



HABITAT PREFERENCE OF INDIAN MACKEREL AND OVAL BONE CUTTLE FISH IN RELATION TO OCEANOGRAPHIC PARAMETERS OFF MUMBAI COAST

Dissertation submitted in partial fulfillment
of the requirements
for the degree of

M.F.Sc. (Fisheries Resource Management)

by

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DEDICATED

TO.....

MY BELOVED

PARENTS, BROTHER AND SISTERS

For their blessings, affection, care, and warm encouragement.



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Dated: 30th June, 2019

CERTIFICATE

Certified that the dissertation entitled “**HABITAT PREFERENCE OF INDIAN MACKEREL AND OVALBONE CUTTLE FISH IN RELATION TO OCEANOGRAPHIC PARAMETERS OFF MUMBAI COAST**” is a record of independent bonafide research work carried out by **Ms. Sahina Akter** during the period of study from August 2018 to June 2019 under our supervision and guidance for the degree of **Master of Fishery Science(Fisheries Resource Management)** and that the dissertation has not previously formed the basis for the award of any degree, diploma, associateship, fellowship or any other similar title.

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*30th JUNE, 2019
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सारांश

मछली पकड़ने के लिए भारत सहित कई देशों में संभावित मछली पकड़ने के स्थान पहचान की आवश्यकता पर जोर दिया है मछुआरों को मछली पकड़ने को बढ़ाने के लिए तथा मछली के स्टॉक का पता लगाने के लिए। किए गए अध्ययन के प्रमुख उद्देश्य सामान्यीकृत योज्य मॉडल (जीएएम) के आधार पर मछली पकड़ने का समय रैस्ट्रेलेगर कनगुर्ता (क्यूवियर, 1817) और सीपिया एलिप्टिका (हॉयल, 1885) के लिए समुद्र संबंधी चर की पसंदीदा सीमा निर्धारित करना था। MODIS (मॉडरेट रेजोल्यूशन इमेजिंग स्पेक्ट्रोमाडोमीटर) और CMEMS (कोपरनिकस मरीन एनवायरनमेंट मॉनिटरिंग सर्विस) ने भारत के मुंबई तट से विशेष आर्थिक क्षेत्र (EEZ) में संभावित मछली पकड़ने के आधार का निर्धारण करने के लिए 2017-19 के छह चयनित पर्यावरण चर और मत्स्य पकड़ डेटा के व्युत्पन्न उपग्रह डेटा का विश्लेषण किया गया। पर्यावरण चर के संबंध में निवास स्थान की वरीयता की जांच करने के लिए एक पर्यावरण मॉडलिंग दृष्टिकोण लागू किया गया था। वें की जांच के लिए एक पर्यावरण मॉडलिंग दृष्टिकोण लागू किया गया था। भारतीय मैकेरल और पर्यावरण चर के बीच संबंधों के प्रारंभिक दृश्य प्रदान करने के लिए, अतिरेक विश्लेषण (आरडीए) लागू किया गया था। सामान्यता का परीक्षण करने के लिए, भिन्नता, और सह-रैखिकता की समरूपता का परीक्षण करने के लिए, आर प्लेटफॉर्म में विभिन्न पैकेजों का उपयोग करके डेटा निदान किया गया था। डेटा निदान परिणाम के आधार पर डेटा को तिरछा और कुर्त्तिसिस को कम करने के लिए परिवर्तित किया गया था। एक जीएएम (GAM) मॉडल में सभी भविष्यवाणियों चर प्रतिक्रिया चर में भिन्नता को समझाने के लिए महत्वपूर्ण योगदान करते हैं। आरआईकेई सूचना मानदंड (AICc) के आधार पर आर प्लेटफॉर्म में मल्टी-मॉडल इंटरेंस का उपयोग करके मॉडल चयन किया गया था। GAM मॉडल चयन के लिए सबसे कम (= सबसे अच्छा) एआईसीसी और उच्च वजन वाला मॉडल माना जाता है। आवश्यक मछली आवास (EFH) और बहुतायत मानचित्र GAM मॉडलिंग के माध्यम से पूर्वसूचक चर के आधार पर उत्पन्न किया गया है। वर्तमान अध्ययन में परिणाम से पता चला है कि भारतीय मैकेरल निवास स्थान एसएसटी (पी <0.001), क्लोरोफिल (पी <0.001), एसएसएस (पी <0.001), एसएसएच (पी <0.001) और एमएलडी (पी <0.05) के साथ महत्वपूर्ण संबंध थे।, जबकि ओवलबोन कटलफिश कैच अक्षांश, देशांतर (पी <0.001), एसएसटी (पी <0.001) और एसएसएस (पी <0.01) से संबंधित थे।

कीवर्ड: GAM, सैटेलाइट डेटा, भारतीय मैकेरल, ओवलबोन कटलफिश, आवश्यक मछली आवास।

ABSTRACT

Identification of potential fishing grounds has stressed the need in many countries, including India, for fishers to locate the fish stocks for increase catch. The major objectives of the undertaken study were to determine the preferred range of oceanographic variables for *Rastrelliger kanagurta* (Cuvier, 1817) and *Sepia elliptica* (Hoyle, 1885) at the point of harvest based on Generalized Additive Model (GAM). MODIS (Moderate Resolution Imaging Spectroradiometer) and CMEMS (Copernicus Marine Environment Monitoring Service) derived satellite data of six selected environmental variables and fisheries catch data of 2017-19 were analyzed to determine the potential fishing ground of Indian Mackerel and Ovalbone Cuttlefish in the EEZ off Mumbai coast of India. An environmental modeling approach was applied to investigate the habitat preference in relation to environmental variables. An environmental modeling approach was applied to investigate the habitat preference in relation to environmental variables. To provide a preliminary view of the relationships between Indian Mackerel and environmental variables, Redundancy analysis (RDA) was applied. To test normality, homogeneity of variance, and co-linearity, the data diagnosis was performed using different packages in the R platform. Based on the data diagnosis result data was log transformed to reduce the skewness and kurtosis. All predictor variables in a GAM model necessarily contribute substantially to explaining variation in the response variable. Model selection was performed using Multi-Model Inference in the R platform based on Akaike Information Criterion (AICc). The model with the lowest (=best) AICc and high weight considered for the best fit GAM model for the given variables. Essential Fish Habitat (EFH) and abundance map have been generated based on the predictor variable through GAM modelling. In the present study the result revealed that Indian Mackerel habitat had the significant relationship with SST ($p < 0.001$), Chlorophyll-a ($p < 0.001$), SSS ($p < 0.001$), SSH ($p < 0.001$) and MLD ($p < 0.05$), while Ovalbone Cuttlefish catches were significantly related to latitude, longitude ($p < 0.001$), SST ($p < 0.001$) and SSS ($p < 0.01$).

Keywords: GAM, Satellite Data, Indian Mackerel, Ovalbone Cuttlefish, Essential Fish Habitat.

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1. INTRODUCTION

Habitat preference is the best suitable habitat most likely to be chosen by a species based on its physiological and biological behavior. Habitat preference is a significant behavioral decision that has many ecological implications, from an individual's fitness (Huey, 1991) to species distribution and abundance (Crowe and Underwood, 1998). The vertical and horizontal distributions of fishes are commonly believed to be influenced by temporal and spatial trends in environmental conditions (Lehodey *et al.*, 1998). The Indian Mackerel and Oval Bone Cuttlefish are generally found in littoral and sublittoral depths between the low tide line and the continental shelf area. The environmental and biological factors affect the spatial distribution of fish populations on varying scales, which may affect the particular fisheries resources (Cury, 2004; Koubbi *et al.*, 2006). According to Jennings, 2004 the same is essential to know the drivers of fish population dynamics and fishery performance or any broader form of fisheries resource management. Climate change now considered to be a major threat to future fisheries, which specifically affects the distribution and abundance of species in ecosystems around the world. Climate-driven fluctuations in regional temperature can further affect growth, maturity, spawning time, egg viability, food availability, mortality, and spatial distribution of marine organisms (Perry *et al.*, 2005; Nye *et al.*, 2009). The differences in temperature, salinity, Chlorophyll-a (Chl-a) concentration lead to changes in primary productivity (PP) of seawater, influences the distribution of phytoplankton and zooplankton which in turn impacts the distribution of mackerel and oval bone cuttlefish fishery.

Recent studies by Magnuson *et al.* (1980) indicated that the changes in oceanographic parameters influence the changes in fishing grounds, which drastically change the abundance, distribution, and availability of fish populations. The distribution of pelagic and demersal fishes is influenced by various oceanographic parameters mainly the sea surface temperature (SST), chlorophyll-a concentration (CC), sea bottom temperature (SBT), sea surface height (SSH), sea surface salinity (SSS), mixed layer depth (MLD) and ocean currents which are also related to fish production. Therefore, the habitat preference study of fish and cuttlefish species by using various models is

essential for addressing the management issues and it will also reveal very interesting behavior pattern of the fish and cuttlefish in relation to climate change. Its applicability can also show at the field level where fisherman and researchers are using these environmental remotely sensed data to determine the habitat preference and essential fish habitat (EFH).

India has a coastline about 8129 Km, Exclusive Economic Zone (EEZ) of 2.02 million Km². Maharashtra coast of India comprising of the Arabian sea has length 720 km and an EEZ of 0.112 million Km², which display a multi-species oriented fishery. Among all Indian mackerel, *Rastrelliger kanagurta* (Cuvier, 1817) and Ovalbone cuttlefish, *Sepia elliptica* (Hoyle, 1885) provide an excellent contribution to the pelagic and demersal fishery of India.

Indian Mackerel of family Scombridae and order Perciformes is second in importance to the oil sardine (*Sardinella longiceps*), widely distributed in the Indian and West Pacific oceans. It is an important pelagic fish which contribute 7.5% i.e. 2.88 lakh tonnes catch to the total Indian marine fish landings during 2017 and more than 14% to the total pelagic fish catch (CMFRI 2017). Along the Indian coast, Indian Mackerel fishery forms the mainstay of the Indian Pelagic fisheries. In Maharashtra coast among all the pelagic species, Indian Mackerel which has high commercial value contribute up to 16% of the total catch, 77.26% mackerel catch was from purse seiners followed by trawl (12.62%) and gillnets (9.7%) which operated from mechanized boats (CMFRI 2017). Indian Mackerel catch size range observed was 120-289 mm during the 2017 landings in Maharashtra coast. This species has been variously classified as a omnivore feeder with varied diet composition (diatoms, copepods, dinoflagellates, crustaceans and occasionally fish and sand particles) in various fishery centers along the Indian coast (Vivekanandan *et al.*, 2009). In the Malabar Coast of India, Indian Mackerel prefers temperature lower than 28°C, which keep fish above thermocline and August-September was the peak catching season for Indian Mackerel (Yohannan *et al.* 1998). The study by Shaari *et al.* (2018) predicted the potential of *Rastrelliger kanagurta* fish habitat by using a generalized additive model (GAM) and habitat suitability index (HSI) in the east coast of Peninsular Malaysia.

Another undertaken species Ovalbone Cuttlefish, *Sepia elliptica* is a species of Cephalopod family Sepiidae, mostly occurs in coastal waters between 10 and 62m in the Gulf of Carpentaria (Reid *et al.*, 2005), and distributed along Australia (Western Australia, Queensland, Northern Territory); Indonesia (Papua); Papua New Guinea (main island group) coast (Reid *et al.*, 2005). In India, it is distributed along the west coast of India and almost certainly misidentified as *Sepia aculeate* (Needle Cuttlefish). In Mumbai coast, high abundance makes it subject of a fishery. It has been assessed as Data Deficient and listed under the Red List category of IUCN Red List of Threatened Species during 2012 as "Least Concern" species. According to CMFRI 2017 report in Maharashtra coast, Cephalopod landing is 38410 tonnes forming 10% of the total fish landing. The trawlers contributed 91% of cephalopod landing (35061 t) with a catch rate of 5.46 kg h⁻¹ where *Sepia elliptica* catch is 1491 tonnes. According to Gutowska *et al.* (2010) increased levels of carbon dioxide in the atmosphere caused ocean acidification. It is potentially causing a threat to all Cuttlefish. It is also observed by them that under high pCO₂ concentrations, and due to Ocean acidification cuttlefishes lay down a denser cuttlebone which is likely to affect buoyancy regulation negatively.

Earlier, many researchers studied modelling on the relationship between species abundance and the physical environment (Masse *et al.*, 1996; Freon *et al.*, 2005; Drexler *et al.*, 2013; Shaari *et al.*, 2017; Salarpouri *et al.*, 2018). Denis *et al.* (2002) applied the generalized additive model (GAM) and studied Spatio-temporal patterns of *Loliginid* squid abundance from trawler data in the north-east Atlantic and suggested that SST has a significant effect on the abundance of *Loliginid* squid and their abundance was increased with the temperature between 8-9.5°C and peaks at an SST close to 10°C. The maximum catch was observed at SST close to 10°C. Murase *et al.* (2009) studied the Generalized Additive Model (GAM) to reveal the relationships between environmental factors and the distribution of pelagic fish and krill in Sendai Bay, Japan. Rajapaksha *et al.* (2013) assessed the Generalized Additive Model (GAM) and Generalized Linear Model (GLM) studies to report the environmental preferences of yellowfin tuna and established the relationships between yellowfin tuna with the three oceanic parameters in the North East Indian Ocean.

The Generalized Additive Model (GAM) to record Global Habitat Preferences of commercially valuable tuna by relating fishery data (catch and effort data) with environmental data was also reported by many researchers (Arrizabalaga *et al.*, 2015; Zainuddin *et al.*, 2008). Solanki *et al.* (2016) studied satellite-derived variables and fishery data to predict the distribution of catfish (*Tachysurus* spp.) and Indian squid (*Loligo* spp.) in the Arabian Sea with the help of Generalized Additive Model (GAM). The impact of sea surface temperature and chlorophyll-concentration variations on the fluctuations of sardine abundance was reported by some researchers in different locations (Longhurst *et al.*, 1990; Giannoulaki *et al.*, 2005; Vivekanandan *et al.*, 2009; Selvin and Lipton 2012; Abdellaoui *et al.*, 2017). Valavanis *et al.* (2004) developed the Essential Fish Habitat (EFH) model by using GIS environmental modeling in Hellenic sea area for short-finned squid which required fishery data and monthly satellite imagery for environmental data. Salarpouri *et al.* (2018) studied Essential fish habitats (EFHs) of small pelagic fishes in the north of the Persian Gulf and Oman Sea, Iran.

Integration of GIS and Remote Sensing technology was simultaneously accelerated which provided the tools to model species-habitat relationships and identify their essential habitat areas (Austin *et al.*, 2002; Agenbag *et al.*, 2004; Bellido *et al.*, 2013; Khudby *et al.*, 2010; Salarpouri *et al.*, 2018). ArcGIS is a useful technique used in GIS platform for the integration and management of spatially distributed data, mapping, and reliable analysis and modelling. Species catch time series data, and satellite imagery provided environmental data can be used in this ArcGIS tools to develop a distribution map of the species. These maps help to identify the Spatio-temporal patterns of species which help to manage resources and provide information for better decision making.

The study of habitat preferences studies along with is an essential step in understanding the distribution patterns of fishes and mollusks. It is imperative to analyze and compare patterns of variation of catch time series data of Indian Mackerel and Oval Bone Cuttlefish. Therefore, the present study is undertaken with the following objectives to identify the habitat preference of Indian Mackerel and Ovalbone Cuttlefish off Mumbai coast using fishery data and environmental data:

Objectives:

1. To study the habitat preference of Indian mackerel and oval bone cuttlefish off Mumbai coast.
2. To study the oceanographic parameters at the point of the harvest of the selected species.

2. REVIEW OF LITERATURE

Fishery oceanography has taken advantage of correlations between the catch of fish and easily measured oceanographic features, usually surface water temperature and other physical and biological parameters (Castillo *et al.*, 1996; Robinson *et al.*, 2004; Krishnakumar *et al.*, 2008; Sachoemar *et al.*, 2010; Shaari *et al.*, 2017). Environmental features often provide better information for locating fishes than geographic position. Knowledge of the abundances and dynamics of target fish populations is essential to effective fishery management. It is also important to know how environmental factors affect the distributions of such populations. Geographic Information Systems (GIS) and Remote Sensing (RS) are effective tools for explaining the temporal and spatial distribution of the species in the presence of different oceanographic parameters (Santos, 2000; Pierce *et al.*, 2001, 2002; Solanki *et al.*, 2005; Zainuddin *et al.*, 2004, 2006). In the present study, GAM were applied to physical-oceanographic data set to examine the effects of environmental variables (e.g., oceanographic parameters) on the distributions of Indian Mackerel and Ovalbone Cuttlefish to predict their spatial distributions and map the potential fishing areas. One of the required information for sustainable fisheries management is about the habitat characteristics of a fish species. This information can be used to map the distribution and the potential fishing grounds of fishes (Guisan *et al.*, 2000; Chandran *et al.*, 2009; Rivai *et al.* 2018).

2.1 Environmental parameters Studies:

2.1.1 Sea Surface Temperature (SST):

Sea Surface Temperature (SST) is a critical oceanographic parameter that influences the distributions of pelagic species and also typically associated with the fish production. Sea surface temperature (SST) has also been used for decades by fisherman and researchers to determine fish habitat and fish sustainability (Shaari *et al.*, 2018). Meteorological phenomena such as El Niño or tropical hurricanes/cyclones are the direct consequences of specific temperature variations at the sea-surface. Now a

day's researcher is using remotely sensed data to identify thermal features typically used averaged SST values over some period (e.g., a week or a month) to determine the locations of SST fronts (Krishnakumar *et al.*, 1998; Garza *et al.*, 2015; Supraba *et al.* 2016; Dabin *et al.* 2018; Abdellaoui.B *et al.* 2017;). The Temperature has often been considered to be the primary determinant for pelagic fish distribution (Magnosun *et al.*, the 1980s). Composition and abundance of individual species are distributed with respect to temperature in relation to time and space (Magnosun *et al.*, the 1980s).

In Malabar Coast of India Indian Mackerel prefers temperature lower than 28°C, which keep fish above thermocline and August-September was the peak catching season for Indian Mackerel (Yohannan *et al.*, 1998). In the north-east Atlantic region, SST has a significant effect on the abundance of *Loliginid* squid and abundance increases with the temperature between 8-9.5°C and peaks at an SST close to 10°C (V. Denis *et al.* 2002). Wang *et al.* (2003) reported that the high cuttlefish LPUE center located in a high-temperature zone in the English Channel or further west in deep waters and the French Atlantic coast high cuttlefish LPUE center located in winter, disappears in summer, and does not show any clear relationship with SST. Sacau *et al.* (2005) reported that the probability of catching Argentine shortfin squid (*Illex argentes*) had been found negatively related to latitude and generally increased at higher SST values in the southwest Atlantic. In the Southwest Atlantic region, the correlations between SST and squid abundances for the fishing season (May-Aug) were negative, i.e., high squid abundances occurred in areas with lower SSTs. High abundances of squid were located in the region of SSTs of between 10°C and 15°C in summer and the region of 7-10°C in winter (Chen *et al.* 2006). SST has a seasonal latitudinal displacement of the ICTZ (Intertropical Convergence Zone) in northeastern Atlantic, which also reflects that for *Thunnus alalunga* SST range approximately from 17°C-23°C (Sagarminaga *et al.*, 2010). According to W. Wang *et al.* (2010), SST range is also based on the variance in temperature and is suggested to be an indicator for upwelling in the north-west Pacific Ocean. The highest range in SST values is observed in the transition zone, rather than in the Kuroshio and Oyashio currents (figure 4). The highest SST range of 16°C–20°C coincides with the most productive fishing ground.

Zainuddin *et al.* (2011) reported that Skipjack tuna spatial distributions in the Bone Bay are nonrandom and tend to aggregate within the preferred environmental conditions like SST range of 29.0-31.5°C. Tugores *et al.* (2011) reported that SST is an important concern for the spawning of *Sardina pilchardus* habitat during winter in the Mediterranean Sea and a higher probability for *Sardina pilchardus* presence associated with a broader range of SST values, i.e., 20 to 26°C. According to Rajapaksha *et al.* (2013), Yellowfin tuna shows an identical pattern followed by each year. Thus, SST can be used to locate yellowfin tuna aggregating areas using this feature. High frequencies of yellowfin tuna catches were found in the areas where Sea Surface Temperature (SST) varied primarily 28°C -30°C. The habitats of yellowfin tuna had a close relationship with sea surface temperature (SST) and preference range was from 27.2°C to 32.5°C in the Western and Central Pacific Ocean (Yen *et al.*, 2012). Skiftesvik *et al.* (2014) have taken temperature measurement from all the sampling station at the 5m depth which shows Wrasse species from family Labridae are mainly abundant in temperate coastal ecosystem up to 50m depth. According to Arrizabalaga *et al.* (2015) temperature (taken at 5m and 100m depth) affect the important biological process of tunas which determine the spatial distribution of the fishes. Tropical tunas prefer warmer surface waters than temperate tunas. In the SE Arabian Sea, where the catch rate of sardine shows a positive correlation with SST and for sardine and mackerel distribution Optimum temperature is 28.1°C-28.38°C (Supraba *et al.*, 2016). A seasonal biphasic cycle for average monthly SST during 2008-2014 found in South Arabian Sea while studying about Sardine sp. Temperature between 18°C - 22°C has a positive correlation, but lower temperature shows a negative correlation, and the maximum yield was determined for the average monthly temperature between 19°C-21°C (Abdellaoui *et al.*, 2017). Temperature appears to influence the distribution of yellowfin tuna in all regions, and a positive association was observed between the catch rates and SST of approximately 25°C–30°C in the Tropical Pacific Ocean (Lan *et al.*, 2017). Dabin *et al.* (2018) studied on chub mackerel (*Scomber japonicus*) from east and south sea where half of the catch occurred from December-January and fish communities were distributed under optimum SST range 14.7°C-25.7°C. Sea Surface Temperature has a stronger influence on Indian Mackerel (*Rastrelli.kanagurta*) distribution with a preferred

range of 29°C to 30°C (Shaari *et al.*, 2018). Temperature and thermocline depth seemed to be the main environmental factors governing the vertical and horizontal distribution of Bigeye tuna in the Eastern Indian Ocean (Lumban-Gaol *et al.*, 2015). The adults of Atlantic thread herring, Scaled herring, Scads, and round *Sardinella* found in the upwelling area with temperature values higher than 25.5°C but during December juveniles of Atlantic thread herring showed the preference for temperatures higher than 27.4 °C in the Colombian Caribbean Sea (Paramo *et al.*, 2003). The abundance of sardines increased with an increase of sea surface temperature; it's increased in the range < 29.7°C and > 29.9°C; decrease within the range 29.7°C – 29.9°C in Tonkin Gulf, Vietnam (Nghia and Hung, 2018). Solanki *et al.* (2016) predict the fishery resources distributions in the Arabian Sea by using GAM to satellite-derived variables (SST, Chl-a and SSH) and fishery data. Their study shows that Squids distribution observed in the Arabian Sea where SST range from 24.5°C to 28 °C and sequence for Squids catch influence of parameters was PAR > Depth > SST > log(CC) > SSHa, as well as sequence for catfish catch influence of parameters, was Depth > log(CC) > PAR > SST > SSHa. SST was generally the least important variables, and a slight peak of positive influence on sardine presence approximately 22°C and 33°C but SST had less effect on anchovy presence in the north of the Persian Gulf and Oman Sea, Iran (Salarpouri *et al.*, 2018).

2.1.2 Chlorophyll-a Concentration (Chl-a):

The concentration of chlorophyll-a is an indicator for the amount of photosynthetic plankton or phytoplankton present in the ocean. Phytoplankton populations influenced by climatic factors such as sea surface temperatures and winds. The chlorophyll–a concentration distribution in the euphotic zone of the coastal waters have a high rate of primary productivity. According to Zainuddin *et al.* (2004) Chlorophyll-a concentration considered as the phytoplankton biomass which is the primary food source of any small pelagic species.

Arrizabalaga *et al.* (2015) opined that tropical tunas and albacore preferred relatively low chlorophyll-a concentration, whereas temperate tunas mainly bluefin tunas

can tolerate a wide range of chlorophyll concentration. Supraba *et al.* (2016) observed a positive correlation of Indian Mackerel abundance with chlorophyll-a concentration in the SE Arabian Sea region. The sardine and mackerel distribution was observed where optimum chlorophyll-a concentration is found i.e., 0.50-0.59mg/m³. A seasonal biphasic cycle for average monthly chlorophyll-a concentration in the South Arabian Sea area found during the study of *Sardine sp.* Winter-spring period shows high chlorophyll-a concentration and summer-autumn shows low chlorophyll-a concentration, and monthly average chlorophyll-a concentration is 0.45-0.91 mg/m³ (Abdellaoui *et al.*, 2017). Dabin *et al.* (2018) reported that in east and south sea total catch of Chub mackerel was 86% when the optimum chlorophyll-a concentration is 0.15-25.43 mg/m³. Shaari *et al.* (2018) reported that compare to Sea Surface Temperature (SST) Chl-a concentration had a lesser influence on the distribution of Indian Mackerel with preferred range 0.20 mg/m³ to 0.30 mg/m³ while availability of Chl-a is important as a food provider for the survival of fish.

Zainuddin *et al.* (2011) used physical and biological environmental data to describe the oceanographic conditions at the tuna fishing ground. High tuna concentrations corresponded well with chlorophyll-a range of 0.15 mg/m³ - 0.40 mg/m³. The interaction plot between SLA and CHLA indicates a higher probability of finding sardine present in areas with SLA values of 2 cm to 10 cm that also have CHLA values of 0.08 mg/m³ to 1.49 mg/m³ from June- December in the Mediterranean Sea (Tugores *et al.*, 2011). The effect of chlorophyll-a (CHL-a) concentration was poorer compared with that of sea surface temperature (SST) and sea surface height (SSH) and yellowfin tuna fishing grounds chlorophyll-a (CHL-a) concentration varied from 0.02 mg/m³ to 3.16 mg/m³ in the Western and Central Pacific Ocean (Yen *et al.*, 2012). Monthly variation of sea surface chlorophyll-a does not show an identical pattern by each year in the North East Indian Ocean, but results showed a stronger association between CPUE with ranges of 0.1-0.4 mg/m³ (Rajapaksha *et al.*, 2013). High CPUE of sardine and scad could found at 0.61-1.1 mg/m³ and at 0.41-1 mg/m³ for anchovy in Kepulauan Seribu Waters (Rivai *et al.*, 2018). Chlorophyll-a concentrations are relatively high concentrations (>0.3 mg/m³) during the southeast monsoon and relatively low concentrations (<0.1 mg/m³) during the northeast monsoon (except La Nina conditions)

in the Eastern Indian Ocean (Lumban-Gaol *et al.* 2015). The seasonal fluctuations of *Ethmalosa fimbriata* landings off Senegal Coastal waters seemed to be governed by the combined effect of SST and Chl-a, decreasing trend of Chl-a and SST warming was unfavorable to *E. fimbriata* abundance (Diankha *et al.* 2013). Swordfish (*Xiphias gladius*) catch in the equatorial Atlantic Ocean occurred in waters with CHL ranging from 0.03 and 0.49 mg/m³, and the optimum CHL tended to be between 0.15 and 0.27 mg/m³ (Chang *et al.* 2013). High yellowfin tuna catches in the Tropical Pacific Ocean mostly didn't occur in areas with the highest Chl-a concentrations but more so in the regions with intermediate Chl-a concentration of approximately 0.05–0.25 mg/m³ (Lanet *et al.* 2017). Squids distribution observed in the Arabian Sea where chlorophyll-a (CHL-a) concentration is from 0.05 to 7 mg/m³ with maximum frequency recorded from 0.5 to 2 mg/m³ and Catfish show discernible higher frequency ranges of chlorophyll-a (CHL-a) concentration, i.e., 0 to 7 mg/m³ (Solanki *et al.*, 2016). According to Wang *et al.* (2010) the chlorophyll-a concentration in the Kuroshio Current is lower than 0.2 mg/m³ while in the offshore region and the main body of the Oyashio current, it is higher than 0.5 mg/m³. Three threshold isolines of 0.2, 0.35, and 0.5 mg/m³ were used respectively to identify the location where the most productive fishing ground present. The relationship between fish presence/absence and chlorophyll-a (CHL-a) concentration in the north of the Persian Gulf and Oman Sea (Iran) is generally weakly positive, chlorophyll-a (CHL-a) concentration was the second effective variable for the anchovy occurrence and third useful variable for sardine occurrence in a range of approximately 0.5 to 2.7 mg/m³ (Salarpouri *et al.*, 2018).

2.1.3. Sea Surface Height (SSH):

The sea surface height is a boundary condition on the general oceanic circulation and a consequence of that circulation affect the fishing activities. Sea surface height (SSH) and currents can be analyzed to identify the mass movement of water, heat and nutrient flow, which can affect the productivity of the marine ecosystem. SSH can also be used to predict other oceanography features such as fronts, eddies, and convergences (Rivai *et al.*, 2018). Satellite altimetry revolutionizes sea-level

measurements because it provides measurements of sea-surface height with global coverage and a revisit time of several days.

Sacau *et al.* (2005) reported that in terms of average fishing depth, the probability of success of catching Argentine shortfin squid (*Illex argentines*) is highest in depths around 600m. Highest squid abundances positively related to three depth ranges: around 200, 400 and 650m in the southwest Atlantic. *Sardina pilchardus* showed a higher probability of being present in shallow waters (less than 65 m depth) during summer but exhibited a wider distribution, reaching deeper waters of up to 100m deep in autumn and winter in the Mediterranean Sea (Tugores *et al.* 2011). Sea Surface Height (SSH) was an only second close relationship to the habitats of yellowfin tuna that of the sea surface temperature (SST) which ranges from 1.51 to 2.23m in the Western and Central Pacific Ocean (Yen *et al.* 2012). Swordfish (*Xiphias gladius*) catch in the equatorial Atlantic Ocean occurred in areas with SSHA ranging between -0.14 and 0.12m, and the optimal range of SSHA was between -0.06 and 0.03m (Chang *et al.* 2013). The lowest association exists between CPUE of yellowfin tuna and Sea Surface Heights (SSH) throughout the year in the North East Indian Ocean, ranging from 205-215 cm (Rajapaksha *et al.* 2013). H.Arrizabalaga *et al.* (2015) reported that tropical tunas prefer slightly positive or negative values of Sea Surface Height (SSH) where Yellowfin and Albacore can tolerate higher SSH than Bigeye and Skipjack tuna. Bluefin tuna show preference for negative SSH where Atlantic Bluefin tuna preferred most negative SSH values. SSHA shows a seasonal pattern, i.e., negative (<-10 cm) during southeast monsoon when upwelling occurs (June-October) and conditions are reversed to positive (>10 cm) during northeast monsoon when downwelling occurs (December-April) in the Eastern Indian Ocean. The decrease of sea surface height during upwelling, has resulted in thermocline shallowing and caused a corresponding shallow Bigeye tuna fishing layer of at least 50 m depth (Lumban-Gaol *et al.* 2015).

According to Solanki *et al.* (2016) squid's distribution observed in the Arabian Sea where SSHa ranges from -10 to 40 cm but most of the catch point frequency in range of 0-10 cm while the Catfish catch locations with SSHa ranges from -5 to 40 cm. The catch rate of yellowfin tuna positively correlated with SSHA values of

approximately 10.0 to 20.0 cm in the Tropical Pacific Ocean and closely associated with edges of warm and cool eddies (Lan *et al.*, 2017). Nghia and Hung, 2018 reported that the abundance of sardines in Tonkin Gulf in Vietnam was increased with depth ranging from i.e. 10-40 m, 54-68 m and >90 m and decreased at the depth ranging from 40-54m and 68-90m. The catch of anchovy and squid were high when the SSH value was in the range of 0.74–0.78m while the catch of scad and sardine were high when SSH value was in the range 0.60–0.64m in Kepulauan Seribu Waters (Rivai *et al.* 2018).

2.1.4. Sea Surface Salinity (SSS):

Sea Surface Salinity is a crucial parameter to estimate the influence of oceans on climate. Along with temperature, salinity is a key factor that determines the density of ocean water and thus determines the convection and re-emergence of water masses. The thermohaline circulation crosses all the oceans in surface and at depth, driven by temperature and salinity.

