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Effect of Climatic Variability on the Fishery of Indian Oil Sardine Along Kerala Coast

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ABSTRACT

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Indian oil sardine (IOS), the commercially and ecologically important pelagic fish of the Kerala coast is susceptible to climatic variation. The study analyzes the impact of climate change on the catch of *Sardinella longiceps* along the Kerala coast and tries to predict the catch trend under the two RCP scenarios 4.5 and 6.0 for the period 2020-2100. Monthly catch of IOS by major gears for the period 1990-2016 was collected and Relative effort (*Effort*) and Weighted CPUE (*cpue*) were accordingly estimated. The climatic variables Sea Surface Temperature (SST), Precipitation (Pr), Chlorophyll *a* (SSC) and Salinity (SSS) were obtained from NOAA/NASA. The relationship of *cpue* and *Effort* of IOS to environmental variables were explored by Generalized Additive Model. The best fit model was selected using lowest Akaike information criterion (AIC) value, Deviance and F statistic. Predictions of *cpue* and *Effort* under RCP 4.5 and RCP 6.0 were done and the catch of IOS was estimated. The GAM model revealed the variations in the catch of IOS in relation to climate change. The SST, SSS and Pr showed a negative relation whereas SSC was found to be positively related to the catch of IOS. The results of the study indicate a decreasing trend of *cpue* and catch and an increasing trend of *Effort* towards 2100 under both climate change scenarios.

ADDITIONAL INDEX WORDS: *Climate change, CPUE, generalized additive model, Indian oil sardine, Kerala coast, RCP.*

INTRODUCTION

The climate of our planet is changing and the effects can be seen as global temperature rising, weather getting more extreme, sea levels rising, the oceans becoming more acidic and nutrient loads changing (Brierley and Kingsford, 2009). Increasing frequency and intensity of extreme climate events are likely to have a major impact on the marine environment and indirectly on fisheries (Brander, 2007). Fish species with rapid turnover of generations may show the most demographic responses to these changes (Perry *et al*., 2005). Fishing shows different trends in response to changes that affect larval stages, reproduction, feeding and migration, as well as anthropic pressures. Possible environmental changes, such as the increased SST, precipitation, chlorophyll concentration and salinity, surge intensity and nutrient concentration mechanisms and can affect the food chain and therefore the abundance, distribution and availability of fish populations (Miller and Schneider, 2000). Tropical species are considered to be especially sensitive to climate change because they live close to their thermal maximum and exhibit limited capacity for acclimation (Stillman, 2003)

India is the second largest producer of fish in the world, contributing about 5.43 percent of the world production.

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The Indian marine fisheries sector thus plays a strategic role in food security, international trade and employment generation in the country (Shyam, Rahman, and Antony, 2015). Among the commercially important marine fish species harvested in India, IOS occupies the foremost position along with mackerel in terms of landings and consumption. Kerala contributes a great magnitude (up to 65%) to the total IOS catch of the country (Shyam, Rahman, and Antony, 2015). Purse seiners, ring seiners (major catch) and the trawlers (by catch) constitute major fishing gears in the region, and are operated actively in locations where the oil sardine schools aggregate. *Sardinella longiceps* or Indian oil sardine (IOS) is one of the key forage organism for marine predators, including fish, squid, marine mammals, and seabirds. They are of increasing interest for conservation because of their perceived role as critical forage for charismatic mega fauna (*e.g*., marine mammals and seabirds) in many regions, and are often in the public eye (Cury *et al*., 2011). The spawning period, (Antony Raja, 1969) feeding habits (Remya and Vivekanandan, 2013) and fishery of IOS is directly and indirectly subjective to changes in climate (Krishnakumar and Bhat, 2008; Kumar *et al*., 2009). Since the variations in pelagic resources particularly sardine and anchovies are closely linked to the environmental changes on different time and spatial scales, realistic models of these fish populations with climate change and fishing at appropriate scale and resolution are achievable. The interactions between fish and their environment can now be examined by incorporating a wide range of remote sensing oceanographic variables into fishery data which can contribute largely to the management of fisheries. Given the importance of pelagic fishing in the Kerala coast, this study analyses a GAM model of IOS and climatic variables, and predicts catch potential up to 2100 under two RCP scenarios 4.5 and 6.0 respectively. This multivariate approach considers the quarterly catches of IOS, local and global environmental variables and fishing effort for the period 1985-2016.

METHODS

Study area was selected. Data on climatic variables and fishery of IOS for the study area were collected. The data was standardized and model fitting and prediction was done using R software.

Study Area

The peculiar feature of marine environment in the Kerala coast is the coastal upwelling and the mud banks especially in the Malabar coast. Climate driven monsoon upwelling with subsequent replenishment of nutrients to the surface waters affect plankton blooms leading to a better fishery. Thus Malabar Coast rich in primary and secondary production, contributes nearly 50% of the total Indian marine fish landings (Smith and Madhupratap, 2005; Vivekanandan *et al*., 2003). Most stocks of IOS by purse seine and ring seine fisheries in the Western Arabian Sea are distributed in the upwelling region along the Kerala coast (Figure 1). The study area comprises the Kerala coast region between 8° N and 12° N latitudes and 75° E and 77° E longitudes.

