ESSAYS ON THE ECONOMICS OF FISHERIES AND CLIMATE CHANGE

BY

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Abstract

Ocean warming due to anthropogenic climate change results in the spatial redistribution of fish and other marine species. Fish move towards higher latitudes or to deeper waters locating to areas with their desired thermal tolerances. The movement of fish in response to ocean warming affects catch, and these effects are expected to vary across geographic locations. This thesis aims to apply a production function approach to establish the relationship between sea surface temperature (SST) and catch of commercial fisheries using spatial data. The three chapters vary in terms of the area covered and the species and fishing method examined. The first chapter applies the production function approach to model catch and SST using high-resolution gridded data for yellowfin and skipjack tuna catch by purse seine in the Eastern Pacific Ocean (EPO). The results show that yellowfin and skipjack tuna catch is increasing with SST. The magnitude of the marginal product of SST varies across species, type of set, and the location of catch effort. A cross-country comparison of the relationship between SST and tuna for countries' exclusive economic zones in the EPO is presented in the second chapter. We show that the highest marginal revenue products, when adjusted for population, are reported for countries with the highest dependency on marine resources. The third chapter is a national and subnational analysis of the relationship between SST and catch of commercial fisheries in Aotearoa New Zealand, focusing on flatfish, jack mackerel, and trevally. Our results show that catch initially increases with SST but decreases beyond a certain threshold. These essays provide relevant insights for the review of fisheries management systems in response to ocean warming.

To my *Nanay* and *Tatay* (†)

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Chapter 1 Introduction

The increase in ocean temperature observed in the last few decades is a direct consequence of climate change, with some regions warming more than others. This trend is expected to continue into the next century (Bindoff et al. 2019; Doney et al. 2012). Fish populations adapt to ocean warming by moving to higher latitudes or deeper waters leading to changes in marine ecosystems (Perry et al. 2011; Vergés et al. 2019). Fish catch at high latitudes is predicted to increase with ocean temperature, while catch at low and mid latitudes is predicted to decrease, allowing for regional variations (Barange et al. 2014).

This thesis is composed of three chapters that establish the relationship between catch and sea-surface temperature (SST) using the production function approach pioneered by Barbier and Strand (1998). The three chapters have different foci, but present complementary objectives. The area of interest of the three chapters vary in scale as one covers the whole of the Eastern Pacific Ocean (Chapter 2), the other a cross-country comparison of countries' exclusive economic zones within the Eastern Pacific (EPO) (Chapter 3), and the last is national and subnational analysis of Aotearoa New Zealand (Chapter 4).

The application of a production function approach to establish the relationship between SST and catch using high resolution spatial data is our main contribution to the general economic literature. We also motivate and model a quadratic relationship between an environmental variable (i.e., SST) and the carrying capacity of the fishery in the model. In this thesis, we conduct analysis for multiple species and fishing gears that cover expansive areas, as opposed to most studies that focus on a spatially homogenous single species caught by a single method.

In Chapter 2, we apply the production function approach for modelling catch and SST using high-resolution gridded data for yellowfin (*Thunnus albacares*) and skipjack

(*Katsuwonus pelamis*) tuna catch by purse seine in the Eastern Pacific Ocean (EPO). We use gridded catch and effort data for tuna from the Inter-American Tropical Tuna Commission (IATTC), which is matched with gridded SST data from the Japan Meteorological Agency. This chapter contributes to the economic literature by both applying a production function approach to estimate the impact of SST increases through the growth function of tuna species and using high-resolution gridded, species- and fishing method-specific data in the area under the jurisdiction of the regional fisheries management organization. We test for different functional forms (i.e., linear, logarithmic, and quadratic) of the relationship between SST and the carrying capacity of tuna fisheries.

Chapter 3 presents a cross-country comparison of the effects of changes in SST on tuna catch in the countries within the EPO. We use tuna catch and effort data for 1° latitude/longitude grids within the exclusive economic zones of all EPO countries. In this chapter, we compare both the marginal product and marginal revenue product of 1°C increase in SST. This chapter fills a gap in the literature by focusing on the countries in the Eastern Pacific Ocean, as most studies on climate change impacts in the Pacific Ocean focus on countries in the Western and Central Pacific. It also examines the re-distribution of fishery resources between countries in the EPO.

We estimate the relationship between SST and commercial catch of flatfish, jack mackerel, and trevally within Aotearoa New Zealand's exclusive economic zone (EEZ) in Chapter 4. The chapter applies the same framework as the previous chapters and uses a comprehensive data set from the Ministry of Primary Industries, including three fishing methods (bottom trawl, set net, and midwater trawl) and two measures of effort (count and duration). The analysis is conducted both at national and subnational levels using fisheries statistical area as the unit of analysis.

Chapter 2 Sea Surface Temperature and Tuna Catch in the Eastern Pacific Ocean under Climate Change

ABSTRACT

The increase in sea surface temperature (SST) is one of the primary direct consequences of climate change and may lead to large-scale redistributions of global fish catch, including tuna in the Eastern Pacific Ocean (EPO). This paper applies the production function approach for modelling catch and SST using high-resolution gridded data for yellowfin and skipjack tuna catch by purse seine in the EPO. We test different forms of relationship and establish a positive but non-linear (i.e., logarithmic and quadratic) relationship between SST and the carrying capacity of tuna fisheries. By considering the area, species, and fishing methods, we provide spatially and biologically relevant information for the management of tuna in response to warming oceans. We find the increase in yellowfin tuna catch is higher in the Northern Hemisphere compared to the Southern Hemisphere, while overall, the effect of ocean warming on tuna catch has a bigger effect on yellowfin tuna compared to skipjack tuna once we consider all types of purse seine sets. This suggests that, collectively, fishers targeting yellowfin tuna in the EPO will benefit more compared to those targeting skipjack tuna.

2.1. Introduction

The observed increase in ocean temperature over the last few decades due to climate change may lead to large-scale redistributions of global fish catch, with an average of 30–70% increase in high-latitude regions and a drop of up to 40% in the tropics (Bindoff et al. 2019; Cheung et al. 2010). The predicted changes in fish production across latitudes are subject to variations in regions and species, requiring flexible fishery governance with schemes for capacity adjustment, catch limits and alternative livelihoods for fishers (McIlgorm et al. 2009). In the Pacific Ocean, the top two species in terms of share of total catch are skipjack and yellowfin tuna (FAO 2019c), both of which are known to be affected by changes in sea surface temperature (SST).

The effects of SST likely vary across tuna species according to their thermal tolerance (Muhling et al. 2011). Research suggests that ocean warming may increase the suitability of some habitats for skipjack tuna (Muhling et al. 2015), while for yellowfin tuna temperature above a threshold may have adverse effects on cardiac functionality of spawning adults and survival of eggs and larvae (Wexler et al. 2011; Dell'Apa et al. 2018). A large literature on tuna in the Pacific Ocean exists, focusing primarily on the physical effects of SST on spawning and redistribution (see, e.g. Erauskin-Extramiana et al. 2019; Muhling et al. 2017; Pecoraro et al. 2017; Monllor-Hurtado, Pennino, and Sanchez-Lizaso 2017; Lehodey et al. 2013; Schaefer, Fuller, and Block 2007) and the geopolitical implications of shifting tuna stocks (see e.g. Bell et al. 2018; Asch, Cheung, and Reygondeau 2018).

In this study, we use catch and effort data for tuna caught using purse seine available from the Inter-American Tropical Tuna Commission (IATTC)[1] and SST data from the Japan Meteorological Agency to analyse the impact of climate change on tuna fisheries in the Eastern Pacific Ocean (EPO). We focus on the two main target species, skipjack,

[1] IATTC is a regional fishery management organization for the management of tuna in the EPO.

and yellowfin tuna, and the three types of purse seine methods used to catch them, which include dolphin sets, floating object sets, and unassociated sets. We consider the set type as tuna catch may be sensitive not only to the varying biological and behavioural impacts of SST on the target species but also the fishing methods employed (Hu et al. 2018; Asche and Guillen 2012). Dolphin sets are made for large yellowfin tuna associated with dolphins; floating object sets have been the dominant set type for the past 20 years targeting mostly skipjack tuna, and unassociated sets catch both small yellowfin and skipjack (Hall 1998).

Our analysis adds to the economic literature by both applying a production function to estimate the impact of SST increases through the growth function of tuna species; and high-resolution gridded, species- and fishing method-specific data in the area under the jurisdiction of the regional fisheries management organization, the IATTC. Production functions have traditionally been used to establish linkages between the habitat of a fishery and its economic productivity (Barbier 2007). We adapt Barbier and Strand's (1998) bioeconomic model to account for temperature effects on the carrying capacity, and apply annual total tuna catch and effort by 1° latitude/longitude grid cells, while controlling for time-invariant grid effects. We test for the possibility of a linear, logarithmic, and quadratic relationship between SST and the carrying capacity of tuna fisheries, the latter of which is often used in terrestrial production functions. The second contribution focuses on the use of gridded, species- and fishing method-specific data, as opposed to most studies that focus on a spatially homogenous, single species caught by a single method.

We show that catch of skipjack and yellowfin tuna increase with SST in the EPO. The magnitude of the increase in tuna catch as a result of a 1°C increase varies across species, types of sets and distance from the equator. For yellowfin tuna, the largest increase in catch occurs for unassociated sets followed by dolphin sets and floating object sets. A similar pattern can be observed for skipjack tuna, where the largest increases in catch occur for unassociated, floating object and dolphin sets. The increase in yellowfin tuna catch is higher in the Northern Hemisphere compared to the Southern Hemisphere, while the reverse is true for skipjack tuna. We also find that there is a nonlinear (i.e., logarithmic and quadratic) relationship between the SST and the carrying capacity of tuna fisheries.

In the following section, we discuss how climate change affects the ocean and fisheries, specifically focussing on tuna. Then, a description of purse seine and the different type of sets is presented, followed by a discussion of how temperature can be included in economic models. The next section then presents the model we estimate, the data, and the estimation procedure used in the study. We then discuss the results of the analysis, and finish with some concluding remarks.

2.2. Review of Literature

Climate driven changes in ocean conditions affect fisheries and their habitat, such as mangroves, seagrass, and coral reefs (Bell, Ganachaud, et al. 2013). Increasing ocean temperatures may force (some) fish populations to move to higher latitudes or deeper waters and lead to changes in marine ecosystems (Bindoff et al. 2019). These changes in the spatial distribution of fish stocks and the composition of fisheries resources may affect fishing operations and consequently the effectiveness of fisheries management measures (Sumaila et al. 2011). Therefore, the economic consequences of ocean warming vary in different areas and fisheries (e.g., negative impacts may be felt in areas where species move out). Besides declining catch in some places, higher capital costs as fishers need to improve gears and vessels and incur higher fuel, ice, and labour costs due to longer search time are also likely (Sumaila et al. 2011). On the other hand, migration of species into some areas can translate into higher revenue and lower costs. Thus, migration of species may be viewed as negative by fishers in established fisheries and positive in new fisheries (Madin et al. 2012).

Economic analysis of the impacts of ocean warming on fisheries must consider characteristics unique to the individual fisheries such as ocean dynamics, harvesting fleet, and region (Haynie and Pfeiffer 2012). For example, as described by (Hayward 1997), the warming of the ocean off California in the 1970s resulted in a decrease in biomass of anchoveta, an increase for sardines, and no change for mackerel.

Tuna is a commercially important species and it is therefore important for policymakers to understand how climate change affects it. For example, the productivity of phytoplankton is projected to decrease with the increase in ocean temperature affecting both zooplankton and micro nekton through the food chain. Zooplankton are preys of tuna larvae and juveniles and adult tuna feeds on micro nekton (Lehodey et al. 2013). Warming ocean waters may also potentially affect the reproductive success and survival of tuna. Tuna spawning occurs throughout the year in tropical waters and seasonally in subtropical waters in all major oceans (Goujon and Majkowski 2000). Sea temperature has already been shown to be an influential environmental variable affecting spawning and growth of tuna (Pecoraro et al. 2017; Ashida and Horie 2015). Indeed, Monllor-Hurtado, et al. (2017) indicate that there is a poleward movement of tropical tuna populations in response to ocean warming.

Seventy percent of the total global catch of tuna in 2010 came from the Pacific Ocean, composed of mainly skipjack, yellowfin, bigeye, and albacore tuna (Lehodey et al. 2013). Skipjack tuna and yellowfin tuna are the top two species in terms of contributions to total global tuna catch weight in 2010 at 58.1 percent and 26.8 percent, respectively (FAO 2019c). Skipjack tuna prefer warm waters and are usually caught with surface gears and usually with the use of fish aggregating devices (FAD). Skipjack tuna commence spawning when surface temperature exceeds 24°C (Ashida and Horie 2015). Simulations on the effects of climate change have concluded there is a steady increase in the skipjack tuna biomass across the whole Pacific Ocean (Muhling et al. 2015) with a progressive displacement of biomass to the east (Dueri et al. 2016) and to higher latitudes (Lehodey et al. 2013).

For yellowfin tuna, Schaefer, et al. (2007) provided evidence that adults move vertically or horizontally to areas with a SST of around 18°C. Results of experiments showed that water temperatures less than 21°C and more than 33°C are lethal for the yolk sac and larvae of yellowfin tuna (Wexler, Margulies, and Scholey 2011), and water temperature above 30°C reduces the cardiac functionality of spawning adults (Dell'Apa et al. 2018).

The primary method to catch tuna in the Eastern Pacific is by purse seine, which is made of a long wall of netting framed with a lead line and a float line designed to catch schooling fish (Bayliff 2001). Purse seine sets are classified based on the way tunas are detected and encircled. The types of purse seine sets recorded in the Inter-American Tropical Tuna Commission (IATTC) dataset include dolphin sets, floating object sets, and unassociated sets.

Dolphin sets are made for tuna that associate with dolphins, mostly large yellowfin tuna. When fishers detect a group of tuna swimming with dolphins, they use the purse seine to encircle and capture them (this method is controversial due to the incidental mortality of dolphins). Floating object sets use fish aggregating devices (FAD) – natural (e.g. logs, branches) or man-made floating objects that may be drifting or anchored on the ocean floor (Girard, Benhamou, and Dagorn 2004). The composition of catch using floating object sets is a mixture of skipjack, bigeye, and yellowfin, with skipjack as the dominant species (Bayliff 2001). Unassociated sets are used to target tuna in association with other species. Hall and Roman (2013) prefers to call this type of sets school sets, given that tuna are caught in association with schools of different species and seabirds. This type of set usually catches small-sized yellowfin and skipjack tuna (Hall 1998). Tuna production input and outputs are affected by the differences in the behaviour of target tuna species depending on the type of set used. There is, therefore, a need to consider both the fishing methods and the target species in any analysis of tuna catch (Hu et al. 2018; Asche and Guillen 2012).

In terrestrial systems, the link between temperature and different economic outcomes has been extensively studied, i.e. temperature is treated as a productive input that explains variations in aggregate (macroeconomic) output (see e.g. Burke, Hsiang, and Miguel 2015; Zivin and Neidell 2014; Dell, Jones, and Olken 2014; Hsiang 2010; Jones and Olken 2010; Deschenes and Greenstone 2007) or output of specific crops (see e.g. Gupta, Sen, and Srinavasan 2014; Schlenker and Roberts 2009). The production function approach in fisheries, however, has been applied to establish linkages between the habitat of a fishery and its economic productivity. Most of these studies apply a static model based on the assumption that the fishery is in a long-run equilibrium (Barbier 2007). This has been applied to linkages of mangrove and shrimp catch in Mexico (Barbier and Strand 1998), mangrove and artisanal demersal and shellfish fisheries in Thailand (Barbier et al. 2002), and cold water coral and redfish catch in Norway (Foley et al. 2010). The inclusion of environmental factors through the application of the fisheries production function is the subject of a growing body of literature (see Vondolia et al. 2019; Armstrong et al. 2017; Kahui, Armstrong, and Vondolia 2016; Armstrong et al. 2016; Hassan and Crafford 2015) but to date has not been applied to tuna fisheries.

The basic model includes two key variables in the growth function of the fish species: the intrinsic growth rate, and the carrying capacity. The intrinsic growth rate defines the rate at which the stock grows as the stock goes to zero while the carrying capacity of the environment determines the largest possible fish stock size given food supplies, habitat, and other factors (Anderson and Seijo 2010). Barbier and Strand (1998) developed a model to demonstrate how an environmental factor, specifically habitat, directly affects the carrying capacity. Foley et al. (2010) extended the model and showed that the environmental factor also indirectly affects the carrying capacity through the intrinsic growth rate. In this paper we extend the theoretical premise of the production function by including SST as a factor in the growth function of tuna. Both feeding and spawning are a function of SST (Lehodey et al. 2013; Pecoraro et al.

2017; Ashida and Horie 2015; Goujon and Majkowski 2000) and can therefore be understood to affect the carrying capacity for tuna. In addition, an important feature of papers examining terrestrial systems is that they establish a quadratic relationship between temperature and economic outcomes (see Gupta, Sen, and Srinavasan 2014; Schlenker and Lobell, 2010). In fisheries, nonlinear relationships are tested only so far as to apply a logarithmic function to model a concave relationship between the environmental input and carrying capacity (Barbier, Strand, and Sathirathai 2002). We extend the production function approach in fisheries by testing for the presence of a quadratic relationship between SST and tuna catch.

2.3. Fisheries Production Function

In the section below we follow Foley et al.'s (2010) exposition of the fisheries production model (based on Barbier and Strand, 1998), but include SST instead of habitat to affect both the intrinsic growth rate and the carrying capacity, as well as testing for a quadratic relationship between SST and the carrying capacity of tuna.

Static Fishery Model

We define X_{it} as the fish stock of tuna, T_{it} as SST, and E_{it} as fishing effort in grid i at time t. The change in the stock of tuna is expressed as

$$X_{it+1} - X_{it} = F(X_{it},\, T_{it}) - h(X_{it}, E_{it}), \qquad F_X > 0,\;\; h_X > 0. \tag{1}$$

The net change in the tuna stock is determined by the difference between biological growth, $F(X_{it},\, T_{it})$, and harvesting, $h(X_{it}, E_{it})$, where biological growth is assumed to follow a logistic growth function. Foley et al. (2012) provide an overview of bioeconomic fisheries-habitat interactions and we follow Foley et al.'s (2010) exposition of the fisheries production model to include SST (instead of habitat) to affect both the intrinsic growth rate and the carrying capacity.

$$F(X_{it},\ T_{it}) = r[K(T_{it})X_{it} - X_{it}^2] \tag{2}$$

The variables r and K denote the intrinsic growth rate and the carrying capacity, respectively. Harvesting is a function of stock and effort and we assume the basic Gordon-Schaefer function

$$h(X_{it}, E_{it}) = qX_{it}E_{it} \tag{3}$$

where q is the constant catchability coefficient.

Substituting Equations (2) and (3) into Equation (1) we get

$$X_{it+1} - X_{it} = \{r[K(T_{it}) - X_{it}] - qE_{it}\} X_{it}. \tag{4}$$

Long run harvest function

In equilibrium, $X_{it+1} = X_{it} = X_i$ equation (4) can be solved for the steady state stock size, which is substituted into equation (3) and rearranged to derive the long run harvest function (Barbier and Strand (1998); Foley et al. (2010)).

$$h_{it} = qK(T_{it})E_{it} - \frac{q^2}{r}E_{it}^2. \tag{5}$$

As mentioned above, applications in the habitat-fisheries model typically assume a linear and/or a logarithmic relationship between the carrying capacity and habitat. We restate the functional form and extend the model by developing and testing for a quadratic function as shown below.

Linear

Barbier and Strand (1998) and Foley et al. (2012) assume a linear relationship between carrying capacity K and SST, such that $K(T_{it}) = \alpha T_{it}$ for $\alpha > 0$ and equation (5) can be expressed as

$$h_{it} = q\alpha T_{it} E_{it} - \frac{q^2}{r} E_{it}^2. \tag{6}$$

or

$$h_{it} = b_1 T_{it} E_{it} + b_2 E_{it}^2 \tag{7}$$

where $b_1 = q\alpha$ and $b_2 = -\frac{q^2}{r}$.

Logarithmic

Barbier, et al. (2002) apply a logarithmic function, such that $K(T_{it}) = \alpha \ln T_{it}$. Equation (5) may be expressed as

$$h_{it} = q\alpha \ln T_{it} E_{it} - \frac{q^2}{r} E_{it}^2. \tag{8}$$

or

$$h_{it} = b_1 \ln T_{it} E_{it} + b_2 E_{it}^2. \tag{9}$$

where $b_1 = q\alpha$ and $b_2 = -\frac{q^2}{r}$.

Quadratic

We then extend the model to assume a quadratic relationship between SST and carrying capacity, such that $K(T_{it}) = \alpha_1 T_{it} + \alpha_2 T_{it}^2$.

Equation (5) may be expressed as

$$h_{it} = q\alpha_1 T_{it} E_{it} + q\alpha_2 T_{it}^2 E_{it} - \frac{q^2}{r} E_{it}^2. \tag{10}$$

or

$$h_{it} = b_1 T_{it} E_{it} + b_2 T_{it}^2 E_{it} + b_3 E_{it}^2 \tag{11}$$

where $b_1 = q\alpha_1$, $b_2 = q\alpha_2$ and $b_3 = -\frac{q^2}{r}$.

The quadratic specification subsumes the linear functional form. The use of a quadratic specification allows the identification of the inflection point, a level of temperature at which fish catch starts to decrease due to increasing temperature. The identification of this "optimal" level of temperature is necessary because the thermal tolerances of fish have an upper limit.

2.4. Model and Estimation Procedure

Firstly, assuming the linear relationship between SST and carrying capacity, we estimate the following equation derived from Equation (7)

$$Tuna_{it} = \beta_1 Sets_{it} * SST_{it} + \beta_2 Sets_{it}^2 + \beta_3 t + \sum_{g=2}^{n} \gamma_g D_g + \varepsilon_{it} \qquad (12)$$

$Tuna_{it}$ is the amount of tuna caught in grid i in year t, $Sets_{it}$ is the number of sets in grid i in year t, which is a measure of effort, SST_{it} is the annual mean SST in grid i in year t, $Sets_{it}^2$ is the square of $Sets_{it}$, D_g is dummy for 1° latitude/longitude grid, ε_{it} is the error term, and α, β, and γ are coefficients. The values of $Tuna_{it}$ and $Sets_{it}$ are expressed in per square kilometre to account for differences in the surface area of grids. The model also includes a time trend, t, to account for technological progress. A year trend was preferred over a year dummy as we do not want t to capture the year-to-year changes from SST. The estimation also showed that models with a time trend have higher R^2 compared to models without. The grid dummy accounts for the time-invariant, grid-specific factors affecting the tuna catch such as area, location, and bathymetry.

The analysis is run as a regression through the origin (RTO) to handle the unrealistic possibility of positive output of tuna without fishing effort. RTO was also implemented in fisheries production functions by Armstrong et al. (2016), Thanh Thuy and Flaaten (2013), and Foley et al. (2010). A synthesis of the literature on RTO approach in modelling is provided in Eisenhauer (2003).

The measure of effort, *Sets*, is the frequency purse seine nets are deployed in a latitude/longitude grid for a given year and type of set. *Sets* is proportionally adjusted for the volume of yellowfin and skipjack caught within a set. This is done to isolate species-specific effort because purse seine catch different species in each set. A similar adjustment to effort was done in Foley et al. (2010). We assume that fishers give equal importance to yellowfin and skipjack tuna consistent with the effort proportion allocation procedure used in Wang et al (2015).

The marginal product of SST at means, MP_{SST}, is derived from Equation (12):

$$MP_{SST} = \frac{\partial Tuna}{\partial SST} = \beta_1 Sets. \tag{13}$$

Secondly, we assume a logarithmic relationship between SST and carrying capacity (see Equation (9)):

$$Tuna_{it} = \beta_1 Sets_{it} * lnSST_{it} + \beta_2 Sets_{it}^2 + \beta_3 t + \sum_{g=2}^{n} \gamma_g D_g + \varepsilon_{it} \tag{14}$$

Accordingly, the MP_{SST} at means is

$$MP_{SST} = \frac{\partial Tuna}{\partial SST} = \beta_1 \frac{Sets}{SST}. \tag{15}$$

Finally, as derived from Equation (11), we assume a quadratic relationship between SST and carrying capacity.

$$Tuna_{it} = \beta_1 Sets_{it} * SST_{it} + \beta_2 Sets_{it} * SST_{it}^2 + \beta_3 Sets_{it}^2 + \beta_4 t + \sum_{g=2}^{n} \gamma_g D_g + \varepsilon_{it} \tag{16}$$

and the MP_{SST} at means is computed as

$$MP_{SST} = \frac{\partial Tuna}{\partial SST} = \beta_1 Sets + 2\beta_2 SST * Sets. \tag{17}$$

We use an unbalanced annual panel data for 1° latitude/longitude grid of fished areas in the Eastern Pacific Ocean from 1970 to 2018.[2] Only those grid cells that contained catch and effort data are included in the analysis. Separate estimations are performed for observations grouped by species, types of set, and by distance from the equator (by latitude group) with standard errors clustered on a 1° latitude/longitude grid.[3]

2.5. Data

We focus on the agreement area of the Inter-American Tropical Tuna Commission (IATTC), which is the portion of Pacific Ocean east of 150°W up to the coastline of North, Central, and South America and between 50°N and 50°S as defined in the Antigua Convention. We refer to this area as the Eastern Pacific Ocean (EPO).

Publicly available tuna catches and effort data for purse seine were obtained from the website of IATTC, showing monthly tuna catches and number of sets by purse seine vessels in every 1°latitude/longitude grid within the EPO. Catch and effort data were disaggregated by set type and by species of tuna caught (IATTC 2018). Annual totals of both catch and effort were computed for every grid and expressed in per square kilometre to account for the differences in the area of the 1°latitude/longitude grid.

SST analyses typically use in situ observations from ships and buoys (Huang et al. 2018). Monthly SST observations for a 1° latitude/longitude grid from 1970 to 2018 were obtained from the Centennial In Situ Observation-Based Estimates of the Variability of SST and Marine Meteorological Variables, version 2.9.2 (COBE-SST2) by

[2] Parameter estimation was done using monthly data and including a dummy variable for the months in the model. We considered the use of monthly data as tuna spawn all throughout the year in tropical areas (Schaefer 2001), however, estimations using annual data show consistently higher R2 values compared to models that use monthly data, thus only the results of annual data are presented.

[3] Panel fixed effects estimation was also considered to control for time-invariant grid level effects and to test for robustness of the results. The use of panel fixed effects model has many advantages including its capacity to control for the effects of omitted variables (Wooldridge 2010). However, the estimation procedure for this model does not allow for an RTO model.

the Japan Meteorological Agency (JMA) (Hirahara, Ishii, and Fukuda 2014).[4] Satellite observations were used by JMA for the reconstruction of SST variability in data sparse regions. We computed the annual averages of SST for each grid using the data from COBE-SST2.

2.6. Summary Statistics

The waters of the Eastern Pacific Ocean are warming over time as shown by the upward trend in the annual mean SST in the IATTC convention area based on the COBE-SST2 data (Figure 2.1). Four of the highest five annual average SSTs were recorded in the last five years. This trend is consistent with records of increased sea temperature driven by anthropogenic climate change.

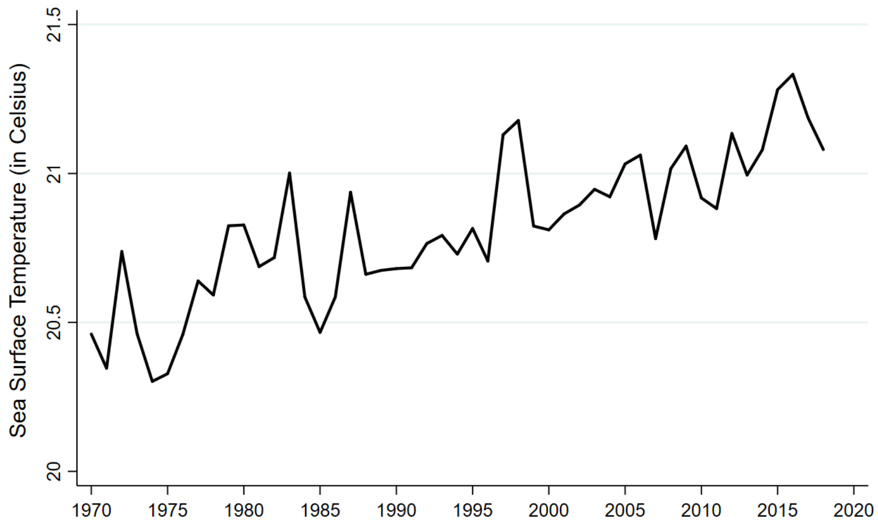


Figure 2. 1. Average annual sea surface temperature in IATTC Convention Area
Data Source: COBE-SST2.

The tuna catch of purse seine in the EPO based on the IATTC data is composed of skipjack, yellowfin, bigeye, black skipjack, bonito, Pacific bluefin tuna, albacore tuna,

[4] COBE-SST2 data used in this study was taken from NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site at https://www.esrl.noaa.gov/psd/.

and some unidentified tuna. Tuna is caught mostly in areas near the equator and closer to the shore (Figure 2.2). Catch within 10° latitude distance from the equator accounts for 64 percent of the catch in the EPO from 1970 to 2018. The average annual catch of tuna is highest near coastal areas in the Southern Hemisphere. Yellowfin tuna comprise 58.7 percent while skipjack tuna comprise 30.8 percent of the total tuna catch. Between 1970 and 2004, yellowfin tuna accounted for the biggest share in terms of total catch, however, since 2003 the share of skipjack tuna catch has started to dominate yellowfin (Appendix Figure 2.2a).

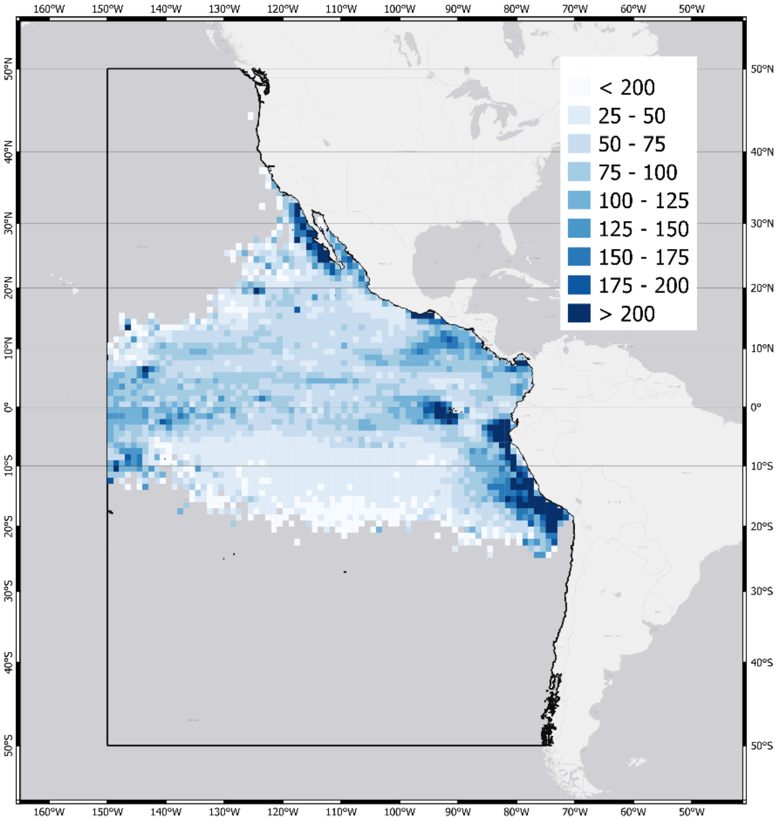


Figure 2. 2. Average Annual Tuna Catch in Eastern Pacific (in metric tons), 1970-2018 [5]

Data Source: Inter-American Tropical Tuna Commission (IATTC)

[5] We used geospatial data from United Nations Food and Agriculture Organization GeoNetwork for the IATTC Convention Area (FAO 2019b) and 1° latitude/longitude grids (FAO 2018b).

