Environmental preferences of yellowfin tuna (*Thunnus albacores*) in the northeast Indian Ocean: an application of remote sensing data to longline catches

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October 19, 2010

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Abstract

Ocean environmental parameters such as sea surface temperature, chlorophyll and sea surface height derived from remote sensing satellites were analyzed with Yellowfin tuna dataset. The dataset were obtained from Sri Lankan longliners fished from 2006-2008 in the northeast part of the Indian Ocean. The results have shown that the relationship between Yellowfin tuna catch rates and oceanographic parameters are significant. These relationships can be used to predict fishable aggregations of Yellowfin tuna using near real–time satellite derived oceanographic parameters. High frequencies of Yellowfin tuna catches were obtained in the areas where sea surface temperature varied primarily between 28–30 °C. The corresponding sea surface heights ranged from 205-215 cm and the Clorophyll_a concentration ranged from 0.1–0.4 mgm^{-3}. The relationships between catch rates and the three environmental parameters have been proved by the results obtained from the empirical cumulative distribution function (ECDF). The degrees of the differences between the ECDF and catch-weighted cumulative distributions of the three variables are statistically significant ($p < 0.01$). The strongest association showed between catch rates and Chlorophyll_a while sea surface heights showed lowest. The results obtained from a Generalized Additive Model (GAM) shown the space-time factor is well above the ocean environmental factors. However, the oceanographic factors were also in significant levels ($p < 0.05$). Therefore, the migratory pathway is an essential factor in predicting Yellowfin tuna habitats in the northeast Indian Ocean.

Key words: yellowfin tuna, remote sensing, fishery forecast, GAM, Indian Ocean

1 INTRODUCTION

Tunas, the family Scombridae are reported to be found in tropical and temperate oceans around the world and account for a major proportion of the worlds fishery products (Collette and Nauen, 1983). Sri Lanka is one of the oldest and most important tuna producing island in the Indian Ocean. During the past three decades, exploration and exploitation of fishery resources have shown that the tuna resources around Sri Lanka consist of yellowfin tuna (*Thunnus albacares*), Bigeye tuna (*Thunnus obsesus*), Skipjack tuna (*Katsuwonus pelamis*), Kawakawa (*Enthynnus affinis*), Frigate tuna (*Auxis thazard*) and Bullet tuna (*Auxis rochei*) species (Joseph et al., 1985; Dissanayake, 2005). With the increasing demand for yellowfin tuna in the export market, more and more efforts have been exerted on yellowfin tuna by longlines and Gillnets. Longline has become more popular than gillnets as it preserves the freshness of the fish. Therefore the current trend is converting gillnet to longline fleets targeting yellowfin tuna.

Yellowfin tuna is known as highly migratory species and distributed over very large oceanic extent of fishing potential. The wide distribution of Yellowfin tuna cause longer search time which is costly and time consuming. Therefore, predicting fishable aggregations making the search more efficient and economic is timely important. To achieve this, it would be useful to analyses long–term fisheries and oceanographic data that could affect the temporal and spatial distribution of yellowfin tuna (Zagaglia, 2004).

Indian Ocean is greatly influenced by two wind systems known as southwest monsoon and northeast monsoon causing characteristic seasonality of rainfall, temperature, phytoplankton concentration, ocean currents and mixed layer properties etc. The southwest monsoon exists from May to September and northeast monsoon from November to March. The NE fishing area (Bay of Bengal) is sheltered to the southwest monsoon–driven sea conditions by the Indian and Sri Lankan landmasses and vice versa. This affects the oceanographic conditions in fishing grounds with respect to the two monsoons. Between the two monsoons, there are two transition periods known as inter–monsoons where the dynamic conditions become weak and, as a result the sea surface get more heated and the thermocline depth become shallower.

Previous studies have shown that the distribution of tuna species is greatly influenced by oceanographic conditions such as sea surface temperature (Sund and Blackburn, 1981; Ramos et al., 1996), hydrographic fronts (Laurs and Lynn, 1977; Laurs and Fiedler, 1984; Fiedler and Bernard, 1987; Stretta, 1991; Kimura and Nakai, 1997), and depth of thermocline (Ueyanagi, 1969). Hence, it is reasonable to assume that these factors may have influence on the abundance and distribution of Yellowfin tuna. Limited studies have been carried out in the Indian Ocean to understand the fisheries oceanography of Yellowfin tuna. Yellowfin tuna fishery is concentrated into the southwest and northeast part of the country by Sri Lankan longliners

The fishery and the oceanography of Yellowfin tuna have been studded taking the fishery and the monsoon driven oceanography into consideration. The data analyses were done dividing the area into two sub divisions namely southwest (SW) and northeast (NE). Very few fishing activities have been recorded in the southeast (SE) part due to difficult in fishing operations as the prevailing current system been strong.

