A bioeconomic model approach to predicting the spatial fishing effort distribution in the global longline tuna fishery

by

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B.Sc., Dalhousie University, 2002

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

in

THE FACULTY OF GRADUATE STUDIES

(Resource Management and Environmental Studies)

THE UNIVERSITY OF BRITISH COLUMBIA

April 2006

Abstract

Tuna (*Scombridae*) are one of the most commercially valuable kinds of fishes on the world market. Much research has been devoted to the study of the population dynamics of tuna stocks worldwide. In contrast, little is known about fisher behaviour in tuna fishery management. Tuna fisheries operate in all oceans and are characterized by multiple highly migratory species, fleets, and gear types. Predictions of fishing effort allocation among species, choice of fishing location, and gear, are thereby made difficult rendering large limitations on effectively setting quotas and restrictions for species and gears. In addition to these difficulties, tuna fisheries management has been hampered by limited collaboration between governing organizations.

To more effectively protect areas where highly migratory species populations are considered most vulnerable, emphasis has recently been placed on spatial management policies such as area closures. A primary component in evaluating such spatial regulations is to understand how fishers choose fishing locations. This study focuses on key economic indicators that could be the drivers in fishers' decisions and choice of fishing locations in all oceans, for all tuna and tuna-like species in the longline fishery. Factors such as market conditions, the cost of fishing and fish abundance were collected from historical catch, effort, and price data for the aggregated global longline tuna fishery to construct a bioeconomic model that predicts spatial fishing effort distribution from 1950-2001. Total fishing effort was distributed to each spatial cell (5° x 5°) each year based on perceived changes in relative profit. A gravity model, as a component of the bioeconomic model, was used to generate a utility weight for each spatial cell based on the expected profit ratio and historical cumulative fishing effort where a higher weight

indicates more profit potential and therefore a higher proportion of effort allocated to that cell.

From 1960-1980, when many players were involved in the fishery and market prices as well as technological advancements were providing strong competition among vessels, expected profit in an area emerged as a key driver in location choice. Difficulties were encountered in predicting effort in the earlier years, when the fishery was still developing and in later years, when certain species were overfished and gear was altered to target the more valuable species. A sensitivity analysis was performed to determine how much better fishing effort distribution could be predicted given changes in costs, species catchability, and prices. Variations in spatial fishing costs of bigeye (*Thunnus obesus*), yellowfin (*Thunnus albacares*), swordfish (*Xiphias gladius*) and bluefin tuna (*Thunnus thynnus, Thunnus maccoyii*) improved the model fit to the observed fishing effort. With the ability to capture how fishing effort has changed historically, the model allows for future management policies to be analyzed in terms of fishing effort response to such regulations.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ICCAT	International Commission for the Conservation of Atlantic Tuna
IATTC	Inter-American Tropical Tuna Commission
IOTC	Indian Ocean Tuna Commission
CCSBT	Commission for the Conservation of Southern Bluefin Tuna
SPC	South Pacific Commission
FFA	Forum Fisheries Agency
WCPFC	Western and Central Pacific Fisheries Commission
RFMO	Regional Fisheries Management Organization
FAO	Food and Agricultural Organization
DWFN	Distant Water Fishing Nation
PIC	Pacific Island Country
UN	United Nations
TAC	Total Allowable Catch
MSY	Maximum Sustainable Yield
EEZ	Exclusive Economic Zone
ALB	Albacore tuna
BET	Bigeye tuna
YFT	Yellowfin tuna
SWO	Swordfish
WHM	White marlin
BUM	Blue marlin
BLM	Black marlin
STM	Striped marlin
SBT	Southern bluefin tuna
BFT	Northern bluefin tuna
USD	U.S. dollars
IFD	Ideal Free Distribution
FOC	Flag of Convenience

Acknowledgements

First, I would like to thank my two supervisors, Rashid Sumaila and Carl Walters and my committee member, Villy Christensen, for their assistance and guidance throughout this study. Rashid, thank you for your continuous enthusiasm, support, help and understanding especially with editing my thesis. Carl, thank you for initiating the project and helping me with the development of the model.

Second, I do not think simple words are enough to show my thanks to Rob Ahrens. I am forever indebted to you and your continuous patience and help.

Third, I cannot forget my three sounding boards at the Fisheries Centre, Louisa, Colette and Dave. Not only did I gain so much from my degree, I also gained three of the most amazing friends.

I have one more important friend to mention, Bianca. I so much admire your positive outlook and optimism in life. It reminds me that I deserve to have fun. Thank you for listening for so many years.

Thank you as well to everyone in the Walters Lab, FERU, the running group and at Koerner's for making my experience at UBC so enjoyable.

Last, but perhaps the most important, I want to thank my family, especially my parents. I am in constant admiration of your endless support and advice. I am not sure where I would be today without your love and understanding to let me choose my own weird path.

For my "hippie" sister, Erin.
You are what I strive to be.

-See the tuna fleets clearing the sea out.
Beautiful Day, U2

Introduction

It is becoming more common in existing fisheries, due to the decline of many fish stocks, that vessels harvest multiple species at any one time, possibly using multiple gear types in order to gain more profit. Within a multispecies fishery, management is increasingly more complex as policies need to assess the fishing pressure on many inter-related fish stocks. The global multispecies, multigear tuna fishery is a primary example of this sort of complex system. With over eighty nations presently fishing for a variety of tuna and tuna-like species under multiple management schemes, there is major uncertainty in stock status as well as capacity in the fishery.

Taking into account that tuna species inhabit different areas, and fishing fleets from all over the world migrate between these areas, regulations need to reflect the spatial dynamics of fishing effort and stock movement. There have been many studies examining spatial fishing effort dynamics in multispecies and single species fisheries [1-5] but there have been only a few that have focused on the understanding of how fishing effort moves in the commercial tuna fisheries [6-11] and even these studies have only focused on management policies to govern tuna fisheries in specific areas or for a particular country. Chakravorty and Nemoto [11] modeled spatial fishing effort allocation in the Hawaiian longline fishery in order to predict the economic impact of area closures to protect swordfish. A second study predicted fishing effort location decisions for the U.S. purse seine fleet based on previous experience and knowledge of fishing areas [6]. Using data such as distance from port and catch rate expectations, the model was able to predict location choices for the fleet. Using survey data from individual fishers, a study near Hawaii also assessed the impact of area closures by modeling fisher location decisions in the longline fishery based on the assumption that fishers share information on the best spots [7]. Baum *et al.* [12] also examined the effect of implementing area closures to protect bycatch species in the Atlantic swordfish fishery. Spatial fishing effort of all gear types was modeled in an eastern Pacific study which found that effort was distributed to areas using gear and fishing methods that rendered the highest catch rates of species with the highest catchability [8]. Finally, a North Atlantic study used a bioeconomic model of the northern bluefin tuna fishery to examine the success of cooperative agreements between countries fishing the same resource [9]. Policies based on cooperative agreements are difficult to implement in a large fishery but are effective in small fisheries with only one or two players. As suggested by the focus of these studies, the understanding of the fishery dynamics has only been examined on a small scale without considering that any policies set in small regions will impact the rest of the vessels fishing for the same tuna species and stocks in other regions. Using a global analysis, this study looked at fishing response and behaviour in all areas combined in an attempt to capture the dynamics through all areas.

Almost all of the major tuna stocks (bigeye, yellowfin, bluefin) in the world are fully exploited or overexploited [13][1]. As of 2003, more than 5 million tonnes of tuna were taken from the oceans on an annual basis, an increase from 0.6 million tonnes in 1950. 65% of the tuna caught is from the Pacific, 21% from the Indian, and 14% from the Atlantic [13]. Some scientists claim that most of the large pelagic fish stocks, which include tuna, have decreased to approximately 10 % of their pre-exploitation biomass

[1] Overexploited status as defined by IATTC is fishing effort levels beyond the level required to produce AMSY (average maximum sustainable yield). Fully exploited status is defined as fishing effort at the level required to produce AMSY.

level and are continuing to decline at an alarming rate [14, 15]. The longline tuna fishery, in particular, has shown major changes both biologically and economically in the past 50 years due to fluctuating market prices, increased competition from other gears and a decline of large pelagic species in all oceans [15, 16].

The expansion of the commercial longline tuna fishery occurred at the end of World War II with very little or no management governing the amount of fishing or the amount of catch. In 1982, under the United Nations Convention on the Law of the Sea (UNCLOS), each country gained jurisdiction over a 200 nautical mile exclusive economic zone (EEZ) surrounding their coastline [17]. Coastal nations were given sovereignty over their waters within these limits which covered the management of approximately 90% of all fish stocks [9]. Although this included the harvesting of tuna species, difficulties arose because tuna are transboundary fish stocks migrating between EEZs and the high seas. Fish stocks occurring in the high seas are common property resources with no sole owner therefore making management more complicated. Essentially the lack of cooperation and transparency between all States whose waters are fished for any highly migratory species also inhabiting high seas areas is limiting to effective management decisions.

To assist in setting regulations, regional fisheries bodies were established as a cooperative group of member States fishing the same stock. In 1995, the United Nations Fish Stocks Agreement designated these bodies as regional fisheries management organizations (RFMO) and obligated States to cooperate through an RFMO in regards to the management of straddling and highly migratory stocks that move through EEZs of more than one State and through the high seas [18, 19]. Decisions within RFMOs made by State parties fall under two distinct subject matters: i) setting total allowable catch (TAC) and allocating quotas to members of the RFMO and ii) setting measures on method and gear restrictions, amount of fishing effort, open and closed seasons, and size limitations [18]. The TAC is set based on catch and effort data and stock assessment models that produce the maximum yield that can be taken from the stock to maintain a healthy biomass. However, as tuna migrate between the areas governed by these regional fisheries organizations and the vessels harvesting tuna also migrate between areas, even RFMOs have not been entirely successful at conserving tuna stocks.

In examining the historical development of the longline fishery, it is evident that there is a lack of coherence among RFMO stock assessments and one factor that seems to be absent from the assessments is fisher behaviour and reasoning for their fishing choices. Fishing location choice decisions and fishing effort response are just as important in assessing policy regulations as the biological dynamics of the harvested species and establishing a maximum sustainable yield. This study, rather than examine policies on a per area basis, will take a global fisheries perspective at assessing the fleet dynamics and fisher behaviour. This study has two objectives:

i) Establish spatial economic indices that appear to motivate fisher location choice decisions; and

ii) Predict fisher dynamics and fishing effort distribution through time and space as a result of these economic indices in a bioeconomic model.

Harvesting activities are usually determined by market prices, cost of fishing and fish abundance. A simple bioeconomic model has been developed to look at whether fishing costs, market prices and relative catch profits are useful predictors of fishing effort movement and whether fishing location choice is an economically motivated decision.

When all fleets are aggregated on a global scale, there is limited data. Amongst all records, there is only spatial catch and effort data for each species kept by RFMOs. Other parameters that may affect fishing location decisions are weather, distance from port, fuel usage, target species, technological variables, and vessel owner wealth which cannot be obtained on such a large scale [1, 7, 20]. Profitability as a function of spatial fishing revenue and costs is therefore the primary available variable to explain the relative attractiveness of each fishing area to assess location choice probability.

Three research questions motivated this study. One, why are fishers fishing where they fish? In other words, do they target a particular species? Two, can fishing effort distribution be explained by the distribution of the highest valued species? And finally, three, can a simple bioeconomic model reasonably capture fishing effort distribution?

The first chapter looks at the history of the longline tuna fishery including changes in fleet dynamics, number of players, target species, catch and fishing effort trends and market fluctuations; followed by the development, background and role of the five regional organizations governing tuna. The second chapter outlines the individual species, their spatial distribution and their importance over time in the fishery as well as the population dynamics component of the bioeconomic model. The third chapter will describe the economic component of the bioeconomic model and the fishing effort prediction model. Chapter 4 will describe and discuss the results of the bioeconomic model and the sensitivity analysis. Finally, in Chapter 5, I will discuss policy implications.

Chapter 1 Background of global tuna longline fishery

1.1 History of the Tuna Longline Fishery

The global longline tuna fishery initially developed in the Western and Central Pacific Ocean. Following the Second World War, Japan immediately rebuilt their fishing operations with new fishing vessels to replace the ones that were destroyed. In 1949-1950, Japan once again resumed fishing for tuna off their coastline with one difference from their pre-WWII fisheries; Japanese fleets had to confine themselves to fishing within the MacArthur Line[2]. Once Japan surrendered in the war, the U.S. allied forces headed by General Douglas MacArthur gained authority over Japan and their economic sectors as well as over the South Pacific Islands originally controlled by Japan [21]. Under U.S. control, Japanese fleets were limited to a fishing area of 40% (or 630 000 square nautical miles) of the area they fished before the war. This barrier was abolished in 1952 when Japan regained its sovereignty allowing them to expand to the east and to the south Pacific under orders by the Japanese government to transfer from a coastal fleet to a distant water fleet [21]. Since the quality of the catch could not be maintained when traveling long distances to fishing grounds, Japan opened ports in the Pacific Island Countries to decrease fuel costs and to keep their catch fresh while continuing to fish the more lucrative tropical areas.

Presently over one third of all tuna catches occur within the EEZs of the Pacific Island Countries [22, 23]. Albacore (*Thunnus alalunga*) and yellowfin tuna (*Thunnus albacares*) were the primary harvested species in the fishery throughout the 1950s and

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[2] The MacArthur Line was created by General Douglas MacArthur from the U.S. Army who gained control over Japan and the South Pacific Islands following the Second World War. Source: Swartz, W. (2004) Global maps of the growth of Japanese marine fisheries and fish consumption. University of British Columbia, Resource Management and Environmental Studies, MSc. Thesis. 74 pp.

into the 1960s as they were distributed in the tropical regions of the Pacific Islands and along the coast of Japan. Towards the end of the 1950s and in the early 1960s, more countries entered the fishery in particular Taiwan, Korea and the United States. The Taiwanese and Korean fleets developed with assistance from Japan who donated their older vessels to these countries. These four countries along with China are the major distant water fishing nations (DWFNs) in the longline fishery, fishing the high seas areas of all oceans.

Longline fishing expanded quickly to the Atlantic Ocean in the 1960s as Asian fleets moved in to the area lead by Japan [22]. With low fuel prices in the 1960s [24] as well as the expansion of distant water fishing, tuna catch increased significantly along with its market demand. During this time, harvesting also began for swordfish first in the Atlantic Ocean along the North American coast and then eventually to the Pacific Ocean also off the North American coast. Mixed catches of yellowfin and swordfish were very common because of their similar distribution ranges. Many European countries also entered the fishery upon discovering large spawning grounds for bluefin and yellowfin in the Mediterranean Sea and in the Gulf of Mexico.

The longline tuna fishery in the Indian Ocean grew slowly and gradually until the early 1980s when it quickly increased because of the switch in targeting species for the Japanese sashimi market. The proportion of world tuna catch for the Indian Ocean soon surpassed the Atlantic from 8% of the total catch to over 20% after 1980. The fishery, originally artisanal, grew quickly when DWFN fleets from Europe moved in [13]. Most of the targeting was for yellowfin by longlines but also in a lesser degree for bigeye and bluefin.

In the 1970s, a major development to the fishery occurred when Japan invented super deep freezers at temperatures between -40 and -55 °C allowing tuna meat to remain fresh for longer periods of time. Before the early 1970s, freezers in vessels went to only -10 °C. As this was not cold enough to keep tuna meat fresh on a long trip, all tuna species went to the canneries where quality of meat was not a requirement. With super freezers, fishers had the ability to travel even further distances on fishing trips and began targeting the more valuable bigeye (*Thunnus obesus*) and bluefin (*Thunnus thynnus* and *Thunnus maccoyii*) tuna located in more offshore areas. These tuna species were considered more valuable because of their size and quality of fatty meat, fetching premium prices on the sashimi market. This switch was first seen among Japanese vessels, but soon Korean and Taiwanese vessels adopted the same method, followed by the rest of the fleets. The major market for fresh or frozen tuna is the Japanese sashimi market and most of the tuna landed by longline fleets went to Japanese ports. Japan soon became the largest importer of tuna [25] and with increasing fuel prices during the 1970s, Japanese ports and canneries in the South Pacific Islands were closed and focus was shifted to their more lucrative sashimi market , moving from an exporting country to an import-oriented country.

The new market for fresh sashimi tuna directly affected species prices. Up until the 1970s, prices for tuna were the same across species since they were all landed at canneries. Once the Japanese sashimi market opened, bigeye and bluefin tuna prices increased relative to the other species, while albacore remained a canning species with lower value. Yellowfin was not as valuable as bigeye but since it is a primary targeting species for coastal regions and had higher quality of meat than albacore, its value increased over time.

The dynamics of the fishery furthered changed when exclusive economic zones were established in the late 1970s. Since DWFNs were not able to move freely through all waters, thereby decreasing competition in coastal areas, a large expansion of small vessel fleets occurred from smaller countries in South America, Africa and the South Pacific Islands (PICs). The establishment of EEZs also pushed more fleets further offshore into unregulated areas which further increased difficulties in proper management. With the establishment of EEZs, distant water fishing nations were required to gain access agreements with coastal countries in order to be able to fish their waters. Japan, relying historically on the waters surrounding the South Pacific Islands, was greatly affected by the new restrictions. In granting access to the DWFNs, the small island countries in turn were given fees contributing to their fishing sector economy ($60 million in access fees were given to PICs in 1999 from foreign activities) [23, 26]. By the 1980s, Japan had decreased their longline production by 20% because of competition with expanding fleets from other countries and high access fee payments. In an attempt to minimize access fees, in the late 1980s, Japan began subsidizing small fleets from the South Pacific Islands in trade for being allowed to fish in their waters with lower access fees [23]. The change in dynamics from the restrictions on high seas fishing vessels significantly altered the behaviour of the longline fishery while at the same time increased productivity of the coastal purse seine fishery.

The development of the purse seine fishery in the 1970s was an additional source of competition for the longline fishery. This fishery takes juvenile tuna before they reach a size where they are vulnerable to longlines as adults. The purse seine fishery primarily targets skipjack tuna (*Katsuwonus pelamis*), not a target species for longlines, but also targets smaller bigeye and yellowfin which does directly impact subsequent longline catch. Some studies in recent years have looked at the impact of purse seiners on longline catch [6, 16, 26]. The purse seine fishery takes such large quantities of tuna for canneries that the market price has decreased over time due to an increase in supply, which also affects the demand for longline caught tuna. Purse seine fleets fishing in EEZ areas has also pushed longliners to the high seas as longliners seek to avoid direct conflict and interaction which may damage their lines. The valuable sashimi market for longline caught tuna and the additional fishing pressure from the purse seine fishery taking most of the catch (65% of the world tuna catch), has lead to overcapacity in the fishery and a decline in catch over the last two decades [13].

The movement and change in the longline fishery since 1950 are important sources of information for effectively managing the fishery in the future. Transformations over time in the fishery clearly indicate that there are other variables than just biological changes and catch trends to consider in stock assessments and setting quotas and regulations.

1.2 Gear Types

There are three major gear types in the tuna fishery; purse seine, pole and line and longline, which together account for almost 95% of the total tuna catch. The other (minor) gear types are trolling and gillnetting. Purse seines account for 65%, longlines for about 14% and pole and lines for 14% of the world production of tuna in tonnage [13].

The catch taken by each gear is not necessarily directly related to their economic value and status. Although purse seines account for the most production, the catch is processed in canneries and is therefore of less value than the same amount of tuna caught from longlines and taken to the sashimi market. Even with decreasing catches in the longline fishery, the revenue obtained from the sashimi grade tuna is almost as high as purse seine revenue [26]. For example, a longline vessel catching 2 tonnes of tuna for the sashimi market delivers a higher economic return than a purse seine vessel landing 20 tonnes for canning [13]. The economic differences between the fisheries as well as the proportion of catch taken by each gear need to be considered when setting effective management regulations.

1.2.1 Longline fishery

The gear of a longline fishing vessel is composed of one long main line (often >100 km) with smaller branching lines (as many as 3000) with large baited hooks (usually squid). At every 300 m interval, the longline is kept afloat in the water column with buoys attached to the main line. A longline is passively put into the water for approximately 8 hours at a specific depth for a particular target species, shallower for yellowfin and albacore, deeper for bigeye. Sets are made during the day for tuna species and during the night for swordfish. The longline gear is indiscriminant in that it can catch anything that eats the bait, leading to a large amount of bycatch [13]. Once landed on board, the fish are packed in ice and put into the freezer on board or else flown to the nearest port to be sold fresh on the market. Longline vessels range in size, with large distant water vessels up to 60 metres long while smaller near shore vessels are 15-20 metres long. The larger offshore vessels target bigeye and bluefin while the smaller vessels close to the coast target yellowfin, swordfish and albacore.

1.2.2 Purse seine fishery

The purse seine fishery targets juvenile tuna, mostly skipjack but also bigeye and yellowfin. Purse seine nets extend vertically into the water column (150 m deep) and extend out about 1.5 km from the vessel. The vessel surrounds a school of fish in order to encircle the fish with the net, then pulls the bottom of the net tight below the school creating a drawstring effect which traps the fish into the pursed sack to bring on board [13]. Purse seine vessels use helicopters and fish aggregating devices (FADs) in order to find schools faster and decrease search time. The use of FADs have lead to a significant increase in purse seine catch in the last 10 years (increase of 19%) in juvenile bigeye and yellowfin tuna [13]. The purse seine fishery operates primarily within EEZ limits, but there are also numerous high seas fleets of very large vessels traveling all oceans. The purse seine fishery harvest tuna for canning because the fish are of lesser quality and smaller size than longline caught tuna.

1.2.3 Pole and line fishery

Occurring mostly within the coastal waters of Small Island States, the pole and line fishery uses a hook and line attached to the end of a pole with live bait to catch tuna. This is the most ancient form of fishing in the Pacific Ocean particularly for the Pacific Island Countries [23]. This method used to catch the greatest proportion of tuna until the improvement in purse seine and longline technology [22].

1.3 Historical Catch and Effort Trends

Figure 1-1 shows the aggregated global catch trends from the longline tuna fishery using data collected from IOTC, IATTC, ICCAT, SPC and CCSBT. The catch for each species increased significantly throughout the 1960s and 1970s and then stabilized. Only swordfish and bigeye have shown a steady increase in catch over time. Although some primary species such as bigeye and albacore still seem to be maintaining high catch levels, it is worth mentioning that the data collected does not include catch from illegal, unreported, unregulated fishing, which in the tuna fisheries, is estimated as 10% of all catches per year [27].

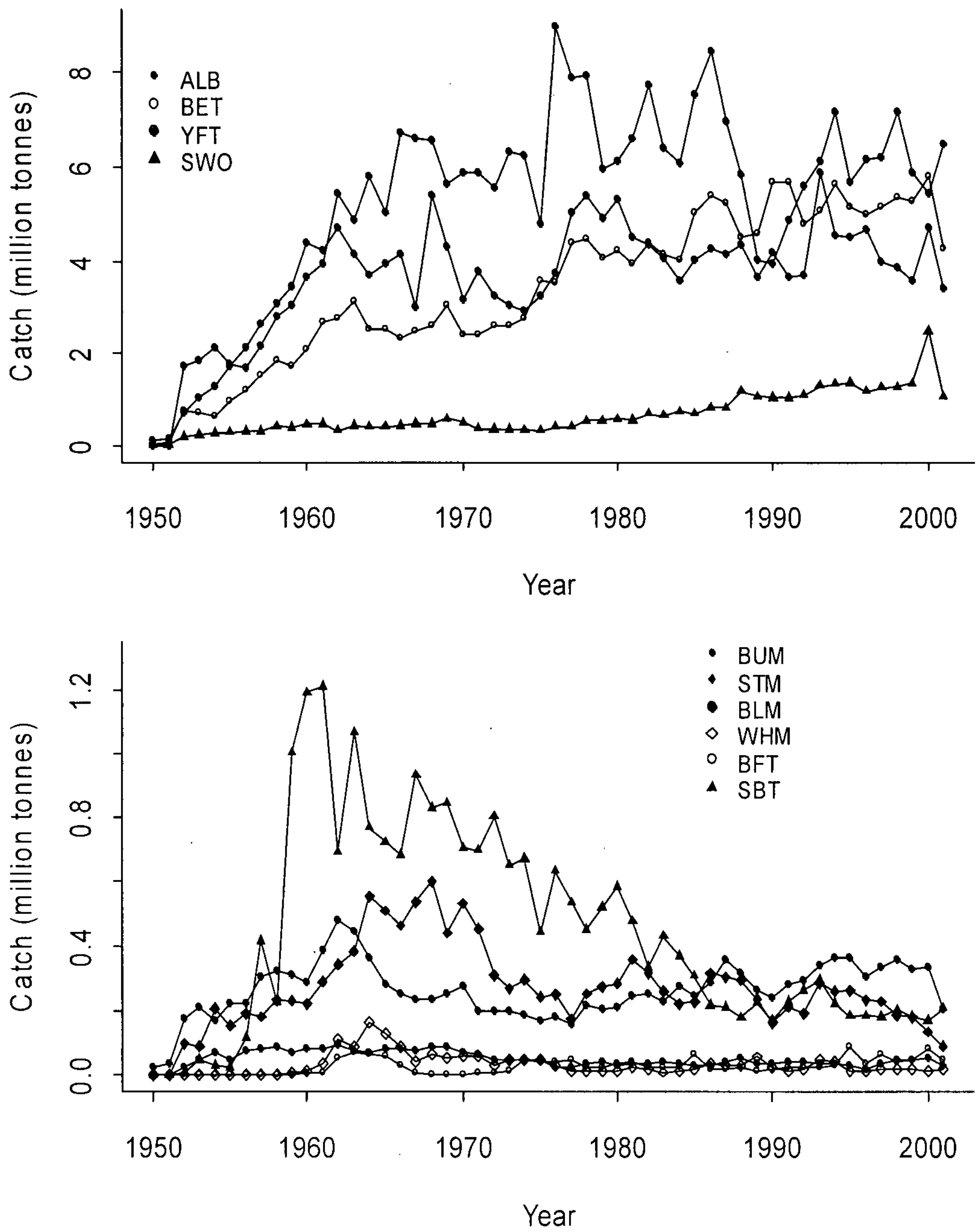

Figure 1-1: Global catches of each species in tonnes from 1950-2001 in the longline fishery.

The amount of fishing effort, in number of hooks set, from 1950-2001 are shown in Figure 1-2. Fishing effort continues to increase throughout the 1960s and 1970s. In the 1980s, effort stabilized and fluctuated around the same level until it decreased in 2001.

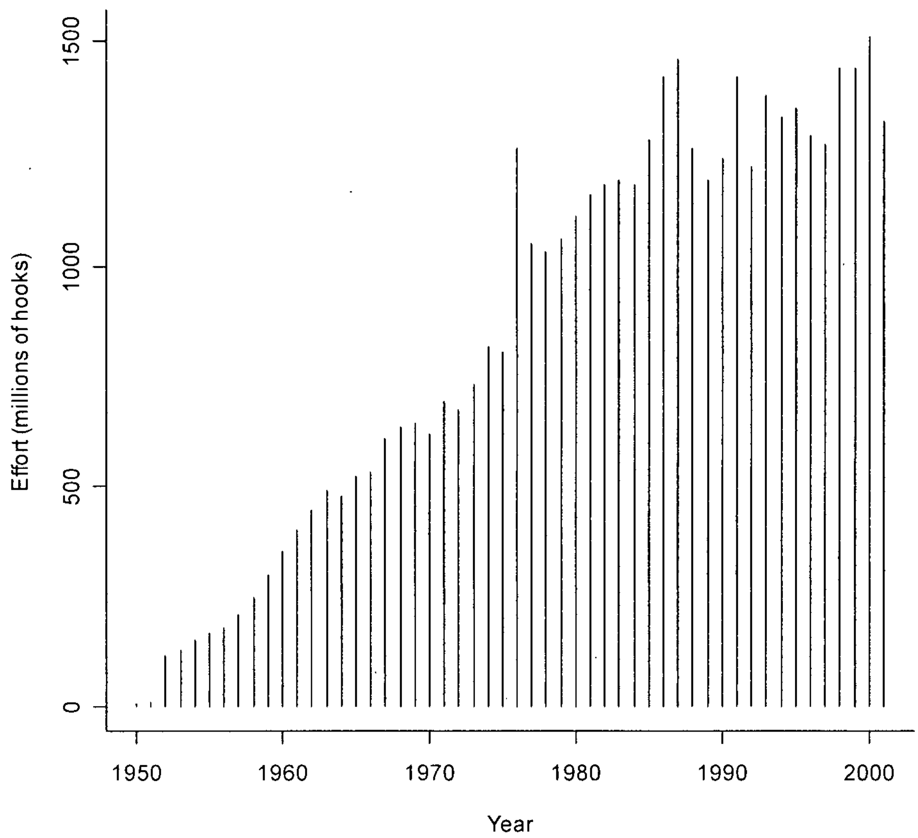

Figure 1-2: Global longline fishing effort in millions of hooks set for all species combined from 1950-2001.