The differences in the spatial distribution of catch are apparent when we examine yellowfin and skipjack separately (Figure 2.3). The average annual catch of yellowfin tuna is higher in areas in the Northern Hemisphere compared to areas in the Southern Hemisphere while for skipjack tuna the opposite is true, i.e., the skipjack catch is higher in the Southern Hemisphere. The differences in the distribution of catch across space support the need to conduct separate analysis by species and location group.

a) Yellowfin Tuna **b) Skipjack Tuna**

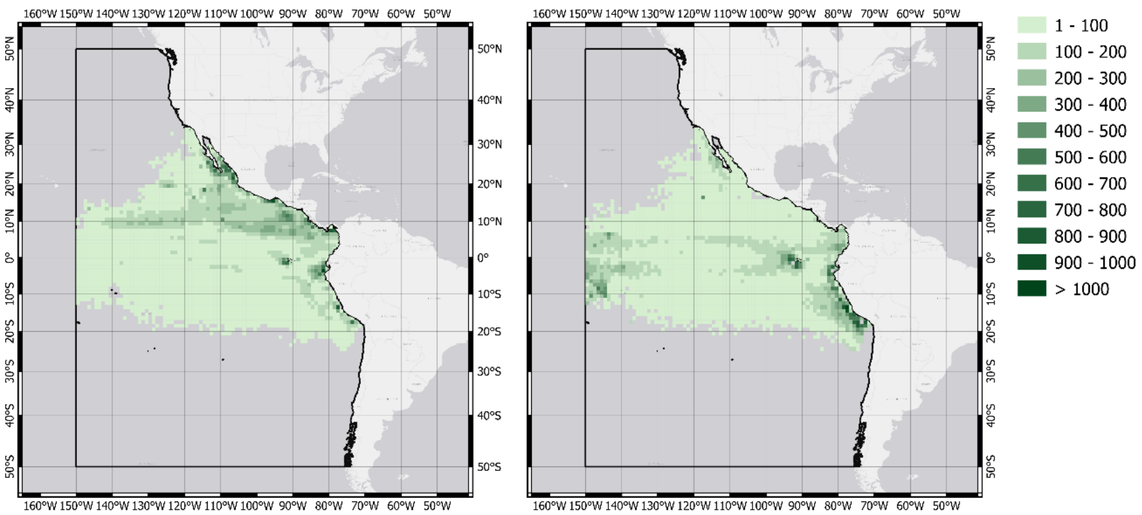


Figure 2. 3. Average Annual Catch of Yellowfin and Skipjack Tuna in Eastern Pacific (in metric tons), 1970-2018

Data Source: Inter-American Tropical Tuna Commission (IATTC)

The largest proportion of purse seine sets are recorded in grids closer to the shore (Figure 2.4). A high concentration of dolphin sets are recorded in the Northern Hemisphere, while most of the floating object sets are in areas close to the equator. For unassociated sets, effort is distributed across latitudes but clustered near the shores.

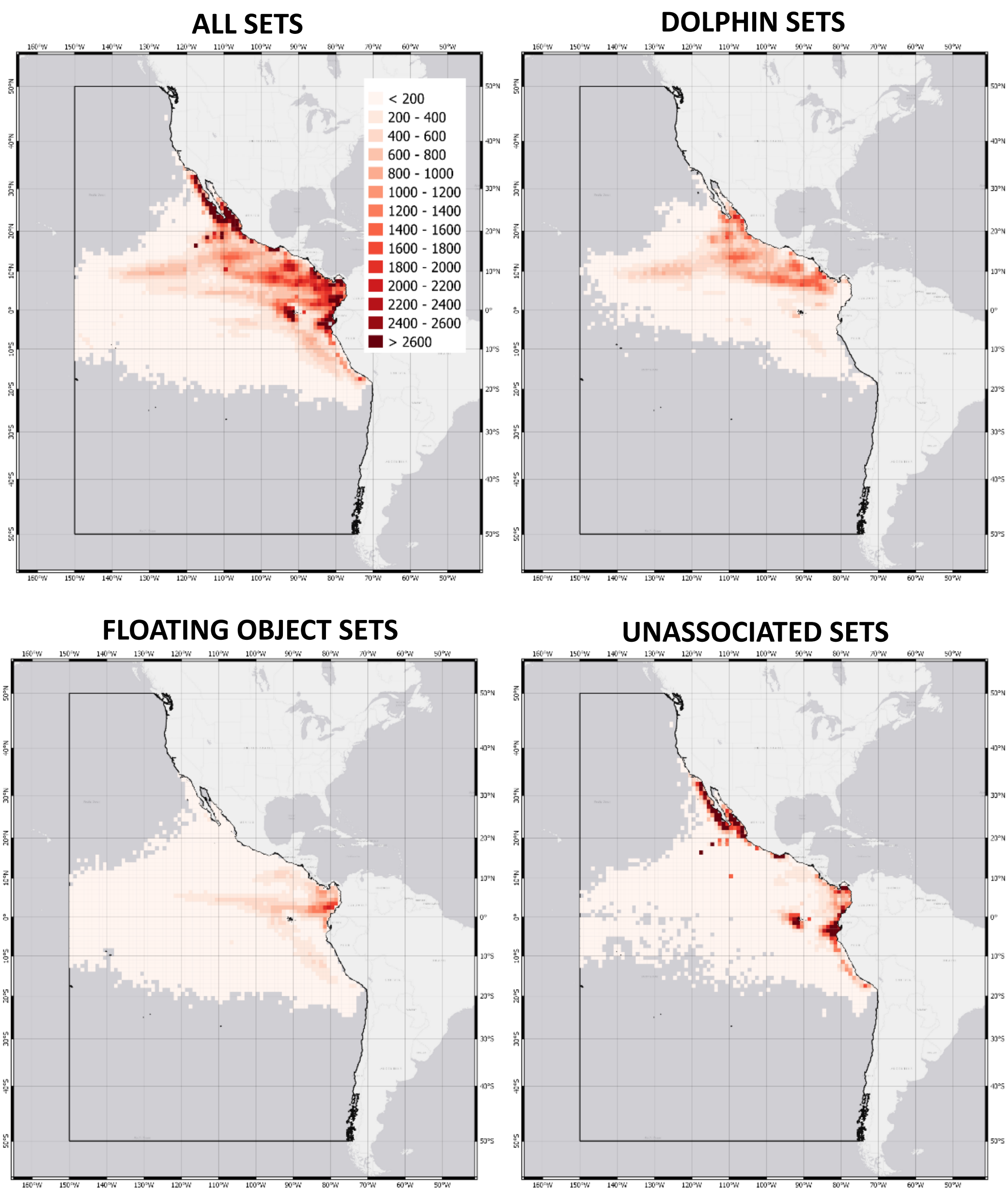


Figure 2. 4. Total Number of Purse Seine Sets in Eastern Pacific, 1970-2018

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Table 2.1 shows the summary statistics for catch and effort data by species, types of set, and location. Unassociated sets have the highest count in terms of effort, but the lowest catch per unit effort, making it a less preferred method more recently. In the early 1970s, most of the sets were made for unassociated schools of tuna, but their share has been decreasing over time (see Appendix Figure 2.1). The share of dolphin associated sets increased until 1992, after which floating-object associated sets have become the dominant set type due to the introduction of FADs in purse seine fishing in the EPO (IATTC, 2018b; Bayliff, 2001). The high catch per set for floating objects sets explains the dominance of this type of set in the later years, i.e., floating object sets have the highest catch per set at 25.9 metric tons followed by dolphin sets and unassociated sets at 15.3 and 11.7 metric tons, respectively.

Yellowfin tuna is the primary target species of dolphin sets, comprising 98 percent of the total catch from 1970 to 2018 (Table 2.1). For floating object sets, skipjack tuna accounts for 55 percent of the total catch. Skipjack and yellowfin are the also the main species caught by unassociated sets, however, the species composition has changed from a majority of yellowfin to skipjack over time (see Appendix Figure 2.2d).

Table 2. 1. Descriptive statistics of Tuna Catch in Eastern Pacific, 1970-2018

	Number of Sets	Catch (metric tons)	Catch per Set (metric tons)	Percentage Distribution of Catch by Species		
				Yellowfin	Skipjack	Other Species
TYPE OF SET						
All sets	**1,222,829**	**20,097,086**	**16.4**	**58.7**	**30.8**	**10.5**
Dolphin sets	451,112	6,884,432	15.3	98.0	2.0	0.0
Unassociated sets	477,009	5,593,239	11.7	44.9	48.8	6.3
Floating object sets	294,708	7,619,415	25.9	25.2	55.0	19.8
LATITUDE GROUP						
40°N to 50°N	1	3	3.0	0.0	0.0	100.0
30°N to 40°N	18,782	167,548	8.9	13.9	17.7	68.5
20°N to 30°N	170,117	1,635,520	9.6	75.9	16.7	7.3
10°N to 20°N	267,778	3,737,941	14.0	89.2	10.3	0.4
0° to 10°N	443,459	8,028,779	18.1	59.6	32.9	7.5
0° to 10°S	258,861	4,846,237	18.7	34.5	49.0	16.5
10°S to 20°S	62,824	1,646,735	26.2	30.0	48.3	21.7
20°S to 30°S	1,007	34,323	34.1	21.3	47.9	30.8

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Table 2.1 also shows that there are more sets and a higher total catch in the Northern Hemisphere but catch per set is higher in the Southern Hemisphere. Yellowfin is the dominant species caught by purse seine in the Northern Hemisphere. The total share of yellowfin tuna catch is higher in subtropical areas (10°N to 20°N and 20°N to 30°N) compared to areas close to the equator (0° to 10°N). In the Southern Hemisphere, skipjack tuna is the dominant species caught by purse seine.

2.7. Results

The computed MP_{SST} at means for yellowfin and skipjack tuna by type of sets using all data for the EPO and period covered are presented in Figure 2.5. The values presented are in metric tons per square kilometre of fished area. The MP_{SST} is computed using Equation 13 for an assumed linear relationship between SST and carrying capacity, Equation 15 for logarithmic, and Equation 17 for quadratic. Only the parameter estimates which are statistically significant at 5 percent are considered in the calculation of the marginal products.

The results of the estimation of parameters of the production function, mean SST, and mean number of sets are presented in Appendix Tables 2.1 to 2.3. The coefficients were estimated separately for yellowfin and skipjack tuna using observations for fished areas with reported dolphin sets, floating object sets, unassociated sets, and all sets. The R^2 for all specifications are high (>0.78). Models assuming logarithmic and quadratic relationships between the SST and carrying capacity, however, have higher R^2 compared to models assuming a linear relationship.

Figure 2.5 shows that the MP_{SST} are mostly positive for the models using the three assumed relationships between SST and the carrying capacity, and for the different set types. The exceptions are the MP_{SST} for skipjack tuna assuming a quadratic relationship with zero values. The MP_{SST} is highest for a linear relationship and lowest for a quadratic relationship.

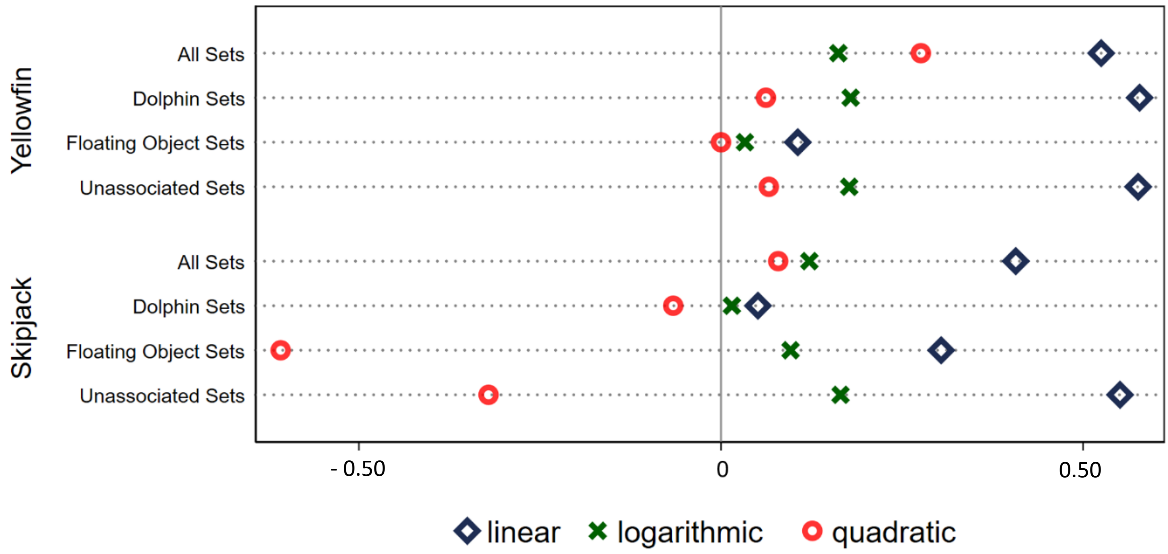


Figure 2. 5. Marginal product of SST per square km (in kilograms)

The increase in SST has a bigger effect on the catch of yellowfin tuna compared to skipjack tuna if we consider all sets. Assuming a logarithmic relationship between SST and carrying capacity, a one-degree Celsius increase in SST results in an increase of 0.162 kilograms of yellowfin tuna catch per square kilometre of fished area per year for all sets made. This is equivalent to 25.2 thousand metric tons (60.7 million USD)[6] per year for the fished area in EPO. Even though the MP_{SST} per square kilometre for floating object sets (0.03) is lower compared to dolphin sets (0.18), the total MP_{SST} for the fished area is almost the same at 30 thousand metric tons (73 million USD) per year. This is because the area fished with floating objects sets is far greater than the area fished with dolphin sets. For skipjack tuna, the MP_{SST} is 0.122 kilograms of

[6] Based on ex-vessel prices of whole yellowfin (2.40 USD per kilogram) and whole skipjack (1.48 USD per kilogram) Ecuador as of January 2019 as reported in the FAO (2019a).

skipjack tuna per square kilometre, equivalent to 20 thousand metrics tons (29 million USD) per year for the EPO. The highest MP_{SST} for the fished area is for floating objects set at 28 thousand metric tons (42 million USD) per year, followed by dolphin sets at 20 thousand metric tons (30 million USD) per year and unassociated sets at 17 thousand metric tons (25 million USD) per year.

The MP_{SST} at means computed by latitude group for both yellowfin and skipjack tuna are presented Figure 2.6. The results for the estimation, mean SST, and mean number of sets for observations grouped by type of set and latitude groups are presented in Appendix Tables 2.4 to 2.6 for yellowfin tuna and Appendix Tables 2.7 to 2.9 for skipjack tuna. Only latitude groups with substantial observations (N>300) are presented in the figures and appendix tables.

Assuming a linear or logarithmic relationship between SST and carrying capacity, the MP_{SST} is positive for all types of sets and latitude groups. The results change, however, if we assume a quadratic relationship. Even though there are still areas where the MP_{SST} is positive, there are also areas where the MP_{SST} is either zero or negative. The values of MP_{SST} vary across space, with higher values recorded in areas farther away from the equator (Figure 2.6).

For yellowfin tuna, the MP_{SST} in areas in the Northern Hemisphere is higher compared to the areas in the Southern Hemisphere. This is true across all types of sets, with highest values in areas between 20°N and 30°N. The MP_{SST} in the Southern Hemisphere are higher compared to areas north of the equator for skipjack tuna.

The MP_{SST} at means for all sets in Eastern Pacific Ocean 1° latitude/longitude grid are mapped in Figure 2.7 for yellowfin tuna and Figure 2.8 for skipjack tuna. The values presented are the computed MP_{SST} multiplied by the area of the grid in square kilometre. Values are presented in thousand metric tons. The MP_{SST} are computed assuming linear, logarithmic, and quadratic relationships between SST and carrying capacity.

Figure 2. 6. Marginal product of SST by latitude group (in x10-4 metric tons)

Figures 7 and 8 clearly highlight the spatial variation in the MP_{SST} for both yellowfin and skipjack tuna. Higher values are recorded in areas above the equator for yellowfin tuna and below the equator for skipjack tuna. The figure also shows areas closer to the coast have higher MP_{SST} compared to areas in the high seas. The highest MP_{SST} for all sets are reported if we assume a linear relationship between SST and carrying capacity both for both tuna species.

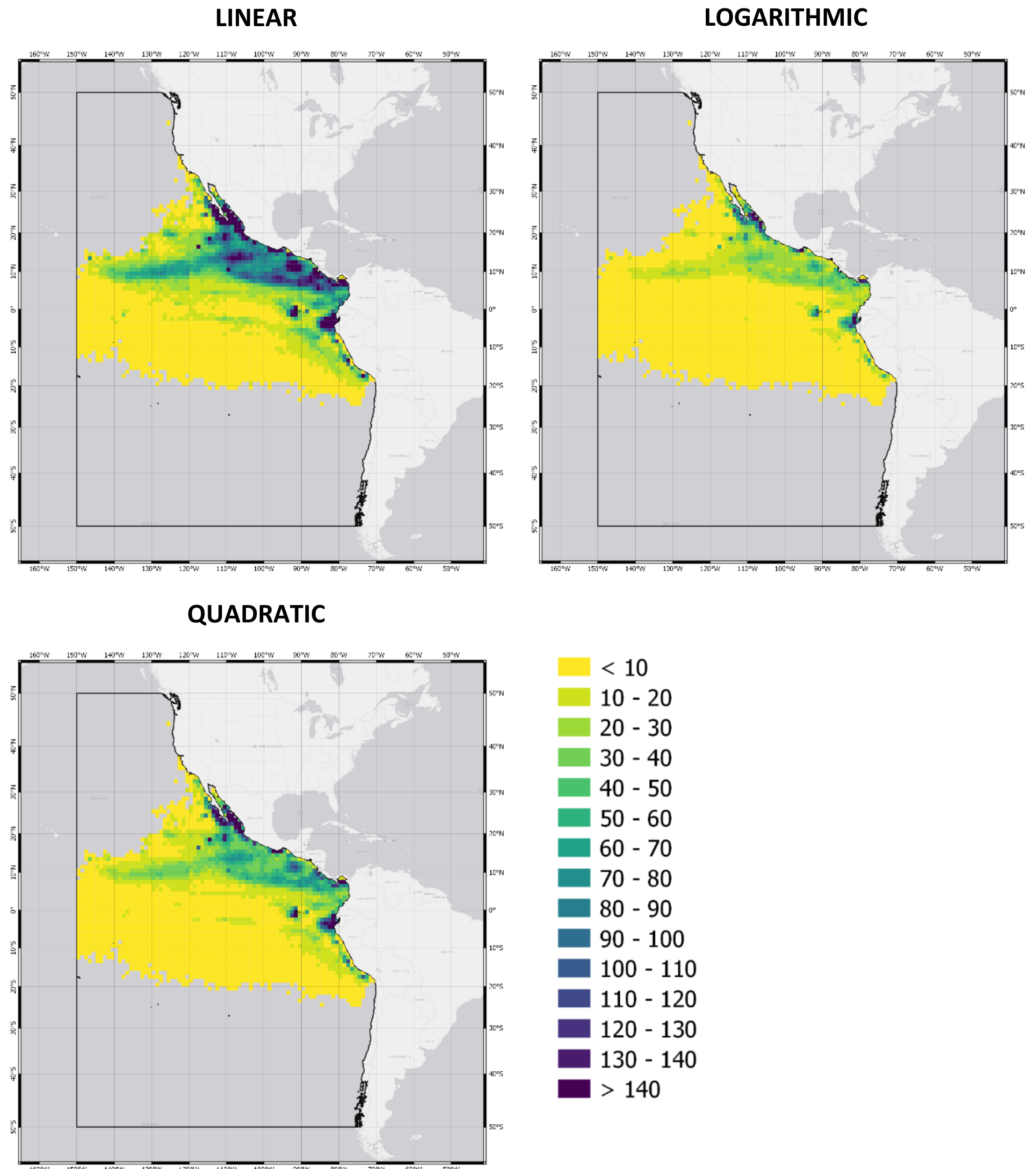


Figure 2. 7. Marginal product of SST at means of yellowfin tuna for all sets (in `000 metric tons)

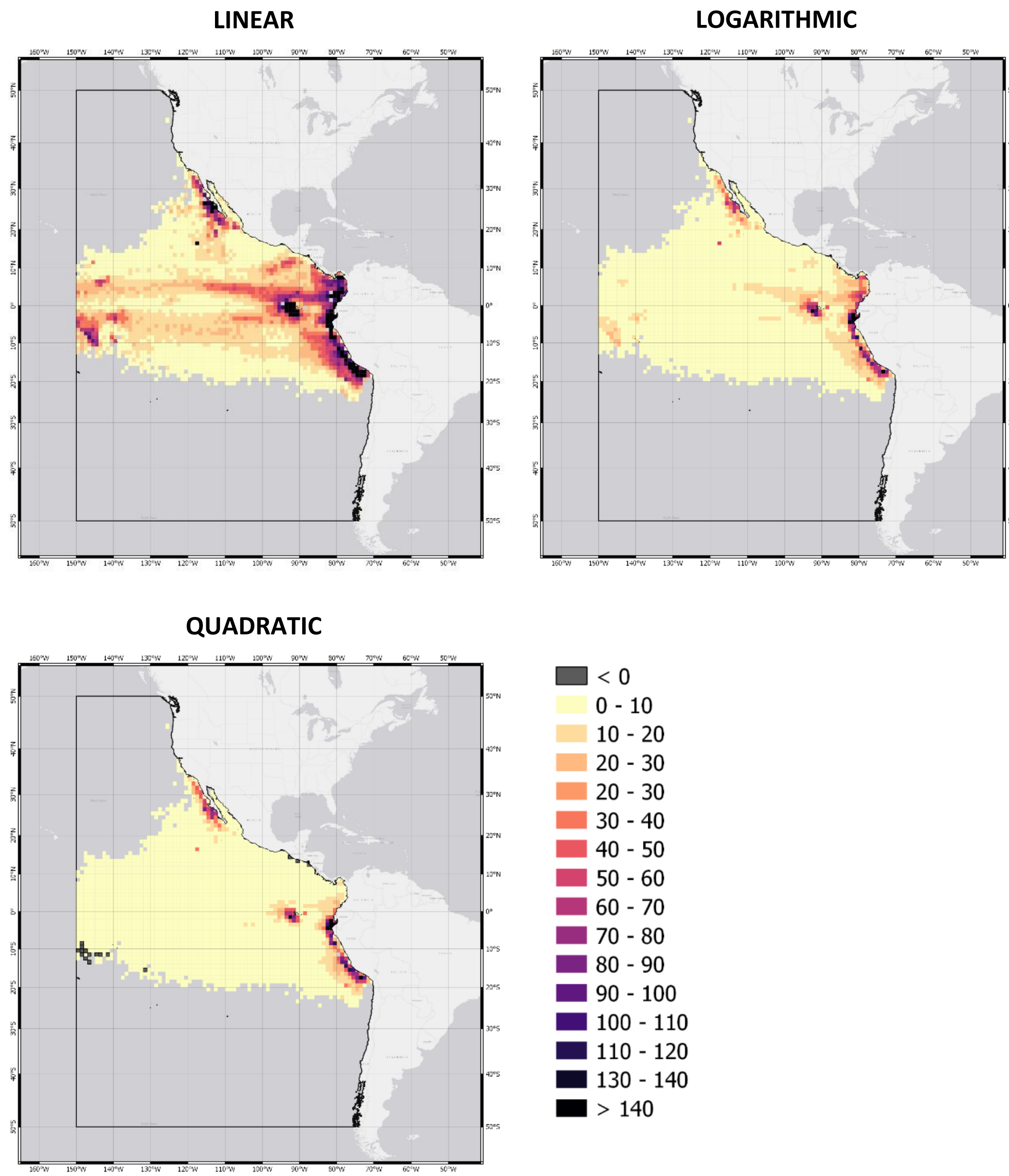


Figure 2. 8. Marginal product of SST at means of skipjack tuna for all sets (in `000 metric tons)

2.8. Discussion

By applying the production function approach, we show that yellowfin and skipjack tuna catch is increasing with SST in the Eastern Pacific Ocean. The magnitude of the MP_{SST} varies across species, type of set, and location of catch and effort, suggesting the need for sector- and species- specific predictions. The MP_{SST} is positive for all types of sets for both yellowfin and skipjack tuna, assuming linear and logarithmic relationships between SST and carrying capacity. These results change for a quadratic relationship, where the MP_{SST} is positive for yellowfin tuna but is negative for skipjack depending on the types of sets considered. We cannot identify the inflection point in the quadratic function with sufficient confidence because of the large variability in the values (from 18°C to 28°C) depending on the location and type of set.

Our results show that the effect of ocean warming on tuna catch has a bigger effect on yellowfin tuna compared to skipjack tuna if we consider all types of purse seine sets. This implies that, collectively, fishers targeting yellowfin tuna in the EPO will benefit more compared to those targeting skipjack tuna. The results also show that the MP_{SST} varies across types of purse seine set. This highlights the importance of looking at the fishing gear in doing an analysis on the effects of SST on fisheries production, as suggested in Hu et al. (2018). The highest MP_{SST} for both yellowfin and skipjack tuna are for unassociated sets. Unassociated sets catch both yellowfin and skipjack tuna, thus both species benefit from the improved suitability of the EPO for spawning and spatial redistribution. Between dolphin sets and floating object sets for each tuna species, the MP_{SST} is higher if the species dominates the catch of that type of set. For yellowfin tuna, the MP_{SST} for dolphin sets is higher compared to floating object sets. On the other hand, the MP_{SST} for floating object sets is higher compared to dolphin sets for skipjack tuna.

The eastward redistribution of tuna in response to ocean warming in our results is consistent with the pattern established through simulations models in other studies (see Lehodey et al. 2013; Dueri et al. 2016). High values of MP_{SST} are predicted for grids on the eastern side of the Pacific Ocean close to the coastal border. Due to habitat preference, more yellowfin tuna are caught in the Northern Hemisphere while skipjack tuna is dominant in the Southern Hemisphere. In the Northern Hemisphere, fishers targeting yellowfin tuna will benefit more as ocean warms compared to those targeting skipjack tuna as MP_{SST} for yellowfin tuna is higher compared to skipjack tuna. Unassociated sets and dolphin sets which both target yellowfin tuna are expected to be the dominant types of purse seine set in this area as sea temperature increases. The MP_{SST} is higher for skipjack tuna compared to yellowfin in the Southern Hemisphere, thus there will be more unassociated and floating object sets as these types of sets target skipjack tuna.

We demonstrate a procedure for including SST in a fisheries production function approach by adopting the fisheries bioeconomic model pioneered by Barbier and Strand (1998). This novel approach allows further work on the impacts of climate change on fisheries and marine systems using an economic framework. The approach we employed is also applicable to models that will use projections of future climate scenarios. We also demonstrate the use of catch and effort data paired with temperature data for latitude/longitude grids, with the expectation that more gridded datasets of fisheries will be available in the future.

We establish that there is a nonlinear relationship between the SST and the carrying capacity of tuna fisheries. The R^2 of models that assume nonlinear (i.e., logarithmic and quadratic) relationship between SST and carrying capacity is greater compared to models that assume linear relationship. This is the result across all species, types of sets, and location. Nonlinear relationships between temperature and economic outcomes have been established in previous studies (Gupta, Sen, and Srinavasan 2014; Schlenker and Lobell, 2010) but not applied for fisheries production.

The availability of gridded catch and effort data and improvements on climate modelling opens opportunities for more research on the economic impact of climate change on fisheries. Studies that focus on a single species should consider all types of fishing gears used to catch that species. The absence of gridded catch and effort data at the same resolution limits our ability to conduct that analysis for this paper. If the focus is for the management of an area, then all target species must be included in the analysis. We show that tuna catch increases with SST, however, it is possible that the net effect for the area is negative as result of reduction in catch of other species. Use of higher resolution catch and effort and ocean temperature data may provide more useful results for fisheries management areas. Our approach in analysing the relationship of SST and tuna catch provides an enabling framework for the application of bioeconomic models to understand impacts of climate change on fisheries.

2.8. Conclusion

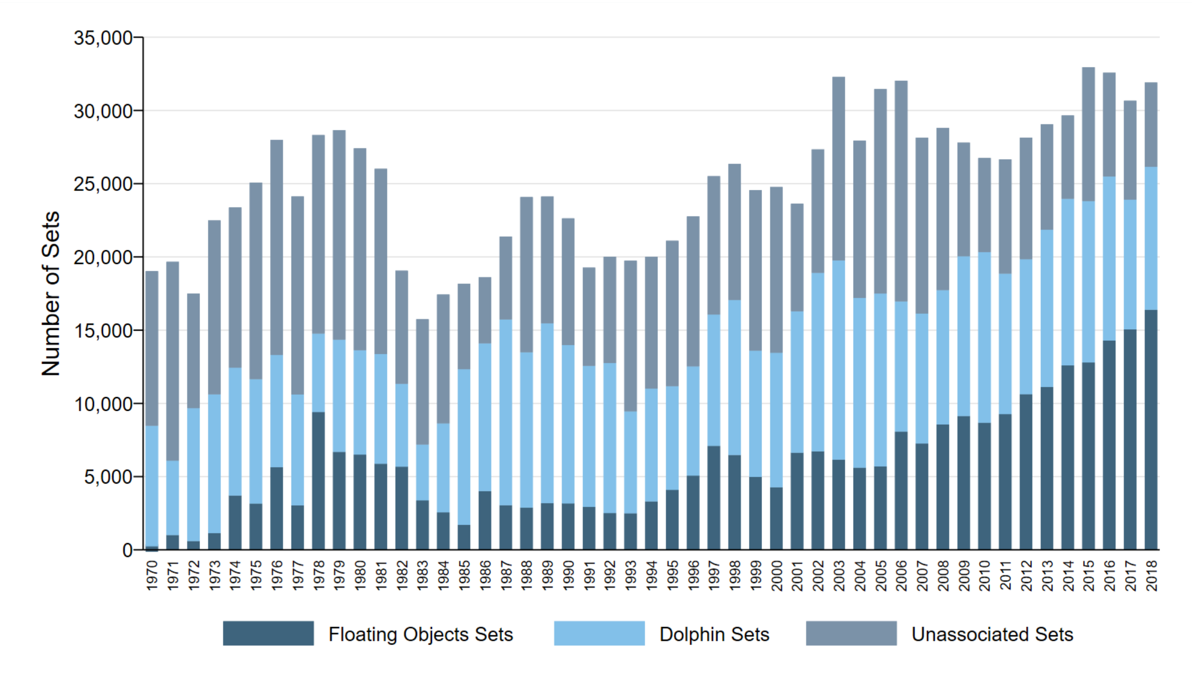
Our results show that catch of both yellowfin tuna and skipjack tuna increases with SST if we consider the whole EPO and all purse seine sets. This is consistent with the results of Dueri et al. (2016) and Bell, Reid, et al. (2013) where it was stated that warming ocean is favourable to tuna fisheries in EPO. However, the magnitude of increase in tuna catch varies across tuna species, type of purse seine set, and location of effort. Ocean warming makes higher latitudes more suitable habitats for tuna species that already dominate the area in terms of catch and effort. Any program to manage tuna fisheries in response to ocean warming must be designed specifically for the species and should consider the different types of gears used. The policy must also be suited for the area being managed.