The adults of Atlantic thread herring, Scaled herring, Scads, and round *Sardinella* were found in the upwelling area with salinity values higher than 36.8 ppt in the Colombian Caribbean Sea (Paramo *et al.*, 2003). Valavanis *et al.* (2004) studied Essential Fish Habitat (EFH) modelling of short-finned squid which shows that minimum sea surface salinity (SSS) is 36.12 ppt and maximum sea surface salinity (SSS) is 38.51 ppt in the Eastern Mediterranean. Yellowfin tuna had wide ranges of Sea Surface Salinity (SSS) selection in the Western and Central Pacific Ocean which contribute lowest to HSI and values were in the range of 34.22–35.25 psu (Yen *et al.*, 2012). Pitchaikani and Lipton, (2012) recorded that Salinity was varied from 33.6 to 36 PSU in Tiruchendur coast, Gulf of Mannar and the minimum value was recorded from October to December due to the massive RF effect while it gradually increased from January to May and attained high value in May due to the summer effect resulting in high evaporation. Salinity negatively correlated with a fish catch (Oil and other sardines). to Arrizabalaga *et al.* (2015) Atlantic Bluefin tuna can tolerate high salinity water (>37 PSU), Albacore and Skipjack tuna clearly preferred the salinity range from 36 to 37 PSU, while Bigeye, Yellowfin and Bluefin tuna showed less salinity preference.

Das et al. (2017) reported the significant relationship with the mackerel catches along the South-West Coast of India during the monsoon at depth 30–50 m and 50–100 m with salinity ranging from 34.85 to 35.9 psu and 35 to 35.95 psu respectively but no catch was reported when salinity ranged from 33.97 to 35.53 psu. During the pre-monsoon, salinity at depth 50–200 m and 30-50 m ranged from 35.4 to 35.85 psu and 35.5 to 36.1 psu respectively which showed no significant relationship with the mackerel catches. During the post-monsoon at depth 30-50 m and 50–100 m salinity ranged from 35.13 to 35.63 psu and 35.3 to 35.68 psu respectively shows a significant relationship with the mackerel catches, but, at depth 100-200 m, the salinity ranged from 35.3 to 35.38 psu and shows no significant relationship with the mackerel catch.

2.1.5. Mixed Layer Depth (MLD):

The mixed layer depth, in this case, is defined as the last water level at which the density of is greater or equal to the surface density 0.01 kg/m^3 , starting from the bottom level.

Swordfish (*Xiphias gladius*) catch in the equatorial Atlantic Ocean occurred in areas where MLD varied from 10.25 to 119.72 m and the optimal ranges of 19.88 and 57.59 m (Chang *et al.* 2013). The increase of SSH would lead to an increase in the depth of mixed layer and, therefore, deeper thermocline. As yellowfin tuna prefer to live in shallower thermocline or layers shallower than the thermocline, the depth of the thermocline, therefore, determines the depth that the yellowfin tuna schools inhabit (Yen *et al.* 2012). According to Arrizabalaga *et al.* (2015) tropical tunas preferred relatively stratified waters (MLD<80m) compared to temperate waters. They also reported that Albacore tuna can tolerance MLD ranges extend to about 200 m, while southern bluefin tuna preference range extends to highly mixed waters with mixed layer depths of several hundred meters.

2.1.6. Surface Ocean currents (OC):

Surface Ocean Currents (OC) is a mass of water moving from one place to another horizontally occur on the ocean surface. Surface Ocean Currents (OC) also

called wind-driven currents because surface winds combined with other atmospheric forces (solar energy, precipitation rate, evaporation rate) and are responsible for ocean currents. Ocean currents mainly help to move drifting organisms (for example plankton) from place to place, carries eggs and larvae, bring food and increase the dissolved oxygen (DO) concentration. This wind force and ocean currents causes the upwelling in the coastal water and enhances the productivity of the pelagic fishery.

Pitchaikani and Lipton, 2012 studied the Impact of environment variables on Indian oil sardine landings off Tiruchendur coast, Gulf of Mannar and recorded the average wind speed from 3.2 to 15.8 km/h. The high wind speed was recorded during June and July and low wind speed during March and April. The abundance of sardines was tended to increase with the absolute geographic current range less than 0.15 m/s; then decreased with the increase of current in Tonkin Gulf, Vietnam (Nghia and Hung, 2018). Downloaded Satellite Imagery product provides the value of Eastern wind velocity (UO) and Northern wind velocity (VO) from which we have to calculate the Ocean Currents (OC) value of each fishing location.

To calculate the Ocean Currents (OC) value following formula is used:

$$\text{Ocean Currents (OC)} = \text{SQRT (UO}^2 + \text{VO}^2)$$

Where UO = Eastern wind velocity in m/sec

VO = Northern wind velocity in m/sec.

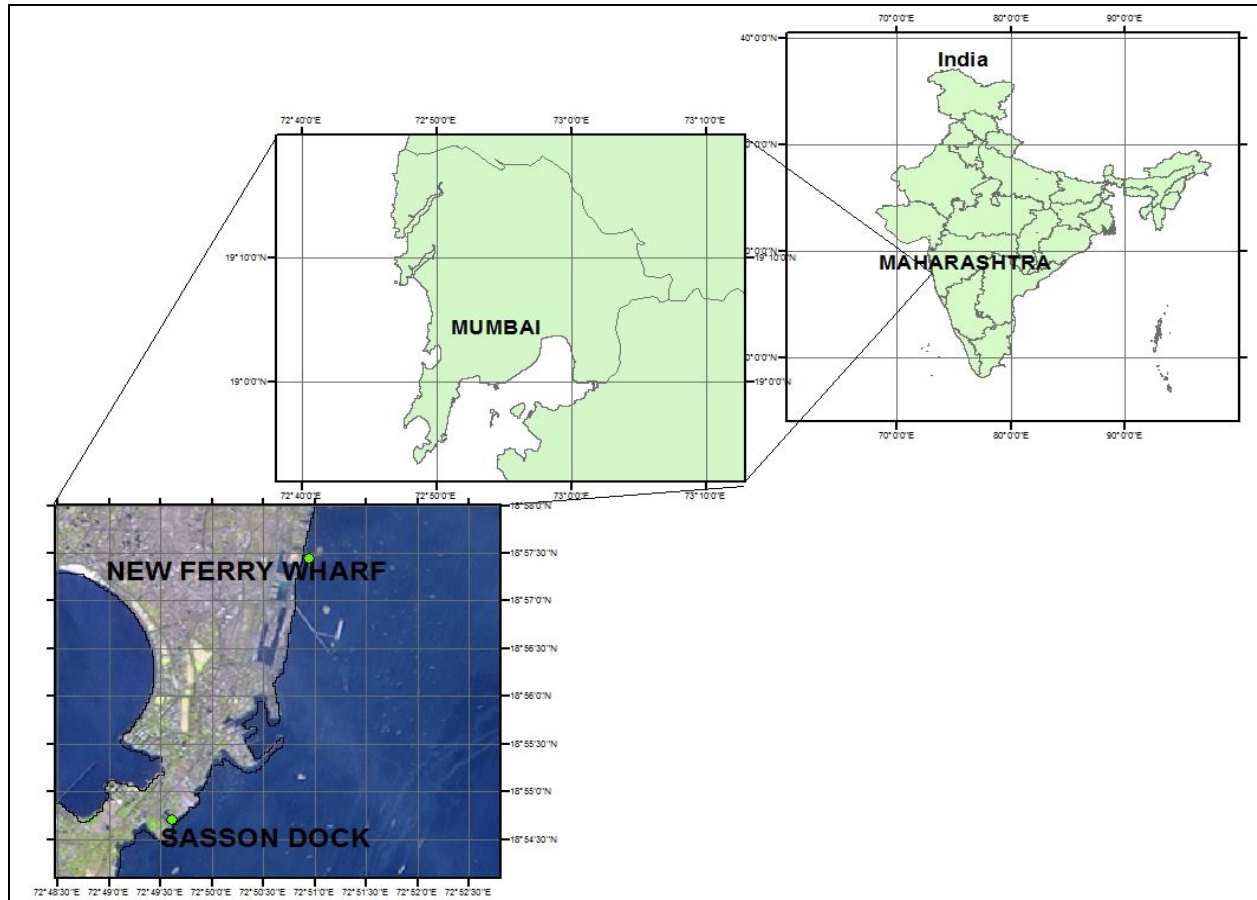
3. MATERIALS AND METHODS

This research study included fisheries data collection, image processing, and satellite data collection, analysis of fisheries data, modeling and mapping of essential fish habitats.

3.1. Description of the study area:

Maharashtra is one of the major maritime states present on the southwest coast of India. Maharashtra state spread all over the seven maritime districts viz., Palghar, Mumbai Sub-urban, Mumbai, Raigarh, Ratnagiri, Sindhudurg, Thane, with 720 km long coastline, i.e. 10% of India's coastline. The estimated marine fish landings of the state were 3.81 lakh tonnes during 2017. The main fishing methods of the state are Trawling, Bag net fishing, Gillnetting, and Purse seining. Pelagic resources contributed a major share with 39% and mollusks contribute 10% to the total landings.

The present study was carried out along the Mumbai coast of India extending between 15^o and 20^o N latitude and 70^o to 73^o E longitudes (Map. 1). Mumbai coast has a coastline of 80 km with a continental shelf area of 2,800 km². In the present study New Ferry Wharf and Sassoon Docks landing centre of greater Mumbai has been selected as sampling locations which are shown in map1. New Ferry Wharf is located along the coast of Dockyard road (Mazagaon). The New Ferry Wharf accommodates the trawlers from Mumbai coast and also the additional trawlers from Gujarat and provides facilities for fish landings. Sassoon Dock is an important landing center situated in South Mumbai, also known as Lower Colaba. Fishermen operating trawlers and purse-seiners from Raigad as well Ratnagiri land their catch in Sassoon Dock. The present study will help fisherman to rely more on advisories to reduce the search time, their effort and fishing expenses.



Map1. Location of the study area with Sampling station.

3.2. Fisheries data:

The commercial time series catch data of Indian Mackerel and Ovalbone Cuttlefish were obtained from the fishing logbook or fishing annual book from the reliable fishermen from January 2017 to March 2018. Logbook data were selected from reliable fishermen who reported the shooting position with GPS data. From October 2018 to April 2019 catch data are collected specially on sampling day (per month four times sampling) basis from the selected landing centre as well as on a daily basis from the fishermen in the selected study area as much as possible. The catch data was supplemented with the position of the net operation (latitude, longitude, and date), depth of operation, fishing duration, number of hauling, individual species catch data, craft and gear type, engine horsepower, etc. These data were tabulated in Excel sheet making it

compatible with the GIS platform i.e. by adding geo-location point of each fishing grounds.

The index of fish abundance, catch per hour (CPH) was calculated as tones/fishing time (per hour) from the logbook data as well as collected data.

To calculate the catch per hour (CPH) following formula is used:

$$\text{CPH} = \text{Kg/hour} \quad \dots\dots\dots (1)$$

Where Kg is the total catch of cuttlefish and hour is the fishing time duration from shooting of fishnet to hauling of the net. The Catch per Hour (CPH) or the catch rate has been used as a standard tool among biologists to determine variation in fish stocks and among economists as an indicator for efficiency of the fishing operation (Hoof and Salz, 2001).

3.3. Satellite environmental data:

The oceanographic parameters covering Mumbai waters, like sea surface temperature (SST), chlorophyll-a concentration (CC), sea bottom temperature (SBT), sea surface height (SSH), sea surface salinity (SSS), mixed layer depth (MLD) and ocean currents (OC) data during 2017 to 2019 were obtained from Internet-based sources like NASA Internet servers Ocean Color Web and Copernicus Marine Environment Monitoring Service (CMEMS). NASA's Ocean Biology Processing Group (OBPG) recently reprocessed the multi-mission for the collection, processing, calibration, validation, archive and distribution of ocean-related time-series products from SeaWiFS, MODIS-Aqua (MODISA), and VIIRS on SNPP (Franz *et al.*, 2018). In the present study sea surface temperature (SST), and chlorophyll-a concentration (CC) data has been also taken from MODIS-Aqua. MODIS (Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. The capability of geophysical product from Moderate Resolution Imaging Spectroradiometer (MODIS) which is Level 3 at 4-km of the spatial resolution were assessed in providing ocean parameters for Mumbai waters from 2017 to 2019 for

better management. MODIS (Moderate Resolution Imaging Spectroradiometer) satellite imagery data was imported to ArcGIS and transformed from ASCII data to raster on which each pixel of 4 km² has his own value. The CMEMS started to operate in April 2015 and operates both for the entire World Ocean as a whole and for marine basins individually. Data from CMEMS are mainly divided based on physical and biological factors which can be weekly, monthly, and annually. The following biotic and abiotic parameters are available in CMEMS web-portal: temperature, salinity, current velocities, sea surface height, sea ice, wind, optics, chemistry, biology, and chlorophyll. The satellite imagery map of these parameters was downloaded from the respective databases (see Table 1) and the value was extracted for each fishing geo-location by using SeaDAS and Snap software.

Table 1: Sources and descriptions of environmental data used in the GIS, in the Mumbai coast (Arabian Sea) fishing grounds (2017-2019)

Data variable	Unit	Abbreviation	Sensor/Model	Source
Sea Surface Temperature	°C	SST	MODIS	NASA ocean color
Sea Surface chlorophyll-a	mg/m ³	CHL	MODIS	NASA ocean color
Sea Bottom Temperature	°C	SBT	CMEMS	NASA ocean color
Sea Surface Salinity	ppt	SSS	CMEMS	NASA ocean color
Sea Surface Height	m	SSH	CMEMS	NASA ocean color
Mixed Layer Depth	m	MLD	CMEMS	NASA ocean color
Ocean current	m/sec	OC	CMEMS	NASA ocean color

3.4. Software used:

3.4.1. R-software:

R is an open-source programming language and software environment for data manipulation, data analysis, and graphical display. The R language is extensively used by statisticians and researchers for software statistics and data analysis. R includes conditional statements, recursive functions, and input/output commands (CRAN 2017). R language also contains a number of advanced data structures, such as matrices and data frames. Data frames are by far the most useful and most widely used advanced data structures in R. One can think of a data frame as a table or an Excel sheet containing data. This table can consist of many columns and row. Each column can be viewed as a vector of the different data type. Each column in a data frame can also have its own name or label.

Once R language is installed using an appropriate distributive from CRAN, the R language can be run by using R-Studio. We cannot run R-Studio without R, and R software must be installed first before installing R-Studio. It adds a more user-friendly and streamlined working environment to R software. R-Studio is an open-source, integrated development environment (IDE) for R-software. R-Studio combines a powerful code/script editor, special tools for plotting and for viewing R objects and code history, and a code debugger. The package tab shows the list of add-ons included in the installation of R-Studio. If checked, the package is loaded into R, if not, any command related to that package won't work, and we will need to load the package to be used in R script. The present study used packages for the most modern statistical techniques such as sophisticated modelling methods, including generalized linear models, generalized additive models, Redundancy analysis, etc.

3.4.2. ArcGIS 10.4:

A Geographic Information System (GIS) is a computer-based (mainly hardware and software) system that used for data capturing, managing, analyzing, and displaying the output in all forms of geographically referenced information. ESRI offers a

complete and integrated server-based GIS platform which is called ArcGIS and used for spatial data management, visualization, and spatial analysis. This ArcGIS system provides an infrastructure for making maps and geographic information from the available data. A new application in ArcGIS included three extensions: 3D Analyst, Spatial Analyst, and GeoStatistical Analyst where Spatial Analyst extension provides a rich set of spatial analysis and modeling tools for both raster (cell-based) and feature (vector) data. Species catch time series data and environmental data are integrated within a GIS platform which potentially can be used to develop a distribution map of the species. These maps help us to identify the spatial patterns of species which help to manage resources and provide information for better decision making. For this study, the version of ArcGIS 10.4 by ESRI was used for making Indian Mackerel and Ovalbone cuttlefish distribution maps and essential fish habitat maps.

3.4.3. SNAP and SEADAS:

Sentinel Application Platform (SNAP):

The Sentinel Application Platform (SNAP) reunites all Sentinel Toolboxes in order to offer the most complex platform for Earth Observation processing and analysis. The basic function includes: opening a product, exploring the product components and extraction of values from the products. In the present study, products are mainly the satellite images of oceanographic parameters (SST, SBT, CHL-a, SSS, SSH, MLD Ocean currents) downloaded from the server as a band or mapped. After exporting the downloaded map in SNAP software we have to make a subset of the map according to our study area by providing appropriate co-ordinates. Geo-location information points of the fishing grounds will be added in the resulting subset product which will provide oceanographic parameters value of each point. In this case, the extracted data can be saved as a text file or other format in a new folder for further analysis.

SeaWiFS Data Analysis System (SeaDAS):

SeaDAS is a comprehensive image analysis package distributed by NASA for visualization, processing, analysis, and display of remote sensing satellite data from a variety of spaceborne multispectral radiometer. SeaDAS includes data processing capabilities of the products from various levels i.e. Level 0 through Level 3 to the users. SeaDAS contains tools for reprojecting geo-located raster images to the desired map projection. This Open-source software incorporates relevant ancillary data into satellite scenes for masking and display image. The basic function of this software is to create, import, and export data shapefile from the remote sensing satellite imagery. SeaDAS has many choices of color palettes which may be selected or loaded by default for configured products. In the present study, this software is mainly used for extracting the environmental variables of fishing grounds for each fishing location.

3.5. Data Analysis:

Data Analysis mainly focused on identifying the habitat preference and distribution of the species, and also identification of environmental variables explaining variations in species abundance. The catch data of the species and the oceanographic parameters of the study area were used directly in the analysis. The Simple correlation was carried out by using excel to identify the oceanographic parameters that significantly correlated with Indian Mackerel and Ovalbone cuttlefish catches. Redundancy Analysis (RDA) was carried out to evaluate the variability of species habitat preference in relation to the selected environmental parameters. Generalized additive models (GAMs) were constructed in R studio to relate the oceanographic parameters to variations in the distribution of Indian Mackerel and Ovalbone cuttlefish.

3.5.1. Redundancy analysis (RDA):

Redundancy analysis (RDA) is a multivariate analysis technique which allows studying the relationship between two sets of variables: dependent variables (i.e. species variables) and independent variables (i.e. environmental variables). This analysis method used to extract and summarize the linear relationships between

components of response variables with a set of explanatory variables. Salarpouri *et al.* (2018) used Redundancy analysis (RDA) to study the Essential fish habitats (EFH) of small pelagic fishes in the north of the Persian Gulf and Oman Sea, Iran. RDA graphics mainly presented in the form of correlation biplot which represents the combination of independent variables that best explain the variations of dependent variables. The length and angles in the RDA correlation biplot reflect the correlation between dependent and independent variables. Sometimes to assume that the effects are linear most of the time independent variables were log-transformed. In the present study, simple correlation analysis and Redundancy analysis has been applied to reveal the relationship between species and environmental variables by using “Vegan Package” in R-studio.

3.5.2. Generalized Additive Model (GAM):

Generalized additive models (GAM) were originally proposed by Trevor Hastie and Robert Tibshirani (1990) and the first applications to fishery data were by Swartzman *et al.* (1992 and 1995). GAM is an extension of the generalized linear models (GLM) which is a non-parametric multiple linear regression method with less strict assumptions than linear regression. GAM consists of two components i.e. additive function and smooth components. These two components have been used to establish the relationship between the mean of the dependent variables and the smooth function of the independent variables.

A GAM can be written as:

$$Y = a + f_1(x_1) + f_2(x_2) + \dots + f_n(x_n) + e \quad (2)$$

Where a = Intercept

f = Smooth function of the variables

e = Random error term.

The principle advantage of this model is that the independent variables have linear effects on dependent variables. To model the abundance and variation of Indian Mackerel and Ovalbone cuttlefish GAMs were fitted using “gam” command and “mgcv” package in R-software. All the catch and environmental data were imported into R-software from Microsoft Excel data files and initially screened to reveal characteristics of data sets and detect outliers (Sacau *et al.*, 2005). GAMs are widely used in habitat preference modelling and in the prediction of spatio-temporal distribution because they use data-driven functions that have superior performance relative to the polynomial functions used in linear models (Zainuddin *et al.* 2011).

The environmental variables were included in the analysis of the present study using GAM equation as shown (as ref Hastie & Tibshirani 1990).

$$Y = a + s(\text{SST}) + s(\text{LCHL}) + s(\text{SSS}) + s(\text{SSH}) + s(\text{LMLD}) + e \quad (3)$$

...For Indian Mackerel

Where Y= Catch of Indian Mackerel (Lcatch = log-transformed)

S = Smooth function of Environmental Variables (SST, LCHL, SSS, SSH, LMLD).

$$Y = a + s(\text{Lat,Long}) + s(\text{SSTM}) + s(\text{SSS}) + e \quad (4)$$

.....Ovalbone cuttlefish

Where Y= Catch per Hour (CPH) of Ovalbone cuttlefish

S = Smooth function of Environmental Variables (SSTM, SSS).

Akaike information criterion (AIC) is a function to produce the relative quality of statistical models for particular sets of data. The AIC static was used to select

the best-fitted model, is the one that has minimum AIC (lowest AIC) among all the other models. So for the present study, Generalized Additive Models (GAMs) has been used to discover the relationship between the relative abundance of the selected species and Oceanographic parameters.

3.5.3. Essential Fish Habitat Maps (EFH Maps):

The essential fish habitat (EFH) is defined as “those waters and substrate necessary to fish for spawning, breeding, feeding, or growth to maturity (SFA 1996). The identification of Essential Fish Habitats (EFH) is very important for the conservation of species and sustainable fisheries management. Now a day’s Scientists and lawmakers were trying to identify EFH; identifying all the possible actions detrimental to that habitat, and possible ways to conserve that habitat to sustain fish stocks. For identifying EFH, one must understand the relationship between fish and cuttlefish with their relative environment because the physiology of species will change with its environmental condition.

In the present study, the GAM approach has been done to model the species habitat preference and relation with the environmental parameters. The graphical and numerical output from GAM will provide regression parameters and significance level which indicates the effects of environmental parameters on the species abundance. These GAM results can be used within the ArcGIS to generate Essential Fish Habitats (EFH) map and to identify those potential fishing areas within the distribution of a species. The extracted environmental parameters for our specific study area (i.e. Mumbai coast) can be applied to satellite data that cover the whole region (i.e. Maharashtra coast) thus providing potential EFH maps for the region of interest (Valavanis *et al.*, 2008). The other approach we can include by using the predicted abundance values and actual abundance values directly in to map where maximum probable areas will provide overall general fishing locations of Essential Fish Habitat (EFH).

4. RESULTS

4.1. *Rastrelliger kanagurta* (Cuvier, 1817)

4.1.1. Catch and Environmental parameters:

4.1.1.1. Catch variability of *Rastrelliger kanagurta* (Cuvier, 1817):

The average Catch of Indian Mackerel has been estimated to be 894 kg during 2017-2019. Highest catch was observed during post-monsoon and winter mainly in December–February (average catch 1800 kg). Moderate catch of *Rastrelliger kanagurta* (i.e. >100kg) was observed in April, May, September. Catch lower than 100 kg was observed during other month (Figure 2).

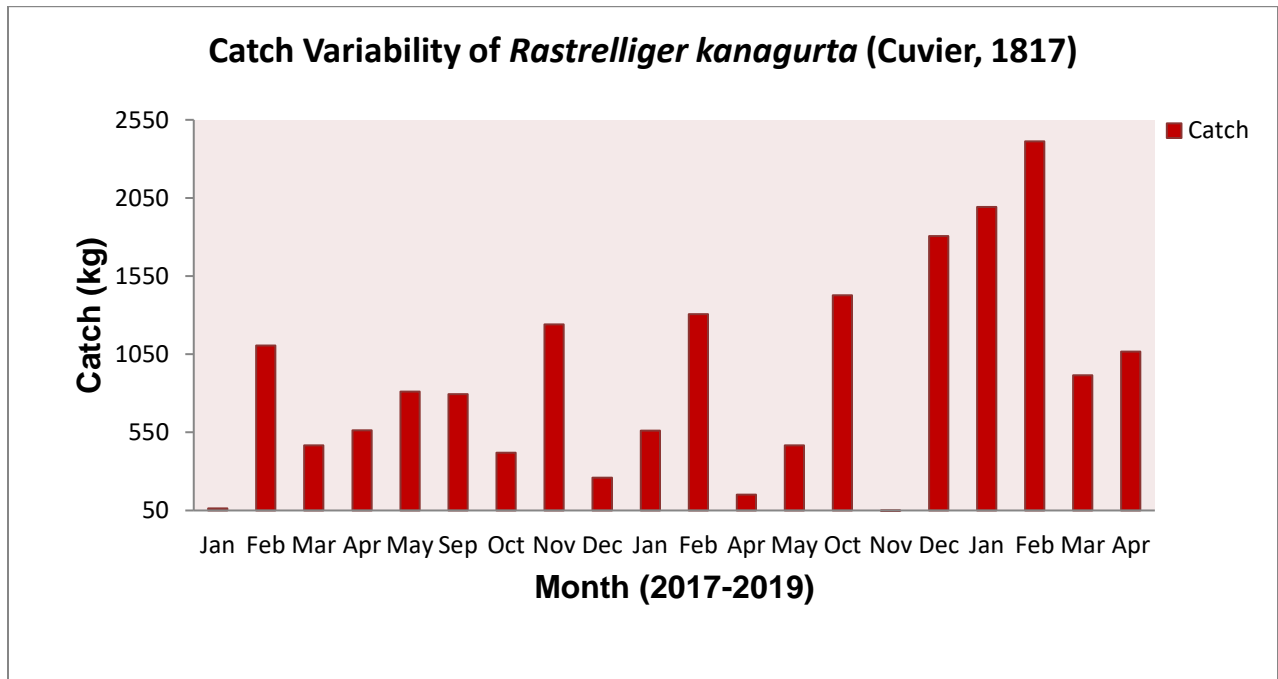


Figure 2: Average Catch trend for *Rastrelliger kanagurta* (Cuvier, 1817) during 2017 to 2019

4.1.1.2. Temperature (SST and SBT):

Sea Surface Temperature (SST) of Mumbai water during winter is 24°C to 26.2°C and was increased during pre-monsoon up to 28.7°C. The maximum SST of Mumbai water is mainly found during Monsoon which is 29.7°C and again it reduced during Post-monsoon up to 28.4°C (Figure 3). Sea Bottom Temperature (SBT) of Mumbai water also follows the same trend as Sea Surface Temperature (SST) where minimum Sea Bottom Temperature found during winter is 26°C and maximum Sea Bottom Temperature found during monsoon up to 29.6°C (Figure 4). From the recorded SST and SBT it has been found that Sea Bottom Temperature (SBT) ($r=0.1109$, $p=0.1204$) shows lesser significant correlation with the catches of Indian Mackerel, but Sea Surface Temperature (SST) showed a significant relationship ($r= 0.1782$, $p= 0.0122$) with the catches (Figure 5).

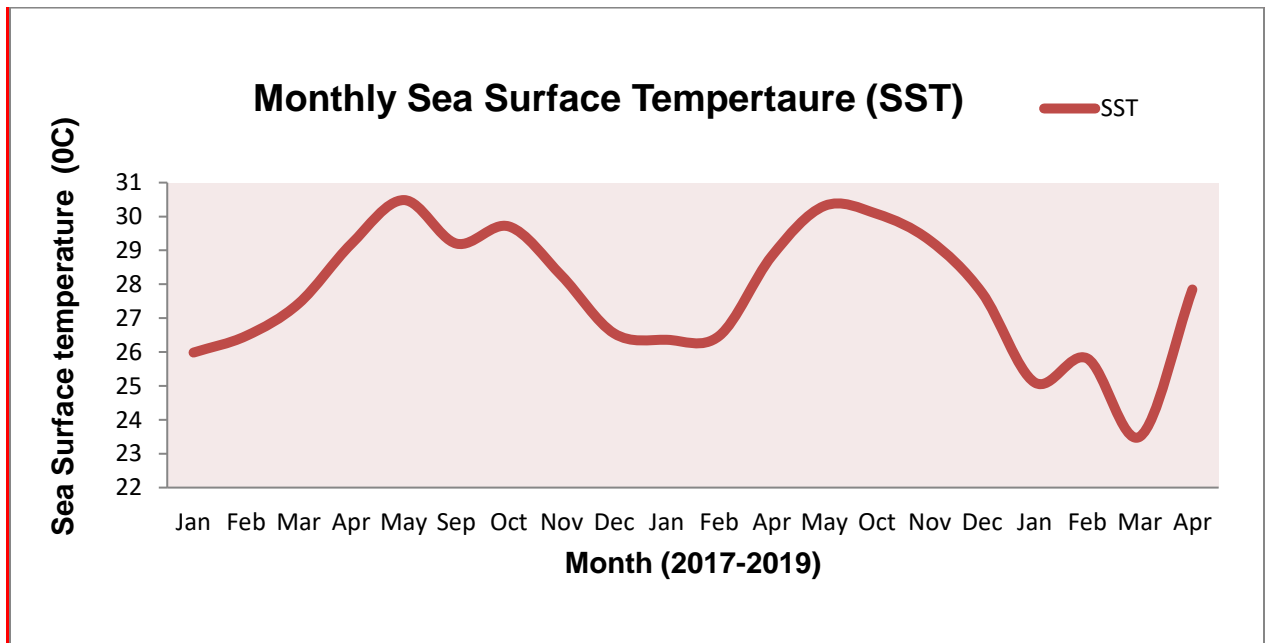


Figure 3: Monthly Variations of Sea Surface Temperature (SST) of Mumbai Water during 2017 to 2019

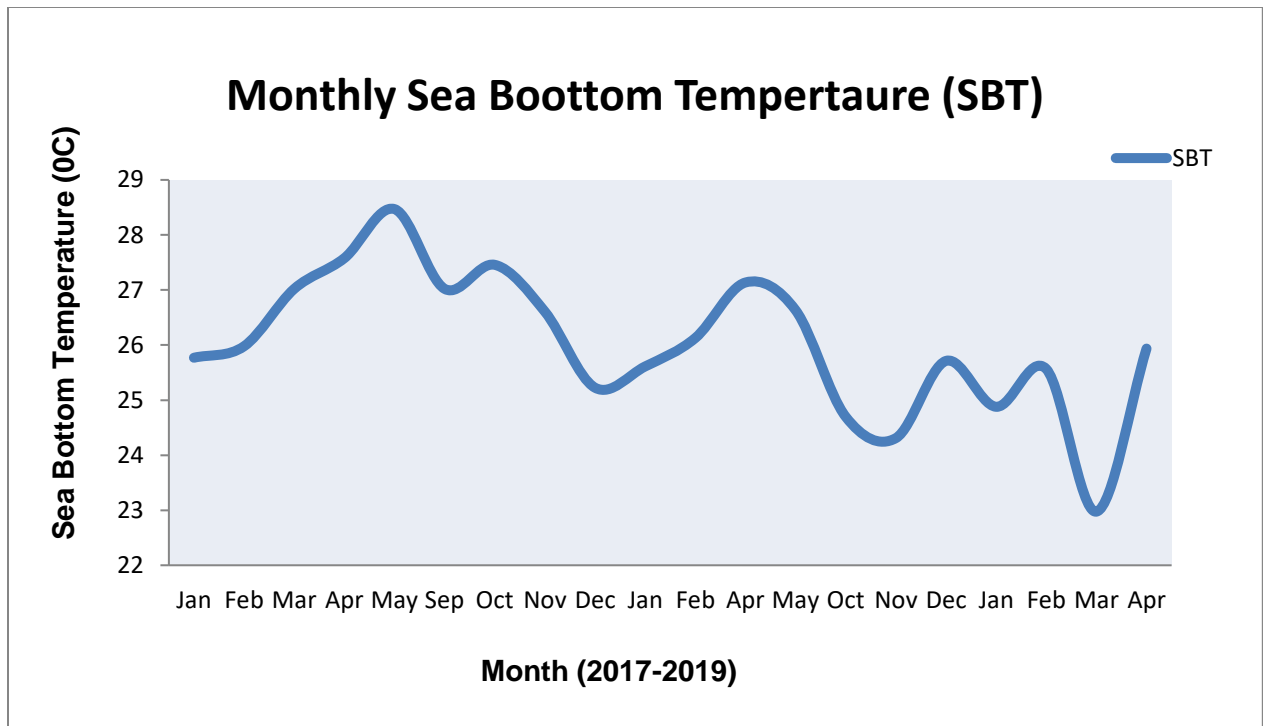


Figure 4: Monthly Variations of Sea Bottom Temperature (SBT) of Mumbai Water during 2017 to 2019

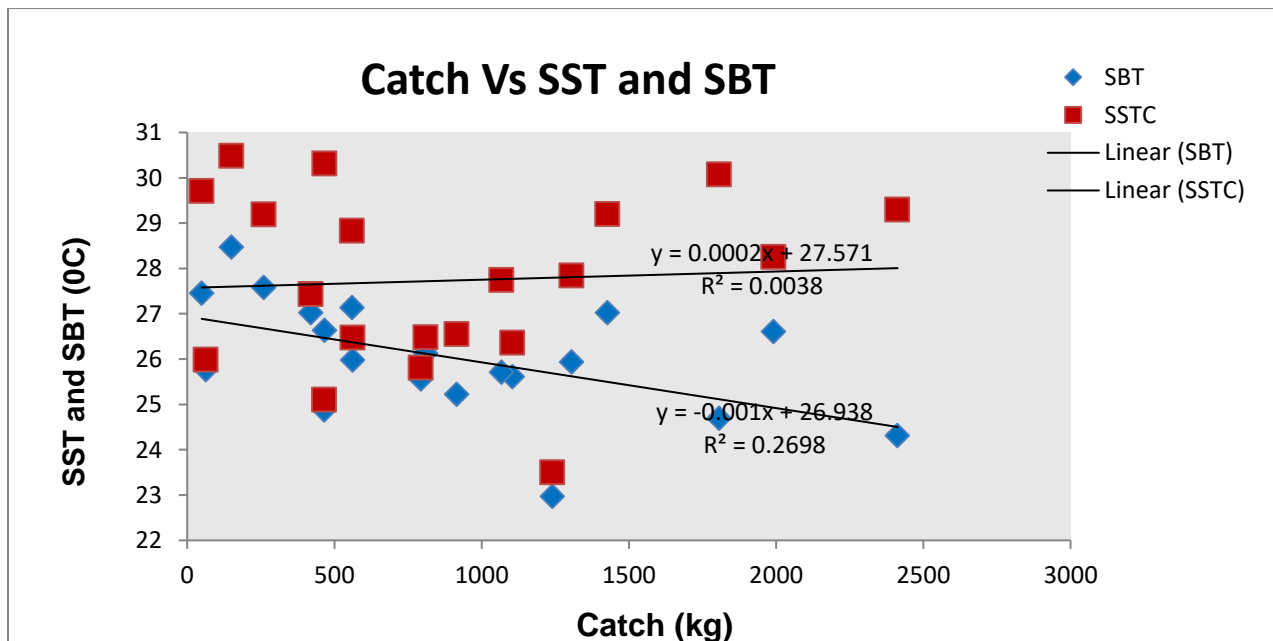


Figure 5: Linear Relationship of Indian Mackerel catches with Sea Surface Temperature (SST) and Sea Bottom Temperature (SBT) of Mumbai Water during 2017 to 2019

4.1.1.3. Chlorophyll-a Concentration (Chl-a):

During the winter and monsoon the chlorophyll concentration of Mumbai water is found to be maximum i.e. 1.40 mg/m³ and 0.94mg/m³ respectively. Chlorophyll-a concentration during monsoon shows maximum variation from ranges of 0.09 mg/m³ to 0.49 mg/m³ (Figure 6). During the pre-monsoon chlorophyll concentration ranged from 0.07 mg/m³ to 0.29 mg/m³ and increased up to 0.59 mg/m³. The chlorophyll concentration during post monsoon ranged from 0.08 mg/m³ to 0.19 mg/m³ and reduced up to 0.45 mg/m³ which is the lowest value. In the present study chlorophyll concentration shows a good significant relationship ($r= 0.1782$, $p= 0.0122$) with the Indian Mackerel catches (Figure 7).

