08. Environmental aspects of tuna catches in the Indian Ocean, southern coast of Java, based on satellite

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Environmental aspects of tuna catches in the Indian Ocean, southern coast of Java, based on satellite measurements

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***Abstract*— The present work seeks to assess the relationship between daily Sea Surface Temperature (SST) and thermal front (Gradient Magnitude method) using AMSR-E, daily Sea Surface Chlorophyll-a (SSC) using MODIS, and daily long line (LL) bigeye (BG), albacore (ALB), yellowfin (YF), and southern bluefin (SBF) tuna catch data expressed as catch per unit effort (CPUE), which was calculated as the number of fish caught by 1000 hooks in 1° latitude by 1° longitude square grid, and integrated into a month of fishing activity for the period of March–December 2010 in South Java (Indian Ocean). Results obtained showed evidences of non-linear relationships between catch yields and environmental data. BG and ALB show largest CPUE values which occurred mainly in the area with SSTs of 26 – 27 °C and SSCs of 0.15 – 0.3mg/m^3. CPUEs appear to be "randomly" dispersed and have a slight positive (negative) correlation with SSC (SST) i.e., 0.33 (-0.38) but not with GM values i.e., -0.02. The weak correlation between CPUE, SST, SSC and GM lead to assume that CPUEs might be linked to other influential parameters that are not assessed in the present study but are needed to give complete prediction of potential fishing ground areas, knowing that the length of observation period is less than 1 year.**

Keywords*—*Tuna catch, SST, chl-a, SST front, southern coast of Java

I. Introduction

Indonesia stretches roughly from 6ºN to 10ºS and from 95ºE to 142ºE and occupies a central position of Indo-Pacific creating permeable barriers between the Pacific and Indian Oceans and the Asian and Australian Continents. Totally, Indonesia has 5.8 million km^2 of marine waters consisting of 3.1 million km^2 of territorial waters (<12 miles) and 2.7 million km^2 of EEZ (12-200 miles). Indonesia started longline fishing for southern bluefin tuna in 1986; the catch has increased continuously. Five main landing sites for Indian Ocean tuna industrial fleet are Benoa Fishing Port (Bali), Muara Baru Port (Jakarta) and Cilacap Port (Central Java), Pelabuhan Ratu (West Java) and Bungus (West Sumatera). Benoa Fishing Port is considered as the main tuna landing port for Indonesian tuna catch. South Java and Bali are main tuna fishing grounds for most of Indonesia tuna liners.

The species of tropical tuna that are commonly found in south Indonesia waters within IOTC competence area are skipjack tuna (SKJ), yellowfin tuna (YF), bigeye tuna (BG), albacore (ALB) and southern blue fin tuna (SBF). These species are targeted by various fishing gears such as tuna long line (LL), purse seine (PS), pole and line (PL), hand line (HL), and gill net (GN). The catch proportion in average since 2005 to 2014 was yellowfin tuna (29.82 %), bigeye tuna (16.76%), skipjack tuna (46.52%) and albacore (6.88%). LL and purse seine are the main fishing gears targeting tuna that contribute significantly to tuna fishery [1].

On the other hand, variations in the environmental conditions affect the recruitment, distribution, abundance and availability of fishery resources. It is not possible to measure remotely the entire range of information needed to assess changes in the marine environment. Knowledge of particular conditions and processes affecting fish populations, however, may often be obtained using measurements made by remote sensors, e.g., variations in primary production, distribution of surface isotherms, regions of upwelling, currents and water circulation patterns. The parameters providing information on these environmental factors may allow a forecast of fish distribution or more generally the definition of marine fish habitats [2].

