



Assessing Hydrological Factors Affecting the Growth of *Cirrhinus cirrhosus* Using Python

Abhirup Mitra^{1,Ξ}, Prosenjit Pramanick^{2,\$}, Goutam Sengupta^{3,¥}, and Abhijit Mitra^{4,†}

¹Department of Management, Techno India University, West Bengal, EM 4 Salt Lake, Sector V, Kolkata 700091, India.

²Department of Oceanography, Techno India University, West Bengal, EM 4 Salt Lake, Sector V, Kolkata 700091, India.

³Rector, Techno India University, West Bengal, EM 4 Salt Lake, Sector V, Kolkata 700091, India.

⁴Department of Marine Science, University of Calcutta, 35 B.C. Road, Kolkata 700019, India & Director, Research, Techno India University, West Bengal, EM 4 Salt Lake, Sector V, Kolkata 700091, India.

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Abstract

This study highlights the role of computer based Python programming (which is an interpreted, object-oriented, high-level computer programming language with dynamic semantics) in carp aquaculture by delivering precise and efficient growth assessments. The condition index of the cultured species, *Cirrhinus cirrhosus*, showed variations across the three ponds, namely Pond 1 (P₁), Pond 2 (P₂), and Pond 3 (P₃). By addressing the hydrological parameters impacting pond performance and harnessing Python programming technologies, aquaculture practices can be optimized for greater productivity and sustainability. Future research should aim to improve the accuracy of Python-based models and explore new applications to further advance aquaculture practice.

Keywords: *Cirrhinus cirrhosus*, Condition Index, hydrological parameters, Python

^ΞEmail: mitraabhirup10@gmail.com

^{\$}Email: ppramanick660@gmail.com

[¥]Email: rector@technoindiaeducation.com

[†]Email: abhijit_mitra@hotmail.com (Corresponding Author)



1. Introduction

The aquaculture industry, particularly in developing countries, has experienced significant growth over the past few decades. This growth is largely driven by the increasing demand for fish as a primary source of protein for a growing global population. Among various aquaculture species, *Cirrhinus cirrhosus*, commonly known as mrigal, is one of the most widely cultivated freshwater fish species in South Asia. Its popularity stems from its high nutritional value, economic importance, and adaptability to diverse environmental conditions [1]. However, optimizing the growth and health of *Cirrhinus cirrhosus* in aquaculture systems remains a challenging task due to the complex interplay of various environmental factors, particularly hydrological parameters of the culture ponds.

Hydrological parameters, including surface water temperature, dissolved oxygen levels, surface water pH, and dissolved nutrient level (preferably nitrate and phosphate), play a crucial role in influencing the growth, health, and overall productivity of carp in aquaculture systems. These parameters directly affect the physiological processes of fish, such as metabolism, respiration, and immune responses [2]. Therefore, maintaining optimal hydrological conditions is essential for achieving sustainable and efficient aquaculture practices. Traditional methods of monitoring and managing these parameters often rely on manual measurements and empirical knowledge, which can be time-consuming, labour-intensive, and prone to human error.

In recent years, advancements in technology and data science have opened new avenues for enhancing aquaculture practices. Machine learning (ML), a subset of artificial intelligence (AI), has emerged as a powerful tool for analyzing complex datasets and extracting meaningful insights. Machine learning algorithms can process vast amounts of data, identify patterns, and make accurate predictions, thereby offering significant potential for optimizing aquaculture operations [3]. By leveraging machine learning techniques, it is possible to develop predictive models that can forecast the growth and health of *Cirrhinus cirrhosus* (using Condition Index abbreviated as CI as proxy) based on relevant hydrological parameters of the culture pond. These models can help aquaculturists take decisions regarding water quality management, feeding regimes, and other critical aspects of fish farming.

The application of machine learning in aquaculture is not entirely new. Several studies have demonstrated the feasibility and effectiveness of using machine learning algorithms for various purposes, such as disease detection, water quality prediction, and feed optimization [4]. However, the specific application of machine learning to optimize the growth of *Cirrhinus cirrhosus* by analyzing the hydrological parameters remains an underexplored area. This study aims to fill this gap by investigating the potential of machine learning algorithms to monitor the CI values of the species during the culture tenure of 210 days during 2023.

The first step in this endeavor is to collect and preprocess relevant data on hydrological parameters and fish growth metrics. Data collection involves continuous monitoring of water quality parameters using sensors and regular measurements of fish growth indicators, such as weight and length [5]. Preprocessing the data includes cleaning, normalization, and transformation to ensure it is suitable for analysis by machine learning algorithms. Once the data is ready, various machine learning algorithms, can be applied to identify the relationships between hydrological parameters and fish growth.