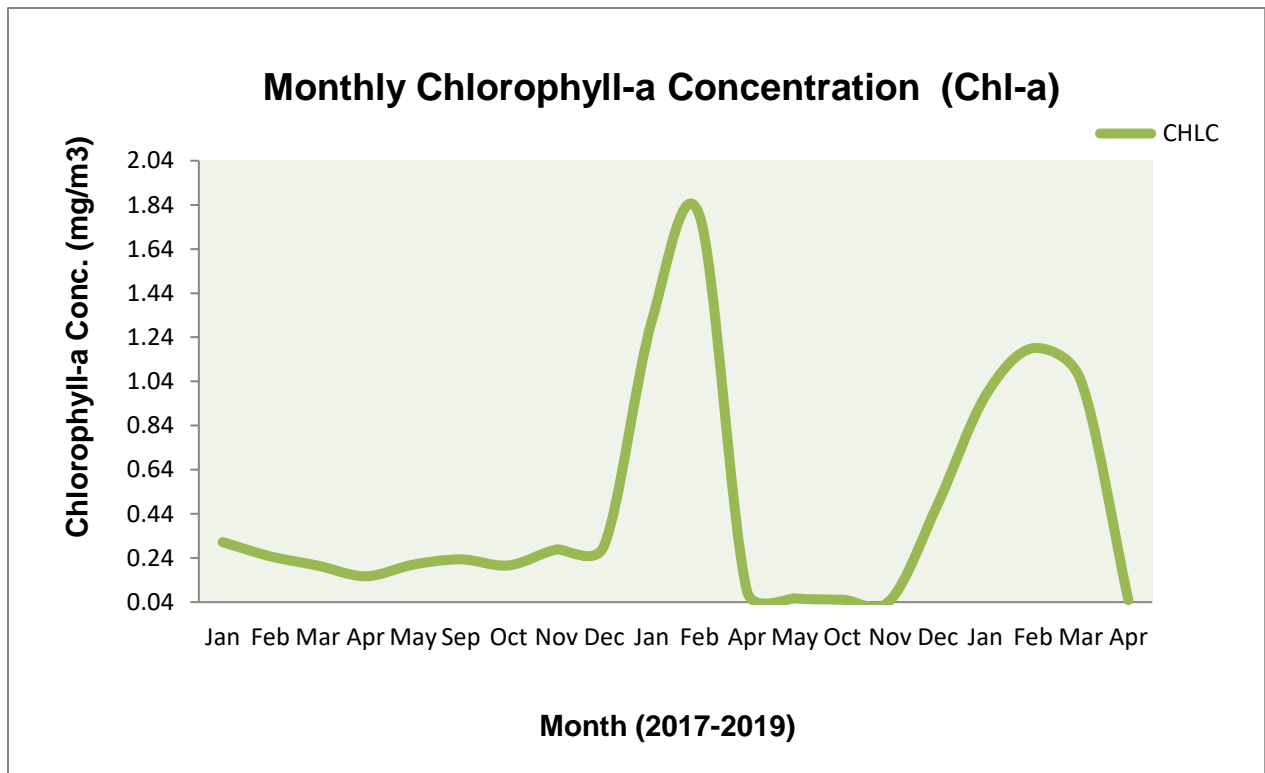


Figure 6: Monthly Variations of Chlorophyll-a Concentration (Chl-a) of Mumbai Water during 2017 to 2019

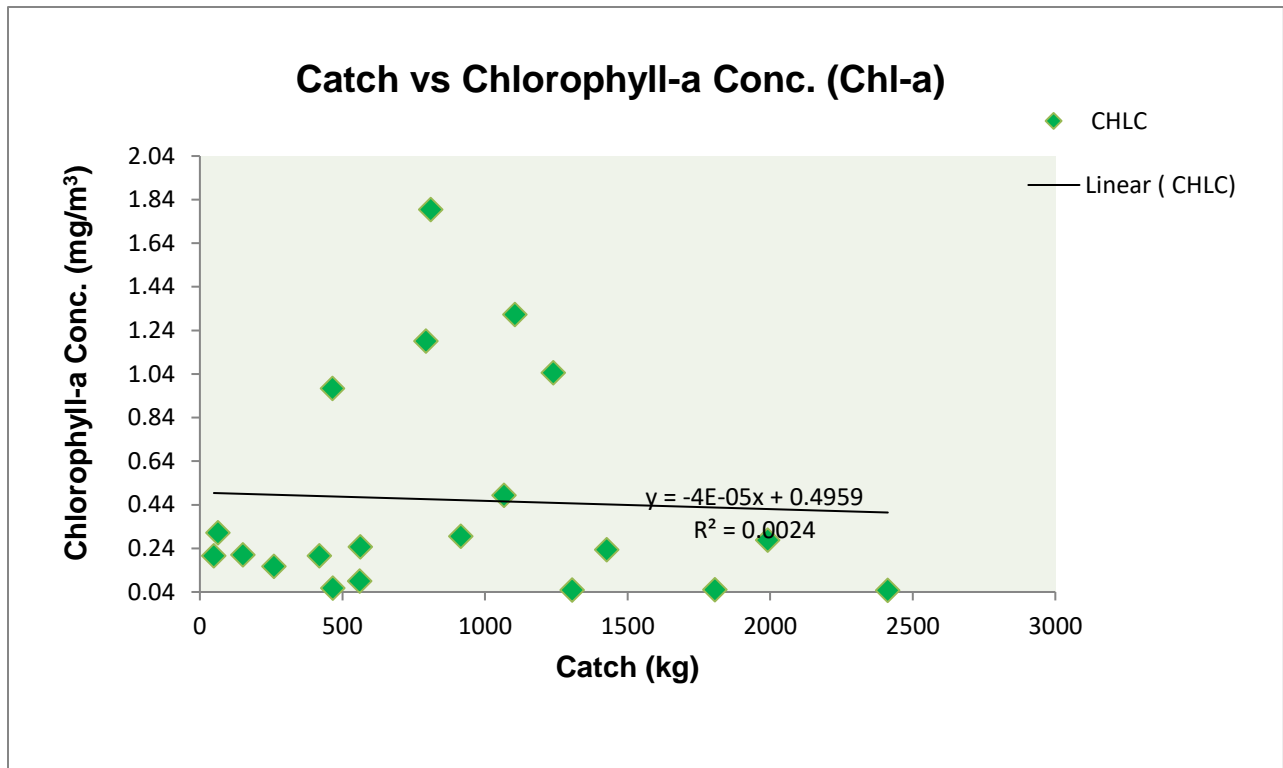


Figure 7: Linear Relationship of Indian Mackerel catches with Chlorophyll-a Concentration (Chl-a) of Mumbai Water during 2017 to 2019

4.1.1.4. Sea Surface Salinity (SSS):

Sea Surface Salinity (SSS) of Mumbai water during winter ranged from 30.63 to 35.7 ppt. The maximum SSS of Mumbai water is mainly found during winter which is 37.40 ppt and again it reduced during pre-monsoon up to 35.63 ppt (Figure 8). During the Monsoon Sea Surface Salinity ranged from 34.32 to 35.6 ppt and reached up to 36.49 ppt. The sea surface salinity during post monsoon ranged from 33.56 to 34.56 ppt and increased up to 35.95 ppt. In the present study sea surface salinity shows a good significant relationship ($r= 0.2558$, $p= 0.0002$) with the Indian Mackerel catches (Figure 9).

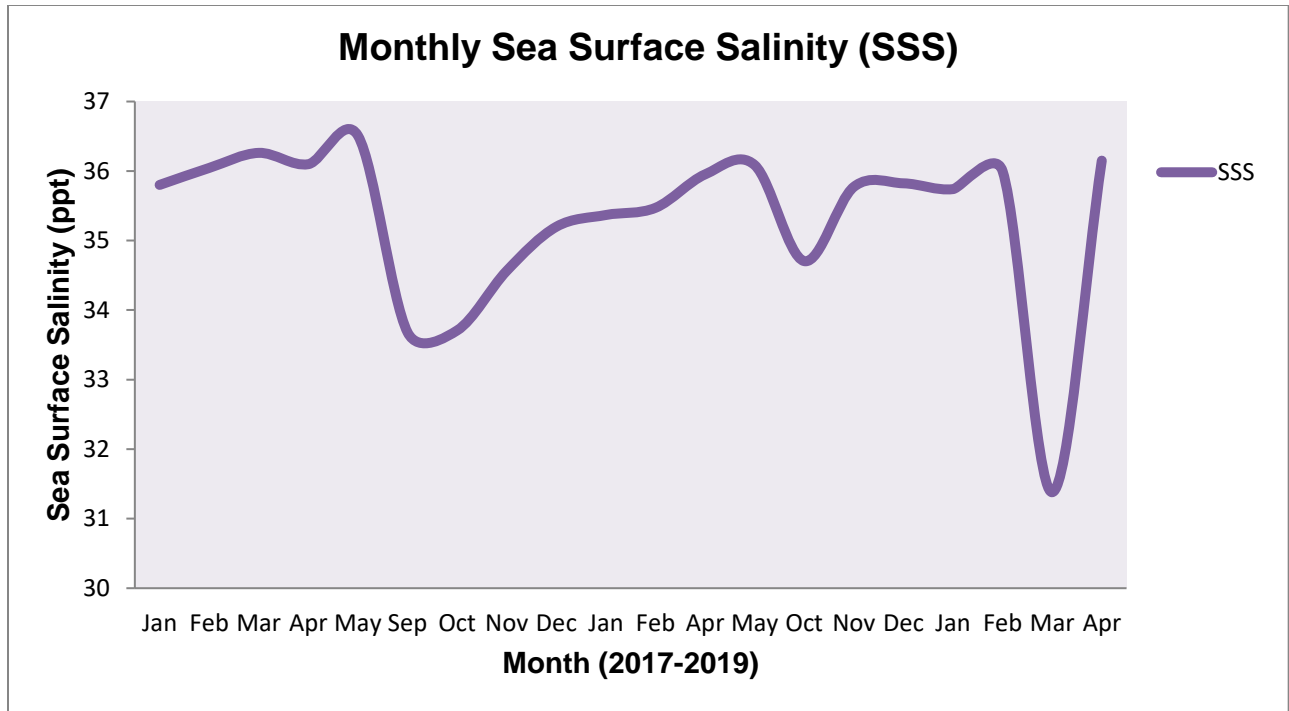


Figure 8: Monthly Variations of Sea Surface Salinity (SSS) of Mumbai Water during 2017 to 2019

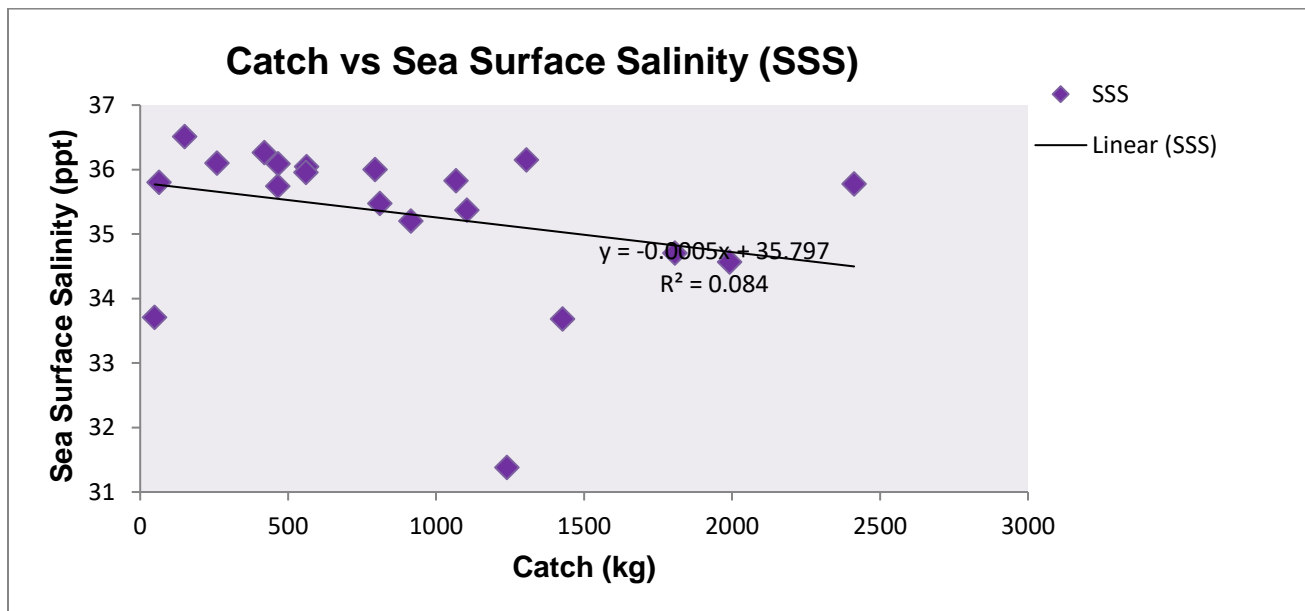


Figure 9: Linear Relationship of Indian Mackerel catches with Sea Surface Salinity (SSS) of Mumbai Water during 2017 to 2019

4.1.1.5. Sea Surface Height (SSH):

During winter and post-monsoon Sea Surface Height (SSH) of Mumbai water is found to be maximum i.e. 38.59 cm and 38.77 cm respectively. Sea Surface Height (SSH) during monsoon shows minimum variation from ranges of 21.35 cm to 22.99 cm and reached up to 24.81 cm. During the pre-monsoon the sea surface height ranged from 31.84 cm to 33.42 cm and increased up to 35.05 cm (Figure 10). Sea Surface Height (SSH) in this present study showed a significant relationship ($r= 0.2114$, $p= 0.0028$) with the Indian Mackerel catches (Figure 11).

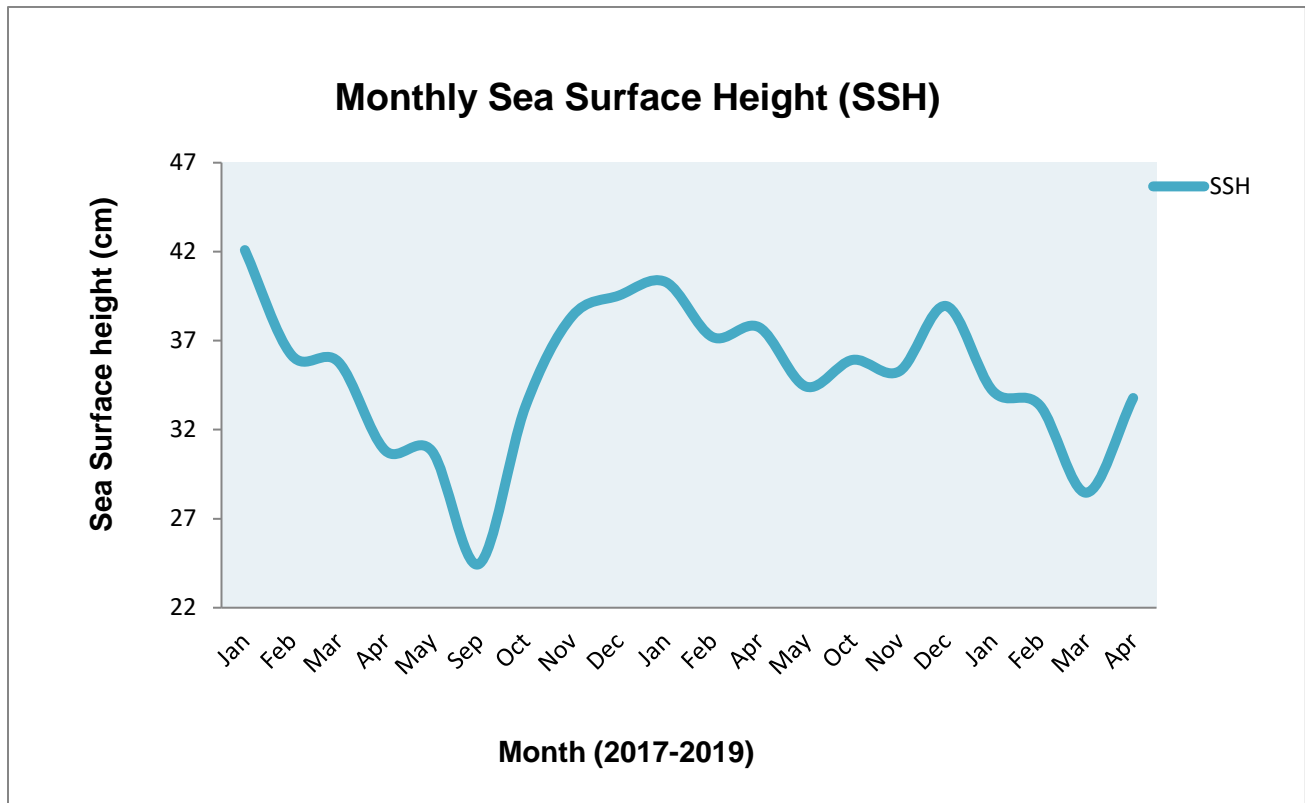


Figure 10: Monthly Variations of Sea Surface Height (SSH) of Mumbai Water during 2017 to 2019

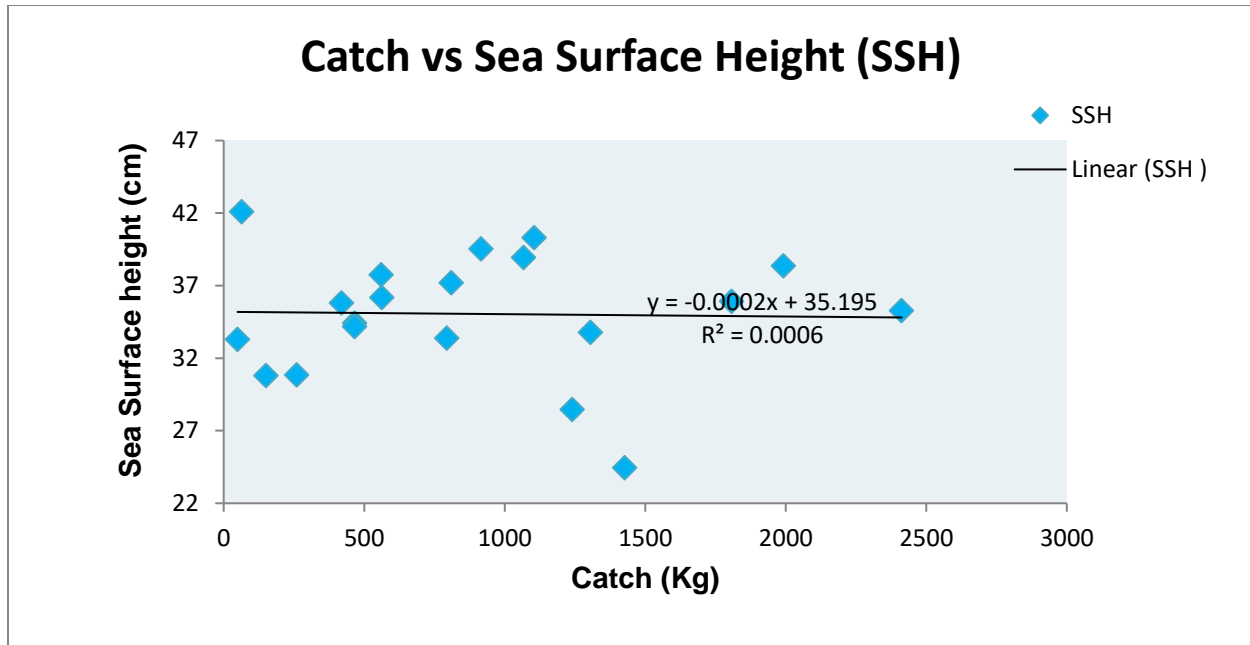


Figure 11: Linear Relationship of Indian Mackerel catches with Sea Surface Height (SSH) of Mumbai Water during 2017 to 2019

4.1.1.6. Mixed Layer Depth (MLD):

Mixed Layer Depth (MLD) of the Mumbai water shows a great variation from January 2017 to April 2018. During winter the mixed layer depth of Mumbai water is ranged from 11.60m to 28.29m and is found to be maximum i.e. 38.91m. The lowest mixed layer depth has been recorded during pre-monsoon ranged from 7.67m to 12.90m with average 16.11m. During Monsoon mixed layer depth of Mumbai water is ranged from 6.96m to 17.70m and reached up to 26.85m (Figure 12). Mixed Layer Depth of the Mumbai water during post-monsoon doesn't show much difference from the monsoon with ranged from 6.99m to 15.59m and reached up to 20.17m. From the recorded data it has been found that Mixed Layer Depth ($r= 0.0717$, $p= 0.3166$) shows no significant correlation with the catches of Indian Mackerel in Mumbai coast (Figure 13).

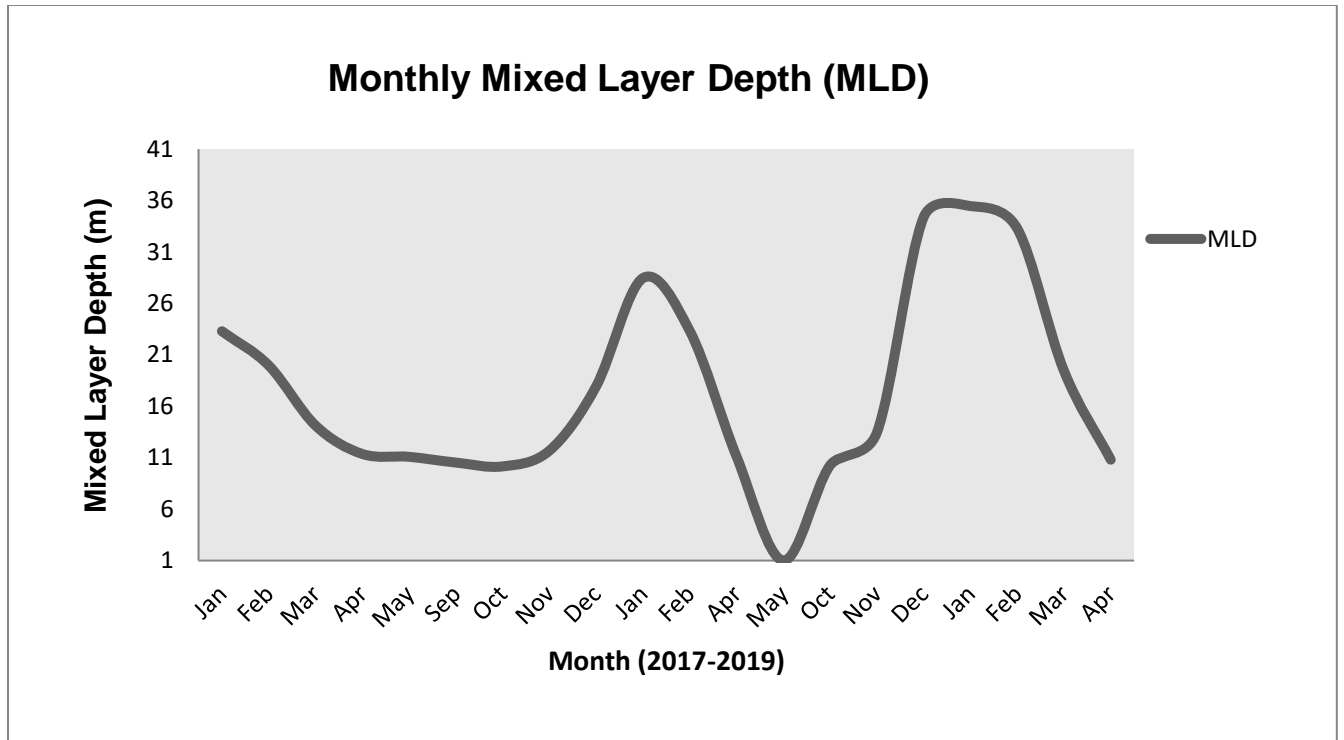


Figure 12: Total Monthly Variations of Mixed Layer Depth (MLD) of Mumbai Water during 2017 to 2019.

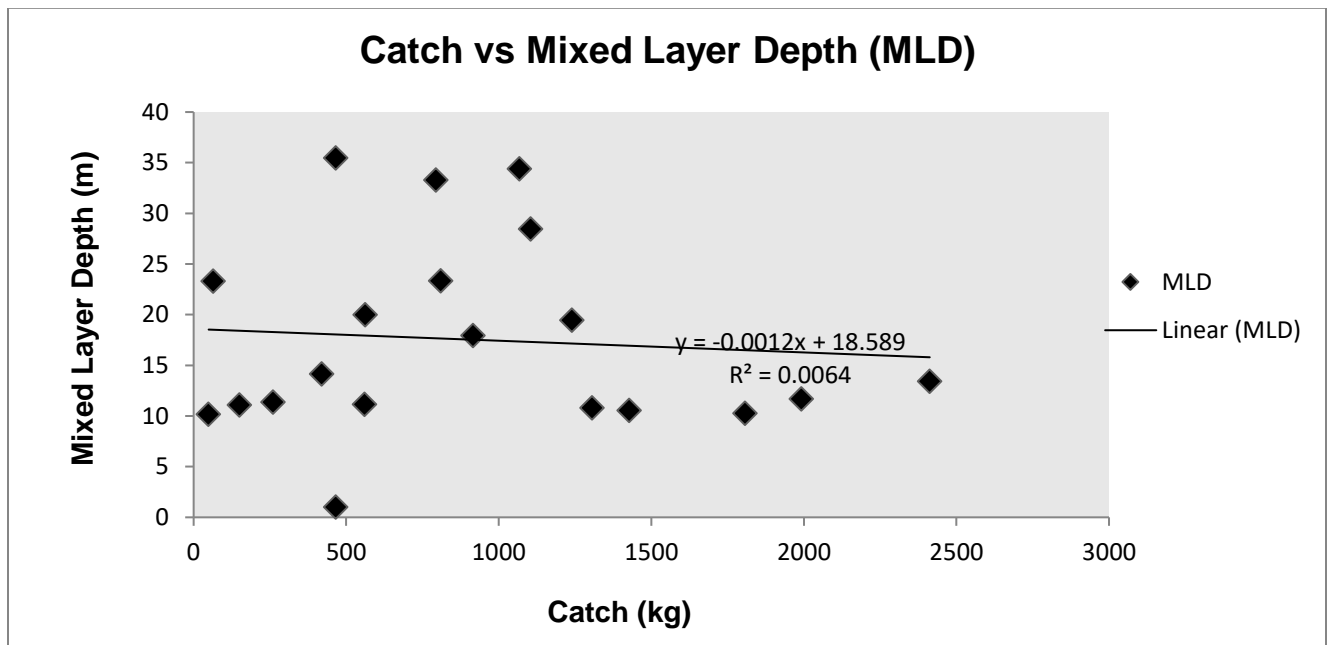


Figure 13: Linear Relationship of Indian Mackerel catches with Mixed Layer Depth (MLD) of Mumbai Water during 2017 to 2019.

4.1.1.7. Surface Ocean Currents (OC):

Ocean Currents (OC) of Mumbai water during winter and pre-monsoon is found to be minimum i.e. 0.11 m/sec and 0.12 m/sec respectively. During Monsoon Ocean current is maximum in Mumbai Water ranged from 0.03 m/sec to 0.13 m/sec and reached up to 0.23 m/sec (Figure 14). Ocean Currents (OC) during post-monsoon shows a great variation from 0.007 m/sec to 0.07 m/sec with average 0.14 m/sec. In present study Ocean Currents showed no significant relationship ($r= 0.0154$, $p= 0.8295$) with the catches of Indian Mackerel (Figure 15).