Ocean water temperature is an important factor influencing the geographic range and movements of large oceanic pelagic fish. Ref [3] concluded that temperature influences the seasonal distribution of yellowfin, skipjack, and albacore tuna in Pacific Ocean. Moreover, spatial discontinuities in temperature, indicating thermal fronts, may be more relevant than temperature itself to oceanic pelagic fish. Thermal front is an area of the confluence from two water masses that have different temperature characteristics. The association of large pelagic fish with fronts is probably not linked directly to temperature changes, but rather to other physical or biological factors associated with frontal regimes. Temperature changes across fronts are often accompanied by changes in other water properties such as salinity, water clarity and current velocity

[4]. More importantly, the biomass of plankton, zooplankton and small forage species may be higher near fronts because mesoscale oceanic processes stimulate primary productivity and physically concentrate primary and secondary production [5]. For instance, the occurrence of large oceanic pelagic fish near fronts has been demonstrated by [6] for albacore tuna in the Pacific Ocean. Ref [7] also found the relationship between high tuna catches with strong SST front in the South-western Indian Ocean.

Phytoplankton contains a photosynthetic pigment called chlorophyll that lends them a greenish color. As the lowest level of the food pyramid in the ocean, chlorophyll-a concentration represents the primary productivity that determine the productivity of marine organisms in the higher level. Many studies have shown that the high Chl-a concentration during upwelling period is often followed by the increase in fisheries productivity [e.g., 8, 9].

Estimation of a fishery resource can be assisted by the measurement of parameters which affect distribution and abundance. Much of the research dealing with environmental effects related to fisheries is concerned with the correlation of a single parameter with the spatial and temporal distribution of fish. It is most likely, nonetheless, that fish respond to the sum of environmental factors. Thus, it becomes necessary to correlate a large number of parameters with fish distribution.

The continuity, global coverage, and high temporal and spatial resolution of satellite data make it an important tool for monitoring and characterizing marine ecosystems. Although satellites do not observe fish stocks directly, measurements such as Sea Surface Temperature (SST), Sea Surface Height (SSH), ocean color, ocean winds and sea ice, characterize critical habitat that influences marine resources. In the present study, SST, SST front and SSC observed from satellites were examined as the environmental aspects that affect tuna catches in the Indian Ocean, Southern Coast of Java.

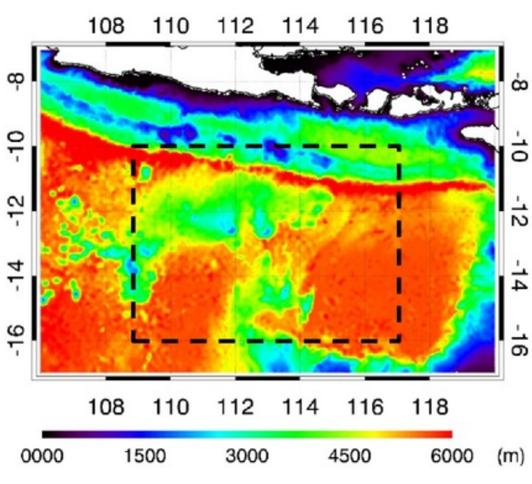

Fig. 1. Study area as denoted by the dashed square. Bathymetry is obtained from ETOPO2.

II. DATA AND METHOD

The study area is located in the Indian Ocean, southern coast of Java (Fig. 1). The subduction zone lies in this area which separate the deep ocean (i.e., > 5000 m) and shallow coastal waters (i.e., < 5000 m) in the zonal band between 10°S and 12°S. Fishery data, consisting of daily YF, BG, SBF, ALB catches and LL fishing efforts for the period from March to December 2010 (Number of hooks deployed in April and December were not available), were provided by one of the commercial fishing boats landing in Bali. The daily catch per unit effort (CPUE) for LL was calculated as the number of individuals captured per 1000 hooks of the LL set. 681 values for CPUE were obtained. From this data set, the CPUE was used as the relative abundance index. Following ref. [10, 11], the CPUE values were divided into three classes (*See Table 1*), but since the spatial distribution of CPUE was superimposed. These values were divided into six categories (C1-C6), which allowed to have more visibility (*See Tab.1*).

