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Improving Abiotic Stress Mitigation via Predictive Modeling of Water Quality Parameters in Recirculated Aquaculture Systems

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Abstract: - A sustainable aquaculture solution can be provided by Recirculated Aquaculture Systems or RAS, nevertheless, Abiotic stress factors can negatively impact aquatic organisms' growth and well-being. This study's purpose is to demonstrate how Random Forests machine learning method helps to develop a predicting model that can aid in forecasting and in the mitigation of abiotic stressors in Recirculating Aquaculture Systems by regulating water quality influences.

The study used the historical data on water quality, such as temperature, dissolved oxygen, pH, ammonia, and TDS levels in constructing a Random Forest-based predictive model. Based from the results reveal, the developed prediction model using random forests machine learning method was 90% accurate in making prediction and improved abiotic stress in RAS.

Understanding the complex relations between water quality indicators and abiotic stress variables in RAS is crucial for identifying major abiotic stress drivers and developing effective models for forecasting water quality parameters, which results in real-time insights and actionable information for making proactive decisions and employing adaptive management techniques.

Furthermore, RAS improves aquaculture productivity while reducing environmental impacts, which results in increased productivity, resource utilization, and system performance. This study makes a vital contribution to the aquaculture sector by proposing a data-driven method to improve the control of water quality parameters in RAS and, eventually, raise the sustainability and effectiveness of Recirculating Aquaculture Systems

Keywords: Abiotic Stress, Nile Tilapia, Random Forest Machine learning algorithms, Water Quality

I. INTRODUCTION

Aquaculture, particularly within recirculating systems, has emerged as a pivotal player in global food security, meeting the escalating demand for seafood while minimizing environmental impacts [1]. Recirculated Aquaculture Systems (RAS) offer a controlled environment, but effective management of water quality remains a critical challenge due to the intricate interplay of various abiotic stressors [2]. These stressors, encompassing factors such as temperature fluctuations, dissolved oxygen levels, and pH variations, can significantly impact the health and growth of cultivated fish [3].

The increase in fish production is heavily reliant on the chemical and biological properties of the water, which must meet the aquaculture water quality requirements. As a result, good fish pond management necessitates knowledge and comprehension of water quality. However, water sampling takes time to monitor water quality, and laboratory results do not disclose the current condition of water in fish ponds, which is vital information for fish growers. It is recommended that Water quality monitoring in fish ponds should be done in real-time, and water parameter analysis should be done as quickly as possible to assure water quality and acceptability for aquaculture goods. Aquacultured goods are susceptible to infections and other issues as a result of poor water quality; real-time water monitoring in

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ponds is a solution to many pond concerns. To conduct proper water monitoring, the appropriate equipment and water parameters should be obtained and processed using acceptable water quality evaluation techniques in consideration of the current aquaculture product that is being nurtured. This information will assist the fish farmer in effectively managing and maintaining the water quality of their ponds [4]–[6]

Abiotic stressors are associated with aquaculture and culture-based fisheries. Extreme weather occurrences occur frequently for a variety of reasons, both natural and manmade. In contrast, the abiotic and biotic stresses associated with these causes exacerbate the condition significantly. Abiotic stress is an environmental element that has an adverse impact on living things. Universal climate change is a worry that threatens aquaculture operations by making the growth, survival, and productivity of culture organisms increasingly subject to climatic variations. When one or more environmental conditions, such as excessive temperature, flood, drought, rainfall, salinity, and so on, approach, the organisms are at serious threat [2].

Moreover, climate change is an unavoidable occurrence that impedes the production of aquaculture farms and culture-based fisheries in open waters. It poses a severe danger to global food security by displacing fish stocks from their natural habitats, affecting biodiversity, ecosystems, and global fish production. To address the effects of climate change, a variety of mitigation and adaptation strategies are being developed [2], [7].

The emergence of Artificial Intelligence with machine learning presents a promising path for addressing the complexities related with water quality management in RAS. Inspired by the human brain's neural architecture, Artificial Neural Networks or ANNs , have established excellent ability in modeling complex systems and prediction patterns [8]. Integrating ANNs into aquaculture systems holds the potential to revolutionize the proactive management of abiotic stressors by making precise predictions of vital water quality parameters.

This study aims to discover and utilize the predictive ability of machine learning based on Random Forests to anticipate disparities in key water quality parameters within a Recirculated Aquaculture System. By reating a predictive framework for parameters such as temperature, dissolved oxygen, pH levels, ammonia, and nitrite concentrations, the study seeks to provide a proactive method to mitigate abiotic stressors and improve environmental conditions for aquatic life.