We adopted the bioeconomic model by Barbier and Strand (1998) that focuses on the fishery-habitat relationship. We also tested three functional relationships between SST and carrying capacity, consistent with the framework we adopted. Future work on the relationship between SST and catch of tuna may adopt other frameworks. Alternative modelling techniques that do not rely on *a priori* information on the functional relationships between SST and catch may be employed.

As discussed, tuna migrate in response to changes in temperature. The movement of tuna to grids with the preferred temperature may result in biased estimates as we are comparing the average catch per grid. We, however, do not see this as much of a problem as the migration of tuna in response to increasing temperature is a slow, gradual process that takes a number of years. This is the case because the increase in temperature is also a slow, gradual process. The average SST in EPO increased by less than 1°C from 1970 to 2018. The large size of grids (10,000 sq km on average) and the fact that the temperature on adjacent grids is not that different from each other are reasons why we believe that the possible bias is not substantial.

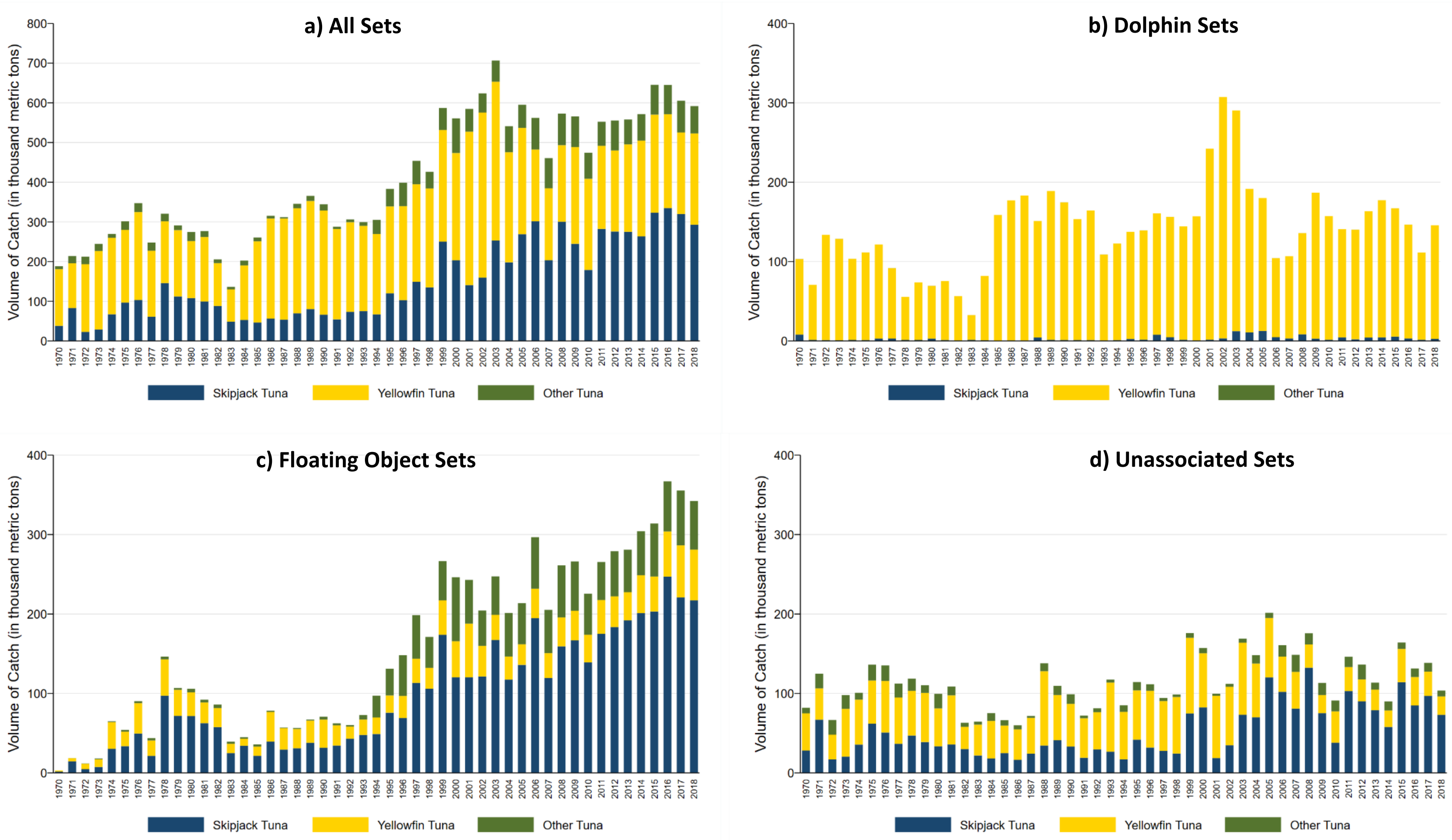
Future work on this topic should recognise the potential endogeneity problem as the effort measure, *Set*, may be endogenous. Also, the measure of fishing effort may likely respond to changes in SST. Estimations using instrumental variables and other procedures may be employed to handle this endogeneity problem.

Appendix



Appendix Figure 2. 1. Total number of purse seine sets in IATTC Convention Area by set type, 1970-2018

Data Source: Inter-American Tropical Tuna Commission (IATTC)



Appendix Figure 2. 2. Total purse seine catch in IATTC Convention Area by set type and species, 1970-2018

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Appendix Table 2. 1. Parameter estimates and marginal product of SST at means for yellowfin and skipjack tuna assuming linear relationship between SST and carrying capacity, by set type
[Dependent Variable: Annual tuna catch (in kilograms)]

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	Mean SST	Mean Number of Sets	MP_{SST}
Yellowfin									
All Sets	62,036	0.848	0.5332	0.00	-94.11	0.00	26.39	0.9840	0.5250
Dolphin Sets	39,581	0.857	0.6289	0.00	-325.16	0.00	26.91	0.9190	0.5770
Unassociated Sets	14,805	0.825	0.4436	0.00	-54.34	0.00	25.86	1.3000	0.5760
Floating Object Sets	36,317	0.754	0.6459	0.00	-654.21	0.00	26.13	0.1640	0.1060
Skipjack									
All Sets	46,808	0.818	0.5911	0.00	-28.38	0.00	26.14	0.6880	0.4070
Dolphin Sets	8,942	0.860	0.5763	0.00	610.34	0.12	26.93	0.0879	0.0507
Unassociated Sets	15,450	0.816	0.5240	0.00	-8.22	0.14	25.56	1.0500	0.5510
Floating Object Sets	38,323	0.782	0.8122	0.00	-446.90	0.00	26.15	0.3750	0.3040

Appendix Table 2. 2. Parameter estimates and marginal product of SST at means for yellowfin and skipjack tuna assuming logarithmic relationship between SST and carrying capacity, by set type
[Dependent Variable: Annual tuna catch (in kilograms)]

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	Mean SST	Mean Number of Sets	MP_{SST}
Yellowfin Tuna									
All Sets	62,036	0.849	4.352	0.00	-109.906	0.00	26.39	0.9840	0.1620
Dolphin Sets	39,581	0.859	5.239	0.00	-336.464	0.00	26.91	0.9190	0.1790
Unassociated Sets	14,805	0.830	3.523	0.00	-64.343	0.00	25.86	1.3000	0.1770
Floating Objects Sets	36,317	0.754	5.236	0.00	-621.885	0.00	26.13	0.1640	0.0329
Skipjack Tuna									
All Sets	46,808	0.820	4.629	0.00	-41.542	0.00	26.14	0.6880	0.1220
Dolphin Sets	8,942	0.865	4.736	0.00	670.461	0.01	26.93	0.0879	0.0155
Unassociated Sets	15,450	0.821	4.022	0.00	-17.218	0.00	25.56	1.0500	0.1650
Floating Object Sets	38,323	0.786	6.671	0.00	-454.964	0.00	26.15	0.3750	0.0955

Appendix Table 2. 3. Parameter estimates and marginal product of SST at means for yellowfin and skipjack tuna assuming quadratic relationship between SST and carrying capacity, by set type
[Dependent Variable: Annual tuna catch (in kilograms)]

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	β_3	p-value (β_3)	Mean SST	Mean Number of Sets	MP_{SST}
Yellowfin Tuna											
All Sets	62,036	0.849	0.782	0.00	-0.009	0.01	-104.060	0.00	26.39	0.9840	0.2910
Dolphin Sets	39,581	0.859	1.199	0.00	-0.021	0.00	-333.542	0.00	26.91	0.9190	0.0805
Unassociated Sets	14,805	0.829	0.817	0.00	-0.014	0.00	-64.596	0.00	25.86	1.3000	0.0889
Floating Object Sets	36,317	0.754	0.766	0.06	-0.004	0.77	-648.193	0.00	26.13	0.1640	0.0000
Skipjack Tuna											
All Sets	46,808	0.820	1.039	0.00	-0.018	0.03	-41.90	0.00	26.14	0.6880	0.0818
Dolphin Sets	8,942	0.869	1.880	0.00	-0.049	0.00	1060.77	0.00	26.93	0.0879	-0.0640
Unassociated Sets	15,450	0.823	1.278	0.00	-0.031	0.00	-24.15	0.00	25.56	1.0500	-0.3100
Floating Object Sets	38,323	0.792	3.350	0.00	-0.095	0.00	-433.49	0.00	26.15	0.3750	-0.5900

Appendix Table 2. 4. Parameter estimates and marginal product of SST at means for yellowfin tuna assuming linear relationship between SST and carrying capacity, by set type and latitude group

Dependent Variable: Annual tuna catch (in kilograms)

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	Mean SST	Mean Number of Sets	MP_{SST}
All Sets									
20°N to 30°N	2,785	0.882	0.4083	0.00	-43.14	0.01	24.12	3.6600	1.4900
10°N to 20°N	14,645	0.878	0.5290	0.00	-103.81	0.00	27.52	1.3400	0.7090
0° to 10°N	22,988	0.878	0.6093	0.00	-165.82	0.00	27.23	0.9380	0.5720
0° to 10°S	14,474	0.793	0.5697	0.00	-91.12	0.00	25.39	0.5550	0.3160
10°S to 20°S	6,782	0.877	1.2266	0.00	-91.74	0.56	24.49	0.2020	0.2480
Dolphin Sets									
20°N to 30°N	1,996	0.842	0.4023	0.00	43.42	0.67	24.97	1.5100	0.6060
10°N to 20°N	14,130	0.867	0.5510	0.00	-183.95	0.03	27.54	1.1100	0.6110
0° to 10°N	17,181	0.881	0.7081	0.00	-486.30	0.00	27.40	0.8880	0.6290
0° to 10°S	5,214	0.877	0.9736	0.00	929.27	0.06	24.93	0.3980	0.3880
10°S to 20°S	1,050	0.818	0.9326	0.00	1723.10	0.53	24.06	0.3420	0.3190
Unassociated Sets									
20°N to 30°N	1,906	0.863	0.3907	0.00	-36.70	0.04	23.49	3.6700	1.4300
10°N to 20°N	3,241	0.873	0.4234	0.00	-40.54	0.17	27.31	1.0200	0.4360
0° to 10°N	5,607	0.839	0.4899	0.00	-108.76	0.00	27.07	0.6150	0.3010
0° to 10°S	2,897	0.803	0.4703	0.00	-56.38	0.00	24.51	1.6700	0.7860
10°S to 20°S	937	0.901	1.1606	0.00	-26.73	0.90	24.04	0.4010	0.4650
Floating Object Sets									
20°N to 30°N	653	0.734	0.4191	0.00	1362.93	0.15	23.26	0.2440	0.1020
10°N to 20°N	3,051	0.853	0.5919	0.00	1088.48	0.00	27.35	0.2490	0.1470
0° to 10°N	14,392	0.794	0.5433	0.00	-360.66	0.01	27.11	0.2260	0.1230
0° to 10°S	11,773	0.704	0.7299	0.00	-1829.49	0.00	25.65	0.0967	0.0706
10°S to 20°S	6,259	0.781	1.2294	0.00	3532.46	0.15	24.60	0.1020	0.1250

Appendix Table 2. 5. Parameter estimates and marginal product of SST at means for yellowfin tuna assuming logarithmic relationship between SST and carrying capacity, by set type and latitude group

Dependent Variable: Annual tuna catch (in kilograms)

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	Mean SST	Mean Number of Sets	MP_{SST}
All Sets									
20°N to 30°N	2,785	0.885	3.169	0.00	-48.304	0.00	24.12	3.6600	0.4800
10°N to 20°N	14,645	0.877	4.403	0.00	-103.895	0.00	27.52	1.3400	0.2140
0° to 10°N	22,988	0.878	5.077	0.00	-167.756	0.00	27.23	0.9380	0.1750
0° to 10°S	14,474	0.799	4.334	0.00	-102.881	0.00	25.39	0.5550	0.0946
10°S to 20°S	6,782	0.876	9.054	0.00	-94.195	0.51	24.49	0.2020	0.0747
Dolphin Sets									
20°N to 30°N	1,996	0.851	3.335	0.00	-3.213	0.97	24.97	1.5100	0.2010
10°N to 20°N	14,130	0.866	4.545	0.00	-159.110	0.05	27.54	1.1100	0.1830
0° to 10°N	17,181	0.883	5.917	0.00	-477.110	0.00	27.40	0.8880	0.1920
0° to 10°S	5,214	0.879	7.722	0.00	798.115	0.09	24.93	0.3980	0.1230
10°S to 20°S	1,050	0.820	7.208	0.00	1740.722	0.51	24.06	0.3420	0.1030
Unassociated Sets									
20°N to 30°N	1,906	0.867	2.988	0.00	-42.331	0.00	23.49	3.6700	0.4670
10°N to 20°N	3,241	0.873	3.468	0.00	-36.644	0.20	27.31	1.0200	0.1300
0° to 10°N	5,607	0.838	4.037	0.00	-108.046	0.00	27.07	0.6150	0.0917
0° to 10°S	2,897	0.815	3.598	0.00	-67.812	0.00	24.51	1.6700	0.2450
10°S to 20°S	937	0.903	8.349	0.00	-0.703	1.00	24.04	0.4010	0.1390
Floating Object Sets									
20°N to 30°N	653	0.733	3.019	0.00	1440.999	0.15	23.26	0.2440	0.0317
10°N to 20°N	3,051	0.853	4.909	0.00	1123.106	0.00	27.35	0.2490	0.0446
0° to 10°N	14,392	0.794	4.465	0.00	-342.775	0.01	27.11	0.2260	0.0372
0° to 10°S	11,773	0.703	5.684	0.00	-1950.053	0.00	25.65	0.0967	0.0214
10°S to 20°S	6,259	0.777	9.221	0.00	3695.603	0.16	24.60	0.1020	0.0380

Appendix Table 2. 6. Parameter estimates and marginal product of SST at means for yellowfin tuna assuming quadratic relationship between SST and carrying capacity, by set type and latitude group

Dependent Variable: Annual tuna catch (in kilograms)

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	β_3	p-value (β_3)	Mean SST	Mean Number of Sets	MP_{SST}
All Sets											
20°N to 30°N	2,785	0.885	0.783	0.00	-0.015	0.01	-48.972	0.00	24.12	3.6600	0.0211
10°N to 20°N	14,645	0.878	0.199	0.50	0.012	0.27	-102.486	0.00	27.52	1.3400	0.0000
0° to 10°N	22,988	0.878	0.950	0.01	-0.012	0.34	-167.530	0.00	27.23	0.9380	0.8910
0° to 10°S	14,474	0.800	1.375	0.00	-0.033	0.02	-110.730	0.00	25.39	0.5550	-0.1800
10°S to 20°S	6,782	0.877	1.263	0.34	-0.002	0.98	-92.144	0.55	24.49	0.2020	0.0000
Dolphin Sets											
20°N to 30°N	1,996	0.858	1.460	0.00	-0.041	0.00	-9.806	0.90	24.97	1.5100	-0.8300
10°N to 20°N	14,130	0.869	-0.120	0.62	0.024	0.00	-211.853	0.01	27.54	1.1100	1.4900
0° to 10°N	17,181	0.885	2.576	0.00	-0.068	0.00	-408.731	0.00	27.40	0.8880	-1.0000
0° to 10°S	5,214	0.880	2.354	0.00	-0.054	0.00	702.850	0.15	24.93	0.3980	-0.1300
10°S to 20°S	1,050	0.821	2.947	0.00	-0.083	0.04	2255.081	0.42	24.06	0.3420	-0.3500
Unassociated Sets											
20°N to 30°N	1,906	0.868	0.823	0.00	-0.018	0.01	-43.572	0.00	23.49	3.6700	-0.0470
10°N to 20°N	3,241	0.873	0.424	0.41	0.000	1.00	-40.533	0.18	27.31	1.0200	0.0000
0° to 10°N	5,607	0.840	-0.086	0.89	0.021	0.34	-107.997	0.00	27.07	0.6150	0.0000
0° to 10°S	2,897	0.829	1.761	0.00	-0.054	0.00	-83.667	0.00	24.51	1.6700	-1.5000
10°S to 20°S	937	0.904	2.788	0.15	-0.073	0.38	35.385	0.86	24.04	0.4010	0.0000
Floating Object Sets											
20°N to 30°N	653	0.735	0.339	0.53	0.003	0.88	1363.353	0.15	23.26	0.2440	0.0000
10°N to 20°N	3,051	0.853	0.538	0.56	0.002	0.95	1084.576	0.00	27.35	0.2490	0.0000
0° to 10°N	14,392	0.795	0.074	0.89	0.017	0.36	-374.831	0.01	27.11	0.2260	0.0000
0° to 10°S	11,773	0.704	0.555	0.12	0.007	0.61	-1783.344	0.00	25.65	0.0967	0.0000
10°S to 20°S	6,259	0.786	-1.514	0.21	0.112	0.02	4272.452	0.09	24.60	0.1020	0.5570

Appendix Table 2. 7. Parameter estimates and marginal product of SST at means for skipjack tuna assuming linear relationship between SST and carrying capacity, by set type and latitude group
Dependent Variable: Annual tuna catch (in kilograms)

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	Mean SST	Mean Number of Sets	MP_{SST}
All Sets									
20°N to 30°N	1,905	0.854	0.4187	0.00	-1.29	0.97	23.56	1.4400	0.6030
10°N to 20°N	6,438	0.909	0.5457	0.00	-129.96	0.03	27.29	0.3960	0.2160
0° to 10°N	17,392	0.824	0.6054	0.00	-125.43	0.00	27.14	0.7190	0.4350
0° to 10°S	14,108	0.821	0.6093	0.00	-33.11	0.04	25.51	0.7700	0.4690
10°S to 20°S	6,627	0.909	1.0536	0.00	-89.84	0.03	24.73	0.4870	0.5130
Dolphin Sets									
20°N to 30°N	772	0.832	0.3574	0.00	5717.72	0.00	24.55	0.1290	0.0461
10°N to 20°N	4,161	0.904	0.4779	0.00	873.54	0.00	27.29	0.0958	0.0458
0° to 10°N	3,262	0.877	0.6460	0.00	1938.52	0.58	27.62	0.0716	0.0463
0° to 10°S	690	0.885	1.0552	0.00	-1745.76	0.80	24.44	0.0763	0.0805
10°S to 20°S									
Unassociated Sets									
20°N to 30°N	1,378	0.855	0.4098	0.00	8.83	0.76	23.00	1.7900	0.7340
10°N to 20°N	1,719	0.894	0.3930	0.00	34.43	0.63	27.08	0.5060	0.1990
0° to 10°N	6,174	0.816	0.4590	0.00	-30.01	0.52	26.89	0.6590	0.3020
0° to 10°S	4,330	0.824	0.5269	0.00	-12.23	0.23	24.70	1.6400	0.8620
10°S to 20°S	1,609	0.917	0.9625	0.00	-41.63	0.40	24.18	0.9070	0.8730
Floating Object Sets									
20°N to 30°N	568	0.771	0.7982	0.00	-2592.15	0.00	23.25	0.2700	0.2150
10°N to 20°N	2,942	0.885	0.7025	0.00	-94.13	0.66	27.25	0.3420	0.2400
0° to 10°N	15,200	0.786	0.6951	0.00	-264.21	0.02	27.08	0.5050	0.3510
0° to 10°S	13,059	0.794	1.1506	0.00	-639.83	0.29	25.66	0.2860	0.3290
10°S to 20°S	6,400	0.823	1.3551	0.00	-1489.24	0.03	24.82	0.2720	0.3690

Appendix Table 2. 8. Parameter estimates and marginal product of SST at means for skipjack tuna assuming logarithmic relationship between SST and carrying capacity, by set type and latitude group

Dependent Variable: Annual tuna catch (in kilograms)

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	Mean SST	Mean Number of Sets	MP_{SST}
All Sets									
20°N to 30°N	1,905	0.856	3.088	0.00	-10.268	0.78	23.56	1.4400	0.1890
10°N to 20°N	6,438	0.910	4.508	0.00	-132.408	0.03	27.29	0.3960	0.0654
0° to 10°N	17,392	0.828	4.985	0.00	-131.069	0.00	27.14	0.7190	0.1320
0° to 10°S	14,108	0.816	4.578	0.00	-39.239	0.02	25.51	0.7700	0.1380
10°S to 20°S	6,627	0.910	7.819	0.00	-117.710	0.00	24.73	0.4870	0.1540
Dolphin Sets									
20°N to 30°N	772	0.837	2.925	0.00	5302.407	0.00	24.55	0.1290	0.0154
10°N to 20°N	4,161	0.905	3.938	0.00	1011.412	0.00	27.29	0.0958	0.0138
0° to 10°N	3,262	0.878	5.424	0.00	1815.660	0.60	27.62	0.0716	0.0141
0° to 10°S	690	0.890	8.258	0.00	-2727.786	0.69	24.44	0.0763	0.0258
10°S to 20°S									
Unassociated Sets									
20°N to 30°N	1,378	0.856	2.982	0.00	3.012	0.92	23.00	1.7900	0.2320
10°N to 20°N	1,719	0.896	3.250	0.00	21.761	0.72	27.08	0.5060	0.0607
0° to 10°N	6,174	0.825	3.768	0.00	-33.890	0.42	26.89	0.6590	0.0923
0° to 10°S	4,330	0.823	3.968	0.00	-18.038	0.10	24.70	1.6400	0.2630
10°S to 20°S	1,609	0.920	7.144	0.00	-71.978	0.13	24.18	0.9070	0.2680
Floating Object Sets									
20°N to 30°N	568	0.770	5.758	0.00	-2333.470	0.00	23.25	0.2700	0.0669
10°N to 20°N	2,942	0.887	5.838	0.00	-99.246	0.63	27.25	0.3420	0.0733
0° to 10°N	15,200	0.788	5.760	0.00	-279.519	0.02	27.08	0.5050	0.1070
0° to 10°S	13,059	0.792	9.181	0.00	-751.617	0.19	25.66	0.2860	0.1020
10°S to 20°S	6,400	0.824	10.539	0.00	-1737.681	0.00	24.82	0.2720	0.1160

Appendix Table 2. 9. Parameter estimates and marginal product of SST at means for skipjack tuna assuming quadratic relationship between SST and carrying capacity, by set type and latitude group

Dependent Variable: Annual tuna catch (in kilograms)

	Observations	R^2	β_1	p-value (β_1)	β_2	p-value (β_2)	β_3	p-value (β_3)	Mean SST	Mean Number of Sets	MP_{SST}
All Sets											
20°N to 30°N	1,905	0.856	0.793	0.00	-0.016	0.12	-12.70	0.73	23.56	1.4400	1.1400
10°N to 20°N	6,438	0.910	1.038	0.00	-0.018	0.17	-133.00	0.03	27.29	0.3960	0.4110
0° to 10°N	17,392	0.832	2.376	0.00	-0.066	0.00	-134.32	0.00	27.14	0.7190	-0.8500
0° to 10°S	14,108	0.824	-0.074	0.79	0.028	0.03	-20.44	0.04	25.51	0.7700	1.1100
10°S to 20°S	6,627	0.910	2.067	0.02	-0.043	0.23	-126.38	0.00	24.73	0.4870	1.0100
Dolphin Sets											
20°N to 30°N	772	0.845	1.644	0.01	-0.051	0.03	5085.34	0.01	24.55	0.1290	-0.1000
10°N to 20°N	4,161	0.905	1.190	0.00	-0.026	0.00	1198.10	0.00	27.29	0.0958	-0.0230
0° to 10°N	3,262	0.879	2.320	0.03	-0.060	0.11	1754.08	0.61	27.62	0.0716	0.0166
0° to 10°S	690	0.907	7.556	0.00	-0.266	0.01	-4959.12	0.47	24.44	0.0763	-0.4100
10°S to 20°S											
Unassociated Sets											
20°N to 30°N	1,378	0.856	0.669	0.01	-0.011	0.33	2.92	0.92	23.00	1.7900	1.2000
10°N to 20°N	1,719	0.899	1.379	0.00	-0.036	0.03	13.72	0.81	27.08	0.5060	-0.3000
0° to 10°N	6,174	0.848	2.659	0.00	-0.084	0.00	-3.76	0.91	26.89	0.6590	-1.2000
0° to 10°S	4,330	0.824	0.645	0.04	-0.005	0.71	-14.20	0.11	24.70	1.6400	1.0500
10°S to 20°S	1,609	0.923	3.213	0.01	-0.097	0.06	-128.25	0.05	24.18	0.9070	-2.9000
Floating Object Sets											
20°N to 30°N	568	0.771	0.890	0.14	-0.004	0.88	-2554.41	0.00	23.25	0.2700	0.0000
10°N to 20°N	2,942	0.892	4.047	0.00	-0.122	0.00	-37.93	0.82	27.25	0.3420	-0.8900
0° to 10°N	15,200	0.792	3.281	0.00	-0.095	0.00	-315.17	0.01	27.08	0.5050	-0.9300
0° to 10°S	13,059	0.795	0.376	0.43	0.029	0.11	-474.90	0.43	25.66	0.2860	0.0000
10°S to 20°S	6,400	0.824	2.580	0.00	-0.049	0.10	-1770.65	0.00	24.82	0.2720	0.7020

Chapter 3 Effects of Sea Surface Temperature on Tuna Catch: Evidence from Countries in the Eastern Pacific Ocean

ABSTRACT

This paper explores how changes in sea surface temperature (SST) affect tuna catch in countries in the Eastern Pacific Ocean (EPO). We apply a production function approach to establish the relationship between SST and the catch of yellowfin (*Thunnus albacares*) and skipjack (*Katsuwonus pelamis*) tuna that use purse seines. We use data for 1° latitude/longitude grids within the exclusive economic zones of countries in the EPO. Catch of yellowfin and skipjack tuna increases with SST in all countries, with high values of catch recorded in the eastern coastal borders. The biggest increase in revenue from yellowfin and skipjack tuna as result on 1°C increase in SST is for Mexico, while Kiribati had the smallest increase. However, if we adjust the increase in revenue by coastal population, the highest values are for Kiribati and French Polynesia. The higher tuna catch translates to higher government revenue from tuna fishing licenses, and more jobs for tuna fishers and those in the tuna processing industry in the state. However, the reduction on catch of other species may offset the positive effects on tuna catch and may even result in a negative impact overall. We highlight the importance of conducting research on SST that is specific to species, gear, and location to fully account for the impact of ocean warming.

3.1. Introduction

Ocean temperature is increasing over time, with some regions warming much faster than others. This trend is expected to continue under climate change conditions (Bindoff et al. 2019). As the ocean warms, fish populations adapt by moving to higher latitudes or deeper waters. The spatial redistribution of fishes may lead to rapid changes in marine ecosystems (Perry et al. 2011; Vergés et al. 2019). In turn, these changes affect fishing operations and how effective measures are for managing fisheries (Sumaila et al. 2011).

The impacts of ocean warming vary across regions. The fish catch at high latitudes is predicted to increase with ocean temperature, while production at low and mid latitudes are predicted to decrease, allowing for regional variations (Barange et al. 2014). Researchers have predicted that low-income countries will experience relatively more reductions in fish catch with climate change because these countries are concentrated in tropical and sub-tropical regions of the world. The spatial redistribution of fishes responding to warming waters would also affect employment and export earnings of economies. Government revenue would be similarly affected through fishing licenses sold to distant fishing nations (Sumaila et al. 2011).

Countries have different levels of vulnerability to climate change. The importance of fisheries to national economies is one of the factors that determines this vulnerability (Allison et al. 2009). Island nations such as Kiribati and French Polynesia depend highly on marine ecosystems, and have major pelagic or high value fisheries, such as tuna. These countries rely on revenue from fisheries or access agreements for foreign fishing (Selig et al. 2019).

Tuna are highly migratory and move between coastal ecosystems and the open ocean, and between domestic jurisdictions and international waters. As the ocean warms, tuna move towards areas with preferred habitat temperatures as a compensatory mechanism (Dizon, Neill, and Magnuson 1977). In the Pacific Ocean, the biomass of yellowfin (*Thunnus albacares*) and skipjack (*Katsuwonus pelamis*) tuna is expected to decrease in areas west of 170 °E, and to increase in exclusive economic zones (EEZ) east of 170°E (Bell et al. 2018). The Pacific Ocean is particularly important for tuna as 70 percent of the total global catch in 2010 came from this fishing ground (Lehodey et al. 2013).

In this paper, we determine the relationship between sea surface temperature (SST) and tuna catch in areas within the EEZ of countries in the Eastern Pacific Ocean (EPO). To determine this relationship, we use gridded data and follow the production function approach used in Mediodia et al. (2020). We focus on yellowfin and skipjack tuna because these are the dominant species caught by purse seine (commercial fishing nets) in the EPO. We consider the different types of purse seine sets in the analysis. We calculate for both the marginal product and marginal revenue product of 1°C increase in SST for the countries included in this study.

We contribute to the literature by providing evidence on the impacts of ocean warming in the countries EPO. The whole Pacific Ocean is affected by ocean warming, but most studies focus on the effects of ocean warming in the western and central Pacific, as most of the small island developing states are in this area. Our study fills a gap in the literature by focusing on the countries in the Eastern Pacific Ocean.

We extend the method used in Mediodia et al. (2020) by expressing the marginal product of SST in international dollar terms to measure the effects of SST on catch. This method allows us to capture differences in purchasing power across countries.