TABLE I. DISTRIBUTION AND DESCRIPTION OF CPUE CLASSES ACCORDING TO THEIR VALUES

C1 (n=113)	C2 (n=320)	C3 (n=176)	C4 (n=43)	C5 (n=21)	C6 (n=9)
Null catches	**Low positive catches**	**Moderately high catches**	**High catches**	**Very high catches**	**Highest catches**
CPUE = 0	0 < CPUE ≤ 3	3 < CPUE ≤ 6	6 < CPUE ≤ 9	9 < CPUE ≤ 12	CPUE >12

Concerning the environmental parameters, SST and SSC for the period of 2010 were obtained from satellite data. High resolution (0.25°) SSTs were derived from the AMSR-E, a passive microwave radiometer flying on NASA's AQUA satellite. Version-6 Level-3 AMSR-E SSTs produced by the Japan Aerospace Exploration Agency/Earth Observation Research Center [12] were used in this study. The original spatial sampling interval of the Level-3 SST product is approximately 25 km (0.25°). The original AMSR-E SST path, in which spatial sampling interval is approximately 10 km, was followed. The path data was calculated for the period from January to December 2010. The swath width of AMSR-E is 1500 km at the sea surface [e.g., 12,13]. In order to detect the daily SST front, the traditional method was applied, using the gradient magnitude (GM) given as follows [14]:

$$GM = \sqrt{\left(\frac{\partial SST}{\partial x}\right)^2 + \left(\frac{\partial SST}{\partial y}\right)^2} \quad (1)$$

Thermal front localization was mapped from the AMSR-E SST generated, with GM unit: °C/25 km.

The daily surface chlorophyll-a concentration data was generated from MODIS Aqua Lv3 with spatial resolution of 0.04° × 0.04° [15], with observation period from January to December 2010. The MODIS SSC product is obtained by combining two algorithms: the O'Reilly band ratio algorithm (OCx) and the Hu color index algorithm (CI). The CI and OCx algorithm are used for Chl-a retrievals below 0.15 mg/m^3 and above 2.0 mg/m^3 respectively. In between these values, both algorithms are blended by weighting method. Among the past and present ocean color sensors, MODIS is currently the primary operational ocean color sensing platform and is also widely used for investigating oceanographic phenomena.

All daily environmental data are composited into monthly data following ref [16] to obtain their spatial distribution and compare them with the fish catch data. Moreover, match-ups of daily environmental parameters and tuna CPUE were also generated, for more performing statistical analysis.

III. Result and Discussion

A. *Tuna Cathces*

The spatial distribution of tuna catches in 2010 is shown in Fig. 2. Tuna catches are mainly located between 111°E-117°E and 10°S to 16°S. In addition, 99.8% of the tuna catches weighted less than 20 kg. Unfortunately, only catch data from the period March and May to December 2010 was available. The depth of hooks deployed varies between 70m and 280m. The length of LL used during this period ranges from 50 to 90 km, depending on the number of hooks deployed.

