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Trends in the Sri Lankan Longline Tuna Fishing Effort (2015-2019): A GIS-Based Spatial-Temporal Analysis

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Cover image: Yellowfin Tuna, Indian Ocean. Source: https://lemag.ird.fr/en (2022)

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Abstract

The Fishing industry play a major role in socio-economic context of Sri Lanka. Even though, there is a significant potential to develop the fishing industry in country, the current economic performances of the industry are not satisfactory due to poor management mechanisms. It is essential to implement sustainable management approaches in order to achieve socio-economic and environmental sustainability. The analysis of the spatial and temporal distribution of fishery resources is an important step toward sustaining the resources. However, acquiring data about the distribution and spatiotemporal allocation of catch and fishing efforts in commercial marine fisheries remains challenging. This study aims to investigate the distribution pattern of the longline tuna fishery and identify sustainable fishing grounds in Sri Lanka. The study uses the fisheries data from VMS and logbook between 2015 until 2019, obtained from the Department of fisheries and aquatic resources. The socio-economic data were collected from thirty multiday boat fishermen covering the south, west and east coasts using a semi-structured questionnaire. The study is based on Geographic Information System (GIS) and descriptive statistical analysis.

The results of the GIS-based analysis show high variations in catch and catch per trip distribution patterns by years and seasons. Hotspots of fishing efforts, catches (quantity) and catch per trips (CPT) were identified. The results show the areas of clusters with high CPT values increased slightly after 2016. The hotspots map show that there is strong seasonal influences in the concentration of fishing efforts and catches. The socio-economic results confirm that Sri Lankan longline fishers predominantly use traditional ecological knowledge (TEK) to determine their potential fishing zone. Natural signs such as birds, floating, group information, and extreme oceanographic conditions such as waves, wind, and currents were the main factors that longline fishers use to decide where they will go fishing. The effective visualization and communication of identified and mapped seasonal, and annual as well as persistent and sustainable fishing grounds maps to stakeholders and managers may provide a great opportunity to sustainable management of fisheries in Sri Lanka. Moreover, the study shows the importance of integrating TEK to understand the fishers behavior in space and time and to support sustainable management of the fishery system.

1 Introduction

As an island nation located in the Indian Ocean, Sri Lanka has sovereign rights to an Exclusive Economic Zone that extends outward 200nm from its shores and covers an area of about 510,000 sq km ((MFAR, 2020). Accordingly, the fisheries sector plays a vital role in the socio-economic context of the country (NARA, 2018). Fisheries are a prominent livelihood approach among the coastal communities and over 2.7 million people depend on fisheries for their livelihood (MFAR, 2020). The fisheries sector provides approximately 585,000 direct or indirect employment for people in the country. Fish is the main source of animal protein for the people and 60% of the annual average protein intake is obtained from fish products (MFAR, 2020; NARA, 2018), The fisheries sector accounts for 1.2% of the annual Gross Domestic Production of Sri Lanka (GDP)(MFAR, 2020). The fisheries industry consists of two main sub-sectors: marine fisheries and aquaculture. The marine fisheries sector contributes about 82% of total the fish production in the country, (Wijayaratne & Maldeniya, 2003).

Even though, there is a significant potential to develop the fishing industry in Sri Lanka the current economic performances of the industry are not satisfactory due to poor management mechanisms (ADB, 2017). Hence, it is essential to implement sustainable management approaches to achieve economic and environmental sustainability. Sustainable management of marine fisheries requires information and knowledge on both ecological (i.e., the biology of target species(es) and its biotic and abiotic ecosystem interaction), and social (i.e., fishers' action, motivation, and responses to fluctuation in-stock status in time and space) systems (Crowder & Norse, 2008). Spatially explicit information on the distribution and abundance of fish species and fishing activities is very important for the sustainable management of fishery resources. In that sense, evaluation of the spatial and temporal distribution of populations or a given species in an ecosystem could provide valuable knowledge on how individuals in its population synchronize and move at the same time or after the synchronization of its meta-community with which it interacts (Chevalier et al., 2018) Furthermore, knowledge of spatial and temporal dynamics of target species is significant for a better understanding of variations in the size of the population (e.g., where and when it fluctuates over time), movement patterns, as well as the driving forces governing such variations and movements (Ruokolainen et al., 2009). Therefore, it is crucial to identify the spatial and temporal distribution and abundance patterns of fish. The distribution patterns of fish across space and time dimensions are determined by the interaction of several factors in the marine environment such as benthic topography, as well as climatic and oceanographic characteristics (Maravelias, 1999).

Changes in oceanographic conditions and benthic habitat due to climate change and/or human activities can result in significant deviations in the spatial and temporal distribution patterns of fish stock and productivity. Recent global climate change may also have an impact on the regional marine environment. Climate change affects the physical and chemical properties of seawater and results in ocean acidification, vertical stratification, and oxygen concentration (Dueri et al., 2014). Studies have shown that climate change has caused i) changes in ecosystem structure, as species that have traditionally cohabited within specific geographical ranges may move apart, affecting predator/prey interactions, ii) changes in species distribution and abundance in space and time, iii) changes in fish migration routes, and iv) changes in the productivity of marine system (Morin et al., 2021).

Fishes are always followed to find suitable habitats for feeding, spawning, migration and protection (Jiménez-Segura et al., 2010), Fishers generally follow the behavioral/ spatial/ temporal patterns of fish species to determine appropriate fishing grounds. Considering the profit maximization nature of the commercial fishers, we can argue that the distribution of fishing activities in a particular geographical location is determined by several factors, including the availability of resources (target fish species). the operating costs (as a function of distance, fuel costs, and labor costs) and the revenue (fish price). Moreover, fishers' behaviors vary based on their knowledge, experiences, traditions and cultural practices. Spatial and temporal heterogeneities of fishing efforts distribution are related to variation in resource availability, fishing practices, motivation, catches, and revenue distribution over space and time. Thus, knowledge about the spatial distribution patterns of fishing activities, efforts, catch and catch per unit efforts helps to understand the dynamics of both ecological and social aspects of fisheries system, and to maintain sustainability while remaining sufficiently responsive to change. Despite that necessity, there are no comprehensive studies which explored the spatial and temporal distribution patterns of fisheries, and fishing efforts in Sri Lanka.

The recent development of tracking of fishing vessels using the Vessel Monitoring System (VMS) and mandatory reporting of catch data provide an unprecedented opportunity to understand fishing behavior across space and time and to map fishing activity, intensity and effort at a high spatial resolution (Thomas-smyth et al., 2013). VMS and logbook data can be considered as the census of vessel movement and fishing activities. In many fisheries, VMS and catch data reported by vessel operators are used to assess fishing activity and understand fishers' behaviors, track fishing efforts, and most importantly to design spatial management of fisheries (Joo et al., 2015). In 2015, Sri Lanka implemented a VMS to collect data on fishing activities at large spatial scales and to monitor offshore and high seas large pelagic fishing activities. In addition, mandatory maintenance of logbooks has been introduced as a strategy for systematic reporting of catch data in 2012 (Gunasekara & Rajapaksha, 2016). The combination of these logbooks and VMS data can be used to explore the spatial distribution of marine biota habitats at much finer spatial or temporal resolution (Thomas-smyth et al., 2013). However, these data have not been adequately used yet in the management and scientific studies in Sri Lanka. In this study, I have used logbook data from 2015 to 2019 to explore the spatial and temporal distribution patterns of longline tuna fishery in Sri Lanka.

However, identification of a spatial and temporal pattern of catch and fishing efforts pattern only is not enough for sustainable fisheries management. It is also important to identify if there are any productive and persistent hotspots, and if so, how these patterns and trends are associated with climatic, oceanographic and/or seafloor characteristics (Jalali et al., 2015). Previous studies have shown that the biophysical parameters such as sea surface temperature, salinity, chlorophyll-a, and depth have significance influence on the distribution of pelagic fish, and these biophysical parameters are frequently used to predict potential fishing grounds (Lanz et al., 2009; Jalali et al., 2015). Studies have shown that the distribution of tuna species is greatly influenced by oceanographic conditions (Nurholis et al., 2020), cost-related variables such as distance to the coast or nearest port (Soykan et al., 2014) and seafloor topographical variables (Jalali et al., 2015).

Remote sensing products have been widely used as primary data sources to derive such topographic and oceanographic characteristics (Santos, 2000). Satellite remote sensing sensors can detect real-time data on physical and biological features. This technology can provide consistent global ocean coverage of sea surface temperature (SST), sea surface salinity (SSS), depth and chlorophyll-a (Chl-a) at a relatively high spatial and temporal resolution, as measured from space (Mustapha et al., 2010: Nurdin et al., 2015). This study uses readily available remote sensing data such as SST, SSS, depth and chlorophyll-a to explore their influence on the temporal and spatial pattern of the longline fishery.

Fishers effectively utilize their traditional, cultural knowledge and social networks to identify potential fishing grounds. Most fishers, in developing countries like Sri Lanka, use traditional methods to locate potential fishing areas. For instance, fishers use using their traditional knowledge of weather conditions and previous experience and information from fellow fishers to find fishing grounds (Suhartono Nurdin et al., 2015). Natural features such as flying seabirds, schools of dolphins, surface bubbles, wood, or other floating objects on the surface are also used to identify fishing areas (Zainuddin, 2011). Ethnographic research is widely used to understand fishers' reactions to changing environmental conditions. In that context, this study also attempts to explore fishers' perceptions, experiences and their responses to changing marine environments and resulting spatial and temporal pattern of fishing efforts based on multiday boat fishers' observations and practices

1.1 Objective and organization of the Study

Using fisheries data from VMS and logbook data and socioeconomic information from the interviews, this study aims to investigate the distribution pattern of the longline tuna fishery and identify sustainable fishing grounds in Sri Lanka. The specific objectives are the following:

i) To identify the temporal and spatial pattern of longline fishery

ii) To identify and map main fishing grounds, clusters of high fishing efforts and high catch per unit efforts, and most productive and persistent fishing hotspots

iii) To identify topographical and/or environmental and socio-economic factors determining sustainable fishing grounds

This thesis is structured into six chapters. The second chapter presents the context of the Sri Lankan fishery industry, the fisheries management system and the conceptual framework of this study. Chapter 3 provides a detailed methodology including a short introduction of the study area. The fourth chapter presents the key findings of the analysis. Chapter 5 discusses the findings of the various methods used and whether the study's objectives were met, as well as makes observations about the study. The study is concluded in Chapter 6 with a summary of major findings.

2 Literature review and conceptual framework

This chapter provides an overview of the fisheries sector in global level, the fisheries sector and management in Sri Lanka by summarizing relevant literature, and provides a conceptual, and methodological framework of the study.

2.1 Fishing and fishery industry

According to the definitions given in the literature, fishing is the art and science of catching or hunting animals that live in water for profit-making or entertainment. Commercial fishing can be defined as the activity of catching and keeping fish or other aquatic animals and selling those animals for profit. The commercial fishing industry primarily aims to deliver fish and other seafood for human consumption or as input for other industrial processes(Guenard, 2021).

Excluding aquatic plants and other aquatic animals, global fish production in 2019 was 177.8 million tons, a decrease of less than 1% compared to 2018. Capture production accounted for 92.5 million tons in 2019, and a 4.3 per cent decrease from the previous year was reported (FAO, 2018). In 2019, the capture fisheries production of the top seven fishing countries accounted for nearly half of total global capture fisheries production. China was the top-ranking fishing country, accounting for 15.1% of total capture production, followed by Indonesia (8.1%), India (5.9%), the Russian Federation (5.4%), Peru (5.2%), the United States of America (5.2%), and Vietnam (5.2%) (FAO, 2018).

Fisheries and aquaculture provide the livelihood for 61.04 million people in the world in 2020. 38.70 million and 22.34 million people were employed in fishing and aquaculture respectively In 2018, Asia has the highest concentration of primary sector workers in fisheries & aquaculture (85%) (FAO, 2018).

The global total of fishing vessels was estimated to be 4.56 million in 2018, representing a 2.8 per cent decrease from 2016. Between 2013 and 2018, several Chinese fishing fleets dropped by nearly 20%, from 1 071 000 to 864 000 vessels. With 3.1 million vessels, Asia has the largest proportion of the global fishing fleets, accounting for 68 per cent of the global total. These figures show a decline in both absolute numbers and the proportion of Asia's fleet in the global total over the last decade (FAO, 2018).

According to FAO's long-term monitoring of and assessment of the marine fish stocks, the state of marine fishery resources has continued to decline. Fish stocks within biologically sustainable levels dropped from 90 percent in 1974 to 65.8 percent in 2017, with 59.6% classified as sustainably fished and 6.2 percent classified as underfished. The proportion of maximally sustainably fished stocks decreased from 1974 to 1989, then increased to 59.6 per cent in 2017, reflecting improved management implementation. In comparison, the proportion of stocks fished at biologically unsustainable levels increased from 10% in 1974 to 34.2 per cent in 2017. In terms of landings, it is predicted that biologically sustainable stocks account for 78.7 per cent of current marine fish landings (FAO, 2018).

2.2 Fishery sector in Sri Lanka

Sri Lanka is enriched with the marine resource. Even though Sri Lanka is a tropical country with diverse species, the narrowness of the continental shelf and the lack of upwelling limit the abundance and fisheries potential of marine fish species (Dissanayake, 2005).

Sri Lanka is the 36th largest fish producing country in the world (FAO, 2018), including marine capture fishery, inland and aquaculture. The fisheries sector plays a key role in the socio-economic context of the country and it contributes about 1.2 per cent to the GDP (MFAR, 2020). The marine fisheries sector in Sri Lanka consists of two main subsectors, namely coastal and offshore/deep-sea fisheries (MFAR, 2020). The total fish production of the country in 2019 was 505,830MT and marine fish production was 415,490MT (MFAR, 2020). Although there are 15 fisheries districts in the country, (Figure 1), Hambanthota (13%) and Galle (13%) districts together contributed 26% to the total marine fish production in 2019. Total marine fish production dropped by 0.8 per cent in 2018 compared to 2017. As a result of the adverse weather conditions that prevailed in the country's western and southern coastal areas during the second quarter of 2018 (NARA, 2018).

There were approximately 224,610 active marine fishers. The fisheries industry provides direct and indirect job opportunities for 585,000 people in Sri Lanka. In Sri Lanka, 2.7 million people depend on the fisheries sector for their livelihood (MFAR, 2020).

This study focuses on Sri Lanka's semi-industrial fleet, which is locally known as multi-day vessels or IMUL (Multiday boat with Inboard engine called – IMUL). IMULs are mediumsized vessels with a crew size of three to ten that typically use gillnets and/or long-lines to target high-value pelagic species such as tuna and sharks. On-board vessel equipment is broadly homogeneous, and all vessels rely on ice-holds to store the catch. These vessels lack advanced technologies detecting fish. In 2020, 4,885 IMULs were operating from 21 Sri Lankan ports. 1,189 of them are licensed for high seas fishing (MFAR, 2020). To operate on the high seas, vessels must have a High Seas License (HSL) and a functional VMS. In 2020, 224,610 people were directly employed in the industry as active fishers. By 2020, there were 185, 390 marine fishing households (MFAR, 2020). There are 149 marine fisheries inspector divisions in Sri Lanka. The quantity of the export of fish and fishery products in Sri Lanka accounts for 13,525 Mt in 2019. To cater for the excess demand, Sri Lanka imported 95 637 Mt of fish and fishery products which were valued at Rs.38 952 million. Thus fisheries industry is a salient aspect of producing foreign exchange for the Sri Lankan economy (MFAR, 2020).

2.3 Sri Lankan fisheries management

Sri Lanka is a party to the United Nations Convention on the Law of the Sea (UNCLOS) of December 10, 1982. Hence, the activities in the territorial sea, contiguous zone, continental shelf, and exclusive economic zone are carried out by the convention's definitions. Sri Lanka's territorial waters extend 22 kilometers (12 nautical miles) beyond the coastline and cover an area of approximately 21,500 square kilometers. The contiguous zone is a band of water that extends from the edge of the territorial sea up to 24 nautical miles. Furthermore, the country has unmandated rights to an 'exclusive economic zone' (EEZ) that extends outward 370km (200nm) from its shores and covers an area of approximately 510,000 sq. km. Not only Sri Lanka has sovereign rights to resources in the water column, seabed, and subsurface, but it also has the full authority to authorize, regulate, and control scientific research within this zone (Maritime Zones Law, 1976).

State institutions such as the Department of fisheries and aquatic resources (DFAR), National Aquatic Resource Research and Development Agency (NARA), Ceylon Fisheries Harbour Corporation (CFHC), National Aquaculture Development Authority (NAQDA), Ceylon Fisheries Corporation, (CFC), Cey-Nor Foundation Ltd. (Cey-nor) involve in high sea fisheries management of Sri Lanka.

The high seas are open to all countries and the countries have the freedom of navigation and fishing. As a result, all states have the right to allow their nationals to fish on the high seas. This freedom, however, is not unrestricted, and it must be exercised by the terms of the Convention and other applicable rules of international law (Edgar, 2007).