We also express the marginal product of SST in international dollars in relation to coastal population to highlight the differences in the dependence of countries on tuna.

Our results show that the volume of catch of skipjack and yellowfin tuna in the EEZ of countries in the Eastern Pacific Ocean increases as ocean warms. This supports the conclusions of fisheries science studies that showed that tuna dispersed towards the EPO as the ocean warms. We find that Mexico will have the highest increase in tuna catch as the ocean warms due to the size of their EEZ. However, if we adjust for coastal population, the marginal revenue product for island nations, such as Kiribati and French Polynesia, are greater compared to other countries in the EPO.

In the next section, we discuss economic impacts of climate change in fisheries focusing on countries in the Eastern Pacific Ocean. This is followed by a presentation of the model, data, and estimation procedure used in the study. We then discuss the results of the analysis, and finish with some concluding remarks.

3.2. Review of Related Literature

3.2.1. Climate change and fisheries

The average ocean temperature is increasing over time due to anthropogenic influences and this trend is expected to continue in the next century (Collins et al. 2013; Rhein et al. 2013; Bindoff et al. 2019). The vulnerability of most organisms to warming is determined by their physiology, which defines their limited temperature ranges and thermal sensitivity (Pörtner et al. 2014), and biological functions such as metabolism, growth, and reproduction (Bindoff et al. 2019). The change in ocean temperature results in the redistribution of marine organisms, from phytoplankton to marine mammals. Recent evidence records observed shifts in the distribution of marine species across regions (Poloczanska et al. 2016).

Projections show that the ocean warming will continue to cause the redistribution of species from the tropics towards the poles. The poleward shift are projected to result in reduction of species richness in the tropics and increase in the mid to high-latitude areas (M. C. Jones and Cheung 2015; Cheung and Pauly 2016; Poloczanska et al. 2016). This then has effects on the timing of activities, abundance, and migration patterns of species (Pörtner et al. 2014). Warming is also projected to impact on the physiological growth of fishes (Pauly and Cheung 2017).

3.2.2. Economic impacts of climate change in fisheries

Fisheries provide food, nutrition, income and livelihoods for millions of people (FAO 2018a). Generally, there is an expected loss of fisheries productivity due to warming ocean. Productivity may expand in higher latitudes as ocean warms but this is offset by reduction in productivity in low- and mid-latitudes (Hoegh-Guldberg et al. 2018). This means that ocean warming will affect income and employment from fisheries.

Global marine fisheries landings are valued at 150 billion in 2010 USD, which is 5 times more than the estimate for 1950 (Tai et al. 2017). Climate change will lead to a global decrease in revenue (Lam et al. 2016). However, spatial variations of climate impacts on and the flexibility and capacities of food production systems can result to regional differences in the impact (Pörtner et al. 2014; Lam et al. 2016). Lam et al. (2016) showed that there will be a projected increase in fish catch in high latitudes as ocean warms but this may not translate into increase in revenues because of the dominance of low value fish and decrease in the catch by the vessels of countries in high latitudes operating in adversely-affected distant waters . They also found that lower income countries with high fisheries dependency are negatively affected. The impact on revenues from fisheries may have implications on other sectors with linkages to the fisheries sector such as boat building and maintenance, equipment supply, and the hospitality sectors.

The changes in the dynamics of fish species will have direct impacts on communities and economies. As fishes move, fishers that target the new fishes will benefit while those in established fisheries will be adversely affected (Madin et al. 2012). Capital costs increase as fishers need to improve gears and vessels and incur higher fuel, ice, and labour costs due to longer search time are expected in areas where species move out. (Sumaila et al. 2011). On the other hand, migration of species into other areas can translate into higher revenue and lower costs.

The economic implications of climate change on fisheries vary between regions and countries. Blasiak et al. (2017) showed that countries most vulnerable to the effects of climate change on fisheries are primarily small island states in the Pacific Ocean and Caribbean, and those along the western and eastern coasts of Africa. The vulnerability of these countries is mainly driven by deficits in the ability to modify fisheries and livelihoods to cope with the adverse impacts of climate change and pursue emerging opportunities. There is no linkage between levels of national development and exposure to the impacts of climate change on fisheries. The high vulnerability of low-income countries is attributable to the importance of the fisheries sector to the economy in terms of employment and revenue.

The dependence of countries on marine ecosystems matter in the assessment of impact of climate change. Selig et al. (2019) measured the nutritional, economic, and coastal protection dependence of countries to marine ecosystem. The patterns they establish vary by country and type of dependence measured. Island nations in Pacific and Indian Ocean have high overall dependence on marine resources. Countries with major pelagic fisheries and high value fisheries like tuna are also the countries that have high economic dependence on marine resources. The measures of dependence and ranks of the countries in our study are presented in Appendix Table 3. 1.

3.2.3. Tuna fisheries and climate change

Tuna fisheries are affected by ocean warming through changes in tuna physiology and behaviour or the abundance of their prey. Increase in temperature is projected to result in a decrease in the productivity of phytoplankton. This affects the tuna larvae and juvenile as they feed on the phytoplankton (Lehodey et al. 2013). Spatial distribution of tuna is conditioned by sea temperature. Tuna move to preferred habitat temperatures as a compensatory mechanism to ocean warming (Dizon, Neill, and Magnuson 1977; Schaefer, Fuller, and Block 2007). Monllor-Hurtado, et al. (2017) showed that tropical tuna species move towards the poles in response to ocean warming.

The two tropical tuna species – yellowfin and skipjack – are among the fish species affected by increasing sea temperature. Sea temperature affects the growth of these species. Skipjack tuna commence spawning when the SST is greater than 24 °C (Ashida and Horie 2015). The development and survival of yellowfin tuna larvae is also affected by SST. Temperatures of about 26° to 31 °C is associated with rapid growth and moderate to high survival in yellowfin tuna larvae (Wexler, Margulies, and Scholey 2011). The spatial distribution of tropical tuna is also affected by temperature. Ocean warming may increase the suitability of some habitats for skipjack tuna (Muhling et al. 2015) and yellowfin tuna (Schaefer, Fuller, and Block 2007). Increase in SST also promotes the tuna-dolphin bond for large yellowfin tuna (Scott et al. 2012).

In the Pacific Ocean, projections show that these tropical tuna species will have a redistribution from the west to the east (Lehodey et al. 2013; Monllor-Hurtado, Pennino, and Sanchez-Lizaso 2017). Bell et al. (2018) showed that there are expected decreases in biomass of yellowfin and skipjack tuna in areas west of 170 °E and increases in EEZ east of 170°E. A progressive biomass displacement towards the poles is also projected (Lehodey et al. 2013). This redistribution of tuna will translate to effects on livelihood and revenue, with countries in the east gaining while countries in the west losing.

3.2.4. Tuna fisheries in the Eastern Pacific Ocean

There is an extensive literature on the effects of climate change on fisheries-dependent countries in the Pacific Ocean (Bell, Ganachaud, et al. 2013; Bell, Reid, et al. 2013; Asch, Cheung, and Reygondeau 2018), but most of the studies are on the Western and Central Pacific. Bell, et al. (2013) showed that the east region of the Western and Central Pacific Ocean is expected to receive more revenue as tuna catch increase in their region. Countries in west may face a reduction in revenue as are tuna are redistributed progressively to the east. There is no work, to the best of our knowledge, which conducts an analysis on the effects of the countries extending towards the eastern coastal boundaries of the Pacific Ocean.

3.2.5. Purse seine

Purse seines are fishing gears designed to catch fishes swimming together in the same direction in a coordinated manner. It is made of a long wall of netting hung on a float line and the bottom is attached to a lead line. A purse line threaded through steel ring (also called purse rings) spaced along the bottom of the net is drawn tight to stop the school of fish escaping downwards under the net. The purse seine is set from one or two boats to surround the fish (ICES 2007). In the EPO, nets have been becoming deeper for the vessels fishing on FADs, and longer for the vessels setting on dolphin (Hall and Roman 2013).

There are different ways in which tunas are detected and encircled, and this gives rise to a classification of purse seine sets in several types. The data from Inter-American Tropical Tuna Commission (IATTC) classify sets either as dolphin set, floating object set, or unassociated set.

Dolphin sets are made for tuna that associate with dolphins in genera *Stenella* and *Delphinus*. These sets are practically monospecific for yellowfin tuna. Other major tuna species are very rare in these sets. Fishers launch speedboats to chase the dolphin pod associated with tuna until it stops swimming. The purse seine then encircles and captures the tuna associated with the dolphins. This method is controversial due to the incidental mortality of dolphins, even though fishers employ mechanisms to allow dolphins to escape (Hall 1998; Hall and Roman 2013).

Floating object sets are made for tuna schools associated with drifting objects. The object can be plant materials (logs, tree branches), aquatic plants (kelps), wooden crates and pallets, lost fishing gears, or dead animals (sharks, whales). Use of fish aggregating devices (FAD) became frequent in the last decade. FADs are man-made floating objects outfitted with tracking devices to ensure re-encounter. The composition of catch using floating object sets is a mixture of skipjack, bigeye, and yellowfin, with a clear predominance of skipjack (Bayliff 2001; Hall and Roman 2013).

Unassociated sets or school sets (Hall and Roman 2013) target tuna associated with schools of different species or seabirds. This type of set is the least predictable of all because fish behaviour may change abruptly in response to environmental or biological factors. Small-sized yellowfin and skipjack tuna are the usual species caught through unassociated sets (Hall 1998).

3.2.6. Fisheries production function

The production function approach in fisheries is applied to establish linkages between the habitat of a fishery and its economic productivity. Barbier and Strand (1998) demonstrated how an environmental factor, specifically habitat, directly affects the carrying capacity, which is the largest possible fish stock size given food supplies, habitat, and other factors. Foley et al. (2010) showed that the environmental factor also indirectly affects the carrying capacity through the intrinsic growth rate of the fish stock.

Studies apply a static fisheries production function model based on the assumption that the fishery is in a long-run equilibrium (Barbier 2007). Application of this framework includes establishing linkages of mangrove and shrimp catch (Barbier and Strand 1998), mangrove and artisanal demersal and shellfish catch (Barbier, Strand, and Sathirathai 2002), and cold water coral and redfish catch (Foley et al. 2010). There is a growing literature that includes environmental factors in the fisheries production function (see Vondolia et al. 2019; Armstrong et al. 2017; Kahui, Armstrong, and Vondolia 2016; Armstrong, Foley, and Kahui 2016; Hassan and Crafford 2015).

3.2.7. Temperature and production function

There is extensive research that includes temperature in the production function in terrestrial systems. These studies treat temperature as a productive input that explains variations in economic outcome. Most of the studies establish a relationship between temperature and macroeconomic variables such as growth of aggregate output (Burke, Hsiang, and Miguel 2015), sectoral output (Hsiang 2010), and export growth (B. F. Jones and Olken 2010). The approach is also applied to study relationship of temperature and crop yields (Schlenker and Roberts 2009; Schlenker and Lobell 2010), agricultural profits (Deschênes and Greenstone 2007), and output of specific crops (Gupta, Sen, and Srinavasan 2014). Deschenes (2014) and Heal and Park (2016) review studies on the relationship of temperature and other economic outcomes.

Mediodia et al. (2020) is first to apply the production approach to establish the relationship between SST and catch using gridded data. They extended the framework pioneered by Barbier and Strand (1998) to show the positive relationship between SST and tuna in Eastern Pacific Ocean. SST and catch were linked directly through the carrying capacity and indirectly through the growth rate of tuna fisheries. There is a nonlinear (i.e., logarithmic and quadratic) relationship between the SST and the carrying capacity of tuna fisheries.

3.3. Model, study area, estimation procedure, and data

We follow the fisheries production function approach used in Mediodia et al. (2020) to link SST and tuna catch. The standard static open access fishery model pioneered by Barbier and Strand (1998) is modified in to account for the relationship between carrying capacity and SST.

We estimate the following equation assuming a logarithmic relationship between SST and carrying capacity:[7]

$$Tuna_{it} = \beta_1 Sets_{it} * lnSST_{it} + \beta_2 Sets_{it}^2 + \varepsilon_{it} \qquad (1)$$

[7] Similar to Mediodia et al. (2020), we also test for a quadratic relationship between SST and carrying capacity. Estimation results produced lower coefficient of determination compared to logarithmic assumption. Coefficients are also not statistically significant for most countries for the four model specifications.

where $Tuna_{it}$ is the amount of tuna caught and $Sets_{it}$ is the number of sets in grid i in year t. The two variables are expressed in per square kilometre terms to account for differences in the surface area of grids. The equation also includes $lnSST_{it}$ which is the natural log of annual mean SST in grid i in year t, $Sets_{it}^2$ is the square of $Sets_{it}$, and ε_{it} is the error term.

Regression through the origin (RTO) is implemented similar to Armstrong et al. (2016), Thanh Thuy and Flaaten (2013), and Foley et al. (2010). RTO handles the unrealistic possibility of positive output of tuna without fishing effort. Eisenhauer (2003) provides a brief review of the literature on RTO approach in modelling.

Sets is the frequency purse seine nets are deployed in a latitude/longitude grid for a given year and type of set. The effort measure is proportionally adjusted to the amount of yellowfin and skipjack tuna caught within a set. This is done to isolate species-specific effort because purse seine catch different species on each set. A similar adjustment to effort was done in Foley et al. (2010). It is assumed that fishers give equal importance to yellowfin and skipjack tuna consistent to the effort proportion allocation procedure used in Wang et al (2015).

The marginal product of SST at means, MP_{SST}, as derived from the previous equation is:

$$MP_{SST} = \frac{\partial Tuna}{\partial SST} = \beta_1 \frac{Sets}{SST}. \tag{2}$$

We extend the model to include time trend to account for technological progress. Another extension is to include dummy variables for grids to control for time-invariant, grid-specific factors affecting the tuna catch such as area, location, and bathymetry. Estimations were also done to include both time trend and dummy variables for grids.

The marginal revenue product of SST is then computed by converting the MP_{SST} to international dollar terms. We use the price of skipjack and yellowfin tuna in January 2019 as reported in the European Price Report by Food and Agriculture Organization (FAO 2019a). Aside from tuna prices for major tuna trading ports, the report also includes on the fishing ground in which tuna sold in that ports are caught. Prices of whole tuna in Ecuador were used because the tuna sold in Ecuadorian ports are from the EPO. The value is then converted to local currency units using average annual nominal exchange rate for 2018 and then converted back to international dollars using purchasing power parity (PPP) rates.[8] The use of PPP rates is important in this case to account for purchasing power of currencies, thus capturing differences in the benefits accruing to the countries.

To account for differences in the dependence of population to fisheries, we divide the marginal revenue product by the coastal population. We use the 2019 coastal population data multiplied by the ratio of the area of the country's EEZ within the EPO to the total area of the EEZ. [9] The adjustment to EEZ size is necessary because the EEZ of some countries (e.g. the United States) cover areas outside the EPO.

We include the countries and territories within the agreement area of the IATTC. This is the portion of Pacific Ocean east of 150°W up to the coastline of North, Central, and South America and between 50°N and 50°S as defined in the Antigua Convention. As the data we used are in 1° latitude/longitude grids, there are grid cells that overlap the

[8] Official (nominal) exchange rates (LCU per USD) and PPP conversion factors for GDP (LCU per international dollars) are from the World Bank's World Development Indicators (World Bank 2020) except for the nominal exchange rate for Nicaragua which is from Banco Central de Nicaragua (2018).

[9] Coastal population data is from the Low Elevation Coastal Zone (LECZ) Urban-Rural Estimates of the Socioeconomic Data and Applications Center (SEDAC) operated by the (Center for International Earth Science Information Network (CIESIN) Columbia University (Center for International Earth Science Information Network (CIESIN) Columbia University 2020).

boundaries between the EEZ of countries and between an EEZ and international waters. The overlap is illustrated in a box in Figure 3.1.

We use countries to refer to the sovereign countries and territories in the IATTC Agreement area. Four definitions to address the discrepancy between the EEZ maritime borders and the 1° latitude/longitude grid cells were considered (Table 3.1). We conduct separate analyses for these groups and compare the results to check for robustness. Results presented are averages of results of analyses using for datasets four model specifications for brevity with detailed results included in the appendices.

Table 3. 1. Data groups

Group	Description
With Overlaps	Grid cells that overlap with EEZ of other countries and international waters are included.
Without Country Overlaps	Grid cells that overlap with EEZ of other countries are excluded but grid cells that overlap with international waters are included.
Without International Waters Overlaps	Grid cells that overlap with EEZ of other countries are included but grid cells that overlap with international waters are excluded.
Without Overlaps	Both grid cells that overlap with EEZ of other countries and international waters are excluded

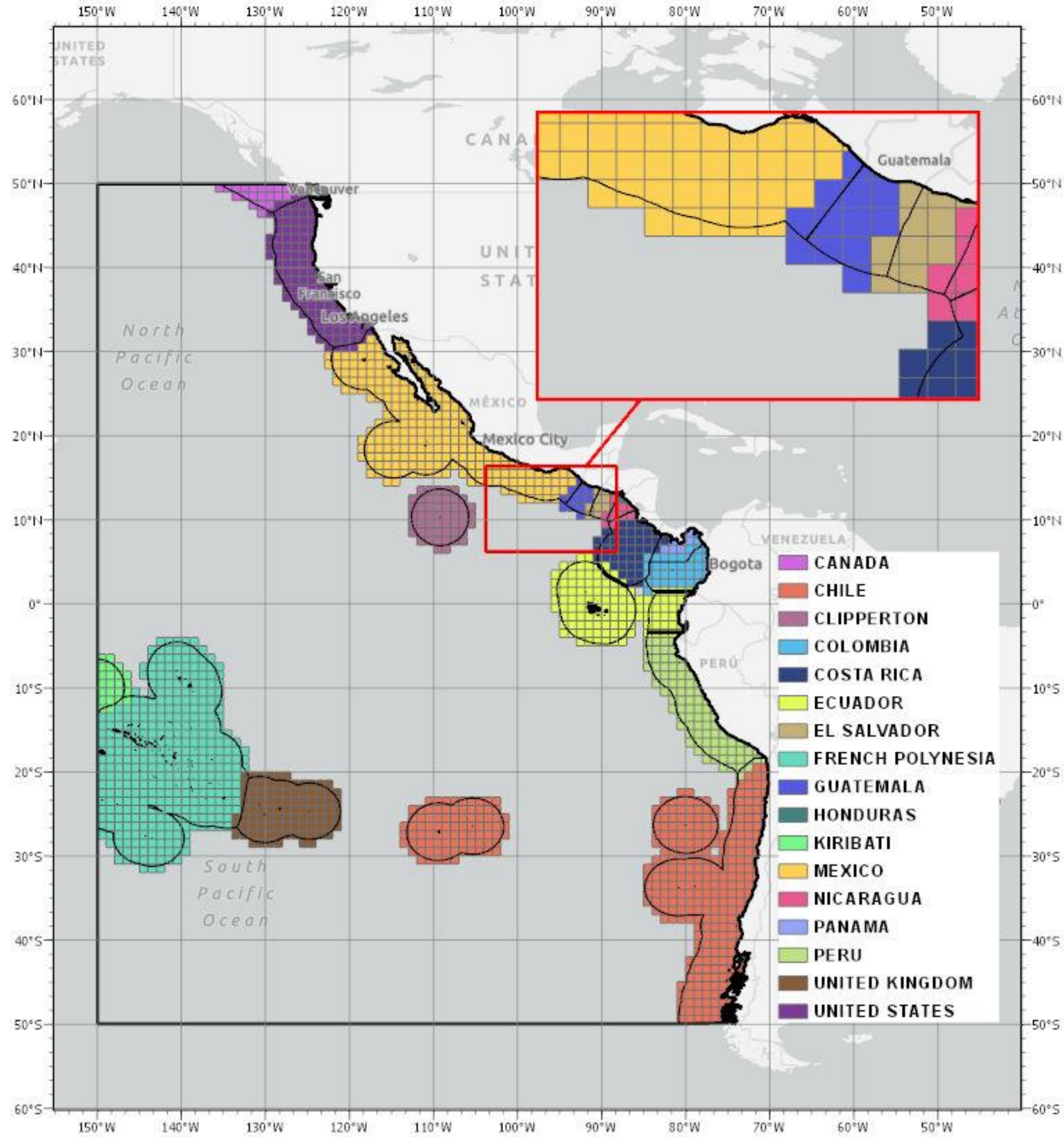


Figure 3. 1. Exclusive economic zones of countries in the Eastern Pacific Ocean

We use tuna catch and effort data for purse seine from the website of IATTC. Data show monthly tuna catches and number of sets by purse seine vessels in every 1°latitude/longitude grid and disaggregated by set type and by species of tuna caught (IATTC 2018). We compute for the annual totals of both catch and effort for every grid and express the data per square kilometre terms to account for the differences in the area of the grid cells.

SST data is from the Centennial In Situ Observation-Based Estimates of the Variability of SST and Marine Meteorological Variables, version 2.9.2 (COBE-SST2) by the Japan Meteorological Agency (JMA) (Hirahara, Ishii, and Fukuda 2014).[10] We compute for the annual averages of SST for each grid from 1970 to 2018 using monthly SST observations from COBE-SST2.

An unbalanced annual panel data for 1° latitude/longitude grid of containing tuna catch and effort data in the Eastern Pacific Ocean from 1970 to 2018 is included in the analysis. We perform separate estimations for observations grouped by species, types of set with standard errors clustered on the grid.[11]

3.4. Summary statistics

Figure 3.2 shows the total area in square kilometres with reported catch and effort data per country for the two data groups. Mexico has the largest fished area for tuna followed by Ecuador, then Peru. Even though the EEZ of the United States of America is larger, only a small portion of this area is fished for tuna. The EEZ of Honduras is covered by only one grid cell, thus it is not included in the presentation of results.

The figure is also indicative of the difference in the area covered for each country for the different data groups. There are wide gaps for Mexico and Ecuador. It is in these countries that there are number of grids that overlap with other countries or with the international waters.

[10] COBE-SST2 data used in this study was taken from NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site at https://www.esrl.noaa.gov/psd/.

[11] Estimation was also done with standard errors clustered both on grid and time to handle heterogeneity due to spatial and temporal correlation. We arrive at the same results.

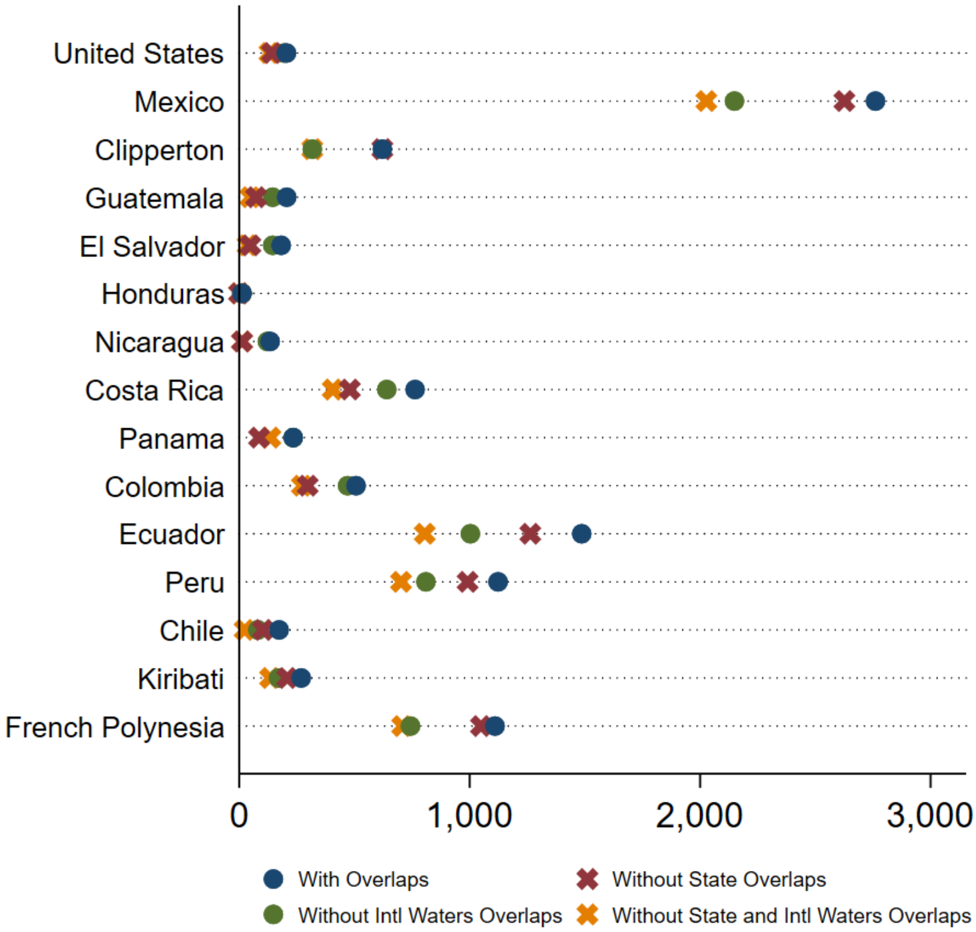


Figure 3. 2. Total area with tuna catch and effort data by country and data group (in '000 square kilometres)

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Table 3.2 presents averages of the number of sets, total tuna catch, catch per set, and share of each species to total catch for all purse seine sets arranged in decreasing order by number of sets. Mexico records the highest number of effort (30%) and catch (24%) if we consider all purse seine sets from 1980 to 2018. This is followed by Ecuador that accounts for 25 percent of the total sets and 26 percent of total tuna catch. Honduras recorded only 15 sets thus this country is no longer included in the presentation of the results.

The data for each type of set is presented in Appendix Table 3.2. Dolphin sets account for 12 percent of the total sets and 13 percent of the catch. Most of the sets are in the Northern Hemisphere mostly recorded in Mexico (53%), Clipperton (21%), Costa Rica (12%). The dominant species is yellowfin tuna comprising 93 to 97 percent of the total catch of the different countries with dolphin sets.

Twenty one percent of the total effort and 30% of the catch from 1980 to 2018 are for floating object sets. Ecuador (33%), Colombia (24%), Costa Rica (15%), and Peru (8%) are the top for countries in terms of effort. These sets mostly catch skipjack tuna except for Guatemala, El Salvador, Nicaragua in which yellowfin tuna is the dominant species caught.

Unassociated sets account for majority of the total catch (56%) mainly in Mexico (34%), Ecuador (27%), Peru (21%). Yellowfin is dominant is Mexico (57%), Panama (69%), Costa Rica (55%), El Salvador (70), Nicaragua (76%), Clipperton (74%). Skipjack is the dominant species in Ecuador (66%), Peru (64%), Colombia (54%), Chile (93%), Line (Kiribati) (98%), French Polynesia (94%).

Catch per unit effort is highest for floating objects sets, followed by dolphin sets, then unassociated set. Looking at data per country, Kiribati has the highest value for all sets (46.7 metric tons) as majority of the effort are floating objects sets with high catch per unit effort at 52.3 metric tons per set.

Table 3. 2. Number of sets, tuna catch, catch per set, percentage distribution of tuna catch by species, by country and data group for all set types (1980 to 2018)

	Number of Sets	Total Tuna Catch (in metric tons)	Catch per set (in metric tons)	Percentage distribution of tuna catch by species		
				Yellowfin	Skipjack	Other species
ALL SETS						
Mexico	204,288	2,097,392	10	67	22	10
Ecuador	166,577	2,295,306	14	35	58	7
Peru	94,966	1,381,747	16	33	64	3
Colombia	66,498	832,114	13	41	56	3
Costa Rica	62,301	960,892	15	67	32	1
Panama	31,898	367,097	12	67	32	1
Clipperton	23,586	364,470	15	84	16	1
Guatemala	11,857	167,101	14	77	23	0
El Salvador	6,333	107,220	16	79	21	0
United States	3,465	28,789	9	17	20	63
Nicaragua	3,278	61,879	21	83	17	0
French Polynesia	1,397	51,114	34	9	76	16
Kiribati	989	42,357	47	7	86	7
Chile	551	16,227	38	21	70	9
Honduras	15	352	24	92	8	0

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Ocean warming in the countries in the EPO is captured by the COBE-SST2 dataset. The annual SST of countries increases over time is fluctuating but there is an upward trend (Figure 3.3). The slope of the trend line is positive and statistically significant for all countries except for Peru in which the slope is not statistically significant but still positive (see Appendix Table 3.3). The magnitude of the slopes across countries are comparable with values between 0.010 and 0.019.

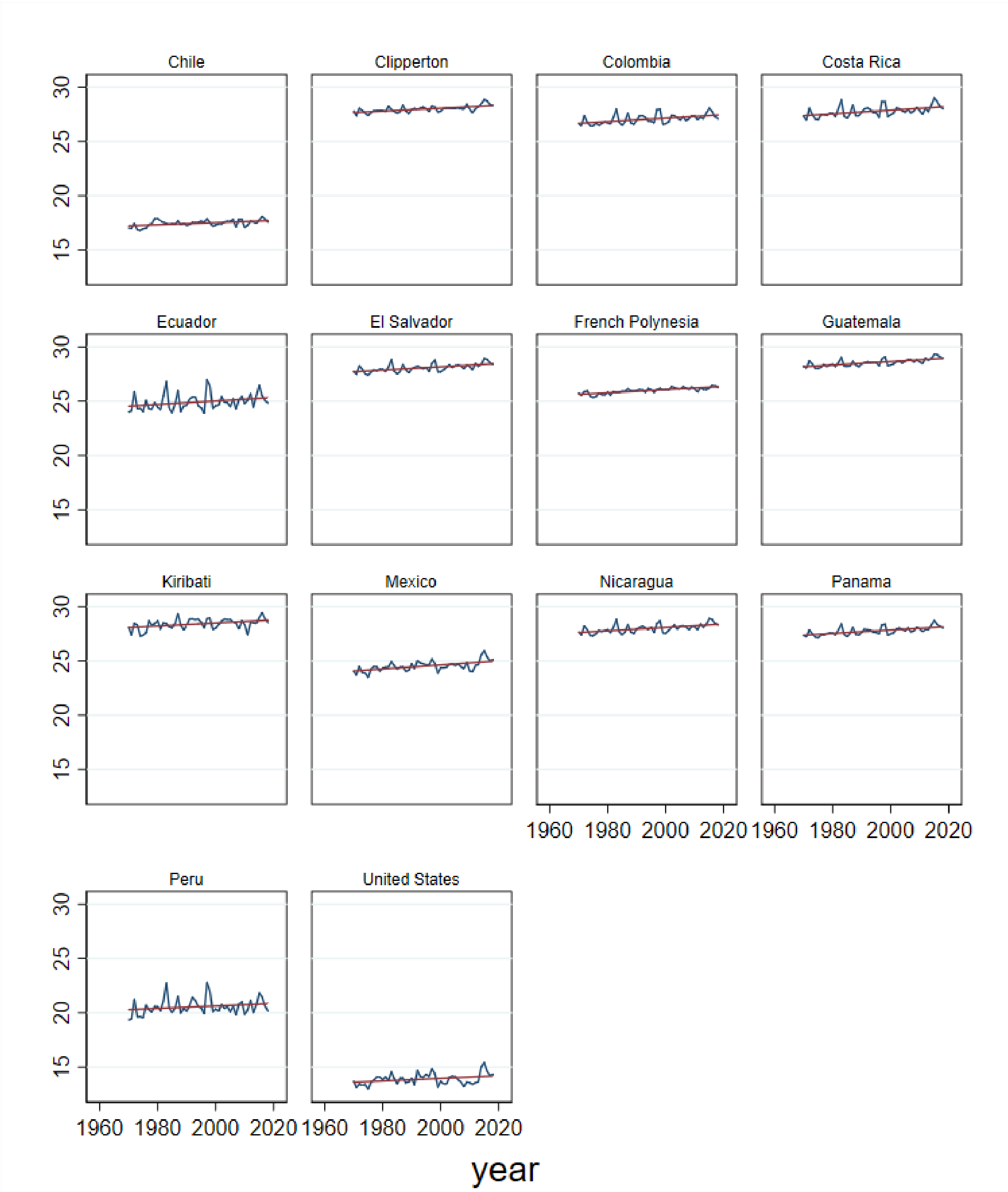


Figure 3. 3. Annual SST by country, 1960-2018

Data Source: COBE SST

3.5. Results

3.5.1. Marginal product of SST

Figure 3.4 shows the increase in tuna catch as a result of 1°C increase in SST for both yellowfin and skipjack tuna for countries arranged from North to South for each type of sets. The results presented are average values of MP_{SST} computed using the four data groups. Values of MP_{SST} for each data group are presented in Appendix Table 3.4. The MP_{SST} are positive except for some countries in which the value is zero for specific species.