1.4 Regional Fisheries Management Organizations

Regional Fisheries Management Organizations (RFMOs) are bodies responsible for the management of straddling, migratory and transboundary fish stocks. Not only do RFMOs have a responsibility to conserve all species targeted by their fisheries, they also have a duty to conserve the species associated or affected by their fisheries, including seabirds, turtles, dolphins, sharks and non-target fish. These responsibilities have been outlined in new international agreements governing the oceans, such as FAO's Code of Conduct for Responsible Fisheries [28], and the United Nations Fish Stocks Agreement

[19]. It is argued that RFMOs are the best organizations to create cooperation between States for the conservation of marine species, especially for wide-ranging species where effective mitigation depends on collaboration between States.

The 1995 UN fish stocks agreement gave the responsibility to RFMOs for governing fisheries for species under their jurisdiction [19]. RFMO scientists perform stock assessments to set quotas that serve as a basis for recommendations in the decision making by member parties. Each RFMO contains member States. Unfortunately, there are many (more than half) member States in RFMOs that are not parties to the UN fish stocks agreement, which allows them to opt out of decisions [18]. There are also non-member, non-contracting parties that do not take part in the decision making process but adhere to the regulations. Once regulations are set, they are passed on to the participating countries that are then responsible for the implementation, the monitoring and the enforcement of these regulations over their own fleets.

There are problems with how RFMOs function, resulting in unsuccessful management schemes that have not proven to effectively maintain the sustainability of the tuna stocks. The first issue is enforcement and compliance of member and non-member States. Once the total allowable catch is set by RFMO members, member states often fail to enforce those measures on their own fishing vessels, and have even less success at ensuring that vessels of non-members comply with these measures. RFMOs do not monitor the regulations that are implemented. This is required by nations with EEZs in the area. When vessels land their catch at various ports around the world, it is often difficult to keep a record to compare with their allocated quota. Compliance with RFMO regulations especially with non-member parties is often low because there is no strict enforcement mechanisms or sanctions for non-compliance [29]. The significant gap between setting regulations and the actual enforcement of the regulations is a fundamental problem in some international and domestic fisheries managed by RFMOs. Monitoring and enforcement is very costly in a fishery and most often not worth the time and money required to apprehend a non-complying vessel. In most cases, especially with developed countries, nations do not have the resources to enforce regulations in their waters [23]. Enforcement in the high seas is also a major concern especially because the high seas are a common property resource, there is no "owner" or governing body to monitor the regulations in these areas [18]. As shown in Figure 1-3, the spatial area where longline fishing occurs is very large (dark grey areas), some of which is common property (lying outside of EEZ areas) [30]. The distant water fishing vessels that fish the high seas are highly mobile, can easily change flags depending on their location and move from ocean to ocean making them difficult to identify and apprehend if they are fishing illegally. The enforcement issue leads to the second problem in fisheries management by RFMOs, which is the complexity of the regulations in place.

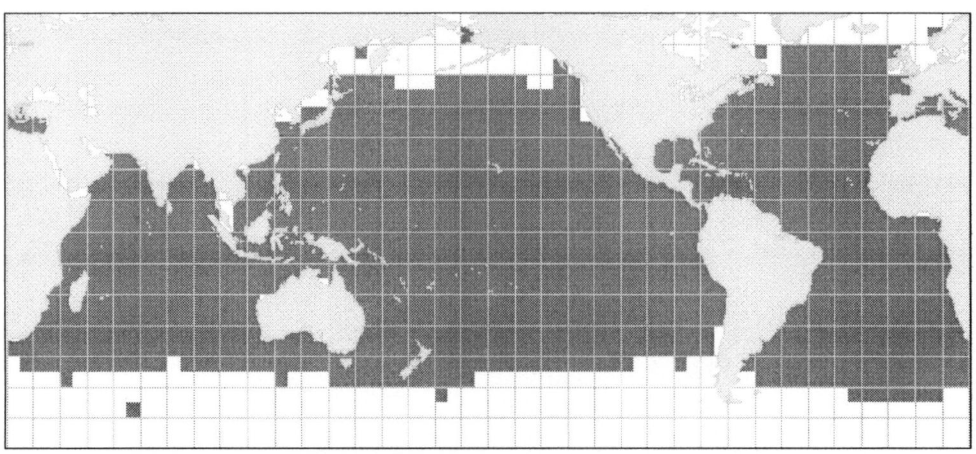

Figure 1-3: Areas where longline catches and effort have been recorded. Source: www.fao.org [30].

Currently and in the past, regulations have been in the form of quotas, closed areas, and gear restrictions. In some cases, all of these restrictions are employed in one fishery sometimes on one single species in order to control the amount of catch [13]. This sort of management, regulating on a small scale is complex, confusing and difficult for fishers to comply with. It is especially more confusing if vessels move between areas and have to comply with different management schemes. This type of micro-management in conjunction with a lack of collaboration between RFMOs, the third issue of concern with management bodies, leads to ineffective regulations.

The third management problem is the lack of cooperation and collaboration between member States and individual RFMOs. Collaborating countries vary in economic status which often leads to a conflict of interest between parties in an RFMO. Some nations want to maximize employment while other nations aim to maximize economic returns [31]. For some contracting parties, fisheries constitute a vital economic interest, while for other States; they constitute a middle or low-level economic interest. When RFMOs contain both developed and developing States, coastal States and distant water fishing States, there are many conflicting agendas [32]. Such diversity results in varied commitments, levels of participation, and expectations regarding the objectives of the State. In theory, international bodies such as RFMOs should account for differences between their wealthy, developed member States and their less wealthy developing members but often fail to make all parties satisfied.

Not only is there a lack of cooperation among parties within an RFMO, there is also a lack of collaboration between RFMOs managing the same species. Each RFMO collects data for its individual area and recommends regulations accordingly for that area, without any regard for the stock assessments or information from other areas despite the fact that the same stocks migrate between areas and the same fishers move between areas.

Currently there are five regional organizations that govern all tuna species world-wide. During the period covered by this analysis (1950-2001), the Western and Central Pacific Fishery Commission (WCPFC) was not yet established. The other four bodies are the Inter-American Tropical Tuna Commission (IATTC), the Indian Ocean Tuna Commission (IOTC), the International Commission for the Conservation of Atlantic Tuna (ICCAT) and the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). These 5 bodies will be outlined in terms of area of governance, member parties and regulations in place.

1.4.1 IATTC

The Inter-American Tropical Tuna Commission is responsible for the management of the eastern Pacific Ocean [33]. Established in 1950, it is solely responsible for the management of tuna and tuna-like species taken by fishing vessels in that region. The area that IATTC manages is from 40°N latitude to 40°S latitude off the coast of Chile to the west coast of Vancouver Island spreading to 150° longitude (Figure 1-4). There are 13 member parties that set policies and regulations for this area; United States, Costs Rica, El Salvador, France, Guatemala, Japan, Mexico, Nicaragua, Panama, Peru, Spain, Vanuatu, Venezuela. There are also 6 cooperating States that operate under the policies set by IATTC but do not take part in the decision process; Canada, China, European Union, Honduras, Korea, and Chinese Taipei. The total allowable catch (TAC) in the longline tuna fishery as well as annual quotas allocated to each member country based on the previous year's catch are set by a consensus or unanimous vote among members [18].

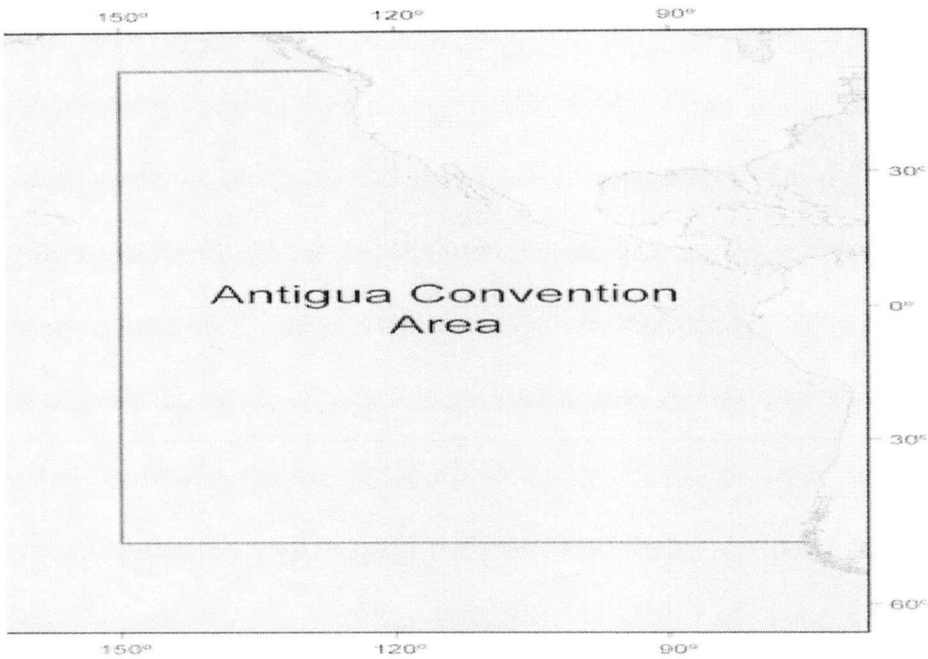

Figure 1-4: Map of IATTC area. Source: www.iattc.org [33].

1.4.2 ICCAT

The International Commission for the Conservation of Atlantic Tuna is the management organization that governs the Atlantic Ocean and adjacent seas (i.e. Mediterranean Sea) [34]. Founded in 1966, ICCAT is responsible for the management of 30 tuna and tuna-like species. There are 40 contracting parties: United States, Japan, South Africa, Ghana, Canada, France, Brazil, Morocco, Republic of Korea, Cote D'Ivoire, Angola, Russia, Gabon, Cape Verde, Uruguay, Venezuela, Guinea, United Kingdom, Libya, China, Croatia, European Union, Tunisia, Panama, Trinidad and Tobago, Namibia, Barbados, Honduras, Algeria, Mexico, Vanuatu, Iceland, Turkey, Philippines, Norway, Nicaragua, Guatemala, Senegal, and Belize. These countries are mostly all Atlantic rim countries except for the DWFNs, for example, Japan (the major importer, fisher and consumer for Atlantic tuna). The TAC is set by a majority rules voting system and the allocation of quotas for each country is set through consensus voting [18].

1.4.3 IOTC

The Indian Ocean Tuna Commission was established in 1993 through the UN supported Indo-Pacific Tuna Development and Management Programme when tuna catches from the Indian Ocean began to exceed the catch in the Atlantic [35, 36]. IOTC is responsible for managing 16 tuna and tuna-like species in the Indian Ocean and adjacent seas. Current members of IOTC are Australia, China, Comoros Island, Eritrea, European Community, France, Guinea, India, Islamic Republic of Iran, Japan, Kenya, Republic of Korea, Sultanate of Oman, Madagascar, Malaysia, Mauritius, Pakistan, Philippines, Seychelles, Sri Lanka, Sudan, Thailand, United Kingdom, and Vanuatu. Cooperating non-member parties include Indonesia and South Africa. The TAC is set by a 2/3 majority vote and quotas are allocated to each member State by consensus voting [18].

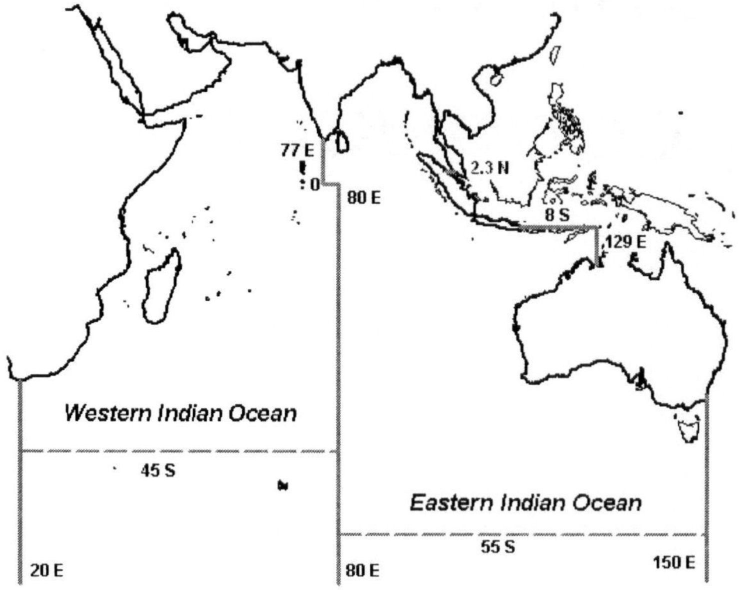

Figure 1-5: Management area under the IOTC. Source: www.iotc.org [36].

1.4.4 CCSBT

The Commission for the Conservation of Southern Bluefin Tuna, established in 1993, is the organization responsible for the management and conservation of southern bluefin tuna (*Thunnus maccoyii*) [37]. CCSBT manages the Southern hemisphere of the world oceans where southern bluefin are distributed between 30ºS and 50ºS. Japan, Australia, Taiwan, Republic of Korea and New Zealand are the primary countries fishing for this species. Non-member cooperating fishing countries are China, the Philippines and Indonesia. Consensus voting determines the annual TAC as well as the allocation of quotas to each Member State.

1.4.5 SPC and FFA

The South Pacific Commission was established in 1947 to provide assistance to the Island nations in management, capacity building, research and technical support [38].

All 22 Pacific island countries and territories (Figure 1-6) as well as the 4 founding countries; Australia, New Zealand, United States and France joined the SPC. Although the SPC assists in data collection, research and the management of the fisheries in this region, it is not responsible for setting policies and regulations. It has no authority over the governance of the tuna fisheries. This task falls under the jurisdiction of the Forum Fisheries Agency (FFA).

The FFA was founded in the late 1970s with the purpose of managing the fish stocks and fisheries in the waters of the South Pacific Islands as well as to govern access agreements with DWFNs and collaboration between Island states [39]. FFA members include Cook Islands, Fiji, Federated State of Micronesia, Kiribati, Marshall Islands, Nauru, Niue, Papua New Guinea, Palau, Solomon Islands, Samoa, Tokelau, Tonga, Tuvalu, and Vanuatu. The major foreign vessels fishing in this area are from Japan, Taiwan, China, Korea and the U.S. As a result, most of the fishing in this area is by foreign fishing vessels with access rights contributing to a large part of the Pacific Island countries economy. Although the FFA was effective at collecting data and assessing the waters around the Pacific Island countries, it was obvious that the pelagic species which were of particular importance also migrate to high seas areas outside of their managing region. This prompted the development through the SPC of the Western and Central Pacific Fisheries Commission which was implemented to establish management policies for the high seas of the central and western Pacific Ocean.

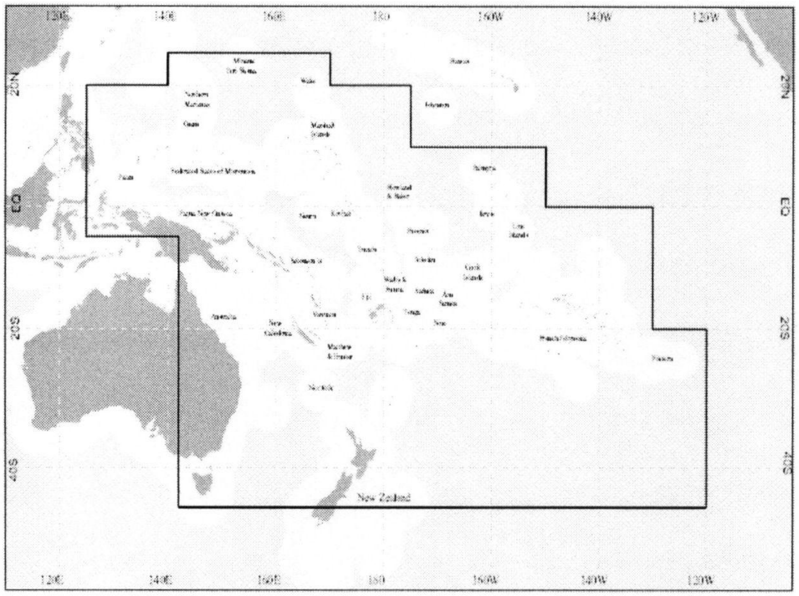

Figure 1-6: The 22 Island countries and territories in the South Pacific Commission. Source: Gilllett *et al.* [23].

1.4.6 WCPFC

The Western and Central Pacific Fisheries Commission was established in 2000 as a convention for the conservation of highly migratory fish stocks in the Western and Central Pacific Ocean (Figure 1-7) [40]. The member parties are Australia, Canada, China, Cook Islands, Federated State of Micronesia, Fiji Islands, France, Indonesia, Japan, Republic of Kiribati, Republic of the Marshall Islands, Republic of Nauru, New Zealand, Niue, Republic of Palau, Independent State of Papua New Guinea, Republic of the Philippines, Republic of Korea, Independent State of Samoa, Solomon Islands, Kingdom of Tonga, Tuvalu, United Kingdom, Northern Ireland, United States, and the Republic of Vanuatu. To set TACs and quotas, a general consensus voting is used unless a consensus cannot be reached, then decisions are made through ¾ majority voting [18].

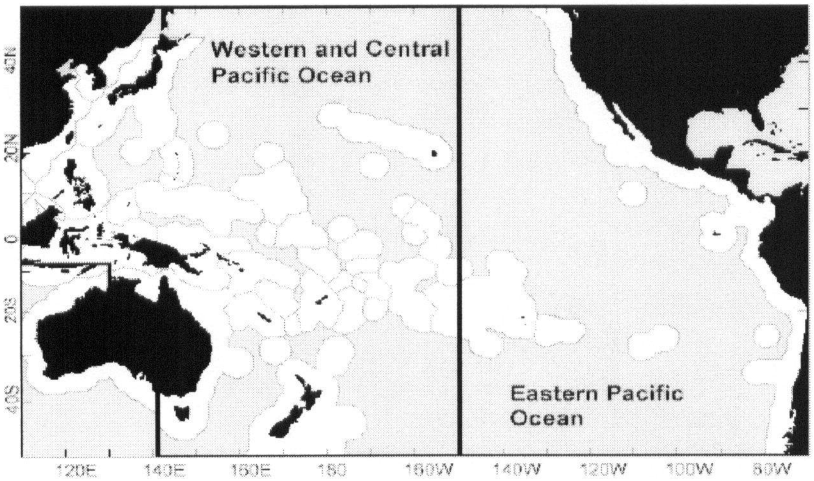

Figure 1-7: The separation between the east Pacific (IATTC) and the western and central Pacific (WCPFC). Source: Reid *et al.* [41].

1.5 Improvements on Present Management Procedures

Fundamentally, for many fisheries, the underlying problem in stock sustainability is overcapacity. There are too many fishers chasing too few fish due to influence of subsidies [42], increasing market prices, and very little control over entry into the fishery especially with the growing number of illegal vessels fishing for tuna [43]. There is also a high degree of discounting for many fishers who most often choose short term gain over long term sustainability and therefore continue to fish regardless of decreasing catches [44]. This overcapacity is leading to increased pressure on the tuna stocks, keeping fishers from obtaining their maximum economic returns rendering it a major factor hampering effective management. Bertignac *et al.* [26] looked at how the western and central Pacific tuna fisheries can maximize resource rent, and found that more profit could be obtained by decreasing the size of fleets. Up until now, regional organizations have focused their efforts on setting quotas for each species. In a multispecies fishery, quotas are difficult to establish. Since most vessels catch a variety of species on any given trip, it is difficult to track the amount of each species caught by each country. The ICCAT, IOTC and IATTC have now realized that although the number of fish caught is important to control, the number of fleets in both the longline and the purse seine fisheries also need to be controlled. Scientists in these organizations have made recommendations on the optimal number of vessels that should be fishing but the actual agreed number by member States is far beyond what was recommended [13]. Due to social and economic pressures by their governments, members find it difficult to decrease the amount of fishing because of short term consequences to their economy [44]. Due to these pressures and the gap in decisions between members and scientists, there can be no logical improvements in management if what experts suggest is not actually implemented by the member States. All restrictions (catch limits, gear restrictions and effort limits) should be taken into consideration when making management decisions. However a better understanding of how the fishery and fishing effort distribution will be impacted in reaction to these regulations can be realized when the fishery is assessed as one entity.

1.6 Global Approach to Management

If fishers were faced with the same type of regulations for each species while fishing with a particular gear, then there would be less confusion and complexity while promoting more understanding, agreement and compliance with regulations such as area closures, catch limits, and gear restrictions.

This study looked at a global approach to management in the longline tuna fisheries as an alternative to the present management scheme. Rather than assess each individual area and the catch and effort on tuna stocks in that area, this study aggregated all catch, effort and fleets from all areas to examine the status of the stocks as a whole. It also looked at the behaviour of all fishers active in the longline tuna fishery to examine the functioning of the global fleet. A global tuna fishery simulation model developed in this study looked at the dynamics of fishing and the resulting effects on each species. Simulation models can provide valuable insight into the movement in a fishery; allowing a formulation of predictions that can then be compared against observation. This study also evaluated the impact of fishing on all species rather than focus on single-species assessments. A single species assessment is not effective for a multi-species fishery when the fishers fish to maximize profit, and capture whatever species crosses their path [13]. Assessments are needed to examine the interaction effects when more than one species is being fished. Regulations need to take into account the fact that regulating only one species will impact fishing effort on another species in the same ecosystem. Scientists need to also look at how fleets move globally and examine why fishers choose certain fishing locations and at what time intervals. Since closed areas or catch restrictions in one ocean or area will in turn increase the amount of fishing in another ocean or area, it is important to gain insight into fisher behaviour over all areas. A global model can then assess quotas and capacity restrictions for each nation depending on their overall performance in the fishery, not solely by their activity in one area. The model can also assess the impact on the stocks as a whole since all catch and fishing effort globally will be available and assessed on an aggregated scale. Finally, global management will also be able to better control the overcapacity in the fishery since the amount of fishing vessels will be known in all oceans.

Chapter 2 Biological Model

2.1 Target Species

This study includes the major species targeted or incidentally caught in the longline tuna fishery. The species are pelagic and highly migratory spanning all oceans in tropical, subtropical and temperate regions. Pelagic species swim continuously throughout the water column rather than periodically resting on the bottom. Five tuna species: bigeye (*Thunnus obesus),* yellowfin (*Thunnus albacares*), albacore (*Thunnus alalunga*), southern bluefin (*Tunnnus maccoyii)* and northern bluefin *(Thunnus thynnus*) tuna as well as white marlin (*Tetrapturus albidus*), blue marlin (*Makaira nigricans*), black marlin (*Makaira Indica*), striped marlin (*Tetrapturus audax*) and swordfish (*Xiphias gladius*) are included in the model[3]. These 10 species contribute the most significant proportion of catch in the longline tuna fishery, and catch and effort records for these species have been collected for the period, 1950-2001. Since the major focus of this study is tuna and swordfish, since they are target species, the distribution and history of each tuna species and swordfish will be described as well as a broad description of all marlins, which are non-targeted species, but still fetch a market price.

2.1.1 Bigeye tuna (*Thunnus Obesus*)

Bigeye tuna accounts for 10% of the catch of all tuna species by all gear types [13] but is the primary species caught by longlines. Bigeye tuna span a large geographic area between 50°N and 45°S, covering a depth of 250 m to 550 m deep and a temperature range of 15-20°C over all oceans [45-47]. This species is primarily located in high seas

[3] To note, the abbreviations for each species that will be used in the results are found in the List of Abbreviations at the beginning of the thesis.

areas, far offshore. There is one stock of bigeye in the Pacific, one in the Atlantic and one in the Indian Ocean [45-47]. Bigeye tuna have a large vertical distribution with spawning grounds located in shallower tropical regions and adult habitat in deeper cold waters. As juveniles, they form large schools in shallower depths together with other tuna species such as albacore and yellowfin. This allows for purse seines to target juvenile bigeye and yellowfin with their shallower nets while fishing for skipjack. As adults, they inhabit deeper waters and swim in smaller schools making them vulnerable to deeper set longlines. Although overlapping with other species at the top of their depth range, they are the deepest ranging tuna species, swimming below the thermocline [35]. Bigeye tuna reach age of maturity at 4 years old and become vulnerable to longline fishing in the adult stage. Prey species include mollusks, fish and crustaceans. Bigeye meat was originally sent to canneries upon landing, but soon became the second most valuable tuna species in the sashimi market when super deep freezers were invented. Bigeye tuna is considered overexploited in all oceans due to the targeting by longlines and the catch of juvenile bigeye by purse seine vessels [13]. Overexploited as explained by stock assessments from RFMOs is a stock level far below the level that produces a maximum sustainable yield (MSY) [46].

2.1.2 Yellowfin tuna (Thunnus albacares)

Yellowfin tuna account for 30% of the total catch of tuna by all gear types and is one of the most important tuna species in terms of catch (next to skipjack) contributing the second largest proportion of all longline catch [13, 30]. Yellowfin tuna are surface swimmers, staying above the thermocline inhabiting a depth range of 50 to 300 m in oxygen rich, warm temperature waters [47-49]. Their distribution is closer to shore than bigeye located within EEZ limits with migration along the equatorial range between 45°N and 40°S. There is only one yellowfin stock in the Indian and one in the Atlantic Ocean while there are two stocks in the Pacific Ocean, one in the east and one in the Western-Central Pacific [47-49]. Yellowfin reach age at maturity at 3 and become vulnerable to longlines in the adult stage. Yellowfin were primarily targeted in the early years of the fishery and still remain the target species for inshore fleets, but are not as important to distant water vessels that mainly harvest bigeye and swordfish. Yellowfin is considered fully exploited due to decreasing catch rates and increasing catches of juvenile fish by the purse seine fishery [50].

2.1.3 Albacore tuna (Thunnus alalunga)

Albacore account for only 5% of the total tuna catch by all gear types [13] but comprises the third largest proportion of all longline catch [30]. Albacore tuna is a slow growing, late to mature fish reaching age of maturity at 5 years and vulnerability to longlines in the adult stage. In the Pacific Ocean, there is a northern stock migrating in waters above the equatorial range and a southern stock located below the equator. Both stocks move between 40°N and 40°S but no albacore fishing occurs between 10°N and 5°S [51]. In the Atlantic Ocean there are 3 stocks, one in each of the northern and southern hemispheres located between 55°N and 45°S and a separate stock in the Mediterranean Sea [52]. There are also two stocks in the Indian Ocean with ranges similar to the stocks in the Pacific [47]. Albacore is a surface species, spawning in subtropical waters but spending a large amount of time in temperate regions [35]. Since the distribution of albacore is very broad, catches vary from year to year depending on climatic events [13, 53]. When super freezers were invented, albacore went from being a targeted species to a bycatch species in the bigeye and bluefin fisheries. This has resulted in a recovery in stock size and an increase in catch per unit effort in the last decade (Figure 2-2). Albacore had been fully exploited until 1980 and then due to a decrease in targeting has now increased to a sustainable level [13]. In the Indian Ocean, albacore are located in temperate waters and are not directly targeted as vessels primarily target the tropical species, yellowfin and bigeye [47].

2.1.4 Southern bluefin (Tunnnus maccoyii) and northern bluefin (Thunnus thynnus) tuna

Bluefin tuna is, in terms of tonnage, the least important of the tuna species due to very low catch sizes (less than 10% of the annual total albacore catch) but is the most valuable on the market [13]. For management purposes, the Atlantic northern bluefin tuna (*Thunnus thynnus*) stock is divided into two stocks by ICCAT, east and west Atlantic Ocean [54]. Although genetically, it is the same stock, it is easier to perform different stock assessments on either side of the division because the fisheries were very different, with catches increasing in the East Atlantic and decreasing in the west Atlantic [35]. The western stock is located primarily in the Mediterranean Sea while the eastern stock is located along the North and South American coastlines. Northern bluefin move to tropical regions to spawn (Gulf of Mexico and the Mediterranean Sea) and juveniles usually remain in subtropical areas near convergence zones while adults migrate to colder waters.

The southern bluefin tuna (*Thunnus maccoyii*) is a separate stock located in the southern hemisphere, between 30°S and 50°S with one stock distributed across the southern hemisphere of all three oceans [47]. ICCAT was originally responsible for the management of southern bluefin tuna until 1993 when CCSBT was established and took control over the management [37]. Southern bluefin tuna spawn in warmer waters south of Java, Indonesia and in a region off northwestern Australia as well as off the southern tip of South America [47].