There are six major international instruments ratified by the Sri Lankan government related to high sea fisheries management. Most of them are directly or indirectly prove legal provisions to manage high sea fishing fleets. However, no information is available regarding the effectiveness of these instruments. Thus multi-day boats built by many of the major national boatyards did not meet international standards (Amarasinghe, 2013).

Molenaar (2001) analyzed the present regional and global institutional and legal framework relating to the management and conservation of high seas fisheries. Regional Fisheries Management Organization along with several international instruments are responsible for governing high sea fisheries. Law of Sea convention (LOS), the Fish Stock Agreement, the Code of Conduct and the Compliance Agreement are the main instruments established for the management of high seas fishery resources. Institutional arrangements characterized by Food and Agriculture Organization and other United Nation bodies represents global institutional arrangements. RFMO is the dominant regional institution that manages high seas fishery resources.

In Sri Lanka, marine fisheries resources and fishing activities are still managed under open access and a common property regime. There are no well-formulated management strategies for fisheries in Sri Lanka. Hettiarachchci (2004) stated that with the high rate of population growth in Sri Lanka, fish demand increases too. To cater to this increased demand, higher rates of exploitation of fish beyond the existing levels may be required. To face this challenge, the state decided to expand fish production by introducing multi-day fishing vessels in the late 1980s to develop offshore fishery which leads to the exploitation of high sea fish resources. Discussion among the word community occurred in 1940 and as a result of that various international instruments related to high-sea fisheries were emerged. United Nations Law of the sea of 10 December 1982 postulated a framework for all fisheries operations.

The government has established several institutes to develop policies, strategies, and facilities for the sustainable use of Sri Lanka's fisheries resources. The fisheries and aquatic resources act (2) of 1996, as well as several other regulations, were implemented to govern the use of aquatic resources and to ensure the sustainable management of fisheries. Despite the existence of a well-established hierarchy for the proper management of the fishery sector, issues such as overfishing, and unsustainable fishing practices continue to impact the country.

Regional fisheries organizations have been formed to advise and coordinate regional countries to promote long-term sustainable fisheries. Regional Fishery Bodies (RFBs) and Regional Fisheries Management Organizations (RFMOs) are two of them that serve different purposes. RFMOs primarily deal with fisheries conservation and management issues, whereas RFBs are generally concerned with consultative or advisory measures for regional or member countries. Asumundsson (2001) defined Regional Fisheries Management Organizations (RFMO) as an asset of central management organizations, covering all the high seas areas and species, implementing the goals and objectives set by the international community which can be enforceable against members and non-members.

Amaralal and co-authors (2009) revealed in their research on the economic efficiency of the deep-sea fishing fleet of Sri Lanka that the size of the multi-day vessel has an inverse relationship to the profit. Smaller vessels are more economical for the deep-sea fisheries in Sri Lanka in terms of periodic (yearly) return on capital investment. Therefore, governing the deep-sea fishing fleet is important. They suggested that the profitability of the deep-sea fisheries can be developed further by increasing collaboration and cooperation between all necessary stakeholders.

Sri Lanka has adopted several bilateral multilateral and regional cooperation agreements with other countries to ensure the long-term sustainability of high sea fisheries. Though Sri Lanka agreed to follow such international regulations, there were loopholes in existing high seas management legislation. As a result of those shortcomings, Sri Lanka was identified as an uncooperative fishing country by the EU in February 2015 and imposed a ban on imports of fish from Sri Lanka. This had a significant impact on the country's fisheries trade. Fortunately, Sri Lanka was delisted again in April 2016 and the EU has lifted the ban on fisheries exports from Sri Lanka (European Comission, 2016).

After the EU ban, a national inspection plan was conducted in 2015 by the Department of Fisheries and Aquatic Resources under the Fisheries and Aquatic Resources Act No 2 of 1996.

This was done to ensure the compliance of the fishing activities of local fishing boats in EEZ or high seas with legally adopted conservation and management measures. The regulations govern the following topics: management and conservation, reservation areas, fishing boat condition, fishing net status and other related issues. A summary of the prominent regulations enacted is given in the following Table 1.

To gain long-term benefits the fisheries industry must optimize production while not over-exploiting its resource base. For the development of fisheries in Sri Lanka, new approaches have been initiated. A policy framework was established by the government of Sri Lanka in 2019 to ensure the sustainable management of fishing resources. It includes the following policy instruments, a). applying ecosystem and precautionary approaches to promote responsible fisheries management, b). ensuring sustainable management of the living marine resources based on the best available evidence from social, economic and ecological sciences, c). enhancing the stocks of endangered, threatened and protected species, d). enhancing fish stocks in the territorial sea and the exclusive economic zone (EEZ) by ranching and habitat enhancement, e). preventing overcapacity of the fishing fleet, f). diverting marine fishing efforts from over-exploited areas to unexploited or underexploited areas, g). Promoting the use of fishing practices and equipment that cause comparatively low adverse impacts on the environment, Maintain the ban on fishing in Sri Lanka waters by foreign fishing vessels except for research and development purposes (Ministry of Fisheries and Aquatic Resources, 2019). The Ministry of Fisheries, FAO, and other stakeholders have identified challenges that need to be addressed to accomplish the objectives listed in the above policy framework.

The fisheries sector in Sri Lanka is a labor-intensive, multi-species and multi-gear fishery. Although the challenges associated with fisheries management change over time, some issues persist for long periods and are difficult to resolve. World Bank report (2020) has mentioned some challenges. To address or mitigate the challenges, the ministry of fisheries has taken several steps, including implementation of rules and regulations, improving public awareness, and developing strategic plans. The following challenges of the Sri Lankan fisheries sector were identified in the 10-year development plan: Indian fishers poaching, lack of sound data and information, lack of comprehensive stock assessment, post-harvest losses and poor marketing and transportation, inadequate and poor management and maintain fishery infrastructure, poor and destructive fishing gear practices, inadequate investment in the fishery sector, poor coordination between Ministry and allied institutes, poor application of the fisheries development plan, insufficient expertise of the fishery sector, high operational cost of fishing (World Bank Report, 2020). These challenges should be addressed to overcome the negative influence of the issues. To address or mitigate the challenges, the ministry of fisheries has taken several steps, including the implementation of rules and regulations, improving public awareness, and developing strategic plans.

International collaboration is one of the important measures to address the above challenges. For example, Sri Lanka–Norway Bilateral Project Phase II has been implemented to improve data collection capacity and practices to achieve sustainable management of Sri Lanka's fisheries resources. NARA, DFAR, and the Norwegian Institute of Marine Research are the main stakeholders in this Project (World Bank Report 2021).

Table 1:Sri Lankan laws related to high seas fishing fleet management

Provision in the Act/ Regulations	Management Measures
Section 14A as amended by Act, No. 35 of 2103	Prohibited to engage in any prescribed fishing operations on high seas without a license granted by DG
Section 14E as amended by Act, No. 35 of 2103	At all the times Fishing boats should carry the license granted by DG for fishing operations in high seas and produced for inspection by an authorized officer when required
Section 14F as amended by Act, No. 35 of 2103	No Sri Lankan fishing boats should be fishing within the national jurisdiction of another State except under the authority and by the laws of that country.
Section 14Nas amended by Act, No. 35 of 2103	DG should subject to the availability of resources, educate fishers on the IOTC regulations and create awareness among fishers about the measures taken by the government to conduct long term training and educational programmes to conserve fish stocks and minimize pollution.
Section 15 as amended by Act, No. 35 of 2103	Without registering a boat as a local boat, should not be used for fishing on high seas
High seas fishing operations regulations, No. of 2014 (Gazette, No. 1878/12)	No person should engage in following prescribed fishing activities in the high sea in contravention of conservation and management measures adopted by Sri Lanka for UNLOS of 1982, UN fish stock agreement, IOTC and FAO port state measure agreement:

	Purse seine fishing operations, Longline fishing operations, Gillnet *cum* long line fishing operations, Gillnet fishing operations, Pole and line fishing operations, Tolling fishing operations, Handling fishing operations, Trolling fishing operations
Section 61(1) (m) and (s) / Fish catch data collection regulations, 2012 (Gazette, No. 1878/ 11)	Every fisher who uses a mechanized boat for fishing in Sri Lanka waters or high seas should carry onboard a logbook. Needs to maintain a record of the catch of each fishing trip and furnish a certificate of the catch to the competent authority in the prescribed form.
Section 61(1) (t) as amended by Act, No. 35 of 2013 / Port State Measures to prevent, deter and eliminate IUU fishing regulation of 2015)	Without a license from DG, no person should land, transship, pack or process fish taken outside Sri Lanka waters by foreign boat at any port in Sri Lanka or obtain port services for such boat.
Section 61(1) (h) / fishing gear marking regulations of 215	All types of fishing gears and fishing aggregating devices carried on board fishing boat fishing boats should be marked as prescribed
Section 61(1) (t) / Satellite based vessel monitoring System for fishing boats operating in high seas regulation of 2015	High seas operating fishing, supply or cargo vessels, refers and carrier vessels of or above 10.3m (34 feet) or above should be installed with a functioning satellite-based VMS device.

2.4 Ecosystem approaches to fisheries management

Recently ecosystem-based fisheries management approach has been developed and adopted to enhance fisheries resource sustainability, i.e., aiming to balance social, economic and ecosystem sustainability. Due to the depleted condition of many fisheries resources, this recognition has grown, and more effort has been made to improve this approach (Zhang ,2005). The term ecosystem approach (EA) was adopted for the first time in the 1992 United Nations (UN) Convention on Biological Diversity (CBD). The FAO defines the ecosystem approach to fisheries as “striving to balance diverse societal objectives, by taking into account the knowledge and uncertainties about biotic, abiotic and human components of ecosystems and their interactions and applying an integrated approach to fisheries within ecologically meaningful boundaries” (Garcia & Cochrane, 2005). According to that, an ecosystem is a geographically defined system of organisms (including humans), their environment, and the rules that influence their behavioral patterns. The biological, chemical, physical, and social conditions that surround organisms are referred to as the environment (Pices, 2005).

It is essential to understand how Sri Lankan fisheries managers are currently applying ecosystem principles into the current management approaches. The following principles are strategically synchronized into the current management approaches by the government. These management principles can be divided into five categories as: enforcement management, community-based management, co-management, environmental management, and special area management. Enforcement management is the management of resources by state laws and regulations. In this community-based management system, the management of aquatic resources is carried out by the communities conducting the relevant aquatic life operations. Co-management is a community-based joint management is the participation of all public sector consumers and other contributing agencies in the formulation and decision-making of management systems. Environmental management refers to the management of the aquatic environment in a manner appropriate to the aquatic life. Specialized area management is the practice of implementing a specialized general management mechanism for the area when all the parties are indirectly or directly linked to the sustainability of the resources in the area.

It requires taking into account the interactions between populations and their physical and biological environments. Ecosystem Approaches to Fisheries (EAF) are adaptive and geographically specified. Those approaches consider multiple external influences and strive to balance diverse ecological and societal objectives (Nelson & Haverland, 2009).The Geographic Information System (GIS) is regarded as an ideal platform for performing the necessary information management and decision-support analysis for implementing a fisheries ecosystem approach (Carocci et al., 2009). Spatial analysis using Geographical Information Systems (GIS) is widely recognized as an important tool for integrating ecosystem data from various sources .Spatial analysis as part of EAF and generally focuses on the fishing catch and effort analysis, area characterization, bycatch analysis, habitat interaction and fisheries oceanographic modelling (Nelson & Haverland, 2009). GIS can be one of the most important tools for facilitating the application of the ecosystem approaches, not only in terms of fisheries management, but also in terms of the development of new knowledge and understanding of the interactions between human activities and the ecosystem (Nelson & Haverland, 2009).

Spatial analysis as part of EAF generally focuses on fishing catch and effort analysis, area characterization, bycatch analysis, habitat interaction and so on. To implement EAF, we need fine scale data about fishers' behaviors as manifested by vessel movements and spatial distribution of fishing efforts and catches, as well as spatial pattern of stock availability.

2.5 VMS and logbook data and vessel-based fisheries monitoring and management

The increasing data set of vessels monitoring systems (VMS) allows fisheries researchers to explore the fine-scale spatial and temporal dimensions of fisheries data, which is a significant for the advancement in fisheries research. A more sustainable approach to fisheries management necessitates the use of spatially explicit fishery data. According to Gerritsen & Lordan (2011), the traditional landings-and-effort data at coarse spatial and temporal scales are no longer adequate for many purposes due to new sustainable fisheries management demands many aspects such as biodiversity preservation, spatial and temporal fisheries closures, and diverse maritime resource uses. The implementation of vessel monitoring systems (VMS) has caused for increasing the availability of data on the distribution of fishing activity by providing vessel-specific high-resolution data from all fishing grounds visited by larger vessels. Despite the fact that VMS were introduced to aid enforcement, processed VMS data are increasingly being used to show the locations and dynamics of fishing activity, typically based on distribution of position records or reconstructed tracks (Jennings & Lee, 2012).

VMS are mainly used for fisheries management, but they can also be used for other applications such as improving the accuracy of fish stock assessment. However, a number of limitations exist including incomplete coverage of vessel activities, a lack of catch information, a long time interval between position records, and whether the vessel actually fished at the time the activity was recorded. (Thomas-smyth et al., 2013).

After introduction of position reporting (VMS) systems and the use of these data to monitor, understand, and analyses commercial fishing activity and behavior have become increasingly popular among authorities and researchers all over the world. Ray Hilborn was a pioneer in this field, publishing his study "Fleet dynamics and individual variation: why some people catch more fish than others" in 1985. Hilborn advocated for a greater emphasis on fishers' behavior and fleet dynamics in fisheries-related research environments around the world using VMS data (Hilborn, 1985).

In 1985, Hilborn emphasized that a more nuanced understanding of fishing dynamics and stock assessments were needed, and he included fishing behavior into his model (Hilborn, 1985). In the study, it was found that this technique is particularly useful in fisheries where multiple species are caught at the same time, where there is technology-mediated interaction between fishing fleets, where different fishing fleets target the same stock in the same area. Hilton successfully used VMS data to map and analyze fishing activities in commercially important fishing areas.

In 2012 the Department of Fisheries and Aquatic Resources introduced logbooks to collect spatial and location-specific catch data in Sri Lanka. Logbooks onboard high seas fishing vessels are a mandatory requirement of IOTC resolutions and managing logbook data is a critical component of IUU fishing management. Logbooks and logbook data were decisively combined with Sri Lanka's high seas fisheries management procedure as part of the road map to lift the EU fish export prohibition. As a result, in 2015, a systematic approach to developing a database was also initiated (Gunasekara & Rajapaksha, 2016). Since it was widely recorded and compiled, logbook data has been considered as a source of fisheries data. However, in many fisheries management systems, logbook information has been consistently argued to be unreliable and not verified as accurate. Until the introduction of VMS in late 2015, there was no cost-effective alternative in Sri Lanka for validating the accuracy of fisheries logbooks (Gunawardane, 2016).

Self-reported logbook data has long been used to monitor catch levels and fishing activity in Sri Lanka's offshore fisheries, providing a low-cost alternative to increased monitoring and enforcement (Gunasekara & Rajapaksha, 2016). Accordingly, this data frequently includes the latitude and longitude coordinates of where fishing activity occurs, as well as the total catch and catch composition. It is required to record the information in logbooks as soon as the catch is landed at the port to ensure the fish was caught using appropriate methods and in approved areas (Thomas-smyth et al., 2013). The logbooks are then compiled, so that each fishery has a complete data set of all the fishing locations reported for a specific time period, including specific information on hot spots of fishing operation and high catch areas. The combination of logbook and VMS data can be effective in describing the spatial distribution of marine biota habitat at much finer spatial or temporal resolution.

Many studies have also explored the possibility of combining VMS data with fisheries logbook data. Murray et al. (2013) investigated the efficacy of combining these two types of data to estimate scallop biomass. The study compared biomass estimates from cruises performed by both fishing vessels and research vessels, using the fishing dependent data from VMS and logbooks. they discovered that the conditions between the estimates varied greatly throughout the fishing season, and that sampling time and location affected biomass estimates over short periods. Maina et al. (2016) created a method for mapping fishing grounds and analyzing existing spatial patterns for Greek trawlers.

Jalali et al. (2015) investigated commercial fishing for blacklip abalone (*Haliotis rubra*) stocks in Australia and discovered that catch per unit effort (CPUE) was not uniformly spatially and temporally located in the study area based on VMS and catch data. The researchers used spatial autocorrelation techniques and hotspot analysis to identify CPUE hotspots, annual cumulative significant hotspots were used as a simple proxy indicator for areas that had sustained fishing pressure.

