Environmental preferences of Billfish in Bay of Bengal: A case study in longline fishery of Sri Lanka

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Abstract

Billfish are an important by-catch species in in the tuna fishery of Sri Lanka. The gillnet and longline, which are frequently used in Sri Lankan Tuna fishery mainly contribute for capturing the billfish too. The present study was undertaken to study the relative influence of three environmental parameters (sea surface temperature (SST), sea surface chlorophyll (SSC) and dynamic height of the sea surface (SSH)) on the billfish catch rates. The fisheries data in longline fishery of Sri Lanka was collected during the period 2006-2010 and used for this audit. The relevant values of above three environmental parameters were obtained from remote sensing data. A Generalized Additive Model (GAM) was fitted for describing the relationships between environment parameters and billfish catch rates. The results of GAM shows that the relationships between billfish catch rates and oceanographic parameters are significant. The GAM model could also be used as a predictive model to find the potential fishing grounds of billfish. The higher catch rates of billfish were observed from the areas where SST varied between 27 – 30.5 °C, SSC ranged from 0.05 - 0.2 mgm^{-3} and SSH ranged from 85 – 105cm. The results of the Empirical Cumulative Density Function (ECDF) show that the degree of the differences between the ECDF and catch-weighted cumulative distributions of the three variables are statistically significant ($p < 0.01$). The ECDF approach identified that high Catch Per Unit Effort (CPUE) of billfish occurred when SST ranged on 27 to 30 °C, SSC ranged on 0.05 to 0.5 mgm^{-3}, and SSH ranged on 85 to 105 cm. Among the environmental parameters, strongest relationship was present between SSC and billfish CPUE whereas the weakest relationship was present between SST and billfish CPUE. The GAM results show that space-time factor has more influence on billfish catch rates. Also, all environmental parameters were significant at 0.05 level ($p<0.05$).

Key words: billfish, Empirical Cumulative Density Function, Generalized Additive Model, longline, environmental parameters

Introduction

Billfishes (Xiphioidei) consist of two families (Istiophoridae and Xiphiidae), which include three genera with eight recognized species (Collete et al., 2006). There are six species widely distributed in tropical and subtropical Indian Ocean: Swordfish (*Xiphias gladius*), Black marlin (*Istiompax indica*), Blue marlin (*Makaira nigricans*), Striped marlin (*Kajikia audax*), Indo-Pacific sailfish (*Istiophorus platypterus*) and Shortbill spearfish (*Tetrapturusangustirostris*). Billfishes are unique among teleost fishes in being regionally heterothermic, which allow these fishes to exploit a wide range of oceanic habitats. Despite these adaptations, the upper and lower bounds of individual species geographic ranges appear to relate to their physiological temperature tolerances (Brill 1994; Brill & Lutcavage 2001). Generally, they are considered as oceanic and epipelagic species with varying horizontal distribution which are overlapped each other with complexity of different species (Nakamura, 1985). Billfish is mostly taken as a by-catch in the tuna fishery, mainly from commercial surface tuna longliners, purse seiners, surface driftnets, set netting and by surface trolling.

Large pelagic fishery plays a major role in Sri Lanka, which mainly comprised with tuna species, billfish, sharks and seer fish resources (Haputhantri and Maldeniya., 2011). Introduction of multiday boats in 1980's boost the large pelagic fishery with a considerable change in the catch composition. This leads to increase the billfish production too in the country. As per 2012 fish production estimates, billfish contributes around 9 % of the total large pelagic landings in Sri Lanka (Herath and Maldeniya., 2013).

Billfish consider as a non-target (by catch) species in offshore gillnet and longline fishery of Sri Lanka (Haputhantri and Maldeniya., 2011). Both gears contributed over 95% of the total billfish production in the country during 2008-2012 (Herath and Maldeniya., 2013). Billfish landings in Sri Lanka mainly comprised with five species: three species of marlin (Black marlin (*Istiompax indica*), Blue marlin (*Makaira nigricans*), Striped marlin (*Kajikia audax*)), one species of sail fish

(Indo-Pacific sailfish (*Istiophorus platypterus*)) and one species of Swordfish (*Xiphias gladius*). Marlins are dominant in billfish landings with highest catches represent by Black marlin (3018.5Mt in 2014 and 3474.3 Mt in 2015) followed by Blue marlin (312.9 Mt in 2014 and 722.5 Mt in 2015) and Striped marlin (21 Mt in 2014 and 7.6 Mt in 2015). Second higher billfish catches come from Sword fish (4363 Mt in 2014 and 5099.5 Mt in 2015). Lowest catch among billfish landings reported from Indo-Pacific sailfish (2340.9 Mt in 2014 and 1979.1 Mt in 2015) (NARA., 2016).

