

Integrated Fuzzy Logic Model for Smart Water Quality Monitoring and Floating Net Cage Optimization in Barramundi Aquaculture

Rozeff Pramana*¹, M. Hasbi Sidqi Alajuri²

^{1,2}Department Electrical Engineering, Faculty of Engineering and Maritime Technology, Raja Ali Haji Maritime University, Indonesia

Email: rozeff@umrah.ac.id

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Abstract

Water quality and aquatic conditions are critical factors in the success of fish farming with Floating Net Cages (FNCs). However, manual monitoring is often delayed due to limited human resources, irregular measurement schedules, and dependence on manual sampling, which can result in late detection of deteriorating water quality and ultimately increase the risk of fish stress, disease outbreaks, and mortality. This study aims to develop an Internet-based water quality monitoring system, integrated with smartphones and PCs, to support rapid decision-making for FNC relocation when water conditions deteriorate. The system is equipped with sensors for temperature, dissolved oxygen (DO), pH, electrical conductivity (EC), total dissolved solids (TDS), turbidity, anemometer, and wind direction, and was field-tested for 36 days in sea-based Barramundi aquaculture. Decision-making was implemented using a Fuzzy Inference System (FIS) with input variables: temperature, DO, pH, and anemometer data, while the output variable was the FNC status: "Relocate" or "Remain." Results indicated that water quality changes occurred across both short-term and long-term intervals, and during a 56-hour fuzzy simulation, 10 data points suggested "Relocate" while 46 data points indicated "Remain." The novelty of this research lies in the integration of real-time IoT monitoring with fuzzy logic specifically for FNC relocation decision-making, bridging environmental sensing and intelligent decision support. These findings demonstrate that the proposed system is more effective and efficient than conventional methods, contributing to the advancement of intelligent aquaculture technologies.

Keywords : *Aquaculture, Barramundi, Fuzzy Logic, Monitoring, Floating Net Cage.*

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1. INTRODUCTION

Barramundi (*Lates calcarifer*) is a high-value fishery commodity capable of thriving in both freshwater and seawater, with a wide salinity tolerance ranging from 0 to 56‰ [1][2]. This species, also known as seabass, contains essential nutrients important for human health, including essential minerals, vitamin A, vitamin D, B-complex vitamins, and omega-3 fatty acids [3]. With such nutritional content, Barramundi not only has the potential as a nutritious food source but also adds value in terms of public health. The high market demand for Barramundi has positioned aquaculture as the backbone of its supply, with farmed production even surpassing capture fisheries [4][5]. One of the widely used methods is floating net cages (FNCs), which vary in construction from wood and bamboo to modern materials such as high-density polyethylene (HDPE).

However, FNC systems face various technical and environmental challenges that affect aquaculture success [6]. Water quality is a critical factor, as fluctuations influenced by tides, waste pollution, and extreme weather changes can disrupt fish health and even cause mass mortality. In addition, storms and large waves have the potential to damage cage structures, allowing fish to escape, which ultimately results in economic losses for farmers [7][8][9]. Another limitation lies in the decision-making methods for FNC relocation, which generally still rely on visual monitoring for example, when many dead fish are observed or water conditions deteriorate [10]. This approach leads to slower

responses to environmental changes and poses high risks to the sustainability of aquaculture operations [11].

With the advancement of technology, various studies have attempted to develop digital based water quality monitoring solutions. Innovations include the work by [12][13], These systems typically employ multiple sensors to monitor key parameters including pH, temperature, turbidity, dissolved oxygen, total dissolved solids (TDS), and electrical conductivity; [14][15], who created an Arduino-based device that transmits water quality data via SMS; and [16][17], who utilized the Blynk smartphone application for automated aquarium monitoring and management. Another study by [18][19] employed Raspberry Pi and Arduino to monitor temperature, pH, conductivity, and water color in fish ponds. Building on these developments, the present study proposes an Internet of Things (IoT)-based water quality monitoring system equipped with water and weather sensors, using fuzzy logic as the basis for FNC relocation decision-making [20]. This system is expected to enable real-time monitoring of aquatic conditions, accelerate responses to environmental changes, minimize losses, and enhance the sustainability of Barramundi aquaculture [21][22].

Unlike previous studies that focused mainly on water quality monitoring or simple alert systems [23], the novelty of this research lies in the integration of real-time Internet of Things (IoT) monitoring with a fuzzy inference system specifically designed for Floating Net Cage (FNC) relocation decision-making in open-sea Barramundi aquaculture [24]. This dual approach not only enables continuous and automated measurement of both water and weather parameters but also translates complex environmental data into practical operational recommendations, namely whether the cages should “Relocate” or “Stay” [25]. By bridging sensor technology, wireless communication, and intelligent decision-support methods, this study provides a comprehensive framework that enhances responsiveness, operational efficiency, and sustainability in aquaculture practices.

2. METHOD

The study was conducted in the waters of Dompak Island, Riau Archipelago, Indonesia, at the coordinates 0°52'03.1"N and 104°28'55.1"E (Figure 1). The research comprised three main stages, namely device design, fuzzy logic system development, and device testing. The system employed water quality sensors, while decision-making for FNC relocation was carried out using fuzzy logic, designed based on standard water quality parameters for Barramundi aquaculture. The field trial was conducted over a period of approximately 36 days on Barramundi FNC units deployed in offshore waters.



Figure 1. Research Location

2.1. Device Design

The device comprises a sensor unit, a processing unit, and a monitoring unit. The block diagram of the device is shown in (Figure 2). The sensor unit is equipped with six water quality parameters, including temperature, dissolved oxygen (DO), pH, electrical conductivity (EC), total dissolved solids

(TDS), and turbidity, all manufactured by DFRobot. Additionally, it includes an anemometer and a wind direction sensor made of aluminum alloy. All sensors were calibrated following the manufacturer's procedures with the aid of standard laboratory equipment to ensure measurement accuracy. Furthermore, the system is equipped with two modified IP cameras for monitoring both surface and underwater conditions. The processing unit utilizes an Arduino Mega R3 as the main component, integrated with an IoT-based ESP8266 module to support data processing and remote monitoring.

