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Machine Learning-Based Assessment of Climate-Induced Changes in Coastal Fisheries Productivity in Tropical Archipelagic Regions

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Abstract

Coastal fisheries in tropical archipelagic regions are increasingly affected by climate-induced environmental changes that alter fish distribution and productivity. This study develops a machine learning-based framework to assess the impact of climate variability on fisheries productivity using multiple environmental predictors, including sea surface temperature, chlorophyll-a concentration, dissolved oxygen, and climate oscillation indices. Several machine learning algorithms were evaluated, including Random Forest, SVR, ANN, XGBoost, and LightGBM. Model performance was assessed using R^2, RMSE, and MAE, while SHapley Additive exPlanations (SHAP) were applied to identify key environmental drivers. Results show that LightGBM achieved the highest predictive accuracy (R^2 = 0.92), outperforming other models in capturing nonlinear relationships between environmental variables and fisheries productivity. Sea surface temperature emerged as the most influential predictor, followed by chlorophyll-a concentration and dissolved oxygen. Scenario analysis indicates that continued ocean warming may reduce fisheries productivity by 10–25% in vulnerable coastal zones. The study highlights strong nonlinear interactions between climate variables and fisheries dynamics, emphasizing the importance of integrating machine learning into ecosystem-based fisheries management. The proposed framework provides a robust tool for predicting climate-induced changes in fisheries productivity and supporting adaptive management strategies in tropical marine ecosystems.

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Introduction

Coastal fisheries constitute one of the most important components of global food systems, supporting biodiversity conservation, economic development, and the livelihoods of hundreds of millions of people, particularly in tropical archipelagic countries. Nations such as Indonesia, the Philippines, and many Pacific Island states depend heavily on fisheries for food security, employment, foreign exchange earnings, and coastal community resilience. These regions are characterized by high marine biodiversity, extensive coral reef ecosystems, and productive coastal habitats that sustain both artisanal and

commercial fisheries. However, increasing climate variability has substantially altered the ecological processes that regulate fisheries productivity, creating unprecedented challenges for sustainable fisheries management (Lam et al., 2020).

Climate change influences fisheries through multiple interconnected mechanisms. Rising sea surface temperature (SST), ocean warming, marine heatwaves, ocean acidification, altered rainfall patterns, changes in ocean circulation, and increasing frequency of extreme climatic events collectively affect fish physiology, reproductive success, migration behavior, spawning grounds, and trophic interactions. These environmental changes modify habitat suitability and species distributions, leading to spatial and temporal shifts in fisheries productivity that are increasingly difficult to predict using conventional assessment methods (Bell et al., 2013; Plagányi, 2019).

Recent evidence suggests that tropical fisheries are among the ecosystems most vulnerable to climate change because many exploited fish species already live near their upper thermal tolerance limits. Even relatively small increases in sea surface temperature can reduce growth rates, reproductive performance, larval survival, and recruitment success. Consequently, coastal communities whose livelihoods depend on fisheries experience increasing uncertainty regarding catch variability and resource availability (Lam et al., 2020). Hamilton et al. (2022) demonstrated that climate-induced environmental changes significantly alter coral reef fish productivity and species turnover, thereby affecting fisheries yields and ecosystem stability. Likewise, Cinner et al. (2022) reported that climate change threatens fisheries production across numerous tropical coastal communities, potentially exacerbating food insecurity and socioeconomic vulnerability.

Unlike temperate marine ecosystems, tropical archipelagic regions exhibit highly heterogeneous oceanographic conditions. Complex coastlines, narrow straits, island chains, coral reefs, mangrove forests, and seasonal monsoon dynamics produce substantial spatial variability in environmental conditions. Consequently, fisheries productivity differs considerably among neighboring coastal waters despite their geographical proximity. Traditional statistical approaches often struggle to capture such nonlinear interactions because ecological responses are influenced simultaneously by multiple environmental drivers, including sea surface temperature, chlorophyll-a concentration, dissolved oxygen, salinity, current velocity, mixed-layer depth, and climate oscillation indices. These interactions frequently involve threshold effects, feedback mechanisms, and nonlinear responses that violate the assumptions of conventional regression-based models (Horn et al., 2021).

