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ORIGINAL RESEARCH ARTICLE

Environmental modeling of yellowfin tuna fishing grounds integrating oceanographic and biological parameters using generalized additive model

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ABSTRACT

BACKGROUND AND OBJECTIVES: Marine environmental variability influences the distribution, productivity, and habitat suitability of yellowfin tuna (Thunnus albacares). However, fishing-ground assessment based primarily on environmental conditions or production may overlook the biological suitability of harvested fish. The study objectives were to develop an integrated generalized additive model framework for assessing yellowfin tuna fishing grounds. The framework combined oceanographic conditions and fishing operational factors with production potential and fish size through two complementary Generalized additive models.

METHODS: The study was conducted in the waters of West Sumatra, eastern Indian Ocean, Indonesia. Fisheries and oceanographic data covered 2019–2024, while biological observations covered 2019, 2020, and 2024. Oceanographic predictors included sea surface temperature, chlorophyll-a concentration, sea surface salinity, and sea surface height. Fisheries predictors included fishing year, month, gear, spatial location, and vessel capacity. A total of 8,771 yellowfin tuna fork-length measurements were analyzed. A fork length of 99 centimeters was used as the maturity-based threshold. Two complementary generalized additive models were developed. The Fishing Ground–Environment, Technology, and Production model used catch as the production response. The Fishing Ground–Environment, Technology, and Size model used fork length as the biological response.

FINDINGS: Sea surface temperature ranged from 29.37–30.45 degrees Celsius. Chlorophyll-a concentration ranged from 0.21–0.43 milligrams per cubic meter. Sea surface salinity ranged from 33.29–33.87 practical salinity units. Sea surface height ranged from 0.46–0.59 meters. Overall, 94 percent of fish were harvest-suitable. The production model had an Akaike information criterion of 155,482.9 and cumulative deviance explained of 11.5 percent. The size model had an Akaike information criterion of 77,913.73 and cumulative deviance explained of 28.74 percent. Medium to high fishing-ground potential occurred more frequently around the Mentawai Islands. Temporal integration identified highly potential and potential fishing-period statuses based on relative production potential and the landing-based biological size indicator.

CONCLUSION: The integrated generalized additive model framework links environmental conditions, fishing operations, production, and biological size. This approach provides a more selective basis for adaptive and sustainable management of yellowfin tuna fisheries.

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45	12	9

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INTRODUCTION

Marine environmental variability influences ecosystem structure, productivity, habitat suitability, and the distribution of pelagic species in tropical systems such as the eastern Indian Ocean (Ducklow *et al.,* 2022; Cartwright *et al.,* 2021). Yellowfin tuna (*Thunnus albacares*) is a highly migratory pelagic predator that responds to environmental variation, making it an important species for examining ecological responses to oceanographic variability (Siregar *et al.,* 2018; Fu *et al.,* 2025; Siregar *et al.,* 2025b). Understanding the relationship between environmental conditions and yellowfin tuna distribution is consequently important for environmental assessment and sustainable management of marine resources. Oceanographic variables, including sea surface temperature (SST), chlorophyll-a concentration (Chl-a), sea surface salinity (SSS), and sea surface height (SSH), represent important physical and biogeochemical characteristics of the marine environment. Their spatial and temporal variability reflects processes such as ocean circulation, water-mass dynamics, productivity gradients, and nutrient enrichment, which influence the distribution, abundance, and habitat utilization of pelagic fish (Siregar *et al.,* 2025a). SST represents thermal conditions, Chl-a provides an indicator of surface productivity, SSS reflects water-mass characteristics and salinity gradients, and SSH represents surface-ocean dynamics and spatial variability. These environmental variables have been used to examine yellowfin tuna distribution and potential fishing grounds, including GAM-based analysis in West Sumatra and remote-sensing-based assessment in the eastern Indian Ocean off Sumatra (Feng *et al.,* 2025; Siregar *et al.,* 2025a). Favorable combinations of these environmental conditions may therefore be associated with variation in yellowfin tuna occurrence and fishing activity. Consequently, SST, Chl-a, SSS, and SSH were selected as complementary oceanographic predictors for evaluating the associations between environmental variability, yellowfin tuna production, and fish size in the study area. However, environmental suitability alone does not necessarily indicate that fish occurring in these areas are biologically appropriate for harvesting or that the areas have high production potential. Biological characteristics provide an important complementary dimension for evaluating the suitability of marine resources. Fish size structure reflects population composition, ontogenetic development, habitat utilization, and ecological responses to environmental variability. Individuals of different sizes may exhibit different habitat preferences, swimming capabilities, feeding strategies, and responses to environmental conditions (Ostman *et al.,* 2023). Therefore, fish size can provide biological information that cannot be obtained from environmental variables, fish occurrence, or catch indicators alone. This consideration is particularly important for fisheries management because fish size is closely related to biological maturity and harvest suitability (Cacciamani *et al.,* 2025; Siregar *et al.,* 2026). Areas with favorable environmental conditions may contain fish that are not yet biologically suitable for harvesting and should therefore not automatically be classified as sustainable fishing grounds. The consideration of biological size is particularly relevant because harvesting immature fish can reduce the reproductive potential of fish populations and increase the risk of growth overfishing. Fish that have not reached an appropriate size for harvest may contribute substantially to future population recruitment and therefore require greater consideration in fisheries management (Mendoza *et al.,* 2024). Thus, the identification of fishing grounds based solely on oceanographic suitability may overestimate their suitability from a biological perspective. Integrating fish size with environmental information can provide a more comprehensive assessment of fishing-ground suitability and support management strategies that consider both resource availability and

biological sustainability. In addition to environmental and biological conditions, fishing technology and operational characteristics influence fishing distribution and production. Fishing gear, vessel capacity, effort, and temporal patterns affect fishing efficiency and vessels' ability to exploit areas under different environmental conditions. Consequently, fishing-ground assessment should consider environmental and biological suitability alongside fishing operations. However, these dimensions are commonly evaluated separately, limiting integrated assessment of fishing-ground suitability. Generalized additive models (GAMs) provide a flexible statistical framework for examining complex and nonlinear relationships between environmental predictors and biological or fisheries responses. Since the introduction of GAMs by Hastie and Tibshirani (1990), these models have been widely applied in ecological and fisheries research because they can accommodate nonlinear responses without requiring a predetermined functional form. GAMs have been used to investigate species–environment relationships, habitat suitability, abundance, and spatiotemporal patterns of pelagic fishes, including yellowfin tuna, bigeye tuna, skipjack tuna, and other commercially important species (Siregar *et al.,* 2018; Azeez *et al.,* 2021; Koropitan *et al.,* 2021; Wang *et al.,* 2022; Lin *et al.,* 2025). The flexibility of GAMs provides an appropriate basis for evaluating multiple environmental, biological, and fishing operational factors within complementary frameworks. Despite increasing GAM application in marine environmental modeling, most fishing-ground studies focus primarily on environmental indicators, fish occurrence, abundance, catch, or catch-per-unit-effort (CPUE). Recent studies have similarly emphasized environmental determinants and integrated resource assessment (Takrina *et al.,* 2023; Shahat *et al.,* 2026). Although these approaches effectively identify areas with favorable environmental conditions or higher fishing productivity, they provide limited information on whether fish are biologically appropriate for harvesting. Similarly, biological size structure is rarely incorporated as an explicit response variable, while fishing technology is often considered separately from environmental and biological conditions. Consequently, existing approaches may identify favorable or highly productive fishing areas without simultaneously evaluating biological suitability and operational characteristics. The novelty of this study lies in developing an integrated environmental modeling framework for yellowfin tuna fishing-ground assessment that combines oceanographic conditions, biological size, and fishing operational characteristics through two complementary GAMs. The first model, fishing ground–environment, technology, and production (FG-ETP), evaluates yellowfin tuna production in relation to environmental and fishing operational factors. The second model, fishing ground–environment, technology, and size (FG-ETS), evaluates yellowfin tuna size in relation to environmental and fishing operational factors using landing-based biological observations. The outputs of these models are integrated temporally to combine production potential with biological size suitability. Unlike conventional fishing-ground approaches emphasizing environmental suitability, catch, or productivity, the proposed framework incorporates production potential and biological size for a more comprehensive assessment of fishing-ground suitability. This integrated approach is consistent with recent resource-management frameworks incorporating environmental and human-use factors (Díaz-Ponce *et al.,* 2026). The integrated framework provides an exploratory approach for assessing yellowfin tuna fishing-ground potential by identifying statistical associations among environmental conditions, fishing operations, production, and biological size, but it does not by itself demonstrate management effectiveness or sustainable fisheries outcomes. This study aims to: 1) evaluate the relationships between oceanographic parameters, fishing technology,

and yellowfin tuna production using the FG-ETP model; 2) evaluate the relationships between oceanographic parameters, fishing technology, and yellowfin tuna fish size using the FG-ETS model; and 3) integrate the outputs of FG-ETP and FG-ETS temporally to characterize yellowfin tuna fishing periods according to production potential and biological size suitability. The study was conducted in the waters of West Sumatra, eastern Indian Ocean, Indonesia, using oceanographic and fisheries data covering 2019–2024, with biological fish-size observations available for 2019, 2020, and 2024.

MATERIALS AND METHODS

Study area and data sources

The study was conducted in the waters of West Sumatra, eastern Indian Ocean, Indonesia, between 11° north (N), –4° south (S) and 95°E–101° east (E) (Fig. 1), including the western Sumatran coastal waters and waters surrounding the Mentawai Islands. The study period was January–December 2024, while the datasets covered January 2019–December 2024. The study integrated environmental, fisheries, and biological datasets. Oceanographic data comprised SST, Chl-a, SSS, and SSH obtained from the Copernicus Marine Environment Monitoring Service (CMEMS) at 0.25° × 0.25° spatial and monthly temporal resolutions. Fisheries data were obtained from the PPS Bungus fishing logbook and included catch (C), fishing location, year, month, fishing gear, vessel capacity expressed as gross tonnage (GT), and fishing effort (E). Biological data comprised fork length (FL) and weight measurements of yellowfin tuna collected in 2019, 2020, and 2024, totaling 8,771 individuals. The 2019–2020 records were obtained from the PPS Bungus database, whereas 2024 measurements were collected during fish landings. Differences in sampling procedures among years may have contributed to variation in FL; therefore, year-related patterns were interpreted as differences in sampled landings rather than definitive changes in population size structure.

