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Mapping anchovy species distribution and identifying potential fishing grounds in the Gulf of Thailand

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Abstract The approach of this study utilized Random Forest Regression of 0.7443, Extreme Gradient Boosting (XGBoost) of 0.8800, and Extra Trees Regression (Extra Tree) of 0.7205. The results indicated that the XGBoost performed better than other approaches in accurately modeling species distribution. The consequence showed an R-squared (R^2) ranging from 0.5574 to 0.8836, demonstrating strong predictive performance across different scenarios. Furthermore, the Root Mean Square Error (RMSE) varied between 0.4821 to 0.5153 kg catch weight, while the Mean Absolute Error (MAE) ranged from 0.1926 to 0.2293. In particular, the variables contributing to model accuracy. In conclusion, the findings of this study demonstrated that the spatiotemporal dynamics of the anchovies distribution in the Gulf of Thailand are found to be accurately represented through the XGBoost model. This capacity is required the ability to assess environmental variables discovered through satellite data to identify the probability of occurrence illustrated the spatial patterns of anchovies, demonstrating that variations in the environment influenced the distribution of anchovies. The results suggested that anchovy offers into the seasonal distribution. For fisheries management. The approach might help to reduce overfishing pressure in ecologically valuable regions by discovering suitable fishing grounds in the Gulf of Thailand.

Keywords: Distribution pattern, Anchovy fisheries, Fishing Ground, The Gulf of Thailand, Machine learning

Introduction

Marine fisheries have significant social and economic value for Thailand. Marine fisheries resources are the primary source of protein and contribute to the well-being and livelihoods of people. Fishery plays an important role in Thailand's economy. The area is blessed with a high abundance of marine fisheries resources because the coastal ecosystem in this zone is very productive and the high biodiversity of marine aquatic animals provides multiple ecosystems

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that are suitable for habitats of fisheries resources. Increasing human populations as well as high demands on marine species and fisheries products that the reasons for overexploitation. To maintain the sustainable development of the sector, several challenges still need to be addressed. These include rebuilding and maintaining the fisheries resources at a level commensurate with strengthening the capacity for effective fisheries management. Thus, allowing the rebuilding of the fishery resources. To promote the sustainable management of marine fisheries resources. The correlation between the fisheries resources and the environment is important (DoF, 2023).

Fishery contributes to a huge amount of Thailand's economy. Overfishing has threatened the sustainability of fisheries resources all over the world, particularly in Thailand. There is an urgent need for adaptation regulating conservation. The spatial information indicating the area of fisheries resources will be essential for timely resource conservation with effective enforcement. The current conservation boundary has long been delineated based on the in-situ data where space application has not been applied for such a regulation. Consequently, it would very helpful if satellite data can supplement these observations to create maps of the distribution of fishery resources at any time of the year.

The monsoon season influenced fishing grounds, particularly for fishing vessels in the Gulf of Thailand, according to a 2020 study on anchovy fisheries in Thailand. Rayong Province was discovered to be a high level of purse seine fishing in the Gulf of Thailand during the northeast monsoon season, with fishing occurring place from 4 to 100 nautical miles offshore. Fishing has been observed between 4.5 and 105 nautical miles offshore in Chumphon Province. Fishing occurred 150 nautical miles offshore during the monsoon season, all along the coast to the center of the Gulf of Thailand. Fishing grounds were found to be comparable to those in the northeast monsoon season during the southwest monsoon season.

During the northeast monsoon season, anchovy lift nets can only be discovered along the Gulf of Thailand coast. In Chon Buri province, they are frequently observed fishing 7–20 nautical miles offshore, and in Prachuap Khiri Khan province, they are discovered fishing 10-65 nautical miles offshore. Their companies cruise 80 nautical miles offshore during the monsoon change, and they can be found fishing in the same location during the southwest monsoon season.

Many types of fishing gear are used to catch many species (multi-species) in Thailand's tropical marine fisheries. Most fishing gear can catch more than 50 species and there are more than 20 types of fishing gear. Moreover, the majority of fishing vessels are commercial fishing vessels, providing a food source for several fishers and fishing communities. This multi-species and multi-fishing gear nature of the Thailand fishery needs to be taken into account when assessing the status of the resources and applying management measures based on the context of temperate fisheries. The global issue of overfishing poses a significant risk to the sustainable utilization of fisheries resources, especially Thailand which has been especially impacted. Accurate geographical data on fish distribution is important for efficient resource management. These ocean views demonstrate various occupancies and abundances of significant foragers such as anchovies and sardines Maria *et al*. (2021). Utilizing ocean satellite sensors in remote sensing. The variables in the research for example, Salinity, temperature, chlorophyll-a, dissolved oxygen, zonal and meridional currents, wave height, nitrate, euphotic depth, and wave height are among the temporal factors. In recent years, vessel monitoring systems data has been more widely available for scientific purposes. There are many opportunities to monitor the water quality in estuaries, coastal and the open ocean utilizing remote sensing (Mohseni *et al*., 2022).

Satellite-based systems providing the coordinates (GPS) are referred to as vessel monitoring systems. The location of the fishing vessel's historical track was provided via GPS, resulting in a collection of sample points that provide the latitude and longitude of the location on the timestamp. In data analysis and management, it is beneficial. Additionally, by utilizing the data from the vessel monitoring systems to identify the location and density of the fishing vessels, the analysis determines the fishing activity, fishing operation, or behavior of the fishing vessels (Chuaysi and Kiattisin, 2020).

