Sea surface temperature and chlorophyll-*a* distribution from Himawari satellite and its relation to yellowfin tuna in the Indian Ocean

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Abstract. The southern Indian Ocean of Java has a variety of fish resources. Many types of fish migrate on a regular basis, on time scales ranging from daily to annually or longer, and over distances ranging from a few miles to thousands of miles. The analysis of oceanographic parameters using satellite observation helps in the study of fish migration for fishing ground observation. This research aimed to determine the dynamics of oceanographic factors in the Indian Ocean, to describe the variability of oceanographic parameters in the fishing ground of yellowfin tuna (*Thunnus albacares*), and to analyse the relationship between oceanographic parameters and yellowfin tuna. The study also attempted to map potential yellowfin tuna fishing grounds in the Indian Ocean. The quantitative descriptive methods applied included spatial analysis, correlation analysis, and biplot analysis. Oceanographic parameters such as sea surface temperature (SST) and sea surface chlorophyll-*a* (SSC) have an impact on the volume of fish caught. During the period 2015-2019, the highest average SST was 29.25°C and the lowest was 25.72°C, whereas the highest SSC was 0.26 mg m^{-3} and the lowest was 0.10 mg m^{-3}. The coefficient of correlation was -0.610 between SST and SSC, -0.461 between SST and yellowfin tuna catch and 0.321 between SSC and yellowfin tuna catch. The negative correlation between SST and SSC and between SST and catch indicate that chlorophyll-*a* and tuna catch decline with increasing temperatures, while the positive correlation between SSC and catch indicates that yellowfin tuna are more likely to be caught in areas with higher SSC.
Key Words: oceanographic parameters, Himawari satellite, yellowfin tuna, Indian Ocean.

Introduction. The movement pattern of water masses affects the fluctuation of oceanographic variables such as sea surface temperature (SST) and sea surface chlorophyll-*a* (SSC). SST and SSC are two important oceanographic parameters that affect fish habitat. SST can be used as an indicator for estimating the location of upwellings, downwellings, and fronts associated with potential fishing grounds. Meanwhile, chlorophyll-*a* is an indicator of the level of the fertility and productivity of marine waters (Yoga et al 2014).

The migration of pelagic fish in marine waters is influenced by oceanographic parameters such as SST, salinity, surface currents, dissolved oxygen, and other ooceanographic factors (Cahya et al 2016). Therefore, oceanographic parameters such as SST and SSC are among the factors that can greatly influence the variability of fish catches. Upwellings bring nutrients to the surface and provide rich feeding grounds for fish. The SST-induced wind stress curl reinforces seaward upwelling through Ekman suction or pumping (Kok et al 2017), a critical effect of the air-sea interaction on both circulation and eddies in coastal waters (Jin et al 2009). Given the sizes of these SST-induced perturbations of the surface wind stress field and the magnitude of the related Ekman upwelling impacts on the sea, it can be considered that this air-sea interaction is a critical component of regional climate systems (Jin et al 2009). For example, Wass et al (2012) reported coastal upwellings in the northern coastal waters of Papua in reaction to

westerly winds and westerly wind bursts (WWBs) during December to March, characterised by low SST, with intensified Ekman transport and maximum Ekman layer depth. The reported SST range for yellowfin tuna is 18-31ºC (Cucalón-Zenck 2017).

Chlorophyll-*a* is an indicator of primary productivity. If the waters are fertile, there will be a lot of phytoplankton which are the primary producers at the base of the food chain and are the main food source for some small fishes, as well as zooplankton which is also food for small fishes. The food chain within the pelagic zone of the seas is generally longer than in terrestrial ecosystems (Sommer et al 2018). Understanding of the complexity of the pelagic food web has advanced from perceptions of a direct food chain (phytoplankton - zooplankton crustaceans - planktivorous fish - carnivores) to an expanded food web including microbial trophic pathways, complex webs within the zooplankton, including gelatinous organisms, and a high prevalence of omnivory (Andersson et al 2017). Yellowfin tuna are large pelagic fish that feed on small fishes, crustacea, squid, and molluscs. The reported SSC range for yellowfin tuna is between 0.38 and 0.52 mg m^{-3} (Lan et al 2012).

The yellowfin tuna (*Thunnus albacares*) is a large pelagic fish with potential as an export commodity and contributes substantially to Indonesian fisheries production. Yellowfin tuna can be found in oceans all around the world. In Indonesia yellowfin tuna are found in the eastern Indian Ocean which includes the western waters of Sumatra, southern waters of Java, and southern waters of Bali; they are also found in the Banda, Molucca, Halmahera, Arafura, and Sulawesi Seas (Jatmiko et al 2016). The southern coast of East Java is one of the main tuna landing centres. The dominant tuna species captured in the waters off southern East Java in the Indian Ocean is yellowfin tuna, comprising 45.2% of the tuna catch from 2011 to 2015 (Arnenda et al 2019).