Although billfish species are highly migratory species with a wide range of horizontal distribution (Nakamura, 1985, Block et al., 1992, Brill & Lutcavage., 2001), many studies showed their habitat preference related with physical factors such as water temperature and dissolved oxygen (Worm et al., 2005; Boyce et al., 2008) and biological factors such as food availability, feeding and reproductive activities (Shimose et al., 2008; Shimose et al., 2009). Therefore, this study attempts to examine the relationship between billfish occurrence in relation to the oceanographic conditions in the Bay of Bengal region of the Indian Ocean.

Material and Methods

Fishery data

Fishery data were collected from Sri Lankan longline fishing fleet through log books for a period of five years 2006-2010. The dataset consists of (1) fishing date, (2) position, (3) number of hooks used and (4) daily catch in numbers. Number of fishermen in each trip is almost equal and the ice storage depends on the vessel size. Other factors of effort such as, true fishing time, search-time, timing (time of the day), bait type, catch of bait, hooking depth, catch in weight were absent in logbooks. Lack of these information on effort data lead to use relative abundance indices based on the catch per unit of effort (CPUE) as number of fish per 100 hooks per fishing day. The null catches in the dataset were removed with considering the fish behavioral, environmental and fishing operational factors which influence on uncertainties of catchability during the study. Raw CPUE is not a good index for relative fish abundance (Maunder et al., 2016). So it is important to note that CPUE can be interpreted as indices of fish availability to Sri Lankan longliners, but not as indices of fish abundance.

Remotely sensed satellite data

Oceanographic data derived from satellites, specifically daily sea surface temperature (SST),sea surface chlorophyll a (SSC) and daily Absolute Dynamic Topography (ADT) / sea surface height (SSH). SST merged data product calculated from two satellite sensors AMSRE and AVHRR were obtained from the NOAA optimum interpolation ¼ degree daily sea surface temperature analyses (NOAA High Resolution SST data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/). SSH data were obtained from the information collected by TOPEX/Poseidon and ERS satellite altimeter data which were produced by Ssalto/Duacs and distributed by Aviso, with support from Cnes (http://www.aviso.altimetry.fr/duacs/). The DUACS 2014 Global products are directly computedon a Cartesian 1/4°x1/4° spatial resolution. SSC were obtained from Glob Colour 8-day composite of MODIS-MERIS weighted average method (AVW) data. GlobColour data (http://globcolour.info) used in this study has been developed, validated, and distributed by ACRI-ST, France.SSH data were obtained from the information collected by TOPEX/Poseidon and ERS satellite altimeter data (ftp://ftp.cls.fr/pub/oceano/AVISO/). It was assumed that the averaging time period of a particular oceanographic parameter is not considerably varies within the averaging period in the region.

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 (~25 miles). Daily SST and SSH data were average to 8-day to match with 8-day SSC composites and gridded in to 1/3 degree. The fishery data (CPUE) were also griddedto1/3 degree and averaged over 8-day fishing activity.

Satellite and fishery data were combined in similar grid space and output results were then statistically analyzed. Analyses were performed in R 3.2.1 statistical language (R Core Team., 2015). Using the RODBC (Ripley and Lapsley., 2016), chorn (James and Hornik., 2015) and geo (Bjornsson et al., 2015), mgcv (Wood., 2011), lattice (Sarkar., 2008), ggplot2 (Wickham., 2009), gridExtra (Auguie., 2016), maps (Becker et al., 2016) and map data (Becker et el., 2016) packages.

The association between the three oceanographic variables and billfish CPUE were analyzed using empirical cumulative frequency distribution function (ECDF). In this analysis, three functions (Andrade and Garcia., 2001; Rajapaksha et al., 2010; Zainuddin., 2011) were used as follows:

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

With the indication function:

$$l\,(X_i) = \begin{cases} 1 \; if \; X_i \leq 1 \\ 0 \;\; otherwise \end{cases} \qquad (2)$$

$$g(t) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i}{\bar{y}}\right) l(x_i) \qquad (3)$$

$$D(t) = \; max|f(t) - g(t)| \qquad (4)$$

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.

Developing a GAM model

Generalized additive model (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 Generalized Linear Model (GLM).

