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Spatio-Temporal Analysis of Thermal Fronts and Indian Ocean Dipole Influence on Yellowfin Tuna (*Thunnus albacares*) Productivity in Palabuhanratu, Indonesia

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ABSTRACT

Thermal fronts are oceanographic features often associated with potential fishing zones for pelagic species such as the yellowfin tuna (*Thunnus albacares*). This study analyzed the spatial and temporal dynamics of thermal fronts and their relationship with thermal front intensity, sea surface temperature (SST), and the Indian Ocean Dipole (IOD) on the yellowfin tuna catch in Palabuhanratu waters from 2016 to 2020. The data included satellite-derived SST imagery, tuna catch records from PPN Palabuhanratu, and the Dipole Mode Index (DMI) as an indicator of IOD variability. Thermal fronts were detected using the Single Image Edge Detection (SIED) algorithm with a 0.5°C gradient threshold. Results indicated that thermal fronts occurred most frequently during transitional and dry seasons, with peak intensity from October to December. Pearson correlation analysis revealed a negative relationship between SST and tuna catch ($r = -0.340$; CI $= -0.547$ to -0.094) and between IOD and SST ($r = -0.549$; CI $= -0.705$ to -0.344), suggesting that warmer waters and positive IOD phases reduce tuna catch volume. In contrast, thermal front intensity showed no significant correlation with tuna catch ($r = 0.104$), IOD ($r = 0.083$), or SST ($r = -0.177$). These findings suggest that while SST and IOD exert measurable influences on tuna catch, thermal fronts may not serve as reliable indicators for the yellowfin tuna fishing in the Palabuhanratu region.

INTRODUCTION

The Indonesian waters, located between the Pacific and Indian Oceans, exhibit highly complex oceanographic characteristics **(Dewi *et al.*, 2020)**. The interaction between water masses from these two oceans, combined with seasonal wind dynamics such as the monsoon and the Indonesian Throughflow (Arlindo), generates a variety of oceanographic phenomena, one of which is the thermal front. A thermal front is defined as a boundary where two water masses with different temperatures meet, resulting in a sharp sea surface temperature (SST) gradient **(Maharani *et al.*, 2020)**. This phenomenon not only characterizes tropical ocean dynamics but also plays a crucial role in ecological processes and fisheries dynamics.

In the context of fisheries, thermal fronts are often identified as key indicators of potential fishing grounds. Several studies have shown that thermal front zones often serve as aggregation areas for marine organisms due to the high nutrient concentrations and physical oceanographic activities such as current convergence **(Simbolon & Tadjuddah, 2008; Nammalwar *et al.*, 2013)**. These areas are typically associated with increased nutrient availability **(Mustasim *et al.*, 2015)**, which stimulates primary productivity in the form of phytoplankton that serves as the base of the food chain for various fish species including the yellowfin tuna. Consequently, thermal fronts are frequently utilized in predictive modeling of fishing grounds using remote sensing data combined with field surveys **(Tangke & Deni, 2013)**. Such predictions are made more accurate when integrated with other oceanographic parameters such as upwelling events and chlorophyll-a distribution **(Simbolon *et al.*, 2013)**.

The Indian Ocean Dipole (IOD) phenomenon is a regional climate anomaly characterized by differences in sea surface temperature between the western and eastern parts of the Indian Ocean. IOD specifically occurs in the equatorial region of the Indian Ocean and plays a significant role in influencing sea surface temperature distribution across the basin **(Saji *et al.*, 1999)**. Temperature changes caused by the IOD can affect ocean current circulation and water mass distribution, ultimately impacting local oceanographic processes, including the formation or intensity of thermal fronts. Previous studies have shown that normal IOD conditions tend to generate wider thermal front areas compared to weak IOD conditions **(Ristyatmaja *et al.*, 2019)**. This indicates that regional-scale climate variability such as the IOD can interact with local oceanographic dynamics, contributing to the formation of productive ocean zones that are important for fisheries activities.

The Government of Indonesia, through the Ministry of Marine Affairs and Fisheries (MMAF), has adopted this approach in the development of the Potential Fishing Zone Forecast Maps **(**Peta Prediksi Daerah Penangkapan Ikan, PPDPI**)**, with thermal fronts serving as one of the primary indicators alongside upwelling. The PPDPI provides spatial and temporal information on high-potential fishing zones, aiming to support more efficient fishing operations **(BROL, 2017)**. This approach underscores the importance of satellite-based environmental indicators for determining fishing locations **(Simbolon *et al.*, 2013)**.