Machine learning has evolved into an essential instrument for ecology and fisheries research Bonino *et al*. (2024), facilitating the examination of complex and extensive datasets, including satellite-derived environmental variables and fisheries data. On analyzing the correlations between environmental variables including salinity, sea surface temperature, particulate organic carbon and chlorophyll-a, and anchovy abundance, this research applies a machine learning algorithm to explore the distribution and habitat preferences of anchovies in the Gulf of Thailand. To generate precise, data-driven models for estimating the spatiotemporal anchovy distribution, this research applies advanced methods such as Random Forest, Extreme Gradient Boosting (XGBoost), and Extra Trees Regression. By directing efforts toward ecologically suitable areas, these models provide useful information for identifying potential fishing grounds, improving sustainable fisheries management, and decreasing overfishing. Machine learning is essential for managing this challenge of optimizing marine resources in a dynamic and changing environment because of the capacity it has to resolve unpredictable interactions and a variety of data sources.

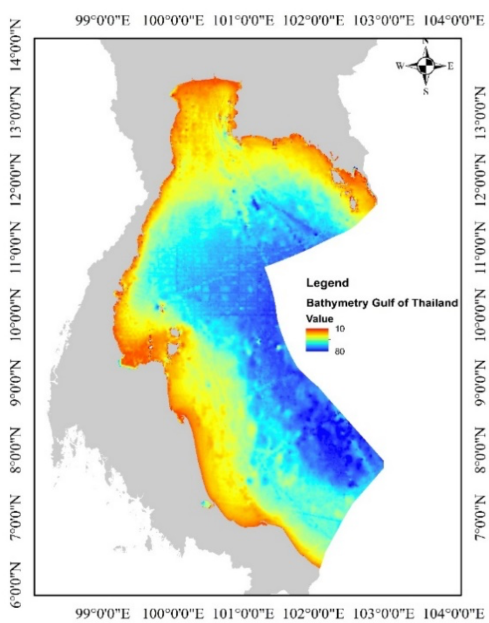
Therefore, this research focused on the main purpose of analyzing and identifying a methodology for determining the optimal approach to integrate Vessel Monitoring System (VMS) positions and remotely sensed data to provide fishing ground information through the application of machine learning algorithms. This approach could be performed on related datasets to learn about the distribution of anchovies in the Gulf of Thailand.

