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Generalized Additive Model (GAM) Approach as an Indicator of Decapterus spp Fishing Areas in the Waters of FMA-RI 573

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Abstract: This study applied a Generalized Additive Model (GAM) to identify potential fishing grounds for layang Scad (Decapterus spp) in Fisheries Management Area 573 (FMA-NRI 573). Environmental variables, including chlorophyll-a concentration, sea surface temperature (SST), salinity, and sea surface height (SSH), were analyzed to assess their spatiotemporal dynamics and influence on fish distribution. Chlorophyll-a levels peaked in May and August (>2 mg/m³), concentrated predominantly in coastal zones, while other months showed relatively uniform values (~0.6 mg/m³). SST exhibited seasonal variability, ranging between 27°C and 32°C, with salinity fluctuating from 32 to 35 PSU. SSH demonstrated distinct seasonal patterns, averaging 0.10–0.90 meters, with higher values observed offshore compared to coastal regions. GAM analysis revealed significant relationships between environmental variables and fishing potential. Chlorophyll-a exhibited a linear association, contributing 10.82% to the model, while SST displayed a non-linear relationship with the highest explanatory power (32.1%). Salinity also showed a non-linear influence, accounting for 10.46% of model variability, whereas SSH contributed substantially (29.94%) through a linear relationship. These findings highlight SST and SSH as dominant predictors of layang Scad distribution, likely due to their roles in shaping thermal gradients and oceanographic conditions favourable for prey aggregation. Spatially, potential fishing grounds were identified between latitudes 6°S–11°S and longitudes 108°E–122°E. The most expansive areas occurred from January to May, coinciding with optimal oceanographic conditions and higher catch per Unit Effort (CPUE), marking this period as the peak fishing season. The study underscores the utility of GAM in integrating environmental variables to delineate fishing hotspots, offering actionable insights for sustainable fisheries management.

Keywords: Decapterus spp, Fishing Areas, Generalized Additive Model, Oceanographic Parameters, FMA-NRI 573.

I. INTRODUCTION

Indonesian waters harbor significant pelagic fish resources, widely distributed across coastal regions. One prominent fishing area is Pacitan Waters, situated within Fisheries Management Area (FMA) 573. According to Nugraha et al. (2021), the dominant catches in Pacitan Regency include Yellowfin Tuna (Thunnus albacares), Skipjack Tuna (Katsuwonus pelamis),Layang Scad (Decapterus spp.) and Kawakawa (Euthynnus affinis). Secondary catches comprise Indian Layang (Rastrelliger kanagurta), Black Pomfret (Formio niger), and Dolphinfish (Coryphaena hippurus).Layang Scad, a small pelagic species, holds substantial economic importance. As per Ministerial Decree No. 19 of 2022 (Ministry of Marine Affairs and Fisheries, Indonesia), FMA 573 exhibits the highest small pelagic fish potential (624,366 tons) among adjacent FMAs (571 and 572), with a Total Allowable Catch (TAC) of 437,056 tons. Suman et al. (2017) note that FMA 572, influenced by the Indian and Pacific Oceans, is dominated by crustaceans (shrimp, lobster, crab) and squid, while FMA 571, encompassing the Malacca Strait and Andaman Sea, is characterized by demersal fish populations in shallow, muddy benthic habitats.

Lelono et al. (2021) emphasize the critical role of Layang Scad as a key fishery resource in FMA 573, primarily caught using small pelagic purse seine gear operated by single vessels. Production trends of Layang Scad in FMA 573 from 2019 to 2023 revealed a sharp decline followed by a notable recovery. Data from the Ministry of Marine Affairs and Fisheries (2024) indicate landings of 80,397 tons in 2019, dropping to 32,493 tons (2020), 29,351 tons (2021), and 25.35 tons (2022), before rebounding to 56,553 tons in 2023. This fluctuation underscores the need for comprehensive investigation to optimize resource utilization. The current exploitation status of small pelagics in FMA 573 is classified as fully-exploited(utilization rate: 0.6), signaling risks of growth overfishing and stock depletion if unregulated (Farizi et al., 2023). Sustainable management strategies are thus imperative to balance harvest efficiency with ecological preservation. A critical challenge in optimizing Layang Scad fisheries lies in production inefficiencies, particularly fuel consumption during fishing operations. Addressing this requires innovative technological solutions, such as precise Fishing Ground Prediction (FGP). Traditional FGP methods, reliant on fisher intuition and historical experience (Samba et al., 2021), lack scientific rigor. Huwaida et al. (2023) advocate for technology-driven approaches like Remote Sensing-Based Fishing Ground Prediction (RS-FGP), which integrates satellite-derived oceanographic data to forecast fish distributions. Key parameters influencing pelagic fish aggregation include sea surface temperature (SST), chlorophyll-a concentration, salinity, and bathymetry (Adivitasari & Wirasatriya, 2022). Generalized Additive Models (GAMs) offer a robust statistical framework for analyzing nonlinear relationships between these variables and fish abundance. Susilo & Wibawa (2016) highlight GAMs' superiority in habitat modeling due to their flexibility in handling complex ecological interactions. While this study focuses on FMA 573, primary data collection is centered at Tamperan Fishing Port, Pacitan, due to its representative oceanographic and fishery characteristics. By employing GAMs, nonlinear associations between environmental variables and catch per unit effort (CPUE) can be modeled, enabling extrapolation to broader regions with similar conditions. This approach supports sustainable resource management by identifying optimal fishing zones, minimizing effort, and reducing ecological impacts. Further research is essential to elucidate the interplay between oceanographic dynamics, phytoplankton biomass, and Layang Scad distribution, ensuring the long-term viability of this critical fishery resource.

