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Influence of satellite-derived oceanographic characteristics on sea truth fishery data of Indian mackerel, *Rastrelliger kanagurta*

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Original Article

Abstract

The study aimed to identify the most relevant variable from remote sensing data that may be utilized to forecast species-specific fish availability. Because of the schooling habits and reliance on surface productivity, the Indian mackerel, *Rastrelliger kanagurta*, has been suggested as a prospective species for such investigations in tropical waters. The current study showed how a geographic database can aid in focusing attention on key oceanic characteristics that can serve as the most dependable predictors of fish abundance. Generalized Additive Model (GAM) on the GIS platform was used to analyze satellite-derived Chlorophyll (Chl.) data, Sea Surface Temperature (SST) data and geo-referenced catch weights of Indian Mackerel. When comparing moderate and low catch weighting to high catch weighting, the Chl. content was highly significant. SST was important when the catch weighting was high, but not when the catch weighting was moderate or low.

Keywords: *Remote sensing, GIS, GAM Model, Indian mackerel, Rastrelliger kanagurta, species distribution analysis*

Introduction

The distribution and abundance of most fishes are influenced by the complex interaction of physical, chemical, and biological features in the ocean. The link between ocean colour and SST has been reported, and its impact on fish productivity has been documented (Arnone, 1987; IOCCG, 2009). The efforts to derive the relationship between satellite-derived oceanic variables with fish abundance have on with a wide range of time and space scales, satellite-derived information proved to be a useful tool for objective quantification of exploited stocks. Habitat mapping of fish stock will be an efficient tool for fishery management in the future (Stuart *et al*., 2011). Habitat mapping and mapping of satellite-derived chlorophyll and SST data bring out a reliable relationship between fishery abundance and oceanic environmental characteristics in many parts of the world (Sanchez *et al*., 2008; Kumari *et al*., 2009). Use of satellite-derived habitat mapping for regulating overfishing and ensuring fisheries management was attempted in tunas, *Thunnus thunnus* (Druon, 2010), *Thunnus albacores* (Zagaglia *et al*., 2004), *Thunnus alalunga* (Zagaglia *et al*., 2004; Zainuddin *et al*., 2006), northern anchovy, *Engraulis mordax* and Pacific sardine, *Sardinops sagax* (Reiss *et al*., 2008). In Indian waters, Solanki *et al.* (2008) and Chandran *et al.* (2009) derived reliable relationships between productivity and oceanographic processes and also derived clues on the predictors of ecological associations using Ocean Color Monitor (OCM) derived Chl. concentrations and AVHRR-derived SST and Solanki *et al.* (2015) demonstrated the utility of geo-referred catch-per-unit-effort (CPUE) data for deriving interrelationship with satellite-derived oceanic variables in the Arabian Sea.

During the last century, the application of GIS gradually extended its range in marine fishery applications. There is an increasing interest in modelling and analyzing spatial patterns in biotic variables to understand the mechanisms that control critical aspects of the ecology of the species, such as their distribution (Meaden, 1999). Fishing methods have undergone several structural changes over the years and present-day mechanized fishing fleets in India are equipped with the Global Positioning System (GPS) and other highly scientific gadgets. GIS offers significant versatility in scale, presentation, classification and categorization to analyze geo-coded databases in fisheries science and management (Fisher, 2010). Recent developments in marine habitat mapping using RS and GIS tools have resulted in increased availability of geo-coded environmental resources data. For marine living ecosystems, the availability of environmental data has significantly improved in the last decade, because of increasing research activities in remote sensing and GIS techniques (Davies *et al.*, 2004; Galparsoro *et al.*, 2012). Modelling and analyzing spatial patterns in biotic variables to understand the mechanisms that control critical aspects of the ecology of the species, such as their distribution and GIS is found of great help in such modelling studies (Nurdin *et al.*, 2015)