Environmental, biological, and fisheries data

The study used oceanographic, biological, and fisheries data from the waters of West Sumatra, eastern Indian Ocean, Indonesia. The four oceanographic variables SST, Chl-a, SSS, and SSH were obtained from CMEMS and processed using Ferret 7.6. Environmental datasets were checked for consistency in parameter definitions, units, and spatial and temporal coverage, then clipped to 1°N–4°S and 95°E–101°E. Monthly environmental fields were matched with fisheries observations by fishing year, month, and geographic location, with each observation assigned the corresponding 0.25° × 0.25° environmental grid cell. Biological observations were recorded at landing ports without equivalent fishing coordinates; therefore, they were not spatially matched with environmental fields or fishing locations but were aggregated monthly and integrated through the FG-ETS model. The fisheries dataset included yellowfin tuna catch (kg), fishing effort based on tuna handline operations, fishing gear, vessel capacity, fishing year and month, and geographic coordinates. CPUE was calculated using Eq. 1 (Chang *et al.*, 2011):

$$CPUE_i = \frac{Catch_i}{Effort_i} \quad (1)$$

Where: $CPUE_i$ is the catch per unit effort at observation *i*, C_i is yellowfin tuna catch, and E_i is fishing effort. CPUE was used as an indicator of relative fishing productivity, while the production GAM used catch in kilograms as the response variable. Standardized CPUE obtained through the FPI procedure was used to support the interpretation of relative fishing productivity and was not used as the response variable in the production GAM. Because different fishing gears have different catching capabilities, CPUE was

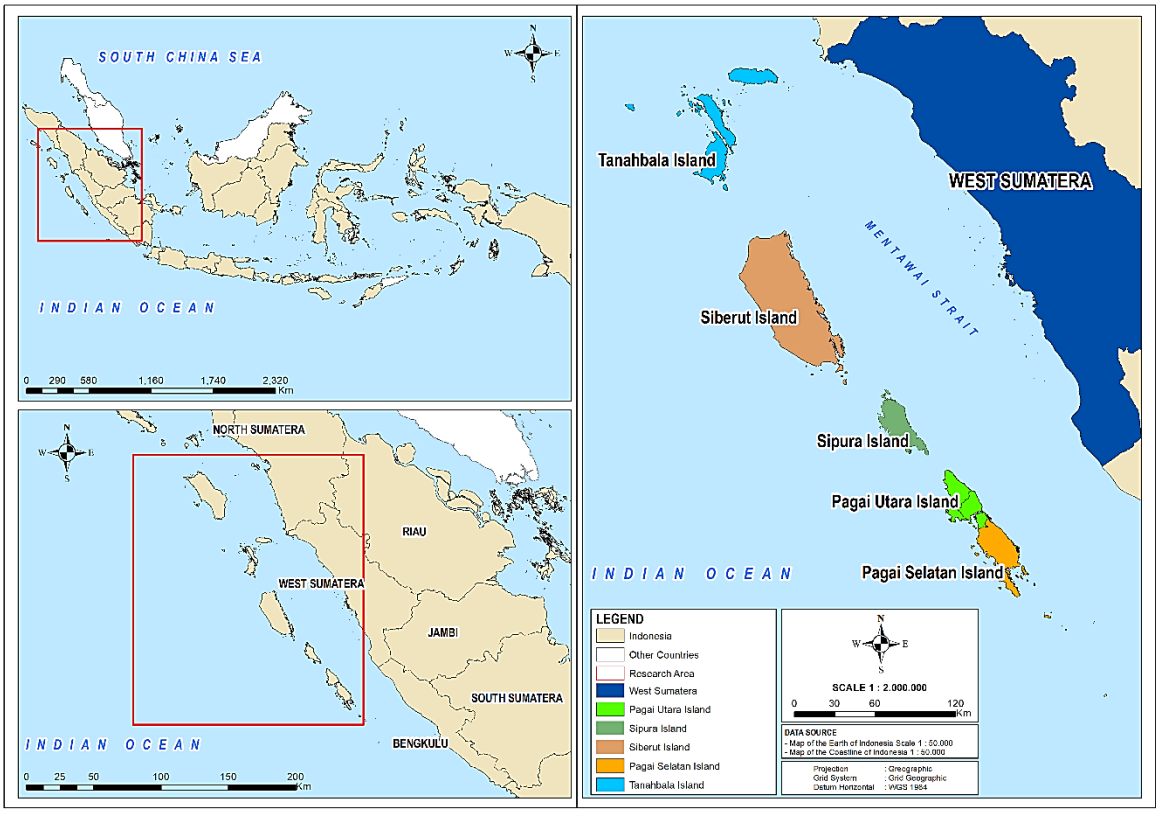

Fig. 1: Geographical location of the study area in the eastern Indian Ocean off West Sumatra, Indonesia

standardized using the Fishing Power Index (FPI), with tuna handline selected as the reference fishing gear. The FPI was estimated to account for differences in relative fishing power among gear types. The FPI was estimated to account for differences in relative fishing power among gear types. The FPI was determined using Eq. 2 (Sparre and Venema, 1998):

$$FPI = \frac{CPUE_r}{CPUE_s} \quad (2)$$

Where: CPUEr is the catch per unit effort of the fishing gear being standardized and CPUEs is the catch per unit effort of the reference fishing gear (tuna handline). The standardized CPUE was used to support the interpretation of relative fishing productivity, whereas fishing gear was retained as a categorical predictor in the GAM to account for gear-specific effects on the production response. Thus, FPI standardization and the gear effect in the GAM served different analytical purposes and were not applied as two successive corrections to the same response variable. CPUE calculation and FPI standardization were performed computationally in R. For the production GAM, fishing effort was incorporated as a log-transformed offset [log(EFFORT)] to account for differences in fishing intensity among observations. Biological observations consisted of 8,771 yellowfin tuna FL measurements collected in 2019, 2020, and 2024. Fork-length observations were available only for these three sampling years, whereas fisheries and environmental data covered the period from 2019 to 2024. The maximum observed FL was determined using Eq. 3 (Hasan *et al.*, 2021; Ostman *et al.*, 2023):

$$L_{max} = \max(FL) \quad (3)$$

Where: Lmax is the maximum observed FL and FL is the fork length of an individual fish. The asymptotic length (L_∞) was estimated using the empirical relationship in Eq. 4 (Laban *et al.,* 2024; Vicente and Palla, 2024; Nurdin *et al.,* 2025):

$$L_\infty = \frac{L_{max}}{0.99} \quad (4)$$

The length at first maturity (Lm) was subsequently estimated using Eq. 5 (Chen *et al.,* 2021; Morbey and Pauly, 2022):

$$\log_{10}(Lm) = -0.0782 + 0.8979 \log_{10}(L_\infty) \quad (5)$$

These empirical relationships provide a length-based approximation of L∞ and Lm,0.95 when direct biological maturity observations are unavailable. Because L∞ was derived from the maximum observed fork length of the landing sample, the resulting Lm,0.95 was interpreted as an empirical estimate for the sampled population rather than as a direct population-specific maturity estimate. The empirical relationships used for estimating Lmax and Lm were derived from previously reported length-based relationships and assume that the observed maximum length provides a reasonable basis for estimating the asymptotic length (Chen *et al.,* 2021; Hasan *et al.,* 2021; Morbey and Pauly, 2022). The calculation conducted in the present study yielded an estimated Lm,0.95 of 98.63 centimeters (cm) FL. The calculation conducted in the present study yielded an estimated Lm,0.95 of 98.63 cm FL. This value was operationally rounded to 99 cm FL and used as a biological maturity-based threshold for size classification in the present study. The resulting size categories are presented in Table 1. The 99 cm FL threshold was derived from the biological analysis conducted in the present study rather than adopted directly from previous studies. The classification was subsequently used as the biological criterion in the FG-ETS analysis and in the temporal integration of FG-ETP and FG-ETS (Siregar *et al.,* 2026).

Table 1: Biological size classification of yellowfin tuna based on the 99 cm FL threshold

Size category	Classification criterion
Below maturity-based threshold	FL < 99 cm
At or above maturity-based threshold	FL ≥ 99 cm

Environmental modeling using GAMs

Statistical modeling in this study was conducted using GAMs to quantify potentially nonlinear relationships between yellowfin tuna responses and environmental and fishing operational factors. GAMs were selected because of their ability to represent complex nonlinear relationships under spatially and temporally heterogeneous environmental conditions. The modeling procedure included data preparation and integration, specification of response and explanatory variables, model formulation, multicollinearity assessment, model selection, and model evaluation. The fisheries, biological, and environmental datasets were harmonized before analysis. The modeling framework incorporated yellowfin tuna responses, oceanographic variables, and fishing operational factors, with fork length representing the biological size response and catch representing the production response. Thus, the final FG-ETP model used catch as the response variable, with fishing effort incorporated as a log-transformed offset [log(EFFORT)]. CPUE and FPI-standardized CPUE were not used as response variables in the GAM. Catch was selected as the production response because it represents the realized fishing production, while the effort offset accounts for differences in fishing intensity among observations. This specification allows the model to estimate relative production potential while accounting for variation in fishing effort. The use of fisheries-dependent observations may introduce sampling bias because fishing activity can be concentrated in areas perceived as productive. This potential bias was not completely eliminated in the present study; therefore, the FG-ETP results were interpreted as relative production potential associated with observed

fishing activity rather than as unbiased estimates of environmental habitat suitability. The general form of the GAM was expressed using Eq. 6 (Hastie *et al.,* 1986; Wood, 2006; Simpson, 2024):

$$g(\mu_i) = \beta_0 + \sum_{k=1}^{p} s_k(X_{ik}) \quad (6)$$

Where: g(μi) is the link function relating the expected value of the response variable to the predictors, β0 is the model intercept, sk(X_{ik}) is the smoothing function for the k-th covariate, X_{ik} is the value of the k-th covariate for observation i, and p is the number of covariates included in the model. The additive formulation allows each covariate to contribute partially to the response without assuming a predetermined linear relationship (Hastie *et al.,* 1986; Wood, 2006; Simpson, 2024). Smoothing functions were applied to continuous variables to represent potentially non-linear relationships between predictors and responses, whereas categorical variables were included as factors without smoothing. The smooth functions allowed the models to identify nonlinear relationships and potential threshold-like changes in the responses across the observed ranges of the oceanographic variables. The relationships were evaluated from the estimated smooth terms, effective degrees of freedom (edf), test statistics, p-values, and partial-effect plots. Interaction terms were not systematically tested in the present study; therefore, the models were interpreted primarily as additive relationships among the selected predictors. The predictors included SST, Chl-a, SSS, SSH, fishing year, fishing month, fishing gear, fishing location, and vessel capacity, depending on the response variable being modeled. Multicollinearity among explanatory variables was assessed using the variance inflation factor (VIF), with VIF values below 5 considered indicative of no substantial multicollinearity. The fisheries and environmental datasets were checked for consistency in variable definitions, units, spatial and temporal coverage, and data completeness before fitting the GAMs. Environmental values were examined against their observed ranges, and biological measurements were checked for consistency with the recorded measurement units and observed length range. Candidate models were compared using Akaike's information criterion (AIC), cumulative deviance explained (CDE), where available, statistical significance, and ecological relevance (Mammel *et al.,* 2022; Gang *et al.,* 2023; Owiredu *et al.,* 2024). The best-supported model was selected based on the lowest AIC, higher explanatory performance, and adequate statistical and ecological support. Spatial and temporal autocorrelation were not explicitly tested or modeled in the present analysis; therefore, potential dependence among observations may remain and could affect parameter uncertainty and model performance. The modeling was implemented in R using the Mixed GAM Computation Vehicle (mgcv) package. The significance of smooth terms was evaluated using estimated degrees of freedom, reference degrees of freedom (Ref.df), test statistics, and p-values. Model diagnostics included assessment of residual patterns and model assumptions to evaluate model adequacy and reliability. Model adequacy was evaluated primarily using AIC, CDE, statistical significance of model terms, and examination of model residual patterns. The selected models were further interpreted based on the edf, Ref.df, test statistics, and p-values of the smooth terms. Given that the objective of the GAM analysis was to identify non-linear relationships between the response variables and environmental and fishing operational factors, the evaluation focused on model fit, explanatory performance, and residual patterns rather than on incorporating additional correlation structures.