Environmental Data

Environmental variables, such as sea surface temperature (SST), sea surface chlorophyll-*a* concentration (SSC), sea surface salinity (SSS) and precipitation (Pr) related to the distribution of IOS were used in the current investigation. To analyze the temporal changes in the climatic and oceanographic variables off Kerala, monthly average data on these variables were downloaded for 8° and 12° N latitudes and 75° and 77° E longitudes for the historic period. From this data set the quarterly data for the period 1998-2016 were averaged. The SST data was downloaded from, International Comprehensive Ocean-Atmosphere Data Set (ICOADS - NOAA, http://www.icoads.noaa.gov), precipitation (Pr) data was obtained from CPC Merged Analysis of Precipitation dataset (COARDS-NOAA, http://www.esrl.noaa.gov). The remote sensing data were aggregated by month in 1°-by-1° square grid cells. Non log-transformed chlorophyll *a* (SSC) data from OCI (SeaDAS-NASA, http://www.seadas.gsfc.nasa.gov) for 4 km resolution and salinity (SSS) from MIROC-ESM-CHEM model output prepared for CMIP5 historical (http://www.cmip.llnl.gov) were obtained.

Two climate change scenarios, as recommended in the IPCC 2014, RCP 4.5 and RCP 6.0 were selected to represent the possible scenarios with the low and high greenhouse gas emissions. Simulation data for these were collected from the CMIP5 climate model from NOAA Geophysical Fluid Dynamics Laboratory (http:// www.gfdl.noaa.gov).

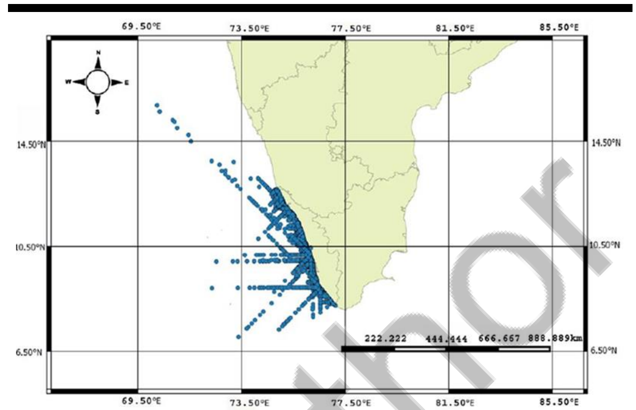

Figure 1. Fishing ground of Ring sienes along Kerala coast in the year 2015 (Figure courtesy Rohit *et al.*, 2018).

Fishery Data

Quarterly catch data of IOS along the Kerala coast was obtained from CMFRI catch log database for the period 1985-2016. The dataset included information regarding fishing date, catch, and fishing effort (actual fishing hours). The catch data was standardized using the standard methodology of FAO (Gulland, 1969). The Weighted catch per unit effort (*cpue or R*) was calculated using yield of individual gears (*Yi*), sum of the yields of gears for which effort is known (*YS*) and relative CPUE of individual gears (*Ri*). The Relative effort (*Effort* or *E*) was then calculated using *YS* and *cpue*. The calculation of *cpue* and *Effort* can be written as:

$$CPUEi(y) = \frac{Yi(y)}{fi(y)} \quad (1)$$

Where, *Yi* is the Total catch, *fi* the effort and *CPUEi* the catch per unit effort of gear *i* for the quarter *y*. Mean *CPUEi* was calculated using the equation n 2 , where $\overline{CPUEi}(y1, y2)$ is the mean for the time period over $y1, y1+1, \ldots . y2$.

$$\overline{CPUEi}(y1, y2) = \frac{1}{y2 - y1} * \sum_{j=y1}^{y2} CPUEi\ (\mathrm{j}) \quad (2)$$

The relative CPUE (*Ri*) of each quarter *y* for individual gears were then calculated as:

$$Ri(y) = \frac{CPUEi(y)}{\overline{CPUEi}\ (y1, y2)} \quad (3)$$

The sum of the yields of gears for which effort is known was estimated using equation 4:

$$YS(y) = \sum_{i=1}^{n} Yi(y) \quad (4)$$

Finally the Weighted catch per unit effort (*cpue or R*) for quarter *y* was calculated using *Ri*, *Yi* and *YS* with the equation:

$$cpue\ or\ R(y) = \sum_{i=1}^{n}\left(Ri(y) * \frac{Yi(y)}{YS(y)}\right) \qquad (5)$$

The Relative effort (*Effort*) for each quarter *y* was also calculated using *YS* and *cpue* (*R*) with the equation:

$$Relative\ effort\ or\ Effort\ (Ey) = \frac{YS(y)}{R(y)} \qquad (6)$$

Construction of the *cpue* Model and *Effort* Model

Generalized Additive Models (GAM) was performed with mgcv (Wood and Augustin, 2002) package in R (3.5.2). Auto correlation function (ACF) was performed to identify suitable lags of environmental variables. GAM was then used to develop models of the *cpue* and lagged climatic variables for IOS along the Kerala coast.