GAM) was applied to identify the nature of relationships between billfish CPUE and the three ocean environmental parameters. The relationships between environmental factors and CPUE are mostly expected as nonlinear.

$$ln(CPUE) = a + s(SST) + s(SSC) + s(SSH) + e \qquad (4)$$

Where a is a constant, $s(.)$ is a spline smoothing function of the variables (*SST*, *SSC*, and *SSH*) and e is a random error term.

Results and Discussion

Results

Sri Lankan tuna longline fishery distributed within the Exclusive Economic Zone (EEZ), as well as in international waters in the Indian Ocean. The tuna longline activities mainly concentrated to the North-East part of the country. Therefore, the study area confined to this region only (Figure 1).

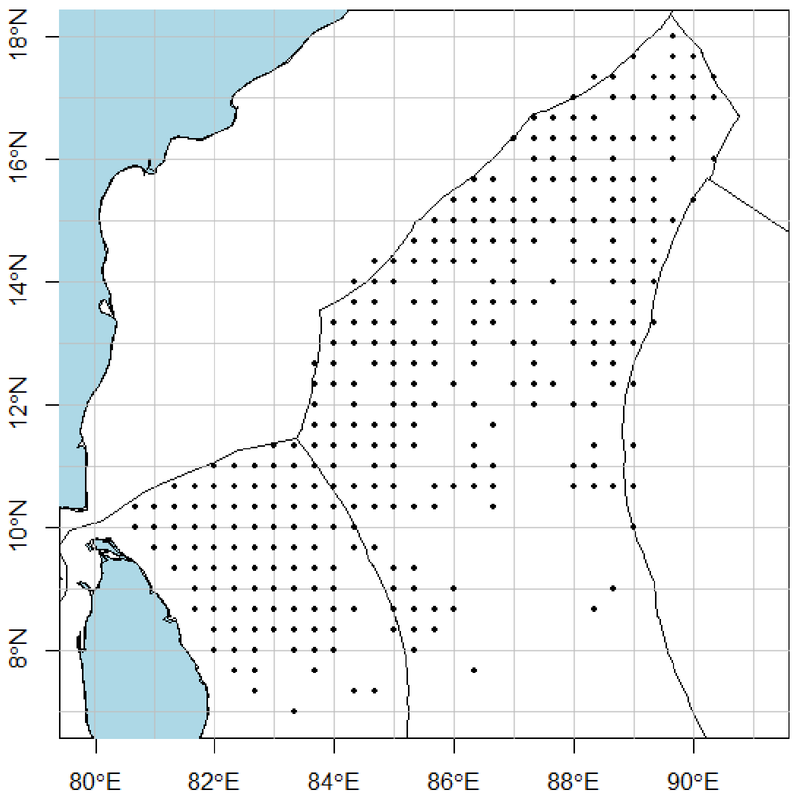


Figure 1: Study area showing the positions of fishery dataset obtained during period of 2006 – 2010. The positions are shown 1/3 ° grids.

The frequency distribution of billfish fishing activities in relation to satellite derived environmental parameters showed that there are specific ranges where billfish tend to concentrate (Figure 2). The fishable area of billfish with relevant to SST is primarily varies between 25.5 to 31.5 °C and more activities concentrated within area of SST between 27 to 30.5 °C. SSC of the environment is varies between 0 to 0.45 mgm^{-3} with higher billfish catches were recorded between 0.05 to 0.25 mgm^{-3}. Negative skewed catch frequencies of billfish within the range of SSC showed that more catches tend to come from waters where SSC is lower. The area of billfish catch records relation to SSH primarily varies between 70 to 115 cm and it follows a Gaussian distribution. The higher billfish catch frequencies concentrated within the SSH range of 85 to 105 cm.

