Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 14 Issue 03s, 2025

Ensemble Machine Learning for Fish Abundance Prediction: A Multi-Model Stacking Approach with Environmental and Fisheries Data

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Peer Review Information

Submission: 05 Nov 2025

Revision: 25 Nov 2025

Acceptance: 17 Dec 2025

Keywords

machine learning, fisheries management, ensem- ble learning, stacking regressor, time series prediction, environ- mental monitoring, sustainable harvest

Abstract

Effective fisheries management demands accurate forecasting of abundance to avoid excessive harvesting and ensuring marine biodiversity is maintained. Typical assessment techniques that mainly use previous catch data often have no predictive capacity to incorporate complicated, time-varying environmental factors. We tackle this problem with a new methodology that implements an ensemble Machine Learning technique. The use of a stacking ensemble is utilized, where four heterogeneous Level 0 base learners, Random Forest, XGBoost, K-Nearest Neighbors, and a Multi-Layer Perceptron, were classi- fied. A Ridge regression model is used as the Level 1 meta-learner to optimally combine the base learners' predictions. The model was trained and validated using a dataset of 1000 observations collected through a timeframe of fifteen years (2010-2024) from the Manila Bay fisheries area. The features executed to forecast abundance include eleven environmental parameters including water temperature, pH, dissolved oxygen, and several nutrients combined with five important fisheries parameters including fish- ing area, gear type, and species. The combined features ensemble achieves excellent predictive performance with an R-squared of 0.9922, Mean Absolute Error of 37.35, and Root Mean Squared Error of 49.37. An ablation study demonstrated that combining all features significantly outperformed a strictly environment- only model, which returned an R-squared of negative 0.0045, and provided a more balanced prediction compared to the fisheries- only model (R-squared 0.9968). The resulting model offers ac- tionable harvest recommendations based on predicted abundance categories (Lean, Moderate, and Abundant), providing a robust tool for adaptive fisheries resource management.

Introduction

The global fishing industry is a critical component of food security and economic activity, yet it faces unprecedented sustainability challenges. Over three-quarters of the world's commercial fish stocks are fully exploited, overexploited, or depleted, largely due to intensifying fishing pressure and the pervasive impact of global climate change on marine ecosystems [7]. Anthropogenic activities alter crucial environmental variables—such as water temperature, acidity (pH), and dissolved oxygen levels—which fundamentally influence the biological processes, migration patterns, and reproduction rates of fish populations.

Traditional fisheries management relies heavily on historical catch and effort data to perform stock assessments, which often involve complex, resource-intensive sampling methods and simplified biological models [5]. These methods are typically retrospective, providing estimates of past stock health, but struggle to provide timely, accurate forecasts that integrate the non-linear, dynamic effects of concurrent environmental shifts. This inherent limitation creates a need for sophisti- cated, forward-looking predictive models that can seamlessly integrate disparate data sources, particularly high-dimensional environmental monitoring data and granular fisheries records. The **problem statement** addressed in this paper is the lack of a robust, holistic predictive modeling framework that leverages the synergistic power of environmental and fisheries data for accurate, seasonal-scale fish abundance forecasting. Existing literature often focuses on one data stream (either environmental or fisheries) or utilizes simpler, single-model Machine Learning (ML) architectures, leaving a significant **research gap** in the application of advanced ensemble methods for this integrated prediction task.