Bluefin tuna species have a broad distribution ranging from tropical to subtropical to temperate regions primarily located in high seas areas outside EEZ limits. Their large body size (largest tuna species) and late maturation (12 years) allows them to adapt easily to all ocean conditions [35]. Bluefin tuna are the largest and most valued tuna species, and the most valued fish species in the world, fetching premium prices on the Japanese sashimi market [10]. Due to high fishing pressure as a result of the value of this species, and the late maturation period, all bluefin stocks are overexploited [47, 54].

2.1.5 White marlin (Tetrapturus albidus), blue marlin (Makaira nigricans), black marlin (Makaira Indica) and striped marlin (Tetrapturus audax)

Marlins are primarily a bycatch species in the longline fishery and are primarily targeted in recreational fisheries. Marlin catch contributes approximately 40 000 tonnes a year of the longline production, which is greater than the bluefin tuna catch but less than the primary tuna species. All marlin species are fast growing, early to mature, and non-schooling. They inhabit the epipelagic region above the thermocline between 45°N and 45°S. They have similar feeding habits as tuna, foraging on the same fish and invertebrate species. Marlins contribute a large proportion of the catch in mixed species fishing as they are distributed in the same regions as yellowfin, albacore and swordfish. Blue marlins are distributed globally [55]. Black and striped marlins are located in the Indian and Pacific Ocean while white marlins are distributed in the Atlantic Ocean [56, 57].

2.1.6 Swordfish (Xiphias gladius)

Increasingly through time, swordfish has become a more important catch species. Mainly caught through recreational fisheries, swordfish contributes approximately 50 000 tonnes to longline production and is an important market species next to the major tuna species [30]. Swordfish is a fast growing, early maturing, non-schooling species found in colder regions compared to the other billfish species with a distribution between 60°N and 45°S in productive upwelling areas [58]. Similar to yellowfin, they feed on the same prey and are found in shallower depths making mixed sets of yellowfin and swordfish very common. Swordfish are found in all oceans in water temperatures ranging from 5-27 °C but prefer temperatures of 18-22°C [59]. In the Atlantic, there are three stocks of swordfish, north Atlantic, south Atlantic and the Mediterranean Sea with most of the swordfish caught in the north Atlantic region [58]. There are two stocks in the eastern Pacific Ocean. Primarily caught by longlines, swordfish are caught as bycatch in daytime tuna sets, and targeted sets are made at night when swordfish are found in deeper waters [59].

2.2 Data Sources and Preparation

If a country is a member of an RFMO or is a contracting party, vessels of that country are required to log the amount of catch of each species as well as the amount of effort used and the coordinates of the area where the catch occurred. Data must be sent to the respective RFMO depending on which ocean and area. Tuna vessels, therefore, must submit their catch and effort data annually to WCPFC, IOTC, IATTC, ICCAT, or CCSBT depending on the fishing location. For this study, data collected from each individual ocean and area was aggregated into one large global dataset. The dataset contains the catch in numbers of fish for each of the ten species and the amount of effort in number of hooks set for each 5° latitude by 5° longitude spatial cell from 1950-2001. The catch recorded is the nominal catch, which is the sum of catches that are landed at port, not including illegally caught fish or the catch that is discarded before the vessel docks at port.

2.3 Population Dynamics Model

The development of the population dynamics model is divided into 4 sections: (i) spatial relative abundance estimates, (ii) species biological parameters (catchability, fishing mortality and natural mortality), (iii) initial population abundance estimates, recruitment to each spatial area and a dynamic annual updating procedure for biomass and (iv) average weight estimates for each species.

The multispecies system in the longline tuna fishery was modeled to compare a simulated predicted fishing effort to compare to the observed fishing effort data through time based on the abundance of species and relative catch indices. In order to simulate the model developed for 1950 to 2001, the biomass for each species in each spatial area was calculated and updated on an annual time step depending on the amount of catch taken and the migration between areas. To calculate biomass and catch per unit effort estimates; catchability, fishing mortality, natural mortality and recruitment estimates were required.

2.3.1 catch per unit effort (cpue)

The catch per unit of effort (cpue) is the proportion of fish taken from a stock by a defined unit of effort, in this study, by one hook. Cpue is assumed to be proportional to abundance in each spatial area:

$$cpue_{i,j,t} = \frac{C_{i,j,t}}{E_{j,t}} = q_i N_{i,j,t} \tag{1}$$

Where $cpue_{i,j,t}$ is the catch per unit of effort in area *j* of species *i* at time *t*[4];

$C_{i,j,t}$ is the catch of species *i* in area *j* at time *t*;

$E_{j,t}$ is the fishing effort in area *j* at time *t*[5];

$N_{i,j,t}$ is the abundance of species *i* in area *j* at time *t*; and

q_i is the catchability of species *i*.

There is some difficulty in estimating cpue when some areas are missing catch and effort data for certain years, if fishing has either not yet occurred in that area or fishing has ceased in that area. Not every spatial cell was fished every year from 1950-2001 in the longline tuna fishery. Observed fishing effort patterns show fishing in a few initial areas until catches declined and then spreading to new regions. Behaviour in which there is a tendency to fish where there is certainty on the amount of production is known as risk adverse behaviour and this behaviour will only change when fishers are forced to

[4] For the remainder of the thesis, *i* will denote the number of species, *j* will denote the number of spatial areas and *t* will denote the number of years.
[5] To note, fishing effort when recorded is not divided by species, only by spatial area.

move to new areas due to declining catch rates or management policies. To simulate the model for all years, the missing cpues needed to be replaced with the most accurate estimates that can be obtained from the available data. According to Walters [60], to fill in the missing cpue estimates at the beginning of the time period, the average cpue from the first 3 years that a cell was fished can be backfilled to the missing years in that cell (Figure 2-1). Similarly, if fishing stopped in a cell earlier than 2001 (final year of study), the average cpue estimate from the final three years of fishing in a cell can be forward filled to replace the missing years in that cell (Figure 2-1). This method assumes that the fishery is stable over time and that each area until it is fished and after fishing has ceased, maintains an average stable biomass.

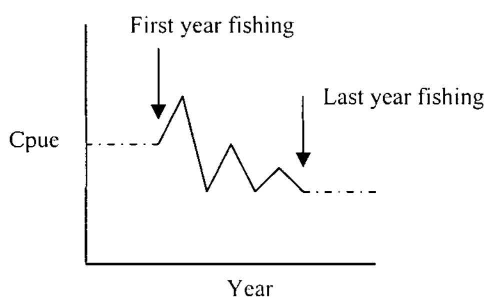

Figure 2-1: Representation of a cpue estimator for one spatial area from Walters [60].

Figure 2-2 displays the aggregated (over spatial areas) cpue estimates for each species through time. For the major tuna species, the cpue has decreased over time as a result of effort increasing at a faster rate than catch (Figures 1-1 and 1-2). Swordfish and albacore cpue, on the other hand, has been increasing since 1990.

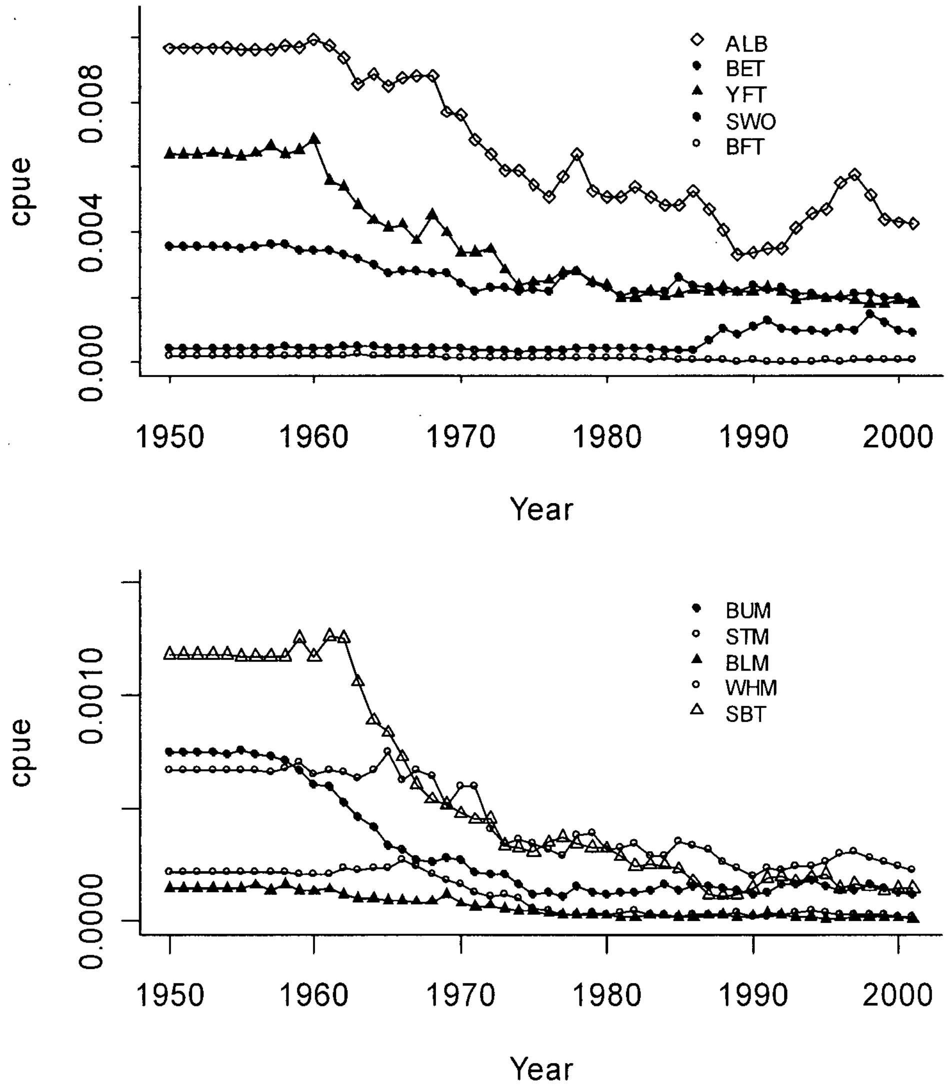

Figure 2-2: Global catch per unit effort from 1950-2001 for each species in the longline tuna fishery (number of fish caught per hook set). Sources: IOTC, ICCAT, IATTC, SPC, CCSBT.

2.3.2 Fishing Mortality

Fishing mortality is the rate at which fish are removed from a stock by means of fishing, measured in terms of the proportion of fish removed per year ($F \cdot yr^{-1}$) or as the ratio between catch and abundance [61]. Regional fishing mortality estimates can be found in stock assessment reports from each RFMO [46, 48, 52, 54-57, 62, 63]. For this study, however, an F estimate for each species over all oceans is needed for a global fishing mortality rate. To standardize the fishing mortality for each species over all oceans, a proportional weight can be placed on each area fishing mortality estimate depending on the biomass of that species in that area versus the total abundance of that species in all oceans:

$$W_{i,RFMO} = \frac{N_{RFMO,i}}{N_{A,i}} \tag{2}$$

where $W_{i,RFMO}$ is the proportional weight on F for species i in each RFMO area;

$N_{RFMO,i}$ is the biomass estimate in each RFMO area; and

$N_{A,i}$ is the total biomass over all RFMO areas.

RFMO fishing mortality estimates were collected from stock assessments for the most recent year, 2001 (Table 2-1). If the F estimate was unavailable for a species in an area, then the global estimate was taken from the mortality rates from the remaining areas where estimates were available.

Table 2-1: Fishing mortality rates for each species by ocean in 2001 from stock assessment reports [45-49, 52, 54].

Species	*Indian*	*Atlantic*	*E. Pacific*	*W. Pacific*	*Southern*
Yellowfin tuna	NA	0.55	1.09	0.15	NA[1]
Bigeye tuna	0.55	0.1	0.05-0.1	0.05	NA
Albacore tuna	0.3	NA	0.11	0.1	NA
Northern bluefin tuna	NA	0.425	0.4	NA	NA
White marlin	NA	0.3	NA	NA	NA
Blue marlin	NA	0.46	NA	NA	NA
Striped marlin	NA	NA	0.7	NA	NA
Black marlin	NA	0.1	NA	NA	NA
Swordfish	NA	0.66	NA	NA	NA
Southern bluefin tuna	NA	NA	NA	NA	0.2-0.25

[1]NA=not available

The global fishing mortality is then estimated as a weighted sum of area F estimates:

$$F_{G,2001,i} = \sum_{RFMO=1}^{n} (F_{2001,RFMO,i} \times W_{RFMO,i}) \qquad (3)$$

where $F_{G,2001,i}$ is the global fishing mortality estimate for each species in 2001; and

$F_{2001,RFMO,i}$ is the fishing mortality estimate from stock assessments for species *i* in 2001 (Table 2-1).

Table 2-2: Global constant fishing mortality estimates ($F \cdot yr^{-1}$) for each species.

Species	*F*
Albacore tuna	0.4
Bigeye tuna	0.3
Yellowfin tuna	0.2
Southern Bluefin tuna	0.2
Northern Bluefin tuna	0.2
White Marlin	0.2
Striped Marlin	0.1
Blue Marlin	0.2
Black Marlin	0.1
Swordfish	0.2

2.3.3 Catchability

The catchability is the average proportion of the stock taken per unit of effort in a given year [61, 64]. The catchability can be estimated as a function of fishing mortality (Table 2-2) and fishing effort.

$$q_i = \frac{F_{G,2001,i}}{E_{2001}} \qquad (4)$$

where q_i is the catchability for each species (results from Table 2-3); and

E_{2001} is the fishing effort in the year 2001.

Assuming that catch is linearly related to population abundance, then catchability is constant over time [64].

Table 2-3: Constant catchability estimates ($q \cdot yr^{-1}$) for each species.

Species	*q*
Albacore	8.32×10^{-7}
Bigeye	3.15×10^{-7}
Yellowfin	5.04×10^{-7}
Northern Bluefin	5.04×10^{-7}
Southern Bluefin	5.04×10^{-7}
White Marlin	1.01×10^{-6}
Blue Marlin	5.74×10^{-7}
Black Marlin	3.06×10^{-7}
Striped Marlin	2.38×10^{-7}
Swordfish	2.36×10^{-7}

2.3.4 Initial spatial abundance estimates

An initial abundance estimate for each species in each area is required to initialize the model at the beginning of the time period (1950). Using the spatial cpue estimates (Equation 1) and catchability estimates (Table 2-3), the initial number of fish in an area is calculated:

$$N_{i,j,1950} = \frac{cpue_{i,j,1950}}{q_i} \tag{5}$$

Where $N_{i,j,1950}$ is the number of fish of each species *i* in each spatial area *j*.

2.3.5 Natural Mortality

Natural mortality, assumed to be constant over time, is the death in the fish stock caused by anything but fishing, including predation, disease and environmental causes, and is denoted as the proportion of the population that die naturally on an annual basis ($M \cdot yr^{-1}$) [64]. The natural mortality estimates were collected from stock assessment reports.

Table 2-4: Constant natural mortality estimates ($M \cdot yr^{-1}$) for each species.

Species	***M***
Albacore	0.25
Yellowfin	0.4
Bigeye	0.4
Northern Bluefin	0.2
Southern Bluefin	0.2
White Marlin	0.2
Striped Marlin	0.2
Blue Marlin	0.1
Black Marlin	0.1
Swordfish	0.15

2.3.6 Annual biomass update

Fish abundance in an area can be predicted over time using a measure of recruitment, previous biomass and total mortality while assuming that the change in abundance through time is a function of recruitment and mortality in the fish stock:

$$dN/dt = R_t - Z_t N_t \tag{6}$$

Where for each period t:

$$N_{t+1,j,i} = \frac{R_{j,i}}{Z_{i,t}} + \left(N_{t,j,i} - \frac{R_{j,i}}{Z_{i,t}} \right) e^{-Z_i} \tag{7}$$

Where $N_{t+1,j,i}$ is the biomass of species i in area j the next year;

$R_{j,i}$ is the constant recruitment of each species i; and

$Z_{i,t}$ is the total mortality of each species i, including natural and fishing mortality and emigration out of an area.

Tuna are highly migratory pelagic species that move between areas on a short time scale depending on oceanic temperatures and climatic events [53, 65]. The movement rate is an instantaneous rate based on tagging data that measures the speed at which tuna travel over a given time period which can be applied to advection/diffusion calculations of spatial biomass [61, 65]. Therefore, in addition to natural and fishing mortality in the total mortality estimate in a cell, the amount of fish emigrating out of the area as a result of migration is another factor to include. As previously stated, total mortality therefore includes:

$$Z_{i,t} = q_i E_{j,t} + M_i + e_{j,i,t} \tag{8}$$

Where $q_iE_{j,t}$ is the fishing mortality;

M_i is natural mortality; and

$e_{j,I,t}$ is net emigration of fish out of area *j*.

In turn, due to migration, fish will move into a cell which is added to the recruitment estimate for that cell.

2.3.7 Recruitment estimates

Recruitment is the amount of fish that become vulnerable to fishing gear each year due to growth and migration to an area [64]. The measurement of growth is defined as the fish that survive to an age exploitable by the longline fishery. With significant immigration of fish into an area from surrounding areas, recruitment is assumed to change over time. Therefore, to estimate growth recruitment in a spatial area, Equation 6 can be rearranged to isolate $R_{i,j,t}$ with an additional measure added to include recruitment from immigration:

$$R_{i,j,t} = \frac{N_{i,t+1} - e^{-Z} N_{i,t}}{(1 - e^{-Z}) Z_{i,t}} + I_{j,t} \tag{9}$$

Where $I_{j,t}$ is the net immigration of fish into an area.

Without immigration included, recruitment may be underestimated in a spatial area depending on the extent of migration in a given year.

2.3.8 Predicted Catch

On a yearly time step, the model predicts the amount of catch in each spatial area as a function of catchability, fishing effort and biomass:

$$C_{t,i,j} = q_i \int_t^{t+1} N_{i,j,t} E_{j,t} \tag{10}$$

Where $C_{t,i,j}$ is the catch of each species *i* in each spatial area *j* for each year *t*;

$E_{j,t}$ is the fishing effort in area *j* each year.

2.3.9 Average weight estimates

The catch data collected from RFMOs is in number of fish, not in weight of catch. To standardize the catch data with price data ($/kg), numbers of fish were converted to weight. For this conversion to catch in tonnes, the average weight of each species caught in the longline fishery was obtained from stock assessment reports [46, 48, 52, 54-57, 62, 63].

Table 2-5: Average weight of each species in kilograms.

Species	*W (kg)*
Albacore tuna	20
Bigeye tuna	35
Yellowfin tuna	35
Northern Bluefin tuna	60
Southern Bluefin tuna	60
White Marlin	60
Blue Marlin	70
Black Marlin	100
Striped Marlin	60
Swordfish	70

Chapter 3 Bioeconomic Model

The bioeconomic model combining the population dynamics component from the previous chapter with an economic component was developed to predict the spatial fishing effort distribution through time in the global longline tuna fishery. The fishing effort prediction model will first be described followed by the economic component that includes ex-vessel prices, revenue and fishing cost estimates.

3.1 Choice Probability Modeling

In order to predict dynamic spatial fishing effort patterns, the model developed in this study is based on models from McFadden [66] and Walters and Bonfil [3]. The theory behind each of these derived models is similar in that both are developed to predict the probability of choosing one choice in a series of choices. McFadden's model has been used in many disciplines and looks at the application of choice probability for any situation. The gravity model developed is one particular extension of McFadden's choice probability developed for application in fisheries ecological modeling [67].

3.1.1 Multinomial logit model

The multinomial logit model developed by McFadden [66] is used as a method for predicting the relative probability of choosing a particular alternative. A multinomial logit term determines the probability of an event occurring, under the biological and market conditions existing at that time, over all possible events [68]. The probability that an individual will select choice x is expressed as the ratio of the utility of choice x to the summation of the utilities of all the alternatives in the set of choices:

$$\Pr(x) = \frac{\exp(u_x)}{\sum_{j=1}^{n} \exp(u_j)} \qquad (11)$$

where $\Pr(x)$ is the probability of choosing alternative x over all the other choices;

u_x is the maximum utility measure attainable if alternative x is chosen; and

u_j is the set of all other alternative choices.

The utility is a measure of the attraction in a particular choice. In the case of the fishery, utility can be predicted from perceived biomass, weather conditions, distance from port, target species, profit expectations, etc. and weighted accordingly for each area. A maximum likelihood function or a minimum sum of squares procedure is used to estimate the best parameters in a utility measure for a particular alternative that will produce the observed probability of choosing alternative x.

3.1.2 Gravity model

A gravity model allocates a proportion of the total fishing effort to each spatial area based on the relative economic attractiveness of that area. The gravity model, derived in Caddy [67] and Walters and Bonfil [3] and discussed in Walters and Martell [61], allocates an attraction weight to each area based on the expected revenue and fishing costs obtained in that area. It is assumed that fishers can redistribute their effort on very short notice in response to changing prices and abundance measures to achieve optimal profitability. Using a one year time step, fishing effort is distributed as a fraction of the ratio of the attraction weight in a cell to the sum of all weights over the entire study area, which is similar to the derivation in the multinomial logit model utility measure

[66]. Individual decisions are impacted by each additional year of experience in the fishery as well as future perceptions of profitability in the fishery from information sharing between vessels and search technology. For this study, the attraction weight referred to as a gravity weight for each spatial area is a function of the mean profitability, $\pi_{j,t}$ and the historical fishing effort in an area. The gravity weight of an individual location choice is defined as

$$W_{j,t} = e^{\pi_{j,t}} \tag{12}$$

where $W_{j,t}$ is the gravity weight to each area in a given year; and

$\pi_{j,t}$ is the economic attractiveness measure of area j in a given year (in logit model terms, Equation 11) and is assumed to be a logarithmic (diminishing returns) function of some measure X in profitability of fishing:

$$\pi_{j,t} = \ln(\overline{X_j}) - c(\text{var } X_j) \tag{13}$$

Where $\pi_{j,t}$ is an uncertain profitability measure with expected value of $\overline{X}_j$ and variance $\text{var}X_j$.

Since fishers are uncertain as to the profit they will receive in terms of catch in an area, their expected utility of that area will depend on the mean profit as well as the variance in that expected profit. Mean profit is assumed to have been assessed by fishers using some running average of past observed revenues:

$$\overline{X}_{j,t} = \frac{(r_{j,t} + s_1 r_{j,t-1})/FC_j}{2} \tag{14}$$

Where $\overline{X}_{j,t}$ is the ratio of revenue to fishing cost in each spatial area;

$r_{j,t}$ is the revenue from the current year of fishing;

$r_{j,t-1}$ is the revenue from the previous year of fishing;

FC_j is the cost of fishing in an area; and

s_1 is a "survival" factor representing how reliable past profitability can be considered as a predictor of present profitability.

The perceived (fishers assumed) variance in expected profit in each area is assumed to be inversely proportional to past fishing effort accumulation based on the assumption that as more fishing effort accumulates in an area, uncertainty of expected profit will decrease. The variance is defined as:

$$VarX = \frac{K}{[(s_2 \sum_{t=1}^{t-1} E_{j,t}) + E_{t,j}]} \tag{15}$$

Where K is a scaling parameter;

s_2 is a "survival" factor representing how reliable past fishing effort is considered as a predictor of present catch rates; and

$E_{t,j}$ is the fishing effort in area j in year t.

Using the mean profit (Equation 14) and variance in profit (Equation 15), the gravity weight of an area can be derived as:

$$W_{j,t} = e^{[\ln(\overline{X}_{j,t}) - (\mathrm{var}\ X_{j,t})]/v} \tag{16}$$

Where v is the variance among fishers in perception of profitability.

And Equation 16 can be further simplified to:

$$W_{j,t} = (\overline{X}_{j,t} e^{-\operatorname{var} X_{j,t}})^{1/v} \tag{17}$$

3.1.3 Parameter descriptions

There are four parameters that need explanation. The decision to fish in an area is assumed to be based on the expected profitability of that area, which is partly based on prior knowledge. Knowledge can be acquired from past experiences of what has been caught in a location and how much fishing effort has previously occurred. As fishing effort in a cell accumulates over time, the uncertainty in the potential profit in that area will decrease. Previous fishing effort can be interpreted as an indicator of the success in catch rates in that location. The variance in mean profitability is assumed to be a ratio between the scaling parameter K and historical fishing effort. The K variance term represents uncertainty in the expected mean profitability of an area related to how much effort has actually occurred in that area recently. As effort accumulates in a cell over time, the scaling parameter will be less significant compared to the accumulation of past fishing effort thereby making the gravity weight towards that cell larger and the uncertainty of fishing in that cell smaller. As more information in the success of a location is acquired with increased fishing effort, more reliable assumptions can be made in a fisher's decision process.

The second variance term included in the model is the variability among individual fishers with respect to their probability of choosing a location given its mean profitability. Since the model cannot capture the variability in individual decision making, the parameter v is included to compensate for the lack of micro-level decision analysis by capturing some variance in the perceived mean profitability of a spatial area.

The assumption in a large-scale commercial fishery is that full information of the best fishing locations is known among fleets. However, due to environmental conditions, risk, vessel size, and cost variances between vessels, there are still some differences in location choice despite almost perfect information. The v parameter allows for deviation in the perception of mean profitability.

The "survival" factors, s_1 and s_2 are weights placed on the importance of past catch rates and past profit earned on the present expectations of the profitability of an area. These factors are measured as the percentage of previous experience that is taken into account when evaluating the attraction of one area over all other areas.

In order to further explain the variables in the gravity model, the economic components are described. The economic model was developed using estimates of fishing revenue and fishing costs in each spatial area. Revenue is a function of catch per unit of effort (a good proxy for fishing cost) and ex-vessel prices. Fishing cost is derived based on theory from "ideal free distribution" (IFD) modeling.

3.2 Price

Ex-vessel price data were collected for each species from 1950-2001. Prices were collected from the Japanese Ministry of Agriculture, Forestry and Fisheries, the National Marine Fisheries Service [69] and the University of British Columbia SAUP and FERU ex-vessel price database (www.seaaroundus.org)[6]. The ex-vessel price is the dockside price given to a fishing vessel when harvest is landed at port. It should be noted that these prices are the drivers in determining which species a fisher will target and when they will

[6] SAUP refers to the Sea Around Us Project and FERU refers to the Fisheries Economic Research Unit at the UBC Fisheries Centre.

return to port to obtain optimal economic return. The ex-vessel prices used in this study are the average prices for each year (prices vary seasonally and are given by month for some species). Since Japan dominates the sashimi market and most of the tuna caught from longline vessels is exported to the Japanese market, most of the prices were taken from the Japanese source as this market is a representation of the world market for longline caught tuna [41]. The prices collected were in dollar value (USD) per tonne of caught fish and converted to USD/kg of fish. Longline caught tuna is landed for three different markets, canned, frozen or fresh. Tuna meant for the fresh market fetches the highest ex-vessel price while those for canned tuna fetch the lowest price. Since the databases do not always specify which market their prices apply to, it is assumed that prior to 1970, prices reflected the canned value while post 1970 (when super freezers were invented), prices reflected the sashimi market value.

From the ex-vessel price trends in Figure 3-1, it is apparent that there are distinct patterns that reflect changes in the longline fishery over time. The ex-vessel prices are determined by market conditions, namely supply, demand, and the elasticity of the product (the amount of substitutes). From 1950-1970, all species were landed for the canning market and therefore fetched approximately the same price. The elasticity of demand, which is the percentage change in a quantity demanded of a good or service that results from a 1 percent change in its price, was very high [70]. Since there were many substitutes on the market because of the variety of canned fish, prices of each species were kept low and equal. An increase in the price of just one species would force consumers to switch products. As the sashimi market developed in the 1970s, the quality and grade of tuna based on the oil content and meat became more important, prompting price increases for higher quality tuna species (bigeye and bluefin). The demand for bigeye, bluefin and yellowfin increased with decreasing demand elasticity as there were fewer substitutes for sashimi tuna on the market. The species landed for canneries fetched lower prices throughout the time period.