Materials and methods

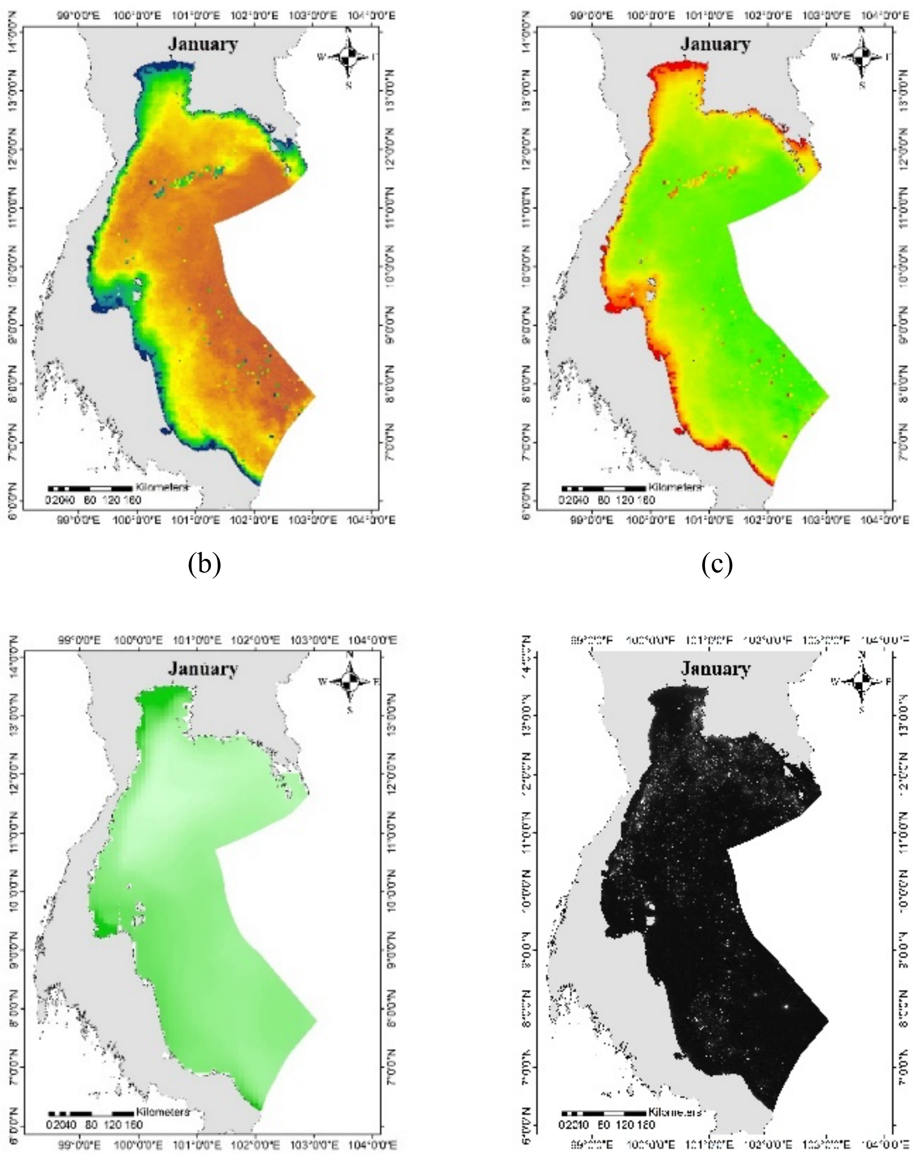
Study area

The Gulf of Thailand is located in Southeast Asia and is positioned between 99 and 103 degrees east of the meridian. The tropical zone covers a region between 6 degrees north latitude and 14 degrees north latitude. (Figure 1).

The Gulf of Thailand, a shallow semi-enclosed basin located in the western equatorial Pacific, undergoes much wind variability on both seasonal and inter-annual timescales that produce complex surface circulation. (Anutaliya, 2023).



(a)



(b) (c)

(d) (e)

Figure 1. The location of the study area. Remotely sensed imagery of Sea Surface Chlorophyll-a. Remotely sensed imagery of Sea Surface Temperature: Remotely sensed imagery of Sea Surface Salinity. Remotely sensed imagery of Night Time Light. in (a)-(e) respectively

Research framework

The overall research methodologies is shown in Figure 2. It was to map the species distribution of anchovies in the Gulf of Thailand by machine learning approach used to investigate the distribution and abundance of anchovies about environmental variables.

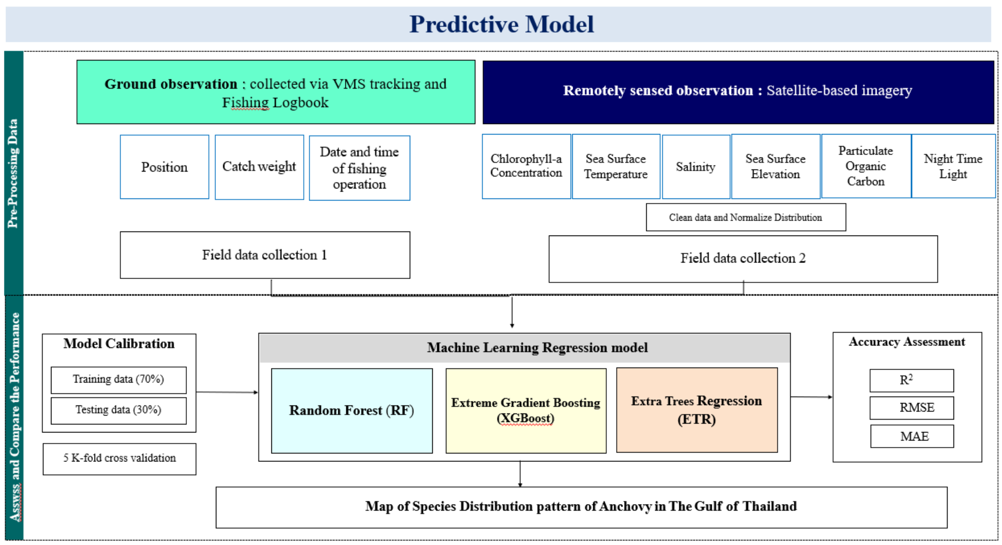


Figure 2. Methodology framework of this study

Data collection and preprocessing

This study combined remote sensing techniques and ground observations to calculate the species distribution. Remote sensing data sourced from Google Earth Engine. Additionally, the position of anchovy fisheries data obtained from the Department of Fisheries contributed to the comprehensive dataset utilized in this calculation of the species distribution.

Remote sensing data

Satellite ocean color data and algorithms are widely used for data analysis. Gather the additional information using the satellite images. MODIS regarding chlorophyll-a data, sea surface temperature, and sea surface elevation, and adjusted geometric inaccuracies in each image in addition amalgamates photos to provide seasonal information, designate the border of the image within the designated area. The Gulf of Thailand as a research region.

Presently, many investigations are determined variables utilizing information gathered through remote sensing. The reflectance regarding remote sensing at various wavelengths is shown in Table 1. Several remote-sensing products are developed.

Table 1. List of Remote Sensing and environment variables

Data	Type Sources	Sources
1. Sea Surface Temperature	Remote Sensing data	Global Change Observation Mission
2. Sea Surface Chlorophyll-a		Global Change Observation Mission
3. Particulate Organic Carbon		NASA OB. DAAC at NASA Goddard Space Flight Center
4. Night Time Light		Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines
5. Salinity		National Ocean Partnership Program
6. Sea Surface Elevation		National Ocean Partnership Program
7. Anchovy Catch Weight	Ground data	Production of anchovy fisheries(kg) / Department of Fisheries
8. Position of Operation details		Latitude /Longitude from VMS data / Department of Fisheries

Machine learning techniques, model validation, and accuracy assessment

Three machine learning models- were used to predict as Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Extra Trees Regression (Extra Tree).

