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Climate change drivers influencing Indian mackerel fishery in south-eastern Arabian Sea off Kerala, India

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ABSTRACT

The Indian mackerel *Rastrelliger kanagurta* (Cuvier, 1816) is one of the most important marine fishery resources along the south-eastern Arabian Sea along the coast of Kerala, south Inida. The effect of selected environmental variables on the Relative effort (*Effort*) and Weighted catch per unit effort (*cpue*) of the fish were investigated using simple correlation and Path analysis. Six major oceanographic variables, namely sea surface temperature (SST), sea surface chlorophyll-*a* concentration (SSC), sea surface salinity (SSS), Precipitation (Pr) Indian Ocean Dipole (IOD) and Southern Oscillation Index (SOI) (ENSO index), were selected for the present study. Among these SST had the highest direct negative effect (-0.282, $p<0.01$), followed by SSS (-0.152, $p<0.1$) and IOD (-0.006, $p<0.01$). The highest positive direct effect on the *cpue* was exhibited by Pr (0.514, $p<0.001$) followed by SSC and SOI (0.178, $p<0.01$). The environmental variables also exerted indirect effects on *cpue* through *Effort*. The residual variance indicated that there are spurious effects exerted by environmental variables not included in the study. According to the coefficient of determination (R^2), the relative importance of the influence of causally dependent environmental variables on the *cpue* of Indian mackerel is Pr> SSC >SSS.

Keywords: Climate impact, CPUE, Effort, Path analysis, *Rastrelliger kanagurta*

Introduction

Climate change reflected in significant aquatic environmental changes such as sea surface warming, sea level rise, shifts in salinity, dissolved oxygen and other ocean conditions is expected to impact marine organisms and associated fisheries (Wabnitz *et al.*, 2018). Changes in thermal conditions of the oceans are accompanied by changes in precipitation (Trenberth, 2011), ocean salinity (Boyer *et al*., 2005) and primary production (Roxy, *et al.,* 2016). El Nino-Southern Oscillation (ENSO), the dominant mode of ocean-atmosphere interaction in the tropical Pacific, also influences tropical and global climate (Zheng, 2013). In recent decades, it has been recognised that Indian Ocean sea surface temperature (SST) anomaly, the Indian Ocean Dipole (IOD), also has environmental links at par with ENSO events. The positive IOD events are often associated with El Nino (Izumo *et al*., 2010) and negative events with La Nina (Lim and Hendon, 2017). The Indian Ocean has shown significant increase in the SST and salinity (Bindoff *et al*., 2007) and decrease in primary productivity (Roxy *et al*., 2016). As per the Intergovernmental Panel on Climate Change (IPCC, 2013) these rapid changes in physical and chemical conditions within ocean sub-regions have already affected the distribution and abundance of marine organisms and ecosystems. The looming challenge of climate change at individual, population, community and ecosystem levels (Harley *et al*., 2006) has added to the economical underperformance of the global marine fisheries sector (Sumaila *et al.,* 2011).

The fisheries sector in India contributes 1.1% to the national GDP and is a principal source of livelihood for a large section of economically underprivileged population of the country. The Indian mackerel *Rastrelliger kanagurta* (Cuvier, 1816) is an important commercial fishery resource in India constituting 7.27% of the annual marine fish landings in 2017, of which 11.5% was contributed by the southern state of Kerala (CMFRI, 2018). It is a pelagic shoaling species with greatest abundance between 8°N and 12°N lat. and 75°E and 77°E long. Environmental variables are known to influence the fishery of mackerel, often leading to wide seasonal and annual fluctuations in landings (Krishnakumar *et al*., 2008). The fish prefers to stay close to the thermocline (Abdussamad *et al.*, 2010). The distribution of Indian mackerel is also found to change in response to climate induced progressive increase in SST in the Indian Ocean. Since the fish is a filter feeder which feeds on plankton (Sivadas and Bhaskaran, 2009), the monsoon upwelling with subsequent replenishment of nutrients to the surface waters directly affects its spawning and recruitment success (Yohannan *et al*., 2002).

