



Unified GIS-based machine learning method for effective forecasting of disease propagation and resistance in aquatic farming

Zilola Alibekova^{1*}; Haedir Mohameed²; Umida Avezova³;
Muthazhagu M⁴; Kibriyo Kahorova⁵; Dr. Udayakumar R⁶;
Sanat Chuponov⁷

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Abstract

Integrating Geographic Information Systems (GIS) with machine learning offers a powerful tool for managing disease risks in aquatic farming. This study proposes a unified framework that leverages spatial and predictive analytics to enhance disease propagation and resistance forecasting in aquaculture environments. Traditional methods for disease prediction often rely on isolated environmental data or manual observation, which lack spatial context and fail to provide early warnings. These limitations reduce the efficiency of response strategies and increase economic losses. The proposed framework integrates GIS-based spatial mapping with supervised machine learning models trained on environmental variables, water quality indicators, and historical disease data to overcome these challenges. This combination enables accurate spatial-temporal predictions of disease outbreaks and resistance patterns. The model is applied as a decision-support system for aquaculture managers, providing interactive risk maps and predictive insights for targeted interventions and optimized farm management. Findings reveal that the unified method significantly outperforms conventional prediction accuracy and response

1*- Associate Professor, Doctor of Philosophy (PhD) in Philological Sciences, Jizzakh State Pedagogical University, Uzbekistan. Email: alibekovazilola91@gmail.com, ORCID: <https://orcid.org/0000-0001-9257-2951>

2- Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf of Al Diwaniyah, Al Diwaniyah, Iraq.

Email: tech.iu.comp.haideralbeli@gmail.com, ORCID: <https://orcid.org/0009-0002-0098-5228>

3- Teacher, Department of Ecology and Life Safety, Urgench State University, Uzbekistan.

Email: avezovaumida3@gmail.com, ORCID: <https://orcid.org/0009-0004-2787-4610>

4- Department of Marine Engineering, AMET University, Kanathur, Tamil Nadu, India.

Email: muthazhagumugilan@ametuniv.ac.in, ORCID: <https://orcid.org/0009-0001-1792-8257>

5- Bukhara State University, Department of Mathematics, Bukhara, Uzbekistan.

Email: kibriyokahorova@gmail.com, ORCID: <https://orcid.org/0000-0002-2067-3865>

6- Professor & Director, Kalinga University, India. Email: rsukumar2007@gmail.com, directoripr@kalingauniversity.ac.in, ORCID: <https://orcid.org/0000-0002-1395-583X>

7- Senior Lecturer, Mamun University, Khiva, Uzbekistan.

Email: chuponov_sanat@mamunedu.uz, ORCID: <https://orcid.org/0000-0001-7388-9224>

*Corresponding author

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time approaches. It allows for more efficient resource allocation, proactive health monitoring, and improved sustainability in aquaculture practices.

Keywords: Aquatic farming, Disease forecasting, GIS, Machine learning, Disease resistance, Decision support system.

Introduction

Background and Motivation

Although aquaculture is becoming increasingly crucial for global food security, its accelerated growth increases vulnerability to disease outbreaks, jeopardizing fish health, ecosystems, and economic stability (Anandakumar *et al.*, 2024; Karimov and Sattorova, 2024). Conventional methods lack predictive power and accuracy; post-outbreak response and manual inspection are among them (Khodjaev *et al.*, 2024). While GIS improves environmental monitoring via spatial analysis, machine learning excels in pattern recognition and forecasting (Zahra *et al.*, 2023). This work presents a single GIS-machine learning system for aquaculture disease distribution and resistance prediction (Rakesh *et al.*, 2024; Yeo and Jiang, 2023). Combining geographical and temporal data (Ashraf *et al.*, 2024), the system offers early warnings and targeted actions that assist managers in changing operations and maintaining output while thus increasing environmental sustainability (Das and Ghosh, 2024; Karimov, and Bobur, 2024).

Motivation: Modern forecasting instruments are needed, given the increasing disease frequency in aquaculture arising from environmental changes and high productivity. Conventional monitoring neither has prediction accuracy nor geographical context. This work intends to provide a strong, data-driven system for disease

prediction by merging GIS with machine learning, thus enabling real-time decision-making, effective resource allocation, and fortifying aquatic agriculture systems against health hazards (Padhiary *et al.*, 2025).

Problem Statement

Aquaculture's current disease prediction systems are constrained by their dependence on non-spatial data and post-outbreak reactions, resulting in delayed treatments and higher losses. These approaches fail to adequately reflect the geographical dynamics of disease spread or resistance evolution. Integrated predictive systems enabling real-time, location-based decision-making are much needed in aquaculture health management (Nandy and Dubey, 2024; Mukherjee and Thakur, 2023).