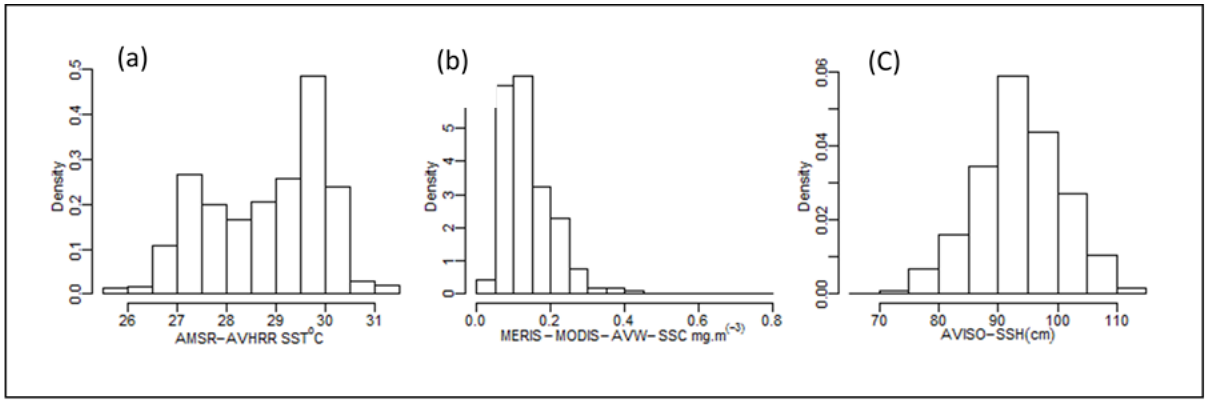
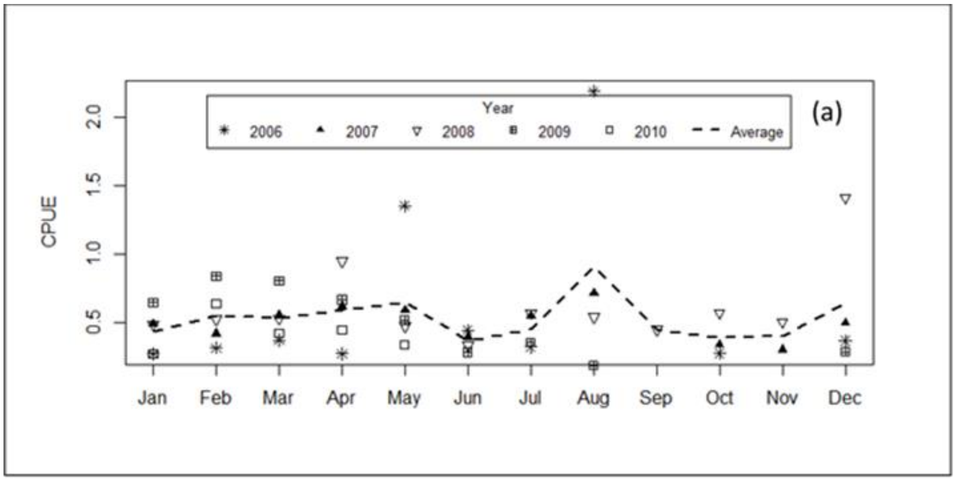


Figure 2: Histograms showing frequencies of billfish caught Sea Surface Temperature (SST), Sea Surface Chlorophyll (SSC) and Sea Surface Height (SSH) in the Bay of Bengal.

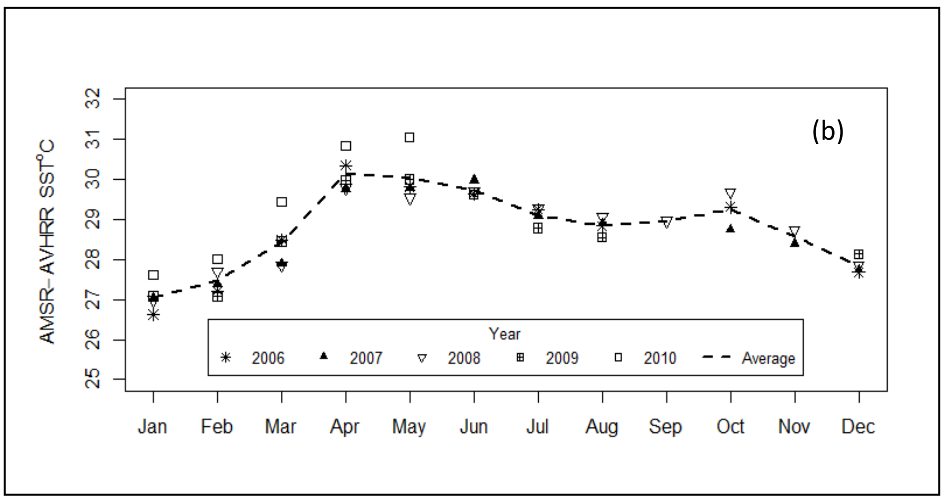
Monthly average CPUE has not considerably fluctuated within the studied period (Figure 3a). Monthly averages of environmental parameters followed a general pattern mainly with the influence of the south-west and north-east monsoonal patterns. The monthly average SST increases from the lowest average of SST (27°C) reported in January up to the highest average reported during April & May (~30°C) with an elevated average reported during the latter part of the study period. Then monthly average of SST gradually decreases up to 28°C reported in December (Figure 3b).