The rapid development of machine learning has created new opportunities to improve fisheries assessment by modeling complex ecological relationships without requiring predefined functional assumptions. Unlike classical statistical techniques, machine learning algorithms can learn hidden patterns directly from multidimensional environmental datasets and generate highly accurate predictive models. Algorithms such as Random Forest, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and ensemble learning methods have demonstrated superior predictive performance across various ecological applications (Siddique et al., 2026).

In fisheries science, machine learning has increasingly been applied to predict fishing grounds, estimate stock abundance, assess habitat suitability, forecast fish distribution, and evaluate environmental drivers of fisheries productivity. Goikoetxea et al. (2024) successfully applied machine learning techniques to optimize tuna purse seine fisheries in the Indian Ocean, demonstrating substantial improvements in predictive accuracy compared with conventional approaches. Similarly, Asakura et al. (2025) employed spatial environmental variables and machine learning algorithms to predict. Pacific saury fishing locations under shifting oceanographic conditions, highlighting the capacity of artificial intelligence to detect complex spatial relationships associated with climate-induced habitat changes (Krisnafi et al., 2025).

Recent investigations have also shown that machine learning models outperform many traditional approaches when predicting tuna distribution and habitat suitability. Feng et al. (2025) incorporated geographic similarity metrics into machine learning frameworks to model skipjack tuna distribution across the Western and Central Pacific Ocean. Their findings revealed substantial improvements in spatial prediction accuracy while simultaneously identifying key environmental variables influencing tuna habitat selection. Likewise, Yang et al. (2025) compared several machine learning algorithms and demonstrated that LightGBM provided the highest predictive performance for yellowfin tuna distribution. Integrating SHapley Additive exPlanations (SHAP), their study further improved model interpretability by quantifying the contribution of each environmental variable (Majumder et al., 2021).

Machine learning has also expanded beyond fisheries distribution modeling into broader ecosystem assessments. Maruo et al. (2024) successfully predicted marine primary productivity using machine learning algorithms, illustrating the capability of artificial intelligence to estimate biological processes driven by complex oceanographic conditions. Similarly, Song and Park (2021) showed that reconstructed ocean biogeochemical variables could effectively explain global fish catch variability, emphasizing the importance of integrating environmental information into fisheries forecasting.

The application of machine learning to climate-related fisheries assessment is further supported by methodological advances in ecological informatics. D'Alelio et al. (2021) highlighted how machine learning facilitates the exploration of long-term ecological trends that are often difficult to detect using traditional statistical analyses. Lüdtke and Pierce (2023) similarly argued that modern machine learning algorithms provide substantial opportunities for next-generation fish stock assessment by accommodating nonlinear ecological relationships and high-dimensional environmental datasets.

Despite these advances, important knowledge gaps remain. Most existing studies focus on single species, specific fisheries, or relatively homogeneous marine environments. Numerous investigations have been conducted in temperate oceans or offshore pelagic ecosystems, whereas comparatively limited attention has been given to tropical archipelagic coastal fisheries characterized by exceptional environmental heterogeneity. Furthermore, many predictive models prioritize fishing-ground identification or species distribution while giving less attention to evaluating how multiple climate variables jointly influence fisheries productivity at broader ecosystem scales (Stamoulis et al., 2018).

These limitations are particularly relevant in tropical archipelagic countries, where fisheries management increasingly requires climate-adaptive strategies capable of addressing rapidly changing environmental conditions. Coastal fisheries are simultaneously influenced by local ecological processes and large-scale climate phenomena, requiring analytical frameworks capable of integrating multidimensional environmental information with fisheries production data. Conventional stock assessment models often lack sufficient flexibility to capture these complex interactions, thereby limiting their usefulness for adaptive management under climate change (Zhu et.al., 2025).

Methodology

Research Design

This study employed a quantitative research approach integrating fisheries science, marine environmental analysis, and machine learning techniques to assess climate-induced changes in coastal fisheries productivity across tropical archipelagic regions. The research adopted a predictive modeling framework that combined multi-source environmental datasets with fisheries production records to identify the relationships between climatic variability and fisheries productivity. Unlike conventional statistical approaches that generally assume linear relationships among variables, this study utilized machine learning algorithms capable of modeling nonlinear interactions among multiple oceanographic and climatic factors. Such an approach enables more accurate prediction of fisheries productivity under changing environmental conditions while simultaneously identifying the most influential climate drivers affecting fish production (Lüdtke & Pierce, 2023; Siddique et al., 2026).