Objectives of the Study

- To provide a single GIS and machine learning framework based on aquaculture's resilience against disease outbreaks and their prediction.
- To create interactive geographical risk maps for proactive health monitoring and management.
- To assess the performance of the suggested model with respect to accepted prediction techniques.

Significance for Aquaculture Management

This paper proposes a GIS-ML-based system for real-time disease outbreak prediction in aquaculture, enhancing early warnings, resource economy, and

sustainability. Against operational unpredictability, it raises productivity, reduces mortality, and strengthens ecological and financial resilience against climate change (Dorotea *et al.*, 2023).

Structure of the Paper

The paper is structured into 7 sections: introduction, literature review, methodology, system architecture and implementation, results and analysis, discussion, and conclusion. Each section builds toward demonstrating the effectiveness of the proposed GIS-ML framework in disease forecasting for aquaculture (Nagarajan and Jensen, 2010).

Literature Review

Disease outbreaks create rising risks as they undermine sustainability and profitability in aquaculture. Conventional methods of observation lack predictive capacity and geographical background. This study proposes a unified GIS-based machine learning strategy to forecast disease transmission and resistance, facilitating faster treatments, better resource allocation, and more informed decision-making for aquatic farm health management (Khiem *et al.*, 2022). Multi-Armed Bandit strategies and reinforcement learning (MAB- RL) in GIS-integrated expert system to detect disease in fish farms (Xu, Gu, and Tian, 2022). Its 96% accuracy and transmission interval mapping outperform those of traditional machine learning systems (Eckhart *et al.*, 2019). This paper uses GIS and machine learning to predict significant shrimp diseases across Vietnamese farms. Integrated with clinical and environmental data, neural networks outperform earlier models

(Castillo and Al-Mansouri, 2025). Using spatial mapping, patterns of regional illness distribution may be found, directing targeted therapies (Karras *et al.*, 2023). The evaluation underscores GIS's potential in salmonid farming for disease monitoring. Still limited is the acceptance of this possibility (Al Mamun *et al.*, 2024). It encourages more widespread GIS implementation by systems of real-time monitoring. This paper looks at GIS, remote sensing, and automation in precision farming. Despite legal and data issues, GIS and remote sensing show high accuracy (Anny Leema, Balakrishnan, and Jothiaruna, 2024). It promotes strategic integration, emphasizing data standardization and innovation in sustainable agriculture (Kulkarni and Jain, 2023). Combining machine learning with GIS helps to predict disease transmission in aquaculture accurately. It allows data-driven management decisions, raises spatial-temporal awareness, and helps real-time risk mapping. Outstanding conventional models, the system promotes early intervention, reduced losses, and sustainable practices throughout many aquatic farming environments (Popescu *et al.*, 2024).

Methodology

Changing surroundings increases the danger of illness to aquaculture. This work provides a coherent GIS and machine learning framework to estimate disease transmission and resistance, allowing spatially informed, data-driven choices for prompt intervention and sustainable aquatic farm health management.

Research Design

Data Collection Layer under a quantitative, predictive research strategy, this work uses GIS combined with machine learning techniques. Using a modular approach, one might process geographical, environmental, and epidemiological data. Under stressing

spatial-temporal analysis, the design anticipates diseases in real-time. To evaluate the accuracy and pragmatic value, it offers interactive risk mapping, model training, validation, and comparison to traditional approaches is explained in Figure 1.