Indian Mackerel (*Rastrelliger kanagurta*) is one of the important commercial marine species in tropical waters. The catch trend of this species has been on the increase globally as well as in India with unpredictable fluctuations (FAO, 2017). *R. kanagurta* is a surface feeder, which preys primarily on phytoplankton and zooplankton. The schooling behaviour of the species and its economic importance make them candidate species for correlating with satellites derived oceanographic parameters. The *R. kanagurta* is generally caught in pelagic gillnets, purse seiners, ring seines, etc., but with the introduction of trawlers, more than 50% of the mackerel catch in India is from trawlers (CMFRI, 2015). Trawl being a dominant gear, with capabilities of modifying into pelagic and mid-water and bottom trawling operations according to species availability (Dineshbabu *et al.*, 2016a) and looking at the continuity of data available throughout the fishing season, catch data from trawlers were used in GIS platform for geo-statistical analysis.

Traditionally, pelagic fishes are harvested by gillnets and seine nets whereas crustaceans are harvested by bottom trawls. Over the years, trawl fisheries have undergone significant market-driven changes, for example, the target has been shifted from bottom resources to column and pelagic resources. The contribution of pelagic fishes in marine fish landing has been increasing steadily with the use of high-speed engines that facilitate both bottom and pelagic trawling operations. Almost 65% of marine landings are contributed by trawl fisheries in Karnataka. The efforts to develop methods for finding the relationship between SST and Chl-a concentration to predict potential fishery zones of *R. kanagurta* in the archipelagic waters of Indonesia were attempted by Nurdin *et al.* (2015) using the integration of satellite data, statistical model and GIS technique in which statistical multiple regression model was used. The present study utilized the wide scope provided by the GIS environment to analyze the relationship between satellites derived oceanic variables and sea truth data on fishery resource availability. For analyzing the relationship between oceanographic environmental parameters like Chl., SST and catch weighting of Indian Mackerel, the Generalized Additive Models (GAMs) were developed.

Material and methods

Study area

The Indian Mackerel, *Rastrelliger kanagurta*, was selected from the dominant gear trawl. The study area covered the important natural resources of the coastal and marine ecosystem in the Arabian Sea and most of the major landing centres from Mumbai to Calicut. The study area is parallel to the West coast of India and it lies between 19° N to 11° N latitude and 71° E to 76° E longitude (Fig. 1). Since the southwest coast of India is recognized as the most productive coast as far as Indian Mackerel landings are concerned (Silas, 1974), this area was selected for the study.

Collection and analysis of GIS-based fishery data

Onboard observers of trawlers operating off the coast of Karnataka collected geocoded fisheries data for the period 2013-2016 on a multiday basis for this study. Because trawlers caught the majority of the fish caught off the coast, the

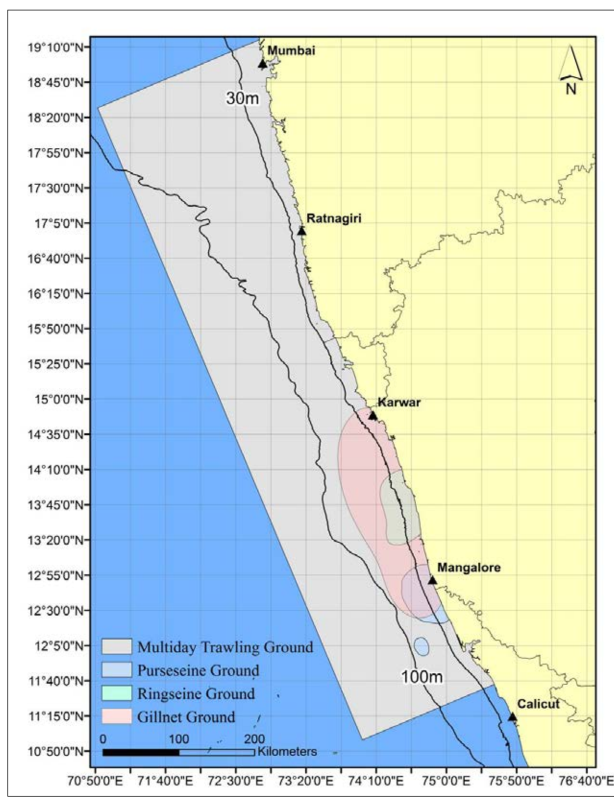

Fig. 1. Study area showing the discription of of fishing grounds used for the study