Integration of FG-ETS and FG-ETP models

The outputs of FG-ETP and FG-ETS models were integrated to link yellowfin tuna production potential with fish-size suitability over the same periods. The FG-ETP model was used to characterize fishing-ground potential based on predicted yellowfin tuna production, whereas the FG-ETS model was used to characterize the

biological dimension based on monthly estimated marginal means (EMMs) of FL. Monthly EMMs of FL were estimated separately for each reference fishing gear, with other covariates and model terms accounted for according to the fitted FG-ETS model specification. The EMMs were not averaged across fishing gears, but were calculated separately to compare the predicted monthly FL patterns among the reference fishing gears. The EMM estimates were presented with 95% confidence intervals to indicate the uncertainty around the estimated monthly FL for each reference fishing gear. The integration was conducted temporally because the biological size data did not have spatial coverage equivalent to the fishing logbook data. Therefore, fish-size information was integrated according to the corresponding month rather than being spatially overlaid with the production predictions. A scoring approach was used to combine fishing-production potential and biological size suitability into a composite indicator. The normalized INDEX FG values ranged from 0 to 1 and were classified into three equal-interval categories: Low (0–0.33), Medium (0.34–0.66), and High (0.67–1.00), with scores of 1, 2, and 3, respectively. These thresholds were based on equal-interval classification of the normalized INDEX FG rather than on quantiles, natural breaks, standard deviations, or biological criteria. The FG-ETS biological output was classified according to the monthly EMMs of FL relative to the maturity-based threshold of 99 cm FL. Months with EMMs of FL < 99 cm were classified as below the maturity-based threshold and assigned a score of 1, whereas months with EMMs of FL ≥ 99 cm were classified as at or above the maturity-based threshold and assigned a score of 3. The binary scoring scheme was used to distinguish months below and at or above the maturity-based threshold, consistent with the objective of identifying periods in which the observed mean fish size was at or above the estimated maturity-based threshold. The score was applied to the monthly EMM rather than to individual fish, so the classification represents the average biological size condition of the monthly landings. The scoring criteria used for the two model outputs are presented in Table 2 (Criteria and scores for integration of FG-ETP and FG-ETS). The scores from the two models were then summed to obtain the total integrated score using Eq. 7 (Siregar *et al.,* 2026):

$$S_{total} = S_{FG-ETP} + S_{FG-ETS} \quad (7)$$

Where: Stotal is the total integrated score, SFG-ETP is the production-potential score, and SFG-ETS is the biological-size suitability score. The resulting total scores were used to classify fishing-ground status into three categories: Less Potential (2–3), Potential (4), and Highly Potential (5–6). The quantitative distinction among the categories was based on the predefined scoring scheme rather than on additional statistical significance testing. FG-ETP scores of 1, 2, and 3 represented Low, Medium, and High relative production potential, respectively, while FG-ETS scores of 1 and 3 represented fish sizes below and at or above the 99 cm maturity-based threshold, respectively. The total score therefore ranged from 2 to 6, with Potential corresponding to a total score of 4 and Highly Potential corresponding to scores of 5–6. Ecologically, Highly Potential represented periods combining relatively higher production potential with a biological size condition at or above the maturity-based threshold, whereas Potential represented a lower production-potential category while the biological size condition remained at or above the threshold. The classification of fishing-ground status based on the integrated score is presented in Table 3 (Classification of fishing-ground status based on the integrated score) (Syah *et al.,* 2020; Siregar *et al.,* 2026). A Less Potential fishing ground indicates that production potential and fish-size suitability do not simultaneously support fishing activity. A Potential fishing ground indicates a moderately favorable combination of production and biological suitability, whereas a highly potential

Table 2: Criteria and scores for integration of FG-ETP and FG-ETS

Indicator	Category	Score
FG-ETP	Low	1
	Medium	2
	High	3
FG-ETS	FL < 99 cm	1
	FL ≥ 99 cm	3

Table 3: Classification of fishing-ground status based on the integrated score

Total score	Fishing-ground status
2–3	Less Potential
4	Potential
5–6	Highly Potential

fishing ground represents high production potential supported by fish sizes that have reached the maturity-based threshold. The temporal integration was conducted for each month and subsequently interpreted according to the four monsoonal seasons. The resulting monthly status was used to strengthen the interpretation of fishing-ground potential by incorporating biological information into production-based fishing-ground assessment. Thus, the integrated approach identifies fishing periods not only according to production potential but also according to the biological suitability of the yellowfin tuna caught.

RESULTS AND DISCUSSION

Environmental and biological variability

The waters of West Sumatra exhibited pronounced spatial and temporal variability in oceanographic conditions during 2019–2024, with distinct characteristics among the coastal waters of West Sumatra, the Mentawai Islands, and the offshore waters of the Indian Ocean. Such variability is important for yellowfin tuna because oceanographic conditions influence habitat suitability, productivity, and the distribution of pelagic fish (Safruddin *et al.,* 2022). SST ranged from 29.37 to 30.45 degrees Celsius (°C), with relatively cooler conditions during the Northwest Monsoon. Temperatures increased during the First Transition Season and subsequently declined toward the Second Transition Season. The highest SST occurred in May, indicating that the First Transition Season represented the main warming phase of the study area (Fig. 2). Chl-a ranged from 0.21 to 0.43 milligrams per cubic meter (mg/m³), with concentrations increasing toward September–November (Fig. 3). SSS ranged from 33.29 to 33.87 practical salinity units (psu), with the highest values occurring during July–August (Fig. 4). SSH ranged from 0.46 to 0.59 meters (m) and reached its highest values during the First Transition Season before declining toward the Second Transition Season (Fig. 5). Spatially, the environmental parameters also showed clear differences among the coastal waters, the Mentawai Islands, and offshore waters (Figs. 2–5). Relatively higher SSH values during the First Transition Season extended across the coastal waters and much of the Mentawai Islands. Lower values became more widespread toward the offshore Indian Ocean during the Second Transition Season (Fig. 5). These spatial gradients reflect differences in water-mass characteristics and surface-ocean dynamics across the study region. The combined variation of SST, Chl-a, SSS, and SSH indicates that the study area comprises heterogeneous environmental conditions that vary systematically among seasons and regions. Such variability provides an ecological basis for the spatial and temporal responses of yellowfin tuna and supports the use of nonlinear environmental modeling (Wiryawan *et al.,* 2020; Wu *et al.,* 2022). Biological observations comprised 8,771 yellowfin tuna measured during 2019, 2020, and 2024. The FL frequency distributions for the three years are presented in Fig. 6, while the comparison of length-frequency distributions among years is shown in Fig. 7. The overall mean FL was 127.58 ± 19.64 cm, with annual mean FL values of 123.95 cm in 2019, 134.07 cm in 2020, and 131.23 cm in 2024. The size distributions were generally unimodal and dominated by medium- to large-sized individuals, with relatively few small fish. However, the dominant size class shifted among years, from 110–120 cm in 2019 to 140–150 cm in 2020 and 130–140 cm in 2024.

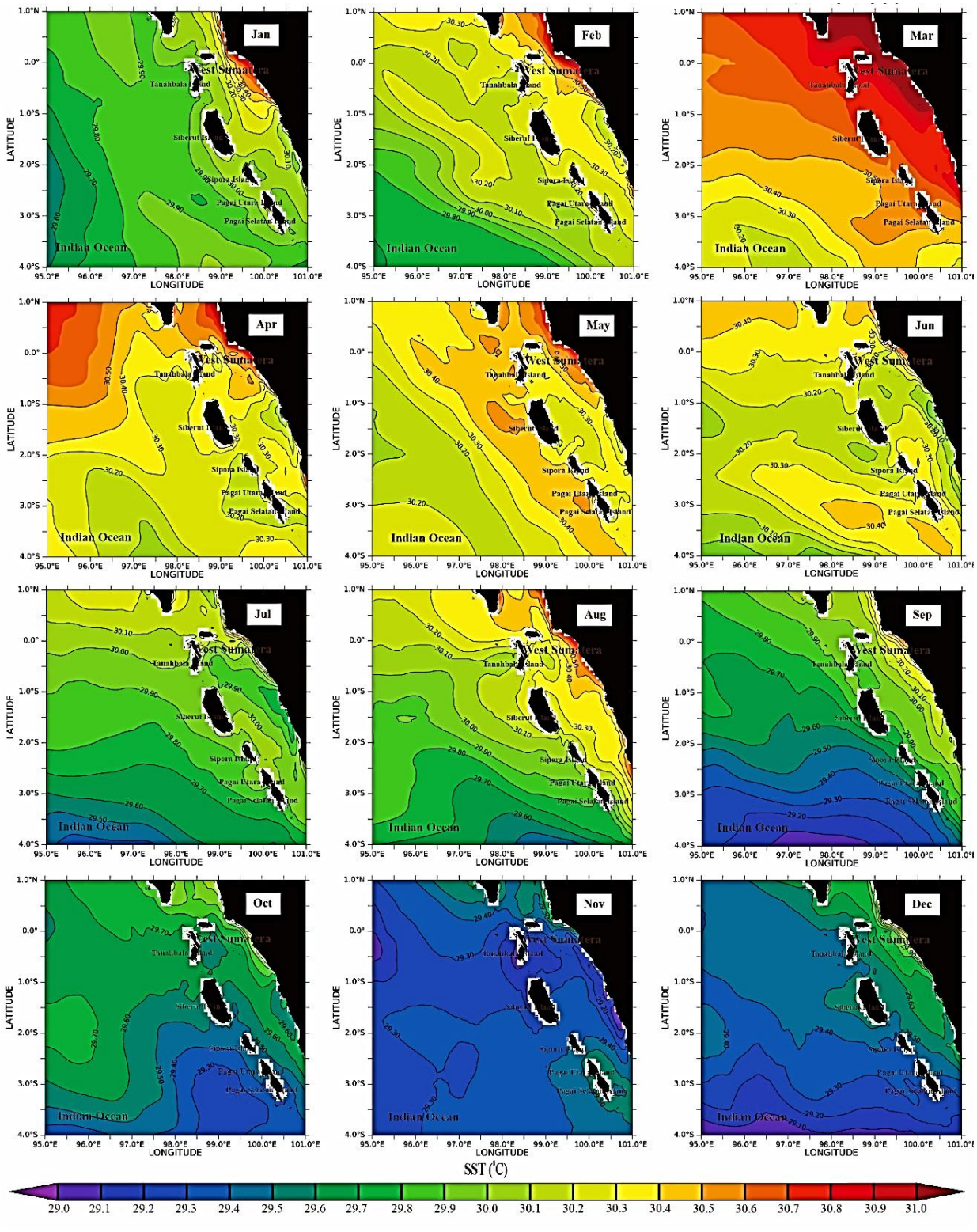

Fig. 2: Spatial distribution of SST based on monthly-averaged values aggregated over the period 2019, 2020, and 2024 in the waters of West Sumatra