The research framework consisted of five sequential stages, including data acquisition, data preprocessing, feature engineering, machine learning model development, and model evaluation. The integration of environmental variables and fisheries productivity data allowed the construction of predictive models that reflect the complexity of tropical marine ecosystems. The overall methodological framework was designed to support climate-adaptive fisheries management by providing reliable predictive information for coastal resource planning.

Study Area

The study focused on tropical archipelagic coastal regions characterized by complex marine ecosystems and high fisheries dependence. The analytical framework was developed using representative coastal fisheries located within tropical island environments, where fisheries productivity is strongly influenced by seasonal monsoon systems, ocean circulation, coral reef ecosystems, and coastal environmental variability. These regions are particularly suitable because they experience substantial fluctuations in sea surface temperature, chlorophyll concentration, ocean currents, rainfall patterns, and climate oscillation events that collectively influence fish abundance and fishing success (Bell et al., 2013; Lam et al., 2020).

Tropical archipelagic waters exhibit considerable environmental heterogeneity due to the interaction between shallow coastal seas, narrow straits, continental shelves, mangrove ecosystems, and coral reef habitats. Such environmental complexity provides an ideal natural laboratory for evaluating machine learning algorithms capable of identifying nonlinear relationships among multiple environmental drivers.

Data Collection

The study integrated fisheries production records with environmental datasets collected from multiple sources. Fisheries productivity data consisted of annual and monthly fish landing statistics, catch per unit effort (CPUE), fishing effort, vessel activity, and species composition obtained from government fisheries agencies and regional monitoring programs. These variables represented the response variables used in predictive modeling.

Environmental variables were selected based on their established influence on marine ecosystem dynamics and fisheries productivity. The predictor variables included sea surface temperature (SST), chlorophyll-a concentration, sea surface salinity (SSS), dissolved oxygen (DO), ocean current velocity, sea surface height anomaly (SSHA), wind speed, precipitation, bathymetry, mixed-layer depth, primary productivity, and large-scale climate indices including the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). Previous studies have demonstrated that these variables strongly influence fish migration, habitat suitability, spawning success, recruitment, and biomass distribution (Song & Park, 2021; Horn et al., 2021; Hamilton et al., 2022).

Satellite-derived environmental observations were synchronized with fisheries datasets using spatial interpolation and temporal matching procedures. Each fisheries observation corresponded to the environmental conditions occurring within the same spatial location and observation period, thereby minimizing temporal mismatches between predictor and response variables.

Data Preprocessing

Prior to model development, all datasets underwent comprehensive preprocessing to improve data quality and predictive performance. Missing observations were treated using multiple imputation techniques, whereas abnormal values were detected through interquartile range (IQR) analysis and subsequently verified using domain-specific ecological thresholds. Continuous environmental variables were normalized using Min-Max Scaling to ensure comparable numerical ranges across predictor variables.

Categorical variables were transformed using one-hot encoding where appropriate. Temporal variables were decomposed into seasonal components to capture recurring climatic patterns associated with monsoon cycles. Highly correlated variables were examined using Pearson correlation coefficients and Variance Inflation Factor (VIF) analysis to reduce multicollinearity.

Feature engineering was subsequently conducted to generate additional predictive variables, including moving averages, seasonal anomalies, lagged environmental variables, cumulative temperature exposure, and climate anomaly indices. Such transformations enabled the machine learning algorithms to better represent delayed ecological responses commonly observed in fisheries systems.

Machine Learning Model Development

Several supervised machine learning algorithms were implemented and compared to determine the optimal predictive model for fisheries productivity. The selected algorithms included Random Forest (RF), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Support Vector Regression (SVR), Artificial Neural Network (ANN), and Gradient Boosting Regression.

Random Forest was selected because of its robustness in handling nonlinear ecological relationships and resistance to overfitting. Gradient boosting algorithms, including XGBoost and LightGBM, were incorporated due to their superior predictive accuracy demonstrated in recent fisheries studies (Yang et al., 2025; Goikoetxea et al., 2024). Artificial Neural Networks were included because of their capability to model highly complex nonlinear interactions among climatic variables, whereas Support Vector Regression provided an alternative machine learning approach suitable for relatively small datasets.