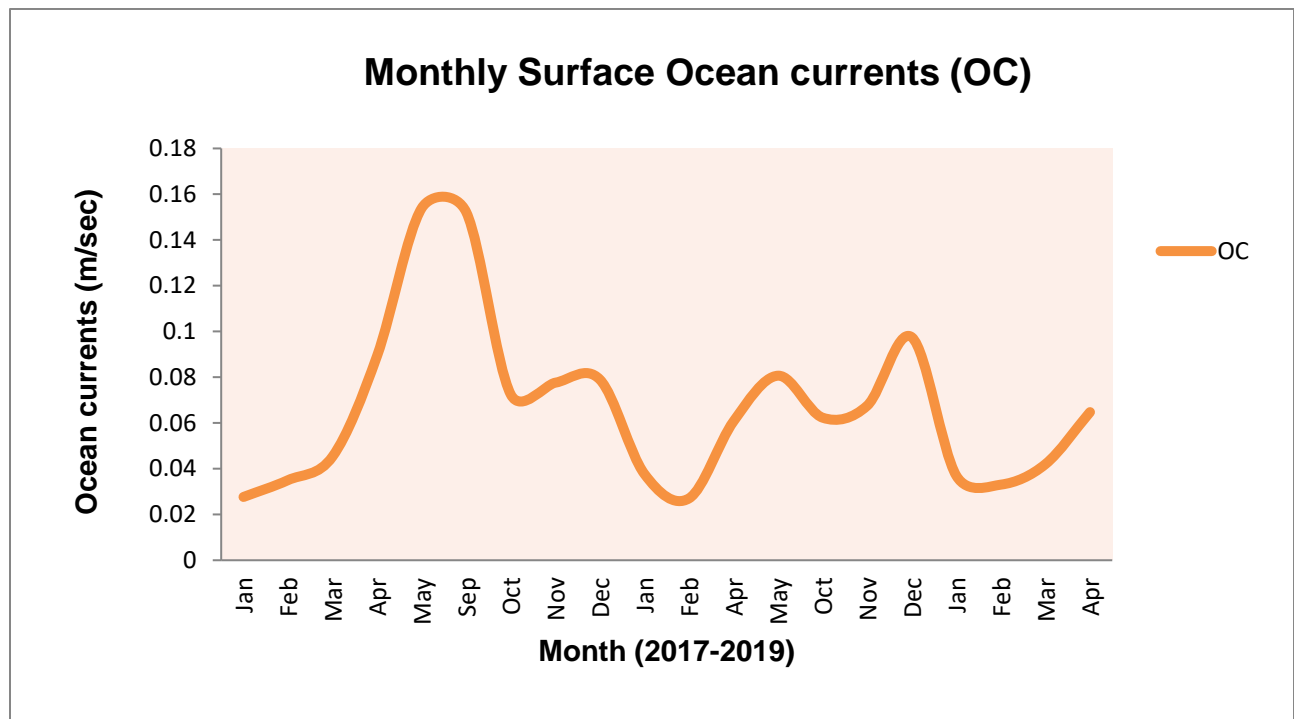


Figure 14: Monthly Variations of Surface Ocean Currents (OC) of Mumbai Water during 2017 to 2019.

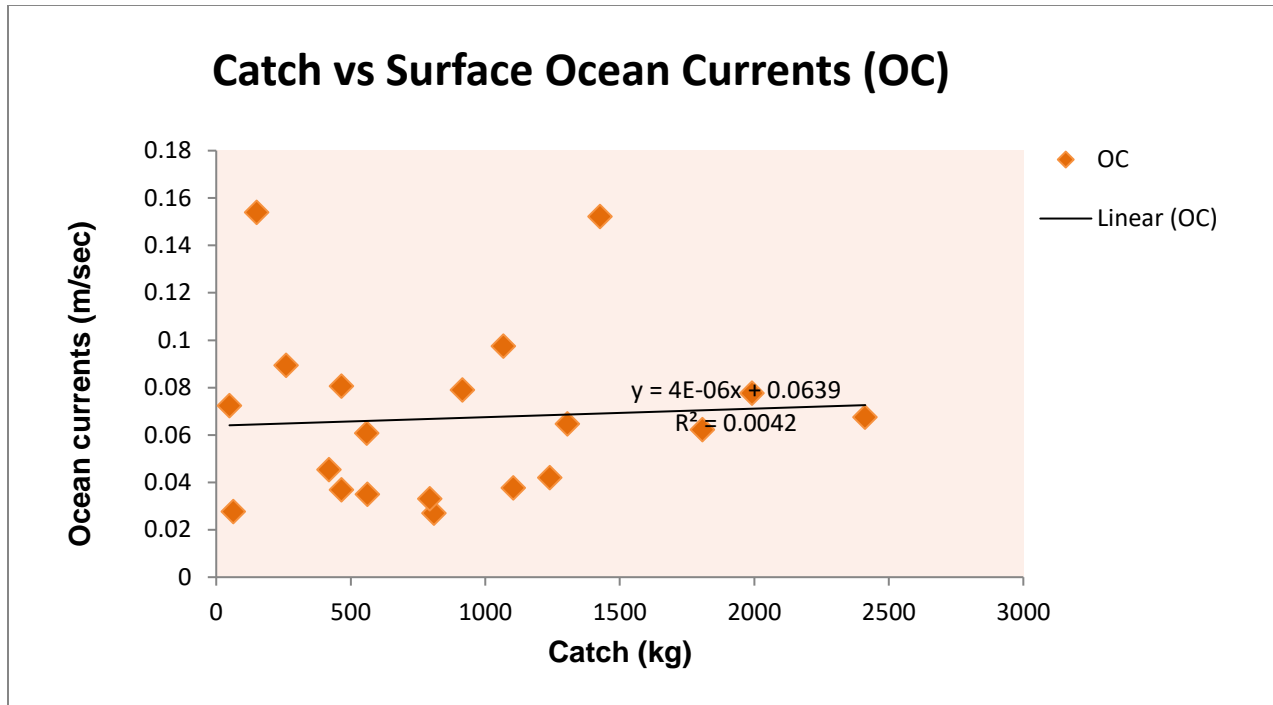
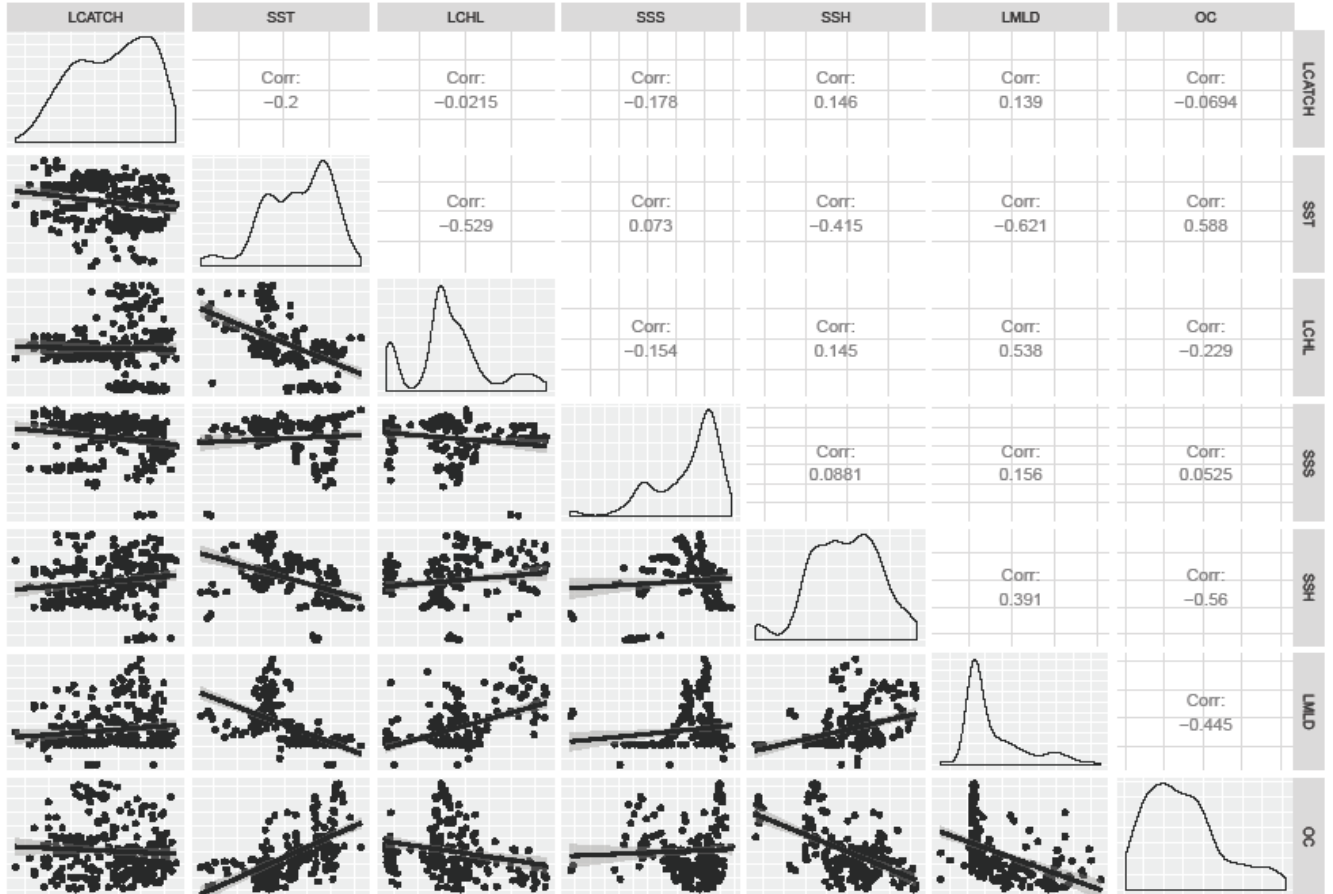


Figure 15: Linear Relationship of Indian Mackerel catches with Surface Ocean Currents (OC) of Mumbai Water during 2017to2019.

4.1.2. GAM output between Indian Mackerel Catch and Environmental parameters:

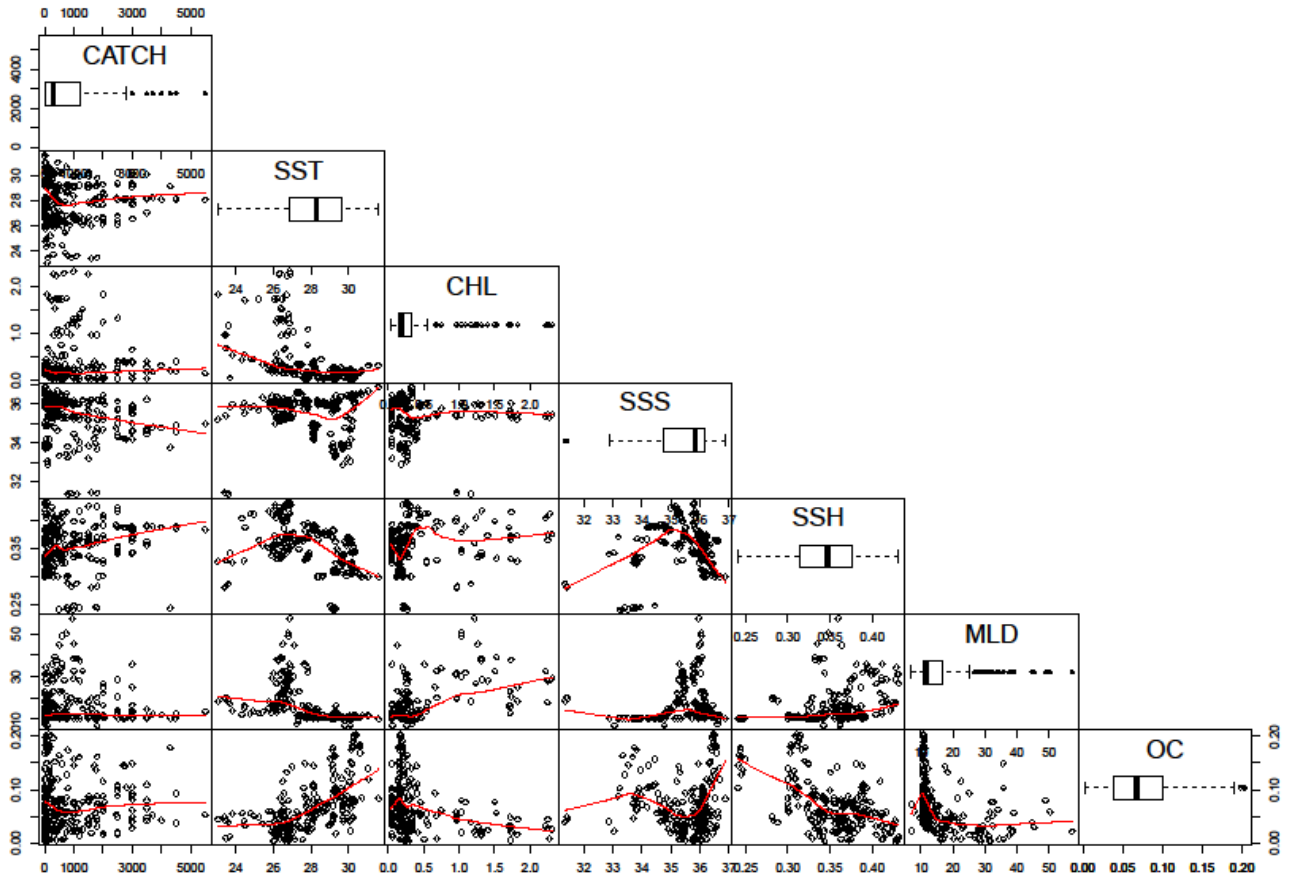
4.1.2.1. ggpairs plot between Indian Mackerel Catch and Environmental variables:



Plot 1: ggpairs plot (with r value) between Indian Mackerel Catch and Environmental variables:

In the above ggpairs plot (Plot 1) the distribution of catch and environmental variables are shown on the diagonal. The bottom of the diagonal shows the bivariate scatter plots with a fitted line which represents the linear relationship. The top of the diagonal shows the value of correlation coefficient, used to measure the strength and direction between variables. This plot is useful to visualize each variable by itself and of their relationship with each other.

4.1.2.2. Boxplot between Indian Mackerel catch and Environmental Variables:



Plot 2: Boxplot Shows the range of environmental variable where *Rastrelliger kanagurta* (Cuvier, 1817) was caught

4.1.2.3. Generalized Additive Modelling (GAM) for *Rastrelliger kanagurta* (Cuvier, 1817)

A GAM using the Gaussian distribution was used to relate Indian Mackerel catch data and the explanatory environmental variables. To find the optimal set of explanatory environmental variables, in all (total 64) GAM model were fitted with a different combination of explanatory variables and basic dimension (k). To decide the best fit model three components models were selected which has given

lowest AIC value among the entire models. The best fit of GAM was obtained from these three models based on lowest (model 12345 AICC= 661.39) AIC value estimator (Table 1). Weight (model 12345 weight =0.61) is totally opposite to AICC value because model with highest weight has been selected as best fit model (Table 1). To estimate the optimal degrees of freedom for each smoother cross-validation was used. The GAM identified Sea Surface Temperature, Chlorophyll-a concentration, Sea Surface Salinity and Sea Surface Height, and Mixed Layer as the best explanatory variable (model 12345).

Table 1: Showing Akaike Information Criteria (AIC) and Weight value of the GAM models

Model	df	logLik	AICc	delta	Weight
12345	8	-322.44	661.39	0	0.61
12356	7	-324.27	662.94	1.55	0.28
1256	6	-326.3	664.91	3.51	0.11

Below the best fit GAM result has been shown;

The RMS GCV score gradient at convergence was 9.440949e-08.

The Hessian was positive definite. Model rank = 46 / 46

Basis dimension (k) checking results. Low p-value (k-index<1) may indicate that k is too low, especially if edf is close to k'(Table 2)

Table 2: Modeled GAM check results between *Rastrelliger kanagurta* (Cuvier, 1817) Catches, SST, LCHL, SSS, SSH and LMLD during 2017-2019

Environmental Variables	k'	edf	k-index	P-value
(LCHL)	9.00	4.47	1.02	0.64s
(LMLD)	9.00	1.00	0.94	0.16s
(SSS)	9.00	8.95	1.01	0.50s
(SST)	9.00	7.50	1.14	0.99s
(SSH)	9.00	2.42	1.03	0.64

Formula:

LCATCH~ SST + LCHL + SSS + SSH + LMLD

Parametric coefficients:

Estimate Std. Error t value Pr (>|t|)

(Intercept) 2.36893 0.03069 77.19 <2e-16 ***

Here parametric estimate is for intercept. Interpretation is also as usual, but the spline is centered at zero, i.e. the intercept measures in this case the overall mean.

Table 3: Significance of smooth terms of best fit of GAM model for *Rastrelliger kanagurta* (Cuvier, 1817)

Environmental Variables	edf	Ref.df	F	P-value
s(LCHL)	4.468	5.486	23.659	< 2e-16 ***
s(LMLD)	1.000	1.000	1.093	0.297 *
s(SSS)	8.950	8.993	9.000	4.40e-12 ***
s(SST)	7.497	8.442	4.874	5.29e-06 ***
s(SSH)	2.425	2.974	14.017	1.24e-08 ***

Signif.codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.586 Deviance explained = 62.1%

GCV = 0.29555 Scale est. = 0.26936 n = 286

In the GAM analysis model R²-value is as usual the proportion of variance explained by the model. The Scale estimate is the variance of the residual.

Table 4: Shows relative variable importance of environmental variables for *Rastrelliger kanagurta* (Cuvier, 1817) catch during 2017-2019

Relative variable importance:	LCHL	LMLD	SSS	SST	SSH
Importance:	1	1	1	1	0.61

The GAM analysis indicates that high distribution of Indian Mackerel related to sea surface temperature, Chlorophyll-a concentration, sea surface salinity, sea surface height and mixed layer depth. GAM test indicated that SSH, SSS and MLD are

imperative than CHL and SST (Table 4). In the present study SST and CHL had significant relationship with the *Rastrelliger kanagurta* (Cuvier, 1817) distribution at $p < 0.001$ and $p < 0.001$ respectively (Table 3). SSS, SSH and MLD also has been showing significant relationship with the *Rastrelliger kanagurta* (Cuvier, 1817) distribution at $p < 0.001$, $p < 0.001$ and $p < 0.001$ respectively (Table 3). In the present study it has been found that in Mumbai coast of India maximum Indian Mackerel is habitat to the area of average 28.18°C Sea Surface Temperature. It has been also found that in Mumbai coast of India Indian Mackerel mostly abundant in the area of Chlorophyll-a Concentration 0.35mg/m³, Sea Surface Salinity 33-34.5 ppt, Sea Surface Height 37cm, and Mixed Layer depth 10-15m. GAM formula visualization has to be done by plotting (Figure 16).

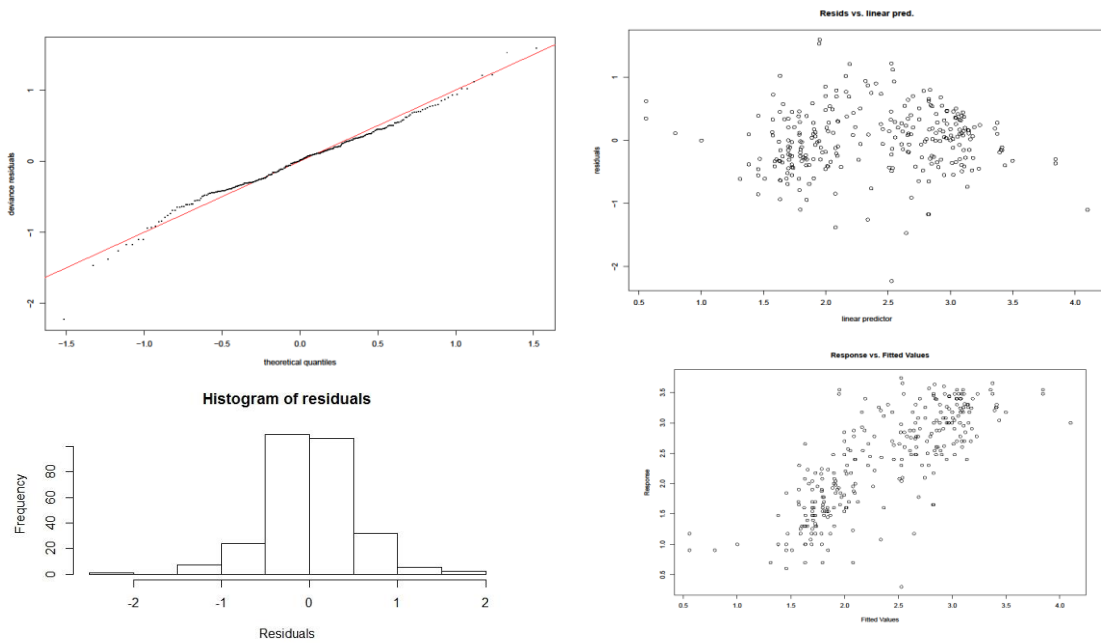


Figure 16: Diagnostics for a fitted GAM model a) Theoretical quantiles and deviance residuals. b) Residuals vs linear predictor plot. c) Histogram of residuals. d) Response vs Fitted value plot.

Theoretical quantiles and deviance residual plot (Figure 16a) shows a linear relationship. Resids vs linear predictor plot (Figure 16b) shows the difference between observed and predict value. Histogram of residuals (Figure 16c) has been used to check whether the variance is normally distributed around the zero. In Response vs Fitted (Figure 16d) value plot points around the zero line assume linear relationship.

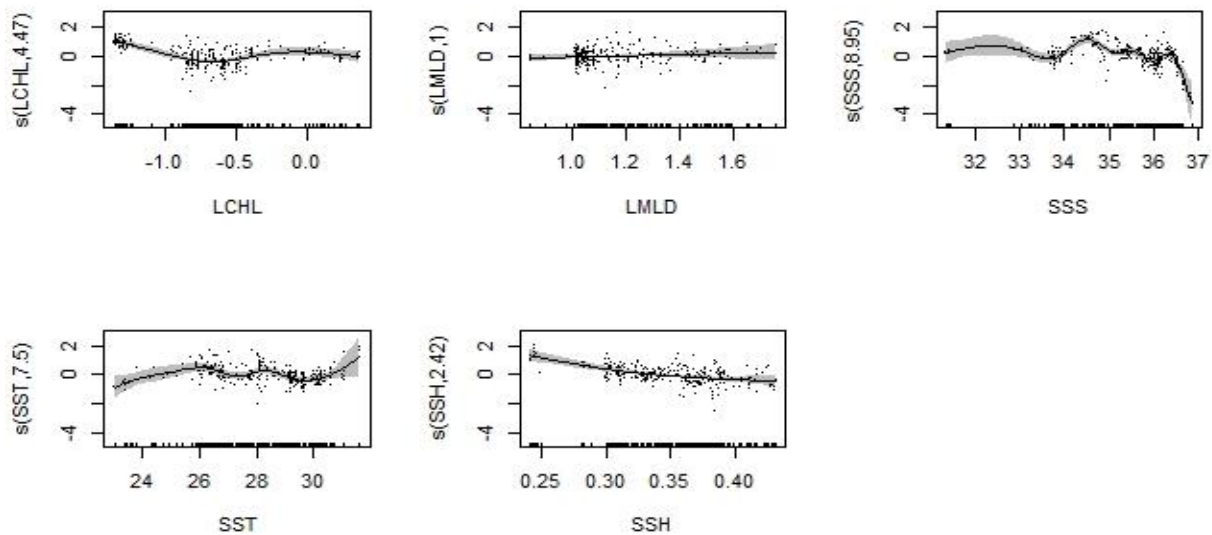
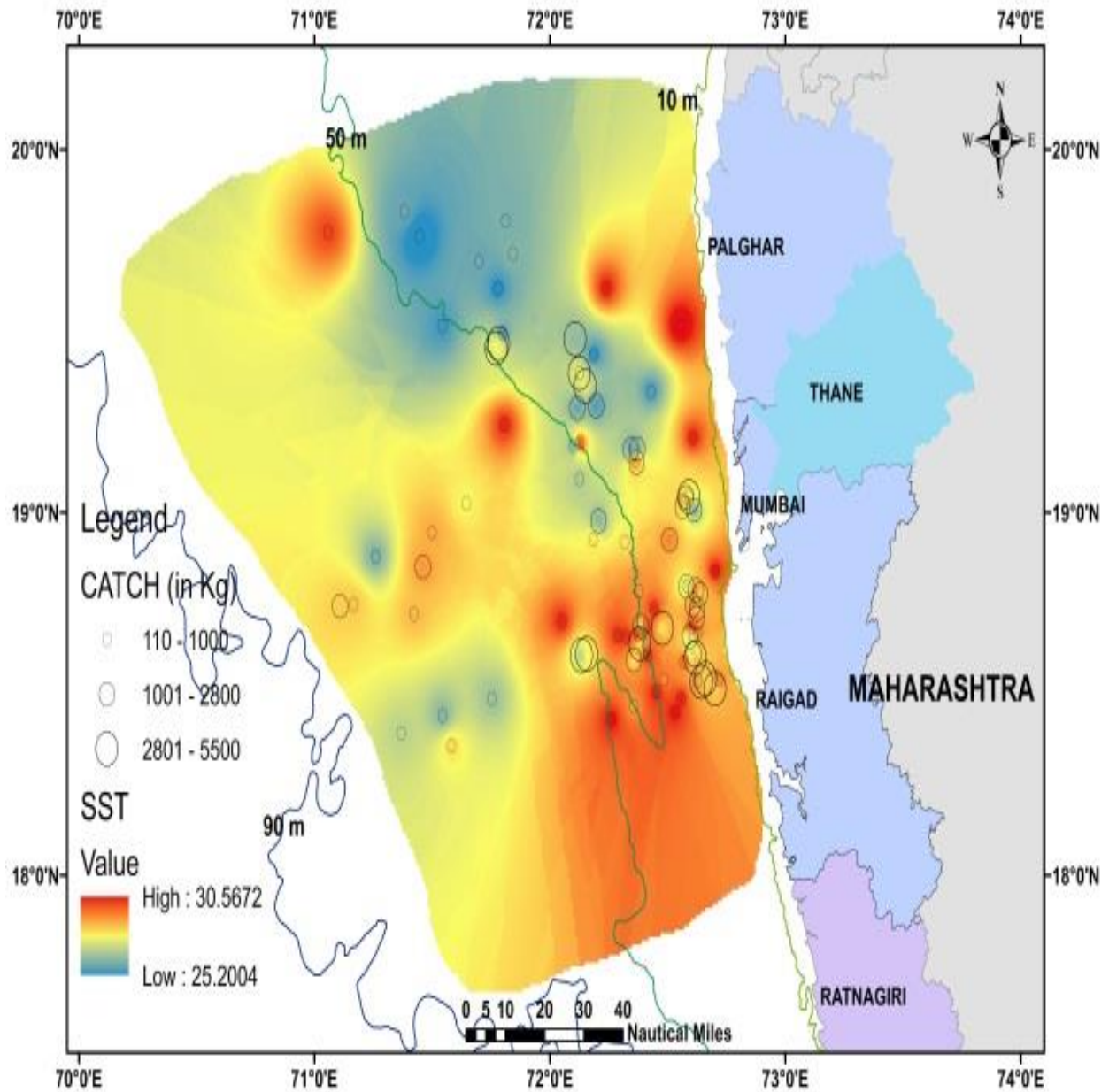


Figure 17: GAM plots for showing the effect of environmental parameters on *Rastrelliger kanagurta* (Cuvier, 1817) catch during 2017-2019

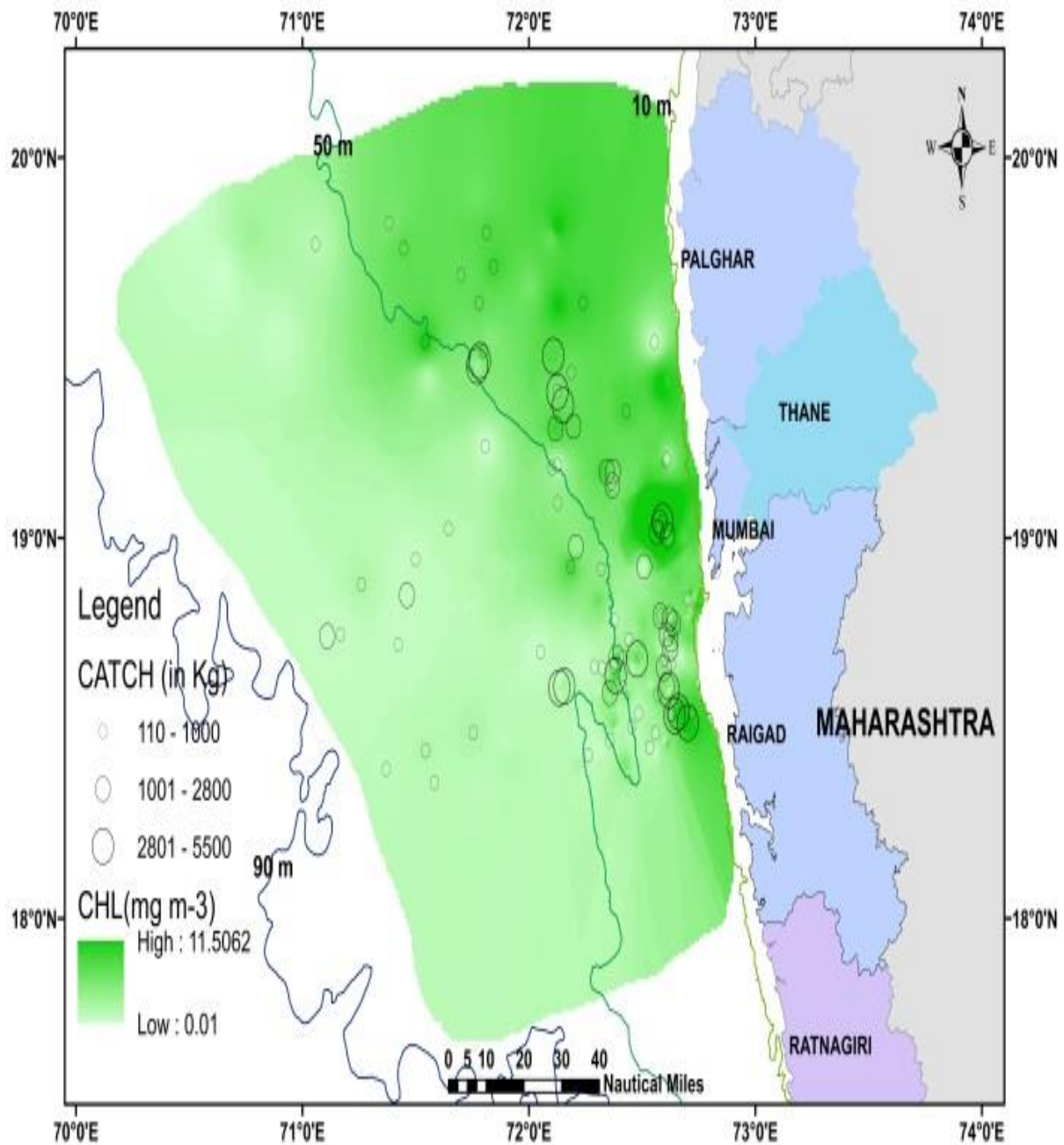
It shows the response to the variable, the relationship with predictor variable is non-linear. That is reason the GAM is best for predicting the response on non-linear relationship.

4.1.2.4. Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) catch with Environmental Variables during 2017-2019.

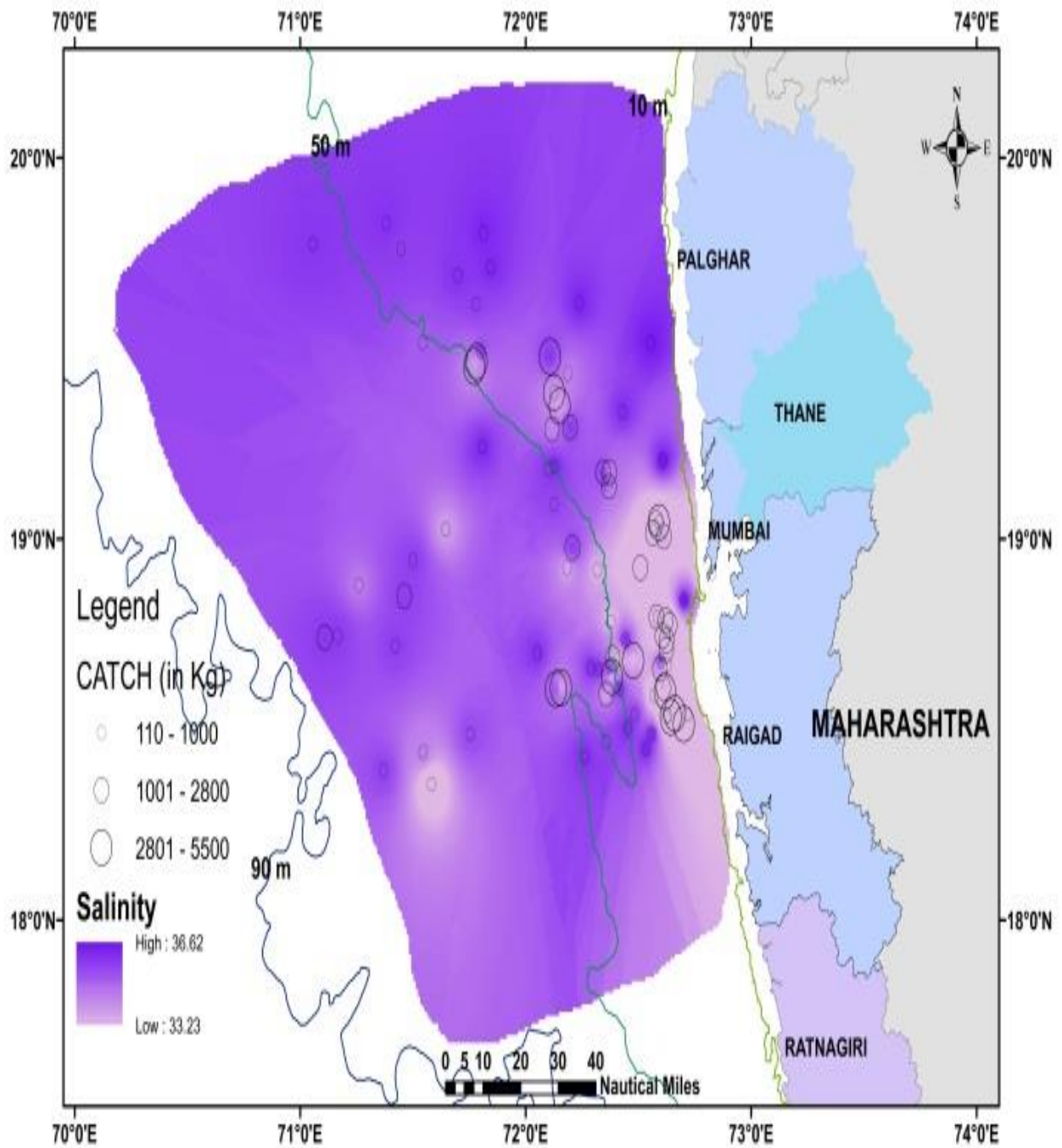
Satellite image retrieved from the sensor were used to produce the mean annual image, which used to make distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) with environmental variables in Mumbai coast during 2017-2019.