study relied on geocoded data from the trawlers. Standard data collecting procedures were used to obtain time series georeferenced data (Dineshbabu *et al.*, 2015, 2016b). The data collected and recorded were transformed into digital mode by storing in MS Access file. Then the digital data were normalized by following standard statistical methods. For advanced analysis of the database and generating resource distribution models, mainly ArcGIS was used for digitizing coastlines, state boundaries of India, and other bathymetric contour lines. For making a map of traditional fishing grounds of various important gears like purse seine, ring seine, trawling, gillnets, etc. respective gridded, scanned, georeferenced toposheets and hydrographic charts have been referred from the Geographical Survey of India.

The fishing distribution map of Indian Mackerel from 2013 to 2016 was interpolated by following the kriging method prepared with high accuracy and availability of geocoded data. In the sense of geostatistical analysis, the 'R' package is a powerful statistical programming language, which has various packages for generating numerous models, plots, graphs, etc. In this paper for developing statistical models "ggplot" and "mgcv" these two packages were used. The ggplot is a Python-based and the Grammar of Graphics plotting system in 'R' for declaratively creating graphics in a professional scientific way. For showing monthly distribution patterns of classified catch trends various scatter plots were built under this "ggplot" package. Mixed GAM Computation Vehicle (MGCV) is one of the advanced packages for developing several GAM models in the 'R' statistical platform. GAM is like an advanced version of the Generalized Linear Model (GLM), which uses a link function to develop relations between the mean of the response variables and a 'smoothed' function of the explanatory variables (Hastie and Tibshirani, 1986, 1990)

Collection and analysis of Satellite-derived environmental data

Satellite-derived environmental data were collected from the National Aeronautics and Space Administration (NASA) Ocean Color Portal on an 8day composite basis. Moderate-resolution Imaging Spectroradiometer (MODIS) is a scientific instrument (radiometer) launched by NASA 2002 onboard the Aqua satellite platform in 2002. It images the entire Earth every one to two days and plays a pivotal role in the development of validated, global, interactive Earth system models 2002 onboard the Aqua satellite platform. The Aqua platform is in a sun-synchronous, near-polar orbit at 705 km altitude. MODIS captures data in 36 spectral bands and the wavelength from 0.4 um to 14.4 um and at varying spatial resolutions. For the present study, the Level 3 standard mapped image (SMI) dataset was used with 4.6 km (at the equator) spatial resolution for the respective environmental variables like Chl. and SST (Fig. 2). The SMI dataset is an image representation of binned MODIS data, which can be found at http://oceancolor.gsfc.nasa.gov website. This MODIS Spectroradiometer is also able to predict global change accurately enough to assist policymakers in making sound decisions concerning the protection of our environment (NASA, 2014).

Results and discussion

Traditional fishing ground of Indian Mackerel on the west coast

Traditional fishing grounds of Indian mackerel were interpolated through GIS techniques according to depth-wise like 0m to 30m, 30m to 100m and above 100m depth (Fig. 1). The total number of the catch was estimated respectively to these categorized fishing grounds through GIS technologies from 2013 to 2016 (Fig. 2). The total number of species was grouped into nine classes, where the highest one was above 5000 and the lowest one was below 50. Maximum fishing occurred between 30m to 100m fishing ground of the area, where all classes of the catch are present and uniformly distributed in the region.