The use of GAM in environmental studies is helpful, especially when the relation between the response and the explanatory variable is non-linear and not well understood in advance. Moreover GAM models have been demonstrated to be powerful tools for predicting future fish distributions (Rutterford *et al*., 2015). The GAMs are semi-parametric approaches that allow for the inclusion of distribution network of independent variables as a function of the response variable. The response variable is modelled by a sum of smooth functions of covariates. The general structure of GAM can be written as:

$$g\big(E(Y_{it})\big) = \beta X_{it} + \sum\nolimits_{j=1}^{n} f_j(x_i) \qquad (7)$$

$$Y_{it} = E(Y_{it}) + \epsilon_{it} \qquad (8)$$

Where g is a link function, Y denotes the response variable, the vector β contains fixed parameters, X_{it} is a row of fixed effects matrix and f_j are smoothing splines of the $\boldsymbol{n}$ explanatory covariates, x_i. The residual errors ϵ_{it} are random Gaussian noise with mean 0. To avoid overfitting, and integrate the optimal smoothing parameters Cross Validation (GCV) described by Golub, Heath, and Wahba (1979) was used, and degrees of freedom were manually estimated by trial and error method. The model was constructed in a stepwise manner and predictor variable subset selection was done by using the lowest Akaike Information Criterion (AIC) score (Greven and Kneib, 2009). GAM model was then developed for *Effort* for two RCP scenarios. Here also SST, Pr, SSC and SSS were considered as predictors and Relative fishing effort as response variables.

Model selection, Validation and Prediction

The candidate models were compared by means of AIC, R squared statistic and F-statistic. The adequacy of the models was confirmed by analysing the independent and random distribution of the residuals over time, homoscedasticity for error variance and normal distribution of errors. The best fit model was then selected. The *cpue* was considered as response variable and SST, SSC, SSS and Pr were treated as predictors in the models. The selected model, in which smoothing spline functions are used to model the *cpue* and the climatic variables, were:

cpue ~ s(SST)+s(SSS)+s (SSC)+s(Pr)
Effort ~ s(SST)+s(Pr)+s(SSC)+s(SSS)

The evaluation of model was done by cross-validation test. Training data set was selected as the 80% total Actual data to build the model. Model validation was then done using a test data containing 20% of actual data and the results were compared.

Prediction was done using *gam.predict* function of mgcv package in R(3.5.2). In order to assess the prediction performance of the models 80% of the data were used to evaluate offset between predicted values of the model and the original values. This was checked based on the root mean squared error (RMSE). The model with smaller RMSE has better predictive performance. The ACF (Auto Correlation Function) and PACF (Partial Auto Correlation function) were used to test the independent random distribution of the residuals of the models.

Estimation of Future Catch

The catch potential of *Sardinella longiceps* for 2020-2100 was estimated using the equation;

$$YS(y) = Relative\ effort\ E(y) * R(y) \qquad (9)$$

Where *y* is the quarter of the year and *E(y)* and *R(y)* are predicted *Effort* and *cpue* respectively for corresponding quarters of the period 2020-2100.

RESULTS

The IOS along Kerala coast experienced large variations overtime. This is illustrated by increased catch after the introduction of Mechanized gears in the middle 1980s followed by a great reduction in the catch during the period 1992-1997 (54118-30607 tons). In the later years the catch again revived and reached peak in 2011 (322102.97 tons) and 2012 (399786.447 tons). Further reduction in catch is observed during the period 2012 to 2017 (126987.786 tons). The fluctuations in the fishery of IOS are shown in Figure 2.

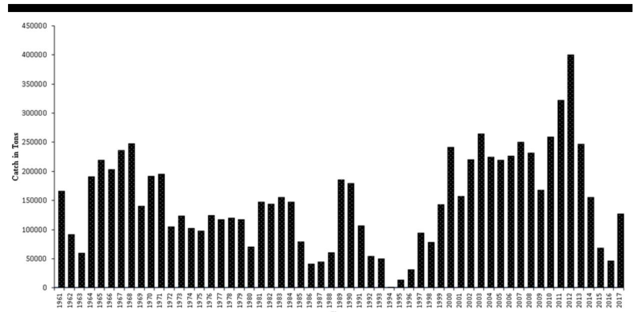

Figure 2. Catch of Indian oil sardine along Kerala coast during the period 1960-2016.

Changes in the Environment

The values of these oceanographic variables, SST, SSS, SSC and Pr of the study region have changed substantially since the

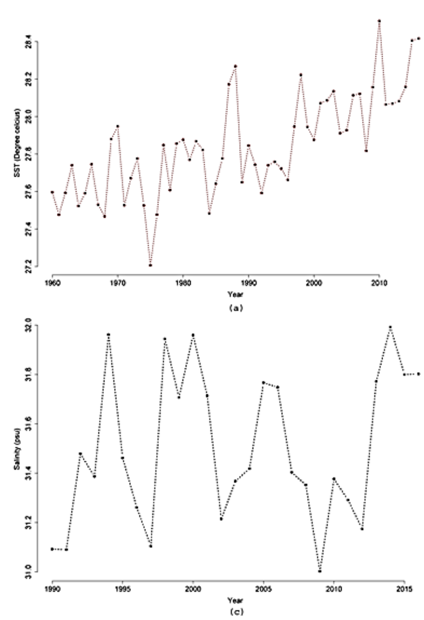

Figure 3. Environmental variables for historic period along Kerala coast - SST (a), Pr (b), SSS (c) and SSC (d).