Understanding the extent of climate change impacts on ecosystems and their interactions are key requirements of policy debates and adaptive management responses on climate change (Harley *et al*., 2006). Environmental variables such as salinity, temperature, Chl-*a* and primary productivity determine the distribution and abundance of marine fishes (Mohanty *et al*., 2017). Therefore the present study aimed to identify the major causal factors among a set of selected climatic variables *viz.,* sea surface temperature (SST), sea surface chlorophyll-*a* concentration (SSC), sea surface salinity (SSS), precipitation (Pr), Indian Ocean Dipole (IOD) and Southern Oscillation Index, SOI (ENSO index); as well as to assess the magnitude of their direct and indirect impacts on the fishery of Indian mackerel along the south-eastern coast of Arabian Sea.

Methods

Area of study

The Malabar coast which lies on the narrow coastal plain of Karnataka and Kerala states between the Western Ghats range and the Arabian Sea is rich in primary and secondary production and contributes nearly 50% of the total Indian marine fish landings (Smith and Madhupratap, 2005). The mackerel stock distributed in this upwelling zone along the south-eastern Arabian Sea (SEAS) coast is usually harvested using purse seine, ring seine and trawlers. The study area comprised Kerala coast of the south-eastern Arabian Sea region between 8°N and 12°N and 75°E and 77°E.

Environmental data

The monthly average data on climatic and oceanographic variables of Kerala coast were downloaded for the study area. From this dataset, quarterly data for the period 1998-2016 were averaged. The SST data was downloaded from International Comprehensive Ocean-Atmosphere Data Set (ICOADS-NOAA) and Pr data was obtained from CPC Merged Analysis of Precipitation dataset (COARDS-NOAA). The remote sensing data were aggregated by month in 1°-by-1° square grid cells. Non log-transformed SSC data from OCI (SeaDAS-NASA,) for 4 km resolution and SSS from MIROC-ESM-CHEM model output prepared for CMIP5 historical were obtained. IOD and SOI data were downloaded from NOAA-NCDC.

Estimation of cpue and effort

Quarterly landing data of Indian mackerel including information regarding fishing date, landing and fishing effort (actual fishing hours) along the study area for the period 1986-2016 was collected from National Marine Fishery Data Centre (NMFDC) of ICAR-Central Marine Fisheries Research Institute (ICAR-CMFRI). The catch and effort data was standardised following the standard methodology of FAO (Gulland, 1969). The Weighted CPUE (*cpue* or *R*) and Relative effort (*Effort* or *E*) were estimated using the equations:

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

$$\text{Relative effort or } Effort \text{ (Ey)} = \frac{YS(y)}{R(y)} \quad \text{(2)}$$

where $Ri(y)$ is the relative CPUE, $Yi(y)$ is yield of individual gear and $YS(y)$ is the sum of yields of the gears in the quarter.

Statistical analysis

Both simple correlation and Path analysis were used to analyse the data. Pearson's Correlation analysis was performed to assess the strength of the relation between Weighted CPUE (*cpue)* and climatic variables. Path analysis (Shipley, 2016) is a method for examining causal patterns among a set of variables. It is an extension of regression model, which is used to test the fit of a correlation matrix with a hypothetical causal model. The most significant difference that distinguishes Path analysis from other multivariate methods is that it determines both direct and indirect effects. A path coefficient is a standardised partial-regression coefficient and measures the direct influence of one variable upon another. It permits the separation of the correlation coefficient into components of direct and indirect effects. The path diagram represents the visual part of the analysis and aids in comparing the magnitude of relationship between variables (Stage and Carter, 2004).