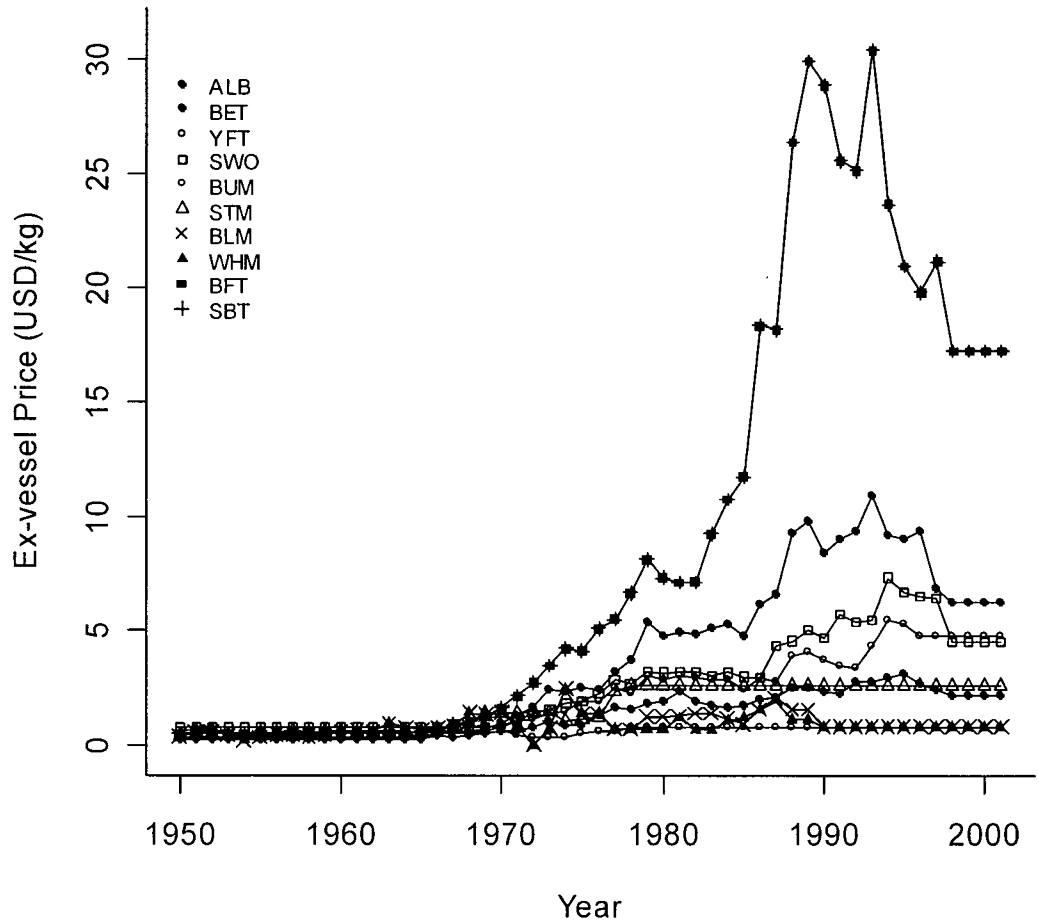

Figure 3-1: Ex-vessel prices for each species (USD/kg) from 1950-2001. Source: NMFS, SAUP/FERU price database, Japan Ministry of Agriculture, Forestry and Fisheries.

To note, the prices are current nominal prices, the actual dollar value of the year when the price is set, not adjusting for inflation and prices are assumed to be constant over time. The reasoning for using current prices is that the expected revenue gained through the perception of the fisher and their location choices are in that specific year and the comparison between years is not necessary.

3.2.1 Total revenue and revenue per unit of effort

Total revenue from the fishery at any given time is a function of the harvested biomass and the price of fish.

$$TR_t = \sum_{j=1,i=1}^{n} (C_{t,j,i} p_{t,i}) \tag{18}$$

where TR_t is the total revenue for each year for each species over all areas;

$C_{t,j,i}$ is the catch of each species over all areas each year; and

$P_{t,i}$ is the ex-vessel price for each species (Figure 3-1).

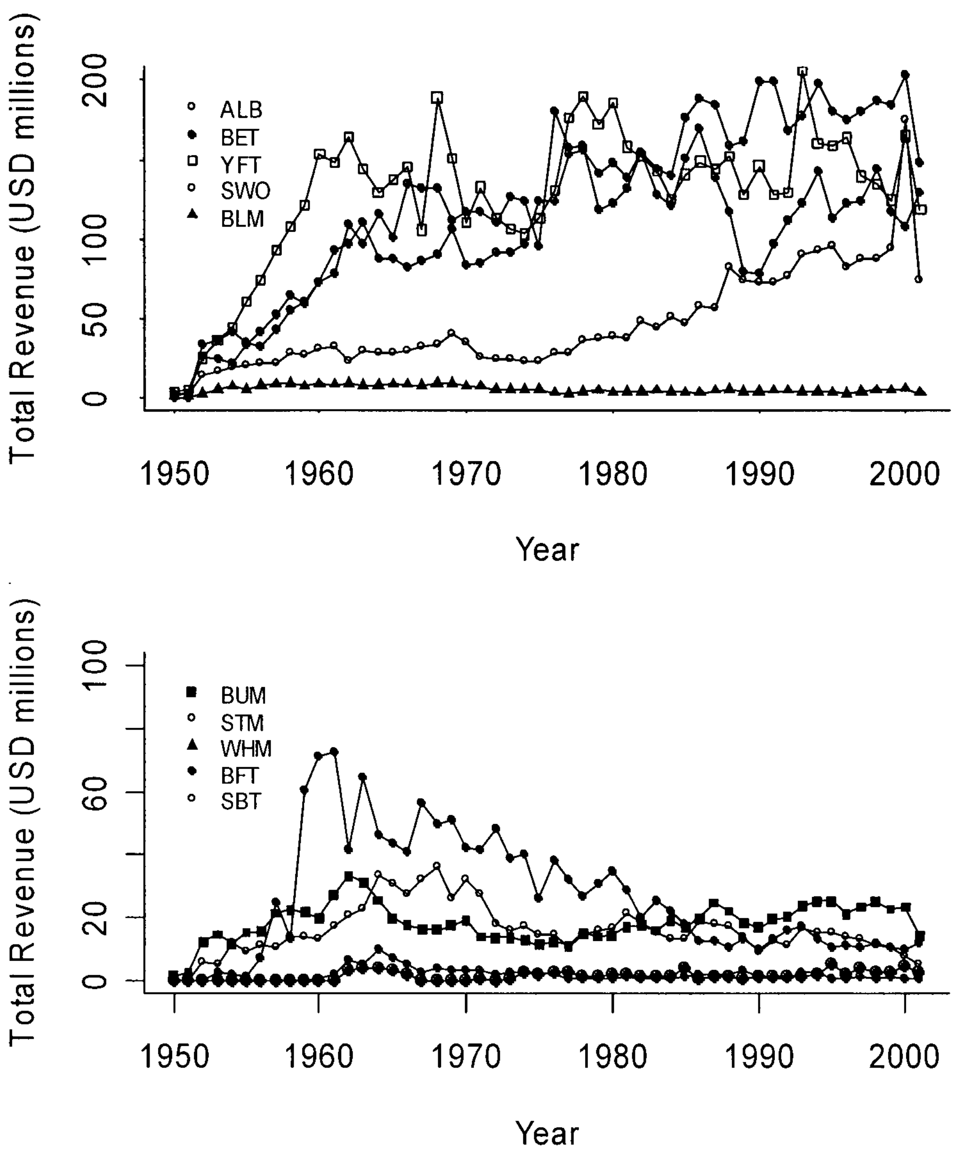

Figure 3-2: Total revenue from the catch in the longline fishery of each species from 1950-2001 in USD.

To compare the attractiveness between spatial areas, a measure of fishers' perceived catch rate expectations in an area was used as an indicator of relative abundance:

$$Y_{j,t,i} = cpue_{i,j,t} \tag{19}$$

Where $Y_{j,t,i}$ is the relative abundance index for each species in an area each year; and

cpue$_{i,j,t}$ is the catch per unit effort from Equation 1 [60].

From this, the revenue per unit effort, a measure of perceived profit expectations in an area, was calculated as:

$$r_{j,t} = \sum_{i=1}^{n} (Y_{i,j,t} p_{i,t} w_i) \tag{20}$$

Where $r_{j,t}$ is the revenue per unit effort in an area;

$P_{i,t}$ is the ex-vessel price for each species; and

w_i is the average weight of each species (see Table 2-6).

Figure 3-3 shows r_t from each species summed over all spatial areas for each year.

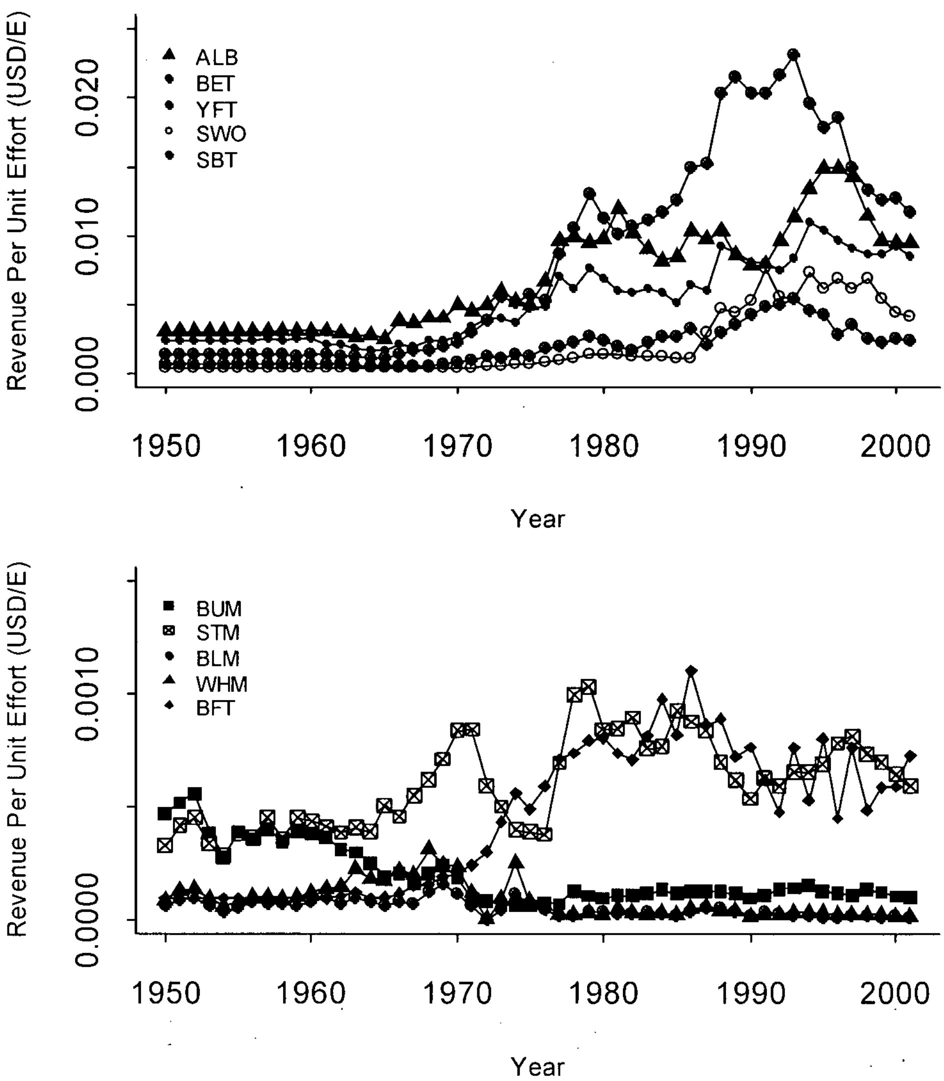

Figure 3-3: Revenue per unit of effort in USD/E for each species from 1950-2001 in the longline fishery.

3.3 Spatial Fishing Cost

According to theory from "ideal free distribution" (IFD) models, fishers will distribute and redistribute their fishing effort over areas until no one area stands out as being potentially more profitable than the others [61]. This is similar to the Equimarginal Principle concept in economics where production at many different sources will be distributed so that the marginal costs of productivity are equal in all areas [70].

Maximization of productivity in all areas occurs when the marginal revenue gained from each area is equal. Based on the original ecological concept, the distribution of animals or predators is “ideal” in that they move to areas where the intake rate is the highest and “free” in that they are allowed to enter any areas on an equal basis with other competitors who are all assumed to be of the same ability to extract the resources [71, 72]. At the beginning of a short time period, let’s say one year, fishers will continue to fish as long as their marginal revenue is greater than or equal to their marginal cost assuming no regulatory constraints. Marginal revenue is the increase in total revenue obtained from producing one more unit of a good or service. In the case of fisheries, marginal revenue refers to the additional revenue from the catch produced by one more unit of effort. On the other hand, the marginal cost is the increase in total cost from exerting one more unit of effort. On an annual basis, it is assumed that fishers will stop harvesting once marginal cost exceeds marginal revenue.

IFD model theory can be supported in the tuna fishery, where in general, with information sharing and efficient search techniques, fishers rarely miss a new and profitable opportunity. In this respect, if an area stands out as a “hot spot” for high catch rates, it will most likely be found and harvested to the point where profitability will be decreased to equal all other areas. An equilibrium will occur when fishing pressure drives the better areas down so that previously poorer areas will become equally attractive [71]. Once effort is distributed and redistributed to the point where all areas are equal in terms of marginal revenue and marginal cost, fishing will stop. This supposed ideal free “equilibrium” did not occur in every year from 1950-2001. When the longline fishery was still developing, there were many areas that were yet to be explored and there was much uncertainty of the best fishing spots due to lack of information, resulting in many opportunities that went undetected in earlier years. To determine when this equilibrium could have occurred, historical fishing effort records were analyzed to find the period of time when fishing effort remained constant from year to year and when all areas had been explored establishing a period when fishers fished until marginal revenue equaled marginal cost. An examination of the longline fishery data, between 1970 and 1990 showed that fishing effort reached and maintained a constant level indicating that all areas were either being fished or had already been fished. This period of time was used to derive the fishing cost estimates for each area. First, the average revenue obtained for each unit of effort in an area during that equilibrium period between 1970 and 1990 was calculated as:

$$ar_j = \frac{\left(\sum_{t=1970, i=1}^{t=1990, n} (cpue_{t,i,j} \, p_{t,i} \, w_i) \right)}{20} \tag{21}$$

where $ar_{j,1970\text{-}1990}$ is the average revenue per unit effort for the 20 year period (1970-1990).

Second, by using IFD model theory and average revenue per unit effort, three different methods are used to estimate spatial fishing cost. The first method is based on the assumption that the fishery operates continuously throughout the year. This method ignores the fact that on an annual basis, even if an area has high overall cpue, fishing in that area might only have occurred at certain times due to migration patterns and increased risk due to environmental conditions. Therefore for this method, fishing cost per unit effort is proportional to average revenue per unit effort in an area in a given year, taking into account that fishers will fish in a given time period until MR=MC indicating that cost is approximately equal to revenue but does not change when effort increases towards the end of the season when search time increases as fish become scarcer. Spatial cost based on the continuous fishery assumption is calculated as:

$$FC_j = \frac{ar_j}{\left(\sum_{t=1970}^{1990} E_{j,t} \Big/ 20 \right)^v} \tag{22}$$

where FC_j is the average fishing cost per unit of effort in a spatial area;

$E_{j,t}$ is the average effort in a cell from 1970-1990; and

v is the variance in individual fisher perception is expected profitability (as defined in Section 3.1.3).

The second method used to estimate fishing cost takes seasonality into account conditioning on the fact that as mean cpue decreases throughout the season, fishing effort increases. In areas where immigration and emigration are frequent in any given year, such as at northern and southern latitudes when fishing is only possible at certain times, annual cpue is high but spatial cost should also be correspondingly higher due to increased risk, uncertainty and search time in these areas. Since tuna migrate between areas frequently during any one given year, the second method seems better suited as a more accurate measure of fishing costs. Spatial fishing cost under a seasonal fishery assumption is derived as:

$$FC_j = \frac{qE_j ar_j}{[1 - e^{(-qE_j)}]} e^{(-qE_j)} \tag{23}$$

Where FC_j is the spatial fishing cost;

q is the catch rate when fishing mortality is at a maximum;

E_j is the average fishing effort from 1970-1990; and

ar_j is the average revenue per unit of effort from 1970-1990.

The exponential term increases the fishing cost when fishing effort increases over time.

The third method applied eliminates the spatial fishing cost component from the model, allocating fishing effort among areas based solely on the expected revenue in that area. For this method spatial fishing cost is taken out of the gravity weight function, as it is assumed to be equal in all areas.

The cost estimate is assumed to be constant in each area through time from 1950-2001. It is normally assumed that biomass of fish is maintained over time in an area, and efficiency in fishing is increased from improved technology which would decrease fishing costs through time. However for this study we are assuming that biomass has been decreasing in all areas through time due to high catches. Therefore, a constant spatial fishing cost estimate will balance the improved technology with the decrease in fishing productivity. The model uses catch and effort data from later years of the study during the assumed IFD "equilibrium" period to estimate a spatial cost variable to be backfilled to earlier years. Each spatial fishing cost derivation is used in the model to examine which provides the most accurate estimates in predicted spatial fishing effort to most closely approximate the observed fishing effort distribution.

3.4 Fishing Effort Prediction Model

Finally, by combining the multinomial logit model and the gravity weight model theory, the probability of choosing alternative fishing area *j* is:

$$\Pr(j) = \frac{W_{j,t}}{\sum_{j=1}^{n} W_{t,j}} \tag{24}$$

Where Pr(j) is the probability of choosing area *j*; and

$W_{j,t}$ is the gravity weight for each area.

To predict fishing effort in each spatial cell over time, a proportion of the total observed fishing effort in a year is allocated to each cell as a function of the gravity weight:

$$PE_{j,t} = \frac{W_{j,t}}{\sum_{i=1}^{n} W_{t,j}} \sum_{j=1}^{n} E_{j,Obs} \tag{25}$$

where $E_{j,obs}$ is the total observed fishing effort in a year; and

$PE_{j,t}$ is the predicted fishing effort for a cell in that year.

The prediction model simulates fishing effort distribution to appropriate spatial areas for each year from 1950-2001.

3.5 Model Fitting Procedure

To fit the model to the observed fishing effort data, the four parameters, K, v, s_1 and s_2 were estimated through an iteration procedure to minimize the difference between the observed and predicted values:

$$SS = \sum_{j=1,t=1}^{n} (OE_{j,t} - PE_{j,t})^2 \qquad (26)$$

where SS is the sum of squares deviation between the observed and predicted fishing effort over all spatial areas and all years;

$OE_{j,t}$ is the observed fishing effort from the collected data; and

$PE_{j,t}$ is the predicted fishing effort.

A second approach to compare the difference between observed and predicted results is the natural log sum of squares method which is appropriate when observations such as fishing effort are proportional contributions to a collection of data and therefore most probably contain log-normally distributed observation error [61]. This method takes emphasis away from large deviances in predicted measurements from observed data placing more weight on smaller deviances between observed and predicted fishing effort. The sum of squares deviation, on the other hand, does not reduce the large deviations thereby making them more prominent in the results. The natural log sum of squares deviations between observed and predicted fishing effort will also be calculated for comparison purposes:

$$\ln SS = \ln\left(\sum_{j=1,t=1}^{n} \frac{OE_{j,t}}{PE_{j,t}} \right)^2 \qquad (27)$$

The fit of the model is analyzed in two ways: i) the two fitting procedures are calculated over all years and spatial areas, and ii) the two fitting procedures are calculated for each year. The first method estimates the best overall fit of the model while the second method examines how well the model predicts fishing effort through time.

An initial assumption is that the variance, v is expected to be higher in early years because information is not fully known and fishers are engaged in exploratory fishing in new areas creating a higher variability in perceived location catch. However, as more areas are explored, the variance in later years could decrease as more information and better technology becomes available. The assumed expectation of the K parameter could be either that: (i) K is large in the early years due to minimal accumulation of fishing effort and a high degree of uncertainty making the ratio of K to past fishing effort large and then smaller in the later years when there is more certainty about fishing location or (ii) K is small in the early years because there is so little information known about new areas, and therefore fishers will rely more heavily on where they have fished in the past. In later years, however, K is larger when there is more technology to help identify where the best locations are regardless of past fishing effort.

For the survival factors which determine how much reliance is placed on past profitability and fishing effort in predicting future profitability and catch rates, it is assumed that these variables would be high since fishers usually revisit areas where they have been successful in the past.

Chapter 4 Results and Discussion

Several trends result from the bioeconomic model simulations; trends in biomass over time, relative spatial fishing cost distribution, and predicted fishing effort and catch through time. The predicted fishing effort and catch trends were compared to the observed catch and fishing effort patterns.

4.1 Predicted Biomass Trends

Biomass trends by species over time are shown in Figure 4-1. There is a general decline in biomass for all species from 1950 to the 1970s, after which the biomass stabilized. Exceptions are yellowfin tuna (YFT) and black marlin (BLM) biomass which continue to decline throughout the study period.

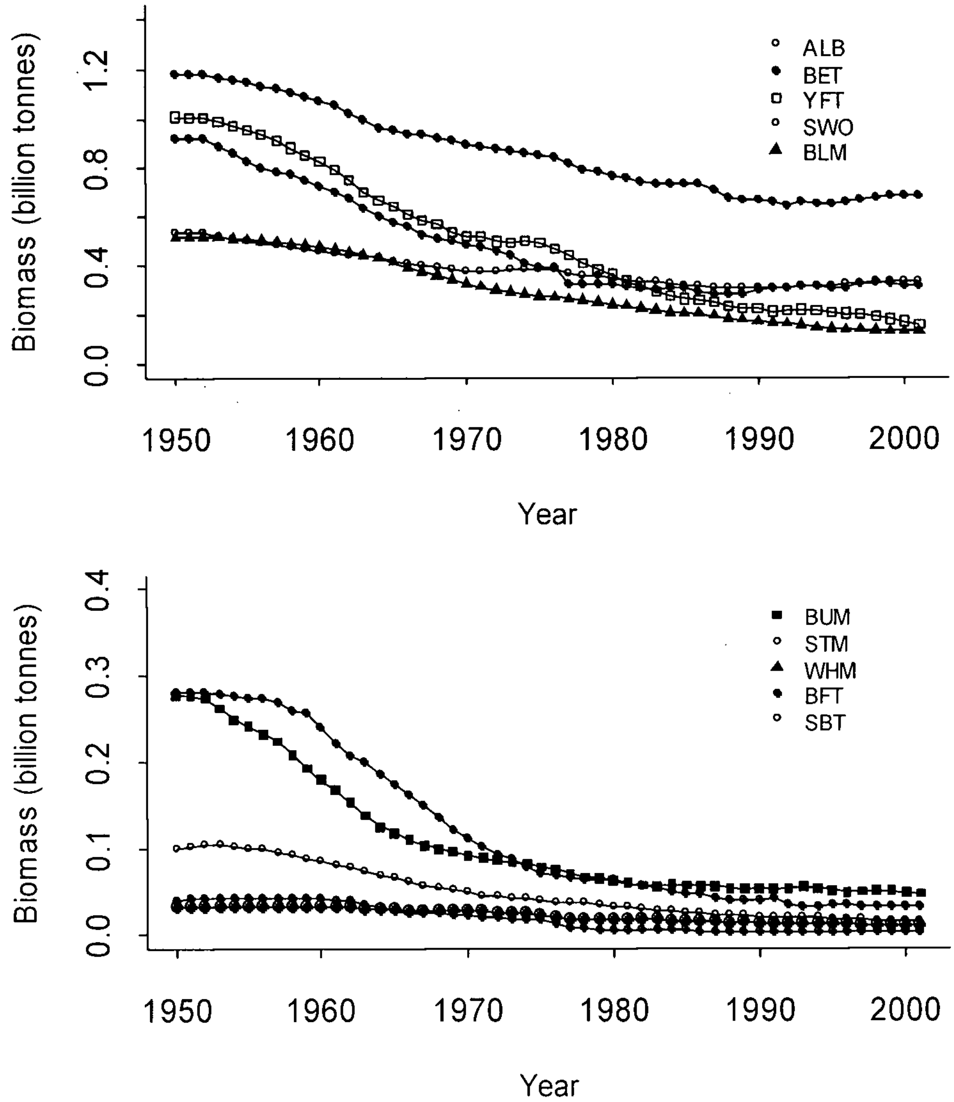

Figure 4-1: Predicted global biomass in tonnes by species from 1950-2001.

4.2 Observed versus Predicted Catch

The observed and predicted catch is compared for each species through time. Figure 4-2 shows the results using observed fishing effort data in the catch function

(Equation 9). Figure 4-3 shows species catch results using the predicted fishing effort in the catch function. The model has difficulty in predicting the appropriate amount of fishing effort to determine catch for northern bluefin tuna, southern bluefin tuna and white marlin. Also, for most of the species, the predicted catch is less than the observed catch. These discrepancies could be a result of inaccurate estimates of catchability and fishing effort, and/or an underestimate of recruitment. A sensitivity analysis is carried out to determine how these may affect the fishing effort prediction results.

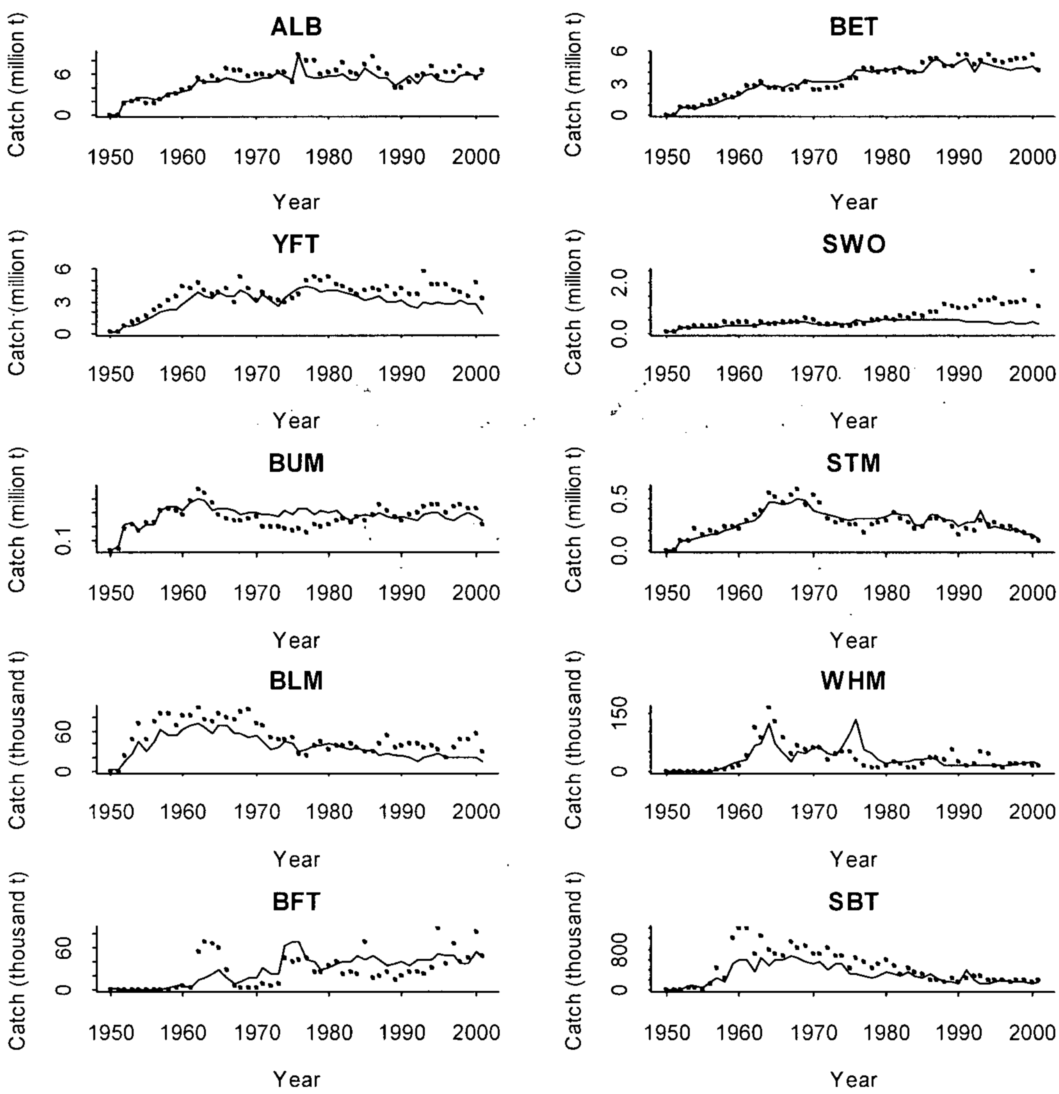

Figure 4-2: Observed (dots) versus predicted (lines) catch in tonnes by species using observed fishing effort in the catch estimates from 1950-2001.