Monthly catch distribution

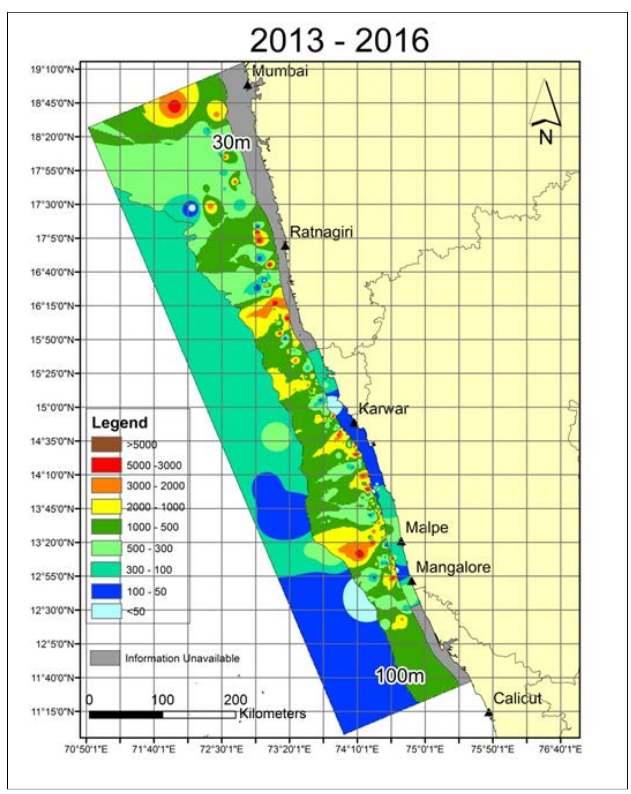

Fig. 2. Fishery distribution and abundance of Indian mackerel in the study area during 2013-2016

The scatter plot model has been built to observe the log catch trends of multiday trawling of the selected species of Indian mackerel from 2013 to 2016. Total catch has normalized to log catch (Maximum 4.5 to Minimum 0.5) by following standard statistical methods then the catch rate has been categorized into three zones; low catch (0.5 to 2.0), moderate catch (2.0 to 3.0) and high catch (3.0 to 4.5). Variations were observed in the seasonal pattern from Jan to Dec of the respective fishing years 2013 to 2016 by trawls. There have been various attempts around to derive the most reliable statistical models to correctly identify the cause of the spatio-temporal distribution change of marine species, in which several models were successfully applied to predict marine fisheries habitat (Reiss *et al.*, 2008)

Satellite-derived environmental information

Environmental information has been derived from the satellite data on an 8-days composite basis from 2013 to 2016. The data has been extracted in this manner to maintain the approximate accuracy level of satellite data with the multiday sea truth trawling data. For the study, the specific value of Chl. concentration and SST were merged with the geocoded species data to build a compact database. This database was used for statistical analysis to observe the impact of oceanographic environmental variables on marine species distribution from 2013 to 2016 in the study area (Fig. 3)

For the study GIS platform was used as a pivotal foundation on which all fishery and environmental correlation studies were designed. The digital form of GPS based sea truth data on mackerel distribution and abundance and the grid-based environmental data derived from satellites were brought to GIS platform to create combined geocoded database creation the combined data sets were subjected to statistical analysis 'R' statistical programming.

Impact of oceanographic environments

The study attempted to characterize the impact of physical oceanographic environmental elements such as Chl. and SST on Indian Mackerel catch weighting. Indian Mackerel catch weighting is likewise divided into three categories: high, moderate, and low. GAM models were created and shown