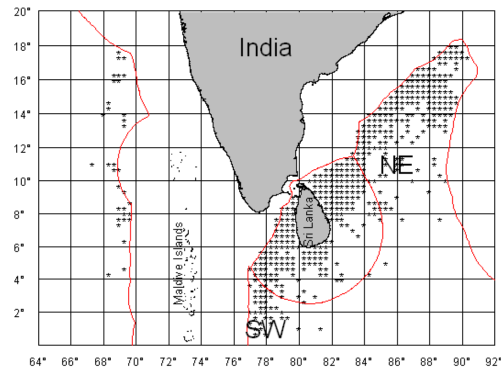

Figure 1: Geographic locations of Yellowfin tuna fishery dataset from 2006 to 2008 by Sri Lankan longliners showing the two subdivisions SW and NE.

Remote sensing techniques show great potential supporting successful exploitation of pelagic fishery resources and global fisheries management ((Santos, 2000; Yamanaka and Ito, 1988). The Remote Sensing technology has proven to be a useful tool to study thermal fronts, eddies and other oceanographic features where tunas are reported to be aggregated. The combination of satellite and biological data could be used to identify habitat preference and migration movements of tuna which ultimately lead to predict the potential fishing zones. In the literature, several attempts have been made to study the associate movements and catch rates with environmental conditions (Uda, 1973; Laurs and Lynn, 1977; Laurs and Fiedler, 1984; Fiedler and Bernard, 1987; Stretta, 1991; Power and May, 1991; Podesta, 1993; Bigelow and He, 1999). The intent of this study is to examine the relationship between Yellowfin tuna occurrence in relation to the oceanographic conditions in the northeast part of the Indian Ocean.

2 DATA AND METHODS

Two types of data sets consisting fishery and satellite derived oceanographic parameters were obtained for the period of three years (2006–2008). Figure 1 shows the gridded locations of Yellowfin tuna catches by Sri Lankan longline fishery in the northeast part (0–20 N, 64–90 E) of the Indian Ocean. To meet the objectives of this study, the data analyses focused on the two sub-divisions, the SW and the NE fishing areas.

2.1 Remotely sensed satellite data

Oceanographic data derived from satellites, specifically sea surface temperature (SST), sea surface chlorophyll_a (CHL) and dynamic sea surface height (SSH) were obtained from the AMSR+AVHRR, MODIS on Terra/Aqua and TOPEX/Poseidon-ERS (AVISO) respectively. Availability of satellite data in the tropical region is limited by the frequent presence of clouds. Satellite data obtained from active and inactive microwave sensors are cloud free. However, ocean colour sensors (visible near infrared) are unable to penetrate clouds. This hampers the use of ocean colour products such as CHL. Increased data coverage is obtained by averaging (composition) several successive images derived from ocean colour data. It was assumed that the averaging time period of a particular oceanographic parameter is not considerably varies within the averaging period in the region.

SST merged data product calculated from two satellite sensors AMSRE and AVHRR were obtained from the NOAA optimum interpolation $\frac{1}{4}$ degree daily sea surface temperature analyses. The $\frac{1}{4}$ degree AMSR+AVHRR data are distributed by NOAA satellite and information service (ftp://eclipse.ncdc.noaa.gov) in netCDF format (http://www.unidata.ucar.edu/). The blended AMSRE+AVHRR data were converted into $\frac{1}{3}$ degree grids to coincide with minimum resolution of sea surface height data obtained from TOPEX/Poseidon altimeter. The blended multiple satellite sensors data fill the data gaps in both time and space.

CHL were calculated from Terra/Aqua MODIS sensor EOS AM and PM data . The minimum period of composting to remove cloudy pixels was found to be at least 10 images which can be taken within two weeks from Terra and Aqua platforms. Therefore, initially 15–day CHL composite image was generated by 3-day composites and been updated every 3-day steps in order to match ups with Yellowfin tuna dataset obtained from Sri Lankan longliners. 3–day composites of 4 km chlorophyll data were obtained from NASA gsfc (http://oceancolor.gsfc.nasa.gov/)

SSH data were obtained from the information collected by TOPEX/Poseidon and ERS satellite altimeter data (ftp://ftp.cls.fr/pub/oceano/AVISO/). The data were available at archiving, validation and interpolation of satellite oceanographic data (AVISO) in netCDF format. These data (gridded $\frac{1}{3}$ latitude x longitude) were obtained in 3-day composts for the period (2006–2008). The data files contain the parameters such the date of data collection, latitude, longitude and sea surface height with respect to the geoid.

2.2 Fishery data

Fishery data were collected from Sri Lankan longline fleets. The dataset consist of fishing (1) date, (2) position, (3) number of hooks and (4) daily catch numbers. Number of fishermen in each trip is almost equal and the ice storage depends on the vessel size. The catch is depending on the number of hooks and availability of bait and the bait-types. Water temperature, search time, catch of bait/bait–type, hooking depth, catch weight and weather conditions were almost absent in logbooks. Owing to the lack of these information the effort data were not standardized for calculating catch per unit of effort (CPUE), which was defined as number of fish per 100 hooks per fishing day regardless of the catch weights. There are many factors that determine the likelihood of a particular hook catching a fish, including the depth of hook, bait type, availability of live food, timing and location of effort. Fish behavior also a factor (Ferno, 1994); not all fish that are present will come close enough to detect the bait, not all fish that detect the bait will bite it and not all fish that do bite bait will get caught on the hook. Similar hooking depth used in a particular area can result very poor catch rates depending on the vertical distribution. Considering all these catch uncertainties, null catches have been removed from the dataset. It is also important to point out that this CPUE cannot consider as a good index of relative fish abundance. Therefore the CPUE can be considered as indices of fish availability to Sri Lankan longlines, but not as indices of fish abundance.