However, several studies have shown that the relationship between thermal fronts and pelagic fish abundance is not always consistent. For instance, **Khoir and Safruddin (2023)** reported that only 8.2% of 61 fishing locations coincided with thermal front zones, indicating that the presence of a front does not necessarily suggest the presence of fish. In contrast, **Prasetya *et al.* (2022)** found a significant influence of thermal fronts on skipjack tuna catch in the Banda Sea (*P*= 0.03363), supporting the hypothesis that thermal fronts can serve as indicators of pelagic fishing grounds. On the other hand, **Mustasim *et al.* (2015)**, **Savetri (2019)** and **Pratama *et al.* (2025)** reported no significant influence. Specifically, **Pratama *et al.* (2025)** found a *P*-value of 0.728 and a correlation coefficient of -0.068 between thermal front intensity and skipjack tuna production at PPN Ternate, indicating a very weak and statistically insignificant relationship. These varying findings suggest that the effectiveness of thermal fronts as indicators of fishing grounds is highly dependent on local oceanographic conditions and climatic factors.

Given this background and the lack of similar studies focusing on the yellowfin tuna (*Thunnus albacares*) landed at the Palabuhanratu Archipelagic Fishing Port **(**PPN Palabuhanratu**)**, and the increasing need for science-based fishing ground prediction to support sustainable fisheries management, this study was conducted to identify the spatial and temporal dynamics of thermal fronts and to evaluate their relationship with the yellowfin tuna catch in the region. One of the current challenges is the limited understanding of how oceanographic features such as thermal fronts interact with regional climatic factors like IOD, which may affect the distribution and availability of large pelagic fish. Therefore, this research also aimed to analyze the link between thermal fronts and the IOD addressing this gap in knowledge.

This study is expected to provide a more comprehensive understanding of the relevance of thermal front application in PPDPI, particularly for the southern waters of Java, and inform more adaptive fisheries management based on marine environmental data. Furthermore, this research focused on completing the findings of **Pratama *et al.* (2025)**, who previously identified a relationship between the yellowfin tuna abundance and chlorophyll-a concentration as well as SST in the waters of Palabuhanratu, by adding a new dimension in the form of thermal front intensity analysis and regional climate influence.

MATERIALS AND METHODS

The current study utilized three primary datasets: sea surface temperature (SST) imagery, yellowfin tuna (*Thunnus albacares*) fishery production data, and the Dipole Mode Index (DMI) as an indicator of the Indian Ocean Dipole (IOD) phenomenon. All datasets were time series spanning the period from 2016 to 2020. The SST imagery was obtained from the website www.oceancolor.gsfc.nasa.gov in NonConformance format, which is commonly used in spatio-temporal oceanographic analysis. Yellowfin tuna production data were sourced from the official catch records of the Palabuhanratu Archipelagic Fishing Port (PPN Palabuhanratu), verified through interviews with longline and pole-and-line fishers who target yellowfin tuna. The DMI data were accessed from www.cpc.ncep.noaa.gov, the official website of the Climate Prediction Center (CPC), which operates under the National Centers for Environmental Prediction (NCEP), part of the National Oceanic and Atmospheric Administration (NOAA), United States.

Thermal front identification in the 4-km resolution SST imagery was conducted using the Single Image Edge Detection (SIED) algorithm. Prior to analysis, the imagery underwent geometric and atmospheric correction to minimize distortion and to improve accuracy. The SIED algorithm works by detecting changes in temperature gradients within the image **(Cayula & Cornillon, 1992)**. A threshold value of 0.5°C was used to identify thermal fronts using the SIED method **(Mustasim *et al.*, 2015)**. The configuration applied included a histogram window size of 32 x 32 pixels and a median filter size of 3 **(Pratama *et al.*, 2025)**. SIED offers higher accuracy compared to visual interpretation methods **(Hamzah *et al.*, 2014)**.

Once spatial thermal front maps were generated, thermal front intensity was calculated by counting the number of oceanic areas exhibiting thermal fronts (in pixel units). The intensity of the thermal front, along with the yellowfin tuna catch data, IOD, and monthly SST data, was then tested for partial correlation using Pearson correlation analysis. This analysis aimed to determine the interaction among variables and whether they exhibit a positive, negative, or no relationship. The strength of these relationships is indicated by the value of the correlation coefficient **(Sekaran *et al.*, 2010; Rassiyani & Pitri, 2024)**. In the context of this study, the correlation value is used to assess the extent to which each oceanographic variable influences the dynamics of the yellowfin tuna catch in the waters of Palabuhanratu. The Pearson correlation coefficient is calculated using the following formula:

$$r_{xy} = \frac{n\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{\{n\Sigma x^2 - (\Sigma x)^2\}\{n\Sigma y^2 - (\Sigma y)^2\}}}$$

r_{xy} = Pearson correlation coefficient
n = Number of samples
Σx = Sum of variable x
Σy = Sum of variable y

