Land suitability modelling for Integrated Mangrove Aquaculture to adapt to salinity intrusion using Machine Learning and Deep Learning approaches in southwestern Bangladesh

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Abstract
The Sundarbans mangrove forest, located in southwestern Bangladesh, neighbors numerous vulnerable coastal communities. The mangrove forests play a crucial role in sustaining local livelihood structures and providing key ecosystem services. Climate-induced change risks contributed saline waterlogging, and salinity intrusion in low-lying lands within polders through extreme weather events, such as cyclones, storm surges, as well as coastal flooding inundation. Furthermore, the uncontrolled expansion of brackish shrimp farming has further exacerbated soil and water salinization, posing severe threats to self-sufficient community-based livelihood options.

Nature-based Solutions (NbS) offer essential tools for protecting the Sundarbans mangroves and addressing environmental challenges and livelihood threats faced by surrounding communities, including climate change, ecological degradation, loss of biodiversity, poverty, and food insecurity. The proposed Integrated Mangrove Aquaculture (IMA) practices, aligned with NbS standards and community involvement, are considered as a solution that balances mangrove ecosystem conservation and sustainable community livelihood management. Specifically, IMA provides adaptive responses to soil salinization and saltwater flooding caused by coupled climate risks, both of which increase the vulnerability of local livelihoods, aiming to develop a production model in the local saline environment that is both ecologically and economically beneficial. This study develops a machine learning-enhanced framework to optimize IMA for combating climate-driven salinity intrusion in Bangladesh's coastal communities. We used four machine learning models that integrated 18 biophysical, environmental and socioeconomic variables to assess land suitability for IMA development. Additionally, the data-driven evaluation model provides scientific support for future planning and management, facilitating implementation of IMA in vulnerable communities and ultimately contributing to the Sustainable Development Goals (SDGs).

Keywords: Machine Learning, Deep Learning, Livelihood Vulnerability, Climate Change, Integrated Mangrove Aquaculture (IMA)

1. Introduction

The Sundarbans Impact Zone (SIZ) is a distinctive region defined by its low-lying, deltaic landscape, woven with a complex network of rivers, tidal channels, and estuaries. This terrain, heavily influenced by seasonal monsoon rains and daily tidal fluctuations from the Bay of Bengal, creates a dynamic estuarine environment. Due to its proximity to the Sundarbans mangrove forest—the largest contiguous mangrove forest in the world - and the Bay of Bengal, the SIZ is exceptionally vulnerable to a range of coastal hazards. Storm surges, tropical cyclones, and saltwater intrusion frequently impact the area, posing significant risks to both human communities and ecosystems. However, this diverse ecosystem also presents challenges to human habitation and agricultural activities. The mixture of saline and freshwater conditions makes water management complex, as local communities must adapt to fluctuating water salinity that affects agriculture, aquaculture, and freshwater availability. The intrusion of saltwater during the dry season exacerbates these challenges, limiting crop choices and requiring adaptive agricultural practices to maintain productivity.

The communities living within the SIZ rely heavily on the natural forest resources of the Sundarbans for their livelihoods (Abdullah et al., 2016; Mallick et al., 2021; Mallick et al., 2021), with many engaged in small-scale fishing, honey collection, and subsistence farming. However, economic vulnerability is widespread, exacerbated by frequent natural disasters and limited infrastructure. Poverty rates are high, and many households depend on seasonal and climate-sensitive livelihoods, making them particularly vulnerable to the impacts of climate change. Despite these challenges, local communities have developed traditional knowledge and adaptive practices that allow them to navigate the complex ecological conditions. For example, some farmers have adapted to saline conditions by cultivating salt-tolerant rice varieties or by practicing integrated farming systems that combine aquaculture with salt-resistant crops. Additionally, community-based resource management practices have been established to promote sustainable use of forest resources, such as honey and non-timber products, which provide supplementary income without significantly impacting the ecosystem (Abdullah et al., 2017).

Coastal communities in the south-west zone of Bangladesh have been facing the ongoing and escalating risk of salinity intrusion, which is expected to increase existing livelihood vulnerability. Given the inevitable trend of higher salinity intrusion conditions, the fragility of current polders, and the limitations of traditional approaches in completely eliminating this risk, a strategic shift from “mitigation” to “adaptation” has become imperative. Integrated Mangrove Aquaculture (IMA) offers an innovative and adaptive solution to this pressing challenge by leveraging saline conditions as an opportunity rather than a constraint. A productive and sustainable pattern of shrimp or fish farming that involves strategic planting mangroves inside or alongside the shrimp ponds is referred as IMA. This approach not only boosts agricultural productivity but also contributes to ecosystem restoration by harnessing the ecological services provided by mangroves, such as nutrient cycling, habitat provision, and coastal protection. It relies on natural tidal water exchange for the effective water quality management and the function of mangrove as natural sources of food and nutrients. By utilizing the controlled facilities of daily tidal flows and absorbing abundant mangrove leaf litter in ponds dikes, IMA operates with minimal external inputs, making it a more eco-friendly and cost-effective approach of adaptive production pattern.

The mangrove-based integrated shrimp farming system represents a sustainable aquaculture model for coastal communities that takes into account both economic benefits and ecosystem protection. It can compensate for the mangrove forests degradation often associated with traditional intensive shrimp farming, and contributes to biodiversity protection, coastal community resilience, climate change mitigation, and enhanced food production (Alam et al., 2022).

This study aims to develop a robust, data-driven spatial framework for assessing and forecasting the land suitability of Integrated Mangrove Aquaculture (IMA) systems in the Sundarbans Impact Zone (SIZ) of southwestern Bangladesh, as an adaptive strategy to mitigate the impacts of climate-induced salinity intrusion and associated environmental challenges. Specifically, the objectives of this research are:

1) To implement and compare the performance of advanced machine learning and deep learning algorithms in assessing the IMA suitability, identifying key drivers of IMA suitability and evaluating model strengths and weaknesses in spatial inference.

2) To project future suitability scenarios (2030, 2050, and 2080) under anticipated environmental and climatic changes, providing actionable insights for climate-resilient coastal production system.

2. Data and Methodology

2.1 Study Area

With an area of about 15,458.90 km2, the Sundarbans Impacted Area (SIZ) is located in the south-west coastal zone, including five districts (Khulna, Bagerhat, Satkhira, Pirojpur, Barguna). The study area spans approximately between latitudes 21°36’N and 23°00’N, and longitudes 88°54’E and 90°00’E. Geographically, the SIZ is positioned adjacent to the Sundarbans mangrove forest, one of the largest tidal halophytic forests in the world and a critical natural barrier against storm surges and coastal flooding. This coastal region is bounded by the Bay of Bengal to the south, forming a significant ecological transition zone where freshwater from the river systems meets the saline waters of the sea.

2.2 Data Collection

Based on a literature study, a multi-class classification framework was implemented to assess IMA suitability using a total of 19 biophysical, environmental and socioeconomic variables across four suitability classes (Not suitable, Marginally Suitable, Moderately Suitable, and Highly Suitable), categorized into four domains: (1) Hydro-chemical Characteristics, including surface water salinity, soil salinity, water total dissolved solids (TDS), water pH, water temperature, dissolved oxygen (DO), and tidal inundation depth; (2) Geomorphological & Soil Properties, encompassing soil texture, soil PH, elevation, slope, and distance to river channel; (3) Ecological and environmental Factors, comprising distance to mangrove area, Land Surface Temperature (LST) and Land Use and Land Cover (LLLC), among others ; and (4) Socioeconomic & Infrastructure, involving distance to drainage, road density, and embankment density. More details are given in Table 1.