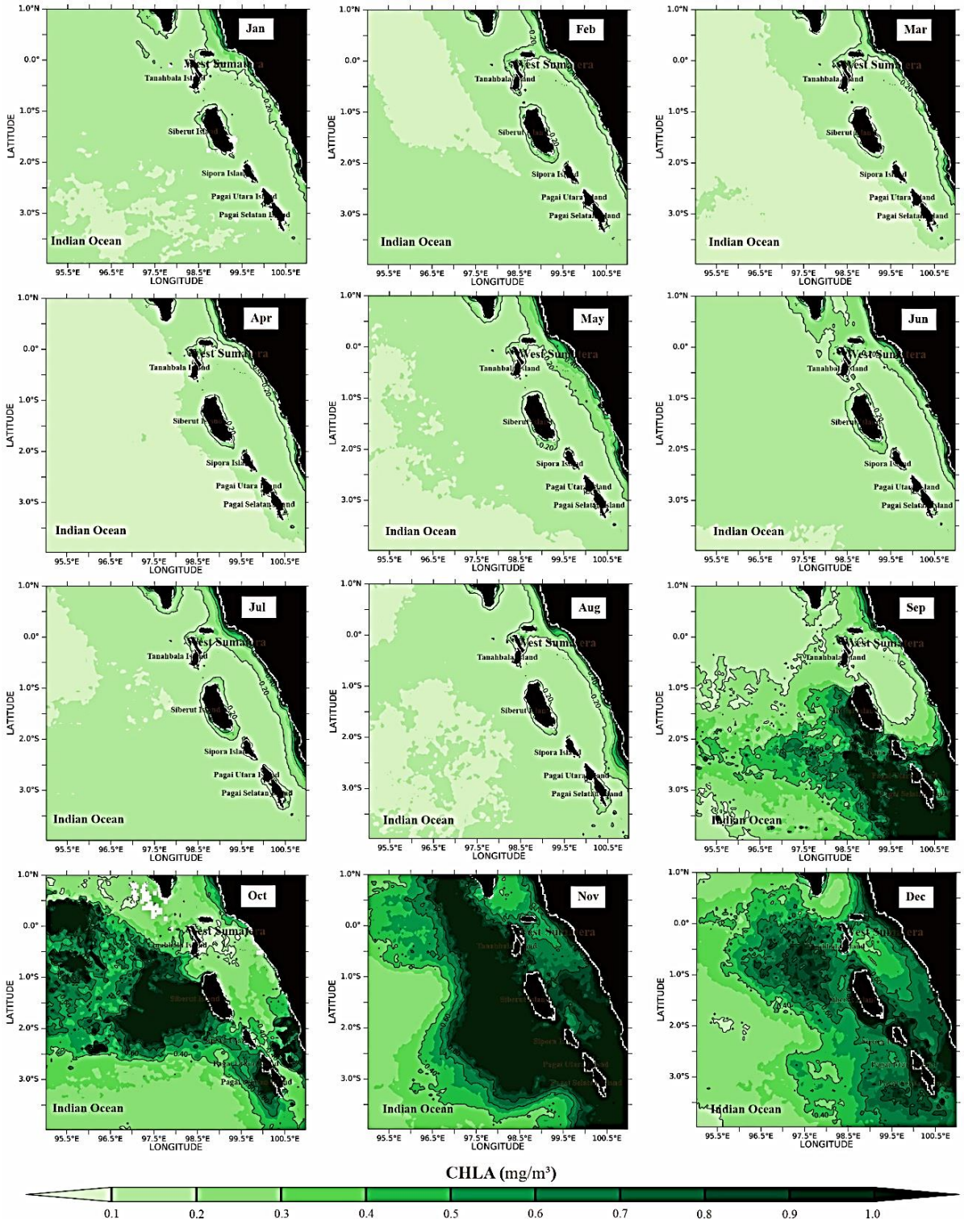

Fig. 3: Spatial distribution of multi-year monthly-averaged chlorophyll-a (2019, 2020, and 2024) in the waters of West Sumatra

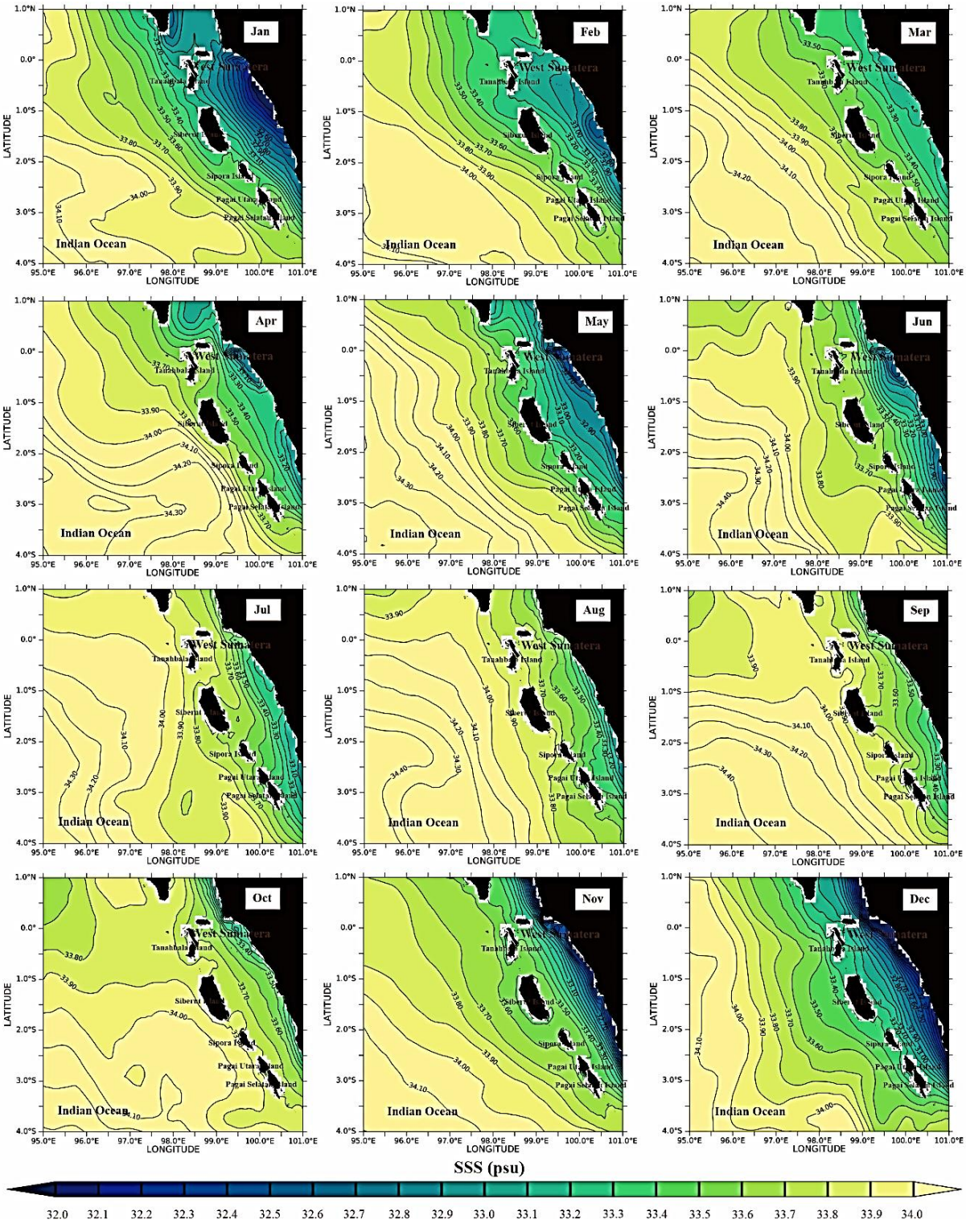

Fig. 4: Spatial distribution map of multi-year monthly-averaged sea surface salinity (2019, 2020, and 2024) in the waters of West Sumatra

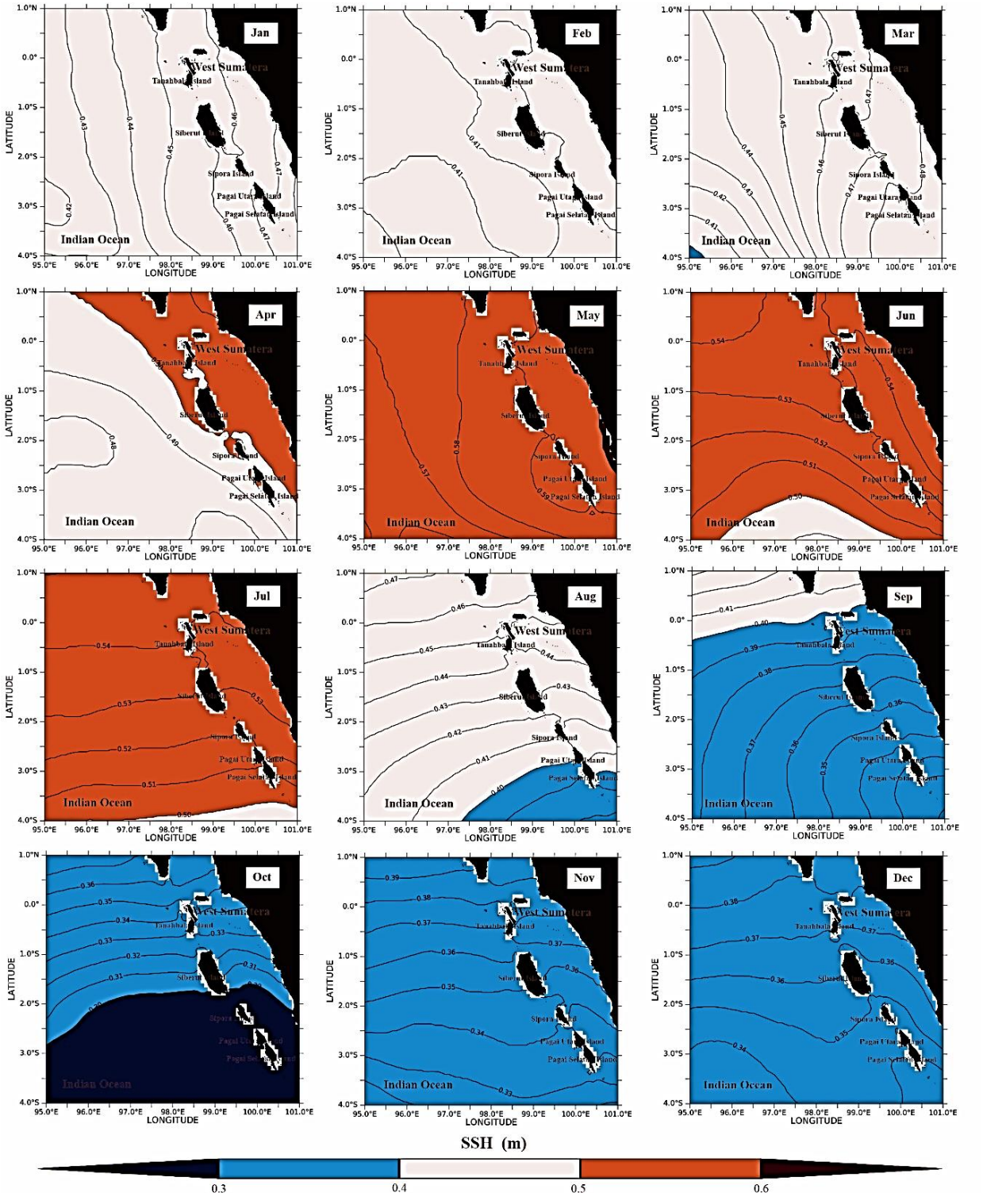

Fig. 5: Spatial distribution map of multi-year monthly-averaged sea surface height (2019, 2020, and 2024) in the waters of West Sumatra