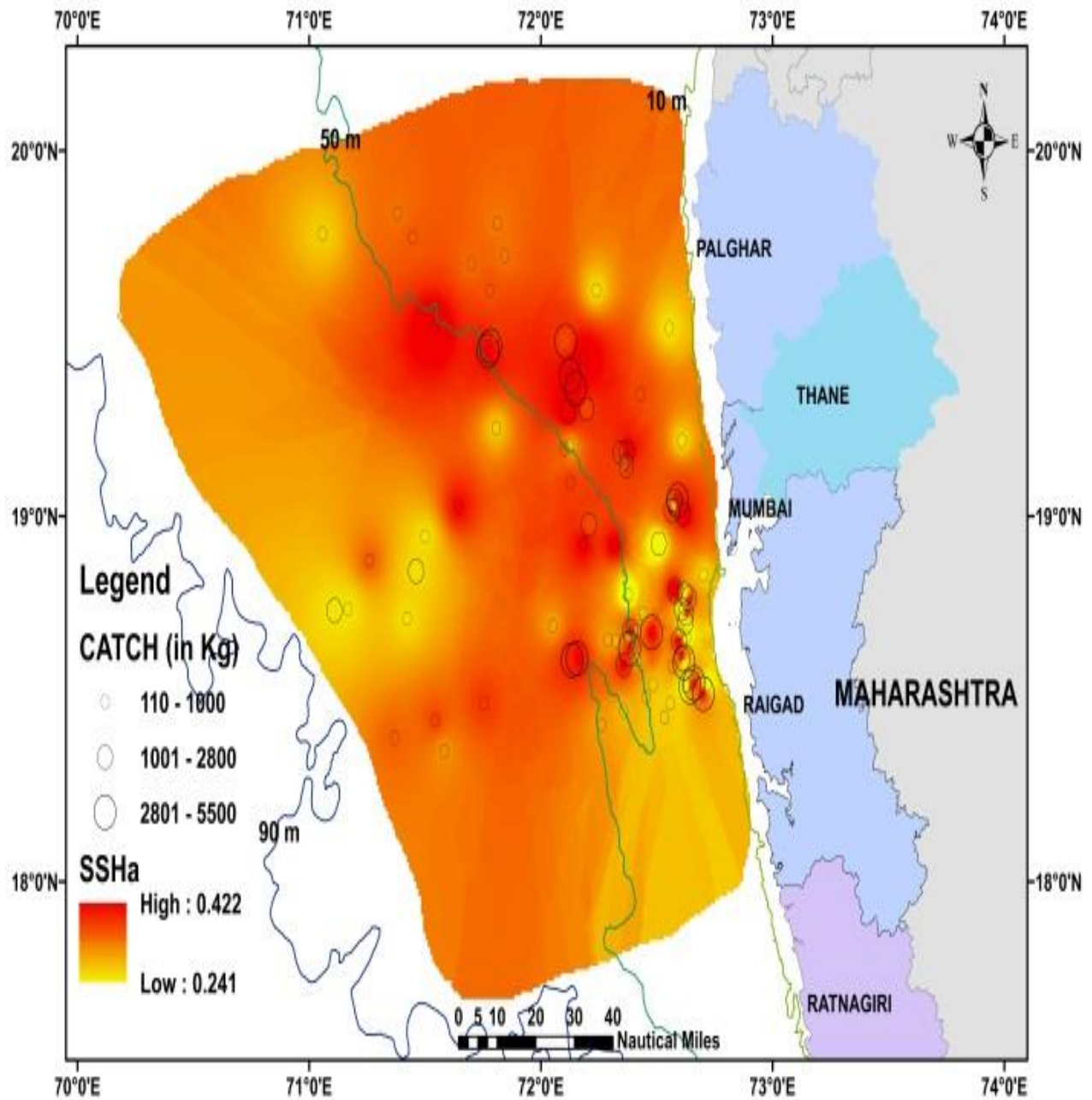
Map 2: Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) with Sea Surface Temperature in Mumbai coast during 2017-2019



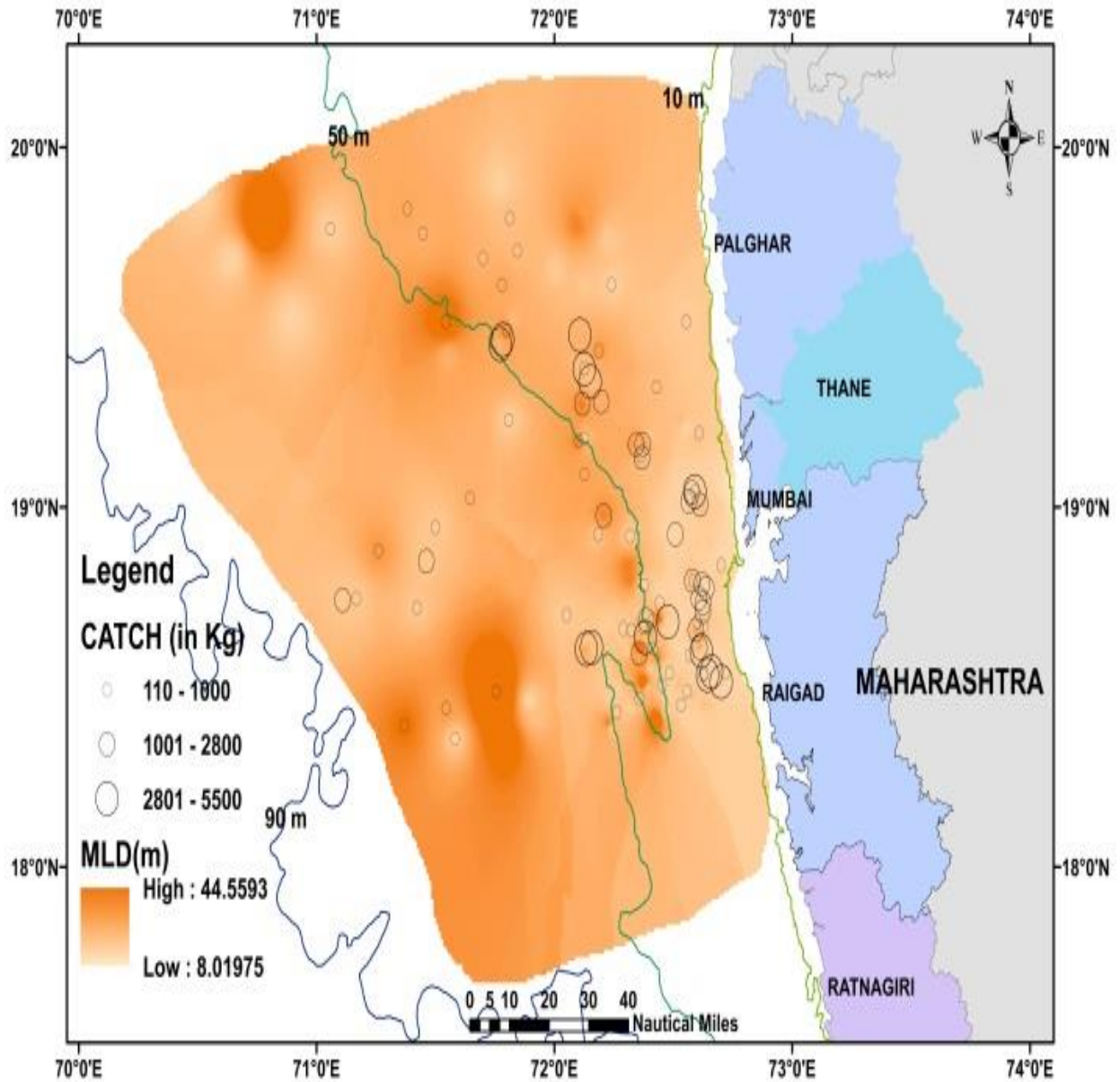
Map 3: Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) with Chlorophyll-a Concentration (CHL-a) in Mumbai coast during 2017-2019



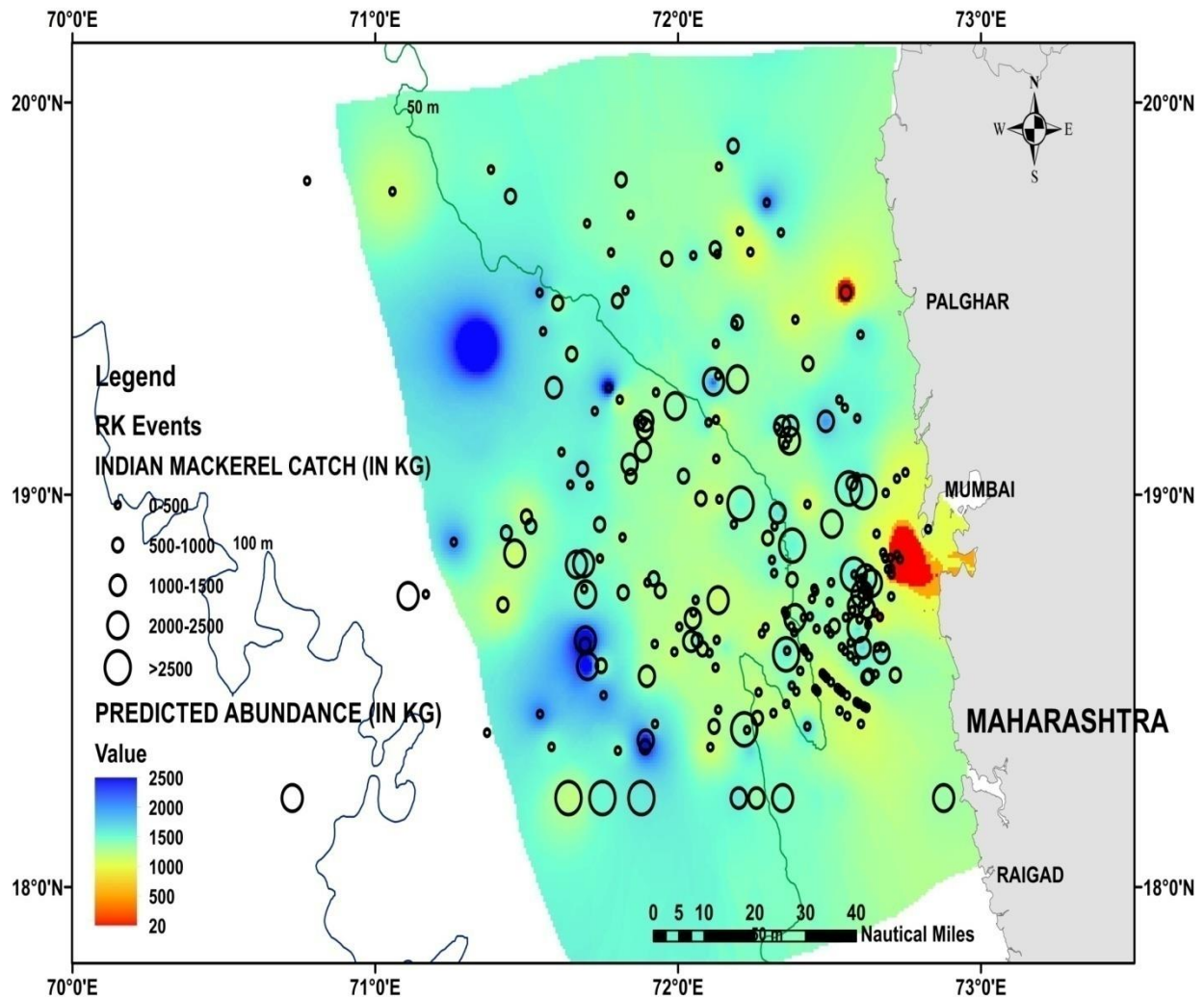
Map 4: Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) with Sea Surface Salinity (SSS) in Mumbai coast during 2017-2019



Map 5: Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) with Sea Surface Height (SSH) in Mumbai coast during 2017-2019



Map 6: Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) with Mixed Layer Depth (MLD) in Mumbai coast during 2017-2019



Map 7: Distribution map of *Rastrelliger kanagurta* (Cuvier, 1817) based on essential habitat preference in Mumbai coast during 2017-2019

Indian Mackerel distribution map generated based on the essential habitat preference to predictor variable (Chl-a, SST...etc) through GAM modeling. The circle are the observed catch overlay on the predict map which shows good result.

4.2. *Sepia elliptica* (Hoyle, 1885)

4.2.1. Catch and Environmental parameters:

4.2.1.1. Catch per Hour (CPH) variability of *Sepia elliptica* (Hoyle, 1885):

The average Catch per Hour (CPH) of Ovalbone Cuttlefish has been estimated to be 3.5 kg/hr from November 2017 to March 2019. Highest CPH was observed during post-monsoon season mainly during November (i.e., 10 kg/hr). Moderate CPH of *Sepia elliptica* (i.e., >3 kg/hr) observed in December. Catch per Hour (CPH) lower than 3 kg/hr observed during other months (Figure 18).

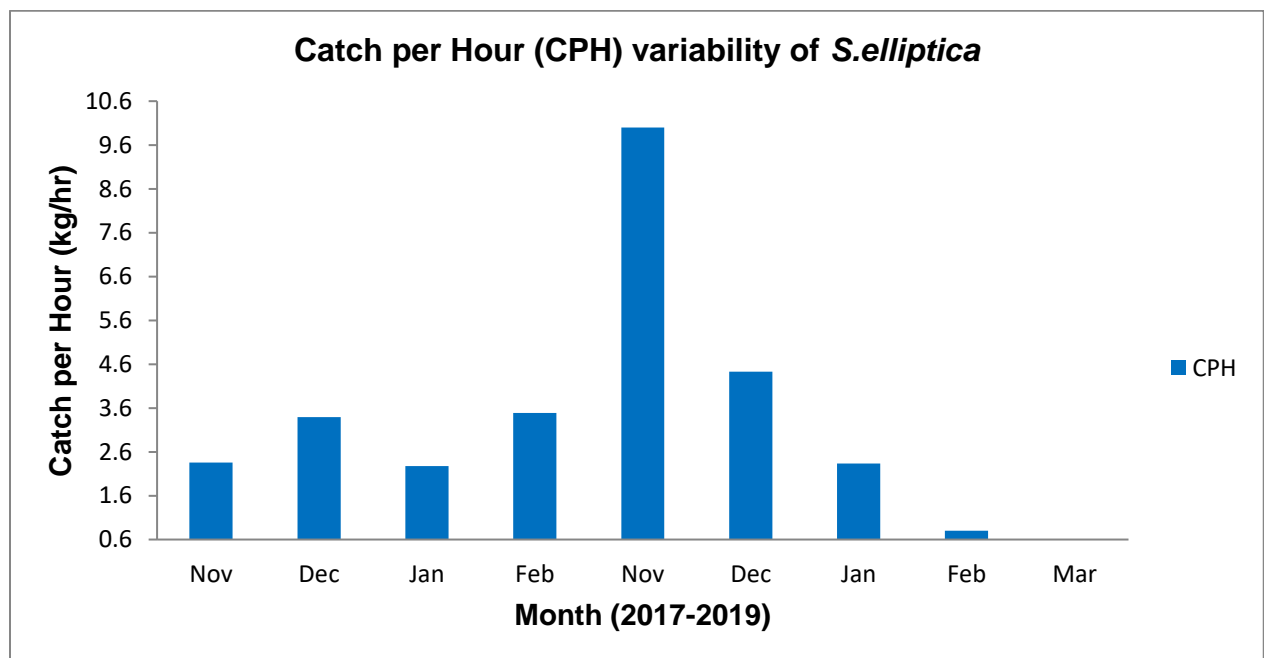
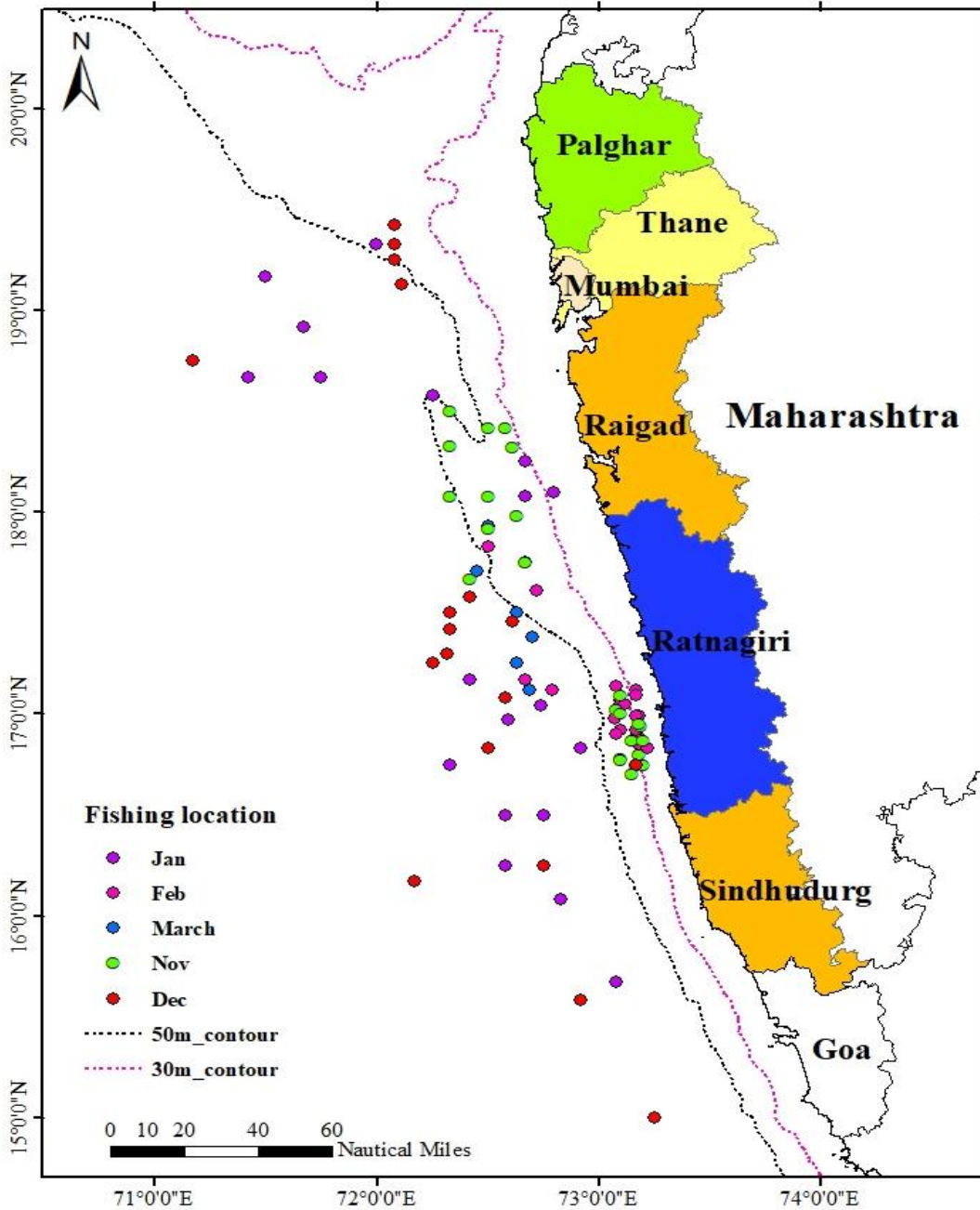


Figure 18: Average Catch per Hour (CPH) for *Sepia elliptica* (Hoyle, 1885) during 2017-2019

4.2.1.2. Fishing extent for *Sepia elliptica* (Hoyle, 1885):

In the present study, for ovalbone Cuttlefish ninety fishing location has been recorded during 2017-2019 from the study area (Map 8). The abundance of

Ovalbone Cuttlefish has recorded between 15° and 19.42° N latitude and 71.18° to 73.20° E longitudes during 2017-2019.



Map 8: *Sepia elliptica* (Hoyle, 1885) fishing location from the study area during 2017-2019

4.2.1.3. Temperature (SST and SBT):

Sea Surface Temperature data has been extracted from MODIS (i.e. SSTM) and Copernicus Marine Environment Monitoring Service (i.e. SSTC). From the recorded Sea Surface Temperature (SST) of Mumbai waters (2017-2019) it has been found that maximum temperature i.e. 29°C mainly occurred during November (Figure 19) and showed a good significant correlation ($r= 0.76723$, $p= 0.01581$) with the catches of Ovalbone Cuttlefish (Figure 22). Maximum Sea Bottom Temperature (SBT) recorded in the range of 26.7°C to 27.4°C in January and February (Figure 21). The minimum Sea Bottom Temperature was 22.9°C recorded in December. It was found that Sea Bottom Temperature (SBT) ($r= 0.2371$, $p= 0.5389$) showed relatively less significant correlation with the catches of Ovalbone Cuttlefish (Figure 22).

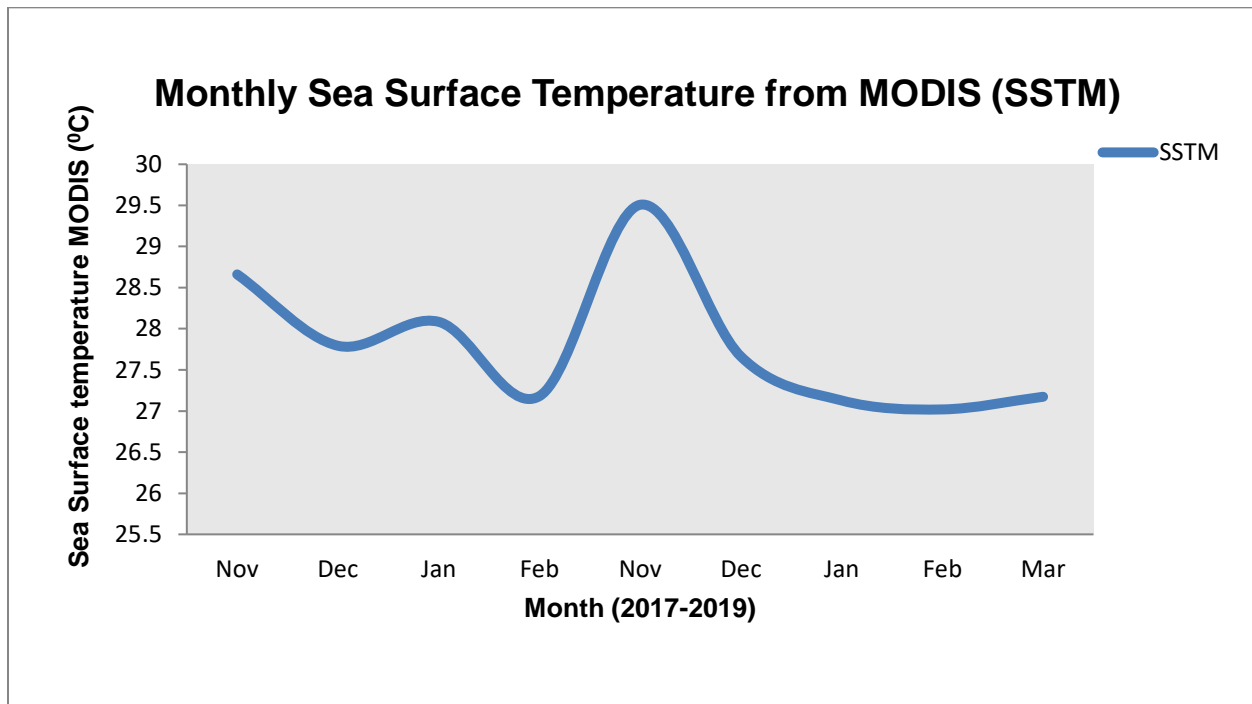


Figure 19: Monthly Variations of Sea Surface Temperature from MODIS (SSTM) of Mumbai Waters during 2017 to 2019

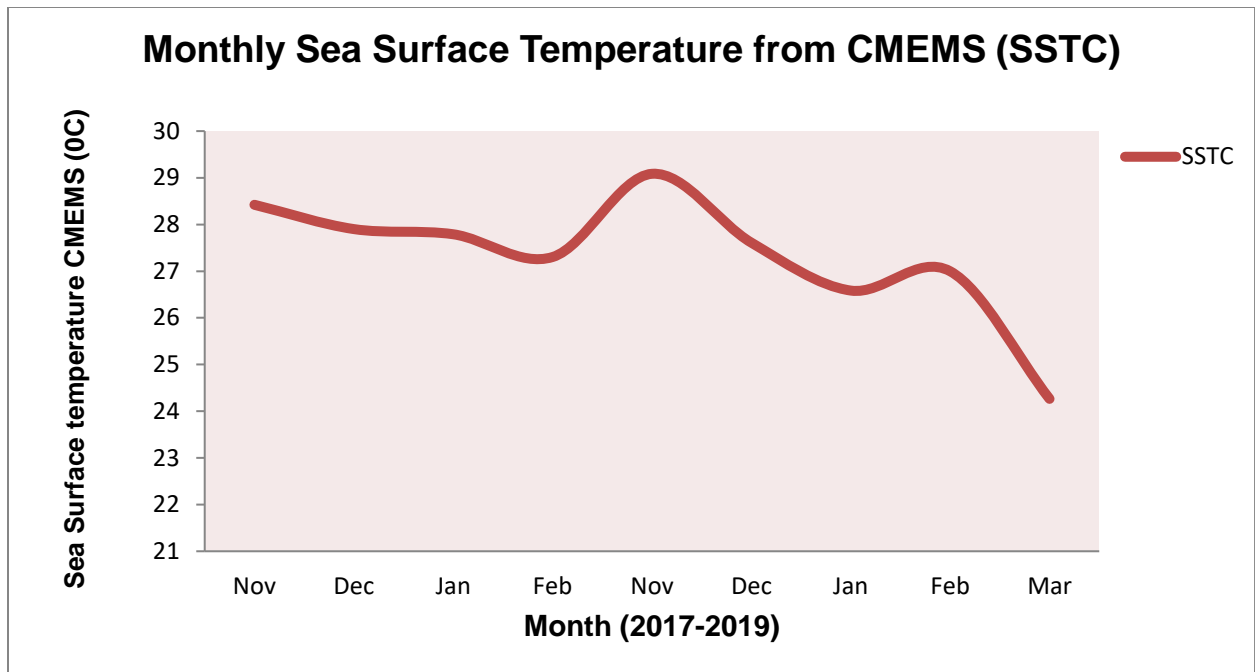


Figure 20: Monthly Variations of Sea Surface Temperature from CMEMS (SSTC) of Mumbai Waters during 2017 to 2019

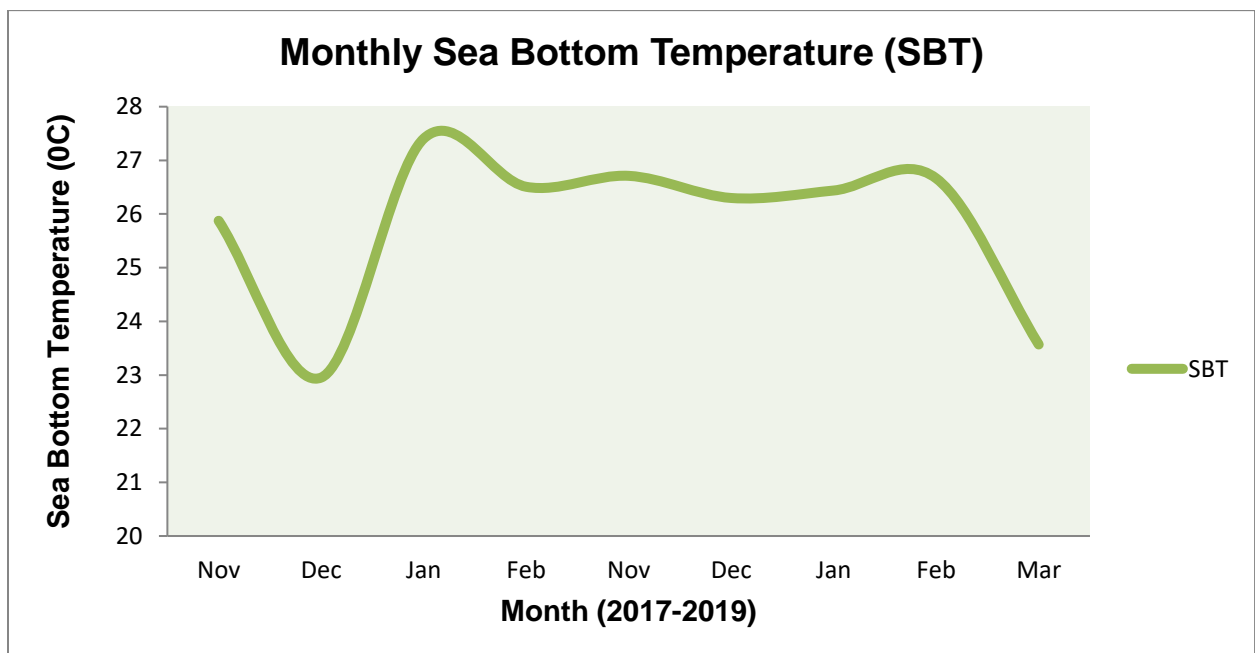


Figure 21: Monthly Variations of Sea Bottom Temperature (SBT) of Mumbai Waters during 2017 to 2019

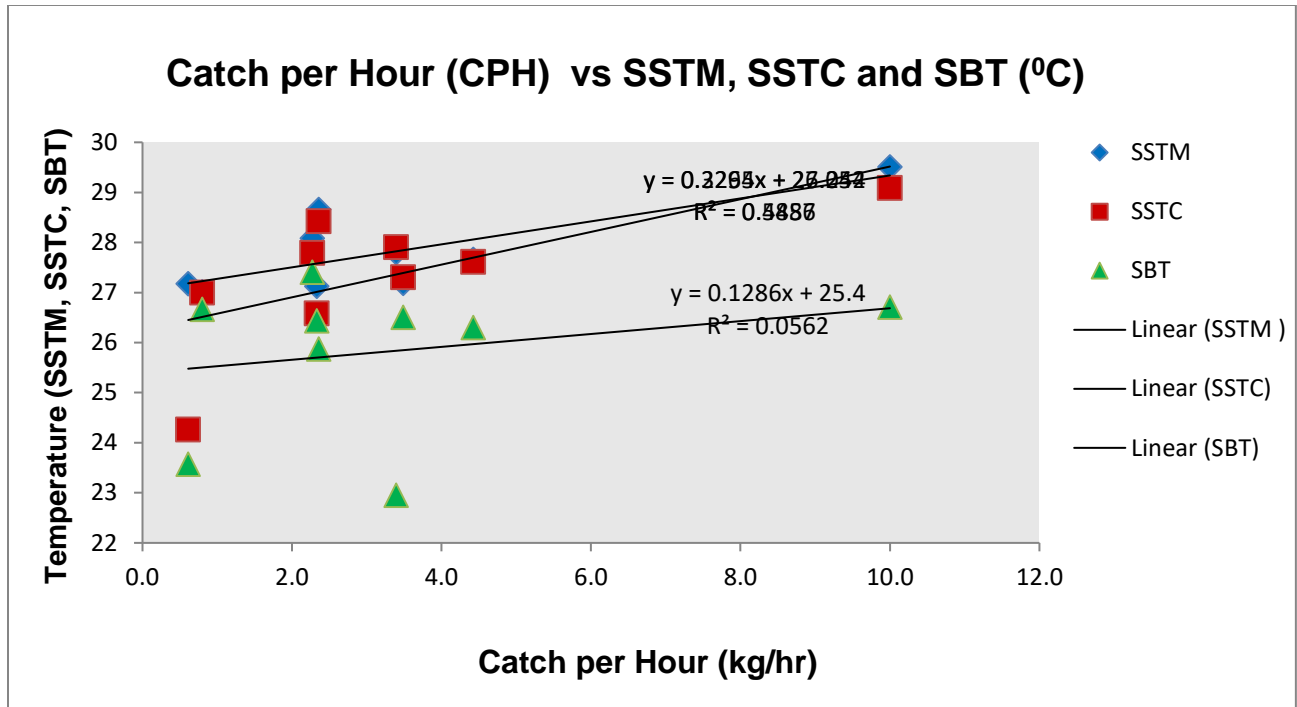


Figure 22: Linear Relationship of Ovalbone Cuttlefish with Sea Surface Temperature (SSTM and SSTC) and Sea Bottom Temperature (SBT) of Mumbai Waters during 2017 to 2019

4.2.1.4. Chlorophyll-a Concentration (Chl-a):

The present study used the Chlorophyll-a concentration data from MODIS (i.e. CHLM) and Copernicus Marine Environment Monitoring Service (i.e. CHLC) simultaneously. It was observed that during December and January the maximum Chlorophyll-a Concentration (Chl-a) through CHLM=2.61 mg/m³ and CHLC= 1.08 mg/m³ while the minimum concentration was found in November i.e. CHLM=0.6 mg/m³ and CHLC= 0.05 mg/m³) (Figure 23 and Figure 24). In the present study chlorophyll concentration thus shows a lesser significant relationship (r= 0.47805, p= 0.19304) with the Ovalbone Cuttlefish catches (Figure 25).