The assessment of the prediction model was performed with K-fold Cross-validation a method used to test prediction models. The model is trained and tested k times, with a different fold serving as the validation set each time. This approach provided information about the model's generalization ability. Then three distinct algorithms are used for training and testing data. The dataset is divided into 70% for training and 30% for testing. To assess the accuracy and reliability of the model in forecasting species distribution, this research performed the 5 - fold cross-validation procedure. This method is repeated 5 times, and the resulting to get the average values of cross-validation R^2 (coefficient of determination), and cross-validation Root Mean Square Error (RMSE). One of the most important steps in generating models is choosen the main environments to investigate the species' niche. Overfitting of the model may result from including too numerous environmental variables (Townsend *et al.*, 2007; Elith, 2019).

Accuracy assessment

The estimation of Anchovy Species Distribution, RF, XGBoost, and Extra Tree models was constructed by machine learning. The model set 70% for Species Distribution training and validated the remaining 30% of data. In this study, the assessment comparison between the regression models was evaluated in terms of the difference between the actual values and the predicted statistical. R^2, RMSE and MAE which commonly used metrics, R^2 to understand the proportion of variance explained by the model, while RMSE indicated the average magnitude of the residuals or errors made by the model. When comparing models, higher R^2 values and lower RMSE values is generally indicated a better model performance.

To assess the predictive efficacy of the model, employed 3 key prediction indices: R^2, RMSE, and MAE. The integration of these metrics provides a well-rounded evaluation of the model's overall predictive accuracy and reliability. Formulas for R^2, MAE, and RMSE follow.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |E_i - M_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (E_i - M_i)^2} \tag{2}$$

$$R^2 = \frac{\sum_{i=1}^{n} (E_i - \bar{M}_i)^2}{\sum_{i=1}^{n} (\mathrm{E} - \bar{M}_i)^2} \tag{3}$$

Where *N* represents the number of samples; E_iRepresent the estimated values (e.g., satellite reflectance values or estimated values); and M_i Represent the measured values, respectively.

Results

Descriptive statistics

Pearson’s correlation analysis was performed to analyze the analyze the correlation between the input features gathered from environmental variables, and Fisheries data (ground data). The consequences of this analysis are presented in Figure 3. It showed that the variable's impact was assessed through model which influenced and permutation importance calculation, enhancing the comparability of these variables, and revealing correlations among all selected parameters. Considering the aforementioned regions indicated productive zones with an abundance of plankton, that provided the primary productivity, anchovy species are frequently discovered in areas with higher concentrations of chlorophyll-a. Emphasizes that high levels of organic matter are identified by their positive correlation with Particulate Organic Carbon. These areas are found to be particularly suitable for fishing because they tended to attract anchovies.

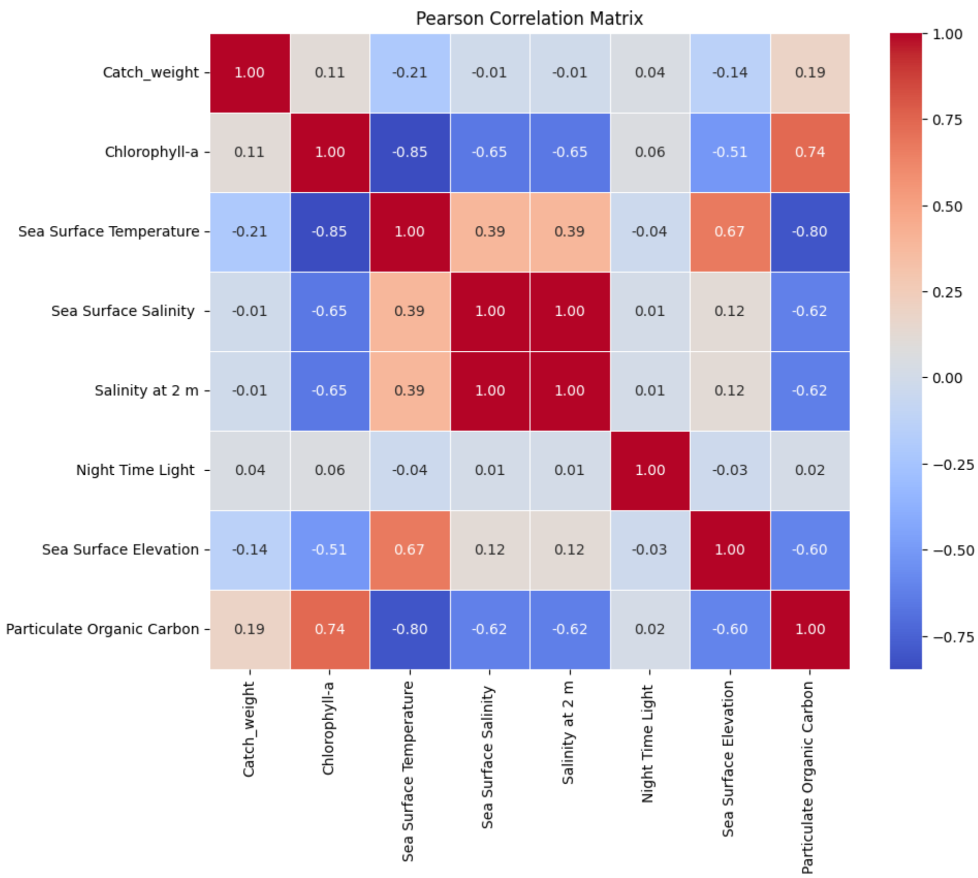


Figure 3. Pearson's correlation analysis of environmental variables

According to the result of feature importance chlorophyll -a, particulate organic carbon, and sea surface temperature are found to be significant factors influencing species distribution. Pearson Analysis of the coefficient of correlation between the observed environmental variables and the data gathered through remote sensing as well as the environmental factors sampled at various sites. The results showed that chlorophyll-a concentration and particulate organic carbon had significantly shown with species distribution in the Gulf of Thailand. It is strongly shown positive correlation with 0.74, 0.6, 0.59, 0.57, 0.58, 0.39 and 0.27.