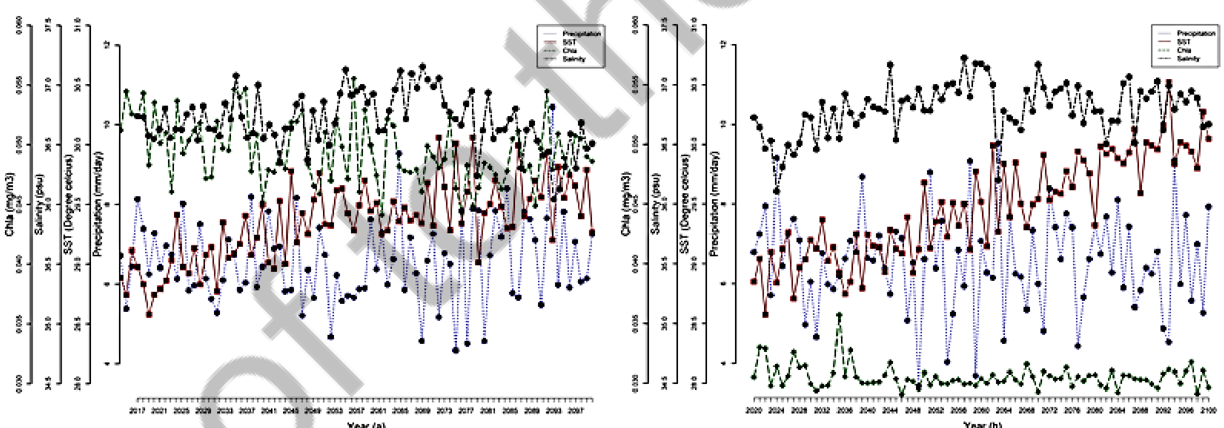

Figure 4. Trend of Average SST, Pr, SSS and SSC of the two climate change scenarios RCP 4.5 (a) and RCP 6.0 (b).

beginning of the 20^{th} century (Figure 3). Notably, the average SST has considerably increased since 1998 (Figure 3a). Average precipitation of the study area shows an increasing trend with more frequent peaks and fall (Figure 3b). The SSS has exhibited a steep increase in the years 1994, 98-'00, 2005-'06 and 2013-'14 (Figure 3c). The SSC concentration shows a decreasing trend since 2004 (Figure 3d).

The expected future temporal variations in environmental variables under the two climate change scenarios RCP 4.5 and RCP 6.0, in the geographical area of interest are shown in (Figure 4). The trend of the change in SSS is increasing under RCP 4.5 (Figure 4a) whereas a decreasing trend of SSS is observed for RCP 6.0 (Figure 4b). Increasing trends in the SST, and a decreasing trend in Pr are expected over the next 80 years from 2020 to 2100, and the increase is enhanced under the RCP 6.0 scenario (Figure 4b). The change in SSC shows a decreasing trend in RCP 6.0 (Figure 4b) when compared to RCP 4.5 scenario.

Model Outputs

The relationships of the *cpue* and fishing *Effort* of IOS with environmental variables were examined in the study. All predictor variables were found to be highly significant (p <0.01) for both the *cpue* and *Effort* models, which suggest that all variables should be included in the models (Table 1). The variables were incorporated by stepwise selection method. The model in which all variables were included show greater R squared values, lower AIC, higher deviance and lower residual deviances. The summary of the models, deviance explained, AIC values and degrees of freedom are shown in Table 2. The best model was determined by the model with the lowest AIC value. The removal of any predictors from the final model reduced the model performance, as shown in Table 2.

The PACF and ACF of the residuals of *cpue* and *Effort* model are shown in Figure 5. The results of the Model evaluation (1985-2016) are shown in Figure 6. The actual and predicted values compared to evaluate the model performance show that both *cpue* (Figure 6a) and *Effort* (Figure 6b) models performed well. When comparing the R square and AIC values of the two models it can be seen that *Effort* model performed better than the *cpue* model.