The path coefficients are calculated as follows (Dewey, 1959):

$$P_{YX} = bS_X * S_Y \quad \text{(3)}$$

where P_{YX} is the path coefficient showing the direct effect of *X* independent variable on the *Y* dependent variable and b is the partial regression coefficient. In Equation 3, *Sx* is the standard deviation of the *X* variable and *Sy* is the standard deviation of the *Y* variable respectively.

The data was normalised and maximum likelihood estimation was used for estimation of the path model. Variance Inflation factor analysis was done and highly correlated variables were set free to avoid multi-collinearity. In the current study, Path analysis was performed using *sem* function of *lavaan* package (R3.5.3). The *'cpue'* and '*Effort*' were considered as endogenous variables and the selected climatic variables SST, SOI, IOD (causally independent), Pr, SSS and SSC (causally dependent) as exogenous variables. A hypothetical path model has been proposed based on thorough literature review. Regression analysis was conducted for each variable in the hypothesised path model, that is dependent or endogenous in relation to other variables and its fit indices were examined. The goodness of fit of the hypothesised model was increased after trimming the model according to theoretically supported modification indices. The re-specified model was then identified using fit indices such as Chi-square, Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Standardised root mean square residual (SRMR) and Root mean square error of approximation (RMSEA).

Results

The total landings of Indian mackerel from 1986 to 2016 are plotted in Fig. 1. The figure shows an upsurge in the landings throughout the decade from the end of 1980s (21,318 t) towards the end of 1990s. Of these years, the highest landing of Indian mackerel was obtained in the year 1996 (32,103 t) but subsequent years witnessed a gradual reduction in the total catch till date.

Both *cpue* and *Effort* of Indian mackerel show gradual reduction from 1986 to 2016 (Fig. 2a and b), with correspondingly high values for both in the peak catch in the year 1996, as well as a gradual reduction mirrored by the catch values in the following years till 2016. The graph of CPUE against Relative Effort, reflected in Fig. 3 illustrates the reduction in *cpue* along with *Effort* over time.

If the environmental variables observed from the study area are plotted as in Fig. 4, significant variation since the beginning of the 21st century is clearly observable. SST, SSS and Pr show increasing trend whereas SSC shows decreasing trend. The variation in SOI and IOD are also shown in Fig. 5.

Descriptive statistics of the fishery data and environmental variables employed in the model are presented in Table 1, with coefficients of variation (CV) reflecting the degree of variation in the analysed data. The *cpue,* which was considered as an endogenous variable for the purposes of the model exhibited the greatest variation out of the two endogenous variables (62%). Correlation analyses were used to assess the magnitude and direction of associations between environmental variables and *cpue* (Table 2).