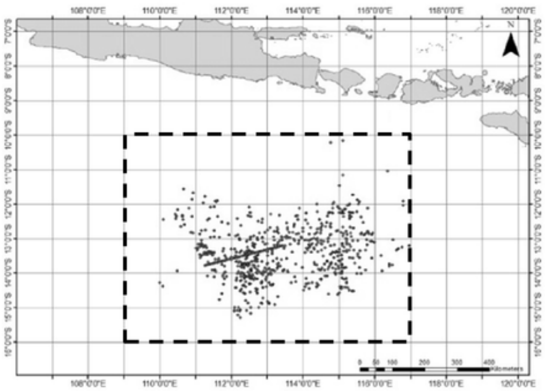

Fig. 2. Tuna catch distribution in the southern coast of Java in 2010

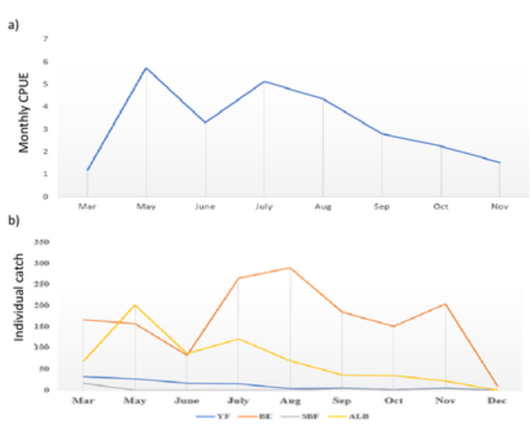

Fig. 3. a) Monthly CPUE of tuna, b) Monthly Individual catch of tuna

Fig. 3a shows that the highest catches occur from the end of first transition season to east monsoon season i.e., May to July denoted by a monthly CPUE higher than 3. Monthly CPUE is the monthly average of daily CPUE. However, the daily CPUE data is based on the total number of hooks deployed to catch BG, ALB, YF and SBF combined. Therefore, the daily and monthly CPUE generated from the data is not able to provide precise information about which species had the highest or lowest CPUE. For instance, high CPUE values that occurred in May indicate high abundance, but it is not possible to tell which species was the most abundant and which one was not. That is why it seemed necessary to generate a graph with monthly catches by individual (n = 2278).

Fig. 3b shows the monthly catches by individual. BE is the most abundant and during the whole year, with a peak recorded during the period of July-August (Southeast Monsoon), and a sharp drop in December (Northwest Monsoon). ALB is the second most abundant species but with lower catches, as can be observed on the graph, the peak is recorded in the period of May. The line increases slightly in July and continues to decrease until December.

Due to the highly migratory and seasonal behavior of tuna species, a space–time factor was systematically included in the final model. This space–time factor was considered by fitting a three-dimensional smoother to the product of the three variables: latitude, longitude and time (month). This factor was taken as a variable in the analysis (Fig. 3b). The study area was reduced in order to increase the CPUEs spatial distribution visibility. The daily CPUE values generated can indicate “where” and “when” the tunas were most abundant, but again, it is not possible to tell when and where “each” species was most abundant since BG, ALB, YF and SBF have different migration paths and vertical distributions. However, making a correlation between the daily CPUE distribution and the monthly catches graph can give more significant results.

B. *Relation between Tuna Catches and Environmental Aspects*

To examine the relation between tuna catches and environmental parameters, the monthly CPUE was plotted, then overlaid with monthly SSC, SST and SST front maps. The spatial distribution of tuna catches which lies between 111°E to 117°E and 10°S to 16°S was considered as the plotting area of this spatial analysis. Fig. 4-6 plot the C1 – C6 CPUEs against the SSC and SST and GM maps respectively, for the period of March – December 2010. It can be seen from the CPUEs superimposed on SSC and SST maps that the C3 – C6 CPUEs occur in the area with SSTs of 26 – 27°C, and SSC of 0.15 – 0.3mg/m^3. While the C1 – C2 CPUEs (black and grey circles) are located mainly in areas with SSC within 0.0 – 0.1mg/m^3, and SSTs within 28 - 31 ◦C. The highest CPUEs occur when SSC (SST) is high (low). High (low) SSC (SST) occur during south east monsoon season which correspond to the upwelling season [e.g., 17, 18, 19].

On the other hand, GM maps do not show any correlation with CPUE. The statistical analysis supports the spatial analysis, showing that the correlation between SST-CPUE, and SSC-CPUE are stronger than the correlation between GM-CPUE i.e., -0.38, 033 and 0.02 for the correlation of CPUE with SST, SSC, and GM, respectively. Furthermore, the correlation among SST, SSC and CPUE is well presented in the scatter plot as shown in Fig. 7. The red circle, representing the null and low catches dominance (C1 – C2), is ranged between 29 < SST < 33°C (SST) and SSC > 0.1 mg/m^3. The blue circle on the other hand, represents positive and high catches (C3 – C6), and is ranged between a lower SST (26 – 29°C) and a higher SSC (< 0.1 mg/m^3). These results mean that SST and SSC can be reliable predictors for tuna fisheries than SST front in the South Coast of Java. This result is different with [7] which shows the strong correlation between SST front and tuna catches in the south-western Indian Ocean.