The application of satellite remote sensing in observing fisheries resources is currently becoming popular due to the fairly representative temporal and spatial resolution of available data. Some research has used satellite images for observing marine environmental and oceanographic parameters in order to analyse fish stock dynamics. Moreover, the geographical information system (GIS) approach can also help in visualizing and analysing multi-layer raster data related to such research themes (Zainuddin 2007; Nurdin et al 2014; Suhartono et al 2015; Setiawati et al 2015; Mustapha et al 2020; Nurholis et al 2020). This research aimed to determine the dynamics of specific oceanographic factors in the Indian Ocean, to describe the variability of these oceanographic parameters in yellowfin tuna fishing grounds, and to analyse the relationship between these oceanographic parameters and the yellowfin tuna catch. The results of the study can be used as basic information for the mapping of potential yellowfin tuna fishing grounds.

Material and Method

Research location. This research was located in the Indian Ocean off East Java (Figure 1). The research area is included in the Fishery Management Area of The Republic of Indonesia No. 573 (FMA 573). This area is a potential fishing ground for tuna species.

Datasets. The oceanographic data on SST and SSC were obtained from Himawari 8 satellite images for the years 2015 to 2019. Himawari 8 is a Japanese weather satellite, the 8th in a series of geostationary weather satellites operated by the Japan Meteorological Agency (JMA). The JMA began the operation of the Himawari-8 satellite in July 2015 with backup-operation by the Himawari-9 satellite in March 2017, with both units scheduled to continue observations until around 2029. The SST and SSC data from Himawari 8 level 3 were downloaded from http://www.eorc.jaxa.jp/ptree/registration_top.html.

The primary instrument aboard Himawari 8, the Advanced Himawari Imager (AHI), is a 16 channel multispectral imager ranging from 0.47 to 13.3 µm and performs disk observations every 10 minutes (Japan Meteorological Agency 2014). The Advanced Himawari Imager (AHI) has several infrared channels, which are useful in masking

features that affect aerosol uptake. In addition, multiple visible bands and NIR provide a major advantage in extracting aerosol properties.

Spatial data on fishing yellowfin tuna fishing activities were collected from fishing trip logbooks of handline fisherman landing tuna at Sendangbiru fishing port in Malang, East Java, Indonesia. The information consisted of the geographical coordinates of yellowfin tuna catches and the oceanographic conditions around the handline fishing grounds. Data collection and analysis was carried out from December 2019 to June 2020.

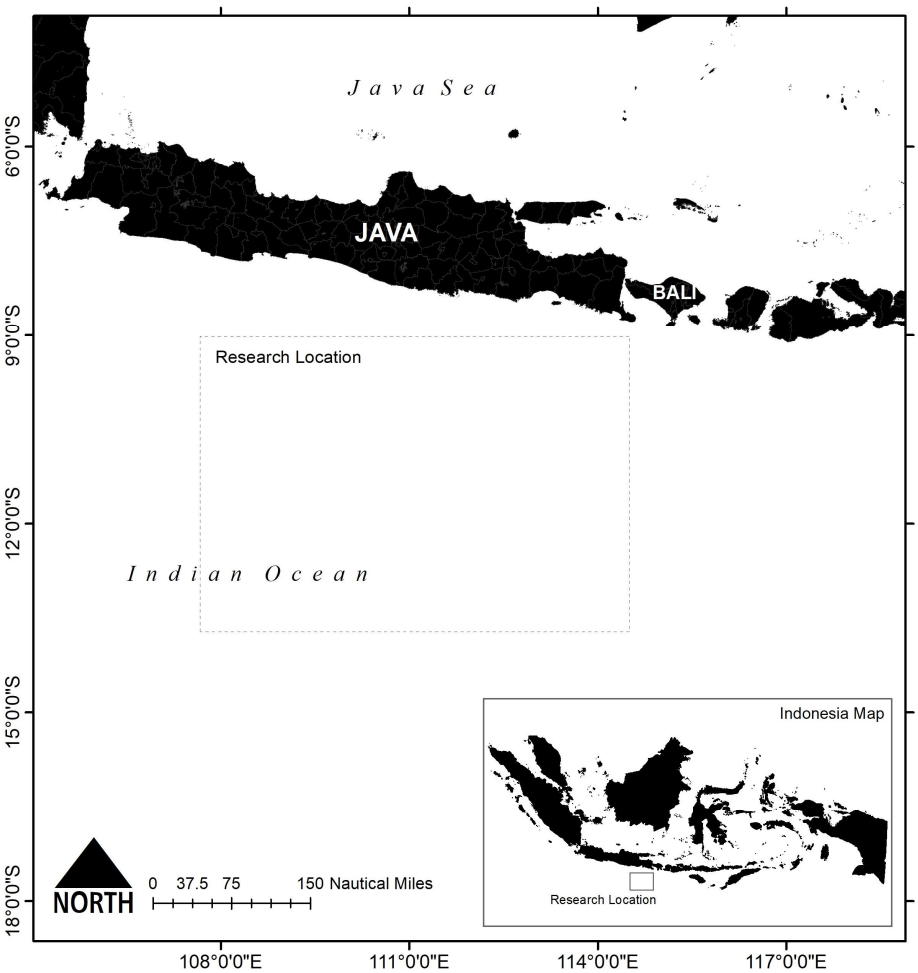

Figure 1. Map of the research area (Indian Ocean off the southern coast of East Java).

