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# Habitat Suitability Modeling Based on Oceanographic Factors for Yellowfin Tuna (*Thunnus albacares*) Fishing Grounds in the Southern Waters of Java

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*Abstract*

*The southern waters of Java are suitable to be the largest supplier of Yellowfin tuna exports in Indonesia, but have not efficiently produced the expected yield. This research minimizes these constraints by modeling the yellowfin tuna fishing grounds in the southern waters of Java based on oceanographic factors such as Sea Surface Temperature (SST), chlorophyll-a (CHL_A), Sea Surface Salinity (SSS), Sea Surface Height (SSH) using an integration between remote sensing, Geographic Information Systems (GIS), and the Generalized Additive Model (GAM) statistical method. This study used oceanographic factor data from Aqua MODIS Level-3 and Copernicus, while yellowfin tuna fishery production was obtained from Palabuhanratu Nusantara Fishing Port (NFP), Cilacap Ocean Fishing Port (OFP), and Pondokdadap Coastal Fishing Port (CFP). The modeling process used 80% of the data, while the remaining 20% was used to validate the model results. The order of influence of oceanographic parameters from largest to smallest is SST > SSS > SSH > CHL-A. The best model from the GAM analysis showed that the combination of four oceanographic parameters had the greatest influence on yellowfin tuna CPUE. The catch per unit effort (CPUE) of yellowfin tuna was predicted to be high in May-October and low in November-April. The prediction model had high accuracy because most of the fishing activity was in the HSI 0.4-0.5 range and the RMSEP value was 0.63. Yellowfin tuna were suitable in habitats distributed from inshore to offshore in June and July, but less suitable in December.*

***Keywords:*** *fishing grounds; GAM; southern waters of Java; Yellowfin tuna*

## Introduction

The waters of the Indian Ocean which are south of the island of Java, Bali, the Nusa Tenggara Islands, the Sawu Sea, and the Timor Sea are part of Indonesian Fisheries Management Area (IFMA) 573 with high capture fisheries potential because they are migratory areas for large pelagic fish such as tuna (Ma'mun *et al.,* 2017; Harlyan *et al.,* 2021). Fishery commodities in IFMA 573, especially the southern waters of Java and Bali, are dominated by large pelagic fish of the Scombridae family, such as tuna, mackerel tuna, Spanish mackerel, and skipjack fish with an estimated average catch of 182,034 tons.$y^{-1}$ in the 2005-2014 period (Jayawiguna *et al.,* 2019). Yellowfin tuna (*Thunnus albacares*) is one of the large pelagic tuna types that migrate in the southern waters of Java. Therefore, it is not surprising that Yellowfin tuna is one of the most popular products from fisheries. The Indian Ocean waters (IFMA 573 and 572) are the primary source of Yellowfin tuna for export (Nimit *et al.,* 2020). Fishermen's operations, however, do not always provide the predicted abundance and composition of Yellowfin tuna. The information about potential fishing grounds spatially is one endeavor that can increase the efficiency of Yellowfin tuna fishing activities. According to (Harlyan *et al.,* 2021), spatial information on fishing grounds is vital for supporting sustainable resource management programs.

Palabuhanratu Nusantara Fishing Port (NFP), Cilacap Ocean Fishing Port (OFP) and Pondokdadap Coastal Fishing Port (CFP) caught 811.80 tons of Yellowfin tuna in 2018, 896 tons in 2019, 1,441.26 tons in 2020, 4,145.52 tons in 2021, and 3,066.442 tons in 2022. The lowest CPUE values of Yellowfin tuna occurred in January 2018, December 2019, January 2020, February 2021, January 2022, respectively. This suggests that the lowest CPUE was recorded during the West Season (December-February). The Yellowfin tuna production data is then

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presented in CPUE format to reflect the amount of resource utilization by dividing fish catches (kg) by fishing effort (trips) (Sartimbul *et al.,* 2018). The CPUE of Yellowfin tuna in the southern waters of Java varies with the seasons. Seasonal shifts, followed by weather changes, affect catch productivity, catch composition, and fishing grounds. Seasonal fluctuations are also associated with the processes of Upwelling and Downwelling, which control the degree of water productivity and have an impact on fishery production (Nurdin *et al.,* 2012).