In 2015, Sri Lanka implemented a Vessel Monitoring System (VMS) to monitor offshore and high seas fishing activities. The vessel monitoring system collects data on fishing activity at large spatial scales (Gunasekara & Rajapaksha, 2016). In addition to the VMS, logbooks were introduced for systematic fishery data collection. Despite the availability, the VMS and logbook data is underutilized in Sri Lanka for management purposes. This is the first attempt to combine

VMS data with corresponding logbooks to identify hotspot areas in the Sri Lankan longline fishery.

2.6 Fishing efforts and CPUE

CPUE is a quantitative parameter used to describe the fisheries industry worldwide. CPUE can be presented as the number of fish per 1000 hooks, number of fish per amount of fishing time, or with any unit of effort that best describes the fishery (e.g., search time, hooks per hour, number of gear) (Appelman, 2015). CPUE is generally used as a proxy indicator for stock abundance, as function of fish abundance and catchability at the time of fishing (Trenkel et al., 2013) These indices are then used in stock assessments to help fisheries managers make informed decisions about how to manage a specific stock or fishery, such as quotas, catch limits, gear and license restrictions, or closed areas (Alizadeh Ashraf, 2021; Appelman, 2015; Milisenda et al., 2021).

The allocation of fishing effort to exploit fish stocks in response to changes in the marine environment, market conditions, and regulations is a prerequisite for successful fisheries management. Fishing effort is influenced by constantly changing environmental conditions such as food availability and sea temperature. Another issue derives from natural uncertainties as well as external disturbances such abrupt oceanographic changes, which might have an impact on catch size and profitability. (Alizadeh Ashraf, 2021; Appelman, 2015).

Vessel movement pattern shows the fishers behavior, trend and spatial pattern of fishing efforts. The data on vessel movement patterns can be effectively used to reveal the interaction of fish availability, economic cost (distance, fuel, time, labor), fishers tradition and practices and profitability. Spatial analysis of CPUE can be used to identify important as well as productive fishing grounds.

2.6.1 Hotspot analysis of CPUE and fishing efforts: Identification of fishing ground

FAO defines fishing effort as "the amount of fishing gear of a specific type used on the fishing grounds over a given unit of time," implying that fishing grounds should be defined as "the areas where fishing effort is deployed."(FAO,1997). fishing grounds can be defined as "crucial areas characterized by both fishing activity and species presence as a result of a strategy to maximize catches and economic gains."(Maina et al., 2016). Currently, most fisheries research attempts to identify fishing grounds using hotspot analysis for fisheries management purposes. As a result, it is essential to identify sustainable (persistent) hotspot areas in order to protect the resources.

The method of calculating hotspots are based on spatial autocorrelation concepts and measures such as global Moran's I and/or Gi * statistics. Hotspot analysis is spatial analysis to identify statistically significant spatial clusters of high values (hotspots). Several studies have used hotspot analysis in recent decades to identify key economic areas, preferred fishing banks for various fishing gear, spatial (eg: expansion) and temporal changes in fishing areas, much / little-used areas, sustainable areas, and areas most affected by fishing activity (Jalali et al., 2015; Maina et al., 2016; Suhartono Nurdin et al., 2015). In this study, I have followed the method which is used in the studies of Jalali (2015) and Maina (2016) to identify important fishing grounds as indicated by significant hotspots and persistent hotspots as indicated by cumulative hotspots.

This method is based on the Getis-Ord Gi* statistics to identify statistically significant spatial clusters of high values (Hot Spot) and low values (Cold Spot), where significant hotspots are considered as important fishing grounds (Jalali et al., 2015; Young et al., 2020; G. Zhang, 2022). The final results of the analysis are the Z-score, p-value, and confidence level bin (Gi Bin).

2.7 Driving factors for fish abundance

The ecosystems in the Indian Ocean have affected by a number of climatic conditions. The Indian Ocean is heavily influenced by two wind systems known as the southwest and northeast monsoons, resulting in seasonal variations in temperature, phytoplankton, ocean currents, and mixed layer properties (Gunasekara & Rajapaksha, 2016). Previous research has shown that oceanographic conditions such as sea surface temperature, Bathymetry, salinity, and chlorophyll-a have a significant impact on tuna species distribution (Barnes & Williams, 1981; Childers et al., 2011; Nurholis et al., 2020). As a result, it is reasonable to assume that these factors may have an impact on tuna abundance and distribution. Only a few studies have been conducted in the Indian Ocean to better understand tuna fisheries oceanography.

The effects of increasing climate change can be seen clearly in the maritime environment. The restructuring of marine biodiversity, for example, is occurring at a fast-enough rate to have an impact on human society. Marine fishes, which respond quickly and on large scales, are among the primary sentinels of such change (Stuart-Smith, 2021) . The Indian Ocean has long been recognized as being particularly vulnerable to climate change. Large-scale climate fluctuations occur in the Indian Ocean as a result of interannual variability in sea-surface and subsurface temperatures, which causes changes in accompanying wind and precipitation anomalies (Saji et al., 1999). Recent research suggested that changes in oceanic circulation caused by rising CO2 concentrations in the atmosphere reduce the primary production in the tropical oceans. This could have an impact on the productivity of medium and higher trophic levels, potentially affecting marine resources such as tropical tuna (Loukos et al., 2003).

Chl-a has been identified as a crucial oceanographic parameter in determining ocean productivity. The Chl-a pigment is a useful indicator of phytoplankton biomass (Solanlki et al., 2001) and it could be related to fish production (Bertrand et al., 2002). Sea surface temperature (SST) is considered as a physical environmental index that controls the physiology of living organisms and influences phytoplankton growth (Tang et al., 2003). It is known that SST plays a key role as the only environmental predictor highly related to diversity of many pelagic fish species (Tseng et al., 2011).

Among the ecological factors, salinity is specific factor of particular aquatic environment. Many authors have demonstrated the influence of external salinity on growth capacities in fish (Bœuf & Payan, 2001); Alabia et al., 2015). Longline hooks deployed at appropriate depths can significantly increase catch of desired species such as big-eye tuna and billfish while reducing bycatch of protected and untargeted species such as sea turtles (Boggs, 1992 ;Zhu et al., 2012).

This study will attempt to explore the influence of SST, salinity, chlorophyll, and benthic topography on the abundance of Longline Tuna fish.

2.8 Importance of fishers' perception, experiences, tradition and practices

In 1981, Posey defined ethnography as indigenous perceptions of "natural" divisions in the biological world and plant-animal human relationships within each division. And also he explained ,this is because cognitively constructed ecological categories do not exist in isolation; ethnoecology must address ideas of interconnectedness among natural divisions as well.(Posey et al., 1984). We can use this concept to develop ecosystem base management in the fisheries sector. Traditional ecological knowledge (TEK) or traditional fishing knowledge can be used to supplement available information on the abundance – and changes in abundance – of the selected species in the ecosystem (Gasalla & Diegues, 2010). TEK is a subfield of ethnoecology or maritime anthropology that examines how fishers perceive the ocean – the physical/biological environment in which they work and live (Gasalla & Diegues, 2010).

In scientific assessments, Hutchings (1996) identified three strategies for using information from guided personal interviews. First, local knowledge of the dates when fish are caught in fixed-gear locations can provide seasonal and directional fish movement information. Second, fishers can provide information about the stock structure. Finally, fishers can provide information on movement patterns (via catch patterns), spawning grounds, juvenile habitat (e.g., juvenile bycatch and spatial patterns in fish morphology) (Gasalla & Diegues, 2010; Hutchings, 1996; Neis et al., 1999; Posey et al., 1984).

In this thesis, I combined TEK and data from VMS and logbook to understand complex relationship in the fisheries system. I believe that integration of fishers' ecological knowledge in this case the fishers' perception, experiences and knowledge about fish resource availability, and their responses can significantly reduce the uncertainty associated with spatial analysis modelling based on only VMS and logbook data.

3 Methodology

This chapter provides a detailed description of the methods and data used to identify spatial and temporal distribution patterns of multiday longline fishery in Sri Lanka.

3.1 Study area

Sri Lanka is an island in the Indian Ocean, located between latitudes 6-10° N and longitudes 80-82° E. The coastline of Sri Lanka is approximately 1585 kilometers long, with numerous bays and shallow inlets. Sri Lanka has the sovereign rights over approximately 517,000 km^2 of the ocean since the declaration of a 200-mile Exclusive Economic Zone (EEZ) (Figure 1) in 1978 (Wijayaratne & Maldeniya, 2003). Fishing occurs all along the coast, but primarily within the continental shelf, which has a width that rarely exceeds 40 kilometers and averages 25 kilometer, with a total area of about 30,000 km^2. This accounts for approximately 6% of the total area of the EEZ.

The Indian Ocean is heavily influenced by two wind systems; the Southwest monsoon from May to September and the Northeast monsoon from November/December to February. These wind systems cause seasonality in temperature, phytoplankton, ocean currents, and differences in water properties. Large-scale oceanic currents associated with regional oceanic circulation predominate in waters beyond the continental shelf. The currents are controlled by wind and temperature variations, and their general pattern changes seasonally. Currents off the east coast are strongest during the northeast monsoon and have an easterly trend, whereas currents off the west coast are strongest during the southwest monsoon and have a westerly trend (Dissanayake, 2005). Hence, it is reasonable to expect that these factors will have an impact on the abundance and distribution of Longline Tuna. Only a few studies have been conducted in the Indian Ocean to better understand the tuna fisheries abundance and activities.

There are 15 Administrative Fisheries Districts in Sri Lanka, and these districts are divided into four geographic regions (Figure 1). In 2019, 38% of marine fishers of Sri Lanka worked on the east coast, 25% on the north coast, 19% on the west coast, and 18% on the south coast. Nonetheless, the production of marine fisheries was highest on the south and west coasts. Table 2 shows the distribution of the marine fish production and number of fishers across four main fisheries regions. The west and south coasts have well-developed marine capture fisheries compared to the east and north coasts. The fisheries industry in north coast is still not performing well as a result of the civil war that lasted from 1983 to 2009.

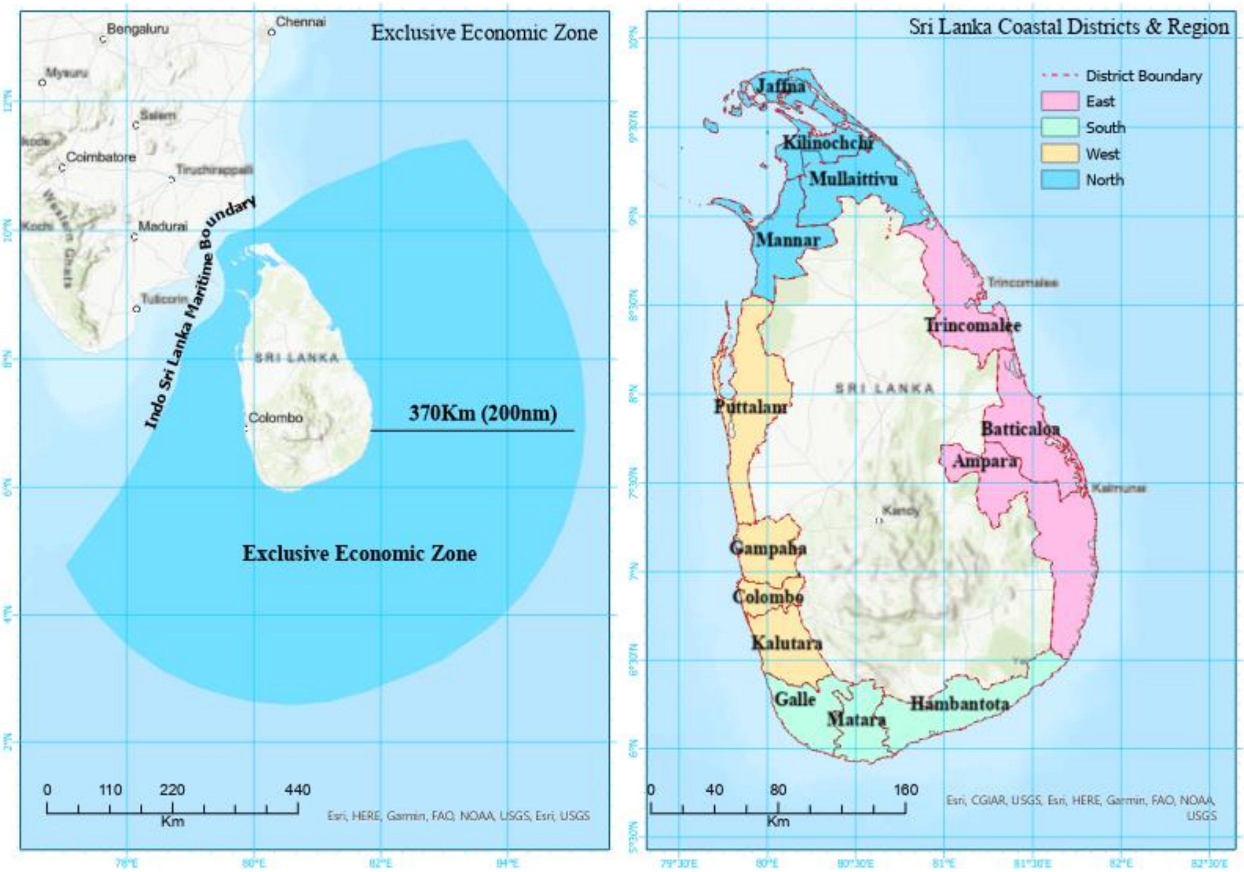

Figure 1:Sri Lanka's Exclusive Economic Zone (EEZ), 4 Coastal Fisheries Regions and 15 Administrative Fisheries Districts

Table 2:Characteristics of Fisheries by Coastal Region, 2019

Region	Marine Production (MT)	Number of Fishers
North Coast	86,310	55,780
East Coast	59,680	86,000
West Coast	133,710	40,010
South Coast	135,790	42,820
Total	**415,490**	**224,610**

There are mainly twenty-one ports that provide anchorage to high sea multiday boats in Sri Lanka (Figure 2). Ceylon Fisheries Harbour Cooperation (CFHC) is the main government body which responsible for the development and management of the fishing harbors and anchorages in Sri Lanka.

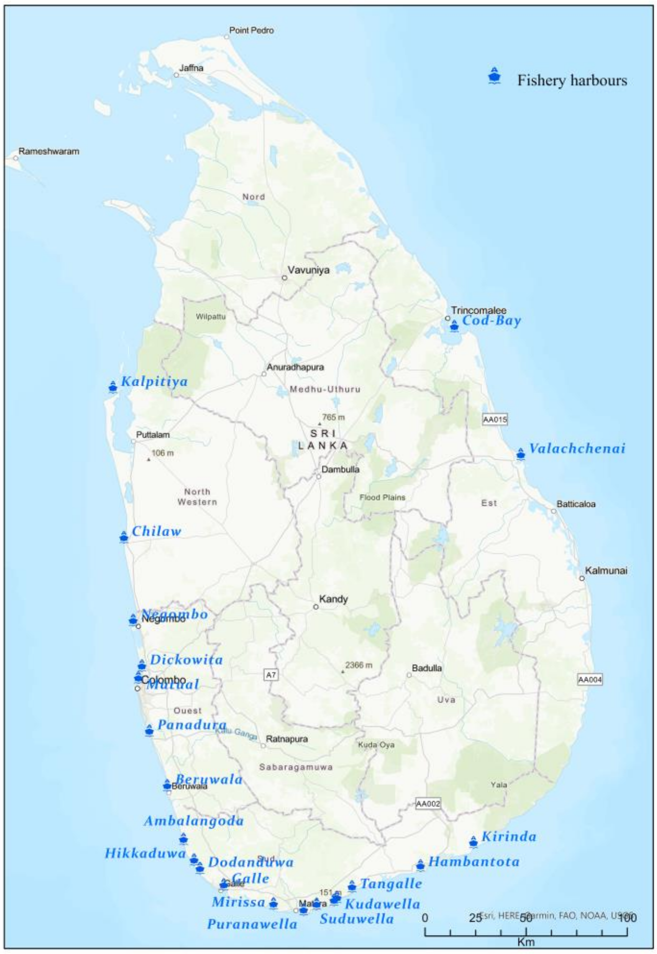

Figure 2:Fishing harbors in Sri Lanka

South Indian Ocean was selected as the study area (Figure 3). The selected area was divided into four subregions based on where the majority of the fishing activities take place: The East coast high sea, South coast high sea, West coast high sea and West coast.

