ASSESSMENT OF ENVIRONMENTAL IMPACT OF UN-ENGINEERED AQUACULTURE PONDS IN THE DELTA REGION OF ANDHRA PRADESH

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

THOTAKURA VAMSI NAGARAJU

(197CV501)

DEPARTMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA,

SURATHKAL, MANGALORE-575025

JULY 2023

ASSESSMENT OF ENVIRONMENTAL IMPACT OF UN-ENGINEERED AQUACULTURE PONDS IN THE DELTA REGION OF ANDHRA PRADESH

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

THOTAKURA VAMSI NAGARAJU

(197CV501)

Under the guidance of

Dr. SUNIL B M

Dr. BABLOO CHAUDHARY

DEPARTMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA,

SURATHKAL, MANGALORE-575025

JULY 2023

DECLARATION

I hereby declare that the Thesis entitled "**ASSESSMENT OF ENVIRONMENTAL IMPACT OF UN-ENGINEERED AQUACULTURE PONDS IN THE DELTA REGION OF ANDHRA PRADESH**" which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Civil Engineering** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

T. Vamsi Nagaraju

Place: Surathkal
Date: 27 July 2023

THOTAKURA VAMSI NAGARAJU
197CV501
Department of Civil Engineering
National Institute of Technology Karnataka
Surathkal - 575 025

CERTIFICATE

This is to certify that the Thesis entitled **"ASSESSMENT OF ENVIRONMENTAL IMPACT OF UN-ENGINEERED AQUACULTURE PONDS IN THE DELTA REGION OF ANDHRA PRADESH"** submitted by **THOTAKURA VAMSI NAGARAJU (197CV501)** as the record of research work carried out by him, *is accepted as the Research Thesis submission* in partial fulfilment of the requirements for the award of degree of **Doctor of Philosophy**.

Research Guides:

28/07/2023

Dr. Sunil B M
Department of Civil Engineering
Research Supervisor

28-07-23

Dr. Babloo Chaudhary
Department of Civil Engineering
Research Co-Supervisor

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA, SURATHKAL
DEPT. OF CIVIL ENGG.

Dr. Subhash C. Yaragal
Department of Civil Engineering
HOD and Chairman, DRPC

Chairman (DRPC)
Department of Civil Engineering
National Institute of Technology Karnataka, Surathkal
Mangalore - 575 025, Karnataka, INDIA

ACKNOWLEDGEMENT

I take this opportunity to express my sincere gratitude and profound thanks to my research supervisor **Dr. Sunil B M**, Associate Professor of Civil Engineering, National Institute of Technology Karnataka, Surathkal. His advice, support, care, expert guidance, constant encouragement, and reference materials provided for the successful completion of the research work.

I thankfully acknowledge the kind help and expert guidance by my co-supervisor **Dr. Babloo Chaudhary,** Assistant Professor of Civil Engineering, National Institute of Technology Karnataka, Surathkal.

I express my profound gratitude to RPAC members, **Dr. K. S. Babu Narayan** (Professor, Department of Civil Engineering), and **Dr. Subrahmanya Kundapura** (Assistant Professor, Department of Applied Mechanics and Hydraulics) for their continuous support and useful suggestions during the entire period of my research work.

I thank **Prof. Subhash C. Yaragal,** Head of Civil Engineering, **Prof. B. R. Jayalekshmi** (former Head), Department of Civil Engineering, and **Prof. K. Swaminathan** (former Head), Department of Civil Engineering, National Institute of Technology Karnataka, Surathkal for providing necessary facilities and sincere cooperation.

I extended my thanks to **Dr. M. Jagapathi Raj**u, Professor and Principal, S.R.K.R. Engineering College, Bhimavaram, for his support and encouragement.

I thank the **Dr. Gobinath R**, Professor, SR University, and **Mr. Ch. Durga Prasad**, Assistant Professor, S.R.K.R. Engineering College, Bhimavaram, for their support and encouragement.

I would like to thank all the teaching and non-teaching staff of the Department of Civil Engineering, National Institute of Technology Karnataka, Surathkal, and S.R.K.R. Engineering College for their cooperation and help during the research work.

I am very thankful to all my fellow research scholars of this institute for their continuous encouragement and suggestions during my research work.

I thank my wife **Sireesha** and my parents for their affection, love, care, constant support, and encouragement in the successful completion of my research work.

I must thank the financial help rendered by the management of S.R.K.R. Engineering College, Bhimavaram.

Finally, I am grateful to everyone who has helped and encouraged me during this research work.

THOTAKURA VAMSI NAGARAJU

(197CV501)

ABSTRACT

Aquaculture is persistent and well-established in the delta regions of Andhra Pradesh. Since 2014, the expansion of aquacultures confers positive economic growth in the newly formed state. However, the enormous development of aqua ponds increases the effluents from aquacultures and could impact the ecosystem negatively. This research work presents the effects of un-engineered aquaculture on the environment in the western delta region of Andhra Pradesh. A quantitative and topography survey, experimental investigation on aquaculture water and pond bottom soil, contaminant exposed soils behaviour, and assessment of ammonia levels using soft computing techniques were carried out.

Based on the questionnaire survey data, the aquaculture practice in the delta region of Andhra Pradesh was classified as intensive, semi-intensive and traditional zones. Land use and land cover changes shows that aquaculture ponds extended towards the northeast from the southwest. Between 2017 and 2021, aquaculture significantly increased by 54.35 km^2 and agriculture land decreased by 87.06 km^2. The physicochemical characteristics of the aquaculture water found higher levels of alkalinity, salinity, calcium, magnesium, and bicarbonates. The quantity of ammonia in the water ranged from 0.05 to 2.8 mg/L. The results show that ammonia levels exceeded the permissible limits; and are a significant concern in aquaculture waters due to toxicity. The average water quality index (WQI) was 126, with WQI values ranging from 21 to 456. Approximately 78% of the water samples were very poor and unsafe for the second crop.

The physicochemical characteristics of the pond subsoil shows higher concentration of potassium, Sulphur, and sodium in the intensive zone than the traditional farming zone. The results of the swell-shrink behaviour of expansive clays blended with aquaculture sludge show a significant decrease in swell potential, swelling pressure, and linear shrinkage. Furthermore, the microstructural analysis revealed the formation of a crystalline structure and the development of flocs and aggregation of clay particles with aquaculture sludge.

Pelican optimization algorithm (POA) and novel hybrid approach discrete wavelet transforms coupled with POA (DWT-POA) were used to predict ammonia levels in aquaculture ponds. DWT-POA model shows a higher performance compared with standard POA, with an average percentage error of 1.964 and a coefficient of determination (R^2) value of 0.822. Moreover, it was found that prediction models were reliable with good accuracy and simple to execute. Furthermore, these prediction models could help stakeholders and policymakers to make a real-time prediction of ammonia levels in intensive farming inland aquaculture ponds.

Keywords: Aquaculture, contaminants, soft computing, climate change, ammonia, sustainable aquaculture

CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

ANN	Artificial neural networks
AS	Aquaculture sludge
ATC	Annual temperature cycle
BIS	Bureau of Indian Standards
BOD	Biochemical oxygen demand
CEC	Cation exchange capacity
CNN	Convolutional neural networks
COD	Chemical oxygen demand
CSH	Calcium silica hydrates
DO	Dissolved oxygen
DWT	Discrete wavelets transform
EC	Electrical conductivity
EDS	Energy dispersive spectrometry
EVI	Enhanced vegetation index
FL	Fuzzy logic
FSI	Free swell index
GA	Genetic algorithm
GHE	Greenhouse emissions
GWO	Gray wolf optimization
ICMR	Indian Council of Medical Research
LST	Land surface temperatures
MODIS	Moderate Resolution Imaging Spectroradiometer
MPA	Marine predators' algorithm
NDTI	Normalized difference turbidity index
NDVI	Normalized difference vegetation index
PA	Producers' accuracy
PSO	Particle swarm optimization
POA	Pelican optimization algorithm
RAS	Recirculation aquaculture system

RF	Random forest
SAVI	Soil adjusted vegetation index
SEM	Scanning electron microscopy
SVM	Support vector machines
TDS	Total dissolved solids
TLBO	Teaching-Learning-Based Optimization
TSA	Tunicate swarm algorithm
UC	User correctness
USGS	United States Geological Survey
WHO	World Health Organization
WOA	Whale Optimization Algorithm
WQI	Water quality index
WRIS	Water Resources Information System
XRD	X-ray diffraction

CHAPTER 1

INTRODUCTION

1.1 GENERAL

In recent years, there has been a significant increase in the demand for food products with the population increase in many countries, especially India. Further, to meet their requirements, agriculture and aquaculture practices dramatically increase production and culture expansion (FAO, 2018). India is currently the second largest aquaculture producer, with production rising exponentially from 0.75 million tonnes in 1950 to 9.6 million tonnes in 2014. The rapid increase in production is due to the uncontrolled and unsafe conversion of coastal habitats, especially from mangrove wetlands to shrimp cultivation ponds, which caused concern among the scientific community, environmental administrators, and policymakers about the effects of aquaculture ponds on existing coastal ecosystems (Prasad et al. 2019). This was a result of India's rapidly increasing aquaculture production. The subject of aquaculture is an interdisciplinary platform to deal with; it involves biology, chemistry, environmental engineering, and soil mechanics (Edwards, 2015; Wu and Song, 2021).

The main problems associated with the intensive aquaculture ponds are seepage of contaminated water from the pond embankment to adjacent agricultural fields, leaching of polluted water from the subsoil to groundwater bodies, improper or untreated aquaculture effluents into nearby irrigation and drinking canals due to lack of drains (Cao et al. 2007; Islam and Yasmin, 2017). Geotechnical engineers have many aspects of dealing with and developing a sustainable aquaculture pond. Geo-environmental aspects of aquaculture to be taken care of, like the revolutionary development, have been taking place in the engineered landfills recently. In aquaculture practice, regular feed to shrimp includes zinc, phosphorous, calcium, sodium, potassium, and magnesium, apart from probiotics (Phillips, 2000; Paez, 2001). The encroachment of contaminated aquaculture ponds at the end of the crop has released both organic matters and diluted minerals and chemicals (Lai et al. 2018). The primary water contamination occurs due to the excess feed and effluents generated by the aquatic shrimp (Islam et al. 2004). Furthermore, it increases the nitrates and ammonia concentration in the pond. The intensity of aquaculture practice discharges large quantities of untreated wastewater containing organic matter, a high concentration of chemicals, plankton, antimicrobial agents, minerals, and antibiotics (Rico et al. 2012). This discharged aquaculture effluents to the irrigation canals and freshwater bodies affect the yield and quality of the adjacent agriculture fields. Also, freshwater bodies such as irrigation canals and drinking water ponds were polluting.

1.2 SITE DESCRIPTION

The western Godavari delta region of Andhra Pradesh is bounded by the Bay of Bengal, Godavari River, and Kolleru lake. It is located between the northern latitudes of 16°19′06″ and 16°56′10″ and the eastern longitudes of 81°18′25″ and 81°52′45″ (Figure 1.1). Geo-hydrologically, this present location is drained by numerous surface water resources such as Tammileru, Errakalava, Kovvadakalava and Gunderu. These resources supplement the groundwater sources on which many socio-economic conditions significantly depend. The Delta region of Andhra Pradesh is one of India's major aquaculture producers due to its desirable topography and climatic conditions.

One-fourth of the inland aquaculture area covered in India is from the western Godavari delta region of Andhra Pradesh (Prasad et al. 2019). Moreover, 5% of the global aquaculture production is generated from the Andhra Pradesh alone (MPEDA, 2022). Aquaculture is the primary source of the state economy and the society of Andhra Pradesh (Kolli et al. 2020). The topography, soil conditions, water availability, transportation facilities, electricity facilities, and other amenities play a vital role in the intensity of aquaculture farming. Aquaculture farming in small pits along the canals and Kolleru lake was traditional in the delta region. In the early 2000s, aquaculture emerged as a significant activity, with individual tank sizes ranging from 1 acre to 30 acres due to the higher demand for shrimp in the global market. The main canals contributing to the expansion of aquaculture in this region are the Undi canal, Venkayya canal, Narsapur canal, and Gostani canal. Over the last few years, intensive farming in terms of overfeeding, chemical usage, disinfectants, and probiotics has led to shallow water and groundwater contamination. The primary environmental concern within this area is due to the effluents generated from the aquaculture (Jayanthi et al. 2006; Muralidhar et al. 2021). Many researchers have carried out research work related to aquaculture practices and their consequences in the recent past (Kathiha et al. 2005; Jayanthi et al. 2019; Prasad et al. 2019).

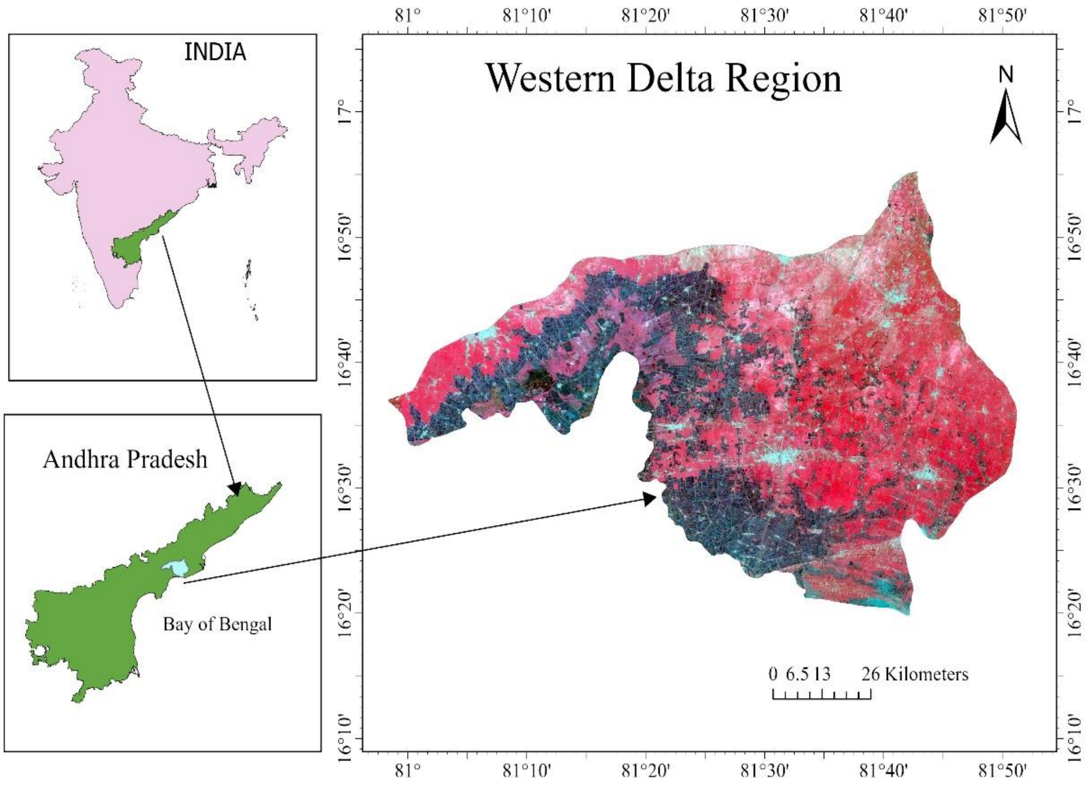


Figure 1.1 Map of the western Godavari delta region

In 2014, Andhra Pradesh state was newly formed by separating from Telangana. So, a new state with favourable regulations and policies shifts the slow aquaculture farming practice into the intensive commercial mode of aquaculture. Another hand, intensive farming harms the environment and causes ecological crises. The effluents generated from the aquaculture ponds are a significant concern because of organic matter and toxic compounds. Moreover, 90% of the surface water sources, canals, and lakes were merged with the aquaculture waters after crop change in this region; hence, the monitoring of aquaculture waters must be addressed (Kolli et al. 2022).

Moreover, aquaculture sediment settlement over a prolonged time could pollute groundwater bodies. So, this water negatively impacts consumers who consume it for drinking and other purposes, and people suffer from various health problems. In the delta region of Andhra Pradesh, a safe and clean drinking water supply to the community is hugely vital in maintaining positive health measures. Unfortunately, about 90% of the water bodies are polluted with aquaculture sediments, and most people need safe drinking water. Areal views of aquaculture ponds were shown in Figure 1.2 to understand better the field scenario of aquaculture ponds in the study area.

Figure 1.2 Aerial view of aquaculture ponds in the study area

1.3 NEED FOR THE STUDY

Improving inland aquaculture's environmental performance is crucial for its long-term sustainability. There is serious concern about the intensive aquaculture effects on the environment and the need to critically assess the water use in aquaculture ponds compared to other competing applications. The present research proposes to assess the environmental impact of un-engineered aquaculture ponds in the western delta region of Andhra Pradesh. This work carries out extensive experimental and field investigations in the study area and proposed ammonia prediction models using soft computing techniques. In the literature, numerous studies focused only on the economic aspects and land conversation of mangroves to inland aquaculture ponds. Moreover, only limited studies on the environmental aspects (Prasad et al. 2019; Duy et al. 2022; Luo et al. 2022). Moreover, previous studies successfully applied standalone and hybrid soft computing algorithms for predicting water quality parameters (Sakaa et al., 2022; Uddin et al., 2023a; Uddin et al., 2023b). However, most studies have focused on the canal or river water quality parameters, and studies have yet to be found to predict the ammonia levels in intensive inland aquaculture waters. Compared to other prediction studies, the present prediction study widely explores, hybridizing a metaheuristic algorithm with a signal processing technique. Here, a comprehensive study focuses on the expansion and intensity of aquaculture practices by evaluating land use land cover dynamics, aquaculture water quality, subsoil properties, and the effect of aquaculture sludge on clays. Further, prediction models assess the study area's toxic ammonia levels using standalone and hybrid soft compu**ting** techniques better to understand the environmental impact of the un-engineered aquaculture ponds.

1.4 RESEARCH OBJECTIVES

The current research investigation's proposed objectives are as follows:

(1) To assess the water quality in order to understand aquaculture expansion rate and its intensity in the study area by conducting lab tests, field investigations and topography mapping.

(2) To characterize subsoil in the aquaculture ponds using physicochemical tests, one-dimensional swell consolidation tests, hydraulic conductivity tests, and aquaculture sludge exposed clays behavior to understand the aquaculture soils quality.

(3) To estimate the aquaculture ammonia levels using hybrid soft computing techniques.

1.5 ORGANIZATION OF THE THESIS

The thesis comprises of eight chapters, list of references, appendix, and annexure. A brief description of each chapter is presented here.

Chapter-1 introduces the intensive inland aquaculture ponds, site description, aquaculture scenario in the study area, and the need for the present study have been discussed.

Chapter-2 presents the comprehensive review of aquaculture practices in India and their consequences on the environment, recirculating aquaculture systems, and application of soft computing techniques in aquaculture.

Chapter-3 Outlines the procedures used to assess aquaculture ponds in the western Godavari delta region of Andhra Pradesh. It includes details on the preliminary investigation with questionnaire and topography surveys, experimental techniques, methodologies, data standardization, consistency checks, and the methodology of soft computing models utilized in the study.

Chapter-4 presents the results of the physicochemical characteristics of the intensive aquaculture pond waters and their quality assessment using the water quality index.

Chapter-5 explains the findings of the effect of aquaculture sludge on clays in terms of swelling and hydraulic conductivity. In addition, microstructural analysis was carried out to know the effect of aquaculture sludge leachate on the clay morphology.

Chapter-6 illustrates the application of DWT-POA hybrid soft computing model to predict ammonia levels in the aquaculture ponds.

Chapter-7 presents the significant conclusions drawn from the study. Recommendations for the future research have also been presented.

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

In many countries in the Asia and the Pacific countries, fish and seafood have been considered an integral part of traditional cuisine. Generally, capture fishing in the marine, freshwater rivers, and inland aquaculture ponds have produced most fish and seafood. In addition to providing food and nutrition, fishing and fish farming are significant sources of income for many people. Many Asian nations have adopted inland aquaculture as a significant and quickly expanding economic activity to meet the rising domestic and global demand. India now ranks second in the world for aquaculture production due to significant improvements brought about by technology in inland aquaculture (FAO, 2021). An important shrimp species called the giant tiger shrimp (*Penaeus monodon*) is raised in India. Additionally, the government of India authorized the large-scale farming of white-leg shrimp (*Penaeus vannamei*), an exotic shrimp species, in 2009 following a thorough risk assessment by the central institute of brackish water aquaculture (CIBA) in 2003 (Salunke et al. 2020).

2.2 AN OVERVIEW OF AQUACULTURE PRACTICE IN INDIA

Aquaculture in brackish or salt water has flourished in India. India's tale of export growth is primarily attributed to shrimp aquaculture in brackish water (Salunke et al. 2020). Based on the Department of Fisheries, India reported that farmed shrimp production increased from 20 metric tons in 1970 to 7.47 lakh metric tons in 2020, adding significantly to the INR 46,662 crores in fisheries export revenues, which has seen tremendous expansion over the past few decades. Since the country barely uses about 13% of its 1.42 million ha of brackish ecosystem, brackish water aquaculture has a lot of opportunities. Therefore, the Government has concentrated on boosting current fish production from 0.7 million metric tons to 1.10 million metric tons by 2025 to use its potential fully. By 2025, a total of 45000 ha of brackish water area would be included, increasing present productivity from 4 tons/ha to 8 tons/ha to achieve a production of 15 lakh metric tons. This will need to use the 3.9 million ha of estuaries and the 0.5 million ha of coastal mangrove regions accessible in the nation to cultivate finfish and shellfish. Prasad et al. (2019) reported that in India, 3200 km^2 area of inland aquaculture ponds in 2017, which more than 90% of the total aquaculture production from four states such as Andhra Pradesh, West Bengal, Gujarat, and Tamil Nadu. Figure 2.1 shows the production stats of the leading states in India (MPEDA, 2022).

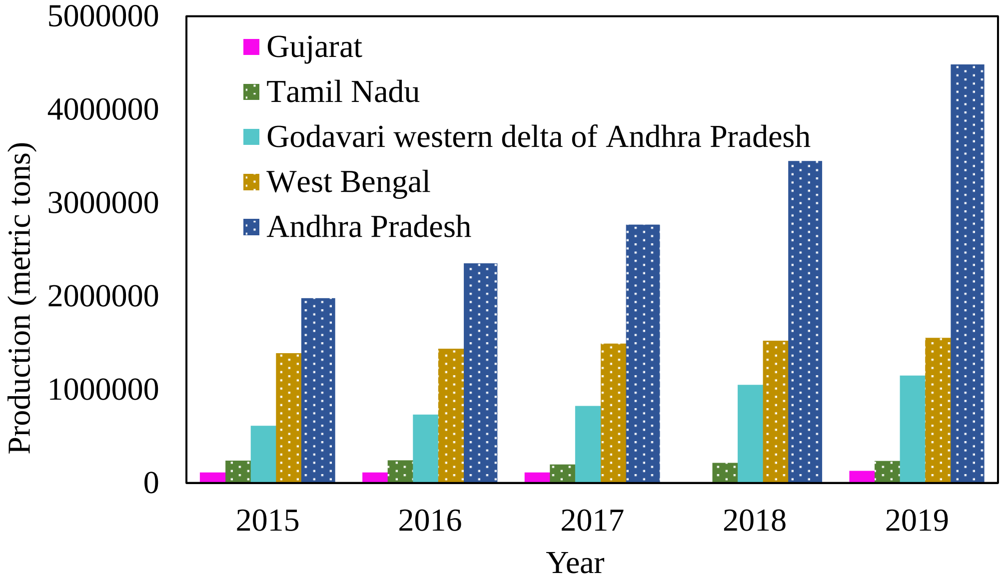


Figure 2.1 Aquaculture production (metric tons) of leading states in India

The development of the newly formed state Andhra Pradesh after state bifurcation has many urgent needs, such as using natural resources, earnings from exports, more employment, and a better living environment. Moreover, inland aquaculture is one of the higher economic growth activities in the coastal delta region. The pervasive aquaculture has been accompanied by many disputes related to environmental concerns. Aquaculture contributes mainly through export earnings. Table 2.1 indicates a rapid growth in the production of fish and shrimps year by year, indirectly hints at the expansion of aquaculture practices in Andhra Pradesh. The significant contribution is from the West Godavari district, and mints share of 25.68% of total production in the A.P during the year of 2018 to 2019.

Table 2.1 Fish and shrimp production in Andhra Pradesh (WGFD, 2022)

Year	Fish and shrimp production in metric tones	
	Andhra Pradesh	West Godavari District
2014-15	1978578	612616
2015-16	2352263	731803
2016-17	2766193	827226
2017-18	3449558	1051754
2018-19	4485200	1152201

2.3 IMPACT OF AQUACULTURE ON ENVIRONMENT

Inland aquaculture is one of the significant activities in the coastal region of India (Jayanthi et al. 2019; Prasad et al. 2019). In recent times, due to the demand for aquaculture-based food, economic growth of the state, and employment for local people, aquaculture practices were rapidly expanded, and farming intensity also increased.s

In addition to intensive farming, factories that process shrimp and fish generate waste streams with various compositions and concentrations that significantly negatively influence the environment. Frequently, activities are performed yearly and with parallel production lines for various raw materials. Therefore, wastewater outflow and aquaculture solid waste are the two main environmental issues raised by the aquaculture sector. Figure 2.2 shows the overview of the environmental consequence with the aquaculture farming and processing.

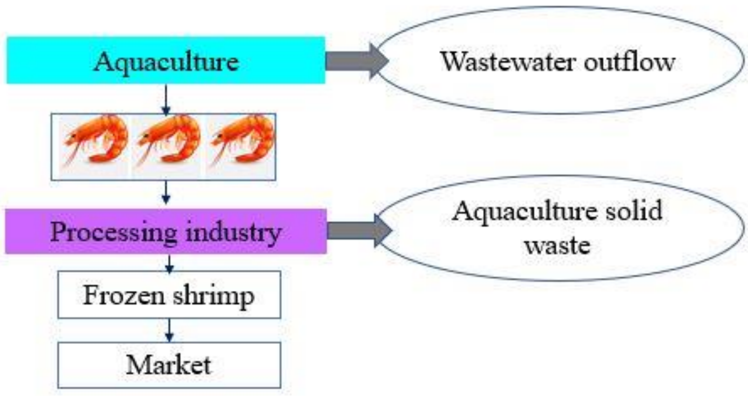


Figure 2.2 Overview of the environmental consequences with the aquaculture farming and processing

2.3.1 Aquaculture wastewater outflow consequences

Current aquaculture practices in India are more concerned due to the negative impact on the environment. Further, without the stricter regime of monitoring leads to a hazardous environment. For instance, many researchers have shown significant studies in aquaculture ponds such as variations in the dissolved oxygen levels, salinity, temperature, pH, total dissolved solids, nitrates, ammonia, calcium, potassium, etc., which have effect on shrimp or fish (Kumar et al. 2012; Ariadi et al. 2019). The most noxious and concern of the above parameters is total ammonia because abnormal levels of ammonia become toxic, thereby causing stress to aquatic species (Liu et al. 2020; Duan et al. 2021). Aquaculture effluents total ammonia bloom at the bottom of the ponds for many months, leading to highly toxic substances. It is essential for quality monitoring band assessment of healthy aquaculture ponds (Zhou and Boyd, 2015). Higher ammonia levels in the aquaculture pond led to phenoloxidase hemolymph antimicrobial activity, reduced dissolved oxygen, and growth disease in shrimps (Liu et al. 2020; Zhao et al. 2020). Furthermore, it causes a decrease in the shrimp survival rate, economic losses to aquaculture framers, and water pollution (Dauda et al. 2019; Chatla et al. 2020).

Ammonia level depends on many factors such as pH, temperature, dissolved oxygen, total dissolved solids, and algal growth (Kim et al. 2006; Collos and Harrison, 2014). In aquaculture ponds, ammonia is usually generated due to many factors such as organic matter, uneaten feed, algae bloom, shrimp feces, decay of aquatic animals, and exogenous substances with nitrogen (Hu et al. 2012; John et al. 2020; Yu et al. 2021). In municipal solid waste landfills, ammonia toxicity is the most concern (Esakku et al. 2006; Akindele and Sartaj, 2018). Ammonia is an inorganic pollutant that accumulates at the bottom of the aquaculture pond and landfills (Mook et al. 2012; Akindele and Sartaj, 2018) (see Figure 2.3). Furthermore, ammonia leachate may affect the groundwater bodies (Kjeldsen et al. 2002). To monitor or evaluate the aquaculture pond ammonia, it is a predominance water parameter, not only for assessing the survival rate of shrimps, but also to know the level of water pollution (Karri et al. 2018).

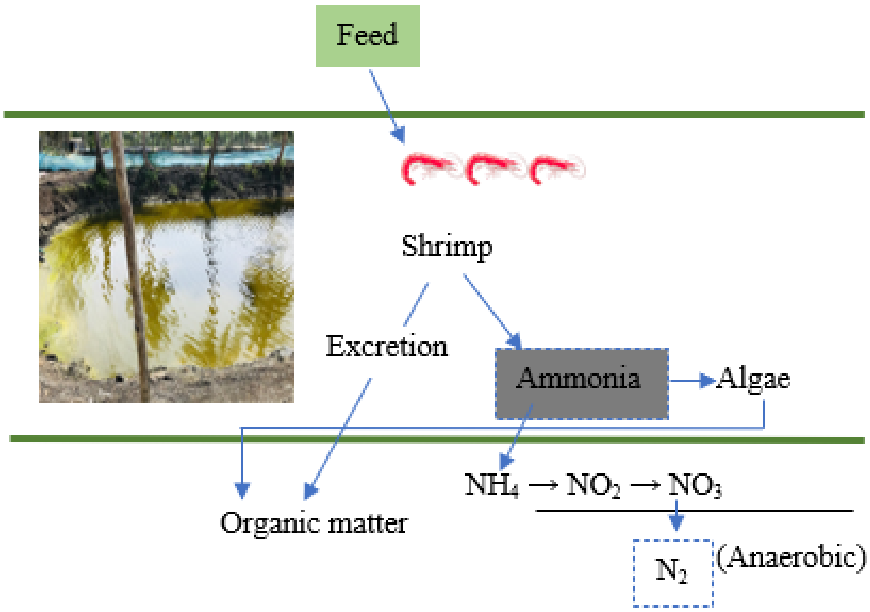


Figure 2.3 Formation of ammonia in aquaculture ponds

Jayanthi et al. (2018) reported that the intensive aquaculture practices in India cause a reduction in the mangroves, a threat to the environment, and a change in land-use patterns. The report results conclude that aquaculture practices should be monitored, and strict environmental regulations must be implemented for a better sustainable environment. Jayanthi et al. (2006) reported a case study on the effect of aquaculture practices on the Kolleru lake, one of India's major freshwater lakes. Before the state bifurcation of Andhra Pradesh, from 1967 to 2004, aquaculture practices (increased aquaculture area is 99.74 km^2) in that region caused a severe environmental impact on the lake ecosystem. Moreover, no regulations for farming result from the watershed region's invasion by thousands of unlicensed aquaculture farms, open water regions are now difficult to recognize in satellite pictures. The following parts detail the condition before and after the commencement of developing the sustainable system, known domestically as "Operation Kolleru." To conserve the ecosystem capabilities and services provided by the Kolleru, "Operation Kolleru" was launched in 2006 to demolish the fishponds located throughout this area as part of the "repair of the lake" (Kolli et al. 2020). In recent years, many parts of the lake ecosystem were still under the burden of illegal intensive aquaculture farms. The data analysis suggests that, in the present scenario globally, protecting freshwater bodies is much needed for future generations.

Jana and Jana Santana (2003) reported that intensive aquaculture practices reduce the yield of the crops adjacent to the aquaculture bodies due to the effluents and salinity of the water. The wastewater should not be directly allowed into irrigation canals because there is a need for recirculating aquaculture system (RAS) to treat aquaculture effluents. Furthermore, using antibiotics in aquaculture is human hazardous because their presence in water will be available for up to six months. Aquaculture practices could generate various chemicals and minerals, negatively impacting the environment. Therefore, proper guidelines should be needed before assessing the impact of aquaculture practices on the environment (Piedrahita, 2003). This rapid phase expansion of aquaculture and its environmental implications has recently grabbed attention worldwide (Eng et al. 1989; Bhavsar et al. 2016; Nhu et al. 2016). Many countries such as Bangladesh, Thailand, China, Mexico, Vietnam, and India face environmental issues with un-engineered aquaculture (Paez et al. 1998; Abdullah et al. 2017).

Moreover, in Thailand, the Thai government banned inland shrimp culture due to environmental concerns (Eng et al. 1989; Szuster, 2006; Abdullah et al. 2017; Bhavsar et al. 2016). Aquaculture practices significantly influence the environment; many aquatic species presences were migrating and disappearing. Furthermore, freshwater bodies are being polluted with contaminants from aquaculture (Islam et al. 2004). In some cases, a high concentration of chemicals causes severe deterioration in irrigation or drinking water quality, further affecting human health. However, to date, only a few research works have been published in India regarding the environmental aspects of aquaculture ponds.

2.3.2 Aquaculture solid waste

Aquaculture effluent and shrimp processing waste comprised most of the solid aquaculture waste. Figure 2.4 show the aquaculture solid waste characterization.

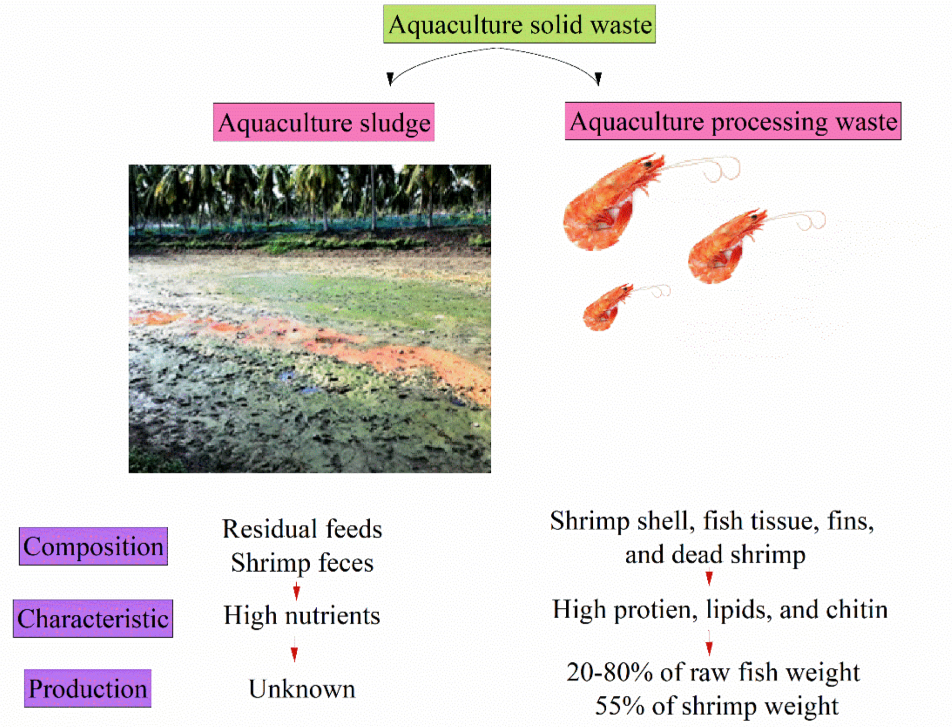


Figure 2.4 Aquaculture waste characterization

The yield of the aquaculture farm was always influenced by the aquaculture method, feed dosage, feed rate, etc., and always contained excess feeds and fish faeces, which were further classified into suspended particles and settled solids (Wu and Song, 2021). For instance, 1.4 million tonnes of fish feeds were used in China's aquaculture sector in the year 2015 (Wu and Song, 2021); however, because of feed coefficient restrictions, some of these feeds could not be eaten by shrimp and were accumulated at bottom of the pond. The aquaculture sludge was not routinely collected in the intensive aquaculture ponds. Instead, aquaculture sludge would be dumped directly at the adjacent pond embankment and into a nearby canal after being collected from the pond bottoms every three years.

Around 70% of fish must be processed before exporting or consumed, the generation of processing waste was unavoidable. shrimp heads, shells, viscera, fins, tails, and bones generate most of the processing weight, accounting for 20% to 80% of raw fish weight depending on processing techniques and types of fish (Wu and Song, 2021). A report by the Food and Agriculture Organization of the United Nations (FAO 2019) states that about 9.1 million tonnes of processing waste are thrown away each year. Moreover, many farmed fish deaths in several countries were mostly caused by infections and other diseases that were categorized as processing waste (Solli et al. 2014). For instance, in 2015, there were over 50 million dead fish in Norwegian aquaculture farms (Solliet al. 2018). Unfortunately, most of the solid waste is typically dumped as garbage, which represents a significant resource waste and may worsen environment (Wu and Song, 2021).

2.4 RECIRCULATION AQUACULTURE SYSTEM

The development of inland aquaculture has enormous potential to contribute to the sustainable feeding of the world's expanding population. However, many studies have indicated that aquaculture production has negative repercussions, particularly its effects on the environment and the ecosystem (Luo et al. 2018; Sampantamit et al. 2020). For instance, the rapid expansion of aquaculture systems is a significant factor in the deterioration of mangrove forests, the loss of natural ecosystems, and the decline in biodiversity (Sharma et al. 2022). Additionally, aquaculture production often concentrates on a small number of chosen species, resulting in a decline in biodiversity and nutritional richness. Additionally, ponds continue to have an ever-increasing carbon impact without engineered aquaculture as the demand for aquatic food has increased with population and economic growth (Boyd et al. 2020; Iber and Kasan, 2021). These factors have led to a steady interest in the environmental sustainability of inland aquaculture techniques. The high concentration of ammonia and nitrates in contaminated water results from intense aquaculture operations. Recently the potential application of geosynthetic materials in the aquaculture system as a seepage control or water barrier is gaining importance. However, in Indian aquaculture practices were still exist in traditional methods. Martins et al (2010) proposed recirculating aquaculture system (RAS) in Europe for new developments based on environmental sustainability. Up to 15% of the entire water volume would be changed daily in a RAS for water treatment and reuse (Groenveld et al. 2019; Yogev et al. 2020). It typically consists of pumps, storage tanks, and biological and mechanical purification elements, and it may also incorporate additional water purification components that enhance the system's capacity to prevent disease. These methods can be employed when there is a lack of sufficient land or water or when the ecosystem is not perfect for the fish or shrimp being raised (Granada et al. 2016).

Additionally, the RAS increases the feed exchange rate while lowering wage costs and those associated with temperature changes in water. However, to operate, the RAS needs significant upfront and ongoing financial commitment and highly skilled technical personnel.

2.4.1 Mechanism of RAS system

The mechanism of the RAS includes two separate geotextile bag systems that were evaluated as a means for capturing and dewatering bio-solids in the effluent stream from RAS. Each geotextile bag system used a high molecular weight cationic polyacrylamide polymer as a flocculant-aid. The two systems were operated under freshwater and brackish water conditions (Guerdat, 2013). Geotextile bag systems using flocculant-aids are an efficient means for capturing and dewatering waste solids from RAS effluents. Optimized geotextile bag system designs depend on flow rate, feed rate, solids dewatering time, and the fate of the treated effluent. This evaluation will aid in predicting the expected performance and determining the appropriate size of a geotextile bag system. The type of treatment required downstream from the geotextile bag system used for solids capture in a RAS wastewater treatment system will depend on the intended fate of the treated effluent. The geosynthetics in the form of geotextiles, geobag, and geotubes can also be commonly used for aquaculture waste management (Hsieh, 2016).

2.4.2 Advantages of RAS system

The benefits of the RAS in this approach might be as follows: better environmental management of the production process to ensure optimal development, minimal water use per tonne of shrimp produced, containment and treatment of effluent, and year-round operation are just a few of the goals (Gunning et al. 2016). In RAS system, re-used water after undergoing treatment. RAS offers the possibility of achieving high production, maintaining optimal welfare conditions, and creating a minimal ecological impact. Recirculating systems, which come in a wide range of system designs and quality levels, are revolutionary innovations. In these systems, maintaining adequate water quality, water recycling, structural management of processing equipment, waste storage and disposal, and disease outbreak control are crucial operational challenges. In this due consideration, researchers and practitioners working on practical RAS solutions aim to minimize energy usage, optimize energy savings, and thus develop the environmentally benign RAS, generating environmentally benign emissions, improving industrial capacity, protecting natural resources, and increasing energy and exergy effectiveness (see Figure 2.5). These initiatives are required to improve the RAS's energies, environmental sustainability, and energy nexus.