II. METHODS

The research method employed in this study is descriptive quantitative. The descriptive quantitative approach in this research aims to delineate the spatial and temporal distribution of Layang fish in FMA-NRI 573, identify regions with high and low catch densities, and present maps of potential fishing zones based on historical data. The descriptive quantitative method serves to systematically and objectively describe and analyze numerical data obtained from research samples. This study utilizes the Generalized Additive Model (GAM) to examine the relationship between environmental factors—such as temperature, salinity, chlorophyll-a, sea surface height—and the presence of Layang fish. According to Priadana and Sunarsi (2021), descriptive quantitative data analysis is applied when evaluating past data performance to derive conclusions. This quantitative analytical technique is particularly suitable when handling datasets of substantial volume.Functionally, the GAM model can be expressed in the following equation:

$$g(\mu i) = \alpha° + s(SPL) + s(chl\text{-}a) + s(salinity) + s(SSH) + \varepsilon$$

Description: g= Spline smooth function, μi= Response variable, $\alpha°$ = Constant coefficient, s = Smoothing function, ε = Standard error

III. RESULTS AND DISCUSSION

Results

A. Condition of Layang Fish (Decapterus spp) Fisheries at PPP Tamperan, Pacitan

The fish production landed at PPP Tamperan, Pacitan Regency, East Java Province, exhibits seasonal variability. The productivity of Layang fish (Decapterus spp) also follows a fishing seasonality pattern, resulting in high production in certain months and significantly low production in others. This condition inevitably impacts the production value and Catch per Unit Effort (CPUE) of Layang fish. The productivity of Layang fish landed at PPP Tamperan is presented in Table 4.1.

Table 1. Productivity of Layang Fish Landed at PPP Tamperan in 2024

No	Month	Catch (Kg)	Total Trips	CPUE (Kg/Trip)
1	January	92.716	25	3.709
2	February	242.610	37	6.557
3	March	35.483	6	5.914
4	April	35.665	6	5.944
5	May	94.667	58	1.632
6	June	86.165	55	1.567
7	July	85.221	70	1.217
8	August	40.510	58	698
9	September	1.858	13	143
10	October	67.238	129	521
11	November	87.163	118	739
12	December	194.201	378	514

Based on Table 1, Layang fish production at PPP Tamperan shows significant seasonal variation. High production volumes are observed from January to April, peaking in February at 242,610 kg.

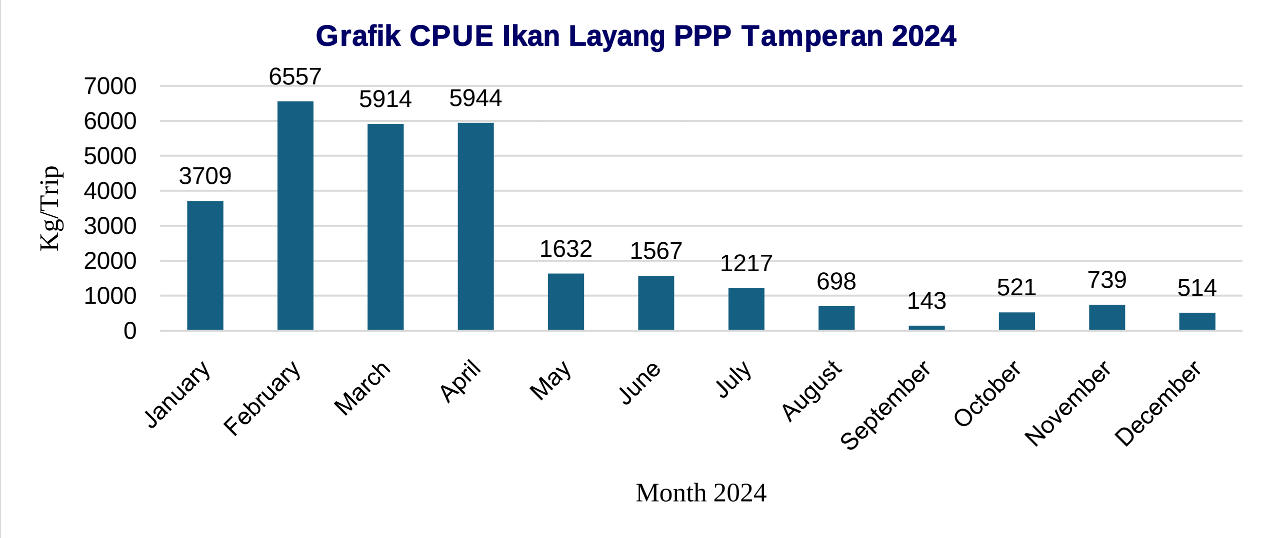

Fig1. CPUE Trend of Layang Fish Landed at PPP Tamperan in 2024

Figure1. depicts the monthly fluctuations in Catch per Unit Effort (CPUE) of Layang fish landed at PPP Tamperan in 2024.