If we consider all purse seine sets, the MP_{SST} is highest for Peru for skipjack in which 1°C increase in SST results to 8.92 x 10^{-5} MT of catch per square kilometre. The highest MP_{SST} for yellowfin tuna is in Panama at 8.48 x 10^{-5} MT of catch. The MP_{SST} for skipjack is greater than MP_{SST} for yellowfin for Colombia, Ecuador, and countries in the Southern Hemisphere. The MP_{SST} for yellowfin tuna is greater than skipjack tuna for other countries in the Northern Hemisphere.

The MP_{SST} for yellowfin is greater than MP_{SST} for skipjack in all countries for dolphin sets. The highest is for Peru 7.67 x 10^{-6} MT per square kilometre of fished area. There are no dolphin set efforts in the United States, Chile, French Polynesia, and Kiribati.

The MP_{SST} for floating object sets are all positive in countries with recorded effort. In most countries, the MP_{SST} for skipjack tuna is higher compared to yellowfin tuna. This is not the case, however, for three countries in the Northern Hemisphere – Guatemala, El Salvador, and Nicaragua.

MP_{SST} for unassociated sets are greater compared to dolphin and floating object sets. The MP_{SST} for skipjack is greater than the MP_{SST} for yellowfin in Chile, Mexico, Ecuador, Peru, and Line Island in Kiribati. The difference is most pronounced in Nicaragua in which the MP_{SST} for skipjack is at 1.55 x 10^{-5} MT compared to 8.60 x 10^{-5} MT per square kilometre of fished area for yellowfin. In the US, Clipperton, Panama, Mexico, Guatemala, Costa Rica, Ecuador, the MP_{SST} for yellowfin is greater than the MP_{SST} for skipjack. These countries are all on the Northern Hemisphere.

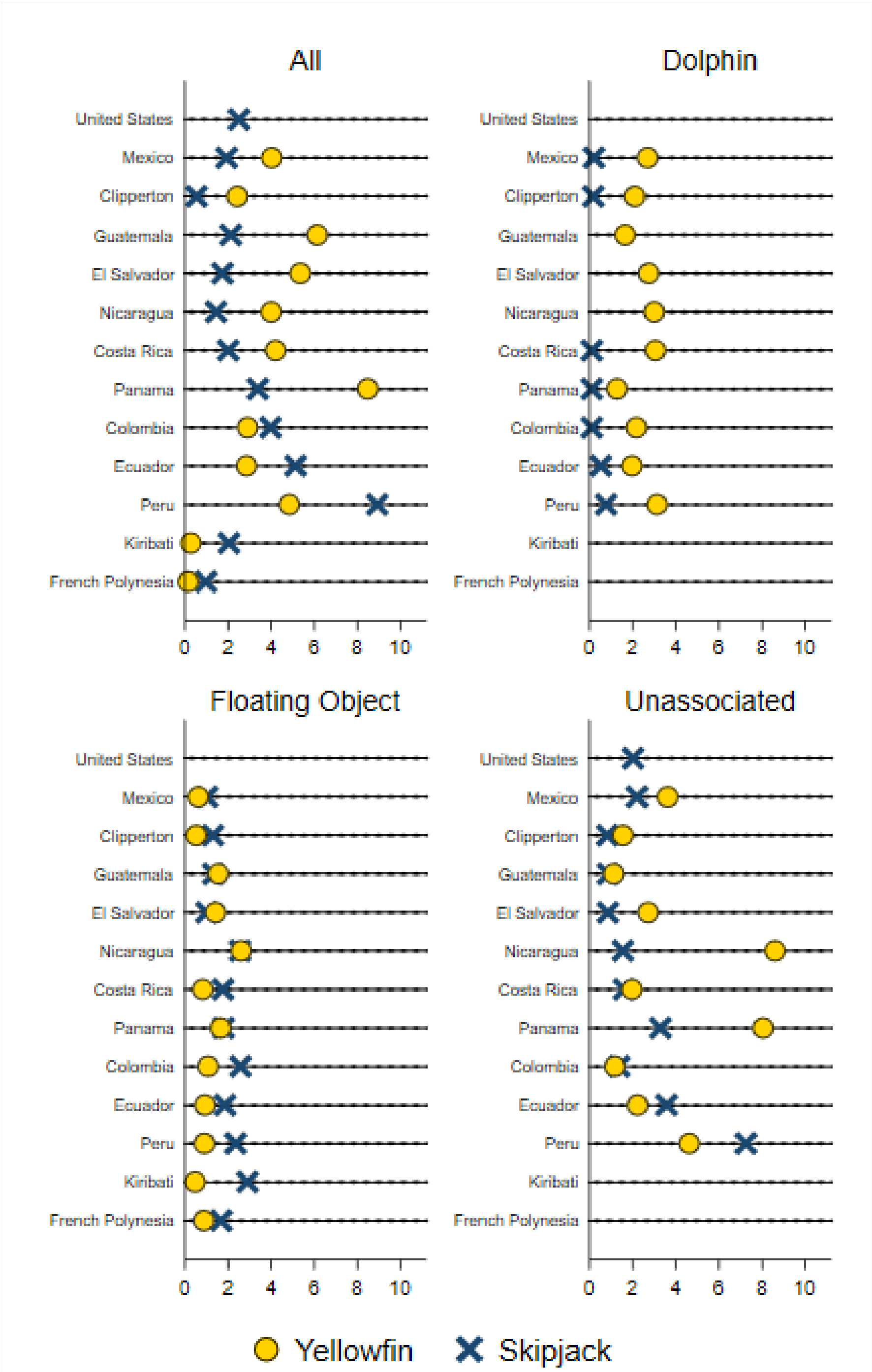


Figure 3. 4. Marginal product of SST at means per square km (in x10^{-5} metric tons)

3.5.2. Marginal revenue product of SST

All countries considered will gain form the increase in tuna catch as a result of increase in SST as indicated by positive marginal revenue product. Figure 3.5 shows the average marginal revenue product by country for the yellowfin and skipjack tuna for the different set types computed using the four data groups.

For yellowfin tuna, highest value is for Mexico at Int$ 437,808 followed by Peru (Int$ 177,861) and Ecuador (Int$ 128,174) considering all types of sets. Lowest values are for Kiribati (Int$ 1,580) and French Polynesia (Int$ 2,995). The values for skipjack tuna are lower compared to yellowfin. The highest for all types of sets is Peru (Int$ 201,837) followed by Ecuador (Int$ 142,134) and Mexico (Int$ 129,122) with low values for the US (Int$7,196) and Clipperton (Int$ 2,887).

The marginal revenue product for dolphin sets is higher for yellowfin tuna compared to skipjack tuna for all countries. Yellowfin accounts for 93 percent of the total value for all countries compared to 7 percent for skipjack tuna.

If we consider floating object sets, skipjack tuna account for 59 percent of the sum of the marginal revenue product of all countries. The marginal revenue product for skipjack is greater than marginal revenue product for yellowfin in most countries, with the greatest difference in Mexico and Ecuador. For Costa Rica, Guatemala, Nicaragua, and El Salvador, MRP for yellowfin is greater than skipjack by more than Int$ 3000.

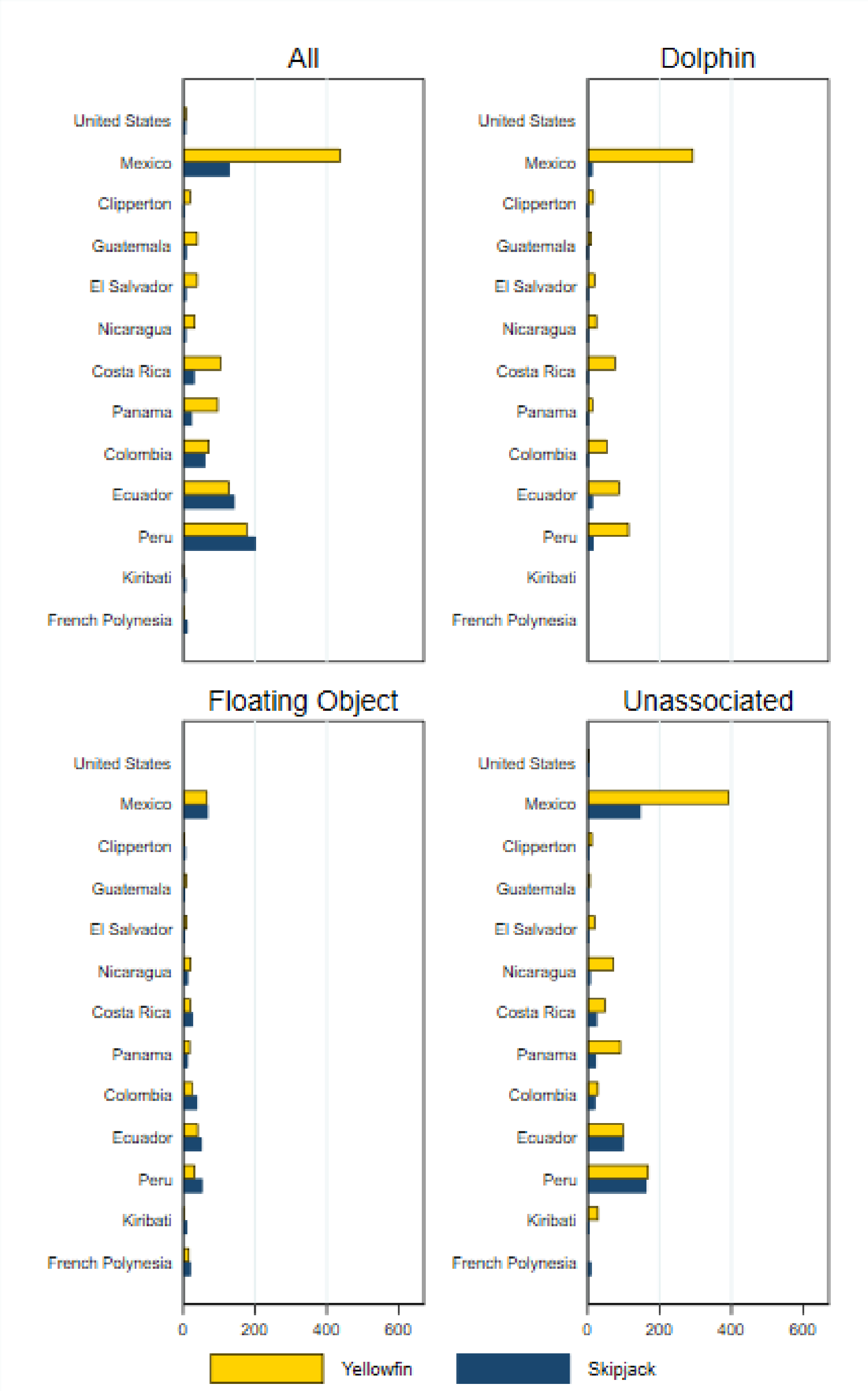


Figure 3. 5. Marginal revenue product of SST at means by country (in thousands of international dollars)

For unassociated sets, the marginal revenue product for yellowfin in bigger compared to skipjack tuna in most countries. Highest for the sum of the marginal revenue products for yellowfin and skipjack is for Mexico at 566 thousand international dollars as a result of 1°C increase in SST. This is followed by Peru (378 thousand international dollars) then Ecuador (270 thousand international dollars).

MP_{SST} and corresponding standard errors computed using models with time trend, with grid dummy, and both time trend and grid dummy are presented in the appendices. Separate estimations were done for data with overlaps (Appendix Table 3.5), without country overlaps (Appendix Table 3.6), without water overlaps (Appendix Table 3.7), and without state and water overlaps (Appendix Table 3.8). Results show that the MP_{SST} is not sensitive to the model specification, given that MP_{SST} is similar across model specifications. The next sections, we compute for the marginal revenue product using results from the RTO model.

3.5.3. Marginal revenue product per coastal population

Table 3.3 shows the marginal revenue product of SST at means per 100 coastal population for the different countries by type of set and species. French Polynesia and Kiribati, countries in the western border of the IATTC agreement area, record the highest marginal revenue product per 100 coastal population if we consider the sum for both yellowfin and skipjack.

If adjusted for the coastal population, then the marginal revenue product is the highest for Kiribati for both species across types of set. There is a wide margin between the Kiribati (Int$ 143.5) compared to French Polynesia (Int$ 6.71) which records the second highest value if we get the sum for both species. Guatemala and United States record the lowest marginal revenue product per coastal population for both species and all types of sets.

Table 3. 3. Marginal revenue product of SST at means per 100 coastal population[12] by country, species, and type of set (in international dollars)

Country	All	Dolphin	Floating Object	Unassociated
Skipjack				
Kiribati	117.69		167.85	82.48
French Polynesia	5.37		9.23	4.41
Panama	0.99	0.03	0.52	0.96
Ecuador	0.82	0.08	0.30	0.57
Costa Rica	0.69	0.03	0.60	0.55
Peru	0.62	0.05	0.16	0.50
Nicaragua	0.39	0.09	0.68	0.41
Colombia	0.28	0.01	0.18	0.10
Mexico	0.14	0.01	0.07	0.16
El Salvador	0.12	0.03	0.07	0.06
Guatemala	0.05	0.00	0.03	0.02
United States	0.03			0.03
Yellowfin				
Kiribati	25.81		44.58	478.67
Panama	4.04	0.61	0.79	3.84
Costa Rica	2.35	1.71	0.46	1.10
Nicaragua	1.73	1.30	1.13	3.73
French Polynesia	1.34		7.82	
Ecuador	0.74	0.51	0.24	0.58
El Salvador	0.63	0.32	0.17	0.32
Peru	0.55	0.35	0.10	0.52
Mexico	0.47	0.31	0.07	0.42
Colombia	0.33	0.25	0.12	0.13
Guatemala	0.25	0.07	0.06	0.05
United States	0.04			0.03
Sum				
Kiribati	143.5		212.43	561.15
French Polynesia	6.71		17.05	4.41
Panama	5.03	0.64	1.31	4.80
Costa Rica	3.04	1.74	1.06	1.65
Nicaragua	2.12	1.39	1.81	4.14
Ecuador	1.56	0.59	0.54	1.15
Peru	1.17	0.40	0.26	1.02
El Salvador	0.75	0.35	0.24	0.38
Colombia	0.61	0.26	0.30	0.23
Mexico	0.61	0.32	0.14	0.58
Guatemala	0.30	0.07	0.09	0.07
United States	0.07			0.06

[12] Population adjusted by the share of the area EEZ within the IATTC Agreement area to the total area of EEZ. Clipperton is not included in this table because it is uninhabited.

3.6. Discussion

We show that the volume of catch of skipjack and yellowfin tuna in the EEZ of countries in the Eastern Pacific Ocean increases as ocean warms. The results of our study support the conclusion in fisheries science studies that showed that the dispersion of tuna towards the eastern part of Pacific Ocean as ocean warms. This result is in contrast with the results of studies on Western and Central Pacific Ocean where there are expected reduction in catch as a result of ocean warming.

Although all countries have positive MP_{SST}, the MP_{SST} of countries on the eastern side of the IATTC area is greater compared to countries in western side of the IATTC. The sum of revenue for yellowfin and skipjack as a result of 1°C increase in SST is higher in countries in the east (e.g., Mexico, Peru) compared to French Polynesia which is the western side of the IATTC agreement area. This again supports eastward movement of tuna species within the IATTC agreement area.

Upper middle-income countries benefit the most from the increase in tuna catch with the increase in SST. Mexico, Peru, and Ecuador have the highest revenue from the increase in tuna catch. These are also the countries with largest fishing areas for tuna in the IATTC. Even though the MP_{SST} per square kilometre for lower middle-income countries such as Nicaragua and Guatemala is positive with a magnitude comparable to other countries, the revenue is low compared to other countries as the fished areas of the countries are comparatively smaller.

Unassociated sets have the highest MP_{SST} in the three types of sets. Unassociated sets target both species, thus it benefits from in the increase in catch in both catch of yellowfin and skipjack tuna. The dominant species caught through unassociated sets in the countries in Northern Hemisphere is yellowfin tuna while skipjack tuna is the dominant species in the countries in Southern Hemisphere. This is consistent with studies on the habitat choice of these species.

If we consider the population adjusted marginal revenue product, however, then the values for the countries on the western side of the IATTC agreement area such as Kiribati and French Polynesia are greater compared to countries in the east. The population adjusted marginal revenue product of SST is positively correlated with the measures of economic dependence on fisheries by Selig et al. (2019). Countries highly dependent on fisheries income and marine resources in general are the same countries that records the highest revenue per capita from the increase in tuna catch as ocean warms.[13] This is not the case if we just consider the MP_{SST} for each species. There is no linear relationship between the measures of dependence and MP_{SST} for both skipjack and yellowfin tuna. [14]

The higher tuna catch due to ocean warming translates to higher government revenue from more tuna fishing licenses that can be issued to purse seiners. As long as this is done sustainably, more jobs can be created for tuna fishers and those in the fish processing industry. Those offering ancillary services to tuna purse seine operators will also benefit from the increase in catch.

Government agencies or regional fisheries management organizations (RFMO) should adopt resource management mechanisms that are adaptive and responsive to tuna redistribution due to ocean warming. Countries in the EPO should exert effort to maintain the current levels of protection given to yellowfin and skipjack tuna as catch increases as ocean warms. Management measures must be designed specifically for

[13] The correlation coefficient between population adjusted marginal revenue product and overall dependence measure is 0.906 (p-value=0.000) and 0.964 (p-value=0.000) with economic dependence.

[14] The correlation coefficient between MP_{SST} of skipjack tuna and overall dependence is -0.078 (p-value = 0.800) and economic dependence is -0.125 (p-value: 0.6832). For MP_{SST} of yellowfin tuna, the correlation coefficient with overall dependence is -0.490 (0.089) and economic dependence is -0.452 (p-value = 0.140).

each location as there are differences in the local oceanographic and biological conditions.

Tuna in EPO may be managed by controlling the fishing effort. Regulators may encourage the use of unassociated sets given than the marginal product is highest for this type of set. The method also spreads the pressure to yellowfin and skipjack tuna and not just on a single species. There are countries, however, that unassociated sets does not provide the highest MP_{SST}. In Guatemala, for example, we can expect more dolphin sets as ocean warms because of higher economic returns. The increase in dolphin sets may affect the sustainability of yellowfin tuna in Guatemala, given that these dolphin sets primarily target yellowfin tuna.

Aside from being species-specific, we show that analysis of impacts of ocean warming should be done specifically for a fishing method. Management of tuna must also consider effort from other fishing method (i.e., longlining) that target tuna in EPO. This will provide a more complete perspective on the impacts of ocean warming on tuna.

The spatial redistribution of tuna due to ocean warming is supported by our findings. This movement of tuna requires updating of the stock assessment for better resource management on both sides of the Pacific. Historical stock assessment may become less reliable as tuna move to areas with their desired thermal tolerances. The new spawning grounds must be identified to ensure the sustainability of the tuna fisheries. A better understanding of the behaviour of other species in response to ocean warming is also necessary.

It is noteworthy also that our results only apply to tuna. We cannot conclude that the overall impact of sea warming is positive. There is a significant possibility of a negative net effect of ocean warming on total catch because of the possible reduction in catch of other species.

We establish the importance of including the fishing-dependent population in analysing the impact of ocean warming. Countries with higher dependence on fisheries are expected to gain more from higher revenue from tuna. This brings to the fore the need to include the fishers and other stakeholders in any discussion about adjustment of resource management practices in any fishery.

There is also a need for better international cooperation among RFMO members so that the tuna is properly managed, because of the different impacts on catch for the different countries. This is important because tuna is a migratory species, and that explains why fishing quotas are determined in international agreements. As the tuna move from west to east and thus redistribute benefits from tuna fisheries, fishing rights of Pacific countries may also need to be adjusted.

To summarise, the relationship we established may not be applicable to other scenarios as it is bound by the species, fishing gear, location, and period covered in this study. As oceans continue to warm, the SST may reach the upper threshold of temperature for desired habitat of tuna resulting to decline in catch in the area. A comprehensive analysis covering all species may also result in a negative net effect on fish catch as the recorded positive effects on tuna catch may be offset by the reduction on catch of other species. Future studies should consider species, gear-, and location-specific analyses so that the impact of ocean warming can be fully accounted.

3.7. Conclusion

Countries within the Eastern Pacific Ocean gain from the redistribution of tuna due to ocean warming. All countries experience increases in tuna catch as the SST increases. We reached this conclusion after applying a production function approach that links SST to tuna catch through the carrying capacity and intrinsic growth of tuna fisheries. The MP_{SST} of countries in the eastern border of the IATTC agreement area is higher compared to countries in the western border. This difference in marginal product highlights the eastward redistribution of tropical tuna species in the Pacific Ocean. Countries highly dependent on marine resources are the same countries that record the highest marginal revenue product when adjusted for population. We demonstrate that analysing the link between SST and catch in an economic framework produces results consistent with conclusions of results models in fisheries science. Countries should consider the results of this study to manage tuna fisheries within their EEZ.

Appendix

Appendix Table 3. 1. Measures of dependence on marine ecosystems

Country	Integrated dependence	Nutritional dependence	Economic dependence	Econ (Jobs)	Econ (Revenue)	Coastal Protection
Kiribati	0.72	0.74	0.86	0.93	0.80	0.07
French Polynesia	0.36	0.46				0.07
Honduras	0.27		0.23	0.23	0.24	0.35
Peru	0.24	0.23	0.19	0.13	0.27	0.07
Nicaragua	0.19	0.1	0.22	0.17	0.30	0.30
Ecuador	0.19	0.06	0.27	0.2	0.36	0.08
Panama	0.17	0.13	0.21	0.31	0.13	0.06
El Salvador	0.15	0.09	0.17	0.16	0.21	0.15
Chile	0.15	0.06	0.20	0.18	0.23	0.05
Mexico	0.11	0.08	0.11	0.13	0.11	0.25
Costa Rica	0.11	0.04	0.16	0.19	0.15	0.05
Guatemala	0.10	0.01	0.16	0.17	0.16	0.26
Colombia	0.08	0.02	0.12	0.18	0.08	0.10
United States	0.05	0.05	0.04	0.04	0.07	0.28

Source: Selig et al. (2019)

Appendix Table 3. 2. Number of sets, tuna catch, catch per set, percentage distribution of tuna catch by species, by country, data group, and set type

	Number of Sets	Total Tuna Catch (in metric tons)	Catch per set (in metric tons)	Percentage distribution of tuna catch by species		
				Yellowfin	Skipjack	Other species
DOLPHIN SETS						
Colombia	1099	16543	15	94	5	0
Costa Rica	8674	132141	15	98	2	0
Ecuador	4518	119828	27	95	5	0
El Salvador	548	9181	17	96	4	0
Clipperton	15395	233975	15	94	6	0
Guatemala	2262	31610	14	97	3	0
Honduras	8	149	19	93	7	0
Mexico	39702	480615	12	94	6	0
Nicaragua	525	11804	27	94	6	0
Panama	1350	18399	14	96	3	0
Peru	895	28142	32	86	14	0
United States	2	65	24	0	100	0
UNASSOCIATED SETS						
Chile	356	8425	30	5	93	1
Colombia	29716	289444	10	44	54	2
Costa Rica	12207	171424	14	55	44	2
Ecuador	110387	1225151	11	31	66	4
El Salvador	1983	26191	13	70	30	0
Clipperton	1285	22228	17	74	26	0
French Polynesia	225	3279	13	5	94	0
Guatemala	2290	23404	10	53	47	0
Honduras	7	203	29	93	7	0
Line (Kiribati)	236	5659	26	1	98	0
Mexico	136795	1298377	9	57	27	16
Nicaragua	1393	20853	15	76	24	0
Panama	19216	208217	11	69	30	1
Peru	83498	1048572	14	33	64	4
United States	3450	28686	9	17	20	63

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Appendix Table 3.2. ***Continuation***

	Number of Sets	Total Tuna Catch (in metric tons)	Catch per set (in metric tons)	Percentage distribution of tuna catch by species		
				Yellowfin	Skipjack	Other species
FLOATING OBJECT SETS						
Chile	179	7582	55	32	56	13
Colombia	30461	445653	15	26	69	5
Costa Rica	18956	352754	19	30	67	3
Ecuador	41521	799004	19	19	66	15
El Salvador	2013	43098	21	70	30	0
Clipperton	2835	55998	20	30	67	3
French Polynesia	1160	47684	40	9	74	17
Guatemala	3255	56270	17	52	47	1
Line (Kiribati)	744	36698	52	8	84	8
Mexico	6838	130571	19	32	68	1
Nicaragua	901	21744	22	71	28	1
Panama	8343	105098	13	46	51	2
Peru	9664	291405	31	26	72	2
United States	9	21	2	19	81	0

Data Source: Inter-American Tropical Tuna Commission (IATTC)

Appendix Table 3. 3. Trend of SST by country
($SST_t = \hat{\beta}_0 + \hat{\beta}_1 Year + \hat{\mu}_t$)

Country	$\boldsymbol{\beta_1}$	se($\boldsymbol{\beta_1}$)	Observations	R^2
Chile	0.010***	(0.003)	49	0.233
Clipperton	0.013***	(0.002)	49	0.398
Colombia	0.016***	(0.004)	49	0.263
Costa Rica	0.017***	(0.004)	49	0.248
Ecuador	0.016**	(0.007)	49	0.092
El Salvador	0.015***	(0.003)	49	0.347
French Polynesia	0.015***	(0.002)	49	0.639
Guatemala	0.016***	(0.002)	49	0.496
Kiribati	0.014***	(0.005)	49	0.168
Mexico	0.019***	(0.004)	49	0.331
Nicaragua	0.016***	(0.003)	49	0.329
Panama	0.016***	(0.003)	49	0.391
Peru	0.011	(0.008)	49	0.046
United States	0.012**	(0.005)	49	0.113

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3. 4. Marginal product by species and data group using RTO model

Country and Set Types	Skipjack								Yellowfin							
	With Overlaps		Without Country Overlaps		Without Water Overlaps		Without Water and Country Overlaps		With Overlaps		Without Country Overlaps		Without Water Overlaps		Without Water and Country Overlaps	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
All																
Chile	7.2	[0.8]	3.9	[0.4]	9.9	[1.3]			2.2	[0.2]	1.1	[0.3]	1.1	[0.3]		
Clipperton	0.6	[0.0]	0.6	[0.0]	0.5	[0.1]	0.5	[0.1]	2.4	[0.1]	2.4	[0.1]	2.4	[0.1]	2.5	[0.1]
Colombia	3.7	[0.2]	4.0	[0.2]	3.7	[0.2]	4.5	[0.3]	3.0	[0.1]	2.9	[0.1]	2.9	[0.1]	2.8	[0.1]
Costa Rica	2.3	[0.1]	1.8	[0.1]	2.2	[0.1]	1.7	[0.1]	3.7	[0.1]	4.4	[0.1]	4.4	[0.1]	4.3	[0.1]
Ecuador	4.5	[0.5]	4.7	[0.3]	5.5	[0.7]	5.8	[0.5]	2.7	[0.3]	2.7	[0.3]	2.7	[0.3]	3.3	[0.4]
El Salvador	1.6	[0.3]	2.3	[0.6]	1.4	[0.3]	1.6	[0.1]	5.2	[0.4]	5.9	[0.6]	5.9	[0.6]	4.4	[0.3]
French Polynesia	1.4	[0.1]	1.4	[0.2]	0.7	[0.2]	0.4	[0.1]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.0	[0.0]
Guatemala	2.2	[0.1]	2.3	[0.1]	1.9	[0.2]	2.1	[0.1]	5.4	[0.2]	6.4	[0.1]	6.4	[0.1]	6.3	[0.1]
Kiribati	2.5	[0.3]	2.6	[0.3]	1.0	[0.4]			0.3	[0.0]	0.3	[0.0]	0.3	[0.0]	0.2	[0.0]
Mexico	1.9	[0.1]	1.9	[0.1]	2.0	[0.1]	1.9	[0.1]	3.9	[0.1]	3.9	[0.1]	3.9	[0.1]	4.4	[0.1]
Nicaragua	1.5	[0.2]			1.4	[0.2]			4.0	[0.3]						
Panama	3.2	[0.1]	3.4	[0.2]	3.2	[0.1]	3.7	[0.2]	6.3	[0.4]	9.6	[0.9]	9.6	[0.9]	8.4	[0.6]
Peru	7.3	[1.4]	8.1	[0.7]	9.7	[1.9]	10.6	[1.0]	6.1	[1.0]	4.1	[0.4]	4.1	[0.4]	5.1	[0.6]
United States	2.9	[0.6]	2.1	[0.1]	2.9	[0.6]	2.1	[0.1]	2.9	[0.2]	1.5	[0.4]	1.5	[0.4]	1.6	[0.4]
Dolphin																
Clipperton	0.1	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	1.7	[0.1]	2.3	[0.1]	2.3	[0.1]	2.1	[0.1]
Colombia	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	3.4	[0.1]	1.8	[0.1]	1.8	[0.1]	1.7	[0.1]
Costa Rica	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	1.2	[0.1]	3.7	[0.1]	3.7	[0.1]	3.6	[0.1]
Ecuador	0.3	[0.1]	0.5	[0.1]	0.6	[0.1]	0.7	[0.1]	3.4	[0.1]	1.4	[0.2]	1.4	[0.2]	1.7	[0.3]
El Salvador	0.5	[0.1]			0.2	[0.1]			4.1	[0.2]	2.7	[0.0]	2.7	[0.0]	1.5	[0.3]
Guatemala	0.0	[0.0]	0.1	[0.0]	0.3	[0.0]			1.4	[0.2]	0.2	[0.0]	0.2	[0.0]	4.8	[0.2]
Mexico	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	1.5	[0.1]	3.6	[0.1]	3.6	[0.1]	2.1	[0.1]
Nicaragua	0.3	[0.1]			0.4	[0.1]			3.0	[0.3]						
Panama	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.9	[0.1]	1.1	[0.2]	1.1	[0.2]	2.0	[0.2]
Peru	0.9	[0.2]	0.9	[0.1]			0.5	[0.2]	0.6	[0.3]	4.9	[0.6]	4.9	[0.6]	2.1	[0.3]