Mapping species distribution

It revealed that the distribution map of anchovies catchs from January to December. The potential fishing grounds was used satellite data and machine learning. Analysis of the Distribution Map is illustrated the variation in the catch weight of anchovies (kg), featuring five unique categories of anchovies catch weight. Covering five specific types of catch weight were composed of 1,000–2,500 kg/ trip, 2,501–5,000 kg/ trip, 5,001–7,500 kg/ trip, 7,501–10,000 kg/ trip, and more than 10,000 kg/trip. It illustrated the spatial patterns of anchovies catch weights, demonstrating that variations in the environment influenced the distribution of anchovies. Using insights from environmental variables showed to include particulate organic carbon, salinity, sea surface elevation, sea surface temperature, sea surface chlorophyll-a concentration, and nighttime light.

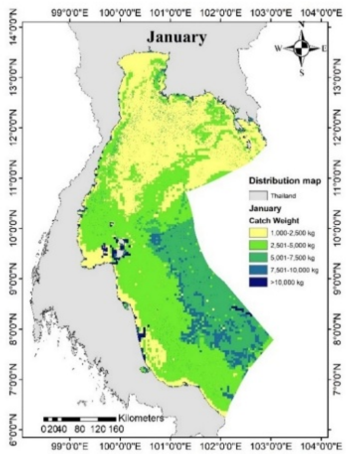
The results suggested that anchovy offered insights into the seasonal distribution of anchovies. The findings suggested that environmental conditions in January - such as cooler sea surface temperatures - promoted the aggregation of anchovies closer to the shore as shown in Figure 4(a).

This result revealed that anchovies aggregation is occurred offshore influenced by climate-related factors, particularly lower sea surface temperatures. The coastal regions, particularly along the western and northern coastlines, showed mostly lower catch weights as shown in Figure 4(b).

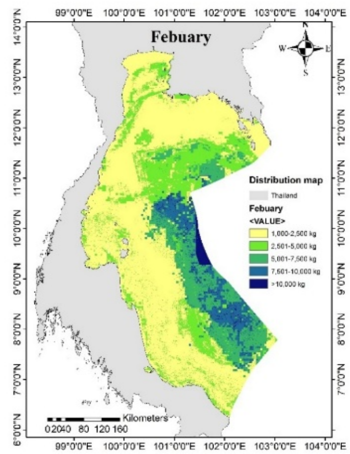
High catch areas (>10,000 kg) are located in the central and eastern to southern areas of the Gulf. Indicating high anchovy abundance in these central the Gulf, offshore waters found that a migration pattern of anchovies toward offshore regions. The distribution pattern observed in March indicated an annual transition of anchovy populations from nearshore to offshore areas of the Gulf. This reposition is associated with environmental factors, such as optimal sea surface temperatures, or species-specific behavioral patterns which is shown in Figure 4(c).

The densities of catch along the coastal regions are found to be minimized. Anchovy abundance was highest in offshore areas in the center and southeastern parts of the Gulf. The anchovies migrated away from shallow coastal and moved further offshore which shown in Figure 4(d).

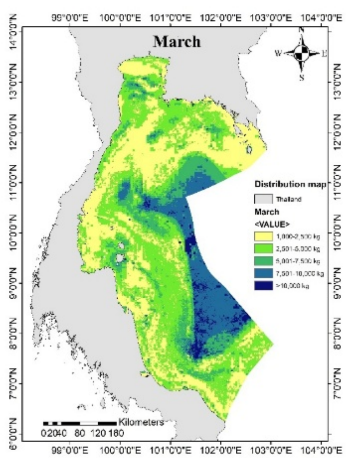
Anchovies found to move between coastal and offshore areas during the transitional month of the May distribution map, and as environmental circumstances begin to change, there are shown in early indications of migration offshore. The anchovies responded to increase sea surface temperatures and nutrient availability, the central and southeast parts of the gulf appeared a potential as possible fishing grounds which shown in Figure 4(e).