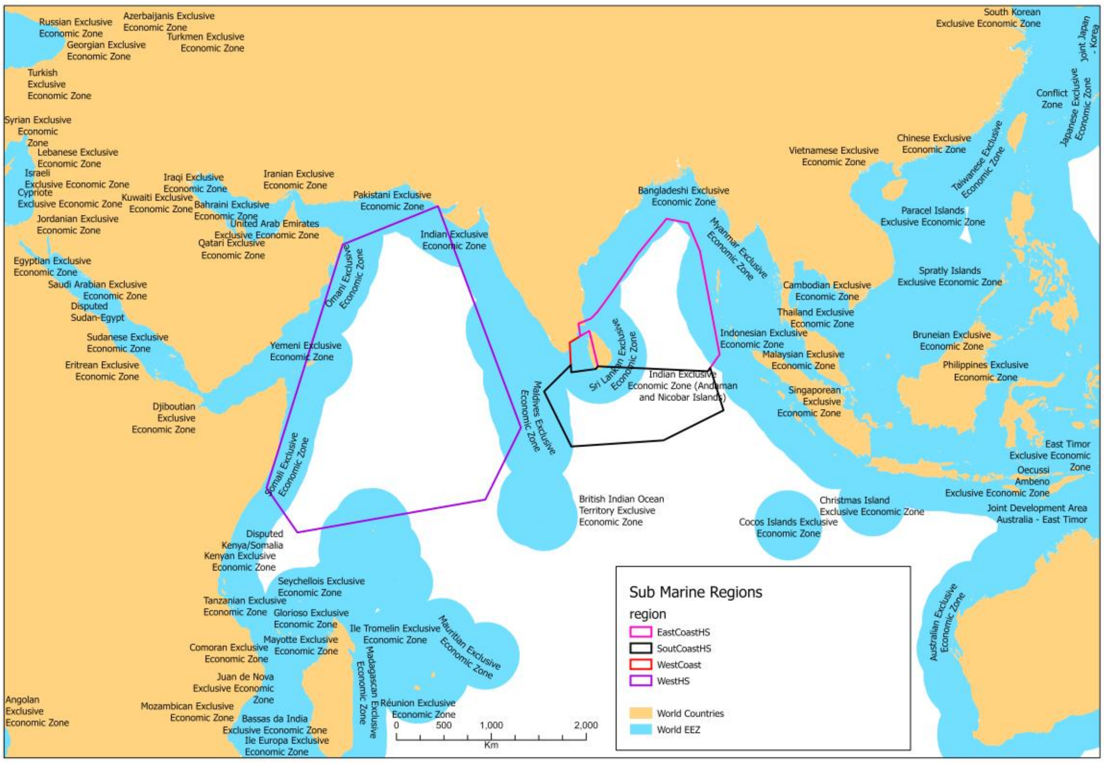

Figure 3:The study area depicts the EEZ, high seas, and subregions where most fishing activities occur in Sri Lanka

3.2 Data and materials

3.2.1 Fishing effort data

Data from daily records of fishers' logbooks for the period 2015 – 2019 were collected from Department of fisheries and aquatic resources. The raw database contains information about fishing trip, geographical coordinates (based on VMS) and catch (kg and number of fish), time of the fishing (month, year), duration (hours/or months) at sea, number of hooks, and so on.

First, the invalid point locations and extreme values in the data set were checked before importing into GIS and cleaned in Excel. The outlier and null data of the dataset were removed, and the raw data was processed. In the dataset, the records on number of days /hours at sea, number of hooks were unreliable, and there were a large number of missing records. For example, a) information about the number of hooks was missing in 2017 and 2015 datasets. b) in several cases the number of hooks was too low (for example, just 0 or < 2). Consequently, use of number of hooks and/or number of days at sea were not usable as the indicators of fishing efforts, so I didn't use these data for further analysis.

I used Asia South Lambert Conformal Conic coordinate system to process and analyze spatial data.

The point data for catch (kg) and effort (Trips) were aggregated and analyzed using 4 km grids. To analyze catch per unit effort, I used the number of trips as the proxy indicator of fishing effort. So, catch per unit trip was defined as catch per trip (CPT). The value was calculated as the sum of the kg divided by total number of trips within a 4 km grid. The amount of catch (kg) for each tuna diver on each fishing trip was estimated by using the allometric relationship: W = 0.000412(SL/10)2.76. Reported catch was then divided by fishing trips derived from fishers' logbook data to estimate CPT. I assumed that effort was evenly distributed across trips.

3.2.2 Interview

I planned to conduct fieldwork in Sri Lanka. Due to time constraints and Covid regulations, I couldn't visit the study site to conduct detailed ethnographic fieldwork as planned. I employed two field assistants from the Department of Fisheries, University of Ruhuna in Sri Lanka. The interviews do not contain any personal information, and the data was collected using a printed questionnaire. The assistants did not use any recording or video devices.

The purposive sampling technique were used to select the respondents. Thirty respondents representing 30 high seas crafts were interviewed. The sample includes the crew members of the high sea fishing vessels of the South, West, and East coasts. Table 3 summarizes the distribution of the respondents across the selected fishing regions and harbors. Data were collected from fishers in Galle (4), Mirissa (4), and Dodanduwa (2) harbours in the South Coastal region, and Negombo (3), Chilaw (5), and Kalpitiya (5) in the West region. Ten fishers from Trincomalee (from the East Region) were included in sample. The majority (43.33%) of the respondents in the sample were skippers, followed by crew members (26.67%). All the respondents were male as females are not involved in deep sea fishing in Sri Lanka.

The questionnaire included information on areas of operations, target species, duration of a single fishing trip, knowledge of topographical and/or environmental factors, socio-economic factors which are important in determining the sustainable fishing grounds and challenges for high seas fishing (Appendix 1).

Table 3: Fishing regions of the respondents

Coastal Region	Harbour Name	No of respondents
Southern Region	Galle	4
	Mirissa	4
	Dodanduwa	2
Western Region	Negombo	3
	Chilaw	5
	Kalpitiya	2
Eastern Region	Trincomalee	10

3.2.3 Environmental and biophysical data

Sea surface temperature (SST), sea surface salinity (SSS), Chlorophyll-a (Chl) and Bathymetry are the environmental and biophysical variables used in this study. Some of these variables were chosen because they had previously been linked to tuna fish presence and pattern (Zainuddin, 2011). The units, spatial resolution, and source of the above- mentioned oceanographic variables used in this study are summarized in the table 4.

Table 4: Environmental variables used in the spatial distribution modeling of longline fishery

Variables	Name	Units	description	Source
SST	Sea Surface Temperature	^{o}C	4km resolution	NASA https://oceandata.sci.gsfc.nasa.gov/
SSS	Sea Surface Salinity	PSU	4km resolution	NASA https://oceandata.sci.gsfc.nasa.gov/
Chl	Chlorophyll-a	mg/m^{-3}	4km resolution, Chlorophyll-a concentration during the daytime as measured by the MODIS Aqua sensor	NASA https://oceandata.sci.gsfc.nasa.gov/
Depth	Benthic topography	m	90 m resolution, GEBCO version …	The General bathymetric Chart of the Oceans GEBCO) https://download.gebco.net/

BPI	Bathymetric Position Index	no unit	The difference in height at a focal point compared to the mean elevation of surrounding cells is used to calculate BPI, which is a measure of a defined elevation at a specific location relative to the overall landscape.	ArcGIS extension benthic terrain modeler (BTM version 3.0)
VRM	Vector Ruggedness Measure	no unit	Terrain ruggedness (VRM) is a measure of the variation in three-dimensional orientation of grid cells within a neighborhood.	ArcGIS extension benthic terrain modeler (BTM version 1.0)

Bathymetric Position Index (BPI) and Vector Ruggedness Measure (VRM) were derived from 90 meter depth data suing BTM extension (NOAA, 2013). The Broad-Scale BPI was used to derive BPI, which allows for the identification of larger regions within the benthic landscape. The terrain ruggedness was used to calculate VRM. The dispersion of vectors normal (orthogonal) to grid cells within the specified neighborhood was calculated using vector analysis. This method effectively combines slope and aspect variability into a single measure.

The Asia south lambert conformal conic coordinate system was used to project all environmental and fish data layers. ArcGIS Pro was used to process exploratory variables and conduct additional analysis. Figure 4 illustrates the processing and analysis workflow.

3.3 Data analysis methods

3.3.1 GIS based spatial and temporal analysis

The longline tuna fishing data sets were investigated by visual analysis and by measuring simple geographical distribution, particularly using two spatial indicators: mean center and directional distributions (Standard Deviational Ellipse). Mean center and standard deviational ellipse were computed by months, seasons and years in the four marine regions (East coast high sea, South coast high sea, West coast high sea, and West high sea) to identify changes in the directional distributions and mean centers.

3.3.2 Kernel density estimation

Kernel Density Estimation (KDE) is a non-parametric neighborhood based approach to estimate the density from a dataset of location point (Laver et al., n.d.). KDE is a non-parametric density function because it does not assume that data conforms to a predefined distribution pattern, such as a circle (Selkirk & Bishop, 2002). It is based on point density and does not make any assumptions about shape. The estimation of kernel density allows for the establishment of utilization distribution by drawing contours around areas of equal density. Non-parametric methods are considered to be the most effective among a variety of animal home range estimators (Worton, 1989).

A KDE is created in a set of steps. A defined kernel is a function that is applied to each point in a dataset, replacing the values in the area surrounding the point with values defined by the kernel function. Each point is assigned a density value based on its proximity to other points in the dataset within a radius. The smoothing parameters describe the radius and, as a result, the area surrounding each point. A grid with defined cell sizes is placed over the weighted point dataset, and a density value is assigned to each grid cell based on the sum of the point values contained in the cell.
I computed the KDE, weighted by total catch (Kg).

3.3.3 Hotspot analysis: Identification of main fishing grounds and productive hotspots

Geospatial statistics, such as hotspot analysis and spatial autocorrelation analysis, were used to analyze spatial and temporal patterns of CPUE. A sample of the data for each year, was tested for spatial autocorrelation in CPUE using Global Moran's I (Jalali et al., 2015). Moran's I is a correlation coefficient that measures the overall spatial autocorrelation of the dataset. It identifies where the distribution of fishing effort and catch is random, clustered, uniform across the study area. The results show that there is a high spatial autocorrelation. After determining spatial autocorrelation patterns for the selected datasets, Optimized Hot Spot Analysis was used to identify areas with high (hotspots) and low (cold spots) CPUE values (Maina et al., 2016)..

Following Jalali et al (2015) and Maina et al. (2016), significant values of the hotspot analysis (z-score > 1.65) were extracted from each hotspot map to create a binary layer for each month. Statistically significant values at a 90% significance level from the hotspot analyzes were then exported and used to create raster files for each month. Combining significant hotspots by months, cumulative hotspot maps by season and year were derived. Each hotspots class in cumulative hotspot map depicts a specific area based on the number of months (or seasons, or years) fished. The annual cumulative hotspot map was classified to three classes, with classes 1–3 indicating whether a specific region was characterized by one to three years of significant hotspots indicative of sustained fishing pressure.

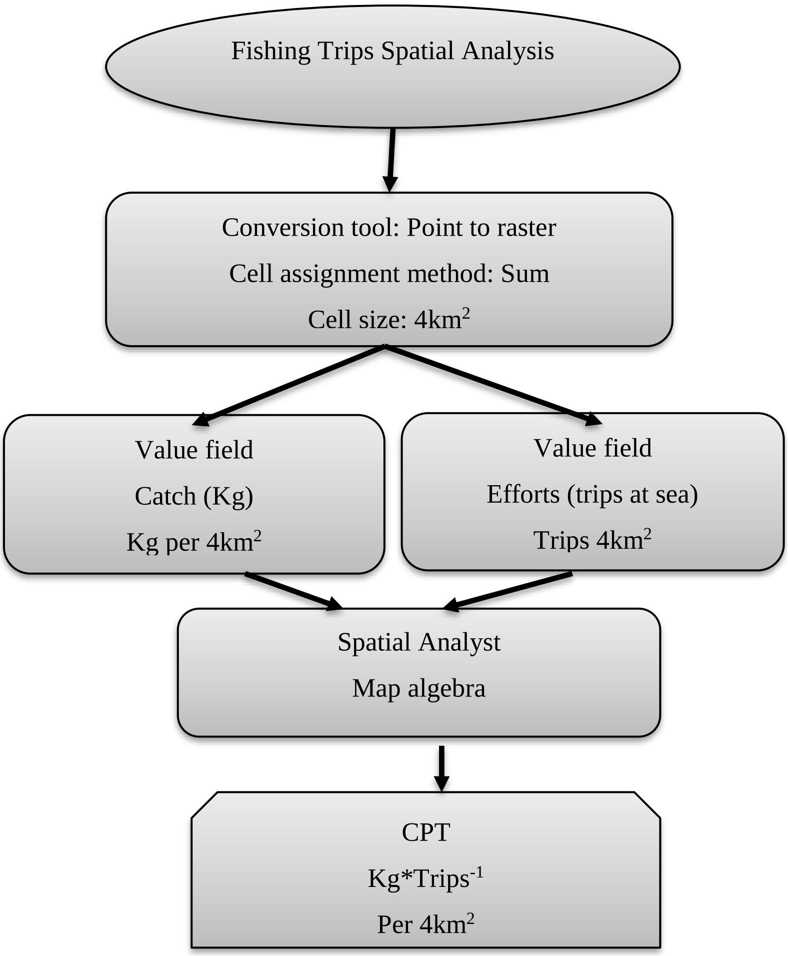

Figure 4:Fishing Catch Spatial Analysis

3.3.4 Influence of climate and socioeconomic factors on spatial fishing effort allocation

Simple overlay analysis, proximity analysis and zonal statistics were used to find general association between fishing effort and environmental, biophysical and socio-economic variables.

A correlation coefficient matrix and correlation scatterplots were created to explore simple linear relationship and test the collinearity. Two statistical models, the Generalized Liner Model (GLM) and the Geographic Weighted Regression (GWR), were used to determine the nature of the relationship between longline fishing (tuna) and geophysical, environmental, socioeconomic parameters (Lu et al., 2014).

CPT and Catch (Kg) were used as dependent variables. Readily available geophysical variables (Bathymetric Position Index, Vector Ruggedness Measure), SST, environmental variables (chlorophyll, Sea surface Salinity, Sea surface Temperature) and socio-economic variables (distance from the coast and distance from the ports) were used as explanatory variables. In this study, I defined port as the primary port from where a vessel operates.

The data were explored using simple descriptive statistics and exploratory data analysis - checked for normality, outliers, distribution patterns and simple zonal statistics were computed and association with fishing data was visually explored.

4 Results

4.1 Descriptive statistics: spatial and temporal variation of fishing effort and catches

4.1.1 Fishers and fisheries: Socioeconomic characteristics

Interview data confirms that all the high seas fishing vessels in the sample are equipped with VMS functionality. The average experience of the fishers in the sample is 16 years while the minimum and maximum experience range from 03 years to 40 years. The majority of the fishers (60%) has less than 20 years of experience and 37% of fishers has 20-30 years of experience. Only 3% of fishers has the more than thirty years of experience (Table 5).

Table 5:Fishing experience of the respondents

Category	Percentage (%)
Less than 20 years	60
20-30 years	36.67
More than 30 years	3.33

Multi-Day vessels are the main type of fishing vessel used in high seas operations in Sr Lanka. These vessels are varying in terms of the length of the fleet and degree of technology. These vessels consist of, water and fuel tanks, gear hauler, GPS, and respondent. Majority of the IMUL fleets are greater than 40 ft in length. Around 30% of the high seas craft belong to 36ft to 40ft length category. Only 15% crafts are recorded within the length category of 34 -35 ft (Figure 5).

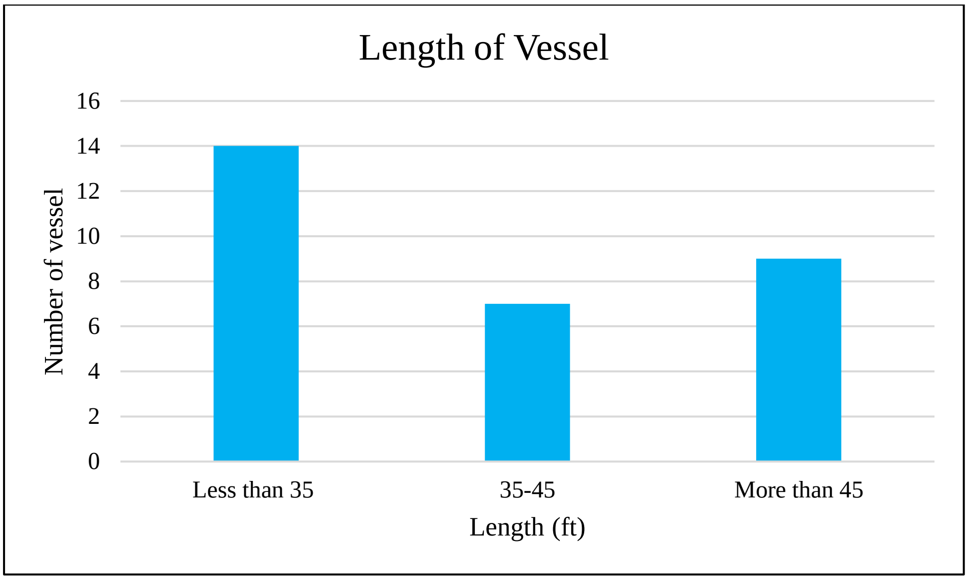

Figure 5: Distribution of vessel size classes (n = 30)

Logline fishing gears mainly target tuna species. The highest number of respondents in the sample target yellowfin tuna (39%). Around 35% and 26% of respondents target Bigeye tuna and Skipjack tuna respectively.