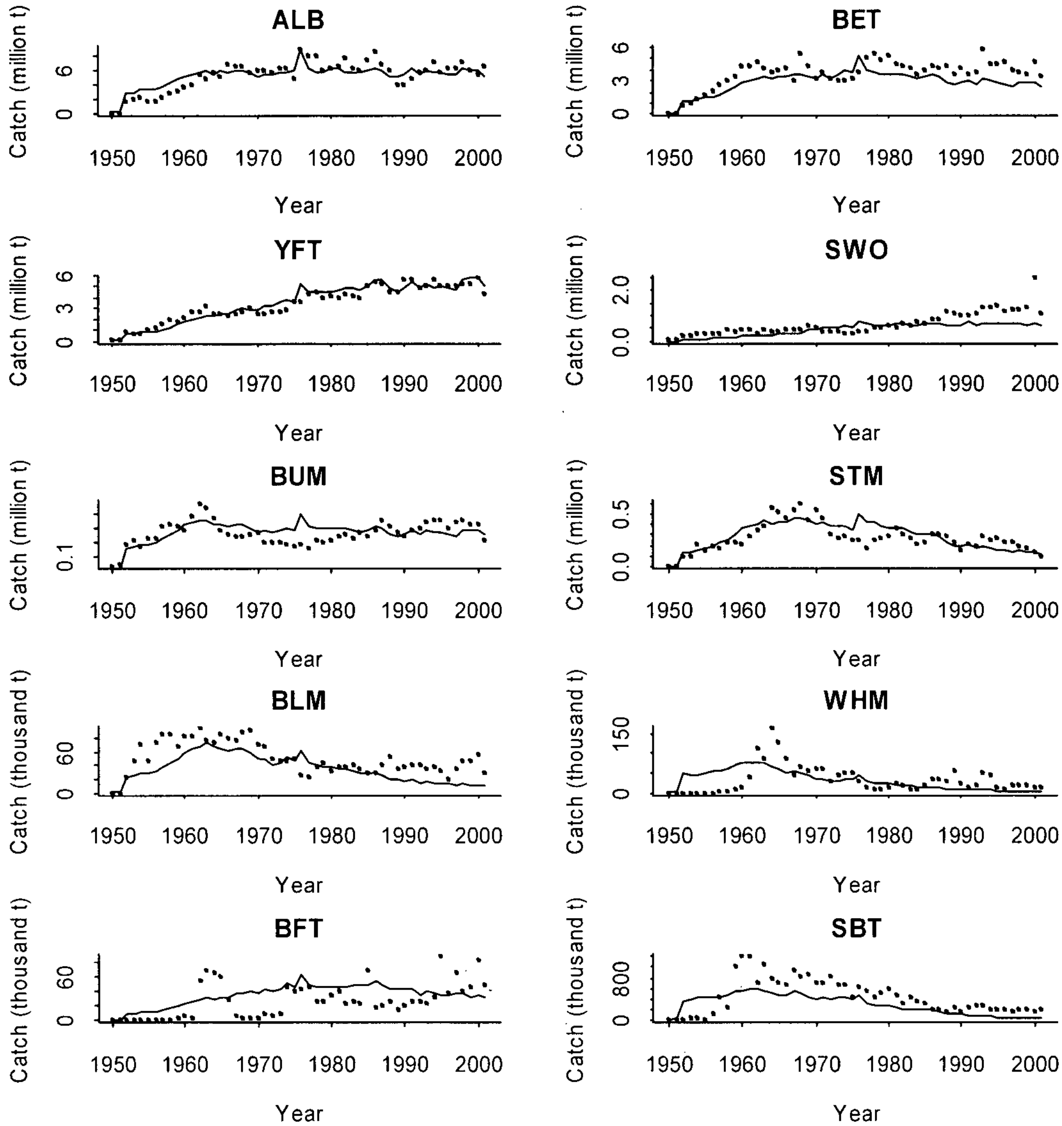

Figure 4-3: Observed (dots) versus predicted (lines) catch in tonnes by species using predicted fishing effort in the catch estimates from 1950-2001.

4.3 Relative Fishing Cost Estimates

Spatial fishing costs are mapped to compare the differences in costs between areas. Fishing cost estimates in each area are relative to the maximum spatial cost that was calculated. Maps showing the spatial fishing costs were generated from the results of the two methods to calculate spatial costs; the seasonal fishery method and the continuous fishery method (Figure 4-4 and Figure 4-5).

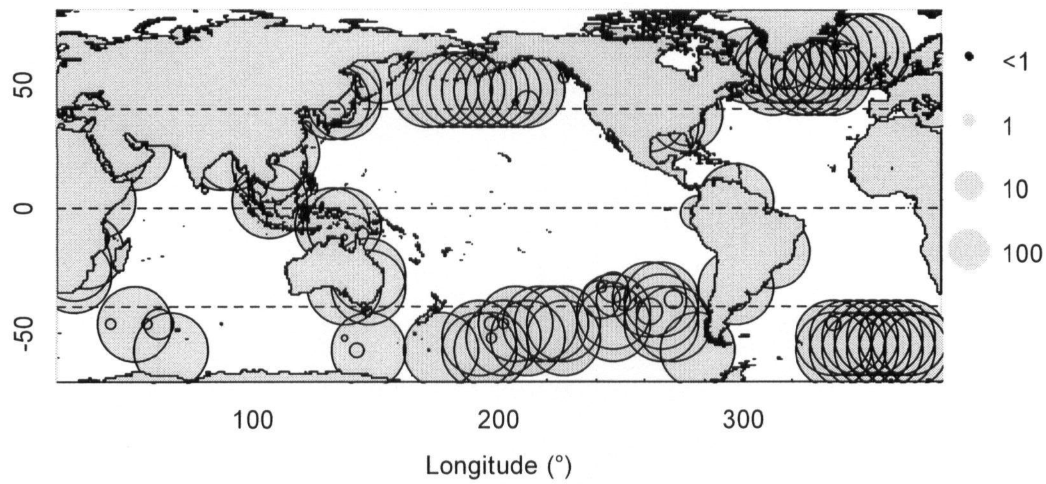

Figure 4-4: Relative fishing cost estimates (USD per unit effort) for each spatial area using the seasonal fishing cost method.

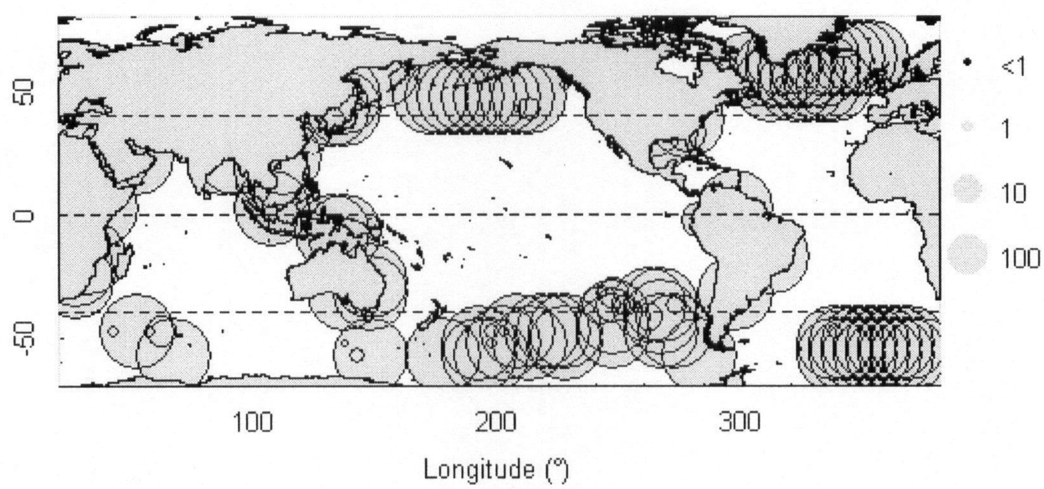

Figure 4-5: Relative fishing cost estimates (USD per unit effort) for each spatial area using the continuous fishing cost method.

There are almost no differences between the seasonal fishery costs and the continuous fishery costs. With both methods, fishing costs are high in the northern and southern latitudes (Figure 4-4 and 4-5). However, there were two dissimilarities in the predicted fishing effort distribution between the two fishing cost methods: i) the seasonal fishery method distributes fishing effort more slowly across oceans and areas similar to the observed distributions and ii) the continuous fishery method spreads effort to all areas with low fishing cost estimates without concentrating effort in more prominent areas where the observed fishing effort occurs. For these reasons, the continuous fishery cost method is not used in the rest of the analysis.

Fishing effort, when fishing cost is eliminated from the model (third method) making the gravity weight based solely on revenue per unit of effort, is poorly predicted. Fishing effort immediately grows around the equator in the earlier years when fishing is primarily off the coast of Japan. The predicted fishing effort moves quickly to the southern latitudes as well as the Indian Ocean when actual fishing effort begins to expand along the equator in the Pacific Ocean. It seems as though there are higher concentrations of fishing effort in the higher and lower latitudes and in areas such as the Gulf of Mexico, where longline fishing does not occur at high volumes. Without a fishing cost estimate, the model also does not seem to predict fishing off the coast of Japan where fishing effort occurs continuously through time. A model that does not include spatial fishing costs will not take into account the uncertainty of moving to areas farther from port because it is only based on the amount of revenue which is often greater due to high valued species in these areas such as bluefin tuna. For these inaccuracies, this method is not used in the rest of the analysis.

4.4 Comparison between Observed and Predicted Fishing Effort

The performance of the gravity model in estimating the best parameter values to fit the predicted fishing effort to the observed fishing effort data is analyzed in 2 ways: i) overall fit for all years and all spatial areas combined, and ii) fit for each year over all spatial areas. The results from these two fitting procedures produce different estimates of v and s_1 for both the overall model fit and the fit through time. The parameter values that minimized the difference between the observed and predicted fishing effort for all years and spatial areas combined are used to examine the observed to the predicted fishing effort for each spatial area through time. For the spatial analysis, the natural log sum of squares parameter estimates predicts spatial distribution more closely matching the observed fishing effort pattern than the parameter estimates from the sum of squares fitting procedure.

4.4.1 Parameter values for overall model

The gravity model produced the predicted fishing effort in each area through time. To fit the predicted fishing effort to the observed fishing effort, Equations 26 and 27 were minimized over a range of possible K, v, s_1 and s_2 parameter estimates in order to find the best fit where the predicted fishing effort most likely approximates the observed fishing effort data. The best parameter values that minimized the sum of squares and the natural log sum of squares are summarized in Table 4-1.

Table 4-1: The fishing effort scaling parameter, K, the perceived profitability parameter, v, the reliance on past profitability factor, s_1, and the reliance on past fishing effort factor, s_2, values that minimize the sum of square deviations and the natural log sum of squares between observed and predicted fishing effort in the overall model.

Parameter	*SS*	*lnSS*
K	1-9	1-9
V	3.3	1.3
S_1	0.9	0.2
S_2	0.1-1	0.1-1

The V parameter did not affect the fit of the model or impact the fishing effort distribution since the sum of squares remained the same over all possible values. Figure 4-6 and Figure 4-7 show the best parameter estimates of v that minimized Equations 26 and 27 between the observed and predicted fishing effort.

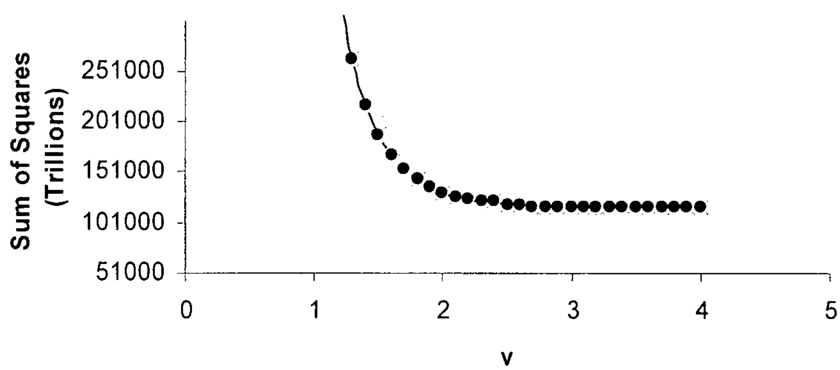

Figure 4-6: Sum of squares deviation between observed and predicted fishing effort over a range of possible values for the variance in perceived profitability parameter, v, for all years and spatial areas combined.

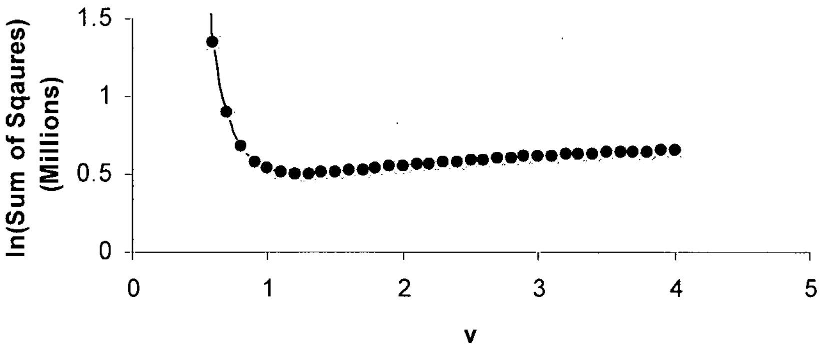

Figure 4-7: Natural log sum of square deviation between observed and predicted fishing effort over a range of possible values for the variance in perceived profitability parameter, v, for all years and spatial areas combined.

For the s_1 parameter estimate, a range of possible values from 0-1, in proportion of how reliable past profitability can be considered as a predictor of present profitability, the best estimate was 0.9 when the sum of squares (Equation 26) was minimized, indicating that 90% of a fisher's consideration of future profitability in an area depends on past profitability in that area. The s_1 parameter estimate resulting in the best fit of the model was 0.2 when minimizing the natural log sum of squares (Equation 27), indicating that 20% of a fisher's consideration of future profitability in an area depends on past profitability in that area.

The s_2 survival factor, representing how reliable past fishing effort is considered as a predictor of present catch rates, did not help to minimize the fitting procedures in Equations 26 and 27. All values of s_2 in a proportional range between 0-1 resulted in the same sum of squares and natural log sum of squares value indicating that a fisher's consideration of future catch rates in an area is not dependent on past fishing effort in that area.

4.4.2 Parameter values for annual model

The model fit was analyzed each year over all spatial areas. The model fit using the sum of squares parameter estimates is better in the earlier decades with increasing deviations between the observed and predicted values in the later years, 1970-2001 (Figure 4-8). During the earlier years, vessels seemed to have relied more on areas where there was a high abundance of many species such as along the equator in coastal areas. Since most species fetched the same ex-vessel price, targeting was not as important in terms of profit (Figure 3-1). However, in later years, with technological advancements and changing market prices, vessels altered their gear to target specific species, i.e., deeper sets with more hooks for bigeye or shallower sets with less hooks to harvest swordfish [73]. With more selective fishing, the model could not capture the degree of variability in fishing location choice.

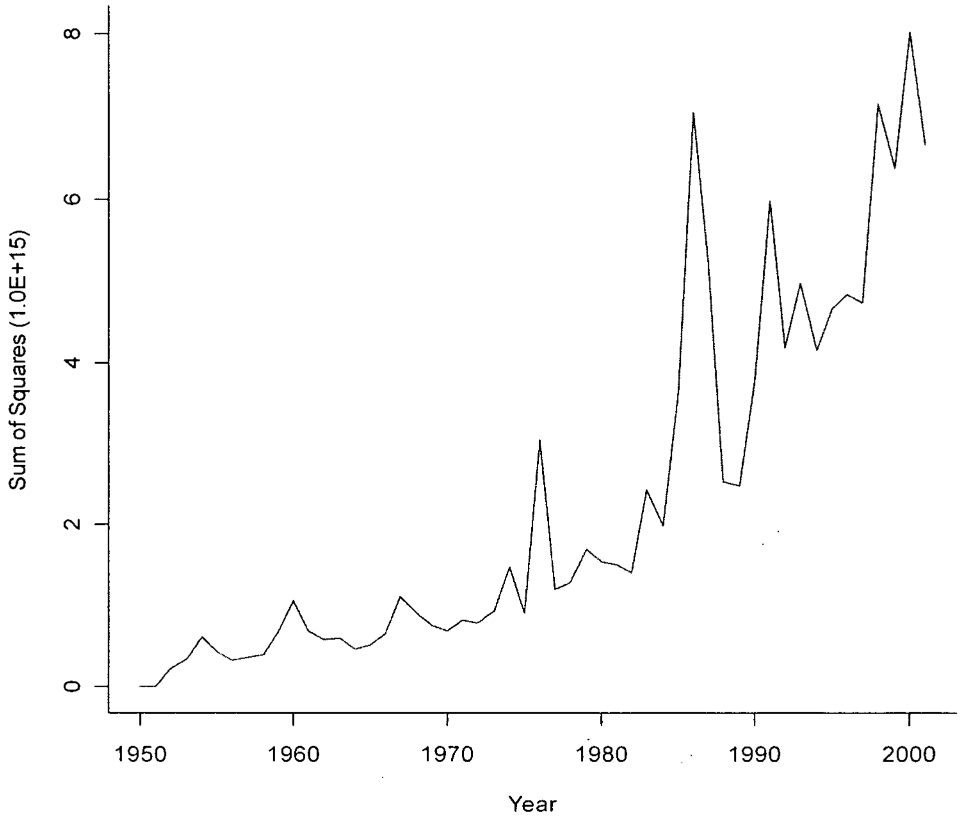

Figure 4-8: Sum of squared deviation between observed and predicted fishing effort through time.

The natural log sum of squares fit (Figure 4-9) shows large deviations between observed and predicted values of fishing effort in the first 10 years (1950-1960). The poor fit in the early years of the study could be due to the difficulty in predicting fishing effort when the longline fishery is still developing which included exploration of unknown areas and experimentation with technology and gear. Therefore, fishers might not have had the most efficient method for fishing that would have maximized profits from all fish stocks and all areas. The sum of squares deviation decreases and remains small from the 1960s to 1990, when the fishery was fully developed and then increases again in the 1990s. During this last decade, the purse seine fishery was increasing its effort and catch dramatically causing increased competition for tuna catch [13]. Large tuna catches from purse seine vessels flooded the market causing an oversupply which lead to a decrease in ex-vessel prices [74]. Since purse seiners target, mainly, juvenile bigeye and yellowfin tuna, purse seine fishing affected the longline catch of adult bigeye and yellowfin [16].

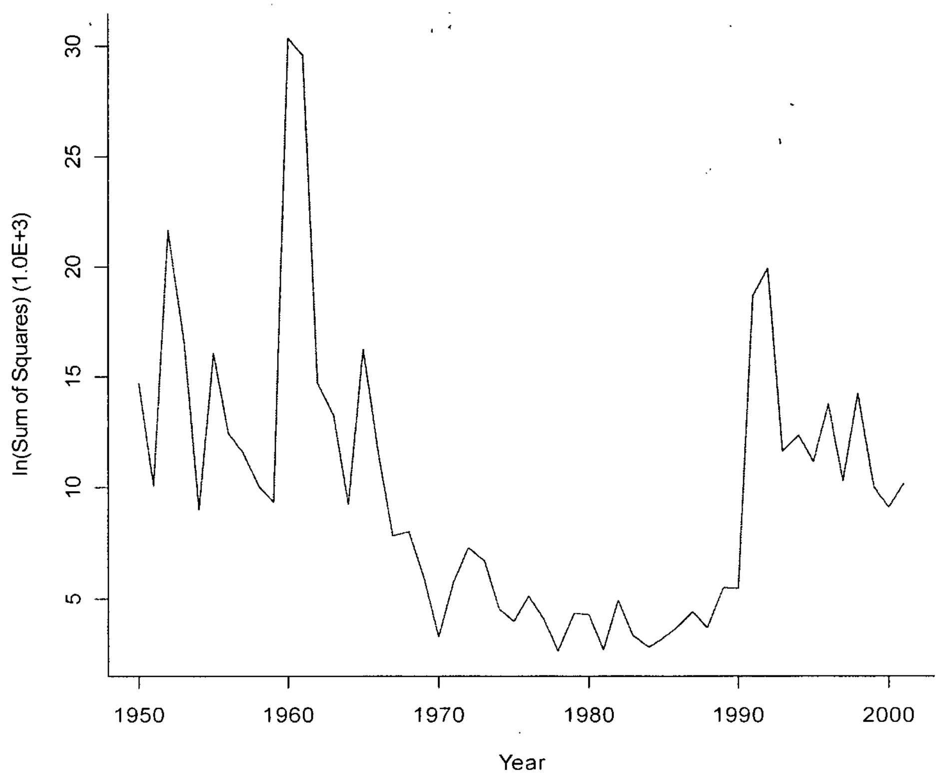

Figure 4-9: The natural log sum of squares value between the observed and predicted fishing effort from 1952-2001.

The K, v and s_1 parameter estimates minimizing the sum of squares deviation and the natural log sum of squares between the observed and predicted fishing effort are shown in Figures 4-10 and 4-11, respectively for each year. The s_2 parameter value did not impact the sum of squares value and was therefore not included. In Figure 4-10, the variance (v) is higher from 1950-1960 and then decreases until 1990 when it began to increase again. This pattern follows the assumptions made in the previous chapter that there will be higher variance between fishers' perception of profits when a fishery is just developing, and will generally tend to decrease when fishers obtain and share more information on the most optimal fishing locations. The K scaling value remains high through time, following the initial assumption that rather than relying on past fishing effort as an indicator of the best spots, search technology and information sharing between vessels is a more likely method used to find areas with the highest catch rates. This is especially obvious in the earlier years when there was uncertainty in exploring new areas that could have rendered poor catches. In the earlier years, past fishing locations and the amount of fishing effort in that area might not have been good indicators of where to fish in the future since previous fishing effort in an area would not necessarily mean a good fishing spot. The s_l parameter value shows large fluctuations in percentage of reliability on past profit as a predictor of present profitability. However, in the second half of the study period, s_l remains around 0.9 for most years indicating a heavy reliance on past profit gained as an indicator of what to expect in that area in future years.

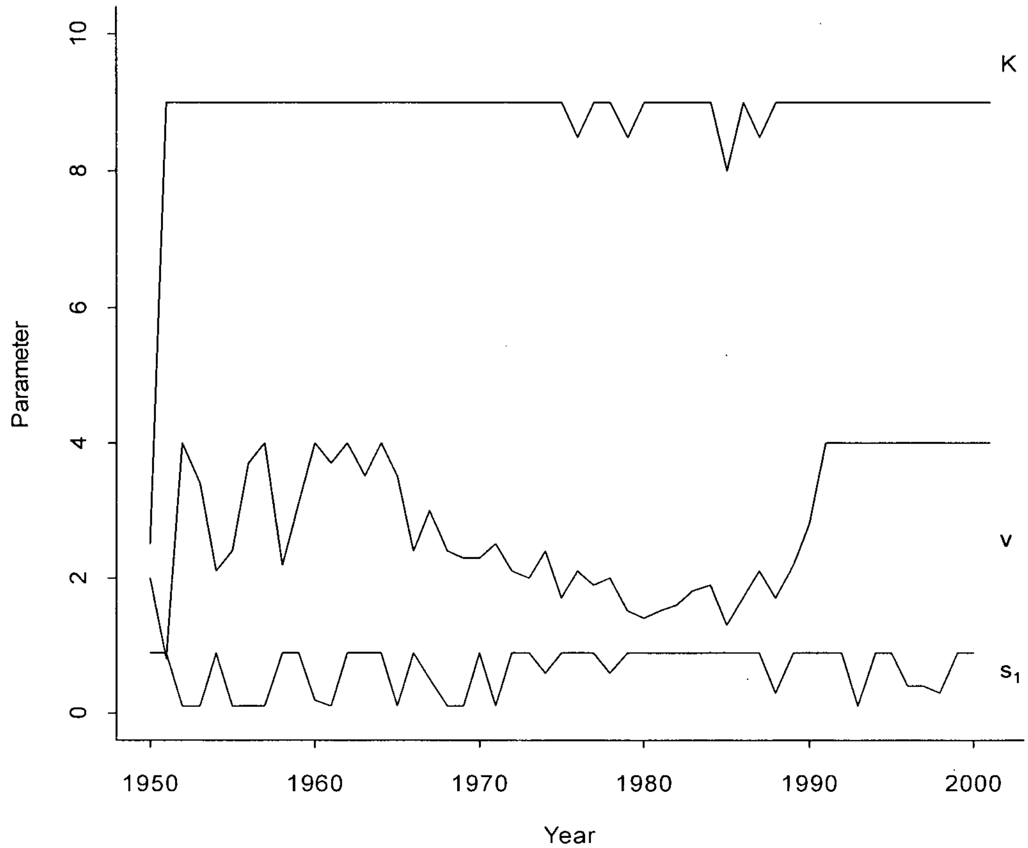

Figure 4-10: Values from 1950-2001 for the fishing effort scaling parameter, K, the perceived profitability parameter, v, and the reliance on past profitability parameter, s_1, that minimized the sum of squares deviation between the observed and predicted fishing effort.

Similarly, the v and K values minimizing the natural log sum of squares have almost the same pattern (Figure 4-11). Variance is higher in the earlier years and then decreases for the remaining years with a peak around 1992. The K parameter follows the exact same trend as in Figure 4-10 indicating the same assumptions as discussed above. The s_1 value, on the other hand, shows large fluctuations throughout the study with a higher average percentage in earlier and later years, with a lower average percentage in the middle years. This indicates that fishers place more reliance on past profitability in their decision-making when there is uncertainty in the best fishing locations (earlier years) and when there is lower abundances of fish and more competition (later years).

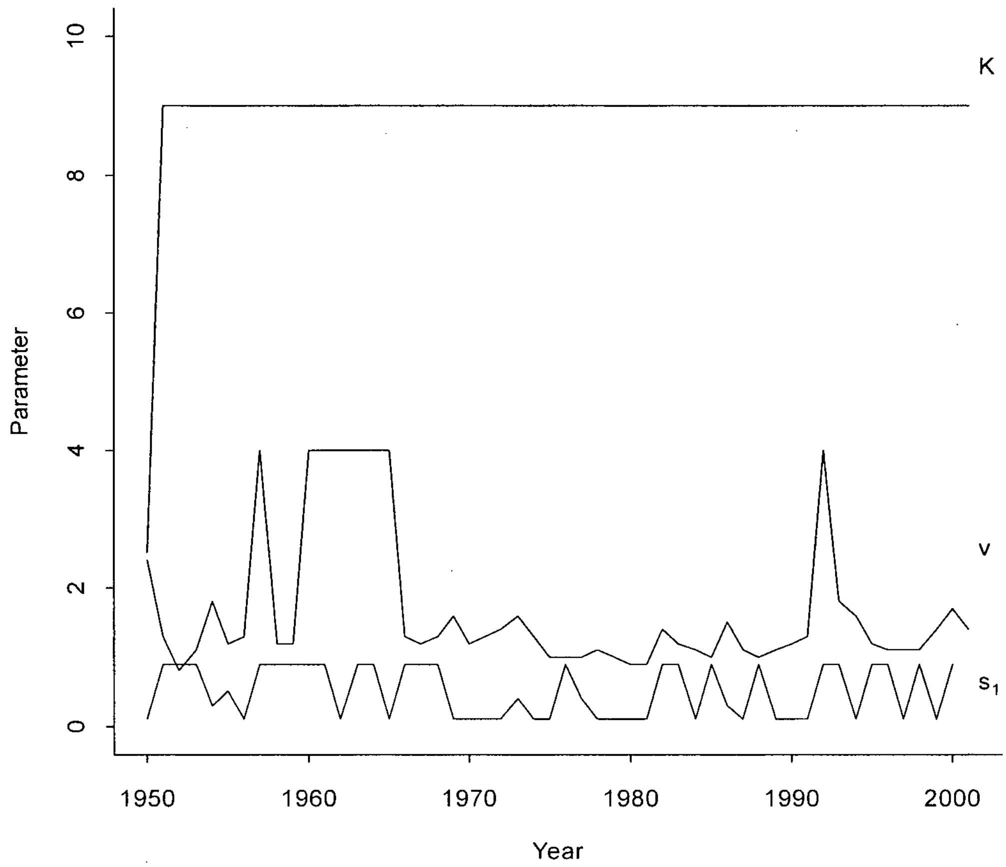

Figure 4-11: Values from 1950-2001 for the fishing effort scaling parameter, K, the perceived profitability parameter, v, and the reliance on past profitability parameter, s_1, that minimized the natural log sum of squares deviation between the observed and predicted fishing effort.

4.4.3 Observed versus predicted spatial fishing effort

Using the parameter values in Table 4-1 from the best overall fit, global maps have been generated to compare the predicted fishing effort from the model to the observed fishing effort data. In Figures 4-12 to 4-17, maps from one year in each decade from 1950-2001 are displayed to show how well the model predicts fishing effort trends and distributions. For comparison, there are maps to show spatial fishing effort distribution using the best parameter estimates from the two fitting procedures.

Throughout time, the parameter values estimated from the natural log sum of squares produce better fishing effort predictions than the parameter values from the sum of squares procedure.