Sea surface temperature analysis. The AHI is an optical radiometer on board the Himawari-8. Its observation frequencies are every 10 min for the full disk and every 2.5 min for the area adjacent to Japan. The AHI has 16 spectral bands from visible to infrared wavelengths. The spatial resolution of the infrared (IR) bands is 2 km (Bessho et al 2016). The IR bands centred at 3.9, 8.6, 10.4, 11.2, and 12.4 μm are usable for SST retrieval. The calculation of temperature applied the vertical temperature difference (ΔT) using the following algorithm (Donlon et al 2002):

$$\Delta T_{subskin} = SST_{skin} - SST_{subskin} \quad (1)$$

where $\Delta T_{subskin}$ is vertical temperature difference (°C), SST (°C) is calculated from two or more than two IR data. IR data for JAXA's SST consisting standard mode SST: 10.4 + 11.2 + 8.6 micron band, and night mode SST: 10.4 + 11.2 + 3.9 micron band.

If the bulk temperature conditions are cooler, the skin temperature value will be obtained by reducing the $SST_{subskin}$ value by a value of 0.14-0.16°K. Subtracting this value gives the MUR-SST skin data.

Hourly Himawari-8 data were combined into daily mean data to match the temporal resolution of the MUR-SST data. The MUR-SST skin data has a spatial resolution of 1 km, so it cannot be directly combined with the SST data from Himawari-8 due to differences in resolution. The resolution of the two data was equalized using an image resampling method. Resampling is the process of rescaling raster data that produces a new raster cell grid with a cell size that is different from the original raster and can also be called a cell resizing operation. This process will reduce the spatial resolution of the MUR-SST from ~ 1 Km to ~ 2 Km, matching the spatial resolution of the Himawari 8 level 3 satellite image data (Wade & Sommer 2006). This analysis was performed in SeaDAS, a comprehensive software package for the processing, display, analysis, and quality control of ocean colour data (https://seadas.gsfc.nasa.gov/).

Chlorophyll-a analysis. Chlorophyll-*a* is a green pigment that has the property of absorbing visible light when present in the water. As a result of this absorption, the VIS rays reflected back and captured by the satellite will be less when compared to Near Infrared (NIR) waves captured by the satellite. From these results, the fertility of the surface waters in an area can be estimated by calculating the difference between the values of NIR and visible (VIS) radiation captured by the satellite sensor. The near infrared channel uses channel 4 while the red light uses channel 3. The transformation formula of *NDVI = (NIR)-(VISred)/(NIR+VISred)* was used for calculating the SSC concentration (Ginting & Jadera 2018), where NDVI is Normalized Difference Vegetation Index, NIR is the reflectance from the Near Infrared band (0.725 – 1 μm), and VISred is the reflectance from the visible Red band (0.5 – 0.68 μm).

The principle of surveying phytoplankton quantity by remote sensing is based on reflection spectrum difference between sea water and chlorophyll-*a*. There is a linear relationship between phytoplankton abundance and chlorophyll-a concentration (Songgun 2010). In the application of remote sensing for estimating chlorophyll concentration, Jones et al (2007) reports that the applied exponential equation provides a stronger correlation between NDVI and biomass and chlorophyll concentration. In addition, the analysis of chlorophyll concentration also improves the predictive ability and accuracy of NDVI. This model can be compared with other vegetation indices for better prediction and data analysis (Prabu & Anouncia 2016).

Chlorophyll-*a* data from JAXA Himawari include water-leaving reflectance of band 01~03, chlorophyll-*a* concentration, absorption coefficient of phytoplankton + cdom + detritus, absorption coefficient of particles, aerosol optical thickness of band 2, and aerosol angstrom exponent in the file type of NetCDF (https://www.eorc.jaxa.jp/ptree/userguide.html). The analysis was performed in SeaDAS, and the analysis of geographic data was performed in ArcGIS, a platform to create, manage, share, and analyse spatial data.

Correlation analysis. Correlation analysis discusses the strength of the relationship between two or more variables. The strength or absence of a relationship in the correlation analysis is indicated by a number in the range 0-1. The number 0 indicates no correlation, and 1 shows a very strong correlation. The correlation criteria between the two variables is as follows: if $0 \leq r \leq 0.2$ then the correlation is very weak; if the value is $0.2 \leq r \leq 0.4$ then the correlation is weak; if the value is $0.4 \leq r \leq 0.6$ there is a moderate correlation; if the value is $6 \leq r \leq 0.8$ the correlation is strong; and if the value is $0.8 \leq r \leq 1$ the correlation is very strong. The Pearson correlation coefficient was calculates using the following formula (Edwards 1976):

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (2)$$

where: r is the correlation coefficient, n is the number of data points, X is the independent variable, Y is the dependent variable.