Monthly average of SSC also followed yearly an identical pattern during the study period. Monthly average of SSC showed a decreasing pattern from December & January (0.25 mgm^{-3}) up to the lowest average of SSC (0.1 mgm^{-3}) reported in April (Figure 3c). Since May, average SSC showed a gradually increasing trend up to the highest average (0.3 mgm^{-3}) reported in September and during the next two months showed a decreasing trend.

Monthly average SSH of the north-east part showed yearly identical pattern during the study period with gradually increasing trend from December/ January (88 cm) to April (97 cm). Since May, monthly average SSH gradually decreased up to August (85 cm) and rest of the year (from August to November) it remains stable (Figure 3d).



(a)
Year
2006
2007
2008
2009
2010
Average
CPUE
0.5
1.0
1.5
2.0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec



(b)
Year
2006
2007
2008
2009
2010
Average
AMSR- AVHRR SST°C
25
26
27
28
29
30
31
32
Jan
Feb
Mar
Apr
May
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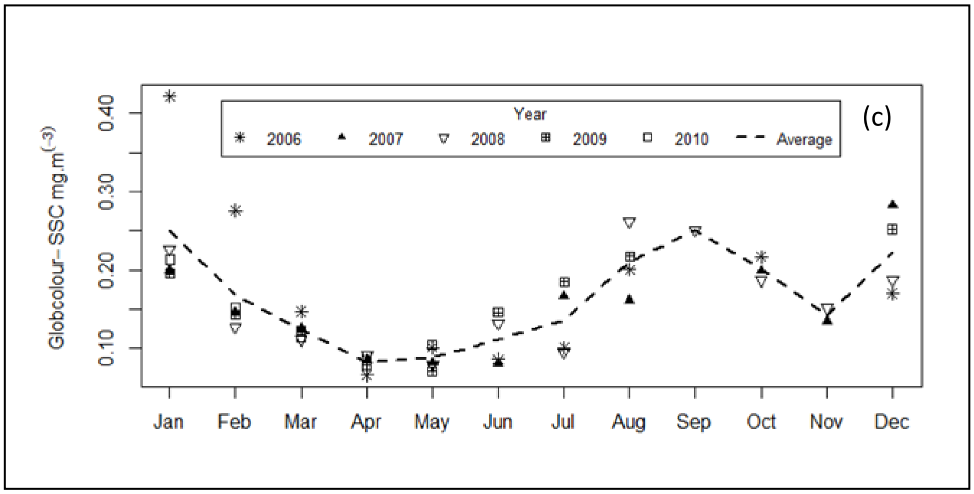
Jul
Aug
Sep
Oct
Nov
Dec



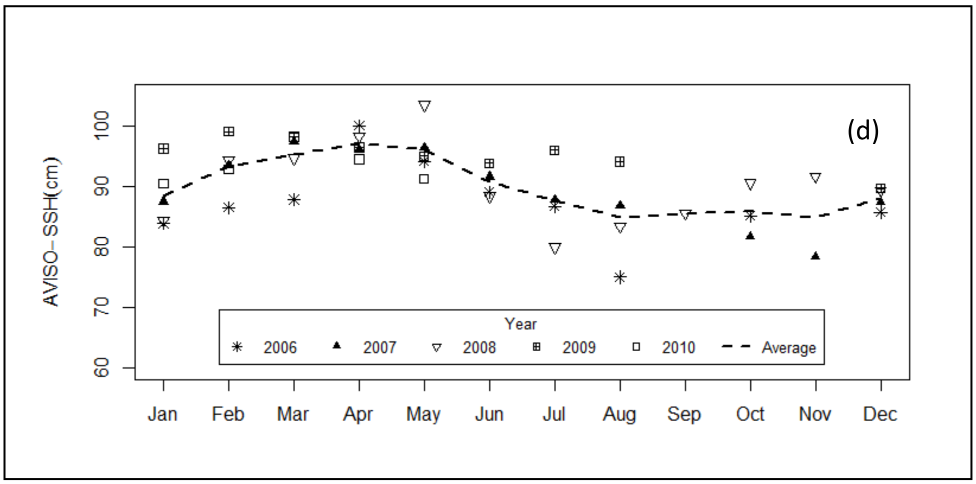


Figure 3: Monthly variability of Catch Per Unit Effort (CPUE) and the variability of Sea Surface Temperature (SST), Sea Surface Chlorophyll (SSC) and Sea Surface Height (SSH) during the study period.