The integration of machine learning models with real-time monitoring systems can further enhance the practical utility of this approach. By deploying sensors and IoT (Internet of Things) devices in aquaculture ponds, it is possible to collect real-time data on hydrological parameters and feed it into machine learning models. These models can then provide real-time predictions and recommendations to aquaculturists, enabling proactive management of water quality and other environmental factors [6]. For instance, if the model predicts a decline in dissolved oxygen levels that could negatively affect fish growth, appropriate aeration measures can be implemented promptly.

Moreover, the use of machine learning in aquaculture is not limited to optimizing growth. It can also contribute to sustainability and environmental conservation. By analyzing data on water quality and fish health, machine learning models can help identify the water quality of the cultured pond, assess the impact of hydrological parameters on the cultured species, and develop strategies for mitigating adverse effects [7]. This holistic approach aligns with the principles of



sustainable aquaculture, which aim to balance economic productivity with environmental stewardship.

In addition to technical and environmental benefits, the application of machine learning in aquaculture also has significant economic implications. By optimizing growth and improving the efficiency of aquaculture operations, machine learning can enhance profitability for fish farmers. Reduced mortality rates, better feed conversion ratios, and improved fish health translate into higher yields and lower operational costs [8]. This is particularly important for small-scale farmers who rely on carp culture as their primary source of livelihood.

Despite the promising potential of machine learning in aquaculture, several challenges need to be addressed to ensure its successful implementation. Data quality and availability are critical factors, as accurate and comprehensive data is essential for training reliable machine learning models. The integration of sensors and IoT devices in aquaculture ponds requires significant investment and technical expertise. Additionally, the adoption of machine learning technologies in aquaculture necessitates training and capacity-building for farmers and aquaculturists to ensure they can effectively use and interpret the outputs of machine learning models [9].

Thus, the application of machine learning algorithms for optimizing the growth of *Cirrhinus cirrhosus* in controlled aquaculture environments holds great promise. By leveraging the power of machine learning to analyze hydrological parameters, it is possible to develop predictive models that enhance growth assessment, improve water quality management, and contribute to sustainable aquaculture practices. This study aims to explore this potential and provide valuable insights into the role of hydrological parameters in fish growth, paving the way for more efficient and sustainable aquaculture systems.

2. Methodology

2.1 Experimental Setup

In this study, three ponds at Moyna in the East Midnapur district of West Bengal (India) were designated for the experiment as shown in Figure 1. Traditional feed was provided twice daily, once in the morning and once in the evening, ensuring that the feed quantity was adjusted based on the biomass of the fish to prevent overfeeding and

maintain water quality. This feeding regime continued from March to October during 2023. Regular monitoring of water quality parameters such as surface water temperature, surface water pH, dissolved oxygen, dissolved nitrate, and dissolved phosphate levels was carried out to ensure optimal conditions for the carp's growth and health. Soil Organic Carbon (SOC) of the pond bottom was also analysed to evaluate the pond bottom environment that often plays important role in maintaining the pond environment.

Fish CI was assessed monthly by measuring the weight and length of a random sample of 23-25 fishes from each pond. Health status of the sampled fishes was evaluated through visual inspection for any signs of disease or abnormalities. At the end of the seven-month experimental period, the final weight and length of the fish were measured, and a comparative analysis was performed to evaluate the CI of the cultured species.

2.2 Monitoring of Hydrological Parameters

Water samples for hydrological parameters were collected from the surface using a clean bucket. Dissolved oxygen samples were directly collected in 150 ml BOD bottles without any agitation and immediately fixed post-collection. Temperature and pH were measured on-site, while additional water samples were collected from each pond in clean plastic bottles and transported to the laboratory at 4°C for nutrient analysis. Hydrological parameters were analyzed from the three selected ponds at Moyna.

(i) **Surface water temperature:** Measured using a mercury Celsius thermometer ranging from 0°C to 100°C.

(ii) **Surface water pH:** Determined using a portable pH meter with a sensitivity of ± 0.02 , calibrated with pH buffers 4.0 and 7.0 before each use.

(iii) **Dissolved oxygen:** Initially measured in the field with a DO meter and then confirmed in the laboratory using Winkler's method [10].

(iv) **Dissolved inorganic nutrients:** Surface water for dissolved nutrient analysis was collected in clean plastic bottles and transported to the lab in ice-cooled conditions. Triplicate samples ensured data quality. Nutrient concentrations in surface water were determined using the standard spectrophotometric method [10]. Nitrate was reduced to nitrite by passing the sample through a glass column with ammonium chloride buffer and