Table 1. Data Collection

Data type	Data source	Time period
Sentinel-2 Land Cover	Esri	2023
ASTER GDEM 30 m spatial resolution	NASA Earth	2013
Landsat 9 OLI/TIRS C2 L1	USGS Explorer	2023
Surface water salinity data	Hydroinformatics and Flood Forecasting Circle, Bangladesh Water Development Board (BWDB)	2024
Soil salinity data	Sarkar et al. (2024). A Root-Zone Soil Salinity Observatory for Coastal Southwest Bangladesh [Data set]. Zenodo. https://doi.org/10.5281/zenodo.14560019 SRDI 2024. Annual Report 2023-24. Soil Resource Development Institute (SRDI), Ministry of Agriculture, Dhaka-1215	2024
Water pH, Water TDS, Water DO	Surface and Ground Water Quality Report 2023. Department of Environment (DoE). Ministry of Environment, Forest & Climate Change.	2023
Soil texture; Soil pH	Bangladesh Agricultural Research Council (BARC)	2014
River channel	Local Government Engineering Department (LGDE) of Bangladesh. Humanitarian OpenStreetMap Team. OCHA Service, HDX.	2024
Drainage	United nations insititue for Training and Reaearch (UNITAR). OCHA Service, HDX. Humanitarian OpenStreetMap Team.	2018
Aquaculture Land Cover Data	Center for Geospatial Analytics. Clark University.	2022
Coastal flood inundation depth	Aqueduct Floods Hazard Maps, World Resource Institute.	2020
Mangrove forests	Explore the world's marine & coastal habitats. Ocean+ Habitats.	2020
Road Network	Local Government Engineering Department (LGED). United nations insititue for Training and Reaearch (UNITAR). OCHA Service, HDX.	2018

2.3 Criteria and Sample Data

In this study, we mapped all the selected criteria factors to convert those into thematic raster layers using GIS and RS techniques. A total of 16 distinct criteria layers were prepared under four components including water parameters, soil parameters, geographic-condition, infrastructure. Each raster layer was aligned and resampled to a common resolution (30m*30m cell) with the Universal Transverse Mercator (UTM) zone 65 north and World Geodetic System (WGS)-1984 datum to ensure spatial consistency. We used ArcGIS 10.8 software with natural break and defined interval (e.g. classes of soil salinity) statistical methods to create all the raster layers. The relevance of chosen criteria with details are provided in below.

To ensure robust and spatially balanced sample set for training and validation of the machine learning and deep learning models for Integrated Mangrove Aquaculture (IMA) suitability assessment, an MCDM-based suitability index map was developed using the Analytic Hierarchy Process (AHP) integrated with GIS overlay techniques. The index incorporated 19 standardized criteria weighted by expert-derived scores. Suitability scores were classified into four categories, from which a total of 3,200 georeferenced sample points were randomly selected using stratified sampling—800 per class - to ensure class balance and spatial dispersion. To avoid spatial autocorrelation and clustering bias, a minimum distance threshold of 300 meters between points was enforced. Approximately 70% of the sample points (n = 2,240) were used for model training, while the remaining 30% (n = 960) formed the validation set. This method is particularly appropriate for complex land-use planning problems such as IMA, where suitability is determined by the interaction of multiple biophysical, environmental, and socioeconomic factors. The sample generation process enables the integration of both quantitative spatial data and qualitative expert knowledge.

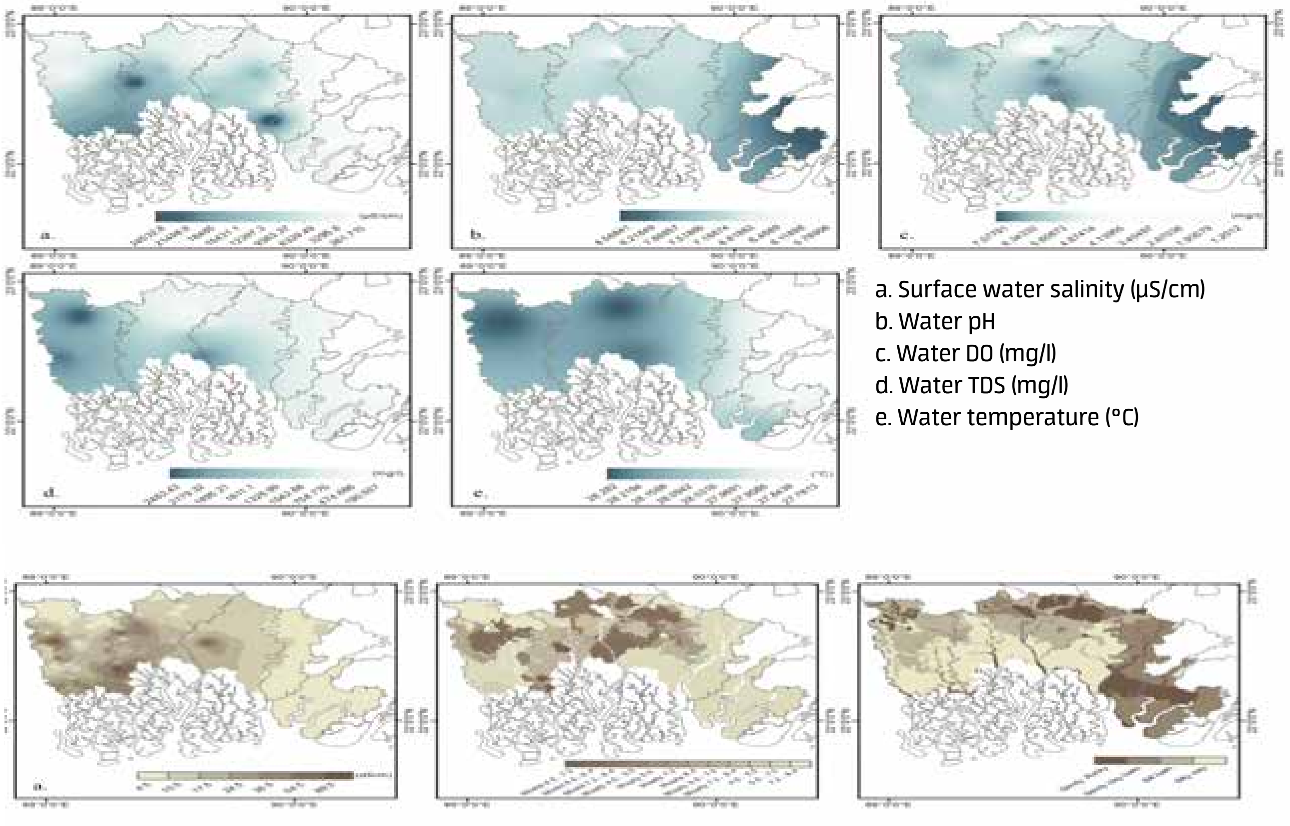


Fig 2-1. Feature maps of water parameters and soil parameters for IMA suitability. a) Soil salinity (dS/m), b) Soil pH, c) Soil texture

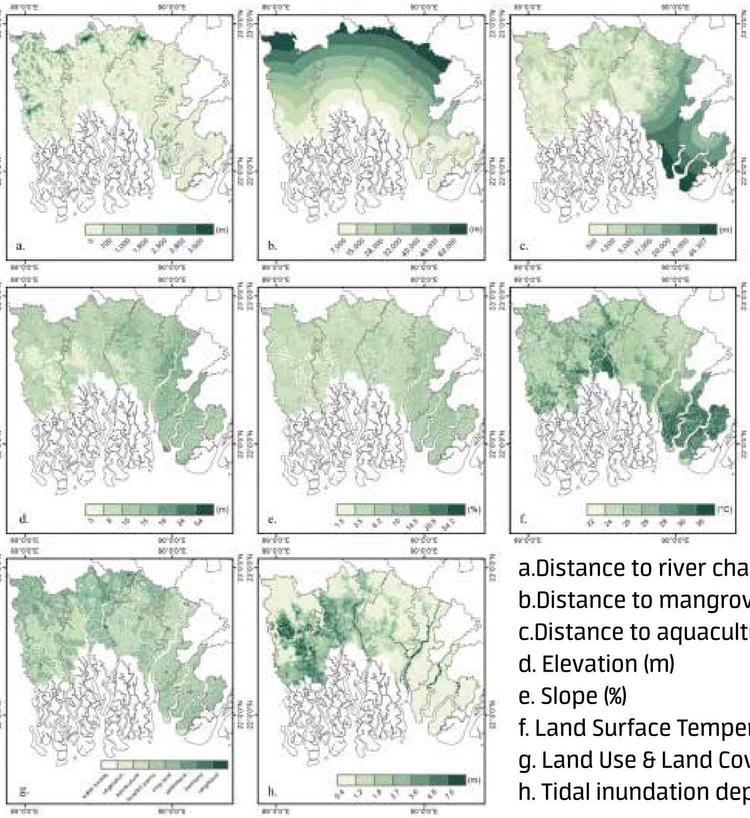


Fig 2-3. Feature maps of geographic-condition factors for IMA suitability.