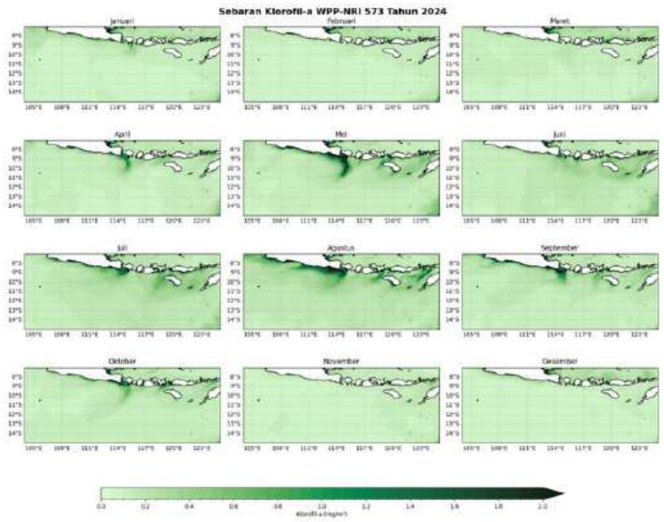

Fig 2. Distribution of Chlorophyll-a in FMA-NRI 573 in 2024

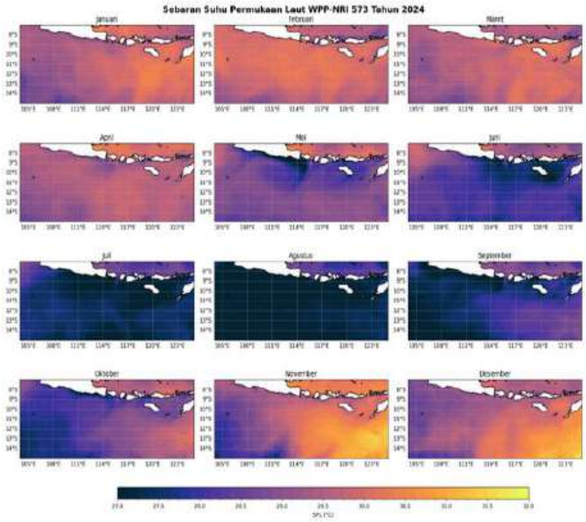

Fig 3. Distribution of Sea Surface Temperature in FMA-NRI 573 in 2024

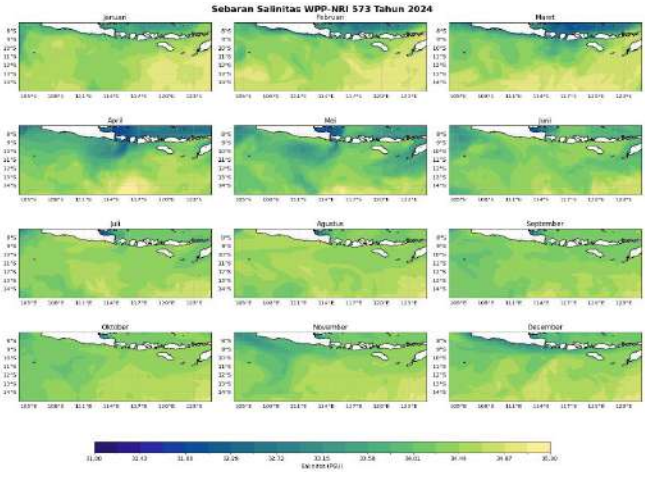

Fig 4. Distribution of Salinity in FMA-NRI 573 in 2024

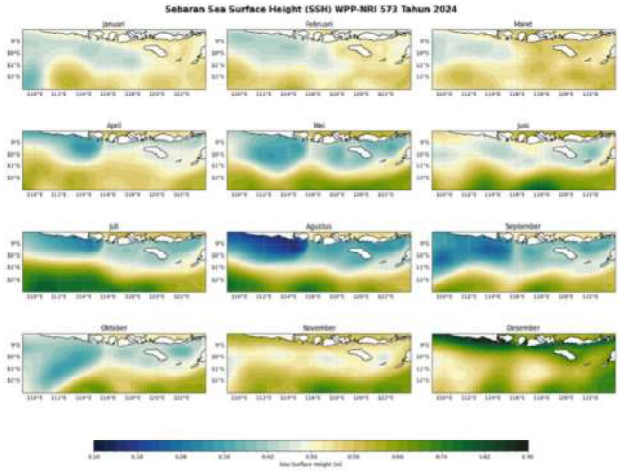

Fig 5. Distribution of Sea Surface Height in FMA-RI 573 in 2024

Subsequently, production declines from May onward, particularly from August to December. The highest Catch per Unit Effort (CPUE) value occurred in February at 6,557 kg/trip and remained relatively high until April (5,944 kg/trip). However, CPUE decreased sharply from May to December, reaching its lowest point in September at 143 kg/trip.

This decline may indicate reduced fish availability or changes in fishing patterns. The monthly fluctuations in CPUE, reflecting productivity per trip, are further illustrated in figure 1. In January, CPUE was 3,709 kg/trip, rising sharply to 6,557 kg/trip in February before declining to 5,914 kg/trip in March. A slight increase to 5,944 kg/trip was observed in April. The chart highlights that high catch productivity per trip occurred in the early months of the year, followed by a drastic decline in CPUE starting in May (1,632 kg/trip), reaching its lowest point in September (143 kg/trip). A moderate recovery in CPUE was observed in October and November, followed by another decline in December. These CPUE fluctuations are critical for sustainable fisheries management, particularly in formulating optimal fishing strategies to maintain Layang fish stocks in the waters around PPP Tamperan, which fall within Fisheries Management Area (FMA-NRI) 573. The observed trends underscore the need for adaptive management practices to address seasonal variability and ensure long-term resource sustainability.

B. Generalized Additive Model (GAM) Analysis

This study employs a Generalized Additive Model (GAM) analysis to examine the relationship between oceanographic parameters and the catch yield of Decapterus (scad fish). These parameters were evaluated based on Effective Degrees of Freedom (EDF), F-value, p-value, Contributions to Deviance Explained (CDE), and Akaike Information Criterion (AIC). EDF quantifies the model's complexity. A higher EDF value indicates that the model has greater flexibility to capture variation within the data, whereas a lower value suggests a simpler, more constrained model that may underfit the observed patterns. The F-value is used to assess the significance of each variable in the model, derived from the F-test, which determines how much of the variation in the data can be explained by a specific variable as opposed to random variation. A higher F-value implies a greater likelihood that the variable has a significant influence on the catch yield. A statistically significant p-value ($p < 0.05$) indicates that the parameter has a meaningful effect on the distribution pattern of Decapterus. Meanwhile, a higher CDE value reflects the extent to which the model explains the variability in catch data, as it represents the percentage of deviance accounted for by a given variable. The AIC is a metric used to evaluate the quality of a model by balancing goodness-of-fit with model complexity. A model with a lower AIC is considered more optimal, as it provides a better explanation of the data with fewer parameters, thereby reducing the risk of overfitting. The results of the GAM analysis conducted in this study are presented in Table 2.