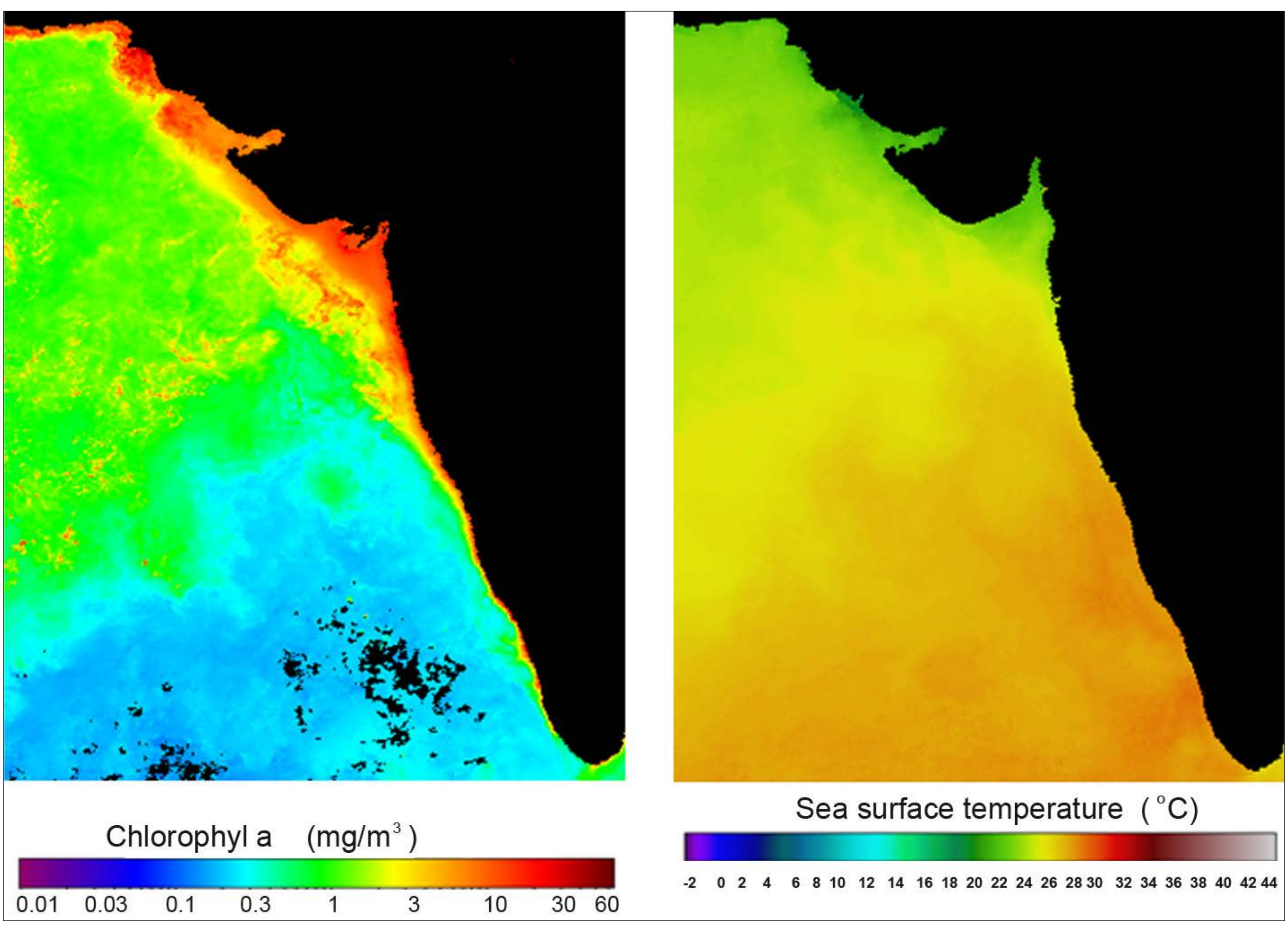

Fig. 3. Maps showing spatial resolution for the respective environmental variables like Chlorophyll and Sea surface temperature

individually to reflect the relationships of all three categories from 2013 to 2016 for advanced statistical analysis. (Fig. 4). In comparison to high catch weighting, Chl. has a significant impact on moderate and low catch weighting (Table 1). The SST is significant for high catch weighting, but not for moderate or low catch weighting (Table 2). Because of changes in Chl. content, SST and other ocean variables, meteorological fluctuations are likely to affect marine fisheries productivity and vertical distribution of species in the sea. The effects of climate change will initially be seen in the distribution of marine living resources and the number of pelagic fishes (Guisan and Zimmermann, 2000).