Table 1. *Analysis of Deviance explained, AIC and significance of each parameter for cpue and Effort models.*

Effort model	df	F	Deviance (%)	AIC	p value
s(SSC)	3.24	7.95	20.20	1513.05	0.000473***
s(SST)	4.75	3.89	40.30	1490.96	1.95e-08***
s(Pr)	11.52	8.89	62.90	1471.10	6.53e-12***
s(SSS)	12.52	3.13	38.30	1508.77	0.00145**
cpue model					
s(SSC)	3.08	3.43	10.90	276.72	0.00614**
s(SST)	12.81	4.06	44.60	262.93	0.000131***
s(Pr)	5.96	0.89	15.60	278.68	0.0397*
s(SSS)	3.09	1.13	17.00	271.72	0.000407***

Table 2. *Deviance explained, AIC, estimated degrees of freedom (df) and Adjusted R-square values of cpue and Effort models (obtained by sequentially adding each variable).*

Model	df	Deviance (%)	AIC	Adjusted R-square
cpue ~ s(SST) + s(Pr)	15.20	49.20	261.66	0.371
cpue ~ s(SST) + s(SSS)	13.23	45.60	262.38	0.351
cpue ~ s(SST) + s(Pr) + s(SSS)	15.38	49.50	261.50	0.374
cpue ~ s(SST) + s(Pr) + s(SSC)	15.76	50.40	261.09	0.38
cpue ~ s(SST) + s(Pr) + s(SSS) + s(SSC)	19.48	55.40	261.00	0.403
Effort ~ s(SST) + s(Pr)	11.63	63.10	1471.06	0.571
Effort ~ s(SST) + s(SSS)	11.63	60.70	1471.06	0.514
Effort ~ s(SST) + s(Pr) + s(SSS)	11.63	63.10	1471.06	0.571
Effort ~ s(SST) + s(Pr) + s(SSC)	15.53	72.40	1458.44	0.655
Effort ~ s(SST) + s(Pr) + s(SSS) + s(SSC)	24.90	81.30	1450.16	0.719

The effect of four environmental variables SST, Pr, SSC and SSS on the *cpue* (R) and *Effort* (E) are shown in Figure 7 and Figure 8 respectively. The y-axis values show the negative and positive effects of the environmental variables on *cpue* and *Effort* respectively. The results of the GAM model strongly suggest the influence of SST on *cpue* (R) of IOS. Increased *cpue* is observed at SST between 27ºC and 29ºC. A further increase or decrease in SST negatively affects the *cpue*. The relation between SST and *cpue* is very wiggly which suggests the sensitiveness of the fish availability to SST (Figure 7a). A positive effect on the catch of IOS is observed at Pr below 4 mm/day, and a gradual declining trend is observed at Pr greater than 6mm/day (Figure 7b). The *cpue* also shows a positive association with SSS. Higher *cpue* values are observed at SSS between 30.5 and 31.5 psu, and further increase or decrease in SSS is negatively associated with the *cpue* (Figure 7c). In contrast, SSC has a positive effect on the *cpue* of IOS. Increase in the *cpue* is observed with increasing SSC values (Figure 7d).

As revealed by GAM results high fishing *Effort* of IOS is expected for waters with temperatures between 27ºC and 29ºC (Figure 8a). The positive and negative effects are consistent with that of *cpue*. The effect of Pr is also similar to that of *cpue* (Figure 8b). The model indicates that the SSS exerts a negative effect on the *Effort* at values greater than 31.5 (Figure 8c). A positive effect of SSC on the *Effort* of IOS fishery is found at SSC concentrations above 1.0 mg/m^3 (Figure 8d).

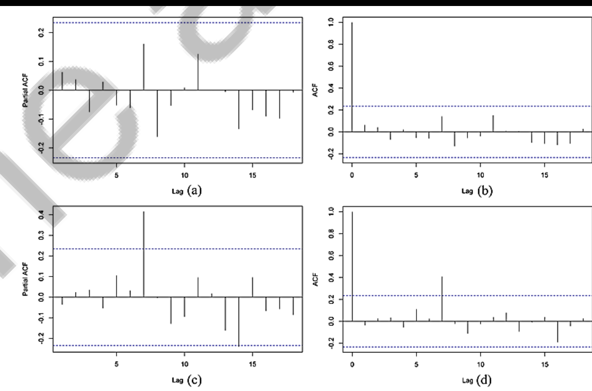

Figure 5. PACF and ACF of GAM model residuals *cpue* model (a, b) and *Effort* model (c, d).

Predicted *cpue*, *Effort* and Catch Potential of Oil sardine

The catch potential of IOS along Kerala coast for 2020-2100 was estimated using the predicted *cpue* and *Effort* values on quarterly basis. The GAM model prediction shows reduction in cpue under both RCP scenarios. The predicted *cpue* obtained for RCP 4.5 is higher when comapred to RCP 6.0. Though the *cpue* reduces in RCP 4.5, it first shows an increasing trend towards 2050 and then a graduall reduction towards 2100 (Figure 9a). The *cpue* of RCP 6.0 shows an increasing trend from 2020 to 2050 which then declines drastically towards 2100 (Figure 9b). The *Effort* predicted show an increase over time under both scenarios (Figure 10a and Figure 10b). Catch estimated (2020-2100) using the predicted *cpue* and *Effort*, for the two RCP scenarios show varying results. The predicted catch for RCP 4.5 show an increase towards 2050s which then gradually reduces towards 2100 (Figure 11). Compared to the catch of RCP 4.5, the predicted catch for RCP 6.0 after reaching a peak in 2050, it collapses drastically towards 2100.