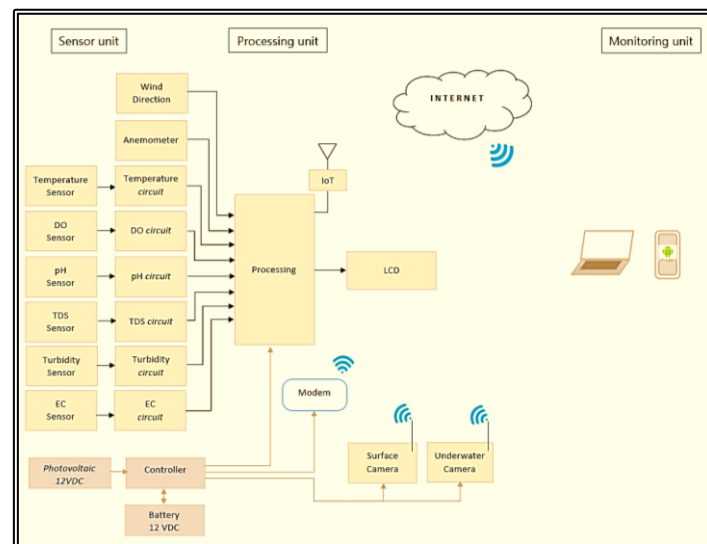


Figure 2. Water Quality Monitoring System Design

The implementation of this design on the Floating Net Cage (FNC) is illustrated in the following figure 3:

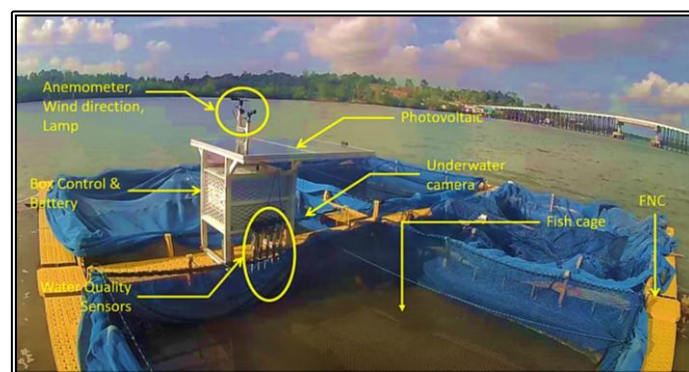


Figure 3. Implementation of the Device on the Floating Net Cage

The device utilizes solar panels as its primary power source (Figure 4). The power system is divided into two circuits: one dedicated to operating the sensor unit and its supporting components, and the other for the monitoring cameras and FNC indicator lights. This design ensures that the main water quality measurement system can operate continuously without power interruptions. The solar setup consists of two polycrystalline panels (100 Wp, 12 VDC), equipped with two 10 A controllers and two 50 Ah, 12 VDC dry batteries.

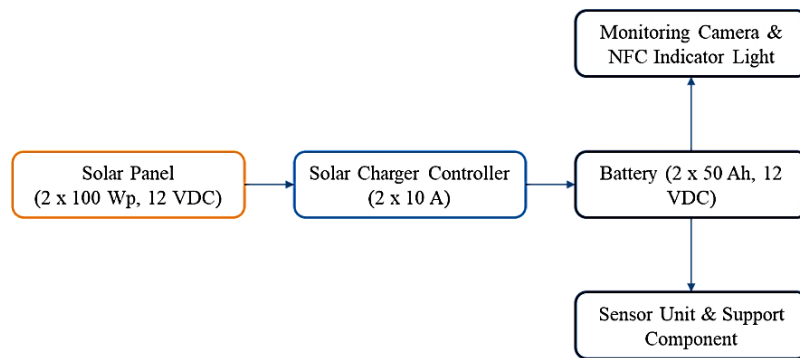


Figure 4. Solar Panel Power Distribution for the FNC Device

The monitoring unit consists of a modem, an LCD, and an internet-based monitoring application. Sensor readings are displayed in real-time on the LCD installed on the floating net cage (FNC) and can also be accessed remotely via the Blynk application (version 1.5.4). This internet-based application can be operated using a personal computer (PC) or a smartphone. Sensor data are presented both numerically and graphically at configurable time intervals. Additionally, all sensor data are stored in a database accessible only to authorized users. The interface of the water quality and weather sensor monitoring application is shown in (Figure 5).

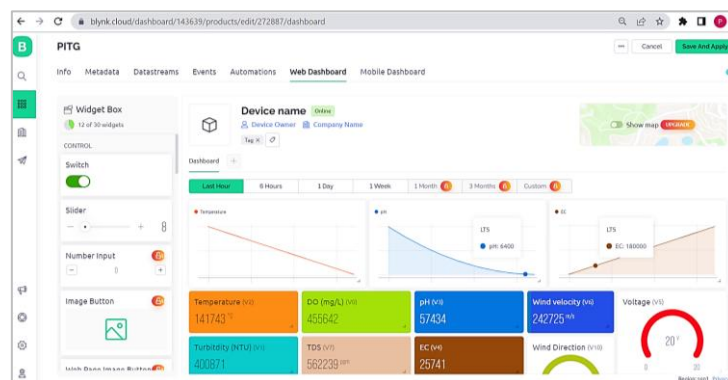


Figure 5. Blynk Application Interface

2.2. Water Quality Standards For Barramundi Aquaculture

Water is a primary component that must be continuously monitored and controlled in aquaculture [26]. Each fish species has specific water quality parameters, which can significantly affect growth, reproduction, and survival if not properly maintained. Parameters such as pH, temperature, and dissolved oxygen are particularly important, especially during incidents of mass fish mortality [27]. Barramundi (*Lates calcarifer*) exhibit a wide physiological tolerance and can thrive in both freshwater and seawater environments; therefore, dissolved oxygen, water temperature, and pH need to be measured and monitored on a daily basis [28]. The water quality standards for barramundi aquaculture [29][30] are summarized in the Table 1:

Table 1. Water Quality Standards for Barramundi Aquaculture

No	Parameters	Units	SNI 01-6493.1-2000
1	Salinity	‰	15 - 35
2	DO	mg/L	>5
3	Temperature	°C	26 - 32
4	pH	-	7 – 8.5
5	Turbidity	m	>5

In addition to water quality parameters, the weather conditions around the floating net cage (FNC) site must also be considered, particularly wind speed. Excessively strong winds can damage the FNC structure. If such conditions persist, the resulting damage may allow fish to escape from the cage. The wind speed tolerance limit for the safe operation of floating net cages is <21 knots (10.80 m/s) [31].