The southern waters of Java are a migratory area for large pelagic fish because they have oceanographic factors that are attractive for fish habitat. The first factor is that the composition of the water mass south of Java comes from the confluence of three high-nutrient seawater masses. The surface water mass is supplied by the Bay of Bengal in India, while the thermocline layer is fed by Pacific Ocean seawater masses through the Indonesian Throughflow and Indian Ocean Gyre moving from southern Australia (Jayawiguna *et al.,* 2019). Second, the southern waters of Java have high primary productivity due to the Upwelling process triggered by Ekman transport along the coast of Java to Bali. Ekman transport in the southern waters of Java is generated by the movement of easterly monsoon winds that blow from the Australian Continent to the Asian Continent (Asia-Australia Monsoon system). Third, the oceanographic dynamics of southern Java waters are also influenced by the ENSO and IOD phenomena which have an impact on the intensity of Upwelling in the Indian Ocean south of Java (Novianto *et al.,* 2019).

Estimating fishing grounds necessitates knowledge of the dynamics of oceanographic factors such as sea surface temperature (SST), sea surface salinity (SSS), chlorophyll-a (CHL_A), and sea surface height (SSH), which correlate with fish quantity and distribution (Solanki *et al.,* 2016). In identifying fishing grounds, SST serves as an indirect signal of biological production and fish prey availability, SSH to determine the occurrence of Upwelling and down welling processes that cause stirring of seawater masses carrying nutrients (Susanto *et al.,* 2001). whereas chlorophyll-a determines fish biomass, serving as an indicator of Upwelling, water productivity, direct fish prey availability, and migration routes (Muskananfola *et al.,* 2021; Wirasatriya *et al.,* 2021). The distribution and migration route of pelagic fish is easily impacted by changes in salinity, estimating fishing grounds also requires salinity parameters (Amri, 2017; Zhou *et al.,* 2023). Spatial determination of fishing grounds (mapping) is accomplished using remote sensing technology combined with a geographic information system since it can give important information both spatially and temporally (Semedi *et al.,* 2023). Furthermore, the use of remote sensing technology enables the analysis of extensive geographical areas without the need for direct physical contact and in a cost-efficient manner (Randin *et al.,* 2020).

The first stage in creating a prediction map of fishing ground is identifying the pattern of the relationship between the abundance of fishery resources and environmental factors. Since the relationship between the abundance of fishing resources and environmental factors is not linear, it is best studied using a semi-parametric statistical approach such as the Generalized Additive Model (Siregar *et al.,* 2018). GAM is a semi-parametric model of multiple regression that is non-linear and does not require normally distributed data. It can minimize the drawbacks of applying the assumption of data normality to the environmental parameters under study and when there is no linear relationship between variables Studies on fish habitats can be appropriately described using GAM statistical modeling and geospatial information systems (Setiawati *et al.,* 2015; Yusop *et al.,* 2021).

The purpose of this study is to establish the suitability of habitat for Yellowfin tuna fishing grounds in the southern waters of Java, utilizing data collected over five years and GAM statistical analysis. The purpose of collecting data for five years is to develop a stronger model with more predictive potential. The GAM test is designed to identify the best oceanographic range for Yellowfin tuna habitat, which is subsequently used to estimate fishing grounds geographically. The findings of the investigation are expected to improve the effectiveness of Yellowfin tuna fishing activities in southern waters of Java, prioritizing sustainable principles.

## Materials and Methods

### *Study area and data source*

The research study encompasses the waters of the Indian Ocean south of Java Island, with coordinates ranging from 102°57'E-114°60'E and 5°35'S-13°86'S (see Figure 1). This study utilized data from Pelabuhanratu NFP, Cilacap OFP, and Pondokdadap CFP on catch weight, number of trips, and fishing site coordinates for Yellowfin tuna from 2018 to 2022. Oceanographic parameters such as sea surface temperature (SST) and chlorophyll-a (CHL-A) were derived from Aqua-MODIS Level-3 satellite imagery with monthly temporal resolution and 4 km x 4 km spatial resolution. The Copernicus Marine Service provided sea surface salinity (SSS) and sea surface height (SSH) oceanographic factor data, with a monthly temporal resolution and a spatial resolution of 0.083°×0.083°.