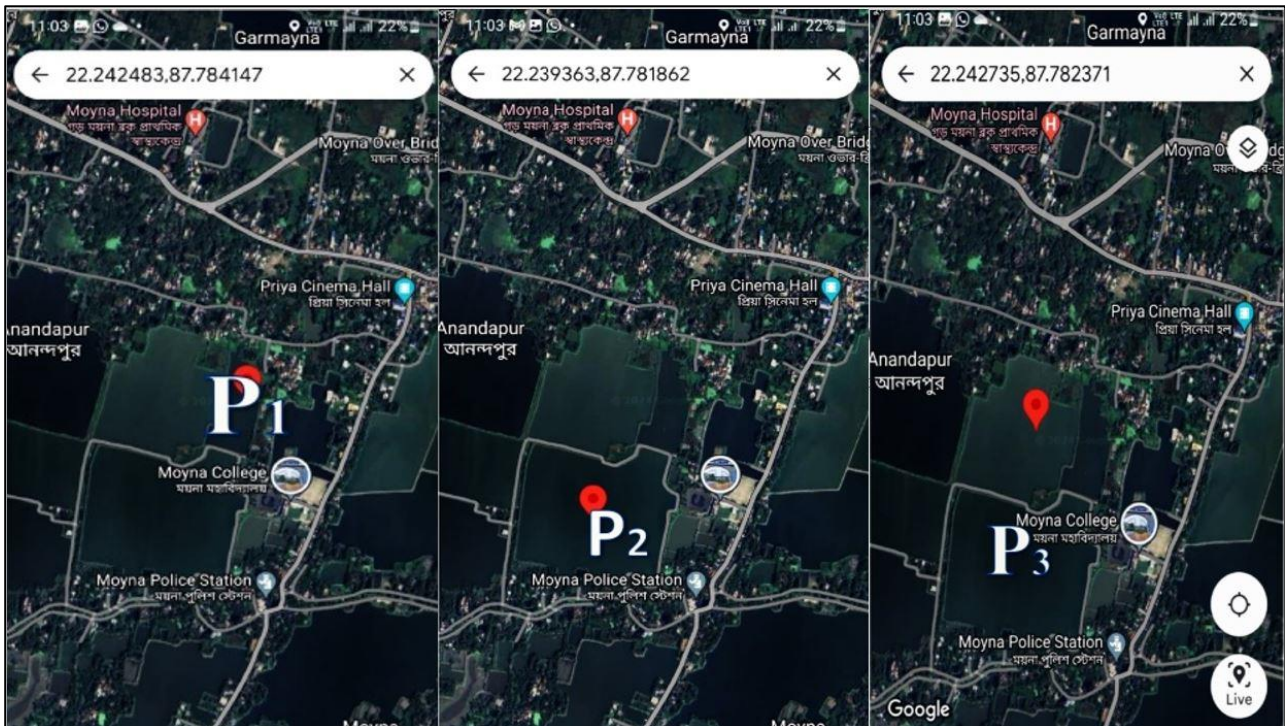


amalgamated cadmium filings. The nitrite was then treated with sulphanilamide to form a diazonium ion, which was coupled with N-1-naphthyl ethylenediamine to produce a pink azo dye. Phosphate was measured by treating a sample aliquot with an acidic molybdate reagent containing ascorbic acid and a small amount of potassium antimony tartrate.

(v) **Soil Organic Carbon (SOC):** Soil samples from the top 5 cm were collected from each pond and dried at 60°C for 48 hours. During preparation, visible plant particles were handpicked and removed from the soil. The soil was then sieved through a 2 mm mesh. A 50-gram sample of bulk soil from each pond was finely

ground using a ball mill. The finely ground samples were then randomly mixed to create a representative sample of the selected pond. The soil organic carbon (SOC) percentage was determined using a modified Walkley and Black method [11]. This meticulous approach to monitoring and maintaining water quality aligns with the broader goals of sustainable aquaculture practices and can significantly contribute to optimizing the health and growth of *Cirrhinus cirrhosus*, much like how advancements in AI and machine learning are transforming various sectors by enhancing efficiency and sustainability.

Figure 1: Location of ponds at Moyna in the East Midnapur district of West Bengal, India.



Source: Authors.

3. Results & Discussion

3.1 Condition Index

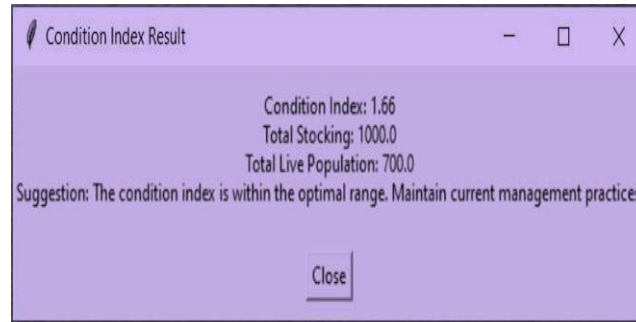
The results indicated that the machine learning models provided accurately the value of condition index for three selected ponds (Figures 2-4). The condition factor (K) values indicate better health and well-being of the fish in the culture pond. Higher K values indicate better health and growth conditions for the carp. The results of our computations are presented here.

- **Pond P₁:** The K value indicated robust growth conditions, reflecting good health and well-being of the carp. The condition index is highest in this pond with a value of 1.66.
- **Pond P₂:** The K value of this pond is 1.36, which is lowest amongst the three ponds suggesting stressful environment.