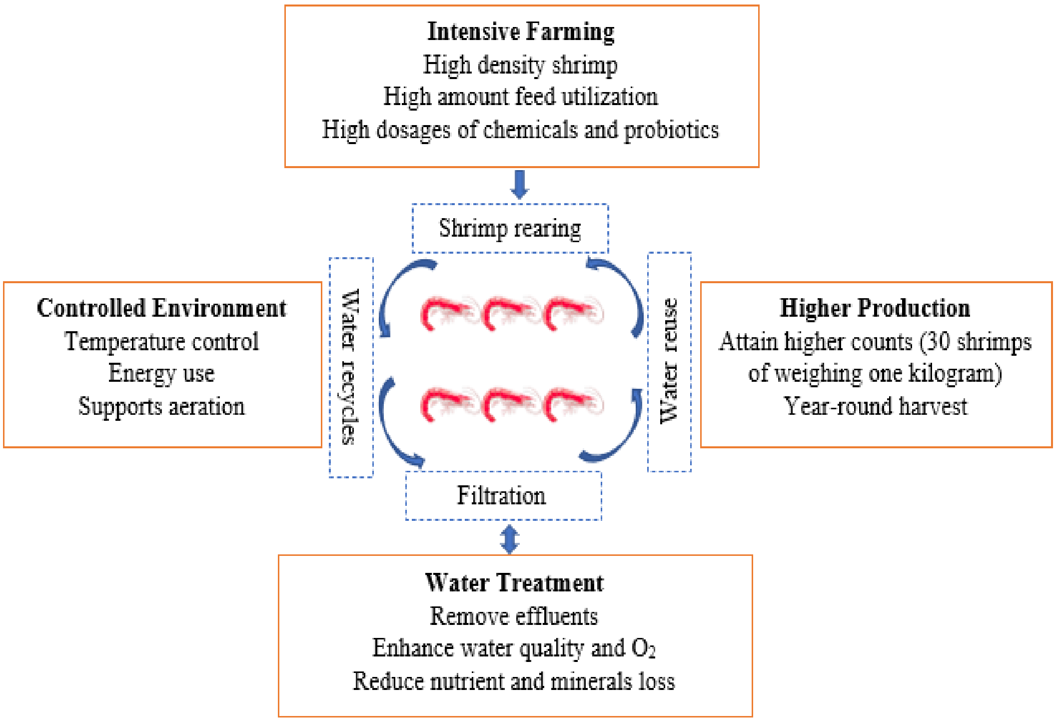


Figure 2.5 Potential of RAS system in inland aquaculture ponds

2.5 REVIEW OF APPLICATION OF SOFT COMPUTING IN WATER QUALITY MONITORING

Due to the complexity of water faces more significant uncertainty. The below sections present the brief details of the different successful soft computing approaches in the water quality assessment.

2.5.1 Artificial neural network (ANN)

The most promising and well-known method that uses the neural network principle is called ANN. The appropriate features of models, including regression, classification, pattern generation, and clustering, are responsible for the network's appeal. To analyze and process any model, ANN typically consists of three parts: the input layer, hidden layer, and output layer. Furthermore, the bias and weight functions determine how accurate the ANN model performs. The linear regression equation in neural networks is Y= mX + n, where m and n are the coefficient and slope, respectively. Data will be learned and trained based on the function to produce appropriate predictions with the least inaccuracy. The water quality, groundwater potential mapping, and contaminant rate were all accurately predicted by ANN models (Palani et al. 2008; Ahmed et al. 2019; Pham et al. 2021).

2.5.2 Convolutional neural network (CNN)

CNN is a unique tool used mostly for image processing using pattern recognition. CNN has shown promising results in numerous medical, environmental, and engineering domains. The CNN technique was extensively used in geotechnical engineering to classify trash, identify earthquakes, predict slope failure, screen for pollution, and analyze clay crack patterns. Convolution, polling, flattening, fully linked, and output layers are all present on CNN. The convolution layer would aid in extracting features from the input layer and filtering each field in CNN models, including features like ANN models. Additionally, network neurons change to recognize and detect the overall answer. Yang et al (2021) developed the CNN model for prediction of water quality parameters with the higher performance.

2.5.3 Support vector machine (SVM)

SVM is one of the most sophisticated algorithms for making predictions using supervised training and pattern recognition. The most excellent technique for classifying and separating data after obtaining raw data is SVM. LINEAR, SIGMOID, and RBF were the most frequently utilized kernel functions in SVM-based classification. The performance of classification models might be improved by using these kernel functions to produce non-linear surface separations. SVM successfully resolves pattern recognition and matter classification issues in environmental engineering. The water quality, groundwater potential mapping, and contaminant rate were all accurately predicted by ANN models are important contributions of the SVM tool (Abobakr et al. 2019; Hasanpour et al. 2022).

2.5.4 Random Forest (RF)

By using decision trees for training, random forests operate on the notion of resampling the original data. The decision trees are constructed using boosting so that each new decision tree works to minimize the errors of the prior one. Each decision tree updates the residual mistakes based on what it has learned from its past. Consequently, the tree that develops later will likely gain knowledge from revised regressions. Additionally, the individual decision split received a random distribution of the RF properties. As a result, features decreased the correlation between the decision trees. Additionally, the learning process increases the model's performance and prediction power. With the help of additional features, RF can effectively model high-dimensional complex data that contains missing, category, and binary information. Random forests (RF) have been modified, and adaptive random forests (ARF) are the most effective classifier for data streams. The ARF's dynamic method can help the data as it changes and enables the training of new trees to provide the best overall answer. In geotechnical engineering, multi-linear regression prediction models have been effectively used to forecast soil water infiltration, water quality, groundwater potential mapping, contaminant rate, soil salinity, soil erosion, and soil categorization (Ahmed et al. 2019; Deng et al. 2021; Xu et al. 2021; Hasanpour et al. 2022).

2.5.5 Genetic algorithm (GA) and particle swarm optimization algorithm (PSO)

The most effective algorithms in history are genetic algorithms, which are widely used. In addition, GA is the first population-based algorithm. The GA searches for a global solution with convergence outcomes based on the genetic selection theory.

Due to the few performance parameters that could be changed, PSO was a successful algorithm that was inspired by nature in many fields. Similar to the population of random search, PSO operates on the GA principle. However, PSO searches the issue space using velocity coefficients that are given to random particles. PSO discovered accurate predictions in small datasets (Deng et al. 2021).

2.5.6 Fuzzy logic (FL)

The four promising elements of fuzzy logic are fuzzification, rule base, inference engine, and defuzzification. Fuzzy logic is a well-known model. In the FL technique, the input data was first divided into various datasets (fuzzified), and then relationships between the input and output variables were developed (rule base). Learning with rule-based and reducing errors (inference engine) were then performed. Finally, the outputs were produced from the fuzzy inference (defuzzification). The FL system can approximate the data with its generalization behaviour rather than duplicate the laboratory data. Due to the robust non-linear simulation performance and the inclusion of fuzzy language rules, the FL system has recently gained prominence. The environmental engineering field is drawn to these non-linear models (Trach et al. 2022).

2.5.7 Application of soft computing in aquaculture

Aquaculture has gradually progressed towards an advanced and intelligent path across the globe due to developments in automation and intelligent technology. As a result, the breeding environment has gradually changed to a sustainable aquaculture industry, significantly increasing aquaculture efficiency (FAO, 2018). Despite this, the substantial labour required, farming lifeforms, the aquaculture ecosystem, and other unpredictable elements have all impacted aquaculture. Due to those mentioned above, there are now several issues with aquaculture, including water contamination, disease, and shrimp nutrition (Lafferty et al. 2015). Intelligent aquaculture will be dedicated to addressing issues with fisheries sustainability and enhancing aquaculture productivity as a component of the agricultural revolution (Yang et al. 2020). When used with powerful computers, machine learning technology can mine data for high-dimensional characteristics and depth information, resulting in a solution for advanced automation aquaculture and heralding a new age for the fishery industry (Liakos et al. 2018).

Machine learning is essential to artificial intelligence and can be learned without much programming, and it is a crucial technology for creating an intelligent decision-making system. Machine learning has been adopted in several fields, including medicine (Cleophas et al. 2013), civil engineering (Vadyala et al. 2021), data security

(Pan et al. 2019), robotics (Alsamhi et al. 2020), and expert systems (Gu et al. 2019) as a result of the ongoing development of online data and low-cost informatics. However, traditional machine learning algorithms significantly rely on manual programming and cannot accomplish specific aquaculture objectives (Spanig et al. 2019). Therefore, aquaculture has been maximized by tightly integrating modern information systems, including the Internet of Things, soft computing, and cloud computing, to establish an intelligent fishing production mode. The efficient fusion and advancement of soft computing algorithms and the suggestion of deep learning as cutting-edge technologies for aquaculture systems have recently opened a new route for advanced automation aquaculture (Bradley et al. 2019). Figure 2.6 shows the structure of application of machine learning in aquaculture.

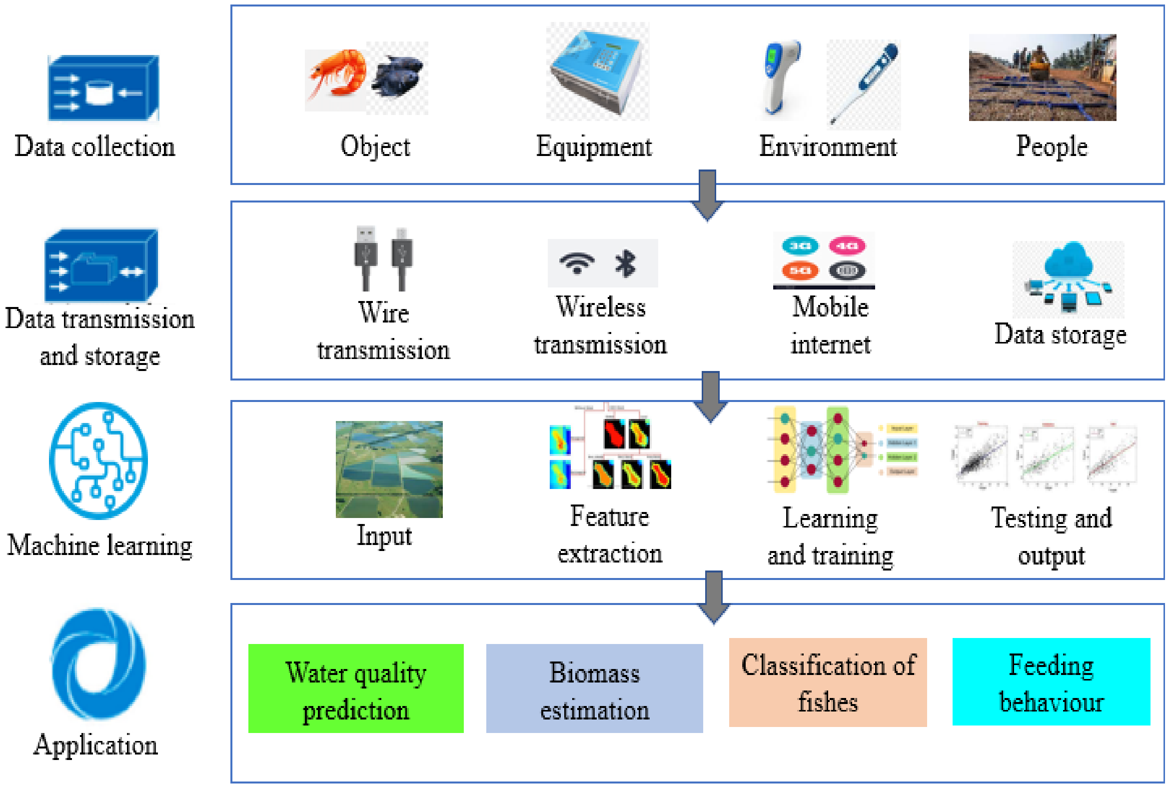


Figure 2.6 Framework of soft computing application in aquaculture

Recent years inland aquaculture ponds were more concern about the higher concentration of ammonia due to mismanagement activities. Aquaculture ponds will generate ammonia due to many factors such as organic matter (uneaten feed, algae bloom, shrimp feces, decay of aquatic animals, and exogenous substances with nitrogen. Even in municipal solid waste landfills, ammonia toxicity is the most concern. Ammonia is an inorganic pollutant that accumulates in the bottom of the aquaculture pond and landfills. Further, ammonia leachate may affect the groundwater bodies in the long term. Ammonia is a predominance water parameter for assessing the survival rate of shrimps and to know the level of water pollution. So, prediction models are much needed to assess the water quality to make sustainable water management. Nowadays, artificial intelligence is gaining potential in solving complex problems. For example, measuring ammonia, many procedures such as spectrophotometer, electrochemical sensors method, sodium hypobromite method, and Nessler's reagent method are in vogue. However, due to the long detection time, toxic chemicals usage in test procedures, and weak scattering of the traces with interference signals, ammonia content is a complex task.

The mentioned artificial intelligence approaches have been proposed to predict ammonia levels and their potential in ammonia prediction. Goyal and Garimella (2019) reported the application of artificial neural networks (ANN) to compute ammonia-water thermodynamic properties. The predicting results found high accuracy in estimating the thermodynamic behaviour of ammonia-water mixtures with the best fit between input and output variables. Huang et al (2020) stated that in the wastewater treatment plant, ammonia nitrogen (NH_4-N) is a significant concern. In the recent past, many soft computing methods were used to assess ammonia nitrogen based on the mean square error (MSE) approach. However, it isn't easy to evaluate accurately due to complex statistical information. So, the best alternative, probability density function-based fuzzy new network prediction results, was accurate and stable compared with other approaches. Pham et al (2021) suggested that adaptive neuro-fuzzy system (ANFIS) and ANN could be helpful to predict the water quality index effectively, and it can also be used for better water resource management by the policymakers.

Moreover, it decreases the running time and testing phase. Yu et al (2021) developed an intelligent model to predict ammonia nitrogen levels in aquaculture ponds. His developed model revealed that the extreme learning machine (ELM) and improved particle swarm optimization algorithm (PSO) show the best convergent fit between input and output variables. Further, and could be helpful for real-time prediction of ammonia levels in the aquaculture ponds.

Other hand, potential application of soft computing tools is emerging to predict water quality parameters due to the rational and systematic approaches. Abyaneh (2014) reported that water quality parameters could be predicted using multi-linear regression (MLR) and artificial neural networks (ANN). By comparison, MLR and ANN models, for predicting the BOD and the COD, ANN prediction models were better convergent than the MLR prediction models. Tomic et al (2016) reported that assessment of BOD in the Danube River, Serbia, using general regression neural networks (GRNN), has convergent results with fewer datasets for training and validation. Moreover, even it could be helpful for real-time prediction of BOD values in the Danube River, Serbia. Other hand, at the sewage treatment plant, effluents rate can be predicted using an advanced PSO-RRBF neural network model, which gives more efficient findings due to the compact structure of the model. PSO-RRBF model for predicting BOD is simple, reliable, and rational to develop correlations between BOD and dependent variables. PSO-ANN-based models are best suitable to predict the heavy metals concentration in the Toyserkan Plain, Hamedan Province. In PSO-ANN-based models, the ANN-based model can enhance by the training data with PSO algorithm to achieve better performance and convergence. Moreover, in a few cases, water parameters have complex behaviour and depend on many factors. So, using ANN, support vector machine (SVM), and ANFIS reduces efficiency in solving complex nonlinearity problems. To counteract this, the datasets were pre-processed to reduce the noise with the help of potential wavelet transformation analysis. This method could help divide into multiple components with the multiresolution decomposition. A few studies have investigated the wavelets coupled with soft computing methods to predict the complex variables (Barzegar et al. 2016; Feng et al. 2020; Zhou et al. 2020). ANN-wavelets models can be used to predict water quality parameters (Alizadeh and Kavianpour, 2015; Barzegar et al. 2016; Rajaee et al. 2020) and salinity intrusion saltwater interface (Yoon et al. 2017; Zhou et al. 2020). Similarly, both ANN-wavelets and SVM-wavelets can predict the fluoride and phenolic contaminants in the rivers (Barzegar et al. 2017; Feng et al. 2020).

2.6 SUMMARY OF LITERATURE

The literature study revealed that the studies on aquaculture methods conducted by various researchers are location specific (Jiang et al. 2022). The contaminants from aquaculture ponds rely on various factors, and each inland aquaculture zone is distinct in its way (e.g., the intensity of farming, topography conditions, etc.). In most case studies, 55% of the data set was from China, followed by Bangladesh with 22% (see Figure 2.7). However, Indian case studies mainly focus on economic impacts and management implications rather than environmental ones (Jayanthi et al. 2019). Research on ecological aspects of aquaculture ponds in India is recent, beginning in 2015, and flagged only four publications. So, studies on the environmental impact of aquaculture have significant potential for future sustainable development.

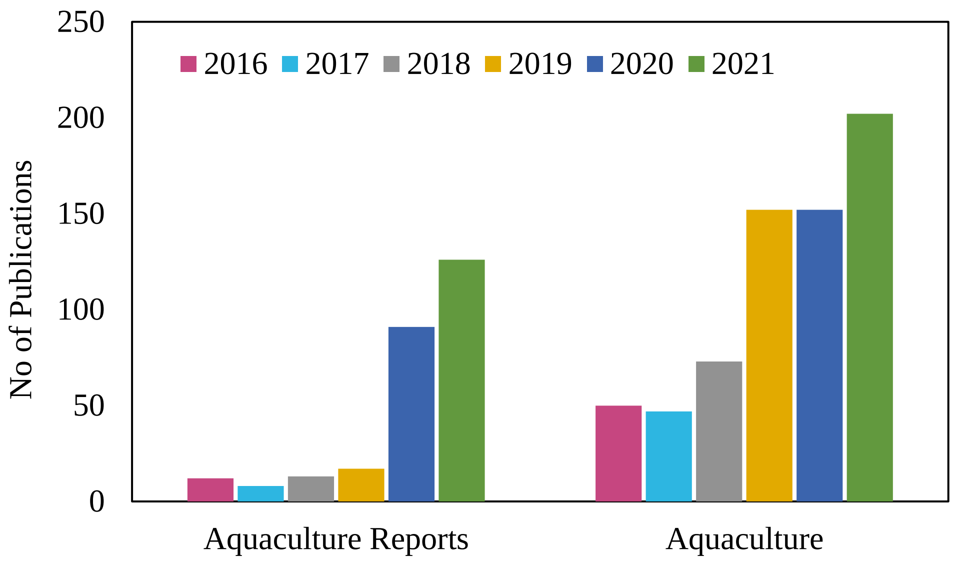


Figure 2.7 Publications at the intersection of environmental impact, climate change and sustainability per journal per year from 2016 -2021

CHAPTER 3

METHODOLOGY

3.1 GENERAL

This chapter presents the methodologies adopted for determining the rate of expansion of aquaculture, intensity of culture, physicochemical properties of aquaculture water, pond subsoil characterization, and effect of aquaculture sludge on clays. The other highlights of this chapter are the future ammonia levels in intensive aquaculture, which are predicted using soft computing techniques.

3.2 PRELIMINARY INVESTIGATION

In this study, a preliminary investigation was carried out with a questionnaire and topography survey. The questionnaire helps collect data on aquaculture activities, land use patterns, and potential pollution sources that may impact water and soil quality. The questionnaire can inquire about the types of aquaculture farming in the study area, including information on the scale of the pond, seed and feed aspects, fertilizer use, and probiotic application. A topography survey provides detailed information about the possible water contamination pathways. By collecting data through questionnaires and conducting topography surveys, researchers can better understand the study area's socioeconomic context, land use practices, potential pollution sources, and the physical landscape. This knowledge serves as a foundation for the subsequent assessment of water and soil quality, allowing for a more comprehensive and informed analysis of the factors influencing environmental conditions in the study area.

3.2.1 Questionnaire survey in the field

The preliminary investigation was conducted to collect the field farming practice data based on questionnaire interviews in the 40 locations and designated the following locations with the sample Id listed in Appendix-I. The locations for the questionnaire survey were selected based on factors such as spatial distribution, ponds density, and potential pollution sources. This ensured representative coverage of the study area and captured variations in socioeconomic, land use, and environmental characteristics. Selecting specific locations within these regions utilized a random sampling technique to reduce bias and ensure a fair population representation. Moreover, a structured questionnaire was used for standardized data collection, including participant instructions, field visits, and data review for accuracy and consistency. According to the aquaculture practice, general variables were: 1) chemicals and biological products used, 2) feed/acre, 3) seed/Acre, 4) water source in and out, 5) lime usage, 6) salinity range, 7) the number of aerations per acre, 8) environmental impact, and 9) sustainable concern. Based on the questionnaire survey, the study area was categorized into three zones such as traditional zone (Zone-I), semi-intensive zone (Zone-II), and intensive zone (Zone -III).

The questionnaires included area or size of the pond, depth of the pond, the density of seed per acre, feed usage per acre, chemicals usage per acre, number of aerations per acre, lime usage, probiotics usage, disinfectants usage, number of times water change per acre, environmental impact, and sustainability concern. Based on the questionnaire survey, the intensity of the aquaculture practice was categorized into three zones: traditional farming (Zone-I), semi-intensive farming (Zone-II), and intensive farming (Zone-III), shown in Table 3.1. In the delta region of Andhra Pradesh, aquaculture mainly involves shrimp and fishponds. The individual fish tanks in the study ranged from 10 acres to 150 acres. Although ponds were huge, the effluents were low because fewer chemicals, probiotics, chemicals, and disinfectants. Shrimp ponds were the significant contribution of effluents because of the severe or intensive cultural practices. The shrimp ponds were operated continuously without the exchange of water for a minimum of two crops (six months). Every year, the sedimented water was discharged out before winter and summer. The quantitative analysis can state that intensive aquaculture practices can negatively impact the ecosystem. Most of the locations were fell in the severe or intensive zones. Agriculture or paddy fields were converting into shrimp ponds due to higher income-generating through aquaculture and low paddy yield due to adjacent aquaculture pond's salinity. It was anticipated that collecting questionnaires from the authorities would not be accessible without farmers' support.

Table 3.1 Classification of aquaculture practices in the delta region of Andhra Pradesh

Description	Intensity of aquaculture practice (*Penaeus Vannamei*)		
	Traditional	Moderate or Semi-Intensive	Severe or Intensive
Area of pond (acre)	2-5 or <	5-10	10-20 or >
Depth of water level in the pond (m)	1-1.5	1-3	1.5-4
Seed density (no/acre)	10,000 – 20,000 or <	20,000 – 60,000	40,000 – 1,00,000
Feed per acre (kgs)	600-850	1600-1700	2100-2200
Survival rate (months)	2-3 or <	1-3 or <	1-3 or <
No of crops per year	4 or <	3-4	3-4
Aeration sets per acre	1-2 or <	2-4	4-5
Production per acre per crop (tons)	1-2 or <	1-5	4-8
Lime used per acre per crop (kgs)	5-10 or <	5-25	10-50
Potassium/magnesium/calcium chlorides used per acre per crop (kgs)	1-5 or <	5-10	5-25
No of times chemicals used per crop	2-4 or <	2-6	4-8
No of times probiotics used per crop	1-3 or <	2-8	4-12
No of times disinfectants used per crop	1-2 or <	1-4	2-6
Salinity range (ppm)	0-4	4-6	5-9
Water exchange per year	3-5 or <	3-5	2-3
Environmental impact	Moderate	High	relative
Sustainability concerns	Moderate	Low	relatively low

The questionnaire results revealed that no guidelines or measures were considered before or during constructing a new aquaculture pond. The survey results also reflected the lack of proper communication between the aquaculture framers and environmental engineers to implement sustainable ecological advancements in aquaculture ponds. Similar trends were witnessed in other regions in India (Jayanthi et al. 2018). Moreover, nowadays, intensive usage of chemicals, minerals, antibiotics, and probiotics with no mentioned ingredients on the bags gives alarming negative signs towards the environment. Based on the visual examination of the bottom surface soil of the pond witnesses grey and orange colour due to the anaerobic sediment (ferrous iron). In most of the ponds in the delta region of Andhra Pradesh, before starting a new crop, large amounts of urea and lime are widely used. Lime is used to reduce ammonia concentration and decompose organic matter in the pond bottom soil. Lime is used to increase the alkalinity hardness and neutralize the acidity of the bottom ground.

Moreover, aquaculture ponds are often classified based on the intensity of farming. Reported literature mentioned that pond bottom with less ammonia load and chemicals in the bottom is being classified as younger ponds (Jayanthi et al. 2019). To better understand the soil profile, physical, chemical, and biological parameters of soils should be tested. Another side, shrimp culture needs a brackish water environment for better yield. However, higher salinity levels in the aquaculture ponds have a significant effect on the yield of adjacent agriculture fields. From Table 3.2, it was observed that most of the locations were fell in the severe or intensive zones. The aquaculture intensity was expanding towards the northeast from the southwest. Agriculture or paddy fields were converting into shrimp ponds due to higher income-generating and low paddy yield due to adjacent aquaculture ponds' salinity.

Table 3.2 Intensity of aquaculture practices

Zones (Intensity of aquaculture practise)	Sample Id
Traditional	V27, V28, V34, V35, V39, V40,
Moderate or Semi-Intensive	V7, V8, V9, V10, V19, V20, V21, V22, V23, V24, V36, V37, V38
Severe or Intensive	V1, V2, V3, V4, V5, V6, V11, V12, V13, V14, V15, V16, V17, V18, V25, V26, V29, V30, V31, V32, V33

3.2.2 Topography survey

A topographical survey is often used to describe the measurement of the surface of the Earth's features. Remote sensing uses tools and sensors to obtain data about a location or object from a distance, usually using satellite-based platforms. In this instance, data on the Earth's surface were gathered via remote sensing to evaluate the land use, land cover, surface temperatures, and vegetation indices.

Researchers and field engineers can gain important information about various ecosystems' distribution, productivity, and health by undertaking a topographical survey utilizing remote sensing techniques to measure land use, land cover, surface temperatures, and vegetation indices. Decisions about land management, for example, where to prioritize conservation efforts, where and how to distribute resources for inland aquaculture, and where to concentrate revegetation efforts, can be made using this information.

3.2.2.1 Land use and land cover

The topography survey was carried out in the western delta region of Andhra Pradesh using the Sentinel-2A satellite data from the open-source United States Geological Survey (USGS) website, which produced images that were all geometrically corrected and taken at Level 1T. Furthermore, there is a year-long gap between each satellite image because of cloud cover or technically problematic scenarios. According to Nazarova et al. (2020), two factors were used to select satellite images for this study, including the requirement that the satellite images have a cloud inclusion percentage of less than 10 percent and the requirement that the satellite image sequence is readily accessible for an extended period (see Figure 3.1).

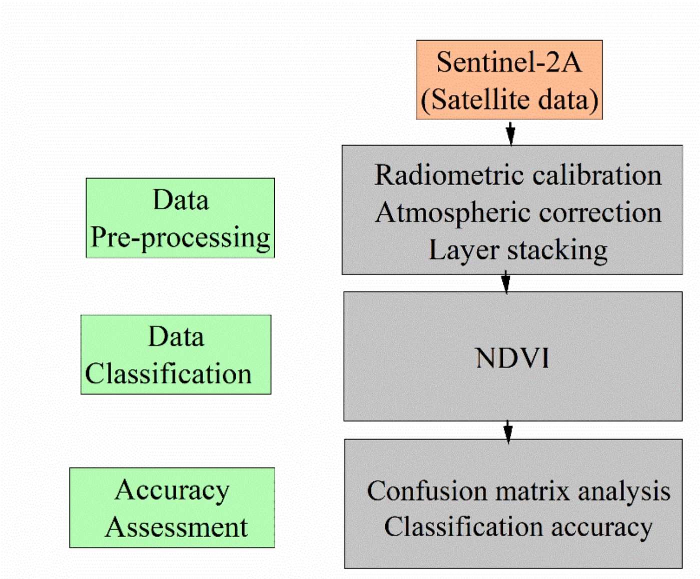


Figure 3.1 Methodology of land use and land cover mapping

Due to its ease of use, authenticity in accuracy, and utility, a classification technique based on the Normalized Difference Vegetation Index (NDVI) has been utilized to produce land use and land cover (LULC) maps. In order to detect and calculate vegetation change throughout the investigation, the study used an NDVI criterion method to classify NDVI into five categories based on NDVI data and the analysis of Google Earth images (2017–2021).

The accuracy evaluation is a crucial stage in determining the result of the categorization process. To make the best use of the data, the user of land-cover output must be aware of how accurate the result is. A confusion matrix (also known as a mistake framework) is a table of whole numbers arranged in columns and rows that compares the number of test objects (such as polygons, groups of pixels, or pixels) assigned to a given class to the actual classification as determined by ground inspection. Often, a classifier will receive various quantitative survey data from an error matrix. Producer's accuracy (PA), user's correctness (UC), precision and recall (PR), and kappa coefficient concepts and calculation methods have all been well-established in the past (Feizizadeh et al. 2022). The Kappa coefficient is a statistical indicator of convergence between two maps (the reference map and the classified map) that demonstrates how each classification varies from a randomized classification of class types. When calculating it, the entire error matrix is taken into account rather than simply the diagonal components, and non-diagonal items are included in the calculation due to row and residual column statistics. To find better accuracy of the classification, field examination was done in the 64 sites to understand the field scenario. the overall classification accuracy was more than 94.5%. Maps of 2017, 2018, 2019, 2020, and 2021 were used to quantify the changing land-use patterns. Only a few studies have been done on the landscape transformation in Andhra Pradesh, especially in the Kolleru basin and Nellore region (Jayanthi et al. 2019; Kolli et al. 2020).

The Godavari River is primarily responsible for forming the canal network in the western delta region (Figure 3.2). For inland aquaculture ponds, the major canal catchments are Venkayya, Attili, Gostanadhi, and Narasapuram offer ideal conditions with a length of 72.65km, 36.47km, 66.77km, and 74km, respectively. Table 3.3 shows the aquaculture catchment in the canal basins and the number of industries located. Among all the canals, Venkayya canal exhibits higher aquaculture catchment, and it is also located along the Upputeru river and Kolleru lake. The combination of dense canal networks and salinity intrusion from the Upputeru River creates favorable conditions for aquaculture ponds, particularly for brackish water species. With the rise of processing industries, aquaculture farmers have an added incentive to capitalize on the potential market demand. This symbiotic relationship between water resources, aquaculture, and industries can contribute to the region's economic development while promoting profitable aquaculture practices.

Table 3.3 Canals aquaculture catchment areas and industries

Canals catchment	Aquaculture area (km^2)	Number of industries
Venkayya canal	194.8	21
Attili canal	35.02	7
Gostanadhi	122.40	14
Narasapuram	137.41	11

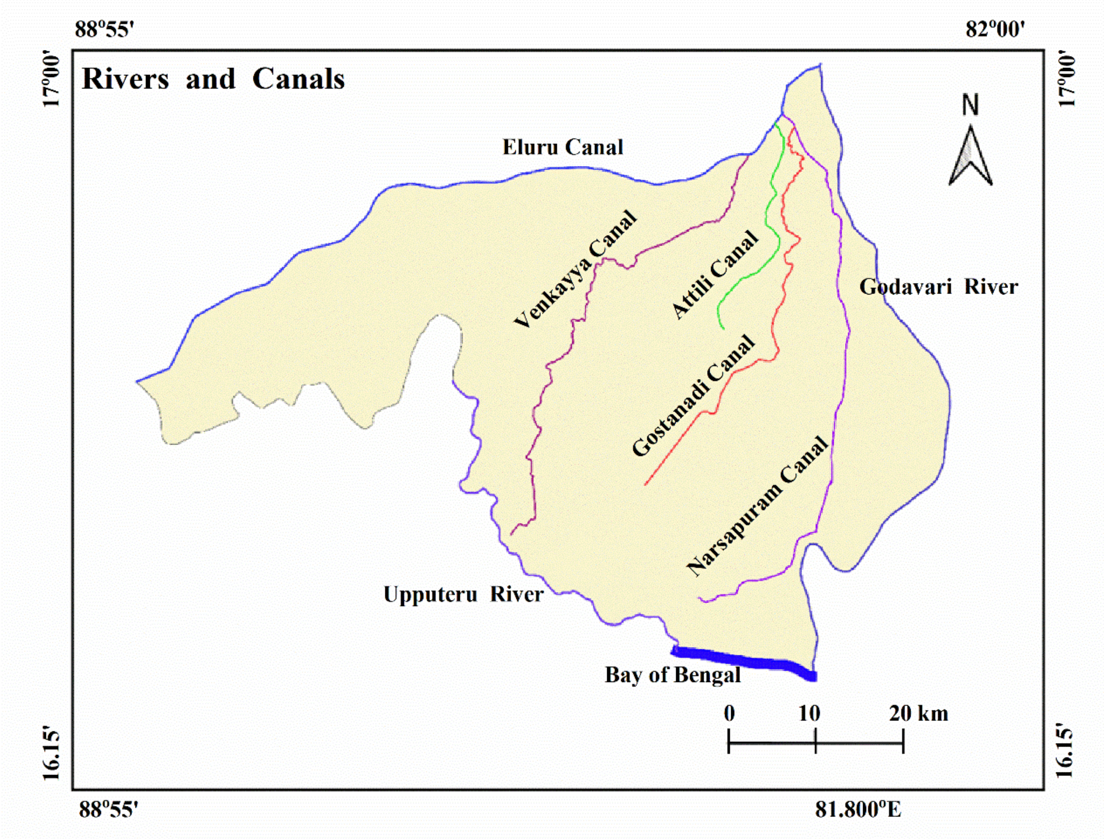


Figure 3.2 Study area canal network

Many farmers who rely on the land for their livelihood live in the area, characterized by a network of rivers, canals, and rice fields. The patterns of land use and land cover in the delta region have changed significantly through time due to various natural and human influences (Kavya et al. 2019). A peer glance at the past study reveals that, before the state bifurcation of Andhra Pradesh, from 1988 to 2013, land use converted to aquaculture ponds was 13524 hectares (Jayanthi et al. 2018). In this study, the land use and land cover classification were performed using the Sentinel-2 satellite data. The land-use and land cover classification maps are shown in Figures 3.3 (a-b). The land-use patterns were dominated by aquaculture throughout this study. Aquaculture ponds are practiced in this region, occupied an area of 723.97 km^2 in 2017 and increased by 6.98% from 2017 to 2021 (see Fig. 3.4).

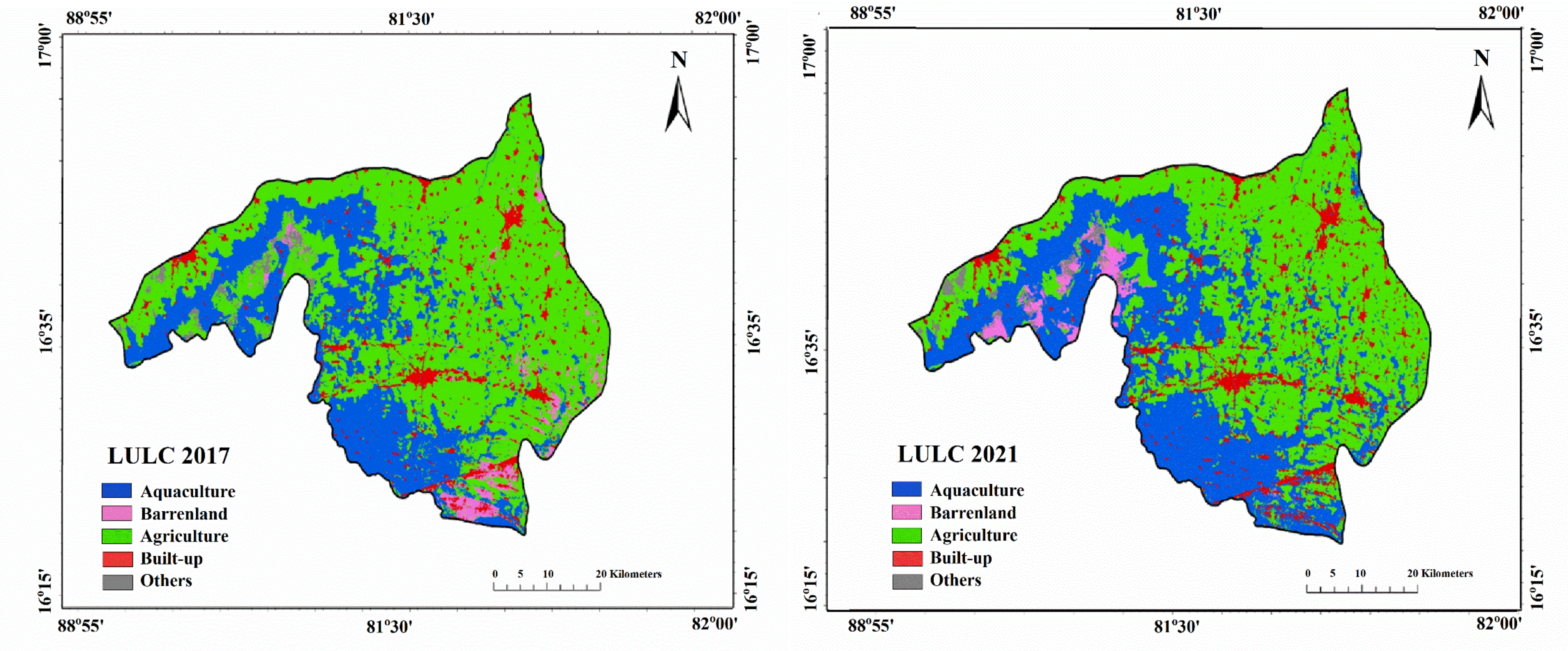
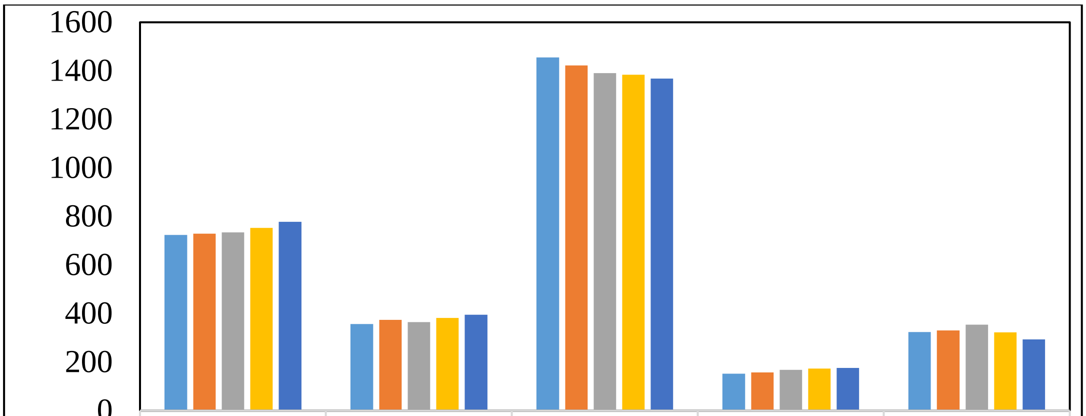


Figure 3.3 Land use and land cover maps of study area (a) 2017, (b) 2021



	Aquaculture	Flooded vegitation	Agriculture	Built-up	Others
2017	723.97	357.18	1455.51	152.41	323.38
2018	728.63	374.18	1421.86	157.82	329.87
2019	734.76	364.56	1390.58	168.54	354.01
2020	752.4	381.25	1384.02	172.97	321.81
2021	778.32	395.46	1368.45	176.48	293.6

Figure 3.4 Land use and land cover classification of study area

From Figure 3.5, between 2017 and 2021, the area geared to aquaculture ponds expanded by 54.35 km^2 (5435 ha), whereas agriculture shrank by 87.06 km^2 (8706 ha). Between 2017 and 2021, the built-up land area grew steadily, from 152.41 km^2 to 176.48 km^2.

From the present study, after state bifurcation, from 2016 to 2022, the land use converted to aquaculture ponds was 8725 hectares (87.25 km^2) (see Figure 3.5). Prasad et al. (2019) reported in India 3200 km^2 area of inland aquaculture ponds in 2017. This shows that, one fourth of the India inland aquaculture ponds were in the western Godavari delta region. The aquaculture intensity was expanding towards the northeast from the southwest. Clear rapid urbanization is also apparent in the delta region due to the increase in the aquaculture processing industries, feed stores, and laboratories. The covered area of drains and their sediments did not show any considerable area changes with a loss rate of 0.2% to 0.3% each year because of the erosion of canals or ponds embankments. This is due to the no stringent regulations for converting agricultural lands into aquaculture ponds. So, an increase in the aquaculture practices in the delta region leads to a negative impact on the vegetation or croplands. This comparative analysis shows that future aquaculture practices face severe conflict with the irrigation waterbodies and habitations. So, adherence to sustainable regulations is much needed for a sustainable environment and to avoid water conflicts.