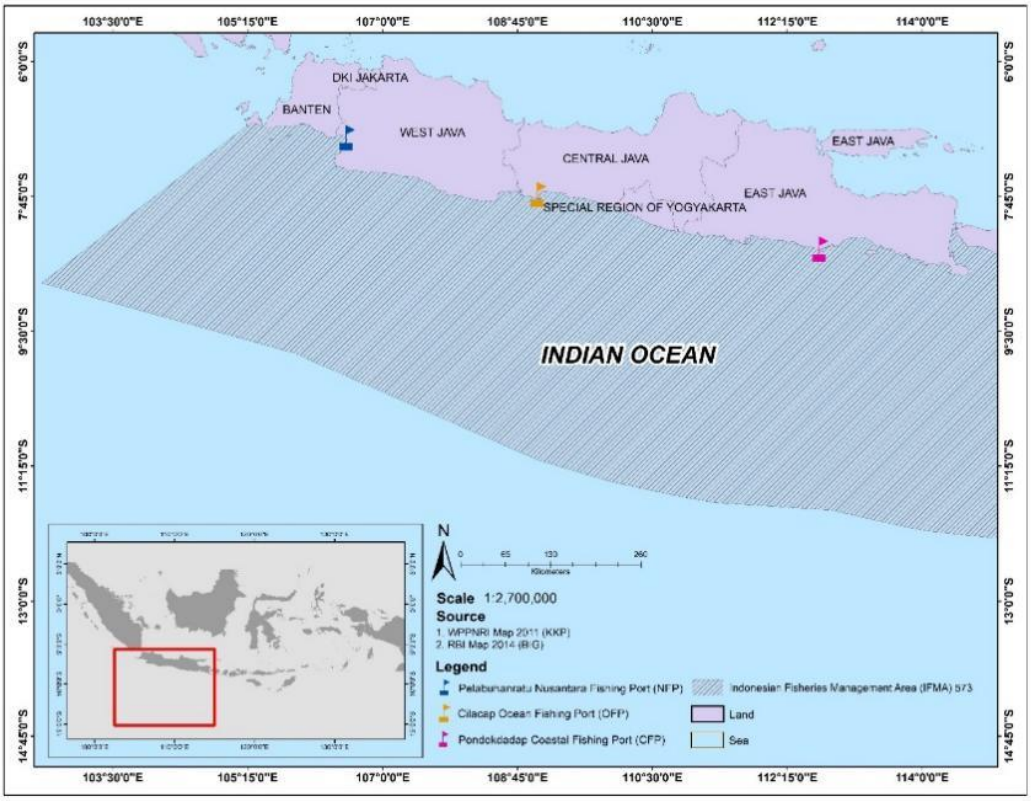


Figure 1. Map showing the study area (red box) and the flags show the data collection stations

### *Catch Per Unit Effort (CPUE)*

The CPUE value is calculated by dividing the total catch by the total effort, which represents the quantity and level of utilization of a captured fishing commodity. The following equation is used to express data on catch weight and the number of trips for Yellowfin tuna from fishing ports in CPUE (Sartimbul *et al.,* 2018):

$$CPUE = \frac{ci}{fi} \quad (1)$$

Note: CPUE= Catch Per Unit Effort (kg.trip$^{-1}$); ci = Catch (kg) fi = Catch Effort (trip)

### *Oceanographic Factors Data*

SeaDAS was used to crop and export mask pixels from downloaded SST and CHL-A satellite imagery. The cropping of imagery aims to reduce the size of the data, focusing on the research study region. Meanwhile, the purpose of exporting mask pixels is to determine the value of SST and CHL-A in each image pixel. Furthermore, SSS and SSH values were extracted using the Ocean Data View software. The extracted values of the four oceanographic parameters were stored in text file format and then trimmed in Microsoft Excel to remove empty pixel values (NaN). The processing of oceanographic factor data proceeds at the Inverse Distance Weighted (IDW) interpolation stage, which uses ArcGIS ArcMap 10.8 to fill in empty image pixels caused by noise. The IDW interpolation method was chosen due to its capability to generate interpolated values by averaging the nearby sample data points (Ajaj *et al.,* 2018; Maulina *et al.,* 2019). The extraction of SST, CHL-A, SSS, and SSH values at each coordinate point of the Yellowfin tuna fishing ground using the Extract Multi Values to Point (Spatial Analyst) tool represents the final stage of processing oceanographic parameter satellite imagery data.