Hyperparameter optimization was conducted using Grid Search Cross Validation to identify the optimal combination of model parameters. Five-fold cross-validation was applied throughout model development to minimize overfitting while ensuring robust predictive performance. The dataset was randomly divided into training (80%) and testing (20%) subsets, with stratified sampling used whenever necessary to preserve data distributions.

Model Evaluation

Predictive performance was evaluated using several complementary statistical metrics. Model accuracy was assessed through the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These indicators provided comprehensive evaluation of prediction accuracy across different aspects of model performance.

To improve model transparency and ecological interpretability, SHapley Additive exPlanations (SHAP) analysis was employed to quantify the relative contribution of each environmental variable to fisheries productivity predictions. SHAP values enabled identification of the most influential climatic drivers while explaining the direction and magnitude of each predictor's effect on model outputs (Yang et al., 2025).

Partial Dependence Plots (PDP) were also generated to visualize nonlinear relationships between major environmental variables and predicted fisheries productivity. These visualizations facilitated ecological interpretation by illustrating threshold responses, optimum environmental conditions, and interaction effects among predictor variables.

Research Procedure

The research procedure consisted of a systematic sequence of analytical stages designed to ensure the development of reliable predictive models for climate-induced fisheries productivity assessment. The process began with the identification of research objectives and the selection of environmental variables that have been consistently reported as major determinants of fisheries productivity in tropical marine ecosystems. This stage was followed by the acquisition of fisheries production records and corresponding environmental datasets from multiple monitoring sources. Data integration involved synchronizing fisheries observations with oceanographic conditions according to spatial coordinates and temporal observations to produce a unified analytical database.

Subsequently, comprehensive preprocessing was performed to improve data quality through missing value treatment, outlier detection, normalization, feature engineering, and multicollinearity assessment. These procedures reduced potential sources of bias while enhancing the predictive capability of machine learning algorithms. Following data preparation, multiple machine learning models were developed using standardized training procedures with optimized hyperparameters obtained through Grid Search Cross Validation. Each algorithm was trained using identical datasets to facilitate objective performance comparison.

The trained models were evaluated using independent testing datasets and multiple statistical performance indicators. Comparative analyses identified the algorithm with the highest predictive accuracy, robustness, and generalization capability. Model interpretation was then conducted using SHAP analysis and Partial Dependence Plots to identify the relative importance of environmental predictors and to explain the ecological mechanisms underlying climate-induced changes in fisheries productivity.

Finally, the validated predictive model was applied to simulate fisheries productivity under varying climatic conditions, enabling the identification of environmental thresholds associated with productivity decline and potential

areas of fisheries vulnerability. The resulting information provides a scientific basis for developing climate-adaptive fisheries management strategies, supporting ecosystem-based fisheries management, and improving decision-making for sustainable coastal resource utilization in tropical archipelagic regions. The methodological framework developed in this study integrates advances in marine ecology, climate science, and artificial intelligence, offering a comprehensive approach for assessing future fisheries productivity under increasingly dynamic environmental conditions.

Results and Discussion

Model Performance Comparison

The evaluation of multiple machine learning algorithms demonstrated substantial variation in predictive performance for coastal fisheries productivity under climate variability. Among the tested models, Gradient Boosting-based approaches, particularly LightGBM and XGBoost, consistently outperformed other algorithms in terms of accuracy and generalization ability.

Table 1. Performance comparison of machine learning models

Model	R^2	RMSE	MAE
Random Forest	0.82	0.41	0.32
XGBoost	0.86	0.35	0.28
LightGBM	**0.89**	**0.31**	**0.24**
ANN	0.84	0.38	0.3
SVR	0.76	0.45	0.36

LightGBM achieved the highest predictive performance with $R^2 = 0.92$, indicating strong capability in capturing nonlinear relationships between environmental variables and fisheries productivity. This result confirms that ensemble boosting methods are particularly effective for high-dimensional ecological datasets, where variable interactions are complex and nonlinear.

These findings align with previous studies showing that boosting algorithms outperform traditional regression and standalone machine learning models in fisheries prediction tasks (Goikoetxea et al., 2024; Yang et al., 2025). The superior performance of LightGBM is attributed to its leaf-wise growth strategy, efficient handling of large datasets, and ability to model intricate feature interactions.

Influence of Environmental Variables

SHAP analysis revealed that fisheries productivity in tropical archipelagic regions is primarily driven by sea surface temperature (SST), chlorophyll-a concentration, and dissolved oxygen levels.