Appendix Table 3.4 *Continuation*

Country and Set Types	Skipjack								Yellowfin							
	With Overlaps		Without Country Overlaps		Without Water Overlaps		Without Water and Country Overlaps		With Overlaps		Without Country Overlaps		Without Water Overlaps		Without Water and Country Overlaps	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
Floating Objects																
Chile	2.3	[0.4]	2.6	[0.5]	4.2	[0.4]			1.4	[0.4]	0.9	[0.3]	0.9	[0.3]		
Clipperton	3.5	[0.0]	0.7	[0.0]	0.5	[0.1]	0.5	[0.1]	1.2	[0.0]	0.3	[0.0]	0.3	[0.0]	0.3	[0.0]
Colombia	1.4	[0.1]	3.1	[0.1]	2.7	[0.1]	3.1	[0.2]	0.6	[0.1]	1.2	[0.0]	1.2	[0.0]	1.3	[0.0]
Costa Rica	2.2	[0.1]	1.5	[0.1]	1.9	[0.1]	1.4	[0.1]	0.9	[0.0]	0.8	[0.0]	0.8	[0.0]	0.8	[0.0]
Ecuador	1.2	[0.2]	2.1	[0.1]	2.0	[0.2]	2.1	[0.2]	1.5	[0.0]	0.7	[0.1]	0.7	[0.1]	0.8	[0.1]
El Salvador	0.5	[0.1]	1.5	[0.3]	1.0	[0.1]	1.0	[0.2]	0.1	[0.2]	2.0	[0.4]	2.0	[0.4]	1.6	[0.1]
French Polynesia	4.5	[0.1]	1.1	[0.1]	0.4	[0.1]	0.7	[0.1]	3.2	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]
Guatemala	0.7	[0.1]	2.0	[0.2]	1.3	[0.2]	1.3	[0.1]	0.1	[0.2]	2.0	[0.2]	2.0	[0.2]	2.1	[0.2]
Kiribati	2.9	[0.3]	2.9	[0.3]					1.3	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Mexico	0.9	[0.1]	1.0	[0.1]	1.1	[0.1]	1.1	[0.1]	1.2	[0.0]	0.4	[0.0]	0.4	[0.0]	0.5	[0.0]
Nicaragua	4.1	[0.1]			1.0	[0.1]			2.6	[0.1]						
Panama	1.0	[0.1]	2.0	[0.2]	2.1	[0.1]	2.0	[0.1]	0.5	[0.1]	2.2	[0.2]	2.2	[0.2]	1.7	[0.1]
Peru	0.8	[0.2]	3.2	[0.1]	2.4	[0.2]	3.0	[0.2]	0.6	[0.1]	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]
Unassociated																
Chile	0.7	[1.8]			11.2	[2.7]			1.9	[0.1]						
Clipperton	2.4	[0.0]	0.3	[0.0]	0.3	[0.0]	0.3	[0.0]	2.6	[0.0]	1.1	[0.0]	1.1	[0.0]	1.4	[0.0]
Colombia	0.6	[0.1]	1.7	[0.1]	1.5	[0.1]	1.7	[0.1]	0.8	[0.1]	1.2	[0.1]	1.2	[0.1]	1.5	[0.1]
Costa Rica	3.8	[0.1]	0.8	[0.0]	0.9	[0.1]	0.9	[0.0]	3.9	[0.1]	1.3	[0.2]	1.3	[0.2]	1.4	[0.2]
Ecuador	1.0	[0.4]	3.7	[0.3]	4.8	[0.6]	4.8	[0.4]	1.2	[0.3]	2.4	[0.3]	2.4	[0.3]	2.9	[0.4]
El Salvador	0.7	[0.1]			1.0	[0.1]			0.5	[0.3]	3.3	[0.5]	3.3	[0.5]	3.8	[0.6]
French Polynesia	1.0	[0.2]	0.6	[0.2]												
Guatemala	0.1	[0.1]	1.2	[0.1]	1.0	[0.1]	1.1	[0.1]	0.4	[0.2]	1.3	[0.1]	1.3	[0.1]	1.5	[0.2]
Kiribati	2.8	[0.5]	1.3	[0.5]	0.8	[0.2]	0.8	[0.2]	15.1	[0.0]	0.1	[0.0]	0.1	[0.0]		
Mexico	1.2	[0.1]	2.6	[0.1]	2.5	[0.1]	2.5	[0.1]	1.3	[0.2]	4.3	[0.2]	4.3	[0.2]	4.6	[0.2]
Nicaragua	2.1	[0.1]			1.0	[0.1]			8.6	[0.2]						
Panama	5.9	[0.1]	2.3	[0.1]	2.1	[0.1]	2.8	[0.2]	7.6	[0.5]	8.4	[0.9]	8.4	[0.9]	7.8	[0.6]
Peru	2.1	[1.3]	7.3	[0.7]	9.7	[1.8]	9.9	[1.0]	2.7	[1.3]	5.0	[0.7]	5.0	[0.7]	5.8	[0.9]
United States	1.0	[0.6]	2.1	[0.1]	2.9	[0.6]	2.1	[0.1]	0.3	[0.2]	1.5	[0.4]	1.5	[0.4]	1.6	[0.4]

Appendix Table 3. 5. Marginal Product of SST by species for four model specifications using data with overlaps

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
All																
Chile	7.2	[0.8]	6.9	[0.9]	6.6	[1.1]	6.8	[1.0]	2.2	[0.2]	2.2	[0.2]	2.3	[0.3]	2.3	[0.3]
Clipperton	0.6	[0.0]	0.5	[0.0]	0.6	[0.0]	0.5	[0.0]	2.4	[0.1]	2.6	[0.1]	2.9	[0.2]	2.9	[0.2]
Colombia	3.7	[0.2]	3.6	[0.3]	3.6	[0.3]	3.7	[0.2]	3.0	[0.1]	2.9	[0.2]	2.8	[0.2]	2.9	[0.1]
Costa Rica	2.3	[0.1]	2.3	[0.1]	2.3	[0.1]	2.3	[0.1]	3.7	[0.1]	3.8	[0.1]	3.8	[0.1]	3.8	[0.1]
Ecuador	4.5	[0.5]	4.4	[0.6]	4.8	[0.5]	4.9	[0.5]	2.7	[0.3]	2.6	[0.3]	2.8	[0.3]	2.8	[0.3]
El Salvador	1.6	[0.3]	1.5	[0.3]	1.5	[0.3]	1.4	[0.3]	5.2	[0.4]	5.3	[0.6]	5.5	[0.5]	5.5	[0.6]
French Polynesia	1.4	[0.1]	1.5	[0.2]	1.4	[0.2]	1.5	[0.2]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Guatemala	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	5.4	[0.2]	5.6	[0.3]	5.7	[0.3]	5.7	[0.3]
Kiribati	2.5	[0.3]	2.3	[0.3]	2.3	[0.4]	2.3	[0.4]	0.3	[0.0]	0.2	[0.1]	0.2	[0.1]	0.2	[0.1]
Mexico	1.9	[0.1]	1.8	[0.1]	1.8	[0.1]	1.8	[0.1]	3.9	[0.1]	3.8	[0.1]	4.0	[0.1]	3.9	[0.1]
Nicaragua	1.5	[0.2]	1.4	[0.2]	1.5	[0.2]	1.4	[0.2]	4.0	[0.3]	4.2	[0.4]	4.2	[0.4]	4.4	[0.4]
Panama	3.2	[0.1]	3.2	[0.2]	3.2	[0.2]	3.2	[0.2]	6.3	[0.4]	6.4	[0.5]	6.2	[0.4]	6.3	[0.4]
Peru	7.3	[1.4]	6.5	[1.4]	6.9	[1.7]	7.6	[1.5]	6.1	[1.0]	5.8	[1.0]	6.3	[1.1]	6.5	[1.1]
United States	2.9	[0.6]	2.9	[0.7]	2.9	[0.8]	2.9	[0.8]	2.9	[0.2]	2.8	[0.3]	2.8	[0.4]	2.8	[0.4]
Dolphin																
Clipperton	0.1	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	1.7	[0.1]	2.5	[0.1]	2.8	[0.2]	2.8	[0.2]
Colombia	0.1	[0.0]	0.1	[0.0]					3.4	[0.1]	1.9	[0.1]	2.0	[0.1]	1.9	[0.1]
Costa Rica	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	1.2	[0.1]	3.1	[0.1]	3.2	[0.1]	3.2	[0.1]
Ecuador	0.3	[0.1]	0.5	[0.1]	0.4	[0.1]	0.4	[0.1]	3.4	[0.1]	1.4	[0.2]	1.5	[0.2]	1.5	[0.2]
El Salvador	0.5	[0.1]	0.2	[0.1]	0.3	[0.1]	0.3	[0.1]	4.1	[0.2]	3.1	[0.3]	3.2	[0.3]	3.3	[0.3]
French Polynesia																
Guatemala	0.0	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	1.4	[0.2]	4.1	[0.2]	4.2	[0.2]	4.2	[0.2]
Kiribati																
Mexico	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	1.5	[0.1]	2.1	[0.1]	2.2	[0.1]	2.2	[0.1]
Nicaragua	0.3	[0.1]	0.4	[0.1]	0.4	[0.1]	0.4	[0.1]	3.0	[0.3]	2.5	[0.3]	2.4	[0.4]	2.6	[0.3]
Panama	0.1	[0.0]							0.9	[0.1]	2.5	[0.2]	2.4	[0.2]	2.4	[0.2]
Peru	0.9	[0.2]	0.7	[0.2]					0.6	[0.3]	2.0	[0.3]	1.9	[0.4]	1.9	[0.4]

Appendix Table 3.5. *Continuation*

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
Unassociated																
Chile	0.7	[1.8]	9.1	[2.1]	9.1	[2.3]	9.7	[2.4]	1.9	[0.1]	2.0	[0.2]	1.8	[0.2]	1.9	[0.3]
Clipperton	2.4	[0.0]	0.3	[0.1]	0.3	[0.1]	0.3	[0.1]	2.6	[0.0]	1.1	[0.0]	1.1	[0.1]	1.1	[0.1]
Colombia	0.6	[0.1]	1.4	[0.1]	1.4	[0.1]	1.4	[0.1]	0.8	[0.1]	1.5	[0.2]	1.5	[0.1]	1.5	[0.1]
Costa Rica	3.8	[0.1]	0.8	[0.1]	0.8	[0.1]	0.8	[0.1]	3.9	[0.1]	1.2	[0.1]	1.2	[0.1]	1.2	[0.1]
Ecuador	1.0	[0.4]	3.8	[0.5]	4.2	[0.5]	4.3	[0.5]	1.2	[0.3]	2.5	[0.3]	2.6	[0.3]	2.6	[0.3]
El Salvador	0.7	[0.1]	1.1	[0.1]	1.1	[0.1]	1.1	[0.2]	0.5	[0.3]	2.4	[0.4]	2.4	[0.3]	2.4	[0.3]
French Polynesia	1.0	[0.2]														
Guatemala	0.1	[0.1]	1.2	[0.1]	1.2	[0.2]	1.2	[0.1]	0.4	[0.2]	1.6	[0.3]	1.7	[0.3]	1.6	[0.3]
Kiribati	2.8	[0.5]							15.1	[0.0]	0.1	[0.0]	0.0	[0.0]	0.0	[0.0]
Mexico	1.2	[0.1]	2.5	[0.1]	2.5	[0.1]	2.5	[0.1]	1.3	[0.2]	4.2	[0.2]	4.1	[0.2]	4.1	[0.2]
Nicaragua	2.1	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]	8.6	[0.2]	2.6	[0.4]	2.6	[0.4]	2.6	[0.4]
Panama	5.9	[0.1]	2.1	[0.2]	2.1	[0.1]	2.1	[0.1]	7.6	[0.5]	5.4	[0.5]	5.1	[0.5]	5.2	[0.5]
Peru	2.1	[1.3]	6.8	[1.4]	7.0	[1.7]	7.8	[1.5]	2.7	[1.3]	7.7	[1.4]	8.1	[1.5]	8.4	[1.5]
United States	1.0	[0.6]	2.9	[0.7]	2.8	[0.8]	2.8	[0.8]	0.3	[0.2]	2.8	[0.3]	2.8	[0.4]	2.8	[0.4]
Floating																
Chile	2.3	[0.4]	3.7	[0.4]	3.2	[0.5]	3.2	[0.6]	1.4	[0.4]	1.8	[0.6]	1.9	[0.6]	1.9	[0.6]
Clipperton	3.5	[0.0]	0.6	[0.1]	0.7	[0.1]	0.7	[0.1]	1.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Colombia	1.4	[0.1]	2.6	[0.1]	2.5	[0.1]	2.6	[0.1]	0.6	[0.1]	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]
Costa Rica	2.2	[0.1]	2.0	[0.1]	1.9	[0.1]	1.9	[0.1]	0.9	[0.0]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]
Ecuador	1.2	[0.2]	2.0	[0.2]	2.0	[0.2]	2.0	[0.2]	1.5	[0.0]	0.6	[0.1]	0.6	[0.1]	0.6	[0.1]
El Salvador	0.5	[0.1]	1.0	[0.1]	1.1	[0.2]	1.1	[0.1]	0.1	[0.2]	2.0	[0.2]	2.1	[0.3]	2.0	[0.3]
French Polynesia	4.5	[0.1]	1.1	[0.2]	1.1	[0.2]	1.1	[0.2]	3.2	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]
Guatemala	0.7	[0.1]	1.7	[0.2]	1.7	[0.2]	1.7	[0.2]	0.1	[0.2]	2.0	[0.3]	2.1	[0.2]	2.0	[0.3]
Kiribati	2.9	[0.3]	3.2	[0.4]	2.9	[0.5]	3.2	[0.5]	1.3	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.1]
Mexico	0.9	[0.1]	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]	1.2	[0.0]	0.5	[0.0]	0.5	[0.0]	0.5	[0.0]
Nicaragua	4.1	[0.1]	1.1	[0.1]	1.1	[0.1]	1.1	[0.1]	2.6	[0.1]	1.7	[0.2]	1.7	[0.2]	1.6	[0.2]
Panama	1.0	[0.1]	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	0.5	[0.1]	1.6	[0.1]	1.6	[0.1]	1.6	[0.1]
Peru	0.8	[0.2]	2.7	[0.2]	2.5	[0.2]	2.6	[0.2]	0.6	[0.1]	1.2	[0.2]	1.2	[0.1]	1.2	[0.2]

Appendix Table 3. 6. Marginal Product of SST by species for four model specifications using data without country overlaps

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
All																
Chile	3.9	[0.4]	4.2	[0.6]	4.3	[0.4]	4.3	[1.2]	1.1	[0.3]	1.1	[0.4]				
Clipperton	0.6	[0.0]	0.5	[0.0]	0.6	[0.0]	0.5	[0.0]	2.4	[0.1]	2.6	[0.1]	2.9	[0.2]	2.9	[0.2]
Colombia	4.0	[0.2]	3.9	[0.3]	4.0	[0.3]	3.9	[0.3]	2.9	[0.1]	3.0	[0.2]	3.0	[0.2]	2.9	[0.2]
Costa Rica	1.8	[0.1]	1.8	[0.1]	1.8	[0.1]	1.8	[0.1]	4.4	[0.1]	4.5	[0.2]	4.5	[0.2]	4.5	[0.2]
Ecuador	4.7	[0.3]	4.6	[0.4]	4.8	[0.4]	4.9	[0.3]	2.7	[0.3]	2.7	[0.3]	2.8	[0.3]	2.9	[0.3]
El Salvador	2.3	[0.6]	2.4	[0.6]	2.5	[0.5]	2.4	[0.7]	5.9	[0.6]	6.3	[0.6]	6.2	[0.6]	6.3	[0.7]
French Polynesia	1.4	[0.2]	1.5	[0.2]	1.4	[0.2]	1.5	[0.2]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Guatemala	2.3	[0.1]	2.4	[0.1]	2.4	[0.1]	2.3	[0.1]	6.4	[0.1]	6.7	[0.3]	6.6	[0.2]	6.7	[0.3]
Kiribati	2.6	[0.3]	2.4	[0.4]	2.4	[0.4]	2.4	[0.4]	0.3	[0.0]	0.2	[0.1]	0.2	[0.1]	0.2	[0.1]
Mexico	1.9	[0.1]	1.8	[0.1]	1.8	[0.1]	1.8	[0.1]	3.9	[0.1]	3.8	[0.1]	3.9	[0.1]	3.9	[0.1]
Panama	3.4	[0.2]	3.3	[0.3]	3.3	[0.3]	3.3	[0.3]	9.6	[0.9]	10.0	[0.9]	9.8	[0.9]	9.8	[0.9]
Peru	8.1	[0.7]	7.8	[0.8]	7.6	[0.8]	8.0	[0.8]	4.1	[0.4]	4.0	[0.5]	4.0	[0.6]	4.2	[0.5]
United States	2.1	[0.1]	2.1	[0.2]	2.1	[0.2]	1.9	[0.4]	1.5	[0.4]						
Dolphin																
Chile																
Clipperton	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	2.3	[0.1]	2.5	[0.1]	2.8	[0.2]	2.8	[0.2]
Colombia	0.1	[0.0]	0.2	[0.0]	0.2	[0.1]	0.2	[0.1]	1.8	[0.1]	1.8	[0.1]	1.9	[0.1]	1.8	[0.1]
Costa Rica	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	3.7	[0.1]	3.9	[0.2]	4.0	[0.2]	4.0	[0.2]
Ecuador	0.5	[0.1]	0.6	[0.1]	0.5	[0.1]	0.5	[0.1]	1.4	[0.2]	1.5	[0.2]	1.6	[0.2]	1.6	[0.2]
El Salvador									2.7	[0.0]	2.8	[0.0]	2.7	[0.0]	2.8	[0.0]
Guatemala	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Mexico	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	3.6	[0.1]	3.6	[0.1]	3.8	[0.1]	3.8	[0.1]
Panama	0.1	[0.0]	0.1	[0.0]	0.2	[0.0]	0.1	[0.0]	1.1	[0.2]						
Peru	0.9	[0.1]	1.0	[0.2]	1.3	[0.3]	1.3	[0.3]	4.9	[0.6]	5.4	[0.8]	4.9	[1.0]	4.9	[1.0]

Appendix Table 3. 7. *Continuation*

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
Unassociated																
Chile											0.3	[0.0]	1.1	[0.0]		
Clipperton	0.3	[0.0]	0.3	[0.1]	0.3	[0.1]	0.3	[0.1]	1.1	[0.0]	1.1	[0.0]	1.1	[0.1]	1.1	[0.1]
Colombia	1.7	[0.1]	1.7	[0.1]	1.8	[0.1]	1.8	[0.1]	1.2	[0.1]	1.1	[0.1]	1.2	[0.1]	1.2	[0.1]
Costa Rica	0.8	[0.0]	0.8	[0.0]	0.8	[0.0]	0.8	[0.0]	1.3	[0.2]	1.3	[0.2]	1.4	[0.2]	1.4	[0.2]
Ecuador	3.7	[0.3]	3.7	[0.3]	4.0	[0.4]	4.1	[0.4]	2.4	[0.3]	2.3	[0.3]	2.5	[0.3]	2.5	[0.3]
El Salvador									3.3	[0.5]	3.5	[0.7]	3.5	[0.5]	3.5	[0.7]
French Polynesia	0.6	[0.2]														
Guatemala	1.2	[0.1]	1.3	[0.1]	1.3	[0.2]	1.2	[0.1]	1.3	[0.1]	1.3	[0.2]	1.3	[0.1]	1.3	[0.2]
Kiribati	1.3	[0.5]							0.1	[0.0]	0.1	[0.0]	0.0	[0.0]	0.0	[0.0]
Mexico	2.6	[0.1]	2.6	[0.1]	2.5	[0.1]	2.5	[0.1]	4.3	[0.2]	4.3	[0.2]	4.2	[0.2]	4.2	[0.2]
Panama	2.3	[0.1]	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	8.4	[0.9]	8.6	[0.9]	8.3	[0.9]	8.3	[1.0]
Peru	7.3	[0.7]	7.2	[0.8]	7.1	[0.8]	7.4	[0.8]	5.0	[0.7]	5.0	[0.7]	4.9	[0.8]	5.3	[0.7]
United States	2.1	[0.1]	2.2	[0.2]	2.1	[0.2]	2.0	[0.4]	1.5	[0.4]						
Floating																
Chile	2.6	[0.5]	3.1	[0.9]	3.1	[0.3]	4.0	[1.6]	0.9	[0.3]						
Clipperton	0.7	[0.0]	0.6	[0.1]	0.7	[0.1]	0.7	[0.1]	0.3	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Colombia	3.1	[0.1]	3.0	[0.2]	3.0	[0.2]	3.0	[0.2]	1.2	[0.0]	1.2	[0.1]	1.2	[0.1]	1.2	[0.1]
Costa Rica	1.5	[0.1]	1.5	[0.1]	1.5	[0.1]	1.5	[0.1]	0.8	[0.0]	0.9	[0.0]	0.8	[0.0]	0.8	[0.0]
Ecuador	2.1	[0.1]	1.9	[0.2]	1.8	[0.2]	1.9	[0.2]	0.7	[0.1]	0.6	[0.1]	0.6	[0.1]	0.6	[0.1]
El Salvador	1.5	[0.3]	1.6	[0.4]	1.7	[0.3]	1.7	[0.5]	2.0	[0.4]			2.1	[0.6]		
French Polynesia	1.1	[0.1]	1.1	[0.2]	1.0	[0.2]	1.1	[0.2]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]
Guatemala	2.0	[0.2]	2.1	[0.3]	2.1	[0.3]	2.0	[0.3]	2.0	[0.2]	2.0	[0.2]	2.1	[0.3]	1.9	[0.3]
Kiribati	2.9	[0.3]	3.4	[0.5]	3.1	[0.5]	3.4	[0.6]	0.2	[0.0]	0.2	[0.1]	0.2	[0.0]	0.2	[0.1]
Mexico	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]	0.4	[0.0]	0.4	[0.0]	0.4	[0.0]	0.4	[0.0]
Panama	2.0	[0.2]	2.0	[0.2]	2.1	[0.2]	2.1	[0.2]	2.2	[0.2]	2.2	[0.3]	2.2	[0.2]	2.2	[0.3]
Peru	3.2	[0.1]	3.1	[0.2]	3.0	[0.2]	3.0	[0.2]	1.0	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]

Appendix Table 3. 8. Marginal Product of SST by species for four model specifications using data without international water overlaps

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
All																
Chile	9.9	[1.3]	9.5	[1.6]	9.3	[1.8]	9.5	[1.8]	1.1	[0.3]	1.1	[0.4]				
Clipperton	0.5	[0.1]	0.5	[0.1]	0.5	[0.1]	0.5	[0.1]	2.4	[0.1]	2.6	[0.1]	2.9	[0.2]	2.9	[0.2]
Colombia	3.7	[0.2]	3.7	[0.3]	3.6	[0.3]	3.7	[0.3]	2.9	[0.1]	3.0	[0.2]	3.0	[0.2]	2.9	[0.2]
Costa Rica	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	4.4	[0.1]	4.5	[0.2]	4.5	[0.2]	4.5	[0.2]
Ecuador	5.5	[0.7]	5.4	[0.8]	6.0	[0.7]	6.0	[0.7]	2.7	[0.3]	2.7	[0.3]	2.8	[0.3]	2.9	[0.3]
El Salvador	1.4	[0.3]	1.2	[0.3]	1.2	[0.3]	1.2	[0.3]	5.9	[0.6]	6.3	[0.6]	6.2	[0.6]	6.3	[0.7]
French Polynesia	0.7	[0.2]							0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Guatemala	1.9	[0.2]	2.0	[0.2]	2.0	[0.2]	1.9	[0.2]	6.4	[0.1]	6.7	[0.3]	6.6	[0.2]	6.7	[0.3]
Kiribati	1.0	[0.4]							0.3	[0.0]	0.2	[0.1]	0.2	[0.1]	0.2	[0.1]
Mexico	2.0	[0.1]	1.9	[0.1]	1.9	[0.1]	1.9	[0.1]	3.9	[0.1]	3.8	[0.1]	3.9	[0.1]	3.9	[0.1]
Nicaragua	1.4	[0.2]	1.3	[0.2]	1.4	[0.2]	1.3	[0.2]								
Panama	3.2	[0.1]	3.2	[0.2]	3.2	[0.2]	3.2	[0.2]	9.6	[0.9]	10.0	[0.9]	9.8	[0.9]	9.8	[0.9]
Peru	9.7	[1.9]	8.6	[1.9]	9.1	[2.3]	10.1	[2.1]	4.1	[0.4]	4.0	[0.5]	4.0	[0.6]	4.2	[0.5]
United States	2.9	[0.6]	2.9	[0.7]	2.9	[0.8]	2.9	[0.8]	1.5	[0.4]						
Dolphin																
Clipperton	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	2.3	[0.1]	2.5	[0.1]	2.8	[0.2]	2.8	[0.2]
Colombia	0.1	[0.0]	0.1	[0.0]					1.8	[0.1]	1.8	[0.1]	1.9	[0.1]	1.8	[0.1]
Costa Rica	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	3.7	[0.1]	3.9	[0.2]	4.0	[0.2]	4.0	[0.2]
Ecuador	0.6	[0.1]	0.6	[0.1]	0.6	[0.1]	0.6	[0.1]	1.4	[0.2]	1.5	[0.2]	1.6	[0.2]	1.6	[0.2]
El Salvador	0.2	[0.1]	0.2	[0.1]	0.2	[0.1]	0.2	[0.1]	2.7	[0.0]	2.8	[0.0]	2.7	[0.0]	2.8	[0.0]
Guatemala	0.3	[0.0]	0.3	[0.0]	0.3	[0.1]	0.3	[0.1]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Mexico	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	3.6	[0.1]	3.6	[0.1]	3.8	[0.1]	3.8	[0.1]
Nicaragua	0.4	[0.1]	0.4	[0.1]	0.4	[0.1]	0.4	[0.1]								
Panama	0.1	[0.0]							1.1	[0.2]						
Peru									4.9	[0.6]	5.4	[0.8]	4.9	[1.0]	4.9	[1.0]

Appendix Table 3.7. *Continuation*

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
Unassociated																
Chile	11.2	[2.7]	11.9	[3.2]	11.3	[3.3]	12.1	[3.7]			0.3	[0.0]	1.1	[0.0]		
Clipperton	0.3	[0.0]	0.3	[0.1]	0.3	[0.1]	0.3	[0.1]	1.1	[0.0]	1.1	[0.0]	1.1	[0.1]	1.1	[0.1]
Colombia	1.5	[0.1]	1.4	[0.1]	1.4	[0.1]	1.5	[0.1]	1.2	[0.1]	1.1	[0.1]	1.2	[0.1]	1.2	[0.1]
Costa Rica	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]	1.3	[0.2]	1.3	[0.2]	1.4	[0.2]	1.4	[0.2]
Ecuador	4.8	[0.6]	4.8	[0.6]	5.3	[0.6]	5.4	[0.6]	2.4	[0.3]	2.3	[0.3]	2.5	[0.3]	2.5	[0.3]
El Salvador	1.0	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]	3.3	[0.5]	3.5	[0.7]	3.5	[0.5]	3.5	[0.7]
French Polynesia																
Guatemala	1.0	[0.1]	1.1	[0.1]	1.1	[0.1]	1.1	[0.1]	1.3	[0.1]	1.3	[0.2]	1.3	[0.1]	1.3	[0.2]
Kiribati	0.8	[0.2]	0.8	[0.3]	0.8	[0.0]	6.6	[0.7]	0.1	[0.0]	0.1	[0.0]	0.0	[0.0]	0.0	[0.0]
Mexico	2.5	[0.1]	2.5	[0.1]	2.5	[0.1]	2.5	[0.1]	4.3	[0.2]	4.3	[0.2]	4.2	[0.2]	4.2	[0.2]
Nicaragua	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]								
Panama	2.1	[0.1]	2.1	[0.2]	2.1	[0.1]	2.1	[0.1]	8.4	[0.9]	8.6	[0.9]	8.3	[0.9]	8.3	[1.0]
Peru	9.7	[1.8]	8.9	[1.8]	9.2	[2.3]	10.2	[2.1]	5.0	[0.7]	5.0	[0.7]	4.9	[0.8]	5.3	[0.7]
United States	2.9	[0.6]	2.9	[0.7]	2.8	[0.8]	2.8	[0.8]	1.5	[0.4]						
Floating																
Chile	4.2	[0.4]	3.9	[0.4]	3.2	[0.4]	3.3	[0.4]	0.9	[0.3]						
Clipperton	0.5	[0.1]	0.4	[0.1]	0.5	[0.1]	0.4	[0.1]	0.3	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]
Colombia	2.7	[0.1]	2.6	[0.1]	2.6	[0.1]	2.6	[0.1]	1.2	[0.0]	1.2	[0.1]	1.2	[0.1]	1.2	[0.1]
Costa Rica	1.9	[0.1]	1.8	[0.1]	1.8	[0.1]	1.8	[0.1]	0.8	[0.0]	0.9	[0.0]	0.8	[0.0]	0.8	[0.0]
Ecuador	2.0	[0.2]	1.7	[0.2]	1.8	[0.2]	1.8	[0.2]	0.7	[0.1]	0.6	[0.1]	0.6	[0.1]	0.6	[0.1]
El Salvador	1.0	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]	2.0	[0.4]			2.1	[0.6]		
French Polynesia	0.4	[0.1]							0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]
Guatemala	1.3	[0.2]	1.2	[0.2]	1.3	[0.2]	1.2	[0.2]	2.0	[0.2]	2.0	[0.2]	2.1	[0.3]	1.9	[0.3]
Kiribati									0.2	[0.0]	0.2	[0.1]	0.2	[0.0]	0.2	[0.1]
Mexico	1.1	[0.1]	1.1	[0.1]	1.1	[0.1]	1.1	[0.1]	0.4	[0.0]	0.4	[0.0]	0.4	[0.0]	0.4	[0.0]
Nicaragua	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]	1.0	[0.1]								
Panama	2.1	[0.1]	2.2	[0.1]	2.2	[0.1]	2.2	[0.1]	2.2	[0.2]	2.2	[0.3]	2.2	[0.2]	2.2	[0.3]
Peru	2.4	[0.2]	2.4	[0.3]	2.0	[0.3]	2.1	[0.3]	1.0	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]

Appendix Table 3. 9. Marginal Product of SST by species for four model specifications using data without overlaps