Biplot analysis. Biplot analysis is performed on a data matrix with each column representing a variable. In the biplot analysis, information is obtained about the closeness between objects, the diversity of variables, the correlation between variables, and the variability in the value of an object. Biplot analysis can describe the data in a summary table in a two-dimensional graph. The information provided by the biplot includes both objects and modifiers in one figure. In addition, this method can also be used to describe data and create mappings with two-dimensional graphic displays. A generalised biplot displays information on both continuous and categorical variables (Gabriel 1971; Greenacre 2010). Biplot analyses have been used in several fisheries-related applications such as to visualize the difference in distribution patterns of fish assemblage composition from before and after the abolishment of fishing lots (Chan et al 2020) and to representing gear selectivity for the most abundant species in a study of capture fisheries trends (San Diego & Fisher 2014). In this research the biplot analysis was applied to the variables of fish catch, SST and SSC. This analysis was performed in XLSTAT software.

Results and Discussion

Yellowfin tuna catch. The production volume of the yellowfin tuna catch reported at Pondokdadap Fishing Port in Sendangbiru, Malang Regency was higher than that of other tuna species. During 2015-2019, the highest yellowfin tuna production volume was obtained in 2019 with a total annual production of 80,189 tonnes and the lowest was in 2016 with a total annual production of 47,560 tonnes (Figure 2).

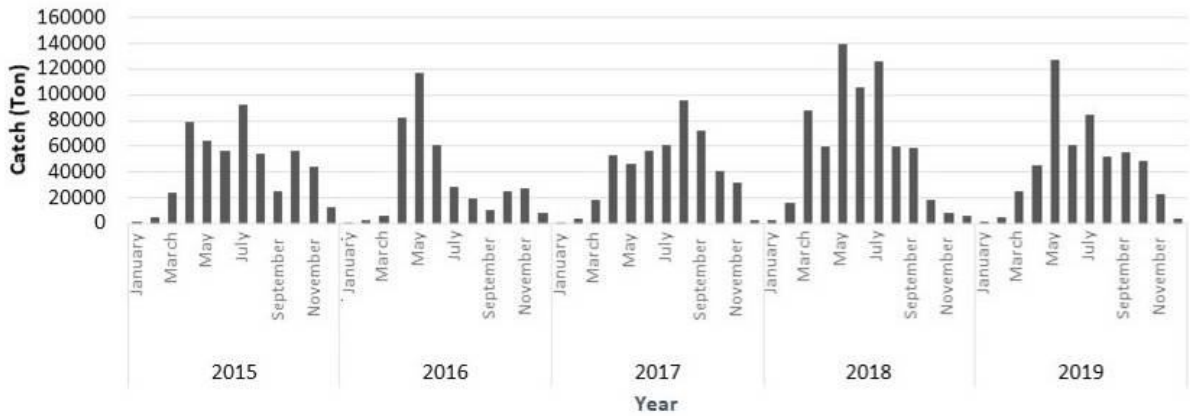

Figure 2. Yellowfin tuna catch volume reported by Pondokdadap Fishing Port, Malang, Indonesia over the period 2015-2019.

Yellowfin tuna is a prime commodity with a higher catch volume than any other tuna species in Indonesia. This is due to the abundant stocks of yellowfin tuna in the Indian Ocean. Most of the yellowfin tuna landed at Sendangbiru Fishing Port, Malang, Indonesia came from the waters off the southern coast of East Java. This area is a very strategic fishing ground, especially for tuna. In addition, these waters are directly adjacent to the Indian Ocean which has a large diversity of pelagic fish species (Jaya et al 2017). Fish seasons in Indonesia are influences by the southeast or east and west monsoons. Annual changes in fisheries catch are influenced by many factors such as oceanographic phenomena, human factors and fishing gear. Seasonal variability in sea-surface conditions is similar from year to year and interannual variability is predictable (Hendiarti et al 2005). A study by Wiryawan et al (2020) revealed a significant correlation between environmental factor fluctuation and regular seasonality and annual abundance of yellowfin tuna which indicated by seasonal and annual patterns of variation in the standardized catch per unit of effort. Seasonal variations in the number of cyclonic eddies, dissolved oxygen concentration and tuna catches were statistically coupled, and these links reflect a causative mechanism. Large pelagic fishes, like yellowfin tuna, are

dynamic swimmers sensitive to low dissolved oxygen concentrations due to their high metabolism (Al Jufaili & Piontkovski 2019).

Oceanographic parameters. During the period 2015-2019, SST values in the southern waters of East Java Province varied between east and west season. During 2015 to 2019, the average SST in the study area ranged from 25.72 to 29.25°C. The average SST during the eastern monsoon for all years based on Himawari image data analysis was around 25.72-27.07°C, while for the west monsoon the SST range was 28.57-28.92°C, and during the transitional seasons I and II the SST range was 26.00-29.25°C (Figure 3).