Table 2. Results of the Generalized Additive Model (GAM)

	Variable	EDF	F_value	P_Value	CDE	AIC
Model_1	s(SST)	7,911309	3,852464	0,000144	32.1%	305,6525
Model_2	s(SSS)	2,225328	0,910298	0,016588	10.46%	319,1777
Model_3	s(CHL)	2,400854	1,033894	0,012549	10.82%	319,1695
Model_4	s(SSH)	8,522711	2,801027	0,004526	24.94%	315,8987
Model_5	s(SST)	7,817053	3,578101	0,00019	36.44%	301,7936
	s(CHL)	1,139724	0,503243	0,02235	36.44%	301,7936
Model_6	s(SST)	7,261022	3,351586	0,000236	50.62%	292,637
	s(CHL)	2,618173	1,51991	0,001948	50.62%	292,637
	s(SSS)	5,854532	2,167053	0,003534	50.62%	292,637

Source: Research data, 2025

Table 3 (continued). Results of the Generalized Additive Model (GAM) analysis

Model	Variable	EDF	F_value	P_Value	CDE	AIC
Model_7	s(SST)	7,551301	2,25571	0,006529	56.88%	283,0143
	s(CHL)	2,618812	1,380274	0,003372	56.88%	283,0143
	s(SSS)	5,809957	2,549544	0,000946	56.88%	283,0143
	s(SSH)	1,040553	0,955898	0,001822	56.88%	283,0143

Source: Research data, 2025

Based on the results of the Generalized Additive Model (GAM) analysis, it was observed that various oceanographic parameters namely sea surface temperature (SST), sea surface salinity (SSS), chlorophyll-a concentration (CHL), and sea surface height (SSH) exhibit varying degrees of contribution to the catch yield of Decapterus (scad fish). The model incorporating a combination of these parameters demonstrated a higher Contribution to Deviance Explained (CDE), with the best-performing model achieving a CDE of 56.88%. The presence of statistically significant p-values ($p < 0.05$) indicates that most of these parameters have a significant influence on the spatial distribution of Decapterus. Among the tested models, the one comprising SST, CHL, SSS, and SSH yielded the lowest Akaike Information Criterion (AIC) value, signifying its superior performance in explaining the variability in catch data. These findings suggest that a modeling approach based on the integration of the four oceanographic parameters can more accurately identify potential fishing grounds for Decapterus.

C. Correlation Between Oceanographic Parameters and Decapterus Catch Yield

The oceanographic parameters examined in this study namely sea surface temperature (SST), chlorophyll-a concentration (CHL), salinity (SSS), and sea surface height (SSH) are found to be correlated with the catch yield of Decapterus in Fisheries Management Area (FMA) 573. The application of the Generalized Additive Model (GAM) in this research also aims to determine the correlation between each oceanographic parameter and Decapterus catch yield. The following section presents the optimal range for each environmental variable. The optimal range refers to the values at which fish abundance is considered to be at its peak.

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Tabel 4. Optimal Ranges of Oceanographic Parameters

Klorofil-a (mg/m³)	SPL (°C)	Salinitas (PSU)	SSH (m)
0.066 –0,23	27.25– 30.56	33.5985 –34.2879	0.4–0.5

Sumber: Peneletian (2025)