The purpose of this research includes the development and validation of a predictive model specifically designed for the unique dynamics of Recirculating Aquaculture Systems. The accuracy of the model in forecasting critical water quality parameters is expected to be beneficial to aquaculturists with real-time insights, which will facilitate in the timely interventions to sustain ideal conditions for fish health.

By proposing this innovative method, we visualize contributing to the sustainable development and effectiveness of aquaculture practices. By utilizing cutting-edge technology to forecast and regulate water quality parameters, we assume a notable decline in the negative effects of abiotic stress on fish populations within a recirculated system.

II. METHODOLOGY

This research focused on the development of a predictive model using random forests-based machine learning that can monitor and analyze water parameters level in a recirculated aquaculture system to improve mitigation of abiotic stress of tilapia. The researchers were able to acquire the water parameters required in this study as well as the aquaculture range of tolerance, which includes the ideal water parameter for tilapia from the local government office Bureau of Fisheries and Aquatic Resources BFAR. Dissolved oxygen, total dissolved solid, PH, temperature, salinity, and ammonia are parameters that have a major impact on the health, growth, and survivability of the aforementioned aquacultures. These parameters have also been confirmed and validated by other study.

1. Recirculated Aquaculture System of Water Quality Prediction Setting

This research study adopted the RAS Architectural Diagram presented in the research of [9] as shown in the figure 1 below.

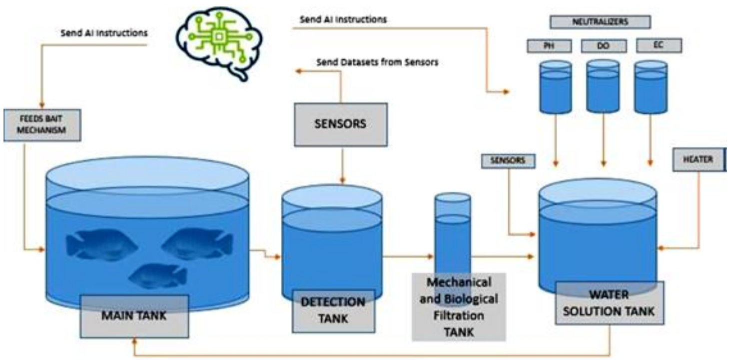

Figure 1. RAS Architectural Diagram[10]

Figure 1 shows the Recirculating Aquaculture System architectural design. The RAS uses different water tanks such as stocking tank, detection tank, filtration tank and Water solution tank with the following specification on table .

Table 1. Material used in RAS [9]

Particular	Specification	Purpose
1 - IBC Water Tank	1000 Liters Capacity 1 x 1 x 1.2 (meters)	Main tank
4 – water container	168 Liters Capacity ordinary	1- Detection, 2- Filtration & 1- Solution Tank
PBC pipe	2 inches	Connect the different tanks
1 - Aerator/ air pump	45 Watts	Generate dissolved Oxygen
1 – submersible water pump	55 Watts, 3000L per hour	Recirculate water from the solution tank going back to the Main tank
1 – portable submersible heater	300 watts	To increase the water temperature level
Mechanical & Biological Filtration	Net, pebbles, sand, stone, foam, water purifier lilies	Filter the water from the Main tank

2. Framework for Recirculated Aquaculture System Water Quality Prediction

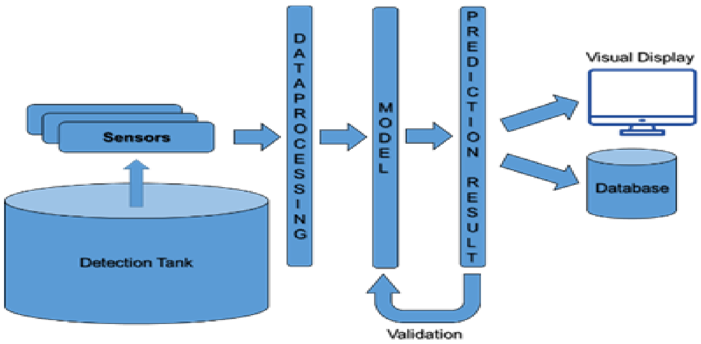

Figure 2. Water Quality Prediction framework in RAS

Fig. 2 depicts the framework for water quality prediction in RAS used in this study. From left to right , the framework is separated into three sections: collecting and processing of raw data , training and prediction model, and storage and display.