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
All																
Clipperton	0.5	[0.1]	0.5	[0.1]	0.5	[0.1]	0.5	[0.1]	2.5	[0.1]	2.6	[0.2]	2.9	[0.2]	2.9	[0.2]
Colombia	4.5	[0.3]	4.4	[0.4]	4.4	[0.4]	4.4	[0.4]	2.8	[0.1]	2.6	[0.1]	2.6	[0.1]	2.6	[0.1]
Costa Rica	1.7	[0.1]	1.7	[0.1]	1.7	[0.1]	1.7	[0.1]	4.3	[0.1]	4.4	[0.2]	4.5	[0.2]	4.5	[0.2]
Ecuador	5.8	[0.5]	5.8	[0.5]	6.1	[0.6]	6.3	[0.5]	3.3	[0.4]	3.3	[0.4]	3.4	[0.4]	3.5	[0.4]
El Salvador	1.6	[0.1]	1.6	[0.1]	1.7	[0.0]	1.5	[0.1]	4.4	[0.3]	4.7	[0.2]	4.5	[0.4]	4.8	[0.2]
French Polynesia	0.4	[0.1]							0.0	[0.0]						
Guatemala	2.1	[0.1]	2.1	[0.1]	2.0	[0.1]	2.1	[0.1]	6.3	[0.1]	6.4	[0.1]	6.5	[0.1]	6.4	[0.2]
Kiribati									0.2	[0.0]	0.1	[0.0]	0.2	[0.0]	0.1	[0.1]
Mexico	1.9	[0.1]	1.9	[0.1]	1.9	[0.1]	1.9	[0.1]	4.4	[0.1]	4.3	[0.2]	4.4	[0.2]	4.4	[0.2]
Nicaragua																
Panama	3.7	[0.2]	3.7	[0.3]	3.7	[0.3]	3.7	[0.3]	8.4	[0.6]	8.6	[0.6]	8.4	[0.7]	8.4	[0.6]
Peru	10.6	[1.0]	10.4	[1.2]	10.1	[1.1]	10.5	[1.1]	5.1	[0.6]	5.0	[0.7]	4.9	[0.8]	5.3	[0.7]
United States	2.1	[0.1]	2.1	[0.2]	2.1	[0.2]	1.9	[0.4]	1.6	[0.4]						
Dolphin																
Clipperton	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	2.1	[0.1]	2.3	[0.1]	2.5	[0.2]	2.5	[0.2]
Colombia	0.1	[0.0]	0.1	[0.0]					1.7	[0.1]	1.7	[0.2]	1.8	[0.1]	1.8	[0.1]
Costa Rica	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	0.1	[0.0]	3.6	[0.1]	3.8	[0.2]	3.9	[0.2]	3.9	[0.2]
Ecuador	0.7	[0.1]	0.8	[0.1]	0.7	[0.1]	0.7	[0.1]	1.7	[0.3]	2.0	[0.4]	1.9	[0.4]	1.9	[0.4]
El Salvador			-0.1	[0.0]	0.0	[0.0]			1.5	[0.3]	1.5	[0.3]	1.4	[0.2]	1.5	[0.3]
French Polynesia																
Guatemala					0.1	[0.0]			4.8	[0.2]	5.0	[0.4]	5.1	[0.3]	5.0	[0.4]
Mexico	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	0.2	[0.0]	2.1	[0.1]	2.1	[0.1]	2.3	[0.1]	2.3	[0.1]
Nicaragua																
Panama	0.1	[0.0]							2.0	[0.2]	2.0	[0.3]	2.1	[0.3]	2.1	[0.3]
Peru	0.5	[0.2]	0.5	[0.3]					2.1	[0.3]	2.1	[0.4]	1.9	[0.5]	2.0	[0.6]
United States																

Appendix Table 3.8. *Continuation*

Country	Skipjack								Yellowfin							
	RTO		TIME		GRID		TIME and GRID		RTO		TIME		GRID		TIME and GRID	
	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE	MP	SE
Unassociated																
Clipperton	0.3	[0.0]	0.3	[0.1]	0.3	[0.1]	0.3	[0.1]	1.4	[0.0]	1.4	[0.0]	1.4	[0.1]	1.4	[0.1]
Colombia	1.7	[0.1]	1.7	[0.2]	1.7	[0.2]	1.7	[0.2]	1.5	[0.1]	1.5	[0.1]	1.4	[0.1]	1.4	[0.1]
Costa Rica	0.9	[0.0]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]	1.4	[0.2]	1.5	[0.2]	1.5	[0.2]	1.5	[0.2]
Ecuador	4.8	[0.4]	4.8	[0.5]	5.2	[0.5]	5.4	[0.5]	2.9	[0.4]	2.9	[0.4]	3.1	[0.4]	3.1	[0.4]
El Salvador									3.8	[0.6]	3.8	[0.8]	3.6	[0.6]	3.8	[0.8]
French Polynesia																
Guatemala	1.1	[0.1]	1.2	[0.0]	1.1	[0.0]	1.2	[0.0]	1.5	[0.2]	1.5	[0.4]	1.4	[0.3]	1.5	[0.4]
Kiribati	0.8	[0.2]			0.9	[0.0]	6.8	[0.7]								
Mexico	2.5	[0.1]	2.5	[0.1]	2.5	[0.1]	2.5	[0.1]	4.6	[0.2]	4.6	[0.2]	4.5	[0.2]	4.5	[0.2]
Nicaragua																
Panama	2.8	[0.2]	2.8	[0.2]	2.8	[0.2]	2.8	[0.2]	7.8	[0.6]	8.0	[0.6]	7.7	[0.7]	7.7	[0.7]
Peru	9.9	[1.0]	9.8	[1.2]	9.6	[1.2]	10.1	[1.2]	5.8	[0.9]	5.8	[1.0]	5.6	[1.1]	6.1	[1.0]
United States	2.1	[0.1]	2.2	[0.2]	2.1	[0.2]	2.0	[0.4]	1.6	[0.4]						
Floating																
Clipperton	0.5	[0.1]	0.4	[0.1]	0.5	[0.1]	0.4	[0.1]	0.3	[0.0]	0.2	[0.1]	0.2	[0.1]	0.2	[0.1]
Colombia	3.1	[0.2]	3.1	[0.2]	3.0	[0.2]	3.0	[0.2]	1.3	[0.0]	1.3	[0.1]	1.2	[0.1]	1.2	[0.1]
Costa Rica	1.4	[0.1]	1.4	[0.1]	1.4	[0.1]	1.4	[0.1]	0.8	[0.0]	0.8	[0.0]	0.8	[0.0]	0.8	[0.0]
Ecuador	2.1	[0.2]	1.8	[0.2]	1.8	[0.2]	1.8	[0.2]	0.8	[0.1]	0.6	[0.1]	0.7	[0.1]	0.7	[0.1]
El Salvador	1.0	[0.2]							1.6	[0.1]	1.4	[0.2]	1.7	[0.1]		
French Polynesia	0.7	[0.1]	1.3	[0.2]	1.1	[0.3]	1.4	[0.4]	0.1	[0.0]	0.1	[0.0]	0.1	[0.1]		
Guatemala	1.3	[0.1]	1.1	[0.2]	1.1	[0.1]	1.0	[0.2]	2.1	[0.2]	2.1	[0.3]	2.1	[0.3]	2.0	[0.3]
Kiribati									0.2	[0.0]	0.1	[0.0]	0.2	[0.0]	0.1	[0.0]
Mexico	1.1	[0.1]	1.1	[0.1]	1.1	[0.1]	1.1	[0.1]	0.5	[0.0]	0.4	[0.0]	0.4	[0.1]	0.4	[0.0]
Panama	2.0	[0.1]	2.1	[0.1]	2.1	[0.1]	2.1	[0.1]	1.7	[0.1]	1.8	[0.1]	1.8	[0.1]	1.8	[0.1]
Peru	3.0	[0.2]	2.9	[0.2]	2.7	[0.3]	2.7	[0.3]	1.0	[0.1]	0.9	[0.1]	0.9	[0.1]	0.9	[0.1]

Chapter 4 The impact of ocean warming on commercial fisheries in New Zealand

ABSTRACT

Oceans are warming due to climate change and are expected to continue to do so in the next decades. The increase in temperature impacts the growth, reproduction, and survival of fish. Fish are also expected to move towards the poles or deeper waters. Using a bioeconomic framework pioneered by Barbier and Strand (1988), we estimate the relationship between sea surface temperature (SST) and the catch of *de facto* open-access commercial fisheries of flatfish, trevally, and jack mackerel within Aotearoa New Zealand's exclusive economic zone (EEZ). We assume either a logarithmic or quadratic relationship between the SST and the carrying capacity of the fishery. We consider three fishing methods (bottom trawl, set net, and midwater trawl) and two measures of effort (count and duration). We show that ocean warming results in an increase in catch of all three fish species if we assume a logarithmic relationship, with the highest increase projected for jack mackerel caught using midwater trawl. The marginal products of SST at means (MP_{SST}) are positive for all species and gears if we assume a logarithmic relationship between SST and carrying capacity. We also show that there is a threshold above which catch starts to decrease as SST increases. If we assume a quadratic relationship, the MP_{SST} for jack mackerel using bottom trawl is -2.89 g/ha. The maximum catch for this method and species is at 12.17°C, which means the MP_{SST} is positive for values below 12.17°C and negative thereafter. These results are relevant in the review of the fisheries management system to respond to ocean warming and are also potentially informative about the likely re-distribution of fishes across different countries' exclusive economic zones.

4.1. Introduction

Ocean warming has been observed over the past several decades and the increasing trend in ocean temperature is expected to continue into the future due to climate change, even if all the Paris Agreement voluntary reductions in greenhouse gas emissions were implemented as promised (Bindoff et al. 2019). The temperature of Aotearoa New Zealand's (NZ) coastal and ocean waters follows the global trend and has warmed since 1981, with some regions warming more than others (Law et al. 2018; Sutton and Bowen 2019) .

Increasing ocean temperatures has been identified as a driver of regional shifts in the distribution and abundance of marine organisms (Poloczanska et al. 2013). The migration of marine species towards the poles and to deeper waters affects species interaction and is expected to have effects on fish catch in NZ as well. The impacts of ocean warming on marine species have been documented in various studies. Ocean warming is expected to likely affect 15 commercially-important marine species and species groups (Cummings et al. 2021). A significant number of commercial fisheries are supported by the waters around NZ. In 2018, commercial fisheries and aquaculture contributed NZD 1.13 Billion to the economy (equivalent to 0.4 percent of the country's gross domestic product (Stats NZ 2020)).

New Zealand's quota management system (QMS) manages 98 fish species and species groups to achieve maximum sustainable yield objectives. Individual transferable quotas (ITQ) grant commercial fishers a share of fish stock, can be traded and are held in perpetuity. An upper limit of annual catch, the total allowable commercial catch (TACC), is set for each species for different management areas. The TACC is then distributed to ITQ owners as annual catch entitlement (ACE) proportional to their quota shareholding. Both the ITQ and ACE can be traded (Ministry of Primary Industries 2021; Mace, Sullivan, and Cryer 2014).

In this paper, we establish the relationship between sea surface temperature (SST) and the catch of selected commercial species caught by bottom trawl, midwater trawl, and set net within Aotearoa New Zealand's exclusive economic zone (EEZ). We use catch and effort data from each statistical area of NZ matched with SST data in an open access bioeconomic model pioneered by Barbier and Strand (1998).

We contribute to the literature by conducting analyses for multiple species and gears in contrast to the usual single-species, single-gear focus of other studies (as discussed in the following section). We focus on three *de facto* open-access fisheries in NZ – flatfish, jack mackerel, and trevally. These species are selected because the total quota of flatfish, jack mackerel, and trevally are non-binding as the total catch is below the TACC (Fisheries New Zealand 2020). The low prices for quota and ACE of all three species support the assumption that there is no pressure to catch a volume that is greater than their respective TACC.[15]

This is also the first study to use a comprehensive database of Aotearoa NZ's Ministry for Primary Industries (MPI) to establish the relationship between SST and catch in a bioeconomic framework. The analysis is conducted at both national and regional levels using fisheries statistical area as the unit of analysis. The use of MPI's data allows us to account for vessel characteristics in determining the effort measure.

We show that ocean warming results in an increase in catch for all three fish species selected for study if a logarithmic relationship between SST and carrying capacity is assumed. The highest increase is projected for jack mackerel caught using midwater trawl. However, we also show that there is a threshold above which catch starts to decrease as SST increases when assuming a quadratic relationship between SST and

[15] ITQ and ACE prices of the three species are presented in Appendix Table 4.1.

carrying capacity, i.e., our results suggest that the catch of flatfish, trevally, and jack mackerel initially increases with SST but will eventually decrease after an 'optimal' level of SST is reached. This optimal level of SST is close to the lower bound of the average annual SST of NZ.

In the next section, we discuss how climate change affects ocean and the selected species. We then present the model, data, and estimation procedure used in this study. The result of the analysis is then presented and discussed, followed by some concluding statements.

4.2. Review of Literature

Ocean temperature is an important indicator of climate change in marine ecosystems. Between 1870 and 1971, the temperature of the upper 70-m layer of the ocean has increased by more than 0.1°C per decade and the rate of ocean warming is likely to continue to increase (Hoegh-Guldberg et al. 2014). Ocean warming affects fisheries as it results in a poleward and depth migration of species. The species redistribution alters ecosystem structures and species interaction. An increase in ocean temperature also affects the availability of prey and the reproduction and survival of fish species. The redistribution of species may result in the transfer of invasive species and fish diseases. These climate change-induced changes inevitably affect the volume and composition of fish catch and pose a challenge to the management of fisheries (Bindoff et al. 2019).

The ocean surrounding NZ is warming and this is attributed to climate change. Sutton and Bowen (2019) showed that all of the ocean adjacent to NZ has warmed by approximately 0.12 to 0.34°C per decade in the last 40 years. This rate is faster than the increase in land surface temperature estimated to be around 0.1°C per decade (Mullan et al. 2018). There is regional variability in the trend of ocean warming, with most the warming occurring off the east coast of the North Island south of East Cape and the least along the northeast coast. This trend is projected to continue in the next decades due to climate change (Sutton and Bowen 2019). Using earth system models, Law et al. (2018) projects that the SST of oceans around NZ will increase by approximately 0.8°C under RCP4.5 and 1°C under RCP8.5 by 2050 compared to the current period (1976-2005). By 2100, the SST is projected to increase by approximately 1.1°C under RCP4.5 and approximately 2.5°C under RCP8.5[16]. There are also spatial differences in the increase in temperature within the subantarctic waters south of the Chatham Rise, which are projected to have the greatest warming, and the Central Tasman Sea, which is expected to be the least affected. Given the spatial variability in warming, the environmental and ecological impacts of climate change are likely to vary across marine areas in New Zealand.

In NZ, the impacts of climate change on marine species are documented in several studies. Modelling in Parsons et al (2020) predicts that snapper catch will decrease by 29 percent in the most pessimistic scenario but increase by 44 percent in the most optimistic scenario. Climate change-induced warming promotes the growth of nearshore snapper and tarakihi (Morrongiello et al. 2021). Aquaculture species such as salmon and mussels (Broekhuizen et al. 2021) and marine birds (McKechnie et al. 2020) are also affected by ocean warming. A shift in the distribution range in response to warming has been reported for different marine species in the global ocean (Poloczanska et al. 2013) and so the projected increase in SST may result in increasing dominance of warmer-water species in NZ waters. Cummings et al (2021) reported that ocean warming will likely affect 15 target species or species groups of NZ commercial fishing. These are blue cod, elephant fish, john dory, red cod, red gurnard,

[16] Representative Concentration Pathways (RCPs) are climate modelling pathways that describe projected changes in radiative forcing resulting from greenhouse gas concentration trajectories under different socio-economic assumptions (van Vuuren et al. 2011).

snapper, tarakihi, arrow squid, hake, hoki, scampi, southern blue whiting, albacore tuna, Pacific bluefin tuna, blue shark, and school shark.

The process through which ocean temperature affects the carrying capacity of flatfishes, jack mackerel, and trevally, is established in various studies in fisheries science. Climate change affects the species through the altering of reproduction and growth. Flatfish includes species with a wide range of life history characteristics, ecology and distributions (Gibson 2005), thus climate risk and vulnerabilities of different flatfish populations may vary substantially. Ryer (2008) stated that temperature affects the behavioural response of flatfishes regarding their catchability. Higher temperature reduces the catchability of flatfishes because they are herding more and longer. Herding is the ordered behavioural response of flatfishes in which they move away from the direction of trawl and become concentrated in the mouth of the trawl. At low temperatures, flatfish may be more likely to startle in response to ground disturbance by trawl rather than initiate a herding response. This would increase their chances of rapidly passing over the trawl footrope and into the net. Swimming endurance of some flatfish species also decreases with temperature, thereby increasing the catchability.

Cheung and Oyinyola (2018) project that climate change driven changes in ocean conditions, including changes in temperature, will affect the distribution and productivity of flatfish stocks. There is an expected range shift for flatfish both in latitude and depth. Flatfish are generally less mobile relative to other active pelagic and demersal species. Their capacity to adjust to climate change is also relatively low making flatfish vulnerable to climate change. Climatic changes will result in an overall decrease in maximum catch potential of flatfish globally. However, there is spatial variability in the expected impact whereby the reduction in catch potential is mainly projected to occur in the tropical regions while there will be an increase in the arctic region (Cheung and Oyinlola 2018). Some flatfish species are particularly at risk from climate change impacts. Those that have narrow geographic distribution, narrow thermal tolerance range, and relatively larger body size are most at risk. The restricted range of some species limits their ability to adjust to ocean warming through spatial shifts.

Trevallies are important fishery resources throughout subtropical and warm temperate oceans. Silver trevally (*Pseudocaranx georgianus*) is the only species of trevally found in NZ. A report of the Ministry of Fisheries (2008) noted that there is a direct correlation between SST during surveys and relative biomass of trevally in NZ. Walsh et al. (2014) suggests that temperature strongly influences spawning and larval survival of trevally in NZ. However, they also recognise the need to do more extensive research on the relationship between temperature and life cycle of trevally. Fowler et al. (2018) show that adult movement of *P. georgianus* in south-eastern Australia primarily occurs over smaller distances than the current spatial scale of management. This means that the redistribution of trevally occurs in a limited spatial reach. A study on related trevally species (*P. dextex*) shows that hatching rate and egg size are negatively correlated with water temperature (Nogueira et al. 2018).

The three species of jack mackerel occurring in NZ have different geographical distributions. *T. novaezelandiae* are in shallower (less than 150m) and warmer (> 13°C) waters while *T. declivis* generally occur in deeper (up to 300m) and cooler (< 16°C) waters. The other species, *T. murphyi* occurs in deeper waters and with wider latitudinal range reaching up to equatorial waters of the Galapagos Islands and the eastern Pacific along coasts of Chile. Patterns of vertical and horizontal movement of jack mackerel are poorly understood. Jack mackerels are presumed to be generally off the bottom at night, and surface schools can be quite common during the day (Fisheries New Zealand 2020).

A rise in SST influences the spatial distribution and increases the catchability of jack mackerel (Lima et al. 2020). Ocean temperature also affects the distribution of prey of jack mackerel. Harris et al (1992) suggests that the redistribution of krill due to changes in temperature affects the behaviour of jack mackerel. As SST affect species growth and development, a model allowing SST to affect carrying capacity of the fishery and growth is appropriate. A quantitative model is presented below.

4.3. Model, Data, and Estimation Procedure

We apply the bioeconomic model, used in Mediodia et al. (2020) and Mediodia (2020) who investigate tuna catch in the Eastern Pacific, to establish the relationship between SST and the catch of flatfishes, jack mackerel, and trevally within the EEZ of NZ. We focus on the top three fishing methods used to catch these species – bottom trawl, midwater trawl, and set net[17]. The model builds on the work pioneered by Barbier and Strand (1998) and subsequently adopted by other studies (see Barbier et al. 2002; Foley et al. 2010). The model applies a production function approach and includes SST as an input affecting catch through the carrying capacity of the fishery.

The analysis is conducted using fisheries statistical areas in NZ as the basic unit (Figure 4. 1). The statistical area is used by fishers to report their catch and by the Ministry for Primary Industries to record and classify catch data. Separate estimations were then conducted for data grouped by the quota management areas (QMAs) for the three species (Figure 4. 2).

[17] Trawls are fishing gears consisting of a cone-shaped body towed by one or two boats. Trawls have large front part made with very large mesh or ropes and narrow end that retains catch. Bottom trawls catch fish species living on or near the bottom of the sea and target benthic and demersal species. Bottom trawls interact with the bottom sediment resulting to damage of seaweeds and corals, stones, and other large objects. Midwater trawls are designed to fish in surface water and midwater targeting pelagic and sometimes demersal fish. This fishing gear has low bycatch rate as it usually target a single species. Midwater trawls are bigger in size compared to bottom trawls. Set nets or set gillnets are passive fishing gears anchored to the sea floor by weights. These gears hang like vertical walls in the water and capture fish as they swim through the mesh of the nets. Set nets capture pelagic, demersal, and benthic fish species. (FAO 2021)

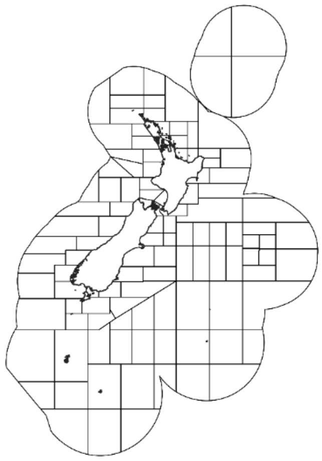


Figure 4. 1. New Zealand Fisheries Statistical Areas[18]

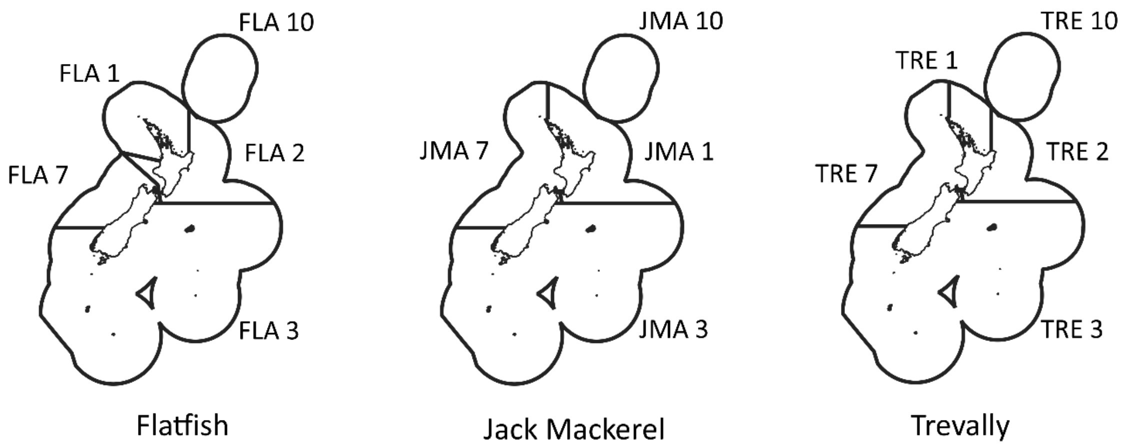


Figure 4. 2. Quota management areas of Flatfish, Jack Mackerel, and Trevally [19]

We use the marginal product at means (MP_{SST}) as the indicator of the relationship between SST and catch. The MP_{SST} is defined as the change in catch due to a 1°C Celsius increase in SST given mean values of effort and SST.

[18] General statistical area shapefile is from Koordinates (https://koordinates.com/layer/4182-nz-fisheries-general-statistical-areas/).

[19] QMA and EZZ shapefiles are from MPI Open Geospatial Data Portal (https://data-mpi.opendata.arcgis.com/)

We assume either a logarithmic or quadratic relationship between the SST and carrying capacity of the fishery. The bioeconomic model and analysis is described in detail in Mediodia et al. (2020).

Assuming a logarithmic relationship between SST and the carrying capacity, we estimate

$$Catch_{it} = \beta_1 E_{it} * lnSST_{it} + \beta_2 E_{it}^2 + \varepsilon_{it}, \quad (1)$$

where $Catch_{it}$ is the total catch of species in kilograms per hectare in statistical area i in year t, E_{it} is the total composite effort measure per hectare in statistical area i in year t, $lnSST_{it}$ is the natural log of the mean SST in statistical area i in year t, β_1 and β_2 are the parameter estimates, and ε_{it} is the error term.

The marginal product of SST at means is computed as

$$MP_{SST} = \frac{\partial Catch}{\partial SST} = \beta_1 \frac{E_{it}}{SST_{it}}. \quad (2)$$

Assuming a quadratic relationship between SST and the carrying capacity, we estimate

$$Catch_{it} = \beta_1 E_{it} * SST_{it} + \beta_2 E_{it} * SST_{it}^2 + \beta_3 E_{it}^2 + \varepsilon_{it}. \quad (3)$$

where $Catch_{it}$ is the total catch of species in kilograms per hectare in statistical area i in year t, E_{it} is the total composite effort measure per hectare in statistical area i in year t, E_{it}^2 is the square of E_{it}, SST_{it} is the mean SST in statistical area i in year t, SST_{it}^2 is the square of SST_{it}, β_1, β_2, and β_3 are the parameter estimates, and ε_{it} is the error term.

The marginal product of SST at means is computed as

$$MP_{SST} = \frac{\partial Catch}{\partial SST} = \beta_1 E_{it} + 2\beta_2 SST_{it} * E_{it}. \quad (4)$$

The quadratic specification subsumes the linear functional form. The use of a quadratic specification allows the identification of the inflection point, a level of temperature at which fish catch starts to decrease due to increasing temperature. The identification of this "optimal" level of temperature is necessary because the thermal tolerances of fish have an upper limit.

Regression through the origin (RTO) is applied to exclude the unrealistic possibility of positive catch without fishing effort. RTO is applied in a fisheries production function in Armstrong et al. (2016), Thanh Thuy and Flaaten (2013), and Foley et al. (2010).

We use a composite effort measure given that trevally, jack mackerel, and flatfishes are caught together with other species of fish using vessels of different sizes. The composite effort measure presented as a multiplication of effort measure and vessel characteristics follows Pradhan et al. (2003) and Campbell and Nicholl (1994).

The composite effort measure (E_{it}) is computed as

$$E_{it} = Eff_{it} * \%Catch_{it} * VLength_{it} \quad (5)$$

where E_{it} is the standardized effort measure in statistical area i in year t, Eff_{it} is the total effort measure in statistical area *i* in year *t*, $\%Catch_{it}$ is the percentage of catch of species to total catch in statistical area *i* in year *t*, and $VLength_{it}$ is the average vessel length in statistical area *i* in year t.

Vessel length accounts for the differences in the characteristics of fishing vessels. This measure is positively correlated with other vessel characteristics such as beam, draught, gross tonnage, and engine power. We use two measures of fishing effort -

total fishing duration in hours and total number of sets. Separate estimations are conducted for each of the effort measures.

We use a large database of catch and effort by species for each fishing event within the EEZ of NZ. Catch and effort data identifies the statistical area for each observation. The data is from the Ministry for Primary Industries' Enterprise Data Warehouse. Fishers report fishing effort and catch for all fishing activities conducted as part of the reporting requirements under the QMS. We exclude observations that were not dated or did not identify the statistical area of the fishing event. The catch and effort data were matched with vessel characteristics through a vessel identifier. Thus, we have information on the total annual catch and effort for each statistical area for the period 1990 to 2018.

The Centennial In Situ Observation-Based Estimates of the Variability of SST and Marine Meteorological Variables, version 2.9.2 (COBE-SST2) by Japan Meteorological Agency (JMA) data is used to measure SST (Hirahara, Ishii, and Fukuda 2014).[20] The monthly SST for 1° latitude/longitude grids is aggregated by year and statistical area. [21]

We include statistical area fixed-effects to control for time-invariant, area-specific factors that may affect catch, such as location and bathymetry. A time trend is also included in a specification to account for technological progress. We use the Akaike Information Criterion (AIC) to evaluate the different model specifications.

[20] COBE-SST2 data used in this study was taken from NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site at https://www.esrl.noaa.gov/psd/.

[21] We also used SST data from the optimum interpolation climate-scale in situ and satellite SST analyses by National Oceanic and Atmospheric Administration (NOAA OISST) (Reynolds et al. 2002) and arrived at similar results. NOAA OISST Version 2 data is provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.html.

4.4. Summary Statistics

Bottom trawl and set net are the top methods used to catch the species considered in this study (Table 4. 1). Though only used in 57.1 percent of the reported events, bottom trawl accounts for 88.1 percent of total flatfish catch from 1990 to 2018. Both bottom trawl and set net are multi-species fisheries, with set net being more efficient in targeting flatfishes (83.3%) compared to bottom trawl (36.7%). However, the catch per unit effort (CPUE) in terms of duration is greater at 99.6 kg per hour for bottom trawl compared to set net at only 10.7 kg per hour.

Table 4. 1 shows that 76.9 percent of total jack mackerel caught in NZ was by midwater trawl, however, midwater trawl (39.5%) comes second to bottom trawl (50.6%) in terms of fishing events. The share of jack mackerel to total catch is highest for midwater trawl at 54.5 percent compared to 17.2 percent for bottom trawl and 10.6 percent for set net. Midwater trawl is included in our analysis for jack mackerel only as this method is not relevant to flatfishes and trevally.

Similar to flatfishes, bottom trawl and set net are the top two methods used to catch trevally, with bottom trawl accounting for 71.5 percent of the total trevally caught. The catch per unit effort in terms of duration for bottom trawl (205.8 kg per hour) is a lot higher than that for set net (27.4 kg per hour).

The total catch in metric tons per species and fishing method used is presented in Figure 4. 3. The concentration of catch of flatfish, jack mackerel, and trevally occur close to the shores. The catch of bottom trawl flatfish is high in the south of the North Island waters and all coastal statistical areas in the South Island. The catch of trevally is concentrated in the coastal areas of the North Island. Jack mackerel is caught by midwater trawls in most of the statistical areas relatively homogeneously. There are very few areas in which trevally and flatfishes are caught using midwater trawls.

Flatfish comprise 83.3 percent of the total catch for set nets and 36.7 percent for bottom trawl (Table 4. 1). For jack mackerel, 52.4 percent of the catch is jack mackerel for midwater trawls, while the share is less than 20 percent for bottom trawl and set nets. The share of trevally to total catch is 24.1 and 22.2 percent for bottom trawl and set net, respectively. The average share of species to total catch for each fishing method for the statistical areas is presented in Appendix Figure 4. 1.

Figure 4. 4 shows the average annual SST by statistical areas in NZ from 1990 to 2018 using COBE-SST2. The SST ranges from a high of 22°C in subtropical areas to a low of 7°C in area closer to the South Pole.