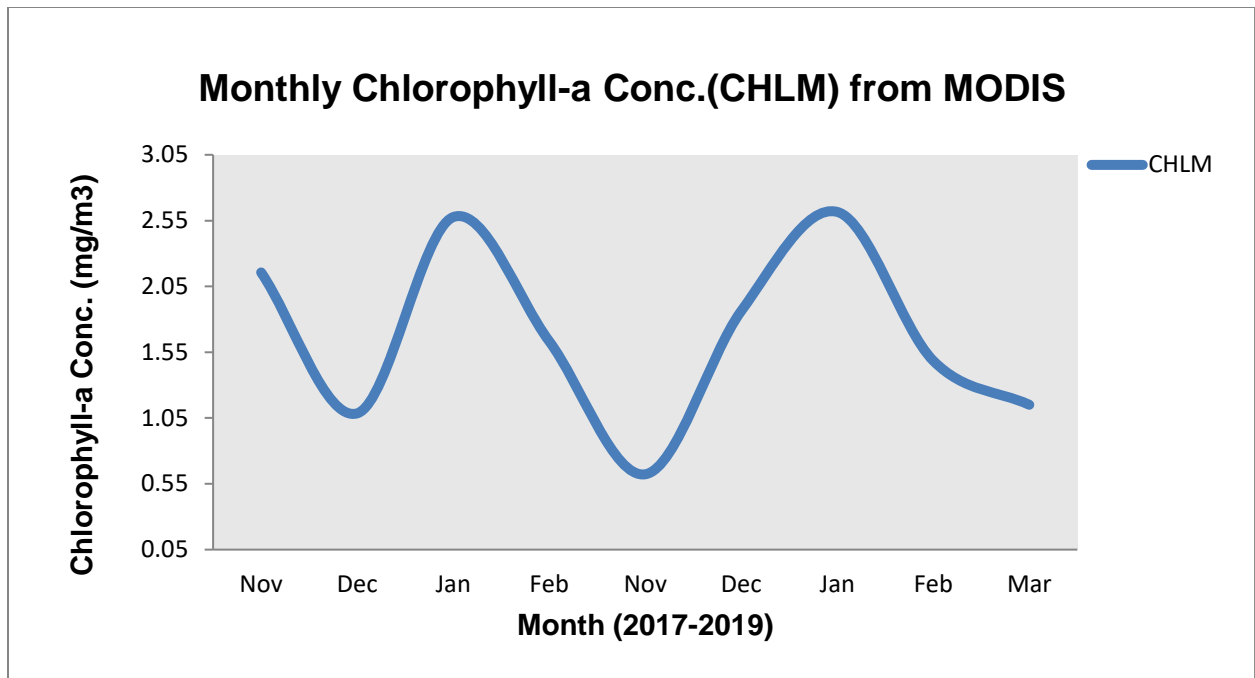


Figure 23: Monthly Variations of Chlorophyll-a Conc. (CHLM) from MODIS of Mumbai Waters during 2017 to 2019

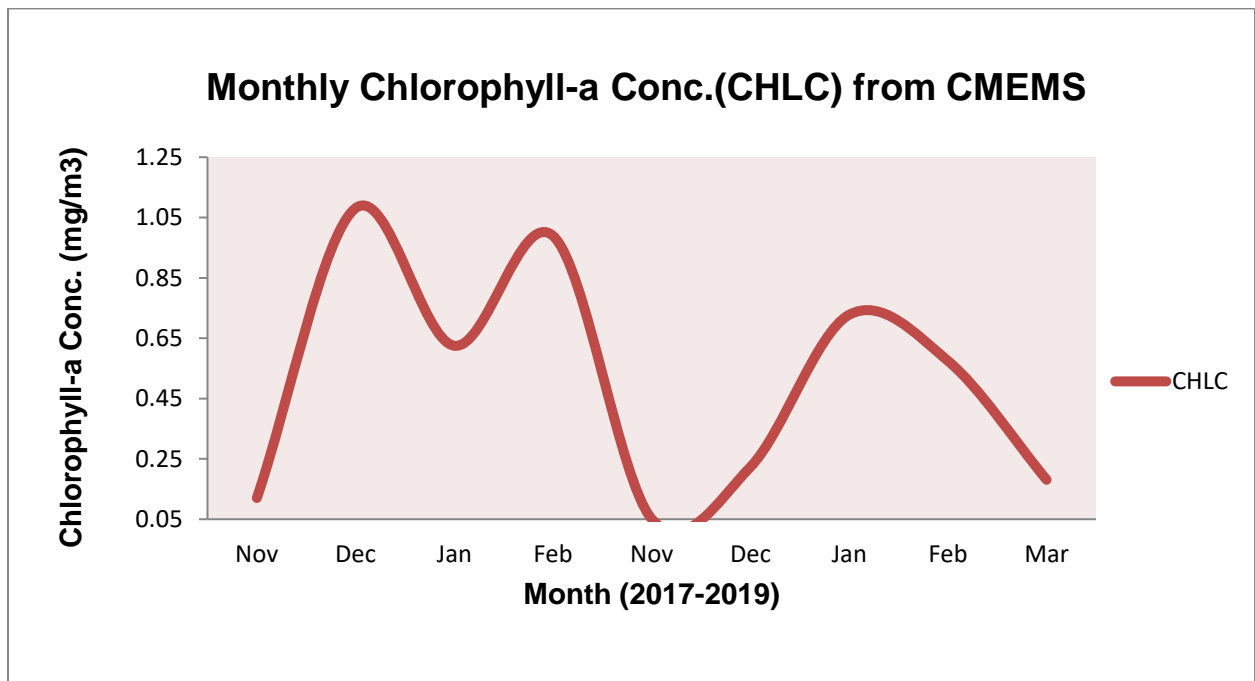


Figure 24: Monthly Variations of Chlorophyll-a Conc. (CHLC) from CMEMS of Mumbai Waters during 2017 to 2019

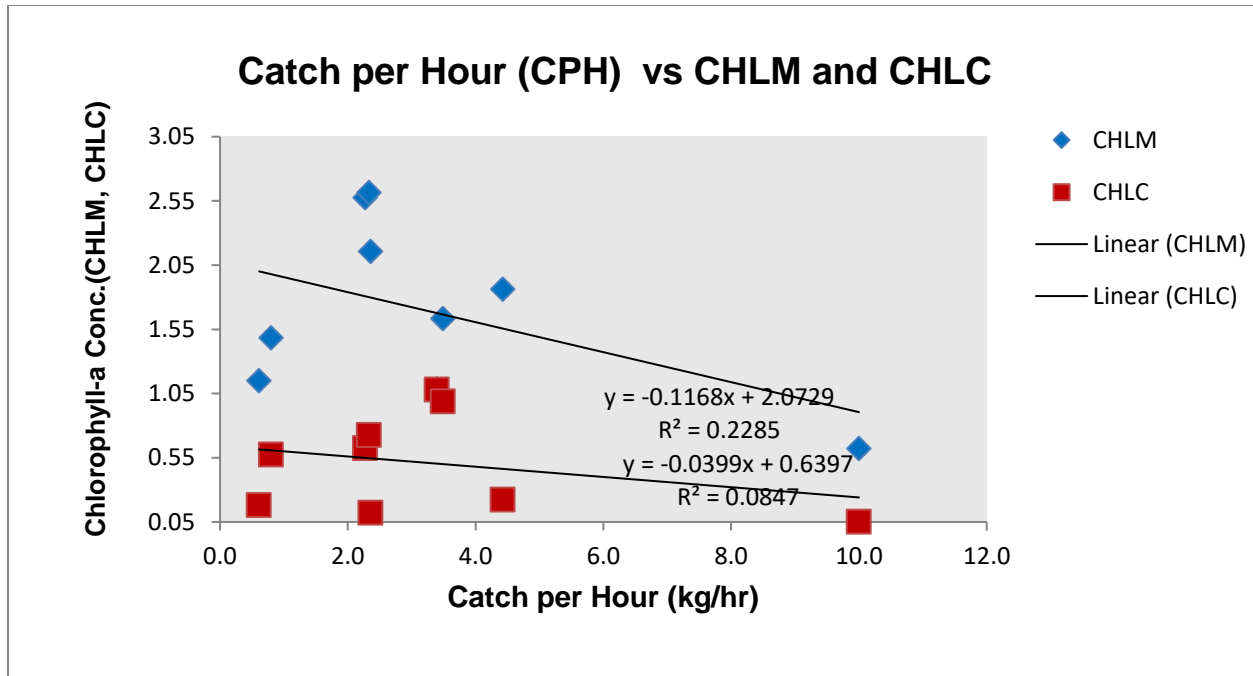


Figure 25: Linear Relationship of Ovalbone Cuttlefish catches with Chlorophyll-a Concentration (CHLM and CHLC) of Mumbai Waters during 2017 to 2019

4.2.1.5. Sea Surface Salinity (SSS):

During 2017-2019, the average Sea Surface Salinity (SSS) of Mumbai waters ranged from 31.06 to 35.69 ppt. The maximum Sea Surface Salinity (SSS) mainly occurred during January-February and minimum in March during the study period (Figure 26). The Sea Surface Salinity shows the less significant relationship ($r=0.36232$, $p= 0.33792$) with Ovalbone Cuttlefish catches (Figure 27).

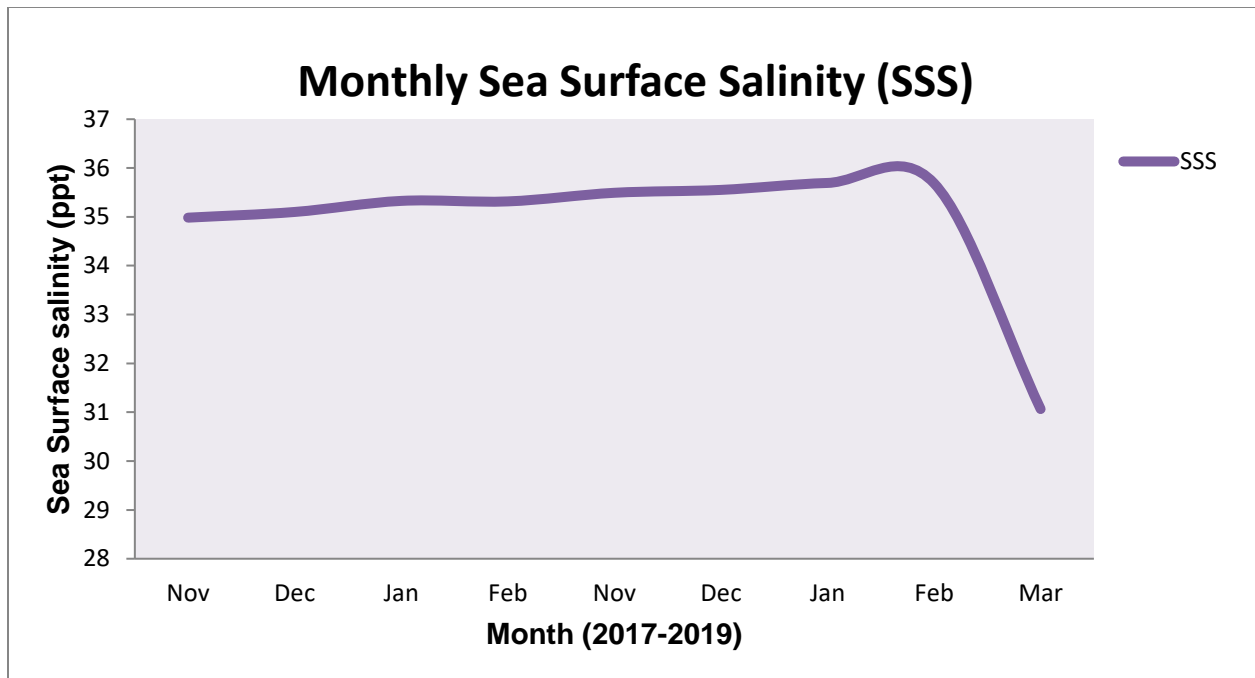


Figure 26: Monthly Variations of Sea Surface Salinity (SSS) of Mumbai Waters during 2017 to 2019

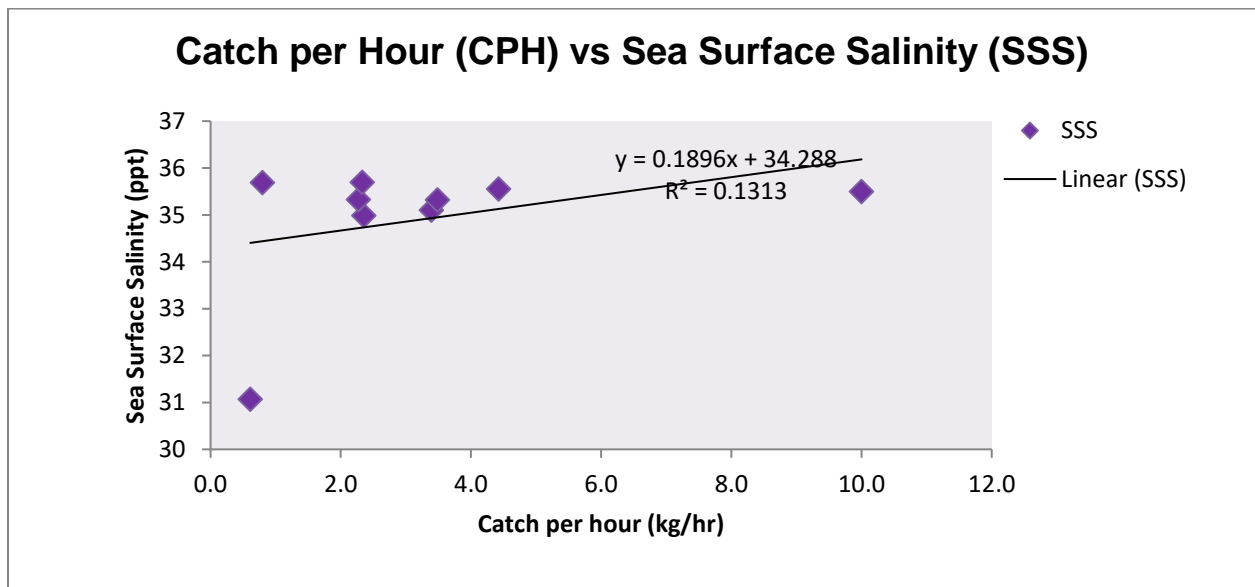


Figure 27: Linear Relationship of Ovalbone Cuttlefish catches with Sea Surface Salinity (SSS) of Mumbai Waters during 2017 to 2019

4.2.1.6. Sea Surface Height (SSH):

The average Sea Surface Height (SSH) of Mumbai water ranges between 31cm to 41cm during 2017 -2019. In the present study, the maximum SSH observed in January and minimum Sea Surface Height (SSH) mainly occurred during March (Figure 28). Sea Surface Height (SSH) show less significant relationship ($r= 0.1961$, $p= 0.6131$) with the Ovalbone Cuttlefish catches (Figure 29).

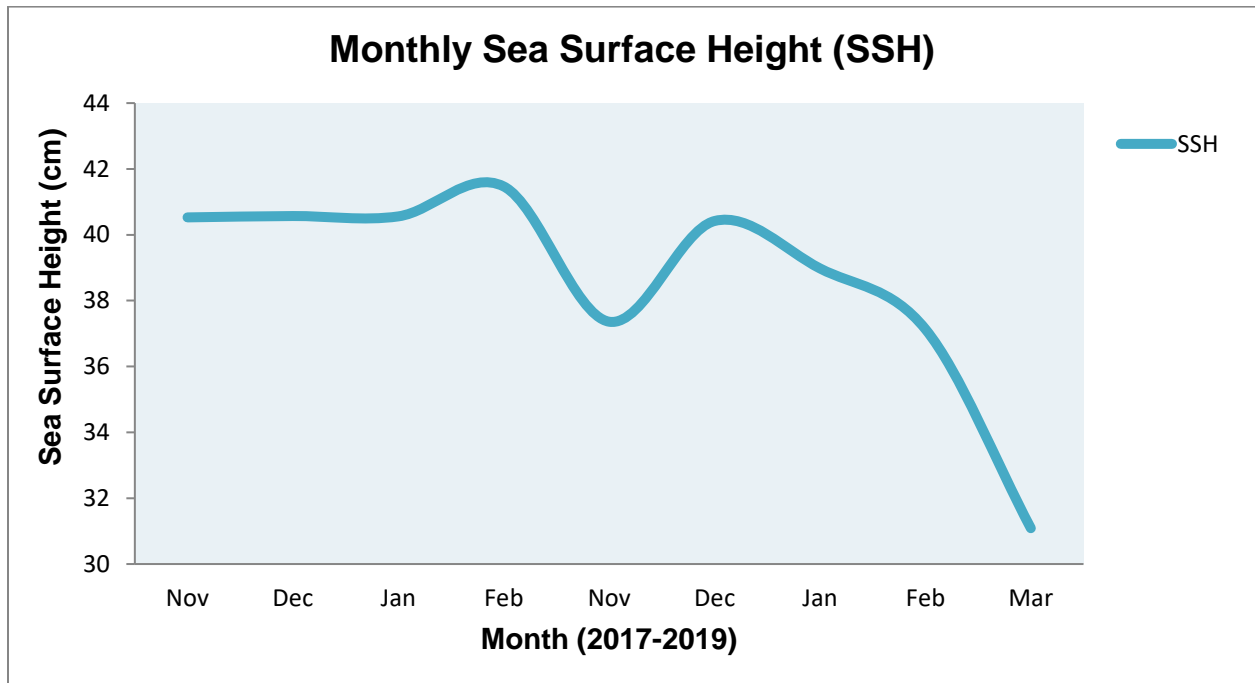


Figure 28: Monthly Variations of Sea Surface Height (SSH) of Mumbai Waters during 2017 to 2019

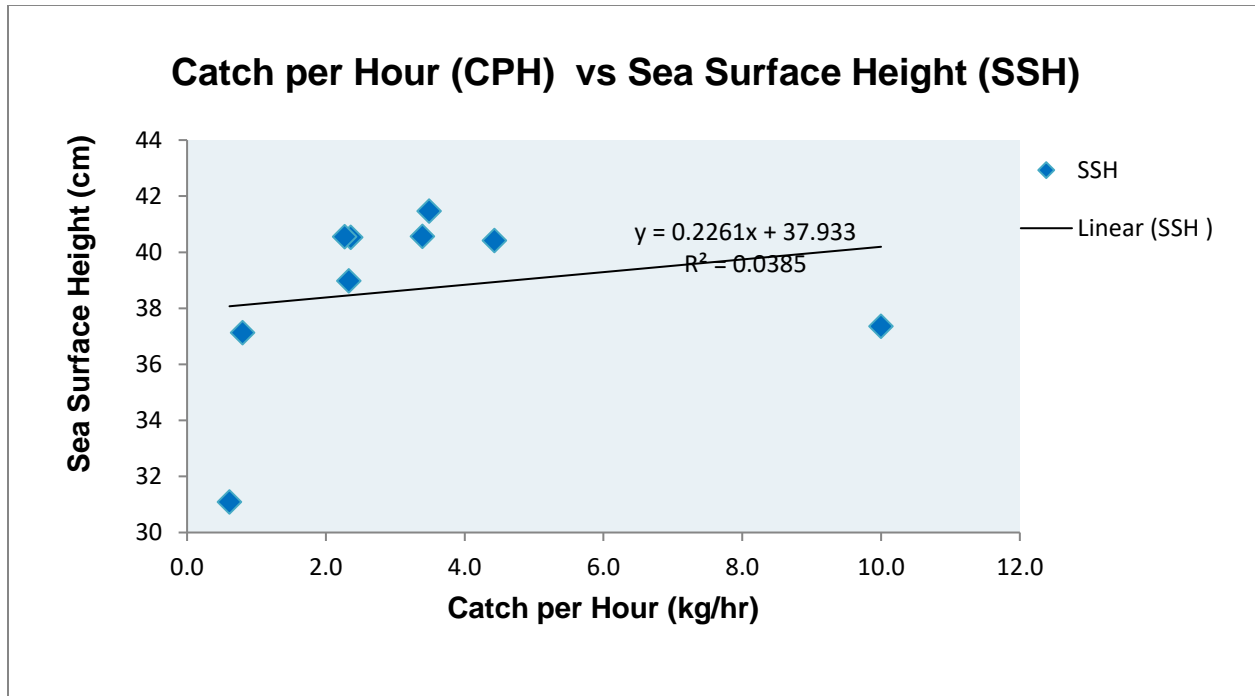


Figure 29: Linear Relationship of Ovalbone Cuttlefish catches with Sea Surface Height (SSH) of Mumbai Waters during 2017 to 2019

4.2.1.7. Mixed Layer Depth (MLD):

Mixed Layer Depth (MLD) of the Mumbai waters showed a great variation during 2017 -2019. From the recorded data mixed layer depth of Mumbai water is ranged from 10.58m to 32.74m. The maximum MLD observed during January 2019 and minimum in November 2017 (Figure 30). Mixed Layer Depth (MLD) does not shows any significant relationship ($r= 0.1356$, $p= 0.7278$) with Ovalbone Cuttlefish catch (Figure 31).

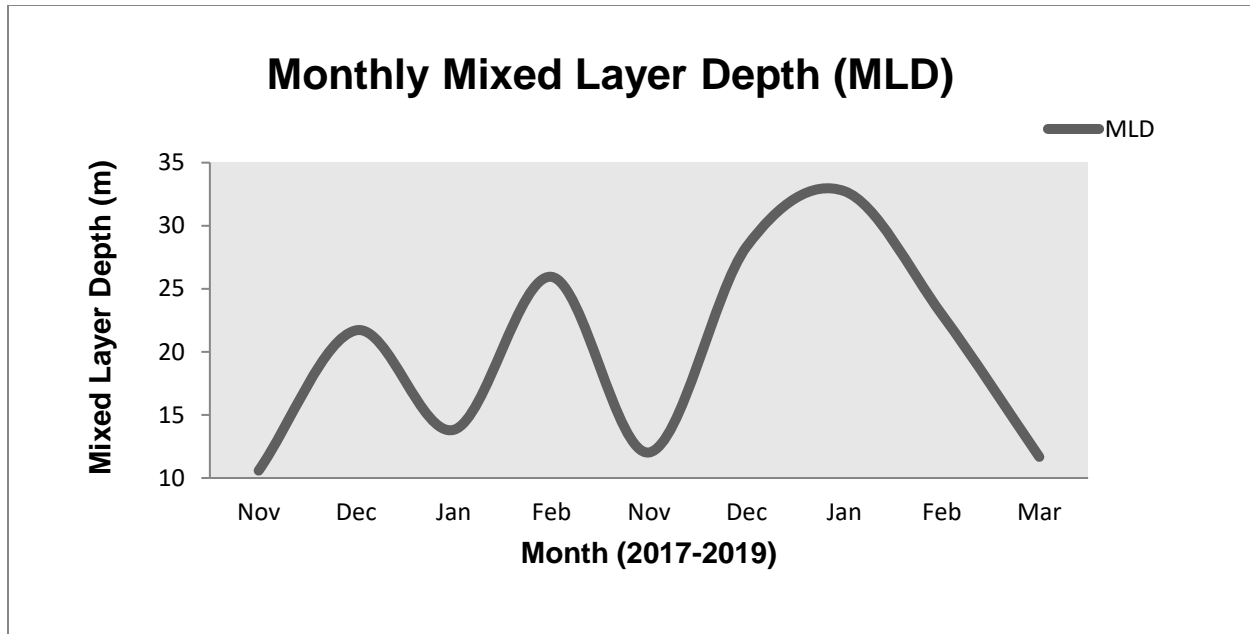


Figure 30: Monthly Variations of Sea Surface Height (SSH) of Mumbai Waters during 2017 to 2019

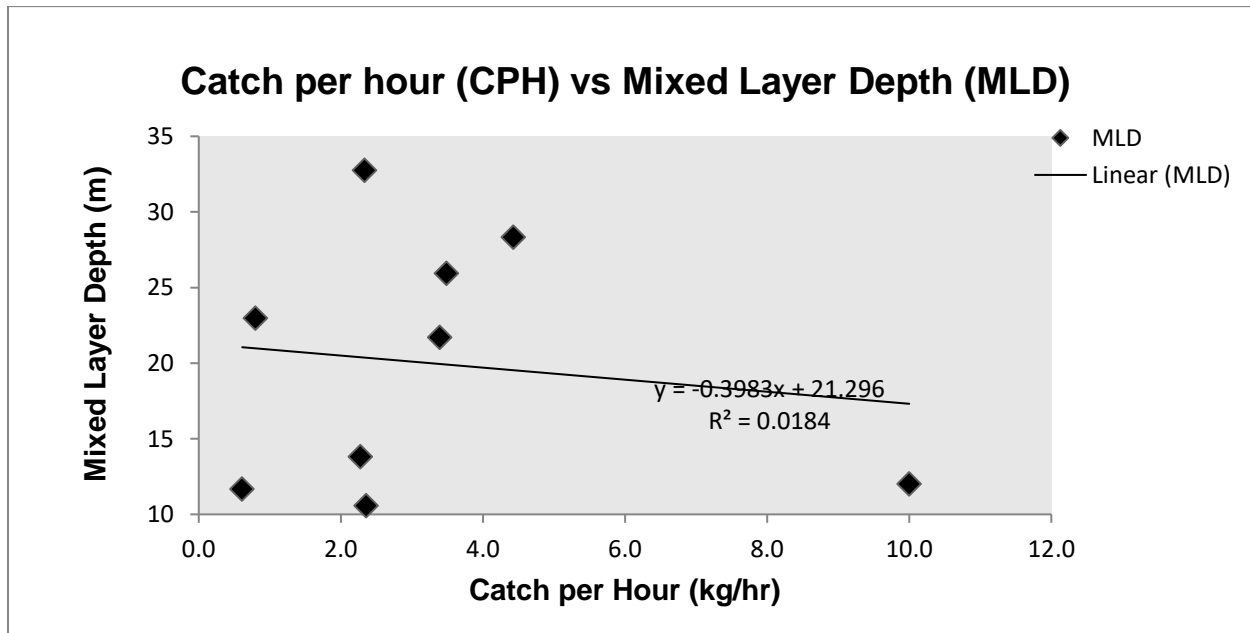


Figure 31: Linear Relationship of Ovalbone Cuttlefish catches with Mixed Layer Depth (MLD) of Mumbai Waters during 2017 to 2019

4.2.1.8. Surface Ocean Currents (OC):

Ocean Currents (OC) of Mumbai waters is minimum during January i.e. 0.02 m/sec and maximum during December i.e. 0.13 m/sec (Figure 32). Surface Ocean Currents (OC) does not shows any significant relationship ($r= 0.1647$, $p= 0.6720$) with the Ovalbone Cuttlefish catches (Figure 33).