2.4 Methodology

To predict the spatial suitability of Integrated Mangrove Aquaculture (IMA), a supervised multi-class classification framework was implemented based on prior spatial analysis of the 19 biophysical, environmental, and socioeconomic features. Specifically, spatial autocorrelation diagnostics (e.g., Moran's I and Local Indicators of Spatial Association) revealed significant non-stationarity and spatial heterogeneity across several key variables - such as surface water salinity, soil texture, and tidal inundation depth—indicating that suitability patterns vary considerably over space. These findings justified the adoption of models capable of incorporating spatial context and handling high-dimensional, non-linear, and multi-class classification tasks.

Accordingly, three algorithms were selected: Geographically Weighted Random Forest (GWRF), Extreme Gradient Boosting (XGBoost), and Convolutional Neural Networks (CNN). GWRF was chosen for its capacity to account for spatially varying relationships between predictors and response variables. XGBoost was included as a state-of-the-art ensemble method offering computational efficiency and strong generalization. CNN, a deep learning architecture, was employed for its ability to capture complex spatial dependencies and multi-scale patterns directly from the gridded input data.

All models were trained to classify each spatial unit (i.e., raster cell) into one of four suitability categories: Not suitable, Marginally Suitable, Moderately Suitable, and Highly Suitable. To evaluate model performance and interpretability in predicting IMA suitability, multiple diagnostic tools were employed, including confusion matrices, multi-class ROC curves, spatial suitability maps, and SHAP (SHapley Additive exPlanations) analysis. These tools not only quantified model accuracy but also enabled in-depth exploration of feature importance and spatial inference quality across the study region.

3. Results

3.1 Model Performance and Interpretation

The Pearson correlation heatmap revealed several linear associations among the 19 biophysical and environmental variables used in IMA suitability modeling. For instance, surface water salinity showed positive correlations with soil salinity (r = 0.63) and tidal inundation depth (r = 0.54), reflecting saline water intrusion mechanisms typical of low-lying coastal zones. In contrast, water temperature was strongly negatively correlated with both water pH (r = -0.82) and dissolved oxygen (r = -0.82), suggesting possible ecological stress or eutrophication. To account for such nonlinear relationships, machine learning models such as GWRF, XGBoost, and CNN were employed, which are better suited to capture high-dimensional and nonlinear patterns in ecological suitability data.

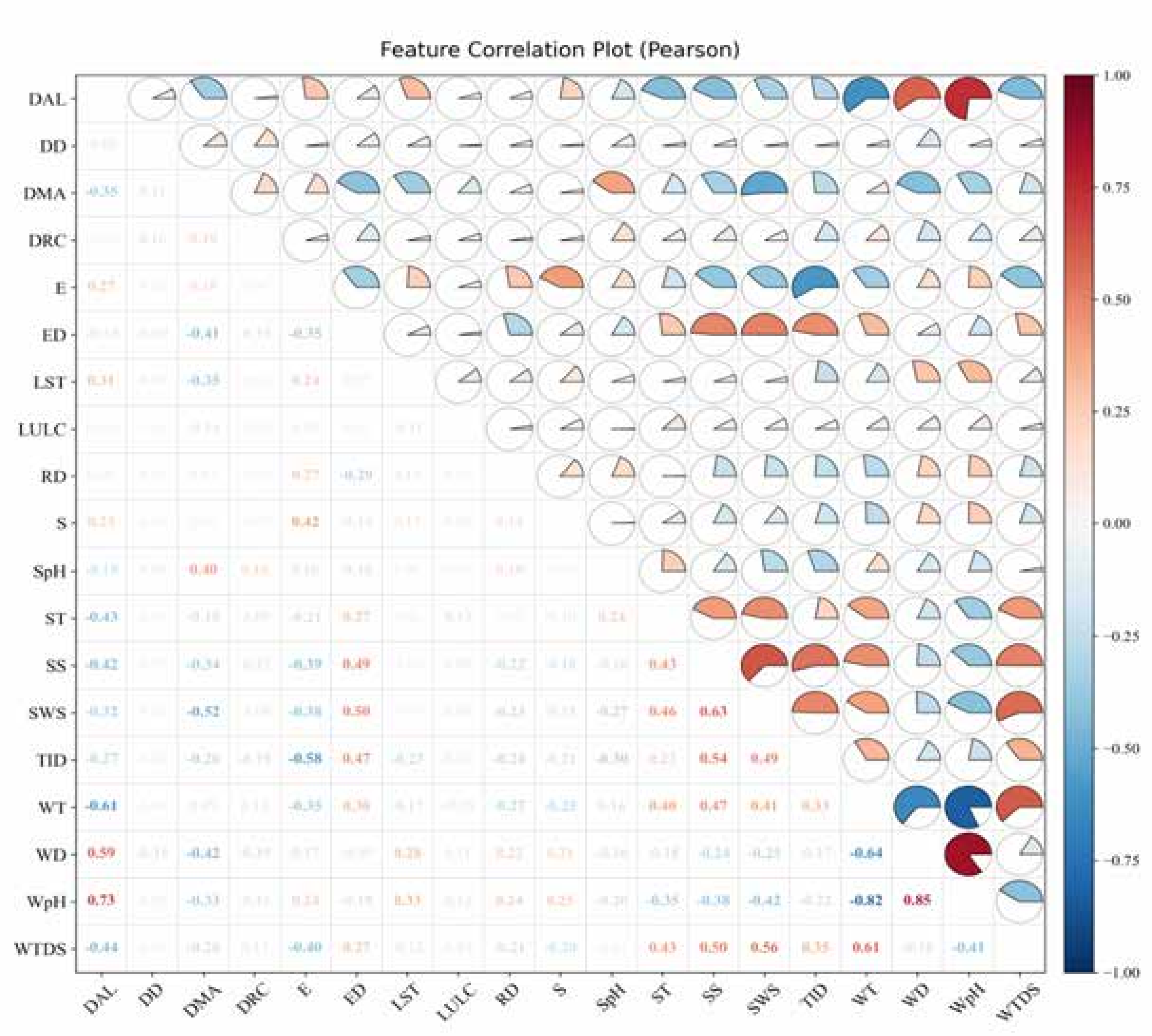


Fig 4. Feature maps of geographic-condition factors for IMA suitability

While these correlations indicate non-spatial associations, spatial dependence among variables was further assessed using Global Moran's I. The results showed that most variables exhibit statistically significant positive spatial autocorrelation ($p < 0.01$), with particularly high Moran's I values observed for soil salinity (I = 1.10), water pH (I = 1.11), and water temperature (I = 1.09). These findings confirm strong spatial clustering of key environmental conditions across the study area, reinforcing the need for spatially explicit modeling approaches. Notably, even typically static features such as distance to aquaculture land (I = 1.05) and surface water salinity (I = 1.01) displayed strong spatial structure, whereas variables like slope (I = 0.16) and land use/land cover (I = 0.38) showed relatively weaker spatial patterns.