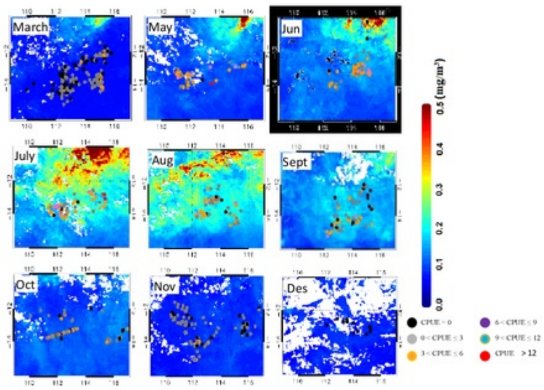

Fig. 4. Monthly SSC maps overlaid with CPUE in 2010

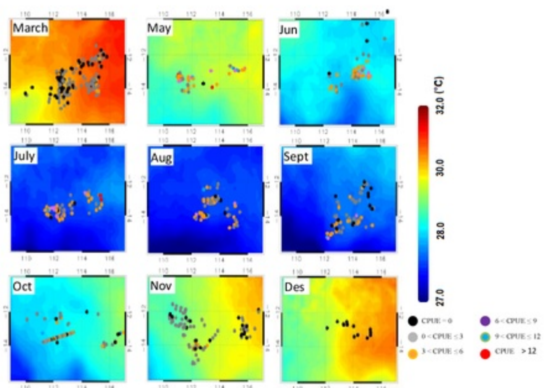

Fig. 5. Monthly SST maps overlaid with CPUE in 2010

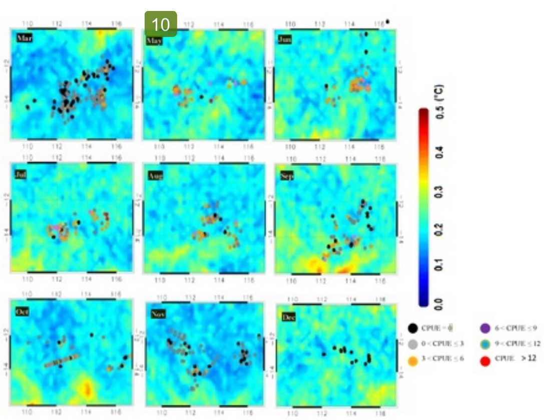

Fig. 6. Monthly GM maps overlaid with CPUE in 2010

C. Discussion

It has been shown that SST and SSC demonstrate a better relationship with CPUE of tuna in the Southern Coast of Java than SST front. However, CPUEs distribution show a "random" trend, without any obvious linear/nonlinear correlation with SST nor SSC since the values appear to be randomly dispersed, despite the periodic variance of SST and SSC. This may be caused by several factors. First, the length of LL increases (decreases) the uncertainty of tuna catches positions, and that could easily lead to biased spatial assessments. More than that, tuna catch data used in this study focuses solely on pelagic longline catches, whereas there are other gears with different tuna selectivity such as purse seines and fish traps that target different tuna species. Hence, collecting catch data of different gears can afford complete information about the variance of spatio-temporal tuna distributions.

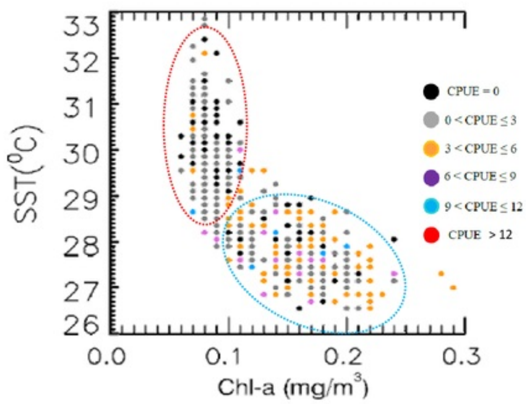

Fig. 7. Scatter plot of CPUE vs SST vs SSC

Second, the depth of LL is not analyzed in the present study. In fact, the variation of longline depth can highly influence tuna catches size and species. The vertical tuna distribution varies remarkably according to water temperature and depth. BE is more likely to swim in colder waters reaching a depth of 480m (8°C – 18°C). Unlike SBF and YF which are usually found in warmer habitats (C° < 16), with a maximum depth of 200m. Furthermore, the present study only analyzed the catch data in 2010 which is marked as the El Nino year, however, it is not possible to assume if the parameters studied are influenced by this event or not. Using longer dataset of at least 10 years, would have allowed to develop a significant comparison.

