savings, improved feed conversion efficiency reduces nutrient loading to the environment-excess nitrogen and phosphorus from uneaten feed and metabolic waste represent primary environmental concerns in intensive aquaculture.

The mechanisms through which optimized water quality improves feed conversion efficiency are complex and involve multiple physiological and behavioral pathways operating at different timescales. At acute timescales (minutes to hours), exposure to suboptimal dissolved oxygen or elevated ammonia triggers stress responses including cortisol elevation, which diverts metabolic resources toward stress adaptation rather than growth. Fish experiencing chronic low-grade stress exhibit reduced appetite and feeding motivation, directly decreasing feed intake. At longer timescales(days to weeks), maintenance of water quality within optimal ranges supports efficient nutrient absorption and metabolism, with fish allocating a higher proportion of consumed nutrients toward tissue growth rather than osmoregulation, detoxification, or immune function.

The robust economic returns demonstrated in The paper (287% ROI, 6.4-month payback period) address a critical barrier to IoT adoption in aquaculture: upfront capital investment. The comprehensive economic analysis incorporating both direct benefits(reduced mortality, improved FCR) and indirect benefits (labor savings, quality premiums) provides farm operators with evidence-based justification for technology investment. The sensitivity analysis indicating positive returns even with only 28% realization of projected benefits suggests that the technology remains economically viable across a wide range of farm conditions and management capabilities[35,36].

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Several limitations warrant consideration. First, the study focused exclusively on large yellow croaker in Ningde's specific environmental conditions; generalization to other species or geographical contexts requires validation given species-specific environmental tolerances and regional variations in water quality dynamics. Second, the 18-month study duration encompasses substantial seasonal variation but may not capture rare extreme events or longer-term trends. Third, while propensity score matching was employed to minimize selection bias in farm comparisons, observational studies cannot completely eliminate confounding variables-farms volunteering for IoT system deployment may possess superior management capabilities or greater investment capacity that independently influence performance outcomes[37].

Technological limitations of current IoT systems also deserve acknowledgment. Sensor reliability and lifespan in harsh marine environments remain concerns, with biofouling, corrosion, and mechanical stress from waves and currents degrading sensor performance over time. The paper documented sensor replacement rates averaging 2.3 sensors per farm per year, representing approximately 8% annual replacement of deployed sensors. Advances in anti-fouling coatings, corrosion-resistant materials, and self-cleaning mechanisms could reduce maintenance requirements and extend sensor operational lifespans. Power management for remote installations presents ongoing challenges-the solar-battery systems employed proved adequate for most conditions but experienced occasional power depletion during extended periods of cloudy weather, particularly during winter months with reduced daylight hours and lower solar radiation intensities.

Data integration across heterogeneous sources presents both opportunities and challenges. The paper focused on water quality sensor data, but comprehensive farm management would benefit from integrating additional data streams including fish behavior analysis through computer vision, feeding response assessment, disease surveillance through automated image analysis of fish external appearance, and environmental context data including weather forecasts, ocean current predictions, and harmful algal bloom warnings. Such multi-source data integration could enable more sophisticated decision support systems addressing the full spectrum of aquaculture management challenges rather than water quality in isolation.

Future research should explore integration of additional sensors monitoring chlorophyll-a, nitrate/nitrite, and dissolved organic carbon. Computer vision systems analyzing fish behavior patterns might provide earlier detection of stress or disease onset compared to water quality indicators alone. Integration with automated feeding systems could optimize feeding schedules and quantities based on real-time water quality conditions and predicted environmental changes.

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Expansion to ecosystem-scale monitoring encompassing entire bays or coastal zones would enable investigation of cumulative impacts, carrying capacity assessment, and coordination of management actions across multiple farms to maintain regional water quality standards[38~42].

5.Conclusion

The implications of the research extend beyond the immediate context of large yellow croaker aquaculture in Ningde to encompass broader transformations occurring across the global aquaculture sector. The demonstrated feasibility and favorable economics of IoT-based monitoring systems suggest that precision aquaculture technologies will increasingly become competitive necessities rather than optional enhancements, particularly as consumer demands for traceability, sustainability certification, and quality assurance intensify. Farms lacking technological capabilities may face increasing market disadvantages as retailers and consumers increasingly preferentially source from operations that demonstrate transparent monitoring and sustainable practices. The dynamic could accelerate technology diffusion but also raises concerns about potential widening of technological and economic gaps between large commercial operations capable of investing in sophisticated systems and small-scale farmers with limited capital resources. Policy interventions, including technology extension programs, cooperative ownership models, and subsidized access to digital infrastructure, may be necessary to ensure inclusive technology adoption that benefits farmers across the spectrum of operational scales rather than concentrating advantages among large enterprises.