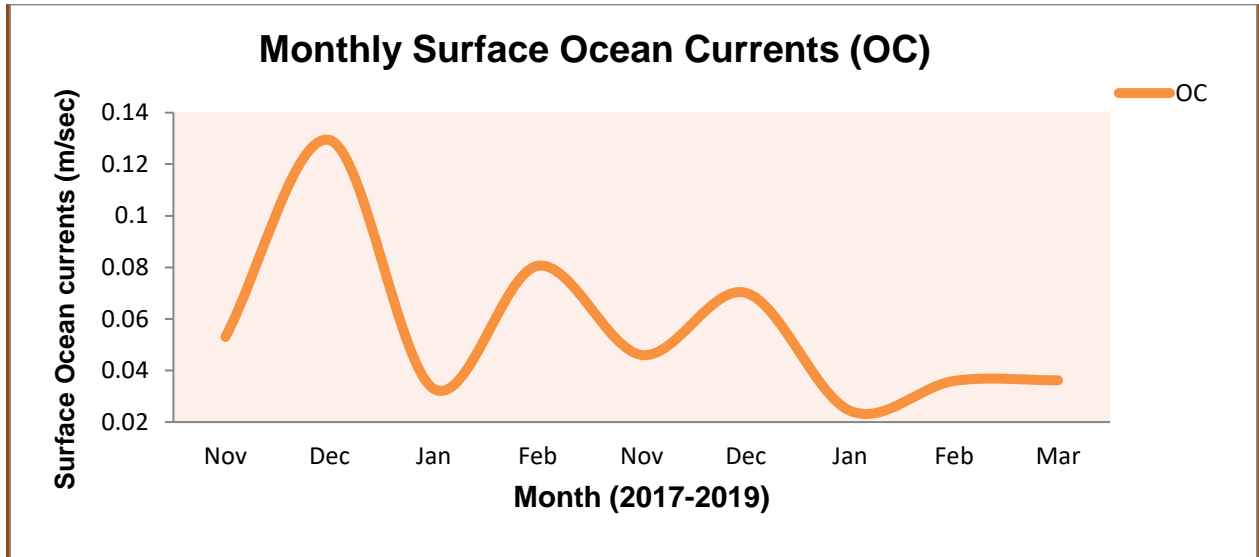


Figure 32: Monthly Variations of Surface Ocean Currents (OC) of Mumbai Waters during 2017 to 2019

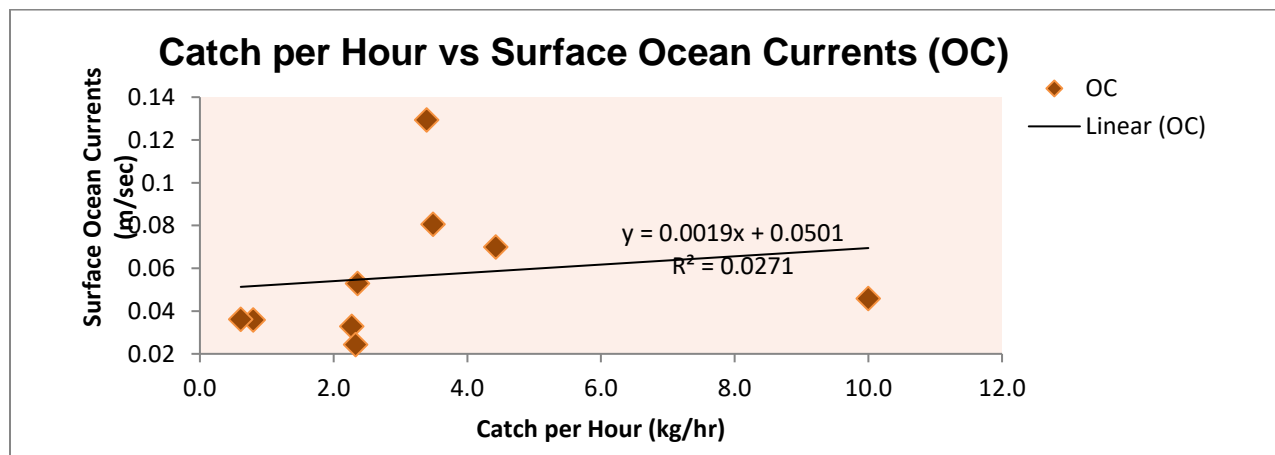
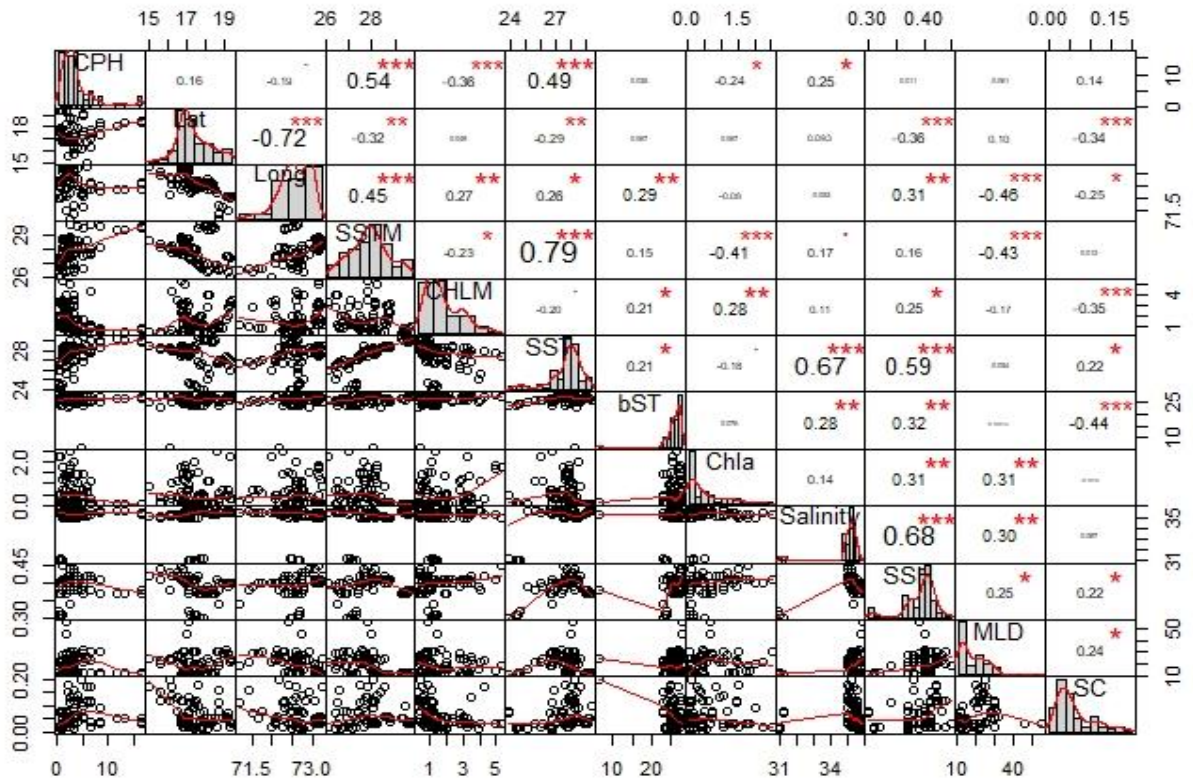


Figure 33: Linear Relationship of Ovalbone Cuttlefish catches with surface Ocean Currents (OC) of Mumbai Waters during 2017 to 2019

4.2.2. GAM output between Oval bone cuttlefish Catch and Environmental parameters

4.2.2.1. Scatter and Correlation plot between Catch per Hour (CPH) of Ovalbone Cuttlefish and Environmental variables:



Plot 3: Scatterplots (with r and p-value) between Catch per Hour (CPH) of Ovalbone Cuttlefish and Environmental variables during 2017 to 2019

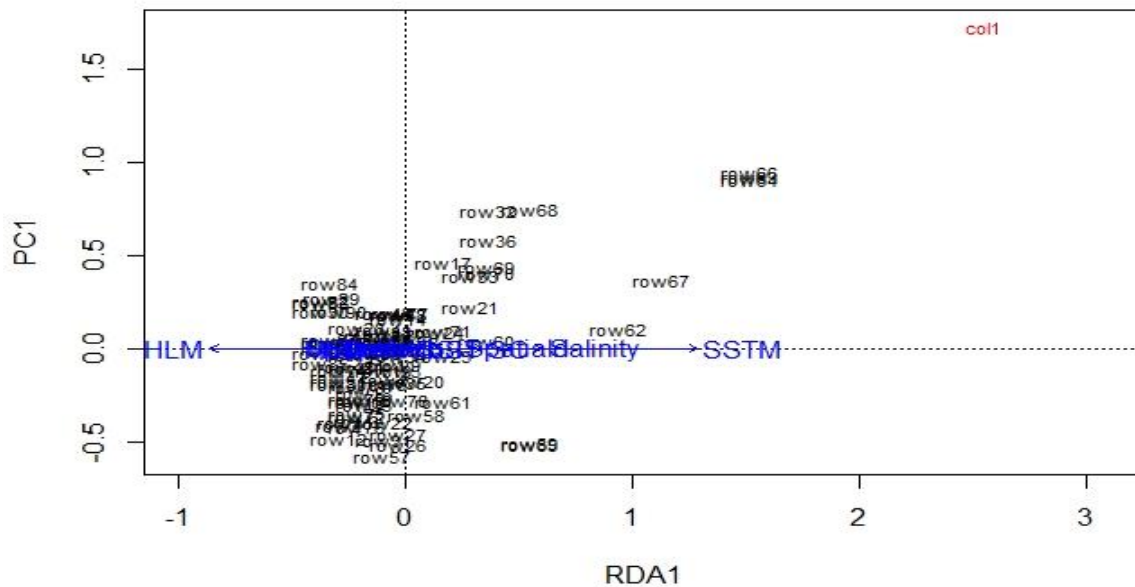
In statistical analysis Correlation coefficient (r = ranges between +1 and -1) mainly used to measures the strength and direction between two or more variables. Significance level (p-value = ranges between 0 and 1) used to weigh the strength of the variables in a set of data. The distribution of catch and environmental variables are shown on the diagonal (Plot 3). The bottom of the diagonal shows the bivariate scatter plots with a fitted line (red line). The top of the diagonal shows the value of correlation coefficient and significance level represent as stars. Value in upper diagonal is the correlation coefficient between different parameters and *S. elliptica*

abundance. Font sizes are proportional to the correlation coefficient (Plot 3). Each significance level is associated to a symbol according to p-values (0, 0.001, 0.01, 0.05, 0.1, 1) and symbols (“****”, “***”, “**”, “.”, “ ”), which meaning is “Not quite statistically Significant * quite statistically Significant ** Statistically Significant ***Very Statistically Significant **** Extremely Statistically Significant”.

In the above plot (Plot 3), Ovalbone Cuttlefish catches shows a good significant relationship with Sea Surface Temperature with a correlation coefficient value of 0.54 (SSTM) and 0.49 (SSTC) and a very strong uphill linear pattern. Ovalbone Cuttlefish catches also partially correlated ($r = 0.25$) with Sea Surface Salinity (SSS). This plot also shows that SST is highly correlated with Sea Surface Salinity (SSS, $r = 0.67$) and Sea Surface Height (SSH, $r = 0.59$). The Sea Surface Salinity (SSS) found to have a significant correlation ($r = 0.69$) with Sea Surface Height (SSH).

Thus correlation plot indicates how each parameter affecting the abundance and habitat preference of *Sepia elliptica*. Results correlation plots direct to fit additive model in order to delineate habitat preference of *Sepia elliptica*.

4.2.2.2. Redundancy Analysis (RDA) results:



Plot 4: RDA correlation biplot. Species variables are CPH: Catch per Hour; Environmental variables are Lat: Latitude; Long: Longitude; SSTM= Sea Surface Temperature; Salinity: Sea Surface Salinity; CHLM: Chlorophyll-a concentration from Mumbai water Ovalbone Cuttlefish fishing grounds (2017-2019)

In the above plot, RDA results reveal the plausible relationship between Ovalbone cuttlefish and environmental variables in the canonical axis. Latitude, Longitude, Sea Surface Temperature (SSTM) and Sea Surface Salinity (SSS) are the most important variables on the canonical axis (Plot 4). These environmental variables showed a positive effect on Ovalbone cuttlefish occurrence. All the other variables do not have much effect on Ovalbone cuttlefish abundance. Latitude and longitude has been taken as secondary variables because as their effect can be hidden in other environmental parameters.

4.2.2.3. Generalized Additive Modelling (GAM) for *Sepia elliptica* (Hoyle, 1885):

A GAM using the Gaussian distribution and identity link function were used to relate *Sepia elliptica* catch per hour (CPH) data and the explanatory environmental variables. To find the optimal set of explanatory environmental variables, in all 26 GAM model were fitted with a different combination of explanatory variables and basic dimension (k). The best fit of GAM i.e. se26, was obtained from the Akaike information criterion (AIC) estimator (Table 5) Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for best GAM fit model selection. The lower the AIC value, the better it is, and cross-validation was used to estimate the optimal degrees of freedom for each smoother. The GAM identified Sea Surface Temperature, Salinity and Latitude-Longitude as the best explanatory variable (model se26).

Table 5: GAM models fitted for *Sepia elliptica* (Hoyle, 1885) data

Model	Equation	AIC
se1	$CPH \sim s(Lat, k=-1) + s(Long, k=-1) + s(SSTM, k=-1) + s(CHLM, k=-1) + s(SST, k=-1) + s(Chla, k=-1) + s(Salinity, k=-1) + s(MLD, k=-1)$	377.6620
se2	$CPH \sim s(Lat, k=8) + s(Long, k=8) + s(SST, k=10) + s(bST, k=10) + s(Chla, k=1) + s(Salinity, k=-1) + s(MLD, k=-1) + s(SC, k=-1)$	381.9391
se3	$CPH \sim s(Lat, Long, k=10) + s(SSTM, k=10) + s(CHLM, k=-10) + s(SST, bST, k=10) + s(Chla, k=1) + s(Salinity, k=-1) + s(MLD, k=-1) + s(SC, k=-1)$	392.1935
se4	$CPH \sim s(Lat, Long, k=30) + s(SSTM, k=10) + s(CHLM, k=-1) + s(SST, k=10) + s(Chla, k=-1) + s(Salinity, k=10)$	398.1298
se5	$CPH \sim s(Lat, Long, k=30) + s(SSTM, k=20) + s(CHLM, k=10) + s(Salinity, k=10) + s(MLD, k=10)$	396.8089
se6	$CPH \sim s(Lat, Long, k=30) + s(SST, k=10) + s(Chla, k=-1) + s(Salinity, k=10) + s(MLD, k=10) + s(SC, k=-1)$	366.8403
se7	$CPH \sim s(Lat, Long, k=30) + s(SSTM, k=20) + s(CHLM, k=10) + s(Salinity, k=10)$	380.0989
se8	$CPH \sim s(Lat, k=30) + s(SSTM, k=20) + s(Salinity, k=20)$	380.6662

se9	CPH~s(Lat,k=-1)+s(Long,k=-1)+s(SSTM,k=-1)+s(bST,k=-1)+s(Chla,k=-1)+s(Salinity,k=-1)+s(MLD,k=-1)+s(SC,k=-1)	394.6863
se10	CPH~s(Lat,k=-1)+s(Long,k=-1)+s(SSTM,k=-1)+s(CHLM,k=-1)+s(Salinity,k=-1)+s(MLD,k=-1)	381.9570
se11	CPH~s(Lat,k=-1)+s(SSTM,k=-1)+s(Salinity,k=-1)+s(MLD,k=-1)	383.0443
se12	CPH~s(Lat,k=-1)+s(SSTM,k=-1)+s(MLD,k=-1)	382.3995
se13	CPH~s(Lat,k=-1)+s(SST,k=-1)	380.8720
se14	CPH~s(Lat,k=30)+s(SSTM,k=20)	380.0896
se15	CPH~s(Lat,k=40)+s(SSTM,k=25)	380.2081
se16	CPH~s(Lat,k=50)+s(SSTM,k=30)	380.2122
se17	CPH~s(Lat,k=60)+s(SSTM,k=30)	380.2122
se18	CPH~s(Lat,k=60)+s(SSTM,k=30)	405.6181
se19	CPH~s(Lat, bs="cr",k=60)+s(SSTM, bs="cr",k=30)	380.3317
se20	CPH~s(Lat, bs="cr",k=60)+s(SST, bs="cr",k=10)+s(Salinity, bs="cr",k=10)+s(CHLM, bs="cr",k=10)	371.7521
se21	CPH ~ s(Long,Lat,k=60) + s(SSTM) + s(l(Salinity^.5))	295.7632
se22	CPH ~ s(Long,Lat,k=60) + s(SST) + s(l(Salinity^.5))	231.5548
se23	CPH~s(Lat, bs="cr",k=60)+s(l(SSTM^.5),k=30)	380.2433
se24	CPH~s(log(Lat), bs="cr",k=60)+s(log(SSTM),k=30)	380.9642
se25	CPH~s(Lat,k=60)+s(SSTM,k=20)+s(CHLM,k=10)	378.1880
se26	CPH ~ s(Long,Lat,k=70) + s(SST,k=-1) + s(l(Salinity^.5),k=-1)	230.1257

Below the best fit GAM i.e. se26 result has been shown;

The RMS GCV score gradient at convergence was 3.521577e-07.

The Hessian was positive definite. Model rank = 88 / 88

Basis dimension (k) checking results. Low p-value (k-index<1) may indicate that k is too low, especially if edf is close to k' (Table 6)

Table 6: Modeled GAM check results between *Sepia elliptica* (Hoyle, 1885) catches, Latitude, Longitude, SST and SSS during 2017-2019

Environmental Variables	k'	edf	k-index	P-value
s(Long,Lat)	69.00	59.72	1.42	1.00
s(SST)	9.00	5.77	1.03	0.54
s(I(Salinity^0.5))	9.00	1.00	1.07	0.68

Formula:

CPH ~ s (Long, Lat, k = 70) + s (SST, k = -1) + s (I(Salinity^0.5), k = -1)

Parametric coefficients:

Estimate Std. Error t value Pr (>|t|)

(Intercept) 3.54956 0.08557 41.48 <2e-16 ***

Here parametric estimate is for intercept. Interpretation is also as usual, but the spline is centered at zero, i.e. the intercept measures in this case the overall mean.

Table 7: Significance of smooth terms of best fit of GAM model *Sepia elliptica* (Hoyle, 1885)

Environmental Variables	edf	Ref.df	F	P-value
s(Long,Lat)	59.71	64.224	10.890	< 2e-16 ***
s(SST)	5.774	6.157	8.262	3.29e-05 ***
s(l(Salinity^0.5))	1.000	1.000	0.841	0.369

---Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.943 Deviance explained = 98.6%

GCV = 2.6345 Scale est. = 0.65895 n = 90

In the GAM analysis model R²-value is as usual the proportion of variance explained by the model. The Scale estimate is the variance of the residual.

The GAM analysis indicates that high distribution of Ovalbone cuttlefish related to latitude, longitude, sea surface temperature and sea surface salinity. GAM test indicated that SST and SSS had significant relationship with the *Sepia elliptica* distribution at $p < 0.001$ and $p < 0.05$ respectively (Table 7). SST has stronger influence compared to SSS suggesting greater influence on the distribution of *Sepia elliptica*. In the present study, in Mumbai region high abundances of Ovalbone Cuttlefish were located between 15° and 19.42° N latitude and 71.18° to 73.20° E longitudes, SSTs of between 28°C and 29.5°C and in the region of average Sea Surface Salinity 35.5 ppt. The abundance of Ovalbone Cuttlefish was recorded from this GAM formula visualization which cannot be done by any interpretation of coefficients or estimation of curve instead by plotting.

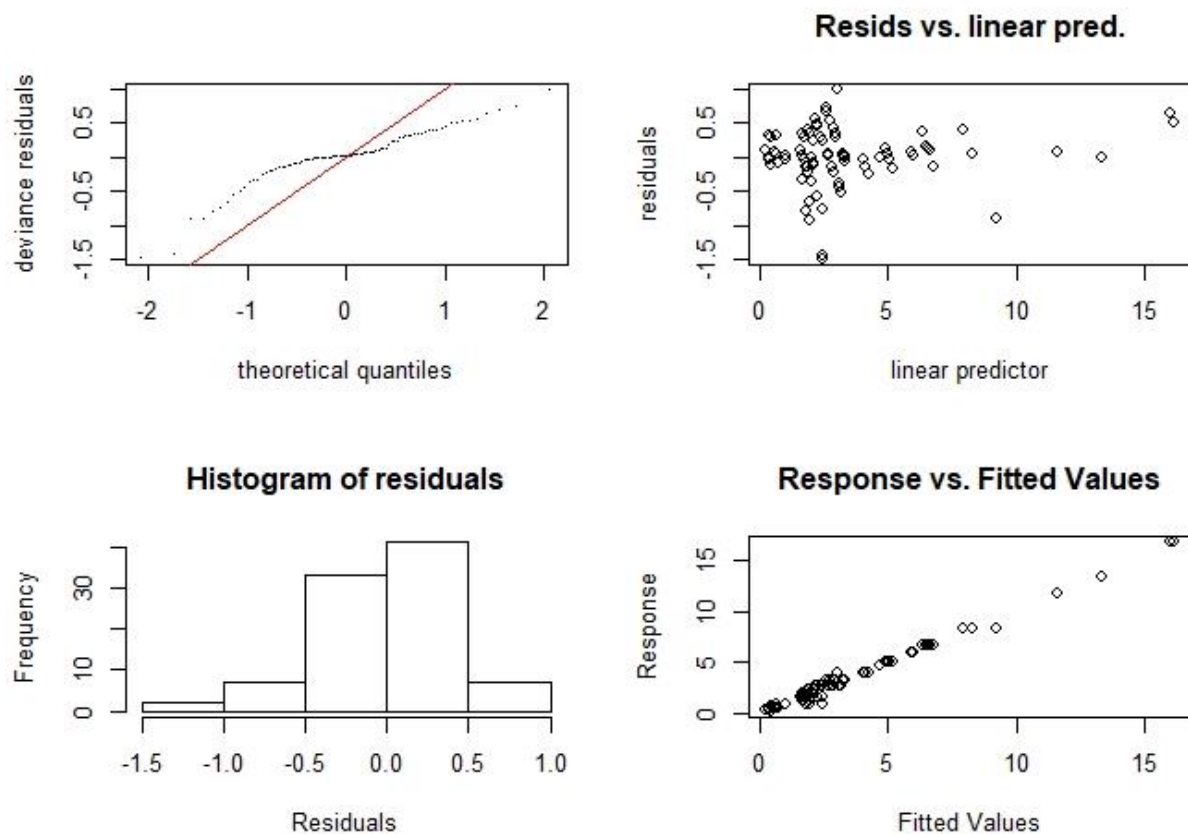


Figure 34: Diagnostics for a fitted GAM model a) Theoretical quantiles and deviance residuals. b) Resids vs linear predictor plot. c) Histogram of residuals. d) Response vs Fitted value plot.

Residual checking is based on two basic assumptions; normality of residuals and equality of variances. In the above plot (Figure 34) theoretical quantiles and deviance residuals shows a linear relationship. Resids vs linear predictor plot (Figure 34b) shows the difference between observed and predict value. Histogram of residuals (Figure 34c) has been used to check whether the variance is normally distributed around the zero. In Response vs Fitted value plot (Figure 34d) points around the zero line assume linear relationship. The model derived from the present study is capable of giving sufficient information to predict fishing grounds of the Ovalbone Cuttlefish around Mumbai waters where R square value is estimated 0.943 and deviance explained was 98.6%.

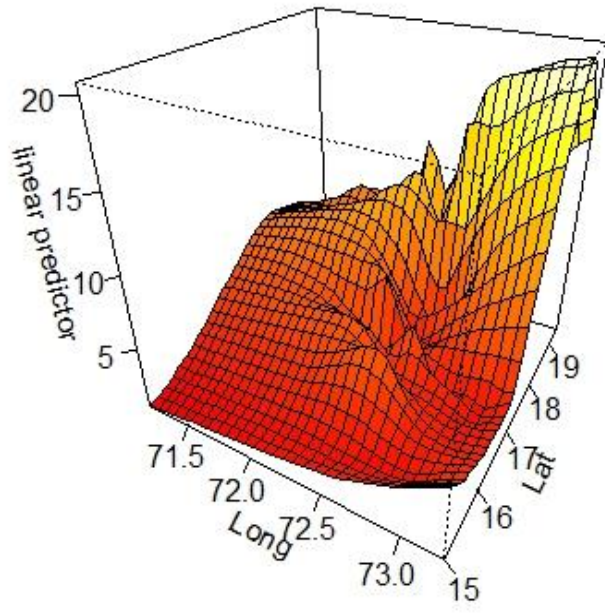


Figure 35: Effect of Latitude and Longitude on *Sepia elliptica* (Hoyle, 1885) abundance

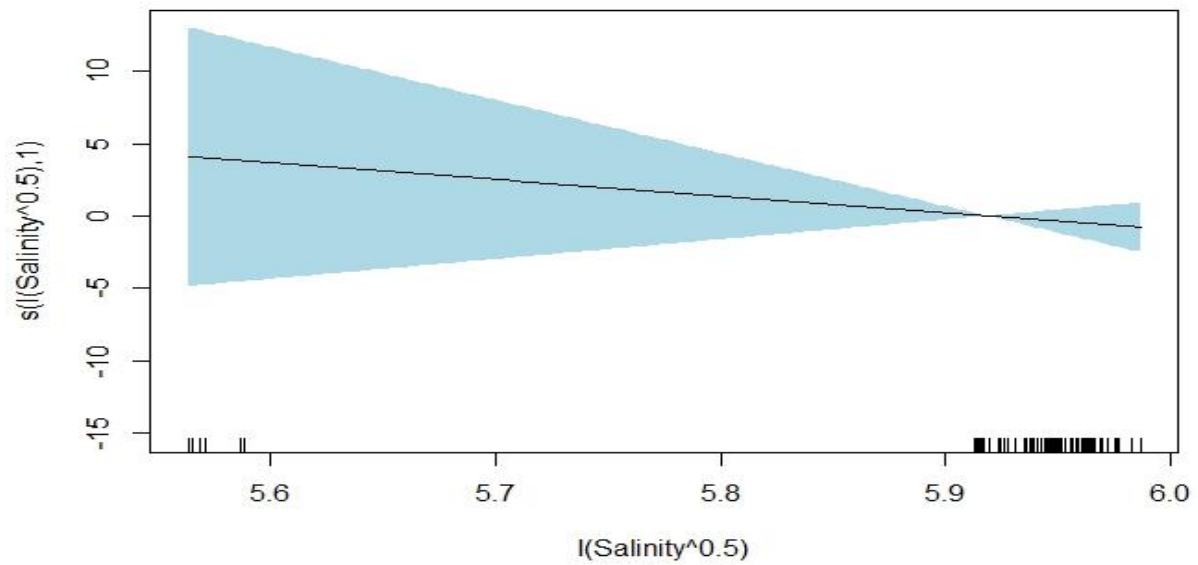


Figure 36: Effect of Sea Surface Salinity on *Sepia elliptica* (Hoyle, 1885) CPH

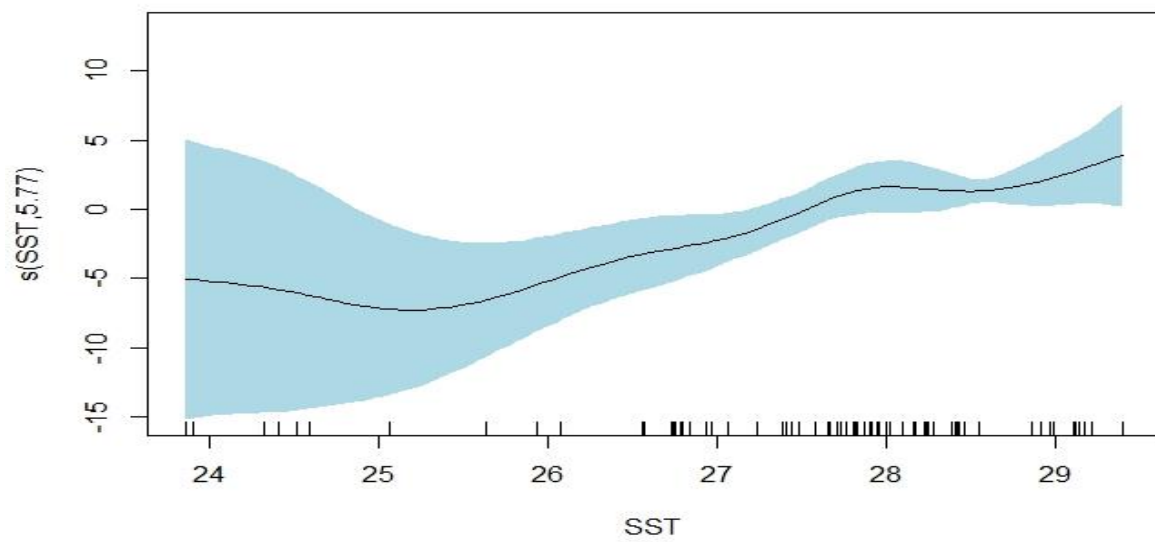
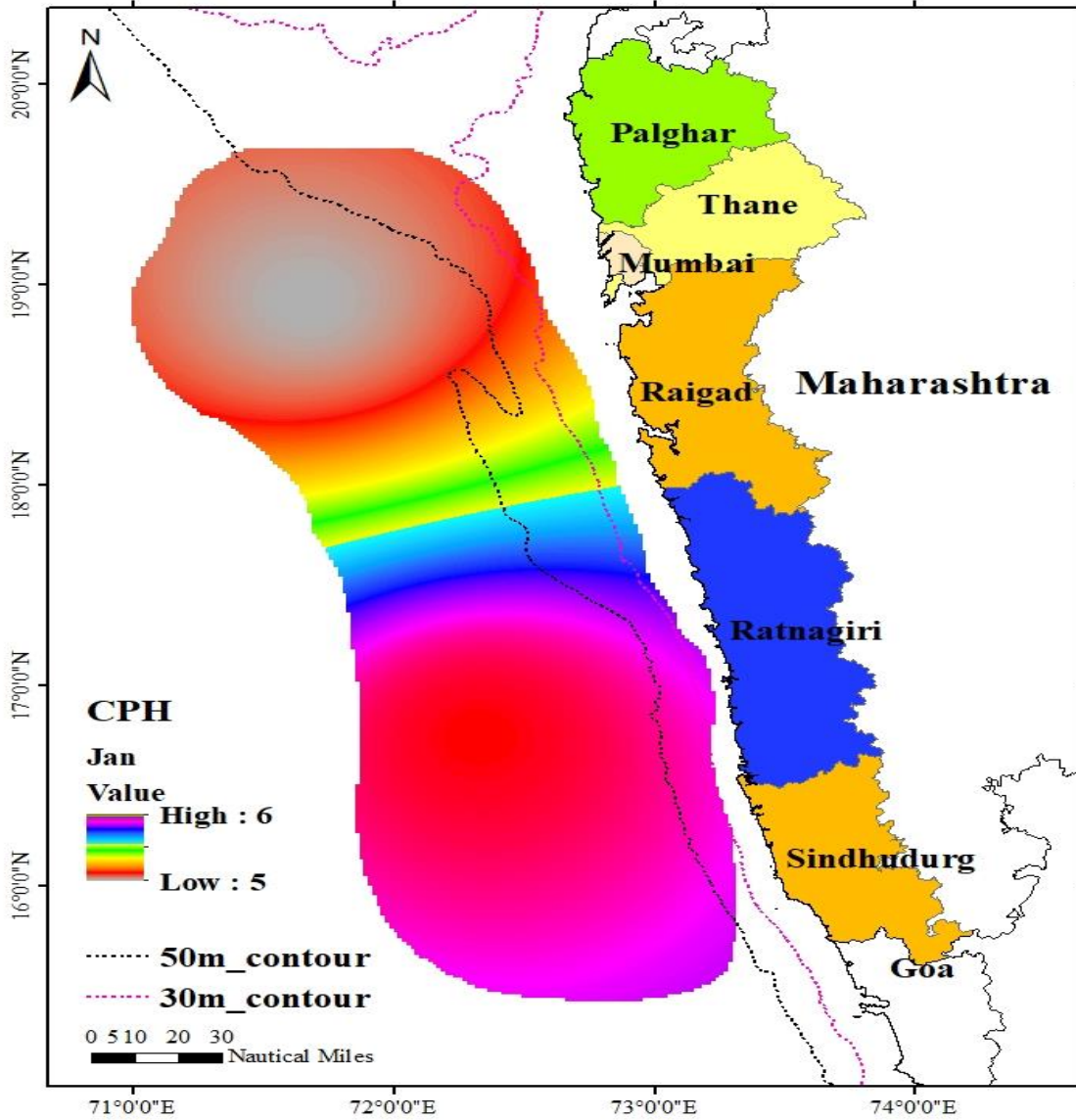
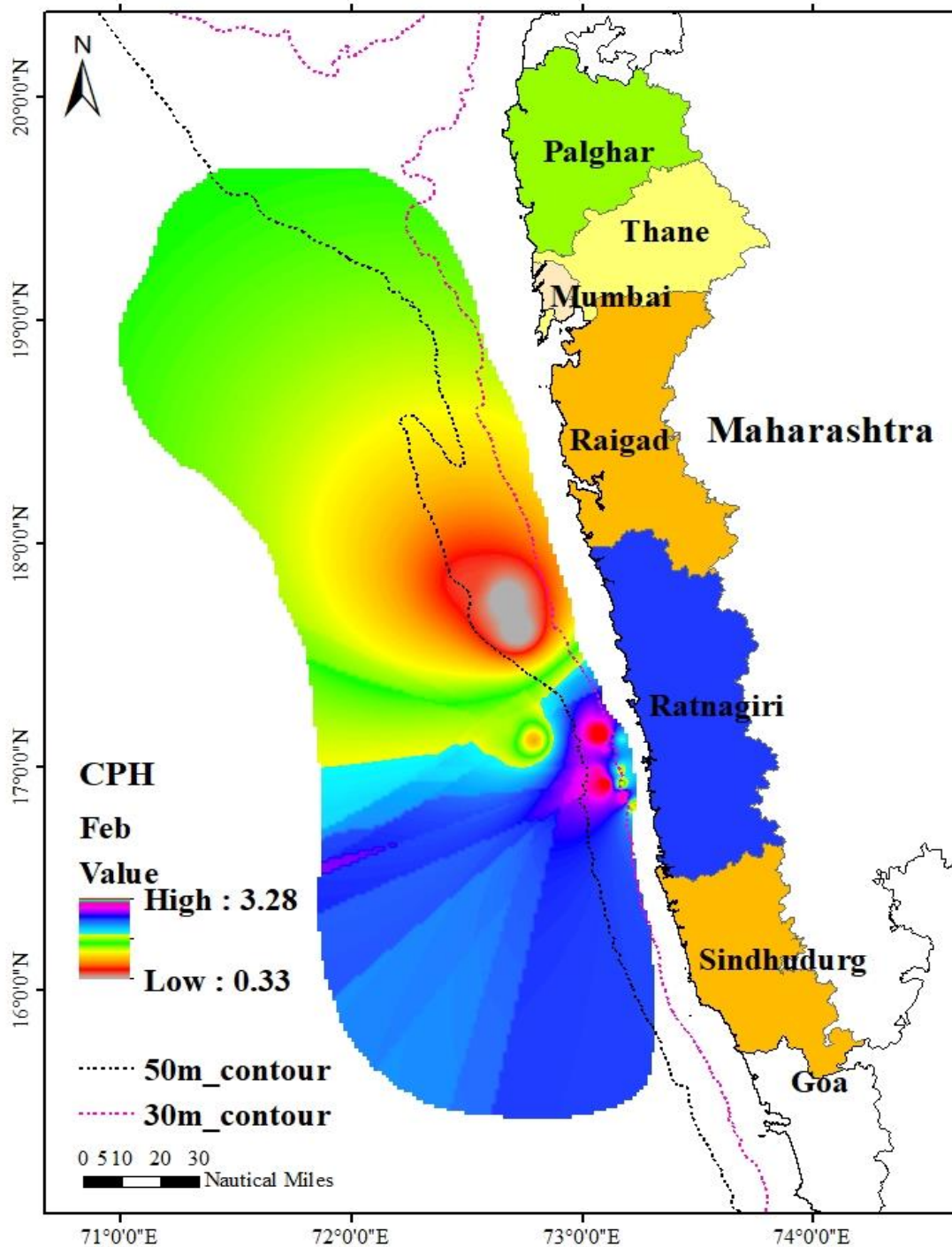