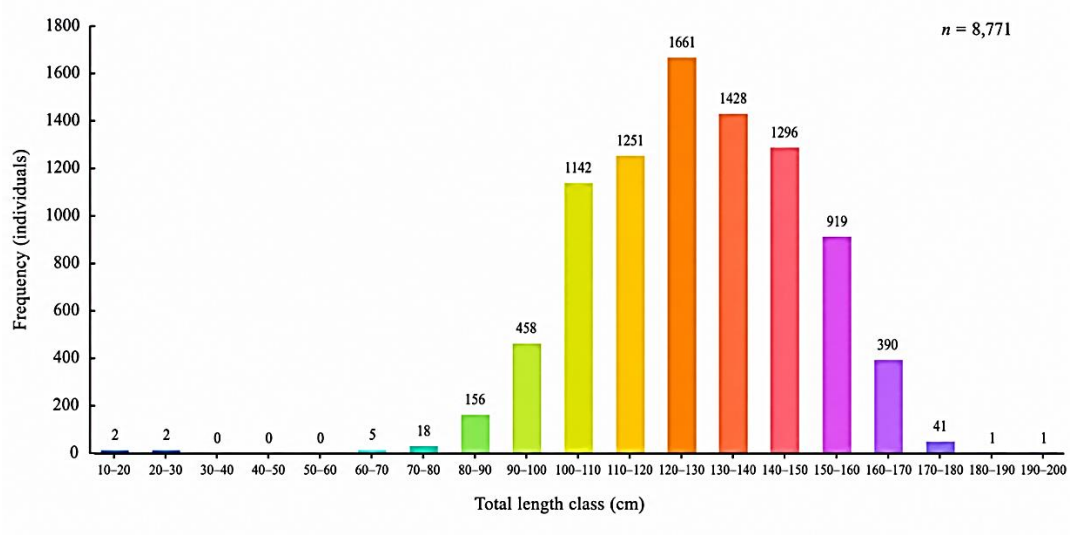

Fig. 6: FL frequency distribution of yellowfin tuna in 2019, 2020, and 2024

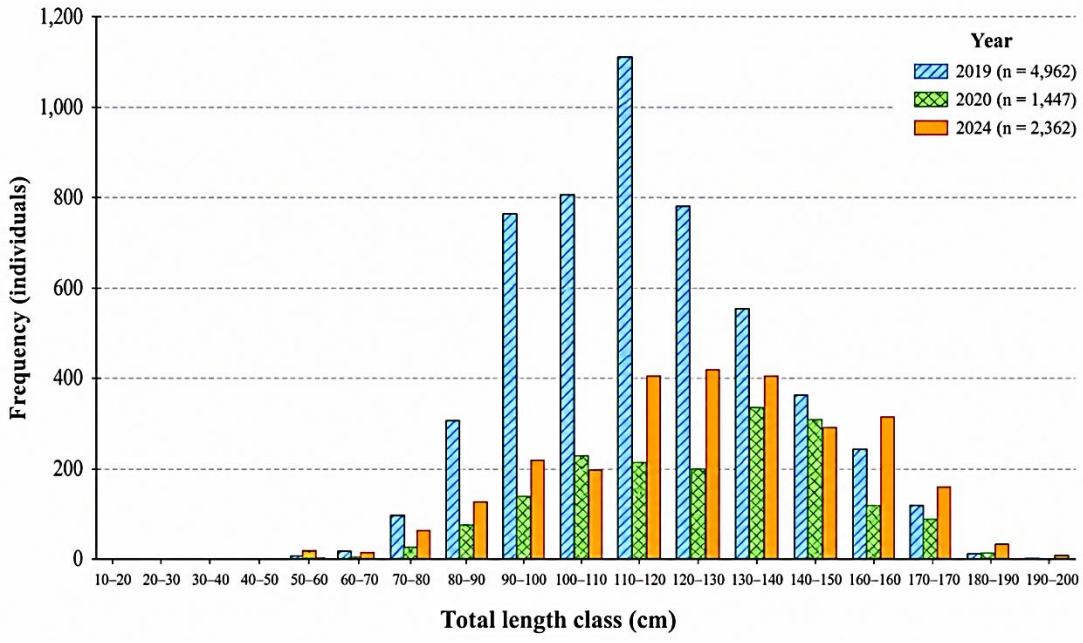

Fig. 7: Comparison of yellowfin tuna FL frequency distributions among years

This pattern indicates temporal variation in catch size structure while maintaining an overall dominance of medium- to large-sized fish. The biological parameters and estimated maturity-based threshold are summarized in Table 4. The estimated Lm,0.95 was 98.63 cm FL and was operationally rounded to 99 cm FL. Based on this maturity-based threshold, 8,207 individuals, representing 94 percent (%), were at or above the threshold, whereas 564 individuals (6%) were below the threshold (Fig. 8). The high proportion

Table 4: Biological parameters and estimated length at first maturity (Lm) of yellowfin tuna

Parameter	Value
Number of individuals (N)	8,771
Lmax (cm)	193
L∞ (cm)	203.16
Lm (cm)	98.63 (rounded to 99)

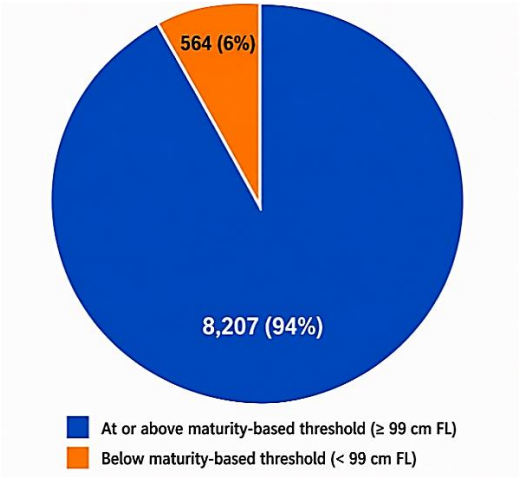

Fig. 8: Size composition of yellowfin tuna above and below the maturity-based threshold based on pooled data from 2019, 2020, and 2024

of fish at or above the maturity-based threshold indicates that sampled landings were predominantly composed of individuals meeting the selected criterion. However, this reflects only landing size composition and does not indicate stock sustainability, spawning biomass, fishing mortality, or recruitment status. Fish length provides an important indicator of size structure and growth stage (Hutubessy *et al.,* 2021; Ostman *et al.,* 2023). The 99 cm threshold, derived from estimated length at first maturity, was used to distinguish fish at or above the maturity-based threshold from those below it. Mean FL varied among gears, ranging from approximately 127 cm for tuna handline to 132 cm for troll line, 129 cm for purse seine, and 130 cm for tuna longline. The proportion of harvest-suitable fish ranged from 93.2% to 97.1%, suggesting that fishing technology contributed to variation in catch size composition, consistent with the role of gear selectivity in pelagic fish populations (Pechon *et al.,* 2022; Orbesen *et al.,* 2025). Overall, oceanographic variability represents the environmental dimension of fishing potential, while fish size provides a biological criterion for harvest suitability. These results provide the basis for subsequent GAM analysis of production and biological responses to environmental and fishing operational factors.

Environmental modeling using GAMs

The GAM analysis demonstrated that yellowfin tuna production and fish size were associated with a combination of environmental, temporal, spatial, and fishing operational factors rather than with a single predictor. The models incorporated SST, Chl-a, SSS, and SSH, together with fishing year, fishing month, fishing gear, GT, and spatial information. This combination is relevant because yellowfin tuna is a highly mobile pelagic species whose distribution and catch may vary with changing environmental conditions and fishing operations (Siregar *et al.,* 2018; Wu *et al.,* 2022; Vaihola *et al.,* 2023). Two response dimensions were evaluated to provide complementary information for fishing-ground assessment. Yellowfin tuna catch represented the production dimension, whereas FL represented the biological size dimension. These response variables describe different aspects of fishing-ground suitability because high production potential does not necessarily indicate that the fish present are biologically suitable for harvest, while favorable fish-size conditions alone do not indicate high fishing productivity. The VIF assessment for the FG-ETP model is presented in Table 5. The VIF values for the continuous covariates ranged from 1.12 to 3.03, with the lowest value observed for X4 (1.12) and the highest for X7 (3.03). All numerical

Table 5: Variance inflation factor (VIF) for the FG-ETP model

Code	Model Variable	VIF	Interpretation
X1	Fishing technology	1.26	No multicollinearity
X2	Fishing technology	2.64	Low multicollinearity
X3	Fishing technology	–	Categorical variable
X4	Fishing technology	1.12	No multicollinearity
X5	Fishing technology	1.30	No multicollinearity
X6	Environmental parameter	1.71	No multicollinearity
X7	Environmental parameter	3.03	Low multicollinearity
X8	Environmental parameter	2.58	Low multicollinearity
X9	Environmental parameter	1.78	No multicollinearity
X10	Fishing technology	1.20	No multicollinearity

Note: Y1 represents the response variable in the FG-ETP model. X3 is a categorical variable and therefore is not presented with a numerical VIF value like continuous covariates.

VIF values were below the threshold of 5, indicating no substantial multicollinearity among the continuous predictors used in the FG-ETP model. X3 was retained as a categorical predictor and therefore was not assigned a numerical VIF value. The relatively low VIF values indicate that the predictors provided relatively distinct information for explaining variation in yellowfin tuna production and support their joint inclusion in the GAM. Low multicollinearity is important because strong linear relationships among predictors can reduce estimation stability and complicate the interpretation of individual covariate contributions (Siregar, 2026). The candidate GAMs developed for yellowfin tuna production and fish size are presented in Table 6 and Table 7, respectively. The comparison of candidate models showed that retaining the environmental and fishing operational predictors generally improved model performance. For both response variables, removal of predictor terms resulted in higher AIC values and lower CDE values within the respective candidate-model comparisons. The selected models therefore retained the predictor combinations that provided the strongest statistical and ecological support for explaining yellowfin tuna production and fish size. Among the four candidate models, Model 1 was selected as the best-supported production model, with the lowest AIC (155,482.9) and highest CDE (11.5%). Sequential removal of predictors increased AIC and reduced CDE, indicating that the complete predictor structure provided the strongest performance. The selected model incorporated temporal, spatial, environmental, and fishing operational predictors and identified significant effects of the spatial smooth s(X4, X5), SSH, GT, SSS, SST, and Chl-a on yellowfin tuna production. The spatial smooth indicated spatial heterogeneity in production, while the environmental variables and GT reflected associations with oceanographic conditions and fishing operational capability. The partial-effect plots showed predominantly nonlinear relationships between the predictors and yellowfin tuna production (Fig. 9). Fishing year, month, and gear showed distinct responses, while the spatial smooth reinforced the spatial variation identified by the model. Chl-a, SST, SSH, and SSS also exhibited nonlinear responses across their observed ranges, with Chl-a varying rather than increasing continuously with production. SST also showed a curved response, indicating that yellowfin tuna production was associated with a range of thermal conditions rather than a simple linear increase. SSH and SSS similarly showed changes in the magnitude and direction of their partial effects across the observed ranges. These patterns support previous findings that yellowfin tuna responses are associated with interacting environmental gradients rather than a single environmental optimum (Siregar *et al.,* 2018; Wu *et al.,* 2022; Vaihola *et al.,* 2023). The partial effect of GT was also nonlinear, indicating that production did not increase proportionally across the entire range of GT. Production increased over

Table 6: Candidate GAMs for yellowfin tuna production

Model	Candidat model	Family	Link	AIC	CDE (%)
1	Y1 ~ X1 + X2 + X3 + s(X4, X5) + s(X6) + s(X7) + s(X8) + s(X9) + s(X10)	Negative Binomial (θ = 0.875)	log	155,482.9	11.5
2	Y1 ~ X1 + X2 + X3 + s(X4, X5) + s(X6) + s(X7) + s(X8) + s(X10)	Negative Binomial (θ = 0.871)	log	155,533.4	11.1
3	Y1 ~ X1 + X2 + X3 + s(X4, X5) + s(X6) + s(X7) + s(X10)	Negative Binomial (θ = 0.859)	log	155,714.4	9.98
4	Y1 ~ X1 + X2 + X3 + s(X4, X5) + s(X6) + s(X10)	Negative Binomial (θ = 0.857)	log	155,746.7	9.67

Note: Y1 = yellowfin tuna catch; X1 = fishing year; X2 = fishing month; X3 = fishing gear; X4 = longitude; X5 = latitude; X6 = Chl-a; X7 = SST; X8 = SSH; X9 = SSS; X10 = vessel capacity (GT); s(·) = smooth function; CDE.

Table 7: Candidate GAMs for yellowfin tuna fish size

No.	Pilihan model	Family	Link	AIC	CDE (%)
1	Y2 ~ X1 + X2 + X3 + X4 + s(X5) + s(X6) + s(X7) + s(X8) + s(X9)	Poisson	log	77,913.73	28.74
2	Y2 ~ X1 + X2 + X3 + X4 + s(X5) + s(X6) + s(X7) + s(X8)	Poisson	log	78,022.46	28.29
3	Y2 ~ X1 + X2 + X3 + X4 + s(X5) + s(X7) + s(X8)	Poisson	log	78,260.55	27.35
4	Y2 ~ X1 + X2 + X3 + X4 + s(X5) + s(X7)	Poisson	log	78,631.90	25.91
5	Y2 ~ X1 + X2 + X3 + X4 + s(X5)	Poisson	log	79,127.56	24.01

Y2 = yellowfin tuna FL; X1 = fishing year; X2 = fishing month; X3 = fishing gear; X4 = fish-size category; X5 = GT; X6 = SSH; X7 = Chl-a; X8 = SST; X9 = SSS; s(·) = smooth function; CDE = cumulative deviance explained.