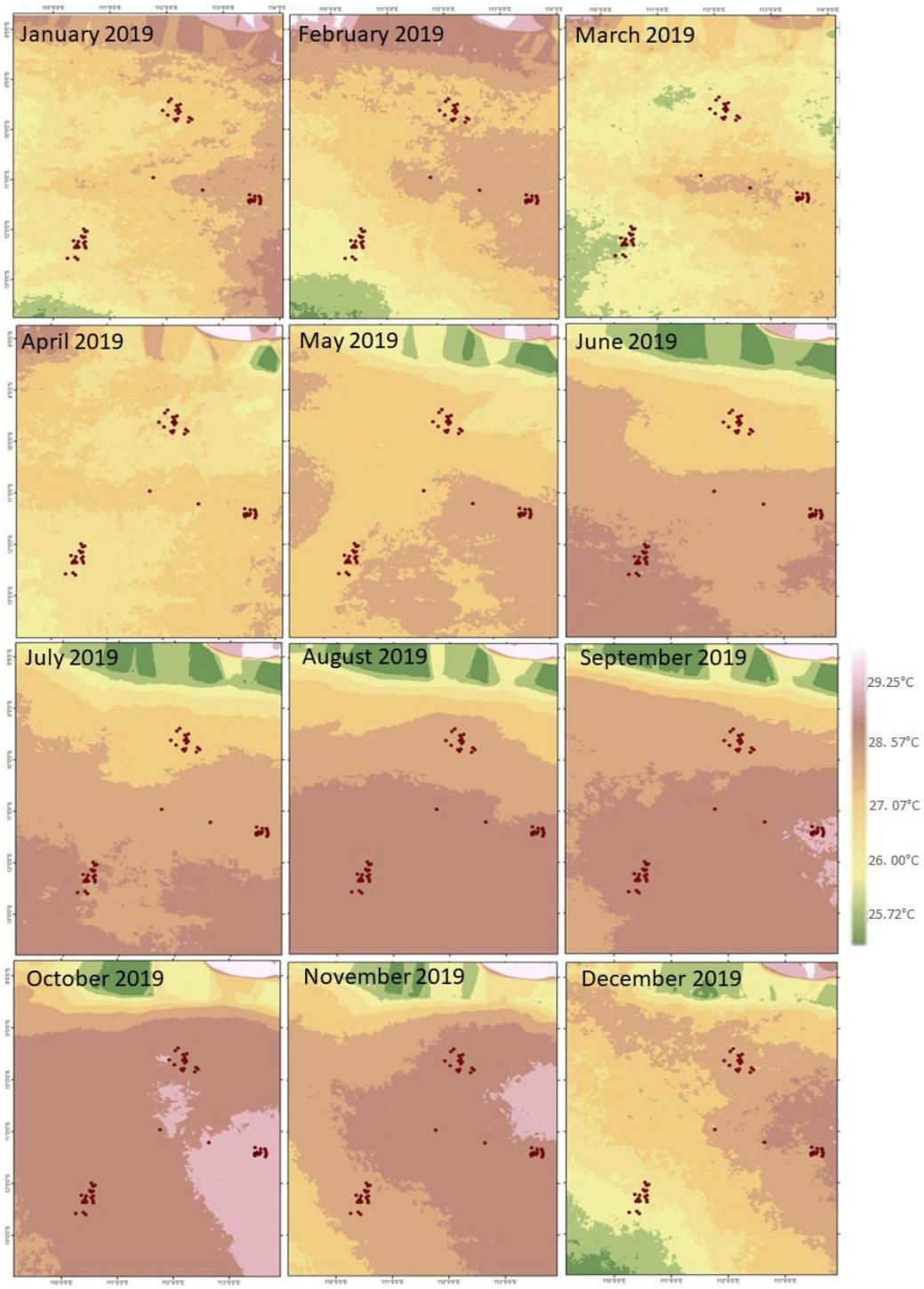

Figure 3. Spatial variability of SST (°C) from Himawari image analysis based on average monthly values for the period 2015-2019.

The variation in the distribution of SSC based on the Himawari satellite data during 2015-2019 ranged from 0.10 to 0.26 mg m^{-3} (Figure 4). The highest SSC occurred in August with an average SSC of 0.26 mg m^{-3} and the lowest in March with an average of 0.10 mg m^{-3}. This is in accordance with the peak fishing season, which was in the transition season I (March-May) and during the east monsoon (June-August), when upwelling phenomena occur.