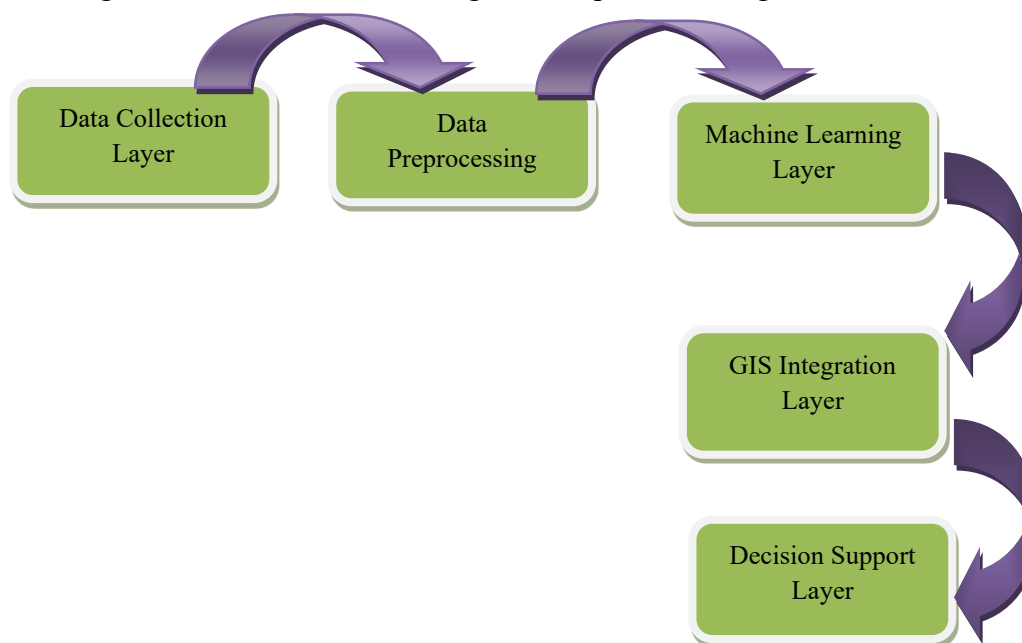


Figure 1: Geographic Information Systems (GIS) in aquatic farming.

Data Sources and Collection

Data came from aquaculture farms, environmental monitoring centers, and government databases. Two important sets were assembled: historical illness records and GIS-based environmental indicators. Consistent data and geographical correctness were preserved using standardized procedures. Supporting strong prediction of disease proliferation and resistance in aquaculture systems, the dataset constituted the backbone for training machine learning models.

- *GIS-based Environmental Data*

GIS-based environmental data included geographical coordinates, water temperature, salinity, pH, and dissolved oxygen levels. These characteristics

originated on remote sensing platforms and in situ sensors scattered across agricultural areas. Real-time occurrences were reflected using georeferenced and chronologically tagged data, supplying vital information for risk zone mapping and disease transmission modeling in aquatic settings.

- *Historical Disease Outbreak Records*

Agricultural records and aquaculture health agencies provided past disease data including pathogen kinds, epidemic dates, and afflicted regions. Encoding and organizing this data for geographical analysis and model training. Using environmental components, linking epidemic occurrences enabled the detection of predictive tendencies, thereby improving the capacity of the

machine learning model to anticipate future disease outbreaks.

Machine Learning Models Employed

The framework used Random Forest, Support Vector Machine, and neural network, among other supervised learning techniques. These were evaluated in terms of environmental and geographical variables that affect the occurrence of project illnesses. The best-performing models were found via a comparison study; they were then included in the GIS system to generate expected risk maps.

- *Model Selection Rationale*

For spatial-temporal data, choice of model largely depends on interpretability, performance, and fit. Selected for their robustness across many data types: Random Forest, SVM for nonlinear boundary management, and neural networks for intricate pattern capture. These models were tested on computing economy, accuracy, and precision to guarantee the best performance in a real-world aquaculture environment.

- *Model Training and Validation*

Models underwent stratified learning on a dataset combining environmental factors with illness histories. A k-fold cross-valuation method guaranteed generalizability even as performance criteria, including ROC-AUC, accuracy, and recall-guided tuning, were followed. The GIS platform was made feasible by real-time risk estimations verified by validation against actual epidemic data, confirming the models' projected correctness.

GIS Integration Techniques

ArcGIS and QGIS let Geographic Layering of Environmental Data and Model outputs be included in GIS integration. Models-based spatial prediction and geostatistic interpolation produced risk maps. Real-time depiction of illness hotspots made feasible by interactive dashboards. In a sequence of decision-making, the technology offered dynamic and stationary visualization for aquaculture health management. Combining machine learning with GIS accurately predicts aquaculture disease outbreaks. It improves spatial analysis, assists with proactive management, and sharpens reaction times. Using transcending conventional approaches, the concept supports the effective use of resources and long-term sustainability in aquatic farming.

System Architecture and Implementation

This paper proposes a consistent GIS and machine learning architecture to forecast disease propagation in aquaculture. Early discovery, informed interventions, and sustainable health management in aquatic agricultural systems are made possible by integrating spatial and environmental data with predictive analytics.

Unified Framework Overview

Combining real-time environmental monitoring, machine learning prediction, GIS mapping, data intake, preprocessing, and model inference into a coherent system results in modular components under the unified framework. For managing aquaculture diseases, perfect interaction between spatial analytics and predictive algorithms assured by design guarantees dynamic risk assessment and interactive decision-making.