The interpretation of the strength of the relationship among variables is based on the data presented in Table (1):

Table 1. Interpretation of Pearson correlation coefficients

No	r_{xy} Value	Interpretation
1	+/- 0.00-1.199	Very weak
2	+/- 0.20-0.399	Weak
3	+/- 0.40-0.599	Moderate
4	+/- 0.60-0.799	Strong
5	+/- 0.80-1.000	Very strong

RESULTS AND DISCUSSION

Sea surface temperature and Indian ocean dipole

The average sea surface temperature (SST) illustrated in Fig. (1) exhibits a consistent seasonal pattern, with peak values typically occurring between March and May, and the lowest values between July and October. SST fluctuations generally follow the variation of the DMI, where SST tends to be lower during positive IOD phases (when DMI increases), and higher during negative IOD phases (when DMI decreases). This pattern is especially evident in 2019, when SST dropped significantly alongside the peak of the positive IOD, and in 2016, when SST remained warm throughout the negative IOD phase. In contrast, 2020 showed relatively neutral and fluctuating conditions, without extreme IOD episodes as observed in the two previous years.

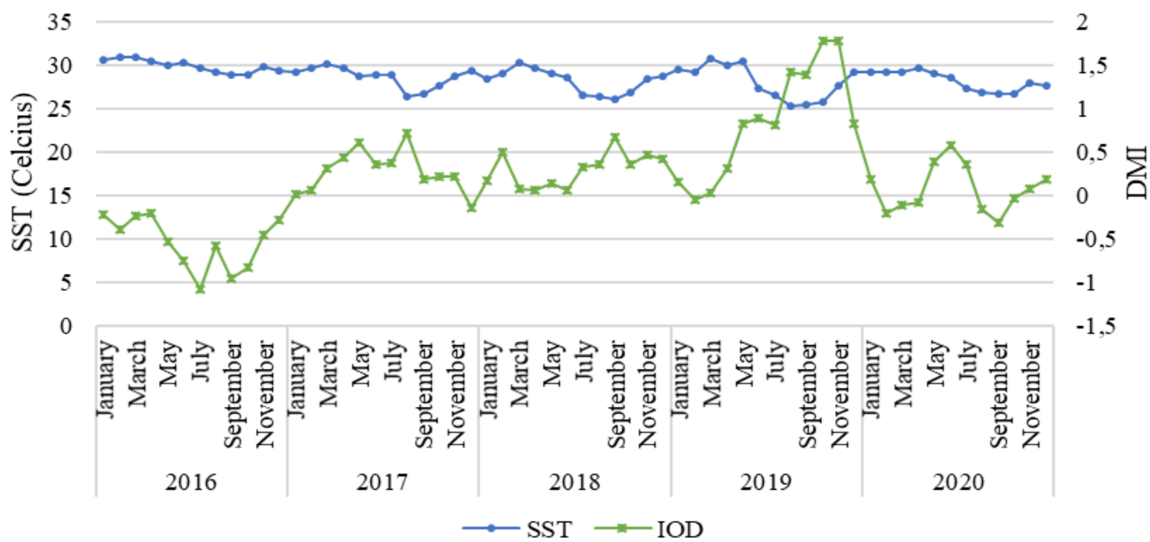

Fig. 1. Variation of DMI and sea surface temperature in Palabuhanratu waters

During the period from 2016 to 2020, the dynamics of the Dipole Mode Index (DMI) exhibited considerable variation (Fig. 1). In 2016, the negative IOD phase was dominant, particularly from July to October, with the DMI reaching -1.08 in July. This period coincided with relatively lower sea surface temperatures (SST), recorded at 29.67°C compared to the previous month. Conversely, the year 2019 was characterized by a strong positive IOD phase, especially from August to November, with a peak DMI value of 1.78 sustained over two consecutive months (October–November). During this extreme positive IOD phase, SSTs were notably low, ranging from 25.28 to 27.56°C, indicating significant ocean surface cooling in the Palabuhanratu waters.