### *Generalized Additive Model (GAM) analysis*

This stage began by adding the value 0.1 to the CPUE value and then transforming it into a logarithmic form to normalize the asymmetric distribution. The addition of 0.1 was done to avoid a CPUE value of 0 following data transformation (Mugo *et al.,* 2010; Wijaya *et al.,* 2021). Furthermore, throughout the period 2018-2022 (n= 7,033), CPUE data and oceanographic parameters data at each fishing coordinate point were randomly divided into training and validation data with an 80:20 split to reduce bias (Solanki *et al.,* 2016).

The GAM test implementation using the RStudio software consists of two stages, the GAM model building stage and the Y variable prediction stage based on the best GAM model. The GAM model is built using training data, which comprises the CPUE value of Yellowfin tuna as the response variable (dependent variable) and the values of the oceanographic variables as the predictive variables (independent variables). The GAM test explains the relationship between the dependent and independent variables using the MGCV package, family Gaussian, and identity link function (Siregar *et al.,* 2018; Shen *et al.,* 2022). During the model-building stage, the GAM equation is as follows:

$$g(u_i) = a_o + s_1(SST) + s_2(CHL - A) + s_3(SSS) + s_4(SSH) \quad (2)$$

Note: g= Link Function; $u_i$= Dependent Variable; $a_o$ = Model Constant

The GAM model building stage produced some GAM model combinations, with the best model formed being used as a reference in the Y variable prediction stage. Among the other models constructed, the best GAM model presented a high level of significance with a P-Value less than alpha, the highest percentage of Deviance Explained (DE), and the shortest AIC value (Siregar *et al.,* 2018). The AIC test was used to assess the model's suitability after adding the independent variables; the lower the AIC value, the better the model fitting results (Wang *et al.,* 2020).

Following the acquisition of the ideal GAM equation model, the GAM analysis procedure proceeds to the stage of predicting the Y variable. In the Y variable prediction step, oceanographic parameter values from both the training and validation data serve as independent variable inputs, while the best GAM equation model is used as a reference for predicting the dependent variable, CPUE. This prediction process is executed using the "predict.gam" function (syntax) from the MGCV package, with covariates similar to those used to build the model (Setiawati *et al.,* 2015).

### *Application of Habitat Suitability Index (HSI)*

Habitat Suitability Index shows the level of suitability of a species for an environmental condition (Shaari and Mustapha, 2018). The HSI application in this study aims to simplify habitat suitability criteria for fishing grounds based on the predicted CPUE values of training data, which have too large a range using the following equation (Yi *et al.,* 2016; Mondal *et al.,* 2021):

$$HSI = \frac{Yjk - Yjkmin}{Yjkmax - Yjkmin} \quad (3)$$

Note: HIS= *Habitat Suitability Index;* Y= Predicted CPUE Value ($kg.trip^{-1}$); Ymin= Lowest Predicted CPUE Value ($kg.trip^{-1}$); Ymax= Highest Predicted CPUE Value ($kg.trip^{-1}$); j,k= Latitude, Longitude

HSI has a range of 0-1 and is classified as low, medium, or high suitability levels (see Table 1). An HSI value close to one implies that the location possesses fish habitat features and hence has the potential to become a fishing ground, and vice versa. The HSI calculations from the CPUE prediction of the training data, which includes the coordinates of the Yellowfin tuna fishing grounds were saved as a text document file and then opened in ArcMap. The IDW approach was used to interpolate the HSI values, resulting in a spatial suitability map for Yellowfin tuna fishing grounds.

## Result and Discussion

### *Generalized Additive Model analysis*

The objective of the GAM model development is to determine the effect of oceanographic conditions on the CPUE of Yellowfin tuna in southern waters of Java. Table 2 shows the results of GAM tests performed on 15 equation models in this study. The best GAM equation model will serve as a reference for predicting CPUE values once oceanographic parameter values are known.