Table 2. Global Moran's I statistics for spatial autocorrelation of input variables.

Feature	Moran I	p value
Distance to aquaculture land	1.0526987996024457	0.001
Distance to drainage	0.9605616756041764	0.001
Distance to mangrove area	1.0016094773476731	0.001
Distance to river channel	0.8768663531565697	0.001
Elevation	0.5754581473503295	0.001
Embankment density	0.8582006908652539	0.001
LST	0.6451942852321254	0.001
LULC	0.3837110055114048	0.001
Road density	0.9625494897166221	0.001
Slope	0.15743058435746807	0.004
Soil pH	0.8356389716159316	0.001
Soil texture	0.848900379598481	0.001
Soil salinity	1.1021263820529454	0.001
Surface water salinity	1.014419641284838	0.001
Tidal inundation depth	0.8346094663166448	0.001
Water temperature	1.0936460986686316	0.001
Water DO	0.9386793823138038	0.001
Water pH	1.1137741311873608	0.001
Water TDS	0.9453313275142926	0.001

The GWRF model demonstrated the highest predictive performance among the three, achieving an overall accuracy of 89.49%, with an F1-score of 0.89. The SHAP analysis (Fig. 5) revealed that surface water salinity, water pH, and distance to mangrove area were consistently dominant features across all suitability classes. The suitability map (Fig. 6a) indicates a more spatially coherent distribution of "Highly Suitable" areas, especially along mid-salinity estuarine zones. Importantly, the geographically weighted structure of this model allowed for localized variation in feature importance, making it highly suitable for modeling environmental heterogeneity - a critical factor in coastal delta systems. However, its reliance on spatial weight matrices introduces potential sensitivity to bandwidth selection and may limit scalability across broader geographies.

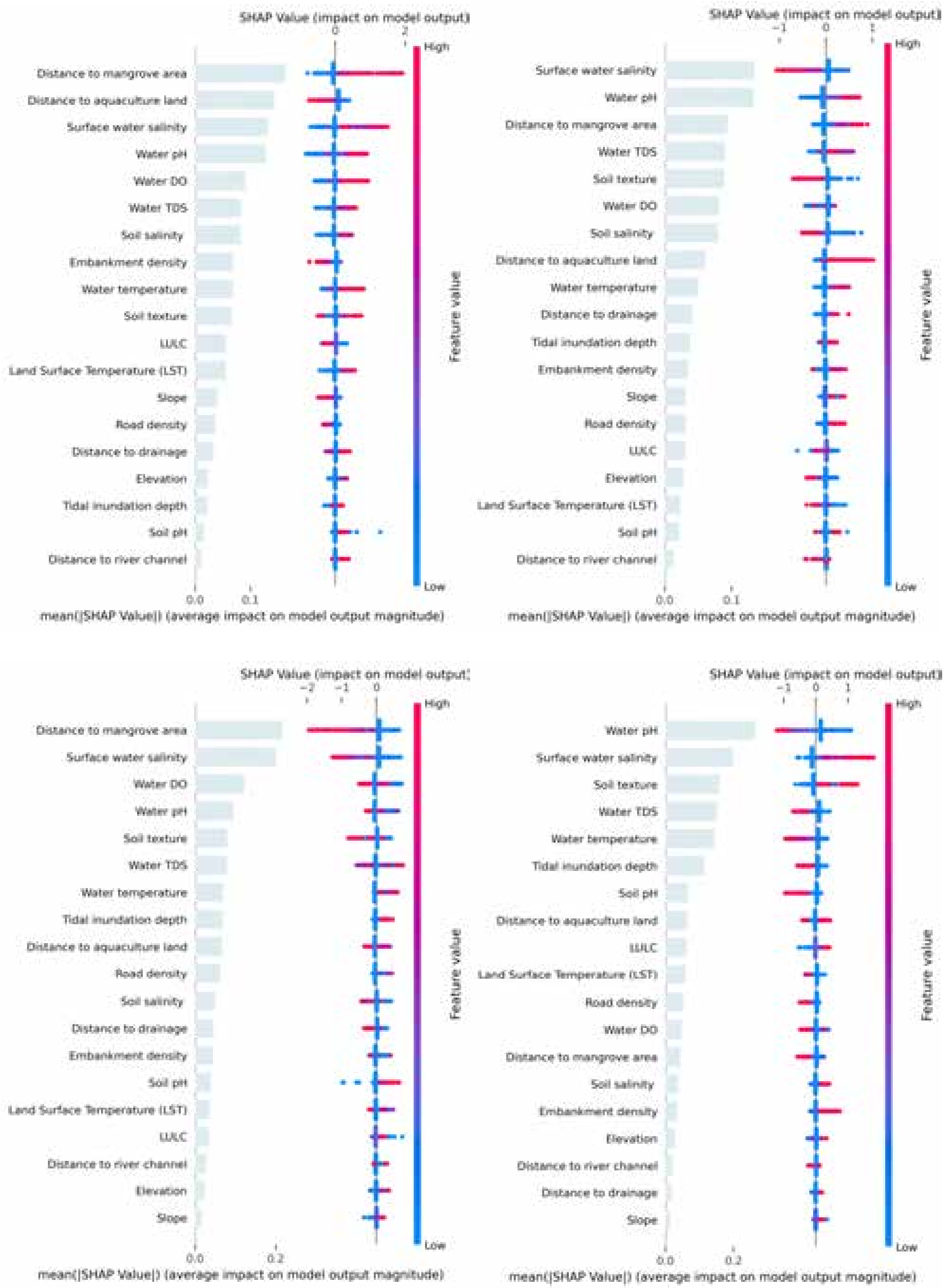


Fig 4. SHAP Value and mean(|SHAP value|) for the 4 suitability classes of IMA by Geographically Weighted Random Forest (GWRF) Model. a) Class 0 - Not suitable, b) Class 1 - Marginally suitable, c) Class 2 - Moderately suitable, d) Class 3 - Highly suitable.

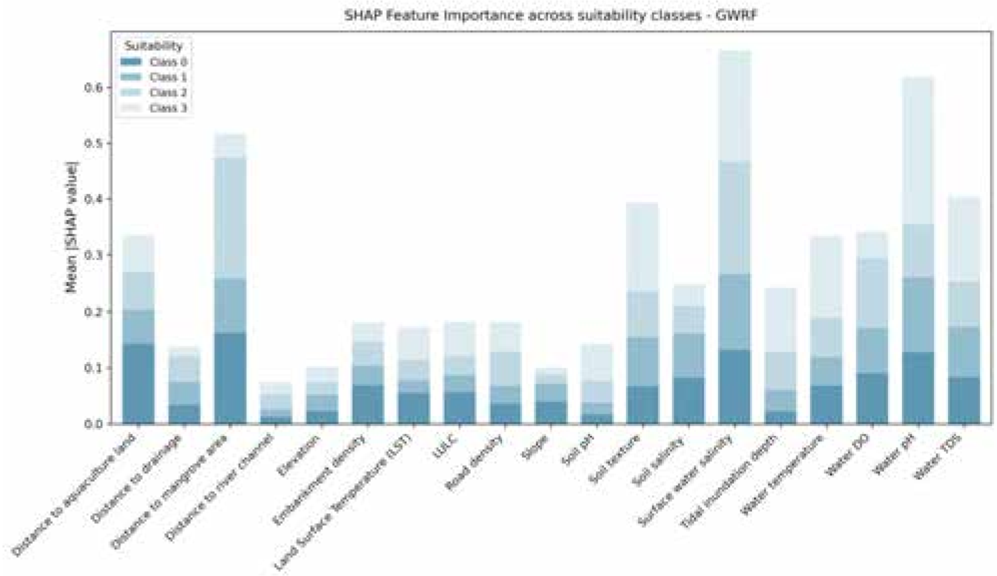
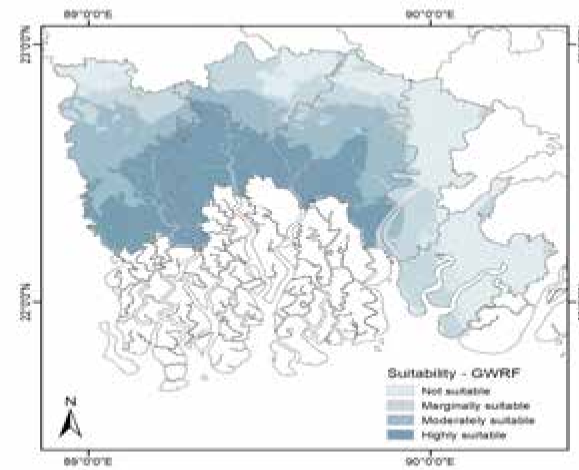
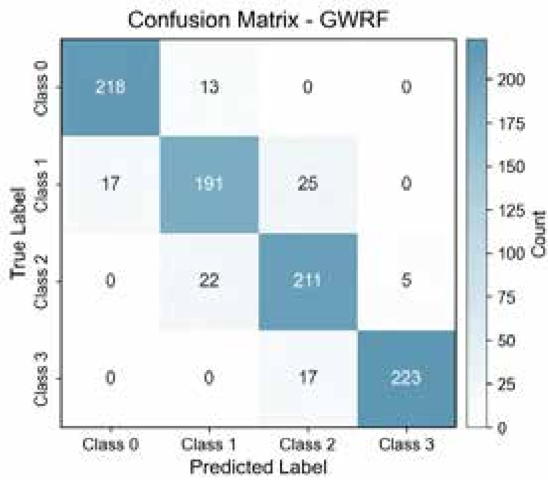