Multi-day boats usually operate within the Sri Lankan EEZ and in international waters too. Boats equipped with VMS facilities are legally authorized to operate in international waters. Thus, it does not imply such boats should necessarily operate in international waters. Area of operation is generally not pre-determined for a particular boat and it depends on environmental and socio-economic factors. The areas of operation of the high sea boats are given in figure 6.

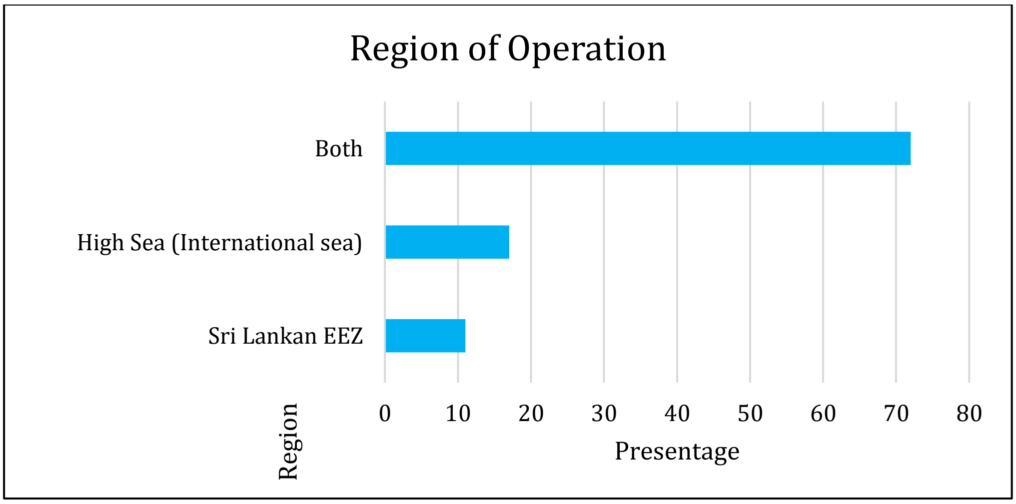

Figure 6: Region of operation multiday vessel

Area of operation, duration and number of fishing trips

The area of operation and duration of fishing trip of high seas vessel change with the length of boats and depend on the available space on the boat for fuel, fish and food. Boat with a higher capacity of ice for fish storage, fuel and water are able to stay at sea for a longer duration rather than a small boat. The boats less than 35ft, operate mainly within Sri Lanka's EEZ, while all other boats operate both within and beyond the EEZ. The duration of a fishing trip of boat less than 35 ft in length is 10 days while boats over 40 ft length are engaged in fishing trips exceeding 30 days. According to the respondents, high sea boats of 35 ft and above operate in international waters (beyond EEZ) area around the Bay of Bengal, Maldives Island, Bangladesh island and etc. However, area of operation of high seas boats depends on whether condition and the wind pattern of the sea (Table 6).

Table 6:Area of operation, duration and number of fishing trips per year

	Type of boat			
Vessel Length	<34 ft	34-35 ft	36-40 ft	>40 ft
Area of Operation	Sri Lanka's EEZ	Sri Lanka's EEZ, International waters (beyond EEZ) area around the Bay of Bengal, Maldives Island, Bangladesh island etc.		
Duration of Fishing	10 days	18 days	30 days	More than 30 days
Number of trips per year	28	12	10	7

4.1.2 Spatial and temporal patterns of catch and fishing effort

The logbook data shows that about 62,745 Mt of total tuna catch was reported from 2,289,890 fishing trips during 2015 – 2019 (Table 7). The results show that the highest catch was reported from yellowfin tuna from 2015 to 2019. The total highest catch was recorded in 2017 and it was 26,082Mt (26,082,195Kg). The total catch has gradually increased from 2015 to 2017. However, from 2018 it has slightly decreased. This similar pattern can be observed in the total number of fish catches. Furthermore, the catch of Bigeye tuna has also fallen from 2015 to 2016 from a considerably high amount nearly 1064Mt (1064031Kg). Interestingly, Bigeye tuna has increased from 2991 Mt (2991,412Kg) by 2017. The highest total was reported in 2017 and the least catch was reported in 2015.

Table 7:Total Longline fishing catch (Kg) and number of fishes during 2015-2019

Fish Name	2015		2016		2017		2018		2019	
	Kg	# fishes	Kg	# of fishes	Kg	# of fishes	Kg	# of fishes	Kg	# of fishes
Yellowfin	3425560	100697	4745929	167046	22761121	642551	16074874	410553	8615562	219832
Bigeye	1156251	35557	92220	7331	3083632	76545	1092947	29059	508364	14052
Skipjack	142124	11744	661827	24537	237442	41872	83480	39236	63217	34383

Figure 7 shows the interannual variation of fishing trips of longline tuna fishing during 2015 to 2019. According to the results, except for 2019, every year in the east coast high seas region have reported high fishing trips. The west coast region has reported the lowest fishing trips during the considered period. The lowest variation in fishing trips among four different fishing regions can be observed in 2015, while the highest variation occurred in 2018.

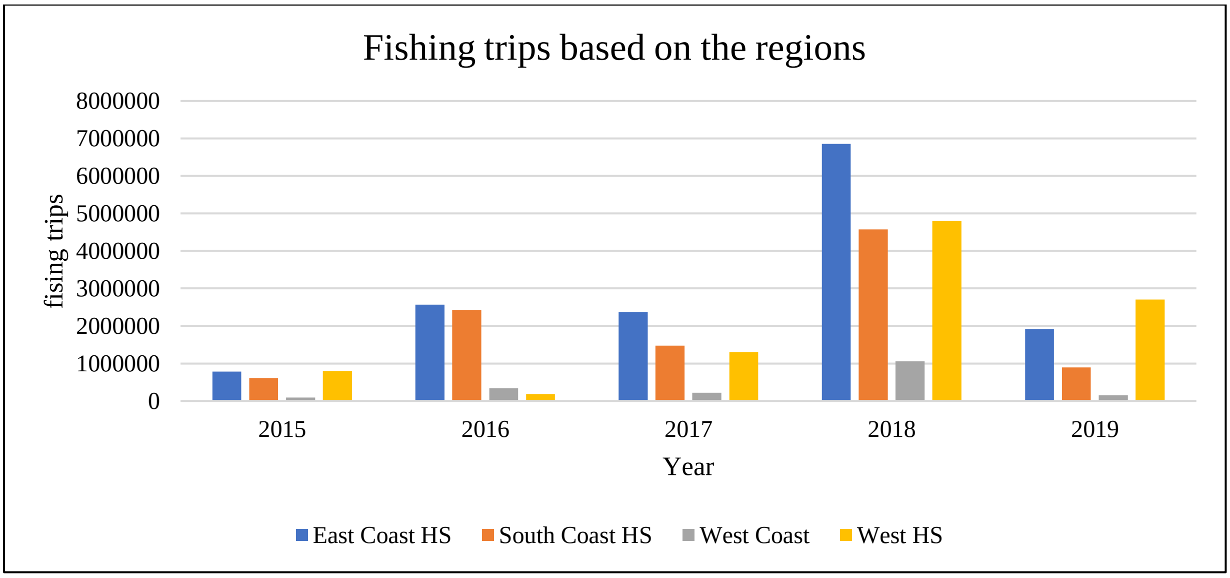

Figure 7:Interannual and regional pattern of fishing trips of longline tuna fisheries in Sri Lankan EEZ and high Sea area

The mean value of tuna catches by year is shown in figure 8. The highest and lowest mean catch value (Kg) were found in 2017 and 2015, respectively. The most dynamic fluctuation was found in the mean catch (Kg) per year, which increased from 2015 to 2017 and decreased from 2018 to 2019. The highest and smallest mean Amount (N) per year values were found in 2017 and 2015, respectively. Based on this variation, we can conclude that 2017 was the most productive fishing year.

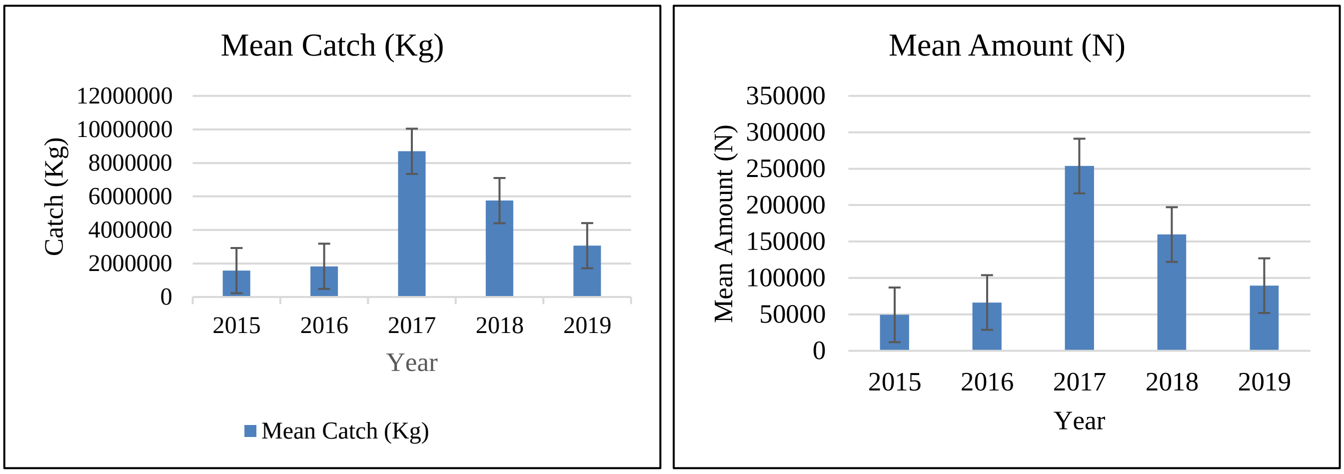

Figure 8:Mean value and standard error of Longline fishing (Tuna) catches

Figure 9 depicts the annual mean centers and directional distribution of longline Tuna catch from 2015 to 2019. The widest distribution of longline fishing activities was reported in the East and West coast high seas regions during the fishing seasons in all years (2015-2019). The results show that there is not any temporal trend, but there is high interannual and spatial variation. Figure 9.c in the west coast within EEZ show very low variation in the mean center and standard deviational ellipse (directional distribution) during the five years periods. The mean center and standard deviational ellipse are distributed within a narrow region along the coast and have approximately the same area and center for all years. But in other regions, there is significant variation but not a trend. Figures9.a and 9.d shows the widest variation in the east coast high sea region and west high sea region during the 5 years. figure 9.d shows there is a similar trend in 2018 and 2019 in the west high sea region. In the west high sea region (fig 9.d), there is a slight shift toward the north, as shown by mean centers and directional distribution also became sider and covering.

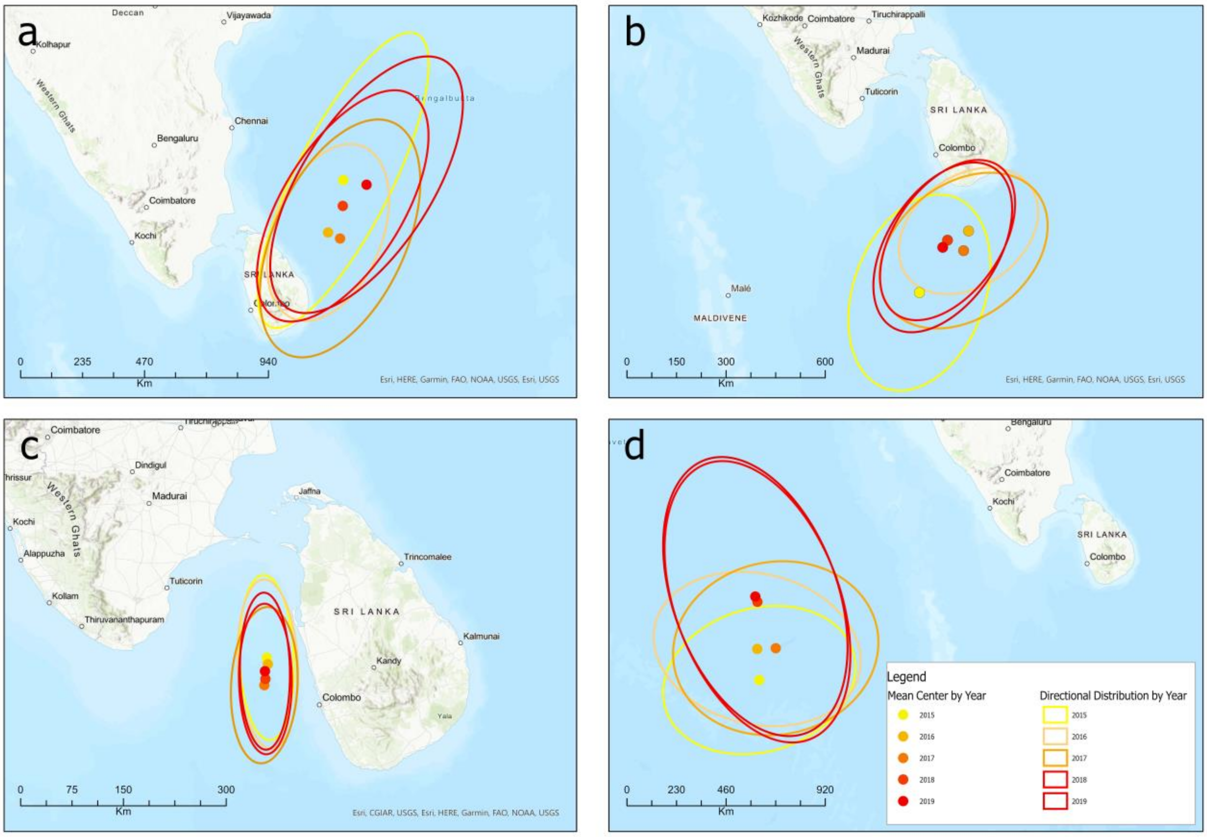

Figure 9:Mean center and directional distribution of longline tuna caches by region a) East coast High sea, b) South coast High sea, c) West Coast, d) West High sea

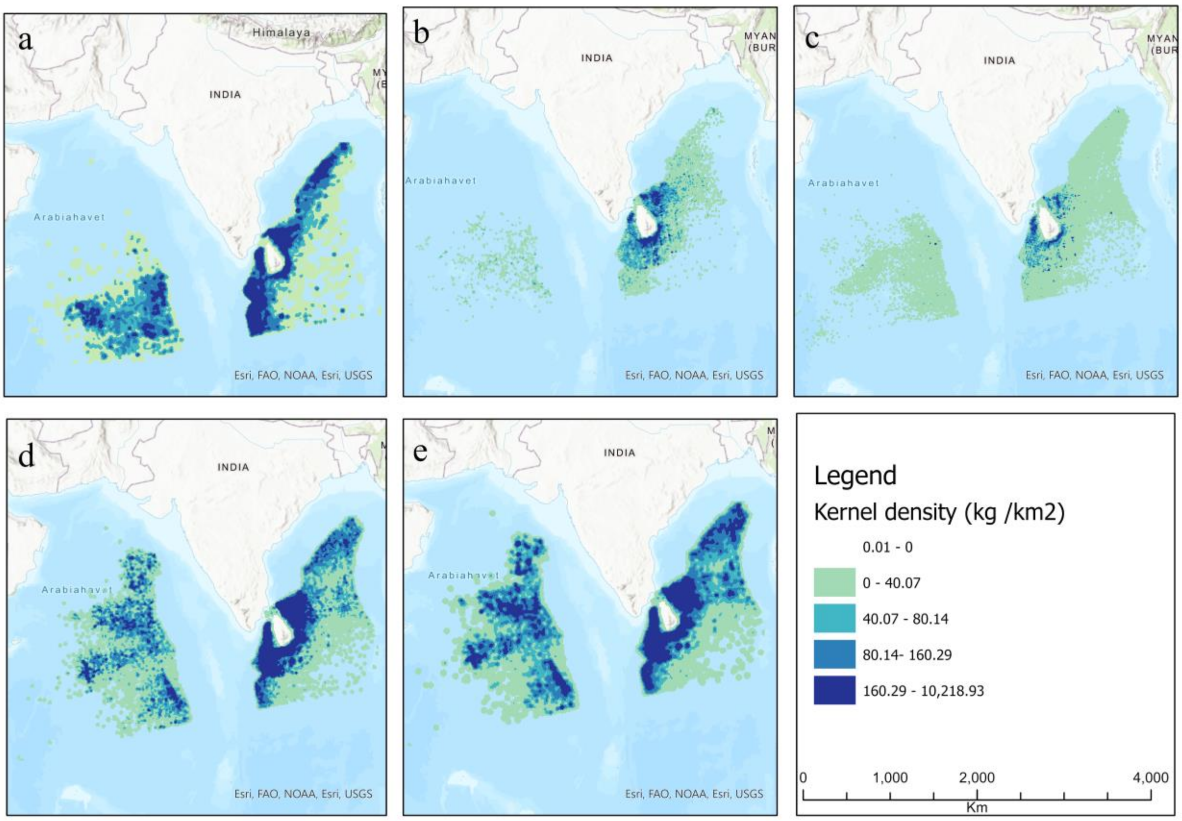

Figure 10: Kernel Density estimation weighted by total catches (Kg) a) 2015, b) 2016, c)2017, d)2018, e)2019

Figure 10 shows the annual pattern of kernel density distribution of total catch (Kg) per square km in Sri Lankan EEZ and high sea areas. Relatively high kernel density, was observed in the year 2015, 2018 and 2019. In 2016 and 2017, the high catch density per sq. km was distributed Within the EEZ. In 2018 and 2019, the density of catch per sq. km was highly distributed in the west high sea region and within the EEZ. In 2017 reported the lowest kernel density per sq. km.