**Table 1.** Habitat Suitability Index (HSI) Category (Vayghan *et al.,* 2020; Mondal *et al.,* 2021; Yu and Chen, 2021)

| Suitability Category | Value Range |
|---|---|
| Low | 0.0 - 0.2 |
| Moderate | 0.3 - 0.5 |
| High | 0.6 - 1.0 |

**Table 2.** The Results of Generalized Additive Model

| Model | Parameters | P-Value | CDE | AIC |
|---|---|---|---|---|
| 1 | SST | <2×10-16 *** | 7.35% | 9,470.642 |
| 2 | CHL-A | <2×10-16 *** | 2.73% | 9,746.551 |
| 3 | SSS | <2×10-16 *** | 6.18% | 9,543.825 |
| 4 | SSH | <2×10-16 *** | 2.92% | 9,734.917 |
| 5 | SST | <2×10-16 *** | 8.98% | 9,386.444 |
| | CHL-A | <2×10-16 *** | | |
| 6 | SST | <2×10-16 *** | 10.5% | 9,291.315 |
| | SSS | <2×10-16 *** | | |
| 7 | SST | <2×10-16 *** | 9.59% | 9,349.759 |
| | SSH | <2×10-16 *** | | |
| 8 | CHL-A | <2×10-16 *** | 8.40% | 9,425.305 |
| | SSS | <2×10-16 *** | | |
| 9 | CHL-A | <2×10-16 *** | 6.31% | 9,549.978 |
| | SSH | <2×10-16 *** | | |
| 10 | SSS | <2×10-16 *** | 7.57% | 9,474.825 |
| | SSH | <2×10-16 *** | | |
| 11 | SST | <2×10-16 *** | 12.60% | 9,176.199 |
| | CHL-A | <2×10-16 *** | | |
| | SSS | <2×10-16 *** | | |
| 12 | SST | <2×10-16 *** | 11.30% | 9,254.111 |
| | CHL-A | <2×10-16 *** | | |
| | SSH | <2×10-16 *** | | |
| 13 | SST | <2×10-16 *** | 12.70% | 9,172.156 |
| | SSS | <2×10-16 *** | | |
| | SSH | <2×10-16 *** | | |
| 14 | CHL-A | <2×10-16 *** | 10.30% | 9,318.597 |
| | SSS | <2×10-16 *** | | |
| | SSH | <2×10-16 *** | | |
| 15 | SST | <2×10-16 *** | 14.40% | 9,076.230 |
| | CHL-A | <2×10-16 *** | | |
| | SSS | <2×10-16 *** | | |
| | SSH | <2×10-16 *** | | |

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The GAM modeling aimed to determine the effect of each oceanographic parameter on the CPUE of Yellowfin tuna in the southern waters of Java, as well as the effect of a combination of many oceanographic parameters. Each of the four oceanographic parameters in this study individually demonstrated a significant effect on the CPUE of Yellowfin tunaas indicated by the P-value less than alpha (*P*< 0.001). The order of influence of oceanographic parameters from largest to smallest was SST > SSS > SSH > CHL-A. The best model resulting from the GAM analysis is Model 15 which consists of a combination of SST, CHL-A, SSS, and SSH variables with the smallest AIC value of 9,076.230, P-Value less than alpha (*P*< 0.001), and the highest DE percentage of 14.40%.

The dominant influence of sea surface temperature on the catch of Yellowfin tuna is also demonstrated by similar research findings by (Lan *et al.,* 2012) in the tropical Pacific Ocean and (Nurholis *et al.,* 2020) in the Eastern Indian Ocean. (Lan *et al.,* 2012) reported that temperature affects the distribution of Yellowfin tuna throughout the waters except in the eastern Pacific Ocean. Sea surface temperature is a crucial factor determining the distribution of Yellowfin tuna because changes in temperature outside the optimal range can lead to decreased mobility, alterations in feeding activity, and reproductive disruptions (Nurholis *et al.,* 2020).

Salinity is the second variable that significantly influences the CPUE of Yellowfin tuna in the southern waters of Java. According to (Amri, 2017), the abundance of pelagic fish is sensitive to changes in the spatial distribution of salinity. The occurrence of salinity changes causes fish to migrate to places with salinity levels that match their body's osmotic pressure (Yunus *et al.,* 2019; Puspita *et al.,* 2023).