Fig 5. SHAP Feature Importance for 4 suitability classes of IMA by Geographically Weighted Random Forest

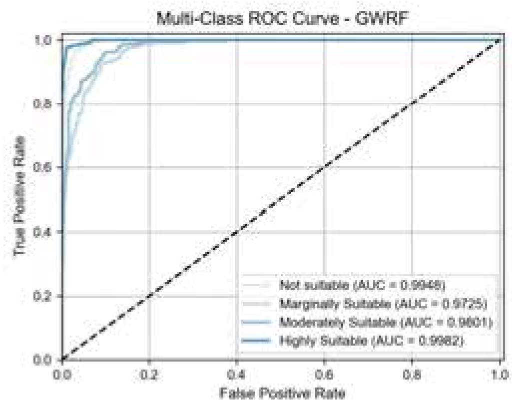


a.



b.

Accuracy
89.49%
F1-score
0.89
recall
0.88
precision
0.88



c.

Fig 6. Suitability map of IMA by Geographically Weighted Random Forest (GWRF) Model. a) Suitability classes map, b) Confusion Matrix, c). Multi-Class ROC Curve.

The XGBoost model achieved slightly lower predictive performance compared to GWRF, with an overall accuracy of 86.09% and precision, recall, and F1-score all registering at 0.86. As a robust gradient-boosted ensemble method, XGBoost is particularly effective at capturing complex, non-linear relationships and interactions among high-dimensional input variables. To account for potential spatial autocorrelation and overfitting, the model was trained and validated using a spatial cross-validation framework implemented via the BlockCV package, which partitions the study area into spatially contiguous folds. This approach ensures that model evaluation reflects true spatial generalizability, avoiding overly optimistic metrics that may result from traditional random sampling. SHAP-based feature attribution revealed that surface water salinity was the top-ranked predictor in both XGBoost and GWRF models, reinforcing its central role in determining IMA suitability across the study area (Fig. 8). For GWRF, the next most important features were water pH and distance to mangrove area, suggesting that the model captured ecologically meaningful local gradients linked to both water chemistry and proximity to natural buffer ecosystems. In contrast, XGBoost identified soil texture and water TDS (Total Dissolved Solids) as key predictors after salinity. This shift toward soil-based and generalized water quality variables likely reflects XGBoost's global optimization approach, which favors variables with consistent predictive power across the entire study area, rather than those with strong but spatially localized effects. However, unlike the geographically adaptive structure of GWRF, XGBoost assigns global feature weights, which may lead to underestimation of localized spatial effects. This limitation was reflected in the resulting suitability map (Fig. 9a), where the spatial boundaries of suitability zones appeared broader and less sharply defined, suggesting a tendency toward regional smoothing and potential overgeneralization in ecologically heterogeneous zones.

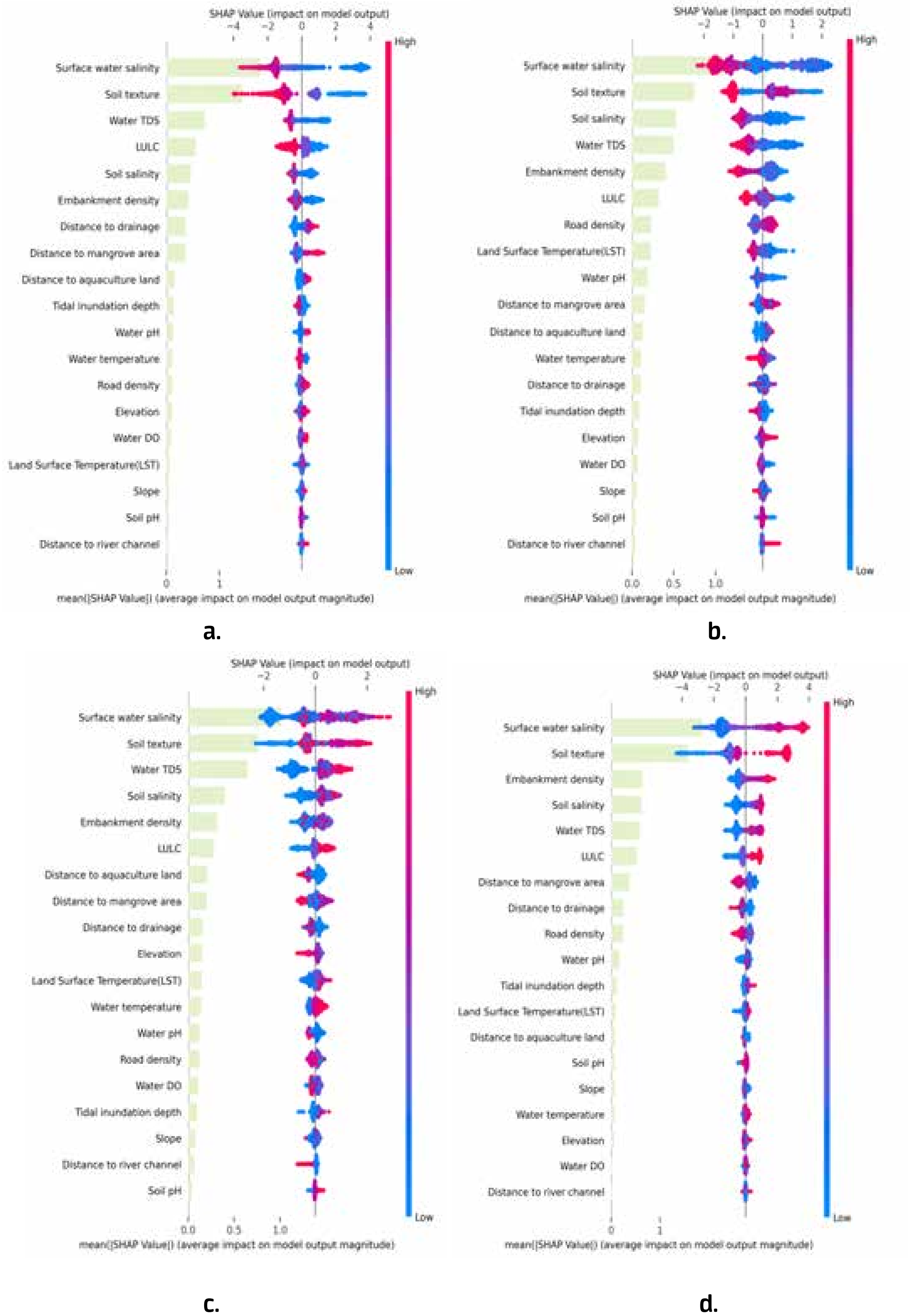


Fig 7. SHAP Value and mean(|SHAP value|) for the 4 suitability classes of IMA by XGBoost Model. a) Class 0 - Not suitable, b) Class 1 - Marginally suitable, c) Class 2 - Moderately suitable, d) Class 3 - Highly suitable.