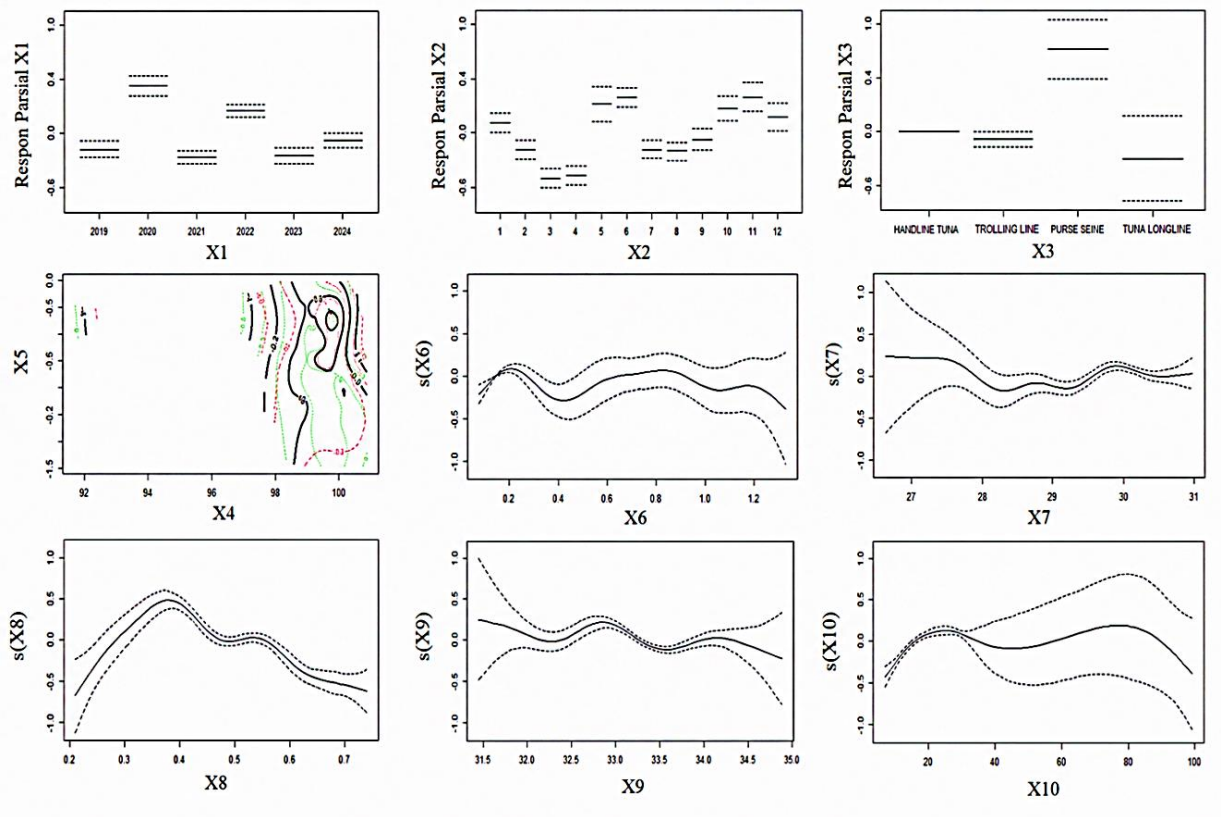

Fig. 9: Partial effects of environmental and fishing operational factors on yellowfin tuna production (Y_1) in the FG-ETP model. X1 = fishing year; X2 = fishing month; X3 = fishing gear; X4 = longitude; X5 = latitude; X6 = Chl-a; X7 = SST; X8 = SSH; X9 = sea surface salinity (SSS); and X10 = vessel capacity (GT)

part of the observed GT range before declining at higher values. This pattern indicates that realized production varied nonlinearly across the observed GT range. The association with GT should be interpreted as an operational relationship rather than a causal effect, because GT may be related to other fishing characteristics, including fishing gear, vessel type, fishing location, and fishing effort. The contribution of spatial and environmental terms indicates that realized production was associated with variation in environmental conditions and fishing operations. This is consistent with the ecological interpretation that yellowfin tuna distribution is related to oceanographic variability, while realized catch additionally depends on how fishing activities are conducted within these environmental conditions. Similar interactions among environmental and operational factors have been reported for pelagic tuna fisheries (Hua *et al.,* 2025). Despite the influence of these predictors, the selected production model explained 11.5% of cumulative deviance. The relatively low CDE indicates that a substantial proportion of production variability remained unexplained. Yellowfin tuna catch may also be affected by prey availability, fish aggregation behavior, fishing decisions, changes in fishing intensity, and other environmental or operational variables not included in the model. Similar complexity has been reported in pelagic fisheries, where environmental variability alone does not fully explain variations in catch and fishing performance (Wang *et al.,* 2023). Therefore, predicted production should be interpreted as relative production potential rather than as a deterministic prediction of catch. A limitation of the present study is that prediction uncertainty and the stability of the spatial classification were not quantified using confidence or prediction intervals. Consequently, the stability of areas classified as high potential under uncertainty could not be directly assessed. Future studies should incorporate spatial prediction uncertainty and sensitivity analysis to evaluate the robustness of fishing-ground classifications and identify areas that remain consistently classified as high potential when prediction uncertainty is considered. The VIF assessment for the FG-ETS model is presented in Table 8. The VIF values for the continuous covariates ranged from 1.28 to 5.21, with the lowest value observed for X5 (1.28) and the highest for X8 (5.21). Most VIF values were below the threshold of 5, indicating no substantial multicollinearity among most continuous predictors. X3 and X4 were retained as categorical predictors and therefore were not assigned numerical VIF values. The relatively low VIF values indicate that most predictors provided relatively distinct information for explaining variation in yellowfin tuna FL. However, the VIF value of X8 (5.21) indicated moderate multicollinearity, which should be considered when interpreting its contribution to the FG-ETS model. Model 1 was selected as the best-supported biological model, with the lowest AIC (77,913.73) and highest CDE (28.74%). Sequential removal of predictors increased AIC and reduced CDE, indicating that the complete predictor structure provided the strongest model performance. The selected size model identified SSS, SSH, GT, Chl-a, and SST as important predictors of yellowfin tuna FL, indicating associations with water-mass characteristics, surface-ocean dynamics, productivity, and thermal conditions (Wu *et al.,* 2022; Srioktoviana *et al.,* 2024). The partial-effect plots further demonstrated nonlinear relationships between fish size and the model predictors (Fig. 10). Fishing year showed differences in predicted FL among the observation years, while fishing month produced substantial variation across the annual cycle. These temporal effects indicate that the size structure of yellowfin tuna catches was not constant throughout the year or among observation years. Such variation may reflect changes in habitat use, movement, population composition, or the seasonal availability of different size groups. Fishing gear produced a pronounced difference in predicted FL**.** Handline, troll line, and purse seine showed relatively similar predicted fish sizes, whereas

Table 8: Variance inflation factor (VIF) for the FG-ETS model

Code	Model Variable	VIF	Interpretation
X1	Fishing technology	2.05	Low multicollinearity
X2	Fishing technology	4.82	Low multicollinearity
X3	Fishing technology	–	Categorical variable
X4	Fish biological factor	–	Categorical variable
X5	Fishing technology	1.28	No multicollinearity
X6	Environmental parameter	4.32	Low multicollinearity
X7	Environmental parameter	1.77	No multicollinearity
X8	Environmental parameter	5.21	Moderate multicollinearity
X9	Environmental parameter	2.03	Low multicollinearity

Note: Y2 is the response variable in FG-ETS; X3 and X4 are categorical variables and therefore have no numerical VIF values.

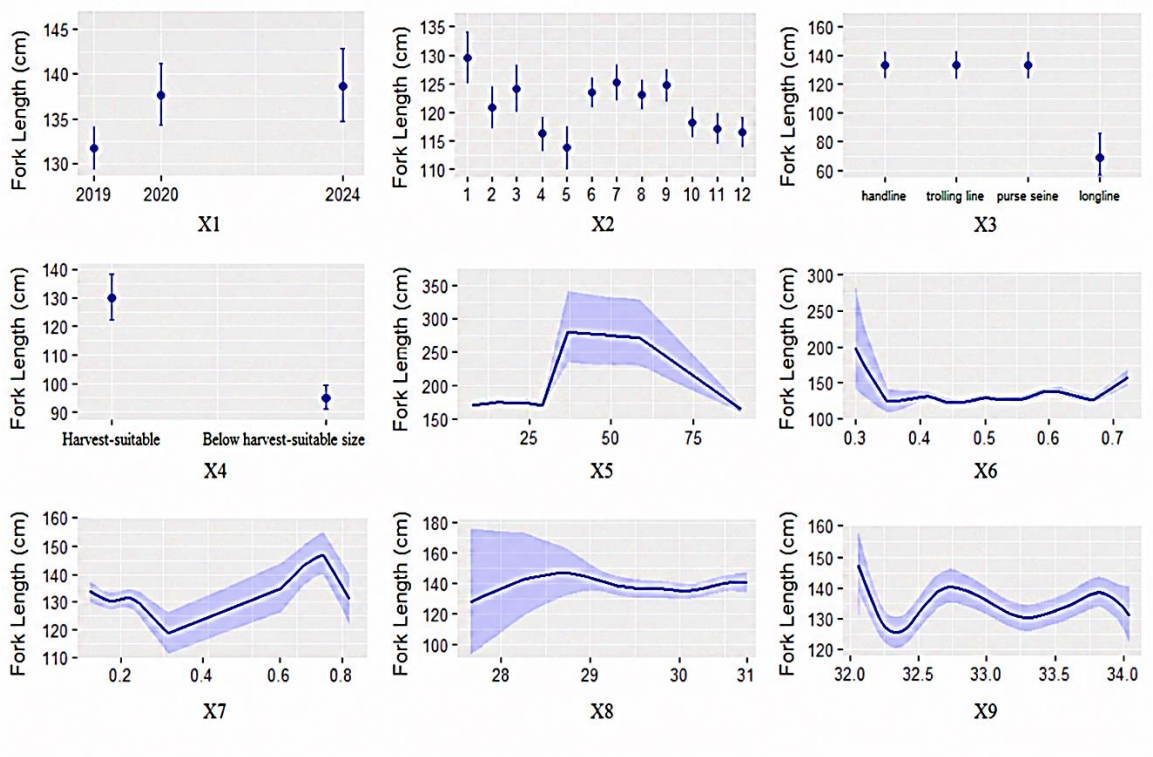

Fig. 10: Partial effects of biological, environmental, and fishing operational factors on yellowfin tuna fork length (Y_2) in the FG-ETS model. X1 = fishing year; X2 = fishing month; X3 = fishing gear; X4 = fish-size category; X5 = GT; X6 = SSH; X7 = Chl-a; X8 = SST; and X9 = SSS

tuna longline displayed a markedly lower response. The parametric results also showed different gear effects, including a positive coefficient for troll line and a negative coefficient for tuna longline relative to the reference gear. These findings indicate that fishing technology contributed to the size composition of the catch. Differences among gears may reflect variation in gear selectivity, fishing depth, fishing location, and operational strategy, consistent with previous evidence that gear characteristics influence the size structure of pelagic catches (Pechon *et al.,* 2022; Orbesen *et al.,* 2025). The fish-size category clearly distinguished predicted FL, with the harvest-suitable category showing substantially larger values than the below-harvest-suitable category. This distinction supports the subsequent fishing-ground integration based on the 99 cm FL maturity-based threshold. GT showed a nonlinear association with predicted FL, with fish size