The sea surface height and chlorophyll-a are the last-order variables affecting the catch of

Yellowfin tuna with DE values of 2.92% and 2.73%. The influence of sea surface height on pelagic fish abundance is less pronounced due to the widely varying impacts on fisheries resources (Mugo *et al.,* 2010). (Nurholis *et al.,* 2020) emphasized that sea surface height values, which depict Upwelling phenomena, have varying time lags in affecting fishing activities. Meanwhile, high chlorophyll-a concentrations do not necessarily result in increased Yellowfin tuna abundance because the Scombridae family consists of carnivorous animals that require a time lag (time delay) to utilize the chlorophyll levels in the water (Sastra *et al.,* 2018; Yin *et al.,* 2022).. This aligns with the explanation provided earlier, which indicates that the maximum concentration of chlorophyll-a during the Upwelling peak will enhance the CPUE of Yellowfin tuna in the southern waters of Java within a period of 1-6 months.

Based on Figure 2, the most suitable oceanographic parameter values for Yellowfin tuna fishing activities were SST 26.5-28.8°C, chlorophyll-a concentration 0.2-0.8 mg.m$^{-3}$, salinity 33.7-34.3 psu, and SSH 0.33-0.64 m. The optimal range of SST, chlorophyll-a, and SSH values in this study aligns with the findings of (Setiawati *et al.,* 2021), which stated that Yellowfin tuna are typically found at SST, chlorophyll-a, and SSH values ranging from 27.2-29 °C, 0.08-0.18 mg.m$^{-3}$, and 0.49-0.64 m. According to (Syah *et al.,* 2020), the optimal temperature and salinity for Yellowfin tuna range from 17-31°C and 32-35 psu. The majority of large pelagic fish are typically found in waters with low chlorophyll-a concentrations of 0.042-0.78 mg.m$^{-3}$ and SSH values of 0.50 m (Tangke, 2014; Harahap *et al.,* 2015). This finding affirms the suitability of the oceanographic parameters in the southern waters of Java for Yellowfin tuna habitat.

### *Habitat Suitability Modeling*

Figure 3 shows the suitability for Yellowfin tuna fishing grounds in the southern waters of Java, with blue areas representing low HSI and yellow to red areas reflecting medium to high HSI. To validate estimates of optimal fishing grounds, 20% of fishing coordinate points which were not included in the GAM model, overlaying with the spatial distribution of habitat suitability. The catch of Yellowfin tuna is predicted to be high from May to October and low from November to April. According to (Sambah *et al.,* 2023), the lean season for Yellowfin tuna in the Indian Ocean south of Java runs from December to February. Yellowfin tuna CPUE increases during the East Season and Transitional Season II, with a peak catch in September (Nurdin and Nugraha, 2008; Nurdin *et al.,* 2018).