A. Contributions

To overcome these limitations, we propose a novel multi-model stacking ensemble approach for predicting fish abundance. The key **contributions** of this work are as follows:

1) We introduce a novel **stacking ensemble architecture** tailored for fisheries prediction, utilizing a heterogeneous set of Level 0 base learners (Random Forest (RF), XGBoost, K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP)) combined via a Ridge regression meta-learner.
2) We perform a systematic **ablation study** comparing model performance across three feature configurations: environment-only, fisheries-only, and the combined fea- ture set.
3) We employ a rigorous **time-based validation strategy** using Group K-Fold Cross-Validation (CV) with a Leave-One-Year-Out (LOYO) approach, ensuring the model's temporal robustness and simulating real-world deployment accuracy.
4) We develop an **interpretable recommendation framework** that translates the predicted continuous abundance into actionable, categorical harvest recommendations (Lean, Moderate, Abundant) with specific harvest fractions.We utilize **SHapley Additive exPlanations (SHAP)** to provide critical model explainability, identifying the most influential environmental and fisheries factors driv- ing the predictions.

B. Related Work

1) Traditional Fisheries Stock Assessment Methods: Traditional methods, such as the Surplus Production Model (SPM) and Virtual Population Analysis (VPA), have long been the backbone of fisheries management [5]. SPMs estimate the maximum sustainable yield based on catch and effort time series, while VPA uses historical age-specific catch data to reconstruct past population sizes. However, these methods rely on assumptions like constant natural mortality or the availability of accurate age data, which are often violated in complex, multi-species ecosystems like Manila Bay.

2) Machine Learning in Fisheries: The application of ML in fisheries has rapidly gained traction, offering non-parametric alternatives to traditional modeling [7]. RF has proven effective due to its ability to handle non-linearity and feature importance extraction, frequently used for species distribution and abundance modeling [2]. Neural Networks (NNs), particularly MLPs, are employed for their universal function approximation capabilities, capturing complex interactions between environmental variables and fish stock size. More recently, advanced boosting techniques like XGBoost have been ap- plied, demonstrating superior accuracy and handling of large, high-dimensional ecological datasets. A key challenge remains in integrating diverse feature types (categorical fisheries data and continuous environmental data) effectively within a unified framework [1].

3) Ensemble Methods in Environmental Prediction: Ensemble learning, which combines multiple models to achieve better predictive performance than any single model, is increasingly common in environmental science. Stacking, a specific ensemble technique, uses the predictions of several base learners as input for a meta-learner, optimizing the combination of diverse model strengths [3]. This approach has been shown to improve accuracy in tasks like air quality forecasting and water resource management by harnessing the complementary strengths of different algorithms. The work by Rasdas et al. [1] demonstrated the effectiveness of ensemble learning for predicting fish abundance in Manila Bay, providing a foundation for our multi-model stacking approach.

4) Time Series Forecasting and Explainable AI: Ecological time series data, especially fish abundance, exhibits strong temporal dependence. Advanced techniques, including incor- porating lag features and rolling statistics, are essential to capture these dynamics. Furthermore, the ’black-box’ nature of complex ML models, particularly ensembles, poses a chal- lenge for adoption by management bodies. Explainable AI (XAI) tools like SHAP [4] are crucial for generating transpar- ent, trustworthy predictions, allowing managers to understand the causal link between features and forecasts.

Dataset and Preprocessing

A. Data Description

The study utilizes an Extended Fish Abundance and Rich- ness Dataset (EFARD) collected from the Manila Bay region, Philippines, spanning a temporal period from 2010 to 2024 (15 years). The dataset comprises 1000 unique samples.

The **target variable** for prediction is *Quantity* (fish abun- dance) in metric units. The **original features** (21 total) are categorized as follows:

1) **Environmental Features (11):** *Mean_Water_Level*, *Wa- ter–Temperature* (◦C), *Air–Temperature* (◦C), *pH*, *Dis- solved_Oxygen* (DO, mg/L), *Conductivity* (μS/cm), *To- tal_Nitrate*, *Total_Phosphate*, *Turbidity* (NTU), *Salinity* (PSU), and *Chlorophyll_a* (μg/L).
2) **Fisheries Features (5):** *Fishing_Area* (categorical), *Fishing_Gear* (categorical), *Landing_Area* (categorical), *Species* (categorical), and *Season* (categorical).
3) **Temporal Feature (1):** *Year*.

