

Environmental distribution patterns and sustainability assessment of mitre squid *Uroteuthis chinensis* in the waters of Bangka, Indonesia

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Manuscript received: 22 November 2025. Revision accepted: 12 May 2026.

Abstract. Ratnapuri VV, Sebayang MB, Rozaki MF. 2026. Environmental distribution patterns and sustainability assessment of mitre squid *Uroteuthis chinensis* in the waters of Bangka, Indonesia. *Biodiversitas* 27 (5): d270517. <https://doi.org/10.13057/biodiv/d270517>. The waters of Bangka were among the main mitre squid *Uroteuthis chinensis* production areas in Indonesia, but they showed signs of increased exploitation pressure that could affect stock sustainability. This study aimed to integrate the satellite-based Environmental Suitability Index and Maximum Sustainable Yield for mitre squid in Bangka, with a monthly distribution resolution that explicitly distinguished between productive and non-productive seasons. Satellite imagery data and catch landings were used for the period September 2024-August 2025, while the Maximum Sustainable Yield was estimated for the period 2020-2024. The weighting of environmental parameters in the Environmental Suitability Index (ESI) was conducted through Principal Component Analysis and Pearson Correlation. The results showed that the Environmental Suitability Index value had a strong and significant positive relationship with CPUE ($r: 0.838$; $p: 0.001$; $R^2: 0.6503$), with periods of moderate to high ESI values (≥ 0.4) being associated with increased CPUE (0.539-0.755 ton/trip), while low ESI values (< 0.4) were associated with low CPUE (0.017-0.552 ton/trip). On the other hand, sea surface temperature (29.558-30.848°C) and chlorophyll-a (0.279-0.375 mg m⁻³) did not show a significant linear relationship with CPUE, thus were interpreted as indicators of habitat conditions rather than direct drivers of productivity. The Maximum Sustainable Yield analysis showed that in 2023, production reached 9,157 tons, exceeding the Maximum Sustainable Yield estimate of 7,865 tons (16.43%), with an effort level of 65,513 trips, surpassing the Fopt of 35,800 trips (82.72%), thereby indicating potential fishing pressure. Overall, these findings affirmed that the multivariate approach based on the Environmental Suitability Index was more effective in representing habitat suitability and highlighted the importance of seasonally adaptive management. However, the interpretation of results and management recommendations in this study required further validation through long-term data and scenario-based implementation before operational application.

Keywords: Bangka Island, catch per unit effort, Environmental Suitability Index, Maximum Sustainable Yield, remote sensing

INTRODUCTION

Fishery resources play a strategic role in Indonesia's marine ecosystem, particularly in the waters of the Bangka Belitung Islands, Indonesia, which are intensively used for fishing. Data from the Sungailiat Nusantara Fisheries Port show that the total catch for January-April 2025 reached 1,278,694 kg, reflecting high exploitation pressure in this area (Kasmono 2025). The Bangka Belitung Islands are also one of the national centers for squid production, meeting export-quality standards. In 2020-2022, annual export growth averaged 14.7% (Sahiddin and Wahyono 2022). However, indications of overexploitation have begun to appear, marked by a 17.59% per year decrease in average production from 2010 to 2013 and a utilization rate reaching 115.94% of the Maximum Sustainable Yield (MSY) in 2010 (Oktariza et al. 2016). In addition to fishing pressure, oceanographic variability also affects fluctuations in catch volume by altering the distribution and availability of squid (Ariyanto et al. 2021).

Ecologically, squid catch production is greatly influenced by spatial-temporal dynamics controlled by seasonal oceanographic conditions (Bukhari et al. 2017). In

the waters of western Indonesia, at least three species of *Uroteuthis* have been identified, with *Uroteuthis chinensis* being the dominant species ecologically relevant to Bangka Waters (Zamroni et al. 2024). The distribution of *U. chinensis* at depths of 40-140 m is closely related to variations in sea surface temperature, chlorophyll a concentration, and salinity. Remote sensing studies show that the increase in *U. chinensis* catch correlates with sea surface temperatures of 22-29°C, chlorophyll-a concentrations of 0-0.3 mg m⁻³, and salinity levels of 32.5-34‰ (Wang et al. 2021). Similar findings in Indonesian waters indicate an optimal range for increased catch at sea surface temperatures of 29.5-30.5°C and chlorophyll-a concentrations of 0.4-0.6 mg m⁻³ (Puspito 2022; Puspito et al. 2022). Based on these findings, this study formulates the first hypothesis that the monthly dynamics of sea surface temperature and chlorophyll a within the optimal range will enhance the habitat suitability and expand the spatial distribution of *U. chinensis*. The short life cycle of *U. chinensis* (approximately ± 200 days) strengthens these hypotheses by enabling rapid population responses to environmental variability within an intra-annual timeframe (Liu et al. 2024). The peak catches, which generally occur

in the middle of the year, further indicate a close relationship between seasonal environmental dynamics and population response (Yunrong et al. 2013; Liu et al. 2024).

Although the relationships between oceanographic parameters and mitre squid distribution (Ningsih et al. 2018; Mondal et al. 2021), as well as stock estimates based on Maximum Sustainable Yield (Ramdhani et al. 2026), have been extensively studied, both are generally analyzed separately. That approach has not yet fully captured the rapid changes in habitat and stock utilization levels due to oceanographic variability. Several recent studies have shown that the habitat suitability index model effectively detects monthly changes in the distribution and quality of mitre squid habitats, with strong influence from oceanographic parameters (Liu et al. 2024; Yu et al. 2024). However, the integration of habitat suitability index results with Maximum Sustainable Yield remains limited, especially in Bangka Waters.

The integration of the Environmental Suitability Index (ESI) and Maximum Sustainable Yield at a monthly resolution is designed to test the hypothesis that months with high Environmental Suitability Index values reflect a combination of optimal surface water temperature and chlorophyll-a levels, and correlate with CPUE and stock utilization rates from Maximum Sustainable Yield (Tanaka and Makino 2023; Yu et al. 2024). Thus, the Environmental Suitability Index represents the ecological dimension, while the Maximum Sustainable Yield represents the bioeconomic dimension. The integration of both allows for simultaneous quantitative evaluation of environmental dynamics and stock status.

Research combining the monthly distribution of *U. chinensis* derived from remote sensing with stock sustainability analysis based on Maximum Sustainable Yield remains very limited in Bangka. Therefore, this study aims to integrate the Environmental Suitability Index derived from monthly-resolution satellite data with the Maximum Sustainable Yield approach to analyze mitre squid stock dynamics and quantitatively distinguish between productive and non-productive seasons. This spatial-temporal and bioeconomic framework is expected to serve as a scientific and operational basis for adaptive, sustainable management of the mitre squid in the waters of Bangka.

MATERIALS AND METHODS

Study area

This study was conducted in the waters of Bangka District, Bangka Belitung Province, Indonesia, over a period of one year, from September 2024 to August 2025, covering the four main seasonal phases in Indonesia, namely the second transition season (October–November), the west monsoon season (December–March), the first transition season (April–May), and the east monsoon season (June–September) (Suhery et al. 2023; Sopaheluwakan et al. 2024; Karnawati et al. 2025). The study area is situated geographically at coordinates $104^{\circ}21'15.12''$ – $108^{\circ}28'45.12''$ E and $00^{\circ}18'45''$ – $03^{\circ}48'45''$ S, as shown in Figure 1.

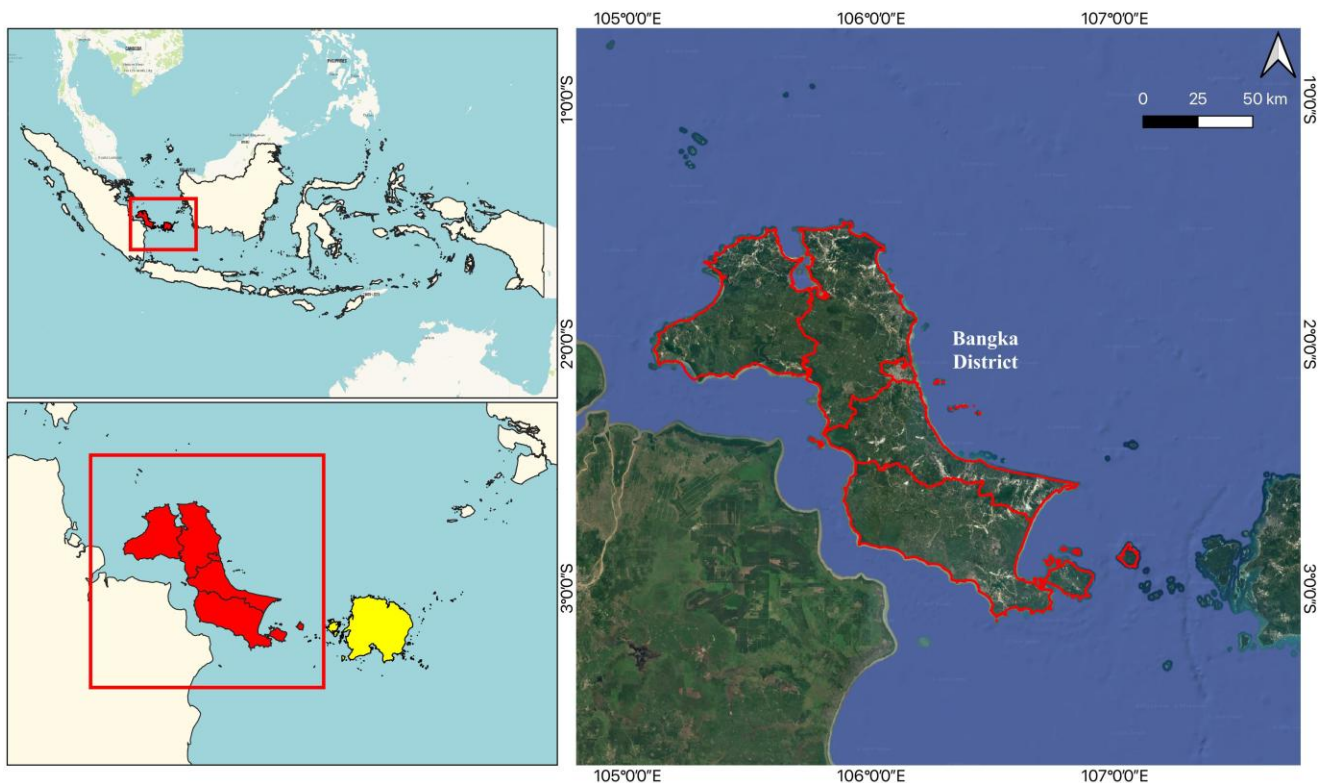


Figure 1. Research location map in Bangka District, Bangka Belitung Province, Indonesia