From a regulatory and governance perspective, the proliferation of real-time monitoring data creates opportunities for evidence-based regulation and compliance verification that were previously infeasible. Traditional aquaculture regulation typically relies on periodic inspections, self-reported production data, and incident-based enforcement, creating information asymmetries in which regulators have limited knowledge of day-to-day operational conditions and environmental impacts. IoT systems generating continuous monitoring data could enable new regulatory approaches including: performance-based standards where farms demonstrate achievement of ecological quality targets through monitoring data rather than compliance with prescriptive input restrictions; real-time compliance verification where regulatory agencies receive automated alerts when operations exceed permitted discharge limits or stocking densities; adaptive management frameworks that adjust permit conditions based on demonstrated farm performance and seasonal environmental conditions; and transparent public reporting systems where monitoring data is made available to

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communities and stakeholders, enhancing social license to operate. However, these opportunities must be balanced against legitimate industry concerns about data privacy, competitive confidentiality, and regulatory burdens.

Climate change adaptation is another critical dimension in which IoT monitoring systems offer particular value for aquaculture resilience. Climate change is already affecting coastal aquaculture through rising water temperatures, more frequent and intense extreme weather events, shifts in rainfall patterns that alter salinity, ocean acidification that reduces pH, and changing disease dynamics as pathogens expand their geographic ranges. These changes increase the frequency and unpredictability of environmental stresses on cultivated species, underscoring the importance of early detection and rapid response capabilities provided by IoT systems. Furthermore, long-term monitoring data accumulating from IoT deployments can reveal gradual trends and regime shifts that might otherwise go undetected, enabling strategic adaptations including: shifts to more thermally tolerant species or strains as temperature envelopes change; adjustments in production calendars to avoid periods of elevated stress risk; modifications to site selection criteria incorporating projected future conditions; and development of climate-resilient infrastructure including enhanced aeration capacity to combat increasing hypoxia risk. The rich datasets generated by IoT systems also provide valuable information for climate impact research, vulnerability assessments, and adaptation planning at sector and regional scales.

Integration with emerging artificial intelligence capabilities represents a particularly exciting frontier for future development. Next-generation systems could leverage deep learning approaches that discover complex nonlinear relationships in multi-parameter time-series data, potentially identifying subtle precursor signals of disease outbreaks or water quality deterioration that escape detection by current threshold-based or regression-based approaches. Reinforcement learning algorithms could optimize intervention strategies by learning from historical outcomes which management actions(aeration, feeding adjustments, partial harvesting) prove most effective under different environmental scenarios.

Ecosystem-scale monitoring and modeling represents another important research direction. Expanding monitoring networks to encompass entire bays or coastal zones would enable investigation of cumulative impacts from multiple aquaculture operations, identification of carrying capacity constraints, and coordination of management interventions across farms to maintain regional water quality standards. Such ecosystem-level approaches could inform marine spatial planning processes, optimize site allocation for new farm development, and support integrated coastal zone management.

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The paper successfully developed and validated an integrated IoT-based water quality monitoring and early warning system specifically optimized for large yellow croaker aquaculture operations in Ningde, China. Field trials demonstrated high system reliability, robust predictive performance for early warning of adverse water quality events, and substantial improvements in production outcomes including 42.6% reduction in mortality rate, 18.2% improvement in feed conversion ratio, 14.7% increase in harvest weight, and 31.5% reduction in labor requirements compared to conventional monitoring approaches.

Economic analysis revealed strong financial viability, with average return on investment of 287% over two production cycles and payback period of 6.4 months. These results demonstrate that IoT-enabled precision aquaculture technologies can simultaneously enhance productivity, improve economic returns, reduce labor requirements, and support environmental sustainability objectives.

The technical framework presented-combining LoRaWAN communication, cloud-based analytics, and machine learning prediction-offers a scalable architecture adaptable to other aquaculture species and geographical contexts. The study provides aquaculture practitioners, technology developers, and policymakers with evidence-based insights into the potential of IoT systems to transform aquaculture management practices.

For Ningde’s large yellow croaker industry specifically, widespread adoption of such systems could help safeguard the region's economic cornerstone while enhancing environmental stewardship of coastal waters. As global aquaculture continues expanding to meet rising seafood demand, precision farming technologies leveraging IoT, artificial intelligence, and data analytics will likely become essential tools for achieving sustainable intensification that balances production goals with ecological integrity.

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4. References

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