2.3. Fuzzy Inference System

Aquaculture was developed using fuzzy logic through the stages of fuzzification, rule base construction, inference, and defuzzification. The Fuzzy Inference System was implemented using the Matlab R2019a toolbox employing the Sugeno method (Figure 6).

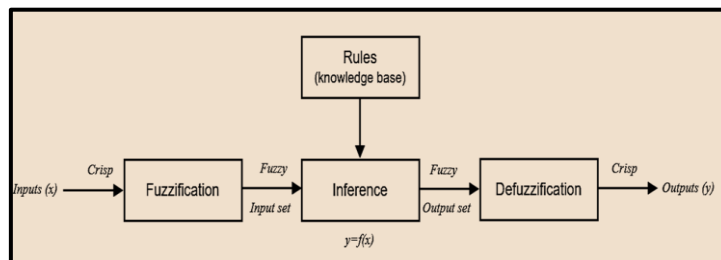


Figure 6. Fuzzy Logic System

The Fuzzy Inference System developed consists of four input variables and one output variable. The input variables include dissolved oxygen, temperature, pH, and wind speed (anemometer). These variables were selected because they represent the primary water quality parameters in barramundi aquaculture. The output variable represents the FNC status, which has two conditions: “FNC Move” and “FNC Stay.” Subsequently, based on standard water quality values, membership functions were defined for each input variable. The types of membership functions used are triangular and trapezoidal (Figure 7). The triangular membership function is defined as follows:

$$0, x \leq a \quad (1)$$

$$\text{Triangle}(x; a, b, c) = \frac{x-a}{b-a}, a \leq x \leq b \quad (2)$$

$$\frac{c-x}{c-b}, b \leq x \leq c \quad (3)$$

$$0, c \leq x \quad (4)$$

The parameters (a, b, c) with $a < b < c$ define the x-coordinates of the three base vertices of the triangular membership function [32][33]. The trapezoidal membership function is defined as follows:

$$0, x \leq a \quad (5)$$

$$\frac{x-a}{b-a}, a \leq x \leq b \quad (6)$$

$$\text{Trapezoidal}(x; a, b, c, d) = 1, b \leq x \leq c \quad (7)$$

$$\frac{d-x}{d-c}, c \leq x \leq d \quad (8)$$

$$0, d \leq x \quad (9)$$

The parameters (a, b, c, d) with $a < b \leq c < d$ define the x-coordinates of the four vertices of the underlying trapezoidal membership function [33]. For the temperature input variable, the standard or normal range for barramundi is 26 – 32 °C. The Fuzzy Inference System (FIS) is constructed with the temperature input divided into three membership functions: Cool, Normal, and Hot. If the input temperature falls below the standard range, it is categorized as Cool; if it exceeds the standard range, it is categorized as Hot. The membership function parameters for the temperature input variable are shown in the Table 2:

Table 2. Membership Functions of the Temperature Input Variable

Standard Temperature	Range	Categories	Type	Parameters
26 - 32 °C	10 - 40	Cool	trapmf	[0 12 25.8 29]
		Normal	trimf	[25.9 29 32.1]
		Hot	trapmf	[29 32.1 39 42]

For the dissolved oxygen (DO) input variable, the optimal standard DO level for barramundi is greater than 5 mg/L. The Fuzzy Inference System (FIS) defines the DO input variable using two membership functions: Bad and Good. A DO reading below the standard is classified as Bad, while a reading meeting or exceeding the standard is classified as Good. The parameters of the membership functions for the DO input variable are presented in the Table 3 :

Table 3. Membership Functions of the DO Input Variable

Standard DO	Range	Categories	Type	Parameters
> 5 mg/L	0-15	Bad	trapmf	[-1 0.5 4.8 5.1]
		Good	trapmf	[4.9 5 14.3 16]

For the pH input variable, the standard or normal pH range for barramundi is 7–8.5. The Fuzzy Inference System (FIS) defines the pH input variable using three membership functions: Acidic, Normal, and Alkaline. A pH value below the standard is classified as Acidic, while a value above the standard is classified as Alkaline. The parameters of the membership functions for the pH input variable are presented in the Table 4 :

Table 4. Membership Functions of the pH Input Variable

Standard pH	Range	Categories	Type	Parameters
7 - 8.5	0-14	Acidic	trapmf	[-2 0 6.9 7.7]
		Normal	trimf	[6.9 7.7 8.6]
		Alkaline	trapmf	[7.7 8.5 14 16]

For the wind speed input variable, the standard value for floating net cages (FNC) is < 10.80 m/s. The Fuzzy Inference System (FIS) defines this input variable using two membership functions: Normal and High. If the wind speed is below the standard, it is classified as Normal, whereas if it exceeds the standard, the wind speed around the cage is classified as High. The parameters of the membership functions for the wind speed input variable are presented in the Table 5 :

Table 5. Membership Functions of the Wind Speed Input Variable

Standard Wind Speed	Range	Categories	Type	Parameters
< 10.80 m/s	0 - 35	Normal	trapmf	[0 0.2024 10 10.8]
		High	trapmf	[10.81 11 32.77 35]

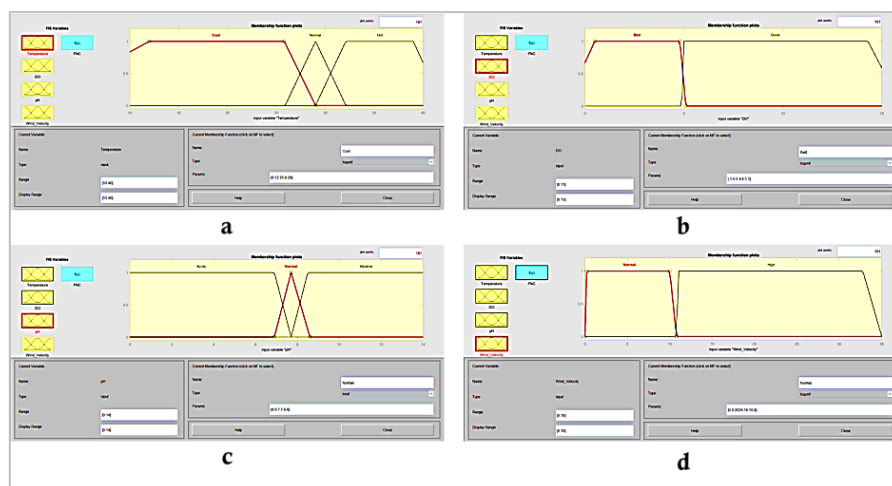


Figure 7. Membership Functions in the Fuzzy Inference System
(a) Suhu, (b) DO, (c) pH, (d) Kecepatan Angin

The fuzzy output variable represents the FNC status (Figure 8), which consists of two conditions: FNC Stay and FNC Move, with fuzzy output values ranging from 0 to 1. If the water quality remains within the normal range and the wind speed is within the tolerance limit, the FNC status is FNC Stay. Conversely, if water quality or wind speed exceeds the defined thresholds, the FNC status becomes FNC Move. The decision to relocate the FNC is made to prevent poor water quality, which could negatively affect the survival of the fish in the FNC.