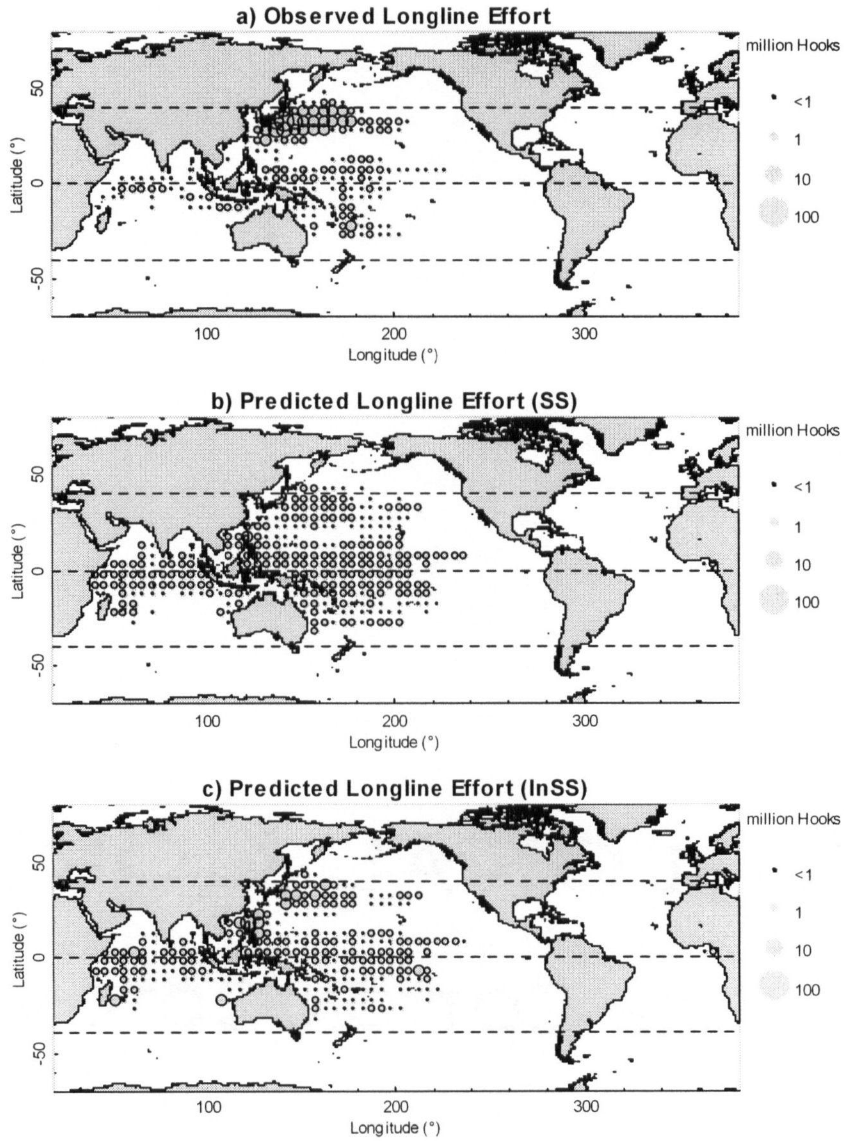

Figure 4-12: Longline spatial fishing effort where a) is the observed fishing effort, b) is predicted fishing effort using parameter values from the sum of squares deviation fitting, c) is predicted fishing effort using the parameter values from the natural log sum of squares fitting in 1955.

In the first decade, the model predicts the initial development of fishing off the coast of Japan (Figure 4-12), pretty well. The model also predicts the expansion towards the equator, in the equatorial region around the South Pacific Islands. It does, however, allocate fishing effort to the Indian Ocean too quickly as opposed to the observed fishing effort movement which does not yet show any expansion away from the Pacific Ocean.

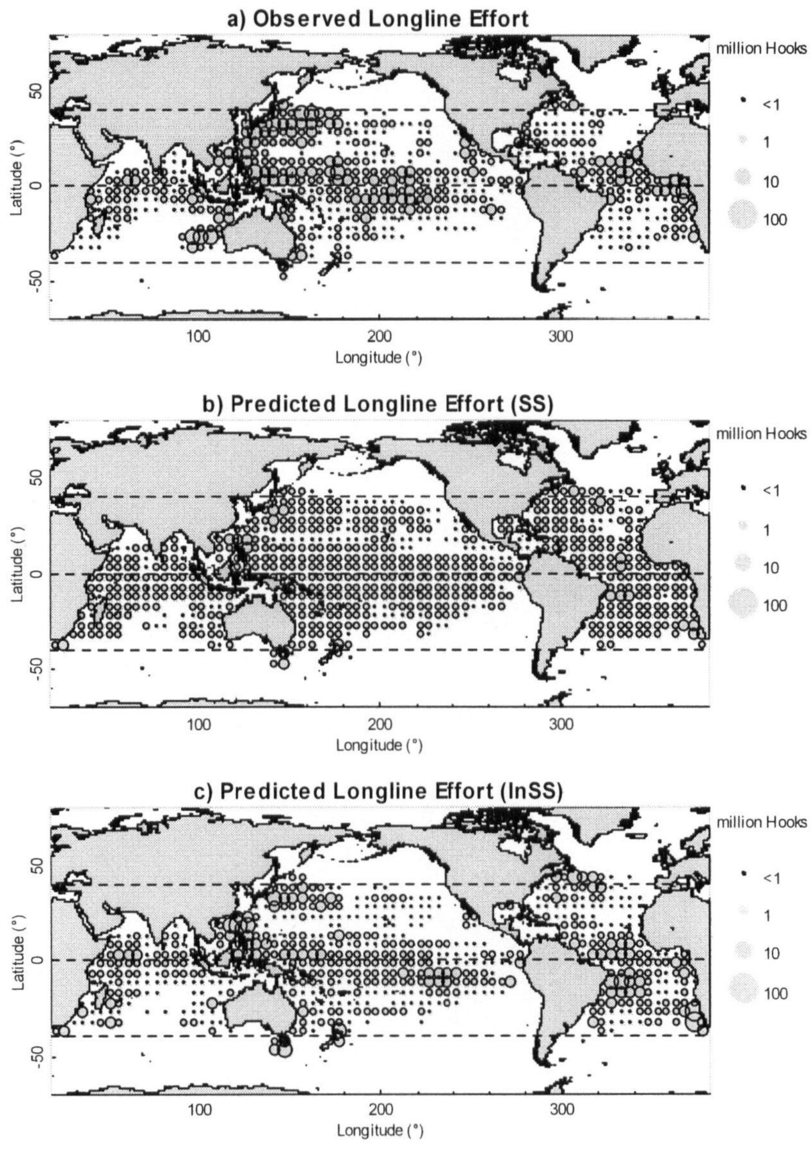

Figure 4-13: Longline spatial fishing effort where a) is the observed fishing effort, b) is predicted fishing effort using parameter values from the sum of squares deviation fitting, c) is predicted fishing effort using the parameter values from the natural log sum of squares fitting in 1965.

The predicted fishing effort improves in the 1960s (Figure 4-13). The spread east in the Pacific as well as the expansion to the Indian and Atlantic Oceans is evident. The predicted fishing effort from the sum of squares fitting procedure is more spread out than the observed effort which is very concentrated in specific areas. The natural log sum of squares distribution more closely resembles the observed fishing effort with more concentrated allocation of effort in appropriate regions.

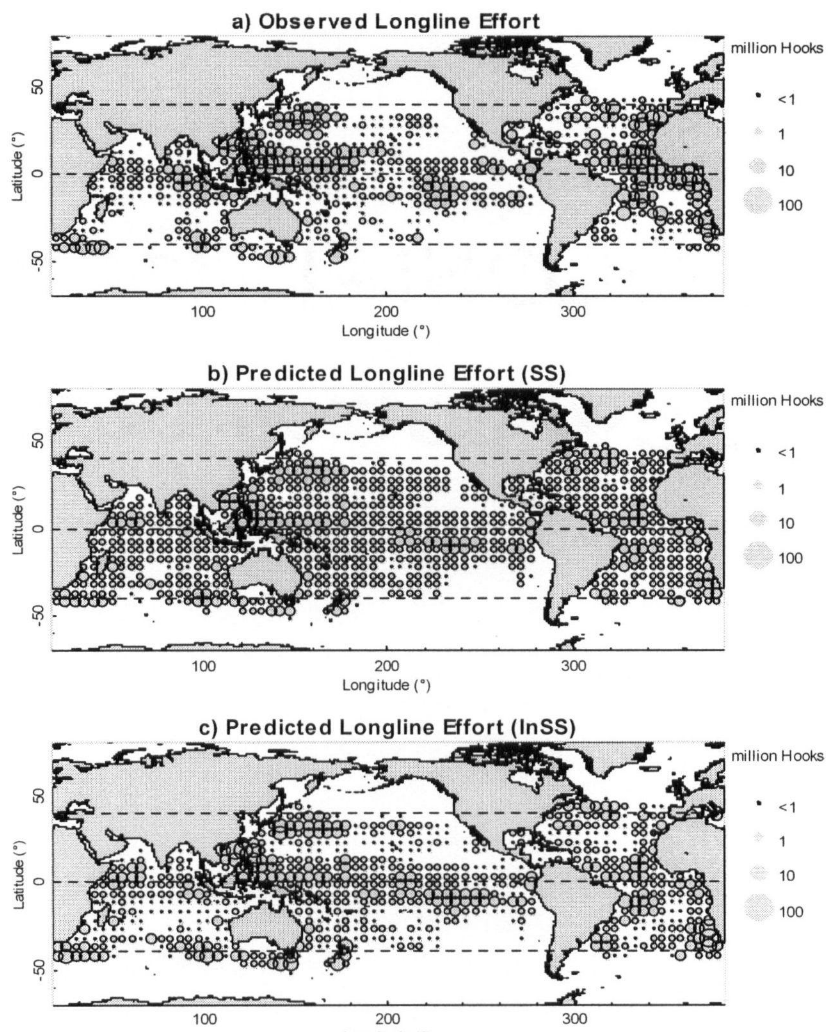

Figure 4-14: Longline spatial fishing effort where a) is the observed fishing effort, b) is predicted fishing effort using parameter values from the sum of squares deviation fitting, c) is predicted fishing effort using the parameter values from the natural log sum of squares fitting in 1975.

The model, when using the parameter estimates from the natural log sum of squares fitting procedure, (Figure 4-14c) is good at predicting fishing effort through the 1970s. In close approximation with the observed fishing effort (Figure 4-14a), predicted effort is concentrated along the equator in all oceans with some effort spreading south of Australia to southern bluefin tuna fishing grounds. The predicted effort distribution in Figure 4-14b again has less concentrated areas and a larger spread of lower amounts of fishing effort allocated to more areas than was recorded.

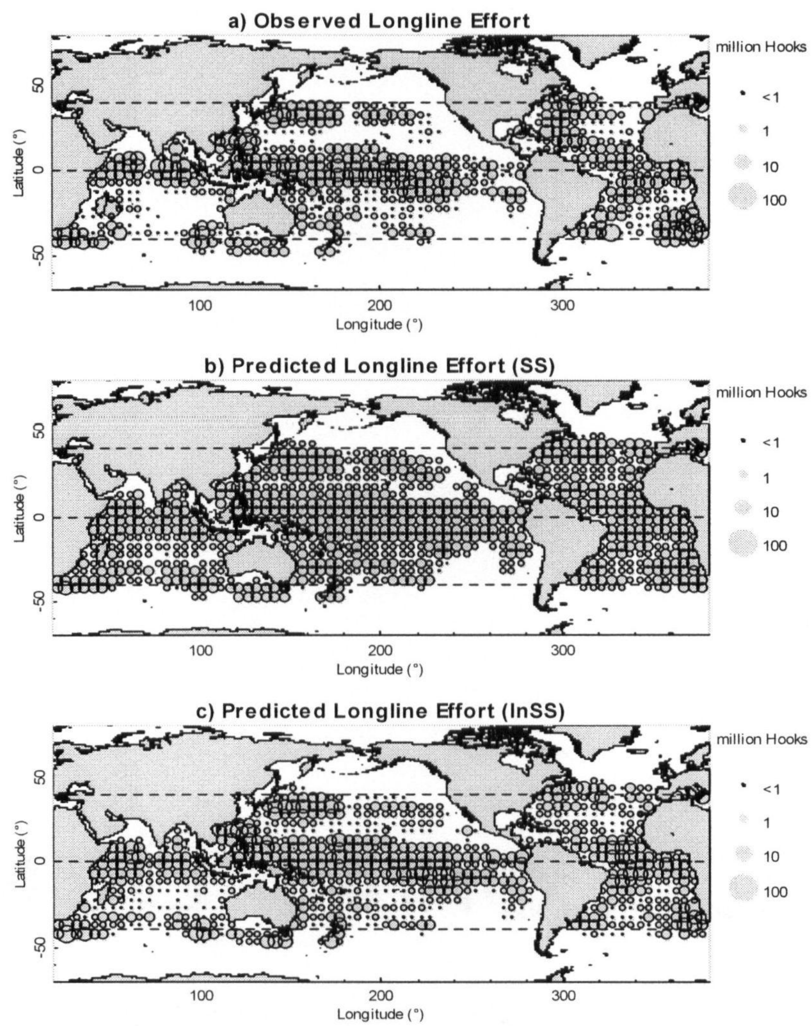

Figure 4-15: Longline spatial fishing effort where a) is the observed fishing effort, b) is predicted fishing effort using parameter values from the sum of squares deviation fitting, c) is predicted fishing effort using the parameter values from the natural log sum of squares fitting in 1985.

Predicted fishing effort allocation and concentration begins to worsen in the 1980s compared to the observed fishing effort. Both prediction procedures seem to spread effort in more areas with lower effort concentrations. However, areas where predicted fishing effort is being allocated still follows the general trend of the actual fishing effort.

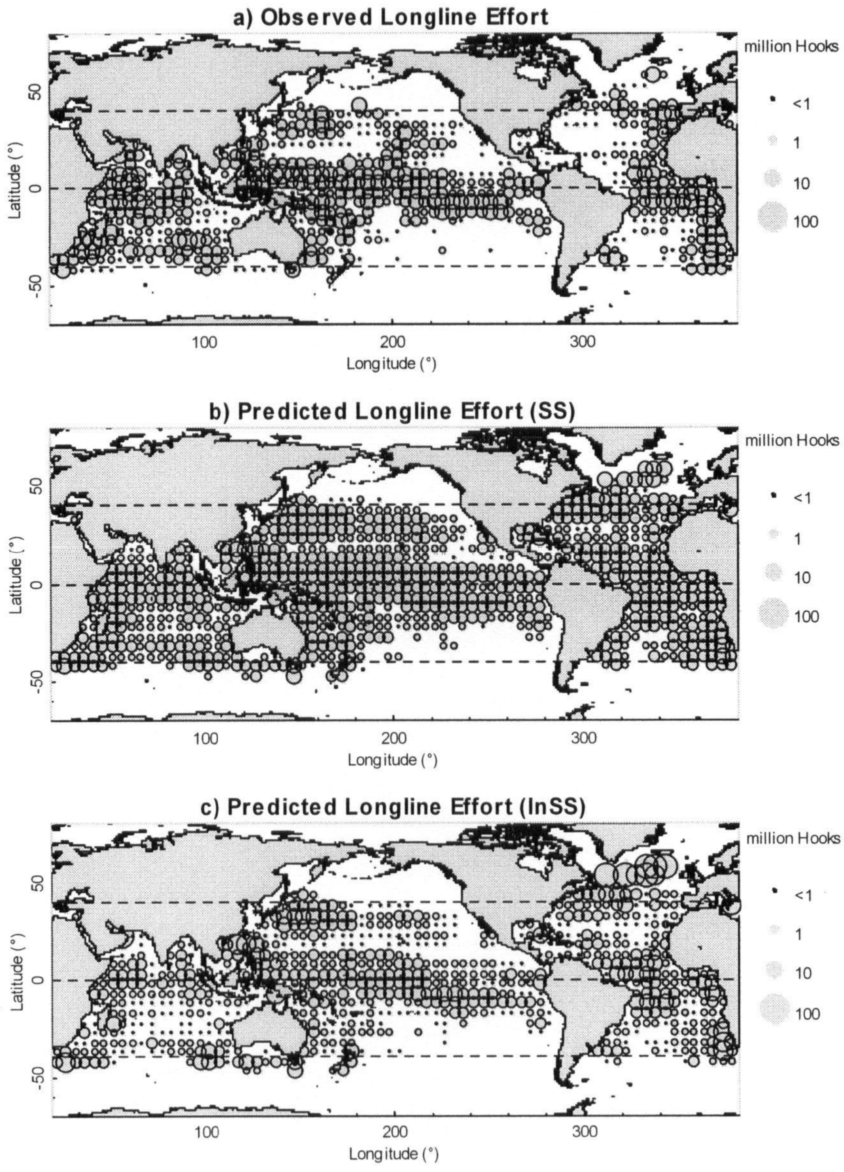

Figure 4-16: Longline spatial fishing effort where a) is the observed fishing effort, b) is predicted fishing effort using parameter values from the sum of squares deviation fitting, c) is predicted fishing effort using the parameter values from the natural log sum of squares fitting in 1995.

The model, using the parameter estimates from the natural log sum of squares procedure, begins to distribute less fishing effort in most areas compared to the observed distribution in 1995 (Figure 4-16c). There is less fishing effort in the Indian Ocean as well as in the area of the South Pacific Islands. During this time, fishing effort using the sum of squares fitting procedure closely resembles the second model predictions but effort is still spread out and less concentrated in terms of number of hooks predicted (Figure 4-16b).

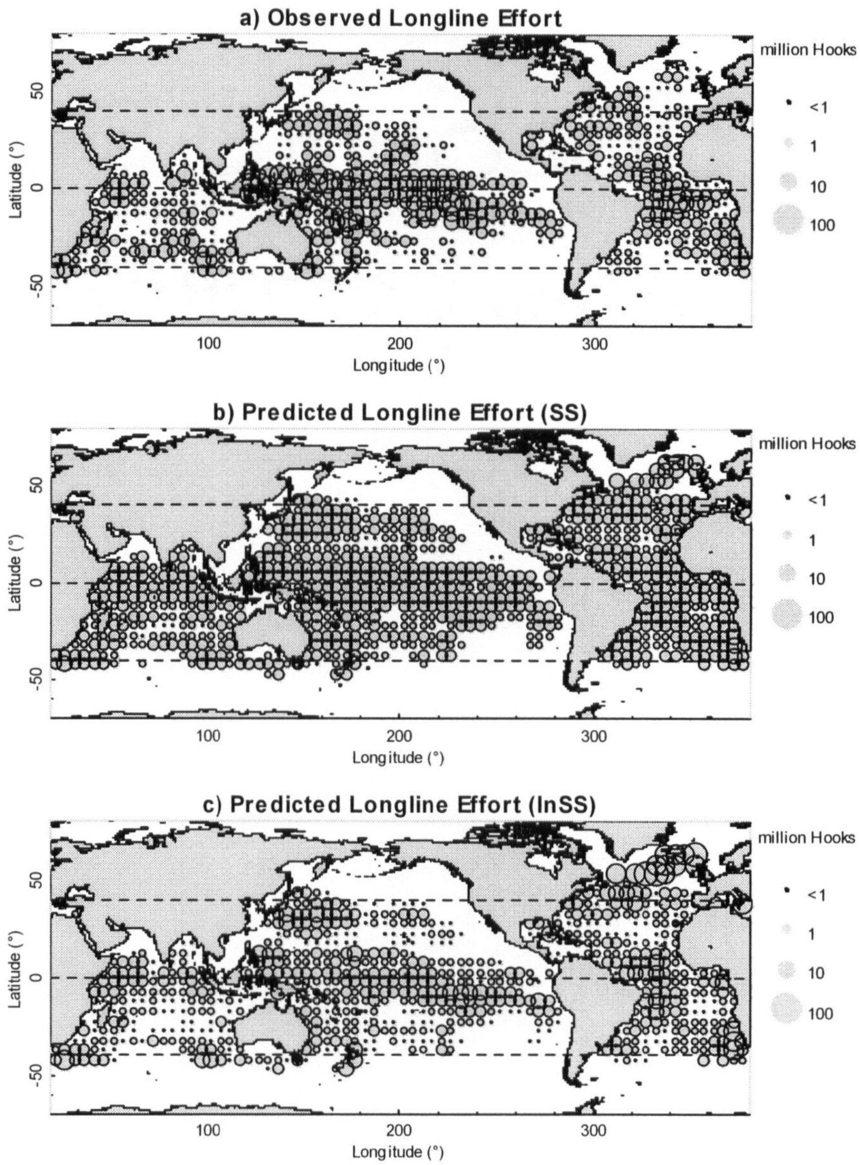

Figure 4-17: Longline spatial fishing effort where a) is the observed fishing effort, b) is predicted fishing effort using parameter values from the sum of squares deviation fitting, c) is predicted fishing effort using the parameter values from the natural log sum of squares fitting in 2001.

Finally in the last year of the study, 2001, the model predicts less fishing effort around the South Pacific Islands than what actually occurred (Figure 4-17). The models from both fitting procedures also predict quite a bit of fishing effort in the North Atlantic which does not happen in the observed fishing effort records. The model deviates from the observed fishing effort in the region most likely because there are factors that the model can not take into account when predicting fishing effort. In this area, there is a high abundance of valuable bluefin tuna, but there must have been other reasons aside from economic motivation as to why there was not more fishing effort, perhaps EEZ restrictions or low catch quotas.

4.4.4 Differences in the amount of observed versus predicted fishing effort

In addition to mapping the fishing effort in number of hooks and comparing the observed distribution to the predicted fishing effort distribution, the differences between the amount of observed and the amount of predicted fishing effort is mapped spatially to examine whether the model is over predicting the amount of fishing effort or whether the number of hooks allocated to each area is underestimated. The difference between the amounts of fishing effort predicted from the two fitting procedures is also mapped spatially for comparison purposes.

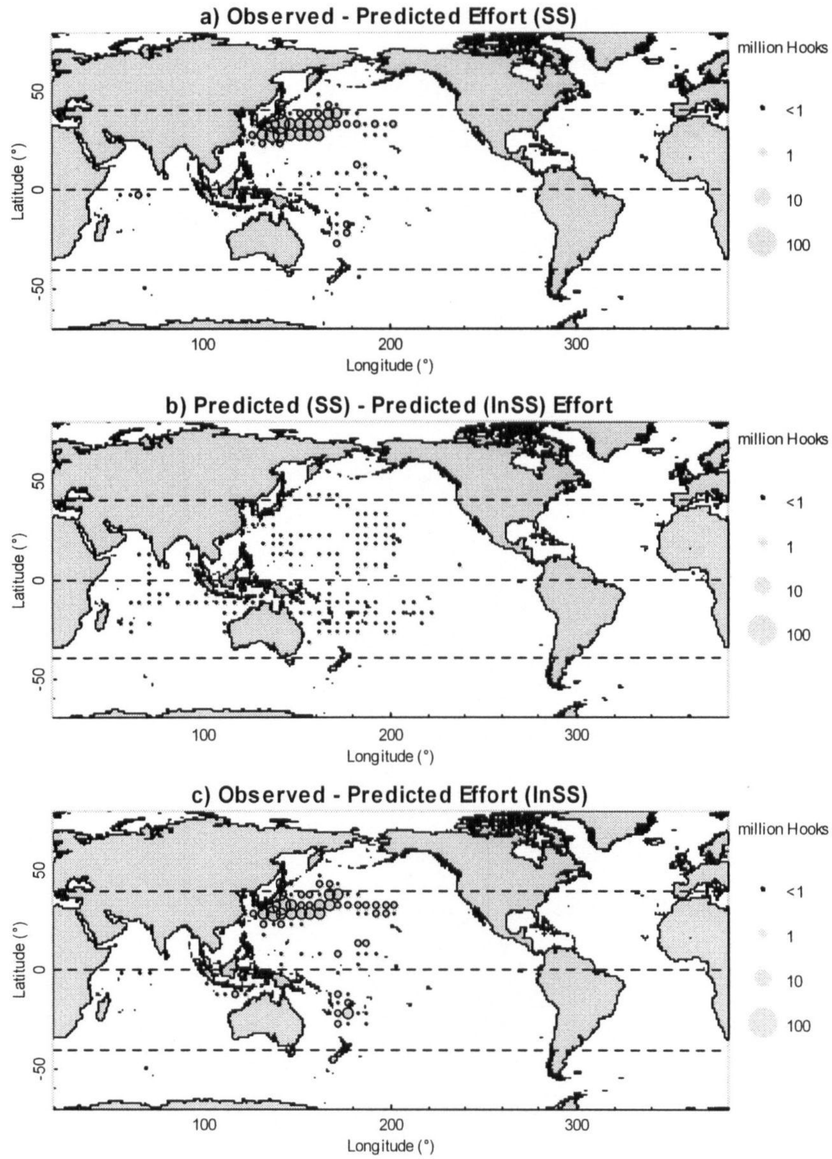

Figure 4-18: The differences in spatial fishing effort distribution between a) the observed and predicted effort using parameter values from the sum of squares fitting, b) the two fitting procedures, and c) the observed and predicted effort using the parameter values from the natural log sum of squares fitting in 1955.

In the first decade, the sum of squares fitted model predicts less fishing effort off the coast of Japan than what was recorded (Figure 4-18a). Most of the spatial areas around Japan have larger circles indicating a greater amount of observed fishing effort than predicted fishing effort, but the circles are smaller along the equator indicating that the model is allocating more accurate amounts of fishing effort. The differences between the two fitting procedures are minimal indicated by the small dots in all areas. The difference between the observed data and the natural log fitted fishing effort are smaller in the Indian Ocean than the other fitting procedure but is the same as the sum of squares fit in all other areas.

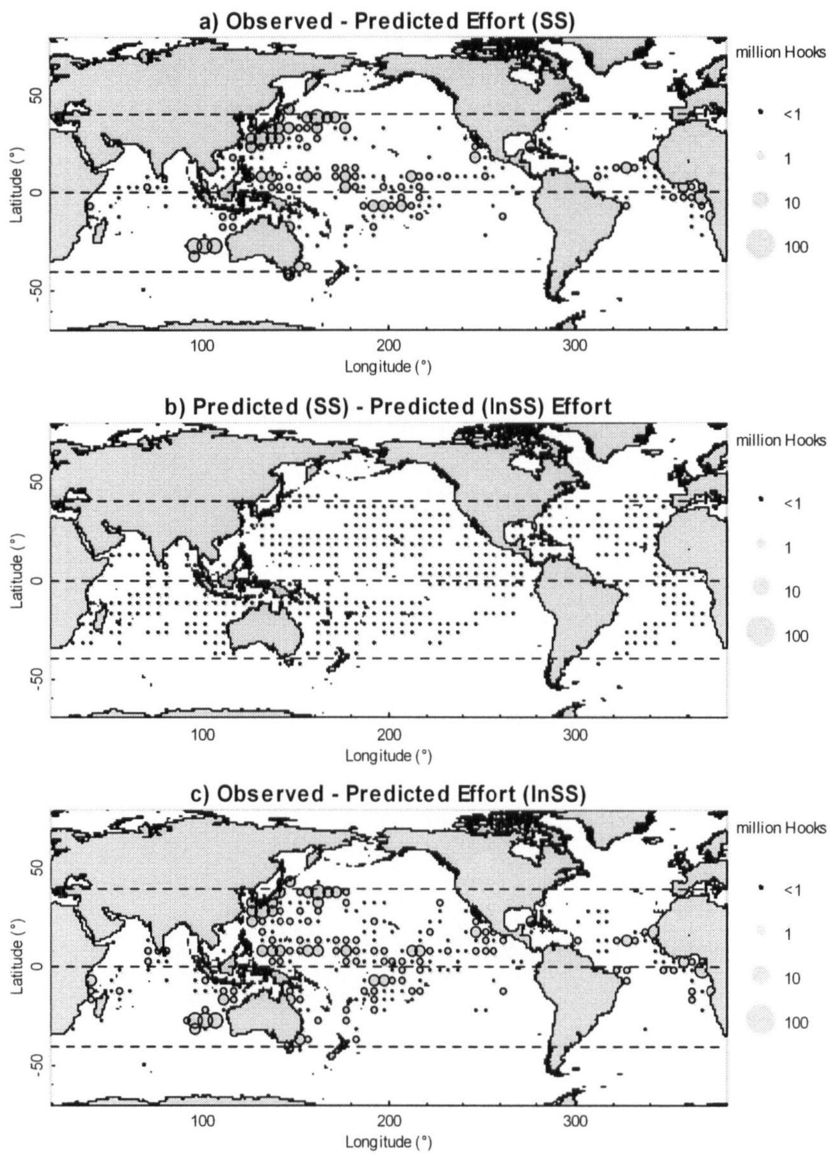

Figure 4-19: The differences in spatial fishing effort distribution between a) the observed and predicted effort using parameter values from the sum of squares fitting, b) the two fitting procedures, and c) the observed and predicted effort using the parameter values from the natural log sum of squares fitting in 1965.

In 1965 (Figure 4-19), the observed fishing effort is higher in equatorial regions compared to both fitted model predictions. The model seems to predict more fishing effort in temperate regions than what occurred in the observed distribution. There is minimal difference between the predictions of the two models, indicated by the small dots.