increasing across part of the observed range before declining at higher vessel capacities. This relationship may reflect differences in fishing area, operational strategy, or gear characteristics associated with GT rather than a direct biological effect of vessel size. The environmental smooth terms also showed nonlinear responses. SSH initially declined before stabilizing, while Chl-a, SST, and SSS exhibited curved relationships with predicted FL across their observed ranges. These patterns indicate that fish size was associated with varying environmental conditions, consistent with the influence of thermal conditions, productivity, water-mass characteristics, and surface-ocean dynamics on habitat use and prey distribution. Ontogenetic differences may further influence the responses of different size groups (Srioktoviana *et al.,* 2024). The selected size model explained 28.74% of cumulative deviance within its candidate-model comparison. The remaining variation indicates that FL is also influenced by biological processes not explicitly included in the model, such as growth, population structure, movement, recruitment, and feeding ecology. The model should therefore be interpreted as describing relationships between environmental and operational factors and fish size rather than as a complete deterministic explanation of individual FL. Taken together, the two GAM analyses showed that yellowfin tuna production and fish size were associated with overlapping environmental, temporal, spatial, and fishing operational factors. The production model was designated FG-ETP, representing production potential, while the fish-size model was designated FG-ETS, representing biological suitability. Both responses showed nonlinear relationships with several predictors, supporting the use of GAMs. The complementary outputs of FG-ETP and FG-ETS provided the basis for subsequent spatial-temporal assessment and integration of production potential with biological size suitability. The spatial and temporal distribution of fishing-ground potential based on FG-ETP predictions is presented in Fig. 11. Because these predictions were not independently validated against withheld observations or an external dataset, they should be interpreted as model-based relative production potential rather than independently validated fishing-ground occurrence. Spatial or temporal cross-validation was not conducted and should be incorporated in future research to assess predictive performance and classification robustness. Spatially, moderate to high potential areas were predominantly concentrated around the Mentawai Islands and adjacent coastal waters, whereas offshore western areas generally showed lower potential. Temporally, fishing-ground potential varied among months. During the West Monsoon, relatively high potential areas occurred in December, followed by a reduction in January and February. During the First Transition Season, higher potential was particularly evident in March, while the distribution became more spatially variable in April and May. During the East Monsoon, moderate to high potential areas were more evident from June to August, particularly around the Mentawai Islands and adjacent waters. During the Second Transition Season, relatively high potential areas were again observed in September, followed by a gradual reduction in October and November. These spatial and temporal patterns indicate that yellowfin tuna fishing-ground potential was not uniformly distributed but varied according to the seasonal environmental and fishing conditions represented in the FG-ETP model. The concentration of predicted potential fishing grounds around the Mentawai Islands suggests that this region may provide relatively favorable conditions for yellowfin tuna production. The temporal shifts in predicted fishing-ground distribution indicate that fishing-area suitability varies throughout the annual cycle. However, the predicted values represent model-based relative production potential rather than deterministic fish abundance or definitive fishing-ground classifications, as FG-ETP explained only 11.5% of cumulative deviance and was not independently validated against withheld or external observations. Spatial or

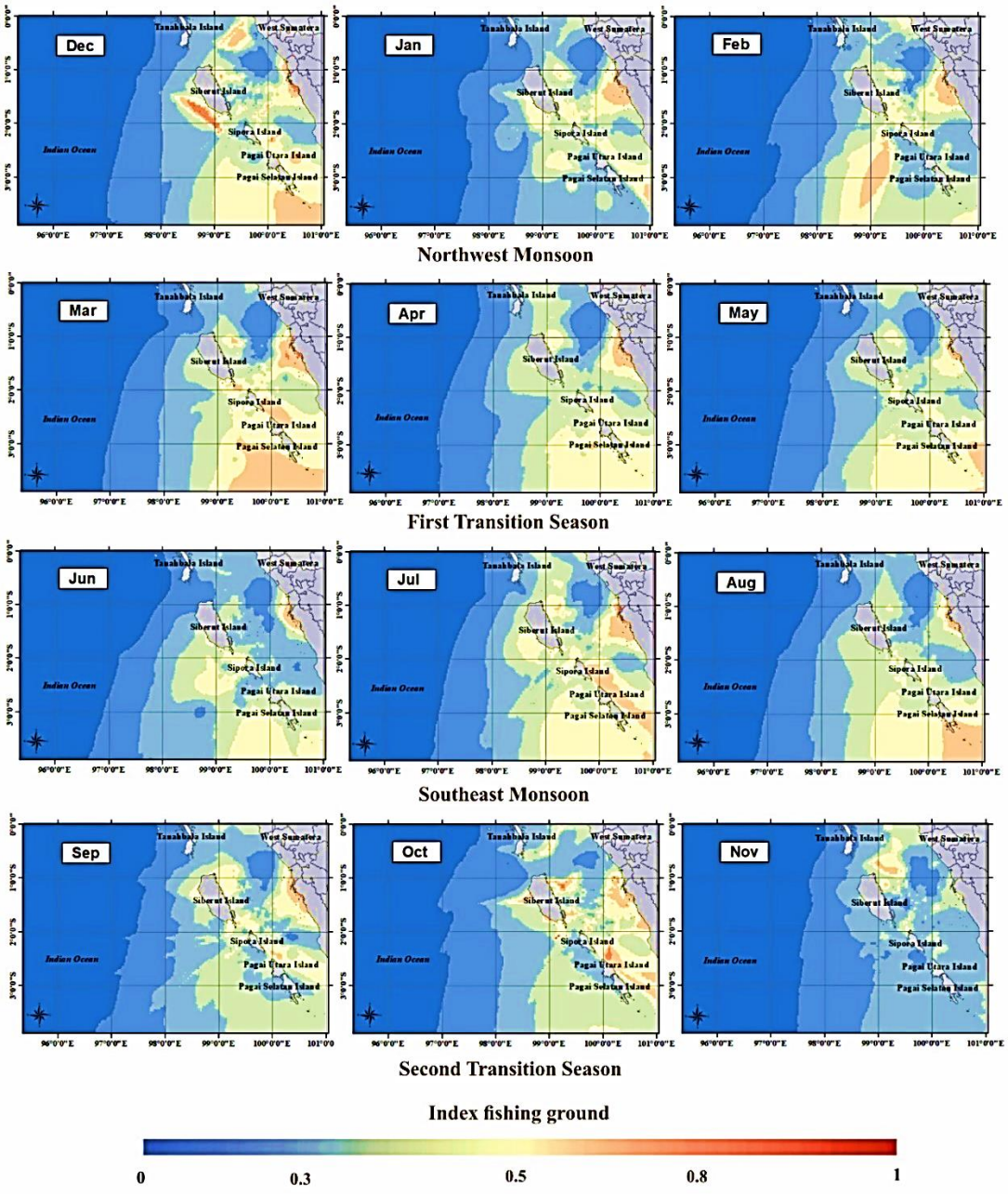

Fig. 11: Spatial and temporal distribution of yellowfin tuna fishing-ground potential based on predictions from the FG-ETP model in the waters of West Sumatra

temporal cross-validation was not conducted, and prediction uncertainty was not quantified; therefore, the generalizability and stability of the spatial classifications remain uncertain, particularly in unsampled areas. The estimated marginal means (EMMs) of yellowfin tuna fork length (FL) from FG-ETS varied among months and reference fishing gears (hand line tuna, pancing tonda, purse seine, and tuna longline), with confidence intervals indicating uncertainty in the estimates (Fig. 12). The temporal pattern was generally similar across gears: FL was relatively

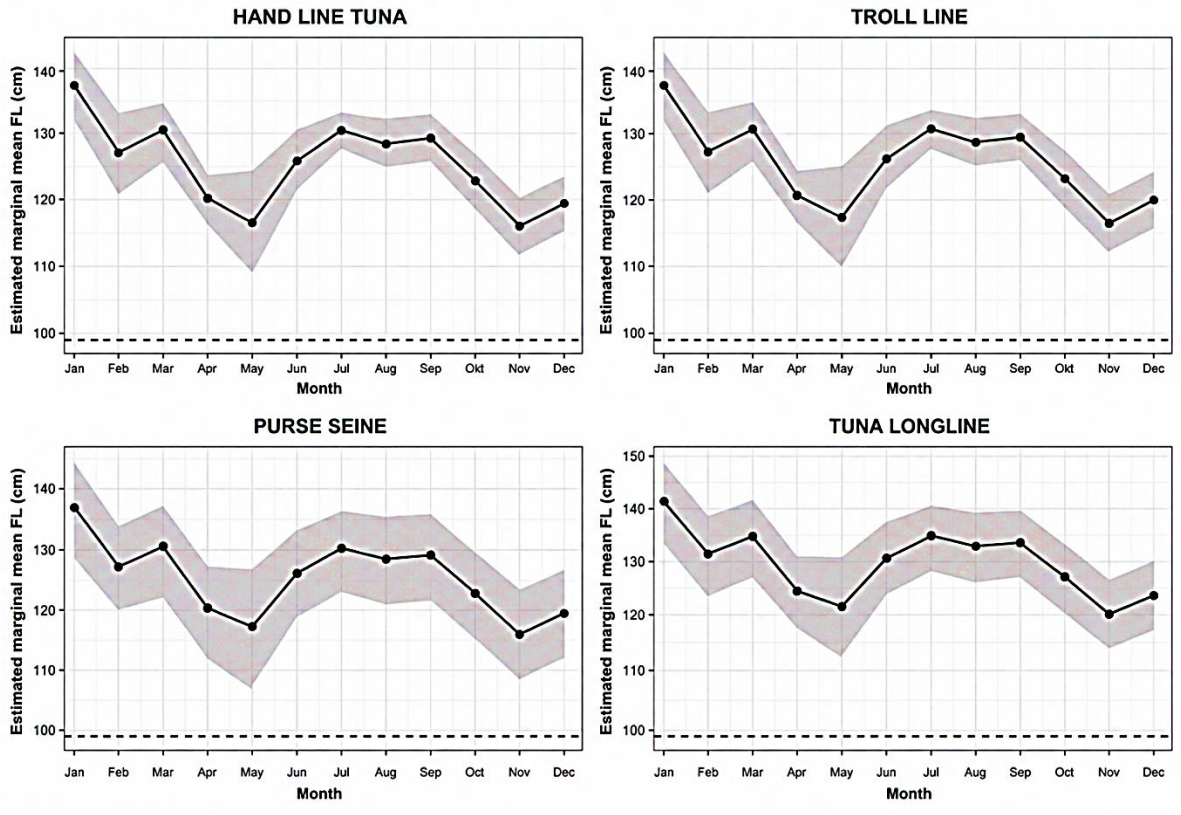

Fig. 12: Monthly estimated marginal means of fork length (FL) of yellowfin tuna based on the FG-ETS model for four reference fishing gears. The shaded areas represent confidence intervals, and the dashed line indicates the 99 cm FL maturity-based threshold

high in January, decreased in February, increased in March, declined during April–May, increased from June to September, and declined again during October–November before a slight increase in December. During the West Monsoon, January showed the highest estimated FL (approximately 136–141 cm), followed by lower values in February (127–132 cm); December remained slightly higher than the November minimum but below January.

Temporal integration of fishing-ground production potential and biological size suitability

The temporal integration of FG-ETP and FG-ETS combined yellowfin tuna production potential with the biological size condition on a monthly basis. The biological observations were obtained at the landing port and were not associated with fishing coordinates equivalent to those recorded in the fisheries logbook. Therefore, the integration was performed temporally rather than through direct spatial overlay. The study did not quantitatively evaluate spatial agreement or mismatch between FG-ETP production potential and the FG-ETS biological size condition. Instead, the integration compared the two dimensions at the monthly temporal scale, with FG-ETP representing relative spatial production potential and FG-ETS representing the biological size condition of landed yellowfin tuna. Consequently, the integrated categories represent temporal correspondence between production potential and biological size condition rather than direct spatial overlap. The integrated results showed that fishing-ground status varied among months, whereas the biological size component remained consistently high throughout the study period overall (Table 9).