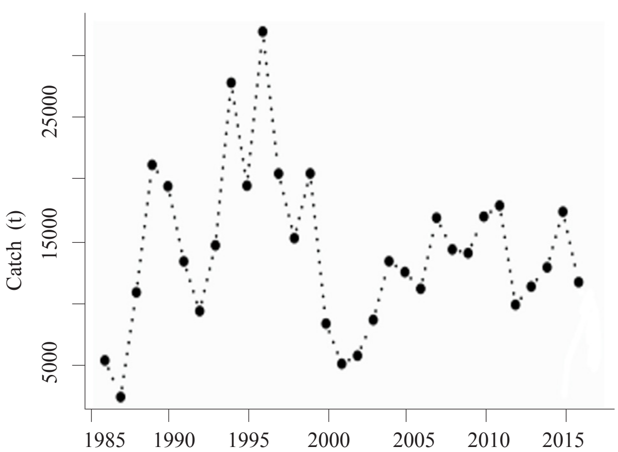


Fig. 1. Total landings of Indian mackerel from 1986-2016

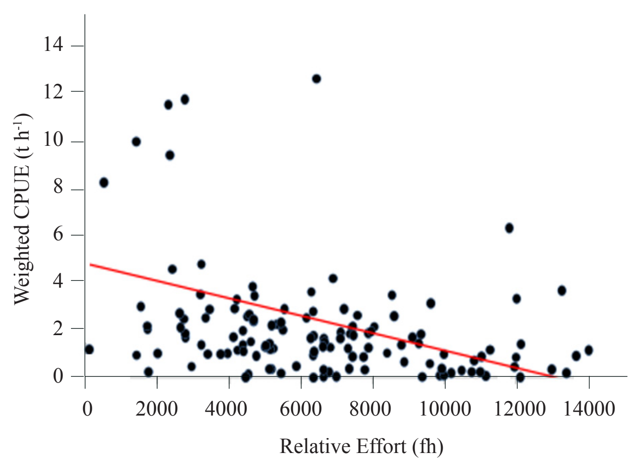
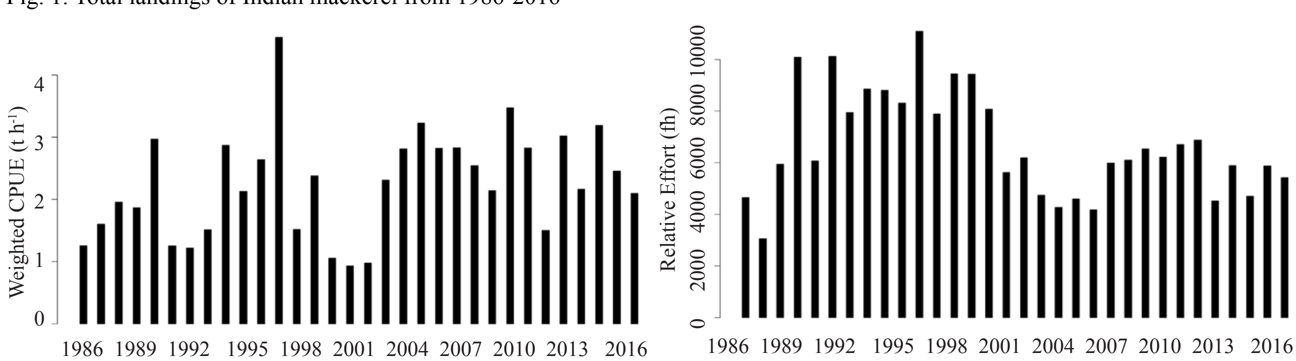


Fig. 3. Relation between *cpue* and *Effort* of Indian mackerel



(a) (b)

Fig. 2. (a) Weighted CPUE (*cpue*) and (b) Relative Effort (*Effort*) of Indian mackerel