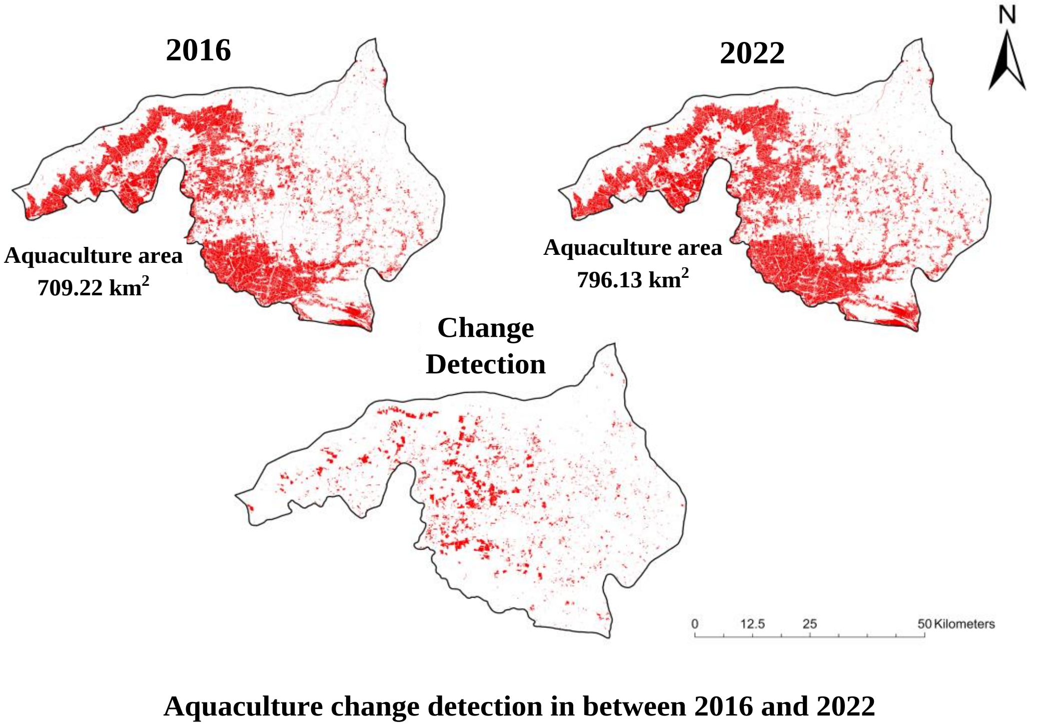


Figure 3.5 Aquaculture change detection in between 2016 and 2022

3.2.2.2 Vegetation indices

The most widely used vegetation indices obtained from remotely sensed information, such as satellite images, are the NDVI and the Soil-Adjusted Vegetation Index (SAVI). The near-infrared (NIR) and red reflectance measurements are divided by their sum to determine the NDVI. The range of NDVI values is -1 to 1, with higher values indicating more excellent vegetation cover. NDVI is frequently used to assess changes in land cover and land use and monitor vegetation's health and productivity. To account for the impacts of soil brightness on vegetation indices in places with high soil brightness, the NDVI was modified to create SAVI. Higher numbers denote higher amounts of vegetation cover; SAVI values range from -1 to 1. In arid and semi-arid areas, where soil brightness can have a significant impact on vegetation indices, SAVI is very helpful.

In agriculture, forests, and environmental monitoring, NDVI and SAVI are frequently used to evaluate vegetation cover, condition, and production and to spot changes in land use and land cover. They can also be used to estimate various biophysical and ecological characteristics, including leaf area index, biomass, and evapotranspiration, in conjunction with other remote sensing data.

Many water-related indices have been developed and used in remote sensing to extract various water properties, including ABDI, AWE, MNDWI, NDAVI, and NDTI. Some of them concentrate on finding algal blooms, while others pay attention to the turbidity of the water. Because turbidity influences other water quality factors, it is one of the essential criteria in aquaculture pond waters. To reduce turbidity in inland aquaculture ponds, lime treatment was typically used to raise pH levels, facilitating optimal photosynthesis and quickly enhancing productivity. However, the water level becomes more turbid when the lime's flocculation action wears off (Chanda et al. 2019).

Figures 3.6 (a-b) shows the vegetation indices such as normalized differential vegetation index (NDVI) and soil-adjusted vegetation index (SAVI) in the study in the period of 2017 and 2021. NDVI and SAVI values were reduced by -0.85 to -0.73 and -0.91 to -0.78 from 2017 to 2021, respectively, which indicates the absence or unhealthy vegetation cover. Due to changes in water quality, aquatic vegetation, and algal growth, NDVI and SAVI readings in intensive aquaculture ponds are lower. For example, lowered NDVI and SAVI readings can be caused by increased algal growth brought on by high nitrogen levels from fish waste and feed inputs. Changes in water clarity and depth can also impact these parameters (Roy et al. 2019). On the other hand, good pond management techniques, including water exchange, silt removal, and input control, can produce greater NDVI and SAVI values (Roy et al. 2019).

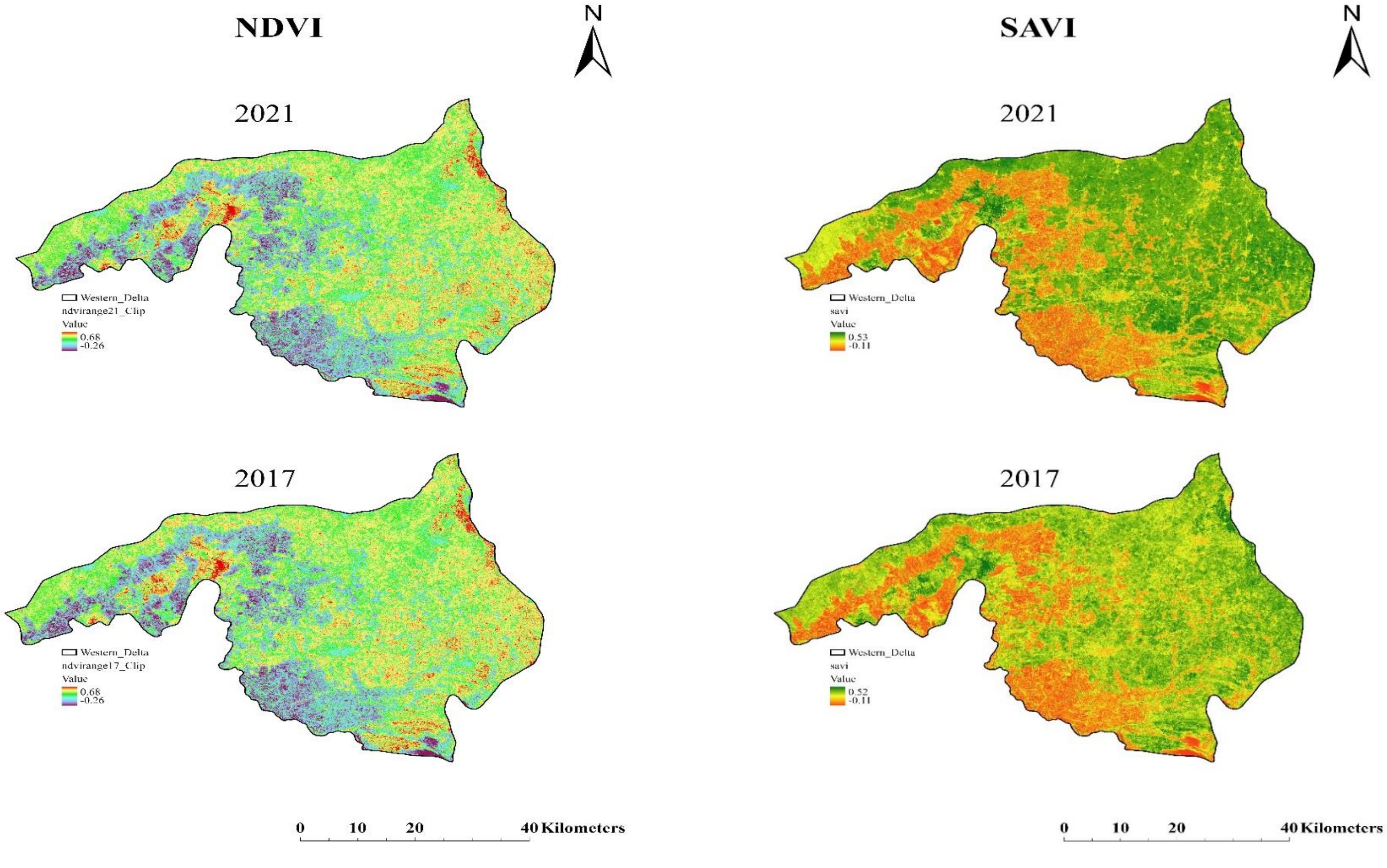


Figure 3.6 Vegetation indices change in the study area (a) NDVI, (b) SAVI

3.2.2.3 Water quality indices

The Normalized Difference Turbidity Index (NDTI) was considered in this study as a suitable remote sensing technique to calculate turbidity for monitoring the water quality of inland aquaculture ponds and other types of water bodies. The NDTI, determined using the spectral reflectance values of the water pixels, is used to assess the turbidity in water bodies (Chen et al. 2022). It uses clear water and has higher electromagnetic reflectance in the green than in the red spectrum. As a result, the reflectance of the red spectrum increases along with turbidity. As a result, the green (band-3) and red (band-4) bands of Sentinel-2 are employed to build the NDTI raster in the current study, allowing for the computation of the NDTI value for each satellite overpass.

The Sentinel-2 Multispectral Instrument (MSI) consists of 13 spectral bands, with spatial resolutions of 10 m for the visible and NIR, 20 m for the red edge and SWIR, and 60 m for the atmospheric bands. Its high-resolution multispectral products have extensively been used for water quality inversion and body mapping. High-resolution optical images from Sentinel-2 were made available by the Google Earth Engine (GEE) platform, which also offered a graphical interface development environment using JavaScript. The original script was improved by choosing the Sentinel-2 dataset and corresponding parameter NDTI computations.

From Figure 3.7, it was observed that both the fishpond and shrimp pond normalized difference turbidity index (NDTI) values varied with the seasons. The study fishpond consists of 5-month-old livestock (Rohu fish) crop, which exhibits higher NDTI values before and after monsoons. By comparison, the fishpond shows higher NDTI values than the shrimp pond. This is because in the study area, the shrimp pond relies on the feed in the form of pallets, and in the case of the fishpond, the feed was powder form packed in a bag with pores and submerged into pond water, causing more turbidity. Profitable aquaculture is also severely constrained by the poor quality of feed and fertilizer sources and the high-water turbidity, which diminishes the availability of natural food sources and oxygen (Pucher et al. 2016; Abdelrahman and Boyd, 2018).

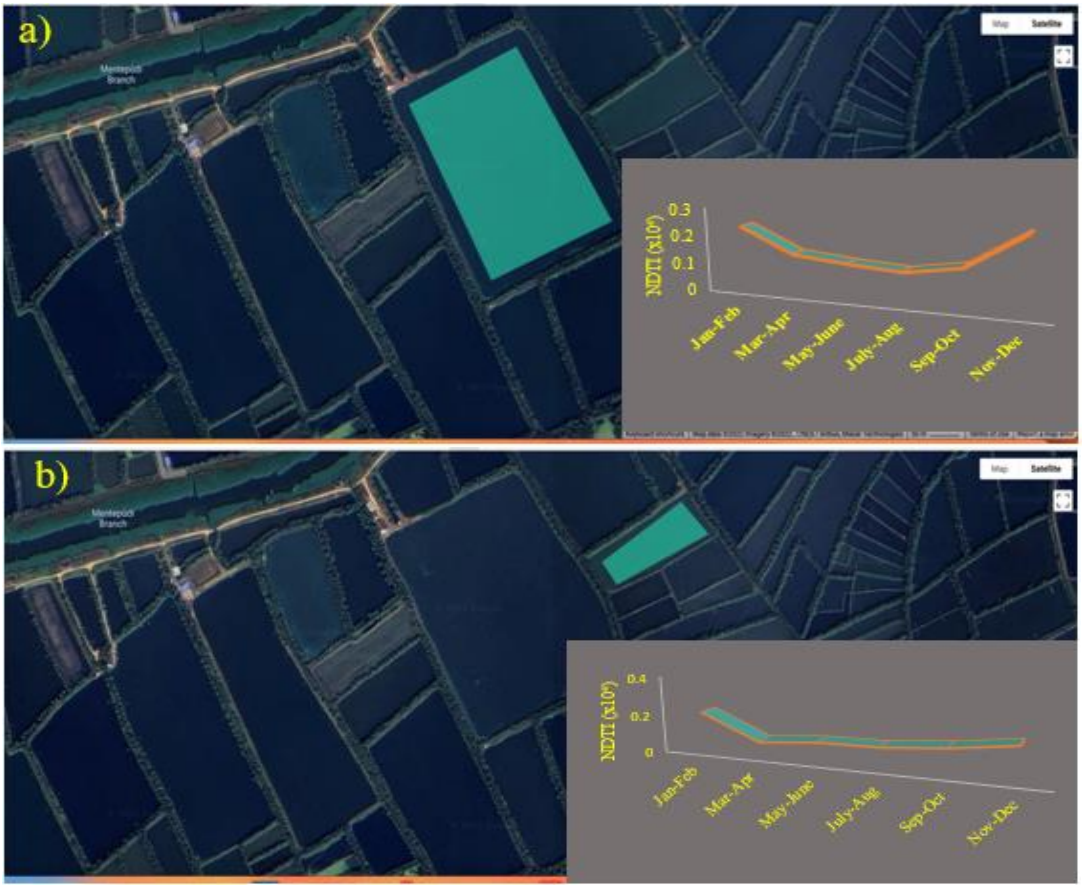


Figure 3.7 NDTI values of (a) fishpond (b) shrimp pond

3.2.2.4 Land surface temperatures (LST) analysis

Regions with intensive aquaculture are frequently described as fragile eco-environments. Due to their great sensitivity to climate change, aquaculture ecosystems respond to global climate warming earlier than the adjacent agricultural lands, making them the perfect indicators for relevant research. As a result, concerns about global climate change that affects aquaculture areas are becoming more widespread, which has led to the creation of numerous political and scientific sustainability agendas, including collaborative regional organizations, seminars, and initiatives (Ahmed et al. 2019).

Intensive aquaculture ponds, one of the world's most fragile ecosystems, play a critical role in providing essential ecosystem services, such as nutrient-rich food and export revenue. However, the consequences of human occurrence and climate change significantly impact these amenities. The most noticeable feature connected to these impacts is the poisoning of surface waters, explosive growth, and the increase in harmful ammonia levels.

Aiming to statistically comprehend the geographical and temporal trends of the climatic environment, increasing focus has been placed on the extensive inland aquaculture ponds, which are of particular importance in the delta region of Andhra Pradesh, over the past ten years. For analysing these changes, meteorological variables such as relatively close air temperature and rainfall data are crucial proxies. Furthermore, such warming patterns have also been found based on measurements from weather data for both the average and the high surface air temperature. In order to help decision-makers develop effective adaptation measures for the changing circumstances therein, it is crucial to comprehend the positive and negative implications of climate change on the environment from intense aquaculture production.

Satellite remote sensing, which offers geographically adjoining high-accuracy and high-resolution data, overcomes the limitations, especially in areas with a higher concentration of aquaculture. As a result, remote sensing represents an alternative method for tracking the evolution of surface environments and their reactions to climate change. For defining the geographical and temporal volatility of the surface thermal conditions and analysing its response to climate change, land surface temperature (LST) measurements based on thermal remote sensing are now essential.

In Bechtel's (2015) report, they demonstrated the potential uses of those parameters in global climatology and evaluated their influencing factors. They used the annual temperature cycle (ATC) to acquire the yearly LST cycle parameters from observations made with the Moderate Resolution Imaging Spectroradiometer (MODIS). In monitoring and evaluating the urban thermal environment, identical studies can be found. Although the impacts of changing land cover on the LST are the focus of analyses of LST fluctuations, interannual climate variability's impact on the changing pattern should also be considered.

The temperature map was generated based on the India Water Resources Information System (India-WRIS) data. Due to its capacity to provide daily global coverage, the

MODIS LST product is frequently used in regional and international investigations. The best option for characterizing the LST temporal and geographic variability is this product, which has a relatively good estimation accuracy according to prior validation tests. It is generally known that the local atmospheric driving environment has a major impact on the LST in addition to surface thermal characteristics. However, cloud cover can easily taint the thermal infrared readings, leading to numerous gaps in the average temperature measurement. As a result, these discontinuous LST data make it difficult to comprehend the surface thermal conditions and their dynamics. Due to the significant influence of the atmospheric forcing environment, a single comparison with data made on a particular day cannot accurately depict the true variance of the thermal environment. Using periodic data at longer intervals should be preferable to using instantaneous values.

The LST parameters help define the geographical and temporal fluctuations in the surface thermal environment because they give annually periodic LST information connected with the irradiance and climate variability conditions.

Climate change is a significant concern globally, particularly in India; the highest temperatures are witnessed before the monsoon starts (i.e., from March to May). In the study area, it was observed that there had been a decreasing trend in the land surface temperatures (LST) in recent years (see Figure 3.8). The temperature map was generated based on the India Water Resources Information System (India-WRIS) data. The map shows that lower temperatures were witnessed in the southwestern region where aquaculture is dominant (see Figure 3.9). Humidity data collected from the India-WRIS of the western delta region indicates 100% humidity during the summers and 80 to 100% humidity during other seasons. Generally, a decrease in the areas of water bodies such as ponds and lakes increase the temperature, and vice-versa. The pond area increased, and temperatures decreased in the current study area. Moreover, in shrimp farms, 4 to 5 aerator sets per acre were used to improve the dissolved oxygen in the ponds, which also decreased the surface temperatures. However, the higher humidity of the region allows heat waves.

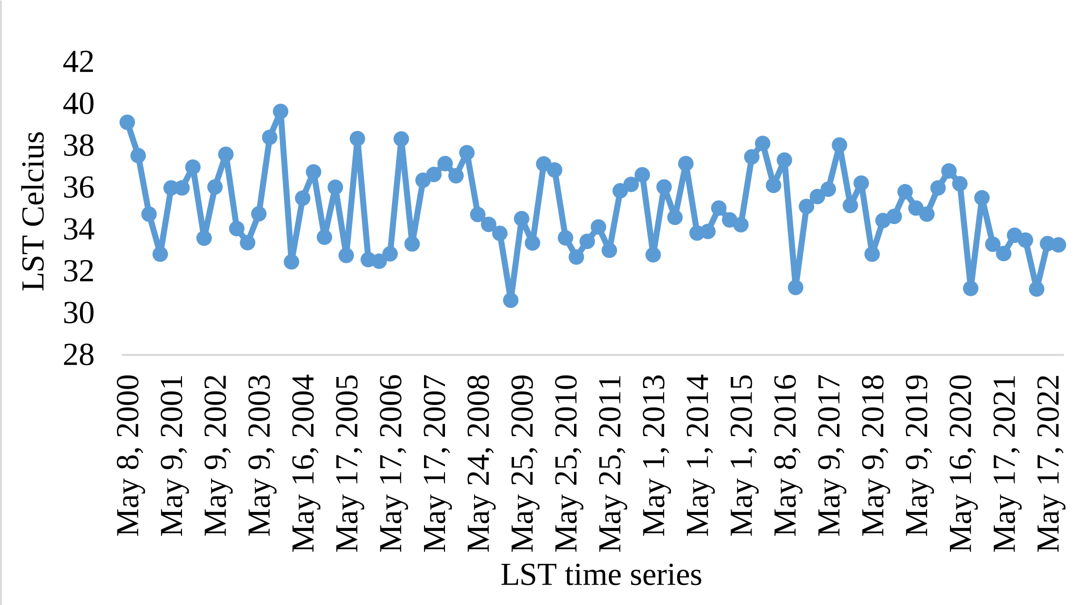


Figure 3.8 Temperature of western Godavari delta region of Andhra Pradesh from 2000 to 2022

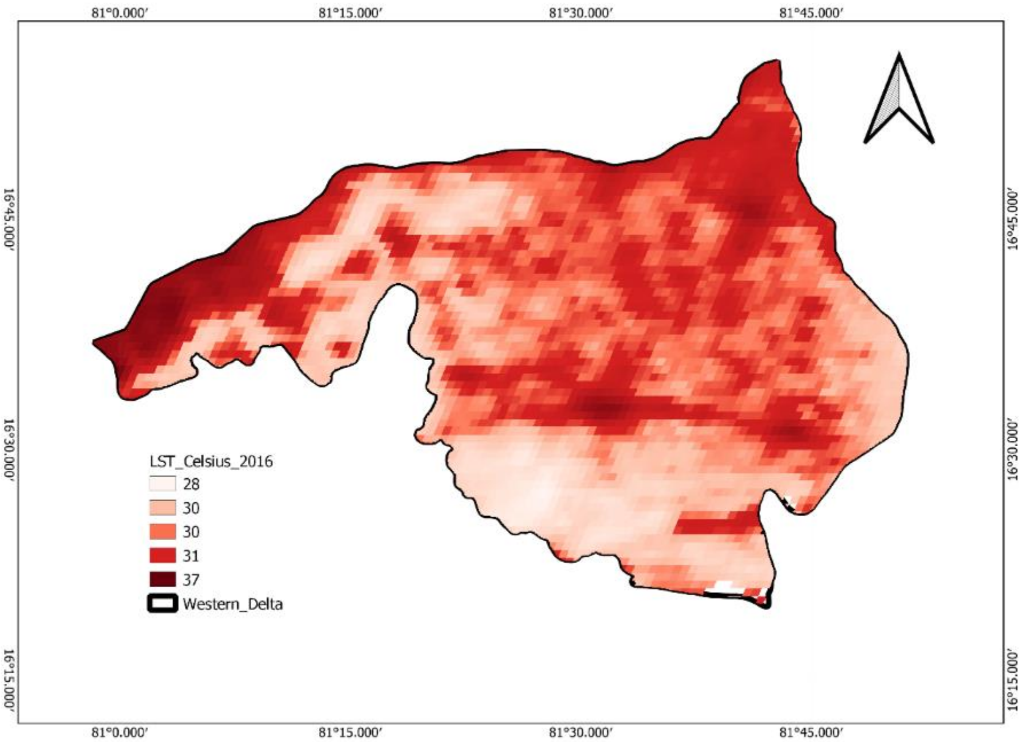


Figure 3.9 Spatial distribution of temperatures in 2016 (pre-monsoon)

Aquaculture catchments were identified as low-temperature zones because of their ability to absorb heat directly from solar radiation and their adequate moisture content. Furthermore, from 2000 to 2022, changes in the lowest LST on aquaculture catchments in the Venkayya canal basin ranged from 38 ^{o}C to 29 ^{o}C, while the highest temperature recorded in the Attili canal catchment basin ranged from 35 ^{o}C to 38 ^{o}C. It means that LST fell as the number of operational aquaculture ponds in the Venkayya canal catchment zone increased. At the same time, LST in the Attili catchment increased due to an increase in the barren land area and degradation of agricultural cover. As a result, the LST varied dramatically with different biophysical compositions.

3.3 WATER QUALITY ASSESSMENT IN THE AQUACULTURE PONDS

Managing aquaculture ponds requires regular water quality assessments to maintain optimal conditions for aquatic species.

3.3.1 Analysis of physicochemical characteristics of aquaculture water

In the present investigation, a field survey was carried out to see the size of the aquaculture pond and cultivation days. Followed by a preliminary field investigation, water samples were collected from the ponds to determine the physicochemical characteristics of aquaculture waters. A total of 190 samples were tested, and datasets include sampling was collected from February 2021 to May 2021 (pre-monsoon consideration) (see Appendix - II). The pre-monsoon season was chosen to represent a distinct period in the annual hydrological cycle. By selecting samples from this specific season, we aimed to understand the typical water quality conditions during a particular period, which can provide valuable insights into contaminant variations. Moreover, the pre-monsoon season is characterized by relatively stable weather conditions, with no rainfall and consistent water flow patterns. This stability allows for more reliable comparisons of water quality parameters and for developing contaminant assessment models. Samples were obtained from aquaculture ponds in the western delta region of Andhra Pradesh. The water samples were collected in the middle of the aquaculture pond between 7 and 9 in the morning; samples were gathered from each area, then put in 250 mL plastic bottles that had been pre-rinsed. First, it was washed with 0.1N HCl, then rinsed with millipore water, before labelling clearly. To ensure appropriate sample preservation while in the field, each container was filled with a water sample, carefully sealed using a plastic bag, and placed right away in a cool box with ice at 5 ^{o}C. The samples were refrigerated after being brought to the lab to prevent external contamination until the same day as sample collection or the following analysis period. The physicochemical characteristics such as pH, salinity, alkalinity, bicarbonates, total hardness, electrical conductivity, calcium, magnesium, and ammonia were tested. Salinity, pH, total dissolved solids (TDS), electrical conductivity (EC), and temperature were determined at the site because of their unstable behaviour. HANNA make portable instruments were used to determine pH (Model: HI 98129 pHep), EC (Model: HI 9833), TDS (Model: HI 9833), salinity (Model: HI 98331), and temperature (Model: HI 9833) (Dey et al. 2021). The spectrophotometer (Model: 2203, Systronics Double Beam Spectrophotometer, India) measured ammonia, nitrate, nitrite, and phosphates. Alkalinity, total hardness, calcium hardness, magnesium hardness, and chlorides are other parameters evaluated using the conventional titrimetric analysis method (Dey et al. 2021).

3.3.2 Water quality index (WQI) evaluation

The water quality of a pond or lake can be evaluated and summarised using various water quality measures based on Water Quality Index (WQI). Physical, chemical, and biological factors are commonly used to compute the index, including pH, dissolved oxygen, temperature, total dissolved solids, turbidity, nutrients, bacteria, and other contaminants. Globally, numerous distinct WQI models have been created and are in use. Each has its own unique set of parameters and grading schemes. While certain WQIs are more specialized and can only be used with specific water sources, such as rivers or lakes, others are more general. One of the most popular techniques for determining a WQI is the Arithmetic Weighing (AW) approach. This method gives weights to several water quality measures based on how significant they are to the water body's overall quality.

In this study, a set of seven parameters, such as pH, TDS, alkalinity, Ca, Mg, total hardness, and nitrates were considered for determining the WQI because they reflect the total water quality of the aquaculture waters. The Weighted Arithmetic Index Method was used to compute WQI (Bora and Goswami, 2017; Chauhan and Trivedi, 2022). The most frequently measured water quality variables were considered for calculation in the weighted arithmetic water quality index approach. The following expression (1) is used to calculate the quality rating (Rn) for water samples:

$$Rn = 100 * \frac{Vn - Vi}{(Sn - Vi)} \quad (1)$$

Where Vn, Vi, and Sn are, respectively, estimated value, ideal value, and standard allowable value of the nth parameter. The parameters' unit weight (Wn) is also crucial when calculating the WQI. The WQI aggregated the quality rating with the unit weight on purpose and expressed in equation (2) given by:

$$WQI = \sum \mathrm{RnWn} \, / \sum \mathrm{Wn} \quad (2)$$

3.4 AQUACULTURE POND SOIL CHARACTERIZATION AND AQUACULTURE SLUDGE BLENDED CLAYS BEHAVIOUR

In general, aquaculture water quality may depend on the pond subsoil. Therefore, assessing the subsoil in an aquaculture pond can provide valuable information on the soil's characteristics and suitability for the aquaculture ecosystem and contaminants load.

3.4.1 Physicochemical analysis of soils

Fifteen soil samples were collected in January 2019 from the ponds bottom in three separate aquaculture zones (Zone-1, Zone-2, and Zone-3). Four samples were collected from each pond, combined, and homogenized. Drying of the composite samples takes place at 60 ^{o}C in a mechanical convection oven. To prepare a portion of each dry sample for chemical analysis, it is crushed with a hammer-type soil crusher until it can pass a sieve with 2.0 mm apertures. According to American Public Health Association (APHA) standards, soil samples are analyzed (APHA, 2008). A pH meter was used to measure pH at a soil and distilled water suspension ratio of 1:5 (Model: HI 98129 pHep, HANNA meter India). A conductivity meter was used to measure electrical conductivity (EC) of soil and distilled water suspension ratio of 1:5 (Model: HI 9833, HANNA meter India). Flame photometer was used to measure the sodium. Total organic carbon (TOC) was measured using heating and oxidation with the potassium dichromate method, and phosphorus (P) and sulphur (S) was determined by a spectrophotometer method. Total nitrogen (TN) was determined using a Kjeldahl distillation-titration unit.

3.4.2 Geotechnical characteristics of soils

Soil samples have been collected from various aquaculture bottom soils in the study area to determine the free swell index, plasticity characteristics, and hydraulic conductivity tests.

3.4.2.1 Free swell index

Free swell index (FSI), According to IS: 2720 Part-40 (2002), was calculated. The FSI tests were carried out using collected pond bottom clay that had been oven-dried and passed through a 425µm sieve. Petrol was utilized as the test's reference liquid. Two 100ml tubular jars holding petroleum and distilled water were filled with ten grams of oven-dried pond clay that had passed a 425µm sieve. After allowing the jars to remain for 24 hours, the soil volumes in the kerosene (Vp) jar and deionized water (Vw) containing jars were recorded. The ratio of the difference between the quantities of soil in water and petroleum to the soil's volume in petroleum, expressed as a percentage, is known as the free swell index (FSI). It is expressed as:

$$FSI = \frac{Vw - Vp}{Vp} * 100 \quad (3)$$

3.4.2.2 Plasticity characteristics

Plasticity characteristics such as liquid limit (LL), plastic limit (PL), and plasticity index (PI) were determined for expansive clay and clay blended with aquaculture sludge of 5%, 10%, and 15% of the dry weight of clayey soil. The plasticity characteristics were determined in accordance with the IS: 2720 Part-5 (2017).

3.4.2.3 Hydraulic conductivity

Tests for proctor compaction were conducted in accordance with IS: 2720 Part-7 (2017). The hydraulic conductivity of the pond soil at their respective OMC and MDD was measured using the variable head permeameter method under IS: 2720 Part-15 (2017).

3.4.2.4 One-dimensional swell-consolidation

Consolidation characteristics were determined for expansive clay and clay blended with aquaculture sludge in accordance with the IS 1498 (1970). Many researchers have conducted experimental investigations on expansive clay and clay blended with additives to evaluate the rate of heave, swell potential, swelling pressure, and linear shrinkage (Rao and Thyagaraj, 2007; Nagaraju and Prasad, 2020). As mentioned in the above sections, the clay samples were blended with different dosages of aquaculture sludge. The clay samples were pulverized and sieved from the 425µm sieve compacted in the oedometer ring with a height of 2cm and a diameter of 6cm. The compacted soil was maintained with a 1.3g/cc prefixed density. To determine rate of heave, the sample was loaded to an initial surcharge of 5kPa. Rate of heave was observed at 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, 60, 120, 240, 360, 1140, 2880, and 4320 min, until it attains maximum swell.

The swell potential was determined by the ratio of change in the height of the specimen to the original height of the specimen (2cm). to evaluate the swelling pressure and compression index, stresses were applied (10kPa, 20kPa, 40kPa, 80kPa, 160kPa, and 320kPa) to observe the deformations. Swelling pressure is defined as the pressure required to bring back the soil from the fully swollen state (maximum void ratio) to the original form of the sample (initial void ratio). Other series, in a similar fashion, the experiments mentioned above were carried out on clay lumps passing from a 2mm sieve to understand the behaviour of clay lumps exposed to aquaculture sludge.

3.4.3 Microstructural analysis

Scanning electron microscopy (SEM) analysis and energy dispersive spectrometry (EDS) was carried to know the grain sizes, grain boundaries, fractured surfaces, textures, and interface reactions. SEM and EDS analysis was performed using the high efficiency FESEM Gemini 300 apparatus. X-ray diffraction analysis was carried to know the embedded particles, residual stresses, texture, and mineralogical characteristics. XRD was performed using the Empyrean 3rd generation model apparatus with features of C_uK_α point focus, 2D detector using PIXCEL, and 3D detector. The raw materials used in this study were expansive clay and aquaculture sludge (AS).

3.4.4 Cation exchange capacity (CEC)

The capacity of soils to retain and exchange cations like calcium (Ca^{2+}), magnesium (Mg^{2+}), potassium (K^{+}), and sodium (Na^{+}) with the soil solution is known as their cation exchange capacity (CEC). A soil sample's CEC can be measured quantitatively using the IS: 2720 Part-24 (1976) standard test procedure for assessing soil CEC.

A soil sample is taken from the field, dried by air to a constant weight, and then weighed. After being pulverized to pass through a 2 mm sieve, the sample is kept in a clean, dry container. Placing a specified quantity of soil (usually 5–10 g) into a 50 ml volumetric flask. The soil is then completely saturated with ammonium acetate solution with a pH of 7.0. To ensure the soil is completely soaked, the beaker is covered and left to stand for 30 minutes.

A known quantity of a solution that contains one cation, such as calcium or potassium, is put into the beaker after the soil has been completely saturated. After that, the beaker is agitated for another 15 minutes to permit cations from the soil and liquid to interchange. The solution is filtered after the exchange of cations has taken place, and the concentration of the cation in the solution is determined. The amount of cation adsorbed is divided by the sample's weight to determine the CEC, which is then represented as milliequivalents per 100 grams of soil (meq/100g). CEC values of clays and clays blended with aquaculture sludge was determined.

3.5 SOFT COMPUTING AMMONIA PREDICTION MODELS WITH POA AND DWT-POA APPROACHES

Stochastic population-based optimization techniques are among the most successful methods for solving optimization problems. Swarm-based, evolutionary, particle, and match optimization algorithms can all be categorized into one of four classes based on the key concepts and sources of motivation that went into their creation.

3.5.1 Pelican optimization algorithm (POA)

To better understand natural phenomena, such as the swarm behaviours of animals, insects, and other living things, swarm-based optimization algorithms have been developed. One of the earliest and most well-known swarm-based algorithms, particle swarm optimization (PSO), was inspired by how birds forage food. According to the PSO, each population member's status is updated based on their best possible position and the right place of the entire population. The development of teaching learning-based optimization (TLBO) came from simulating the dynamics of a classroom and the interactions between the teacher and students. Members of the population in TLBO are kept current through teacher training and share knowledge among themselves. Grey wolves' hierarchical organization and social behaviour during hunting are the sources of inspiration for gray wolf optimization (GWO). The hierarchy management of grey wolves is modelled in GWO using four sorts of wolves. Most are updated based on models of three primary feeding stages, such as the search for animals, surrounding prey, and eating prey. Based on the modelling of humpback whale group interactions and their bubble-net fishing technique, the whale optimization algorithm (WOA) is a swarm-based optimization algorithm that draws inspiration from nature. The three phases of hunting: looking for prey, surrounding prey, and humpback whale bubble-net eating behaviour are maintained for each population individual in WOA. A tunicate swarm algorithm (TSA) is created based on a model of jet engines and tunicates' swarm behaviour throughout the navigation and foraging phase. In TSA, the community is maintained based on four phases: minimizing search agent conflicts, migrating toward the best neighbour, convergent toward the search agent, and swarm behaviour. The marine predator’s algorithm (MPA) is modelled after how marine predators manoeuvre to catch food in the ocean. The population increase process in MPA has three stages because of the different prey and predator speeds.

In 2022, Trojovsky and Dehghani introduced a novel stochastic nature-inspired optimization approach known as Pelican Optimization Algorithm (POA). This technique is renowned for its remarkable capacity to balance exploration and exploitation while seeking the global optimum (Trojovsky and Dehghani, 2022). The fundamental principles behind POA stem from pelicans' hunting strategy and behavior, which serves as a source of inspiration for this innovative optimization method. By drawing from nature's wisdom, POA has demonstrated promising potential in solving complex optimization problems efficiently (Trojovsky and Dehghani, 2022; Alamir et al. 2023). The pelican is a massive bird with a long tongue and a wide pouch in its throat for catching and swallowing prey. This bird enjoys social interactions and lives in colonies with many hundred pelicans. Pelicans have the following physical characteristics: they weigh between 2.75 and 15 kg, are between 1.06 and 1.83 m tall, and have a wingspan between 0.5 and 3 m. When a pelican is extremely hungry, it will even consume seafood. Frogs, tortoises, and crabs are only occasionally eaten by pelicans. Pelicans frequently cooperate during hunting. When the pelicans locate their prey, they dive into it from ten to twenty meters. Naturally, certain species also drop to catch their prey at lower elevations. The fish are then forced into shallow water by the spread of their wings, making it easier for them to catch their prey. When capturing fish, the pelican's beak fills up with much water, which causes it to tilt its head forward before eating it to release extra water. Pelicans have become skilled hunters due to their clever hunting behaviour and tactics. The modelling of the strategy above served as the primary source of guidance for the creation of the proposed POA.

Pelicans are included in the population of the proposed POA, which is an algorithm based on populations. Each population element represents a potential solution in population-based techniques. According to where they are in the solution space, each population member suggests values for the variables in the optimization process. The equation (4) randomly initializes population members based on the problem's lower and upper limits.

$$Z_{ij} = mj + vand\ (xj - mj), i = 1,2,3, \dots n, j = 1,2,3, \dots, m \tag{4}$$

where *mj* is the *jth* lower limit and *xj* is the *jth* target value of problem variables, *n* is the number of accessible populations, *m* is the number of decision variables, *vand* is a random variable in the range [0, 1], and *Zi,j* is the value of the *jth* variable indicated by the *ith* solution space.

Equation (5) uses the population matrix to identify the pelican individuals from the population within the proposed POA. The columns of this matrix reflect the suggested values for the random function, and each row represents a potential solution.

$$X = \begin{bmatrix} X1 \\ \vdots \\ Xi \\ \vdots \\ Xn \end{bmatrix} = \begin{bmatrix} x_{1,1}^{1} & . & x_{1,j}^{1} & . & . & x_{1,m}^{1} \\ . & . & . & . & . & . \\ x_{i,1}^{1} & . & x_{i,j}^{1} & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ x_{N,1}^{1} & . & x_{N,j}^{1} & . & . & x_{N,m}^{1} \end{bmatrix} \quad (5)$$

If *Xi* is the *ith* pelican and *X* is the pelican population matrix.