Spatial distribution of the thermal front phenomenon

The spatial map of thermal front distribution in the study area is presented in Figs. (2, 3), where regions with thermal fronts are indicated by black contour lines representing high sea surface temperature (SST) gradients, frequently appearing from coastal bay areas to open waters. Overall, the spatial distribution of thermal fronts in the study area exhibits a seasonal pattern throughout the years 2016 to 2020. As shown on the maps, thermal fronts are more frequently identified during transitional months and the dry season, particularly from June to October. Spatial variability is also evident in the shifting distribution of thermal fronts, which occasionally expand eastward or westward depending on the dynamics of SST and regional oceanographic conditions.

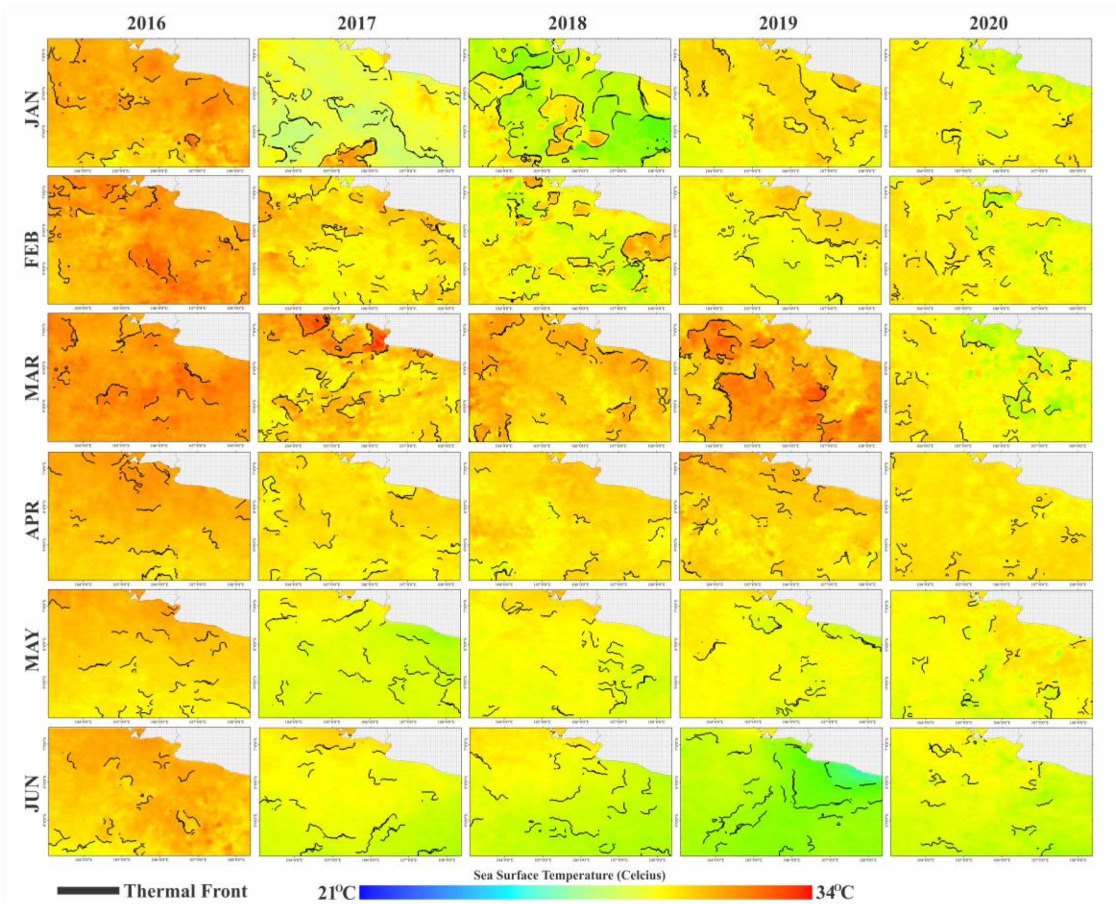

Fig. 2. Distribution of thermal fronts from January to June (2016–2020) in Palabuhanratu waters