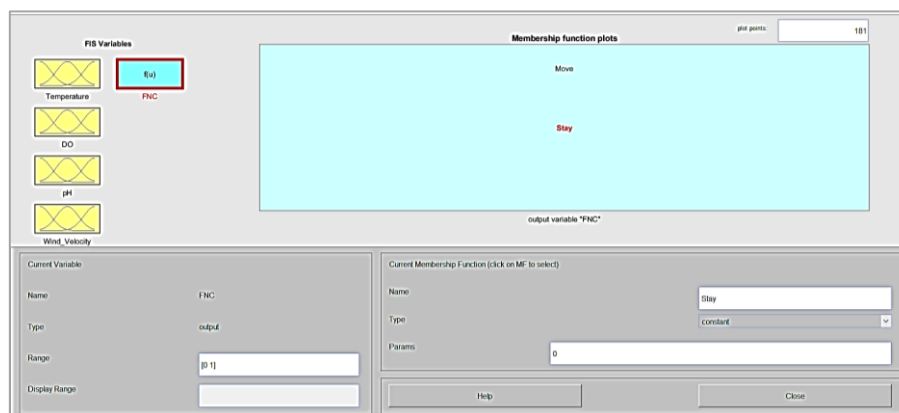


Figure 8. Output Variable Membership Function

Fuzzy logic statements are expressed in the form of IF–THEN rules (Figure 9), where IF represents the antecedent and THEN represents the consequent, which is expressed as a linguistic variable [34]. The establishment of 36 fuzzy rules in this study was guided by the need to balance theoretical completeness with practical applicability. Although the full combination of linguistic variables for temperature, dissolved oxygen (DO), pH, and wind velocity could generate more than one hundred possible rules, only 36 were selected as they represent the most relevant and realistic scenarios encountered in barramundi aquaculture. These rules were constructed based on water quality standards, empirical observations, and expert knowledge, ensuring that the decision-making process reflects both scientific guidelines and field-based experience. By limiting the rule base to 36, the system remains computationally efficient while still capturing the critical environmental variations necessary for accurate recommendations on Floating Net Cage (FNC) relocation. An example of the textual rule base is as follows:

Rule 1. If (Temperature is Cool) and (DO is Bad) and (pH is Acidic) and (Wind_Velocity is NORMAL) then (FNC is Move) (1)

Rule 2. If (Temperature is Cool) and (DO is Bad) and (pH is Acidic) and (Wind_Velocity is HIGH) then (FNC is Move) (1)

...

Rule 33. If (Temperature is Hot) and (DO is Good) and (pH is Normal) and (Wind_Velocity is NORMAL) then (FNC is Stay) (1)

Rule 34. If (Temperature is Hot) and (DO is Good) and (pH is Normal) and (Wind_Velocity is HIGH) then (FNC is Move) (1)

Rule 35. If (Temperature is Hot) and (DO is Good) and (pH is Alkaline) and (Wind_Velocity is NORMAL) then (FNC is Move) (1)

Rule 36. If (Temperature is Hot) and (DO is Good) and (pH is Alkaline) and (Wind_Velocity is HIGH) then (FNC is Move) (1)

The rules built using the toolbox are displayed in the rule editor in Figure 9 below :

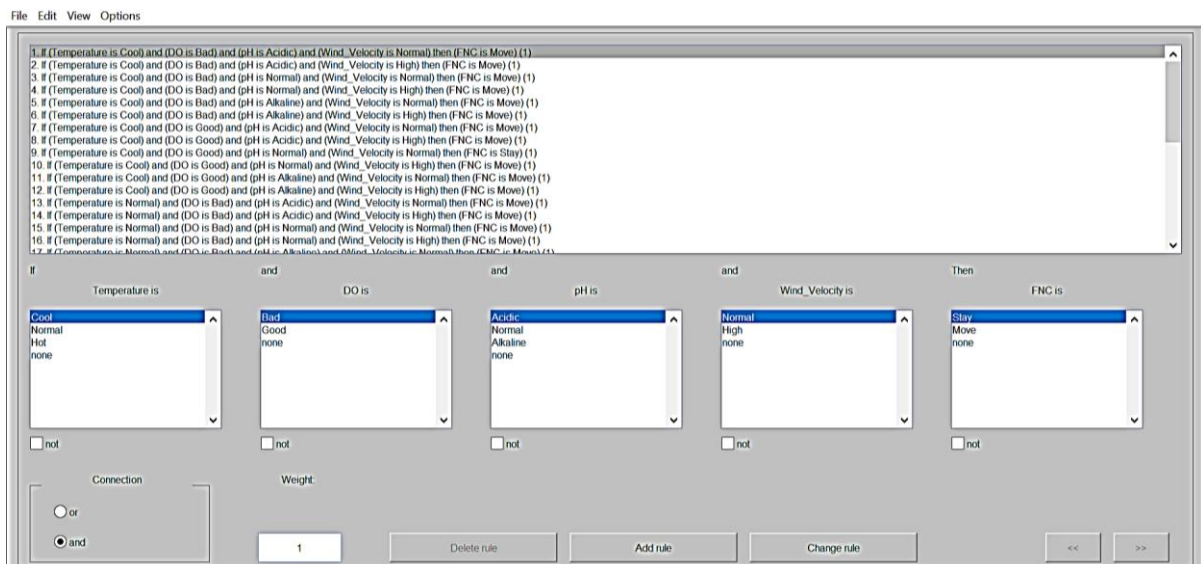


Figure 9. Rules for Quality Data Editor of Floating Net Cage

The overall research procedure is presented in Figure 10.