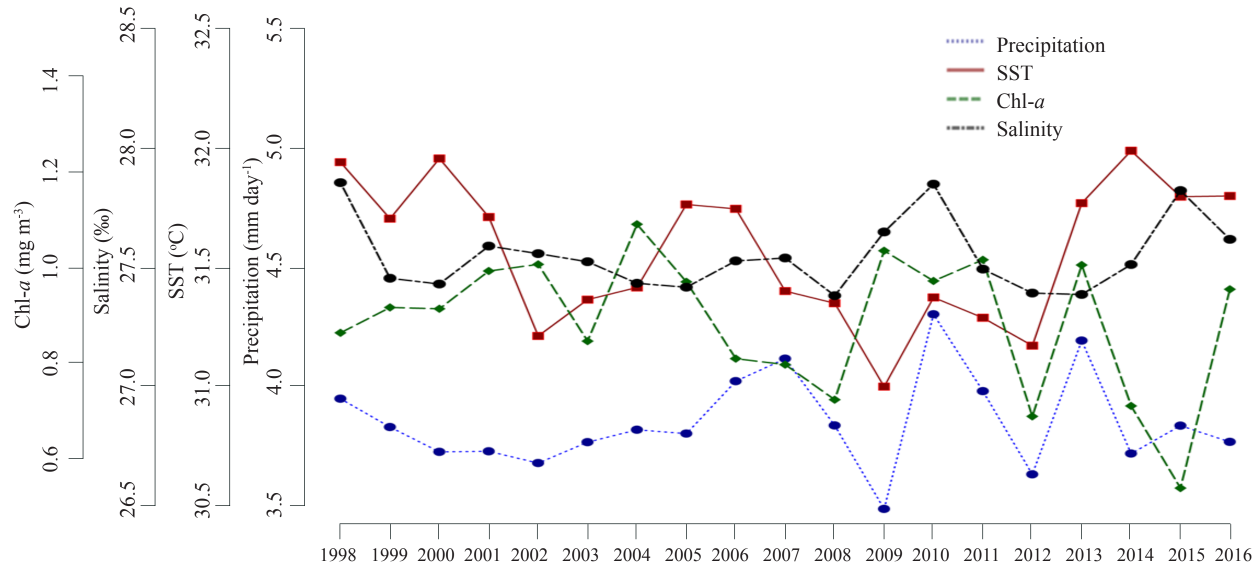


Fig. 4. Trend of SST, Pr, SSS and SSC along SEAS for 1998-2016

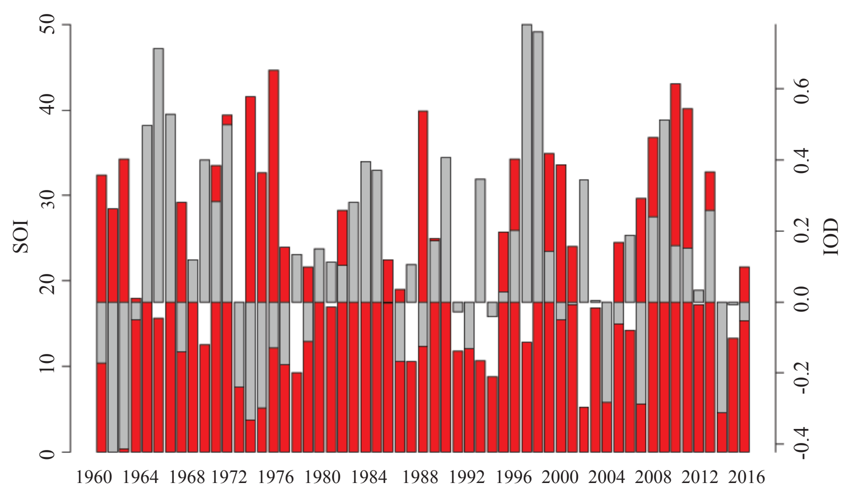


Fig. 5. Trend of SOI and IOD for the period 1960-2016

Table 1. Descriptive statistics of *cpue, Effort* and environmental variables

Variables	Mean	SD	Range	CV (%)
Effort	6105.151	2763.037	1443.088-14049.363	45.257
cpue	2.327	1.445	0.525-6.636	62.117
SST	27.552	1.060	25.448-29.173	3.849
Pr	3.855	1.565	1.252-6.021	40.586
SSS	31.569	0.466	30.507-32.340	1.475
SSC	0.888	0.686	0.238-2.665	77.283
SOI	24.654	13.364	2.333-55.0	54.206
IOD	0.213	0.229	-0.28-0.876	107.591

SD : Standard Deviation; CV : Coefficient of Variation

Table 2. Correlation coefficients among *cpue*, *Effort* and environmental variables

Parameter	*cpue*	SST	Pr	SSS	SSC	SOI	IOD
cpue	1						
SST	0.232**	1					
Pr	0.366***	0.822***	1				
SSS	-0.159	0.129	-0.035	1			
SSC	0.261*	0.577***	0.785***	-0.273*	1		
SOI	0.133	-0.092	-0.124	0.046	-0.114	1	
IOD	0.109	0.086	0.108	-0.229*	-0.034	0.111	1