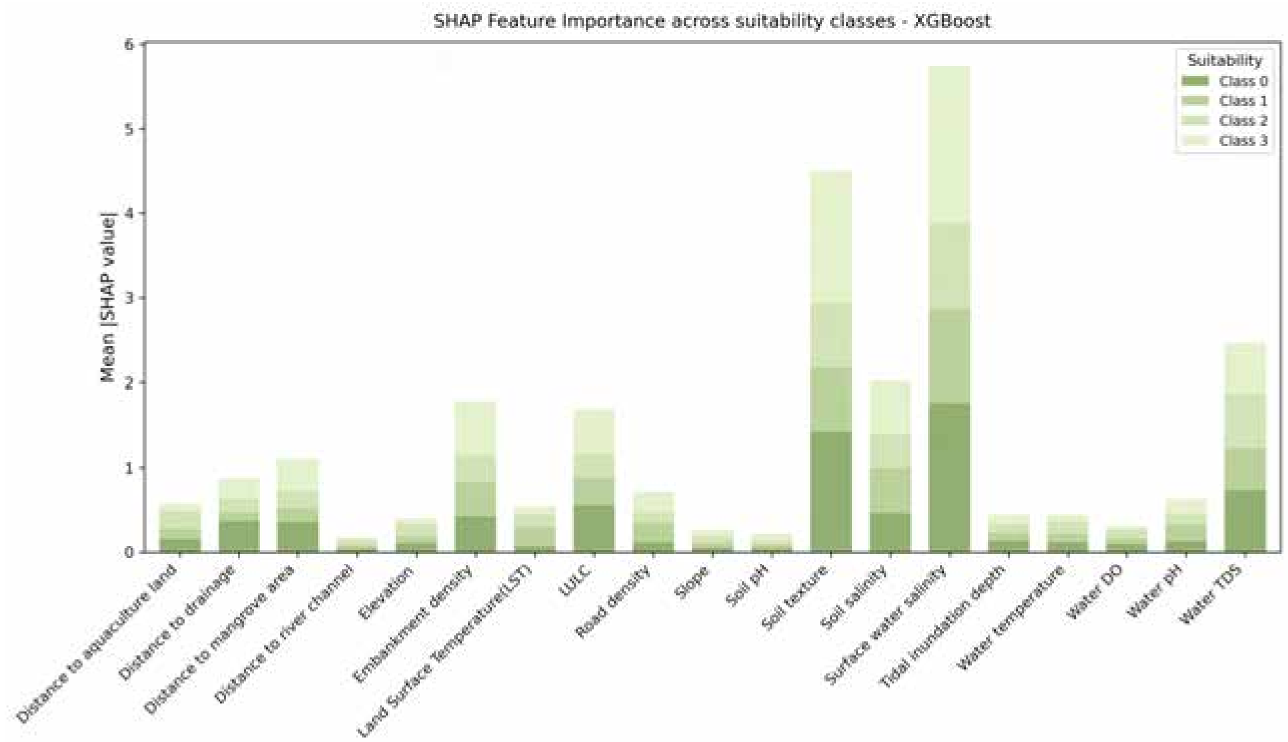
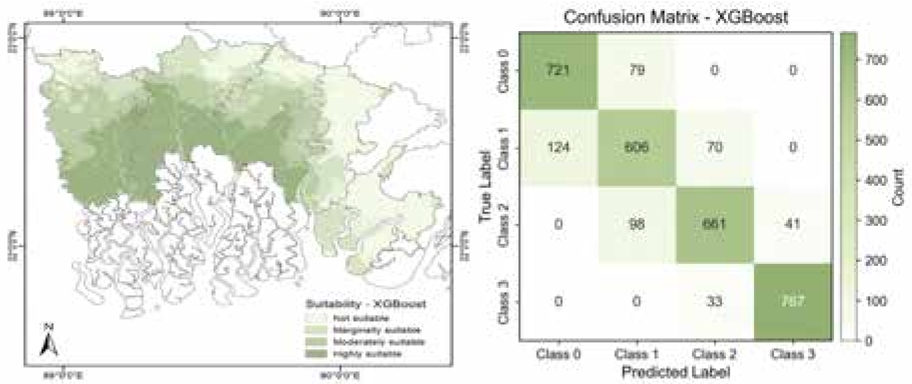
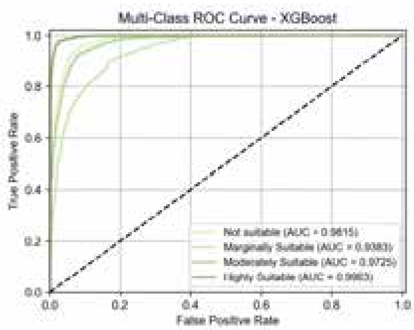


Fig 8. SHAP Feature Importance for 4 suitability classes of IMA by XGBoost Model.



a. b.

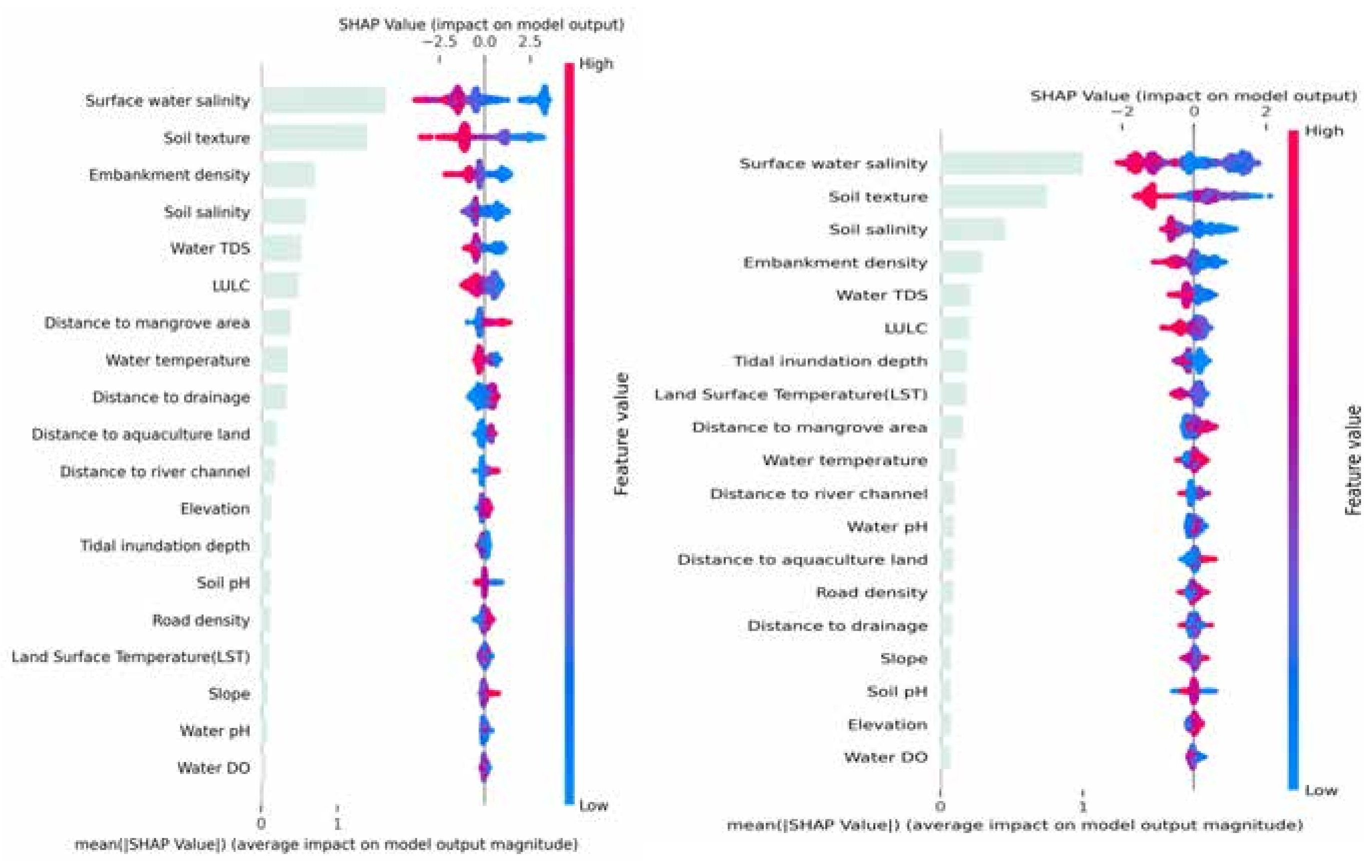
Accuracy
86.09%
F1-score
0.86
recall
0.86
precision
0.86