The relationship between CPUE and three environmental parameters have been proven by the empirical cumulative distribution function (ECDF). Results of ECDF showed that curves of three variables are different and the degrees of the difference between two curves $D(t)$ are statistically significant ($p < 0.01$). The stronger association presented between CPUE and environmental variables: SST ranging from 27 to 30 °C, SSC ranging from 0.05 to 0.45 mgm^{-3} and SSH ranging from 80 to 105cm. Among the three environmental variables, SSC shows strongest association with billfish CPUE whereas SST shows the weakest association with billfish CPUE (Figure 4). Billfish CPUEs tended to decrease in areas of outside to those favorable ranges.

GAM results showed that all environmental factors are in significant level ($p < 0.01$) and influence the average catch rates of the billfish. The GAM results show that the SST and SSH are the main environmental factors influenced on billfish catch rates (Figure 5 and Table 1) GAM results further shows that within 27 to 30∘C range of SSC, CPUE remains approximately constant (Figure 5a). Also, a slight increasing trend in the average CPUE could be observed with increased SSC (Figure 5b). Moreover, a decreasing trend in the average CPUE could be observed within the range 70-90cm of SSH (Figure 5c). But, CPUE does not fluctuate largely on the range of 90 -105cm of SSH. Finally, a clear decrease trend could be observed beyond this range of SSH. The space-time factor (lat×lon×month), explains the largest portion of the CPUE variance (Table 1), GAM results further suggested that combination of environmental parameters and space-time factor are important in predicting the billfish CPUE.

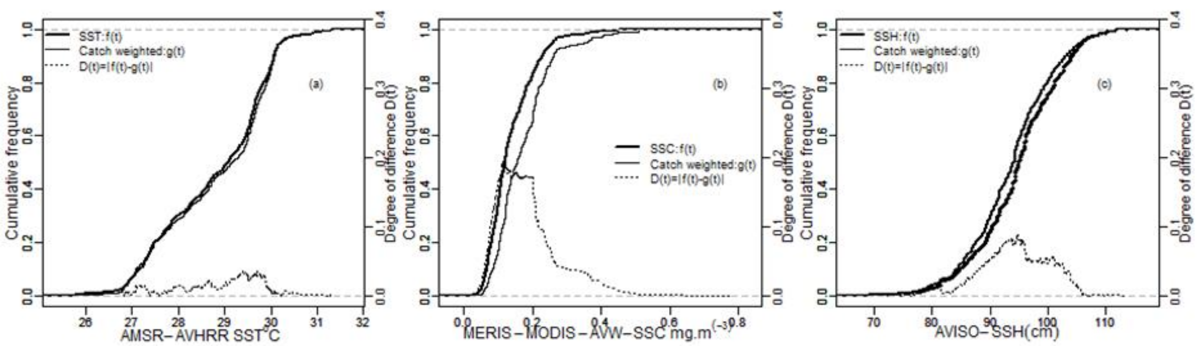


Figure 4: Empirical cumulative distribution frequencies of (a) Sea Surface Temperature (SST), (b) Sea Surface Chlorophyll (SSC) and (c) Sea Surface Height (SSH) superimposed of billfish catch weighted SST, SSC and SSH during 2006 to 2010. The dashed lines show the degree of differences of the two curves.

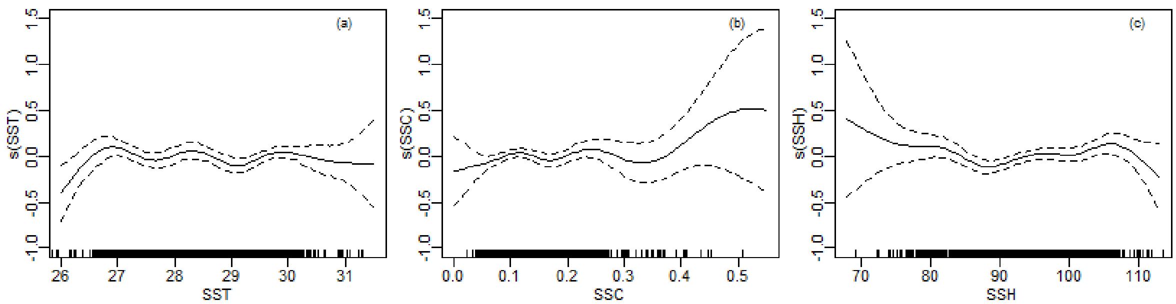


Figure 5: Generalized Additive model (GAM) derived effect of environmental variables (a) Sea Surface Temperature (SST), (b) Sea Surface Chlorophyll (SSC) and (c) Sea Surface Height (SSH) on billfish CPUE (log transformed). Dashed lines indicate 95 % of the confidence intervals. The relative density of data points is shown in rug plots along the x axis.