All spatial analyses were conducted using ArcGIS Pro version 3.4 (ESRI Inc.) with the Universal Transverse Mercator (UTM) Zone 48S projection system based on the WGS 84 datum (EPSG:32748). This projection system was selected to minimize spatial distortion in the southern equatorial region, thereby ensuring accurate distance and area measurements. All vector layers were reprojected using the Project tool, while raster layers were reprojected using the Project Raster tool. For resampling, bilinear interpolation was applied to continuous variables, while nearest-neighbor interpolation was used for categorical variables to maintain the integrity of the original pixel values.

Spatial resolution harmonization standardizes the entire dataset to an 8 km grid resolution as the reference for analysis. Data with initial resolutions of 25 km and 50-70 km are resampled to 8 km using bilinear interpolation, while the GEBCO v2023 bathymetry data (500-1000 m) is aggregated to 8 km resolution using the mean cell aggregation approach to avoid distortion of extreme depth values. Pixel position alignment is carried out through Snap Raster settings and raster extent adjustments to ensure uniformity of grid, origin, and cell size across layers.

Determination of the final study area through a sequential spatial overlay procedure that includes: (i) Limiting the area of Indonesia's ZEE and the administrative waters of Bangka District; (ii) Creating a 300 km buffer from the Sungailiat Nusantara Fisheries Port using the Buffer tool; (iii) Extracting depths ≤ 100 m using the Raster Calculator; (iv) Formation of the convex hull of catch points using Minimum Bounding Geometry; (v) The process of intersecting all layers to produce the final study polygon. All spatial operations are performed in the EPSG:32748 projections and documented in the geoprocessing workflow to ensure transparency and reproducibility of the analysis.

The mitre squid fishing activities in the study area involve an average of 356 fishing vessels, primarily those sized less than 10 GT. The fleet is dominated by small-

scale vessels (<10 GT) with a one-day fishing trip operation pattern. The main fishing gear is trolling lines that operationally target mitre squid, while fish caught by other gear constitute bycatch. The mitre squid production data analyzed in this study are expressed as wet weight (kg) and aggregated monthly to maintain consistency with the temporal resolution of the environmental variables.

Environmental and fishery data

This study obtained the environmental data presented in Table 1 from remote sensing products and oceanographic reanalysis, including sea surface temperature, chlorophyll a, salinity, nitrate, phosphate, silicate, wind, and water depth. All environmental data were extracted from the final study polygons to obtain monthly average values, enabling the researchers to directly link each catch location to the corresponding local oceanographic conditions, both spatially and temporally. This approach enables a more accurate, methodologically consistent analysis of the spatial and temporal distribution of mitre squid (Mammel et al. 2022).

The researchers addressed differences in spatial resolution in this study (8 km, 25 km, 50-70 km, and 500-1000 m) through a resolution harmonization process, in which they standardized the entire dataset to an 8 km spatial grid before analysis. The study resampled the data to a coarser resolution using bilinear interpolation. In contrast, GEBCO bathymetric data is aggregated to 8 km resolution using the mean cell aggregation approach to maintain the representation of average depth values. All raster's are aligned using Snap Raster settings and by equalizing extent and cell size to ensure spatial consistency between layers. Temporally, daily and 3-hour data are averaged into calendar monthly average values to align with the monthly mitre squid production data obtained from the Sungailiat Nusantara Fisheries Port and the Bangka Belitung Province Marine and Fisheries Department.

Table 1. Aquatic environment data from remote sensing and reanalysis products

Data type	Product name and version	Spatial resolution	Temporal resolution	Depth/Layer	Access date	Data source
Sea Surface Temperature (SST) (°C)	SST Copernicus, v2	8 km	Monthly (average from first to last day of calendar month)	Surface layer	09/12/2025	https://data.marine.copernicus.eu
Salinity (%)	Salinity Copernicus, v2	8 km	Monthly	Surface layer	09/12/2025	https://data.marine.copernicus.eu
Chlorophyll a (mg m ⁻³)	OC-CCI, v5	25 km	Monthly (daily data every 3 hours)	Surface layer	09/12/2025	https://data.marine.copernicus.eu
Nitrate (mmol m ⁻³)	Reanalysis Biogeochemical Copernicus, v3	25 km	Monthly (daily data every 3 hours)	Surface layer	09/14/2025	https://data.marine.copernicus.eu
Phosphate (mmol m ⁻³)	Reanalysis Biogeochemical Copernicus, v3	25 km	Monthly (daily data every 3 hours)	Surface layer	09/14/2025	https://data.marine.copernicus.eu
Silica (mmol m ⁻³)	Reanalysis Biogeochemical Copernicus, v3	25 km	Monthly (daily data every 3 hours)	Surface layer	09/14/2025	https://data.marine.copernicus.eu
Wind (m s ⁻¹)	NASA POWER, v8	~50-70 km	Monthly (average from daily hourly data)	Surface layer	09/19/2025	https://power.larc.nasa.gov/
Depth water (m)	GEBCO, v2023	500-1000 m	Static	Full water column	08/08/2025	https://www.gebco.net/

Remote sensing products and reanalysis data in this study undergo a preprocessing stage before analysis. The data preprocessing stages include:

Cloud masking

This step removes pixels identified as clouds or invalid based on satellite image quality flags. This study used SeaDAS version 9.2.0 with the level-2 quality flag. In this study, the chlorophyll a layer is significantly affected by cloud cover; therefore, the analysis excludes low-quality and high-cloud-probability pixels to minimize estimation errors. Conversely, other environmental parameters, such as sea surface temperature, salinity, and nutrients, do not require cloud filtering because they originate from reanalysis products or datasets that have undergone internal gap-filling processes by the data providers.

Temporal aggregation

The quality-filtered data is then averaged per pixel to reduce short-term variability (daily) and represent the dominant environmental conditions on a monthly scale relevant to mitre squid habitat dynamics.

Gap filling

For chlorophyll-a data with gaps due to cloud cover or limited coverage, the study performs spatial interpolation using the Inverse Distance Weighting (IDW) method in ArcGIS Pro version 3.4. The analysis applies IDW interpolation with a power parameter of 2, a minimum of 12 neighboring points, and a variable search radius to maintain the local spatial gradient. The interpolation's reliability underwent testing using leave-one-out cross-validation. The study calculates accuracy using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). An R^2 value >0.70 and relatively low RMSE indicate that the interpolation does not produce significant spatial deviation from the original observational data.

Reprojection

All environmental raster data underwent reprojection to the UTM Zone 48S coordinate system based on the WGS 84 datum (EPSG:32748) in ArcGIS Pro 3.4 to ensure spatial consistency between layers and compatibility with other reference maps.

Principal Component Analysis and Pearson Correlation

Principal Component Analysis was applied in this study as an exploratory multivariate method to reduce the dimensionality of correlated environmental data and to identify dominant variables contributing to system variability (Legendre and Legendre 2012; Jolliffe and Cadima 2016). The variables included in the Principal Component Analysis comprised Catch Per Unit Effort (CPUE), sea surface temperature, chlorophyll a, salinity, wind speed, nitrate, phosphate, and silicate. All Principal Component Analysis procedures were conducted using MINITAB software. Before analysis, all variables were standardized to ensure comparability across measurement

scales and to prevent dominance by variables with larger numerical ranges.

The sample comprised 12 monthly observations. The selection of the number of principal components was based on multiple criteria, including eigenvalues greater than one (eigenvalue >1) and the cumulative proportion of variance explaining the majority of data variability. Principal Component Analysis in this study was not intended to test causal relationships but rather to identify patterns of variability and structural relationships among environmental and fisheries-related parameters. Consequently, the Principal Component Analysis results were interpreted with caution, particularly given the high complexity and dynamic nature of marine oceanographic and fisheries systems (Planque and Arneberg 2018).

Pearson's correlation analysis was employed as a complementary parametric approach to evaluate linear relationships among variables identified by Principal Component Analysis. The correlation analysis was based on 12 monthly observations and selected for its suitability for quantifying the strength and direction of linear relationships between quantitative variables measured on interval or ratio scales. Although the underlying statistical assumptions were generally met, the relatively small sample size limited the analysis's inferential power. Therefore, correlation results were interpreted in an exploratory context. Pearson Correlation coefficients (r) range from -1 to $+1$, with values approaching ± 1 indicating strong linear relationships and values close to 0 indicating the absence of linear association (Schober et al. 2018).