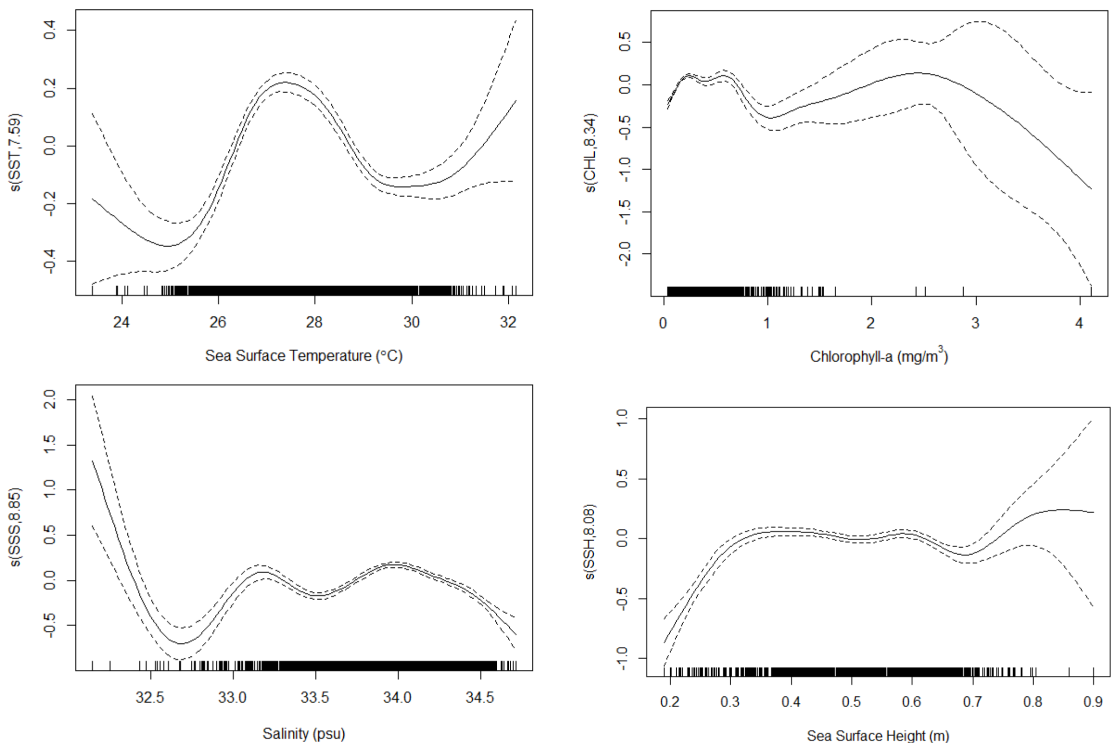


**Figure 2.** Smoothing Curve Generalized Additive Model

**Table 3.** Percentage of HSI Validation Points

| Suitability Category | Value Range | Validation Points Percentage |
|---|---|---|
| Low | 0.0 - 0.2 | 0.15% |
| Moderate | 0.3 - 0.5 | 96.21% |
| High | 0.6 - 1.0 | 3.64% |