Table 1: Single predictor GAM fitted for billfish CPUE. For each predictor, the percentage of deviance and the generalized cross validation scores is given

Parameter	% deviance	GCV score
SST	1.53	0.4261
SSC	1.01	0.4280
SSH	1.50	0.4260
lat×lon×month	22.6	0.4260

Discussion

Offshore longline fishery in Sri Lanka rapidly growth since its introduction in early 80's. However, the technological improvements in this fishery have not grown up considerably. Necessity of new technological application in the sector emerged in recent decades within local fishers due to increased fishing effort in offshore longline sector.

Satellite remote sensing data in a high temporal resolution has a great capability to provide the required environmental data that can be used as an indicator for the pelagic species abundance/ CPUE. Combining satellite observations with ocean dynamic data and in situ observation related to the fisheries is highly valuable to develop long term accurate data. These data improve the precision of models in fish forecasting which helps to reduce searching time of vessels in particular fishery. Furthermore, these technological inputs are directly affects the productivity of fishing activities with leaving minimum impacts.

During this study, limited fishery data for a longer time period were used with relevant environmental parameters to develop the ECDF and GAM models. The ECDF results showed that higher CPUEs are associated with SST ranging from 27 to 30 ◦C. This SST range could represent the preferable temperature range for billfish as feeding grounds and spawning ground in the Indian Ocean (Nakamura., 1985). Ortega-García et al., (2014) shows that environmental preferences of striped marlin are warm (26–28 ◦C) waters with high CHL concentration (>1 mg m^{-3}). Therefore, the results of the present study are in agreement with that study.

Sword fish are normally associated with deeper layers during day time compare to other billfishes, but remain at surface layers during night time (Carrey., 1990). As Sri Lankan longliners mainly operate during the night time (except few longliners operates during day time on the new moon days) at the shallow depth ranges (50 -100 m) where billfish are frequently found on this layer.

The concentration of chlorophyll-a is an indirect substitute of abundance of forage that is available to large pelagic species (Brill and Lutcavage., 2001) and some authors show that high abundance of pelagic species with several month lag relevant peak chlorophyll concentration (Sartimbul et al., 2010). This time lag in the areas with abundant fish resources could be considered as feeding grounds for billfish and other large pelagic fish. The present ECDF results show that SSC ranging from 0.05 to 0.45 mgm^{-3} showed higher CPUE of billfish in the study area. Billfish normally associate pelagic layers above thermocline (Nakamura., 1985). Relationship between SSH and thermocline depth in the study area can further be used to improve the predictability of billfish abundance/ CPUE.

Monthly distribution and CPUE of billfish are changed throughout the study area which showed the changing space-time factor during the study period. This fluctuation of billfish abundance might be relevant to their feeding and spawning behavior. GAMs are widely used to explore and determine the effects of environmental, spatial, and temporal variables on marine species (Ortega-García et al., 2008). GAM results in the study show that all the environmental factors influence on billfish catch rates Also , space-time factor (lat×lon×month) explains a largest portion of the CPUE variance and play the most significant role in the CPUE prediction (Figure 6). This shows that both environmental and space-time factor improve the accuracy of the CPUE predictability of billfish.