January
Distribution map
Thailand
January
Catch Weight
1,000-2,500 kg
2,501-5,000 kg
5,001-7,500 kg
7,501-10,000 kg
>10,000 kg
Kilometers

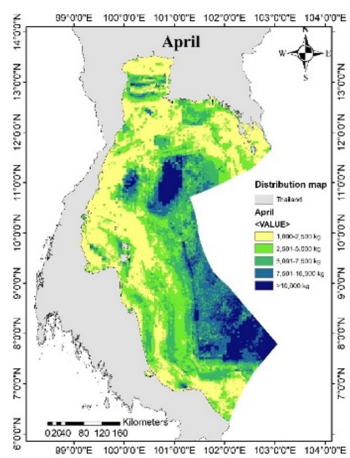
(a)


Febuary
Distribution map
Thailand
Febuary
<VALUE>
1,000-2,500 kg
2,501-5,000 kg
5,001-7,500 kg
7,501-10,000 kg
>10,000 kg
Kilometers

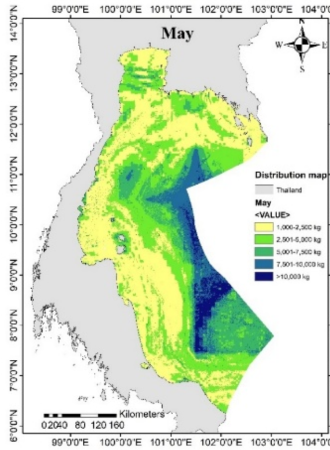
(b)


March
Distribution map
Thailand
March
<VALUE>
Kilometers

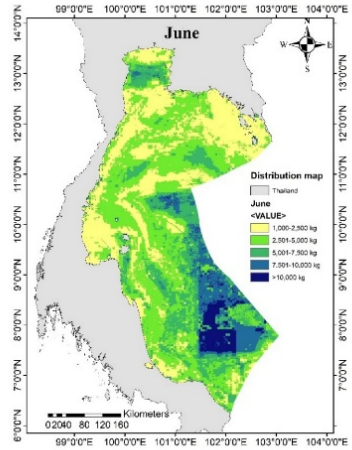
(c)


April
Distribution map
Thailand
April
<VALUE>
Kilometers

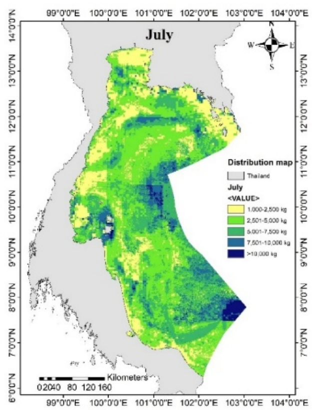
(d)


May
Distribution map
Thailand
May
<VALUE>
1,000-2,500 kg
2,501-5,000 kg
5,001-7,500 kg
7,501-10,000 kg
>10,000 kg
0 20 40 80 120 160 Kilometers

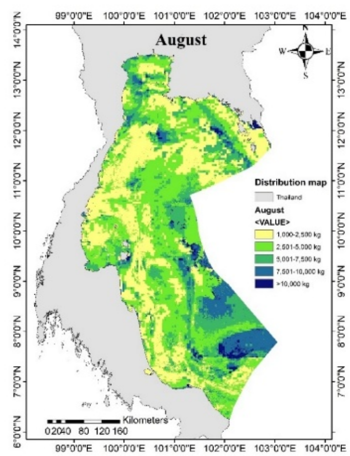
(e)


June
Distribution map
Thailand
June
<VALUE>
1,000-2,500 kg
2,501-5,000 kg
5,001-7,500 kg
7,501-10,000 kg
>10,000 kg
0 20 40 80 120 160 Kilometers

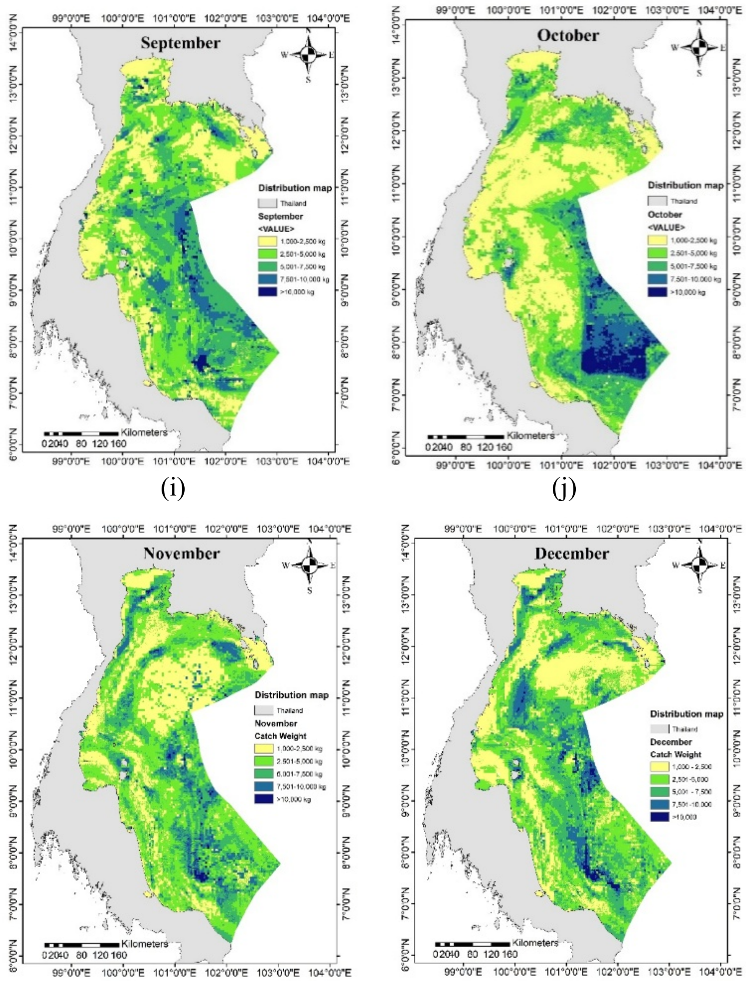
(f)