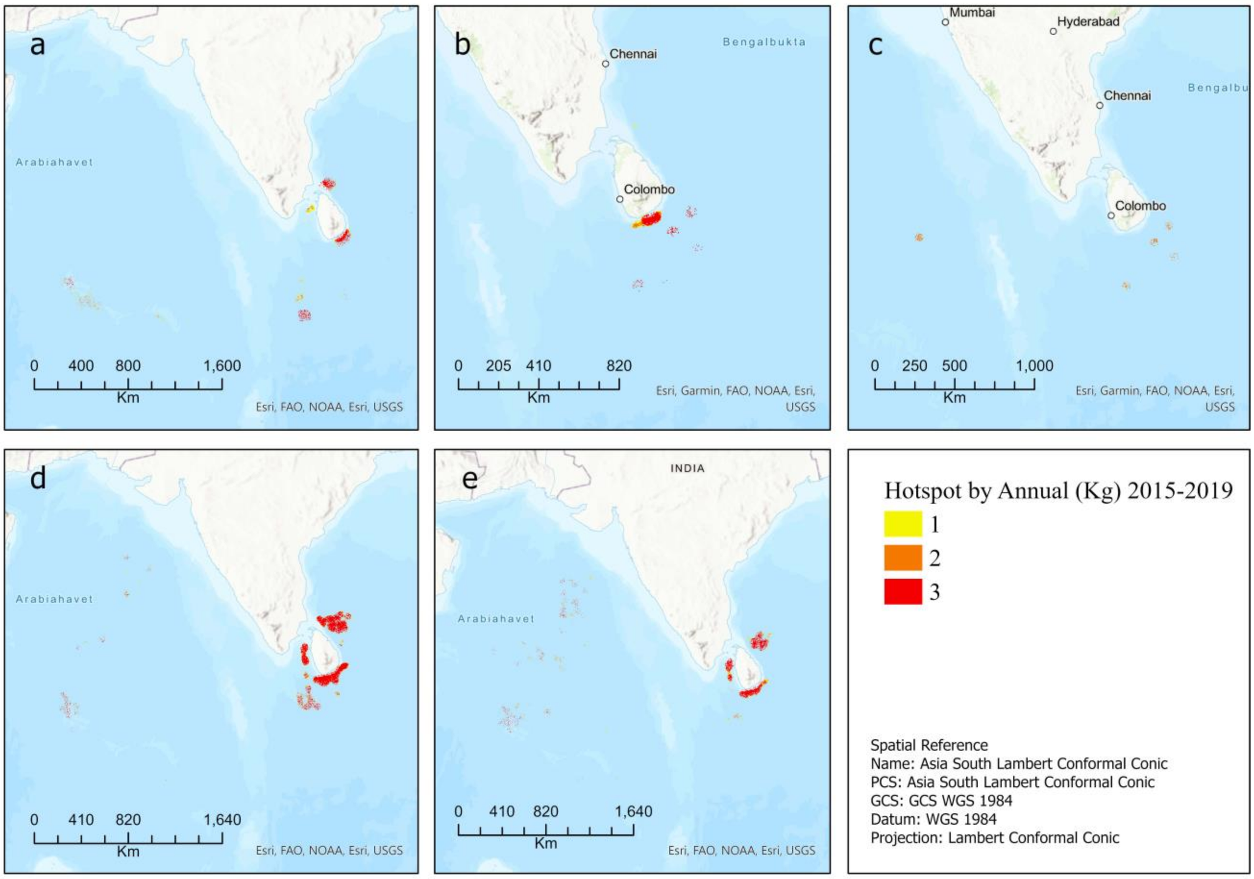

Figure 11: Annual Catch variation from hotspot analysis of longline tuna catches in the period 2015-2019 a) 2015, b) 2016, c)2017, d)2018, e)2019

Hotspot clusters for longline tuna fishing during 2016 to 2019 are shown in Figure 11. Relatively high hotspot clusters were observed in the year 2018 and 2019.The lowest hotspot clusters were located in 2017. In 2015, significant clusters of high catch of longline tuna were observed close to the Bay of Bengal along the east high sea area, and close to the Maldives EEZ in the southern high sea areas. In 2016, all hotspots clusters were distributed in the south coast high sea area. After 2017, there is an increasing pattern of hotspot clusters than in previous years. In 2018, the highest catch hotspot areas were reported within EEZ and small clusters were in west high seas areas. In 2019, large clusters of hotspots were discovered near the Bay of Bengal on the east coast and on the west coast sea, near Bangladesh and the Maldives EEZ on the west coast, and on the south coast.

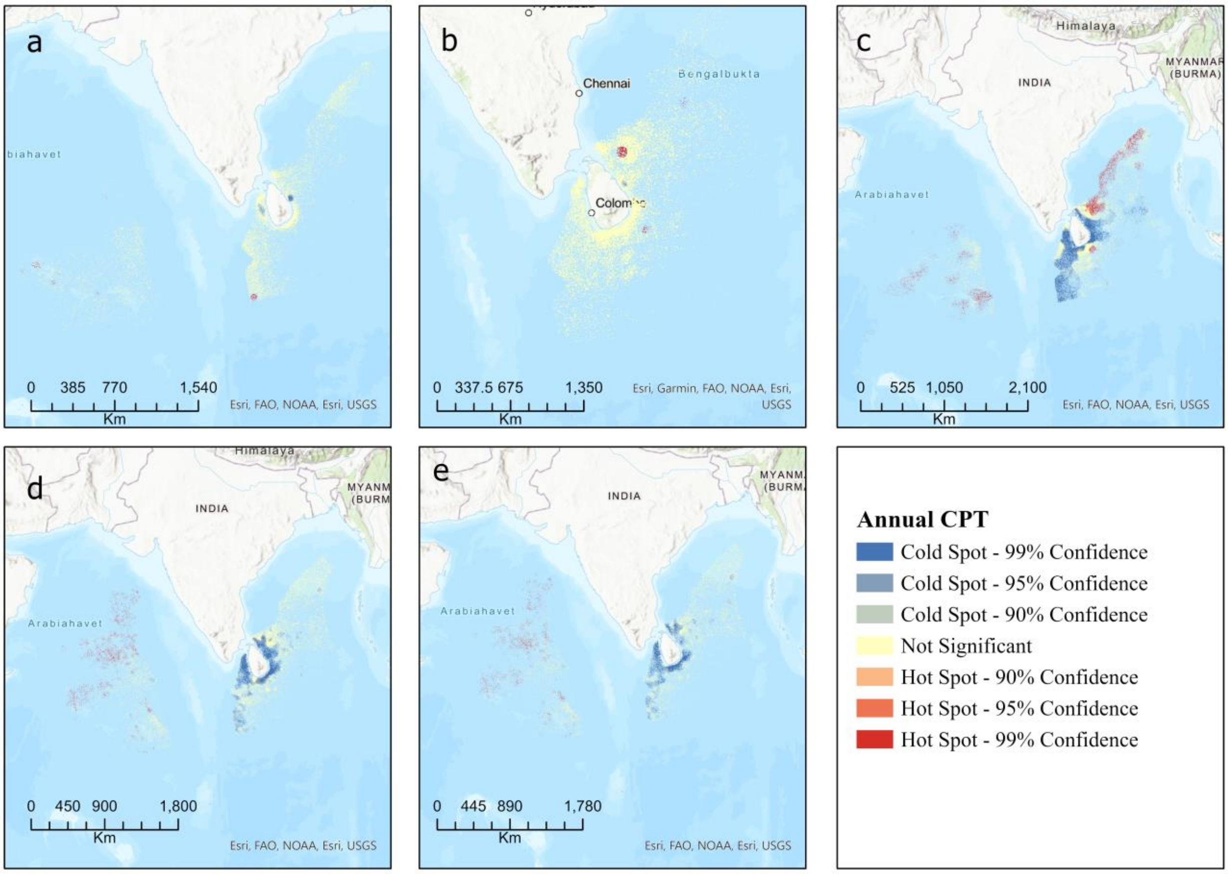

Figure 12: Hotspot analysis of CPT distribution of longline tuna catches in the period 2015-2019: a) 2015, b) 2016, c)2017, d)2018, e)2019

There has been an increasing trend since 2017 in the number of significant hot spot clusters, showing clusters of the location having high catch per trip (Figure 12). After 2016, CPT hotspots for the longline tuna fishery largely distributed to the EEZ and high seas areas. In 2015 and 2016, there were relatively few clusters of hotspots. However, significant concentrations of high CPT values can be found in the west and south high seas regions in 2015. Significant concentrations of a few high CPT values appear in the east high sea region in 2016. In 2017, the hotspot areas were primarily found in the east and west high seas. There is a clear increasing trend of concentration location, while the total area of clusters with high CPT values increased slightly after 2016. After 2016, the area with cold spots (cluster of the areas having low catch per trip) increased significantly, primarily around the south high seas and west coast region. Hotspots are mostly found in the west and east high seas, and their locations have varied slightly throughout the study period. Significant concentrations of high CPT values are found primarily within the high sea in Sri Lanka.

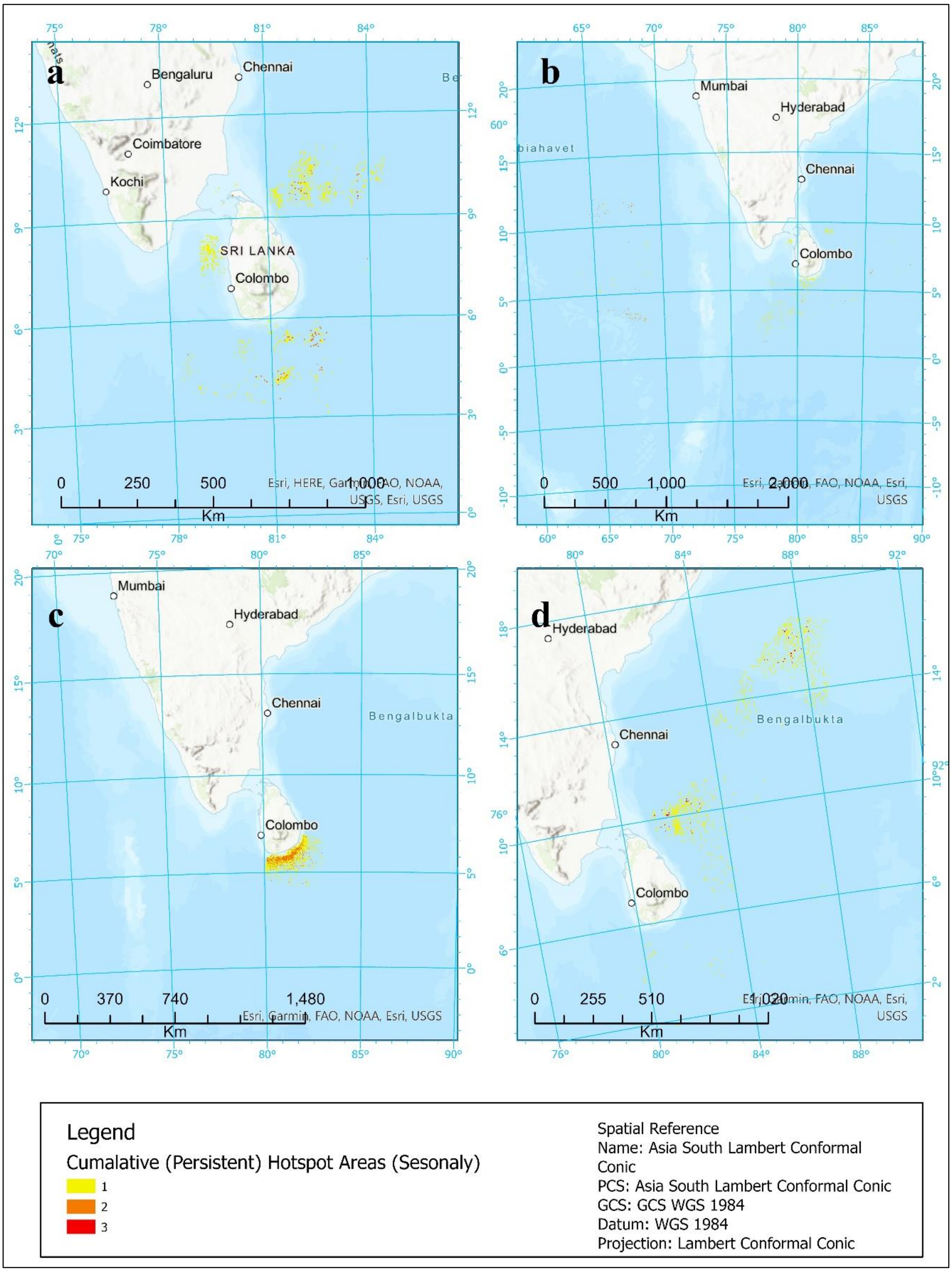

Figure 13:Cumulative hotspot distribution. Cumulative CPUE hotspot showing the number of years that CPUE was clustered a) December to February (North East Monsoon), b) March to April (First Inter Monsoon), c) May to September (South west Monsoon), d) October to November (Second Inter Monsoon)

During the study period, the longline fleet's tuna spatial and temporal variations were mapped, and high seasonal pattern in CPT between seasons were observed. Most of the hotspots showing significant cluster of high catch per fishing trip in south coast high sea and east coast high sea regions of Sri Lanka. During north-east monsoon period (December to February) (figure 13a), most of the clusters of high catch per fishing trip concentrated in the East and South coast high sea areas. Fishing trips from March to April (First Inter Monsoon) focused on the west high sea region. From May to September (South-West Monsoon) the vessel targeted the areas along the south coast sea (Second Inter Monsoon) The majority of the multiday boats aimed the East Coast high seas region the from October to November. Figure 13 depicts the highly dynamic tuna fishing activity, particularly in the Indian Ocean, based on high-value fluctuations in catches, and CPT.

4.2 Driving factors

The simple proximity analysis shows that the distribution of fishing effort was not random in the study area. The results clearly show that total number of longline fishing efforts (as expressed by number of fishing trips) within Sri Lankan EEZ continuously (linearly) decline as distance from the coast increases (figure 14), showing a clear distance decay pattern. However, there is highest concentration of the number of longline fishing efforts in high sea areas (for example as shown by # events in the distance > 500 km).

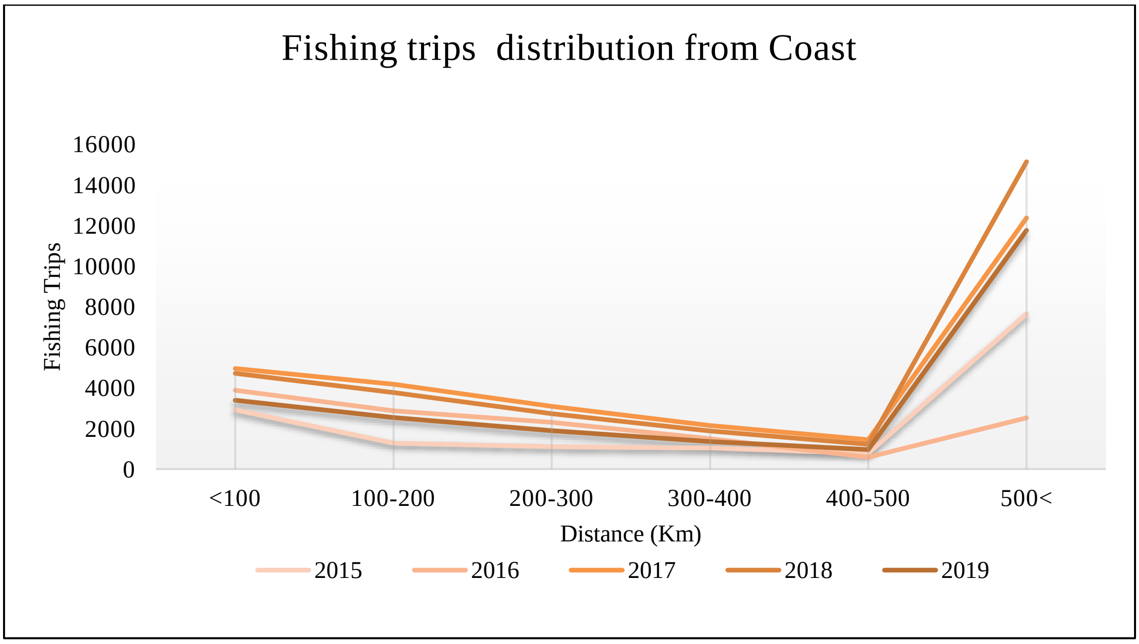

Figure 14:The distribution of fishing trips from coast

The results show that there is a clear pattern of fishing trips from port in the study area except 2016. The results clearly show that total number of longline fishing trips within Sri Lankan EEZ continuously (linearly) decline as distance from the coast increases (figure 15), showing a clear distance decay pattern. However, there is highest concentration of the number of longline fishing efforts in high sea areas, as we can see the highest number of fishing trips each year (distance > 500 km from the fishing ports) (fig. 15).