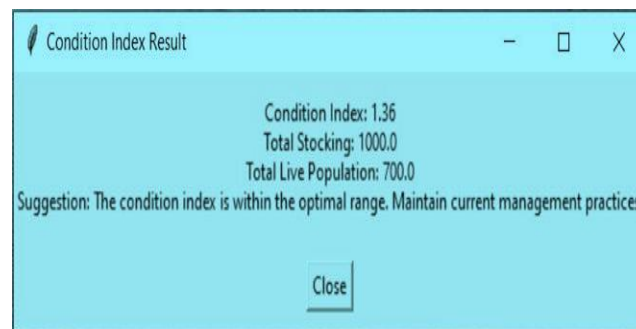
- **Pond P₃:** The K value of this pond is 1.58, which indicate that the environment is better than pond P₂.

Figure 2: Condition Index of *Cirrhinus cirrhosus* in Pond P₁ based on ABW and ABL during October, 2023.



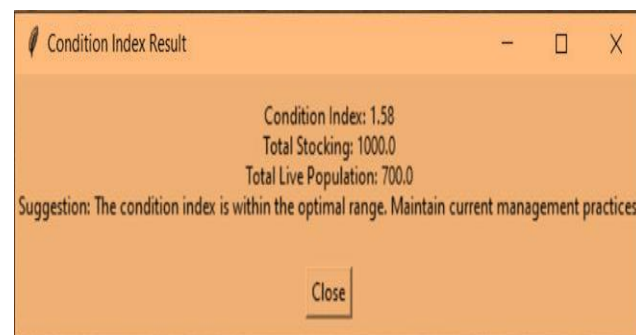
Source: Authors.

Figure 3: Condition Index of *Cirrhinus cirrhosus* in Pond P₂ based on ABW and ABL during October, 2023.



Source: Authors

Figure 4: Condition Index of *Cirrhinus cirrhosus* in Pond P₃ based on ABW and ABL during October, 2023.



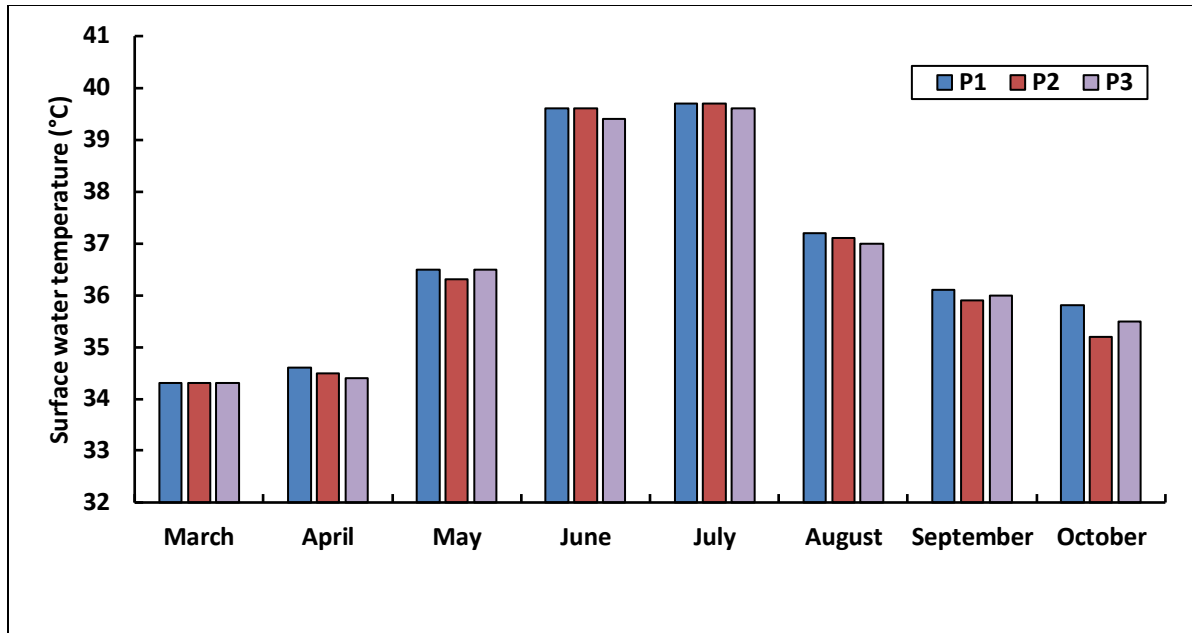
Source: Authors.

3.2 Hydrological Parameters

The relevant hydrological parameters of three ponds along with the soil organic carbon is presented in the Figures 5-10.