B. Feature Engineering

To capture the time-dependent nature of fish populations and environmental conditions, we applied various feature engineering techniques:

1) **Lag Features:** We created 1-step and 3-step lag vari- ables for all 11 numeric environmental features and key numeric representations of categorical fisheries features. For example, $F_{\mathrm{lag1}}(t) = F(t-1)$.
2) **Rolling Statistics:** To capture short-term trends and dampen noise, we calculated a 3-period rolling mean for the numeric features.
3) **Anomaly Detection:** We generated deviation features, defined as the current value minus the 3-period rolling mean (anomaly $= F(t) - F_{\mathrm{rolling\ mean}}(t)$).

After one-hot encoding for categorical features and the above transformations, the total number of engineered features used as predictors was 79.

C. Data Preprocessing

Data preprocessing steps were critical to preparing the features for the heterogeneous ensemble:

1) **Missing Value Imputation:** Missing feature values were imputed using the median of the respective feature column via the *sklearn SimpleImputer*. The median was chosen for its robustness against outliers.
2) **Feature Scaling:** The k-Nearest Neighbors (KNN) and Multi-Layer Perceptron (MLP) models are highly sensi- tive to feature scale. For these base learners, we applied *StandardScaler* (zero mean and unit variance) within their respective model pipelines. Tree-based models (RF, XGBoost) are scale-invariant and did not require scaling.

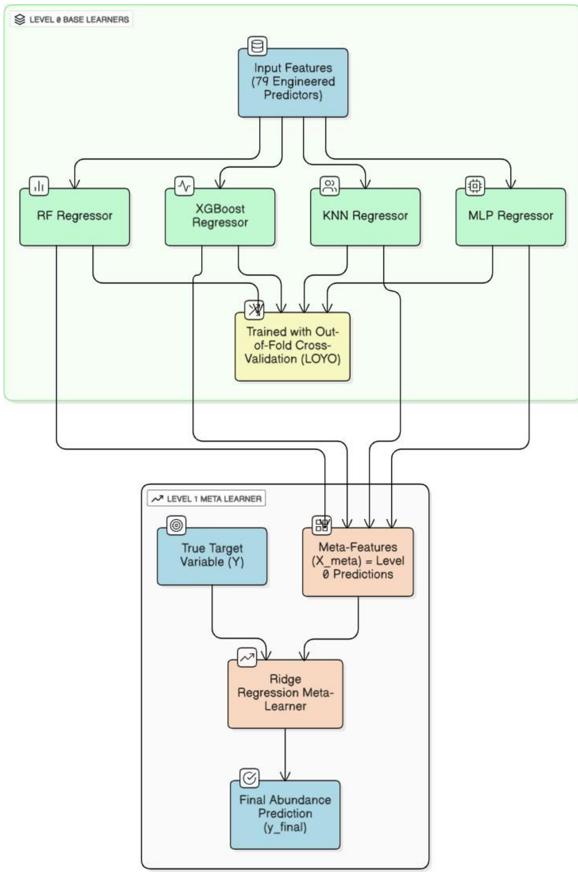

Fig. 1. System architecture of the Multi-Model Stacking Ensemble. Data is split temporally via Group K-Fold (LOYO). Level 0 Base Learners generate predictions (meta-features) which are then fed into the Level 1 Meta- Learner (Ridge Regression) to produce the final fish abundance prediction and subsequent harvest recommendation.

3) **Temporal Ordering:** The dataset was strictly sorted by the *Year* column to maintain the chronological order, a requirement for the time-aware cross-validation strategy.

Proposed Ensemble Architecture

Our proposed solution is a stacking ensemble regressor designed to mitigate the weaknesses of individual models while combining their predictive strengths. The architecture is composed of a diverse set of four Level 0 Base Learners and a single Level 1 Meta-Learner, as illustrated in Fig. 1.