* Significant at p<0.1 ,**Significant at p<0.01 and *** Significant at p<0.001

Correlation analyses were used to assess the magnitude and direction of associations between environmental variables and *cpue* (Table 2). The *cpue* showed significant positive correlations with Pr (0.366, p<0.001), SSC (0.261, p<0.05) and SST (0.232, p<0.05). A significant negative correlation was observed between *cpue* and SSS (-0.159, p<0.05). Correlations between environmental variables were also observed. SSC showed significant correlations with SST (0.577, p<0.001), Pr (0.785, p<0.01) and SSC (-0.273, p<0.05). Pr was highly correlated with SST (0.822, p<0.001). IOD showed a significant association with SSS (0.229, p<0.05). SOI did not show any significant correlation with endogenous (*cpue*) or exogenous variables (environmental variables).

Even though *Effort* was not used in correlation analysis it was included in Path models so as to identify the indirect effects of climatic variables on *cpue* through *Effort*. The fit indices of the Path model identified were Chi-square (0.38, p=0.829), CFI (1), TLI (1), SRMR (0.008) and RMSEA (0.001). Fig. 6 shows the Path diagram of the selected Path model. The direct and indirect effects of environmental variables on *cpue* are shown in Table 3 along with the determination coefficients.

Table 3. Decomposition table showing direct and indirect effects of environmental variables and *Effort* on *cpue*

Variable	Direct effect	Indirect effect through							Total effect	Determination coefficient
		Effort	SST	Pr	SSS	SSC	IOD	SOI		
Effort	-0.284***	-	0	0	0	0	0	0	-0.284**	0.247
SST	-0.282**	-0.154*	-	0.451*	0.001	0.112	-0.003	0	0.238*	exogenous
Pr	0.514***	0.193*	-0.246*	-	-0.001	0.112*	0.001	0	0.232***	0.842
SSS	-0.152**	0.078*	0	0	0.003	-0.002	0	0	-0.076	0.057
SSC	0.011	-0.229**	0	0	0	-	0	0	-0.218	0.77
IOD	-0.006	0.047	-0.001	0.074	-0.035*	-0.001	-	0	0.113	exogenous
SOI	0.178***	0.01	-0.018	-0.088	0.001	0.001	-0.003	-	0.124*	exogenous

*Significant at p<0.1 ,**Significant at p<0.01 and ***Significant at p<0.001, Residual effect : 0.23 (*cpue*)

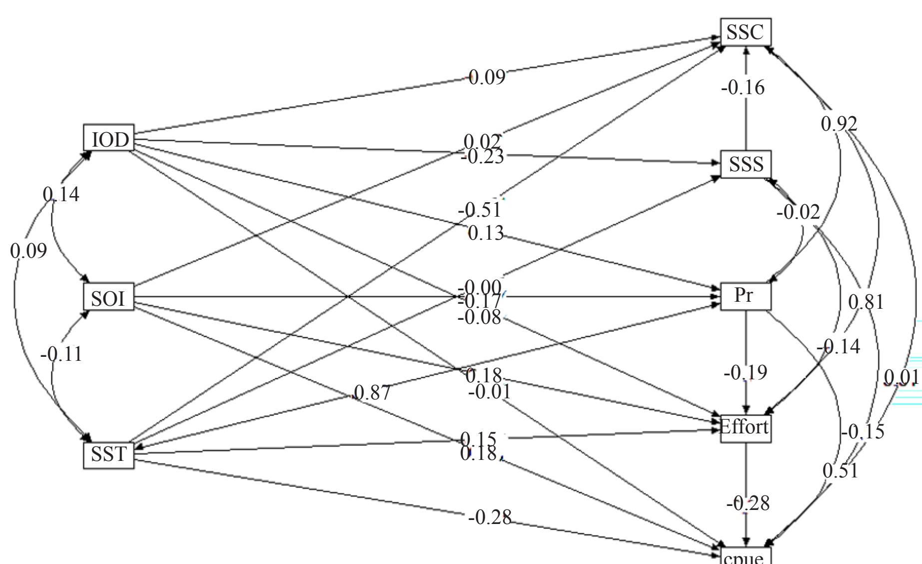


Fig. 6. Path diagram of selected Path model for *cpue*, *Effort* and environmental variables