Each member of the population in the suggested POA is a pelican, which is a potential fix for the stated issue. As a result, depending on each potential solution, the given problem's objective function can be assessed. Equation (6) uses a vector known as the objective function vector to determine the values acquired for the objective function.

where *Di* is the objective function value of the *ith* candidate solution and *D* is the optimal solution vector. The updated optimal solutions use the suggested POA, which simulates pelicans' behavior and strategies when approaching and hunting prey. Two steps of this hunting technique are emulated, including moving toward the prey and winging over the water. Figure 3.10 shows a flowchart of the proposed POA's various steps.

$$D = \begin{bmatrix} D1 \\ \vdots \\ Di \\ \vdots \\ Dn \end{bmatrix} = \begin{bmatrix} D(X1) \\ \vdots \\ D(Xi) \\ \vdots \\ D(Xn) \end{bmatrix} \quad (6)$$

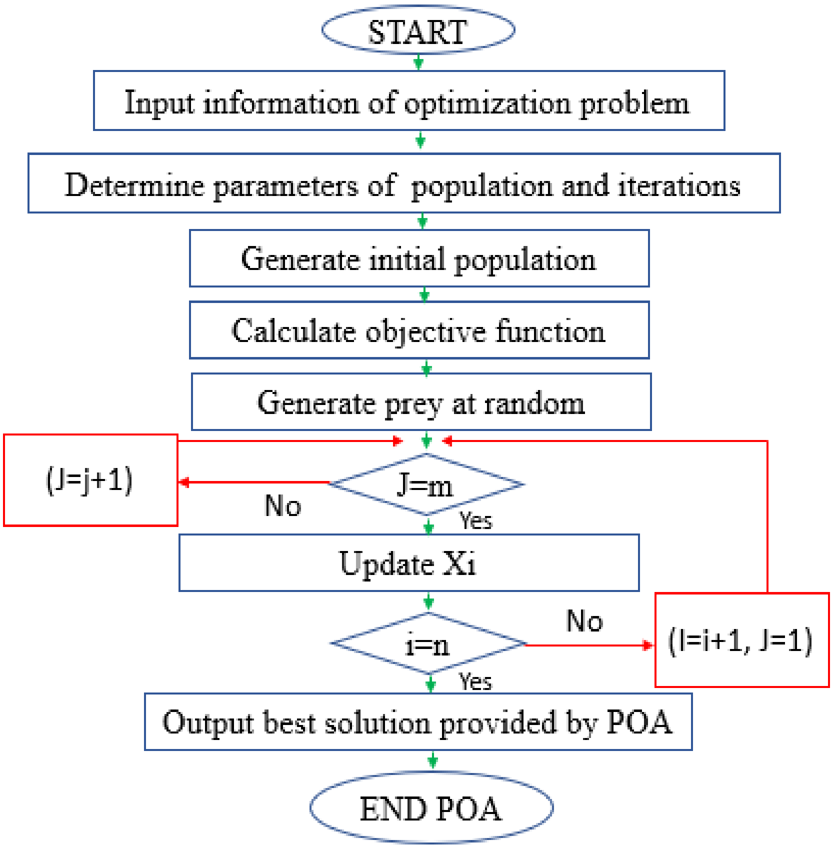


Figure 3.10 Process of POA model

3.5.2 Ammonia prediction model using DWT-POA

To predict the ammonia based on the availability of the metrices like area of the pond, cultivation days, pH, salinity, alkalinity, bicarbonates, total hardness, calcium, and magnesium, a forecasting model is needed. Since there are no predefined equations to calculate the ammonia using these metrices, a statistical model must build with soft computing approaches. In this study, a novel DWT coupled POA approach was proposed that merges the POA with the DWT, which introduces a unique and powerful combination of optimization and signal processing techniques, aiming to enhance the algorithm's efficiency and effectiveness in solving complex optimization problems (Trojovsky and Dehghani, 2022). Each independent input data which affect the output is processed through DWT to extract low and high frequency components and a statistical regression model is developed with the decomposed coefficients to predict the ammonia. The optimal values of the regression model are identified with POA algorithm to minimize the errors between the actual ammonia and predicted ammonia of data collection. The input components for the regression model are DWT coefficients extracted when the data is processed through low pass and high pass filters. When the data is processed through DWT, approximated (a_n), and detailed coefficients (d_n) are extracted for each level of decomposition (n) using equation (7)

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t)\varphi_{a,b}(t).dt \tag{7}$$

In equation (7), $f(t)$ is the input data in time-domain and $\varphi_{a,b}(t)$ is the wavelet basis function with fixed and controllable parameters which influences the process of decomposition. Based on the decomposition level, the regression model used for the forecasting with the single input variable is:

$$\begin{bmatrix} y_1(k+1) \\ y_1(k) \\ \vdots \\ y_1(2) \\ y_1(1) \end{bmatrix} = \alpha_1 \begin{bmatrix} d_1^{x_1}(k+1) \\ d_1^{x_1}(k) \\ . \\ . \\ d_1^{x_1}(2) \\ d_1^{x_1}(1) \end{bmatrix} + \alpha_2 \begin{bmatrix} d_2^{x_1}(k+1) \\ d_2^{x_1}(k) \\ . \\ . \\ d_2^{x_1}(2) \\ d_2^{x_1}(1) \end{bmatrix} + \cdots + \alpha_n \begin{bmatrix} d_n^{x_1}(k+1) \\ d_n^{x_1}(k) \\ . \\ . \\ d_n^{x_1}(2) \\ d_n^{x_1}(1) \end{bmatrix} + \beta \begin{bmatrix} a_n^{x_1}(k+1) \\ a_n^{x_1}(k) \\ . \\ . \\ a_n^{x_1}(2) \\ a_n^{x_1}(1) \end{bmatrix} + \gamma \begin{bmatrix} 1 \\ 1 \\ . \\ . \\ 1 \\ 1 \end{bmatrix} \tag{8}$$

In equation (8), $\alpha_i (i = 1,2, \ldots n)$ is the coefficient of detailed component d_i of the input variable x_1. Approximated components corresponding coefficient is denoted by β and constant of the regression model is represented by γ. When the number of independent variables is increased from 1 to p $(x_1, x_2, \ldots, x_p)$, the regression equation to predict the output variable is given by:

$$\begin{bmatrix} y_1(k+1) \\ y_1(k) \\ \vdots \\ y_1(2) \\ y_1(1) \end{bmatrix} = \sum_{i=1}^{p} \alpha_1^i \begin{bmatrix} d_1^{x_i}(k+1) \\ d_1^{x_i}(k) \\ . \\ . \\ d_1^{x_i}(2) \\ d_1^{x_i}(1) \end{bmatrix} + \sum_{i=1}^{p} \alpha_2^i \begin{bmatrix} d_2^{x_i}(k+1) \\ d_2^{x_i}(k) \\ . \\ . \\ d_2^{x_i}(2) \\ d_2^{x_i}(1) \end{bmatrix} + \cdots +$$

$$\sum_{i=1}^{p} \alpha_n^i \begin{bmatrix} d_n^{x_i}(k+1) \\ d_n^{x_i}(k) \\ . \\ . \\ d_n^{x_i}(2) \\ d_n^{x_i}(1) \end{bmatrix} + \sum_{i=1}^{p} \beta_n^i \begin{bmatrix} a_n^{x_i}(k+1) \\ a_n^{x_i}(k) \\ . \\ . \\ a_n^{x_i}(2) \\ a_n^{x_i}(1) \end{bmatrix} + \gamma \begin{bmatrix} 1 \\ 1 \\ . \\ . \\ 1 \\ 1 \end{bmatrix} \tag{9}$$

Based on the decomposition level (n), the coefficients of the regression model are defined. To find a suitable set of regression coefficients which minimize the error between the predicted output and actual output values, a random search is required in large search space. Therefore, population search-based algorithms are useful to find such optimal solutions. In this work, POA is used to find the optimal solution of regression model for best prediction. To support POA, a cost function is required which measures the fitness of each solution generated by POA identified based on the deviation of actual and predicted outputs. For a specific output variable y, the predicted and actual outputs are $y_{predicted}$ and y_{actual}, respectively. The absolute error for forecast interval $k+1$, is expressed as equation (10).

$$e(k+1) = \frac{y_{actual}(k+1) - y_{predicted}(k+1)}{y_{actual}(k+1)} \tag{10}$$

Based on the actual and predicted information of output, the cost function is developed shown in equation (11) used to find fitness values of the solutions generated by POA

$$Cost\ Function\ (C) = \frac{1}{k+1} \sum_{i=1}^{k+1} e^2(i) \tag{11}$$

The best solution set of coefficients of the regression model shown in equation (9) are identified with a new population search-based algorithm known as pelican optimizer. POA is a heuristic algorithm that mimic nature of pelican bird during food searching and hunting. Initialization of the search process is started randomly like other population search-based methods using the initial vector is shown in equation (12).

$$\begin{bmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ X_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & . & . & . & x_d^1 \\ x_1^2 & x_2^2 & . & . & . & x_d^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ . & . & . & . & . & . \\ x_1^n & x_2^n & . & . & . & x_d^n \end{bmatrix} \quad (12)$$

The initial solution (x_j^i) matrix size depends on the population size (n) of the POA and decision variables (m) in the objective function of the optimization problem. The solutions need to be generated within the boundaries/limits using equation (13)

$$x_j^i = l_j + r.(u_j - l_j) i = 1,2, \dots n; j = 1,2, \dots m \quad (13)$$

In equation (7), u_j and l_j are the upper and lower limits of the coefficient j of the regression problem. Getting food with initial positions is not guaranteed and therefore pelicans updating their positions using equations (14) and (15)

$$x_j^{i(p1)} = \begin{cases} x_j^i + rand.\left(p_j - I.x_j^i\right), & C_p < C_i \\ x_j^i + rand.\left(x_j^i - p_j\right), & else \end{cases} \quad (14)$$

$$x_j^{i(p2)} = x_j^i + R.\left(1 - \frac{t}{T}\right)(2.rand - 1).x_j^i \quad (15)$$

Where, $x_j^{i(p1)}$and $x_j^{i(p2)}$ are the new positions of x_j^i after stage 1 and 2, respectively. Location of prey for jth decision variable is represented by p_j and I is number either 1 or 2, R (constant 0.2), t (current iteration number), and T (Total number of iterations). When current iteration number is equal to maximum number of iterations, then the process is terminated. Once the positions of pelicans are updating using stage1 and 2, fitness values corresponding to new positions are evaluated and best solutions are achieved at the end of the iterations. The best POA solution is optimal regression model coefficient values that fit the output data with minimum prediction errors. The overall process of the prediction is presented in Figure 3.11.

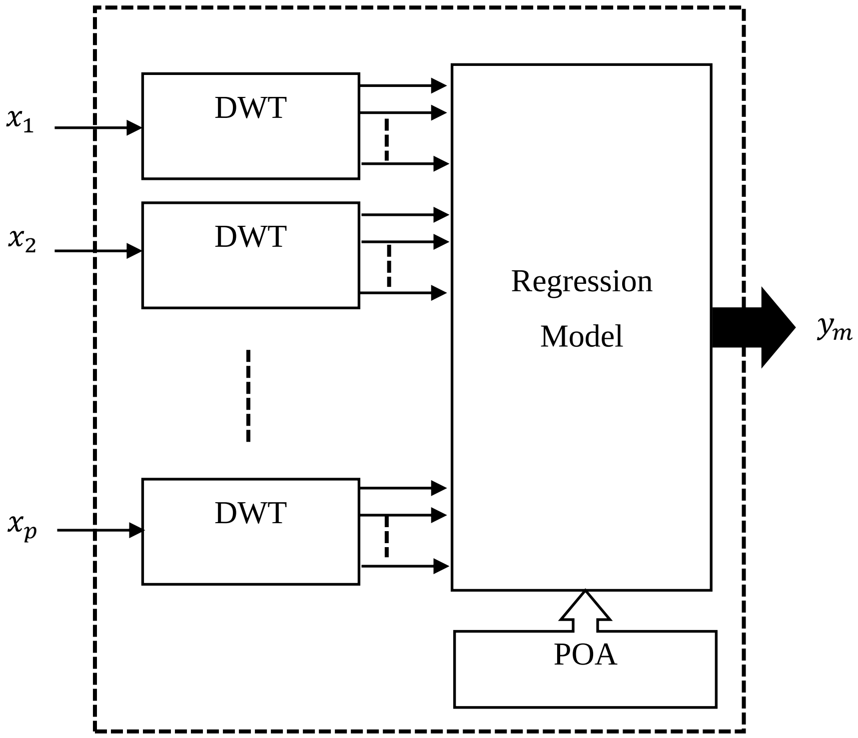


Figure 3.11 Process of identification of regression model

CHAPTER 4

ASSESSMENT OF WATER QUALITY IN THE INLAND AQUACULTURE PONDS

4.1 GENERAL

One of the vital pathways for human survival in the delta region is the canals, which play a special part in the development and growth of human societies. They have always been considered essential freshwater supplies for life because most currently being developed activities rely on them. Ancient people have also flourished beside them. Water is supplied through canals for various purposes, including aquaculture, drinking water, industry, and other applications.

Measurements of physicochemical characteristics indicate the viability of the tested water for different types of aquatic life. Therefore, assessing the water quality of aquaculture ponds is essential for figuring out the potential classes of limnological change. Additionally, fish and shrimp's physiological and behavioural processes, including feeding, mating, movement, respiration, and excretion, can all be directly impacted by the quality of the water. Therefore, good water quality is essential for improved development, survival, and increased farmed fish or shrimp production. Furthermore, in the study area, more than 230 villages depend only on aquaculture-discharged water resources for drinking purposes after traditional sand bed filtration treatment. Therefore, water quality assessment could be helpful for the management of aquaculture waters.

4.2 EVALUATION OF INLAND AQUACULTURE PONDS WATER QUALITY

Based on the preliminary investigation in Chapter-3, the study area was classified into three zones (traditional, semi-intensive, and intensive farming). This classification facilitated comprehensive coverage and allowed for the representation of different environmental conditions. A stratified random sampling strategy was employed for each zone by considering their accessibility and suitability. One hundred ninety water samples were collected from the aquaculture ponds in the study area to evaluate water quality parameters (see Figure 4.1). The water quality results of the aquaculture samples are shown in Appendix-II.

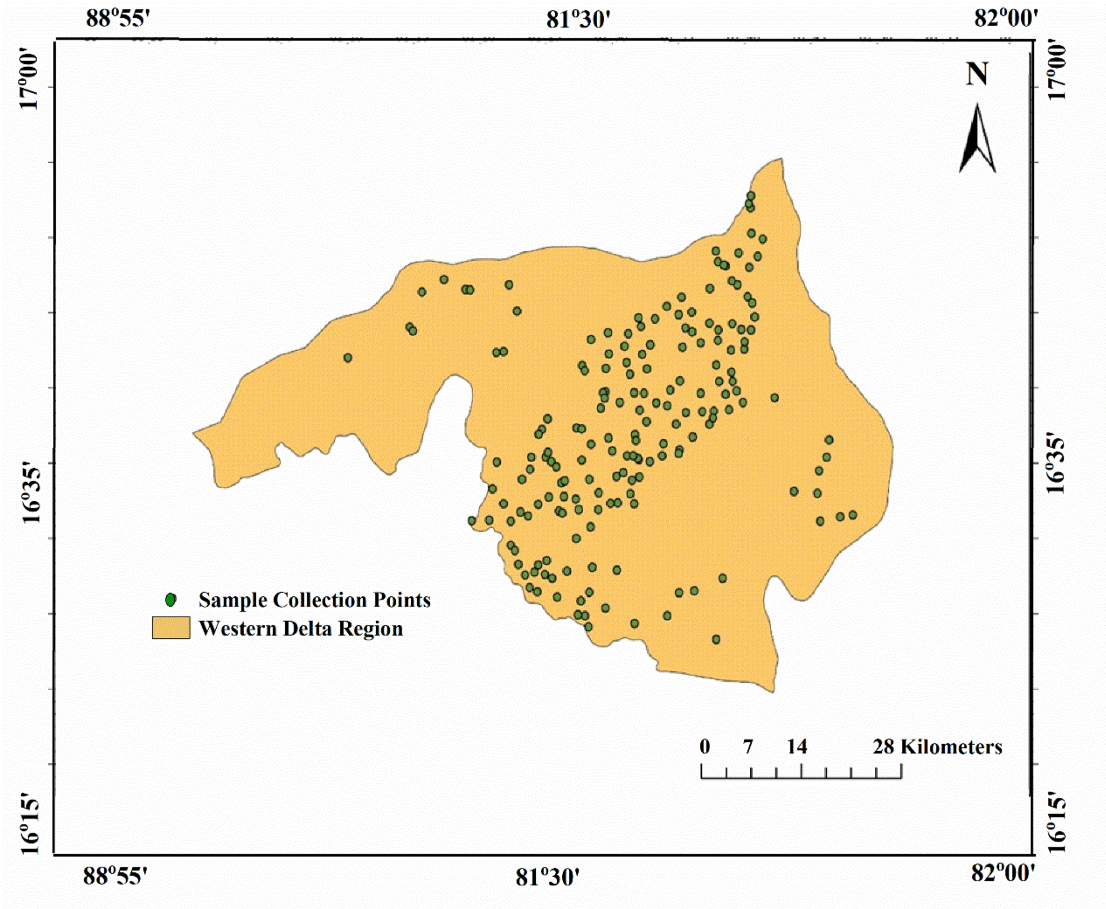


Figure 4.1 Sample collection points

The statistical indices for the water quality indicators acquired from all 64 locations, including the minimum (Min), maximum (Max), mean, standard deviation (STD), and cumulative variance (CV) values, are shown in Table 4.1. Moreover, Table 4.1 reflects the desirable ranges for both aquaculture (shrimp) culture and drinking purpose (Ray et al. 2011; Tallar and Suen, 2016; Mohanty et al. 2018; Ma et al. 2020; Kothari et al. 2021; Nagaraju et al. 2022). In the inland aquaculture environment, the temperature is vital in controlling various biological and physicochemical processes. The temperatures at the sampling locations in this study tended to be similar, ranging from 29.9 °C to 31.0 °C, and these temperatures fell within the ideal range for aquaculture, which is between 20-32 °C (Kasnir et al. 2014). The delta region of

Andhra Pradesh experiences typical surface temperatures of 30 ± 1.24°C (Nagaraju et al. 2022).

Table 4.1 Statistical data and standard values of physicochemical characteristics of the aquaculture waters

Parameters	Statistical data					Desirable range for shrimp aquaculture	Drinking water quality standards (Indian Standard)	Irrigation water quality standards (Indian Standard)
	Min	Max	Mean	SD	CV			
pH	7.12	8.98	7.88	0.45	0.21	7.5-8.5	6.5-8.5	6-8.4
Electrical conductivity (µS/cm)	54	39000	3245	5826	$3.9*10^6$	-	<1500	800-2500
TDS (ppm)	155	9200	1349	2182	$47.59*10^5$	<1000	<500	<2000
Salinity (ppt)	0	24.80	12.40	8.42	11.20	3-25	0	<0.75
Alkalinity (ppm)	50	490	259.71	79.65	6344	<140	200-600	
Bicarbonates (ppm)	45	1100	253.47	92.61	8578	100-300	<200	<120
Total Hardness (ppm)	58	3465	637.42	744.91	$55.49*10^4$	>500	200-600	<500
Calcium (ppm)	25	412	76.14	72.28	5225.20	>150	75-200	<100
Magnesium (ppm)	12	745	126.47	146.82	21557.40	>450	30-100	<50
Ammonia (ppm)	0.05	2.8	0.15	0.27	0.07	<0.1	<0.5	<0.5
NO_3 (ppm)	4	89.70	21.09	24.83	616.90	<5	<45	<45
WQI (%)	21	456.37	125.85	98.94	9791.05	-	0-50	-

A pH range of 7.5 to 8.5 must be maintained for the shrimp culture because any deviation could result in the death of the shrimp or fish. The delta region's aquaculture water's average pH reading was 7.88. Most pH readings fall within the range that is ideal for aquaculture. In addition, the pH in the current study was greater than that of earlier research done in the western delta region (Nageswara Rao et al. 2015; Nagaraju et al. 2022), who claimed that conventional aquaculture activities might cause a pH variance between 6.9 and 7.7. Moreover, in past years, there has been a continuous flow of rain waters with silt particles in the canals, resulting in lower pH values. In recent years, intensive farming and longer-term storage of aquaculture waters have been key factors that change pH concentration and, if not managed, will have a detrimental effect on ecosystems. The reading for the EC ranged between 54 and 39000 µS/cm, with an average of 3245 µS/cm. However, less than 1500 µS/cm is the acceptable amount established by Indian norms. Therefore, a lower value of EC indicates that the water contains fewer dissolved ions, such as sodium and organic particles (Ameen, 2019). In the case of aquaculture, a higher EC value reflects higher salinity which is desirable for brackish shrimp culture (Jayanthi et al. 2019).

The study area alkalinity values show the highest levels, with the total mean alkalinity values ranging from 50 to 490 ppm. Additionally, these values are below the 140 mg/L threshold, which is ideal for aquaculture (Mishra et al. 2008; Bhatnagar and Devi, 2013). Alkalinity is a term used to describe how much water uses carbonate, bicarbonate, and hydroxide ions to buffer or neutralize acids. This aids in preventing significant pH variations from harming aquatic life. The pH drops to 6 throughout the night due to massive volumes of free carbon dioxide being converted to weak carbonic acid, produced if there is no buffering capacity. Because of the high rate of photosynthesis, where the phytoplankton utilizes most of the available carbon dioxide, the pH values can rise over 9.0 (Ma et al. 2020; Mutea et al. 2021). Nagaraju et al. 2022 reported that intense aquaculture activities without a proper canal network and treatment facilities impacted the water quality in the aquaculture ponds and environs, resulting in excessive alkalinity levels.

TDS values for the aquaculture water samples ranged from 155 to 9200 mg/L. The TDS values fell outside what is considered acceptable by aquaculture guidelines. Continuous use of aerators in shrimp farming (to maintain dissolved oxygen) results in mixing aquaculture waste with water on the bottom soil, which raises TDS levels and turbidity.

Salinity values ranged from 0 to 24.8 ppt between sampling sites, which was under the permissible limits for shrimp aquaculture (>3 ppt). According to a survey conducted in the western delta region of Andhra Pradesh by Nagaraju et al. (2022), continuous saltwater pumping from subsurface water sources throughout the crop season causes groundwater deprivation and surface water contamination. Saline waters reach nearly 50 km inland from the Bay of Bengal through salt intrusion during the summers. Furthermore, similar trend was observed in the aquaculture ponds of Tamilnadu state, adjacent to the study area state (Jayanthi et al. 2020).

White-legged shrimp spend much of their time on the pond's bottom surface; the bottom soil conditions are more critical for survival. Intensive aquaculture farming generally causes large amounts of ammonia, phosphorus, and organic material to be deposited in the bottom soils of aquaculture ponds. In addition, the quality and amount of pond bottom sediment reflect pond production. They are crucial for the oxidation of organic matter, the uptake and nutrient release into the water, and the effect on water quality and shrimp survival rates (Mohanty et al. 2018). Intensive aquaculture practices contribute to a higher sedimentation rate in this study area. In the delta region of Andhra Pradesh, utilizing lime (Ca) for pond bottom treatment was quite common, which aids in balancing the pH of the pond waters and reduces pCO_2 levels in water (Chanda et al. 2022; Nagaraju et al. 2022; Patil et al., 2022).

Cations like calcium and magnesium and anions like bicarbonate, chloride, and sulfate are the leading causes of water hardness. The overall hardness ranged from 58 to 3465 mg/L. Bicarbonates and carbonates are vital in inland shrimp culture, the most crucial elements are Mg, Ca, K, and Na. Na, Ca, and Mg is essential in white-legged shrimp culture (Zacarias et al. 2019). Calcium values of few samples fall out of the permissible limits (200 mg/L). Moreover, calcium concentrations exceeded 100 mg/L, which is the standard in natural water sources, particularly groundwater (Zhao et al. 2013). However, most samples exhibit Ca values of more than 250 mg/L in aquaculture waters (Mohanty et al. 2018). Magnesium is present in natural groundwater, usually at lower concentrations (Singh and Hussain, 2016). However, most samples exceed the limit (100 mg/L), and only a few samples fall within the permissible limit. This is due to the regular usage of Mg throughout the aquaculture crop for better shrimp growth (Zacarias et al. 2019).

Bicarbonates ranges from 45 to 1100, with an average of 253 ppm. Furthermore, most of the cases bicarbonates are with the desirable range of aquaculture waters (100-300 ppm). CO_2 and HCO_3 naturally regulate the pH. When CO_2 and H_2O mix to form H_2CO_3, which increases pH, HCO_3 is formed. Because minerals and salts are frequently used in aquaculture ponds during shrimp moulting, salts and minerals can be observed in the soil at the bottom of ponds (Rasid et al. 2021; Nagaraju et al. 2022). Most of the ponds in the current research area have an alkaline environment because of the widespread aquaculture (Nagaraju et al. 2023). As a result, the hydrogeochemical facies is dominated by the HCO_3 ion. Additionally, while some metrics, like pH, salinity, and Ca, have a smaller range of standard deviations, others, like EC, TDS, alkalinity, bicarbonates, total hardness, and Mg, show a considerably wider range of standard deviations. These imply the mixing of chemical reactions brought on by seawater pumping from deep aquifers and other marine sources and the flow of water channels (Nageswara Rao et al. 2017). In the study area, Nageswara Rao et al. (2020) observed that the most prevalent ion enrichment was Na-Mg-Cl-HCO_3 and Na-Ca-Cl-HCO_3 in the groundwater. This dominance causes similar results in the surface aquaculture waters due to the continuous year-round pumping of groundwater to aquaculture ponds.

Ammonia is a vital parameter that decides the yield and growth of the shrimp/fish in the aquaculture ponds. In the study area, due to the intensive aquaculture farming, excess feed, shrimp waste, and shrimp shells increase the ammonia levels. Most of the locations witness the higher ammonia levels exceeding the permissible limit (0.1ppm). The rise of ammonia levels in aquaculture waters against the intensity of aquaculture farming is analysed to affirm the above water quality analysis. A close examination of water quality of aquaculture waters and field survey related to the intensity of farming can be linked-to know the dominance of ammonia levels in the severe farming areas. According to Yuvanatemiya and Boyd (2006) and Zhou and Boyd (2014), Ca^{2+} and Mg^{2+} usage before and during the crop can reduce or balance the ammonia levels due to the adsorption capacity (cation exchange capacity).

In aquaculture waters, nitrate can be found due to effluents and uneaten feed etc. A nitrate surplus can lead to eutrophication, which poses significant health risks and the demise of aquatic life (WHO, 1998). Nitrate levels reached their greatest point at 89.70 ppm. In addition, compared to nitrate levels detected in aquaculture waters by Alfiansah et al. (2018) and Azis et al. (2022), the concentration of nitrate load observed in the aquaculture waters in the present study is severely polluted. Few farmers used biofloc fertilization to perform shrimp aquaculture in the study area. To grow the autotrophic organisms, the biofloc was fertilized by combining calcium carbonate ($CaCO_3$), urea (CH_4N_2O), ammonium sulfate ($(NH_4)_2SO_4$), and minerals. After fertilization, biofloc inoculum (molasses, rice bran, wheat flour, and probiotic bacteria) are regularly introduced to change the autotrophs into heterotrophic systems. According to Panigrahi et al. (2022), the biofloc system was found to maintain pH, salinity, ammonia, and nitrates needed for successful shrimp production.

4.3 EVALUATION OF WATER QUALITY INDEX OF INLAND AQUACULTURE PONDS

After physicochemical analysis, an index was calculated to simplify the data. WQI was evaluated using the recommendations of the Bureau of Indian Standards (BIS) and the World Health Organisation (WHO) (WHO, 2004; WHO, 2017; Thatai, 2019). Figure 4.2 summarizes the WQI values of the aquaculture water samples from 64 locations in the western delta region. The findings indicated that most aquaculture waters are unsuitable (WQI > 100) for the next crop. In the southwestern portion of the delta, where the intensive aquaculture farming WQI values shows that the water is only for single crop (i.e., 3 to 4 months period) usage and unfit for long-term aquaculture. The continuous year-round aquaculture crop's lack of sufficient flow caused the water to stagnate, reducing the self-assimilation capacity of the delta region ecosystem, which is another reason behind the region's high pollution level. In addition, high ammonia and nitrate levels cause eutrophication of aquaculture waters and adjacent waterbodies (Zakaria et al. 2022). The WQI values ranged from 21 to 456 in various sites and showed considerable variation. As discussed, the intensity of aquaculture ponds is severe in the delta region of Andhra Pradesh, where many villages are bounded by aquaculture ponds. In this context, the water quality limits were compared with the drinking water standards because most of the study area locations depended on the aquaculture waters for their drinking purposes. WQI values shows that the water is unfit for usage, including drinking, long-term aquaculture, and residential purposes.

The WQI values ranged from 21 to 456 in various sites and showed considerable variation. According to sample locations and prior research, the southwestern region of the delta had higher water quality index values. As one moves upstream, the pollution level steadily rises from the southwestern delta to the north-eastern delta (Nagaraju et al. 2022). Moreover, the same situation is reflected in the expansion of land cover of aquaculture bodies from the southwestern delta to the north-eastern delta from 2017 to 2020 (Nagaraju et al. 2022).

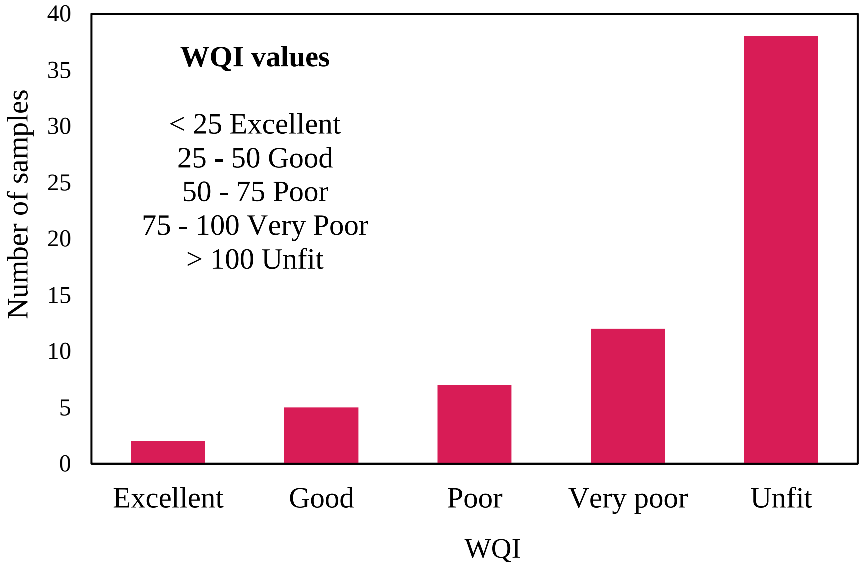


Figure 4.2 Water quality index of aquaculture waters

In inland aquaculture-intensive regions, ammonia is the primary concern in aquaculture waters due to intensive farming. Nagaraju et al. (2023) reported the exciting finding that due to ionic exchange, the hydraulic behaviour of aquaculture pond bottom clays exposed to effluents exhibits a considerable detrimental impact on the permeability of clays. Higher permeability is observed in the clay particles interacting with the ammonia in the effluents. Even prolonged exposure to ammonia and clays has adverse effects on the ecosystem. Researchers have addressed the adverse effects of ammonia levels in aquaculture ponds globally. According to Luo et al. (2018) aquaculture scenario study from China, nitrogen releases, aggregation, sediment deposition, and discharge into the ocean waters increased by 9.05 times, 0.24 times, 9.04 times, and 2.56 times from 1978 to 2015, respectively. Recently, Sultana et al. (2022) reported intensive aquaculture increases the toxic algal blooms, which could result in significant fish fatalities. A single hazardous algal bloom fish-kill event in Japan was estimated to have cost the country US$330 million. No single research publication highlighting nutrient pollution (eutrophication) and the danger of toxic algae blooms in India was recognized.

Generally, ammonia is influenced by temperature, salinity, alkalinity, nitrates, organic particulate matter, calcium, and magnesium. However, ammonia can be varied with the parameters mentioned above but not vice versa. Assessing or monitoring ammonia levels is a significant task for practitioners and engineers.

The nutrients with phosphorus (P) and nitrogen (N) bases are primary suspended particles dissolved in the feed-derived wastes (Herath and Satoh, 2015). The efficiency of nitrogen in shrimp N assimilation has significant effects on the economics of inland shrimp farming as well as the quality of the water. The inherent efficiency of nutrient use by shrimp suggests that the ability of aquaculture ponds to assimilate nitrogenous effluent may be a limiting factor for N loading, which could negatively affect water quality and shrimp growth. In aquaculture ponds, dissolved inorganic nitrogen build-up will most likely restrict the feeding rate after dissolved oxygen. Protein catabolism results in the excretion of ammonia, which can be hazardous if left to build up. Hyperactivity, convulsions, loss of equilibrium, lethargy, and coma are symptoms of ammonia intoxication. However, rather than manifesting as acute toxicity that causes mortality, ammonia toxicity in aquaculture ponds is most likely represented as the sublethal inhibition of shrimp growth or immunocompetence. The pH, temperature, alkalinity, and total ammonia concentration measured in the shrimp shell affect how hazardous unionized ammonia (Venkateswarulu et al. 2019). At high pH and temperature, ammonia is more toxic to shrimp, which causes the ionization equilibrium to change in favour of the poisonous, unionized gaseous form. In the late afternoon, low alkalinity ponds that are poorly buffered are more likely to have high pH and unionized ammonia. Ammonia excretion contributes to the N flux in aquaculture ponds (Zhong et al. 2015).

To understand the severity of the aquaculture scenario in the delta region of Andhra Pradesh, a peer glance at the nutrient levels in the aquaculture waters and their intensity was mentioned in Table 4.2. The nitrogen compounds levels in the current study area show higher concentrations compared to the previously published studies

(Alfiansah et al. 2018; Azis et al. 2022). Few authors have reported that aquaculture wastewater can be utilized for shrimp rearing and adjacent farming (Chatla et al. 2020; Iber and Kasan, 2021). However, in the field, the diseased and contaminated waters in the aquaculture ponds affect the adjacent aquaculture farms and, in the case of paddy fields, due to salinity. Strengthening this statement, Yuan et al. (2019) reported that inland aquaculture ponds considerably influence agriculture and may lead to greenhouse gases and global warming.

Table 4.2 Ammonia and nitrates levels in aquaculture waters

Parameter	Current study	Alfiansah et al. (2018)	Azis et al. (2022)
NH_3	0.18-6.14 mg/L	0.37-0.60 mg/L	0.01-0.18 mg/L
NO_2	0.04-2.39 mg/L	0.20-0.33 mg/L	0.37-0.44 mg/L
NO_3	1.21-91.21 mg/L	0.18-0.21 mg/L	1.69-1.96 mg/L

CHAPTER 5

SUBSOIL CHARACTERIZATION AND EFFECT OF AQUACULTURE SLUDGE ON CLAY PROPERTIES

5.1 GENERAL

In general, constructing new ponds involves the excavation of surface soil and use as a fill material for earthen embankments. Most aquaculture ponds are typically on clayey deposits with a low amount of organic matter and nutrients at the initial stage of the crop. Chemicals and pesticides are sometimes used carelessly in some areas, especially in intensive shrimp farms in the delta region of Andhra Pradesh. In aquaculture facilities, there is no special legislation for disease control. Using excessive feed and antibiotics results in microbial degradation and organism mortality, which worsens the pond's anaerobic environment. The control of sediment in pond-based aquaculture has a significant impact on the development of carbon and the emission of carbon dioxide. The deposition of organic carbon in the aquaculture pond makes the environment more anaerobic, which promotes the emergence of hazardous microbial by-products and the instability of benthic ecosystems. In the study area, ponds are commonly drained, and the deposited sediments are kept exposed to the air to encourage organic matter mineralization. Fertilizing is occasionally used to encourage rapid oxidation, and lime is regularly added to the pond to raise the pH and disinfect the water.

In an intensive aquaculture zone, continuous year-round crops and surface soil exposed to aquaculture effluents may increase the nutrients, organic matter, particulate matter, and phytoplankton blooms. This may further influence the physicochemical and geotechnical characteristics of the surface and subsoil. In this study, in dried aquaculture ponds after crop, soil samples were collected with the help of PVC pipe with a diameter of 15cm and length of 1.8m penetrated subsoil and collected undisturbed soil samples. The collected samples were tested for physicochemical characteristics and geotechnical properties in one series. Another series, collected aquaculture sludge, was exposed to the expansive clay and determined the blended clays' swell-shrink behaviour and cation exchange capacity. Moreover, the micro-structure of the blended clays was assessed to understand the variations in the texture and morphology.

5.2 PHYSICOCHEMICAL CHARACTERISTICS OF AQUACULTURE POND SOILS

Table 5.1 shows the physicochemical test results of soil samples collected from the soils exposed to various concentrations of aquaculture sediments. From Table 5.1, by comparison, it was clear that Zone-III soils exhibited higher potassium and phosphorus contents. This is because the uneaten feed (phosphorus) strongly adsorbs the clay. Moreover, aquaculture pond soil-adsorbed phosphorus will not release into the water due to the highly insoluble behaviour of phosphorus.

Table 5.1 Physicochemical characteristics of aquaculture pond soils

Zone	Village	p^H	TDS (ppm)	EC (ds/cm)	TOC (%)	TN (kg/acre)	P (kg/acre)	K (kg/acre)	S (kg/acre)	Na (ppm)
Zone-III	V1	8.2	2.5	5.1	1.45	116	507	570	245	238
	V2	8.0	4.2	2.2	2.28	1077	472	432	230	215
	V3	7.7	2.9	2.5	3.98	125	491	848	218	178
	V4	7.5	2.1	5.4	3.72	32	484	564	156	165
	V5	7.4	1.7	2.3	2.99	118	490	388	165	182
Zone-II	V7	7.2	1.8	2.7	2.22	188	377	375	154	174
	V8	7.2	1.6	2.4	1.12	85	257	415	145	163
	V9	7.8	1.2	1.8	1.18	102	186	345	205	162
	V10	7.7	0.5	0.7	1.45	78	154	386	88	125
	V19	7.6	1.1	1.9	1.85	84	132	243	106	128
Zone-I	V27	7.6	1.7	2.6	0.84	95	195	334	115	134
	V28	7.6	1.2	2.3	0.74	68	88	355	125	185
	V34	7.4	1.2	1.8	0.84	76	85	245	155	215
	V35	7.0	1.4	1.3	1.05	82	157	175	145	113
	V39	7.4	1.2	1.7	1.16	82	165	235	165	151

In the study area, test results exhibited cations trend was $Ca^{2+} > Na^{+} > Mg^{2+} > K^{+}$. This could be due to the excessive lime, potassium, and magnesium usage in the ponds. The discharged effluents from the aquaculture ponds had a higher concentration of nutrients, which leads to eutrophication, higher contents of salinity reduce the vegetation growth, and higher concentrations of chemicals lead to ecological imbalance.

5.3 GEOTECHNICAL CHARACTERIZATION OF POND SOILS

The assessment of the index and engineering properties of the soils that comprise the pond bed and embankment constitute geotechnical characterization of pond soils.

5.3.1 Plasticity characteristics and hydraulic conductivity of pond soils

Table 5.2 shows the test data of the plasticity characteristics and hydraulic conductivity of soil samples collected in the aquaculture ponds. All the tested expansive clay samples possess intermediate to high compressibility. The samples' free swell index ranged from 55 to 145%, and Zone -I samples exhibited higher free swell index values than Zone-II and Zone-III.

This could be due to the lime content in the aquaculture water that reacts with the clayey soil. Further, hydraulic conductivity also improved due to the flocculation of particles and ion exchange. By comparison, Zone-III and Zone-I, the plasticity behaviour of the Zone-III pond bottom clays exhibits low plasticity behaviour due to the cation exchange of clays and aquaculture sludge. The observed trends are in agreement with Khodary et al. (2020) that the leachate concentration of industrial solid waste landfill shows that reduction of plasticity behaviour of clays due to the free ions such as K^{+}, NH_4^{+}, Ca^{+2}, and Na^{+} replaced the cations of the clay surface (double diffusion layer). Further improves the pores between the particles. Moreover, monovalent cations reduce the double diffusion layer of clays and adsorbed water. Hydraulic conductivity is high in Zone-III because of the flocculation and agglomeration of particles and ion exchange of clay particles and lime content.

Table 5.2 Plasticity and hydraulic behaviour of the soils

Zone	Sample Id	Liquid limit, LL (%)	Plastic limit, PL (%)	Plasticity index, PI (%)	FSI (%)	Hydraulic conductivity (cm/sec)
Zone-III	V1	65	21	44	85	3.2×10^{-5}
	V2	60	24	36	80	5.1×10^{-5}
	V3	68	20.5	47.5	75	6.8×10^{-6}
	V4	44	18	26	55	5.5×10^{-5}
	V5	54	21.5	32.5	85	3.6×10^{-5}
Zone-II	V7	62	32.5	29.5	75	2.8×10^{-6}
	V8	64	33	31	55	5.6×10^{-7}
	V9	84	33.5	50.5	130	6.9×10^{-7}
	V10	64	19.5	44.5	80	4.4×10^{-6}
	V19	84	29	55	120	4.5×10^{-6}
Zone-I	V27	80	30	50	105	4.2×10^{-7}
	V28	89	31	58	130	4.6×10^{-6}
	V34	82	32	50	114	5.0×10^{-6}
	V35	76	34	42	145	5.5×10^{-7}
	V39	88	25	63	136	4.4×10^{-7}

5.4 Aquaculture sludge leachate interaction with clays

In this study, expansive clay was collected from a residential area away from aquaculture ponds, was not contaminated with the aquaculture sludge, and a thorough sampling process was conducted. Aquaculture sludge was collected from the five years old dry shrimp pond where solid waste from the aquaculture operation accumulates over time. The source of aquaculture sludge was selected to ensure it was representative of the organic-rich waste generated in aquaculture ponds. Before the series of experiments, both the expansive clay and aquaculture sludge underwent oven drying (24 hours) and pulverized to 425μm passing IS sieve, as highlighted in the Chapter 3.

In general, the swelling behaviour of expansive clays depends on moisture content, surface area, particle dimension, morphology, and suction (Estabragh et al. 2013; Rao et al. 2021). Moisture content present in the soil reflects the behavior of the structure of clays and densities. Several investigations showed the behavior of expansive clays exposed to continuous wetting and drying in terms of suction, void ratio, water content, and chemical additives (Estabragh et al. 2013; Yilmaz and Marschalko, 2014). Besides the moisture content, another major factor is surface area which reflects the surface attractions or forces. Positive ions generally attract dry clay surfaces, and moist clay with an unbalanced negative charge strongly attracts cations.