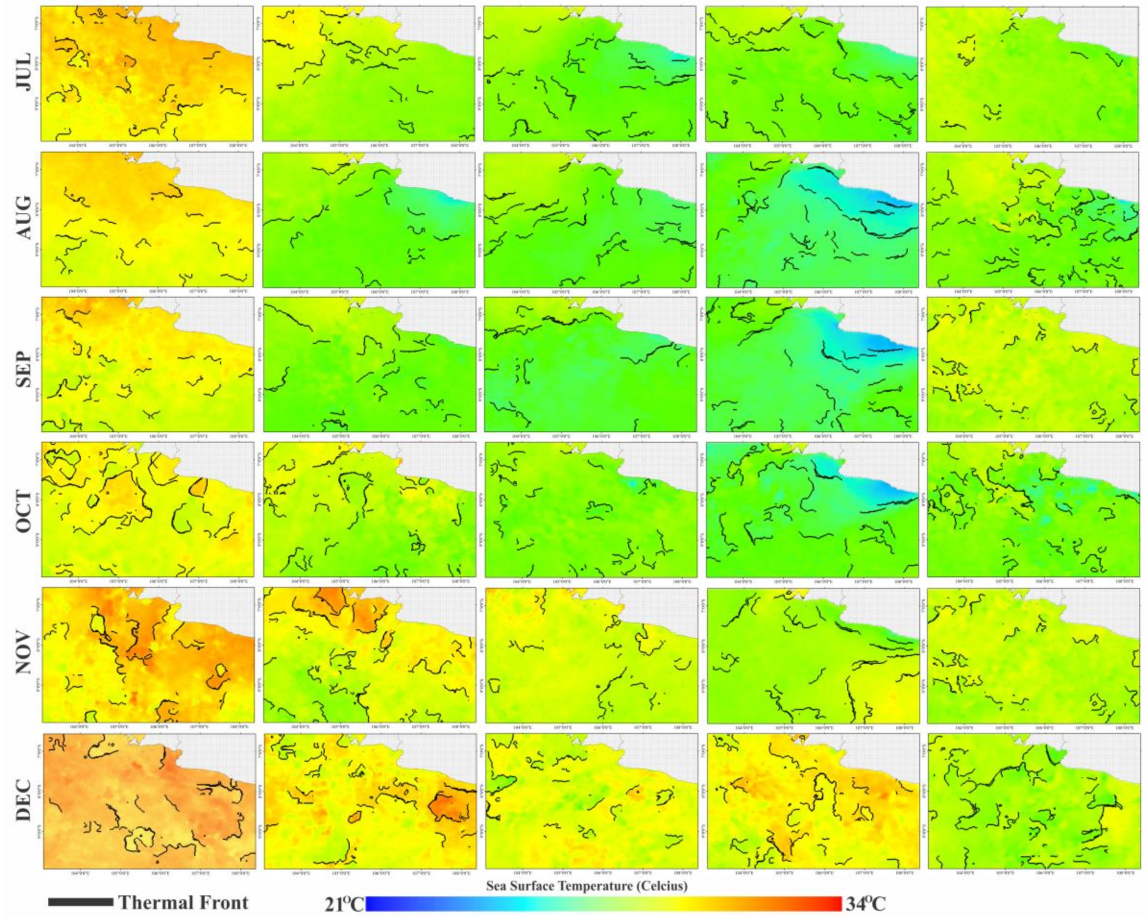

Fig. 3. Distribution of thermal fronts from July to December (2016–2020) in Palabuhanratu waters

On an annual basis, the year 2019 exhibited more intensive and widespread occurrences of thermal fronts compared to other years, particularly from March to October. The presence of thermal fronts during this period coincided with notable sea surface temperature (SST) anomalies and significant Dipole Mode Index (DMI) dynamics, particularly the extreme positive IOD event in 2019. In contrast, from 2017 to 2018 and most of 2020, thermal fronts were less frequently detected, with SST appearing more uniform and generally lower during the mid to late part of the year.

Furthermore, the time-series data of thermal front intensity from January 2016 to December 2020 revealed substantial temporal variation throughout the years (Fig. 4). The highest intensity was recorded in January 2018, with 5,488 pixels, while the lowest occurred in July 2020, with only 876 pixels. In general, the months of October, November, and December consistently showed high values across nearly all years, averaging over 3,000 thermal front pixels. This suggests that the transitional season leading into the rainy period is characterized by heightened front activity. Conversely, the months of June through August tend to exhibit lower values, especially during the peak dry season and upwelling events.