The length of Sri Lankan longlines varies between 10-15 miles and the drift due to ocean currents during the deployed period (4-6 hrs) is 5-10 miles. Thus, the longline data fall within the minimum resolution of satellite data ($\sim$ 25 miles). The resolution of SST was $\frac{1}{4}$ degree and SSH was $\frac{1}{3}$ degree while CHL has 4 km. The CHL images were taken in 15–day composites (averaging over time and space) by which the detailed information is disappeared although the original images were in higher resolution. The SST and SSH were taken in 3-day composites and CHL in 15-day and then were updated every 3-day steps. The fishery data (CPUE) were also gridded $\frac{1}{3}$ degree latitude x longitude) and averaged over 3-day fishing activity assuming that the SST, CHL and SSH are not significantly varies within the averaging periods. Satellite and fishery data were combined in similar grid space and output results were then statistically analyzed using R software (http://www.r-project.org/).

The association between the three oceanographic variables and Yellowfin tuna CPUE were analyzed using empirical cumulative frequency distribution function ECDF. In this analysis, three functions (Perry and Smith, 1994; Andrade and Garcia, 2001) were used as follows:

$$f(t) = \frac{1}{n}\sum_{i=1}^{n} l(x_i) \tag{1}$$

With the indication function

$$l(x_i) = \begin{cases} 1 & \text{if } x_i \leq 1 \\ 0 & otherwise \end{cases}$$

$$g(t) = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i}{\overline{y}} l(x_i) \tag{2}$$

$$D(t) = max|f(t) - g(t)| \tag{3}$$

where $f(t)$ is empirical cumulative frequency distribution function, $g(t)$ is catch-weighted cumulative distribution function, $l(x_i)$ is indication function, and $D(t)$ is the absolute value of the difference between the two curves $f(t)$ and $g(t)$ at any point t, and assessed by the standard Kolmogorov-Smirnov test. n is the number of fishing activities, x_i the measurement for satellite derived oceanographic variables in a fishing activity i, t an index ranking the ordered observations from the lowest to highest value of the oceanographic variables, y_i the CPUE obtained in a fishing activity i, and the estimated mean of CPUE for all fishing activities. The maximum value of $D(t)$ represents specific values of the oceanographic variables at which the height CPUE can be obtained.

2.3 Optimizing fishable oceanographic conditions

Two statistical models, generalized additive model (GAM) and generalized linear model (GLM) were applied to identify the nature of relationships between Yellowfin tuna and the three ocean environmental parameters. The relationships between environmental factors and CPUE are mostly expected as non–linear. Once the shape of the relationships between the response variable and each predictor was identified, the appropriate functions were used to parameterize these shapes in the GLM model. Generalized linear models have been used to study Yellowfin tuna CPUE variability in eastern Pacific Ocean (Punsly, 1987; Zagaglia, 2004). The shapes resulting from the GAM were reproduced as closely as possible using the piecewise GLM. Three environmental variables were included in the analysis using a GAM (eq. 4) and a GLM (eq. 5), as follows:

$$\begin{aligned} ln(CPUE) &= a + s(SST) \\ &+s(CHL) + s(SSH) + e \end{aligned} \tag{4}$$

$$\begin{aligned} ln(CPUE) &= b + b_1(SST) + b_2 \\ &\times ln(CHL) + b_3(SSH) + e \end{aligned} \tag{5}$$

where a and b are constants, $s(.)$ is a spline smoothing function of the variables (SST, CHL, and SSH) and e is a random error term, b_1, b_2, and b_3 are the vectors of model coefficients.

GAM is a non-parametric generalization of multiple linear regressions which is less restrictive in assumptions of the underlying statistical data distribution (Hastie and Tibshirani (1990)). The GAM has no analytical form (Mathsoft., 1999), but explain the variance of CPUE more effectively and flexibly than the GLM. The GLM was constructed based on the trend of Yellowfin CPUE in relation to the predictors estimated by GAM with the least different residual deviance (Mathsoft., 1999). GLM estimates a function of mean response (CPUE) as a linear function of some set of predictors. Hence, the GLM fit was used to predict a spatial pattern of Yellowfin tuna CPUE.

The GLM were fitted using a Normal distribution as the family associated with identity link function (McCullagh and Nelder, 1989). The data distribution and the link function in the GLM were exactly the same as those used in the GAM. A logarithmic transformation of the CPUE was used to normalize asymmetrical frequency distribution. The model selection process for the best predictive model for explaining CPUE data was based on a forward and backward stepwise manner. The predictors were considered to be significant for explaining the variance of CPUE, if the residual deviance and Akaike Information Criteria (AIC) decrease with each addition of the variables and the probability of final set of variables was lower than 0.01 ($p < 0.01$).