Table 3. Decomposition table showing direct and indirect effects of environmental variables and *Effort* on *cpue*

Variable	Direct effect	Indirect effect through							Total effect	Determination coefficient
		Effort	SST	Pr	SSS	SSC	IOD	SOI		
Effort	-0.284***	-	0	0	0	0	0	0	-0.284**	0.247
SST	-0.282**	-0.154*	-	0.451*	0.001	0.112	-0.003	0	0.238*	exogenous
Pr	0.514***	0.193*	-0.246*	-	-0.001	0.112*	0.001	0	0.232***	0.842
SSS	-0.152**	0.078*	0	0	0.003	-0.002	0	0	-0.076	0.057
SSC	0.011	-0.229**	0	0	0	-	0	0	-0.218	0.77
IOD	-0.006	0.047	-0.001	0.074	-0.035*	-0.001	-	0	0.113	exogenous
SOI	0.178***	0.01	-0.018	-0.088	0.001	0.001	-0.003	-	0.124*	exogenous

*Significant at p<0.1 ,**Significant at p<0.01 and ***Significant at p<0.001, Residual effect : 0.23 (*cpue*)

Direct effects

The direct effect of *Effort* on *cpue* was high and negative (-0.284, p<0.001). Path coefficient analysis revealed that among the selected environmental variables, SST had the highest direct negative effect (-0.282, p<0.01), followed by SSS (-0.152, p<0.1). The highest positive direct effect on the *cpue* of Indian mackerel was exhibited by Pr (0.514, p<0.001). SSC also had a low direct positive effect on *cpue*. The direct effect of IOD on *cpue* was weak and negative (-0.006, p<0.01). Conversely, SOI showed a significant direct positive effect on *cpue* (0.178, p<0.01).

Indirect effects

The path coefficient value of SST on *cpue* was found to be the result of strong positive indirect effects *via* Pr (0.451, p<0.01) and *Effort* (-0.154, p<0.05), followed by SSC, IOD and SSS. The effect of SST *via* SSS, SSC and IOD was found to be low and non-significant. The highest significant indirect effect of Pr was shown *via* SST (-0.246, p<0.05) followed by *Effort* (0.193, p<0.05) and SSC (0.112,p<0.05). The indirect effect of SSS exhibited *via Effort* was found to be significant (0.078, p<0.05), whereas the effect through SSC and IOD was non-significant. The indirect effect of SSC was mainly through *Effort* (-0.229, p<0.01). The total effect of IOD is the sum of indirect effect *via Effort* (0.047) and SSS (-0.035, p<0.05). The total effect of SOI was a result of the sum of indirect effects *via* Pr, *Effort*, IOD and SST. The determination coefficients of the causally dependent exogenous variables were obtained as *Effort* (0.247), Pr (0.842), SSS (0.057) and SSC (0.77).

Discussion

Correlation analysis revealed significant relations between *cpue* of Indian mackerel and environmental variables (Table 2). Path coefficient analysis revealed significant positive direct effect of Pr on the *cpue* of Indian mackerel. The positive effect of Pr may be due to reduction in SST, increase in salinity stratification, mixed layer depth, light availability and nutrient entrainment with increase in precipitation (rainfall). These may lead to increased Chl-*a* production as reported by Kim *et al.* (2014). Roxy *et al*. (2016) reported that the monsoonal wind forcing in the SEAS leads to a strong coastal upwelling, supplying nutrients to the surface and thereby elevating the rates of primary productivity.