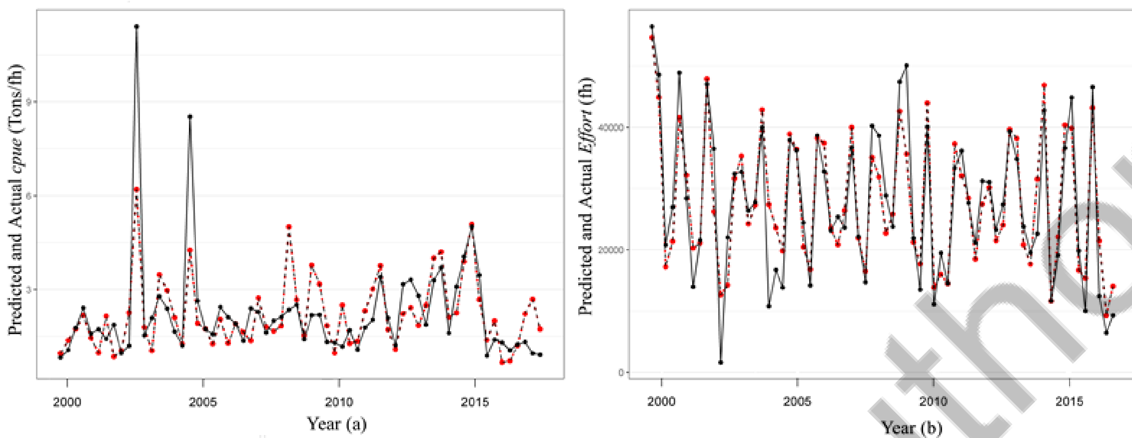

Figure 6. Model evaluations of *cpue* (a) and *Effort* (b) models.

The average catch of 2005-2015 period is used as a reference to compare with 5 year average of predicted catch for both climate change sceanrios. The observation shows that though the predicted yearly catch of IOS shows peaks in certain years, the average catch over 5 years first increases and then reduces in both climate change scenarios. In RCP 4.5 the 5 year average is expected to show an increase (50%) followed by a decrease (-150%). But the catch predicted for RCP 6.0 though shows an increase of 158 % in 2050, it falls abruplty by 2100 (Figure 12).

DISCUSSION

The *cpue* and *Effort* based models are suitable for investigating abundance and distribution of the fishery of interest in relation to environmental variables (Yen *et al*., 2016). In this study, the relation between oceanographic variables and IOS over time could not foresee any method to predict exact '*cpue'* or '*Effort'* to assimilate changes in fish abundance and distribution. But the study could forecast yearly averages that can suggest trends in IOS abundance and distribution along the Kerala coast in the forecasted climate change scenarios.

IOS is an abundant coastal pelagic species, with high ecological and economic relevance that is often affected by inter-annual fluctuations and distributional shifts in the SW coast of India. The GAM model output indicates the sensitivity of IOS fishery to changes in SST, Pr, SSS and SSC. Each environmental variable is found to influence *cpue* of IOS in a sequence as SST > SSS > SSC > Pr and *Effort* of IOS as Pr > SST > SSC > SSS as shown in Table 1. Rutterford *et al*. (2015) has reported seasonal temperatures, salinity and likely co-varying habitat variables to be major determinants of species distributions, and can be considered as good predictors of their distribution changes. Increase in SST influence the marine biological systems at organismal, population, community and ecosystem levels (Vivekanandan, 2013). The chlorophyll abundance is a vulnerable factor to oil sardine fishery as it determines the feeding ground and controls its recruitment (Piontkovski, Al-Oufi, and Al-Jufaili, 2014; Zaki *et al.*, 2012). With the advent of satellite remote sensing techniques (George, 2014), satellite aided information of chlorophyll abundance were utilized for unravelling the fluctuation in the abundance of IOS fishery (George *et al.*, 2012; Menon *et al.*, 2019). Rainfall (precipitation) data was utilized in previous studies to explain the inter-annual variability in IOS by Jayaprakash (2002). The results of the current study confirm that the changes in *cpue* and *Effort* are in relation with environmental variables. Long-term changes in climatic conditions are affecting the distribution and abundance of the population of IOS.

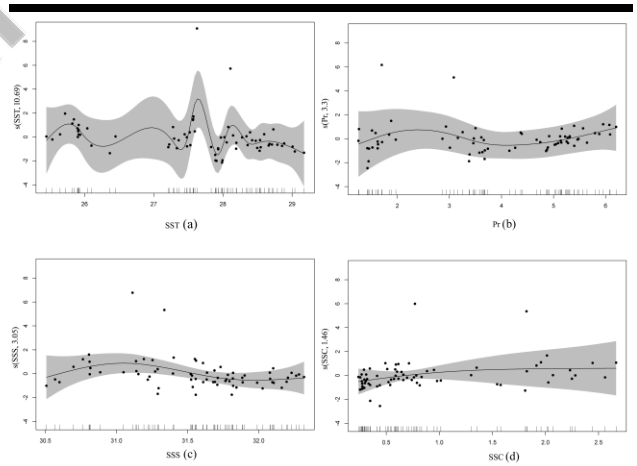

Figure 7. GAM model results of *cpue* model showing effect of SST (a), Pr (b), SSS (c) and SSC (d).