3 RESULTS

3.1 Catch per unit of effort

Initial displays (Fig. 2) of monthly median CPUE in the two fishing areas consist of 3–year catch records from 2006–2008. The CPUE in the SW area is above the median during the SW monsoon prevails while it is below during the NE monsoon. Monthly median CPUE in the NE has been stable and yearly increased is observed from 2006 to 2008. This may be due to increase of effort, improvements of gears, vessels and the technology recently introduced. The CPUE in the NE is more promising and stable the year around. The CPUE are not normally distributed in the two fishing areas and the median CPUE is 0.8 and 0.9 in the SW and

NE respectively. The standard deviations of CPUE were 1.2 in the SW and 1.3 in the NE and the CPUE is statistically significant ($p < 0.05$) between the two areas.

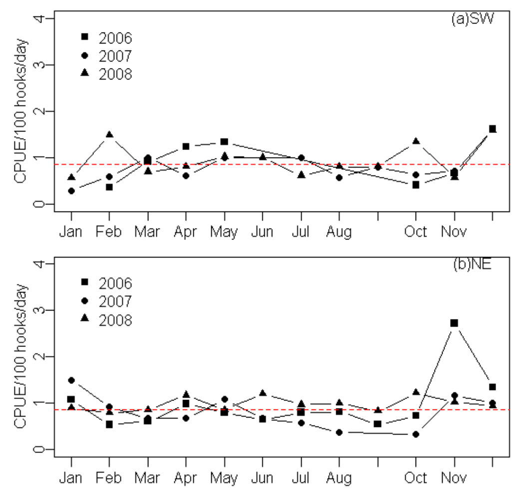

Figure 2: Temporal variation of median CPUE of Yellowfin tuna by Sri Lankan longlines in the two fishing grounds from 2006–2008. The dotted line shows the overall median CPUE.

Figure 3 shows the temporal variability of CPUE as well as the corresponding oceanographic variables in the NE area. The oceanographic parameters followed yearly cycles during the 3–year period. The CPUE in the NE doesnt show any seasonality which means that the fishable aggregations are found throughout the year although the spatial existence is vary with time. Fishable Yellowfin tuna found in warmer (28.5–30 °C) sea surface temperatures during southwest and inter monsoons while relatively cooler temperatures (27–28.5 °C) during the northeast monsoons (Fig. 3b) period. SST variation in the 3–year period follows an identical pattern which can be used to predict Yellowfin tuna inhabitant for Sri Lankan longliners. CHL concentrations of Yellowfin tuna catches have been found between 0.1–0.4 mgm^{-3} and did not change over the years. The SSH of Yellowfin tuna catches also follow an identical yearly cycle helping predictions of potential fishing grounds.

3.2 Fishable oceanographic conditions

SST of Yellowfin tuna catches varies from 26-31 °C and the fishable SST is varies over the year within this range as shown in the Fig. 3b. However, high frequencies of catches were obtained primarily between 28-30 °C (Fig. 4a). The tendency of temperature is centered at 29 °C where more catches have been taken.

CHL of Yellowfin tuna catches primarily varies between 0.05–0.8 mgm^{-3} and most of the catches have been obtained from 0.1–0.4 mgm^{-3} (Fig. 4b). Temporal variability is minimal of CHL on Yellowfin tuna catches.

Frequency of Yellowfin tuna fishing days in relation to sea surface height follows a Gaussian distribution. The distribution of SSH indicates that Yellowfin tuna were found in areas where sea surface height ranged from 185-235 cm (Fig. 4c). However, the most catches have been obtained from the waters where SSH varies from 205-215 cm (210 ± 5 cm) while it slightly varies over the year as shown in Fig. 4d.

The relationship between CPUE and the three environmental variables above (Fig. 4) is proven by the empirical cumulative distribution function (ECDF). The cumulative distribution curves of the three variables are different and the degrees of the differences between two curves $D(t)$ are highly significant ($p < 0.01$) for CHL. The results showed strong association between CPUE and SST ranging from 28–30 °C, CHL ranging from 0.1–0.4