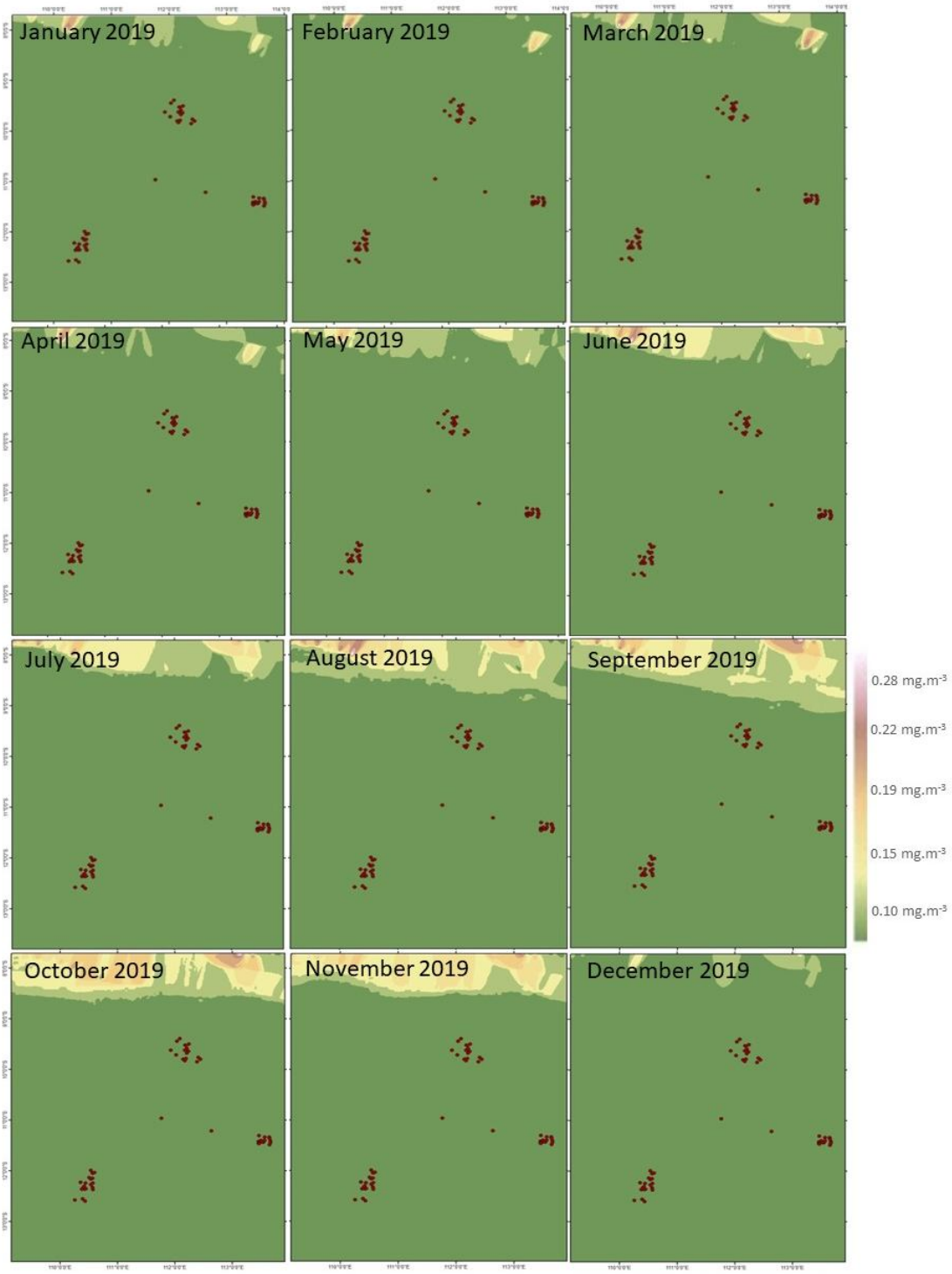

Figure 4. Spatial variability of SSC (mg.m^{-3}) from Himawari image analysis.

The relationship between oceanographic parameters. The correlation analysis between SST and SSC was performed on the anomalies (departure from the mean value) in each parameter (Figure 5). The analysis showed that the highest SST anomaly occurred in July 2016 (2.05) and the lowest in September 2019 (-0.77). The highest SSC anomaly occurred in July (0.1) and the lowest was in July 2016 (-0.12). The correlation value was -0.6108 which shows a strong negative relationship (absolute value in the interval 0.6-0.799).

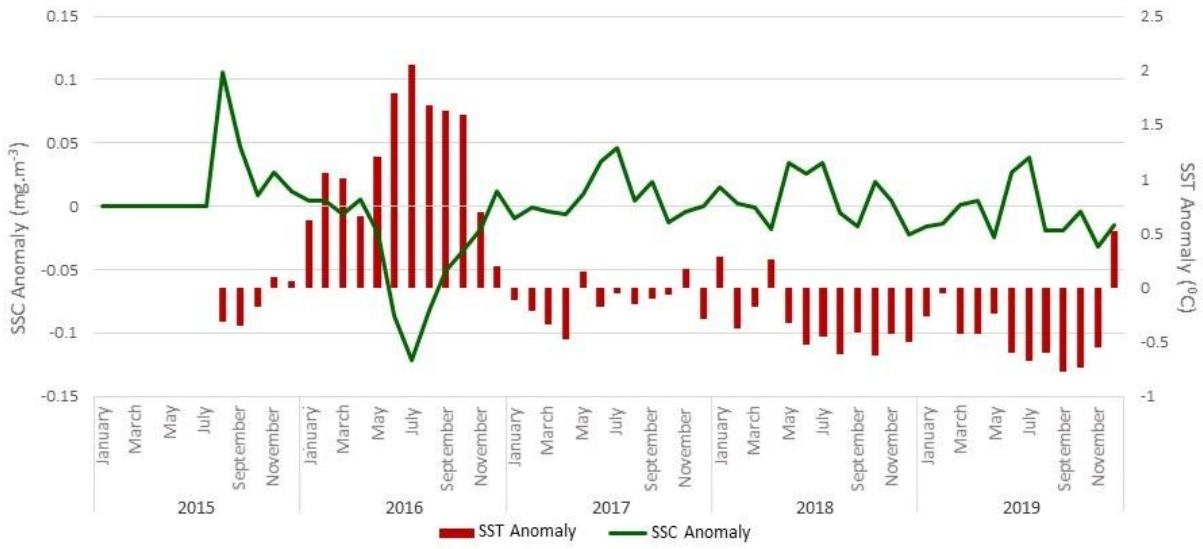

Figure 5. Negative correlation between anomalies in SST and SSC during 2015-2019.