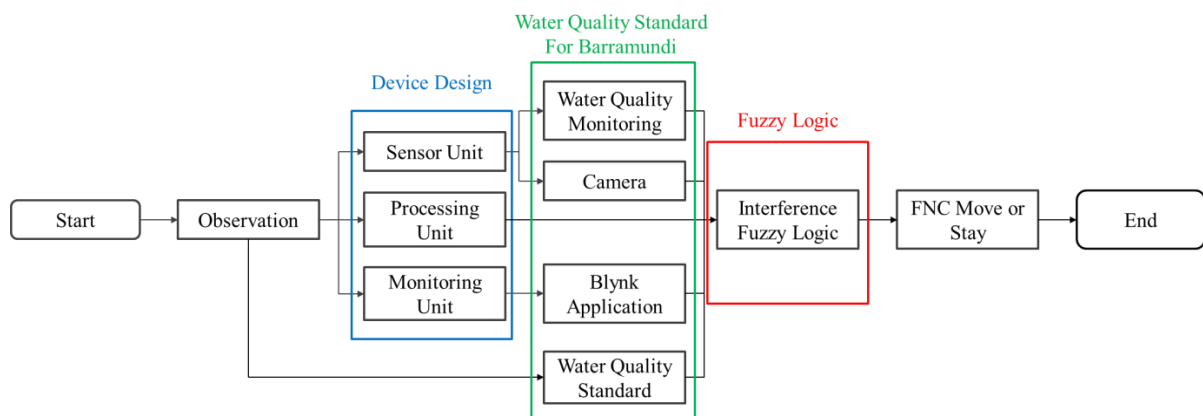


Figure 10. Research Procedure

3. RESULT

3.1. Device Result

The devices installed on the Floating Net Cage (FNC) are used to measure and collect water quality data at the Barramundi (*Lates calcarifer*) farming site. The water quality measurements are displayed in real time through the Blynk application, which can be accessed using a computer connected to the internet [35]. In addition, measurement results from the anemometer, wind direction sensor, and battery voltage are also presented in the application. The sensor data are displayed in both graphical and numerical formats, enabling users to perform real-time monitoring (Figure 11).

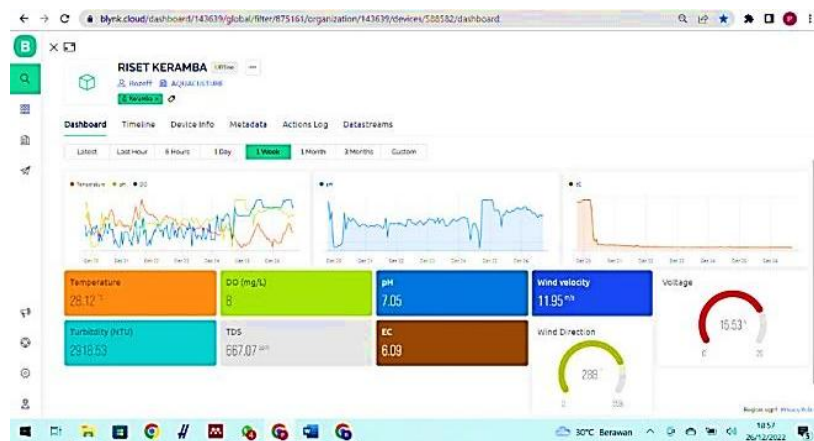


Figure 11. Real-time monitoring on the Blynk application

The aquatic conditions around the Floating Net Cage (FNC) can also be visually monitored through cameras installed on the FNC structure (Figure 11). Weather conditions, water surface, waves, water clarity, as well as the condition of the fish inside the FNC can be observed in real time (Figure 12), this is consistent with the work of [11][36]. The camera application used is open-source from the camera manufacturer and is equipped with video recording and image capture features.



Figure 12. Camera visualization at the FNC site

3.2. Sensor Measurement Result

The Dissolved Oxygen (DO) levels at the Floating Net Cage (FNC) site fluctuated with an average value of 6 mg/L. According to [37] these fluctuations were influenced by weather conditions and the surrounding aquatic environment; however, the changes were relatively insignificant. Barramundi (*Lates calcarifer*) is a species that requires higher DO concentrations compared to other fish species. Therefore, this value is considered highly favorable and meets the water quality standards required for Barramundi aquaculture.

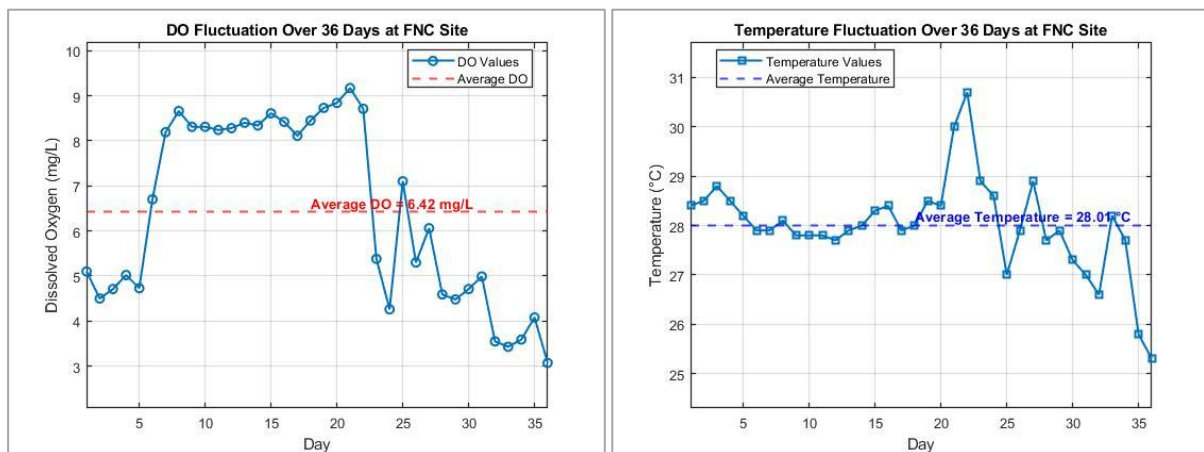
The water temperature parameter during the observation period remained relatively stable, with an average of 28.01 °C. Temperature fluctuations ranged from 25 °C to 31 °C, with most data falling within 27–29 °C. This range is still within the optimal threshold for Barramundi culture, which is 26–32 °C. The stable temperature conditions indicate that the aquatic environment is supportive of fish growth and metabolism, thereby posing no significant risk to the sustainability of the culture [38].

pH measurements showed a considerable fluctuation between day 10 and day 15, during which the pH dropped below 3 before returning to the normal range of 6–7 in the following days. The recorded average pH value was 5.72, indicating relatively acidic conditions. Such low pH levels may be influenced by external factors such as high rainfall, organic matter decomposition, or the influx of particles from the surrounding environment [39]. Considering that the optimal pH range for Barramundi is 7–8.5, prolonged exposure to low pH conditions may cause stress and reduce fish health [28].