A. Base Learners

The choice of base learners was driven by the need for maximum model diversity, ensuring that they capture different aspects of the underlying data structure (linear vs. non-linear, global vs. local patterns). The hyperparameters for each model are summarized in TABLE I.

1) Random Forest Regressor (RF): RF is an ensemble of decision trees, trained via bagging, that averages the predictions to control overfitting. We used 100 decision trees. The prediction $\hat{y}$ is the average of the predictions from B individual trees $T_b(\mathbf{x})$:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(\mathbf{x}) \quad (1)$$

RF is advantageous for its robustness to outliers and non-linear data without requiring feature scaling [2].

2) XGBoost (Extreme Gradient Boosting): XGBoost is an optimized distributed gradient boosting library. It builds trees sequentially, with each new tree correcting the errors of the previous ones. The objective function to be minimized is a combination of the loss function l and a regularization term Ω:

$$L(\vartheta) = \sum_{i} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k) \quad (2)$$

XGBoost's regularization and handling of sparse/missing data contribute to its high performance in many ecological modeling tasks.

3) K-Nearest Neighbors (KNN): KNN is a non-parametric, instance-based learning algorithm that predicts the target variable based on the average of the $k = 5$ nearest neighbors in the feature space $N_k(\mathbf{x})$.

$$\hat{y} = \frac{1}{k}\sum_{x_i \in N_k(x)} y_i \quad (3)$$

We used the Euclidean distance metric after the input data was standardized to ensure all features contribute equally.

4) Multi-Layer Perceptron (MLP): The MLP, a foundational deep learning model, serves as a universal function approximator. The architecture consisted of an input layer, two dense hidden layers with 64 and 32 neurons, respectively, followed by a single output neuron. The Rectified Linear Unit (ReLU) activation function was used for the hidden layers. Training was performed with the Adam optimizer for a maximum of 300 iterations.

B. Stacking Architecture

The ensemble strategy employs a two-level stacking approach.

1) Level 0 (Base Layer): The four base learners (RF, XGBoost, KNN, MLP) are trained independently on the full training set of features. During cross-validation (Section IV-A), each base learner's out-of-fold predictions serve as the **meta-features** for the Level 1 model.

2) Level 1 (Meta-Learner): **Ridge Regression** was selected as the meta-learner. Its simplicity and intrinsic regularization property (L2 penalty) make it an ideal choice to combine the predictions from the diverse base learners without overfitting to their correlation patterns. The objective function is:

$$\min_{\boldsymbol{\beta}} ||\mathbf{y} - \mathbf{X}\boldsymbol{\beta}||_2^2 + \alpha||\boldsymbol{\beta}||_2^2 \quad (4)$$

where $\mathbf{X}$ is the matrix of meta-features (predictions from base learners), $\boldsymbol{\beta}$ is the vector of coefficients (model weights), and

TABLE I
HYPERPARAMETER CONFIGURATION FOR ENSEMBLE LEARNERS

Layer	Model	Key Hyperparameters
Level 0	Random Forest	*n_estimators* = 100, *max_depth* = None
	XGBoost	*n_estimators* = 100, *learning_rate* = 0.1
	KNN	*n_neighbors* = 5, *metric* = Euclidean
	MLP	*hidden_layers* = (64, 32), *activation* = ReLU
Level 1	Ridge Regressor	α = 1.0, *solver* = auto

$\alpha = 1.0$ is the regularization strength. A 5-fold CV was used internally to generate the meta-features, minimizing the risk of data leakage.

C. Model Variants (Ablation Study)

To ascertain the relative importance of different feature types, an ablation study was performed using three model configurations, all employing the same stacking architecture:

1) **Combined Model:** Used all 79 features (environmental + fisheries + engineered).
2) **Environment-Only:** Used only the 11 environmental features and their 34 corresponding engineered (lag and rolling) features (45 total).
3) **Fisheries-Only:** Used the 4 fisheries features (one-hot encoded) and their 2 corresponding engineered features (4 total).