July
Distribution map
Thailand
July
<VALUE>
1,000-2,500 kg
2,501-5,000 kg
5,001-7,500 kg
7,501-10,000 kg
>10,000 kg
0 20 40 80 120 160 Kilometers

(g)


August
Distribution map
Thailand
August
<VALUE>
1,000-2,500 kg
2,501-5,000 kg
5,001-7,500 kg
7,501-10,000 kg
>10,000 kg
0 20 40 80 120 160 Kilometers

(h)



(i) (j)

(k) (l)

Figure 4. The monthly Species Distribution map of anchovy in The Gulf of Thailand from January to December 2021 Species Distribution map are presented in (a)-(l) respectively

The continuous variation in anchovy distribution in response to change the climatic conditions throughout the early rainy season is illustrated in the June distribution map. Anchovies' larvae are found to be more broadly distributed throughout the gulf. The favorable environmental conditions are shown to be more widely distributed (Figure 4 f).

The spatial patterns of the July distribution map showed notable changes, as illustrated in this map. These variations are driven by the southwest monsoon season's surroundings, resulting in an influence on the accessibility and location of possible fishing areas as compared to previous months. High catch densities

(>7,501 kg) are found to be increasingly specific to particular areas in the central and southeast offshore regions which indicated a broader distribution of anchovy populations this month (Figure 4 g).

The distribution August map provided the insight of anchovy populations move during the monsoon season which discovered from the distribution map. Anchovy behavior is influenced by the month's heavy precipitation, coastal runoff, and dynamic oceanographic conditions. A detailed analysis based on the environmental variables and the map's observed spatial patterns is provided (Figure 4 h).

The map showed a broader distribution of moderate to high values especially in the southern and southeastern parts of Thailand which included the coastal areas along the Gulf of Thailand. The anchovy fishing in September is predicted to be fairly profitable covering a larger area of the Gulf of Thailand (Figure 4 i).

In october tended to demonstrate outstanding value in the southern part of the gulf, because of the significant high catch covering the coast. This is consistent with the Gulf of Thailand's seasonal production cycle because the post-monsoon could result in nutrient-rich waters that feed anchovy populations. More notably, the highest concentration areas are found in the southeast area of the Gulf of Thailand. In october distribution map is shown in Figure 4(j).

In November, potential anchovies fishing grounds seem to be spreaded across a wider area with moderate concentrations in several areas of the gulf. This wider distribution indicated that more areas than in previous months which have favorable environmental conditions for anchovy presence. November distribution map is shown in Figure 4(k).

In December, Anchovy fishing grounds tended to be distributed throughout the Gulf of Thailand, and cooler climates are being found in the central and northern areas as compared to earlier months, the distribution is found to be more regular and broader, which resulted of seasonal temperature variations. The December distribution map is shown in Figure 4(l).

Model performance

To assess the performance of the proposed XGBoost model, which utilized multi-source satellite data and environmental variables fusion, machine learning algorithms were chosen for comparison. The outcomes of machine learning algorithms on species distribution with all feature variables are shown in Table 2. The XGBoost model is emerged as the most promising candidate for species distribution prediction in The Gulf of Thailand, demonstrating competitive performance.

Table 2. Performance comparison of machine learning algorithms on species distribution with all feature variables

Predictive Model	R^2	RMSE	MAE
Random Forest	0.736	0.711	0.299
XGBoost	0.880	0.489	0.203
Extra Tree	0.735	0.712	0.298