Environmental Suitability Index and Geographic Information System

The Environmental Suitability Index was developed as an advanced analytical framework based on Principal Component Analysis results to integrate dominant environmental variables into a spatial index that represents the habitat suitability of mitre squid. The Environmental Suitability Index approach has been widely applied in cephalopod habitat studies to reduce the complexity of correlated multivariate environmental data and to identify key variables with the highest ecological relevance (Liao et al. 2018; Gao et al. 2023).

The results of the Principal Component Analysis in Table 3 show that Principal Component (PC)1 and PC2 together explain 73.7% of the total environmental variance. However, the Pearson Correlation analysis in Table 5 shows that neither PC1 nor PC2 is significantly correlated with catch per unit effort. In contrast, PC3 shows a strong and statistically significant correlation with CPUE (r : 0.869; $p < 0.01$). Therefore, it was chosen as the basis for determining the weighting scheme in the construction of the Environmental Suitability Index. The selection of variables for the Environmental Suitability Index is based on their loadings on PC3 and their direct ecological relevance to the habitat and availability of mitre squid.

The methodological success of this study lies in using principal components that do not dominate environmental variance but show the strongest association with biological response variables (CPUE) to weight the Environmental

Suitability Index. This approach allows the Environmental Suitability Index to reflect more functionally relevant ecological relationships than conventional methods, which typically rely on components that explain the most significant proportion of environmental variance. Based on these criteria, nitrate concentration, sea surface temperature, and chlorophyll a were selected as the main parameters for constructing the Environmental Suitability Index.

Each environmental parameter was converted into a single-parameter Suitability Index (SI) ranging from 0 to 1 using linear normalization (Xue et al. 2017), expressed as:

$$SI_i = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where, SI_i is the suitability index value at location i , X_i is the observed value of the environmental parameter at location i , X_{min} and X_{max} are the minimum and maximum values of that parameter in the study area, respectively. This transformation standardizes all parameters to the range 0-1, enabling comparison and aggregation across variables.

When the ecological optimum of a parameter is known, the suitability index is calculated using a Gaussian function to represent the nonlinear response of mitre squid habitat suitability to environmental gradients (Zhang and Thas 2016), expressed as:

$$SI_i = \exp \left[-\frac{(X_i - X_{opt})^2}{(2\sigma^2)} \right]$$

Where, X_{opt} is the ecological optimum value of the parameter, σ is the standard deviation that represents the ecological tolerance range of the species to that parameter, and exp indicates the natural exponential function. This formulation produces a maximum value (approaching 1) under optimal conditions and decreases symmetrically as the deviation from the optimal value increases.

The Environmental Suitability Index value is then calculated as a weighted linear combination of all SI values, with weights derived from the standardized loading value PC3:

$$ESI = \sum (w_i \times SI_i)$$

$$ESI = (0.46 \times SI_{Nitrat}) + (0.30 \times SI_{SST}) + (0.24 \times SI_{chl-a})$$

Where, w_i is the standardized weight of the i -th parameter obtained from the absolute loading value on PC3, with the condition that $(\sum w_i = 1)$ to maintain the mathematical consistency of the index.

Principal component analysis shows that nitrate has substantial loading on PC3 and is statistically significantly correlated with CPUE ($r: 0.869$; $p < 0.01$). However, before the final construction of the ESI model, additional diagnostic evaluations were conducted to avoid redundancy and model instability. The multicollinearity evaluation in this study is an additional statistical evaluation using the Pearson Correlation matrix (2-tailed), Variance Inflation

Factor (VIF), and Condition Index within the framework of multiple linear regression with CPUE as the dependent variable and all environmental parameters as predictors. The analysis results indicate substantial multicollinearity in the oceanography-nutrient system, as reflected by the maximum Condition Index value of 1006.719, which far exceeds the conservative threshold (>30). The VIF value for nitrate is 4.779, indicating moderate redundancy with other environmental variables, although it has not yet exceeded the classical threshold ($VIF > 10$). Furthermore, although nitrate shows a significant bivariate correlation with CPUE ($r: -0.658$; $p: 0.010$), its partial regression coefficient in the multiple model is not significant ($p: 0.638$). The difference between simple correlation and partial regression indicates that the variation explained by nitrates largely overlaps with that of other oceanographic variables, making its unique contribution to CPUE statistically unstable.

Based on these objective criteria, nitrate was removed from the final formulation of the Environmental Suitability Index to enhance model parsimony and numerical stability. Ecologically, nitrates also play an indirect role as a driver of primary productivity, as reflected in chlorophyll a. The weights of the remaining parameters are then renormalized so that the total weight remains equal to one ($\sum w_i = 1$), thus maintaining the mathematical consistency of the index. Thus, the Environmental Suitability Index is calculated by weighting sea surface temperature and chlorophyll a as follows:

$$w'_i = \frac{w_i}{\sum w_{remaining}}$$

$$ESI = (0.56 \times SI_{SST}) + (0.44 \times SI_{chl-a})$$

The Environmental Suitability Index produced represents the environmental suitability level of the study area for mitre squid habitats and is subsequently used in spatial analysis to interpret distribution patterns and seasonal dynamics of potential fish catches.

Maximum Sustainable Yield

The analysis of Maximum Sustainable Yield in this study uses the Gordon-Schaefer surplus production model, which utilizes total annual mitre squid catch (C , in tons) and fishing effort (E , in trips) over five years. The initial analysis step was carried out by calculating Catch Per Unit Effort (CPUE) using the equation (Zulghaffar 2019):

$$CPUE = \frac{C}{E}$$

The relationship between $CPUE$ (ton per trip) and fishing effort (E) is analyzed using simple linear regression based on the Gordon-Schaefer model formulation, where:

$$C = aE - bE^2$$

Where, the parameter a represents the theoretical CPUE level under zero exploitation conditions and b describes the

rate of productivity decline due to increased fishing pressure.

Considering the limited time series length ($n: 5$), the validity of the surplus production approach is evaluated not only based on the coefficient of determination (R^2) but also through statistical significance testing of the parameters, biological consistency of the parameter signs ($a > 0$ and $b > 0$), and residual diagnostic checks to ensure the fulfillment of regression assumptions. In addition, the standard error and 95% confidence interval were calculated and subsequently propagated into the estimation of optimal catch effort and Maximum Sustainable Yield using the delta method approach as a quantitative measure of uncertainty. This approach aligns with the practice of data-limited stock assessment, where the surplus production model is commonly used when only catch and effort data are available (Cousido-Rocha et al. 2022).

The optimal fishing effort value (f_{opt}) is obtained by differentiating the catch function with respect to fishing effort and setting it equal to zero, resulting in:

$$F = -\frac{a}{2b}$$

Next, the value of the Maximum Sustainable Yield is calculated by substituting the optimal fishing effort value into the catch equation, resulting in:

$$MSY = -\frac{a^2}{4b}$$

Where, a : Intercept, b : Slope, C : Catch (ton per year), E : Fishing effort (trips per year).

The data range used in this study is relatively short (five years), so the estimated Maximum Sustainable Yield should be understood as an initial picture of resource utilization conditions, not as a definitive biological limit. In this context, the Maximum Sustainable Yield serves as an initial reference point to help interpret utilization trends and support a more cautious, adaptive approach to fisheries management.

RESULTS AND DISCUSSION

Water parameter dynamics

The monthly average data of water parameters presented in Figure 2 show that sea surface temperature

ranges from 28.39-31.20°C, chlorophyll-a ranges from 0.26-0.38 mg m⁻³, salinity ranges from 31.89-32.55%, wind speed ranges from 2.02-4.45 m s⁻¹, nitrate ranges from 0.04-0.12 mmol m⁻³, silica ranges from 4.94-10.14 mmol m⁻³, and phosphate ranges from 0.01- 0.06 mmol m⁻³.

Figure 2.A shows that chlorophyll a appears relatively stable, with minor fluctuations, reflecting primary productivity conditions that remain relatively unchanged throughout the year. Wind speed shows a more dynamic pattern, with significant decreases in November 2024 and April 2025, followed by recoveries in January and July 2025. Meanwhile, sea surface temperature shows an opposite pattern to the wind. Sea surface temperature tends to rise when the wind weakens, as seen in November 2024 and May 2025. Sea surface temperature decreases again when the wind strengthens, for example, in January 2025-February 2025. Salinity is relatively constant, but it still shows small seasonal fluctuations, such as a slight increase from September to October 2024 and a decrease from May to August 2025.

The average environmental parameters in Table 2 show seasonal variations at different levels of significance. Sea surface temperature shows a statistically significant difference between seasons at a 95% confidence level ($F: 10.166$; $p: 0.004$). The highest sea surface temperature value was recorded during the first transition season at 30.681±0.598°C, while the lowest value occurred during the west monsoon season at 29.003±0.711°C. This condition indicates that water temperatures tend to be higher during the transition season compared to the monsoon season. The wind speed in this study showed a significant seasonal difference ($F: 6.790$; $p: 0.014$). The highest value occurred during the east monsoon season at 3.903±1.166 m s⁻¹, while the lowest value was recorded during the first transition season at 2.253±0.485 m s⁻¹. This pattern indicates that wind intensity increases during the monsoon period compared to the transition seasons.