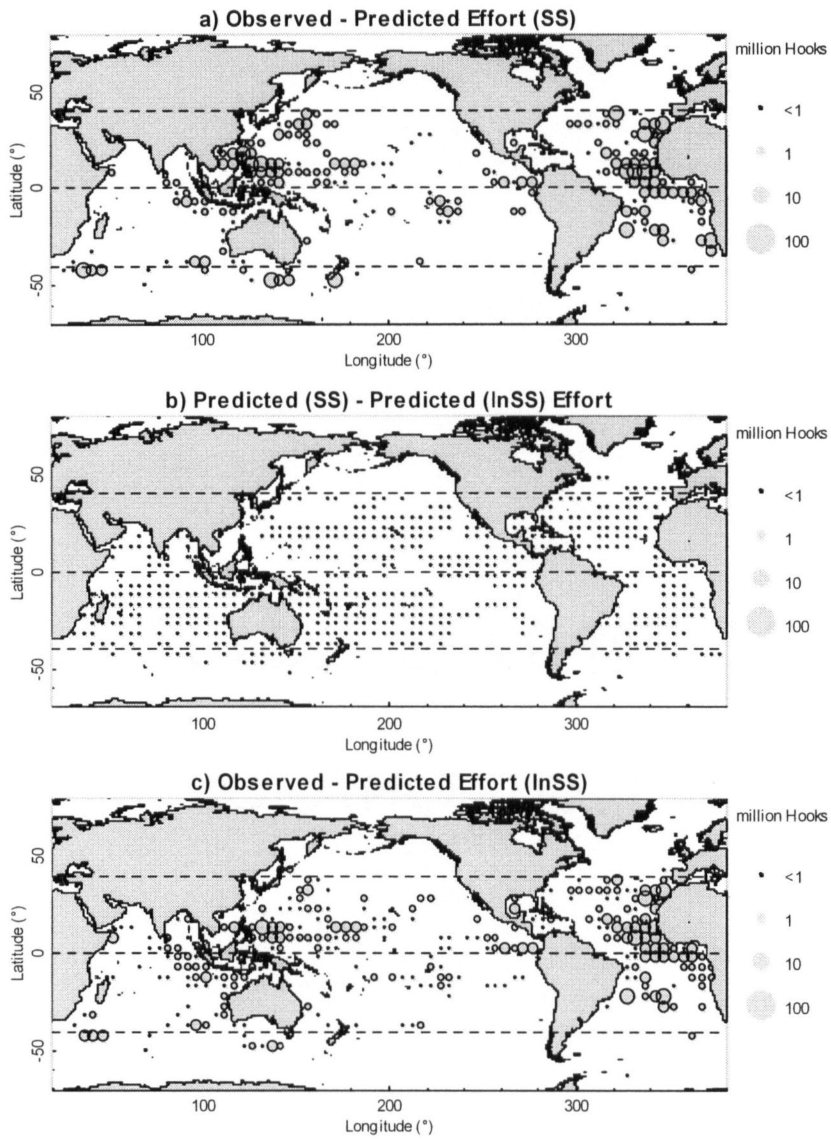

Figure 4-20: The differences in spatial fishing effort distribution between a) the observed and predicted effort using parameter values from the sum of squares fitting, b) the two fitting procedures, and c) the observed and predicted effort using the parameter values from the natural log sum of squares fitting in 1975.

In 1975, the observed fishing effort is greater in areas around the west coast of Africa, and in the coastal equatorial region of the Pacific Ocean. The magnitude of circles is greater when comparing the sum of squares model to the observed effort than when the observed data is compared to the natural log sum of squares model (Figure 4-20a, c). In Figure 4-20b, the difference in the amount of fishing effort predicted by the two models is larger with a greater amount of fishing effort predicted by the sum of squares model.

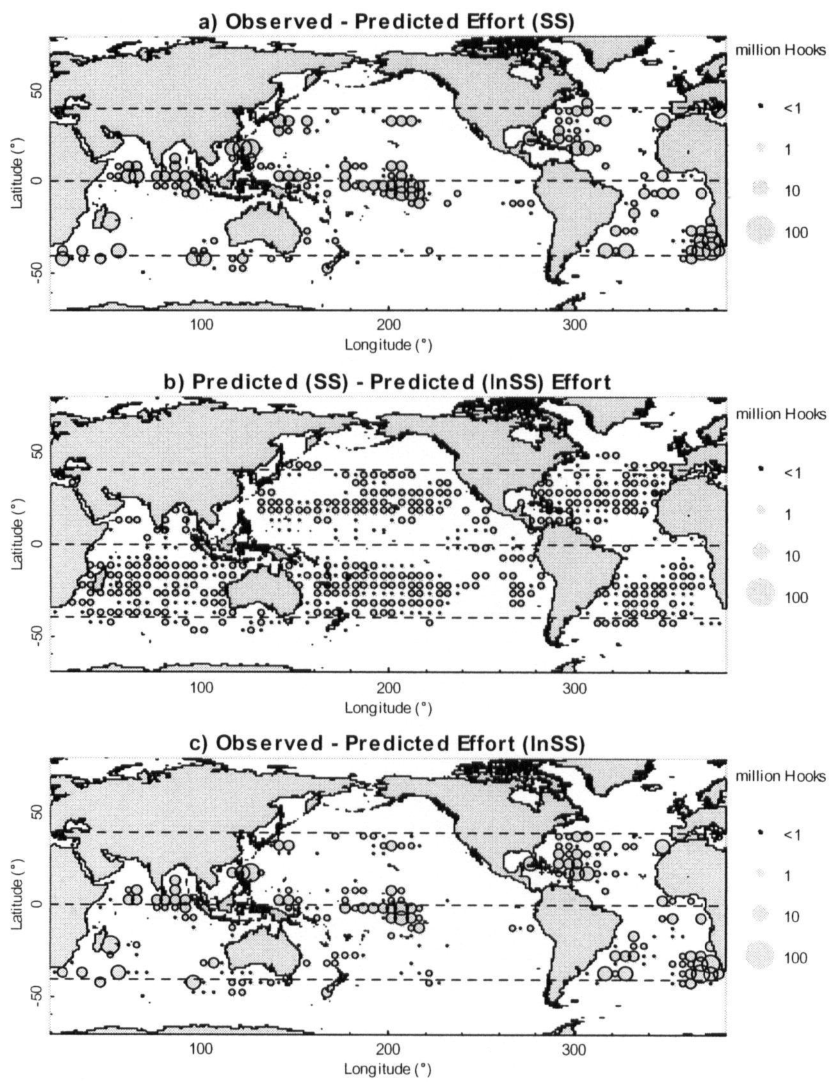

Figure 4-21: The differences in spatial fishing effort distribution between a) the observed and predicted effort using parameter values from the sum of squares fitting, b) the two fitting procedures, and c) the observed and predicted effort using the parameter values from the natural log sum of squares fitting in 1985.

In 1985, the observed fishing effort is higher in all areas fished compared to the two model fits. However, the difference is smaller between the observed data and the natural log sum of squares model (Figure 4-21c). The difference between the two model fits is greater than in previous years where the sum of squares model predicts greater fishing effort (Figure 4-21b).

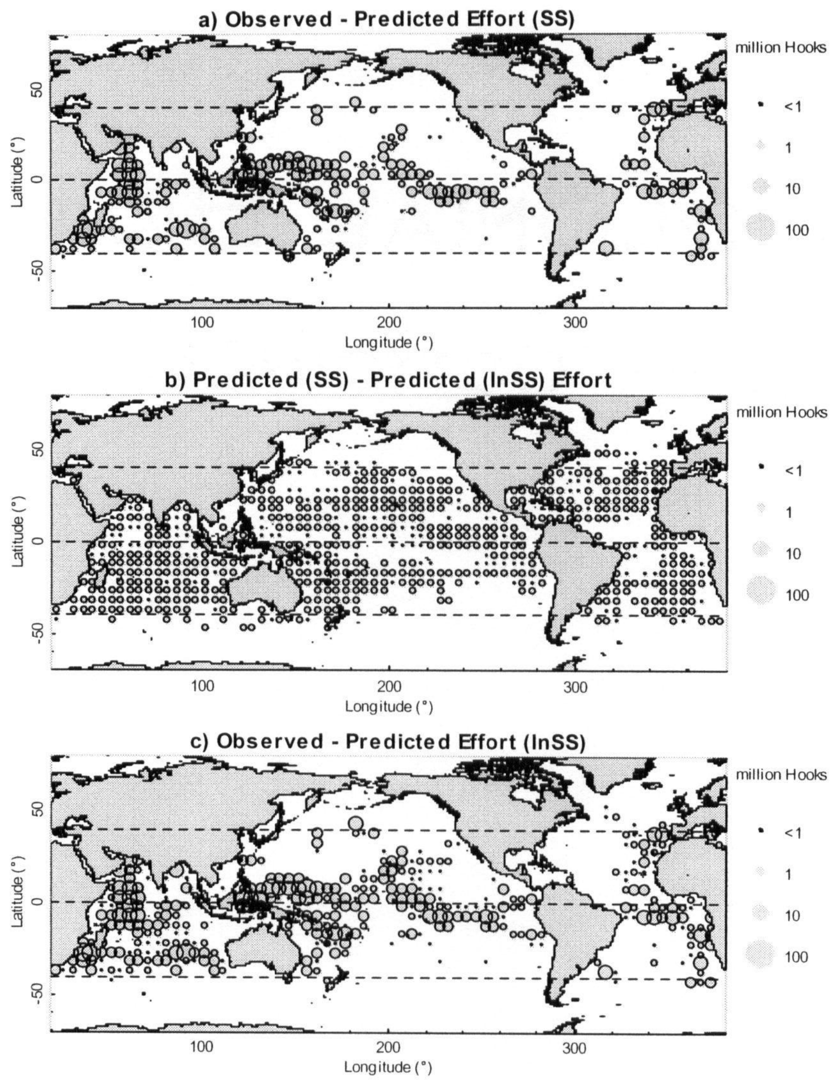

Figure 4-22: The differences in spatial fishing effort distribution between a) the observed and predicted effort using parameter values from the sum of squares fitting, b) the two fitting procedures, and c) the observed and predicted effort using the parameter values from the natural log sum of squares fitting in 1995.

In 1995, the observed fishing effort is higher for areas along the equator compared to the predicted fishing effort from both models (Figure 4-22a, c). In comparing the fishing effort from the two fitting procedures, the differences are comparable to 1985 (previous map) where the sum of squares model predicts greater fishing effort in most areas (Figure 4-22b).

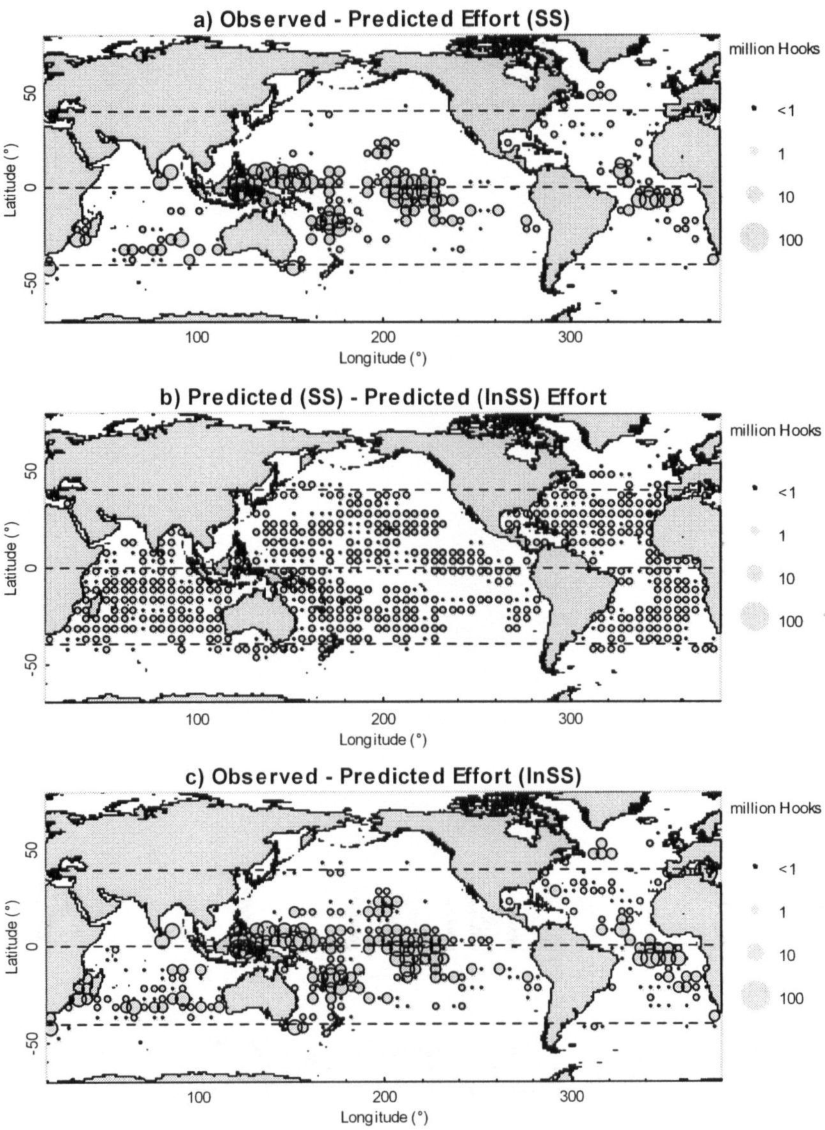

Figure 4-23: The differences in spatial fishing effort distribution between a) the observed and predicted effort using parameter values from the sum of squares fitting, b) the two fitting procedures, and c) the observed and predicted effort using the parameter values from the natural log sum of squares fitting in 2001.

In the last year, the differences between the observed and predicted fishing effort distributions are similar to previous years where there is more observed fishing effort along the equator than what the model predicts (Figure 4-23a, c).

4.5 Total Predicted Revenue

The total revenue gained from the fishery using the predicted fishing effort to obtain catch over time is examined to compare with the total revenue from the observed catch data (Figure 4-24).

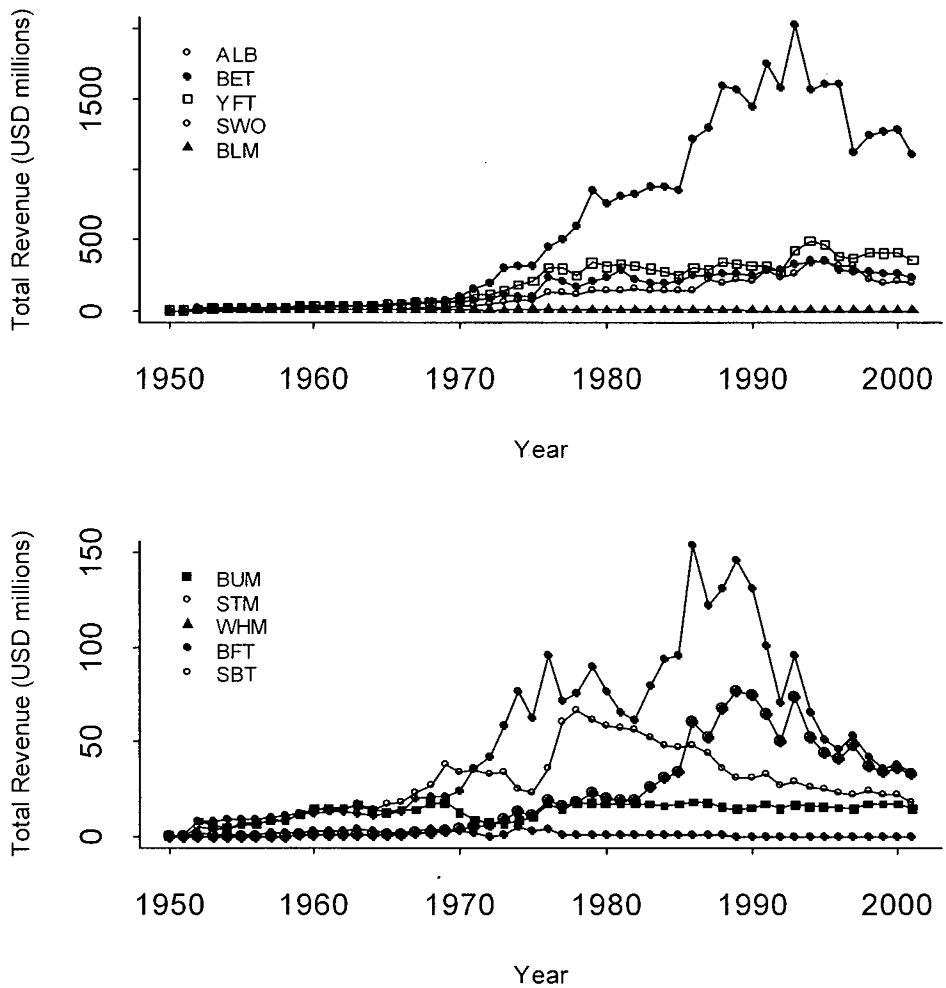

Figure 4-24: Total predicted revenue by species using the predicted catch from the bioeconomic model from 1950-2001.

In comparison to Figure 3-2, which shows total revenue gained from the observed catch in the longline fishery, the revenue gained from the predicted catch using the model is much higher, by almost an order of magnitude, particularly for bigeye catch. With both the observed catch and the predicted catch, the revenue gained begins to decrease from 1995 onwards. Also, total revenue increases much earlier from observed catch in the fishery. The differences could possibly suggest that the model is distributing fishing effort in a more efficient manner to maximize profit than what actually happened in the fishery.

4.6 Total Predicted Profit

The total profit, that is, total revenue minus total cost (costs from all fishing areas summed) is shown in Figure 4-25. Profit increases significantly from 1950-1965 and then begins to stabilize and fluctuate around a current value of 500-600 million USD from 1970-2001.

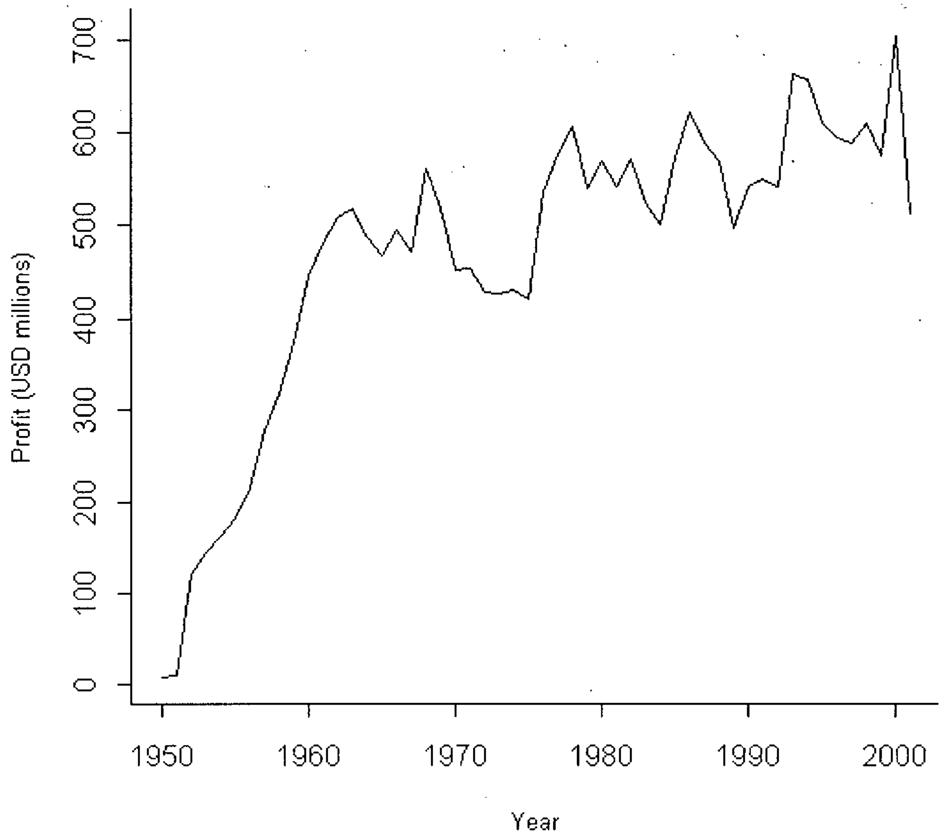

Figure 4-25: Total predicted profit in current values in the longline tuna fishery from all species from 1950-2001.

4.7 Sensitivity analysis

The bioeconomic model is based on assumed constant ex-vessel prices, $p_{i,t}$ (Figure 3-1), spatial fishing costs, FC_j (Figure 4-3), and species catchability, q_i (Table 2-4) through time. However, by keeping these variables constant, the model might not be fully capturing the changes in fisher behaviour that occurred in the fishery. Due to subsidies, technological innovation and fluctuating market conditions, these variables presumably might have changed through time. Ex-vessel prices tend to decline if there is a flood in the market of the same product or products that are good substitutes causing relative demand to decrease because of oversupply. On the other hand, ex-vessel prices increase when supply decreases causing a wider gap between supply and demand. If one species becomes overexploited, for example bluefin tuna, the market price tends to increase due to its scarcity. The profitability of fishing normally increases when subsidies are introduced to the fishing sector. Subsidies are usually monetary assistance given to fishing vessels to help them continue fishing even when profits are negative. The tuna fisheries are known to enjoy significant subsidies [74]. Catchability will often increase and fishing costs will further decrease when technology for finding fish and gear efficiency improves; making it faster and easier to harvest large catches and target specific species, *ceteris paribus*. On the other hand, catchability will decrease when stocks become overexploited due to increased search hours and decreased catch rates on any given trip.

In order to examine the possible effects of the changes in these parameters, a sensitivity analysis was performed where each of the three variables, p_i, FC_j, and q_i, were altered in an attempt to decrease the deviations between observed and predicted fishing effort and better predict fishing effort movement. In analyzing the major discrepancies between the observed and predicted fishing effort, it shows that the areas where bigeye and yellowfin tuna are primarily fished, lack higher concentrations of effort. First, focusing on changes in fishing cost, these areas where yellowfin and bigeye are most abundant were decreased in fishing cost in the sensitivity analysis. This is justified since these two species are the main species targeted, and fishing gear and technology would therefore be aimed at finding these species the fastest, making costs lower. The predicted fishing effort also shows more fishing effort allocated to northern and southern latitudes where northern and southern bluefin tuna are fished. However, with risk and lower abundances despite higher prices, observed fishing effort was not as high in these areas. Therefore, fishing costs where these species are abundant were increased in the sensitivity analysis.

The original model fit had a natural log sum of squares value of $8.41x10^5$. To test the predictions from the observations above, the spatial fishing costs in areas with yellowfin and bigeye were first increased which made the model fit worse ($8.55x10^5$). The spatial fishing costs for these areas were then decreased and the sum of squares value correspondingly decreased ($8.26x10^5$). Further analyses were performed to examine if a change in fishing costs in areas with high abundances of other species would impact the model fit. The fit of the model remained the same when areas with blue marlin and swordfish were decreased in fishing costs but the addition of the decrease in costs of these areas with the decrease in costs in yellowfin and bigeye areas improved the model ($8.25x10^5$ at 50%). Then, the model fit further improved when the fishing costs were increased for areas with bluefin tuna in addition to the previous scenario. This combination of changes in fishing costs resulted in the minimum natural log sum of squares. Using this scenario, fishing costs were decreased over a percentage range to examine the best fit (Table 4-2).

Table 4-2: Overall change in natural log sum of squares between observed and predicted fishing effort when fishing costs were decreased across a range of values for bigeye, yellowfin, swordfish and blue marlin areas and increased across the same range of values for bluefin tuna.

Change in Fishing Cost (%)	*lnSS* ($x10^5$)
0	8.41
0.1	8.33
0.2	8.26
0.3	8.19
0.4	8.13
0.5	8.07
0.6	8.03
0.7	7.99
0.8	7.98
0.9	8.05

From Table 4-2, it was found that the best fit was when spatial fishing costs were decreased by 80% for bigeye, yellowfin, blue marlin and swordfish areas and increased by 80% for bluefin tuna areas. This scenario improved the model fit in the earlier years (1955-1970) in particular and then throughout the 1980s, but the fit did worsen towards the final years of the study.

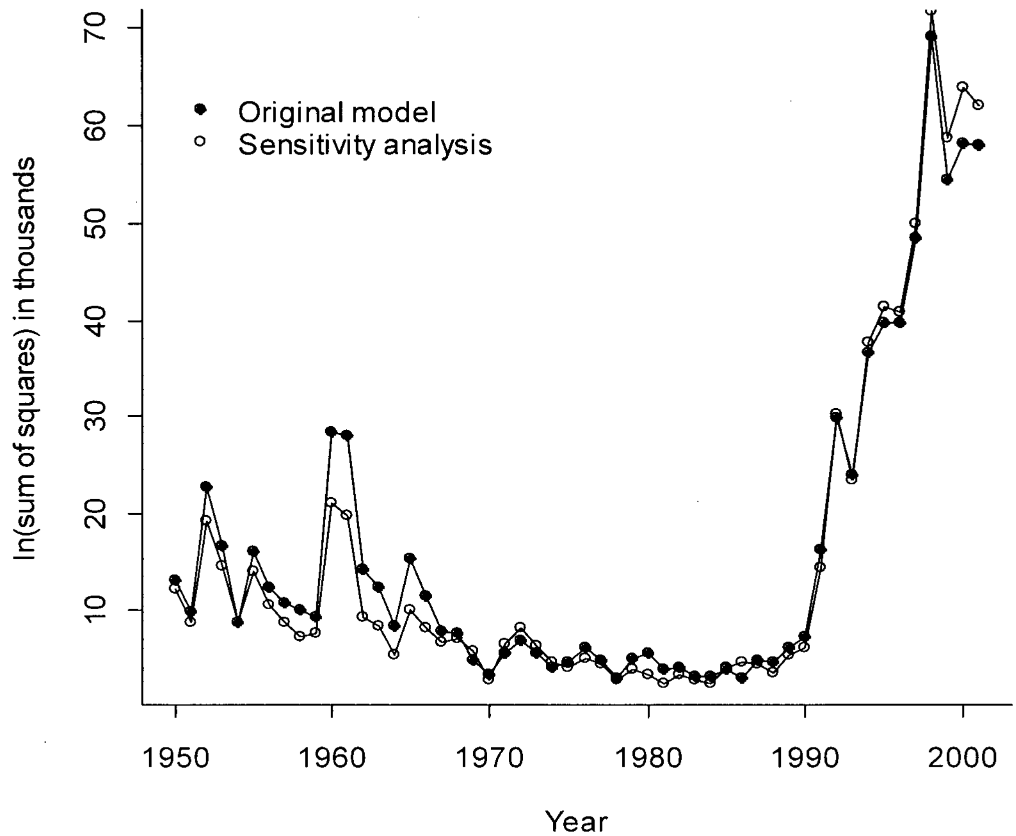

Figure 4-26: Change in natural log sum of squares through time as a result of a decrease in spatial fishing costs for bigeye, yellowfin, blue marlin and swordfish and an increase in fishing costs for southern and northern bluefin tuna.

When catchability and ex-vessel prices were altered using the same range of possible values as the fishing cost analysis, there was no change in the sum of squares value. Reasons for this could be that with such a large model, a small reasonable change in either of these variables does not get noticed in the amount of fishing effort predicted.

4.8 Discussion of Results

4.8.1 Discussion on bioeconomic model

From the reported results, it can be seen that the observed fishing effort initially develops in the north Pacific off the coast of Japan targeting mainly albacore tuna but then quickly moves towards the South Pacific Island region in the late 1950s targeting yellowfin. At this time, longline fishing effort was developing in the east Atlantic off the west coast of Africa (for yellowfin and northern bluefin catch). In the early 1960s, fishing effort in the Pacific spread eastwards targeting bigeye in high seas areas. During this period, fishing effort also expanded from east to west in the Indian Ocean, as well as to the Southern Ocean to exploit southern bluefin tuna. In the later years, effort was primarily concentrated in regions where bigeye is distributed. Most longline vessels in the last 15 years have focused on targeting bigeye in high seas areas because of their high value but also to avoid competition with the purse seine fishery targeting coastal tuna species. Since the late 1970s, longline fishers have set their lines deeper to catch bigeye which has resulted in increased catchability for this species [73].

The model similarly predicts fishing effort off the coast of Japan in the earlier years of the 1950s (Figure 4-12) but with less amounts of fishing effort. During the 1950s, Japan was the only fleet in the longline tuna fishery and the model was not able to predict the initial development and expansion during this exploratory period. It would be expected that Japanese fleets would still be harvesting in a suboptimal manner because of the lack of information compared to a fully developed large-scale commercial fishery and therefore, the model would not be able to predict fishing effort appropriately. Japan did not behave in the same manner as fishers in a developed commercial fishery in that they lacked perfect information, which is normally acquired through sharing of information between fleets, technology and skills. According to Little *et al.* [75], information flow between vessels play a critical role in the response of fishers to species abundance.