2.1. Data Acquisition and Pre-Processing

The deep well was the water source of the Recirculated Aquaculture System, and the Two sources of raw data are used to predict the water quality of the RAS: the sensors located at the detection tank provide the raw data, while the other source of data were acquired by using handheld water quality parameter measuring devices [11].

Water quality criteria for aquaculture such as tilapia, milkfish, and shrimp were provided by the office of the BFAR office and were validated based from previous related studies [12]–[15]. Water ammonia was used in a study by [16], which stated that it was frequently altered due to the feeding of cultured fish in fish ponds. This has an impact on aquaculture development and survival, thus the experiment was often examined. Total ammonia was calculated using pH and temperature data. First, determine the ammonium ion's ionization constant, pKa. To calculate the pKa value, the researcher utilized the following equation:

$$pKa = 0.0901821 + \frac{2729.92}{T\,°C + 273.2}$$

Where T= temperature in Degree Celsius.

To compute the fraction of NH3 or Ammonia, the equation below was used:

$$NH3 = \frac{1}{(10(pKa-pH)+1}$$

Observations indicated that water temperature and pH play significant roles in determining ammonia levels in water. Elevated levels of feed waste in the water lead to an increase in ammonia levels. Additionally, the water temperature affects tilapia's feeding habits and metabolism [9]. If the temperature decreases from the optimal level (25 - 30 degrees Celsius) tilapia fish tend not to eat [17] [18].

2.2 Development of prediction model using Random Forest.

The purpose of employing a random forest is to create a forest consist of decision trees and combine them to reach a more precise and consistent outcomes. Random forest comprises two forms of randomness. Initially, the samples are chosen is a random manner: a specific quantity of selections is taken from the training set to form the root node samples of the classless decision tree. Secondly, the process of creating each decision tree involves the random selection of a certain number of potential attributes. The split node is then selected based on the most suitable attribute. In order to create numerous training sets for decision trees, the random forest model randomly resamples the input data set. The final prediction is then derived from the average or majority of the decision trees' outputs. The random forest training method is depicted in Figure 3.

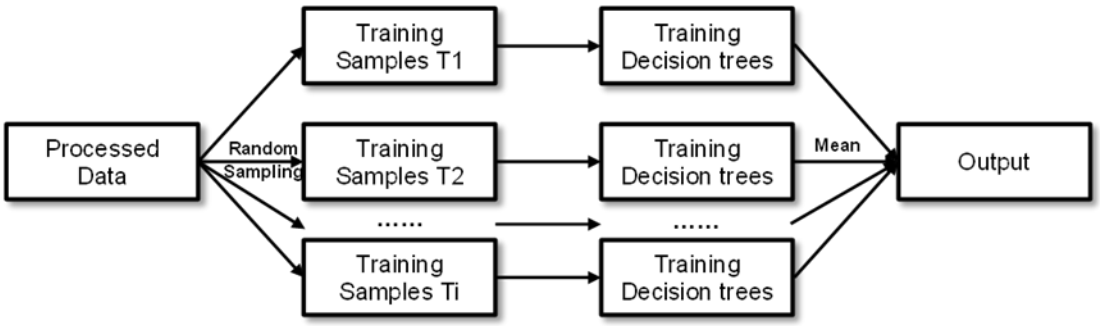

Figure 3. Training process of random forest

The following are the basic steps of the random forest algorithm [11]:

• Sampling: K sets of datasets are generated from the training set T using Bootstrap sampling with replacement. Each dataset is divided into two a) sampled data and b) unsampled data (out-of-bag data). A decision tree is then generated for each dataset through training.

• Growth: Every decision tree is trained through a training data. At each sub-node, m features are randomly selected from M attributes, and the ideal features are carefully chosen based on the Gini metric for full branching growth until no further growth is likely, without pruning.

• Testing: By means of out-of-bag data to assess the accuracy of the model, to some extent, model effects and generalization capabilities can be tested since out of bag data are not used in modeling. The prediction error of out-of-bag data is utilized to determine the best decision tree in the algorithm and to refine the model consequently.

• Prediction: Using the determined model for new data and prediction, the average of all decision trees prediction results is the final output.

III. RESULTS AND DISCUSSION

As presented by[19], abiotic stress is an environmental condition that negatively impacts organisms. Global climate change is a topic that poses a hazard to aquaculture enterprises as they expand, survive, and the productivity of cultural organisms is becoming increasingly subject to climate change. Extreme environmental conditions, including temperature, flood, drought, rainfall, and salinity, pose a significant threat to organisms.