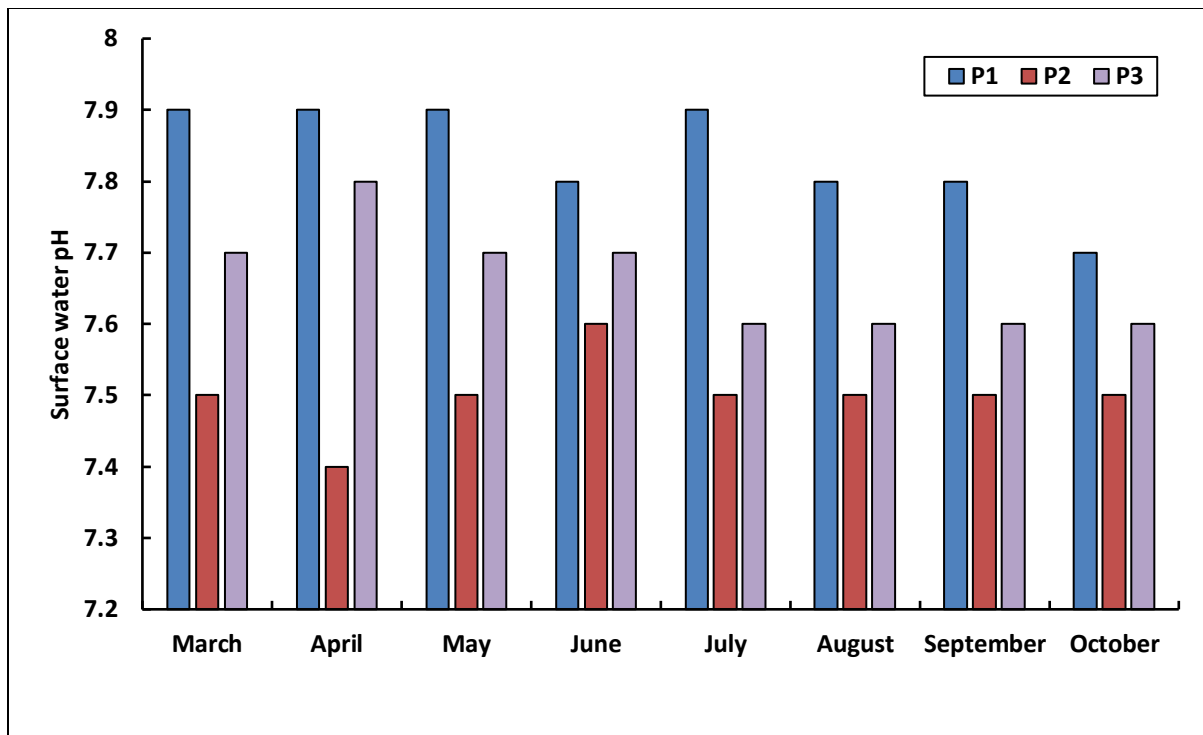


Figure 5: Monthly variation of surface water temperature (°C) in the three selected ponds



Source: Authors.

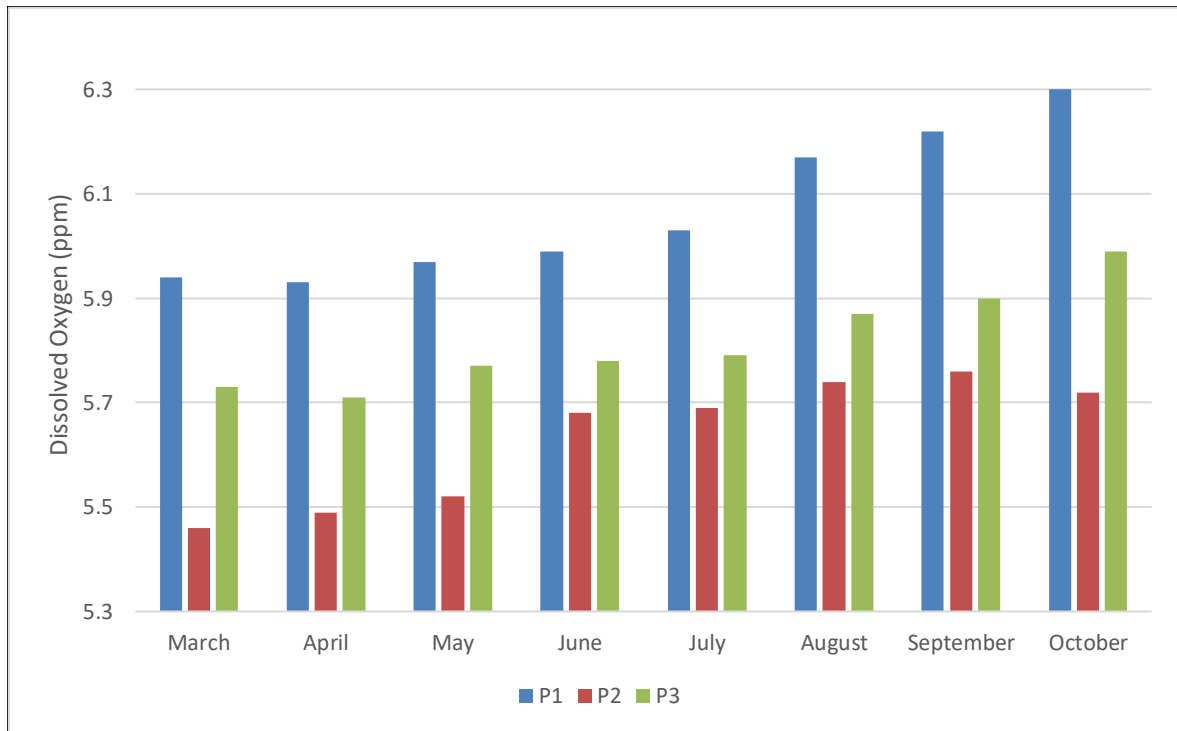
Figure 6: Monthly variation of surface water pH in the three selected ponds.