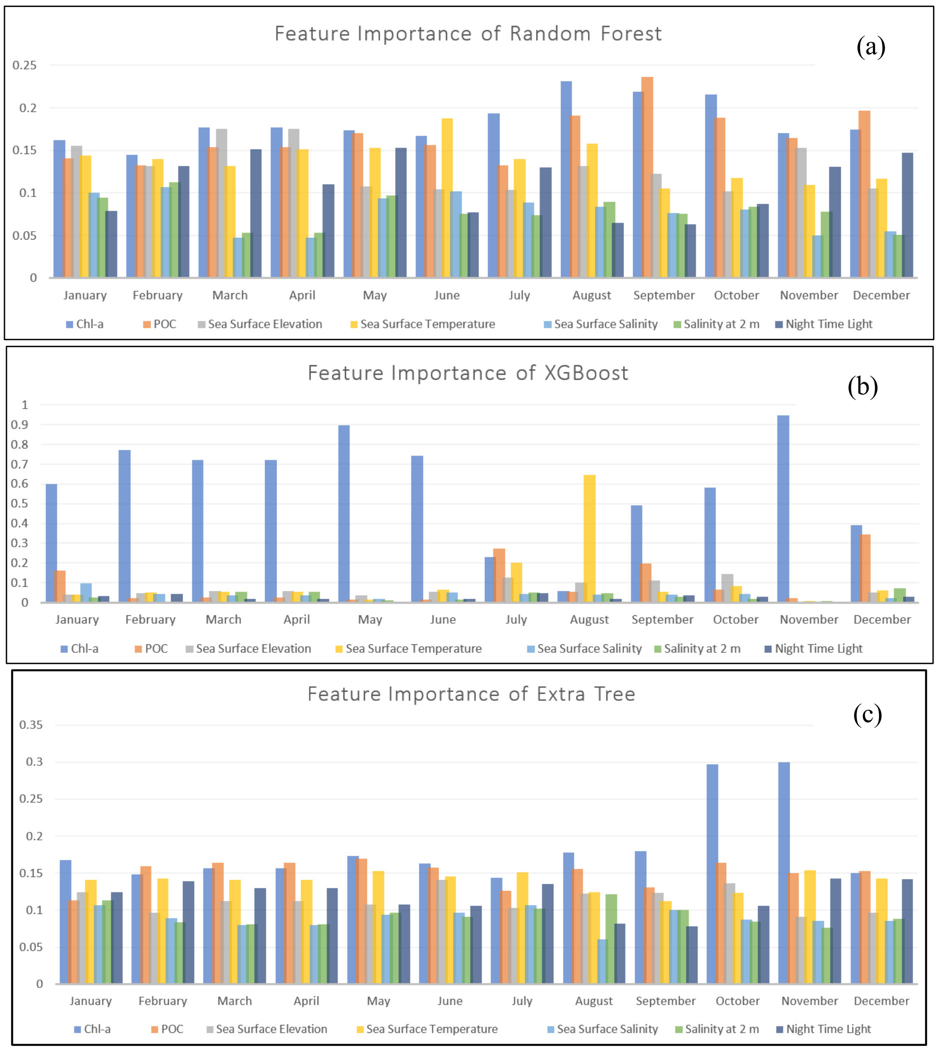


Figure 5. The relative importance of Random Forest (a), Extreme Gradient Boosting (b) and Extra Tree (c)

The results showed of several models were found to be different when combined with environmental variables and remote sensing data. The performance of several machine learning models, including XGBoost, Random

Forest, and Extra Tree, in prediction species distribution in the Gulf of Thailand which applied variables from the environment and remote sensing revealed that the accuracy of all three models were differed according to the measurements and datasets provided (Table 2, Figure 5). The XGBoost model is found to be the most promising candidate for species distribution prediction in The Gulf of Thailand.

Using all remote sensing data and environmental variables, a model was developed to predict species distribution. According to the results, The XGBoost model was able to perform the best prediction of species distribution. However, accuracy varied depending on the size of the study area and location. The spatial mapping of species distribution in the Gulf of Thailand from January to December 2021 was conducted using the XGBoost model.

Discussion

This study is focused on the distribution of anchovies in the Gulf of Thailand. The non-monsoon (NOM), southwest-monsoon (SWM), and northeast-monsoon (NEM) seasons all have distinct characteristics of species distribution. High and low precipitation and variations of environmental conditions were associated with water quality and anchovies distribution right through the southwest monsoon and northeast monsoon (Luang-on *et al*., 2021).

The distribution in October map the consequence is found to be consistence with the findings of Phutchapol (2013). There were some relationships between satellite imagery and data from survey vessels of the Marine Fisheries Research and Development Division, Department of Fisheries showing the numerous fish larvae have been discovered in Thai waters. A model is developed to identify the potential fish larvae distribution utilizing vessel data and satellite-derived parameters, enabling the operational application of satellite data for mapping and monitoring fish larvae distributed in Thai waters.

The results demonstrated that different mechanisms influenced the environmental conditions in offshore and coastal areas. Environmental conditions in coastal areas were influenced by shoreward breezes, precipitation, and river flow; in addition, offshore areas' environmental conditions were associated with wind speed and Sea Surface Temperature, indicating the relevance of upwelling and seawater mixing. These results are consistent with Leenawarat *et al*. (2022). Fishing grounds can be identified using satellite Vessel Monitoring System (VMS) data to investigate the dynamics of fishing activity and fish abundance through time and space.

The distribution of hot spots and the spatial characteristics of fishing intensity were analyzed the spatial characteristics of vessels to describe their fishing behavior. Fishing efforts paid attention to fish stock search displays a spatial distribution pattern of aggregation and nearby aggregation, according to the global spatial autocorrelation investigation. The areas of greatest activity on visualization for identifying fish are spatially tightly enclosed, according to the findings of a hot-spot investigation (Zhang *et al*., 2021), and investigated the activities of fisheries (Behivoke *et al*., 2021).

The predicted probability of anchovy presence was displayed on the habitat map. Predictions relied on the condition of the environment at an individual point in time. The quality of essential fish habitat was assessed by the pattern of predictions. Considerable temporal variation in the distribution of areas that was classified as essential fish habitats results in large inter-annual variations in the prediction features. Both ecology and population management were significantly impacted by these factors. Significant interannual fluctuations in essential fish habitat are reported as management implications due to their impact on aquatic animal catchability (Bellido *et al*., 2008).

This observation demonstrated the anchovy's distribution and movement characteristics. The dynamics of population are influenced by environmental conditions resulting in variations in suitable habitats, which likewise related to fishing grounds and patterns of distribution. The powerful relationships between optimal habitat, stock productivity, and environmentally responsive movement behavior were found. The strong upwelling of nutrient-rich water maintaining high primary productivity was the highest concentration of centers of attraction in the central area. In addition it contributed to the high abundance of small pelagic species in the region and along the front, which provided a feeding area for an extensive diversity of pelagic species (Ebango *et al*., 2020).

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Conflicts of interest

The authors declare no conflict of interest.

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