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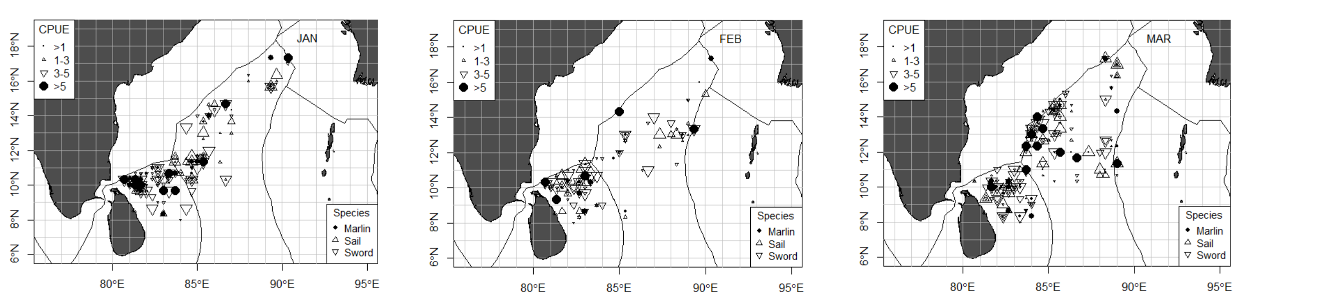

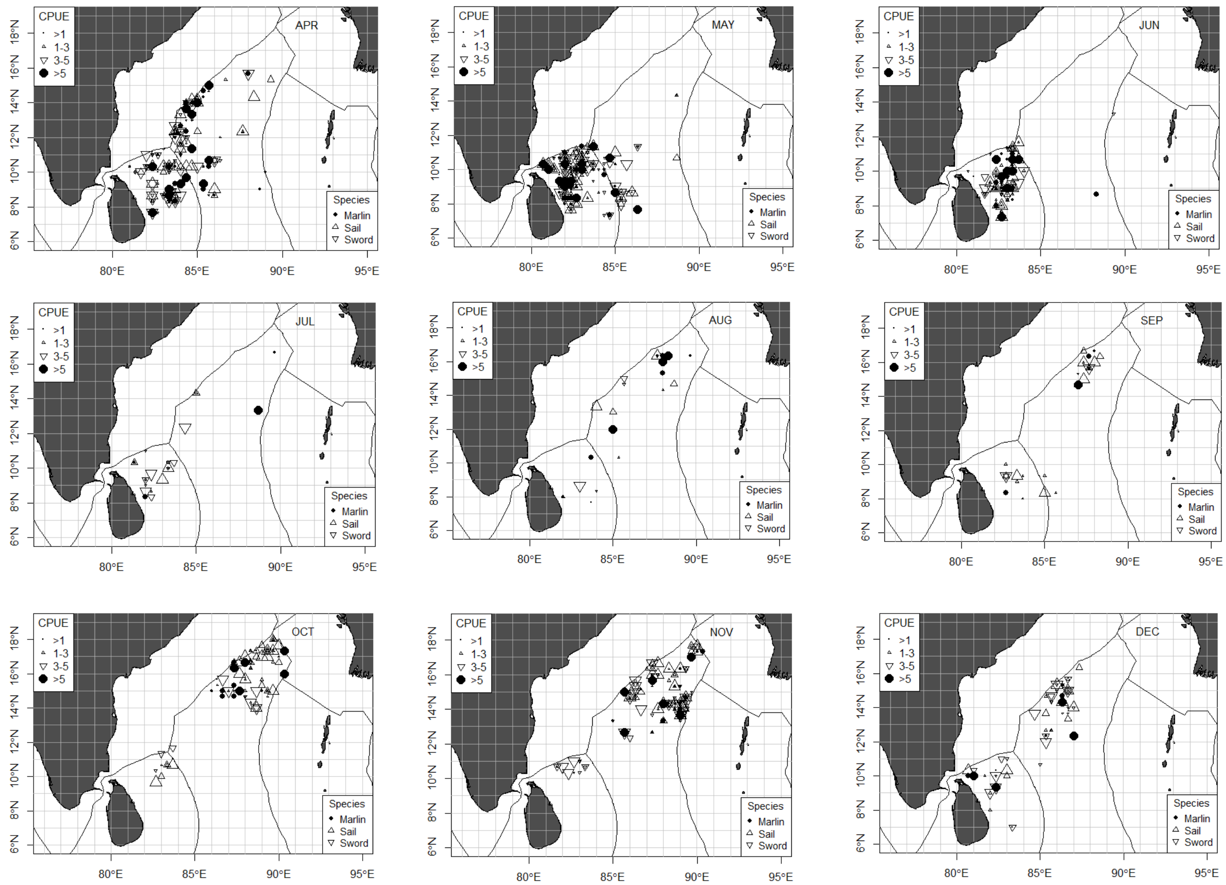

Figure 6: Monthly variation of distribution and Catch Per Unit Effort (CPUE) of Marlin, Sail fish and Sword fish within the study area during 2006 to 2010.

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