The Electrical Conductivity (EC) measurements showed significant fluctuations during the early days of observation, particularly on day 5 and day 10, when values exceeded 70 µS/cm. In the subsequent days, however, EC values tended to stabilize below 10 µS/cm. The average EC recorded during the observation period was 7.33 µS/cm, which is considered low. This condition indicates that although there were spikes in conductivity at the beginning of the observation, overall, the water quality in terms of EC remained within a safe range for Barramundi aquaculture.

Observations of Total Dissolved Solids (TDS) indicated several extreme spikes, with peaks exceeding 7000 PPM, although most data remained below 500 PPM. The average TDS value recorded during the observation period was 743.21 PPM, which is considered relatively high. Such extreme TDS increases may result from the influx of dissolved solid particles originating from sediments, feed residues, or runoff from surrounding land [40]. According to [41] excessive TDS concentrations can disrupt the osmoregulation process in fish and reduce water quality, making it necessary to implement control measures to prevent levels from exceeding thresholds that could endanger fish.

The turbidity parameter exhibited very large fluctuations, with an average value of 1296.42 NTU and peak levels exceeding 4500 NTU. These values are far above the optimal turbidity threshold for fish farming, which is generally below 50 NTU. The high turbidity levels are presumed to be caused by the abundance of suspended solids in the water, originating from bottom sediments, organic particles, or uneaten feed [42]. Elevated turbidity can reduce light penetration into the water, decrease phytoplankton photosynthetic activity, and interfere with fish respiration, thereby posing negative impacts on the sustainability of aquaculture [43]. The results of the water quality parameter observations are presented in the Figure 13:



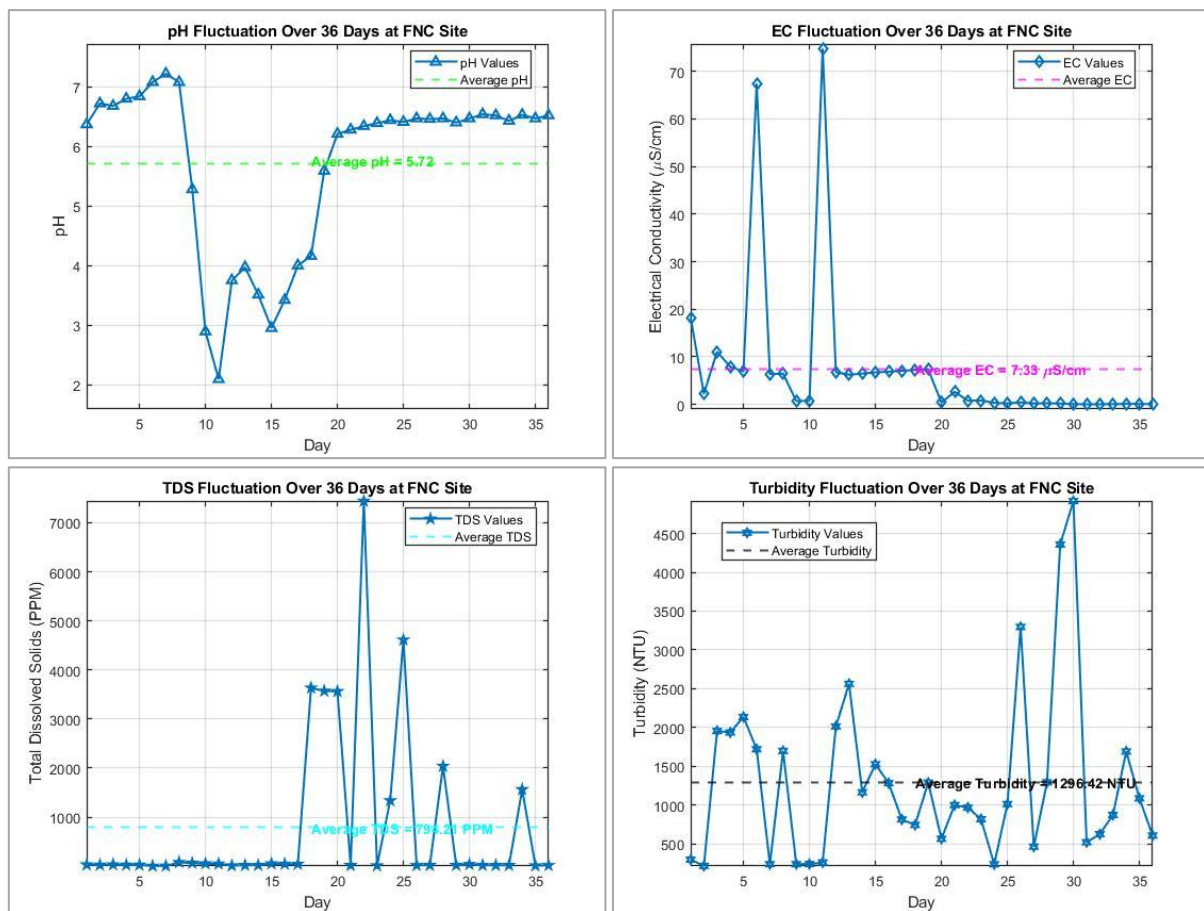


Figure 13. Water quality measurement results in floating net cages

The measurement results of wind speed and direction are presented in Figure 13. The observed wind speed ranged from 0.5 m/s to above 3 m/s, with the Floating Net Cage (FNC) location predominantly experiencing wind speeds exceeding 3 m/s, accounting for 82.3% of the observations. During the observation period in December 2024, the prevailing wind direction was from north to south. According to [44], wind speeds in Tanjung Pinang range between 0 and 2.56 m/s.