The *cpue* of RCP 4.5 and 6.0 predicted during 2020-2100 increases to the middle of the century followed by a reduction, which is more prominent in RCP 6.0 (Figure 9b). The *Effort* predicted for both climate change scenario showed increase over time. The reduced *cpue* compared to the increased *Effort* indicates a decline in the abundance and distribution of the fish in the region. The *cpue* and *Effort* for the total gears operating can also be used to predict the future catch. Hence by analyzing environmental variables and fishery data using GAM models, the approximate trend of future changes in the fishery of IOS along the Kerala coast is predicted for two climate change scenarios.

According to the GAM model prediction a large decline in the IOS fishery along Kerala coast with an intense recession after 2050 is expected for RCP 6.0 scenario. On the other hand the 4.5 scenario shows a gradual reduction in catch. The increasing effort which results in Fishing down the web leads to a great reduction in the prey population of small pelagic fishes such as IOS (Vivekanandan, Srinath, and Kuriakose, 2005).

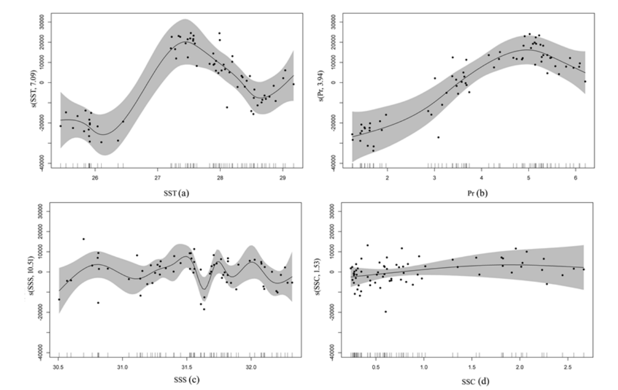

Figure 8. GAM model results of *Effort* model showing effect of SST (a), Pr (b), SSS (c) and SSC (d).

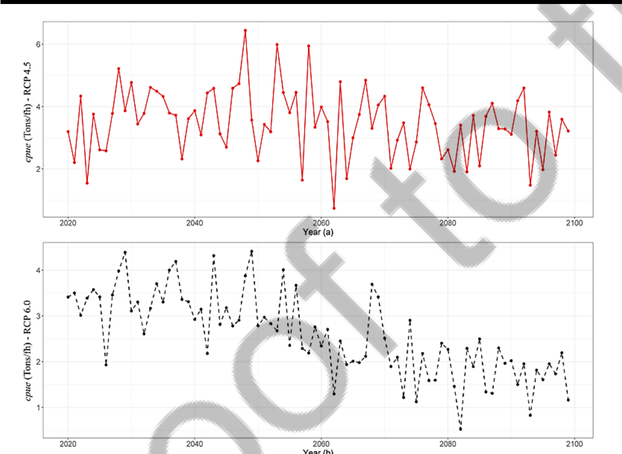

Figure 9. Predicted *cpue* for two RCP scenarios RCP 4.5 (a) and RCP 6.0 (b).

This in turn causes a surge in the biomass of small pelagic fish, which explains the initial increasing trend in the *cpue* and increasing catch of IOS with *Effort* till the middle of the century. Once the pelagic biomass surge has reached its maximum in the environment, there is a need for sustained production of chlorophyll to support the increasing grazing fish population. Adverse habitat conditions in our long term forecasts indicate the reduced availability of food items such as diatoms further leading to a competition among other peer fish species along with increased fishing pressure results in sudden collapse of the IOS.

Thus, the increase in SST (>29°C), increase in Pr (>5 mm/day) and lower SSC concentrations (<0.03 mg/m^3) contribute to the collapse of the population in RCP 6.0 scenario. Studies have shown decline in the biomass of large predators and eventual increase in the population of small pelagic fishes (by 130%) over the past century, which is not expected to be sustainable in the marine ecosystem conditions. A similar result forecasted in our model explains the reduction in catch beyond 2050 though the *Effort* increases further under both scenarios.

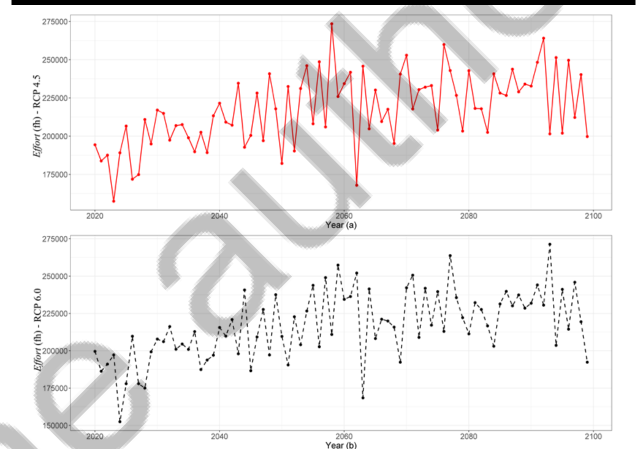

Figure 10. Predicted *Effort* for two RCP scenarios RCP 4.5 (a) and RCP 6.0 (b).