Silicate concentration showed a significant difference in seasonal variation ($F: 5.704$, $p: 0.022$). The highest value was recorded in the First Transition Season at 9.418±9.065 mmol m⁻³, while the lowest value was found in the Second Transition Season at 5.267±4.744 mmol m⁻³. This variation indicates the dynamics of nutrient supply, which are likely influenced by water-mass mixing and monsoon dynamics. Meanwhile, the parameters of chlorophyll a, salinity, nitrate, and phosphate did not show significant differences between seasons ($p > 0.05$).

Table 2. Average environmental parameters per season

Parameter	Reference range	Second transition season (n: 2)	West monsoon season (n: 4)	First transition season (n: 2)	East monsoon season (n: 4)	ANOVA (F)	p-value (Sig)
SST (°C)	29.5-30.5 ^{a,b}	30.573±0.352	29.003±0.711	30.681±0.598	29.897±0.479	10.166	0.004
Chlorophyll-a (mg m ⁻³)	0-0.3 ^c	0.298±0.281	0.295±0.292	0.361±0.325	0.332±0.275	1.246	0.356
Salinity (%)	32.5-34 ^c	32.463±0.516	32.203±0.593	32.064±0.844	32.079±0.675	1.498	0.287
Wind Speed (ms ⁻¹)	2-5 ^{b,d}	2.502±0.665	3.643±0.984	2.253±0.485	3.903±1.166	6.790	0.014
Nitrate (mmol m ⁻³)	0.01-0.05 ^e	0.047±0.233	0.067±0.336	0.096±0.377	0.059±0.279	3.797	0.058
Phosphate (mmol m ⁻³)	0.02-0.05 ^e	0.048±0.022	0.043±0.020	0.0305±0.198	0.034±0.031	0.787	0.534
Silica (mmol m ⁻³)	5-10 ^{a,f}	5.267±4.744	5.855±4.225	9.418±9.065	7.634±6.599	5.704	0.022

Notes: a. Puspito et al. (2022), b. Puspito (2022), c. Wang et al. (2021), d. Cabanellas-Reboredo et al. (2012), e. Maishal (2024), f. Demuyneck et al. (2020)

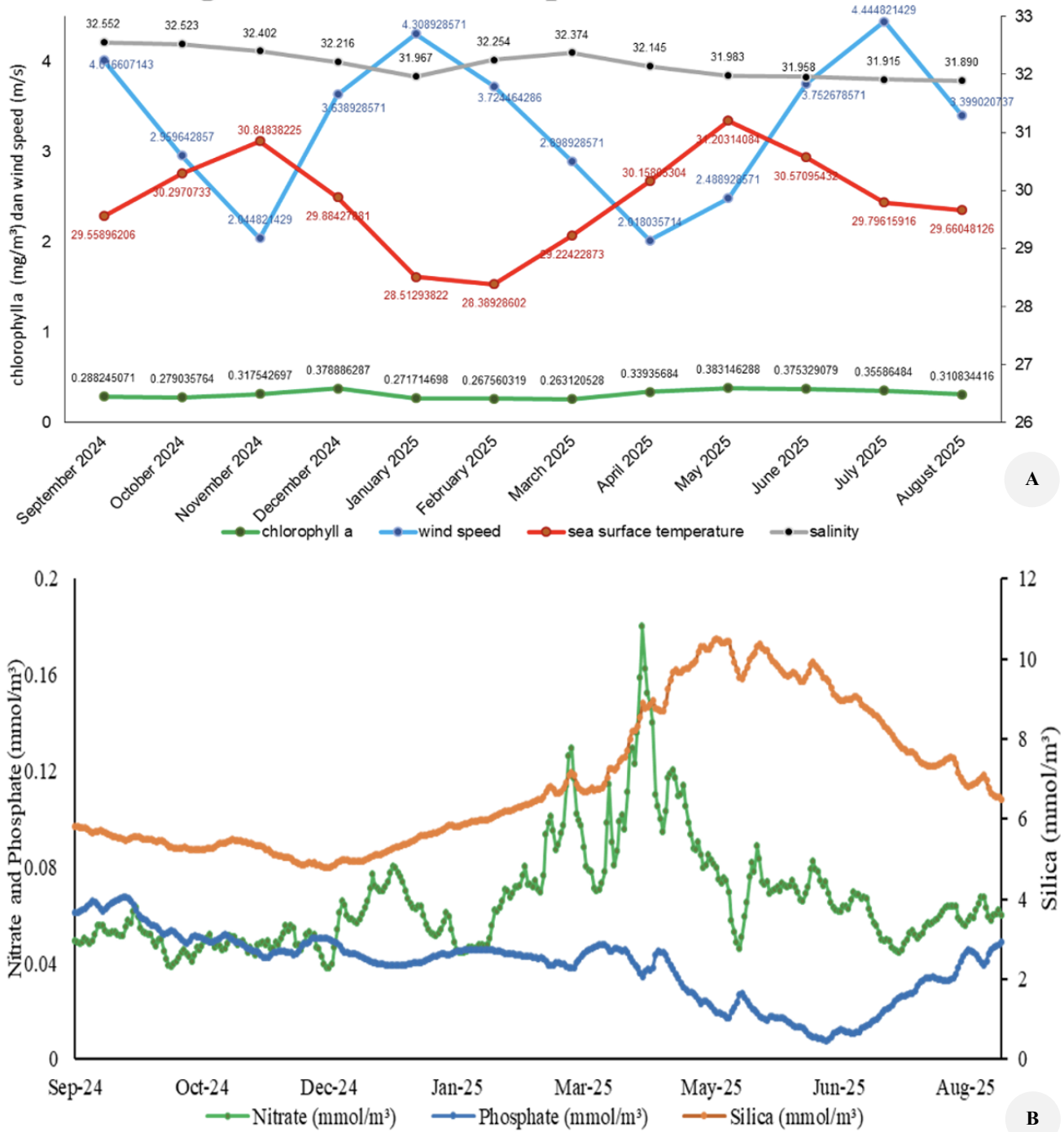


Figure 2. Water parameter data: A. Monthly averages of chlorophyll-a, wind, sea surface temperature, and salinity; B. Daily fluctuations in nitrate, phosphate, and silica)

The wind direction depicted in Figure 3 illustrates the seasonal influence on wind direction. In September-October 2024 and May-August 2025, the wind direction at the research location was consistently southwest. The southwest wind blowing from the sea toward the land of Bangka Island pushes the surface water mass toward the coast. Meanwhile, from November 2024 to April 2025, the wind direction is irregular, with the wind blowing north in November 2024, northeast in December 2024, south in January 2025, northeast again in February and March 2025,

and northwest in April 2025. The wind direction from November 2024 to April 2025 is predominantly blowing from the mainland of Bangka Island toward the sea.

Principal Component Analysis and CPUE-environment relationships

Based on the results of the Principal Component Analysis presented in Table 3 and Figure 4, the first three principal components have eigenvalues greater than 1, namely PC1 (3.4198), PC2 (1.7370), and PC3 (1.1576).

These three components cumulatively explain 90.2% of the total data variation, thus sufficiently representing the variance structure of the analyzed multivariate system. Principal Component Analysis in this context describes the relative relationships among oceanographic variables in a multivariate space, but it is not intended to measure the strength of bivariate linear relationships. To quantify the relationship between the multivariate structure and fishery dynamics, the scores of the three principal components were subsequently used as predictor variables in a linear regression analysis with CPUE as the dependent variable. This approach allows for a quantitative evaluation of each PCA component's contribution to explaining CPUE variation.

The first Principal Component (PC1) explains 48.9% of the total variation (Table 3). This component more accurately reflects the gradient in oceanographic conditions and water productivity, characterized by positive contributions from silica (0.494) and chlorophyll-a (0.443),

and negative contributions from phosphate (-0.484) and salinity (-0.384). This load structure indicates that PC1 primarily describes environmental variations related to nutrient availability and water characteristics, which form the background for general oceanographic conditions. The second Principal Component (PC2), which explains 24.8% of the total variation (Table 3). This component represents an oceanographic gradient primarily determined by the positive contributions of sea surface temperature (0.441) and salinity (0.444), as well as a substantial negative contribution from wind speed (-0.696). Additionally, nitrate and phosphate exhibit a moderate positive charge on PC2, while chlorophyll a and silica have minimal charges, suggesting their roles in shaping variation in these components are relatively limited. This loading pattern indicates that PC2 reflects a combination of physical water conditions related to atmospheric dynamics and water mass properties.