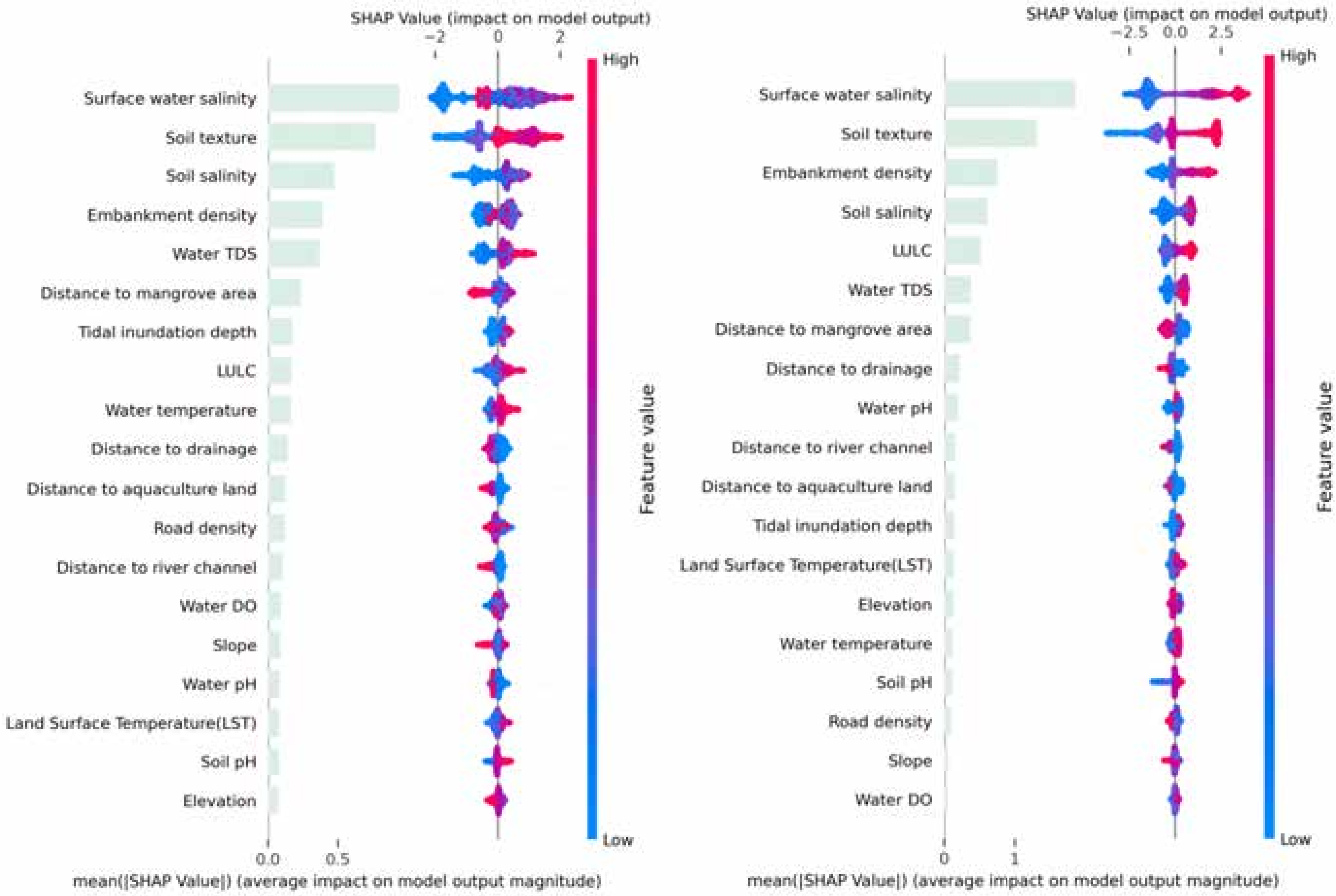
c.

Fig 9. Suitability map of IMA by XGBoost Model. a) Suitability classes map, b) Confusion Matrix, c). Multi-Class ROC Curve.

The Convolutional Neural Network (CNN) model, while achieving slightly lower overall performance metrics compared to the GWRF and XGBoost models - 84.79% accuracy and an F1-score of 0.85 - demonstrated unique strengths in learning spatial patterns and feature interactions from gridded data. The IMA suitability map produced by the CNN model (Fig. 12a) exhibited greater spatial granularity and higher sensitivity to fine-scale landscape heterogeneity, reflecting the model's capacity to detect ecological transitions - such as embankment boundaries, soil texture shifts, or micro-salinity zones - that may be underrepresented in coarser models. SHAP analysis (Fig. 10) revealed that the CNN model prioritized a distinctive set of influential variables. The top-ranked features included surface water salinity, soil texture, embankment density, and soil salinity, indicating that the model was sensitive to both hydrological and physical infrastructure factors. Notably, the high importance assigned to embankment density - a variable less emphasized in GWRF and XGBoost - suggests that CNN was particularly adept at identifying the influence of anthropogenic structures in shaping land suitability patterns, likely due to its spatial feature extraction capabilities. The prioritization of soil texture also highlights CNN's potential to capture interactions between micro-topography and hydrological properties that are difficult to model using traditional approaches. However, the CNN model's complexity comes with certain trade-offs. Its training process is computationally intensive and more data-hungry than tree-based algorithms. The relatively moderate dataset size (n = 3,200) may have limited its full learning capacity, and overfitting risks were mitigated through regularization and dropout techniques. Moreover, while SHAP was used to enhance interpretability, the black-box nature of deep learning still poses challenges for transparent decision support in applied contexts.



a. **b.**



c. d.

Fig 10. SHAP Value and mean(|SHAP value|) for the 4 suitability classes of IMA by Convolutional Neural Networks (CNN) Model. a) Class 0 - Not suitable, b) Class 1 - Marginally suitable, c) Class 2 - Moderately suitable, d) Class 3 - Highly suitable.