The oceanographic dynamics of the eastern Indian Ocean are influenced by the complex relationship between remote forcing from the equatorial part of the Indian Ocean and strong local influences. The dynamics of these waters are influenced by factors such as the monsoon system, the Indian Ocean Dipole (IOD), El Nino Southern Oscillation (ENSO), Kelvin waves, Indonesian Cross Flow (ARLINDO), and the Southern Equatorial Current and currents from the west coast of the Island of Sumatra (Susanto et al 2001; Setyadji & Amri 2017; Sambah et al 2020). In addition, there are also other factors, namely the South Java Coastal Current which is a branch of the west coast of Sumatra current which affects the physical dynamics of the southern waters of Java Island (Purba 2007). The process of mass movement of water results in fluctuations in oceanographic parameters such as SST and SSC conditions in the waters (Kunarso et al 2011).

The relationship between oceanographic parameters and yellowfin tuna catch. As described above, the highest SST anomaly was in July 2016 and the lowest was in September 2019. Meanwhile, the highest yellowfin tuna catch was in August 2017 and the lowest was in September 2015. The correlation between SST and yellowfin tuna catch was -0.461, in the moderate range (0.4-0.599). The correlation was negative, so the relationship between SST and yellowfin tuna catch was inversely proportional. There was a time lag of 2-3 months between changes in SST and changes in fish catch volume; this time lag is though to be due to the upwelling processes being followed by an increase in the amount of SSC, resulting in higher productivity and increasing food availability so that tuna catch volume increased.

The correlation between SSC and yellowfin tuna catch was 0.321 and classified as a low or weak correlation. The correlation value was positive so that the relationship between SSC and yellowfin tuna catch was directly proportional. This means that an increase in SSC concentration was followed by an increase in tuna catch volume. The relationship between SSC on yellowfin tuna also had a time lag of 1-2 months. Figure 6 shows these correlations.