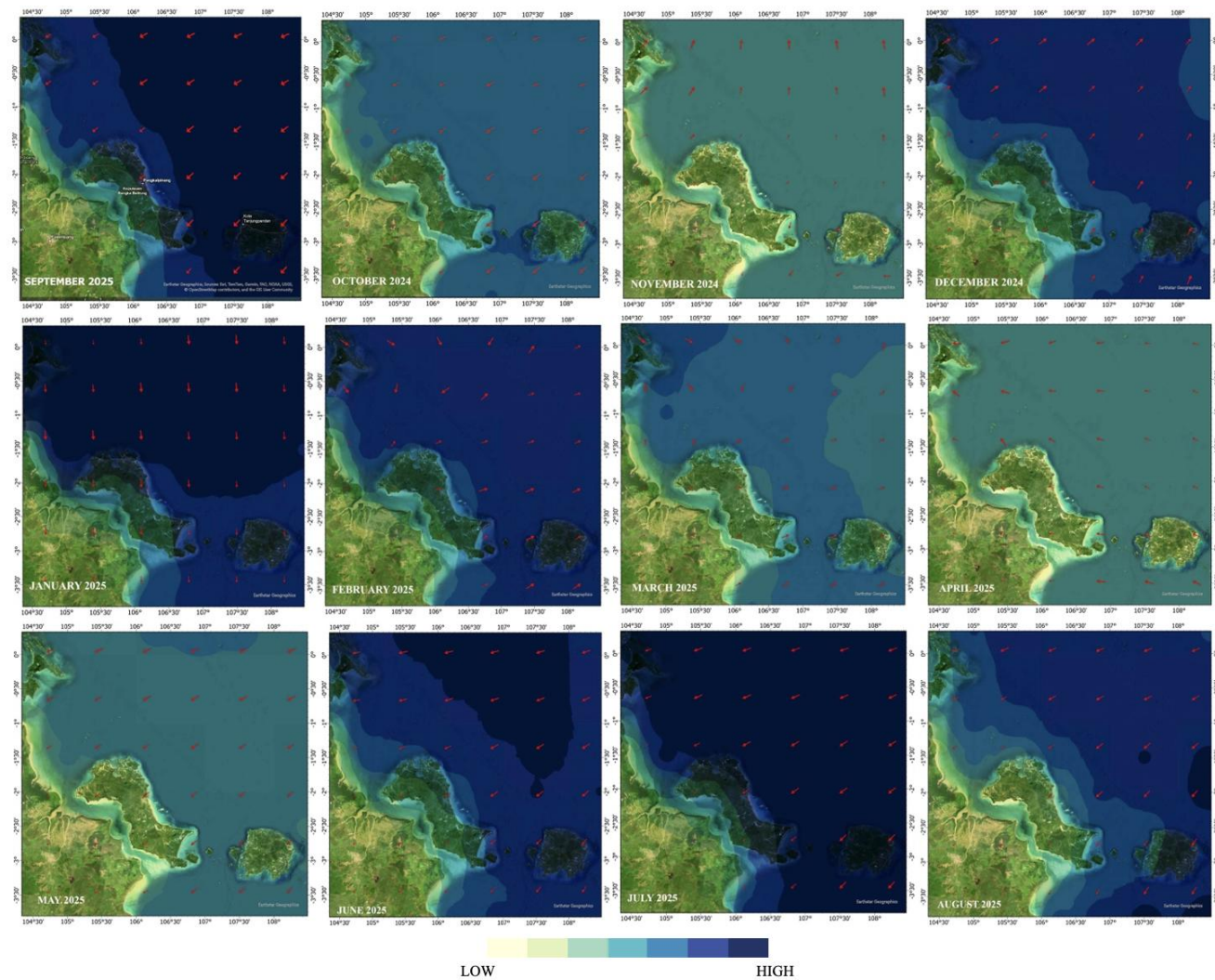


Figure 3. Monthly wind direction and speed distribution

Meanwhile, the third Principal Component (PC3) explains 16.5% of the total variation in the data (Table 3). This component is primarily characterized by an extreme positive loading for nitrate (0.742), indicating that the variation in PC3 is dominated by the gradient in nitrate availability in the water. Additionally, sea surface temperature has a relatively large negative loading on PC3 (-0.482), while chlorophyll-a also shows a moderate negative loading (-0.383). Thus, PC3 can be interpreted as a specific nutrient gradient that primarily represents nitrate dynamics, which are relatively independent of the water productivity gradient depicted in PC1 or the water physical gradient reflected in PC2. Thus, the PCA results indicate that nutrient variables and water physical parameters contribute differently to shaping the structure of environmental variance in each principal component. This PCA interpretation reflects the presence of interconnected oceanographic gradients within the multivariate system, but it cannot be interpreted as a direct causal relationship between variables. Instead, it represents a pattern of structural covariance within the complex water dynamics.

The results of the regression analysis in Table 4 indicate that among the three main components, only PC3 significantly influences CPUE variation (β : 0.869; t : 5.124; p : 0.001). In contrast, PC1 (β : 0.060; p : 0.734) and PC2 (β : 0.108; p : 0.542) do not show a significant relationship with CPUE. These findings indicate that although PC1 and PC2 explain a larger proportion of environmental variation in the oceanographic system, the nutrient gradient represented by PC3 has a stronger predictive value for catch dynamics. Specifically, the dominance of nitrate loading in PC3 indicates that variations in nutrient availability likely play an important role in supporting biological productivity, as reflected in changes in CPUE.

The PCA score plot in Figure 4 shows a clear seasonal pattern in the variation of oceanographic parameters. From May to August 2025, the distribution is predominantly on the positive PC1 axis, where the variables on the biplot are related to chlorophyll-a, silica, nitrate, and sea surface temperature. This pattern indicates that this period is characterized by water conditions with relatively different nutrient and productivity characteristics compared to other months. April 2025 is also on the positive PC1 axis, but in

a more isolated position than May-August 2025, indicating a transitional phase in oceanographic conditions toward a period of higher water productivity dominance.

Meanwhile, the months of September to November 2024, along with March 2025, tend to cluster on the positive PC2 axis. In the biplot, this variable is related to sea surface temperature and salinity, and is inversely related to wind speed. This reflects the dominance of relatively stable physical gradients in water bodies during that period. Conversely, December 2024, along with January and February 2025, lies on the negative PC2 axis, which is aligned with the wind speed vector on the variable biplot. This condition indicates a more substantial influence of atmospheric dynamics on the oceanographic characteristics of the waters, which is generally associated with the rainy season.

The results of the Principal Component Analysis were then compared with those of the two-tailed Pearson Correlation test, as presented in Table 5. This test is used to evaluate the bivariate linear relationship between CPUE and each environmental variable. However, this correlation analysis is based on a relatively small sample (N : 12), so its statistical power is low, and the results should be interpreted with caution. The analysis results show that CPUE has a significant negative correlation with nitrate (r : -0.658; p : 0.020). Although the value is statistically significant, the small sample size can increase the uncertainty of the correlation estimate, so the observed relationship cannot be directly interpreted as a strong ecological pattern.

In contrast, sea surface temperature shows a moderate positive correlation with CPUE (r : 0.566), but this relationship is not statistically significant (p : 0.055). Similarly, chlorophyll a has a weak positive correlation with CPUE (r : 0.310) and is not significant (p : 0.327). These results indicate that most environmental variables do not show a strong linear relationship with CPUE at the scale of the available data. Other environmental variables, namely silica, phosphate, salinity, and wind speed, also show very weak and insignificant correlations with CPUE ($p > 0.05$), indicating that a direct linear relationship between these variables and CPUE cannot be reliably identified in this dataset.

Table 3. Eigenanalysis of the Correlation Matrix

	3.4198	1.7370	1.1576	0.2961	0.2611	0.0942	0.0342		
Eigenvalue	3.4198	1.7370	1.1576	0.2961	0.2611	0.0942	0.0342		
Proportion	0.489	0.248	0.165	0.042	0.037	0.013	0.005		
Cumulative	0.489	0.737	0.902	0.944	0.982	0.995	1.000		
Variable			PC1	PC2	PC3	PC4	PC5	PC6	PC7
Chlorophyll-a			0.443	0.021	-0.383	0.720	-0.034	0.135	-0.346
Sea surface temperature			0.328	0.441	-0.482	-0.123	0.099	-0.243	0.618
Salinity			-0.384	0.444	-0.118	0.046	0.687	0.378	-0.158
Wind speed			-0.120	-0.696	-0.121	0.264	0.498	-0.114	0.395
Nitrate			0.239	0.252	0.742	0.407	0.100	0.106	0.378
Silica			0.494	-0.020	0.206	-0.279	0.505	-0.464	-0.406
Phosphate			-0.484	0.243	0.024	0.390	-0.067	-0.735	-0.099

Table 4. Principal Component Linear Regression with CPUE

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
		B	Std. error	Beta			Tolerance	VIF
1	(Constant)	8.333E-7	.162		.000	1.000		
	PC1	.060	.170	.060	.352	.734	1.000	1.000
	PC2	.108	.170	.108	.637	.542	1.000	1.000
	PC3	.869	.170	.869	5.124	.001	1.000	1.000

Table 5. Pearson Correlation between CPUE and water parameters

		Correlations						
		Nitrate	Silica	Phosphate	Chlorophyll-a	SST	Salinity	Windspeed
CPUE	Pearson Correlation	-.658*	-.173	.014	.310	.566	.097	.034
	Sig. (2-tailed)	.020	.590	.966	.327	.055	.763	.917
	Sum of squares and cross-products	-.045	-1.044	.001	.047	1.966	.078	.093
	Covariance	-.004	-.095	.000	.004	.179	.007	.008
	N	12	12	12	12	12	12	12

Notes: *: Correlation is significant at the 0.05 level (2-tailed)

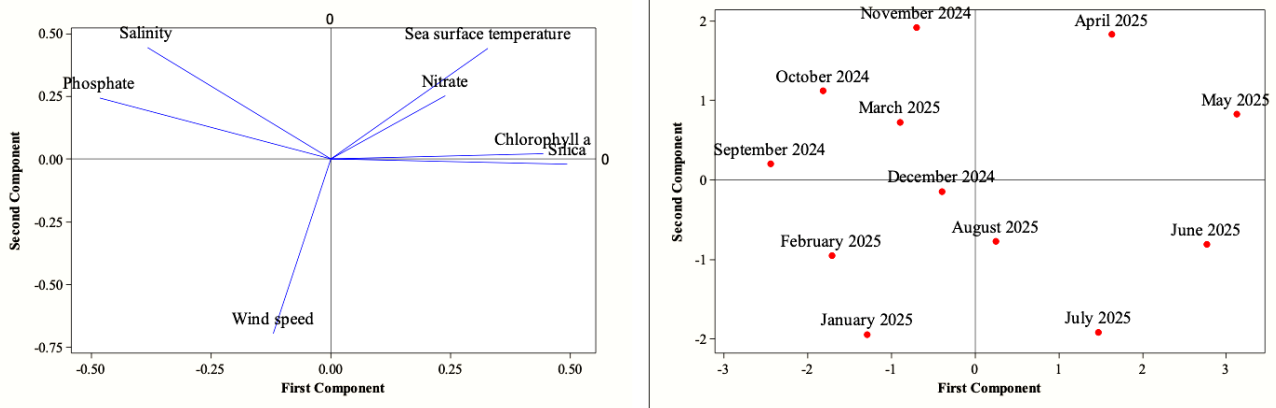


Figure 4. Principal Component Analysis of mitre squid CPUE with water parameters and period

The difference in patterns between the PCA results and the Pearson Correlation indicates that PCA captures the multivariate covariance structure among environmental variables, whereas Pearson Correlation captures only the direct linear relationship between two variables. Given the limited number of observations, the correlation results in this study are more appropriately viewed as an initial indication of the possibility of relationships between variables, rather than as strong evidence of a specific ecological mechanism. Therefore, the insignificance of several variables in the bivariate analysis does not automatically negate their role in the overall oceanographic system; rather, it reflects the complexity of interactions among environmental variables and the statistical limitations imposed by the small sample size.