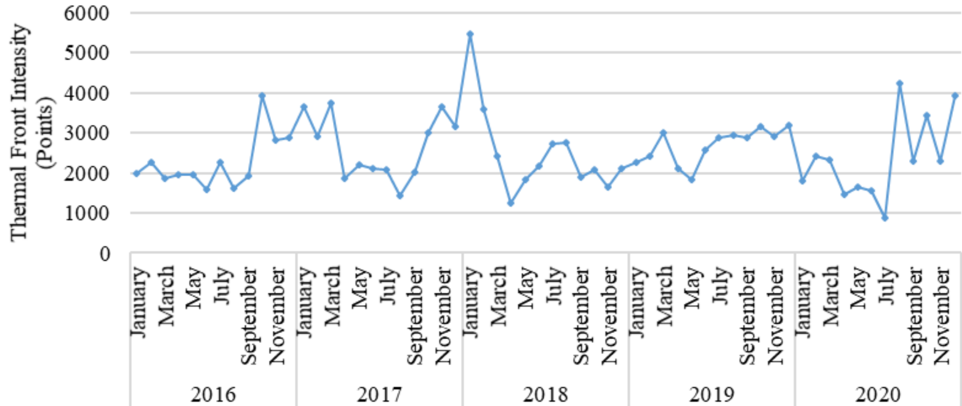

Fig. 4. Dynamics of thermal front intensity in Palabuhanratu waters (2016–2020)

On an annual basis, the year 2018 recorded the highest accumulation of thermal fronts, particularly during the first half of the year, which may be linked to extreme climatic anomalies. In contrast, 2020 showed substantial fluctuations, with low values in mid-year followed by a sharp increase in August and toward the end of the year.

Yellowfin tuna fisheries production at PPN Palabuhanratu

The time-series data of the yellowfin tuna production from 2016 to 2020 (Fig. 5) show significant annual fluctuations. In 2016, production levels were generally high, with peaks in January (87.973 tons) and December (86.026 tons), but there was a sharp decline in February (13.827 tons). The years 2017 and 2018 were marked by a general decline in production, with lower monthly averages compared to 2016, particularly in 2018, which recorded the lowest point in February (12.522 tons) and only slight increases in July and September.

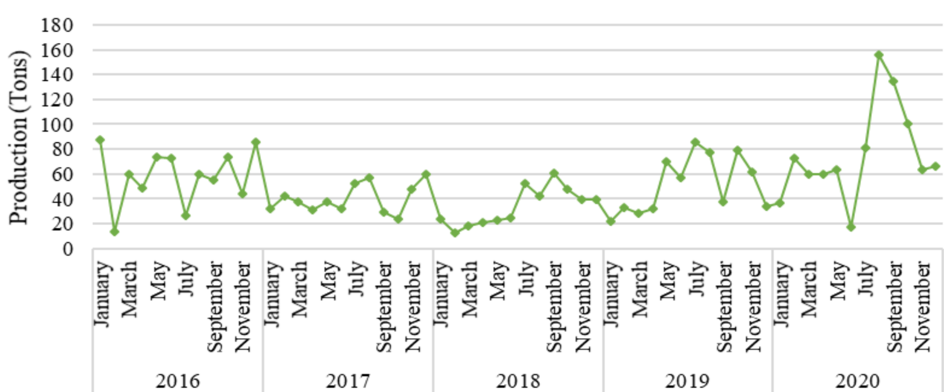

Fig. 5. Dynamics of yellowfin tuna fisheries production at PPN Palabuhanratu (2016–2020)

Entering 2019 and 2020, the production trend began to rise again. In 2019, a significant surge was observed in July (85.895 tons) and October (79.264 tons). A sharper increase was recorded in 2020, particularly in August (156.181 tons) and September (134.863 tons), marking the highest figures over the five-year observation period. A clear seasonal pattern can also be identified, where the months from July to October tend to show higher production volumes compared to other months.

Correlation between yellowfin tuna production and oceanographic phenomena

The Pearson correlation analysis among the four variables which is thermal front, IOD, SST, and yellowfin tuna catch (Fig. 4), revealed varying relationships between variable pairs. The most statistically significant correlation was found between SST and yellowfin tuna catch, with a coefficient of r = -0.340 and a confidence interval (CI) of (-0.547, -0.094), indicating a moderate negative correlation. This suggests that an increase in sea surface temperature tends to be followed by a decrease in yellowfin tuna catch volume. Additionally, the correlation between IOD and SST also showed a relatively strong negative relationship (r = -0.549, CI = -0.705 to -0.344), indicating that positive IOD conditions are associated with a drop in sea surface temperature.