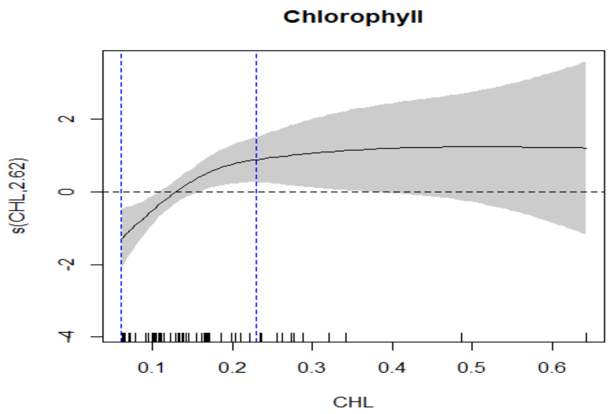

Figure 6. Optimal Range of Chlorophyll-a Concentration vs. Catch Data

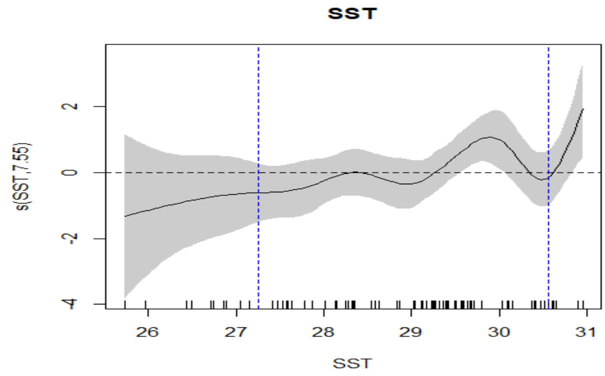

Figure 7. Optimal Range of Sea Surface Temperature vs. Catch Data

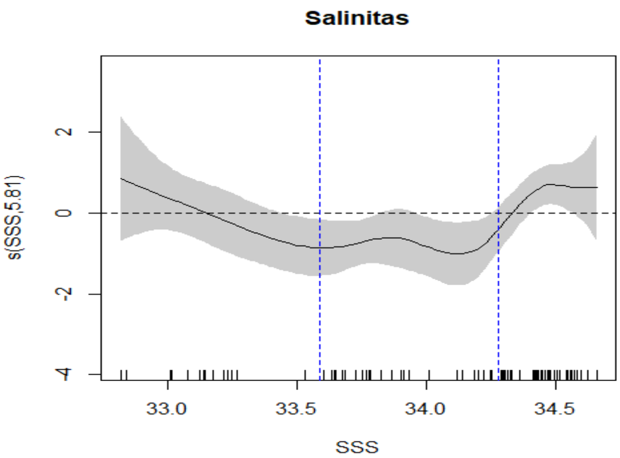

Figure 8. Optimal Range of Salinity vs. Catch Data

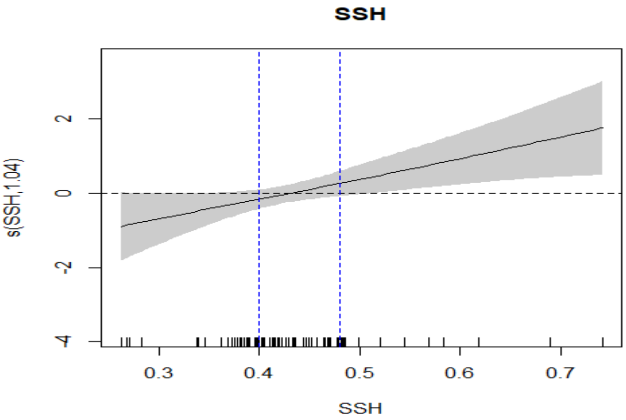

Figure 9. Optimal Range of Salinity vs. Catch Data

This figure represents the output of the Generalized Additive Model (GAM), illustrating the influence of four oceanographic parameters—chlorophyll-a concentration (CHL), sea surface height (SSH), sea surface temperature (SST), and sea surface salinity (SSS)—on the response variable, which is the catch yield of Decapterus. The X-axis in each plot indicates the actual values of the respective parameter, while the Y-axis represents the smoothed function values estimated by the model, depicting the non-linear relationship between the parameter and the response (i.e., the strength or contribution of the parameter to the catch yield). This relationship is not linear; instead, it may increase or decrease at specific value ranges. The black line in each graph shows the modeled relationship, and the shaded grey area represents the 95% confidence interval, reflecting the uncertainty range around the estimated effect. Short vertical tick marks along the bottom of each plot denote the distribution or density of the observed data across the range of parameter values. The blue dashed lines indicate the optimal value range i.e., the interval where the parameter is predicted to have the most positive impact on the response variable. When the black line lies above the zero line on the Y-axis, it indicates that the parameter at that specific value has a positive effect on the catch yield. This information can be used to spatially identify potential fishing grounds (PFGs) for more effective fishery resource management.

D. Validation of the Generalized Additive Model (GAM)

The analysis conducted in this study, namely the Generalized Additive Model (GAM), was validated to assess how well the model can predict the relationship between oceanographic parameters and fish catch yields. A strong and reliable relationship is essential for identifying potential fishing grounds. The results of the GAM model validation are presented in Figure 9. Figure 9 presents the validation results of the GAM model used to predict the abundance of Decapterus in Fisheries Management Area (FMA) 573 of the Republic of Indonesia, based on oceanographic parameters including sea surface temperature (SST), chlorophyll-a concentration (CHL), salinity (SSS), and sea surface height (SSH). The first validation step employs a regression equation illustrating the linear relationship between the observed log-transformed catch values and the predicted catch values. The regression coefficient of 0.5315 indicates that for every one-unit increase in observed values, the predicted value increases by 0.5315.

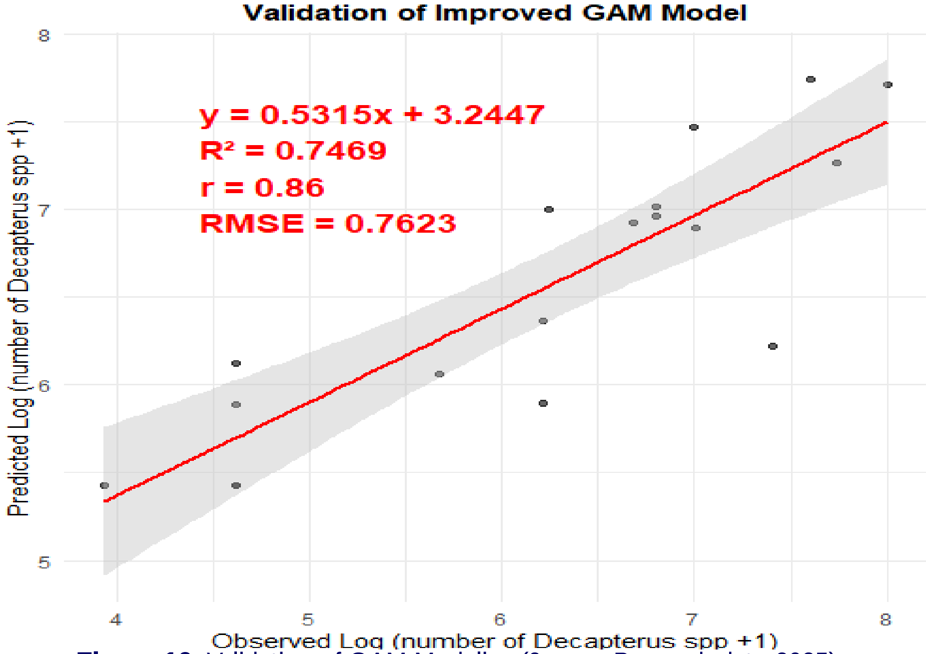

Figure 10. Validation of GAM Modeling (Source: Research data, 2025)