Further surface area contributes to the thickness of the clay sheets and the formation of a double diffusion layer (Eyo et al. 2019; Rao et al. 2021). Morphology and particle dimension depended on the clay mineralogy, chemically bonded water, pore spaces, and applied load (Fityus and Buzzi, 2009; Ito and Azam, 2010). Volume change of clays was influenced by suction in unsaturated clays. Moreover, lateral confinement, compaction or surcharge, degree of saturation, and suction decide soil stability (Estabragh et al. 2013; Eyo et al. 2019; Ikeagwuani and Nwonu, 2019; Adem and Vanapalli, 2005). From the previous studies, chemical constituents significantly influence the volume change behaviour of expansive clays. It is certain that ensued chemical reactions between clays and foreign materials are strongly dependent on many factors such as the chemical composition of additives, surface area, clay state (powders and lumps), humidity, and curing condition (Chaiyaput et al. 2022) To the author's knowledge, no research was documented on the effect of aquaculture sludge on the swell-shrink behaviour of expansive clays due to the interdisciplinary domain. In general, inland aquaculture practices in developing countries are worrisome due to the negative environmental impact. Aquaculture sludge and solid waste are more concerned nowadays because they are rich in proteins, volatile solids, organic particulate matter, ammonia, nitrates, minerals, and other chemicals (Estevez et al. 2022).

5.4.1 Effect of aquaculture sludge content on plasticity characteristics of clays

In this study, understanding geotechnical properties such as Atterberg limits, free swell index, and swell-consolidations is crucial for evaluating the potential impacts of aquaculture pond subsoil on the surrounding environment. The study of these parameters allows for a comprehensive assessment of subsoil and potential effects on surface and groundwater systems. Moreover, in the study area, a common practice of excavation of aquaculture effluent sedimented subsoil every 2 or 3 years, and the same used as fill material for many sites (expansive clays) were developing as commercial and residential apartments, commercial complexes, schools, hospitals, and industries. So, understanding the behaviour of aquaculture sludge, blended expansive clays, should be studied with various methods to effectively deal with aquaculture sludge and lessen the environmental concerns it may raise. Plasticity characteristics were significantly improved by adding aquaculture sludge to clays. Table 5.3 shows the plasticity characteristics testing data with varying percentages of aquaculture sludge as 0%, 5%, 10%, and 15% of the dry weight of clayey soil.

The liquid limit value decreased with an increasing aquaculture sludge content. This is due to the rich Si^+ and Ca^+ ions in the aquaculture sludge contributing to ion exchange between clays and aquaculture sludge. Plastic limit value show increased with an addition of aquaculture sludge content. The plasticity index value is the numerical difference between the liquid and plastic limits. The plasticity index value shows reduced with an increase in aquaculture sludge content. The significant reduction in plasticity index is because of the effective chemical reactions of calcium-rich aquaculture sludge leading to flocculation wherein particles in the blends increase in their sizes, apart from the replacement of expansive clay particles by them.

It is well known that the plasticity index of expansive montmorillonite clays is high. This is because the size of the montmorillonite clay particles are the smallest. If their size increases through flocculation brought about by aquaculture sludge, the plasticity index decreases significantly. This is in accordance with previous research (Phanikumar and Nagaraju, 2018).

Table 5.3 Effect of aquaculture sludge content on soil properties

Parameters	Aquaculture sludge content			
	0 (%)	5 (%)	10 (%)	15 (%)
Plasticity characteristics				
FSI, %	155	127	98	77
Liquid limit, %	84	75	58	44
Plastic limit, %	23	25	26	28
Plasticity index, %	61	50	32	16
Swell-consolidation characteristics (clay powders)				
Rate of heave, mm	1.44	1.31	1.25	1.07
Swell potential, %	7.20	6.55	6.25	5.35
Swelling pressure, kPa	115	140	180	205
Rebound, mm	0.45	0.35	0.28	0.18
Linear shrinkage, %	11	7	5	3
Cation exchange capacity (CEC)				
CEC, mEq/100g	48.4	42.6	37.5	29.8
Chemical constituents (weight, %)				
SiO_2	68.29	30.53	19.60	10.86
Al_2O_3	25.91	11.20	5.31	4.94
MgO	3.64	1.76	1.13	1.04
CaO	2.16	4.89	8.97	9.65
K_2O	-	2.33	6.42	4.84
$CaCO_3$	-	10.82	32.32	46.26

Table 5.3 presents the effect of aquaculture sludge content on the free swell index of the clay blended with the aquaculture sludge content. A decrease in the free swell index was observed with the addition of aquaculture sludge content from 0% to 15%. As clayey soil particles are replaced by aquaculture sludge content, flocculation occurs in the blend, which further reduces the thickness of the double diffusion layer.

FSI values decreased from 155% to 77% when the addition of aquaculture sludge content increased from 0% to 15%, rendering the blends non-swelling.

Apart from plasticity behaviour and free swell index, understanding the effect of the cation exchange phenomenon in the blended clay is advantageous. In this study, to comprehend this, cation exchange capacity (CEC) values were determined, and the results were tabulated in Table 5.3. The CEC values were decreased with an increase in aquaculture sludge content. Aquaculture sludge was rich in Ca^{2+}, K^{+}, and NH_4^{+}. K^{+} and NH_4^{+} ions were more dominant in attracting clay surfaces, decreasing double diffusion layer thickness, and swelling. The dominance of NH_4^{+} ions present in the aquaculture sludge in the blend can be reasoned to be the collapse of the double diffusion layer and the flocculation of clay particles.

In general, CEC is the fundamental property by which swelling occurs in expansive soils. Almost every piece of literature proposes the same fact (Lilkov et al. 2011). However, swelling in clays can occur when they are dominant with mineral montmorillonite. Keeping a side natural expansive soil, aquaculture sludge blended clays are generally referred to as either Ca^{2+} rich or NH_4^{+} rich. This inherently indicates that these soils are predominant with either Ca^{2+} or NH_4^{+} content, which controls the overall behaviour of the soil. This is how the role of Ca^{2+} or NH_4^{+} contents become critical when dealing with expansive grounds. It is well understood and proven that Ca-based soils exhibit lesser swelling or volume change than NH_4^{+} based soils due to their innate affinity to adsorb more secondary water. Ca having higher valance forms a thinner diffuse double layer than NH_4^{+} does. This is the primary reason behind the evolution of Ca-based additives. Besides this, Ca is highly pozzolanic, and when it is admixed with water, it hydrates (Mitchel and Saga, 2005). The entire process of Ca reaction is subdivided into (a) hydration, (b) cation exchange, (c) flocculation and agglomeration, (d) pozzolanic reaction, and (e) potential carbonation.

5.4.2 Effect of aquaculture sludge on swell-consolidation behaviour of clays

The influence of aquaculture sludge content on the rate of heave and swell potential of clays was presented in Figures 5.1 and 5.2.

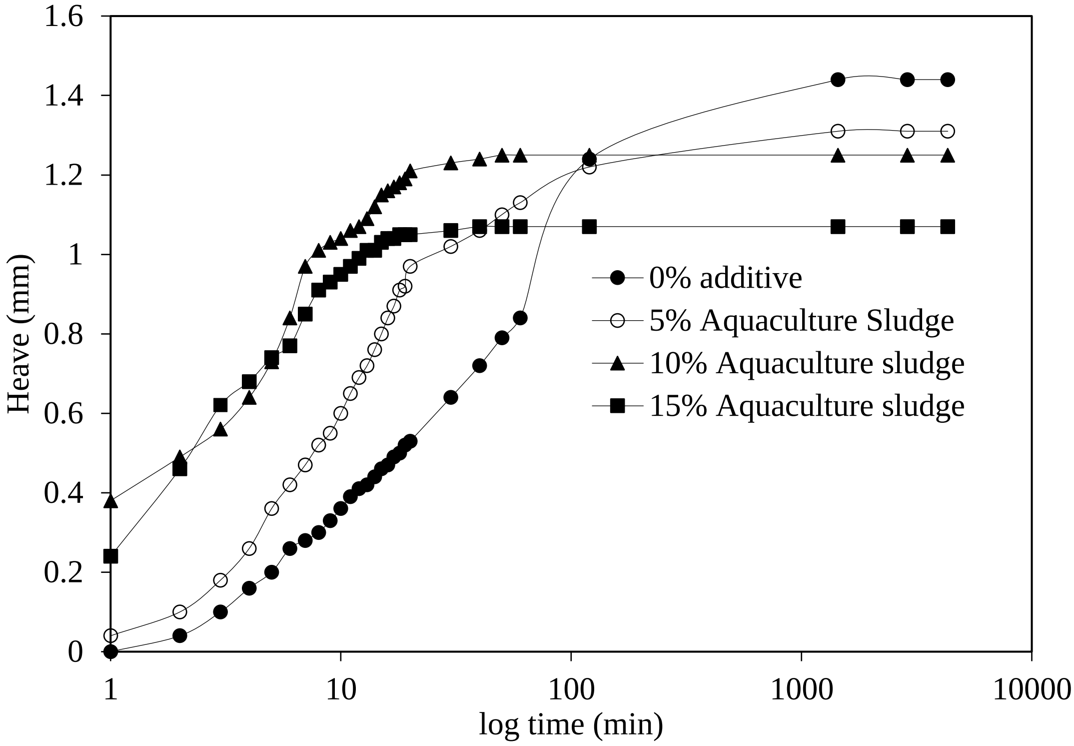


Figure 5.1 Effect of Aquaculture sludge on rate of heave

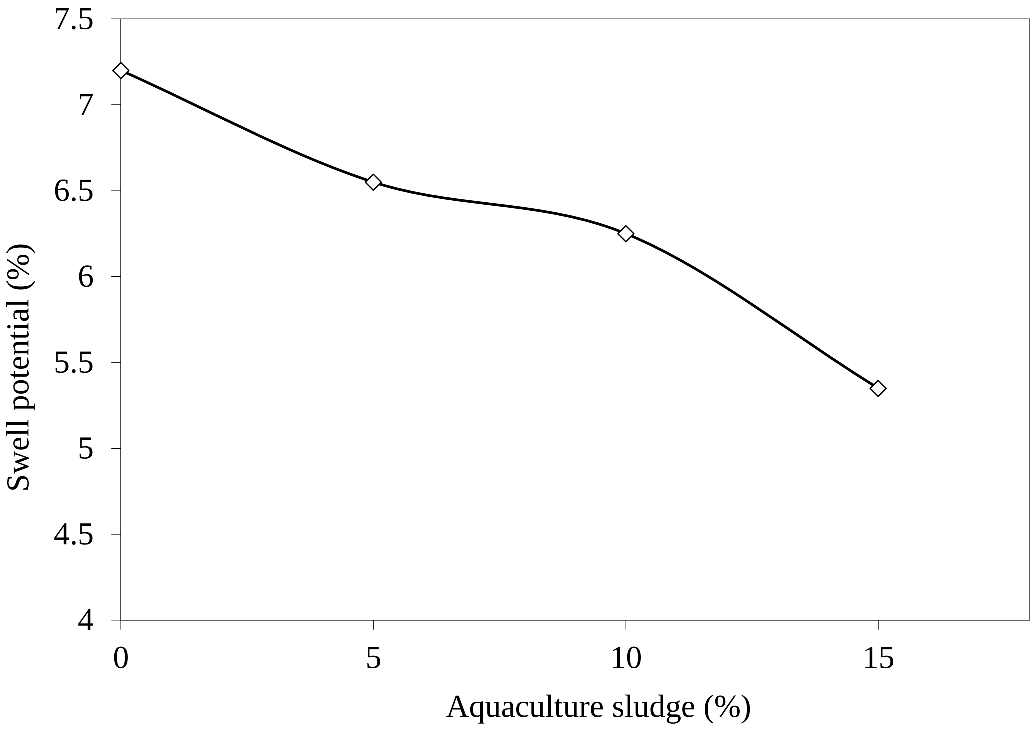


Figure 5.2 Effect of aquaculture sludge on swell potential

A decrease in the heave and swell potential rate was observed with the addition of aquaculture sludge. This might be due to the cation exchange between the clays and aquaculture sludge. The interesting point was aquaculture sludge leachate having an alkaline environment (pH value greater than 8.5) allows the dissolution of silica and alumina ions in the clays. Further, dissolved ions react with Ca^{2+} ions, contribute to dense phases of calcium silicates and aluminates. This was associated with the formation of cementitious compounds, which had a significant effect on the rate of heave and swell potential.

Figures 5.3 and 5.4 present the e-logp curves and variation of swelling pressure of the expansive clay blended with an aquaculture sludge, respectively. The e-logp plots exposed clearly that swelling pressure values significantly increased with increasing aquaculture sludge content. Swelling pressure values increased from 115kPa to 205kPa when aquaculture sludge content increased from 0% and 15%. This is due to the exchangeable ions and flocculation of soil particles.

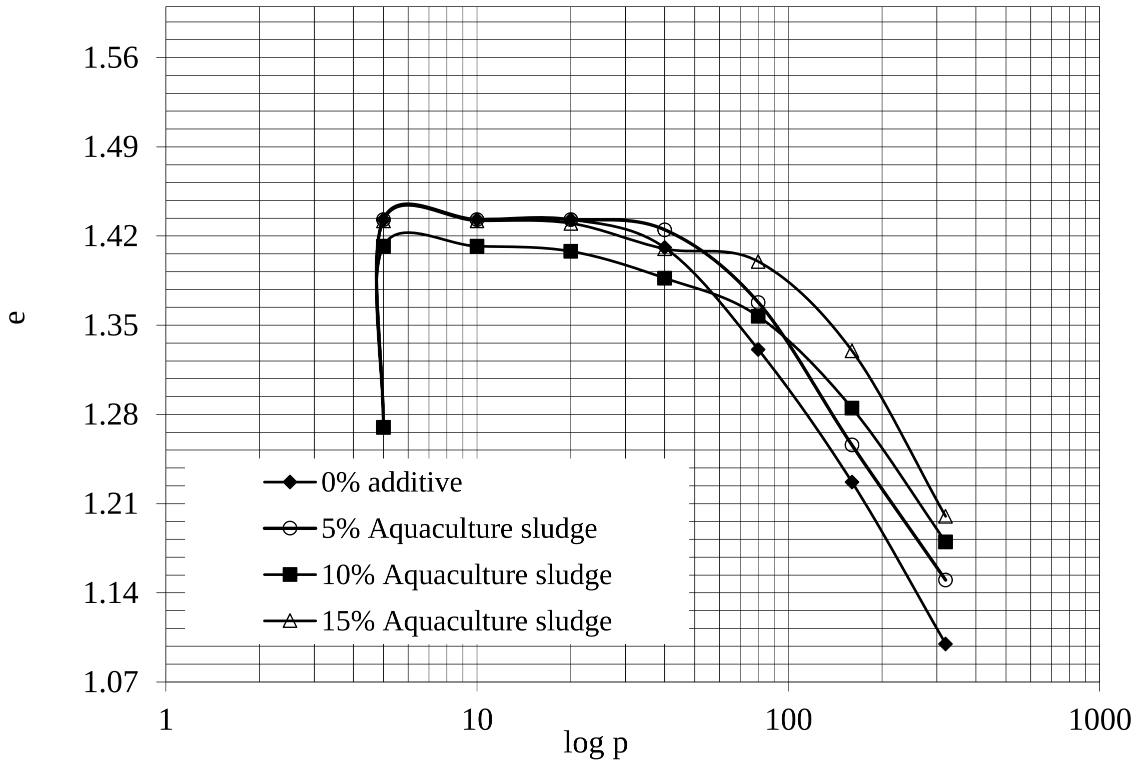


Figure 5.3 e-log p curves

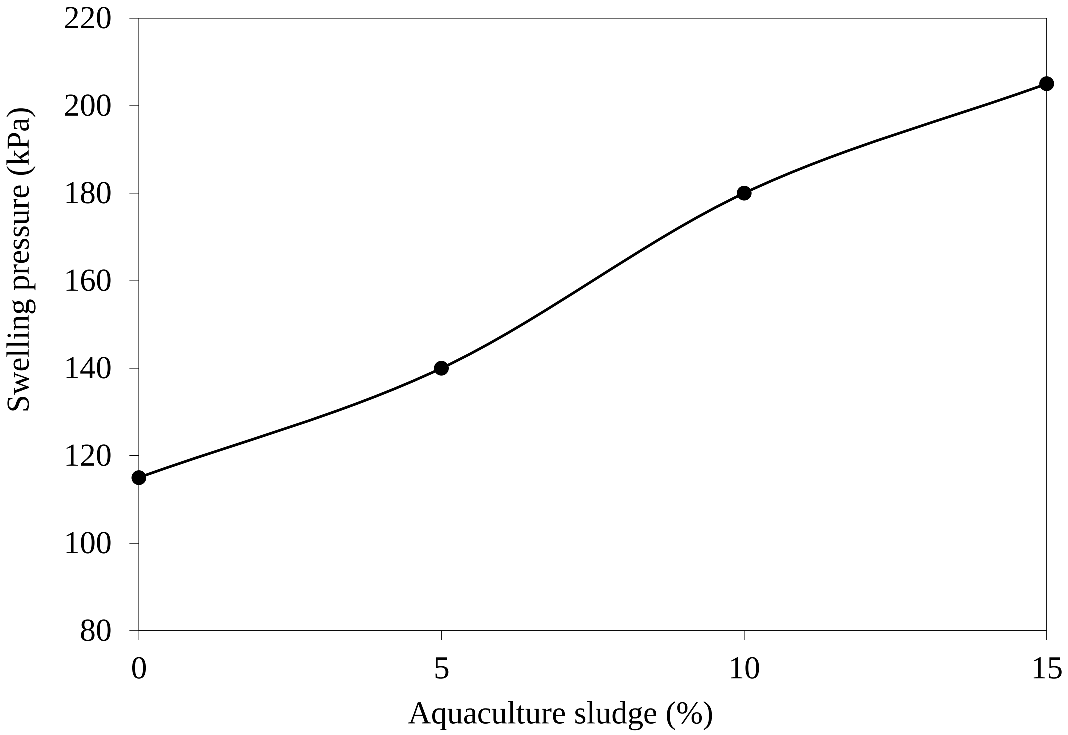


Figure 5.4 Effect of aquaculture sludge on swelling pressure

This helps the specimens to form dense phases and resist the compressive loads. As per Mitchel and Soga (2005), the cation replaceability order of Al^{3+}>Ca^{2+}>Mg^{2+}>NH^{+}>K^{+}>Na^{+}. Moreover, ions' exchangeable capacity (adsorption or desorption) depends on the valance and hydrated radius.

Aquaculture sludge consists of proteins and volatile solids due to excess feed and shrimp species. Prolong the time of culture, aquaculture sludge release ammonia and nitrates. Ammonia is one of the favourable monovalent cations for exchangeable ions. During aquaculture, sludge exposed to clays cause adsorption of NH^{+} with the clay surfaces, which reduces the double diffusion layer and pore water adsorption capacity. Further, it allows the aggregation of clay particles and increases swelling pressure.

Figure 5.5 presents the variation of rebound and linear shrinkage with the addition of aquaculture sludge in the composite samples. Rebound and linear shrinkage values decreased with an increase in aquaculture sludge content.

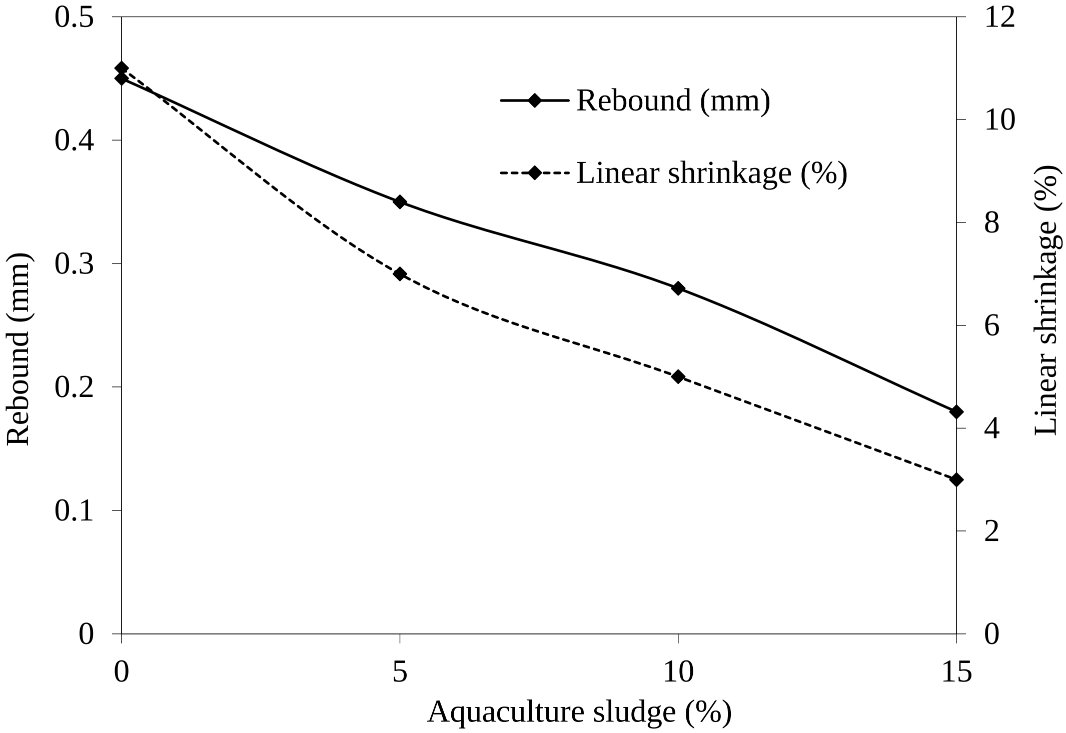


Figure 5.5 Effect of aquaculture sludge on rebound and linear shrinkage

Rebound and linear shrinkage values dropped from 11 to 3 and 0.45 to 0.18, respectively, when aquaculture sludge content increased from 0% and 15%. The decrease in linear shrinkage may be due to Ca ions contributing flocculation of particles and suppressing the adsorption capacity of clays. For the same reason, the rebound was decreased with the addition of aquaculture sludge content.

Several researchers have brought out the influence of chemical additives on the one-dimensional swell-consolidation behaviour of clay powders (passing from the 425µm sieve) (Phanikumar and Nagaraju, 2018; Phanikumar et al. 2022). However, the least attention is paid to understanding the chemical constituents of one-dimensional swell-consolidation of clay lumps. To understand the swell-shrink behaviour of clay lumps blended with aquaculture sludge was studied. Figure 5.6 shows the effect of aquaculture sludge (15% by dry weight of soil) on clay powders and lumps.

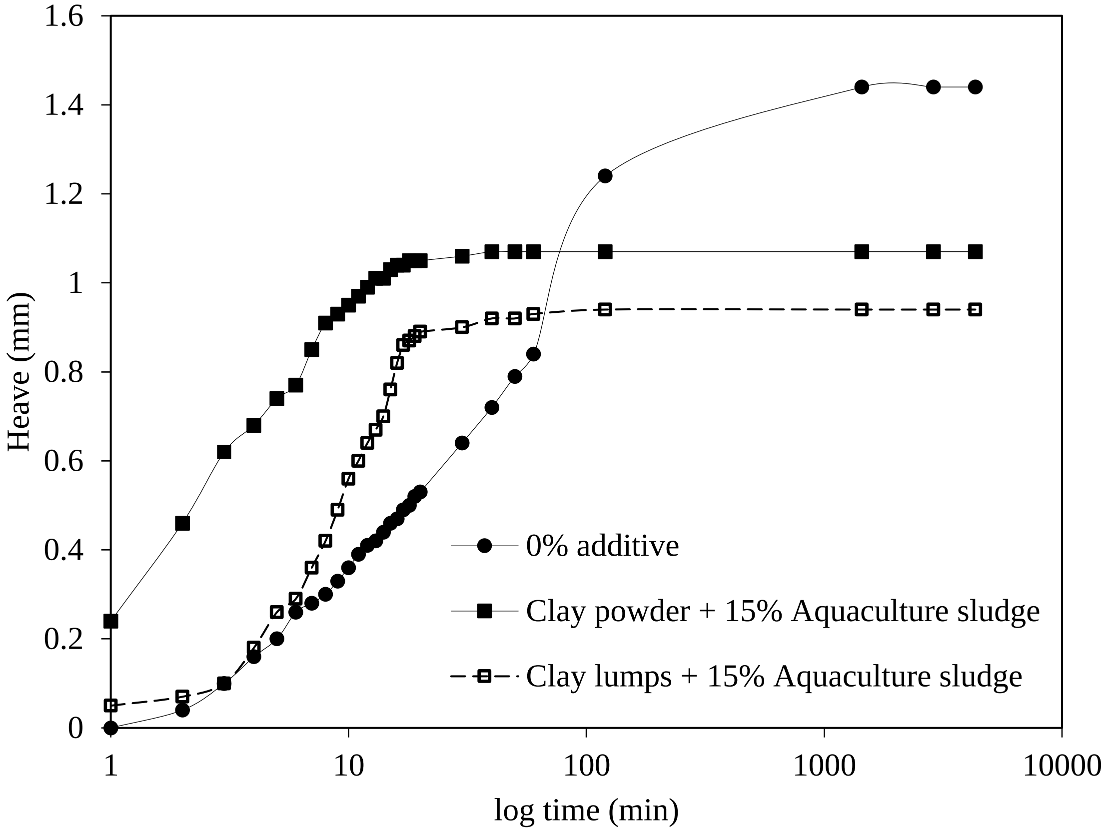


Figure 5.6 Rate of heave plots of clay powder and clay lumps

The heave rate was found less in altered clay lumps than in the clay powders. This is due to the flocculated clay lumps exhibiting unsaturated pores within the clay lumps. Moreover, exchangeable cations vary with the size of the particles, surface area, and clay-pore fluid matrix. In general, bentonite exhibits a higher heave phenomenon than expansive clays due to the higher surface area and chemical composition of bentonite. Swelling pressure values of 15% aquaculture sludge blended clay powders and lumps are 205kPa and 218kPa, respectively. The increase in swelling pressure of blended clay lumps than the clay powders is due to the more compressive resistance offered by the clay lumps (Phanikumar and Nagaraju, 2018; Phanikumar et al. 2022).

5.4.3 Effect of aquaculture sludge on micro-structural behaviour of clays

Scanning electron microscopy (SEM) analyses were carried to expansive clay and clay blended with the aquaculture sludge content. The surface texture and particle sizes were clearly observed in the SEM images of all the blends.

Figures 5.7 to 5.10 demonstrate the significant effect of aquaculture sludge content on the clays, revealing flocculation and aggregation of clays. Figures 5.9 and 5.10 indicate the SEM micrographs of the clays blended with 10% and 15% aquaculture sludge content, respectively, which displayed an increase in the size of the particles and pore radii. Moreover, examinations under the magnification of 2000 show that clay's structure has been transformed from individual particle form to integrated form. This might be due to the dissolution of Al and Si ions contributing to the hydrates of Al and Si (vide Figures 5.9 and 5.10).

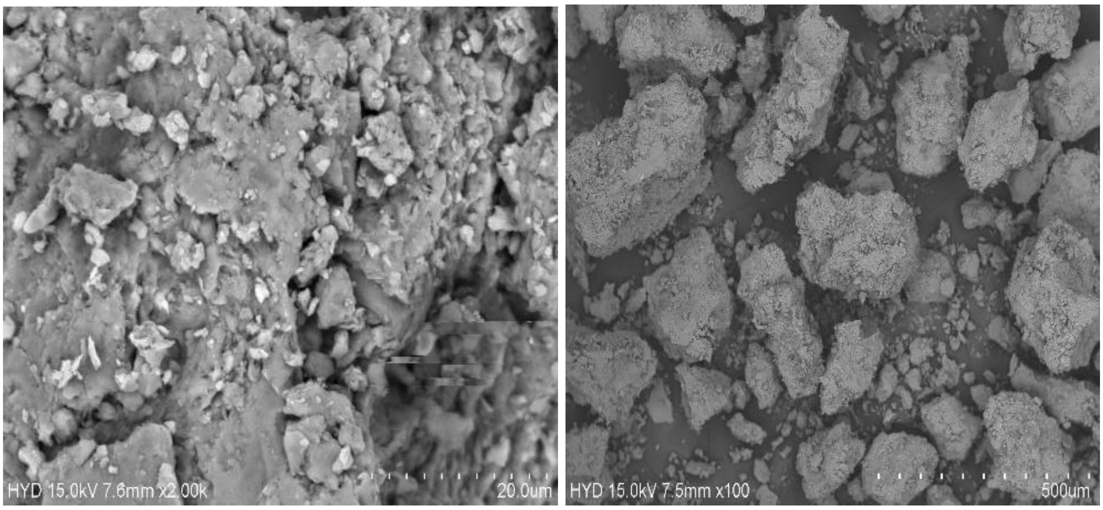


Figure 5.7 SEM images of the virgin clay sample

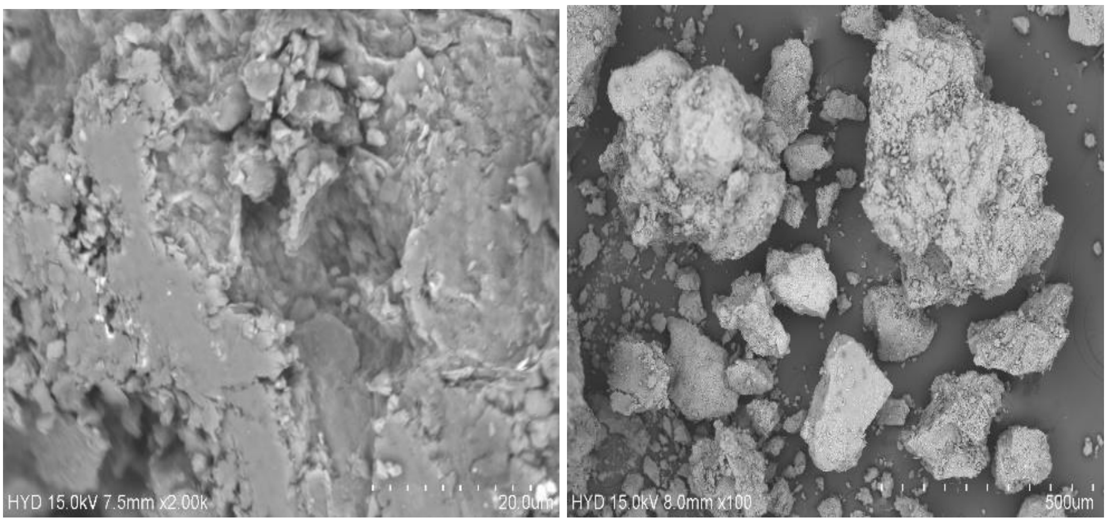


Figure 5.8 SEM images of the clay blended with 5% AS

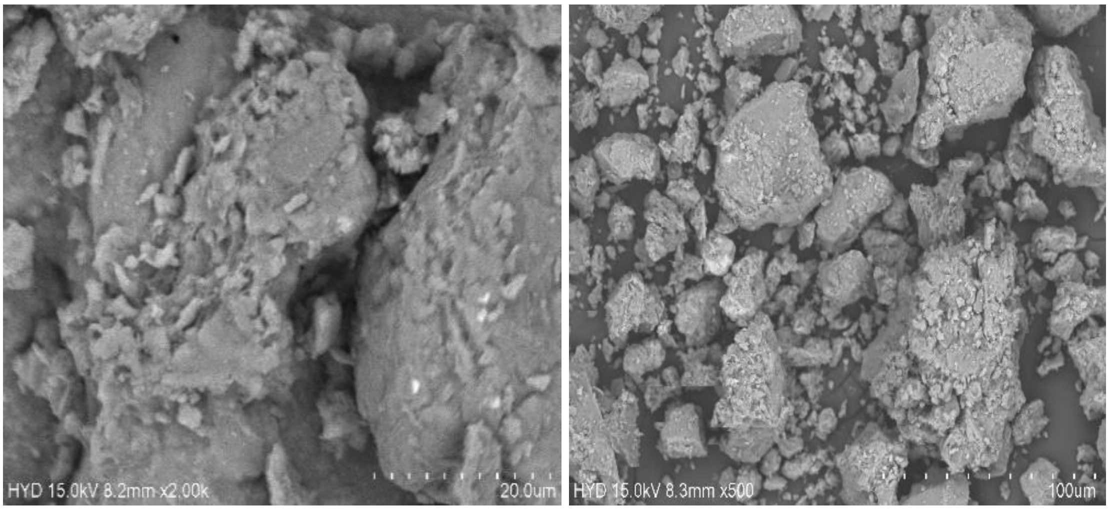


Figure 5.9 SEM images of the clay blended with 10% AS

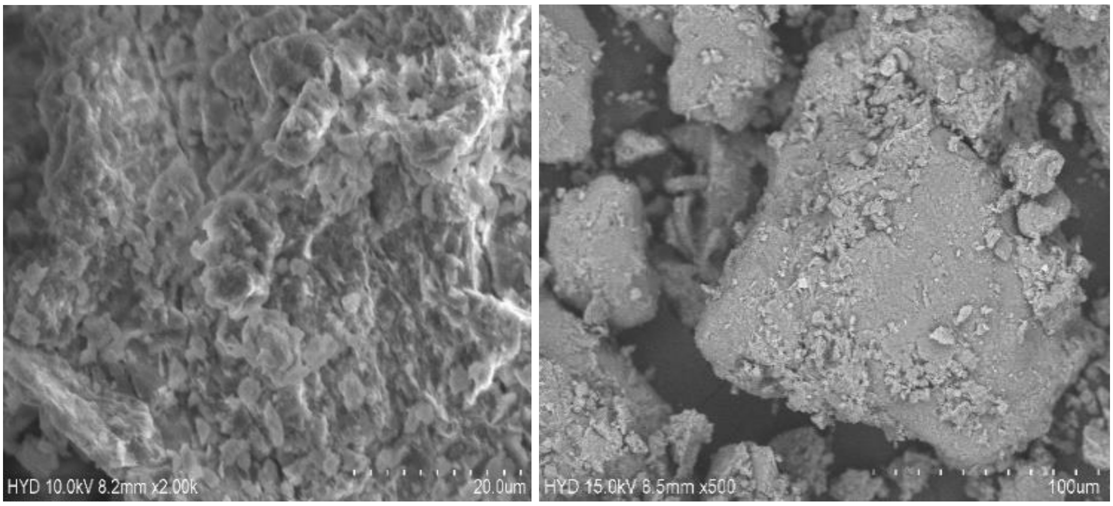


Figure 5.10 SEM images of the clay blended with 15% AS

The integrated form of soil particles reduces the surface forces and voids between the particles. Further, it is likely to have higher resistance against compression and shear forces. In aquaculture sludge blended samples, leachate exposed to the clay surroundings forms a dense fabric agglomeration of particles. The formation of agglomeration or flocculation of clay particles is responsible for the decrease in the plasticity nature and swelling behaviour of clays (Bhuvaneshwari et al. 2020).

Energy dispersive spectrometry (EDS) analyses were carried to expansive clay and clay blended with the aquaculture sludge content to know the chemical compounds and their reactions. The mineralogical analysis is presented in Table 5.3. Figures 5.11 to 5.14 show the variation of the chemical composition of the blends with an increase in aquaculture sludge content.

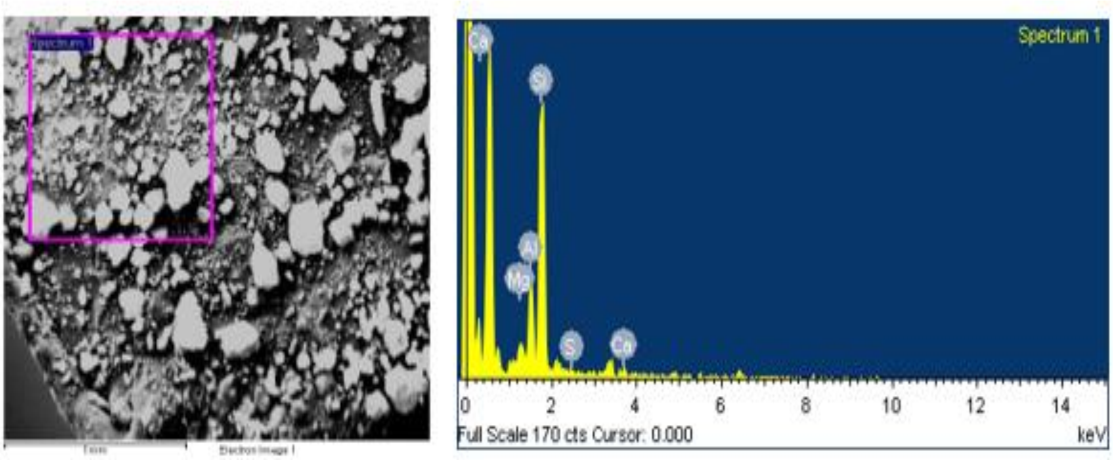


Figure 5.11 EDS spectra of the virgin clay sample

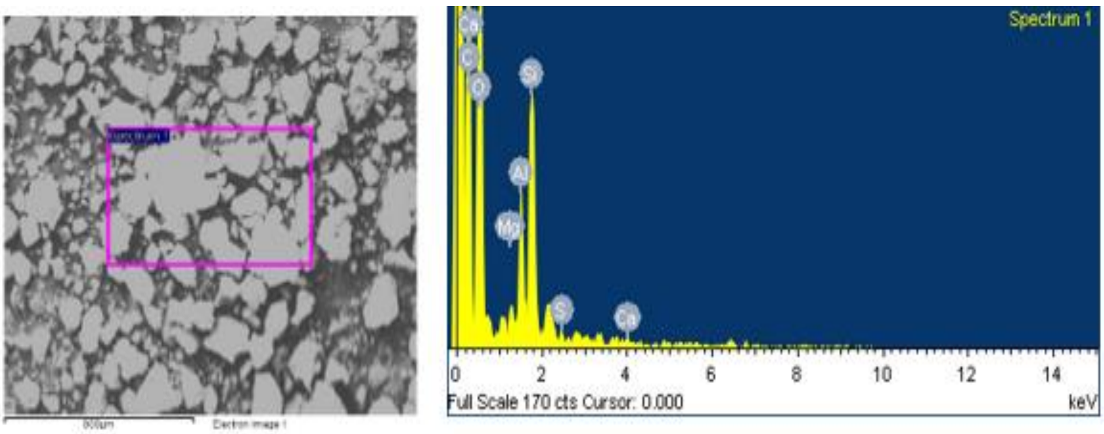


Figure 5.12 EDS spectra of the clay blended with 5% AS

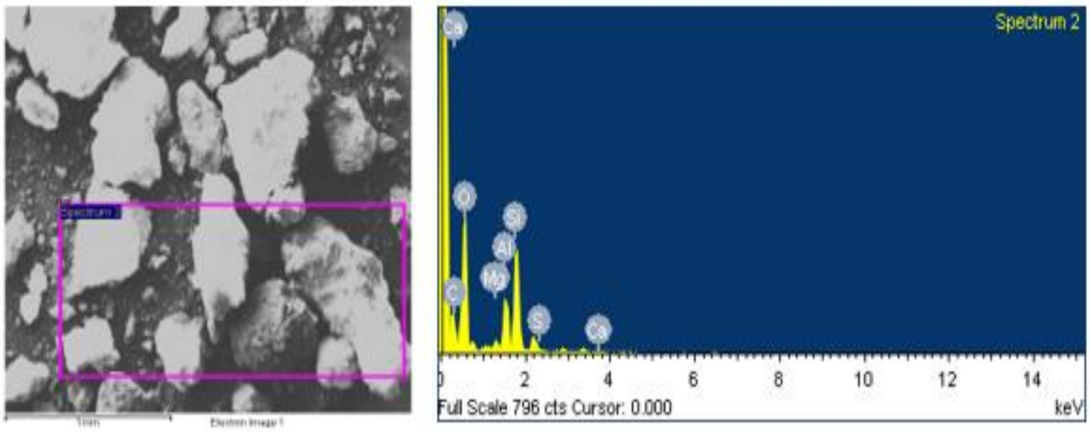


Figure 5.13 EDS spectra of the clay blended with 10% AS

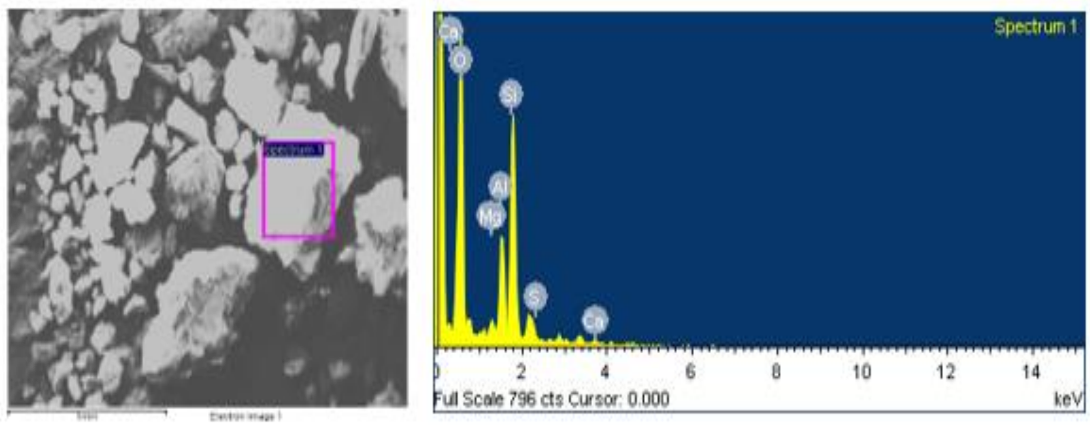


Figure 5.14 EDS spectra of the clay blended with 15% AS

Based on the EDS analysis, chemical composition (%) reflects the SiO_2 and Al_2O_3 decrease with the addition of aquaculture sludge content. This is due to the dissolution of Si and Al ions.