The results of the two-tailed Pearson Correlation test in Table 6 between the principal component scores (PC1, PC2, and PC3) and CPUE based on monthly data (N: 12) indicate that PC3 shows a relatively strong, significant positive correlation with CPUE (r: 0.869; p<0.01). This

correlation result indicates that the monthly variation in CPUE is closely correlated with the environmental gradient represented by the third principal component. Meanwhile, PC1 (r: 0.060; p: 0.854) and PC2 (r: 0.108; p: 0.738) do not show a significant relationship with CPUE. Thus, these results indicate only a possible statistical association between PC3 and CPUE in this dataset, without implying a causal relationship.

PC3 is characterized by a relatively large contribution from nutrient variables (nitrate) and a negative relationship with sea surface temperature and chlorophyll-a (Table 3). However, given the limitations of the sample size and the exploratory nature of this analysis, these components are cautiously interpreted as indicators of environmental variation in nutrient dynamics, rather than as direct indicators of the ecological mechanisms controlling CPUE variations. Therefore, the selection of variables for the construction of the Environmental Suitability Index initially considered oceanographic parameters that contribute to the structure of environmental variance in

PCA and have potential relevance to CPUE variations, namely nitrate, sea surface temperature, and chlorophyll-a. However, to avoid ecological redundancy as explained in the Methods section, the final selection of variables was limited to sea surface temperature and chlorophyll-a. These two variables were retained primarily due to their well-documented roles in the oceanographic literature as controllers of aquatic productivity and habitat conditions, while the correlation results in this study only provide exploratory empirical support.

Spatial distribution and Environmental Suitability Index

The Environmental Suitability Index presented in Figure 5 illustrates the spatial distribution of mitre squid by applying the same interval classification method across the Environmental Suitability Index range (0-1). The index values are divided into five classes: Very Low (0-0.20), Low (0.20-0.40), Medium (0.40-0.60), High (0.60-0.80), and Very High (0.80-1.00). Each class represents a different level of environmental suitability for mitre squid distribution, as determined by the Environmental Suitability Index. This approach is consistent with standard index classification practices in habitat suitability studies, in which the index is divided into five zones for spatial mapping and analysis.

Months with a moderate to high Environmental Suitability Index indicate high habitat suitability and relatively wide spatial distribution. September-November 2024 and June-August 2025, which were dominated by medium-high ESI values (≥ 0.4), coincided with an increase in CPUE from 0.539 to 0.755 ton per trip (Figures 5 dan 6.A). During this period, oceanographic conditions were characterized by average monthly sea surface temperatures ranging from 29.558 to 30.848°C and chlorophyll-a concentrations between 0.279 to 0.375 mg m⁻³.

Conversely, from December 2024 to May 2025, during the west monsoon and the first transitional season, low ESI values (< 0.4) were observed, indicating limited habitat suitability for mitre squid (Figures 5 dan 6.A). During this period, CPUE was also relatively low, ranging from 0.017 to 0.552 ton per trip (Figure 6.A). The oceanographic conditions during these low ESI months were characterized by average monthly sea surface temperatures of 28.389 to 31.203°C and chlorophyll-a concentrations of 0.263 to 0.383 mg m⁻³, which spatially correlated with a more limited potential distribution of mitre squid.

To quantitatively validate the performance of the ESI model, correlation and linear regression analyses were conducted between the predicted ESI values and the observed CPUE (Table 7 and Figure 6.B). The analysis

results showed a strong and significant positive relationship ($r: 0.838$; $p: 0.001$; $n: 12$). Additionally, the linear regression model produced the equation $CPUE: 2.2568x - 0.2765$, with a coefficient of determination (R^2) of 0.6503, indicating that approximately 65.03% of the variation in CPUE can be explained by variation in ESI values. These results indicate that ESI has strong predictive ability for representing the spatial habitat suitability of mitre squid.

Maximum Sustainable Yield analysis

The Schaefer surplus production model is used to estimate stock parameters and the Maximum Sustainable Yield (MSY) value, with the general form of the equation $CPUE: a + bE$, where CPUE is the catch per unit effort, E is the fishing effort, a is the intercept representing the theoretical CPUE under no fishing conditions, and b is the slope coefficient reflecting the rate of decline in CPUE due to increased effort. Based on these parameters, the total catch (C) is expressed as $C: aE + bE^2$, while the optimum effort (E_{opt}) and MSY are calculated using the equations $E_{opt}: -a/(2b)$ and $MSY: -a^2/(4b)$. The linear regression model yields the equation $y: -4E - 0.06x + 0.3419$ (Figure 7), with an intercept (a: 0.3419 ton per trip) representing the estimated CPUE when fishing effort approaches zero and reflecting the relative stock abundance under minimal fishing pressure. The slope coefficient (b: -4×10^{-6} ton per trip) indicates that each additional fishing trip reduces CPUE by 0.000004 ton per trip, which suggests that increased fishing effort is associated with a decrease in productivity per unit of effort due to heightened exploitation pressure. The coefficient of determination ($R^2: 0.7248$) indicates that approximately 72.48% of the variation in catch decline is explained by fishing effort, while biological and environmental factors influence the remaining 27.52%.

The results of the MSY analysis for mitre squid, as shown in Figure 8, indicate an MSY value of 7,865 ton per year at an optimal fishing effort level of 35,800 trip per year. However, it should be noted that this estimate is based on a relatively limited time series (n: 5 years; 2020-2024), so the results obtained are indicative and require careful interpretation. In 2020, 2021, 2022, and 2024, mitre squid production was below or close to the MSY curve, indicating a relatively optimal utilization level and remaining within sustainable limits. Meanwhile, mitre squid production in 2023 exceeded the MSY value. However, this condition cannot be taken as definitive evidence of overfishing; rather, it should be interpreted as an indication of a potential increase in the risk of fishing pressure, which needs to be monitored.

Table 6. Pearson Correlation (2-Tailed) between Principal Component and CPUE

		Correlations			
		PC1	PC2	PC3	CPUE
CPUE	Pearson Correlation	.060	.108	.869**	1
	Sig. (2-tailed)	.854	.738	.000	
	N	12	12	12	12

Notes: **: Correlation is significant at the 0.01 level (2-tailed)