Source: Authors.

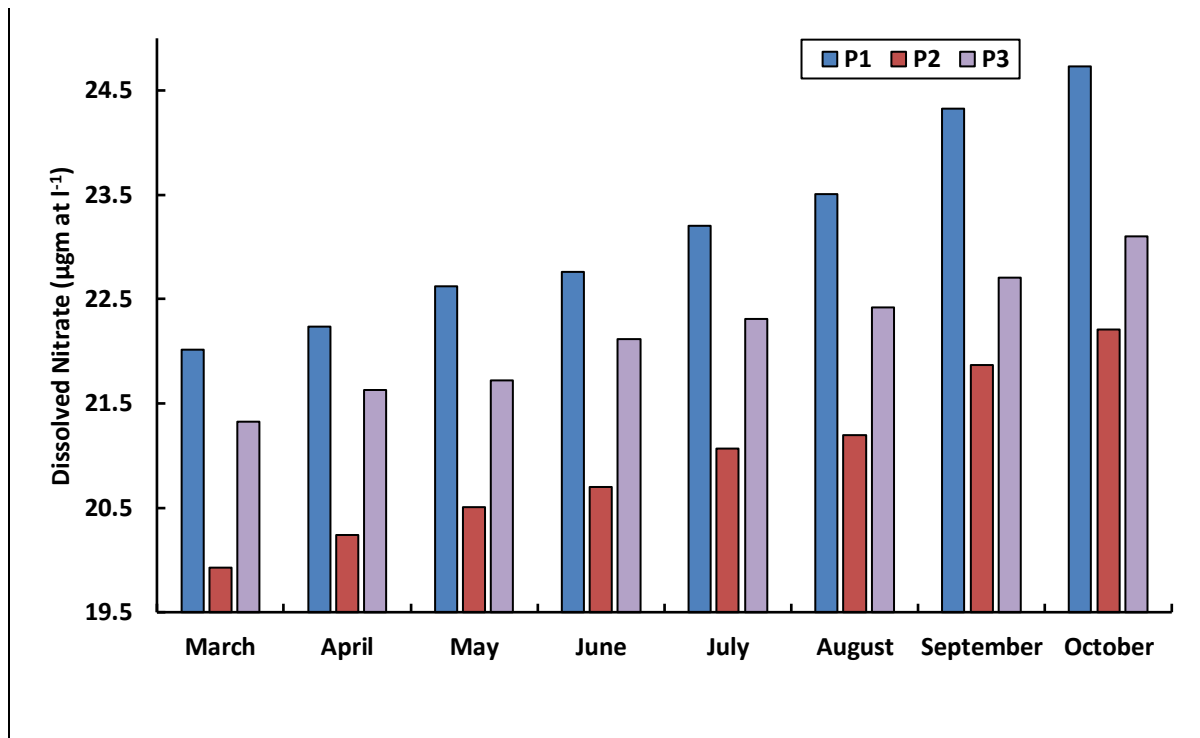


Figure 7: Monthly variation of dissolved oxygen (in ppm) in the three selected ponds.



Source: Authors.