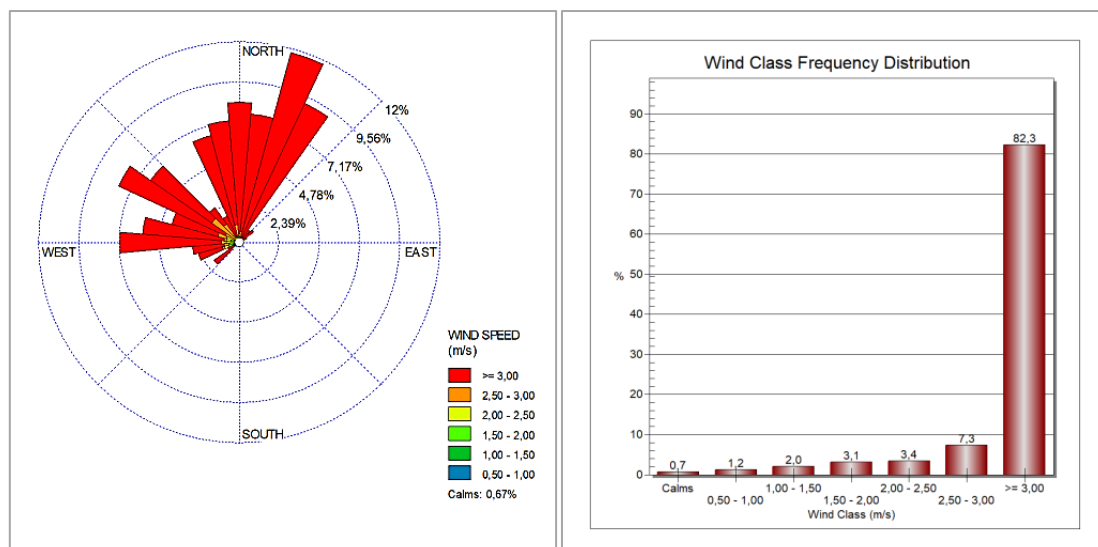


Figure 14. Wind Speed and Wind Direction

3.3. Interference Fuzzy Result

Natural changes in water quality occur gradually over a certain period and do not take place instantly. In the cycle of water quality changes, such as in the DO parameter, the recorded values from the device show fluctuations at certain levels until the sensor stabilizes and records a constant value. The observations indicate that changes in water quality in this test may occur within a time range of 10–30 minutes or even up to 60 - 135 minutes. The fuzzy inference system that was developed, along with all knowledge-based rules designed using the MATLAB toolbox, produced a fuzzy system. The water quality assessment at the FNC site for Barramundi (*Lates calcarifer*) aquaculture can be simulated by inputting the measured data of temperature, DO, pH, and wind speed into the input notation “[]”. The fuzzy rules are presented in the Figure 15:



Figure 15. Fuzzy logic rules

The fuzzy output or FNC status based on water quality sensor measurements over two days at the FNC site is presented in the Table 6:

The results of the rule viewer calculations are presented in the fuzzy output, as shown in Table 6. Based on the analysis, the fuzzy output takes a value of 1 with the FNC status “Move” when two out of the three main sensor parameters (temperature, DO, and pH) fall outside the water quality standards suitable for Barramundi culture, and wind speed exceeds the threshold. Conversely, the fuzzy output approaches 0 with the FNC status “Stay” when DO values remain above 5 mg/L, and either temperature or pH, along with wind speed, remain within normal conditions or do not exceed the established thresholds.

The fuzzy inference system table indicates that the FNC status “Stay” dominated for most of the observation period, suggesting that water quality remained relatively stable for Barramundi culture. However, on the first day (09:00–15:00) and the second day (11:00, 13:00, 14:00), the system assigned the FNC status “Move.” This condition was triggered by a combination of high DO levels (9–10 mg/L), increased pH, and relatively strong wind speeds (≥ 10 m/s), which were interpreted as potentially disrupting water stability. On the third day, despite temperature fluctuations reaching up to 31.86 °C, the system still produced the FNC status “Stay,” indicating that overall conditions remained safe. In general, the fuzzy system successfully distinguished between normal and critical conditions and provided adaptive recommendations for FNC positioning management based on real-time changes in water quality.

Table 6. Results of the fuzzy calculations 2 Days

Day	Hr	Fuzzy Input (T, DO, Ph, WS)	Fuzzy Output	FNC Status
1	00:00	[27.81;8.01;3.64;6.55]	0.376	FNC Stay
	01:00	[27.80;8.00;3.63;5.16]	0.38	FNC Stay
	02:00	[27.81;8.00;3.81;6.99]	0.376	FNC Stay
	03:00	[27.75;8.00;4.03;1.62]	0.396	FNC Stay
	04:00	[27.70;8.00;4.02;0.00]	0.5	FNC Stay
	05:00	[27.65;8.00;4.02;0.00]	0.5	FNC Stay
	06:00	[27.67;8.00;4.01;2.48]	0.421	FNC Stay
	07:00	[27.63;8.03;4.06;8.73]	0.434	FNC Stay
	08:00	[27.77;8.98;3.89;7.86]	0.389	FNC Stay
	09:00	[27.75;9.00;4.02;11.27]	1	FNC Move
	10:00	[27.99;9.02;4.13;13.43]	1	FNC Move
	11:00	[28.14;9.00;4.28;15.99]	1	FNC Move
	12:00	[28.18;9.01;3.97;12.36]	1	FNC Move
	13:00	[28.14;9.03;4.08;12.32]	1	FNC Move
	14:00	[28.26;9.01;4.18;13.67]	1	FNC Move
	15:00	[28.40;9.00;4.19;11.73]	1	FNC Move
	16:00	[28.41;9.00;4.77;9.95]	0.185	FNC Stay
	17:00	[28.32;8.98;4.77;6.54]	0.214	FNC Stay
	18:00	[28.23;8.67;4.74;5.01]	0.243	FNC Stay
	19:00	[28.20;8.05;4.66;3.67]	0.252	FNC Stay
	20:00	[28.14;8.05;4.64;0.00]	0.5	FNC Stay
	21:00	[28.08;8.04;4.50;0.16]	0.29	FNC Stay
	22:00	[28.01;8.02;4.33;0.00]	0.5	FNC Stay
	23:00	[28.22;8.02;4.01;0.00]	0.5	FNC Stay
2	00:00	[28.10;8.01;3.84;0.00]	0.5	FNC Stay
	01:00	[28.12;8.00;3.77;0.00]	0.5	FNC Stay
	02:00	[28.09;8.00;3.71;0.43]	0.287	FNC Stay
	03:00	[28.06;8.00;3.65;0.00]	0.5	FNC Stay
	04:00	[28.04;8.00;3.61;0.00]	0.5	FNC Stay
	05:00	[27.94;8.00;3.79;0.00]	0.5	FNC Stay
	06:00	[27.92;8.00;4.43;0.00]	0.5	FNC Stay
	07:00	[27.92;8.27;4.53;1.25]	0.341	FNC Stay
	08:00	[27.99;9.00;4.28;6.32]	0.319	FNC Stay
	09:00	[28.12;9.00;4.17;9.91]	0.277	FNC Stay
	10:00	[28.31;9.01;4.46;9.85]	0.217	FNC Stay
	11:00	[28.44;9.02;4.74;10.87]	1	FNC Move
	12:00	[28.58;9.77;4.98;9.96]	0.132	FNC Stay
	13:00	[28.87;10.00;5.15;13.73]	1	FNC Move
	14:00	[28.78;10.00;5.27;10.93]	1	FNC Move
	15:00	[29.15;9.99;5.39;9.42]	0.0484	FNC Stay
	16:00	[29.13;9.25;5.94;6.85]	0.0419	FNC Stay
	17:00	[29.20;9.00;6.01;8.26]	0.0645	FNC Stay
	18:00	[29.02;9.00;6.05;7.53]	0.00645	FNC Stay
	19:00	[28.94;8.97;6.07;7.50]	0.0188	FNC Stay
	20:00	[28.74;8.93;6.07;7.11]	0.0815	FNC Stay
	21:00	[28.65;8.51;6.09;7.27]	0.11	FNC Stay
	22:00	[28.44;8.06;6.10;7.79]	0.176	FNC Stay
	23:00	[28.39;8.04;6.11;5.52]	0.192	FNC Stay