Moreover, in clays, Si/Al ratio greater than 2.1 represents the clay has montmorillonite mineral (Ramirez et al. 2011). Another hand, CaO, and $CaCO_3$ values show a significant increase with an addition of aquaculture sludge content. This will partly destroy the tetrahedral and octahedral structures of montmorillonite clays. Further, it decreases the thickness of the interlayer distance between the sheets and improves the structure of clays.

The influence of the chemical composition of clays blended with various chemical additives such as fly ash, rice husk ash, ground granulated blast furnace slag, cement, and lime on the swell-shrink behaviour of clays has been brought out by many researchers (Mitchel and Saga, 2005). However, limited research was carried out on the clays to quantify and illustrate the effect of chemical constituents on clay structure. To quantify the exact effect of chemical composition and their effects on clay structure, XRD traces were identified to characterize the structure of the clays.

X-ray diffraction analyses (XRD) was carried to expansive clay and clay blended with the aquaculture sludge content. Figure 5.15 represents the XRD traces of the clay and clays blended with the aquaculture sludge content. XRD patterns indicate the quartz (crystalline) structure in the blends has higher contents of aquaculture sludge. By comparison, it is evident that the highest diffraction peaks at 2θ, equalling 21^{o}, 27^{o}, and 50°, were observed for the clays blended with aquaculture sludge content. The peaks equalling 21° and 27° indicates the crystalline structure, and the peaks at 50° indicate the formation of C-S-H gel. Moreover, peaks equalling 29°, 39°, and 44° indicate the $CaCO_3$, which is formed due to the reactions between the Ca ions present in the clays and carbon content (organic matter) presence in the aquaculture sludge (Ramirez et al. 2011). The silica in the clay matrix combines with ammonia to create silica gel, which can then crystallize into quartz. The inclusion of quartz in the XRD traces shows that the ammonia addition to the clay caused it to mineralize. In XRD patterns of expansive clay combined with aquaculture sludge, the calcite (C) and C-S-H gel content was produced. This is caused by the aquaculture sludge's high Ca content. Furthermore, the presence of the Tobermorite (T) mineral was found in a higher percentage of AS mixed clays due to the formation of calcium carbonate.

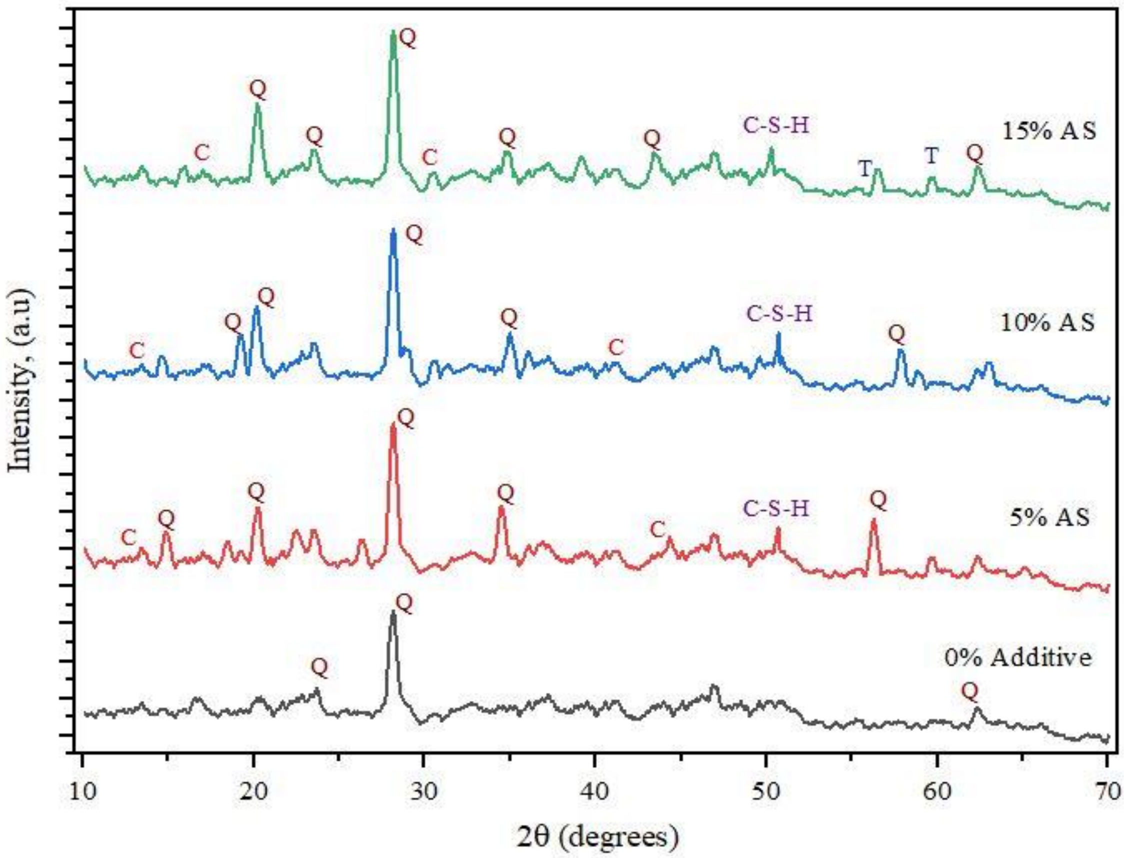


Figure 5.15 XRD traces with varying AS content

CHAPTER 6

PREDICTION OF AMMONIA LEVELS IN THE INTENSIVE AQUACULTURE PONDS USING SOFT COMPUTING TECHNIQUES

6.1 GENERAL

Aquaculture ponds frequently face ammonia problems because, if not adequately controlled, and it can build up quickly and become hazardous to aquatic life. Ammonia is generated in aquaculture by decomposing organic materials, including uneaten food, excrement, and dead aquatic species. High ammonia levels can significantly impact the survival and growth of shrimp and other aquatic organisms in aquaculture ponds, resulting in poor water quality. In addition, it may harm the gills, resulting in slower development rates, poorer reproductive outcomes, and even death. Regular water analysis of water quality indicators, including ammonia, nitrates, dissolved oxygen, and pH, can help identify possible issues early on and allow for immediate remedial action to manage concentration in freshwater aquaculture.

6.2 PREDICTION OF AMMONIA IN AQUACULTURE PONDS USING HYBRID SOFT COMPUTING TECHNIQUE

Aquaculture ponds serve as important sources of both food and revenue. Still, they must be managed carefully to preserve the water's quality and prevent the formation of toxic pollutants like ammonia. A hybrid soft computing approach, which combines different artificial intelligence techniques to make predictions, is one option for monitoring ammonia levels in aquaculture ponds.

6.2.1 Dataset preparation

A total of 64 samples were tested, and datasets include sampling was collected from March 2021 to May 2021 (pre-monsoon consideration). Samples were obtained from aquaculture ponds in the western delta region of Andhra Pradesh. Ammonia is the primary concern in aquaculture ponds. In this context, it is required to predict the ammonia levels in the water samples. Ammonia is considered an organic parameter associated with organic matter in water, it can be influenced by various inorganic factors (Boyd and Tucker, 2012). Certain inorganic elements and water parameters can affect ammonia's conversion, transport, and fate in the inland aquaculture ponds (Boyd and Tucker, 2012; Boyd, 2017). Therefore, considering organic and inorganic parameters in water quality assessment allows for a more comprehensive understanding of the system. For example, pH, salinity, alkalinity, bicarbonates, total hardness, calcium, and magnesium are essential parameters that play a significant role in inland aquaculture ponds (Boyd et al. 2016; Silva et al. 2023). These factors can influence the bioavailability, toxicity, and transformation of ammonia in water (Silva et al. 2023).

To this aim, nine variables were selected for inputs, including area of the pond in acres (x_1), cultivation days (x_2), pH (x_3), salinity (x_4), alkalinity (x_5), bicarbonates (x_6), total hardness (x_7), calcium (x_8), and magnesium (x_9) with an output of ammonia in ppm (y). The dataset used in the study is shown in Appendix-III.

6.2.2 Ammonia prediction using DWT-POA model

The input data is processed through DWT, extracted approximated and detailed coefficients of the data to predict the output. The approximated and detailed coefficients of various levels of each input variable of 64 samples are presented in Figures 6.1 to 6.9. For each input, three additional decomposed coefficients ($d_1, d_2,$ and d_3) features are available for prediction since the decomposition level is 3. This process is carried out for input data sets and the DWT coefficients are used for implementing forecasting models.

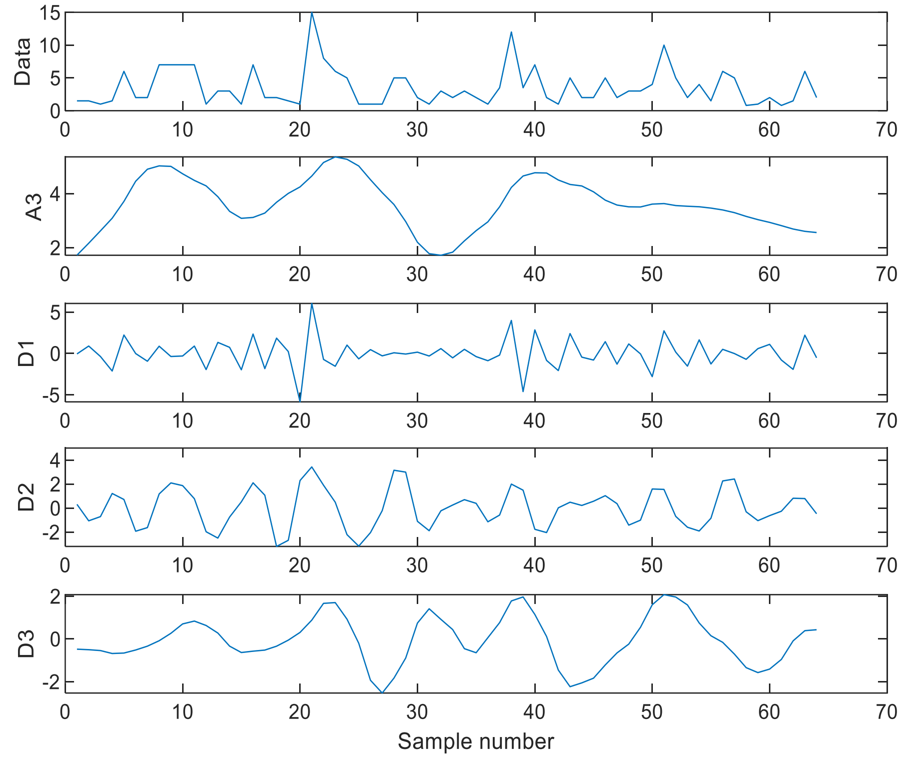


Figure 6.1 Decomposition process of input variable x1 using DWT

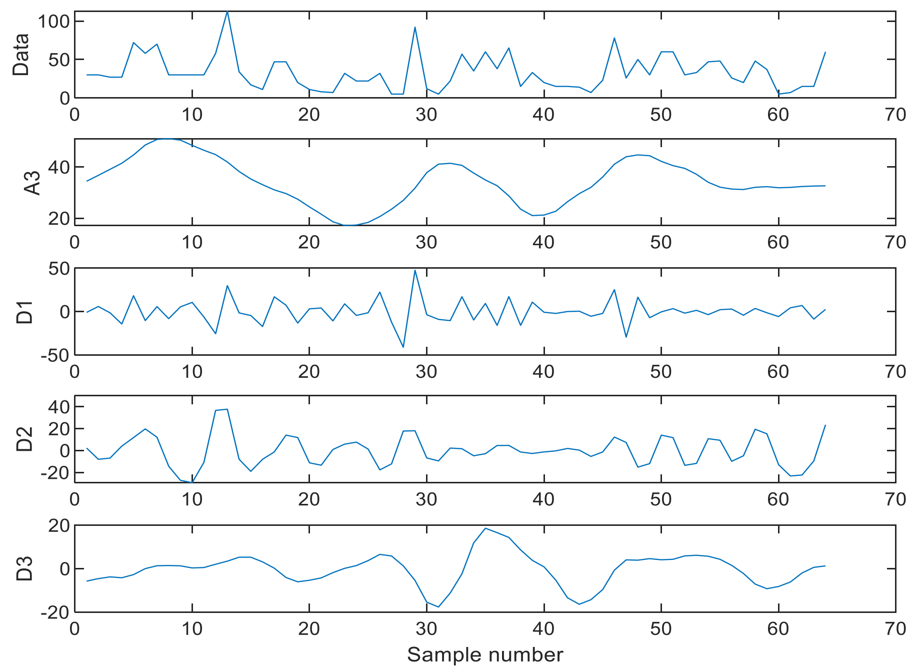


Figure 6.2 Decomposition process of input variable x2 using DWT

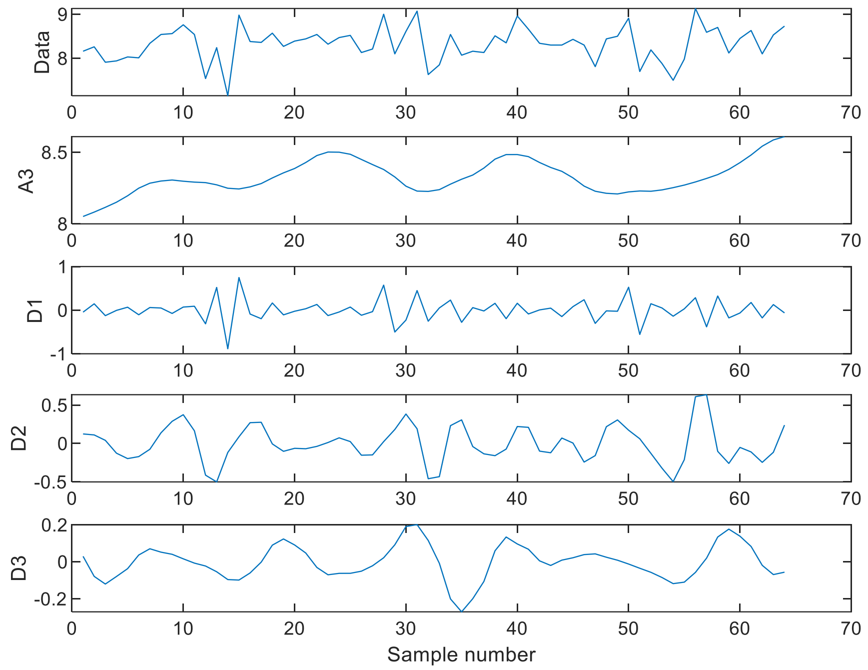


Figure 6.3 Decomposition process of input variable x3 using DWT

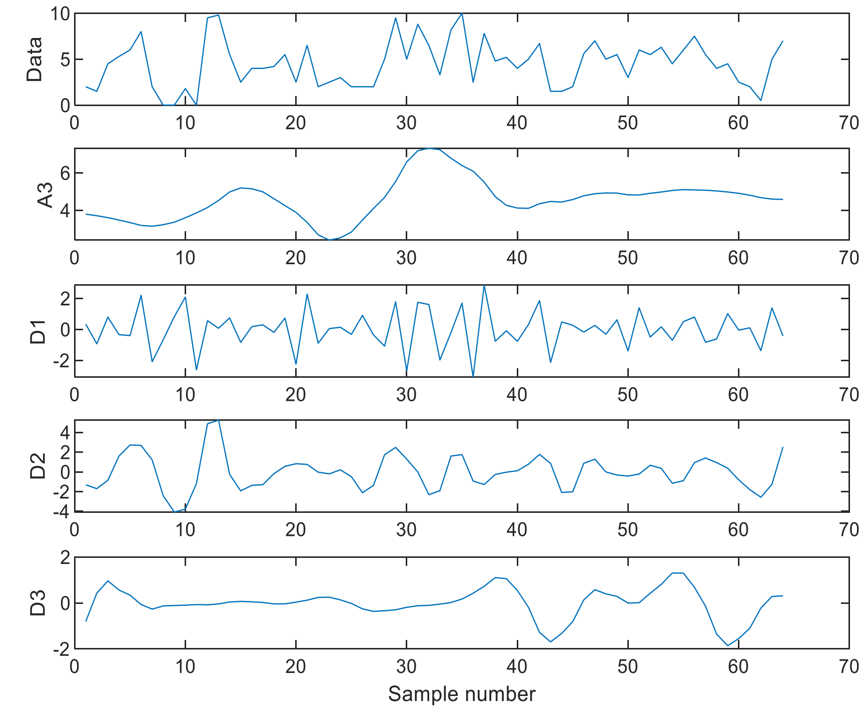


Figure 6.4 Decomposition process of input variable x4 using DWT

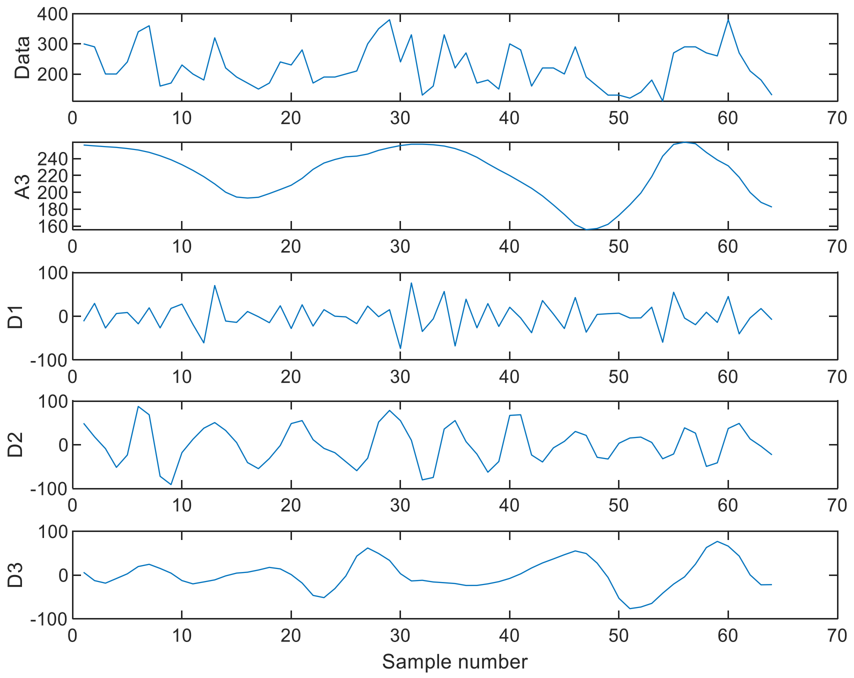


Figure 6.5 Decomposition process of input variable x5 using DWT

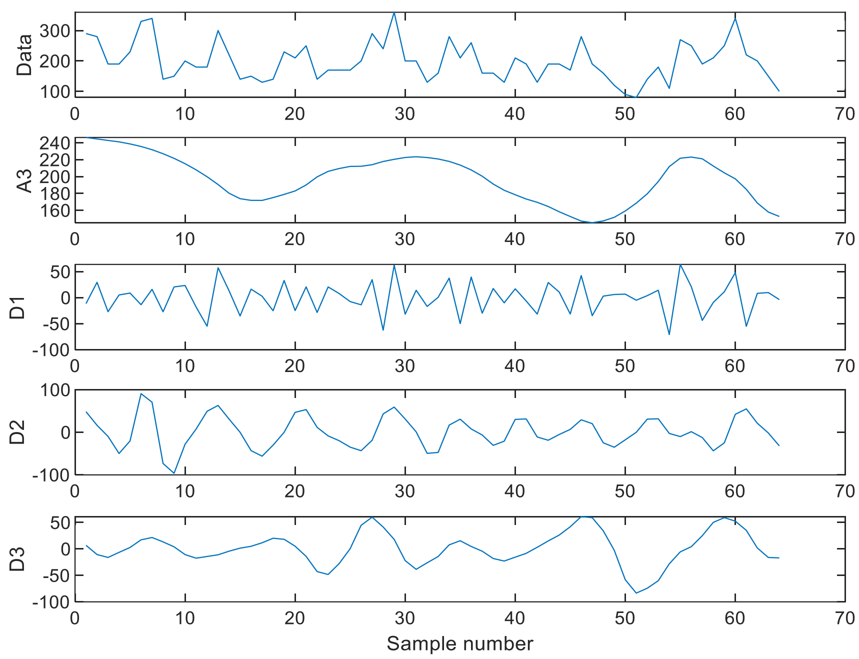


Figure 6.6 Decomposition process of input variable x6 using DWT

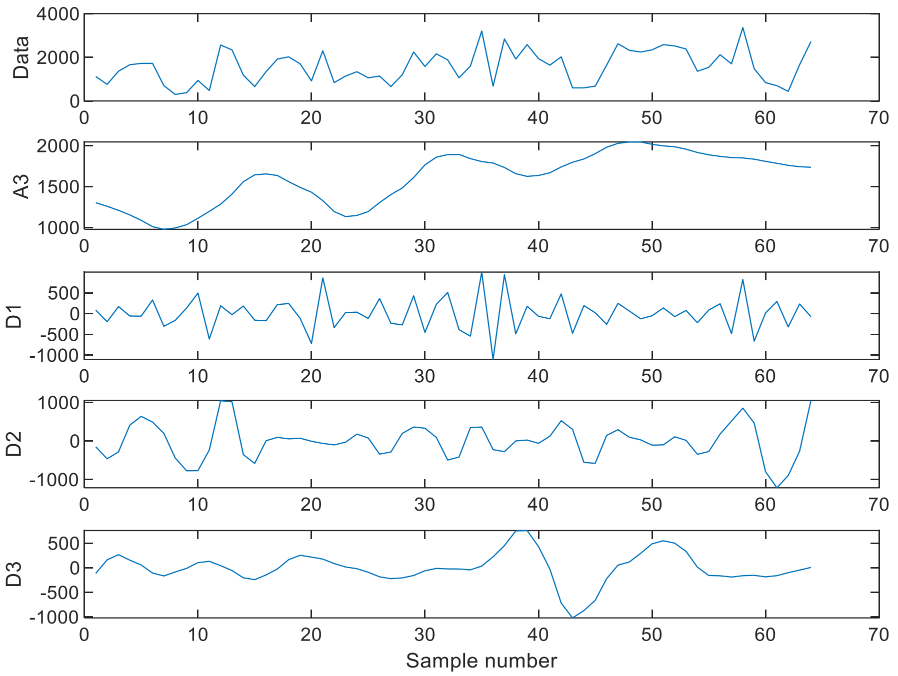


Figure 6.7 Decomposition process of input variable x7 using DWT

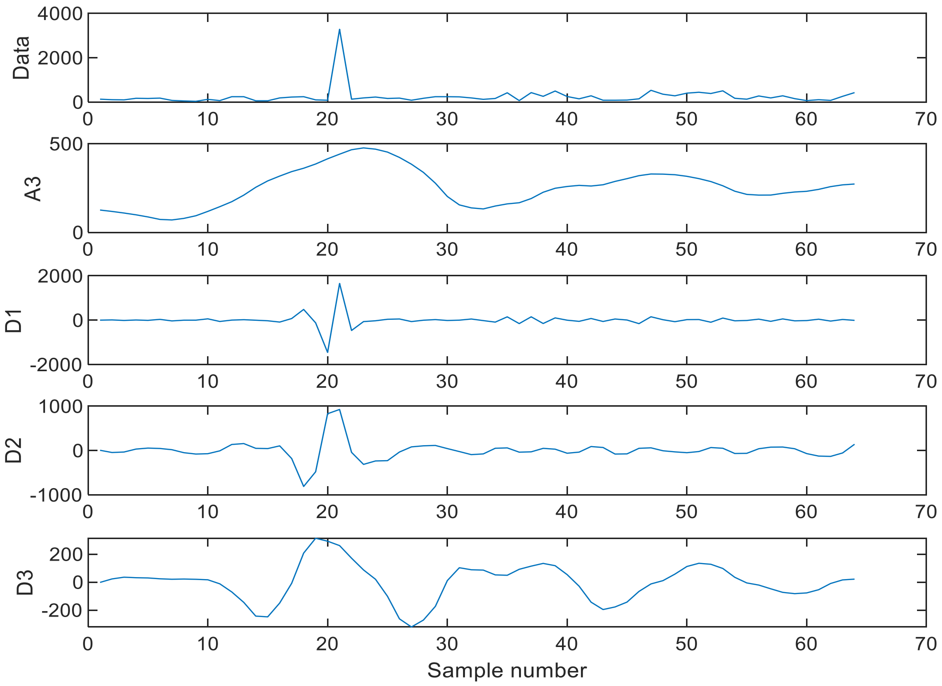


Figure 6.8 Decomposition process of input variable x8 using DWT

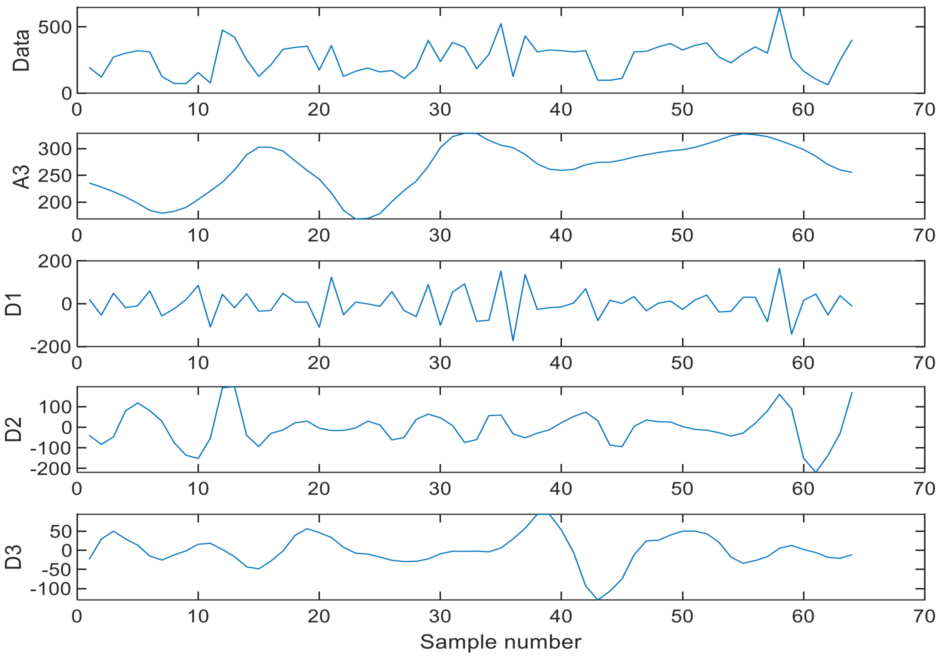


Figure 6.9 Decomposition process of input variable x9 using DWT

The process utilizes 9 inputs, and each input produces 4 features when they are processed by DWT and therefore, a total of 36 features are available for predicting ammonia. Moreover, an additional constant in using the prediction model leads to the total number of coefficients of the model being 37. The decomposition of input variables reduces the noises of the data and enhances the efficacy of the data sets (Li et al. 2009; Muhuri et al. 2020). These changes are made in Equation (1) and optimal values of the regression model are identified with POA using cost function provided in Equation (2).

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t)\varphi_{a,b}(t).dt \tag{1}$$

$$\begin{bmatrix} y_1(k+1) \\ y_1(k) \\ \vdots \\ y_1(2) \\ y_1(1) \end{bmatrix} = \sum_{i=1}^{p} \alpha_1^i \begin{bmatrix} d_1^{x_i}(k+1) \\ d_1^{x_i}(k) \\ . \\ . \\ d_1^{x_i}(2) \\ d_1^{x_i}(1) \end{bmatrix} + \sum_{i=1}^{p} \alpha_2^i \begin{bmatrix} d_2^{x_i}(k+1) \\ d_2^{x_i}(k) \\ . \\ . \\ d_2^{x_i}(2) \\ d_2^{x_i}(1) \end{bmatrix} + \cdots +$$

$$\sum_{i=1}^{p} \alpha_n^i \begin{bmatrix} d_n^{x_i}(k+1) \\ d_n^{x_i}(k) \\ . \\ . \\ d_n^{x_i}(2) \\ d_n^{x_i}(1) \end{bmatrix} + \sum_{i=1}^{p} \beta_n^i \begin{bmatrix} a_n^{x_i}(k+1) \\ a_n^{x_i}(k) \\ . \\ . \\ a_n^{x_i}(2) \\ a_n^{x_i}(1) \end{bmatrix} + \gamma \begin{bmatrix} 1 \\ 1 \\ . \\ . \\ 1 \\ 1 \end{bmatrix} \qquad (2)$$

The final regression model for prediction using DWT is given as Equation (3):

$$\begin{aligned} y(k+1) = {} & 0.0277 a_3^{x1}(k+1) + 0.00083 d_1^{x1}(k+1) - 0.00434 d_2^{x1}(k+1) \\ & - 0.0103 d_3^{x1}(k+1) + 0.0006 a_3^{x2}(k+1) + 0.0009 d_1^{x2}(k+1) \\ & + 0.00136 d_2^{x2}(k+1) - 0.00885 d_3^{x2}(k+1) - 0.0425 a_3^{x3}(k+1) \\ & - 0.00714 d_1^{x3}(k+1) - 0.0541 d_2^{x3}(k+1) + 0.0113 d_3^{x3}(k+1) \\ & + 0.0401 a_3^{x4}(k+1) + 0.01372 d_1^{x4}(k+1) + 0.03259 d_2^{x4}(k+1) \\ & - 0.01487 d_3^{x4}(k+1) - 0.00107 a_3^{x5}(k+1) - 0.00059 d_1^{x5}(k+1) \\ & + 0.000524 d_2^{x5}(k+1) - 0.00509 d_3^{x5}(k+1) + 0.00173 a_3^{x6}(k+1) \\ & + 0.00088 d_1^{x6}(k+1) - 0.00085 d_2^{x6}(k+1) + 0.00621 d_3^{x6}(k+1) \\ & + 5.965x10^{-7} a_3^{x7}(k+1) - 4.46x10^{-5} d_1^{x7}(k+1) \\ & - 8.11x10^{-5} d_2^{x7}(k+1) + 0.00055 d_3^{x7}(k+1) \\ & + 3.169x10^{-5} a_3^{x8}(k+1) - 4.68x10^{-5} d_1^{x8}(k+1) \\ & + 5.027x10^{-5} d_2^{x8}(k+1) - 0.00013 d_3^{x8}(k+1) \\ & - 0.00025 a_3^{x9}(k+1) + 0.00021 d_1^{x9}(k+1) - 0.0002 d_2^{x9}(k+1) \\ & - 0.003 d_3^{x9}(k+1) + 0.04596 \end{aligned} \qquad (3)$$

Using the regression model, estimated values of the ammonia along with actual values measured, and errors are plotted in Figure 6.10 (a and b).

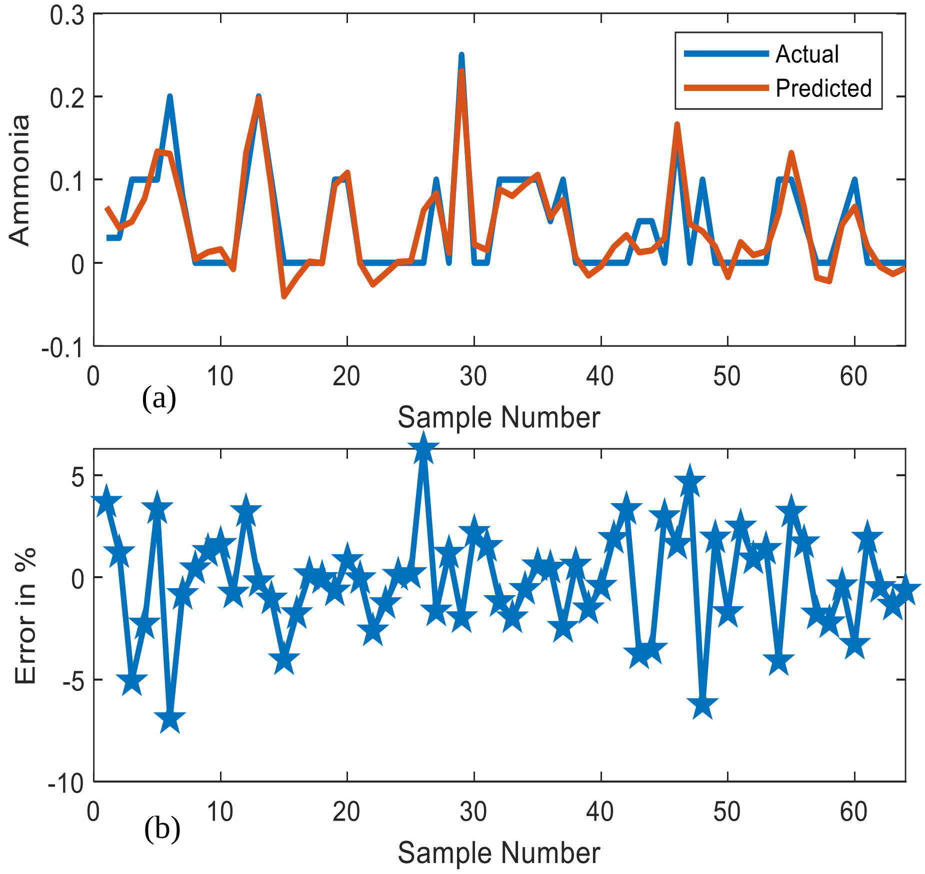


Figure 6.10 Prediction performance (a) actual vs predicted ammonia, (b) errors

The percentage errors of each predicted sample are provided in Figure 6.10. The proposed method enhances prediction accuracy due to DWT processing of input information. Without coupling DWT to POA, the average error is comparatively higher than the proposed method shows in Figures 6.11 and 6.12 reveals the merits of the approach.

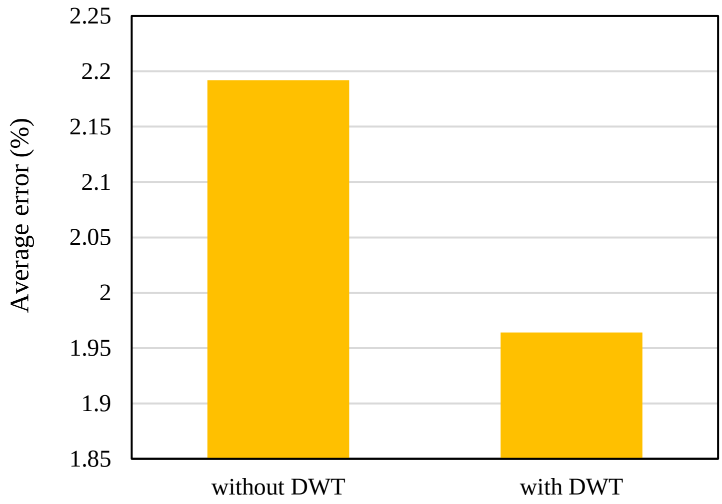


Figure 6.11 Average Errors of the models

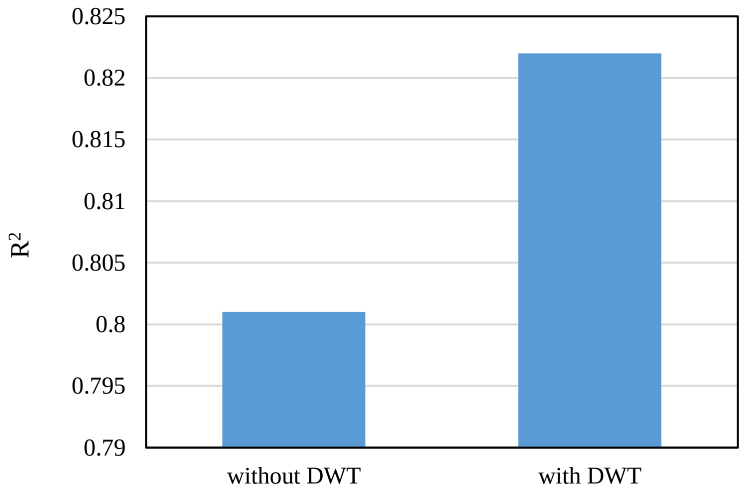


Figure 6.12 Coefficient of determination of the models

CHAPTER 7

CONCLUSIONS

7.1 CONCLUSIONS

This environmental impact assessment study aims to demonstrate aquaculture practices in the western Godavari delta region of Andhra Pradesh while assessing their potential impact on the environment. Various methodologies were employed for a comprehensive understanding of the issues related to intensive farming. These methodologies included a field-based questionnaire survey, a topography survey using GIS, a water quality analysis of aquaculture ponds, an analysis of soil samples, and an investigation into the effect of aquaculture sludge on clays. Additionally, the study involved the assessment of ammonia levels in the aquaculture ponds using soft computing techniques. The following conclusions were drawn from the study:

1. Questionnaire survey results show most of the locations in the western Godavari delta region fall in the intensive farming zone. The growing extent of aquaculture ponds operated continuously without water exchange for a minimum of two crops with a higher concentration of chemicals and minerals is worrisome and needs proper guidelines or attention to make a sustainable ecosystem.
2. Dynamic changes in land use and land cover were witnessed in aquaculture ponds that have significantly increased by 6.98% (54.35 km^2) from 2017 to 2021. Despite poor laws and state economic growth concerns, croplands were converted to aquaculture ponds. Moreover, intensive aquaculture causes a decrease in surface temperatures and increases unhealthy vegetation.
3. Ammonia and nitrate levels of aquaculture water in the study area were unsafe for the next crop. The experimental results showed that the mean alkalinity, TDS, Ca, and Mg in the inland water bodies were found exceeding the limits of specified for safe aquaculture practice. The average WQI was 126; approximately 78% of the pond water samples were unfit for the second crop. A severe concern to nearby canals is the direct discharge of contaminated

aquaculture water. Managing water quality for a healthy ecosystem depends on treating aquaculture effluents before discharge or reuse.

4. Physicochemical characteristics of the intensive farming zone soils exhibits higher levels of the calcium, potassium, and sodium. This is due to the excess chemical usage and the uneaten feed (phosphorus) strongly adsorbs to the subsoil.
5. CEC values of aquaculture sludge blended clays were significantly decreased with the increase in the sludge content. This is due to the exchangeable cations between the aquaculture sludge and clay surfaces. Therefore, it is necessary to have sound water barriers (geosynthetic membranes) and effluent purification systems to reduce the contaminants loading on the environment. SEM images revealed that the surface texture and pore size differences with adding aquaculture sludge content. This is due to the integrated form of blends reduces the surface forces and improves the aggregation of particles.
6. This study used a novel approach with POA and POA paired with DWT to forecast ammonia by considering the crucial characteristics as input variables. DWT improves the model's effectiveness by reducing noise in the input variables used for prediction. In contrast, predictions made using the DWT-POA technique had a higher R^2 value (0.822) than those using the POA alone. The model first examined the hidden layer node selection, hidden weight optimization, and threshold value optimization. The ammonia estimate results can be significantly enhanced by choosing the best weight and threshold. As a result, the proposed DWT-POA approach helps predict ammonia.
7. The study suggests using the DWT-POA algorithm for estimating ammonia levels in aquaculture waters, which benefits field engineers, farmers, and government organizations.

7.2 LIMITATIONS OF THE STUDY

One of the study's major limitations is that the models are site-specific and can only be utilized if similar site conditions exist. For example, the MLR method assisted with WT coefficients of the input variables provided acceptable results to predict the ammonia. However, the method is highly suitable for the data with low imbalance rate. The 64 samples data provided in this work is correlated with respect to independent variables and the method proposed is suitable to predict the ammonia as shown in Figure 7.1a. This clustered data is mixed with other data sets and analysis is carried out in the similar way to predict the ammonia for the mixed data with 428 samples. Due to high imbalance, the method failed to provide acceptable results as shown in Figure 7.1b. For both cases, actual and predicted outputs are plotted in Figure 7.1c and Figure 7.1d. Therefore, data clustering based on the similarities of the input variables and data processing are must to carry the proposed methodology.