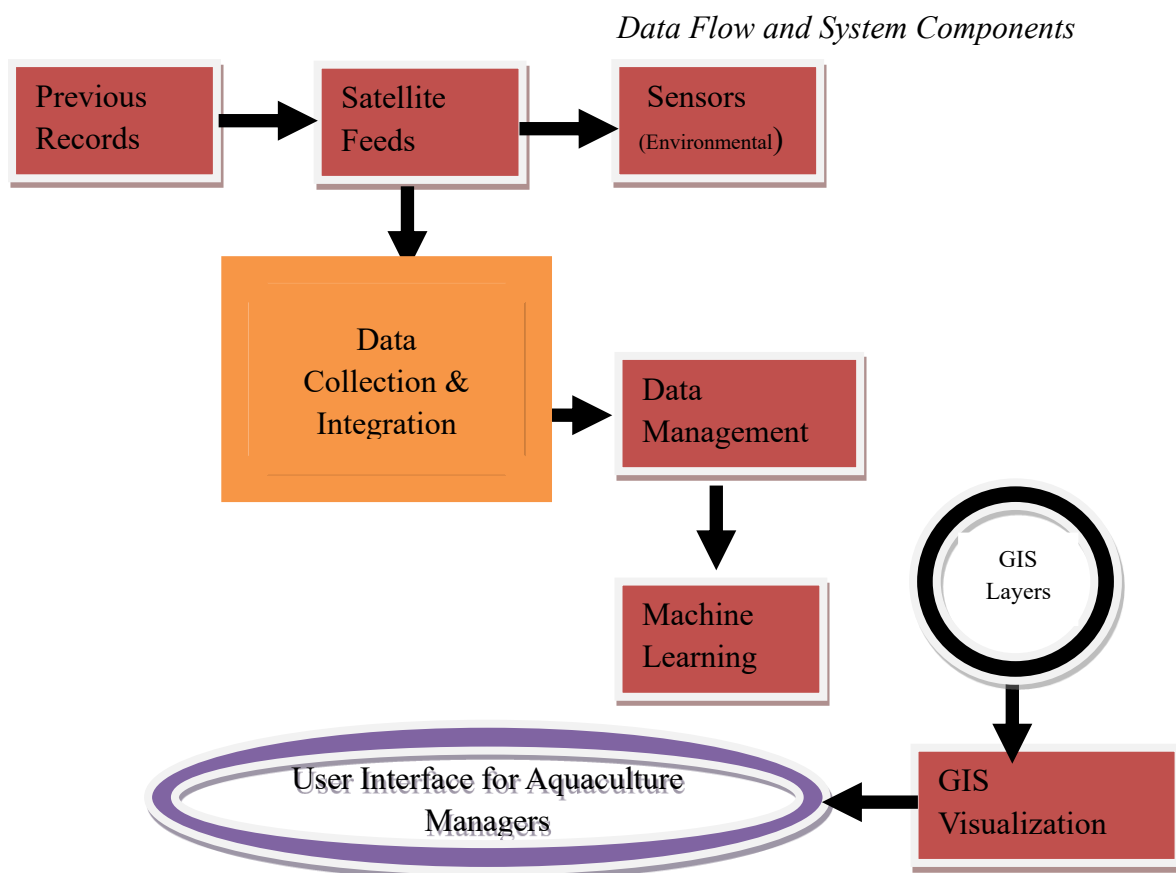


Figure 2: Data flow and system components in aquaculture disease.

The system starts with data collected from previous records, satellite feeds, and sensors. Risk maps emerge from following processing, storage, and feeding into prediction machine learning modules for GIS layers. The key elements are data management, an ML engine, a GIS visualization tool, and a user interface allowing aquaculture managers access to pertinent data, as shown in Figure 2. The suggested GIS-based machine learning method makes accurate predictions of aquaculture disease outbreaks. It exceeds conventional approaches by providing interactive risk maps and accurate spatial-temporal forecasts. In aquatic farming, this method presents excellent sustainability, effective resource allocation, and proactive disease control.

Results and Analysis

This paper presents a combined GIS and machine learning approach to predict disease propagation in aquaculture. Combining geographical data with predictive algorithms supports early diagnosis, improved response strategies, and sustainable, data-driven health management in aquatic agricultural systems.