4. DISCUSSIONS

The implementation of fuzzy logic in water quality monitoring systems makes a significant contribution by simplifying complex parameter assessments into clear operational decisions, such as whether to relocate or maintain the position of floating net cages (FNCs). In practice, this transformation involves converting multi-dimensional sensor inputs such as temperature, DO, pH, and wind velocity into linguistic categories (Good, Bad, Normal), which are then processed through rule based inference. This allows aquaculture operators to interpret environmental data not as isolated measurements but as holistic conditions that directly inform operational strategies. This approach is particularly relevant in the context of open-sea aquaculture, which is characterized by highly dynamic environmental conditions where variables such as DO, pH, turbidity, currents, and wind can fluctuate rapidly and unpredictably. For instance, a sudden drop in DO accompanied by high wind velocity might signal both deteriorating oxygen levels and increased stress on fish due to water turbulence, conditions that cannot be adequately captured by a single-threshold system. Compared with conventional methods that often rely on single-threshold values, fuzzy logic is capable of handling uncertainty and “gray areas” in decision boundaries, thereby enhancing system flexibility in responding to fluctuating sensor data and measurement noise [45].

In line with the growing trend of precision aquaculture, integrating IoT with fuzzy logic offers an adaptive framework that enables real-time and contextual decision-making. This aligns with [46], who emphasized the importance of adaptive control to enhance the sustainability of open-sea farming. Furthermore, [47] demonstrated that fuzzy logic can be effectively applied not only in open-water environments but also in closed systems, particularly for managing critical parameters such as ammonia. These examples highlight that fuzzy logic is not limited to one specific environmental setting; instead, it provides a versatile framework that can be tailored to different aquaculture infrastructures, ensuring that diverse challenges from water exchange limitations in ponds to extreme fluctuations in the open sea can be addressed through a consistent decision-making mechanism. Complementing this, the review by [48] highlights that IoT technologies, including sensor networks and wireless communication, serve as a fundamental backbone for the success of intelligent aquaculture systems.

Nevertheless, to achieve greater precision and predictive capability, integrating fuzzy logic with machine learning models is strongly recommended. Predictive modeling can complement fuzzy inference by forecasting water quality trends, such as DO fluctuations during weather changes or turbidity increases driven by strong winds. Machine learning models, particularly time-series approaches like LSTM or ensemble methods, can learn from historical patterns and predict upcoming environmental conditions with higher accuracy than rule-based systems alone. When combined with fuzzy inference, these predictions can be immediately translated into operational recommendations, such as preemptive relocation of cages before conditions become critical. Recent studies have also developed hybrid intelligence models capable of accurately predicting DO dynamics [49]. Therefore, the integration of fuzzy logic and machine learning is expected to produce a decision-making framework that is not only responsive but also anticipatory, thereby supporting the development of a more reliable and sustainable intelligent aquaculture system.

5. CONCLUSION

The implementation of remote monitoring devices in Barramundi (*Lates calcarifer*) aquaculture using the floating net cage (FNC) method has proven to be more effective and efficient. Changes in water quality and weather conditions can be monitored at any time through the Blynk application, which is accessible via internet-connected personal computers or smartphones. The application presents data in both numerical and graphical formats. Visual conditions above the cages, as well as fish conditions

inside the ponds, can also be clearly and in real time observed through surface and underwater cameras installed on the cage structure.

The 36-day field trial of the devices at the Barramundi aquaculture site demonstrated that the system can operate continuously and be monitored remotely without the need for direct visits to the offshore cage location. Test data analysis showed that changes in water quality parameters may occur within short intervals (10–30 minutes) or longer intervals (60–135 minutes), influenced by tides, weather conditions, currents, waves, and human activities around the cages. Sensor readings were automatically updated every 4–6 seconds.

During the testing period, water quality parameters at the FNC site exhibited fluctuations. The average DO value was recorded at 6 mg/L, the average temperature at 28 °C, and the average pH at 6. According to water quality standards, both DO and temperature values were favorable and within the normal range for Barramundi aquaculture, whereas pH was slightly below the required standard. The tolerance time for making decisions on cage relocation was set at 1 hour. From the continuous testing conducted over 48 hours (2 days), the simulation results showed 38 instances of “FNC Stay” decisions and 10 instances of “FNC Move” decisions.

This study is also significant in the field of informatics, as it demonstrates how Internet of Things (IoT) technologies, real-time data acquisition, wireless communication, and intelligent decision-support systems such as fuzzy inference can be integrated into aquaculture management. The system not only enhances efficiency in monitoring but also provides a model for applying informatics solutions to complex environmental problems, bridging the gap between computer science and marine resource management.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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