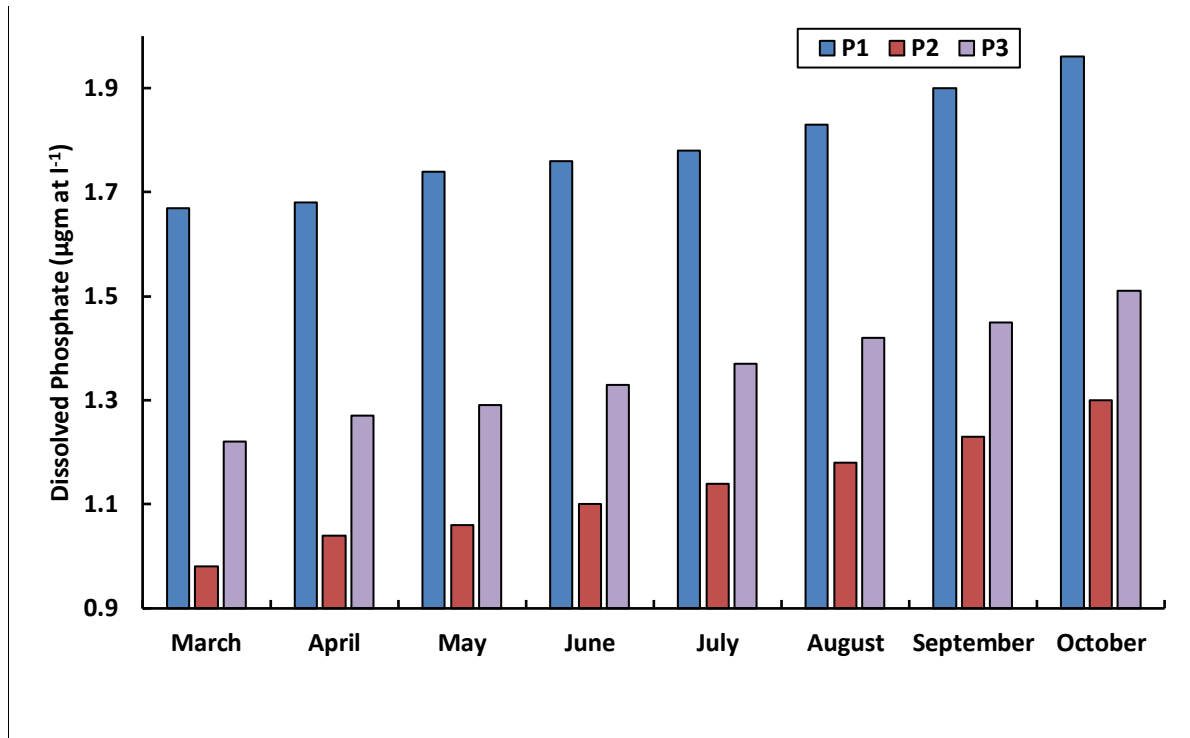
Figure 8: Monthly variation of dissolved nitrate (in $\mu\text{g m at l}^{-1}$) in the three selected ponds.



Source: Authors.

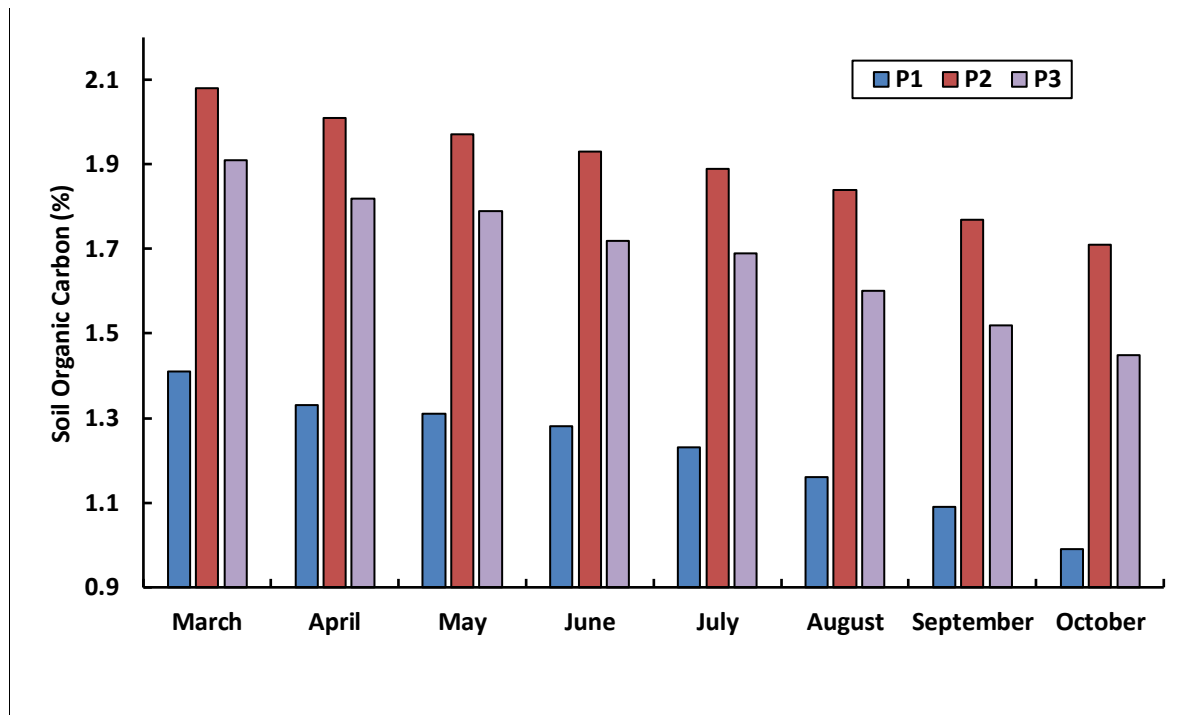


Figure 9: Monthly variation of dissolved phosphate (in $\mu\text{gm at l}^{-1}$) in the three selected ponds.