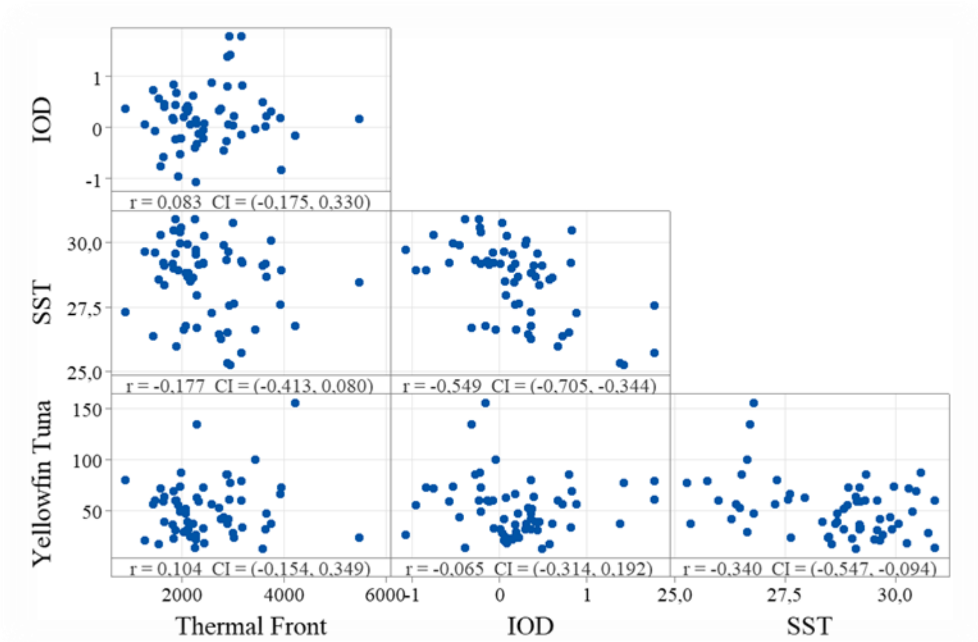

Fig. 5. Pearson correlation matrix plot between thermal front intensity, IOD, SST, and catch of yellowfin tuna in Palabuhanratu waters

Meanwhile, the relationship between thermal front and the other three variables did not show a statistically significant correlation. For example, between thermal front and yellowfin tuna , the correlation value was only r = 0.104 (CI = -0.154, 0.349), indicating a weak and statistically inconclusive relationship. A similar trend was observed in the correlation between Thermal Front and IOD (r = 0.083), as well as thermal front and SST (r = -0.177). This suggests that the number of thermal fronts is not strongly correlated with oceanographic variables or the catch of the yellowfin tuna within the analyzed time scale.

DISCUSSION

Variations in the Dipole Mode Index (DMI) directly influence sea surface temperature (SST) in the Indian Ocean, including the waters of Palabuhanratu **(Rahayu *et al*., 2018)**. The Indian Ocean Dipole (IOD) phenomenon occurs due to temperature anomalies between the western and eastern parts of the Indian Ocean **(Saji *et al*., 1999**; **Aldrian, 2008)**. This study shows that the IOD is significantly correlated with SST dynamics, with a correlation coefficient of -0.549. This value indicates that a positive IOD phase tends to lower sea surface temperatures in the study area. This finding is consistent with previous research that also reported strong negative correlations between DMI and SST, such as -0.451 in the southern waters of Java during the first transitional season **(Asyam *et al*., 2024)**, -0.53 in the waters of Bengkulu and -0.56 in the waters of Lampung **(Berliani *et al*., 2025)**. The consistency of these values indicates a strong and widespread inverse relationship between IOD intensity and sea surface temperature across various Indonesian waters.

During a positive IOD phase, the center of low pressure shifts westward in the Indian Ocean, causing cooling in the eastern region, including Indonesia **(Saji *et al*., 1999)**. For example, in 2019, an increase in the DMI value to 1.78 was accompanied by a significant decrease in SST in Palabuhanratu. This cooling triggered upwelling, which enriched the waters with nutrients, enhanced primary production, and ultimately supported the abundance of yellowfin tuna **(Lan *et al*., 2013)**. Research on the impact of the extreme positive IOD event in 2019, particularly in the southern waters of Java Island, showed a significant decrease in sea surface temperature (SST) to 25.27°C, followed by an increase in nutrient concentrations (N and P) and an intensification of biological parameters such as chlorophyll levels, primary productivity, and jellyfish bloom events **(Firdaus, 2020; Iskandar *et al*., 2022; Wahyudi *et al*., 2023)**. Conversely, during a negative IOD phase such as in 2016, sea temperatures remained high throughout the year, affecting the productivity of the waters **(Rahayu *et al*., 2018)**.