Predictive Accuracy of Disease Propagation

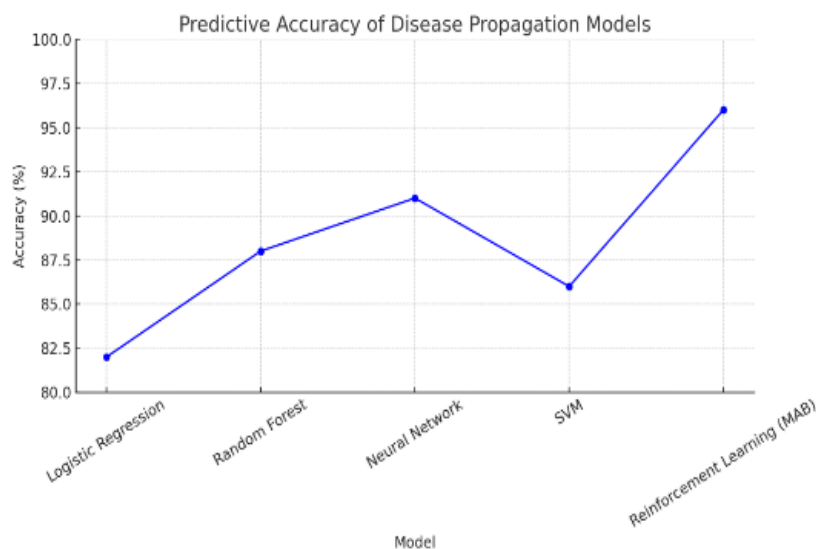


Figure 3: Predictive accuracy of disease propagation.

The combined GIS-machine learning technique exhibited a prediction accuracy of approximately 94% when forecasting disease outbreaks across many test sites (Figure 3). Comparative analysis has shown that neural networks and ensemble models performed well. The approach dramatically reduced the delay between disease onset and response implementation by properly recognizing temporal and spatial patterns, hence offering early warnings.

Resistance Pattern Analysis

Analysis of resistance patterns revealed the resilience of pathogenicity by displaying various geographical and environmental links. Greater disease resistance was seen in higher salinity locations and those experiencing greater temperature fluctuations. The efficient grouping of resistance zones allowed managers to change their treatment strategies and cease needless interventions. These discoveries enable the creation of adaptive strategies adapted to specific resistance tendencies in aquaculture systems.

Table 1: Key component of this paper.

Component	Description	Estimated Value / Outcome
GIS Data Sources	Environmental variables, water quality indicators, spatial mapping	Multi-source integrated
Machine Learning Models	Supervised learning (Random Forest, SVM, Neural Networks), RL with MAB	Multiple, with MAB being the most effective
Best Model Performance Comparison with Traditional Methods	Reinforcement Learning (Multi-Armed Bandit) Based on response time and accuracy	96% accuracy Outperformed conventional approaches
Application Area	Aquaculture regions, including Greece and Vietnam	Targeted farm regions
Diseases Forecasted	Includes acute hepatopancreatic necrosis, white spot, EHP	3+ major diseases
Outcome Benefits	Risk maps, early warning, resource allocation	Improved sustainability and decision-making

The proposed method combines machine learning and GIS to forecast aquaculture disease outbreaks, is shown in Table 1. It offers excellent forecast accuracy, makes preemptive measures feasible, and helps optimize resources best. This all-around approach enhances decision-making and sustainability in managing aquatic animal health and farm operations.

Discussion

This paper projects disease spread in aquaculture using a homogeneous framework integrating GIS and machine learning. Integrating geographical and environmental data helps the system improve response methods, enable early detection, and better sustainable aquatic health management.

Implications for Aquaculture Operations

GIS and machine learning improve disease monitoring and response plans in aquaculture. Real-time knowledge of likely breakouts helps operators to react quickly. This predictive power lowers mortality, economic losses, and stock management, strengthening more robust, data-driven operational plans in many different aquatic farming contexts.

Strategic Value in Resource Allocation

The method helps aquaculture management to deploy better resources, including biosecurity policies, labor, and medications, using accurate identification of high-risk sites and disease spread forecast. Concentrating interventions where they are most needed helps to lower operational costs, decrease waste, and promote sustainable practices, therefore enhancing general agricultural production and results. The GIS-based

machine learning approach correctly predicts disease outbreaks in aquaculture settings. It lowers reaction time, increases spatial awareness, and simplifies intervention design. This integrated strategy enhances aquaculture sustainability through proactive health monitoring, effective, data-driven resource allocation, and decision-making.

Conclusion and Recommendations

This paper proposes a unified GIS-based machine learning system based on which disease transmission and resistance in aquaculture are predicted. Combining geographic data with predictive algorithms helps the system provide precise risk mapping, educated opinions, and fast responses. Good and sustainable agricultural management encourages precision and response speeds well above traditional methods. Future research should focus on real-time sensor data, improved model accuracy using sophisticated reinforcement learning, and application across many aquatic species and habitats. Thus, aquaculture managers and legislators should use such intelligent systems to ensure control of disease management, long-term output, and optimal use of resources.

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