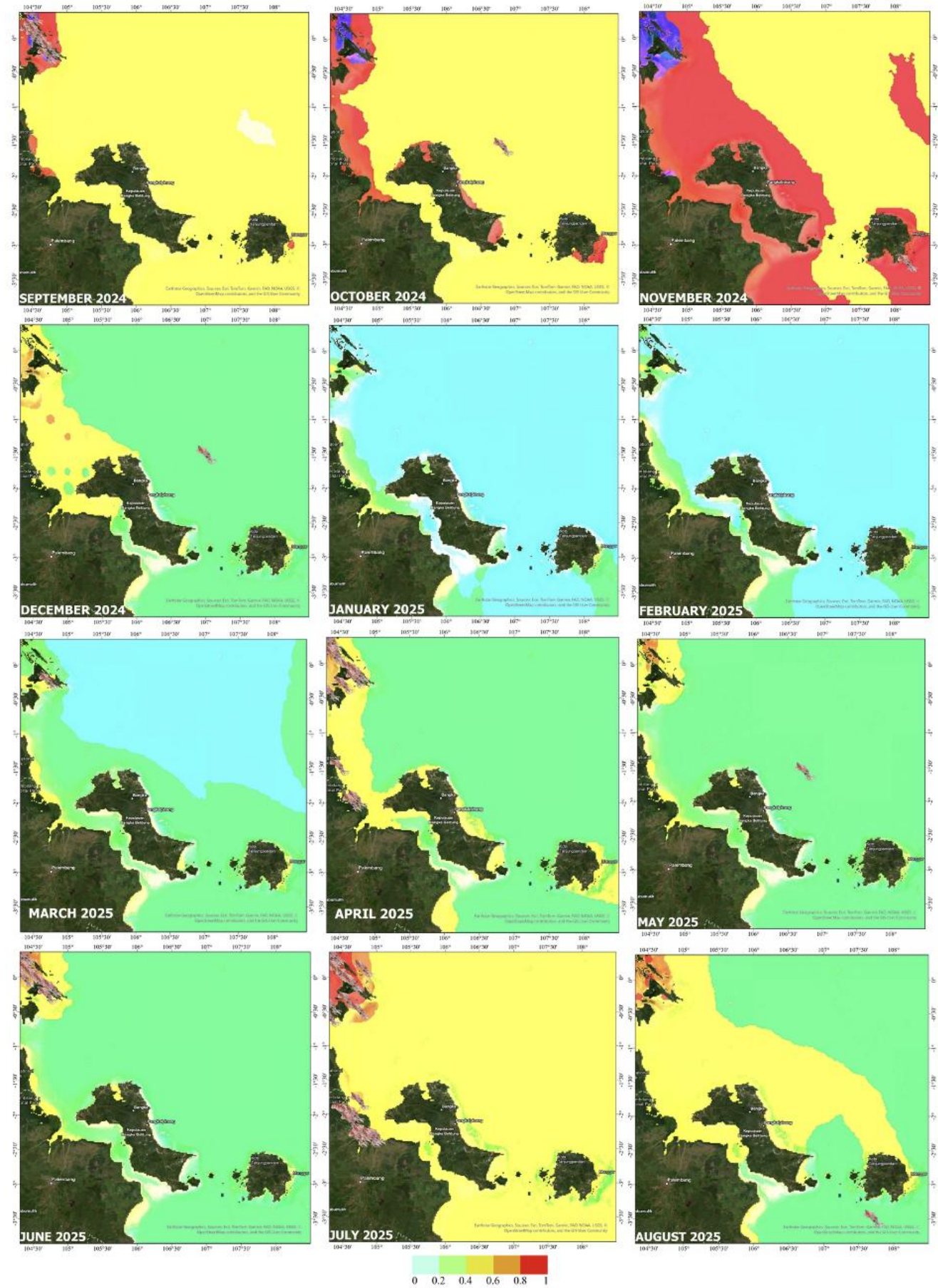


Figure 5. Monthly potential mitre squid distribution zone

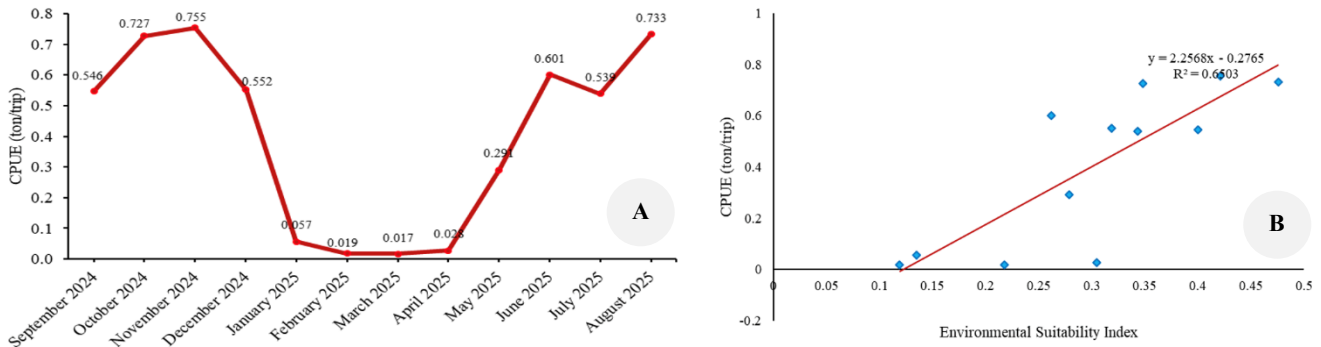


Figure 6. A. Monthly catch per unit effort for mitre squid, B. Linear regression between ESI and CPUE

Table 7. Pearson Correlation (2-Tailed) between ESI and CPUE

		CPUE
ESI	Pearson Correlation	.838**
	Sig. (2-tailed)	.001
	N	12

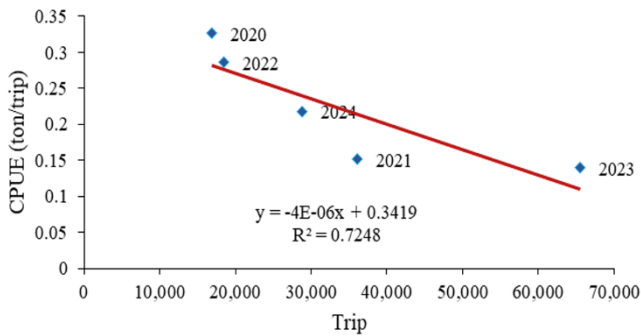


Figure 7. Comparison of annual catch per unit effort with fishing trip

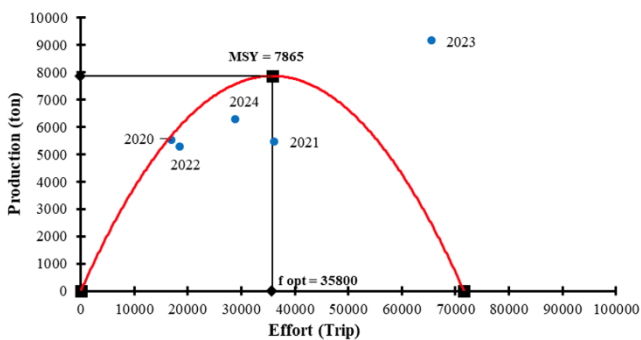


Figure 8. Maximum Sustainable Yield for mitre squid

The MSY analysis is also consistent with variation in mitre squid CPUE, which ranges from 0.151 to 0.327 ton per trip, with the lowest value recorded in 2023 and the highest in 2020. Based on Table 8, mitre squid production in 2023 reached 9,157 tons with 65,513 fishing trips, or

approximately 16.43% higher than the MSY value and 82.72% above Eopt. These findings indicate a relatively high level of exploitation pressure that year, but the interpretation must still consider the limitations of the available temporal data. Furthermore, in 2021, mitre squid production of 5,469 ton remained below MSY, but fishing effort (36,132 trips) slightly exceeded Eopt without a proportional increase in catch, as reflected in the relatively low CPUE (0.151 ton per trip). This condition indicates the potential inefficiency of the fishing effort and suggests the need for more adaptive management.

Discussion

Water quality and implications for CPUE

Water quality in this system reflects the complex interaction between nutrient gradients and physical parameters, rather than being controlled by a single variable (Cael et al. 2018). Nitrate emerges as a prominent parameter in the structure of environmental variability; however, bivariate analysis consistently shows a significant negative relationship with CPUE (Table 5). This pattern confirms that nitrate concentration better represents water-mass dynamics and mixing processes than it is a direct driver of fishery productivity (Le et al. 2017; Torres-Martínez et al. 2021).

Ecologically, the negative relationship between nitrate and CPUE (Table 5) indicates a decoupling between increased nutrients and high-level trophic responses (Radenac et al. 2020; Zhang et al. 2023). This phenomenon is likely influenced by trophic lags, spatial redistribution of organisms due to water-mass dynamics, as well as vertical mixing and advection (Martin et al. 2010; Tsutsumi et al. 2020). In tropical systems, energy transfer in the food web is nonlinear and controlled by spatial-temporal heterogeneity, so increases in nutrients do not directly enhance nekton biomass or catch yields (Hu et al. 2021; Wang et al. 2021).

Sea surface temperature and chlorophyll a are important ecological indicators, but they do not show a significant linear relationship with CPUE (Sinaga and Siburian 2025). The SST range of 28.39-31.20°C (Figure 2.A) reflects thermal conditions suitable for mitre squid *U. chinensis* and is consistent with the previously reported optimum catch range of 29.5-30.5°C (Puspito 2022). However, the homogeneity of temperatures within that range limits its

ability to explain catch variability. Other studies show that SST functions more as an ecological boundary that controls the distribution and physiology of organisms (Puerta et al. 2015; Yu et al. 2020), rather than as a direct predictor of CPUE (Wen et al. 2024; Xiang et al. 2025).

Relatively stable chlorophyll *a* in Figure 2.A (0.263-0.383 mg m⁻³) indicates low variability in primary productivity during the observation period. This condition reduces the sensitivity in detecting statistical relationships with CPUE and indicates that catch fluctuations are more influenced by the dynamics of organism distribution and aggregation (Yu et al. 2019; Setiawan et al. 2024). Previous studies have asserted that the relationship between chlorophyll *a* and catch yield is indirect, mediated by trophic processes and the spatial heterogeneity of the marine ecosystem (Lara et al. 2016; Cai et al. 2022). Overall, the water quality in this study does not show a single parameter that directly controls CPUE. Instead, catch variability results from a nonlinear interaction among nutrients, thermal conditions, and primary productivity, operating through interconnected ecological and physical mechanisms (Jebri et al. 2022; Kim et al. 2025).

Structure of environmental variability and multivariate interpretation (PCA)

Principal component analysis shows that environmental variability is structured in a multivariate manner, reflecting the covariance between parameters. Nitrate emerges as the dominant contributor to one of the principal components (Table 3), while other parameters such as SST and chlorophyll *a* provide more moderate contributions. This pattern confirms that the system is controlled by interactions between variables, rather than by a single influence (Le et al. 2017). However, a comparison with bivariate correlation results reveals significant discrepancies, where the dominant variables in the multivariate space do not always show a direct relationship with CPUE (Cömert et al. 2025). The result emphasizes that PCA identifies statistical patterns, not cause-and-effect relationships, so ecological interpretation must be done with caution (Erzini et al. 2005).