Validation Strategy

A. Group K-Fold Cross-Validation

Given the time series nature of the data, standard randomized k-fold CV is unsuitable as it introduces temporal data leakage, artificially inflating performance metrics. We implemented a **Leave-One-Year-Out (LOYO)** strategy using *GroupKFold* with *n_splits* = 15 (corresponding to the 15 years in the dataset).

The LOYO approach partitions the data into 15 groups based on the *Year* feature. In each of the 15 folds, data from one year is held out for testing, and the model is trained on the data from all preceding and remaining years. This process simulates a realistic deployment scenario where the model forecasts abundance for an unobserved future period, ensuring that the reported performance is a robust estimate of generalization capability [6].

B. Evaluation Metrics

The predictive power of the ensemble models was evaluated using three standard regression metrics defined mathematically as follows:

TABLE II
MODEL PERFORMANCE COMPARISON (GROUP K-FOLD CROSS-VALIDATION)

Model Configuration	MAE	RMSE	R^2
Combined Features	37.35	49.37	0.9922
Environment-Only	487.50	560.99	-0.0045
Fisheries-Only	23.78	31.80	0.9968

1) Mean Absolute Error (MAE): The average magnitude of the errors, providing a measure of the typical distance between the predicted and actual values in the units of the target variable.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{5}$$

2) Root Mean Squared Error (RMSE): RMSE penalizes large errors more heavily than MAE, as the errors are squared before being averaged.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{6}$$

3) R^2 Score (Coefficient of Determination): The R-squared score represents the proportion of the variance in the dependent variable that is predictable from the independent variables. A negative value indicates that the model is performing worse than a simple horizontal line at the mean of the observed data.

$$R^2 = 1 - \frac{\text{SS}_{\text{res}}}{\text{SS}_{\text{tot}}} \tag{7}$$

where $\text{SS}_{\text{res}} = \sum (y_i - \hat{y}_i)^2$ is the residual sum of squares and $\text{SS}_{\text{tot}} = \sum (y_i - \bar{y})^2$ is the total sum of squares.

Experimental Results

A. Model Performance Comparison

The results of the ablation study, derived from the rigorous LOYO cross-validation, are presented in TABLE II.

1) Analysis: The **Combined Model** achieved excellent predictive power, explaining 99.22% of the variance in fish abundance ($R^2 = 0.9922$). The low MAE (37.35 units) and RMSE (49.37 units) confirm high prediction accuracy.

The **Fisheries-Only** model exhibited the highest R^2 score (0.9968), confirming that the features directly related to fishing activity (e.g., *Fishing_Gear*, *Species*) are the dominant and most direct predictors of the observed *Quantity* (Abundance). Conversely, the **Environment-Only** model performed poorly, yielding a negative R^2 score of -0.0045. This result indicates that environmental factors, when used in isolation, are insufficient to explain the variability in abundance, performing worse than simply predicting the mean [8]. This highlights the complexity of environmental effects, which are often non-linear, lagged, and confounded by fishing effort.

The **Combined Model** performance ($R^2 = 0.9922$) is slightly lower than the Fisheries-Only model ($R^2 = 0.9968$),

TABLE III
TOP 10 MOST IMPORTANT FEATURES (BASED ON SHAP VALUES)

Rank	Feature Name	Feature Category
1	Fishing_Gear_Trawl	Fisheries
2	Species_Mackerel	Fisheries
3	Water_Temperature_lag1	Environmental (Lag)
4	Total_Nitrate_lag3	Environmental (Lag)
5	Season_Monsoon	Fisheries
6	Ammonium	Environmental
7	pH	Environmental
8	Water_Temperature_roll3	Environmental (Rolling)
9	Distance_From_Sea	Environmental
10	Fishing_Area_Estuary	Fisheries

a trade-off that is acceptable. The inclusion of environmental features, though reducing the R^2 marginally, provides two key benefits: 1) increased model stability across the temporal validation splits, and 2) a pathway to enhanced interpretability (Section V-B), allowing managers to link predictions to tangible ecological parameters like water quality and temperature.