Conversely, a significant change in SST can negatively affect the Chl-*a* production as reported by Behrenfeld *et al*. (2006). Moreover, temperature is considered to be the most important factor governing both metabolic and spawning activities in fishes. It has been reported that pelagic species are able to detect temperature variations causing them gravitate towards areas favourable to their metabolism, or detect areas of greater prey availability (Sund *et al*., 1981; Freon and Misund, 1999). On contrary, studies by Suprabha *et al*. (2016) revealed that Chl-*a* concentration has greater influence on the distribution of Indian mackerel compared to that of SST.

The direct path coefficient of SSS (-0.152) shows that the negative effect is moderate and significant. Salinity may directly influence the osmotic balance of the body fluid of fishes thereby influencing their distribution as reported by Pradhan and Reddy (1962). Additionally, studies by Silas (1974) show the importance of salinity in the survival of the larval stages of Indian mackerel. Furthermore, SSS has a significant role in the productivity of marine environment. Increases in salinity have been reported to affect the growth and distribution of phytoplankton (Sushanth and Rajashekhar, 2012) and zooplankton (Santangelo, 2014). The current investigation also reveals that SSS has a negative effect on *cpue* through SSC. SSC exhibits a strong indirect effect *via Effort* and an increase in SSC are reflected by a corresponding increase in *Effort*, strongly suggesting that the distribution of Indian mackerel is directly affected by the availability of food.

The positive and negative effects of SOI on *cpue*, *Effort* and other environmental variables were found to be counter-balanced by the effects of IOD. The direct effect of SOI on *cpue* was found to be positive, medium and significant, whereas the effect of IOD on *cpue* was weak and negative. IOD is shown to have negative indirect effect through SSS whereas the most significant effect of SOI is the direct effect that it exerts on *cpue*. The relationship between the Indian monsoon, ENSO and IOD has been the subject of numerous studies. Wang *et al*. (2003) have demonstrated that SST tends to be below normal in the developing phase of ENSO and can provide negative feedback on the Indian monsoon. The Indian monsoon also depends on the relative intensities of the IOD and the El-Nino/La Nina events (Ashok, 2004). Changes in the intensity of monsoon in response to the El-Nino events in turn bring about changes in the hydrological conditions and thereby affect the distribution of fish. Since the distribution of pelagic fish resources are sensitive to hydrological conditions and availability of food, the distribution of Indian mackerel can also be expected to be influenced by changes in Pr, SST, SSS and SSC. In the current investigation, the indirect effects of SST, Pr, SSS and SSC on *cpue* through *Effort* are highly significant. The present study indicated a strong effect of environmental variables on the *Effort* which is a direct measure of fish abundance and distribution as proposed by Yen *et al*. (2016). Although the model was statistically significant and explained a modest portion of the variance, in some places it can be seen that correlation and total path coefficients are different. This residual variance may be due to spurious effects exerted by environmental variables not included in the model. Considering the coefficient of determination (R^2) of environmental variables included in the study, it can be inferred that the relative importance of the influence of causally dependent environmental variables on the *cpue* of Indian mackerel is in the order Pr> SSC >SSS.

The present study attempted to identify both magnitude and direction of the effect of a set of selected environmental variables on the *cpue* of Indian mackerel. The results clearly indicated that all the environmental variables exerted indirect effects on *cpue* through *Effort*. The direct effect of *Effort* on *cpue* was negative. The direct effect of SST, SSS and IOD on *cpue* was negative whereas the effects of Pr, SSC and SOI were positive. SST, SOI and IOD also exerted indirect effects on *cpue* through Pr, SSC and SSS. The study also indicates that there are likely to be unknown effects of other environmental variables on the fishery of Indian mackerel which once taken into consideration may refine the model results. Since *cpue* and *Effort* are considered as measures of abundance and distribution of fishes, the effect of environmental variables have a direct impact on their fishery. As Indian mackerel is one of the major fishery resources along the south-eastern coast of Arabian Sea, the influence of environmental variables on its landings under changing climatic conditions is expected to directly affect the livelihood of fishermen in the long run.

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