The lack of correlation among the results obtained lead to assume that tuna distribution seems to depend on other parameters that were not assessed in the present work but were mentioned in many previous studies that assessed the strong relation between CPUE and Sea Surface Height Anomalies (SSHA), winds direction and currents. Ref. [20] suggested a plausible explanation for the dependence of CPUE on SSH as the following: higher SSH is mostly due to thicker surface layer where water is usually clearer, sunlight can penetrate deeper, and since BE tends to dive into deeper and colder waters to hide or to hunt, it loses its body heat faster and has to swim back to surface more frequently, hence, has higher probability to notice the hooks (above 150 m depth) and be caught. Consequently, it can be said that CPUE and SST have positive correlation. Ref. [21] confirmed what is mentioned above, but from a rather meteorological point of view. The sea surface height anomaly (SSHA) field is coupled to the dynamics (currents) and thermodynamics (heat, balance) of the upper ocean. Convergences and divergences of the mass transport in the surface layer of the ocean result in positive and negative sea level anomalies, respectively. Variations in water density, which are dominantly controlled by changes in temperature or in the heat storage (changes in mixed layer depth or its temperature), also give rise to sea level anomalies [22]. Consequently, it is natural to expect that changes in SSHA can be related to variations of the CPUE. Other studies indicated that high wind speed is reported to affect fish vulnerability to capture by modifying fish behavior and availability to a specific depth of the fishing gear [23]. For example, *Carey and Robinson (1981)* show that swordfish swim to greater depths with strong winds, reducing their vulnerability to capture. It is, thus, possible that the seasonal decrease of tuna species in the equatorial western Atlantic in higher winds could be affected by these factors, favoring higher catches in the low wind zone of the ITCZ. Accordingly (1) including SSH and wind parameters might show higher correlation with CPUE and lead to more important conclusions. (2) In order to assess the temporal variation of the environmental parameters, collecting data over a period of more than 10 years is necessary. (3) LL length increases position uncertainty, leading to less accurate CPUE positions. Improving data collection methods may lead to higher correlations with environmental parameters. (4) Using JSD instead of GM method to identify the thermal front can generate better results.

IV. Conclusions

Satellite data is an effective tool used for marine productivity study as well as for identifying and assessing fish abundance in the tropical water area. Using the cloud-free AMSR-E SST, MODIS SSC and daily longline CPUE data for 2010, the relationships between these parameters and bigeye, albacore, yellowfin and southern bluefin tuna fishing grounds in South Java (Indian Ocean) were investigated. The following conclusions were obtained:

(1) The CPUEs plotted on SSC and SST maps show that high catches (C3 – C6) are found in areas with SST of 26 – 27 °C, and SSC of 0.15 – 0.3mg/m^3 which occur during the end of the transition period and south east monsoon season (i.e., May to July). Null and low catches (C1 – C2) are located mainly in areas with SSC within 0.0 – 0.1 mg/m^3, and SST within 28 – 31°C. The spatial distribution of GM did not show a significant correlation with the CPUE.

(2) CPUEs have positive (negative) correlation with SSC (SST) i.e., 0.33 (-0.38) but not with GM values i.e., -0.02. The CPUEs appear to be "randomly" dispersed. Therefore, developing potential fishing ground areas depends on other factors since CPUE distributions seem to be correlated to other more influential parameters.

(3) Lack of yearly data and other fishing gears catch data may have biased the correlation between CPUE, SST and SSC.

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