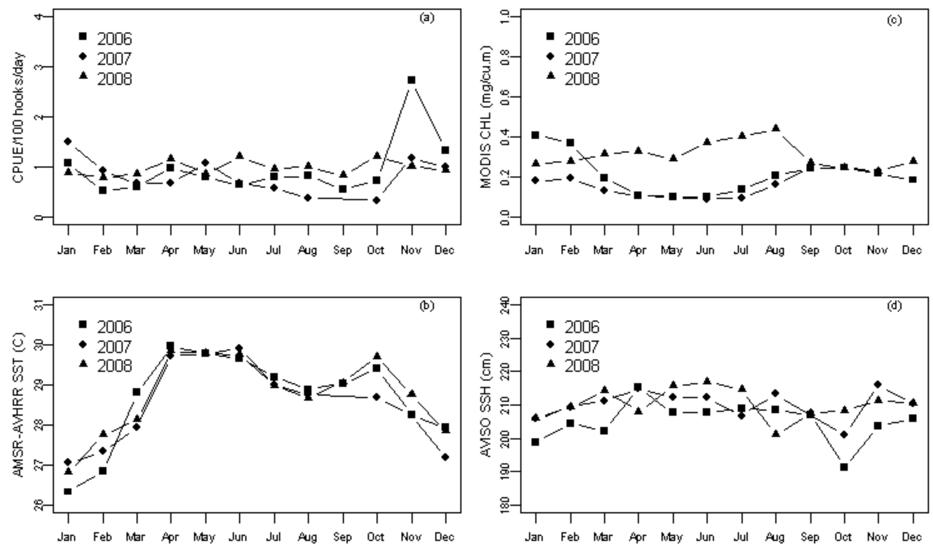

Figure 3: Temporal variability of (a) Yellowfin CPUE, (b) SST and (c) CHL and (d) SSH extracted from NE fishing locations from 2006–2008.

mgm^{-3}, SSH ranging from 205–215 cm (Fig. 4). The highest association of CHL occur at 0.3 mgm^{-3} catch rates tend decrease at either sides.

The space-time factor (lat/lon and month), explains the largest portion of the data variance (Table 2), being the most significant factor amongst all the independent variables included in the GAM. This explains the migratory behavior of Yellowfin tuna, where the largest CPUE observed close to Sri Lanka during the early year and migratory movements towards Bangladesh waters parallel to the Indian coast.

The relationship between the given predictor and the density of Yellowfin tuna was analyzed according to the percentage of deviance explained and the GCV scores of the GAM models (Table 1). Space (lat/lon) and time (month) were the best predictor explained the density of Yellowfin tuna with the highest deviance (19.9%) and the lowest GCV score (0.5965) and it was subsequently followed by SST (4.63%), CHL (2.57%) and SSH (1.5%). The other remaining environmental factors, SST, CHL and SSH, being statistically significant, showed associated $p-values$ (Table 2).

The GAM results show that the SST influences on Yellowfin tuna catch rates and the SST is not only the parameter that predicts Yellowfin tuna potential habitats in the northeast Indian Ocean (Fig. 6). Indeed, SST has been used to describe tuna habitats as it relatively easy to obtain and the SST become particularly very useful in strong surface thermal gradients, where the fishing grounds are normally located (Laurs and Lynn, 1977; Laurs and Fiedler, 1984).

The environmental parameters, SST, CHL

Table 1: Single predictor GAM fits for yellowfin tuna in the NE fishing ground. For each predictor, the percentage of deviance and the Generalized Cross Validation score is given

Parameter	**%Devience**	**GCV Score**
SST	04.63%	0.67658
CHL	02.57%	0.69039
SSH	01.50%	0.69595
$lat \times lon \times month$	19.90%	0.59650

Table 2: Significance of the smooth terms included in the GAM for yellowfin occurrence in the NE fishing ground

	Standard error	**Standard error**	$\boldsymbol{p}$	$\boldsymbol{n}$
Intercept	0.01526	0.774	0.437	1673
Variable	edf	F	P	
SST	6.620	8.216	< 0.001	
CHL	5.786	5.913	< 0.001	
SSH	2.905	7.791	< 0.001	

and SSH, showed associated p–values well below those found for the space-time factor (Table 1). In fact, considering their p–values ($p < 0.05$) the oceanographic parameters are also in significance levels. Therefore, the environmental parameters influence on the CPUE of Yellowfin tuna in the northeast Indian Ocean.

4 DISCUSSION

Longline fishery in Sri Lanka was started about 3 decades ago and several limitations caused inefficient development of the fishery. Fleet facilities and the knowledge on longline techniques were not adequate for the development of this fishery. However, the fishermen disperse their fleets with the gathered knowledge during the short history of longline fishery by Sri Lankan fleets. Single–Side–Band (SSB) radios have been helping them to communicate and reach more fish productive areas. Therefore, the Yellowfin tuna fishery operates in more abundant areas and thus, it is reasonable to assume that the space and time factor of CPUE follows their migratory path to some extent. The Sri Lankan fleets operates comparatively deeper (100-130 m) long-lines in the SW while it is shallow (50–75 m) in the NE. Therefore, the the Bay of Bengal can be considered as a feeding ground. This existence of year around fishery in the NE is explained by the stock structure proposed by (Nishida, 1992). That is a western and eastern stocks mixing around Sri Lanka in their migratory path.

The fishermen have been able to follow the migratory paths with their experience and communication. Thus, it is assumed that the fishing operations takes place in the areas of high vulnerability. This assumptions is based on the established Yellowfin tuna fishery in the NE part of the country. The fishermen have buildup their effective knowledge on distribution and abundance of fishery resources in their short history of longlining. There are many reasons to occur null catches such as hooking depth, bait, time of fishing, availability of live food, prevailing oceanographic and weather conditions. Therefore the null catches have been removed from the