Furthermore, the results show that the relationship between environmental variables and CPUE is nonlinear and cannot be adequately explained through a univariate approach. Catch variability more accurately reflects the simultaneous interaction between oceanographic factors and fishing processes (Maynou et al. 2003; Zhou et al. 2022). In monsoon-affected tropical systems, the relationship between nutrients and fishery productivity is often nonlinear and can be disrupted by the complexity of trophic and physical dynamics (Sasikumar et al. 2018; Singh et al. 2025).

The relatively small variability of nutrients compared to CPUE fluctuations further emphasizes that increased nutrition does not automatically enhance fishery productivity (Galligan and McClanahan 2024). Therefore, using a single parameter as the sole predictor can lead to estimation bias (Zhang et al. 2025). Conversely, a

multivariate approach becomes essential to better capture the system's complexity, especially for nektonic species such as squids, which respond rapidly to environmental changes (Sasikumar et al. 2018).

Environmental Suitability Index in the spatial dynamics and interaction of mitre squid ecosystems

The Environmental Suitability Index (ESI)-based approach in this study emphasizes that the spatial distribution of mitre squid results from the integration of various environmental factors that interact within a complex system. Instead of reflecting the influence of a single parameter, the Environmental Suitability Index represents habitat conditions formed through a nonlinear combination of physical and biogeochemical variables, thereby providing a more realistic picture of potential areas for the presence and aggregation of squids (Yu et al. 2019; Yu et al. 2024). The relationship between habitat suitability and fishery productivity is generally analyzed by correlating CPUE with environmental variables (Tian et al. 2009). However, various studies emphasize that CPUE and catch distribution do not fully reflect the actual distribution of organisms because they are influenced by fishermen's behavior and the dynamics of fishing operations (Yu et al. 2019). Therefore, ESI is better understood as a probabilistic approach that generates maps of species presence probability, rather than as a deterministic predictor of catch outcomes.

In line with this pattern, Figure 5 shows that the period with high mitre squid distribution potential occurs in September-December 2024 (Transition Season II) and June-August 2025 (East Wind Season). However, this temporal correlation does not indicate a direct cause-and-effect relationship with a specific environmental variable, but rather reflects co-variation within a broader oceanographic system (Wang et al. 2023). In this context, wind speed and direction can be hypothesized to play an indirect role through modifications of physical processes such as upwelling and vertical mixing, which potentially affect nutrient distribution and prey availability. These processes are generally known to support primary productivity and energy transfer to higher trophic levels (Ye et al. 2019; Moore-Maley and Allen 2022). However, since there is no statistically significant relationship between wind parameters and CPUE in this study, the role of wind parameters remains inferential and cannot be considered the main driver of catch variation.

Table 8. Production value and effort

Year	Production (Ton)	Effort (Trip)	CPUE (Ton per Trip)
2020	5,524	16,891	0.327
2021	5,469	36,132	0.151
2022	5,292	18,513	0.285
2023	9,157	65,513	0.139
2024	6,292	28,852	0.218

Within the same framework, nutrient dynamics play a fundamental role in shaping habitat structure by influencing primary productivity. Nutrients such as nitrate, phosphate, and silicate act as primary regulators of phytoplankton growth, thereby determining the availability of trophic resources at higher levels (Makareviciute-Fichtner et al. 2024; Xue et al. 2024). However, as demonstrated in this study, the relationship between nutrient availability and fishery response is neither strictly linear nor direct. Although nitrate exhibits a statistically significant relationship with CPUE, it more likely reflects underlying water mass characteristics and nutrient system dynamics rather than functioning as a direct driver of mitre squid productivity. This pattern suggests a decoupling between bottom-up processes and catch responses, a phenomenon commonly observed in tropical marine ecosystems characterized by high variability and complex ecological interactions (Tosetto et al. 2024).

Overall, these findings highlight the advantage of a spatially explicit Environmental Suitability Index approach for capturing system complexity over single-variable analyses. The integration of multiple environmental parameters into a composite index provides a more holistic representation of potential habitat distribution, particularly in systems where interactions among variables are inherently multiplicative and nonlinear (Moëzzi et al. 2022). This approach enables a more ecologically realistic identification of suitable areas than reliance on individual environmental predictors (Huang et al. 2023). Nevertheless, the model's inability to fully explain catch variability indicates that additional factors, such as organism behavior, movement dynamics, and fishing operations, remain influential. Therefore, the application of ESI in fisheries management should be complemented by other approaches that explicitly account for uncertainty and system complexity, ultimately supporting more adaptive, ecosystem-based management strategies.

Maximum Sustainable Yield and management implications

The results of the Maximum Sustainable Yield analysis, presented in Figure 8, indicate that in 2023, both production and fishing effort for mitre squid exceeded the estimated MSY threshold. This imbalance between effort levels and stock capacity suggests the potential for increased exploitation pressure, particularly if the upward trend in effort continues without effective regulation. Elevated catch levels under such conditions are likely associated with fishing effort per trip exceeding the optimal level, as well as gear selectivity factors that may contribute to overcapacity

and increased pressure on the stock (Kurniawan et al. 2019). Furthermore, fishing activities during periods of low productivity may increase the proportion of small individuals in the catch, which can negatively affect stock productivity over time, as reflected in relatively low CPUE despite high effort (Zamroni et al. 2025).

One of the primary management recommendations (Table 9) is to concentrate fishing activities during periods characterized by relatively high CPUE and Environmental Suitability Index values, to improve catch efficiency while minimizing unnecessary effort expansion outside peak productive periods. Based on the estimated F_{opt} and its comparison with observed effort levels, seasonal or monthly effort restrictions represent a relevant management option, particularly when fishing effort exceeds the optimal threshold. However, it is important to emphasize that these recommendations are conceptual in nature and derived from the empirical relationships identified in this study; therefore, their practical effectiveness requires further validation through quantitative simulations or field-based implementation.

During periods characterized by low CPUE and ESI values, seasonal closures or substantial reductions in fishing effort are precautionary measures to mitigate excessive exploitation pressure. In addition, implementing minimum catch size regulations and restrictions on non-selective fishing gear could help protect juveniles and sustain recruitment potential. Nevertheless, these proposed strategies have not yet been operationally tested within the local fisheries system and should therefore be regarded as a preliminary management framework requiring validation through scenario-based approaches or policy evaluation. Accordingly, integrating CPUE, ESI, and F_{opt} indicators into these recommendations reflects an evidence-informed conceptual approach rather than a fully validated predictive model.

The Maximum Sustainable Yield estimate in this study is still indicative because it is based on a relatively short time series (2020-2024). Therefore, the resulting management reference values need to be updated periodically as longer and more continuous time series data become available. The limited time frame of this study also leads to data and analysis gaps that need to be addressed in future research. These efforts include multi-year CPUE data collection, mitre squid biological sampling for size and spawning structure analysis, validation of predicted high habitat suitability zones using independent data, and the application of Generalized Additive Models (GAMs) to quantify the non-linear relationship between environmental factors and catch.

Table 9. Seasonal management recommendations based on CPUE, ESI, and F_{opt}

Seasonal condition	CPUE and ESI status	Observed effort relative to F_{opt}	Recommended management action
Productive season	High	$\leq F_{opt}$	Fishing permitted under monitoring; maintain effort $\leq F_{opt}$
Productive season	High	$> F_{opt}$	Limit fishing trips to match F_{opt} ; apply monthly trip quota
Transitional season	Moderate	Approaching F_{opt}	Conduct monthly evaluation; gradual effort reduction if CPUE declines
Low-productivity season	Low	$\geq F_{opt}$	Implement seasonal closure or substantial effort reduction
All seasons	-	-	Enforce minimum catch size and restrict non-selective gear

In conclusion, the findings indicate that the variability of mitre squid CPUE in the waters of Bangka District is influenced by interactions among environmental gradients, with sea surface temperature and chlorophyll-a serving as the main indicators of habitat conditions and productivity, although the relationship between these indicators and CPUE is not entirely linear. The Environmental Suitability Index and CPUE show consistent seasonal patterns, reflecting the dynamics of habitat suitability and the spatial distribution of mitre squid. Further production analysis indicates that the exploitation rate during certain periods has exceeded the optimal threshold, potentially reflecting increased fishing pressure. These findings emphasize the importance of season-based management through effort regulation, the implementation of optimal exploitation limits, and stock protection through catch size control and gear selectivity. However, the interpretation of the results in this study should be done with caution, given several main limitations, including the relatively small sample size and the limited time series, which can affect the strength of statistical inference. In addition, the lack of biological data, such as size structure and reproductive parameters, limits the ability to evaluate stock responses comprehensively. On the other hand, the habitat suitability model used has not been independently validated through field data, so its spatial accuracy still requires further testing. Therefore, future research needs to integrate long-term data, biological parameters, and validation and advanced modeling approaches to enhance the robustness of the results and support the development of more adaptive, ecosystem-based management strategies.

ACKNOWLEDGEMENTS

The authors would like to thank the Directorate General of Research and Development, Indonesian Ministry of Higher Education, Science, and Technology, for their assistance in funding research for early-career lecturers under Master Contract Number 116/C3/DT.05.00/PL-BATCH II/2025. Gratitude was also expressed to the Bangka Belitung State Manufacturing Polytechnic for their support and facilities. Additionally, the authors would like to thank the parties who contributed research data, including the Sungailiat Nusantara Fisheries Port, Indonesia, the Bangka Belitung Province Marine and Fisheries Department, Indonesia, the Copernicus Marine Service, NASA POWER, and GEBCO. The authors declare no conflict of interest and that the data used in this study were obtained with proper authorization.

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