According to Holland and Sutinen [76], habit is also a characteristic of fisher behaviour. With very little information and certainty of other areas, the Japanese fleet was comfortable in habitually fishing waters off their coast and down towards the South Pacific Islands, partly because of familiarity and also for traditional purposes [21]. This can be linked to risk aversion in that fishers move to locations where they know what to expect and it is only lower catch rates or changing management policies in these locations that force vessels to explore new areas. Vessel size, limited freezer space and fishing costs might have also kept Japanese fishers from expanding to locations further from port.

Considering the differences in the behaviour of fishers in a developing fishery versus a developed fishery, the model was still able to capture Japanese fishing quite possibly because i) perception of fish abundance was very high in those coastal areas as fishing had not occurred there since before World War II, and ii) since ex-vessel prices were the same among species, Japan focused their efforts on places that had overall high abundance without having to travel long distances from their port.

From the 1960s to the 1980s, when the model neared the ideal free distribution "equilibrium" of fishing effort, the accuracy of predicting spatial fishing effort trends was very good. Most fishers, at this time, switched to targeting species of higher value on the sashimi market. The model captures the transition because it is designed to allocate fishing effort to areas where the biomass that could be caught would return the greatest profits. Since the model predicts fishing effort based on optimal fisher behaviour, a switch to harvesting tuna species that fetch higher market values was captured in the model.

During the last decade of the analysis, the model did not do a good job at predicting fishing effort patterns. It is clear that fisher behaviour in the later years is not based on moving to areas with the highest abundance of fish overall, but perhaps rather more concentration is put towards targeting a particular species such as bigeye and swordfish by altering gear to solely harvest that particular species. This type of high grading could have lead to increased discards of less valuable species. Catch recorded by the RFMOs is often an underestimate of what was actually caught, discarding being one reason [56].

Previous studies have predicted fisher behaviour choices in small regions for the longline fishery or for vessels solely targeting a certain species, for example swordfish and yellowfin [6, 8, 77]. These studies have been able to represent decisions made by individual fishers through survey analysis [78]. Characteristics such as distance from port, fuel usage, weather conditions, type of gear, age of vessel can be surveyed in these analyses and used as utility measures when predicting fishing location decisions. Specific gear regulations and policies can be explored in these smaller studies because information is generally available. These individual decisions cannot be obtained for all fishers in the global longline fishery because of the lack of finite detail but the model still manages to predict general trends over time and space using less parameters and less information in terms of the factors influencing decision making to achieve the same outcome. In terms of policy implications, a large model might be advantageous when regulating areas with overexploited species since the behaviour of all fleets can be analyzed. The major uncertainty in the analysis is the method used to determine fishing cost since there is no previous study at this scale to which we could compare our estimates.

4.8.2 Discussion on the differences in the amount of fishing effort

The amount of actual fishing effort is greater in equatorial regions where harvesting is targeted towards either yellowfin in coastal areas or bigeye in offshore regions. The model allocates more fishing effort to convergence zones, where overall species abundance is high due to abundant productivity in these areas. The difference in the fishing effort allocation indicates that the model is more likely to allocate fishing effort where overall abundance, as a means to maximize profit, occurs whereas the observed data shows that effort was actually in areas where profit maximizing was most likely based on targeting just one species, namely, bigeye tuna.

4.8.3 Discussion on the sensitivity analysis

The fit of the model only changed when spatial fishing costs were changed but was not affected when prices were changed by the same magnitude or when catchability coefficients were changed by one order of magnitude. By decreasing the spatial fishing costs in the areas where yellowfin, swordfish, blue marlin and bigeye are primarily caught, the fit through time improved (Figure 4-25d). Appendix A shows the spatial allocation of fishing effort when the fishing costs were decreased by 80% for areas with bigeye, yellowfin, swordfish and blue marlin and increased by 80% for areas with bluefin tuna, which resulted in the best model fit in the sensitivity analysis. The improvement in effort allocation in this last scenario, pulling effort away from the northern and southern regions, indicates that vessels are altering their gear to efficiently harvest bigeye and yellowfin and plan their trips purposely to areas where these species are distributed regardless of distance traveled because the profit gained is worthwhile.

Chapter 5 Policy Implications

With the ability to predict in a general sense how fishers will function and behave to changes in a fishery, in terms of effort distribution, policy implications can be examined to see how the majority of fishing vessels will alter their practices. Now that the basic global bioeconomic model has been built, this study can be further expanded by simulating potential management policies. Simulations to examine how regulations could affect the behaviour of fishers will be helpful in deciding the most effective method in ensuring long term sustainability of tuna stocks.

The creation of the WCPFC (Section 1.4.6) occurred when it was evident that an organization was needed to govern the Western and Central Pacific Ocean including adjoining high seas areas. This is an attempt to more effectively manage the fishing occurring in waters not belonging to any one State [40]. This organization is an attempt to minimize the amount of FOC (flag of convenience) vessels in the fishery as well as the tendency of vessels to exploit these areas rather than comply with regulations in areas governed by RFMOs [79]. Spatial management through area closures is one possible method to decrease the exploitation in high seas areas by creating opportunities to selectively protect and exploit species to maintain healthy levels of each stock [61]. To examine whether a marine reserve would be effective, simulations can be run where certain spatial areas are closed to fishing effort (increasing fishing cost in those cells). Based on location choice in effort reallocation when an area is closed, most likely to the next best fishing location, the success of the reserve can be evaluated in terms of the impact of redirected effort on other species and the recovery of the protected species. Several issues arise when establishing a marine reserve in the high seas. First, monitoring and enforcement is very costly in such a large area. Further, a reserve might create more illegal fishing due to low monitoring percentage, thereby increasing the amount of unrecorded catch which could be more detrimental to stock assessments than if no reserve was established. Although a marine reserve to protect certain tuna stocks could benefit the sustainability of the fishery, there are certain issues that need to be solved before this could be an effective management policy.

A second policy measure would be to set regulations on the market side of the industry. In order to decrease the amount of fishing pressure on a species that has been fished more severely than others, ports and processing facilities could restrict the amount that is landed or refuse to process that species. A simulation could be performed in the model where the protected species could be given a zero ex-vessel price. Without a market for a species, fishers will most likely redirect their harvesting to less exploited species. In 2001, no U.S. vessels were allowed to land swordfish and were restricted from certain areas in the Atlantic in order to reduce pressure on swordfish stocks especially on juvenile fish [58]. A simulation model could be helpful in this situation to give some indication of where fishing effort might move as a result of these restrictions [12].

Finally, the underlying problem in the longline tuna fishery is the amount of subsidies given to fishers that allows them to fish beyond their means and promotes overcapacity [80]. Milazzo estimates that fisheries subsidies are at the level of US$ 14-20 billion per year or 17-25 % of global fishing industry revenues [81]. The countries contributing to this global estimate of fishery subsidies are Japan, the EU, USA, Canada and China (all major participants in the tuna fishery) [81]. As long as fishers are able to fish without having to pay their operating costs themselves, the pressure on fish stocks will continue to increase. Simulations to look at how to manage subsidies would have to be on a per country basis. It would be difficult to examine the fishery as whole in this respect, since effort allocation changes could only be examined when costs of certain fleets were increased. However, a global management body or coherence through RFMOs could potentially improve the lack of control over subsidies.

The results in this study show that most fishers' decisions in choosing where to fish are economically motivated. Factors such as previous profitability in an area as well as perceived profitability to be gained in an area based on abundance and value of fish are important in the location choice process. Using just economic variables in this study rather than more detailed information as in previous studies, we were able to capture the distribution of fishing effort through time indicating that perhaps other variables such as weather, distance, and fuel usage for example are not as significant as profit gained or are somehow captured by the profit function. The results also showed that fishers target certain species depending on their market value. Fishing effort, once the longline fishery was fully developed, generally remained in areas where bigeye and yellowfin were distributed because their ex-vessel prices were much higher than those of the other species. Being able to simulate how the fishery moves through time in such a simple model is valuable in terms of looking at management policies that will regulate all fleets in all areas targeting the same group of species.

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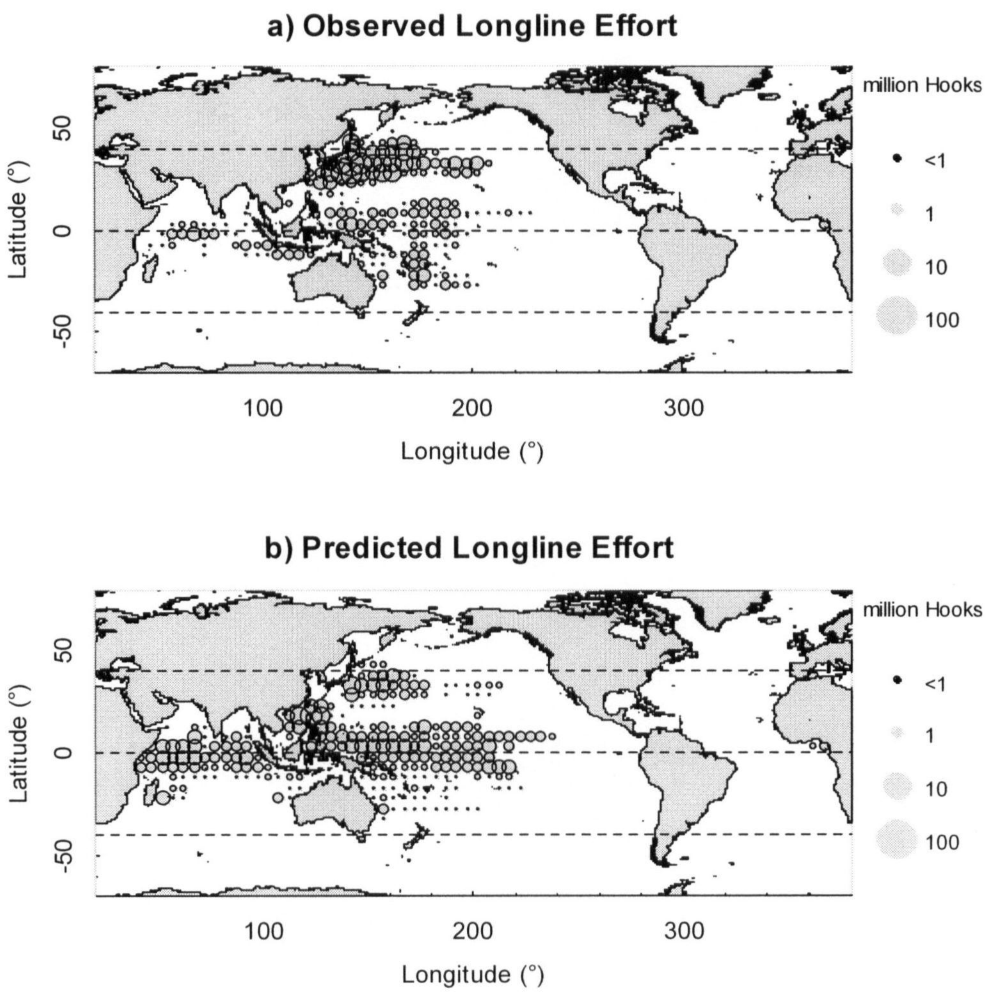
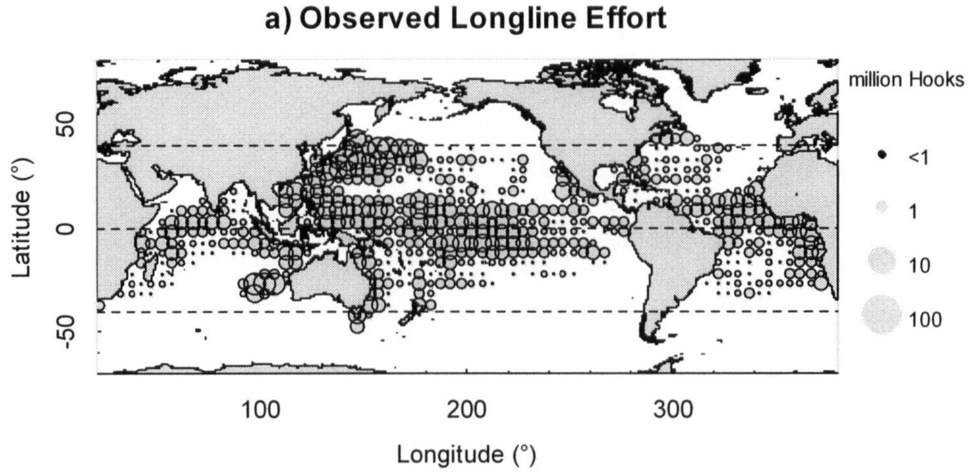
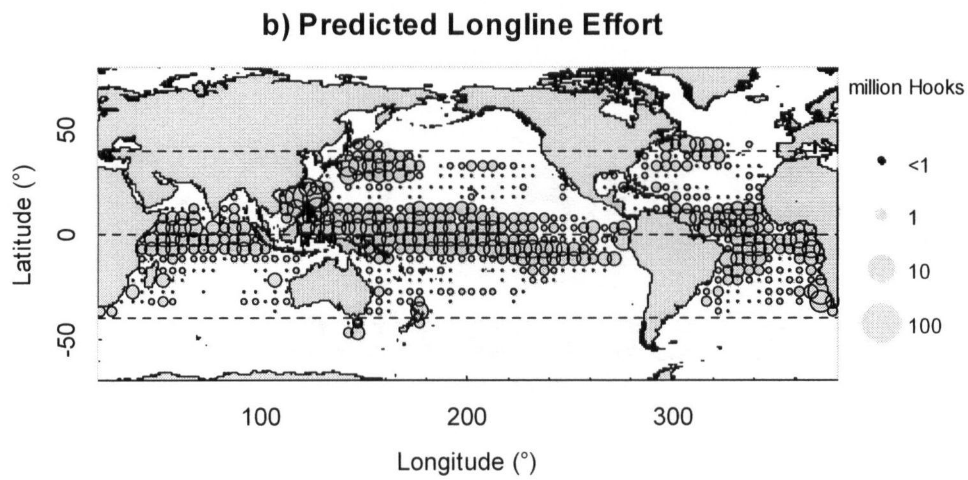
Appendix A Results from Sensitivity Analysis

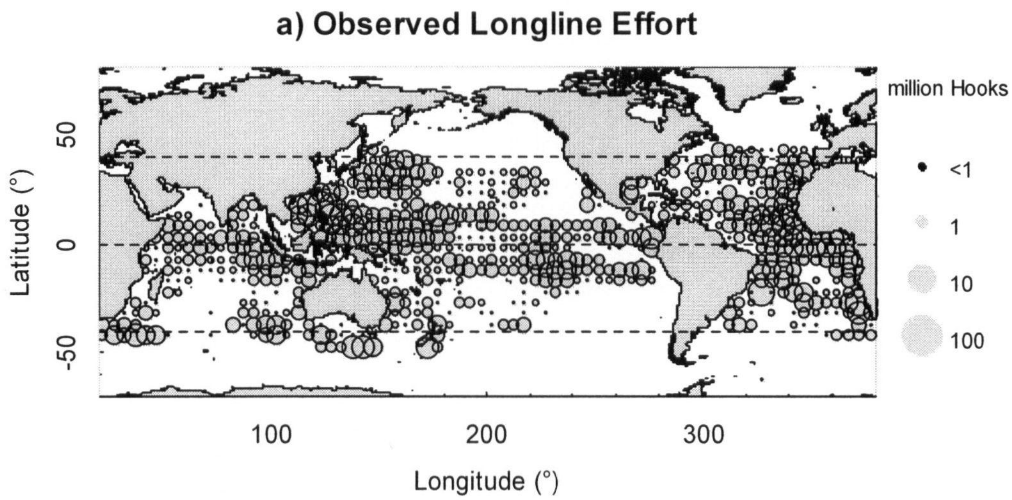


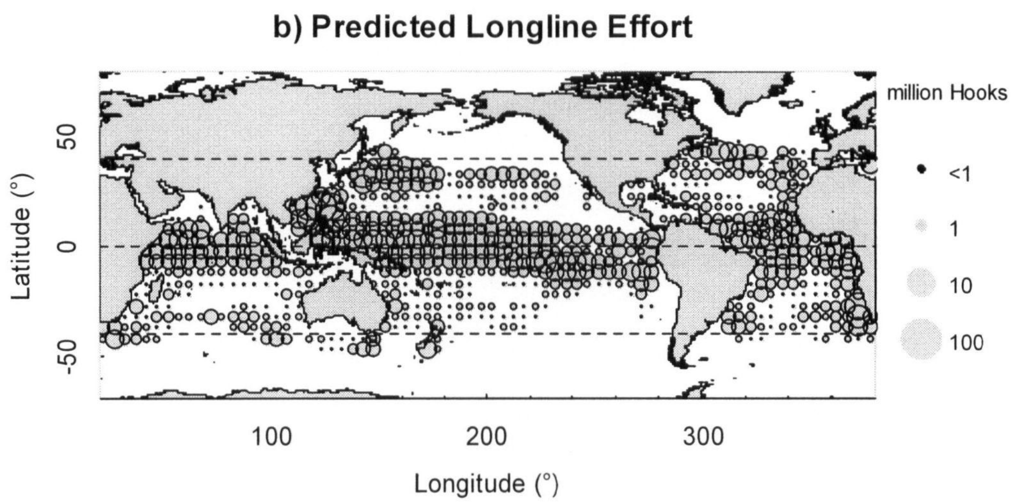
A-1: Observed versus predicted spatial fishing effort using the results from the sensitivity analysis when fishing costs were decreased in areas where bigeye, yellowfin, swordfish and blue marlin abundance was high and increased in areas where bluefin tuna abundance was high for 1955.



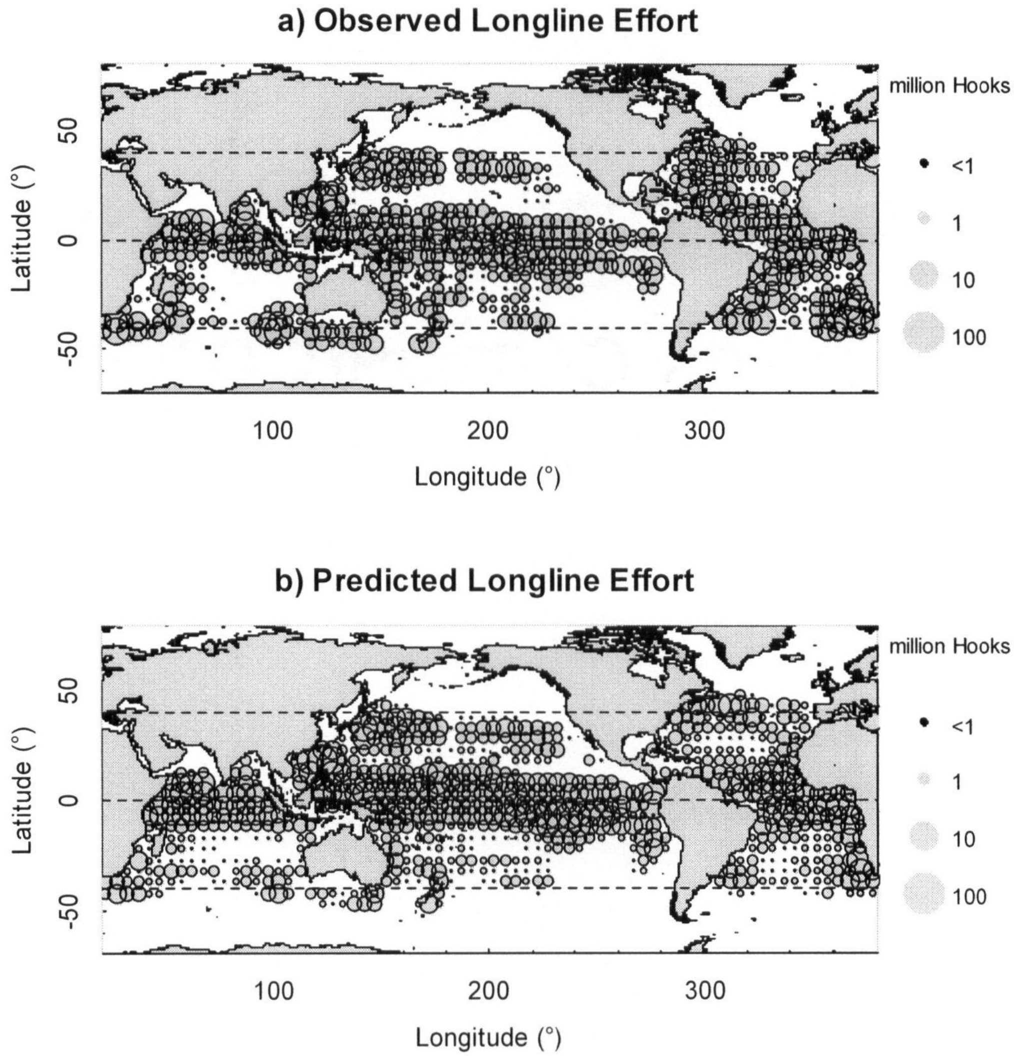


A-2: Observed versus predicted spatial fishing effort using the results from the sensitivity analysis when fishing costs were decreased in areas where bigeye, yellowfin, swordfish and blue marlin abundance was high and increased in areas where bluefin tuna abundance was high for 1965.

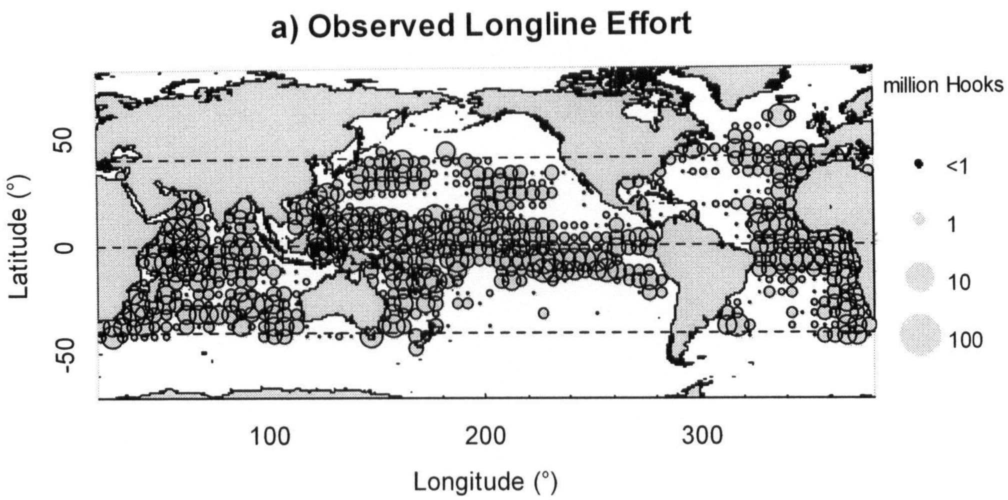


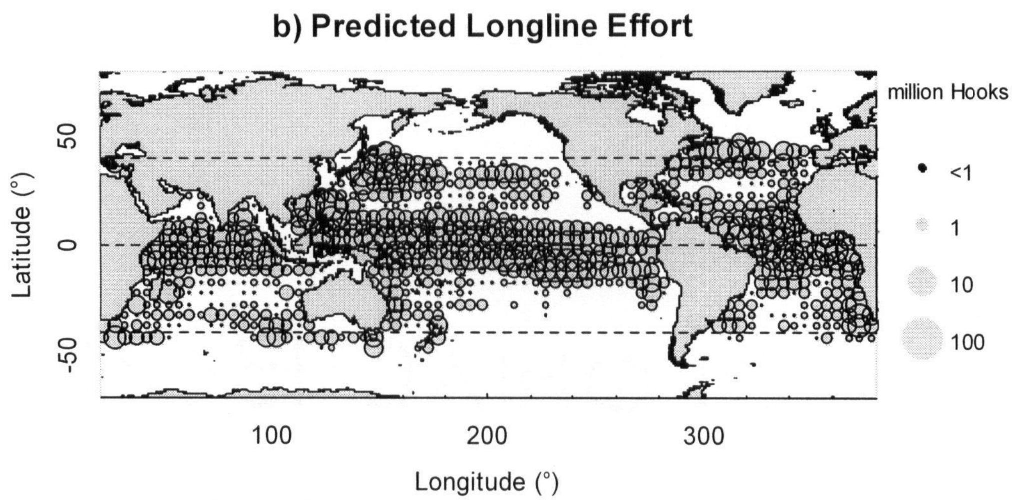


A-3: Observed versus predicted spatial fishing effort using the results from the sensitivity analysis when fishing costs were decreased in areas where bigeye, yellowfin, swordfish and blue marlin abundance was high and increased in areas where bluefin tuna abundance was high for 1975.

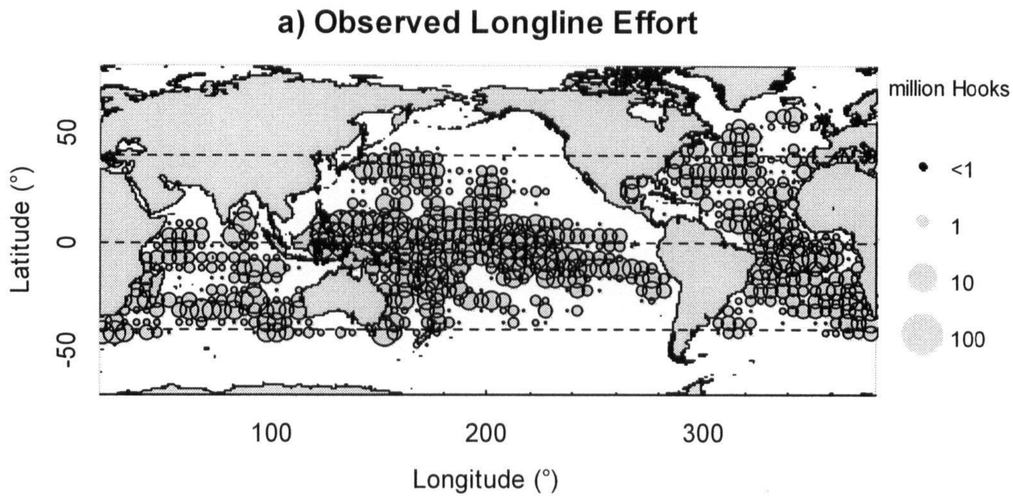


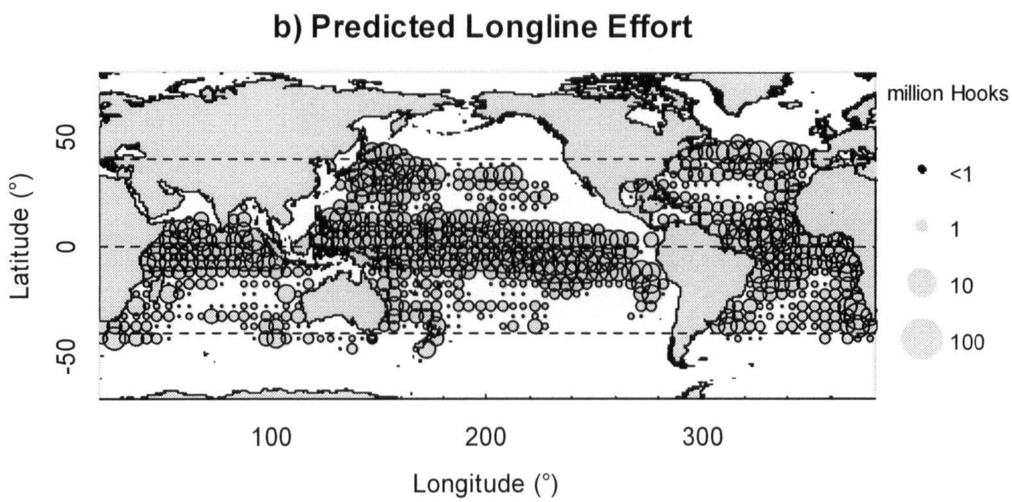
A-4 Observed versus predicted spatial fishing effort using the results from the sensitivity analysis when fishing costs were decreased in areas where bigeye, yellowfin, swordfish and blue marlin abundance was high and increased in areas where bluefin tuna abundance was high for 1985.





A-5: Observed versus predicted spatial fishing effort using the results from the sensitivity analysis when fishing costs were decreased in areas where bigeye, yellowfin, swordfish and blue marlin abundance was high and increased in areas where bluefin tuna abundance was high for 1995.





A-6: Observed versus predicted spatial fishing effort using the results from the sensitivity analysis when fishing costs were decreased in areas where bigeye, yellowfin, swordfish and blue marlin abundance was high and increased in areas where bluefin tuna abundance was high for 2001.