The coefficient of determination (R^2) is 0.7469, suggesting that the model explains approximately 74.69% of the variability in the catch data. This relatively high R^2 value indicates strong predictive performance. According to Setiawati et al. (2015), a higher coefficient of determination reflects a better model fit in describing the relationship between observed and predicted values. In ecological and spatial modeling contexts, an R^2 above 0.7 is generally considered indicative of a well-fitted model. The Pearson correlation coefficient (r) is 0.86, indicating a very strong positive relationship between predicted and observed values. As stated by Setiawati et al. (2015), correlation coefficients close to +1 or -1 signify a strong relationship between variables, while values near zero indicate a weak relationship. The magnitude of the correlation is absolute, while the sign (+ or –) only indicates the direction of the relationship. The Root Mean Square Error (RMSE) is 0.7623, which is lower than the standard deviation of the log-transformed catch values (SD = 1.4865). This indicates that the prediction error of the model is within an acceptable tolerance range. A low RMSE suggests not only statistical accuracy but also the model's stability in predicting catch amounts in the test dataset. According to Avinash et al. (2024), RMSE is a standard metric for evaluating average prediction error in the context of log-transformed fish abundance. Overall, the GAM developed in this study is considered accurate and reliable for catch prediction purposes. This accuracy is further supported by the scatter plot visualization, which shows that the data points are closely clustered around the regression line, indicating a high level of agreement between predicted and actual values.

E. Potential Fishing Grounds for Layang Fish (Decapterus spp) in FMA-NRI 573

Fisheries resources are characterized by open access, allowing for maximal exploitation. Layang fish, a species with high economic value, requires science-based and sustainable management to optimize utilization. As living organisms, fish possess life cycles and environmental adaptation needs. Overfishing without regard to spawning seasons risks depleting fish stocks. According to Rahmawati et al. (2013), defining seasonal fishing patterns is critical to ensure natural breeding and stock replenishment. For Layang fish, a small pelagic species reliant on plankton, potential fishing grounds outside spawning seasons can be identified through parameters such as chlorophyll-a concentration, sea surface temperature (SST), salinity, and sea surface height (SSH). Figure 6 illustrates the potential fishing grounds for Layang fish in FMA-NRI 573 in 2024, derived from a Generalized Additive Model (GAM) analysis incorporating oceanographic variables: chlorophyll-a, SST, salinity, and SSH. The results reveal the following spatial and temporal patterns:

1. January: Potential fishing grounds (PFGs) are widely distributed across the northern and central regions of FMA-NRI 573.
2. February: PFGs remain concentrated in the northern waters.
3. March–April: A decline in PFGs is observed, with distribution shifting toward the eastern region.
4. May–June: Slight expansion occurs in June compared to May, particularly in the western sector.
5. July–September: PFGs are minimal, appearing only in isolated areas.
6. October: Resurgence in PFGs is noted, marking the onset of increased fishing potential after the July–September low.
7. November–December: PFGs progressively expand, peaking in December and signaling the start of the primary fishing season in FMA-NRI 573.

September serves as the transitional period into the fishing season, with PFGs gradually increasing from December into the following year. These findings emphasize the necessity of adaptive, science-based management to align fishing efforts with ecological cycles, ensuring sustainable exploitation of Layang fish stocks.

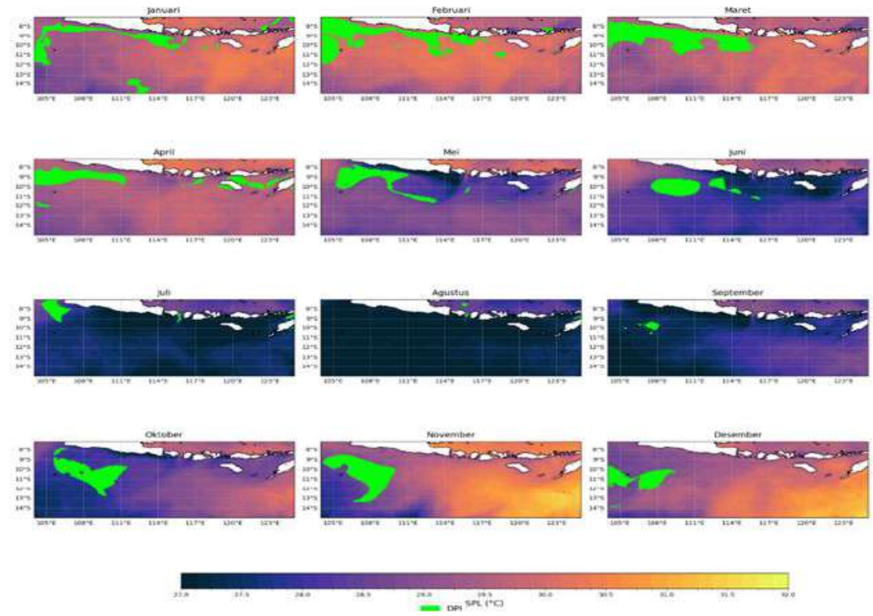

Figure11. Potential Fishing Grounds for Layang Fish (Decapterus spp) in FMA-NRI 573