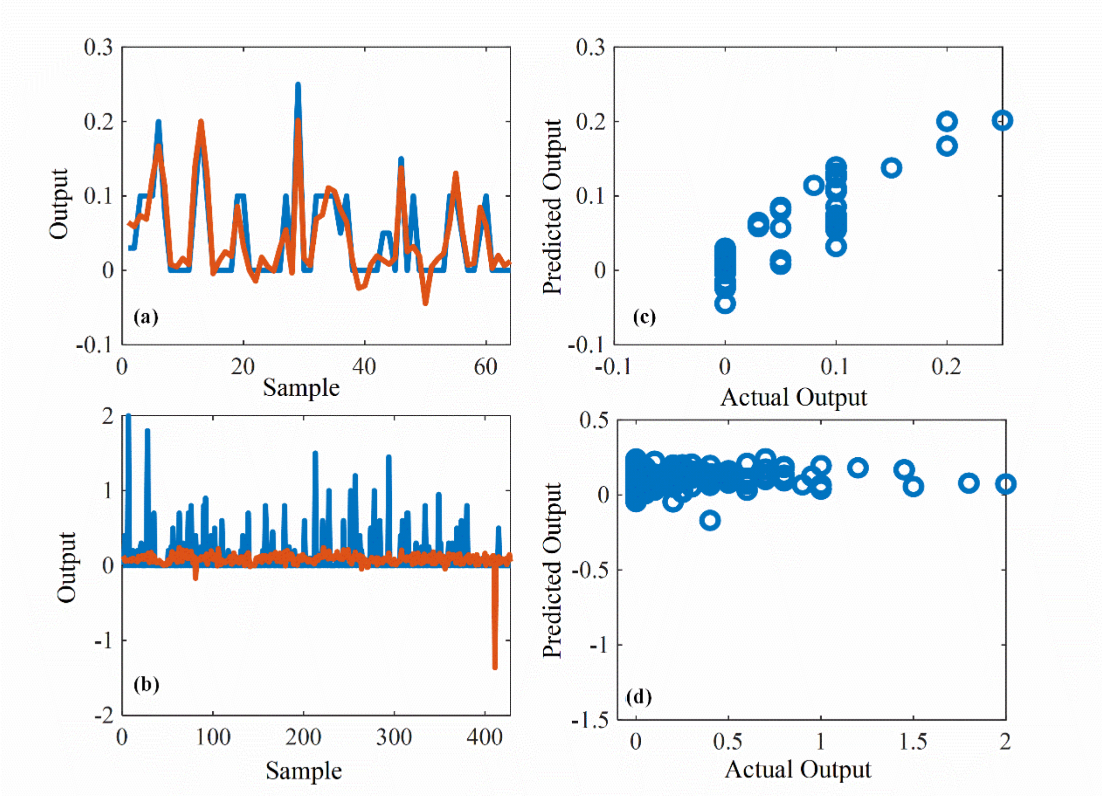


Figure 7.1 Predicted outputs (a) after data clustering, (b) before data clustering, Actual vs predicted outputs, (c) after clustering, (d) before clustering.

7.3 SCOPE FOR FUTURE WORK

1. The present study mainly focused on the physicochemical properties of aquaculture waters. The study can be further continued to assess metal and pharmaceutical traces in the aquaculture waters.
2. To investigate cross-contamination between intensive aquaculture water and adjacent canals.

3. The present study identifies hotspots and risk zones where ammonia concentrations are particularly high. The study can be further continued to develop mitigation strategies for developing and restoring sustainable ecosystems.
4. There is scope to carry out a similar study for ammonia prediction, employing other hybrid techniques such as extreme learning machines coupled with particle swarm optimization (ELM-PSO) and extreme learning machines coupled with invasive weed optimization algorithm (ELM-IWO), which could be explored.

REFERENCES

Abdullah, A. N.; Myers, B.; Stacey, N.; Zander, K. K.; & Garnett, S. T. The impact of the expansion of shrimp aquaculture on livelihoods in coastal Bangladesh. Environment, Development and Sustainability, 2017, 19(5), 2093-2114.

Abobakr Yahya, A. S., Ahmed, A. N., Binti Othman, F., Ibrahim, R. K., Afan, H. A., El-Shafie, A., ... & Elshafie, A. (2019). Water quality prediction model based support vector machine model for ungauged river catchment under dual scenarios. Water, 11(6), 1231.

Abyaneh, H. Z. (2014). Evaluation of multivariate linear regression and artificial neural networks in prediction of water quality parameters. Journal of Environmental Health Science and Engineering, 12(1), 1-8.

Adem, H. H., & Vanapalli, S. K. (2015). Review of methods for predicting in situ volume change movement of expansive soil over time. Journal of Rock Mechanics and Geotechnical Engineering, 7(1), 73-86.

Adimalla, N. (2019). Groundwater quality for drinking and irrigation purposes and potential health risks assessment: a case study from semi-arid region of South India. Exposure and health, 11(2), 109-123.

Adimalla, N., & Taloor, A. K. (2020). Hydrogeochemical investigation of groundwater quality in the hard rock terrain of South India using Geographic Information System (GIS) and groundwater quality index (GWQI) techniques. Groundwater for Sustainable Development, 10, 100288.

Adusumilli, R.; & Laxmi, S. B. Potential of the system of rice intensification for systemic improvement in rice production and water use: the case of Andhra Pradesh, India. Paddy and Water Environment, 2011, 9(1), 89-97.

Ahmed, A. N., Othman, F. B., Afan, H. A., Ibrahim, R. K., Fai, C. M., Hossain, M. S., ... & Elshafie, A. (2019). Machine learning methods for better water quality prediction. Journal of Hydrology, 578, 124084.

Ahmed, N., & Turchini, G. M. (2021). Recirculating aquaculture systems (RAS): Environmental solution and climate change adaptation. Journal of Cleaner production, 297, 126604.

Ahmed, N., Thompson, S., & Glaser, M. (2019). Global aquaculture productivity, environmental sustainability, and climate change adaptability. Environmental management, 63(2), 159-172.

Akindele, A. A., & Sartaj, M. (2018). The toxicity effects of ammonia on anaerobic digestion of organic fraction of municipal solid waste. Waste management, 71, 757-766.

Alfiansah, Y. R., Hassenrück, C., Kunzmann, A., Taslihan, A., Harder, J., & Gärdes, A. (2018). Bacterial abundance and community composition in pond water from shrimp aquaculture systems with different stocking densities. Frontiers in microbiology, 9, 2457

Alizadeh, M. J., & Kavianpour, M. R. (2015). Development of wavelet-ANN models to predict water quality parameters in Hilo Bay, Pacific Ocean. Marine pollution bulletin, 98(1-2), 171-178.

Alamir, N., Kamel, S., Megahed, T. F., Hori, M., & Abdelkader, S. M. (2023). Developing hybrid demand response technique for energy management in microgrid based on pelican optimization algorithm. *Electric Power Systems Research*, *214*, 108905.

Alsamhi, S. H., Ma, O., & Ansari, M. S. (2020). Convergence of machine learning and robotics communication in collaborative assembly: mobility, connectivity and future perspectives. Journal of Intelligent & Robotic Systems, 98, 541-566.

Ariadi, H., Fadjar, M., & Mahmudi, M. (2019). The relationships between water quality parameters and the growth rate of white shrimp (Litopenaeus vannamei) in intensive ponds. Aquaculture, Aquarium, Conservation & Legislation, 12(6), 2103-2116.

Artiola, J. F., Walworth, J. L., Musil, S. A., & Crimmins, M. A. (2019). Soil and land pollution. In Environmental and pollution science (pp. 219-235). Academic Press.

Ayyam, V., Palanivel, S., & Chandrakasan, S. (2019). Land and water conservation: dealing with agriculture and aquaculture conflicts. In Coastal Ecosystems of the Tropics-Adaptive Management (pp. 391-406). Springer, Singapore.

Azis, H. Y., Tresnati, J., & Tuwo, A. (2020, September). Seaweed Gracilaria changii as a bioremediator agent for ammonia, nitrite and nitrate in controlled tanks of Whiteleg Shrimp Litopenaeus vannamei. In IOP Conference Series: Earth and Environmental Science (Vol. 564, No. 1, p. 012059). IOP Publishing.

Babu, G. S., Reddy, K. R., De, A., & Datta, M. (Eds.). (2017). Geoenvironmental Practices and Sustainability: Linkages and Directions. Springer.

Barzegar, R., Adamowski, J., & Moghaddam, A. A. (2016). Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay River, Iran. Stochastic environmental research and risk assessment, 30(7), 1797-1819.

Barzegar, R., Asghari Moghaddam, A., Adamowski, J., & Fijani, E. (2017). Comparison of machine learning models for predicting fluoride contamination in groundwater. Stochastic Environmental Research and Risk Assessment, 31(10), 2705-2718.

Batabyal, A. K., & Chakraborty, S. (2015). Hydrogeochemistry and water quality index in the assessment of groundwater quality for drinking uses. Water Environment Research, 87(7), 607-617.

Bechtel, B. (2015). A new global climatology of annual land surface temperature. Remote Sensing, 7(3), 2850-2870.

Bhavsar, D. O.; Pandya, H. A.; & Jasrai, Y. T. Aquaculture and Environmental Pollution: A Review Work. International Journal of Scientific Research in Science. Engineering and Technology, 2016, 2, 40-45.

Bhuvaneshwari, S., Robinson, R. G., & Gandhi, S. R. (2020). Effect of functional group of the inorganic additives on index and microstructural properties of expansive soil. International Journal of Geosynthetics and Ground Engineering, 6(4), 1-15.

Bora, M., & Goswami, D. C. (2017). Water quality assessment in terms of water quality index (WQI): case study of the Kolong River, Assam, India. Applied Water Science, 7(6), 3125-3135.

Boyd, C. E., D'Abramo, L. R., Glencross, B. D., Huyben, D. C., Juarez, L. M., Lockwood, G. S., ... & Valenti, W. C. (2020). Achieving sustainable aquaculture: Historical and current perspectives and future needs and challenges. Journal of the World Aquaculture Society, 51(3), 578-633.

Boyd, C. E. (2017). General relationship between water quality and aquaculture performance in ponds. In *Fish diseases* (pp. 147-166). Academic Press.

Boyd, C. E., Tucker, C. S., & Somridhivej, B. (2016). Alkalinity and hardness: critical but elusive concepts in aquaculture. *Journal of the World Aquaculture Society*, *47*(1), 6-41.

Boyd, C. E., & Tucker, C. S. (2012). *Pond aquaculture water quality management*. Springer Science & Business Media.

Bradley, D., Merrifield, M., Miller, K.M., Lomonico, S., Wilson, J.R., Gleason, M.G. (2019). Opportunities to improve fisheries management through innovative technology and advanced data systems. Fish Fisher. (Oxford, England) 20, 564–583. https://doi.org/ 10.1111/faf.12361.

Bryan, N. S., & Ivy, J. L. (2015). Inorganic nitrite and nitrate: evidence to support consideration as dietary nutrients. Nutrition Research, 35(8), 643-654.

Burford, M. A., Costanzo, S. D., Dennison, W. C., Jackson, C. J., Jones, A. B., McKinnon, A. D., & Trott, L. A. (2003). A synthesis of dominant ecological processes in intensive shrimp ponds and adjacent coastal environments in NE Australia. Marine pollution bulletin, 46(11), 1456-1469.

Cao, L., Wang, W., Yang, Y., Yang, C., Yuan, Z., Xiong, S., & Diana, J. (2007). Environmental impact of aquaculture and countermeasures to aquaculture pollution in China. Environmental Science and Pollution Research-International, 14(7), 452-462.

Chaiyaput, S., Awaedo, N., Kingnoi, N., Nghia-Nguyen, T., & Ayawanna, J. (2022). Effect of Curing Conditions on the Strength of Soil Cement. Case Studies in Construction Materials, e01082.

Chanda, A., Das, S., & Pramanik, N. (2022). Characterizing the Drivers of the Productivity and Greenhouse Gas Fluxes from the Aquaculture Ponds of Indian Sundarbans. In Pond Ecosystems of the Indian Sundarbans (pp. 163-199). Springer, Cham.

Chanda, A., Das, S., Bhattacharyya, S., Das, I., Giri, S., Mukhopadhyay, A., ... & Hazra, S. (2019). CO2 fluxes from aquaculture ponds of a tropical wetland: potential of multiple lime treatment in reduction of CO2 emission. *Science of the Total Environment*, *655*, 1321-1333.

Chapman, D. (2021). Water quality assessments: a guide to the use of biota, sediments and water in environmental monitoring. CRC Press.

Chatla, D., Padmavathi, P., & Srinu, G. (2020). Wastewater treatment techniques for sustainable aquaculture. Waste management as economic industry towards circular economy, 159-166.

Chen, X., Chen, W., Bai, Y., & Wen, X. (2022). Changes in turbidity and human activities along Haihe River Basin during lockdown of COVID-19 using satellite data. *Environmental Science and Pollution Research*, *29*(3), 3702-3717.

Chofqi, A.; Younsi, A.; Mania, J.; Mudry, J.; & Veron, A. Environmental impact of an urban landfill on a coastal aquifer (El Jadida, Morocco). Journal of African earth sciences, 2004, 39(3-5), 509-516.

Cleophas, T. J., Zwinderman, A. H., & Cleophas-Allers, H. I. (2013). Machine learning in medicine (Vol. 9). Dordrecht, The Netherlands:: Springer.

Collos, Y., & Harrison, P. J. (2014). Acclimation and toxicity of high ammonium concentrations to unicellular algae. Marine pollution bulletin, 80(1-2), 8-23.

Das, M., & Ghosh, S. K. (2020). Enhanced Bayesian network models for spatial time series prediction. Springer International Publishing.

Das, S. K., Mandal, A., & Khairnar, S. O. (2022). Aquaculture Resources and Practices in a Changing Environment. Sustainable Agriculture Systems and Technologies, 169-199.

Datta, M. Geotechnology for environmental control at waste disposal sites. Indian Geotechnical Journal, 2012, 42(1), 1-36.

Dauda, A. B., Ajadi, A., Tola-Fabunmi, A. S., & Akinwole, A. O. (2019). Waste production in aquaculture: Sources, components and managements in different culture systems. Aquaculture and Fisheries, 4(3), 81-88.

Deepika, B. V., Ramakrishnaiah, C. R., & Naganna, S. R. (2020). Spatial variability of ground water quality: a case study of Udupi district, Karnataka State, India. Journal of Earth System Science, 129(1), 1-20.

Deng, T., Chau, K. W., & Duan, H. F. (2021). Machine learning based marine water quality prediction for coastal hydro-environment management. Journal of Environmental Management, 284, 112051.

Dey, S., Botta, S., Kallam, R., Angadala, R., & Andugala, J. (2021). Seasonal variation in water quality parameters of Gudlavalleru Engineering College pond. Current Research in Green and Sustainable Chemistry, 4, 100058.

Duan, Y., Xiong, D., Wang, Y., Li, H., Dong, H., & Zhang, J. (2021). Toxic effects of ammonia and thermal stress on the intestinal microbiota and transcriptomic and metabolomic responses of Litopenaeus vannamei. Science of the Total Environment, 754, 141867.

Duy, D. T., Nga, N. H., Berg, H., & Da, C. T. (2022). Assessment of technical, economic, and allocative efficiencies of shrimp farming in the Mekong Delta, Vietnam. *Journal of the World Aquaculture Society*.

Edwards, P. Aquaculture environment interactions: past, present and likely future trends. Aquaculture, 2015, 447, 2-14.

Eng, C. T.; Paw, J. N.; & Guarin, F. Y. The environmental impact of aquaculture and the effects of pollution on coastal aquaculture development in Southeast Asia. Marine pollution bulletin, 1989, 20(7), 335-343.

Esakku, S., Selvam, A., Palanivelu, K., Nagendran, R., & Joseph, K. (2006). Leachate quality of municipal solid waste dumpsites at Chennai, India. Asian Journal of Water, Environment and Pollution, 3(1), 69-76.

Estabragh, A. R., Moghadas, M., & Javadi, A. A. (2013). Effect of different types of wetting fluids on the behaviour of expansive soil during wetting and drying. Soils and Foundations, 53(5), 617-627.

Estevez, M. M., Tomczak-Wandzel, R., & Kvamme, K. (2022). Fish sludge as a co-substrate in the anaerobic digestion of municipal sewage sludge-maximizing the utilization of available organic resources. EFB Bioeconomy Journal, 2, 100027.

Eyo, E. U., Ng'ambi, S., & Abbey, S. J. (2019). Effect of intrinsic microscopic properties and suction on swell characteristics of compacted expansive clays. Transportation Geotechnics, 18, 124-131.

FAO (2021). National aquaculture sector overview. India. http://www.fao.org/fishery/co untrysector/naso_india/en. (Accessed 22 July 2021).

FAO, F.A.A.D, (2018). The State of World Fisheries and Aquaculture 2018 - Meeting the Sustainable Development Goals. http://www.fao.org/documents/card/en/c /I9540EN/.

FAO. The State of World Fisheries and Aquaculture: Meeting the Sustainable Development Goals. Licence: CC BY-NC-SA 3.0 IGO. 2018, ISBN:978-92-5-130562-1, 210 pp.

Feizizadeh, B., Darabi, S., Blaschke, T., & Lakes, T. (2022). QADI as a New Method and Alternative to Kappa for Accuracy Assessment of Remote Sensing-Based Image Classification. Sensors, 22(12), 4506.

Feng, J., Pan, L., Cui, B., Sun, Y., Zhang, A., & Gong, M. (2020). New Approach for Concentration Prediction of Aqueous Phenolic Contaminants by Using Wavelet Analysis and Support Vector Machine. Environmental Engineering Science, 37(5), 382-392.

Fityus, S., & Buzzi, O. (2009). The place of expansive clays in the framework of unsaturated soil mechanics. Applied Clay Science, 43(2), 150-155.

Furuya, K., Glibert, P. M., Zhou, M., & Raine, R. (2010). Global Ecology and Oceanography of Harmful Algal Blooms in Asia: A Regional Comparative Programme.

Gautam, S., Hoyos, L. R., He, S., Prabakar, S., & Yu, X. (2020). Chemical treatment of a highly expansive clay using a liquid ionic soil stabilizer. Geotechnical and Geological Engineering, 38(5), 4981-4993.

Goyal, A., & Garimella, S. (2019). Computing thermodynamic properties of ammonia–water mixtures using artificial neural networks. International Journal of Refrigeration, 100, 315-325.

Granada, L., Sousa, N., Lopes, S., & Lemos, M. F. (2016). Is integrated multitrophic aquaculture the solution to the sectors' major challenges?–a review. Reviews in Aquaculture, 8(3), 283-300.

Groenveld, T., Kohn, Y. Y., Gross, A., & Lazarovitch, N. (2019). Optimization of nitrogen use efficiency by means of fertigation management in an integrated aquaculture-agriculture system. Journal of cleaner production, 212, 401-408.

Gu, W., Foster, K., Shang, J., & Wei, L. (2019). A game-predicting expert system using big data and machine learning. Expert Systems with Applications, 130, 293-305.

Guerdat, T. C., Losordo, T. M., DeLong, D. P., & Jones, R. D. (2013). An evaluation of solid waste capture from recirculating aquaculture systems using a geotextile bag system with a flocculant-aid. Aquacultural engineering, 54, 1-8.

Gunning, D., Maguire, J., & Burnell, G. (2016). The development of sustainable saltwater-based food production systems: a review of established and novel concepts. Water, 8(12), 598.

Gyawali, S., Techato, K., Yuangyai, C., & Musikavong, C. (2013). Assessment of relationship between land uses of riparian zone and water quality of river for sustainable development of river basin, A case study of U-Tapao river basin, Thailand. Procedia Environmental Sciences, 17, 291-297.

Hasanpour Kashani, M., Nikpour, M. R., & Jalali, R. (2022). Water quality prediction using data-driven models case study: Ardabil plain, Iran. Soft Computing, 1-10.

Herath, S. S., & Satoh, S. (2015). Environmental impact of phosphorus and nitrogen from aquaculture. In Feed and feeding practices in aquaculture (pp. 369-386). Woodhead Publishing.

Hsieh, C. W. (2016). Geotextiles in agriculture and aquaculture. In Geotextiles (pp. 511-530). Woodhead Publishing.

Hu, Z., Lee, J. W., Chandran, K., Kim, S., & Khanal, S. K. (2012). Nitrous oxide (N2O) emission from aquaculture: a review. Environmental science & technology, 46(12), 6470-6480.

Huang, W., Liu, D., Huang, W., Cai, W., Zhang, Z., & Lei, Z. (2020). Achieving partial nitrification and high lipid production in an algal-bacterial granule system when treating low COD/NH4–N wastewater. Chemosphere, 248, 126106.

Iber, B. T., & Kasan, N. A. (2021). Recent advances in Shrimp aquaculture wastewater management. Heliyon, 7(11), e08283.

Ikeagwuani, C. C., & Nwonu, D. C. (2019). Emerging trends in expansive soil stabilisation: A review. Journal of Rock Mechanics and Geotechnical Engineering, 11(2), 423-440.

Islam, M. S.; Khan, S.; & Tanaka, M. Waste loading in shrimp and fish processing effluents: potential source of hazards to the coastal and nearshore environments. Marine pollution bulletin, 2004, 49(1-2), 103-110.

Islam, M.; & Yasmin, R. Impact of aquaculture and contemporary environmental issues in Bangladesh. International Journal of Fisheries and Aquatic Studies, 2017, 5(4), 100-107.

Ito, M., & Azam, S. (2010). Determination of swelling and shrinkage properties of undisturbed expansive soils. Geotechnical and Geological Engineering, 28(4), 413-422.

Jana, B. B.; & Jana, S. The potential and sustainability of aquaculture in India. Journal of Applied Aquaculture, 2003, 13(3-4), 283-316.

Jayanthi, M., Ravisankar, T., Nagaraj, G., Thirumurthy, S., Muralidhar, M., & Saraswathy, R. (2019). Is aquaculture abandonment a threat to sustainable coastal resource use?–a case study of Andhra Pradesh, India, with options for reuse. Land Use Policy, 86, 54-66.

Jayanthi, M., Thirumurthy, S., Samynathan, M., Manimaran, K., Duraisamy, M., & Muralidhar, M. Assessment of land and water ecosystems capability to support aquaculture expansion in climate-vulnerable regions using analytical hierarchy process based geospatial analysis. Journal of Environmental Management, 2020, 270, 110952.

Jayanthi, M.; Nila Rekha, P.; Kavitha, N.; & Ravichandran, P. Assessment of impact of aquaculture on Kolleru Lake (India) using remote sensing and Geographical Information System. Aquaculture research, 2006, 37(16), 1617-1626.

Jayanthi, M.; Thirumurthy, S.; Muralidhar, M.; & Ravichandran, P. Impact of shrimp aquaculture development on important ecosystems in India. Global environmental change, 2018, 52, 10-21.

Jayanthi, M.; Thirumurthy, S.; Muralidhar, M.; & Ravichandran, P. Impact of shrimp aquaculture development on important ecosystems in India. Global environmental change, 2018, 52, 10-21.

Jiang, Q., Bhattarai, N., Pahlow, M., & Xu, Z. (2022). Environmental sustainability and footprints of global aquaculture. Resources, Conservation and Recycling, 180, 106183.

John, E. M., Krishnapriya, K., & Sankar, T. V. (2020). Treatment of ammonia and nitrite in aquaculture wastewater by an assembled bacterial consortium. Aquaculture, 526, 735390.

Karri, R. R., Sahu, J. N., & Chimmiri, V. (2018). Critical review of abatement of ammonia from wastewater. Journal of Molecular Liquids, 261, 21-31.

Kasnir, M., Harlina, R., & Rosmiati, R. (2014). Water quality parameter analysis for the feasibility of shrimp culture in Takalar Regency, Indonesia. Journal of Aquaculture Research & Development, 5(6), 5-7.

Katiha, P. K., Jena, J. K., Pillai, N. G. K., Chakraborty, C., & Dey, M. M. (2005). Inland aquaculture in India: past trend, present status and future prospects. Aquaculture Economics & Management, 9(1-2), 237-264.

Khanjani, M. H., & Sharifinia, M. (2020). Biofloc technology as a promising tool to improve aquaculture production. Reviews in aquaculture, 12(3), 1836-1850.

Khodary, S. M.; Elwakil, A. Z.; Fujii, M.; & Tawfik, A. Effect of hazardous industrial solid waste landfill leachate on the geotechnical properties of clay. Arabian Journal of Geosciences, 2020, 13(15), 1-12.

Kim, D. J., Lee, D. I., & Keller, J. (2006). Effect of temperature and free ammonia on nitrification and nitrite accumulation in landfill leachate and analysis of its nitrifying bacterial community by FISH. Bioresource technology, 97(3), 459-468.

Kjeldsen, P., Barlaz, M. A., Rooker, A. P., Baun, A., Ledin, A., & Christensen, T. H. (2002). Present and long-term composition of MSW landfill leachate: a review. Critical reviews in environmental science and technology, 32(4), 297-336.

Kolli, M. K., Opp, C., Karthe, D., & Groll, M. (2020). Mapping of major land-use changes in the Kolleru Lake freshwater ecosystem by using landsat satellite images in google earth engine. Water, 12(9), 2493.

Kolli, M. K., Opp, C., Karthe, D., & Groll, M. Mapping of major land-use changes in the Kolleru Lake freshwater ecosystem by using landsat satellite images in google earth engine. Water, 2020, 12(9), 2493.

Kolli, M. K.; Opp, C.; Karthe, D.; & Pradhan, B. Automatic extraction of large-scale aquaculture encroachment areas using Canny Edge Otsu algorithm in Google Earth Engine–the case study of Kolleru Lake, South India. Geocarto International, 2022, 1-17.

Kothari, V., Vij, S., Sharma, S., & Gupta, N. (2021). Correlation of various water quality parameters and water quality index of districts of Uttarakhand. Environmental and Sustainability Indicators, 9, 100093.

Koul, B., Yakoob, M., & Shah, M. P. (2022). Agricultural waste management strategies for environmental sustainability. Environmental Research, 206, 112285.

Kumar, L., Kapoor, N., & Tiwari, A. (2022). Water–Energy Nexus in Wastewater Management for Irrigation.

Kumar, P. (2019). Numerical quantification of current status quo and future prediction of water quality in eight Asian megacities: Challenges and opportunities for sustainable water management. Environmental monitoring and assessment, 191(6), 1-12.

Kumar, P., Jetani, K. L., Yusuzai, S. I., Sayani, A. N., Dar, S. A., & Rather, M. A. (2012). Effect of sediment and water quality parameters on the productivity of coastal shrimp farm. Advances in Applied Science Research, 3(4), 2033-2041.

Kurniawan, S. B., Ahmad, A., Rahim, N. F. M., Said, N. S. M., Alnawajha, M. M., Imron, M. F., ... & Hasan, H. A. (2021). Aquaculture in Malaysia: Water-related environmental challenges and opportunities for cleaner production. Environmental Technology & Innovation, 24, 101913.

Lafferty, K.D., Harvell, C.D., Conrad, J.M., Friedman, C.S., Kent, M.L., Kuris, A.M., Powell, E.N., Rondeau, D., Saksida, S.M. (2015). Infectious diseases affect marine fisheries and aquaculture economics. Annu. Rev. Mar. Sci. 7, 471–496..

Lai, W. W. P.; Lin, Y. C.; Wang, Y. H.; Guo, Y. L.; & Lin, A. Y. C. Occurrence of emerging contaminants in aquaculture waters: cross-contamination between aquaculture systems and surrounding waters. Water, Air, & Soil Pollution, 2018, 229(8), 1-12.

Le, C., Zha, Y., Li, Y., Sun, D., Lu, H., & Yin, B. (2010). Eutrophication of lake waters in China: cost, causes, and control. Environmental management, 45(4), 662-668.

Li, H., Yi, T., Gu, M., & Huo, L. (2009). Evaluation of earthquake-induced structural damages by wavelet transform. Progress in Natural Science, 19(4), 461-470.

Liakos, K., Busato, P., Moshou, D., Pearson, S., Bochtis, D. (2018). Machine learning in agriculture: a review. Sensors-Basel 18. https://doi.org/10.3390/s18082674.

Lilkov, V., Petrov, O., Petkova, V., Petrova, N., & Tzvetanova, Y. (2011). Study of the pozzolanic activity and hydration products of cement pastes with addition of natural zeolites. Clay minerals, 46(2), 241-250.

Liu, F., Li, S., Yu, Y., Sun, M., Xiang, J., & Li, F. (2020). Effects of ammonia stress on the hemocytes of the Pacific white shrimp Litopenaeus vannamei. Chemosphere, 239, 124759.

Luo, J., Sun, Z., Lu, L., Xiong, Z., Cui, L., & Mao, Z. (2022). Rapid expansion of coastal aquaculture ponds in Southeast Asia: Patterns, drivers and impacts. *Journal of Environmental Management*, *315*, 115100.

Luo, Z., Hu, S., & Chen, D. (2018). The trends of aquacultural nitrogen budget and its environmental implications in China. Scientific reports, 8(1), 1-9.

Ma, Z., Li, H., Ye, Z., Wen, J., Hu, Y., & Liu, Y. (2020). Application of modified water quality index (WQI) in the assessment of coastal water quality in main aquaculture areas of Dalian, China. Marine Pollution Bulletin, 157, 111285.

Maja, M. M., & Ayano, S. F. (2021). The impact of population growth on natural resources and farmers' capacity to adapt to climate change in low-income countries. Earth Systems and Environment, 5(2), 271-283.

Mallin, M. A., & Cahoon, L. B. (2003). Industrialized animal production—a major source of nutrient and microbial pollution to aquatic ecosystems. Population and Environment, 24(5), 369-385.

Martins, C. I. M., Eding, E. H., Verdegem, M. C., Heinsbroek, L. T., Schneider, O., Blancheton, J. P., ... & Verreth, J. A. J. (2010). New developments in recirculating aquaculture systems in Europe: A perspective on environmental sustainability. Aquacultural Engineering, 43(3), 83-93.

Martins, C. I. M., Eding, E. H., Verdegem, M. C., Heinsbroek, L. T., Schneider, O., Blancheton, J. P., ... & Verreth, J. A. J. (2010). New developments in recirculating aquaculture systems in Europe: A perspective on environmental sustainability. Aquacultural Engineering, 43(3), 83-93.

Mishra, R. R., Rath, B., & Thatoi, H. (2008). Water quality assessment of aquaculture ponds located in Bhitarkanika mangrove ecosystem, Orissa, India. Turkish Journal of Fisheries and Aquatic Sciences, 8(1), 71-77.

Mitchell, J. K., & Soga, K. (2005). Fundamentals of soil behavior (Vol. 3, p. USA). New York: John Wiley & Sons.

Mohanty, R. K., Ambast, S. K., Panigrahi, P., & Mandal, K. G. (2018). Water quality suitability and water use indices: Useful management tools in coastal aquaculture of Litopenaeus vannamei. Aquaculture, 485, 210-219.

Mook, W. T., Chakrabarti, M. H., Aroua, M. K., Khan, G. M. A., Ali, B. S., Islam, M. S., & Hassan, M. A. (2012). Removal of total ammonia nitrogen (TAN), nitrate and total organic carbon (TOC) from aquaculture wastewater using electrochemical technology: a review. Desalination, 285, 1-13.

MPEDA. (2022). The Marine Product Development Authority (MPEDA) State-wise Details of Shrimp and Scampi Production. http://mpeda.gov. (Accessed 26 December 2022).

Muhuri, P. K., Ashraf, Z., & Goel, S. (2020). A novel image steganographic method based on integer wavelet transformation and particle swarm optimization. Applied Soft Computing, 92, 106257.

Muralidhar, M., Kumaran, M., Jayanthi, M., Syama Dayal, J., Ashok Kumar, J., Saraswathy, R., & Nagavel, A. (2021). Impacts of climate change and adaptations in shrimp aquaculture: A study in coastal Andhra Pradesh, India. *Aquatic Ecosystem Health & Management*, *24*(3), 28-38.

Mutea, F. G., Nelson, H. K., Au, H. V., Huynh, T. G., & Vu, U. N. (2021). Assessment of Water Quality for Aquaculture in Hau River, Mekong Delta, Vietnam Using Multivariate Statistical Analysis. Water, 13(22), 3307.

Nagaraju, T. V., & Prasad, C. (2020). Swarm-assisted multiple linear regression models for compression index (Cc) estimation of blended expansive clays. Arabian Journal of Geosciences, 13(9), 1-11.

Nagaraju, T. V., Malegole, S. B., Chaudhary, B., & Ravindran, G. (2022). Assessment of Environmental Impact of Aquaculture Ponds in the Western Delta Region of Andhra Pradesh. Sustainability, 14(20), 13035.

Nagaraju, T. V., Sunil, B. M., & Chaudhary, B. (2023). A Study on Aquaculture Waste Leachate Transport Through Soil. In Recent Trends in Civil Engineering (pp. 485-491). Springer, Singapore.

Nageswara Rao, P. V., Appa Rao, S., & Subba Rao, N. (2015). Suitability of groundwater quality for drinking, irrigation and industrial purposes in the Western Delta Region of the River Godavari, Andhra Pradesh. Journal of the Geological Society of India, 86(2), 181-190.

Nazarova, T., Martin, P., & Giuliani, G. (2020). Monitoring vegetation change in the presence of high cloud cover with Sentinel-2 in a lowland tropical forest region in Brazil. Remote Sensing, 12(11), 1829.

Nhu, T. T.; Schaubroeck, T.; Henriksson, P. J.; Bosma, R.; Sorgeloos, P.; & Dewulf, J. Environmental impact of non-certified versus certified (ASC) intensive Pangasius aquaculture in Vietnam, a comparison based on a statistically supported LCA. Environmental pollution, 2016, 219, 156-165.

Nie, X., Mubashar, M., Zhang, S., Qin, Y., & Zhang, X. (2020). Current progress, challenges and perspectives in microalgae-based nutrient removal for aquaculture waste: A comprehensive review. Journal of Cleaner Production, 277, 124209.

Oswald Spring, Ú. (2020). Environmental Management in a Globalised World. In Earth at Risk in the 21st Century: Rethinking Peace, Environment, Gender, and Human, Water, Health, Food, Energy Security, and Migration (pp. 193-214). Springer, Cham.

Ottinger, M., Clauss, K., & Kuenzer, C. (2016). Aquaculture: Relevance, distribution, impacts and spatial assessments–A review. Ocean & Coastal Management, 119, 244-266.

Paez-Osuna, F. The environmental impact of shrimp aquaculture: a global perspective. Environmental pollution, 2001, 112(2), 229-231.

Páez-Osuna, F.; Guerrero-Galván, S. R.; & Ruiz-Fernández, A. C. The environmental impact of shrimp aquaculture and the coastal pollution in Mexico. Marine Pollution Bulletin, 1998, 36(1), 65-75.

Palani, S., Liong, S. Y., & Tkalich, P. (2008). An ANN application for water quality forecasting. Marine pollution bulletin, 56(9), 1586-1597.

Pan, Z., Yang, C. N., Sheng, V. S., Xiong, N., & Meng, W. (2019). Machine learning for wireless multimedia data security. Security and Communication Networks, 2019.

Parmar, K. S., Soni, K., & Singh, S. (2021). Prediction of river water quality parameters using soft computing techniques. Intelligent Data Analytics for Decision-Support Systems in Hazard Mitigation: Theory and Practice of Hazard Mitigation, 429-440.

Patil, P. K., Mishra, S. S., Pradhan, P. K., Manna, S. K., Abraham, J. T., Solanki, H. G., ... & Jena, J. (2022). Usage pattern of chemicals, biologicals and veterinary medicinal products in Indian aquaculture. Reviews in Aquaculture.

Pham, Q. B., Mohammadpour, R., Linh, N. T. T., Mohajane, M., Pourjasem, A., Sammen, S. S., ... & Nam, V. T. (2021). Application of soft computing to predict water quality in wetland. Environmental Science and Pollution Research, 28, 185-200.

Pham, Q. B., Mohammadpour, R., Linh, N. T. T., Mohajane, M., Pourjasem, A., Sammen, S. S., ... & Nam, V. T. (2021). Application of soft computing to predict water quality in wetland. Environmental Science and Pollution Research, 28(1), 185-200.

Phanikumar, B. R., & Nagaraju, T. V. (2018). Influence of fly ash (FA) and rice husk ash (RHA) on properties of expansive clays-a comparative study. Geotech. Geol. Eng. https://doi. org/10.1007/s10706-018-0544-5.

Phanikumar, B. R., & Nagaraju, T. V. (2019). Swell and compressibility of GGBS–clay mixes in lumps and powders: effect of 4% lime. Indian Geotechnical Journal, 49(2), 161-169.

Phanikumar, B. R., Nagaraju, T. V., & Mounika, K. N. (2022). Swell and compressibility of fly ash− clay blends in lumps and powders: effect of 4% lime. Proceedings of the Institution of Civil Engineers-Ground Improvement, 175(1), 82-91.

Phillips, M. The use of chemicals in carp and shrimp aquaculture in Bangladesh, Cambodia, Lao PDR, Nepal, Pakistan, Sri Lanka and Viet Nam, 2000.

Piedrahita, R. H. Reducing the potential environmental impact of tank aquaculture effluents through intensification and recirculation. Aquaculture, 2003, 226(1-4), 35-44.

Pillai, S., Peter, A. E., Sunil, B. M., & Shrihari, S. (2014, March). Soil pollution near a municipal solid waste disposal site in India. In International Conference on Biological, Civil and Environmental Engineering (BCEE-2014) March (Vol. 1718).

Prasad, K. A., Ottinger, M., Wei, C., & Leinenkugel, P. (2019). Assessment of coastal aquaculture for India from Sentinel-1 SAR time series. Remote Sensing, 11(3), 357.

Rajaee, T., Khani, S., & Ravansalar, M. (2020). Artificial intelligence-based single and hybrid models for prediction of water quality in rivers: A review. Chemometrics and Intelligent Laboratory Systems, 200, 103978.

Ramírez, A., Sifuentes, C., Manciu, F. S., Komarneni, S., Pannell, K. H., & Chianelli, R. R. (2011). The effect of Si/Al ratio and moisture on an organic/inorganic hybrid material: thioindigo/montmorillonite. Applied clay science, 51(1-2), 61-67.

Rao, B. H., Reddy, P. S., Mohanty, B., & Reddy, K. R. (2021). Combined effect of mineralogical and chemical parameters on swelling behaviour of expansive soils. Scientific Reports, 11(1), 1-20.

Rao, S. M., & Thyagaraj, T. (2007). Swell–compression behaviour of compacted clays under chemical gradients. Canadian Geotechnical Journal, 44(5), 520-532.

Ray, A. J., Dillon, K. S., & Lotz, J. M. (2011). Water quality dynamics and shrimp (Litopenaeus vannamei) production in intensive, mesohaline culture systems with two levels of biofloc management. Aquacultural Engineering, 45(3), 127-136.

Reddy, K. R. (2014). Evolution of geoenvironmental engineering. Environmental Geotechnics, 1(3), 136-141.

Rico, A.; Satapornvanit, K.; Haque, M. M.; Min, J.; Nguyen, P. T.; Telfer, T. C.; & Van Den Brink, P. J. Use of chemicals and biological products in Asian aquaculture and their potential environmental risks: a critical review. Reviews in Aquaculture, 2012, 4(2), 75-93.

Rowe, R. K. (2007). Advances and remaining challenges for geosynthetics in geoenvironmental engineering applications. Soils and Rocks, 30(1), 3-30.

Sakaa, B., Elbeltagi, A., Boudibi, S., Chaffaï, H., Islam, A. R. M. T., Kulimushi, L. C., & Wong, Y. J., 2022. Water quality index modeling using random forest and improved SMO algorithm for support vector machine in Saf-Saf river basin. *Environ. Sci. Pollu. Res. 29*(32), 48491-48508.

Salunke, M., Kalyankar, A., Khedkar, C.D., Shingare, M., Khedkar, G.D., (2020). A review on shrimp aquaculture in India: historical perspective, constraints, status and future implications for impacts on aquatic ecosystem and biodiversity. Reviews in Fisheries Science & Aquaculture 28 (3), 283–302. https://doi.org/10.1080/ 23308249.2020.1723058.

Sampantamit, T., Ho, L., Lachat, C., Sutummawong, N., Sorgeloos, P., & Goethals, P. (2020). Aquaculture production and its environmental sustainability in Thailand: Challenges and potential solutions. Sustainability, 12(5), 2010.

Sharma, D., Rao, K., & Ramanathan, A. L. (2022). A Systematic Review on the Impact of Urbanization and Industrialization on Indian Coastal Mangrove Ecosystem. Coastal Ecosystems, 175-199.

Silva, G. C., Limeira, A. C., de Almeida Costa, G. K., da Silva, S. M. B. C., de Oliveira Filho, P. R. C., & Brito, L. O. (2023). Effects of different forms of artificially salinized in low-salinity water of Penaeus vannamei in the grow-out phase in a synbiotic system. *Aquaculture International*, *31*(3), 1303-1324.