Source: Authors.

Figure 10: Monthly variation of soil organic carbon (in %) in the three selected ponds.



Source: Authors.



The provided ANOVA table (Table 1) present the variations of hydrological parameters and Soil Organic Carbon (SOC) among different ponds and across different months during the culture period of *Cirrhinus cirrhosus* in the Moyna region, East Midnapur district, West Bengal.

- **Surface Water Temperature:** ANOVA results indicate significant variations between months ($F = 811.2837$, $p < 0.0001$) and between ponds ($F = 5.30562$, $p = 0.0372$). This suggests that both temporal and spatial factors significantly influence the variations of surface water temperature that can affect the CI of *Cirrhinus cirrhosus*.
- **Surface Water pH:** Similar to temperature, surface water pH showed significant variations between months ($F = 813.2097$, $P < 0.0001$) and ponds ($F = 5.48462$, $p = 0.0372$), indicating that the pH levels fluctuate over time and vary across different ponds.
- **Dissolved Oxygen (DO):** The variations in dissolved oxygen were also significant between months ($F = 15.4274$, $p < 0.0001$) and between ponds ($F = 152.6417$, $p < 0.0001$),

suggesting that dissolved oxygen levels are influenced by both temporal and spatial factors. The abundance of natural fish feed of carp may influence the values of DO.

- **Dissolved Nitrate:** ANOVA results for dissolved nitrate show highly significant variations between months ($F = 43.2739$, $p < 0.0001$) and ponds ($F = 227.9101$, $p < 0.0001$), indicating that nitrate concentrations vary significantly over time and among ponds.
- **Dissolved Phosphate:** The dissolved phosphate levels exhibited significant variations between months ($F = 226.8215$, $p < 0.0001$) and between ponds ($F = 6619.6170$, $p < 0.0001$), highlighting that both temporal and spatial differences significantly affect phosphate concentrations.
- **Soil Organic Carbon (SOC):** The SOC content showed significant variations between months ($F = 156.1110$, $p < 0.0001$) and ponds ($F = 2550.7040$, $p < 0.0001$), indicating that the SOC levels are influenced by both the time of the year and the specific pond.

Table 1. ANOVA for hydrological parameters.

| Parameters | Variation (Between) | F_{cal} | F_{crit} | p-value |
|----------------------------------|---------------------|-----------|------------|----------|
| Surface water temperature | Months | 811.2837 | 2.9941 | 6.31E-15 |
| | Ponds | 5.30562 | 3.8752 | 0.0372 |
| Surface water pH | Months | 813.2097 | 2.9971 | 6.31E-15 |
| | Ponds | 5.48462 | 3.8842 | 0.0372 |
| Dissolved Oxygen | Months | 15.4274 | 2.7161 | 1.37E-05 |
| | Ponds | 152.6417 | 3.7588 | 3.14E-10 |
| Dissolved Nitrate | Months | 43.2739 | 2.9541 | 2.39E-08 |
| | Ponds | 227.9101 | 3.8488 | 2.1E-11 |
| Dissolved Phosphate | Months | 226.8215 | 2.7641 | 2.59E-13 |
| | Ponds | 6619.617 | 3.7188 | 1.47E-21 |
| Soil Organic Carbon | Months | 156.111 | 2.7841 | 3.57E-12 |
| | Ponds | 2550.704 | 3.7388 | 1.15E-18 |

Note: F_{cal} = Calculated value of F; F_{crit} = Critical value of F; p-value = standard deviation.

Source: Authors.



These findings underscore the importance of considering both temporal and spatial variations in hydrological parameters and SOC during aquaculture practices. Future research should focus on identifying the underlying factors causing these variations to optimize aquaculture productivity and sustainability.

Conclusions

The Python program accurately determined the condition index values for the three ponds (Figures 2-4), reflecting the health and well-being of the fish under different environmental conditions. Pond P₁ exhibited the highest condition index value of 1.66, indicating robust growth conditions. In contrast, Pond P₂ had the lowest condition index value of 1.36, suggesting a more stressful environment. Pond P₃ had a condition index value of 1.58, indicating better conditions than Pond P₂ but not as optimal as Pond P₁. These variations highlight the differing environmental impacts on fish health across the ponds. This study demonstrated the potential of Python programming to monitor the condition index and management in carp aquaculture, offering a promising approach to improving productivity and sustainability in the industry. Several factors could influence the variation in the values of condition index across the ponds. The quality of water, including parameters such as pH, dissolved oxygen, and temperature, plays a critical role in fish health. Deviation of their values from the optimum levels could lead to alteration in the condition index.

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