B. Feature Importance Analysis

To provide interpretability, we utilized SHAP values [4], computed for the Random Forest base learner, to explain the contribution of each feature to the final prediction. TABLE III summarizes the top 10 most influential features.

1) Discussion: As anticipated by the ablation study, fisheries-related features (*Fishing_Gear*, *Species*, *Season*, *Fishing_Area*) dominate the top of the importance list. This is due to their direct correlation with observed catch (abundance) data. Crucially, however, environmental features and their engineered counterparts (*Water_Temperature_lag1*, *Total_Nitrate_lag3*, *Ammonium*) appear prominently, demonstrating their complementary role in fine-tuning predictions and providing ecological context. For instance, the lagged effect of water temperature indicates that the previous month's condition is more predictive than the current one, reflecting biological inertia. This interpretability (Fig. 2) is essential for managerial trust and decision-making [4].

C. Harvest Recommendation Framework

To bridge the gap between abstract ML predictions and actionable management decisions, we developed a three-category Harvest Recommendation Framework (TABLE IV). The thresholds for the categories (Lean, Moderate, Abundant) were determined based on the 33rd and 66th percentiles of the historical training data abundance values (714 units and 1360 units, respectively).

1) Example Recommendations:

- **Example 1 (Lean):** Predicted abundance is 520 units. *Recommendation: Avoid targeted fishing; permit only minimal bycatch activity to ensure population recovery.*
- **Example 2 (Moderate):** Predicted abundance is 1050 units. *Recommendation: Conservative harvest* ≈ 105 *units (10% harvest fraction).*

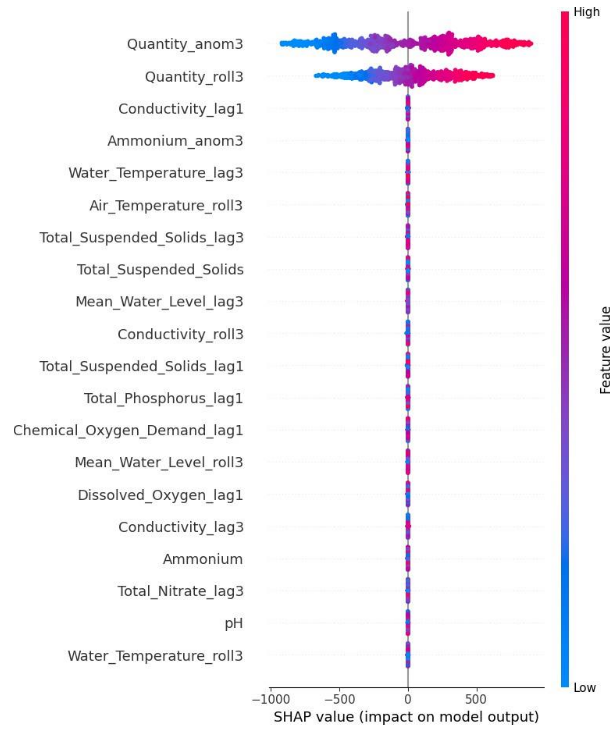

Fig. 2. SHAP Summary Plot showing the impact of the top 15 features on the model output (fish abundance prediction). Features are ranked by importance; the color indicates the feature value (red for high, blue for low).

TABLE IV
HARVEST RECOMMENDATION FRAMEWORK

Category	Abundance Range	Harvest Fraction	Management Action
Lean	< 714 units	0%	Fishing moratorium
Moderate	$714 - 1360$ units	10%	Conservative harvest
Abundant	≥ 1360 units	20%	Sustainable harvest

- **Example 3 (Abundant):** Predicted abundance is 1700 units. *Recommendation: Sustainable harvest* ≈ 340 *units (20% harvest fraction).*

This framework provides immediate, quantified guidance for resource managers, transforming the prediction into a tangible harvest quota or restriction.