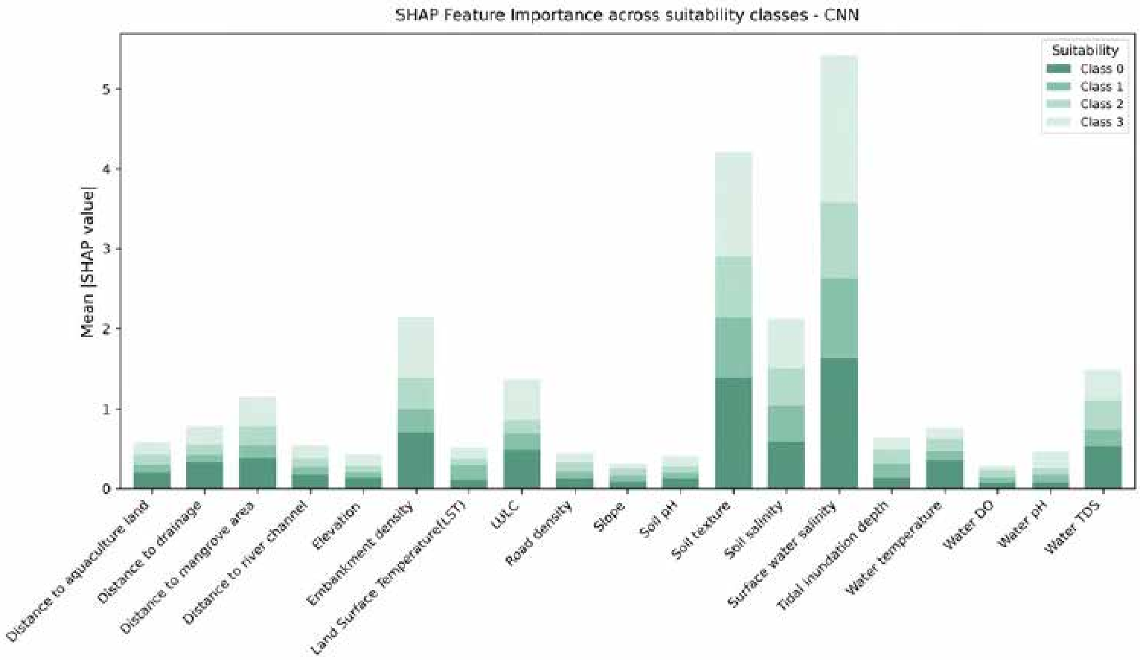


Fig 11. SHAP Feature Importance for 4 suitability classes of IMA by Convolutional Neural Networks (CNN) Model.

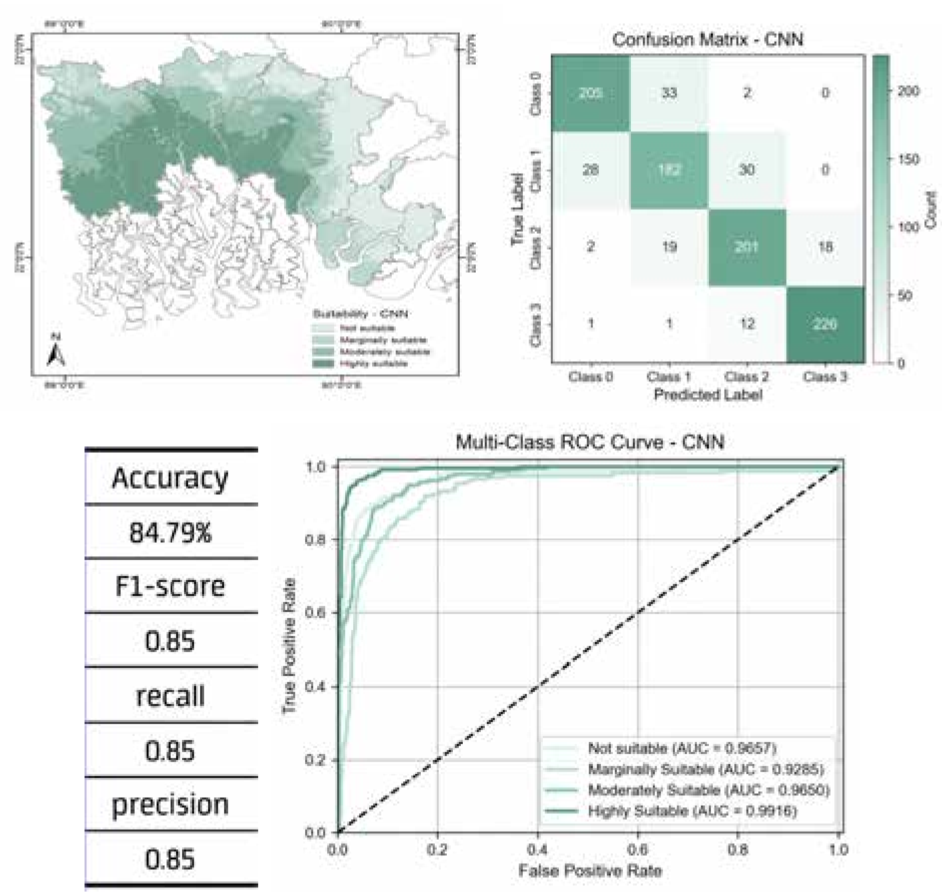


Fig 12. Suitability map of IMA by Convolutional Neural Networks (CNN) Model. a) Suitability classes map, b) Confusion Matrix, c). Multi-Class ROC Curve.

3.2 Spatial Verification of IMA Suitability Using Sentinel-2 NDWI Data

In order to verify the spatial rationality of the IMA model prediction results, this study conducted a spatial overlay analysis between the model-predicted suitability zones and the actual water body distribution derived from Sentinel-2 satellite imagery. Specifically, NDWI (Normalized Difference Water Index) was calculated using cloud-free Sentinel-2 surface reflectance data to extract surface water features for the year 2024. The resulting water body vector layer was then intersected with the suitability maps generated by the GWRF, XGBoost, and CNN models.

The results showed that the majority of NDWI-detected water bodies were spatially concentrated within areas predicted as "Moderately suitable" and "Highly suitable" by all three models, indicating strong spatial consistency between model predictions and real water features. Specifically, as shown in Table 3, the GWRF model identified 42.19% of the water bodies within "Highly suitable" areas and 27.51% within "Moderately suitable" areas, with marginal representation in "Marginally suitable" areas (3.41%) and none in "Not suitable" zones. This distribution suggests a clear spatial preference of GWRF predictions toward ecologically plausible IMA zones. In contrast, the XGBoost and CNN models further enhanced spatial alignment, with over 69% of the water body area located within "Highly suitable" zones. These two models also reduced the proportion of water bodies falling into "Not suitable" areas to below 3.5%, demonstrating better exclusion capability for unsuitable zones.

Overall, the spatial overlay verification supports the reliability of the model outputs, particularly those generated by the XGBoost and CNN frameworks, which exhibit strong agreement with actual hydrological patterns captured by NDWI. These findings reinforce the ecological validity of the predicted IMA suitability zones and provide robust support for their application in integrated aquaculture planning.

Table 3. Distribution of NDWI water body area within model-predicted suitability classes

suitability_level	GWRF	XGBoost	CNN
Not suitable	0	3.51%	3.47%
Marginally suitable	3.41%	28.09%	27.73%
Moderately suitable	27.51%	41.46%	40.02%
Highly suitable	42.19%	69.50%	69.25%

4. Conclusion

This work advances the integration of machine learning in nature-based adaptation planning, offering a replicable methodology for vulnerable coastal regions globally. The findings have direct implications for climate-resilient aquaculture planning in coastal Bangladesh, where salinity intrusion and livelihood vulnerability necessitate adaptive, nature-based interventions. The proposed methodology supports strategic zoning for IMA expansion, aligning ecological restoration with sustainable development objectives. More broadly, this study contributes to the growing literature on machine learning for nature-based adaptation, offering a transferable framework applicable to other deltaic and estuarine systems facing similar biophysical constraints. Future work may integrate temporal dynamics, stakeholder preferences, or economic optimization to further enhance the practical deployment of IMA in climate-sensitive coastal regions.

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