Singh, S., & Hussian, A. (2016). Water quality index development for groundwater quality assessment of Greater Noida sub-basin, Uttar Pradesh, India. Cogent Engineering, 3(1), 1177155.

Solli, L., Schnürer, A., & Horn, S. J. (2018). Process performance and population dynamics of ammonium tolerant microorganisms during co-digestion of fish waste and manure. *Renewable Energy*, *125*, 529-536.

Solli, L., Bergersen, O., Sørheim, R., & Briseid, T. (2014). Effects of a gradually increased load of fish waste silage in co-digestion with cow manure on methane production. *Waste Management*, *34*(8), 1553-1559.

Song, P., Wu, L., & Guan, W. (2015). Dietary nitrates, nitrites, and nitrosamines intake and the risk of gastric cancer: a meta-analysis. Nutrients, 7(12), 9872-9895.

Spanig, S., Emberger-Klein, A., Sowa, J.P., Canbay, A., Menrad, K., Heider, D. (2019). The virtual doctor: An interactive clinical-decision-support system based on deep learning for non-invasive prediction of diabetes. Artif. Intell. Med. 100, 101706

Subasinghe, R. P. (2005). Epidemiological approach to aquatic animal health management: opportunities and challenges for developing countries to increase aquatic production through aquaculture. Preventive veterinary medicine, 67(2-3), 117-124.

Sunil, B. M., Nayak, S., & Shrihari, S. (2006). Effect of pH on the geotechnical properties of laterite. Engineering geology, 85(1-2), 197-203.

Sunil, B. M.; Shrihari, S.; & Nayak, S. Soil-leachate interaction and their effects on hydraulic conductivity and compaction characteristics. In 12th International Conference on Computer Methods and Advances in Geomechanics, 2008, Vol. 3, pp. 2380-2386.

Szuster, B. W. A review of shrimp farming in central Thailand and its environmental implications. Shrimp Culture: Economics, and Trade. Leung, PS & Engle, C.(eds). Oxford OX4 2DQ, UK, 2006, 155-164.

Thatai, S., Verma, R., Khurana, P., Goel, P., & Kumar, D. (2019). Water quality standards, its pollution and treatment methods. In A new generation material graphene: applications in water technology (pp. 21-42). Springer, Cham.

Tomić, A. N. Š., Antanasijević, D. Z., Ristić, M. Đ., Perić-Grujić, A. A., & Pocajt, V. V. (2016). Modeling the BOD of Danube River in Serbia using spatial, temporal, and input variables optimized artificial neural network models. Environmental monitoring and assessment, 188(5), 300.

Trach, R., Trach, Y., Kiersnowska, A., Markiewicz, A., Lendo-Siwicka, M., & Rusakov, K. (2022). A Study of Assessment and Prediction of Water Quality Index Using Fuzzy Logic and ANN Models. Sustainability, 14(9), 5656.

Trojovský, P., & Dehghani, M. (2022). Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. Sensors, 22(3), 855.

Uddin, M. G., Nash, S., Rahman, A., & Olbert, A. I., 2023. A novel approach for estimating and predicting uncertainty in water quality index model using machine learning approaches. *Water Research*, *229*, 119422.

Uddin, M. G., Nash, S., Rahman, A., & Olbert, A. I., 2023. Performance analysis of the water quality index model for predicting water state using machine learning techniques. *Process Saf. Environ. Prot. 169*, 808-828.

Vadyala, S. R., Betgeri, S. N., Matthews, J. C., & Matthews, E. (2021). A review of physics-based machine learning in civil engineering. Results in Engineering, 100316.

Vasanthavigar, M., Srinivasamoorthy, K., Vijayaragavan, K., Rajiv Ganthi, R., Chidambaram, S., Anandhan, P., ... & Vasudevan, S. (2010). Application of water quality index for groundwater quality assessment: Thirumanimuttar sub-basin, Tamilnadu, India. Environmental monitoring and assessment, 171(1), 595-609.

Venkateswarlu, V., Seshaiah, P. V., Arun, P., & Behra, P. C. (2019). A study on water quality parameters in shrimp L. vannamei semi-intensive grow out culture farms in coastal districts of Andhra Pradesh, India. International Journal of Fisheries and Aquatic Studies, 7(4), 394-399.

Verdegem, M. C. (2013). Nutrient discharge from aquaculture operations in function of system design and production environment. Reviews in Aquaculture, 5(3), 158-171.

WGFD. (2022). West Godavari Fisheries Department (WGFD) year-wise details of shrimp and fish production. https://westgodavari.ap.gov.in/fisheries/. (Accessed 26 December 2022).

World Health Organization (WHO) (1998) Guidelines for drinking water quality, 2nd edn. Geneva. ISBN 9241545143:36

World Health Organization (WHO) (2004) Guidelines for drinking water quality. Recommendations, Geneva, Switzerland, Vol 3

World Health Organization (WHO) (2017) Guidelines for drinking-water quality, 4th edition, incorporating the 1st addendum ISBN: 978-92- 4-154995-0

Wu, Y.; & Song, K. Source, Treatment, and Disposal of Aquaculture Solid Waste: A Review. Journal of Environmental Engineering, 2021, 147(3), 03120012.

Xu, J., Xu, Z., Kuang, J., Lin, C., Xiao, L., Huang, X., & Zhang, Y. (2021). An alternative to laboratory testing: Random forest-based water quality prediction framework for inland and nearshore water bodies. Water, 13(22), 3262.

Yang, L., Liu, Y., Yu, H., Fang, X., Song, L., Li, D., Chen, Y. (2020). Computer vision models in intelligent aquaculture with emphasis on fish detection and behavior analysis: a review. Arch. Comput. Method E. https://doi.org/10.1007/s11831-020- 09486-2.

Yang, Y., Xiong, Q., Wu, C., Zou, Q., Yu, Y., Yi, H., & Gao, M. (2021). A study on water quality prediction by a hybrid CNN-LSTM model with attention mechanism. Environmental Science and Pollution Research, 28(39), 55129-55139.

Yilmaz, I., & Marschalko, M. (2014). The effect of different types of water on the swelling behaviour of expansive clays. Bulletin of Engineering Geology and the Environment, 73(4), 1049-1062.

Yogev, U., Barnes, A., Giladi, I., & Gross, A. (2020). Potential environmental impact resulting from biased fish sampling in intensive aquaculture operations. Science of The Total Environment, 707, 135630.

Yoon, H., Kim, Y., Ha, K., Lee, S. H., & Kim, G. P. (2017). Comparative evaluation of ANN-and SVM-time series models for predicting freshwater-saltwater interface fluctuations. Water, 9(5), 323.

Yu, H., Yang, L., Li, D., & Chen, Y. (2021). A hybrid intelligent soft computing method for ammonia nitrogen prediction in aquaculture. Information Processing in Agriculture, 8(1), 64-74.

Yuan, J.; Xiang, J.; Liu, D.; Kang, H.; He, T.; Kim, S.; & Ding, W. Rapid growth in greenhouse gas emissions from the adoption of industrial-scale aquaculture. Nature Climate Change, 2019, 9(4), 318-322.

Yuvanatemiya, V., & Boyd, C. E. (2006). Physical and chemical changes in aquaculture pond bottom soil resulting from sediment removal. Aquacultural engineering, 35(2), 199-205.

Zacarias, S., Schveitzer, R., Arantes, R., Galasso, H., Pinheiro, I., Espirito Santo, C., & Vinatea, L. (2019). Effect of different concentrations of potassium and magnesium on performance of Litopenaeus vannamei postlarvae reared in low-salinity water and a biofloc system. Journal of Applied Aquaculture, 31(1), 85-96.

Zahoor, Z., Latif, M. I., Khan, I., & Hou, F. (2022). Abundance of natural resources and environmental sustainability: the roles of manufacturing value-added, urbanization, and permanent cropland. Environmental Science and Pollution Research, 29(54), 82365-82378.

Zakaria, K. A., Yatim, N. I., Ali, N. A., & Rastegari, H. (2022). Recycling phosphorus and calcium from aquaculture waste as a precursor for hydroxyapatite (HAp) production: a review. Environmental Science and Pollution Research, 1-16.

Zhao, M., Yao, D., Li, S., Zhang, Y., & Aweya, J. J. (2020). Effects of ammonia on shrimp physiology and immunity: a review. Reviews in Aquaculture, 12(4), 2194-2211.

Zhao, P., Tang, X., Tang, J., & Wang, C. (2013). Assessing water quality of Three Gorges Reservoir, China, over a five-year period from 2006 to 2011. Water Resources Management, 27(13), 4545-4558.

Zhong, D., Wang, F., Dong, S., & Li, L. (2015). Impact of Litopenaeus vannamei bioturbation on nitrogen dynamics and benthic fluxes at the sediment–water interface in pond aquaculture. Aquaculture international, 23(4), 967-980.

Zhou, F., Liu, B., & Duan, K. (2020). Coupling wavelet transform and artificial neural network for forecasting estuarine salinity. Journal of Hydrology, 588, 125127.

Zhou, L., & Boyd, C. E. (2014). Total ammonia nitrogen removal from aqueous solutions by the natural zeolite, mordenite: A laboratory test and experimental study. Aquaculture, 432, 252-257.

Zhou, L., & Boyd, C. E. (2015). An assessment of total ammonia nitrogen concentration in Alabama (USA) ictalurid catfish ponds and the possible risk of ammonia toxicity. Aquaculture, 437, 263-269.

APPENDIX-I

Locations in the study area

S.No	Location	Latitude (N)	Longitude (E)	Designation/ Sample Id
1	Kalla	16.5283^o	81.4087^o	V1
2	Kallakuru	16.5283^o	81.3832^o	V2
3	Kallavapudi	16.4620^o	81.3881^o	V3
4	Dodanapudi	16.5245^o	81.3870^o	V4
5	Elurupadu	16.5187^o	81.3468^o	V5
6	Juvalapalem	16.5190^o	81.3695^o	V6
7	Sessali	16.5296^o	81.4334^o	V7
8	Pedhaamiram	16.5443^o	81.4903^o	V8
9	Chinnaamiram	16.5291^o	81.4911^o	V9
10	Bhimavaram	16.4851^o	81.4883^o	V10
11	Annakoderu	16.4840^o	81.4825^o	V11
12	Vempa	16.4421^o	81.5750^o	V12
13	chilukuru	16.6232^o	80.4354^o	V13
14	kolamuru	16.6329^o	81.4589^o	V14
15	Undi	16.5864^o	81.4636^o	V15
16	yendagandi	16.6433^o	81.5336^o	V16
17	Akividu	16.5823^o	81.3784^o	V17
18	cherkumilli	17.0711^o	81.6109^o	V18
19	Kolleru	16.6629^o	81.3372^o	V19
20	pedakapavaram	16.6434^o	81.4306^o	V20
21	chinakapavaram	16.6348^o	81.4162^o	V21
22	palakoderu	16.5862^o	81.5480^o	V22
23	Mogallu	16.6036^o	81.5638^o	V23
24	vissakoderu	16.5511^o	81.5665^o	V24
25	Attili	16.6885^o	81.6037^o	V25
26	Manchili	16.6565^o	81.6062^o	V26
27	Aravalli	16.6316^o	81.6049^o	V27
28	Eduru	16.6458^o	81.5689^o	V28
29	ganapavaram	16.6994^o	81.4635^o	V29
30	kesavaram	16.6810^o	81.5439^o	V30
31	Pippara	16.7109^o	81.5418^o	V31
32	Kasipadu	16.7361^o	81.5514^o	V32
33	Ardhavaram	16.6889^o	81.5061^o	V33
34	Eluru	16.7107^o	81.0952^o	V34
35	Kokkirailanka	16.6382^o	81.2354^o	V35
36	Komadavole	16.7117^o	81.1258^o	V36
37	Chataparru	16.6966^o	81.1665^o	V37
38	Chebrolu	16.8289^o	81.3922^o	V38
39	Unguturu	16.8230^o	81.4238^o	V39
40	Denduluru	16.7609^o	81.1665^o	V40

APPENDIX-II

Aquaculture ponds water quality data

S. No	Latitude ° (N)	Longitude ° (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
1	16.7508	81.6012	8.45	360	500	7.8	180	310	150	200	110	0	6.05
2	16.7168	81.6113	7.64	450	420	2	240	280	180	45	86	0	11.20
3	16.4230	81.4915	7.34	230	1480	2	315	180	1100	48	45	0	2.40
4	16.4155	81.4567	8.15	180	11465	8.4	300	200	760	160	111	0.16	61.80
5	16.5385	81.5274	7.85	3240	301	5	280	190	1010	128	194	0.03	4.45
6	16.5317	81.4581	8.15	540	45568	8.7	300	1100	1120	120	199	0.18	66.07
7	16.5001	81.4548	8.24	300	500	4	220	400	320	64	87	2	81.50
8	16.4599	81.4151	8.2	240	1355	2	110	190	100	36	42	0	3.45
9	16.6412	81.6278	7.85	210	989	2	260	300	560	35	94	0.04	2.91
10	16.7346	81.5361	8.15	140	842	1	300	280	560	30	32	0.03	4.42
11	16.5381	81.3629	8.08	2400	12695	4	320	330	600	112	140	0.3	4.50
12	16.5899	81.4163	8.07	130	580	2	350	400	560	38	52	0.1	3.08
13	16.8124	81.6831	8.32	200	1290	2	300	330	90	120	34	0	9.05
14	16.6115	81.4951	7.31	180	378	0	70	190	80	25	4	0	3.04
15	16.6325	81.4184	8.14	530	1800	4	200	270	890	124	257	0.1	2.45
16	16.5462	81.4392	7.94	200	190	2	200	190	1150	36	30	0.1	51.62
17	16.7571	81.5687	8.19	240	300	1	140	150	1220	35	35	0.1	67.40
18	16.6265	81.6225	7.45	180	1590	1	120	230	80	30	22	0.1	2.48
19	16.6405	81.6133	7.44	210	1020	1	120	150	100	24	26	0	1.34
20	16.7121	81.5881	7.32	520	978	7.5	160	160	1180	192	218	0.54	3.21
21	16.5251	81.3937	8.18	1100	11380	7.5	290	270	1450	176	272	0.5	1.40
22	16.4100	81.4329	8.24	1500	13600	7	240	220	1660	128	325	0.45	1.00

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
23	16.5844	81.3543	7.56	450	21205	8	210	210	1180	88	233	0.54	2.17
24	16.7768	81.6229	7.88	200	600	1	130	220	80	15	28	0	23.50
25	16.6468	81.5693	7.52	120	1380	2	160	260	120	20	47	0	10.90
26	16.5203	81.3447	8.15	400	500	6.5	110	110	1280	64	272	0.42	11.80
27	16.5643	81.5251	7.56	8000	2010	5	210	210	1280	88	257	0.35	4.45
28	16.6919	81.4622	7.543	240	240	1	130	130	80	32	7.8	1.8	82.07
29	16.6149	81.5285	7.88	5000	1790	7	140	330	1720	176	311	0.2	18.90
30	16.5982	81.5847	8.32	8200	1095	7.5	250	200	1600	160	291	0.32	87.70
31	16.8160	81.6591	8.25	360	620	7	370	350	840	96	145	0.2	52.91
32	16.5873	81.5335	8.15	850	1190	4	450	480	920	152	145	0	4.42
33	16.4650	81.5058	8.24	230	1268	2	160	340	80	32	26	0	69.70
34	16.4350	81.4306	8.45	240	1750	2	120	200	85	36	32	0	3.08
35	16.5914	81.5186	7.35	180	1230	2	190	190	140	36	49	0.1	9.05
36	16.7193	81.6329	7.9	540	350	8.8	180	210	125	80	77	0.56	59.20
37	16.6206	81.4113	8.88	420	500	5	370	310	620	88	97	0.45	71.10
38	16.4403	81.4712	8.38	2340	1110	5.5	210	170	1420	168	243	0.2	1.62
39	16.5913	81.5628	8.15	200	1589	1	120	200	85	25	13	0	37.40
40	16.4756	81.4175	8.26	230	900	2	220	190	120	24	56	0	2.48
41	16.7206	81.4731	8.24	2400	238	7	260	250	1220	96	189	0.45	61.34
42	16.5434	81.4543	8.15	4200	500	4	240	220	800	152	150	0.2	73.21
43	16.6818	81.5221	7.54	200	500	1.5	240	260	115	20	12	0	1.40
44	16.7276	81.4944	8.53	760	1000	4	210	200	480	32	121	0	1.00

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
45	16.6632	81.6566	8.44	240	1200	0	150	140	85	24	12	0	2.17
46	16.5191	81.372	7.55	200	230	0	140	150	80	22	8.2	0	3.50
47	16.5728	81.5139	8.66	450	1280	2	285	200	140	86	89	0	4.50
48	16.5495	81.5225	8.15	1200	1265	6	210	210	800	120	121	0	2.65
49	16.5764	81.3966	8.25	250	668	4	250	230	680	100	97	0	4.45
50	16.5853	81.4231	8.13	520	500	2	140	350	108	44	46	0	6.07
51	16.4594	81.3904	7.64	210	235	0	160	230	120	26	14	0	4.90
52	16.8378	81.67517	8.37	1500	1250	4	150	130	2100	240	369	0	7.70
53	16.6626	81.4912	7.46	450	880	3	180	170	1260	136	223	0.25	72.91
54	16.4022	81.4701	7.89	200	1235	3	270	320	188	28	124	0	4.42
55	16.5791	81.4295	7.81	2300	650	6.8	260	310	1840	160	349	0.4	9.70
56	16.5378	81.4067	7.78	3400	1150	5.5	180	180	1820	256	286	0	3.08
57	16.5292	81.3844	8.09	8000	1250	7	250	240	1620	208	267	0	2.45
58	16.6397	81.5926	7.88	230	1600	3	50	180	186	24	36	0	5.75
59	16.7432	81.5534	7.88	240	1200	3	190	180	200	36	65	0	2.44
60	16.7760	81.3151	8.12	210	300	2	270	250	150	26	36	0	1.62
61	16.7870	81.2883	8.18	360	15900	8.5	320	310	2200	248	383	0.54	88.45
62	16.7340	81.2452	8.08	850	1020	5	360	350	3300	288	626	0	2.48
63	16.7070	81.3631	7.88	6200	978	3	280	250	214	84	56	0	1.34
64	16.4560	81.6391	8.15	210	1380	1	330	300	80	25	88	0	3.21
65	16.4420	81.6038	7.88	210	600	1	350	280	85	22	45	0	1.40
66	16.3881	81.6314	8.76	540	12400	10.5	240	240	3240	256	631	0.3	61.00

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
67	16.4142	81.5691	7.22	200	240	0	180	190	80	18	9.8	0	2.17
68	16.5523	81.7294	7.54	2340	1380	3	180	180	134	20	125	0.1	3.50
69	16.6646	81.57252	7.19	180	1692	7	290	270	1880	184	345	0.18	66.50
70	16.5684	81.5341	8.12	320	2010	6	320	300	2340	240	422	0.2	6.80
71	16.8181	81.6322	8.47	2400	11200	11.5	200	170	1240	88	247	0	14.45
72	16.5952	81.4191	8.45	4200	34000	9.7	290	290	1000	88	189	0.7	21.80
73	16.4924	81.3722	8.43	7240	1095	2	220	200	120	25	383	0	8.90
74	16.6501	81.5552	8.65	760	620	5	370	320	960	96	174	0	17.70
75	16.5128	81.4729	7.77	230	1190	1	290	290	122	17	30.8	0.8	2.91
76	16.7479	81.5836	7.56	200	1268	0	360	350	90	18	6.5	0	4.42
77	16.4306	81.4604	7.22	210	2400	1	280	260	95	20	10.2	0	5.45
78	16.7096	81.6657	8.04	1200	1200	6	280	280	520	80	77	0.25	13.08
79	16.6884	81.4919	8.27	250	248	6	310	290	820	96	140	0	9.05
80	16.5751	81.7625	8.35	220	1000	2	430	40	90	41	88	0.4	5.70
81	16.6094	81.7732	7.92	1100	1240	8	280	280	1360	192	213	0.45	81.10
82	16.6562	81.7041	8.05	1500	1589	4	300	290	840	144	116	0.04	1.62
83	16.4142	81.4663	7.54	200	238	0	300	290	80	14	16.5	0	7.40
84	16.4682	81.4747	7.3	210	700	0	300	280	80	12	8.4	0	2.48
85	16.5967	81.4999	8.24	2300	500	6.5	310	300	880	120	240	0.25	11.34
86	16.4556	81.4243	7.12	230	240	1	340	320	100	14	12.4	0	3.21
87	16.6744	81.6518	8.06	230	700	2	250	250	140	12	11.6	0	1.40
88	16.4629	81.4021	8.24	3600	420	9.5	350	350	660	88	106	0.8	21.40

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (μS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
89	16.6335	81.6265	8.14	210	1480	1.5	330	320	110	12	13.1	0	2.17
90	16.6614	81.6109	8.45	8200	3000	7	350	320	1200	104	155	0.16	23.50
91	16.7382	81.6512	7.45	230	568	1	300	210	70	28	12.2	0	8.90
92	16.5618	81.4361	7.36	240	600	1	300	280	88	43	5.9	0	6.75
93	16.7334	81.5919	8.42	6200	1355	7	360	330	2040	240	349	0.24	14.45
94	16.4638	81.4427	8.4	260	989	3	290	260	125	19	125	0.2	6.07
95	16.4709	81.4065	8.6	3240	842	8	420	380	280	176	447	0.4	18.90
96	16.4409	81.4057	8.32	540	580	5	230	220	1100	96	208	0.12	57.70
97	16.6054	81.5642	8.39	420	1290	8	260	240	720	56	140	0.32	52.91
98	16.8066	81.6329	7.87	2340	1378	8.5	190	190	1660	96	345	0.5	64.42
99	16.7444	81.5326	8.15	180	1800	6.2	210	280	1420	136	262	0.16	89.70
100	16.6951	81.5181	8.15	320	11200	5.5	220	220	1180	56	252	0.1	46.08
101	16.6292	81.5427	8.98	2400	18000	9	190	140	660	56	126	0.45	79.05
102	16.8317	81.6895	7.44	210	1590	1	220	220	120	26	5.58	0.1	35.70
103	16.5897	81.3981	7.45	220	1020	1	240	210	80	32	25	0	22.10
104	16.5688	81.5051	7.47	280	978	2	220	210	120	56	67	0	1.62
105	16.5388	81.4979	7.38	310	380	1	170	150	100	18	38	0	7.40
106	16.6595	81.6426	7.35	8700	280	1	290	260	100	48	23.4	0.6	2.48
107	16.6088	81.5294	7.3	200	1205	0	260	230	100	26	8.2	0	1.34
108	16.8663	81.6741	7.37	230	600	1	340	290	120	15	19.9	0	3.21
109	16.5854	81.5471	8.15	250	1380	6	190	190	220	32	34	0	1.40
110	16.6741	81.6345	8.81	520	1692	8	200	200	200	32	29	0.45	21.34

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
111	16.4712	81.3818	8.65	1100	24000	8	170	170	220	32	34	0.48	22.14
112	16.6745	81.5849	8.37	1500	1198	5.2	260	240	1780	128	354	0.12	23.50
113	16.6223	81.4551	7.24	210	179	1	240	240	65	18	3.49	0.2	4.50
114	16.6614	81.4883	7.4	210	1095	1	260	230	120	20	3.15	0	4.50
115	16.6553	81.4924	8.2	2300	12000	6.5	200	200	2680	288	476	0.05	44.45
116	16.8024	81.6426	8.36	220	390	4	150	130	192	224	330	0	6.07
117	16.5505	81.4826	7.35	8000	430	0	170	140	115	38	9.8	0	8.90
118	16.5641	81.4401	7.39	210	1750	0	360	300	112	14	8.45	0	6.44
119	16.6424	81.6465	7.61	5000	1230	4	370	320	340	56	90	0	2.91
120	16.7143	81.5475	7.65	450	350	3	310	250	112	85	112	0	4.42
121	16.4867	81.3775	7.94	360	500	4	390	350	1980	200	359	0	9.70
122	16.6214	81.4614	7.67	220	1110	2	240	230	170	26	35	0	3.08
123	16.7316	81.6621	7.42	210	340	0	260	220	126	36	12.4	0	9.05
124	16.6924	81.6306	8.24	180	900	4	280	260	1540	128	296	0.18	15.70
125	16.7674	81.5871	7.48	140	238	0	230	210	120	25	17.4	0.1	3.45
126	16.6508	81.5095	8.55	540	500	8	310	270	2720	22	524	0	11.62
127	16.5396	81.50691	8.1	420	500	3	210	200	2440	34	500	0.2	7.40
128	16.7088	81.64925	7.65	320	1000	1	370	320	240	20	14.6	0	2.48
129	16.7609	81.6763	7.65	310	500	1	210	200	174	22	12.4	0.4	1.34
130	16.6856	81.4652	7.25	120	42	0	270	250	85	18	3.74	0.05	63.21
131	16.8003	81.6721	7.45	240	460	0	280	250	120	32	3.59	0	1.40
132	16.5304	81.4326	8.1	4200	11456	5.5	410	360	2200	192	417	0	13.45

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
133	16.6605	81.5399	7.53	7240	301	6	340	340	1120	12	199	0	22.40
134	16.5281	81.4369	8.11	760	568	3	290	270	800	10	131	0	12.40
135	16.8712	81.6718	8.32	530	14000	9.5	490	490	1020	104	184	0.7	60.90
136	16.5894	81.5316	8.54	8700	11890	10.7	170	140	840	128	126	0	14.80
137	16.6269	81.5802	7.88	210	842	1.5	130	120	125	56	9.2	0	4.45
138	16.6841	81.6524	7.27	240	265	1	170	160	120	22	20.4	0	6.07
139	16.5456	81.4201	7.32	210	580	1	190	170	120	18	16.5	0	28.90
140	16.8029	81.6405	7.21	180	1290	1	190	170	80	22	18.9	0	27.70
141	16.5654	81.3862	7.24	180	1378	0	200	170	80	16	16.2	0	22.91
142	16.6881	81.5435	8.13	1500	1800	5	210	200	1140	176	170	0	4.42
143	16.7678	81.6721	7.2	510	1190	0	325	310	85	30	9.8	0	26.07
144	16.6157	81.4071	7.61	210	300	1	290	270	160	10	14.5	0	3.08
145	16.7811	81.6576	8.1	2300	1590	5.3	280	270	1120	120	210	0	29.05
146	16.5548	81.3491	8.23	3400	1100	4.5	230	220	1005	152	179	0	35.70
147	16.7294	81.6003	8.21	8000	18900	6.5	230	230	1380	112	267	0	3.40
148	16.5917	81.5263	7.67	230	1380	1	330	320	80	208	35	0	31.62
149	16.5865	81.4616	7.26	300	600	1	180	100	136	18	12.8	0	5.40
150	16.6125	81.6011	7.39	210	240	0	280	280	120	15	3.5	0.2	32.48
151	16.6613	81.5273	7.52	210	600	1	210	200	100	20	12.8	0	41.34
152	16.6442	81.4853	8.24	850	380	5	270	270	2040	224	354	0	33.21
153	16.7853	81.6504	7.39	230	1692	2	230	230	138	45	24.5	0.8	81.40
154	16.7268	81.5201	7.22	240	2010	0	210	210	58	12	12.4	0.4	81.00

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (µS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
155	16.7132	81.5152	7.34	210	1198	0	320	300	80	17	13.4	0	2.17
156	16.5654	81.4709	7.34	210	1790	1	300	280	168	18	9.45	0	3.50
157	16.7046	81.4955	7.28	200	295	0	180	250	80	15	4.9	0	4.90
158	16.7386	81.6221	7.52	240	260	0	330	310	120	19	12.9	0	8.90
159	16.4456	81.3961	7.21	210	300	1	170	220	88	21	10.4	0	2.22
160	16.7309	81.6745	7.31	210	268	0	310	300	100	17	12.4	0.2	56.07
161	16.6507	81.6643	8.61	2400	1750	9.6	290	270	3360	312	626	0.45	58.90
162	16.6041	81.4733	7.42	220	1230	1	290	260	100	20	13.6	0	7.70
163	16.7454	81.6794	7.41	210	1000	0	320	310	80	22	4.8	0	2.91
164	16.7178	81.6662	8.22	760	36500	8.4	320	300	2260	216	417	0.45	64.42
165	16.5318	81.4823	7.35	210	1110	1	260	240	202	17	13.8	0	45.45
166	16.5942	81.5834	7.31	200	1589	0	300	290	80	25	7.4	0.1	51.18
167	16.7041	81.5375	7.54	200	900	0	290	290	90	14	5.6	0	2.34
168	16.6424	81.5342	7.51	210	238	0	290	270	90	13	2.9	0	34.50
169	16.7312	81.6336	7.24	200	500	0	430	400	90	20	3.9	0	6.75
170	16.3933	81.4488	7.24	210	500	0	190	220	85	15	4	0	32.45
171	16.3782	81.4993	8.65	1100	1000	6	380	320	880	72	170	0	7.40
172	16.4931	81.3522	7.86	1500	1050	1	300	320	80	10	6.33	0	2.48
173	16.5196	81.3232	7.61	210	260	0	340	280	80	14	3.5	0	1.34
174	16.8796	81.6743	7.61	210	1000	0	350	300	80	19	4.1	0.8	2.22
175	16.8742	81.6611	7.65	200	249	0	350	240	80	16	1.8	0	21.40
176	16.5244	81.7871	8.1	210	1340	0	220	230	90	22	5.6	0	31.00

Aquaculture ponds water quality data

S. No	Latitude (N)	Longitude (E)	pH	TDS (ppm)	EC (μS/cm)	Salinity (ppt)	Alkalinity (ppm)	HCO_3 (ppm)	TH (ppm)	Ca (ppm)	Mg (ppm)	NH_3 (ppm)	NO_3 (ppm)
177	16.5264	81.8031	8.1	8000	1200	5	380	360	1100	180	256	0.25	22.17
178	16.5542	81.7582	7.43	230	200	0	240	260	134	16	12.4	0	3.50
179	16.5192	81.7624	7.45	210	1000	0	370	280	140	20	6.4	0.25	3.45
180	16.4431	81.5842	8.26	8200	500	7	340	140	125	152	204	0	41.80
181	16.4061	81.5281	8.54	8000	680	6	440	280	2120	192	398	0	44.45
182	16.5897	81.7733	7.56	3600	1240	2	250	150	320	26	631	0	36.07
183	16.8321	81.5841	8.34	5000	10000	4	240	230	1580	240	238	0.45	18.90
184	16.7811	81.3724	7.54	200	280	0	280	240	120	20	7.3	0.2	6.45
185	16.7752	81.3211	8.45	420	500	5	370	280	420	88	97	0.45	71.10
186	16.7324	81.1673	8.88	420	500	5	370	300	450	88	97	0.45	71.10
187	16.7327	81.2492	8.14	3600	420	8.5	350	330	600	88	106	0.8	21.40
188	16.7061	81.3541	8.15	3600	420	9	350	320	660	88	106	0.8	61.40
189	16.7521	81.3824	7.33	210	340	0	260	200	126	36	12.4	0	9.05
190	16.7733	81.2612	7.32	210	340	0	260	210	85	36	12.4	0	9.05

APPENDIX-III

Dataset for ammonia prediction model

S. No	X1	X2	X3	X4	X5	X6	X7	X8	X9	Y
1	1.5	30	8.16	2	300	290	1120	128	194	0.03
2	1.5	30	8.26	1.5	290	280	760	104	121	0.03
3	1	27	7.91	4.5	200	190	1360	96	272	0.1
4	1.5	27	7.94	5.3	200	190	1660	168	301	0.1
5	6	72	8.03	6	240	230	1720	160	320	0.1
6	2	58	8.01	8	340	330	1720	176	311	0.2
7	2	70	8.34	2	360	340	700	72	126	0.08
8	7	30	8.54	0	160	140	300	48	73	0
9	7	30	8.56	0	170	150	380	32	72	0
10	7	30	8.76	1.8	230	200	940	120	155	0
11	7	30	8.54	0	200	180	480	64	77	0
12	1	58	7.54	9.5	180	180	2560	240	475	0.1
13	3	113	8.24	9.8	320	300	2340	240	422	0.2
14	3	34	7.15	5.5	220	220	1180	56	252	0.1
15	1	17	8.98	2.5	190	140	660	56	126	0
16	7	11	8.38	4	170	150	1340	184	213	0
17	2	47	8.36	4	150	130	1920	224	330	0
18	2	47	8.57	4.2	170	140	2020	240	345	0
19	1.5	20	8.27	5.5	240	230	1700	96	354	0.1
20	1	11	8.39	2.5	230	210	920	80	174	0.1
21	15	8	8.44	6.5	280	250	2300	3280	359	0
22	8	7	8.54	2	170	140	840	128	126	0
23	6	32	8.32	2.5	190	170	1140	184	165	0
24	5	22	8.47	3	190	170	1340	224	189	0
25	1	22	8.52	2	200	170	1060	160	160	0
26	1	32	8.13	2	210	200	1140	176	170	0
27	1	5	8.21	2	300	290	660	80	111	0.1
28	5	5	9	5	350	240	1200	168	189	0

Dataset for ammonia prediction model

S. No	X1	X2	X3	X4	X5	X6	X7	X8	X9	Y
29	5	92	8.1	9.5	380	360	2240	240	398	0.25
30	2	12	8.61	5	240	200	1580	240	238	0
31	1	5	9.07	8.8	330	200	2160	232	383	0
32	3	22	7.63	6.5	130	130	1880	184	345	0.1
33	2	57	7.85	3.3	160	160	1060	120	184	0.1
34	3	35	8.54	8.2	330	280	1600	160	291	0.1
35	2	60	8.07	10	220	210	3200	416	524	0.1
36	1	38	8.16	2.5	270	260	680	64	126	0.05
37	3.5	65	8.13	7.8	170	160	2840	424	432	0.1
38	12	15	8.51	4.8	180	160	1920	256	311	0
39	3.5	33	8.35	5.2	150	130	2580	496	325	0
40	7	20	8.96	4	300	210	1940	248	320	0
41	2	15	8.66	5	280	190	1640	144	311	0
42	1	15	8.34	6.7	160	130	2020	280	320	0
43	5	14	8.3	1.5	220	190	600	80	97	0.05
44	2	7	8.3	1.5	220	190	600	80	97	0.05
45	2	23	8.43	2	200	170	680	88	111	0
46	5	78	8.3	5.6	290	280	1640	144	311	0.15
47	2	26	7.81	7	190	190	2620	528	315	0
48	3	50	8.44	5	160	160	2320	352	349	0.1
49	3	30	8.5	5.5	130	120	2240	280	374	0
50	4	60	8.91	3	130	90	2340	400	325	0
51	10	60	7.7	6	120	80	2580	440	359	0
52	5	30	8.19	5.5	140	140	2520	384	379	0
53	2	33	7.88	6.3	180	180	2380	504	272	0
54	4	47	7.5	4.5	110	110	1360	168	228	0.1
55	1.5	48	7.98	6	270	270	1540	128	296	0.1

Dataset for ammonia prediction model

S. No	X1	X2	X3	X4	X5	X6	X7	X8	X9	Y
56	6	26	9.13	7.5	290	250	2120	272	349	0.05
57	5	20	8.59	5.5	290	190	1700	184	301	0
58	0.8	48	8.7	4	270	210	3360	280	646	0
59	1	37	8.12	4.5	260	250	1480	152	267	0.05
60	2	5	8.45	2.5	380	340	840	64	165	0.1
61	0.8	7	8.63	2	270	220	700	104	106	0
62	1.5	15	8.1	0.5	210	200	440	72	63	0
63	6	15	8.53	5	180	150	1660	256	247	0
64	2	60	8.73	7	130	100	2720	424	403	0

Input variables

X1 Area of the pond (acres)

X2 Cultivation days

X3 pH

X4 Salinity (ppt)

X5 Alkalinity (ppm)

X6 Bicarbonates (ppm)

X7 Total hardness (ppm)

X8 Calcium (ppm)

X9 Magnesium (ppm)

Output variable

Y Ammonia (ppm)

PUBLICATIONS BASED ON CURRENT WORK

Journals:

1. Nagaraju, T. V., Malegole, S. B., Chaudhary, B., & Ravindran, G. (2022). Assessment of Environmental Impact of Aquaculture Ponds in the Western Delta Region of Andhra Pradesh. Sustainability, 14(20), 13035. https://doi.org/10.3390/su142013035
2. Nagaraju, T. V., Sunil, B. M., Chaudhary, B., Prasad, C. D., & Gobinath, R. (2023). Prediction of ammonia contaminants in the aquaculture ponds using soft computing coupled with wavelet analysis. *Environmental Pollution*, *331*, 121924. https://doi.org/10.1016/j.envpol.2023.121924
3. Nagaraju, T.V., Sunil, B.M., Chaudhary, B., Ch. Phanindra, & Ch Durga Prasad (2023). Novel assessment tools for inland aquaculture ponds in the western delta region of Andhra Pradesh, Environmental Science and Research Pollution, Springer (*under review*)
4. Nagaraju, T.V., Sunil, B.M., and Chaudhary, B. (2023). Bio-adsorbents and waste-to-energy nexus in inland aquaculture ponds, Total Environment Research Themes, Elsevier (*under review*)
5. Nagaraju, T.V., Sunil, B.M., and Chaudhary, B. (2023). Inland aquaculture ponds in the western delta region of Andhra Pradesh: Economic, Environmental, and Sustainability aspects, Green and Low Carbon Economy (*under review*)

Book chapters:

1. Nagaraju, T. V., Sunil, B. M., & Chaudhary, B. (2023). Understanding the Role of Biological Oxygen Demand in Aquaculture Waters in the Western Delta Region of Andhra Pradesh. In Recent Advances in Sustainable Environment (pp. 13-20). Springer, Singapore. DOI: 10.1007/978-981-19-5077-3_2
2. Nagaraju, T. V., Sunil, B. M., & Chaudhary, B. (2023). A Study on Aquaculture Waste Leachate Transport Through Soil. In Recent Trends in Civil Engineering (pp. 485-491). Springer, Singapore. DOI: 10.1007/978-981-19-4055-2_39
3. Nagaraju, T. V., Sunil, B. M., & Chaudhary, B. (2023). Impact of Aquaculture Solid Waste on Environment in the Delta Region of Andhra Pradesh: A Case Study. In Indian Geotechnical Conference (pp. 369-374). Springer, Singapore. DOI: 10.1007/978-981-19-6774-0_35
4. Nagaraju, T. V., Sunil, B. M., & Chaudhary, B. (2023). Influence of Aquaculture Sludge on Volume Change Behavior of Expansive Clays. In Indian Geotechnical Conference (pp. 43-49). Springer, Singapore. DOI: 10.1007/978-981-19-6727-6_5
5. Nagaraju, T. V., Sunil, B. M., & Chaudhary, B. (2023). Assessment of nitrate fluxes in intensive aquaculture region in Godavari delta using spatial interpolation kriging. Lecture notes in civil engineering, Springer, Singapore. DOI: 10.1007/978-981-99-2905-4_14
6. Nagaraju, T. V., G. Sri Bala., Sunil, B. M., & Chaudhary, B. (2023). Prediction of Inland Aquaculture Ammonia using Hybrid Intelligent Soft Computing. Lecture notes in civil engineering, Springer, Singapore. (*accepted*)

BIODATA

Name	:	Thotakura Vamsi Nagaraju
Date of Birth	:	05-01-1993
Address	:	Assistant Professor Department of Civil Engineering SRKR Engineering College, Bhimavaram India - 534204
Contact Number	:	+919949636738
Email	:	Varshith.varma@gmail.com tvnraju@srkrec.edu.in
Qualifications	:	B.E. in Civil Engineering M. Tech. in Geotechnical Engineering
Publications		
Journal (Scopus/SCI)	:	18
Book Chapters (Scopus)	:	21
Conference Papers	:	33
Achievements	:	Springer Best Paper Award for presentation titled “Prediction of Inland Aquaculture Ammonia using Hybrid Intelligent Soft Computing.” under the “Environmental Engineering” theme, IACESD-2023, Jyothi Institute of Technology, Bangalore, July 2023 Young Researcher Award 2022, STEM Research Society, NIT Jalandhar Best Oral Presentation Award for the work titled “Effect of chemical and pozzolanic additives on micro-structural behaviour of expansive clays”, 4th International conference on advances in civil and ecological engineering research (ACEER 2022), China (online) IGS – YGE Best Paper Biennial Award – 2020 for the paper entitled on “New Prediction Models for Compressive Strength of GGBS-Based Geopolymer Clays Using Swarm Assisted Optimization” in the theme Computational Geomechanics by Indian Geotechnical Society Best Paper Award in “Young Researchers Symposium for Geotechnical Engineers”, NIT Warangal, 2018, Oct 1st-2nd.