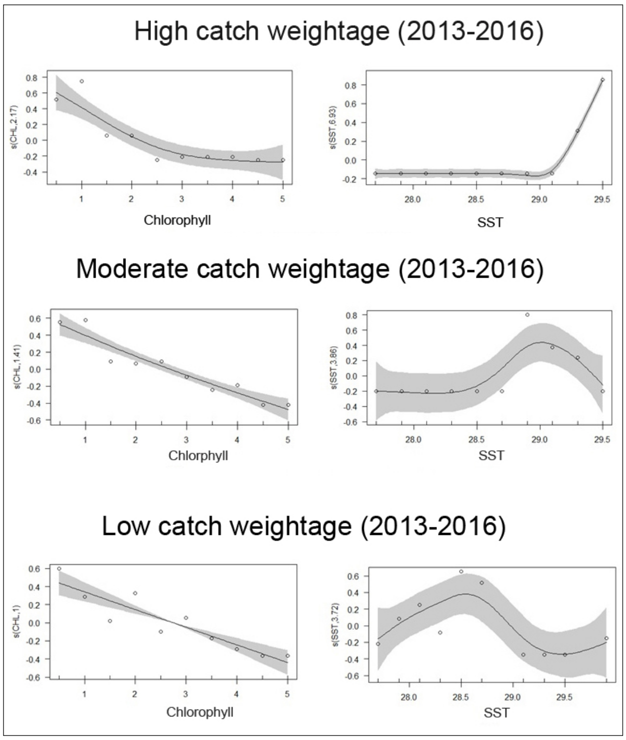

Fig. 4. GAM Plots shows relation between Environmental parameters (Chl & SST) and Catch Weighting of Indian Mackerel in the study area

Solanki *et al.* (2015), while conducting spatiotemporal analysis of satellite-derived variables and fishery abundance, the CPUE of mackerel was found to reduce in the areas of high productivity (high Chl.) and low SSHa/SST. They inferred that low SSHa regions are important biologically active areas in fishery abundance since these areas are rich in nutrients, which enhance the phytoplankton growth. Studies by Nurdin *et al.* (2015) indicated that SST and Chl. a have a significant influence on the abundance of Indian Mackerel. However, the coefficient of regression of both parameters showed that Chl-a ($p=0.000 < 0.05$) was more dominant in influencing the catch of *R. kanagurta* in comparison to SST ($p=0.05 \leq 0.05$). Chandran *et al.* (2009) reported that pelagic fishes were found to aggregate in the areas of high phytoplankton represented by high Chl-a concentration and relatively stable temperature as their sties showed a less significant relationship between the abundance of small fishes with SST in the Bay of Bengal, India. These environmental parameters are more dynamic in the marine system compared with terrestrial systems, with a significant short-term or long-term variability (Franklin, 2009). As a useful modelling context, environmental parameters ideally represent natural or anthropogenic factors that have an impact on the distribution of marine species and their habitat (Guisan and Thuiller, 2005; Guisan and Zimmermann, 2000; Elithand Leathwick, 2009). The methodology used in this paper reduces

Table 1. Significance of Chl. on catch weighting of Indian Mackerel (2013-2016)

Approximate significance of smooth terms	High catch weighting	Moderate catch weighting	Low catch weighting
p-value	0.00251	$7.06e^{-06}$	$8.58e^{-05}$
Significance code	0.001**	0***	0***
R-sq. (adj.)	0.799	0.901	0.818
Deviance explained	84.8%	91.7%	83.8%

** significant, *** highly significant

Table 2. Significance of SST on catch weighting of Indian Mackerel (2013-2016)

Approximate significance of smooth terms	High Catch Weighting	Moderate Catch Weighting	Low Catch Weighting
p-value	0.0025	0.143	0.13
Significance code	0.001**	-	-
R-sq. (adj.)	0.992	0.57	0.571
Deviance explained	99.8%	75.4%	74.8%

** significant

the complexity of analysis by using weightages to the catch, as well as GAM analysis, which has been demonstrated to provide higher resolution for correlative investigations using specific geographic grids.

The findings suggested that high-resolution geo-temporal data on fish availability and abundance are valuable in determining their relationship with satellite-derived variables. By reducing the complexity of variable interactions, the Generalized Linear Model (GLM) can aid in the development of the most influential Oceanic variable in fishery forecasting. The SST generated from satellite data has a strong link with high Indian mackerel catch weighting, but not with moderate or low catch weighting. Many pelagic fisheries resources are subject to huge yearly and seasonal changes in landings, and utilizing this approach, satellite-derived oceanographic signals can be used effectively in fisheries management.

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