Changes in sea surface temperature influenced by IOD have significant implications for the habitat of yellowfin tuna, which is known to be sensitive to water temperature. SST affects various life stages of this fish, from egg and larval development to food availability **(Sambah *et al*., 2021)**. The correlation between SST and the yellowfin tuna catch in this study shows a value of -0.340, indicating that a decrease in sea temperature tends to be followed by an increase in catch. This finding is consistent with studies by **Sambah *et al*. (2021)**, **Habibullah *et al.* (2022)** and **Pratama *et al.* (2025)**, who stated that the relationship between SST and the abundance of the yellowfin tuna is negative at moderate to weak levels. Although the direct correlation between IOD and catch is not significant, this result suggests that SST can act as a mediating variable, indirectly explaining the influence of IOD on yellowfin tuna catch. Therefore, IOD does not affect catch directly, but rather through mechanisms involving sea temperature changes, which then influence the distribution and presence of the yellowfin tuna in the southern Java waters.

Furthermore, the relationship between IOD and the thermal front was found to be weak and not significant. This can be explained by differences in the scale of influence, where IOD is a regional climate phenomenon affecting sea temperature over large areas, while thermal fronts are formed by local oceanographic dynamics such as currents, seasonal winds, and underwater topography. Therefore, changes triggered by IOD do not always directly result in the formation of thermal fronts in coastal areas like Palabuhanratu. However, in terms of intensity (Fig. 4), the positive IOD phase appears to be associated with an increase in thermal front intensity, as seen in 2019, which recorded 32,194 thermal front points. This number was 5,185 points higher than in 2016, 351 points higher than in 2017, 2,232 points higher than in 2018, and 3,950 points higher than in 2020. This finding aligns with that of **Jatiandana and Nurdjaman (2020)**, who reported an increase in thermal front intensity in Indonesia during the positive IOD season.

Spatially and temporally, the thermal front in this study spread from the bay to the open sea, with peak intensity from October to December, when the convergence of warm and cold water masses occurs most frequently. In contrast, from June to August, thermal front intensity tends to decrease due to the homogeneity of temperatures outside the bay. This seasonal pattern is influenced by monsoon current dynamics **(Saraswati *et al.*, 2013)** and IOD events **(Lukman *et al.*, 2022)**, which also shape sea surface temperature patterns **(Pratama *et al.*, 2025)**. Although theoretically, thermal fronts are indicators of water productivity due to their relationship with upwelling and nutrient accumulation **(Maharani *et al.*, 2020; Silaban *et al.*, 2025)**, the correlation between thermal fronts and yellowfin tuna production was not significant. This suggests that the presence of thermal fronts does not directly determine catch outcomes on a temporal scale, likely due to other factors such as sea temperature and chlorophyll-a concentration being more dominant in determining fish presence **(Rahman *et al.*, 2019; Pratama *et al.*, 2025)**.

Thus, the use of PPDPI relying solely on thermal fronts is not sufficiently representative for illustrating the abundance of yellowfin tuna in Palabuhanratu. These findings underscore the need for a more comprehensive predictive approach, such as the use of Species Distribution Models (SDMs), which incorporate various key oceanographic parameters **(Pratama *et al*., 2022**; **Yati *et al.*, 2024)**. In addition to SDMs, other methods such as regression models have been successfully applied to predict fish distributions based on multiple oceanographic variables **(Saifudin *et al*., 2014; Fajar *et al.*, 2020)**. The effectiveness of SDMs in identifying suitable fishing zones for tuna and other pelagic species has been demonstrated, particularly in data-limited regions and dynamic marine environments, as shown in the studies of **Akita *et al.* (2022)** and **Pratama *et al*. (2022)**. This integrative modeling approach enables more accurate and context-sensitive mapping of potential fishing grounds and is expected to support adaptive, efficient, and sustainable fisheries management amid ongoing climate and oceanographic variability.

CONCLUSION

The results of this study show that the Indian Ocean Dipole (IOD) phenomenon significantly influences sea surface temperature (SST) in the waters of Palabuhanratu, which in turn affects the habitat and abundance of the yellowfin tuna (Thunnus albacares). Although IOD does not have a direct significant relationship with catch or thermal front intensity, its indirect effect through changes in sea temperature is relevant. Furthermore, the Pearson correlation results indicate that thermal front intensity is not significantly related to the yellowfin tuna production, as reflected by a correlation value of r = 0.104 with a confidence interval (CI) ranging from -0.154 to 0.349, indicating a weak and statistically inconclusive relationship. These findings suggest that other oceanographic factors play a more substantial role in determining the distribution and abundance of the yellowfin tuna. Therefore, the use of thermal fronts as a single parameter for predicting fishing grounds is insufficiently accurate, particularly in the waters of Palabuhanratu. It is necessary to incorporate additional oceanographic parameters to enhance prediction accuracy, especially local factors such as upwelling, chlorophyll distribution, and water quality indicators including nutrient concentration, salinity, and ocean currents.

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