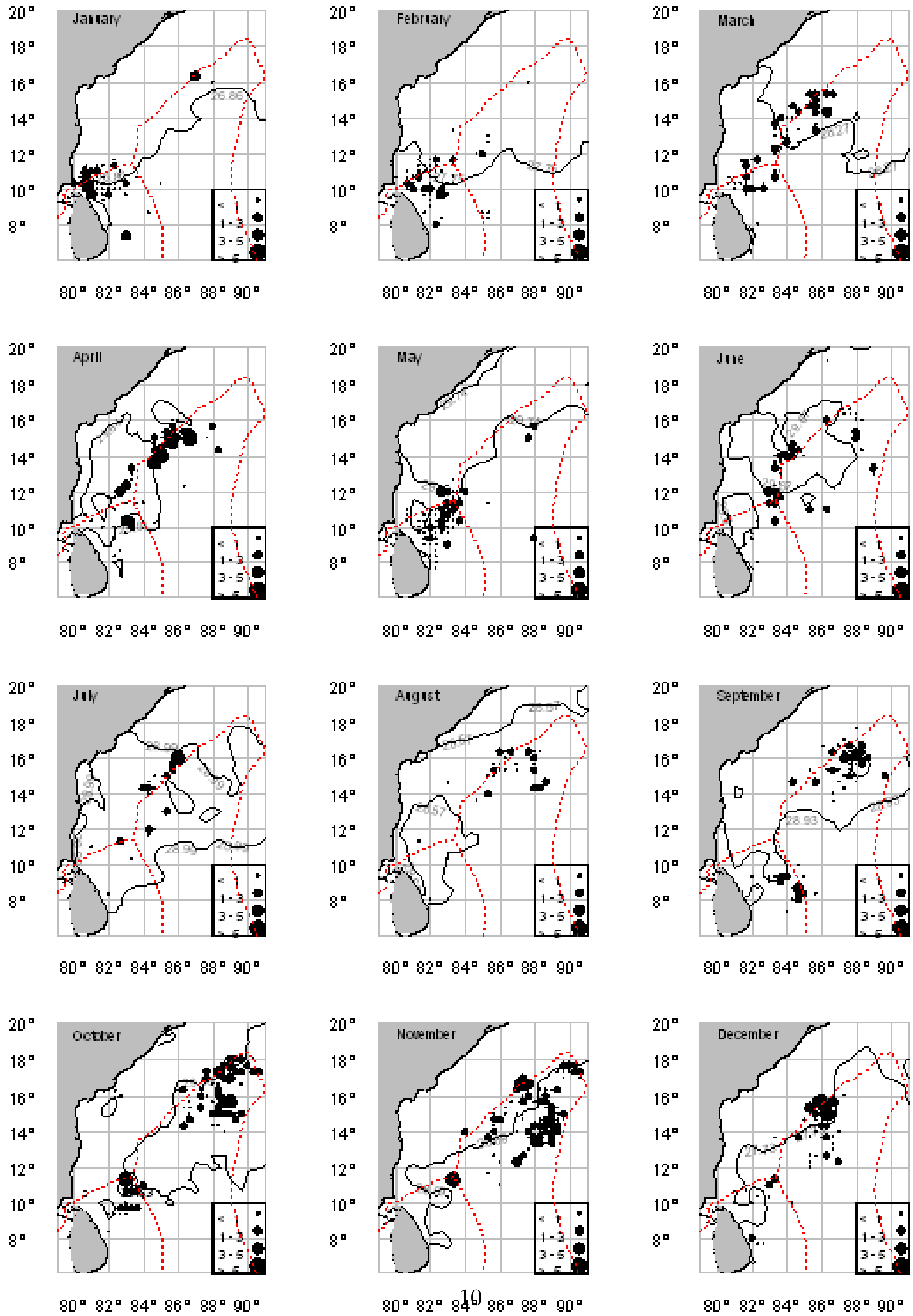

Figure 7: Sea surface temperature contour of Yellowfin tuna availability to Sri Lankan longlines, superimposed of Yellowfin tuna CPUE from 2006–2008. Dashed-line shows the approximate 200–mile EEZ boundary.

Table 3: Deviance and GCV scores of Yellowfin tuna CPUE in the NE fishing ground explained in GAM with variables added.

Variable	**Residual d.f.**	**Residual deviance**	**GCV Score**	
Mean	1664.8	1120.8		
SST	1659.7	1098.8	0.67658	4.63%
CHL	1656.7	1077.3	0.66729	6.50%
SSH	1611.8	903.76	0.65667	8.33%

Table 4: Construction of GLM as each variable is added, residual deviance, the approximate AIC, and F-statistic for yellowfin availability in the NE fishing ground.

Variable	**Residual d.f.**	**Residual deviance**	**AIC**	**F**
NULL	1672	1175.2		
SST	1671	1147.3	4122.7	40.665
CHL	1670	1132.9	4103.6	21.182
SSH	1669	1125.2	4094.2	11.423

dataset as null catches might not be due to the less abundance but may be due to other factors. Considering all these facts, it has been assumed that the dataset represent the real availability of Yellowfin tuna in relation to environmental parameters such as sea surface temperature.