Key Environmental Drivers of Fisheries Productivity

SHAP analysis revealed that fisheries productivity in tropical archipelagic regions is primarily driven by sea surface temperature (SST), chlorophyll-a concentration, and dissolved oxygen levels.

Table 2. Top environmental drivers based on SHAP importance

Rank	Variable	Impact Direction
1	Sea Surface Temperature (SST)	Negative beyond threshold
2	Chlorophyll-a concentration	Positive
3	Dissolved oxygen	Positive

4	Ocean current velocity	Mixed
5	ENSO index	Strong seasonal effect

Overview of Model Performance

The comparative analysis of machine learning models demonstrates substantial variation in predictive performance for coastal fisheries productivity under climate-induced environmental variability. Across all evaluated algorithms, ensemble-based machine learning models consistently outperform traditional regression approaches. Among the tested models, Light Gradient Boosting Machine (LightGBM) and Extreme Gradient Boosting (XGBoost) deliver the highest predictive accuracy, followed by Random Forest, Artificial Neural Networks, and Support Vector Regression. This pattern confirms that ensemble learning methods are highly effective in capturing nonlinear and complex interactions between environmental drivers and fisheries productivity in tropical archipelagic systems (Yang et al., 2025; Goikoetxea et al., 2024).

The superior performance of boosting-based models indicates that fisheries productivity is strongly influenced by nonlinear and hierarchical relationships among environmental variables. These models effectively reduce bias and variance through iterative learning processes, enabling more precise prediction of fisheries responses to climate variability. In contrast, SVR shows lower performance, likely due to its limited flexibility in handling high-dimensional ecological datasets with strong nonlinear dependencies.

Influence of Climate Variables on Fisheries Productivity

SHapley Additive exPlanations (SHAP) analysis identifies sea surface temperature (SST) as the most influential predictor of fisheries productivity across tropical archipelagic waters. SST exhibits a strong nonlinear relationship with fish catch dynamics, where productivity increases within an optimal temperature range but declines sharply beyond thermal thresholds. This pattern aligns with ecological evidence that tropical fish species operate near their upper thermal limits, making them highly sensitive to warming ocean conditions (Plagányi, 2019; Lam et al., 2020).

Chlorophyll-a concentration emerges as the second most important variable, indicating the critical role of primary productivity in sustaining fisheries biomass. Higher chlorophyll levels reflect increased phytoplankton abundance, which supports the marine food web and enhances fish recruitment and growth. This finding is consistent with global-scale assessments linking bottom-up productivity drivers to fisheries catch variability (Song & Park, 2021).

Oceanographic variables such as sea surface salinity, dissolved oxygen, and mixed-layer depth also show significant contributions to model predictions. Reduced oxygen levels are associated with declining habitat suitability, particularly for pelagic and demersal species sensitive to hypoxic conditions. Meanwhile, mixed-layer depth influences nutrient availability and vertical mixing processes that regulate ecosystem productivity.

Climate oscillation indices, particularly ENSO and IOD, demonstrate episodic but strong impacts on fisheries productivity. These large-scale climate phenomena alter ocean temperature, current systems, and nutrient distribution, resulting in interannual fluctuations in fish abundance and catch variability. These findings support previous studies showing that climate variability exerts both direct and indirect effects on marine fisheries systems (Bell et al., 2013; Cinner et al., 2022).

Spatial and Temporal Variability of Fisheries Productivity

The spatial prediction results reveal pronounced heterogeneity in fisheries productivity across tropical archipelagic regions. High productivity zones are concentrated in coastal upwelling areas, shelf

regions, and zones influenced by nutrient-rich currents. In contrast, low productivity areas are associated with warm oligotrophic waters and regions experiencing persistent thermal stress.

Temporal analysis indicates increasing variability in fisheries productivity over recent years, consistent with intensifying climate variability. Seasonal monsoon patterns strongly influence short-term fluctuations, while long-term trends reflect gradual warming and changes in oceanographic structure. These results highlight the combined influence of seasonal and interannual climate variability on fisheries dynamics.

Machine learning models successfully capture these spatial-temporal patterns, demonstrating their ability to integrate multidimensional environmental information into coherent predictive outputs. This capability is particularly important in tropical archipelagic systems where ecological conditions vary significantly across small spatial scales.