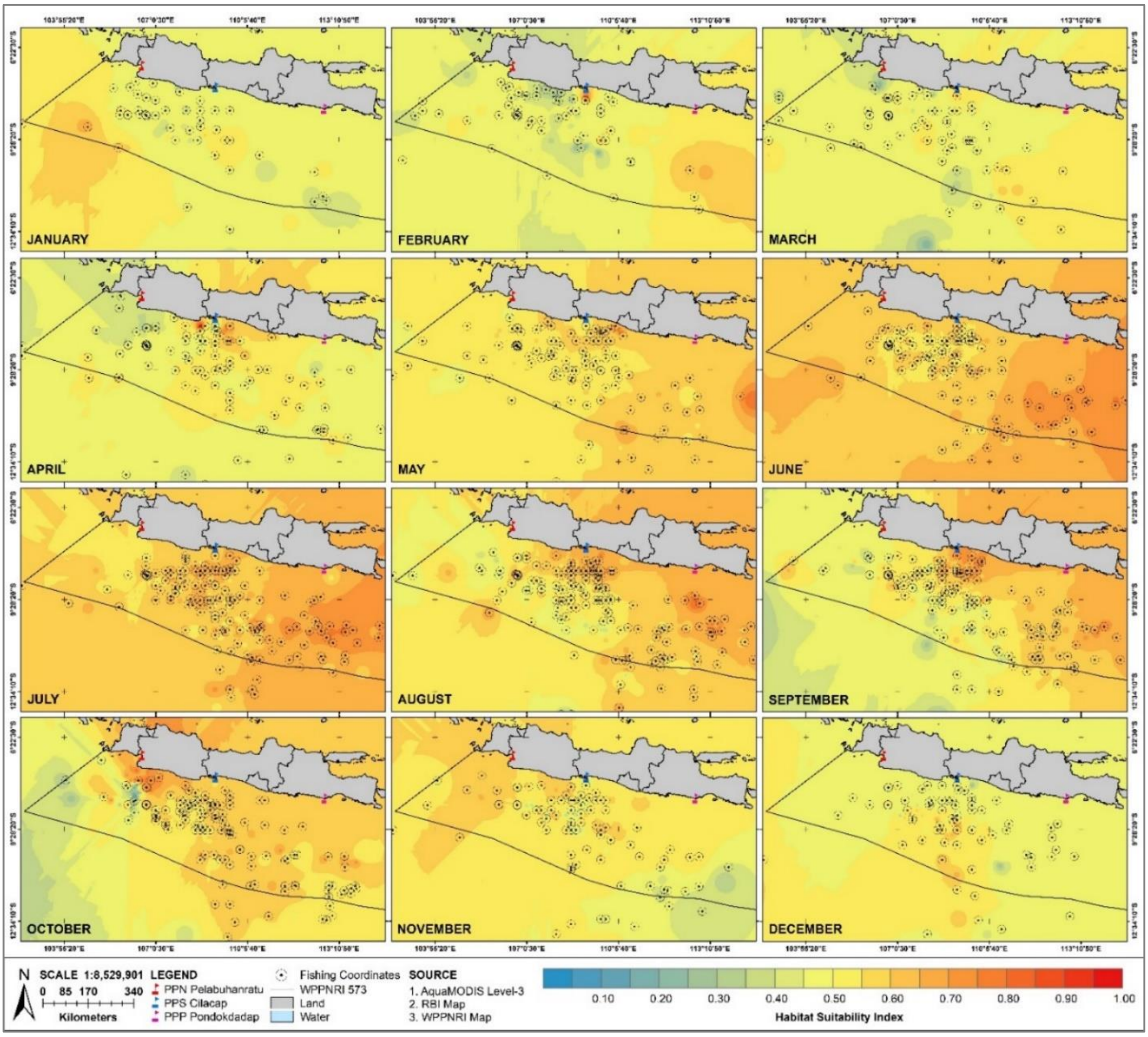


**Figure 3.** Habitat Suitability for Yellowfin Tuna Fishing Grounds in the Southern Waters of Java

Figure 3 shows that the values of sea surface temperature and sea level height tend to increase in the West Season-Transition Season I (December-May). The values of chlorophyll-a and salinity tend to increase in the East Season-Transition Season II (June-November). The decrease in sea surface temperature and sea level height, as well as the increase in chlorophyll-a and salinity simultaneously indicate an Upwelling event. Seasonal fluctuations in the average values of the four oceanographic factors can explain that the dynamics of oceanographic parameters in the southern waters of Java are greatly influenced by seasonal changes due to monsoon winds (Asian-Australian Monsoon system).

Most validation points are in the moderate HSI range of 0.4-0.5. The percentage of validation points identified in locations with low, medium, and high HSI categories was 0.15%, 96.21%, and 3.64% (Table 3). This value moderately aligns with the distribution of actual fishing grounds, which supports the fact that our best model from the GAM test (Model 15) explains only 14.40% of the CPUE of Yellowfin tuna based only on environmental variables. As suggested by (Wijaya *et al.,* 2021), habitat predictors do not entirely influence fishing ground locations because the interaction between physical and biological processes in the sea, food chains, fish-eating behavior, and so on must also be considered.

Based on the model (Figure 3), in January, February and March, the area, especially in the coastal area, it appears to be less suitable for Yellowfin tuna habitat. In April and May, the habitat that is relatively more suitable for Yellowfin tuna is in the waters of Central Java and is spread in the eastern part of the study area. The most suitable habitat for Yellowfin tuna occurs in June and July, which is spread from the coast to the offshore. This means that June and July are the most suitable periods for catching Yellowfin. In August, September and October, the suitability of Yellowfin tuna habitat begins to decline in the western offshore. In November, the suitable habitat is located in the western offshore. The lowest habitat suitability found in December, meaning that Yellowfin tuna will be very rarely caught during this period.

## Conclusion

This study successfully modeled the Yellowfin tuna fishing area in the southern waters of Java based on oceanographic factors of sea surface temperature, chlorophyll-a, salinity, sea level using the integration of remote sensing, GIS, and the Generalized Additive Model (GAM) statistical method. The results of the GAM test showed that the combination of oceanographic parameters of sea surface temperature, chlorophyll-a, salinity, and sea level, had the most significant effect on the CPUE of Yellowfin tuna as evidenced by the P-Value value smaller than alpha ($P$< 0.001), the smallest AIC value of the entire model, namely 9,076.230, and the highest DE percentage of the entire model, namely 14.40%. The GAM smoothing curve explains that the optimal oceanographic parameter values for Yellowfin tuna fishing activities are in the range of sea surface temperature of 26.5-28.8°C, chlorophyll-a concentration of 0.2-0.8 mg.m$^{-3}$, salinity of 33.7-34.3 psu, sea surface height of 0.33-0.64 m. The values of sea surface temperature and sea level tend to increase in the West Season to Transition Season I (December - May). The values of chlorophyll-a and salinity tend to increase in the East Season - Transition Season II (June - November). The decrease in sea surface temperature and sea level accompanied by a simultaneous increase in chlorophyll-a and salinity indicates an Upwelling event. Based on the model, in June and July, the most suitable habitat for Yellowfin tuna which is distributed from the coast to the offshore. In January, February and March, it seems to be less suitable for Yellowfin tuna habitat, especially in the coastal areas. The lowest suitable habitat occurs in December.

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