The reported CPUE of Yellowfin tuna in the present study was comparatively lower than the other fishing nations in the Indian Ocean. This may be due to several factors such as inefficient longline fishery. Fleet size, number of hooks, hooking depths and hooking depth adjustments, suitable baits, on board technology and the overall knowledge on fishing skills were identified as the limiting factors for the inefficiency. Limited fishery data were used in this study and longer time–series fishery data may provide more precise representation of oceanographic parameters for Yellowfin tuna aggregations. Therefore, the biophysical environmental data that have been selected to describe the Yellowfin tuna habitat may not be precise. The AMSRE–AVHRR blended SST was selected as the AMSRE microwave sensor is capable of measuring SST through clouds. Combinations of SST data with MODIS CHL and AVISO SSH have provided fishable conditions of Yellowfin tuna in time and space. The relationship between Yellowfin tuna catches and environments clearly indicates that the specific times and locations for Yellowfin tuna abundant.

In the present study, highly productive habitats of Yellowfin tuna are linked with the physical oceanographic structures. The results showed that catchable aggregation of Yellowfin tuna can be located using SST which specific to a time period. The highest CPUE exist within a narrow SST range (~ 1) between 28.0–30.0 depending on the time of a year. This implies that the SST does not represent the actual temperatures preferred by Yellowfin tuna to live, although chronological SST can be used to locate more abundant areas combining the migratory pathways. It has been proven that the Yellowfin tuna live slightly above thermocline where rapid decrease of temperature occurs helping them to reach favorable temperature ranges. Thermocline around Sri Lanka fluctuates from 50–100 m due to seasonal monsoons wind stress. Thus, Yellowfin tuna shows vertical movement to find their favorable temperatures while

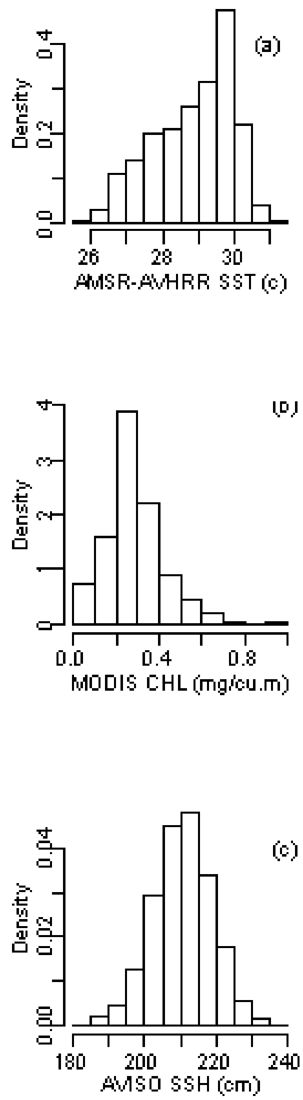

Figure 4: Relationship between environmental variables of SST (a), Chlorophyll (b) and SSH (c) and fishing frequency of Yellowfin tuna in the NE during 2006–2008.

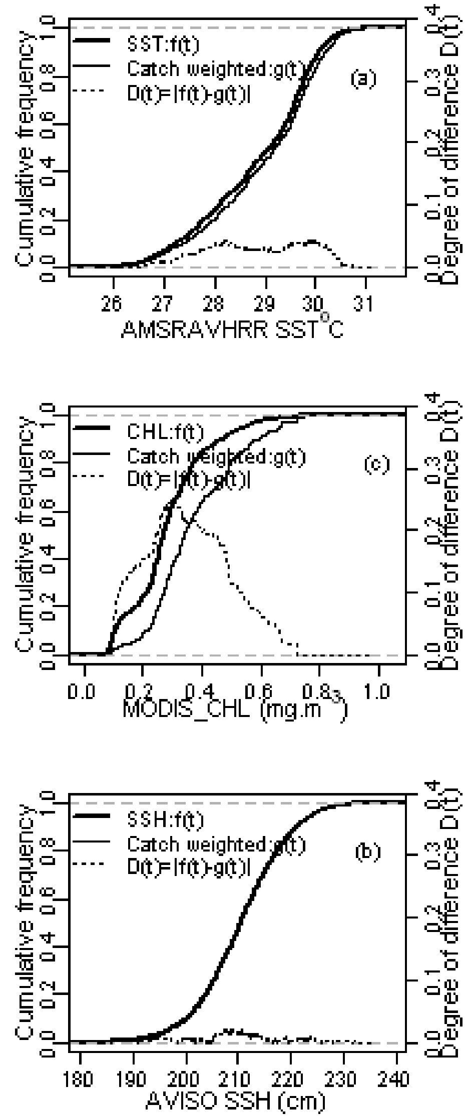

Figure 5: Empirical cumulative distribution frequencies for (a) AMSR-AVHRR SST, (b) MODIS CHL and AVISO SSH and SST, CHL and SSH as weighted by Yellowfin tuna CPUE during 2006-2008. The dashed–lines show the degree of differences of the two curves.