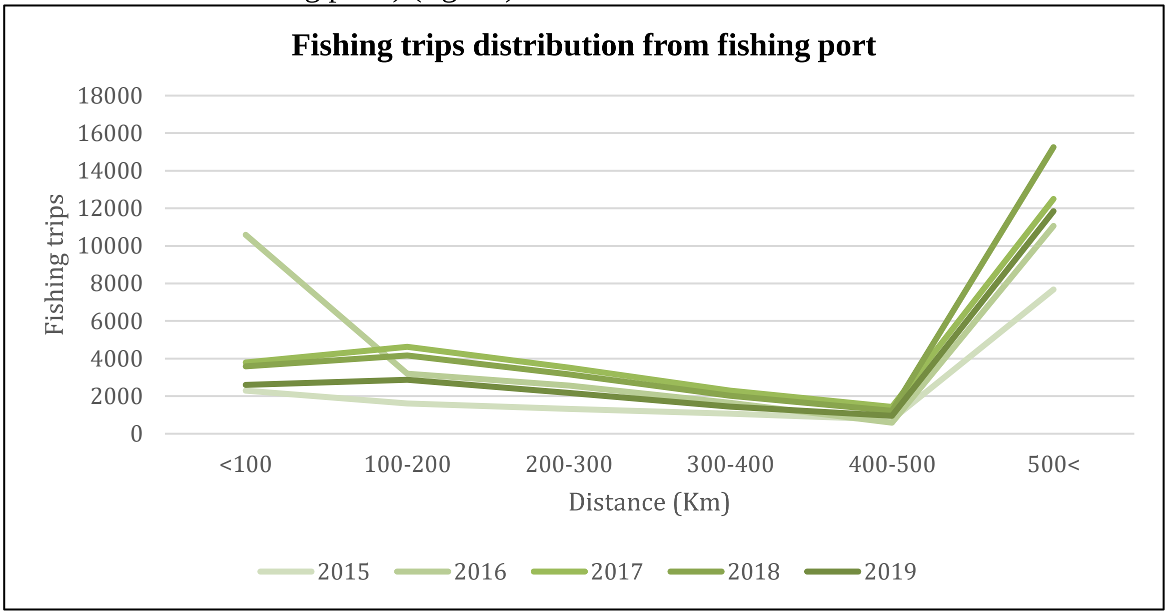

Figure 15: The distribution of fishing trips from fishing port

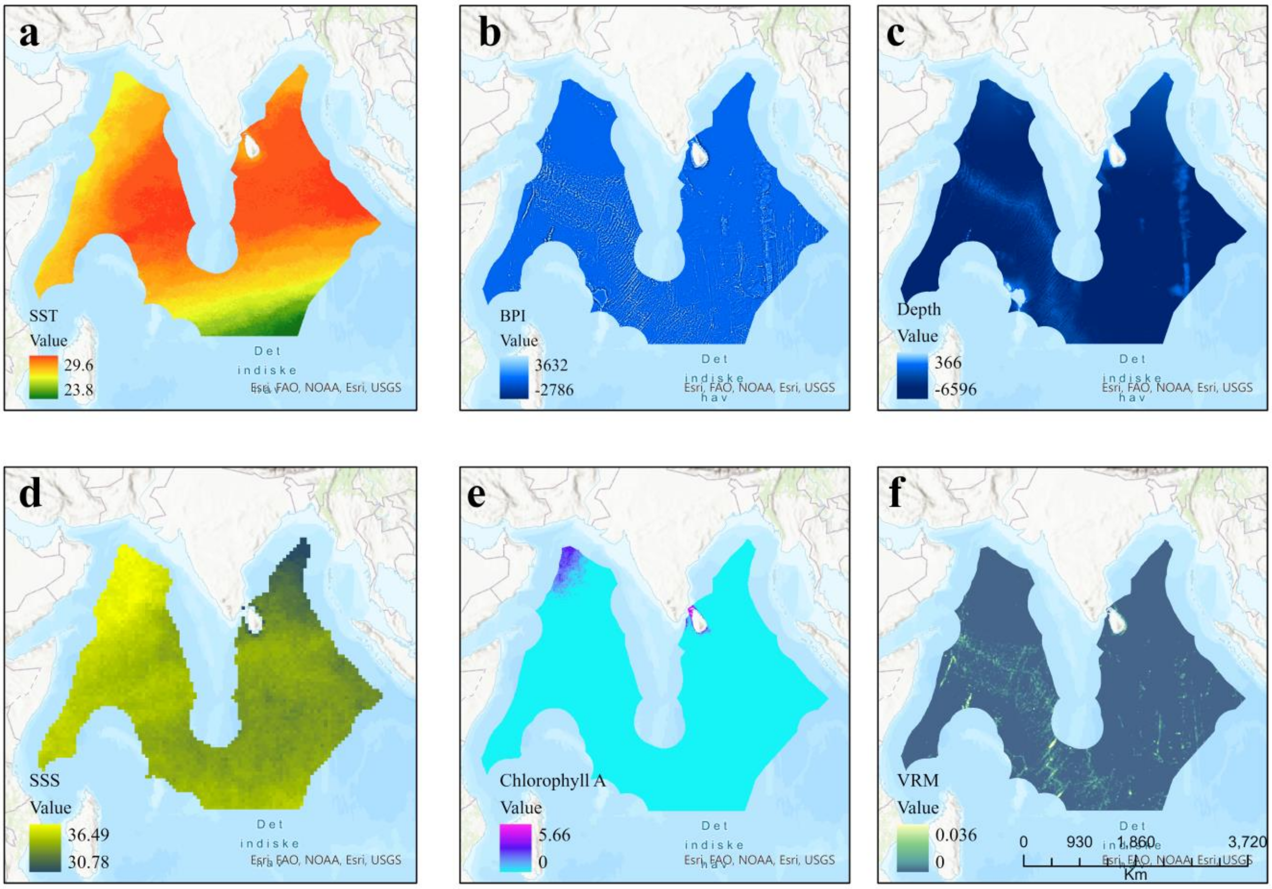

Figure 16:Maps of six selected environmental variables

a) average SST (five years), b) broad BPI , c) Depth , d) average SSS (five years) , e) average chlorophyll A (five years) f) VRM)

A summary of average environmental variable characteristics for five years in the study area is shown in figure 16. In the study area's middle regions, warmer water was observed (figure 16. a). However, the middle part of the study area was warmer water temperatures than the southern region. The maximum temperature was around 29.6C^0. Figure 16 b shows BPI values with a broad BPI, with the highest reported value of 3632. Longline tuna was detected at varied depths in the research area, with the maximum depth being 6596 meters. Figure 16. c depicts the study area depth distribution pattern. Figure 16.d depicted the average distribution over the salinity gradient. The maximum salinity was 36 g/kg. Figure 16.e shows the average surface chlorophyll-a concentration, with the greatest value being around 5.66 mg/m3. The study area south section has the highest Vector Ruggedness Measure (VRM) of 0.036.

The relationship between catch per trip (CPT) and selected explanatory variables was investigated using Pearson product-moment correlation coefficient. The results show that there is low to moderate correlation between CPT and the distant from the port, distant from the coast, SSS, and SST (Table 8).

Table 8: Correlation coefficient between CPT and environmental and socioeconomic variables (only significant variables, significant level: 0.05)

Explanatory variable	Correlation Coefficient (r)
Distant from Port	0.36
Distant from Coast	0.35
SSS	0.18
SST	-0.13

I attempted to fit the multiple linear regression and GWR both without and with data transformation. The results indicate that there is no linear correlation between CPT and explanatory variables, as well as between total catches and explanatory variables (See appendix 2).

The interview data shows that fishers change their fishing location year to year and season to season. More than half of the respondents in the sample (53.33%) revealed seasonality as the major reason for changing fishing ground. The abundance of fish and climate changes were stated as the reason by 23% and 20% of respondents respectively. Only a small percentage of them (3.33%) consider warm water as the reason for changing their fishing locations (figure: 17).

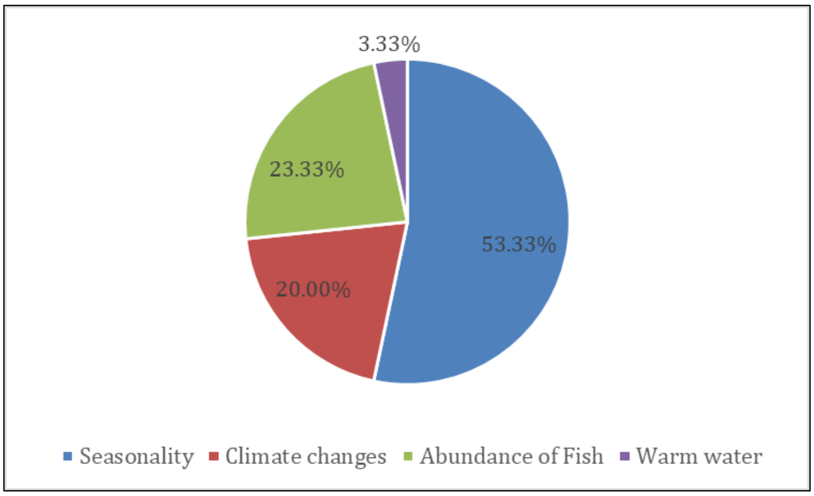

Figure 17:Reasons for changing the fishing locations

The interviews further show that previous experience, traditions, and consultation with other fishers (social network) are the important factors for spatial and temporal distribution of fishing efforts (Table 9). The oceanographic characteristics were least ranked (1.93), among other factors. Within oceanographic factors, fishers considered wind and currents as the most important factors to consider before going fishing. Fishers uses GPS and Logbook from the previous years, to follow the fishing routes and to make decision about fishing locations. There is a good network system for sharing information among the fishers. As a result, information from other fishers and locations visited by other skippers are given a similar mean rank level.

Table 9:Factors considered when deciding where to fish (1= the most considered factor, 5 = the least considered factor)

Factor	Mean rank
Oceanographic pattern and assumptions	1.93
The experience from the last visits	2.23
Information from others	2.83
Where other skippers visit	2.87
Other	5.00

The most considered factors that affect the decision of fishers on determining the time and field of fishing are previous experience (1.53), where is the fishing going at the moment (1.60), and weather conditions (1.73) respectively. The least considered factors for this decision are the community decisions (4.53), government regulations (4.43), avoidance of bycatch (4.37), and sea floor topography (4.10).

As shown in the table 10, the majority of respondents regard previous experience and assumption of 'where is the fishing going right now' to be the most important considerations. also considered the distance to the harbour and the distance to the fishing grounds as important factors.

Table 10: Factors determining the choice of time and ground of fishing

Factor	Mean rank
Previous experience	1.53
Where is the fishing going at the moment?	1.60
Weather conditions	1.73
Information from other	2.30
Distance to harbor	2.33
Ocean currents	2.40
Distance to fishing ground	2.70
Market	3.27
Number of Crew	3.43
Ocean topography	4.10
Avoidance of bycatch	4.37
Government regulations	4.43
Community decisions	4.53

GPS (1.50) is the most used factor by the fishers when finding a good fishing ground. In addition to that, experience about the area (2.07), information received from others (2.13), and AIS are some other important factors utilized when finding a good fishing ground. However, using an echosounder is the least used factor for determining a good fishing ground. Because there are few multiday boats equipped with echosounder facilities in Sri Lanka (figure 18).

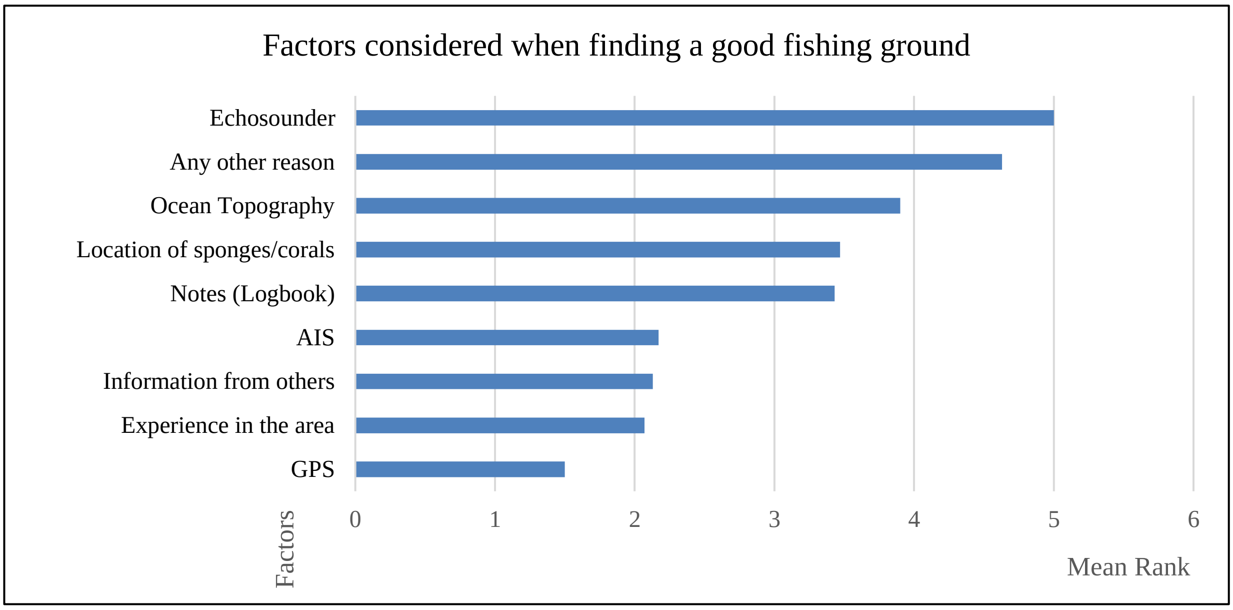

Figure 18:Ranks given for each factor by all respondents when finding a good fishing ground

According to fisherman, the main concern is that more pollution is occurred (2.20) in relation to fishing. Furthermore, they are concerned about increasingly harsh weather events (2.23) and warming (2.27). They are, however, the least concerned about new species (Figure 19).

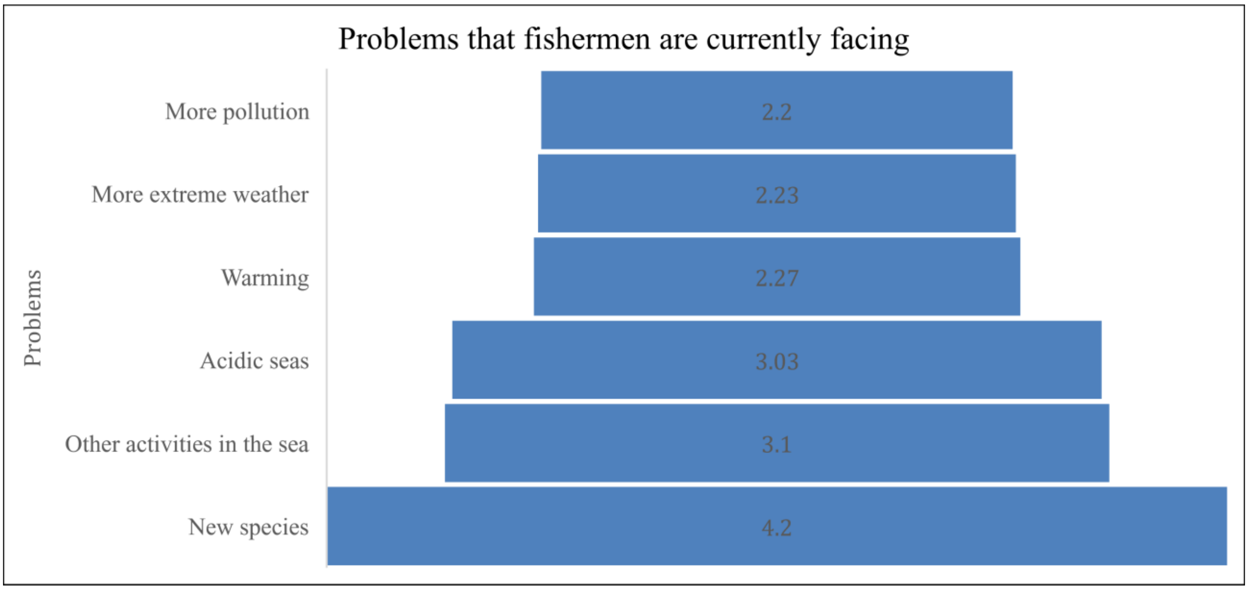

Figure 19:Problems that fishers are currently facing

5 Discussion

The thesis main objective was to explore the spatiotemporal patterns of the Sri Lankan longline tuna fishery in the south Indian Ocean from 2015 to 2019, as well as to identify sustainable fishing grounds in Sri Lanka.