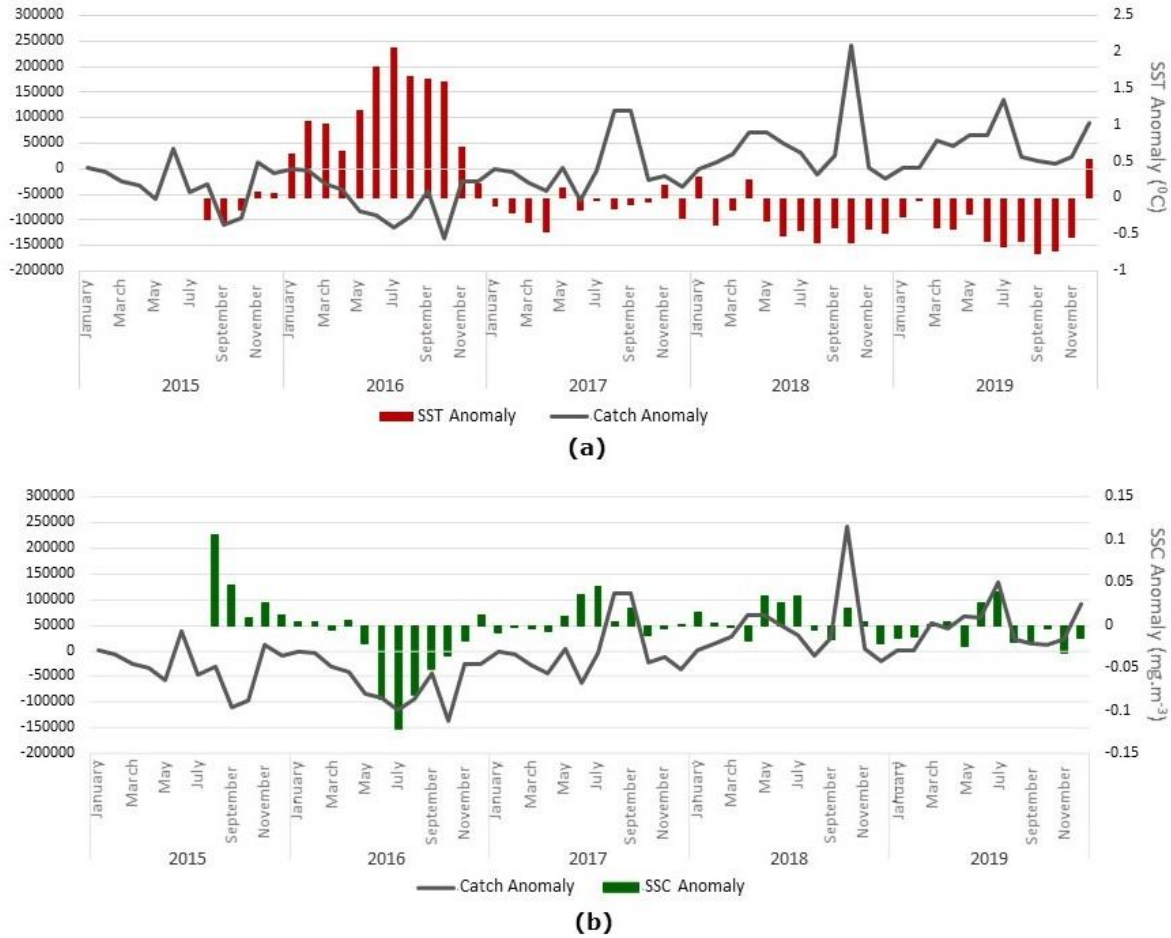

Figure 6. The relationship between oceanographic parameters and yellowfin tuna catch volume: (a) SST anomalies; (b) SSC anomalies.

SST and SSC are oceanographic factors that affect the distribution of fish. Fish will tend to move towards waters with warm temperatures and a high abundance of phytoplankton (Kuswanto et al 2017). The distribution of chlorophyll-*a* is influenced by differences in sunlight intensity and nutrient concentrations in the water. The distribution of chlorophyll-*a* is generally relatively lower in offshore waters and increases towards the coast. Movements of water masses such as upwellings mean that nutrient-depleted surface waters will be replaced by nutrient-rich water masses from a lower layer (Kok et al 2017). Chlorophyll-*a* concentration can be caused by a high occurrence of nutrient-enriched on the surface layer of the waters through the various processes of the dynamics of water masses (Nababan & Simamora 2012; Utari 2013; Trenggono et al 2018).

The biplot analysis was carried out to find out how the distribution of yellowfin tuna catches was influenced by SST and SSC. This graphic representation indicates which parameters have more influence on the fisheries catch (Figure 7). Yellowfin tuna catch was more influenced by chlorophyll-*a*, with a total number of 16 points in quadrant 2 that were affected by chlorophyll-*a*. In quadrant 1 12 points were affected by SST. Quadrant 3 described 23 points, while quadrant 4 described 8 points with no influencing factors. This shows that the most dominant factor influencing fish catch volume was SSC.

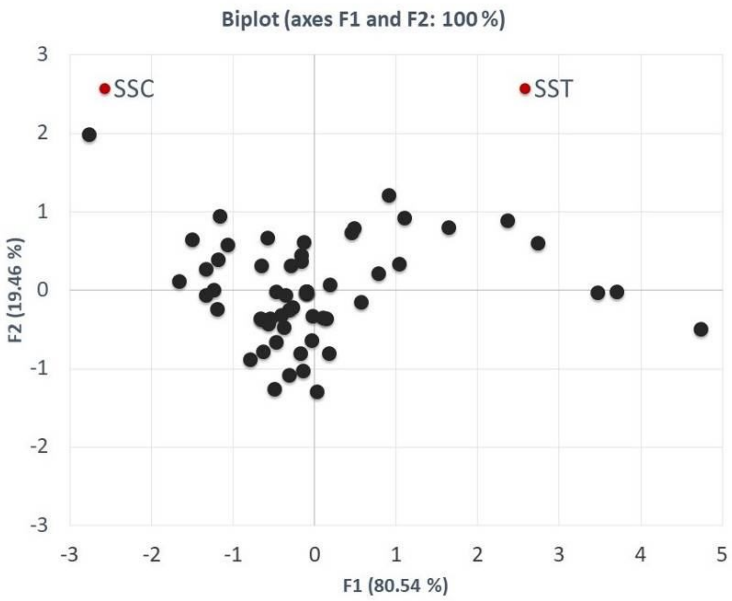

Figure 7. Biplot analysis describing the effect of oceanographic parameters on the distribution of yellowfin tuna catch volume.

Conclusions. It can be concluded that the Himawari satellite data performed well in describing the spatial variability of the oceanographic parameter SST and SSC. In turn, these could be used in a correlation analysis with yellowfin tuna catch volume based on fishing trip data. The analysis of oceanographic parameters showed that SST and SSC were inversely correlated, as were SST and yellowfin tuna catch. Meanwhile, the correlation between SSC and yellowfin tuna catch was directly proportional. There was a time lag of 2-3 months in the relationship between SST and fish catch, and a time lag of 1-2 months in the relationship between SSC and yellowfin tuna catch. Recommendations for the sustainable management of tuna fisheries in the study area can be formulated based on temporal and spatial adjustments in fishing grounds, based on the areas predicted as potential fishing grounds in each season. Future research on the relationship between oceanographic parameters and fish catch, including statistical analysis to determine which oceanographic parameters have the strongest influence, could use a GAM (Generalized Additive Model) approach, modelling oceanographic parameters to map potential fishing grounds.

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