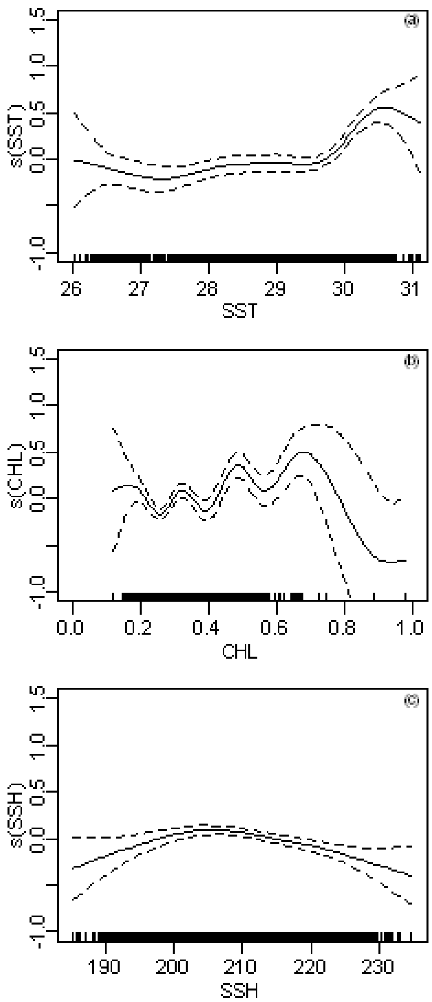

Figure 6: Generalized additive model (GAM) derived effect of oceanographic variables (a) AMSR-AVHRR SST, (b) MODIS CHL and (c) AVISO SSH on Yellowfin tuna CPUE (log transformed). Dashed line indicates the 95% confidence intervals.

they reach surface for shorter time searching foods. These feeding fishes are vulnerable to the Sri Lankan shallow water longlines. Therefore Sri Lankan longline data will not provide true favorable environment condition of Yellowfin tuna that prolonger exist.

Block et al. (1997) and Brill et al. (1999) found that the depth of the mixed layer is more important than the SST for the abundance of Yellowfin tuna. According to their findings, adult Yellowfin tuna were found inside the mixed layer or immediately below it while juveniles are associated in much shallow areas. It was unable to correlate the mixed layer depth (depth of thermocline) and the CPUE during the present study as less information in the dataset. The knowledge on the relations between CPUE and thermocline depth can be used to further improve the methodology of locating potential fishing grounds.

According to Stretta (1991), Yellowfin tuna prefers warmer waters and the abundance of this species was higher with temperature limits between 18-31.0 °C. It was reported in the tropical Atlantic, the most of the Yellowfin tuna catch occurs with temperatures between 22.0-29.0 °C and preferentially above 25.0 °C. The flat relationship was evident in the temperature and distribution of Yellowfin tuna catches in Brazil coast within the range of 26-28.5 °C (Zagaglia, 2004). It has also been observed that the SST values above 28.0 °C seem to form a pathway of favorable thermal conditions to the migratory movements of Yellowfin tuna (Zagaglia, 2004). The results of this study are also consistent with the other findings in tropical waters.

It is well established that the SST is an important predictor of CPUE in Yellowfin tuna longline fishery. View on an ocean scale, SST represented not only the temperature but also correspondence with latitudes and longitudes.

Studies on albacore tuna in Indian and pacific oceans have shown that the favorable SST limits are depended on the season as well as life history stages. Therefore, the effect of SST on the different life history stages of Yellowfin tuna ensure the higher CPUE by avoiding young and juvenile in catches.

The optimum SSH ranges for the abundance and distribution of Yellowfin tuna in the northeast Indian Ocean was estimated as 205-215 cm. The importance of SSH to predict Yellowfin tuna fishing habitats have been discussed by various authors (Zagaglia, 2004). It has been pointed out that the relationship between the SSH and CPUE may vary considerably as SSHA (Sea Surface Height Anomaly) is the result of a complex combination of dynamical and thermodynamical factors, which could affect in opposite ways the concentration of the fishing resources (Zagaglia, 2004). However it is difficult to make any comparison with others findings as the present study has not used SSHA.

Based on the results, Yellowfin tuna catchable oceanographic parameters in the northeast Indian Ocean were characterized by; SST of 28-30 °C, CHL of 0.1-0.4 mgm^{-3} and SSH 205-215 cm. These results are closer to the previous study for Yellowfin tuna in relation to SST (Uda, 1973)) and CHL (Polovina et al., 2001). The results were confirmed by statistical models. The results obtained from this study can be used to understand the relation between the catchable Yellowfin tuna with respect to some oceanographic parameters for shallow water longliners. Spatial and temporal variations of oceanographic parameters estimated in this study can be used to predict potential Yellowfin fishing grounds with near real–time satellite data.

5 Acknowledgments

The Icelandic International Development Agency (ICEIDA) is greatfully acknowledged for financial support provided through the project ICE/SL/FIS/2006/04. Dr. Tumi Tomasson, country director, ICEIDA is Acknowledged for his invaluable support and comments providedfor this work. Remote sensing data processing and archiving systems such as MODIS ocean color products (http://oceancolor.gsfc.nasa.gov/), AVISO (ftp://ftp.cls.fr/pub/oceano/AVISO/) and AMSR-AVHRR (ftp://eclipse.ncdc.noaa.gov) (ftp://eclipse.ncdc.noaa.gov/) are greatfuly acknowledged.

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