5.1 Spatial and temporal variations in the Sri Lankan Longline fleet

This thesis analyzes fishing efforts and catch of longline tuna fisheries, because many longline fleets target the tuna species mainly yellowfin tuna, bigeye tuna, and skipjack tuna. Longline fishing activity with tuna had relatively different spatial and temporal pattern, with more activity concentrated on the East Coast high sea, and West high sea during the 2015 to 2019 while activity on West Coast had a minimum distribution pattern.

In this research I used kernel density estimation to visualize spatial pattern of longline tuna catch. The kernel density estimation approach has been used to identify catch hotspots from a tuna distribution because it improves boundaries and is non-parametric (Ellen et al. 2014). Interpolation estimates the data values for points between the data, whereas density estimation counts the number of discrete objects in a given area and creates a field from those objects (Kenchington et al., 2014).

Several authors have used KDE, a non-parametric neighbor-based smoothing function in ecology to identify hotspots, that is, areas of relatively high biomass/abundance (Fieberg, 2007). Kenchington et al. (2014) used kernel density estimation to create an indicator taxon surface for four vulnerable marine ecosystems (VMEs): large sponges, sea pens, and small and large gorgonian corals, using vessel trawl survey data from inside the fishing footprint of the Northwest Atlantic Fisheries Organization (NAFO) (Kenchington et al., 2014).

I computed the KDE weighted by total catch (Kg). The results show relatively high kernel density, i.e., kg per sq. km, was observed in the year 2015, 2018 and 2019. In 2016 and 2017, the high catch density per sq. km was distributed Within the EEZ.

5.2 Determine the most productive and persistent fishing hotspots

Hotspot analysis is a spatial analysis and mapping technique that identifies clusters of spatial phenomena, and these spatial phenomena are mapped as points on a map and indicate the locations of events or objects. Investigating the Spatial-temporal persistence of hot spots could provide a useful way to determine the importance of fishing grounds. Fishers have developed an understanding of productive fishing grounds over time, so the closure of a hotspot (preferential fishing area) to protect the fishery or as part of marine spatial planning approaches can actually change the behavior of fishers (Maina et al., 2016) . Several authors have used this method to find important and productive fishing grounds.

I used hotspot analysis to identify areas with concentrations of both high and low values of activity catch and CPT for Longline fishing for Tuna. Furthermore, the identified areas from the analysis were used to map the relevant fisheries' variations in time and space. There were some similarities in spatial and temporal patterns of CPT hotspots, fishing efforts (number of trips), and catches, so CPT was analyzed as a combination of catch, effort, and stock availability.

When compared to other studies of spatial and temporal variations in commercial fishing behavior, Jalali et al. (2015) revealed that some areas had significant clusters of high/low CPUE values between seasons and years. The presence of such areas indicates that some areas are consistently and purposefully approached for fishing and that the choice of fishing area is thus not random. CPT hotspots for longline tuna-caught have been observed primarily along the west coast, adjacent to the east coast high sea and the Bay of Bengal, the south coast high sea, and, in recent years, in areas of the west high sea beyond the Maldives EEZ.

Maina et al. (2016) used commercial fishing data from 1985 to 2008 to identify bottom trawl fishing grounds in Greek water. They studied fifteen demersal species, all of which are important target species for Mediterranean bottom trawlers. Maina (2016) methodology is based on estimating the probability of species presence. Hotspot shows cluster of high fishing effort, or cluster of high catchability (fish abundance) which can be considered as high probability of presence (Maina et al., 2016).

During the study period, the longline fleet's tuna spatial and temporal variations were mapped, and high seasonal pattern in CPT between seasons were observed. The North-East Monsoon and Southwest Monsoon had a relatively different distribution of clusters of high CPT values and during the southwest monsoon period, CPT activities were located on the south coast high sea region. Considering the annual CPT distribution there is a variation between the year. After the 2017 year, there is an increase in effort as well as CPT in the High sea area. Introducing the VMS system in 2015 multiday fishers tried to move high seas areas more than the previous year

This approach provides a spatial visualization of species richness in important fishing grounds in the Sri Lankan fishing region. Aggregated hot spots showed that the most important fishing grounds, based on the total catch of longline tuna, are in the East coast high sea region, some locations in the West high sea, and in the South coast high sea.

5.3 Environmental and socio-economic factors determining sustainable fishing grounds

As expected, distance decay pattern was observed when comparing distribution of fishing efforts with reference to d distance from the coast and distance from the ports. The highest fishing trips was reported by the vessel which sail the highest distance from the coast and port. The analysis also revealed that high sea areas are important point of concentration for longline tuna fishing. Though operating cost (labor, time fuel and other operating cost) could be higher, because of the distance from the ports/coast, high seas areas have been points of the concentration of fishing efforts. It may be due to resource availability. Accordingly, fishers prefer to find high sea fishing ground to maximize their economic returns. Even though the operational cost is increasing with the distance from the coast fishers can earn more due to high fishing trips (Amaralal et al., 2017).

Variations in the activity of the Longline fleet were investigated from 2015 to 2019 by analyzing the number of fishing trips and catch annually, respectively. The results confirm the hypothesis that spatial structure and distribution of pelagic species are not random (Planque et al., 2011). They are especially vulnerable and change quickly in response to dynamic environmental factors and global changes, resulting in diverse distributions. This complexity makes determining the fishing grounds more difficult for fishers (Suhartono Nurdin et al., 2015).

Several GIS based modelling, including the Generalized Additive Model (GAM) (Nurdin et al., 2017), (Rajapaksha, 2015), Multiple Linear Regression (Nurdin et al., 2015), frequency analysis

(Zainuddin, 2011), and Suitability Index (SI) (Nurdin et al., 2017) `, have been used to determine spatial and temporal fish distribution patterns and potential fishing grounds. This study began by assessing and exploring spatial statistical relationships between environmental variables and fish abundance using the basic Generalized Linear Regression Model (GLM) and Geographic Weighted Regression Model (GWR). However, a correlation coefficient of very low to moderate values between environmental and socio-economic factors indicated the nonlinear nature of the relationship. I attempted to use a linear model (both local -GWR and global- OLS) with both raw and transformed data, but the results show a non-linear relationship.

The OLS and GWR results show non-linear relationship pattern as indicated by very low correlation coefficient, very high residual errors, very low coefficient of determination (R2 value) and violence of the linear regression assumptions. Furthermore, the analysis and modelling of fishing efforts or CPUE need to use GAM as used by Maina and Jalali or data driven approach such as boosted regression trees (Soykan et al., 2014) .Due to time constraints I could not use GAM and or other such data driven approach in this study. Integration of interview data helps to understand the relationship between environmental and socioeconomic factors.

In this study the spatial and temporal scales of tuna data may limit the ability to analyze these patterns in more detail. Although, the results provide some insight on the distribution patterns of tuna in the Indian Ocean. The results showed an increase in numbers of larger tuna caught in tropical regions in recent years. The results also indicate that those highly productive fishing grounds are not always where the largest fish are caught.

5.4 The importance of TEK

The results show that fishers environmental and socioeconomic knowledge has been shown to play an important role in their decision-making process when it comes to appropriate fishing practices at specific times. This is reflected in their preference to go fishing (Table 8), How they decide to go fishing (Table 7), how they determine fishing ground (figure 9), or the unanimous agreements on when or how to target certain species. Fishers' ecological knowledge is sophisticated, having evolved over generations. Researchers consistently study fishers ecological knowledge, including their understanding of fish behavior and the environmental factors that influence and predict it (Mccormack & Forde, 2020; Sabetian, 2002). The concept is also evident in the understanding of seabird behavior and their role as fish finders, as well as the creation of a lunar calendar that forecasts fish behavior and where, when, what, and how-to fish. It not only predicts the time of day and approximate height of the tide, the strength and direction of tidal currents, the brightness of the night, and the accessibility of fishing zones, but it also predicts their locations, behavior, and vulnerability to capture (Sabetian, 2002).

The results confirm the assumption that Sri Lankan longline fishers predominantly uses TEK to determine their potential fishing zone. Natural signs such as birds, floating, group information, and extreme oceanographic conditions such as waves, wind, and current were the main factors that longline fishers use to decide where they will go fishing, as evidenced by socioeconomic data from fishers.

This study's findings highlighted the importance of integration of spatial analysis using GIS and ethnographic method to understand spatial and temporal pattern of fisheries. The use of GIS for spatiotemporal analysis has made it easier to interpret large datasets both spatially and temporally. As a result of these findings, we can conclude that GIS-based analysis is a powerful method that is clearly more understandable both practically and analytically.

5.5 Management implication: towards a sustainable fishery

It is possible to apply the methodological approach proposed in this study to identify a broader range of fishing grounds (Maina et al., 2016). It is useful to include ecological and socio-economic attributes to understand complex fishers' behavior and to provide long-term management objectives for fisheries. A major goal of fisheries management is the creation of sustainable fisheries in sustainable ecosystems, and this includes responding appropriately to important environmental and biodiversity issues.

The method of analysis for defining fishing grounds also allows for the study of the temporal dynamics of fishers' behavior. An examination of temporal changes in hotspot areas in relation to socioeconomic and environmental factors can provide valuable insight into the evolution and reliance of fisheries. Potential trends in the variability of spatiotemporal persistence in hot or cold spots could be a better index for explaining changes in fishing activities, species allocation, or productivity that can occur as a result of environmental or socioeconomic changes (Alabia et al., 2015; Crowder & Norse, 2008; Jalali et al., 2015; Maina et al., 2016; S Nurdin et al., 2012; Suhartono Nurdin et al., 2015; Nurholis et al., 2020). The method and approaches I used, and the findings could be immensely beneficial to ecosystem-based marine spatial management. Methodological approaches that used in this study can assist in bridging the gap between science and practice and supporting ecosystem-based management implementation (Maina et al., 2016).

5.6 Limitation

This study was based on available VMS and logbook data. The main limitation was the spatial resolution of the data as latitude and longitude coordinate values were provided in Degree and Minutes only. There was a lack of reliable information about effort (eg: Number of hooks, time spent at the sea, number of Crew workers) that is the major issue of this study. Similarly, there was lack of information about vessels (for example, vessel size, engine power and so on). Considering the time limitation, I couldn't go further with different analyses (particularly using GAM model and/or data driven approach like boosted regression trees). Considering the time limitation (data processing time), I have used low resolution data for environmental factors (for example, Bathymetry, SST, SSS and chlorophyll). I have to rely on others for interview and group discussion to acquire socioeconomic information from the fishers because of the the time constraints and covid-19 travel restrictions at that time.

6 Conclusion

The study has explored the Longline tuna fishing spatial and temporal variations in the EEZ and high sea region in Sri Lanka in the period 2015-2019 using available VMS/logbook data and socioeconomic information from interviews. The results show significant seasonal, annual and spatial variations in fishing behavior and catch pattern. The Kernel density results show relatively high kernel density, i.e., kg catch per sq. km, in the year 2015, 2018 and 2019. The results of the GIS-based analysis show high variations in catch and catch per trip distribution patterns by years and seasons. High catch clusters were observed in the year 2018 and 2019 and there is a clear increasing trend in concentration location, while the total area of clusters with high CPT values increased slightly after 2016. Cumulative CPT hotspot showing that there is a spatial pattern by seasons. As a result of the socio-economic study, it can be concluded that Sri Lankan longline fishermen use Traditional Ecological Knowledge (TEK) to determine their potential fishing grounds. Longline fishers consider sources of natural information such as birds, floating objects, and group information as well as extreme oceanographic conditions such as waves, wind, and currents when deciding where to fish.

An effective visualization and communication of these data to stakeholders may provide a great opportunity to demonstrate the ability to integrate fisher knowledge into the fishery management process.

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Appendix

Appendix 1: Questionnaire

Questionnaire for the Spatial and Temporal Distribution Patterns of Multiday Longline Fishery in Sri Lanka

Date: ……………………….

Harbor: ………………………

VMS: Yes ☐ No ☐

1. General Information

1.1 Respondent: - Owner ☐ Skipper ☐ Crew worker ☐

1.2 How long have you been an Owner /Skipper/ Crew worker =............................

1.3 What is the main Gear?

Type of Gear	
Long Line	
Purse Seine	
Gillnet	
Pole and line	
Handline	
Trolling	

2 Specific Information

2.1 How many Vessel do you have?..................

2.2 What is the length of the Vessel?.....................

2.3 The vessel:

i) Own ☐

ii) Rented ☐

iii)Other ☐

2.4 How many gears do you carry per fishing trip?

………………………………………………………………………

2.5 What are the target species?

Species	√/×
Tuna	
Albacore	
Sharks	
Spanish mackerels	
Dolphin	
Rainbow runner	
Other	

2.6 Number of fishing trips per month? ……………………………………..

2.7 What is the duration of a single fishing trip?

Days		Months	

2.8 Where do you prefer to fish?

Area	√/×
Sri Lankan EEZ	
International water (high sea)	
Both	

3 To identify topographical and/or environmental and socio-economic factors determining sustainable fishing grounds

3.1 Who decides where to fish when you go fishing?

Yourself ☐ Join decision ☐ Committee ☐

3.2 Have you Observed Changes over time in how the fish behave in different locations?

Yes ☐ No ☐

3.3 How do you choose where to fish?

a. Where other skippers visit ☐
b. The experience from the last visits ☐
c. Oceanographic pattern and assumptions of where most fishes could be ☐
d. Information from others ☐
e. Other ☐

3.4 We see that fishing varies significantly from year to year. What determines your choice of time and field for fishing (On scale of 1 to 5)

1) Government regulations ☐
2) Market ☐
3) Ocean topography ☐
4) Current ☐
5) Distance to fishing ground ☐
6) Distance to harbor ☐
7) Number of Crew ☐
8) Where is the fishing going at the moment? ☐
9) Weather conditions ☐
10) Previous experience ☐
11) Information from other ☐
12) Community decisions ☐
13) Avoidance of bycatch ☐

3.5 How do you find the good fishing grounds?

a. Experience about the area ☐
b. Echosounder ☐
c. GPS ☐
d. AIS ☐
e. Notes (Logbook) ☐
f. Information from others ☐
g. Location of sponges/corals ☐
h. Ocean Topography ☐
i. Any other reason ☐

3.6 Are there anything you are worried about about fishing?

- Acidic seas ☐

☐

- Warming
- More extreme weather ☐
- More pollution ☐
- New species ☐
- Other activities in the sea (what...?) ☐

3.7 Remarks

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....

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Appendix 2

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              Summary of Multicollinearity
Variable             VIF Violations Covariates
SST                 1.12      0      --------
SSS                 1.26      0      --------
YEAR                1.05      0      --------
BPIFINAL            1.01      0      --------
DISTANCE_COAST1   618.93     26      DISTANCE_PORT1 (96.30)
DISTANCE_PORT1    620.44     26      DISTANCE_COAST1 (96.30)
VRM1                1.04      0      --------

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              Summary of Residual Normality (JB)
      JB    AdjR2          AICc    K(BP)       VIF        SA   Model
0.000000 0.043901 252952.968076 0.000000 1.000000 0.000000  +YEAR***
0.000000 0.025209 254924.696247 0.000000 1.000000 0.000000  +SSS***
0.000000 0.010100 256491.091107 0.000000 1.000000 0.000000  -SST***

------------------------------------------------------------------------------

                                   Summary of Residual Spatial Autocorrelation (SA)
      SA    AdjR2          AICc       JB    K(BP)        VIF   Model
0.000000 0.141305 242014.727289 0.000000 0.000000 600.071090  -SST***  +SSS***  +YEAR***  -DISTANCE_COAST1***  +DISTANCE_PORT1***
0.000000 0.139844 242187.847612 0.000000 0.000000 620.437490  -SST***  +YEAR***  -DISTANCE_COAST1***  +DISTANCE_PORT1***  -VRM1***
0.000000 0.139191 242265.182111 0.000000 0.000000 600.671802  -SST***  +YEAR***  -BPIFINAL  -DISTANCE_COAST1***  +DISTANCE_PORT1***

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