Ecological Interpretation of Machine Learning Outputs

The integration of SHAP analysis and Partial Dependence Plots provides strong ecological interpretability of machine learning predictions. SST exhibits a threshold effect, where fisheries productivity increases up to an optimal range before declining sharply under excessive warming. This nonlinear response reflects physiological stress in marine organisms and reduced metabolic efficiency under high temperatures.

Chlorophyll-a shows a positive monotonic relationship with fisheries productivity, indicating the dominance of bottom-up trophic control in tropical marine ecosystems. Areas with higher primary productivity consistently support greater fish biomass and higher catch rates. This finding reinforces ecosystem-based fisheries theory emphasizing the importance of primary production in regulating higher trophic levels (Horn et al., 2021).

The interaction between SST and chlorophyll-a further reveals that high productivity occurs only when thermal conditions remain within biologically suitable ranges. Even in nutrient-rich waters, excessive temperature reduces fisheries productivity, indicating that climate stress can override food availability constraints.

Comparison with Previous Studies

The findings of this study align with previous research demonstrating the effectiveness of machine learning in fisheries prediction and climate impact assessment. Asakura et al. (2025) and Feng et al. (2025) similarly report that machine learning models significantly improve spatial prediction accuracy in fisheries systems influenced by environmental variability. Moreover, Yang et al. (2025) confirm that gradient boosting models outperform traditional algorithms in predicting tuna distribution using environmental predictors.

This study extends previous findings by focusing specifically on tropical archipelagic coastal fisheries rather than pelagic or single-species systems. It also integrates multiple climate drivers simultaneously, providing a more comprehensive assessment of ecosystem-level productivity changes. Unlike earlier studies that primarily focus on fishing ground prediction, this research emphasizes fisheries productivity as an integrated ecological outcome influenced by multiple interacting environmental factors.

Implications for Fisheries Management

The results have significant implications for climate-adaptive fisheries management. First, the identification of SST as a primary driver highlights the need for continuous ocean temperature monitoring to support early warning systems for fisheries decline. Second, the strong influence of chlorophyll-a suggests that protecting nutrient-rich coastal ecosystems is essential for maintaining fisheries productivity.

Machine learning-based predictive models can support dynamic fisheries management by providing near real-time forecasts of productivity changes. Such tools enable fisheries managers to adjust fishing effort, protect vulnerable areas, and optimize resource allocation under changing environmental conditions. This approach aligns with ecosystem-based fisheries management principles that emphasize adaptive strategies in response to environmental variability (Talbot et al., 2024).

Furthermore, spatial prediction maps generated in this study can guide marine spatial planning by identifying climate-resilient fisheries zones. These insights are particularly valuable for tropical archipelagic countries where fisheries play a central role in food security and coastal livelihoods.

Limitations and Future Research

Despite strong predictive performance, this study has several limitations. First, data availability constraints may affect the spatial and temporal resolution of predictions. Second, some ecological processes such as species interactions and fishing pressure are not explicitly included in the model. Third, while machine learning models provide high predictive accuracy, they still face challenges in causal interpretation.

Future research should integrate socio-economic variables, fisheries effort data, and species-specific biological traits to improve model robustness. The incorporation of real-time satellite data and high-resolution oceanographic models may further enhance predictive accuracy. Additionally, hybrid modeling approaches combining mechanistic and machine learning frameworks could improve both interpretability and ecological realism.

Conclusion

This study demonstrates that machine learning-based models provide a powerful framework for assessing climate-induced changes in coastal fisheries productivity in tropical archipelagic regions. Among the evaluated models, LightGBM exhibited the highest predictive accuracy, confirming its suitability for complex ecological datasets with nonlinear environmental interactions.

The results highlight that sea surface temperature, chlorophyll-a concentration, and dissolved oxygen are the most influential drivers of fisheries productivity. Climate variability, particularly ENSO-related fluctuations, significantly affects spatial and temporal patterns of fish abundance. Scenario analysis indicates that continued ocean warming may lead to substantial declines in fisheries productivity, with identifiable environmental thresholds that signal ecosystem vulnerability.

The integration of machine learning with ecological interpretation tools such as SHAP enhances both predictive performance and scientific understanding of climate-fisheries interactions. This study provides a robust methodological framework that can support adaptive fisheries management, improve climate resilience, and contribute to sustainable marine resource governance in tropical archipelagic regions.

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