Table 9: Temporal integration of FG-ETP and FG-ETS for yellowfin tuna fishing-ground status

Season	Month	FG-ETP category	Score	FG-ETS category	Score	Total score	Fishing-ground status
Northwest monsoon	December	High	3	High	3	6	Highly potential
	January	Medium	2	High	3	5	Highly potential
	February	Medium	2	High	3	5	Highly potential
First transition season	March	High	3	High	3	6	Highly potential
	April	Low	1	High	3	4	Potential
	May	Low	1	High	3	4	Potential
Southeast monsoon	June	Medium	2	High	3	5	Highly potential
	July	Medium	2	High	3	5	Highly potential
	August	Medium	2	High	3	5	Highly potential
Second transition season	September	Medium	2	High	3	5	Highly potential
	October	Low	1	High	3	4	Potential
	November	Low	1	High	3	4	Potential

Note: FG-ETS categories were determined from monthly EMMs of fork length (FL) relative to the 99 cm maturity-based threshold. All months were classified as high because the EMMs FL for the four reference fishing gears remained above 99 cm.

During the Northwest Monsoon, December was classified as Highly Potential, while January and February remained Highly Potential despite lower production-potential categories. During the First Transition Season, March was Highly Potential, whereas April–May were Potential. During the East Monsoon, June–August was consistently Highly Potential. In the Second Transition Season, September was Highly Potential, while October–November were Potential. As shown in Table 9, Highly Potential status occurred during December–March and June–September, when higher production potential coincided with fish sizes at or above the maturity-based threshold. April–May and October–November was classified as Potential because production potential was lower, while biological size remained above the threshold. Thus, temporal variation in integrated status was primarily associated with FG-ETP, whereas FG-ETS remained in the higher category throughout the evaluated months. The consistently high FG-ETS classification indicates that monthly EMMs of FL remained above the 99 cm maturity-based threshold. Although mean FL differed among sampling years, classification was based on monthly EMMs relative to the threshold rather than pooled individual observations. Therefore, the consistently high classification reflects the monthly mean size condition of the available observations and does not imply identical size distributions among years. Consequently, differences in integrated fishing-ground status were primarily associated with changes in FG-ETP production potential. This indicates that production potential varied seasonally even when the biological size condition remained favorable. The absence of the Less Potential category resulted from the consistently high biological suitability score, with 94% of sampled yellowfin tuna at or above the 99 cm maturity-based threshold. Thus, monthly changes between Highly Potential and Potential were primarily determined by FG-ETP production potential. The 94% proportion reflects the sampled landings and should not be interpreted as evidence of population-wide size structure or sustainable exploitation. The composite categories represent relative fishing-ground potential based on the predefined scoring framework and were not independently validated against fishing success or fisheries-management indicators. Highly Potential periods represented higher production potential coinciding with fish reaching the maturity-based threshold, whereas Potential periods had lower production potential despite suitable fish size. This integration adds a biological dimension to conventional fishing-ground assessment based on environmental suitability, catch, or fishing productivity and strengthens the interpretation of fishing potential

from a sustainability perspective (Hutubessy *et al.,* 2021; Ostman *et al.,* 2023). The combined assessment of production potential and fish size provides a more comprehensive basis for identifying fishing periods that are both productive and biologically appropriate.

Environmental and fisheries management implications

The results demonstrate that yellowfin tuna fishing grounds in the waters of West Sumatra are dynamic in both space and time and cannot be represented by a single permanent fishing zone. The relatively higher production potential observed around the Mentawai Islands and during specific periods, particularly December and March, indicates that environmental variability should be incorporated into adaptive fishing-ground management. Changes in SST, Chl-a, SSS, and SSH may alter environmental conditions and consequently influence the spatial and temporal patterns of modeled fishing production potential (Siregar *et al.,* 2018; Wu *et al.,* 2022; Hua *et al.,* 2025). The identified oceanographic conditions provide context for spatial and temporal variation in fishing-ground potential. Areas and periods with relatively higher FG-ETP production potential can be prioritized for fisheries monitoring and seasonal fishing planning, while the consistently high FG-ETS component provides a biological reference based on the 99 cm FL maturity-based threshold. Temporal integration therefore links environmental conditions, production potential, and fish-size composition, supporting management attention to relatively productive periods while maintaining size monitoring. However, these implications represent potential management applications rather than demonstrated effects because spatial predictions were not independently validated and biological observations were not spatially matched with fishing locations. The higher potential around the Mentawai Islands and during selected periods may reflect the combined statistical association of production with SST, Chl-a, SSS, and SSH, representing thermal conditions, productivity, water-mass characteristics, and surface-ocean dynamics. However, these relationships represent statistical associations rather than demonstrated causal mechanisms, and the low CDE of FG-ETP indicates that other factors contribute to the observed patterns. The integration of FG-ETP and FG-ETS indicates that fishing-ground assessment should consider both production potential and biological suitability. All evaluated months had fish sizes above the 99 cm FL maturity-based threshold, while differences in fishing-ground status were primarily associated with temporal changes in production potential. This approach distinguishes periods of relatively high production supported by biologically suitable fish from periods with lower production potential (Hutubessy *et al.,* 2021; Ostman *et al.,* 2023). From a fisheries management perspective, areas with higher FG-ETP potential can be prioritized for monitoring, while Highly Potential periods can support seasonal fishing planning. The 99 cm FL threshold provides a biological reference for monitoring landed yellowfin tuna. Areas with lower production potential should not automatically be considered unfavorable habitats because the model represents relative potential rather than deterministic catch. The relatively low CDE (11.5%) highlights the importance of prediction uncertainty; therefore, predicted fishing-ground patterns should be considered decision-support information rather than definitive representations of fish abundance or catch. The exclusion of additional environmental and habitat descriptors, including dissolved oxygen, ocean currents, mixed-layer depth, primary productivity, bathymetry, and prey-related variables, may have limited the representation of processes associated with yellowfin tuna distribution. These variables provide information not fully represented by SST, Chl-a, SSS, and SSH. Consequently, the identified patterns represent relative model-based associations within the selected predictor set rather than a complete representation of habitat

suitability. Future studies could incorporate additional physical, biological, and habitat descriptors with appropriate model comparison and validation. The scientific novelty of this study lies in integrating production potential and biological size with environmental and fishing operational information within a unified fishing-ground assessment framework. FG-ETP represents the spatial dimension of relative production potential, while FG-ETS represents the monthly biological-size dimension based on the maturity-based threshold; their integration evaluates whether higher production potential coincides with biologically suitable fish. This framework extends conventional assessments based primarily on environmental conditions or fishing production by combining four complementary dimensions: environmental conditions, fishing operations, production potential, and biological size. However, it remains an exploratory decision-support approach because biological observations were obtained from landings without spatial matching to fishing locations, and FG-ETP had relatively low explanatory performance. Future studies should incorporate longer time series, repeated biological sampling, climate-related indicators, and fishing-pressure measures using time-varying or spatiotemporal GAMs to strengthen fisheries assessment.

CONCLUSION

The study demonstrates that yellowfin tuna fishing-ground suitability in the waters of West Sumatra is associated with environmental variability, fishing operations, production potential, and biological size. Environmental conditions ranged from 29.37–30.45 °C for SST, 0.21–0.43 mg/m³ for Chl-a, 33.29–33.87 PSU for SSS, and 0.46–0.59 m for SSH. Among 8,771 measured fish, mean FL was 127.58 cm, with 8,207 individuals (94%) at or above the 99 cm FL maturity-based threshold, demonstrating the complementary value of biological size in fishing-ground assessment. The selected FG-ETP model identified spatial variation, SSH, GT, SSS, SST, and Chl-a as influential predictors of production, while FG-ETS identified SSS, SSH, GT, Chl-a, and SST as important predictors of FL, with temporal and fishing-gear effects also contributing. The nonlinear responses indicate that production and fish size were not proportionally related to individual predictors. FG-ETP and FG-ETS therefore provided complementary information for fishing-ground assessment. Their CDE values were 11.5% and 28.74%, respectively, indicating meaningful relationships but substantial unexplained variation. Consequently, the outputs should be interpreted as relative model-based patterns rather than deterministic estimates of fish abundance or catch, particularly in areas with limited observations where prediction uncertainty was not independently quantified. Relatively higher fishing-ground potential occurred more frequently around the Mentawai Islands and adjacent waters, while lower potential generally occurred offshore toward the west. Potential also varied seasonally, with relatively higher production potential particularly evident in December and March. These findings can support seasonal fishing planning and effort allocation, while the 99 cm FL maturity-based threshold provides a biological reference for monitoring landed fish size and supporting selective fishing practices. Temporal integration of FG-ETP and FG-ETS produced two fishing-ground statuses: Highly Potential and Potential. The absence of the Less Potential category resulted from the consistently high biological suitability component. Highly Potential periods combined relatively higher production potential with fish sizes above the 99 cm FL threshold, whereas Potential periods had lower production potential despite suitable fish size. This integration demonstrates the value of combining production potential with biological size in fishing-ground assessment. The findings support an adaptive and selective approach to fisheries management in the waters of West Sumatra. Fishing-ground management should

consider changing spatial and seasonal conditions rather than fixed fishing zones, while lower predicted potential should not automatically be interpreted as unfavorable habitat because of the relatively low CDE of FG-ETP. Other factors, including prey availability, fish aggregation, population structure, movement, recruitment, and fishing decisions, may contribute to unexplained variation. Overall, the proposed framework extends conventional fishing-ground assessment by integrating environmental conditions, fishing operations, production potential, and biological size through complementary GAMs, providing a basis for identifying fishing periods according to relative production potential and biological harvest suitability while recognizing uncertainty in model-based predictions.

AUTHOR CONTRIBUTIONS

E.S.Y. Siregar, the corresponding author, conceptualized the study, conducted data processing and analysis, developed the GAMs, prepared the maps and figures, interpreted the results, and prepared the manuscript. D. Simbolon supervised the research, contributed to the study design and methodology, and critically reviewed the manuscript. R.I. Wahju contributed to the fisheries methodology, data interpretation, and manuscript review. I. Yulianto contributed to fisheries data analysis, interpretation of the results, and manuscript review. V.P. Siregar contributed to spatial analysis and interpretation of fishing-ground distribution. T.A. Pianto contributed to data analysis and interpretation. Rosmasita contributed to data processing and manuscript review. M.S. Sangadji contributed to fisheries data analysis and interpretation. F. Andika contributed to data processing and analysis. R.A. Mulyadi contributed to data processing and interpretation. M.Y.U. Putra contributed to data processing and manuscript review. Rasidi contributed to data processing and manuscript review. All authors reviewed and approved the final version of the manuscript.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. The authors also declare that no ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, duplicate publication and/or submission, or redundancy, are involved in this study.

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POSITIVE AI STATEMENT

During the preparation of this work, the author(s) have used Artificial Intelligence [ChatGPT] in order to language editing and proofreading. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

ABBREVIATIONS

%	Percent
°C	Degree Celsius
AI	Artificial intelligence
AIC	Akaike's information criterion
BPI	Indonesian Education Scholarship
C	Catch
CDE	Cumulative deviance explained
Chl-a	Chlorophyll-a concentration
cm	Centimeter
CMEMS	Copernicus Marine Environment Monitoring Service
CPUE	Catch per unit effort
E	Fishing effort
edf	Estimated degrees of freedom
EMMs	Estimated marginal means
FG-ETP	Fishing Ground–Environment, Technology, and Production
FG-ETS	Fishing Ground–Environment, Technology, and Size
FL	Fork length
FPI	Fishing power index
GAM	Generalized additive model
GT	Gross tonnage
kg	Kilogram
km	Kilometer
L∞	Asymptotic length
Lm	Length at first maturity
Lm,0.95	Length at which 95% of individuals reach maturity
Lmax	Maximum observed length
LPDP	Indonesia Endowment Fund for Education
m	Meter
mg/m³	Milligrams per cubic meter
mgcv	Mixed GAM Computation Vehicle
n	Number of observations
PSU	Practical salinity unit
R²	Coefficient of determination
Ref.df	Reference degrees of freedom
SD	Standard deviation
SSH	Sea surface height
SSS	Sea surface salinity
SST	Sea surface temperature
VIF	Variance inflation factor

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