Discussion

A. Characteristics of Chlorophyll-a, Sea Surface Temperature, Sea Surface Height, and Salinity in FMA-NRI 573

The oceanographic parameters in Indonesian waters, particularly within Fisheries Management Area (FMA) 573, exhibit dynamic and complex interactions that influence fish resource distribution. Continuous monitoring of these parameters is essential to discern spatial-temporal patterns in fish abundance and optimize sustainable fishery practices. This study focuses on four key oceanographic variables—sea surface temperature (SST), chlorophyll-a concentration, salinity, and sea surface height (SSH)—as critical indicators for identifying potential fishing grounds and fish biomass. Ma'mun et al. (2018) emphasize that marine biological resource distribution is intrinsically linked to the variability of these oceanographic conditions, underscoring the necessity of accurate environmental data for effective fishery management. Chlorophyll-a distribution in FMA 573 during 2024 (Figure 2) displayed minimal seasonal variation. As a photosynthetic pigment in phytoplankton, chlorophyll-a serves as a proxy for water fertility and potential fish aggregation zones (Bukhari et al., 2017). Elevated chlorophyll-a levels were observed during the transitional period (March–May), peaking between July and October before stabilizing in November. This aligns with findings from the Indian Ocean by Demi et al. (2020), who reported peak chlorophyll a concentration from March to November, with maxima in August. Seasonal fluctuations are attributed to monsoon-driven upwelling and downwelling. During the southeast monsoon (June–October), Ekman transport induces coastal upwelling, uplifting nutrient-rich deep waters (Putri et al., 2023). Conversely, the northwest monsoon (December–June) promotes downwelling, suppressing vertical mixing (Yoga et al., 2014). Coastal regions exhibited higher chlorophyll-a concentrations due to terrestrial nutrient runoff, contrasting with oligotrophic offshore waters (Syetiawan, 2015). SST in FMA 573 (Figure 3) demonstrated pronounced seasonal contrasts. Warmer conditions prevailed during the northwest monsoon (December–February), driven by the Java Coastal Current transporting warm (>27°C) surface waters (Susanto et al., 2001). Cooling occurred during the transitional period (March–May), reaching minima in the southeast monsoon (June–August) due to intensified Ekman transport and upwelling of cold subsurface waters (Yuniarti et al., 2013). Offshore regions exhibited lower SST due to vertical mixing in deeper water columns, which facilitates heat exchange with cooler subsurface layers (Pickard & Emery, 1966). Salinity distribution (Figure 4.3) revealed higher values during the southeast monsoon (June–August) and transitional period II (September–November), contrasting with lower salinity in the northwest monsoon (December–February) and transitional period I (March–May). Freshwater input from rainfall and river discharge during the wet season reduced coastal salinity (Prihatiningsih et al., 2022). Upwelling during the southeast monsoon elevated salinity by advecting saline deep waters, while downwelling during the northwest monsoon diluted surface layers (Safitri et al., 2012). Offshore areas maintained higher salinity due to limited freshwater influence, whereas nearshore zones exhibited greater variability from riverine inputs (Erfanda & Widagdo, 2020). SSH in FMA 573 (Figure 5) showed seasonal variability, with elevated levels during the northwest monsoon due to thermal expansion from warmer SST and reduced during the southeast monsoon due to upwelling-induced surface cooling (Ichikawa, 2023). Deeper offshore regions exhibited higher SSH owing to greater hydrostatic pressure, while shallow coastal areas experienced amplified SSH variability from interactions between ocean currents and bathymetry (Lubis et al., 2024). Monsoon winds, precipitation, and oceanic currents collectively modulate SSH dynamics, reflecting the interplay between thermohaline processes and regional topography.

B. Relationship Between Oceanographic Parameters and Potential Fishing Grounds of Layang Scad (Decapterus spp)

The interaction between chlorophyll-a, sea surface temperature (SST), salinity, and sea surface height (SSH) in influencing Layang Scad (Decapterus spp) distribution was analyzed using Generalized Additive Models (GAMs).

Catch data from Tamperan Fishing Port were integrated with satellite-derived oceanographic parameters to assess habitat preferences and environmental tolerances. These variables collectively govern physiological thresholds, prey availability, and habitat suitability, offering insights into spatiotemporal resource distribution. As Sadly and Awaluddin (2017) emphasize, elucidating these relationships aids in formulating sustainable fishery management strategies. Seven GAM configurations were tested (Table 3). Models 1–4 evaluated individual parameters (chlorophyll-a, SST, salinity, SSH), while Models 5–7 combined variables to assess synergistic effects. Model 5 integrated SST and chlorophyll-a; Model 6 added salinity; and Model 7 included all four parameters. Single-variable models identified key drivers, whereas multi-variable models quantified cumulative explanatory power via Akaike Information Criterion (AIC) and coefficient of determination (CDE) metrics. Chlorophyll-a exhibited a weakly positive linear relationship with Layang Scad abundance (CDE = 10.82%), plateauing at higher concentrations (Table 4). This aligns with Dwiyanti et al. (2023), who attributed chlorophyll-a's limited influence (28.47% explanatory power) to trophic lag: phytoplankton biomass precedes zooplankton blooms, the direct prey of Layang Scad. Optimal chlorophyll-a ranges (0.2–0.5 mg/m³) reflect intermediate productivity zones, balancing prey availability without eutrophic stress. SST demonstrated the strongest individual influence (CDE = 32.1%), with a non-linear relationship peaking at 27.25–30.56°C (Figure 4). This thermal range aligns with Layang Scad's tropical affinity, enhancing metabolic rates and foraging efficiency (Ramadhani, 2023). Temperatures exceeding 30.56°C induced stress, triggering migratory behavior to cooler habitats (Larasati et al., 2024). Seasonal SST fluctuations further modulate oxygen solubility, indirectly affecting vertical distribution. Salinity showed a non-linear association (CDE = 10.46%), with optimal catches occurring at 33.60–34.29 PSU (Table 4). Layang Scad's stenohaline nature confines it to narrow salinity regimes (32–34‰), as observed by Katarina et al. (2021). Lower salinity during monsoon-driven runoff (December–May) reduced abundance, while upwelling during the southeast monsoon (June–October) elevated salinity, correlating with higher catches (Amri, 2017). SSH contributed significantly (CDE = 29.94%), displaying a positive linear correlation with fish abundance. Elevated SSH (>0.4 m) coincided with stable thermal layers and nutrient retention, enhancing habitat suitability. Conversely, low SSH (<0.1 m) marked upwelling zones, where cold, nutrient-rich subsurface waters boosted primary productivity but disrupted pelagic aggregation (Purba & Tarya, 2024). Offshore regions with deeper bathymetry exhibited higher SSH, favoring sustained fish presence. Model 7 (all variables) achieved the highest explanatory power (CDE = 68.3%), underscoring the interdependence of SST, SSH, and chlorophyll-a. Optimal Layang Scad habitats emerged in areas with moderate SST (28–30°C), elevated SSH (>0.3 m), and chlorophyll-a concentrations of 0.3–0.45 mg/m³. Salinity played a secondary role, primarily filtering nearshore vs. offshore distributions. These findings highlight the necessity of holistic oceanographic monitoring for dynamic fishery management.