This study investigated water quality indicators as an abiotic stressor for Nile tilapia. Water quality characteristics such as dissolved oxygen (DO), pH level, ammonia, and Total Dissolved Solids (TDS) all have a direct impact on tilapia survival and growth in a recirculating aquaculture system [20]. Other abiotic stresses were mitigated by this controlled environment, the RAS.

Table 2. Abiotic stresses related to water quality characteristics

Abiotic Stressor	Impact of stressor	Level	Reference
Low Temperature	Stop food taking and increase in mortality	18°C and below	[21]
High water temperature	slow growth, reduce feeding efficiency and increase mortality	Above 31°C	[22][23]
Ammonia Stress	cause body lesions, necrosis, and lesions on the fins	0.05 mg/L and death at approximately 2.0 mg/L	[24] [25]
Low Dissolved Oxygen (DO)	Lethargic, lose their appetite, and show reduced activity levels. Their growth rates can also be stunted, and they may become more susceptible to diseases and infections.	3ppm and below	[26][27][28]
Low pH level (Acidic)	Reduced growth Increased susceptibility to disease Reproductive problems Severe exposure lead to death	5 and below	[29]
TDS	Reduce the amount of dissolved oxygen in the water, which can make it difficult for tilapia fish to breathe.	Above 350ppm	[30]

Table 2 shows the different abiotic stressors related to the water quality indicators. Long exposure to these stressors can lead to increase in mortality rate.

Using these water quality indicators and random forest machine learning, the researchers were able to achieve 90% accuracy on the prediction of these abiotic stresses as shown in the figure below. As shown in the study of [11] random forest performs the best out of all the machine learning models that have been examined.

```
In [35]: prediction_test=model.predict(X_test)
         print(prediction_test)

         [1 1 1 0 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 1 1 0 1 1 1 0 0 0 1 1 1 1 0 1
          1 1 1 0 1]

In [36]: from sklearn import metrics
         print("Accurary = ", metrics.accuracy_score(Y_test,prediction_test))

         Accurary =  0.9047619047619048

In [40]: feature_list = list(X.columns)
         feature_imp = pd.Series(model.feature_importances_, index=feature_list).sort_values(ascending=False)
         print(feature_imp)

         NH      0.348707
         DO      0.204857
         PH      0.188835
         TEMP    0.148829
         TDS     0.108772
         dtype: float64
```

Figure 4. Abiotic Prediction Model using Random Forest Machine Learning

Table 3. Stressor Impact Rate

Stressor	**Impact Rate**
Ammonia	35%
Dissolved Oxygen (DO)	20%
pH Level	19%
Temperature	15%
TDS	11%

Table 2 shows that Ammonia was the predicted most impactful water quality stressors on tilapia. Increase on Ammonia level can be contributed by the high temperature, pH level and TDS. Increase in the TDS and acidity of the water were associated with the poor filtration of water in the RAS that eventually may lead to low dissolved oxygen (DO).

IV. SUMMARY AND CONCLUSION

This study's aim is to improve abiotic stress mitigation in recirculated aquaculture systems (RAS) by conducting a thorough analysis of water quality measures and their relationship to abiotic stress factors such as temperature, dissolved oxygen, pH, and ammonia concentration which can be done through the development of prediction model using random forest machine learning algorithm with the different water quality parameters.

The prediction model provided valuable insights and results. This significant developments in prediction models offers aquaculturists with suitable tools for forecasting and regulating water quality fluctuations, reducing stress on aquatic species and promoting ideal growth and health in aquaculture systems. Recognizing the critical importance of understanding complex relations between water quality parameters and abiotic stress variables in RAS leads to the identification of major abiotic stressors and the development of effective models for forecasting water quality parameters, resulting in real-time insights and actionable information for making proactive decisions and implementing adaptive management techniques.

Furthermore, Recirculating Aquaculture Systems improve aquaculture productivity and sustainability while limiting environmental footprint, leading to increased productivity, resource utilization, and system performance.

V. IMPLICATIONS AND RECOMMENDATIONS

This study highlights predictive modeling as an instrument for reducing abiotic stress within recirculating aquaculture systems (RAS). This prediction model is strongly recommended for practitioners for better water quality regulation. Implementing this method into their RAS operations can effectively reduce stress on aquatic life.

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Conflicts of interest

The author(s) of this research declare(s) that there is no conflict of interest regarding the publication of this paper.

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