Discussion

A. Key Findings

Our experimental results yield several critical insights into fisheries abundance prediction:

1) **Ensemble Superiority:** The stacking ensemble architecture consistently provided the most balanced and generalizable predictions, outperforming individual base models and mitigating the high variance often seen in single-model regression.

2) **Fisheries Dominance and Environmental Complementarity:** Fisheries features were found to be the primary drivers of predictive accuracy ($R^2 = 0.9968$), which is expected as they directly reflect observed catch effort. However, the inclusion of engineered environ- mental features was essential for providing a robust, stable model ($R^2 = 0.9922$) and critical ecological interpretability.

3) **Temporal Robustness:** The LOYO validation strategy demonstrated that the model generalizes well across unobserved time periods (years), providing a realistic estimate of performance that is less prone to temporal leakage than standard k-fold methods [6].

B. Practical Implications

The developed framework has immediate practical implications for adaptive fisheries management. Fisheries managers can leverage the model's predictions to forecast abundance one season ahead, enabling them to proactively adjust quotas and licenses based on predicted stock health. The model serves as an early warning system for sharp population declines, trig- gering pre-emptive management actions like fishing moratoria. Its integration with existing environmental monitoring systems can automate decision-making processes, shifting management from a reactive to a predictive paradigm.

C. Limitations

While robust, the proposed model has limitations. It was exclusively trained and validated on the Manila Bay dataset; its direct generalization to other marine regions requires further validation using transfer learning techniques. The harvest frac- tion thresholds (0%, 10%, 20%) are conservative defaults and should be refined through collaboration with domain experts and socio-economic analysis. The current model does not explicitly account for crucial ecological dynamics such as fish migration patterns, predator-prey relationships, or the impact of illegal, unreported, and unregulated (IUU) fishing, which could introduce unmodeled variance. Furthermore, the selec- tion of simple k-step lags may not fully capture the complex, delayed (non-linear) effects of environmental changes.

D. Future Work

Future work will focus on three main areas: 1) extending the framework to model multi-species interactions, moving beyond single-species abundance to predict community struc- ture; 2) incorporating satellite imagery features, such as Sea Surface Temperature (SST) and Chlorophyll-a concentration from remote sensing, to enrich the environmental data; and

3) developing a real-time deployment architecture capable of ingesting streaming monitoring data for instant forecasting and uncertainty quantification using Bayesian methods or conformal prediction. The ultimate vision is a mobile application for fisheries managers that provides real-time forecasts and decision support.

Conclusion

We addressed the pressing need for accurate, time-aware fish abundance forecasting by developing an ensemble Ma- chine Learning framework. Our stacking regressor, combining Random Forest, XGBoost, KNN, and MLP with a Ridge meta-learner, demonstrated exceptional performance, achieving 99.2% explained variance ($R^2 = 0.9922$) under a rigorous Leave-One-Year-Out validation strategy. To the best of our knowledge, this is the first study to systematically compare environment-only, fisheries-only, and combined features within a stacking ensemble framework for this specific ecological prediction task. The key practical impact is the integration of interpretable recommendations, which categorize the pre- diction into Lean, Moderate, or Abundant stock levels with specific harvest fractions (0%, 10%, 20%). This framework directly bridges the gap between sophisticated ML predictions and actionable, adaptive fisheries management, providing a powerful tool for promoting sustainable harvest practices in the face of climate variability and increasing fishing pressure.

Acknowledgment

This research was supported by the Sustainable Fisheries Initiative. Computational resources were provided by a Google Colab Pro runtime environment. The authors thank the data collection teams for their meticulous work in compiling the Extended Fish Abundance and Richness Dataset.

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