Figure 37: Effect of Sea surface Temperature on *Sepia elliptica* (Hoyle, 1885) CPH

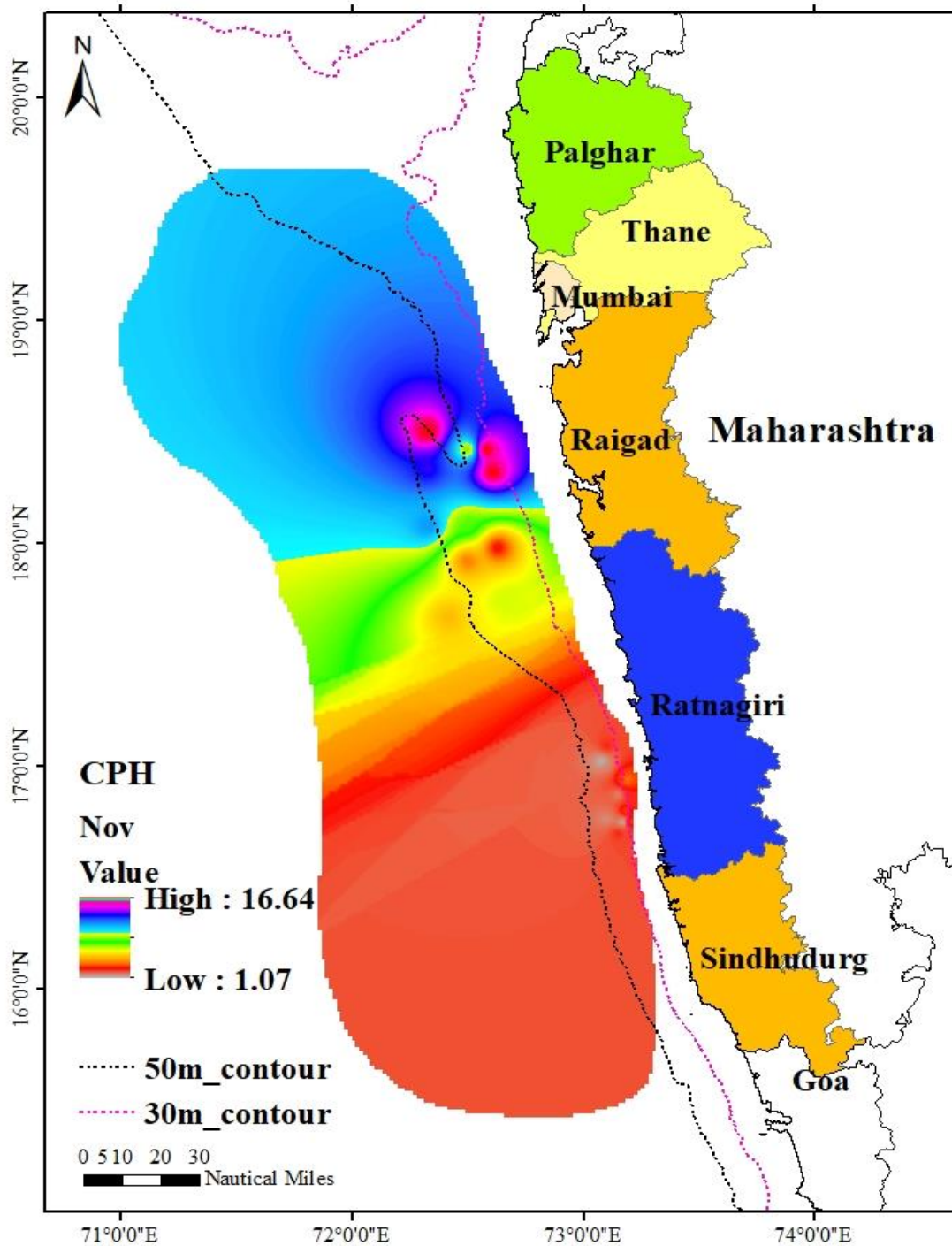
4.2.2.4. Month-wise spatial distribution map of *Sepia elliptica* (Hoyle, 1885) CPH during 2017-2019



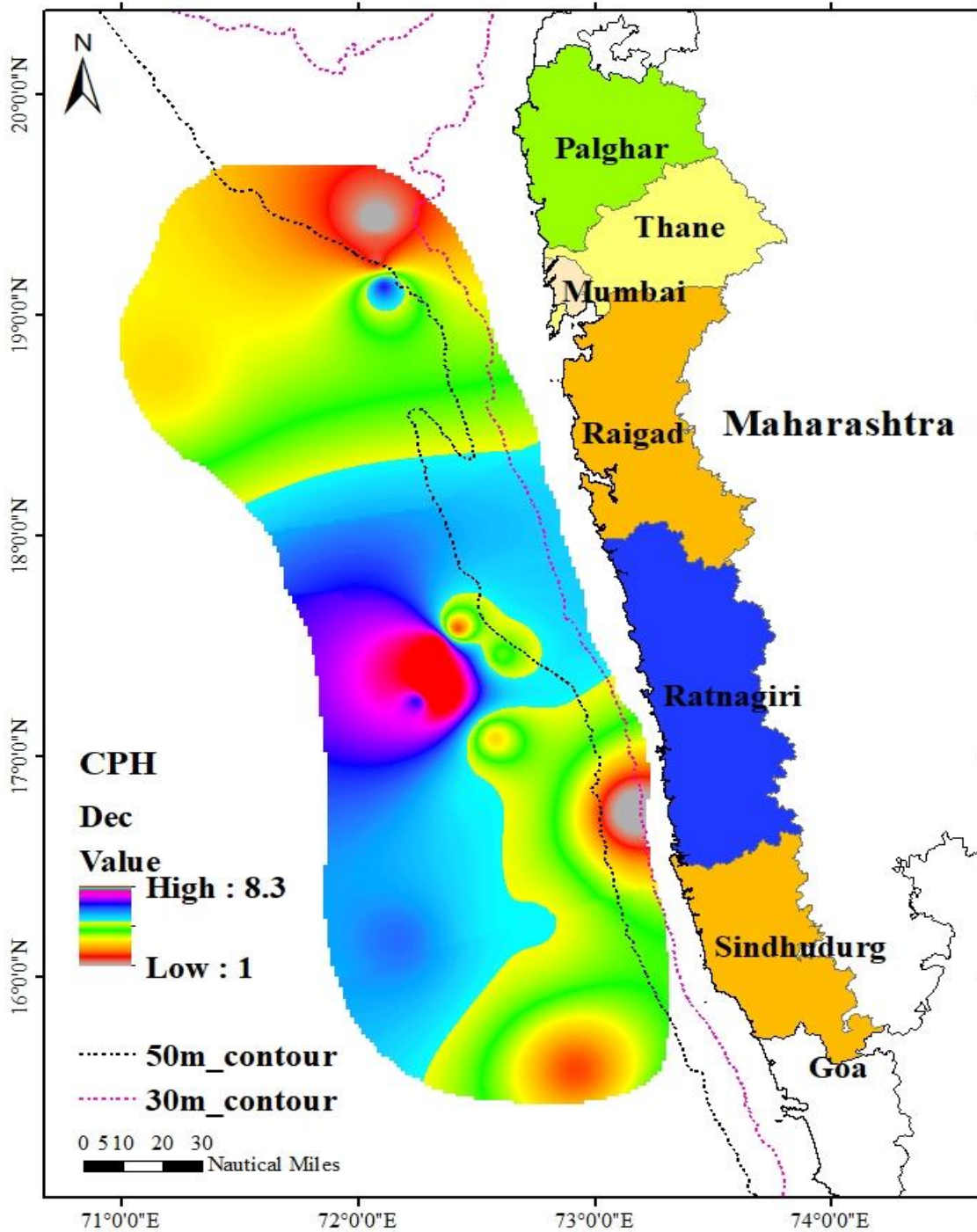
Map 9: Distribution of *Sepia elliptica* (Hoyle, 1885) during January (2017-19)



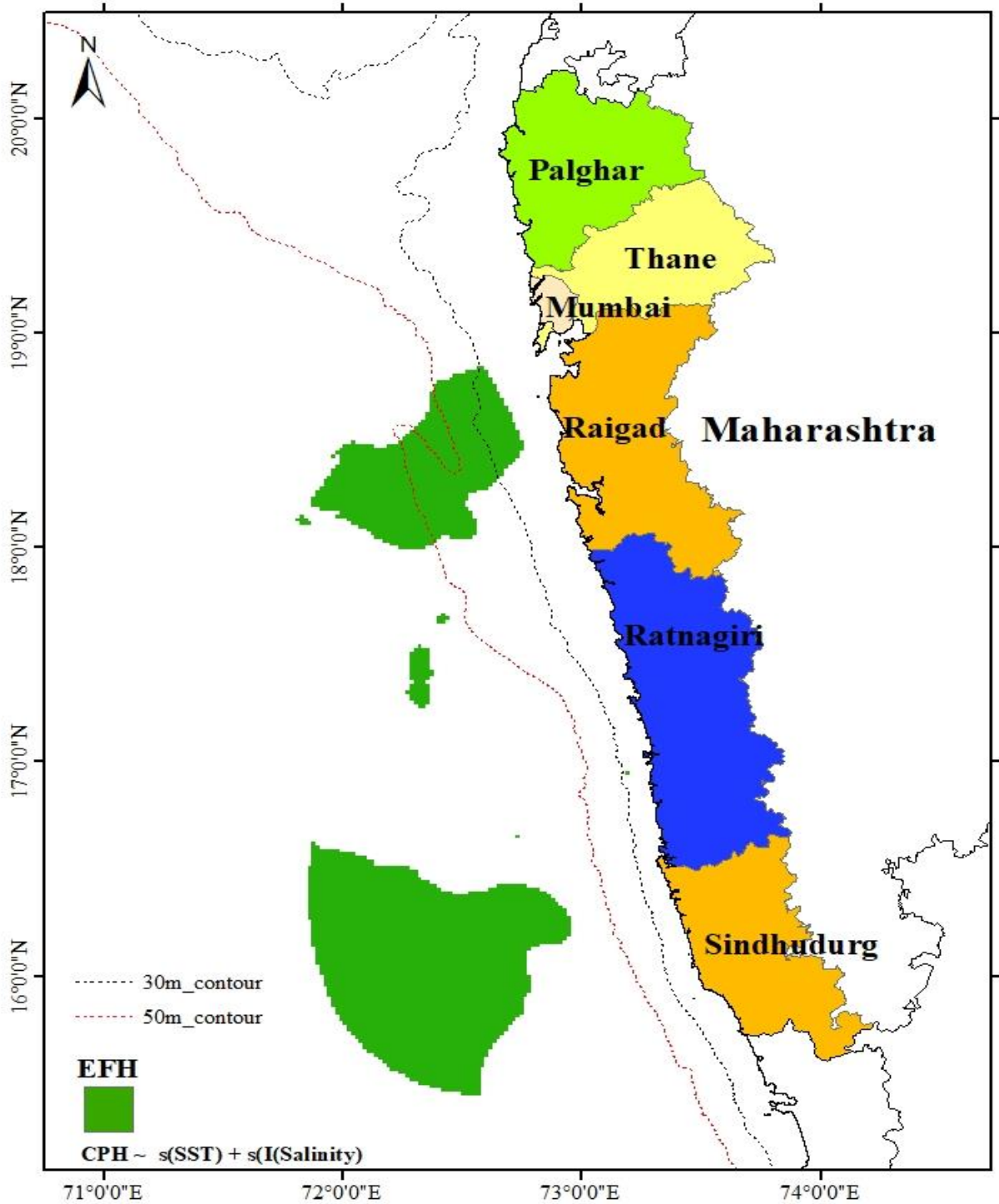
Map 10: Distribution of *Sepia elliptica* (Hoyle, 1885) during February (2017-19)



Map 11: Distribution of *Sepia elliptica* (Hoyle, 1885) during November (2017-19)



Map 12: Distribution of *Sepia elliptica* (Hoyle, 1885) during December (2017-19)



Map 13: Essential Fish Habitat (EFH) map of *Sepia elliptica* (Hoyle, 1885) off Maharashtra coast

Essential Fish Habitat (EFH) map shows the predicted probability of the presence of Ovalbone Cuttlefish in Mumbai coast during 2017-2019. The areas within 15⁰N and 19.42⁰N latitude and 72⁰E to 73.20⁰ E longitudes (Map 13) show the high abundance of *Sepia elliptica* (Hoyle, 1885).

5. DISCUSSION

The study showed that Indian Mackerel and Ovalbone Cuttlefish distributed throughout the Mumbai coast, India. Essential Fish Habitat (EFH) areas were identified where both the species could be found in high abundance. In this present study, a much more comprehensive and thorough analysis of the habitat preferences of Ovalbone Cuttlefish and Indian Mackerel in relation to oceanographic parameters off Mumbai coast was accomplished by using generalized additive model (GAM) and Essential Fish Habitat (EFH) model. Environmental parameters of Mumbai waters for Indian Mackerel and Ovalbone Cuttlefish shows variation in values due to differentiation in fishing grounds geo-location of both the species.

The Indian mackerel, *Rastrelliger kanagurta* is a commercially important pelagic species widely distributed along east and west coast of India, but as far as its fishery concerned South west coast is the most productive zone (Abdussamad *et al.* 2006). During the late nineties the abundance of the resource extended to deeper waters, the variation observed in depth of operation of the gears and variation in vertical distribution of the species in the sea with respect to prevailing environmental conditions (Abdussamad *et al.*, 2006).

The present study is in agreement with a number of previous works on *R. kanagurta* (Qasim, 1973; Helser and Almeida, 1997; Asokan *et al.*, 2009; Hiseh *et al.*, 2009; Das *et al.*, 2017), where they studied the species abundance and distribution in relation to the marine environment, which has significant influences on the survival, growth, reproduction, and migration of the species. The Generalized Additive Model (GAM) studied by many researches to identify the relationship between Indian Mackerel distributions with oceanographic parameters and create map to detect the potential fishing grounds (Mustapha *et al.*, 2012; Razib *et al.*, 2013; Nurdin *et al.*, 2012,2015.2017; Shaari *et al.*, 2018). Salarpouri *et al.* (2018) studied on the effect of Sea Surface Temperature on sardine and anchovy, and observed that SST was generally the least important variable where a slight peak of positive influence was observed on presence of sardine (approximately 22⁰C and 33⁰C) but less effect of SST

was seen on the presence of anchovy in Persian Gulf, Iran. Helser and Almeida (1997) suggested that, the changes in the Sea Surface Temperature (SST) can change the habitat preference and the distribution pattern of the species.

Asokan *et al.* (2009) observed shifts in distribution and abundance of the Indian mackerel fishery is due to the rising in temperature and climatic change effects. Sea Surface Temperature has a stronger influence on Indian Mackerel (*R. kanagurta*) distribution with a preferred range of 29°C to 30°C (Shaari *et al.*, 2018) in EEZ of Malaysia. From the present study it has been found that Sea Surface Temperature (SST) showed a significant relationship with the Indian Mackerel catches than Sea Bottom Temperature (SBT). Yohannan *et al.* (1998) recorded that in Malabar Coast of India, Indian Mackerel prefers temperature lower than 28°C. In the present study it has been found that, in Mumbai coast of India, the maximum Indian Mackerel availability was observed in the area with an average Sea Surface Temperature of 28.18°C. Suresh and Reddy (1980) also indicated that mackerel prefers warmer water i.e. 28.4°C to 29.9°C, where as Ramamurthy (1965) reported the favorable temperature preference range of 26.4°C to 28.1°C for the species. Both these findings are in agreement with the results of the present study. Nurdin *et al.* (2012, 2017) reported from Indonesian waters that during 2012 and 2015 preferred Sea Surface Temperature for Indian Mackerel abundance was 29.71°C - 30.17°C and 30°C - 31°C respectively, which agree with our present study. Razib *et al.* (2013) also support the findings of present study where they have recorded preferred SST for Indian Mackerel ranges from 26°C -28°C in the off shore of Pahang coast, China.

Chaturvedi *et al.*(2013) studied the impact of climate change on biological productivity in the Indian Ocean and recorded that Chl-a concentration remains quite higher (0.5–1.5 mg/m³) in northern and central region of Arabian Sea, but the southern sector of Arabian sea had low Chl-a values (0.1– 0.5 mg/m³). According to Nurdin *et al.* (2012) in Indonesian waters SST had higher influence on Indian Mackerel distribution than Chlorophyll-a concentration and preferred chl-a ranges from 0.21-41 mg/m³. In Malaysian waters SST had high influence on the distribution of Indian mackerel in comparison to chlorophyll concentration (Nurdin *et al.*, 2017; Shaari *et al.*, 2018). The

present study also supports it where SST influence is more than Chlorophyll-a concentration on Indian Mackerel catches and mostly abundant in the area of average 0.35mg/m³ concentration chlorophyll. Razib *et al.* (2013) also support present study by providing average preferred SST for Indian Mackerel in Pahang coast of china is 0.3-0.5 mg/m³. The present study findings also show that the maximum chlorophyll concentration of Mumbai water is 1.40 mg/m³ and 0.94 mg/m³ during winter and monsoon respectively.

The pelagic fishes (Herring, Scad, *Sardinella*) are strongly connected to high salinities in different parts of world Ocean. Several studies has been done to establish significant correlations between a number of fish species with water temperature, salinity, depth and other environmental parameters (Marshall and Elliot, 1998; Paramo *et al.*, 2003; Perry *et al.*, 2005a, 2005b; Yenet *et al.*, 2012; Pitchaikani and Lipton, 2012; Das *et al.*, 2017). Along the South-West Coast of India during the monsoon, mackerel catches showed highly significant correlation with salinity ranges of 34.85 to 35.95 ppt, but no catches were found when salinity ranged from 33.97 to 35.53 ppt (Das *et al.*, 2017). In the present study maximum Sea Surface Salinity (SSS) of Mumbai waters is mainly found during winter, i.e. 37.40 ppt and Indian Mackerel preferred 33-34.5 ppt Sea Surface Salinity (SSS). *Sardina pilchardus* inhabit in the shallow waters (<65 m depth) during summer but reach deeper waters (up to 100m) in autumn and winter in the Mediterranean Sea (Tugores *et al.*, 2011). According to Yen *et al.* (2012), Sea Surface Height (SSH) had second close relationship followed by SST to the habitats of yellowfin tuna, which ranged from 1.51 to 2.23m in the Western and Central Pacific Ocean. Swordfish (*Xiphias gladius*) catch in the equatorial Atlantic Ocean occurred in areas with optimal range of SSH between -0.06 and 0.03m (Chang *et al.*, 2013). The catch of scad and sardine were high when SSH value was in the range 0.60–0.64m in Kepulauan Seribu Waters (Rivai *et al.*, 2018). Similarly the present study also recorded a preferred optimal SSH of 37cm for Indian Mackerel along Mumbai waters.

In the equatorial Atlantic Ocean, Swordfish (*Xiphias gladius*) abundance occurred in areas with the optimal MLD ranges of 19.88m and 57.59m (Chang *et al.*,

2013). According to Arrizabalaga *et al.* (2015), tropical tunas preferred relatively stratified waters (MLD<80m) compared to temperate tunas and Albacore tuna tolerate MLD ranges up to 200m. Present study also recorded that Mixed Layer Depth (MLD) of the Mumbai water shows a great variation during the study period that ranged from 11.60m to 28.29m and Indian Mackerel species preferred the optimal MLD ranges of 10-15 m. Present results also revealed that the average catch of Indian Mackerel in Mumbai waters is 894 kg during 2017-2019. The catches of Indian Mackerel are mostly abundant during post-monsoon and winter generally in December–February (average catch 1800 kg).

The seasonal variability in the catches may due to high chlorophyll-a concentration and the availability of high phytoplankton biomass. Moderate catch of *Rastrelliger kanagurta* (i.e. >100kg) was observed in the months of April, May and September. Catch lower than 100 kg was observed during other month mainly during monsoon due to unfavorable environmental conditions. From the present study it has also been found that in Mumbai coast of India Ocean currents and wind speed does not influence the catch of Indian Mackerel. During the study high catches of mackerel were observed when, the average sea surface temperature, chlorophyll-a concentration, sea surface salinity, sea surface height and mixed layer depth values were 28.18°C, 0.35mg/m³, 33-34.5 ppt 37cm and 10-15 m respectively. In the present study, high abundance of *Rastrelliger kanagurta* has been found in the region with latitude 18° N to 20° N of South West coast, where as Bhargava (1999) studied the biological aspect of Indian Mackerel along North West coast along latitude 18° N to 23° N. The GAM study by Nurdin *et al.* (2017) in Indonesia waters shows the acceptable level of *R. kanagurta* distribution map accuracy at 83.34%. The present GAM study of *R. kanagurta* from Mumbai water is showing that the potential fishing grounds were found located along the Mumbai coast with at accuracy of 62.1% deviance explained and r² is 0.586.

The Ovalbone Cuttlefish, *Sepia elliptica* (Hoyle, 1885) is widely distributed along the West Coast of India and shows seasonal aggregation in particular areas within its distribution range. This species reported under category of IUCN Red List of Threatened Species as "Least Concern" species. It is assessed as Data Deficient since

no detailed work on the habitat preference of Ovalbone Cuttlefish (*Sepia elliptica*) in relation to oceanographic parameters has been done earlier by any other researchers in Mumbai coast.

The spatial and temporal pattern of cuttlefish abundance shows annual migration in English Channel and adjacent areas (Dunn 1999; Denis and Robin 2001; Wang *et al.*, 2003). Relationships between environmental variables, cephalopod abundance and biology have been widely reported in the literature (Jackson, 1995; Pierce and Boyle, 2003). Temperature and currents are likely to be the most important variables influencing cephalopod recruitment (Walsh and Martin, 1986; Turrell, 1992; Waluda *et al.*, 1999). Swartzman *et al.*, 1992; Daskalow 1999; Bellido *et al.*, 2001) reported the spatial modeling of cephalopods using GAM technique model. Bellido *et al.*, (2001) studied the preliminary application of GAM to describe intra annual variation in squid abundance in Scottish waters. Solanki *et al.* (2016) predicted the distribution of squids in the Arabian Sea by using GAM to satellite-derived variables (SST, Chl-a, and SSH) and fishery data. According to their study the preferred range of SST for distribution of squids from 24.5 to 28°C and the degree of relationship of squids catches with the environmental parameters is in the tune of PAR > Depth > SST > log(CC) > SSHa.

The present study shows that the chlorophyll-a concentration in Mumbai coast of India does not show any relation with Ovalbone Cuttlefish abundance. In the North-East Atlantic region, SST has a significant effect on the abundance of *Loliginid* squid and abundance increases with the temperature and peaks at an SST close to 10°C (Denis *et al.*, 2002). Wang *et al.* (2003) reported that the high cuttlefish LPUE center located in a high-temperature zone in the English Channel. They also reported that in the French Atlantic coast, high cuttlefish LPUE center located in winter, disappears in summer, and does not show any clear relationship with SST. In the English Channel and adjacent waters, spatial correlations between cuttlefish abundance and SST in their study area are overwhelmingly positive, and significant except in May (Wang *et al.*, 2003). They have also assumed that sea bottom temperature (SBT) has

similar relationship to cuttlefish abundance as that of SST because SBT is linearly and positively related to SST in shallow waters (<100m depth) as well as in deeper waters.

In the present study, along Mumbai region, high abundances of Ovalbone Cuttlefish were significantly related to SST of the range between 28⁰C and 29.5⁰C ($p < 0.001$). According to Chen *et al.*, (2006) high abundances of squid were located in the region of SST between 10⁰C and 15⁰C in summer and the region of 7⁰C -10⁰C in winter. Sacau *et al.* (2005) studied that the probability of catching Argentine shortfin squid (*Illex argentine*s) had been found negatively related to latitude and generally increased at higher SST values in the southwest Atlantic. In the Southwest Atlantic region, the correlations between SST and squid abundances for the fishing season (May-Aug) were negative, i.e., high squid abundances occurred in areas with lower SST. In terms of average fishing depth, the probability of success of catching Argentine shortfin squid (*Illex argentine*s) is highest in depths around 600m and suggested that in the southwest Atlantic, squid abundances positively related to three depths ranges: around 200, 400 and 650m.

Present results revealed that the average Catch per Hour (CPH) of *Sepia elliptica* in Mumbai waters is 3.5 kg/hr during 2017-2019. The highest CPH of Ovalbone Cuttlefish was found during post-monsoon season mainly during November. Moderate CPH of *S. elliptica* (i.e. >3 kg/hr) was observed in December. Catch per Hour (CPH) lower than 3 kg/hr was observed during other months due to unfavorable environmental conditions. In the Mumbai waters Ovalbone Cuttlefish catch relatively significant ($p < 0.01$) to Sea Surface Salinity of average 35.5 ppt. The abundance of Ovalbone Cuttlefish was recorded between 15⁰ and 19.42⁰ N latitude and 71.18⁰ to 73.20⁰ E longitudes and showing a good significant relationship ($p < 0.001$). The potential fishing grounds of Ovalbone Cuttlefish were found to be located along the Mumbai coast (at accuracy of 98.6% and r^2 value is 0.943). Ocean currents and wind speed does not influence the catch of Ovalbone Cuttlefish in Mumbai coast of India. These Generalized Additive Models (GAMs) confirm not only the influence of oceanographic parameters on Ovalbone Cuttlefish distribution and abundance but also the importance of environment into account for the definition of stock limit.

6. SUMMARY AND CONCLUSION

India has a very long coastline of around 8129 km (including Andaman, Nicobar and Lakshadweep Islands) with the Arabian Sea to the west and the Bay of Bengal to the east. The wide range of marine activities dominates the maritime zone of India. Marine ecosystems are complex ecosystem due to the frequent changes in their physiochemical properties. Habitat characteristics information is valuable for use in resource management and better decision making. Generalized Additive Modelling (GAM) techniques used for species-environment relationships and to find out the distribution pattern of species to understand fish population sizes, recruitment pattern, and growth. This study was conducted to assess the effect of oceanographic variables in *Rastrelliger kanagurta* (Cuvier, 1817) and Ovalbone Cuttlefish, *Sepia elliptica* (Hoyle, 1885) abundance and distribution for future monitoring. Generalized Additive Modelling (GAM) techniques used for species-environment relationships and to find out the distribution pattern of species.

In the present study, six remotely sensed environmental variables like Sea Surface Temperature (SST), Chlorophyll-a concentration (Chl-a), Sea Surface Salinity (SSS) and Sea Surface Height (SSH), Mixed Layer Depth (MLD) and ocean current metrics utilized for investigations into habitat and distribution of fishes. Satellite remote sensed data is useful for monitoring environmental correlates of marine species for identification of appropriate habitats, behavior and ecology. The distribution of phytoplankton and zooplankton influenced by the changes in environmental variables and primary productivity (PP) affects the distribution of Indian mackerel and oval bone cuttlefish fishery. This study also determined the seasonal and spatial variability of the environmental parameter off the Mumbai coast. Further, species distribution modelling provides a suitable tool for mapping essential fish habitat and helps in studying their influence on the fish population, as well as evaluates management actions for habitat conservation.

The major findings of the research revealed that maximum Indian Mackerel catches mostly abundant during post-monsoon and winter in December–February (average 1800 kg), the moderate catch of (i.e. >100kg) observed in April, May and September, and lowest catch (i.e., <100kg) observed during other months. This study also points to the strong influence of SST and CHL on Indian Mackerel distribution. The preferred environmental variables for high catches of mackerel were observed when, the average sea surface temperature, chlorophyll-a concentration, sea surface salinity, sea surface height and mixed layer depth values were 28.18°C, 0.35mg/m³, 33-34.5 ppt, 37cm and 10-15m respectively. In Mumbai coast of India Ocean currents and wind speed does not influence the catch of Indian Mackerel has also been found from the present study.

The Ovalbone Cuttlefish is widely distributed along the West Coast of India, reported under IUCN Red List of Threatened Species as “Least Concern” species and shows seasonal aggregation in particular areas within its distribution range. It is observed that no detailed study was carried out on the habitat preference of *Sepia elliptica* (Hoyle, 1885) in relation to oceanographic parameters off Mumbai coast. In this connection a detailed comprehensive study on generalized additive model (GAM) and essential fish Habitat model (EFH) was undertaken to address the same.

The Present results also revealed that the average Catch Per Hour (CPH) of *Sepia elliptica* in Mumbai waters is 3.5 kg/hr, where highest CPH found during post-monsoon season mainly in November. Moderate CPH of Ovalbone Cuttlefish (i.e. >3 kg/hr) was observed in December and lowest CPH (i.e. <3 kg/hr) was observed in other months. In the Mumbai waters Ovalbone Cuttlefish catch shows a significant relationship with SST ($p < 0.001$), SSS ($p < 0.01$), latitude, and longitude ($p < 0.001$). The preferred SST and SSS for the high abundance of Ovalbone Cuttlefish are between 28°C to 29.5°C and 35.5 ppt respectively.

Therefore, the objective of this study is to produce a simple, yet effective Generalized Additive model to predict the respective fish habitat and their distribution with oceanographic parameters which can contribute greatly to the development of effective management for the sustainable exploitation of economically important fisheries resource.

Findings of this study are important for conserving the particular species with their preferred ecosystem or habitat. Climate change now considers as a big threat to specific fish species, other marine species and marine habitat as well. The impacts of climate change on the ecosystems where fish were caught became a central issue because it has a direct and indirect effect on recruitment to, and growth of, fish stocks. Climate change and advance fishing methods increase the vulnerability of the species and their habitat, which may lead to the extinction of the particular species. Hence, there is a need for an integrated conservation strategy for the species which will help in ecosystem-based management.

For the future study distribution modeling of species and ecosystem can be combined with anthropogenic pressures for ecosystem-based management of human activities. The integration of distribution modeling approaches with environmental variables analyses provides an exciting future direction for exploring change in the ecosystem to climate change. For future works, more datasets of ecological variables, populations dynamics, species catch and fishing location can be used to obtained and analyze the better and significant relationship.

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Plate 1. *Rastrelliger kanagurta* (Cuvier, 1817)



Plate 2. *Sepia elliptica*, (Hoyle, 1885)



Plate 3. *Rastrelliger kanagurta* bulk landing in Sassoon Dock Landing centre



Plate 4. *Sepia elliptica* bulk landing in Sassoon Dock Landing centre



Plate 5. Catch Unloading from Purse seiner



Plate 6. Catch preservation in Flake ice



Plate 7. Collecting Craft and Catch related data



Plate 8. Collecting Fishing location data

ABBREVIATIONS

MODIS	Moderate Resolution Imaging Spectroradiometer
CMEMS	Copernicus Marine Environment Monitoring Service
ESRI	Environmental Systems Research Institute
SNAP	Sentinel Application Platform
SeaDAS	SeaWiFS Data Analysis System
RDA	Redundancy Analysis
GAM	Generalized Additive Model
EFH	Essential Fish Habitat
HSI	Habitat Suitability Index
AIC	Akaike Information Criteria
GIS	Geographic Information System
RS	Remote Sensing
CPH	Catch per Hour
CPUE	Catch per Unit Effort
LPUE	Length per Unit Effort
LAT	Latitude
LONG	Longitude
SST	Sea Surface Temperature
SBT	Sea Bottom Temperature
CHLA	Chlorophyll-a
SSS	Sea Surface salinity
SSH	Sea Surface Height
MLD	Mixed Layer Depth
OC	Ocean Currents
PP	Primary Productivity
ppt	Parts Per Trillion
psu	Practical Salinity Unit