C. Potential Fishing Grounds for Layang Scad (Decapterus spp) in FMA-NRI 573

The identification of potential fishing grounds for Indian scad was based on Generalized Additive Model (GAM) analysis, as detailed in Table 3 Model 7 was selected as the optimal model due to its highest CDE value, incorporating key parameters such as chlorophyll-a concentration, sea surface temperature (SST), salinity, and sea surface height (SSH). Determination of fishing grounds was further refined using the optimum ranges identified in Table 4, also derived from the GAM analysis. Indian scad fishing activities were conducted throughout all seasons—easterly, westerly, and transitional.Although the easterly season is characterized by ideal oceanic fertility and potential upwelling events—as indicated by chlorophyll-a distribution, salinity, and SST—the spatial extent of fishing grounds during this season was narrower compared to other seasons. Hariati et al. (2019) noted that the seasonal pattern of purse seine fishing activities aligns closely with Indian scad catch trends, with peak fishing activity occurring during the first and second transitional seasons. Similarly, the lowest levels of fishing activity, observed in June and July, coincide with periods of reduced Indian scad catches.The spatial extent of potential fishing areas, as illustrated in Figure 5, begins to expand from the second transitional season (September) and continues to increase through the early part of the year, reaching a maximum during the westerly season. Broad fishing grounds persist into the first transitional season (March–May), corresponding to the optimal environmental conditions determined by the GAM analysis. Additionally, the period spanning the easterly season (June–August) to the second transitional season (September–November) features high fertility levels, creating favorable spawning conditions for Indian scad. According to Winata et al. (2024), natural upwelling events stimulate spawning by ensuring the availability of larval and juvenile food sources. It is crucial to consider spawning seasons when managing fisheries to avoid disrupting the reproductive cycle. Capturing mature fish during peak spawning periods may significantly hinder recruitment and accelerate population decline.During the westerly season (December–February), Indian scad fishing grounds are concentrated in the western part of FMA-NRI 573, particularly in the northern waters off western Java. During this period, SSH tends to increase from west to east, indicating water mass movements originating from the South China Sea and the Indian Ocean. Suwarso and Zamroni (2015) identified two major Indian scad populations entering the Java Sea, originating from both the west and the north. In the first transitional season (March–May), fishing grounds shift eastward with wider but less intense distributions, consistent with the changing currents driven by prevailing southeast winds. During the easterly season (June–August), high-intensity fishing grounds are observed in the central and western Java Sea, aligning with Indian scad migration patterns. Larasati et al. (2024) reported that Indian scad populations from the Makassar Strait and Flores Sea migrate westward toward the Java Sea during the easterly season. In the second transitional season (September–November), potential fishing areas reappear in the central and eastern waters south of Java, reflecting a reverse eastward migration.Peak fishing seasons occur during the westerly season and the first transitional season, although these peaks are not always directly correlated with oceanographic parameter distributions. Suhery et al. (2023) emphasized that capture production figures often reflect fishing seasons; even when fish stocks are abundant, if fishing operations are not effectively conducted, production levels may not rise.

Muzayanah et al. (2022) also demonstrated that the Fishing Season Index (FSI) can guide optimal fishing efforts. Their findings indicated that Indian scad fishing peaks in December, January, February, April, and May, as reflected by FSI values exceeding 100% during these months. Time lags in environmental response also influence the distribution of potential fishing grounds, consistent with the broader fishing areas identified during these months. Furthermore, Siswantoputri et al. (2024) observed that Indian scad primarily feed on zooplankton and small fish rather than directly consuming phytoplankton, despite the association between high chlorophyll-a concentrations and their habitat. Elevated chlorophyll-a levels generally coincide with lower SSTs. While Indian scad prefer relatively warm waters, as noted by Siswantoputri et al. (2024), factors such as chlorophyll-a, SST, salinity, and SSH all significantly contribute to the delineation of suitable fishing grounds. Among these, SST plays a particularly vital role in the GAM model's predictive power. Migration behaviour also underscores the species' need to travel across different areas to access optimal feeding grounds.

IV. CONCLUSIONS

1. The distribution of chlorophyll-a in FMA-NRI 573 peaked in May and August, with values exceeding 2 mg/m³, while in other months, it remained relatively uniform at around 0.6 mg/m³. Higher chlorophyll-a value were observed in coastal areas. Sea Surface Temperature (SST) showed seasonal variability, with the highest value at 32°C and the lowest at 27°C. Salinity distribution also exhibited seasonal variability, ranging from 32 PSU (lowest) to 35 PSU (highest). Sea Surface Height (SSH) demonstrated seasonal variability, with values ranging from 0.10 meters (lowest) to 0.90 meters (highest), indicating higher SSH offshore than near the coast.
2. The relationship between chlorophyll-a and fishing potential was linear, contributing 10.82% to the model. SST showed a non-linear relationship with significant influence, contributing 32.1% to the model. Salinity exhibited a non-linear relationship, contributing 10.46% to the model. SSH had a linear relationship with significant influence, contributing a substantial 29.94% to the model.
3. The potential fishing grounds for Layang Scad in FMA-NRI 573 span latitudes 6°S–11°S and longitudes 108°E–122°E. The most extensive potential fishing areas occurred from January to May due to favorable oceanographic conditions, marking this period as the peak fishing season with high Catch per Unit Effort (CPUE) values.

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