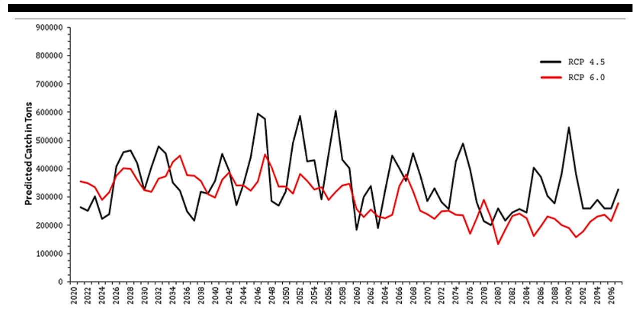

Figure 11. Predicted catch for two RCP scenarios RCP 4.5 and RCP 6.0.

The late recession of *cpue* (Figure 9a) and catch (Figure 11) predicted for IOS under RCP 4.5 might be due to a lower SST (<29°C), decrease in Pr (<5 mm/day) and increased SSC (>0.05 mg/m^3) after 2049 till 2070s. This may provide a comparatively more productive environment for the IOS population to survive in RCP 4.5 than a sudden collapse during corresponding periods under the RCP 6.0 scenario (Figure 11 and Figure 12). The results also reveals that increase in SST is one of the major factors that affects the changes in the distribution and abundance IOS. According to the current investigation the IOS along the Kerala coast is predicted to increase till 2050 which then reduces towards the end of 2100 under both climate change scenarios. This is supported by the findings of Cheung *et al.* (2010) which predicts maximum global catch potential in the year 2055, using models that linked geographic range of species with ocean conditions under low and high emission scenarios. IOS is a tropical fish whose tolerance range tends to be wider and the changes in temperature may not directly affect their survival, but can influence the life processes such as reproduction, spawning, food utilization and migration (Peck, 2011).

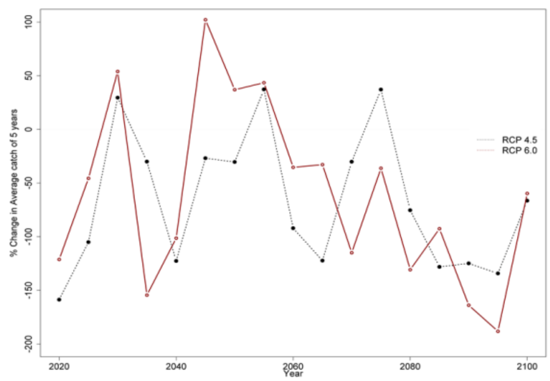

Figure 12. Percentage change of predicted 5 year Average catch of IOS compared to 10 year Average of 2005-2015.

The chances of migration of IOS is also supported by the studies of Vivekanandan, Rajagopalan, and Pillai (2008) which points out the emergence of the fish as a major fishery along SE coast and minor fishery along NE and NW coasts during 1950-2006, thereby reducing the percentage contribution of SW coast. Thus migration to favourable habitats can also be considered as a cause for reduction in the abundance of IOS after 2050 under RCP 6.0 and RCP 4.5. Since the ecological response of fishes to climate change are unknown, the predicted effect of decline in the fishery of IOS under the two RCP scenarios can also be expected to be influenced by their acclimation (Donelson, 2012; Stillman, 2003) and adaptation (Jennings, 2004) capacities.

IOS being a pelagic fish, is ecologically important as their large biomass is a crucial link in coastal food-webs, transferring the energy in plankton and small organisms to larger fishes, sea birds and marine mammals. It has also been stated earlier that Kerala contributes a great magnitude (up to 65%) to the total catch of IOS of the country. Moreover, IOS has a significant role in fish food security in the state as it is considered as a low cost delicacy in adding to the poor men's protein (Shyam, Rahman, and Antony, 2015). The reduction in the abundance of IOS along Kerala coast not only cause loss in income but also leads to loss of fishing operations and employment days. Hence the reduced IOS catch in the fishery is expected to have ecological, economic and food security impacts. The decline in the IOS catch in both climate change scenarios points towards the alarming need for sustainable fisheries management practices.

CONCLUSION

The study elucidates the historic changes of oceanographic parameters and its trend along the Kerala coast. The future projections of the fishery of IOS suggest that if the fish fails to adapt or acclimatize to changing climatic conditions it might lead to reduction in the distribution and abundance of IOS along the Kerala coast, thereby affecting the fishery. Since IOS is a major marine fishery resource and mostly consumed fish species in Kerala state, its catch fluctuations in relation to climate change is of concern which points towards the alarming need of sustainable exploitation of the resources. The current investigation also shows the relevance of GAM models for predicting the future trend of fishery resources in relation to climate change. Inclusion of more predictor variables and subsequent refinement of the model can improve GAM model predictions to get more accurate forecasts for fisheries management.

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