Table 4. 1. Summary Statistics

Fishing Methods/ Species	Fishing Events		Catch (kg)		Effort Count			Effort Duration (hours)			Percent Catch of Species to Total catch
	Freq	%	Total	%	Total	%	CPUE	Total	%	CPUE	
Flatfish											
Bottom Trawl	488,743	57.1	274,059,549	88.1	946,486	83.5	289.6	2,750,649	45.5	99.6	36.7
Set Net	363,613	42.5	35,002,694	11.2	123,396	10.9	283.7	3,282,988	54.3	10.7	83.3
Other Methods	2,849	0.4	2,094,882	0.7	63,270	5.6	33.1	14,378	0.2	145.7	
Total	855,205	100.0	311,157,125	100.0	1,133,152	100.0	274.6	6,048,015	100.0	51.4	
Jack Mackerel											
Bottom Trawl	117,075	50.6	357,879,126	22.5	146,702	45.1	2439.5	530,284	49.8	674.9	17.2
Midwater Trawl	91,373	39.5	1,222,492,614	76.9	90,886	27.9	13450.8	320,644	30.1	3812.6	54.3
Set Net	17,201	7.4	4,213,299	0.3	16,662	5.1	252.9	204,008	19.1	20.7	10.6
Other Methods	5,898	2.5	5,760,795	0.3	71,026	21.9	81.1	10,932	1.0	527.0	
Total	231,547	100.0	1,590,345,834	100.0	325,276	100.0	4889.2	1,065,868	100.0	1492.1	
Trevally											
Bottom Trawl	191,983	54.5	174,274,937	71.5	278,418	20.0	625.9	846,806	42.5	205.8	24.1
Set Net	92,766	26.4	28,466,078	11.7	92,300	6.6	308.4	1,040,658	52.3	27.4	22.2
Other Methods	67,285	19.1	41,081,027	16.8	1,019,004	73.4	40.3	103,260	5.2	397.8	
Total	352,034	100.0	243,822,042	100.0	1,389,722	100.0	175.4	1,990,724	100.0	122.5	

NOTES: CPUE – catch per unit effort; A small portion of jack mackerel and trevally are caught using bottom longlining

Data Source: Ministry for Primary Industries

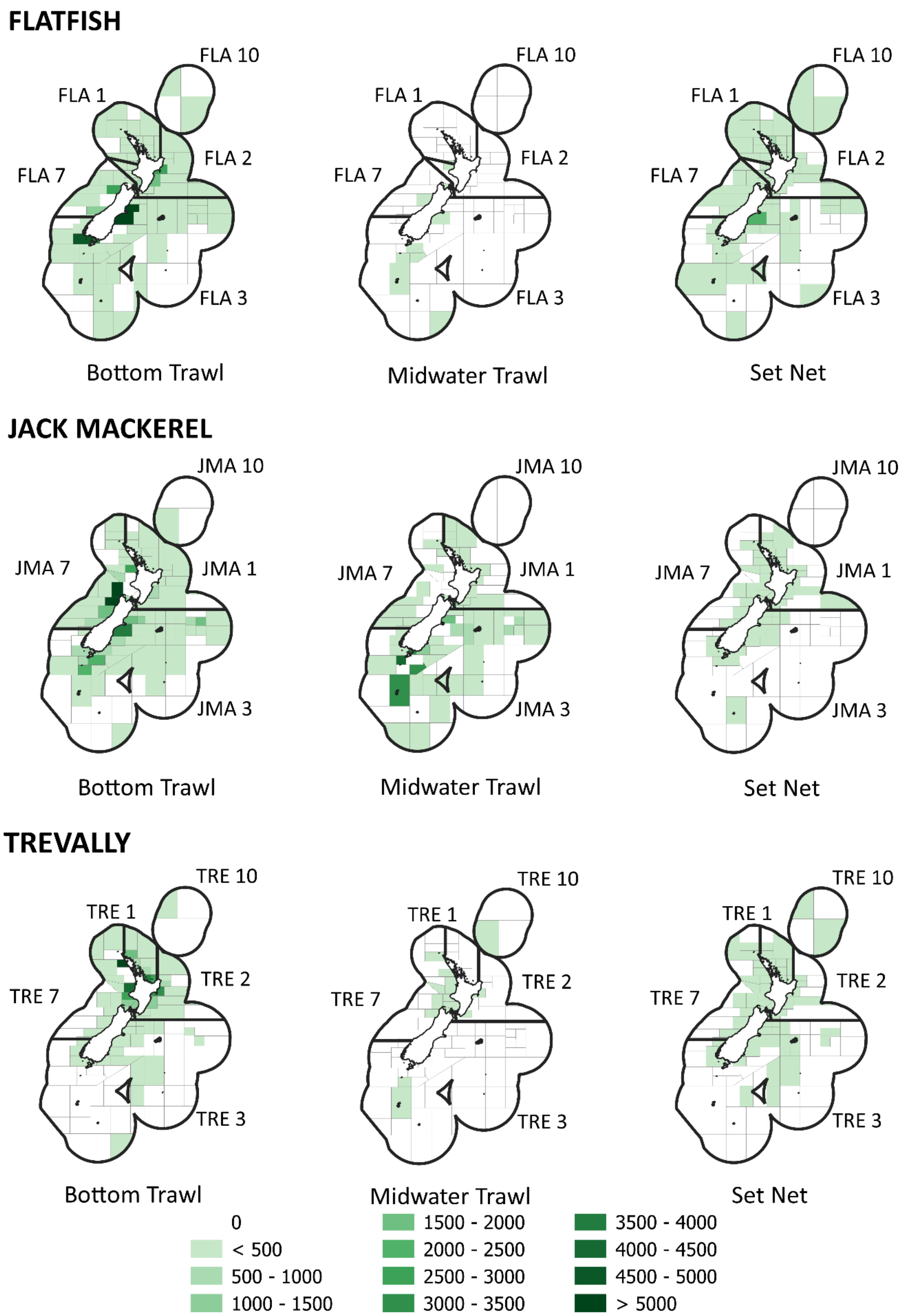


Figure 4. 3. Total catch per species and fishing method (1990-2018) (in metric tons)
Data Source: Ministry for Primary Industries

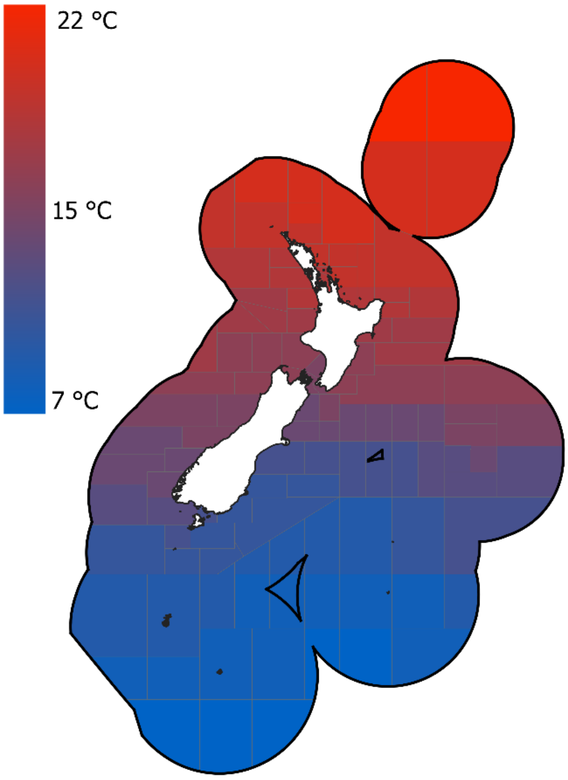


Figure 4. 4. Average Annual Sea Surface Temperature (1990-2018)
Data Source: COBE-SST

4.5. Results

The estimation using models with different specifications showed the lowest AICs for models which include a time trend and statistical area fixed effects, for both assuming a logarithmic relationship (Equation 1) and quadratic relationship (Equation 3). Table 4. 2 shows the MP_{SST} of flatfish, jack mackerel, and trevally for the three fishing methods using the model with trend and statistical area fixed effects for estimations with more than 200 observations. The MP_{SST} computed using other specifications yielded similar results (Appendix Table 4. 4). Only the parameter estimates which are statistically significant at 10 percent are considered in the calculation of the marginal products.

Assuming a logarithmic relationship between the SST and the carrying capacity, the catch of the three species increases with a 1°C increase in SST for the three fishing methods, albeit only marginally. For flatfish, the MP_{SST} for set nets is greater than bottom trawl. The catch of flatfish by set net is expected to increase by 3.89 grams per ha of area fished compared to 1.05 grams per ha for bottom trawl. The opposite is true for trevally with the MP_{SST} for bottom trawl (0.96 grams per ha) being higher compared to set net (0.31 grams per ha). The highest MP_{SST} is for midwater trawl for jack mackerel is at 16.33 grams per ha.

Figure 4. 5 shows the MP_{SST} for each statistical area using the logarithmic model. All values are positive for statistical areas with fishing effort, with higher values in areas close to the coast. The MP_{SST} for all species using set nets is low (5.2x 10^{-6} to 85 grams per ha) and the values for jack mackerel midwater trawl are high ranging from 1.1 x 10^{-4} to 101.1 grams per ha.

Assuming a quadratic relationship, the MP_{SST} is negative for flatfish-bottom trawl, flatfish-set net, jack mackerel bottom trawl, and trevally set net. For flatfish, a 1°C increase in SST results in 4.61 grams per ha reduction in catch of flatfish using bottom trawls and 13.47 grams per ha if using set nets. The highest catch is expected if SST is at 10.01°C for bottom trawl and 11.61°C for set nets. If the MP_{SST} is computed using means values of the SST and effort for each statistical area, then higher values of MP_{SST} are observed in areas closer to the South Pole, with some values being positive (Figure 4. 6).

Table 4. 2. Akaike Information Criterion, R^2, and Marginal Product of SST at means (in grams per ha) for each species and fishing method

Method/Species	n	Logarithmic			Quadratic			
		R^2	AIC	MP_{SST}	R^2	AIC	MP_{SST}	Opt. Temp
Flatfish								
Bottom Trawl	1,392	0.95	-6297	1.05	0.96	-6544	-4.61	10.01
Midwater Trawl	21							
Set Net	1,235	0.93	-1524	3.89	0.94	-1690	-13.47	11.61
Jack Mackerel								
Bottom Trawl	1,472	0.96	-4441	1.81	0.96	-4510	-2.89	12.17
Midwater Trawl	906	0.96	216	16.33	0.96	150	47.84	
Set Net	638	0.97	-6791	0.03	0.97	-6853		
Trevally								
Bottom Trawl	1,019	0.91	-4834	0.96	0.92	-4862		
Midwater Trawl	57							
Set Net	966	0.96	-5327	0.31	0.96	-5440	-2.38	10.65

NOTE: Using COBE-SST2 as source of SST data and Duration as measure of effort.

MP_{SST} of flatfish, jack mackerel, and trevally for the three fishing methods using observations grouped by QMA is presented in Table 4. 3. The model assumes either logarithmic or quadratic relationships between SST and carrying capacity and includes time trend and statistical area fixed effects. Computed MP_{SST} for other specifications in Appendix Tables 4.5 and 4.6 reported similar results. The MP_{SST} for the logarithmic model is positive while the MP_{SST} when a quadratic relationship is assumed is negative. The QMAs on the western side of NZ have higher MP_{SST} compared to other areas. For flatfish, the highest $MP_{SST}$is QMA 1 for set net and QMA 7 for bottom trawl. QMA 7 has the highest MP_{SST} for both bottom and midwater trawls and QMA1 for net nets for jack mackerel. For trevally, higher MP_{SST} is for QMA7.The QMAs that record high MP_{SST} in the logarithmic model also has the lowest MP_{SST} in the quadratic model.

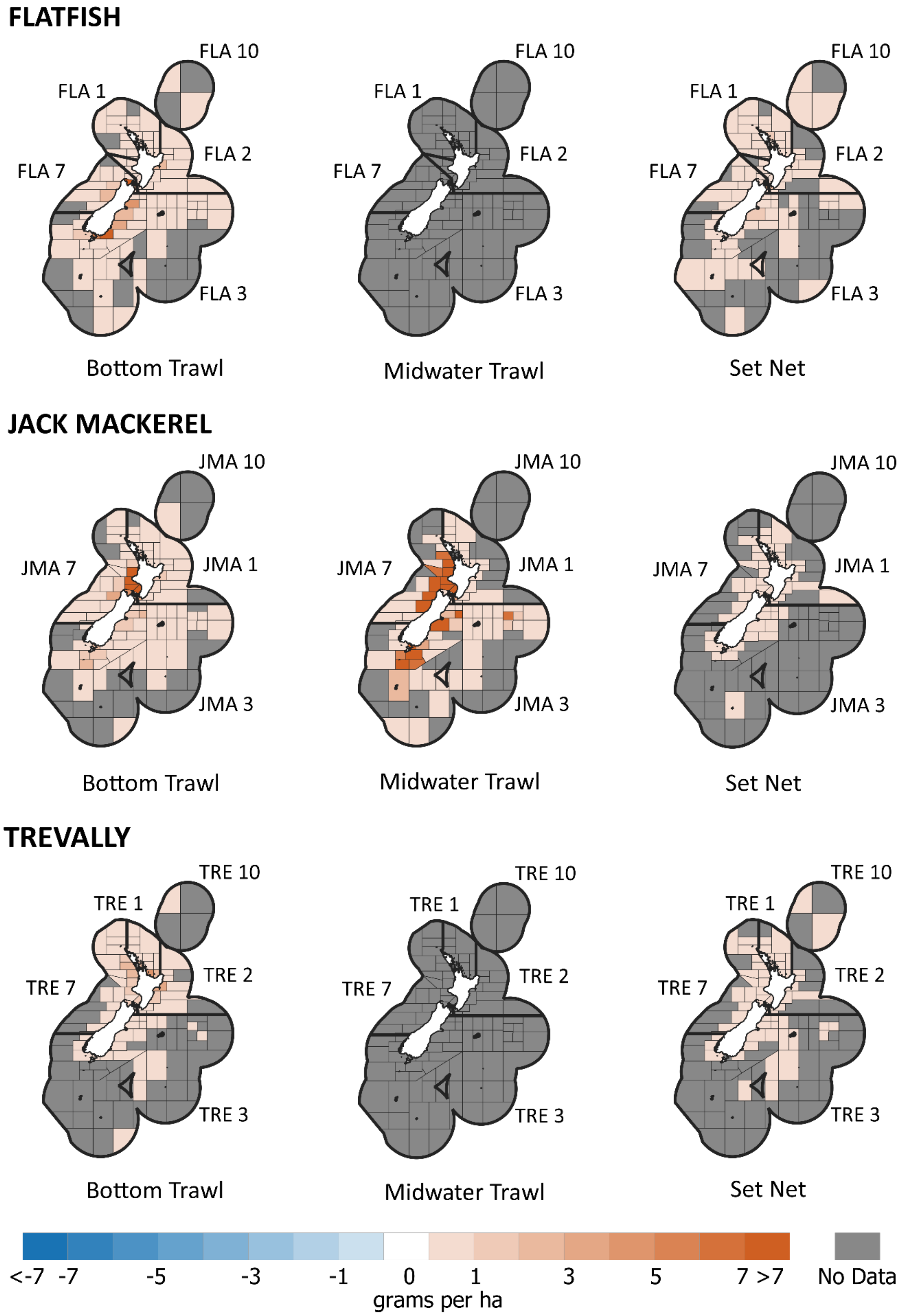


Figure 4. 5. Marginal Product of SST assuming logarithmic relationship between SST and carrying capacity of fishery (in grams per ha)

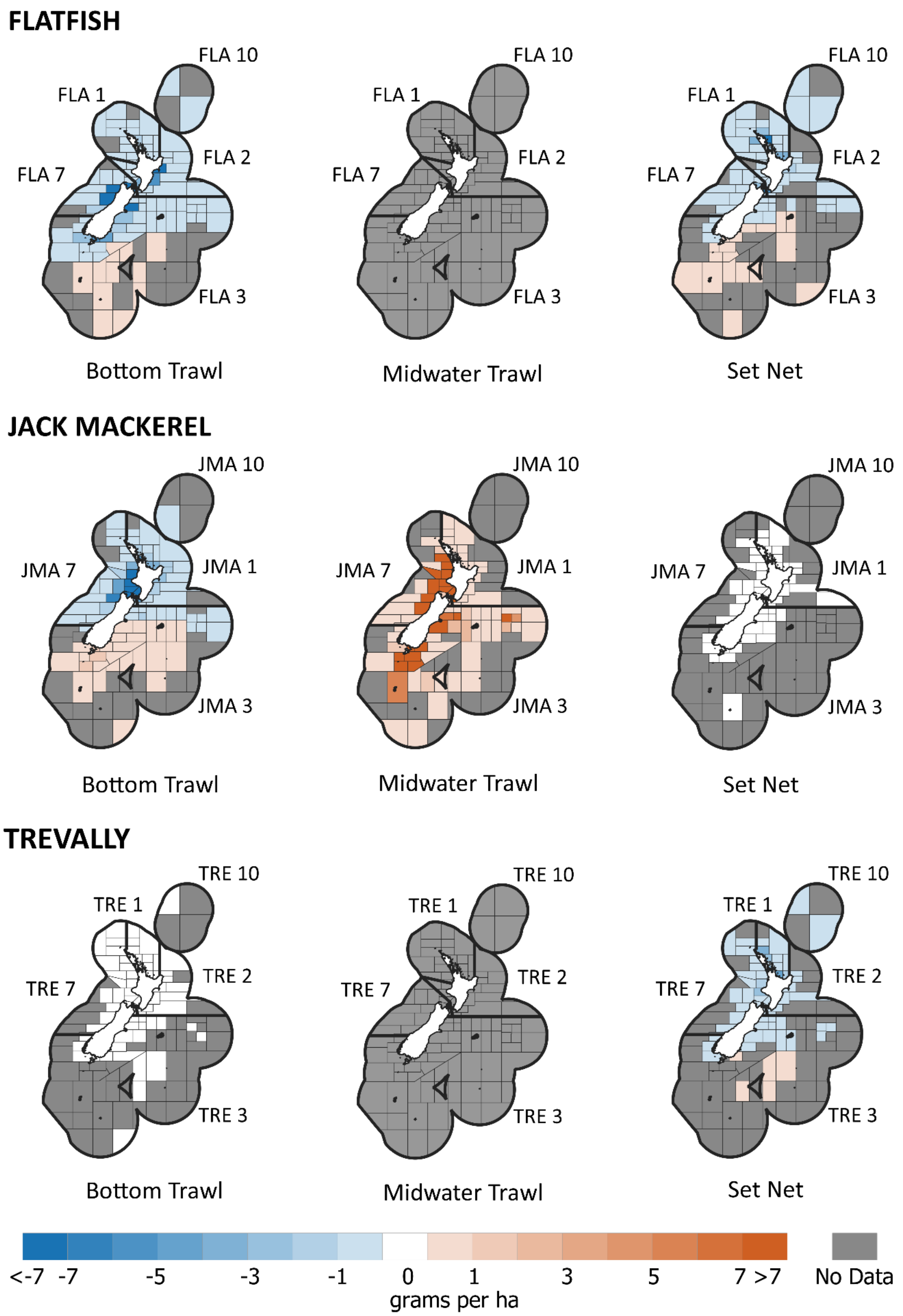


Figure 4. 6. Marginal Product of SST assuming quadratic relationship between SST and carrying capacity of fishery (in grams per ha)

Table 4. 3. Marginal Product of SST at means (in grams per ha), Akaike Information Criterion, and R^2 for each species, fishing method, and QMA

Species/ Method	QMA	n	Logarithmic R^2	Logarithmic AIC	Logarithmic MP_{SST}	Quadratic R^2	Quadratic AIC	Quadratic MP_{SST}	Opt. Temp
Flatfish									
Bottom Trawl	1	358	0.86	-2646	0.14	0.90	-2745	-1.84	10.14
Bottom Trawl	2	268	0.95	-1835	0.50	0.97	-1918	-2.86	10.43
Bottom Trawl	3	536	0.94	-2272	1.09	0.94	-2315	-5.98	8.19
Bottom Trawl	7	227	0.97	-881	2.03	0.98	-912	-11.75	9.85
Set Net	1	511	0.93	-205	7.77	0.94	-264	-48.55	11.50
Set Net	2	229	0.91	-2003	0.17	0.92	-2014		
Set Net	3	308	0.81	-2383	0.14	0.81	-2382		
Set Net	7								
Jack Mackerel									
Bottom Trawl	1	454	0.85	-2919	0.24	0.91	-3164	-4.62	9.72
Bottom Trawl	3	555	0.91	-3013	0.75	0.92	-3049	-0.67	10.42
Bottom Trawl	7	460	0.97	-917	4.08	0.97	-937	-11.47	11.89
Midwater Trawl	1								
Midwater Trawl	3	442	0.93	-206	8.11	0.95	-403		
Midwater Trawl	7	343	0.97	309	28.94	0.97	297		
Set Net	1	292	0.98	-3128	0.04	0.98	-3139		
Set Net	3								
Set Net	7	241	0.98	-2880	0.01	0.98	-2887		
Trevally									
Bottom Trawl	1	268	0.92	-1157	1.11	0.92	-1169		
Bottom Trawl	2	206	0.96	-1393	0.77	0.96	-1392		
Bottom Trawl	3								
Bottom Trawl	7	449	0.91	-2032	1.13	0.92	-2062		
Set Net	1	271	0.95	-2119	0.17	0.95	-2117		
Set Net	2								
Set Net	3								
Set Net	7	433	0.96	-2055	0.60	0.96	-2108	-4.20	10.71

4.6. Discussion

We establish a nonlinear relationship between the SST and the catch of selected commercial fisheries in NZ using a bioeconomic model pioneered by Barbier and Strand (1998). This research uses an unusually comprehensive catch and effort data that allows us to account for vessel characteristics in defining the effort measure. Given the depth of detail in this data, the analysis is conducted for three species of fish and for three fishing methods separately. It also allows us to distinguish between different QMAs and identify the spatial pattern of these differences.

If a logarithmic relationship between SST and carrying capacity of the fisheries is assumed, then the MP_{SST} for the three species for all areas of NZ is positive. This means a 1°C increase in SST results in a statistically significant but small increase in catch (expressed in grams per hectare of fished areas). However, the MP_{SST} for all areas of NZ is negative if we assume a quadratic relationship between SST and catch. If the MP_{SST} is computed for each statistical area, then the MP_{SST} is still negative for most areas but positive for areas closer to the South pole. Our results show that the catch of flatfish, trevally, and jack mackerel initially increases with SST but will eventually decrease after an 'optimal' level of SST is reached. The computed optimal level of SST are close to the lower bound of the average annual SST of NZ currently obtained in most of NZ's waters.

The importance of conducting analysis specific to species and fishing method is highlighted in our study. Flatfishes and trevally are demersal species that have limited latitudinal range. Therefore, these species cannot easily migrate to other areas within their temperature preference. Jack mackerel, on the other hand, is a pelagic species and can swim in wider latitudinal range. This explains why the SST for jack mackerel is still positive even in the assumption of quadratic relationship between SST and carrying capacity. The negative MP_{SST} of flatfishes may also be explained by the behavioural response of flatfish to ocean warming, as (Ryer 2008) has already reported that the catchability of flatfish decreases as the ocean warms.

Our results indicate a poleward redistribution of catch for flatfish and trevally with ocean warming. The increase in SST results in an increase in catch in areas closer to the South Pole for these two species. This is consistent with the expectations described in Cheung et al. (2012) that marine species more towards the poles as oceans warm.

In terms of policy, we show that efforts to manage fisheries must consider the responses of species to ocean warming. Our results show that there are difference in MP_{SST} within each QMA. A blanket policy for the existing QMA may thus be counterproductive. The management of a fishery accounting for increases in temperature requires dividing the existing QMAs. For example, JMA 3 may be divided into two QMAs that differentiate areas close to the coast of South Island and areas close to the South Pole.

Though flatfish, trevally, and jack mackerel are commercially important fish species, there are limited studies on how SST affects the behaviour of these species. This limits our ability to discuss our results in the context of the biological and ecological drivers of the responses of these species to ocean warming. However, our study provides an indicative direction of the response of fish species to ocean warming in the absence of fisheries science research.

We acknowledge that our work considers species groups in this study with six species of flatfish and three species of jack mackerel. These species are managed in NZ collectively, fishers are not required to report catch of each species, and thus we only have aggregate data on each species group. This is a limitation in as far as each species, within each group, may have a somewhat different sensitivity to changes in the ecosystem in which it swims. The different geographical distributions and thermal tolerances of these species of flatfishes and jack mackerels require further elucidation, and potentially species-specific policy adjustment in response to ocean warming, once this information is available. Further work should also include estimating the economic impacts of ocean warming in terms of revenue, cost of fishing, and fisher behaviour to mitigate the impacts of ocean warming.

4.7. Conclusion

We establish the relationship between SST and catch of flatfishes, jack mackerel, and trevally caught using bottom trawl, midwater trawl, and set nets within the exclusive economic zone of Aotearoa NZ. We use a production function approach pioneered by Barbier and Strand (1998) and show that catch increases with SST but starts to decrease beyond a specific temperature threshold. The magnitude of the established relationship varies across species and gears. In the absence of a comprehensive biological assessment, our results provide an indicative direction of responses of fish species to increasing SST. This analysis suggests a need to rethink fisheries management policies in response to fish redistribution due to ocean warming.

Future work on this may adopt alternative modelling techniques that do not rely on *a priori* information on the functional relationships between SST and catch may be employed. This paper adopted the bioeconomic economic model by Barbier and Strand (1998) and tested three functional relationships between SST and carrying capacity.

Future work on this topic should recognise the potential endogeneity problem as the effort measure may be endogenous. The measure of fishing effort may also likely respond to changes in SST. Estimations using instrumental variables and other procedures may be employed to handle this endogeneity problem.

Appendix

Appendix Table 4. 1 ITQ and ACE Prices (2001-2019)

Species/ Stock	Average Quota Price				Average ACE Price per metric ton	
	Per share		Per metric ton			
	Mean	SD	Mean	SD	Mean	SD
Flatfish	0.062	0.090	4223.6	6172.1	576.4	246.2
FLA1	0.023	0.013	1908.1	1088.2	432.7	96.0
FLA2	0.018	0.008	2432.6	1097.6	489.7	147.3
FLA3	0.170	0.124	10586.4	9662.4	590.0	205.2
FLA7	0.033	0.005	1595.7	221.6	848.8	308.7
FLA10						
Jack Mackerel	0.146	0.160	640.3	479.0	65.1	40.8
JMA1	0.062	0.039	621.7	393.8	61.6	14.8
JMA3	0.050	0.013	279.9	69.5	31.5	7.7
JMA7	0.253	0.189	776.9	581.4	102.1	47.5
JMA10						
Trevally	0.061	0.044	4795.4	2720.7	446.2	139.7
TRE1	0.055	0.020	3629.5	1296.2	418.6	73.0
TRE2	0.020	0.006	8122.0	2685.6	621.1	91.4
TRE3	0.000	.	22.2	.	341.4	33.7
TRE7	0.098	0.047	4559.3	2168.0	333.8	57.6
TRE10						

Note: Data from FishServe

Appendix Table 4. 2 Names and Characteristics of Fish Species

Common Name (Scientific Name)	Biology and Ecology	Preferred Temperature (°C)	Size[22]	Distribution	Depth
Flatfishes					
Yellowbelly flounder (*Rhombosolea leporina*)	• Demersal species • Inhabits coastal waters down to about 50 m • Temperate environment	11.7 - 20.2, mean 17.6	To about 50 cm TL	Known only from New Zealand	A few to 50 m
Sand flounder (*Rhombosolea plebeian*)	• Demersal species • Inhabits shallow waters at depth of less than 50 m, and to around 100 m • Temperate environment	10 - 18.2, mean 14.4	To about 45 cm TL.	Widespread. Known only from New Zealand.	A few to 75 m.
Black flounder (*Rhombosolea retiaria*)	• Demersal species • Inhabits shallow waters at depth of less than 50 m. • This species is poorly studied, fast growing and short lived (to at least 4 years) • Temperate environment		To about 45 cm TL.	Known only from New Zealand.	A few to 50 m.
Greenback flounder (*Rhombosolea tapirina*)	• Demersal species • Common on silty sand substrates from estuaries and inshore waters down to 100 m depth • Temperate environment	11.9 - 18.3, mean 16.6	To about 50 cm TL.	Southern New Zealand, including around Auckland and Campbell Islands. Also southern Australia.	A few to 300 m.
Lemon sole (*Pelotretis flavilatus*)	• Demersal species • Inhabits shallow waters • Temperate environment	8.5 - 16, mean 13.3	To about 50 cm TL	From Stewart Island to North Cape, also Chatham Rise. Known only from New Zealand.	20 to 500 m
New Zealand sole (*Peltorhamphus novaezeelandiae*)	• Demersal species • Inhabits shallow waters • Temperate environment	11.2 - 18.2, mean 16.6	To about 55 cm TL	Widespread but more common around the South Island. Known only from New Zealand	A few to 100 m

[22] FL (fork length) is the straight line distance from the tip of the snout to the fork of the tail while TL (total length) is the straight line distance from tip of the snout to the tip of the tail (McMillan et al. 2019).

Appendix Table 4. 2. ***Continuation***

Common Name (Scientific Name)	Biology and Ecology	Preferred Temperature (°C)	Size	Distribution	Depth
Brill (*Colistium guntheri*)	• Demersal species • Inhabits shallow waters • Temperate environment	11.2 - 18.2, mean 16.6	To about 95 cm TL.	Widespread patchy distribution. Known only from New Zealand.	A few to 100 m
Turbot (*Colistium nudipinnis*)	• Demersal species • Inhabits shallow waters • Temperate environment	11.5 - 19.4, mean 17.5	To about 100 cm TL.	Most common on the west coast of the South Island. Known only from New Zealand.	A few to 100 m.
Jack Mackerel	•				
Yellowtail (horse) jack mackerel (*Trachurus novaezelandiae*)	• Pelagic species • Adults occur in coastal waters, including estuaries • Found on the bottom, in midwater, and occasionally at the surface, in large schools. • Adults are generally found over offshore rocky reefs, while juveniles are generally found in shallow, soft substrate areas. • Subtropical environment (23°S - 50°S, 112°E - 176°W)	13.1 - 21.2, mean 15.3	To about 47 cm FL	Common around northern and central coastal New Zealand but absent from Chatham Rise and Campbell Plateau. Southern half of Australia.	A few to 150 m
Slender (Chilean) jack mackerel (*Trachurus murphyi*)	• Pelagic species • Adults are found in the shore and open oceanic waters, in schools. • They feed mainly on fish larvae and small crustaceans. • Subtropical environment (2°N - 51°S, 106°E - 79°W)	14.1 - 22.6, mean 16.5	To about 60 cm FL	Common around New Zealand, especially southern areas including the Chatham Rise but absent from the Campbell Plateau. Also found off Peru, Chile, and Pacific subantarctic zone (southern Australia to east Pacific)	A few to 500 m

Appendix Table 4. 2. *Continuation*

Common Name (Scientific Name)	Biology and Ecology	Preferred Temperature (°C)	Size	Distribution	Depth
Greenback (horse) jack mackerel (*Trachurus declivis*)	• Pelagic species • Adults are commonly found near the bottom, in midwater, and occasionally at the surface in continental shelf waters. • They form pelagic schools for most of the year but may move close to the seabed during winter. • Found at less than 300 m water depth with temperature less than 16° C. • Juveniles inhabit coastal and estuarine waters although they may sometimes be found offshore. • Adults feed mostly during the day mainly on krill and other planktonic crustaceans at the edge of the continental shelf. • Temperate environment (9°S - 53°S, 112°E - 177°E)	11.1 - 20.2, mean 14.4	To about 55 cm FL	Common around New Zealand, including the Chatham Rise, but absent from the Campbell Plateau. Southern half of Australia.	A few to 300
Trevally					
Silver Trevally (*Pseudocaranx georgianus*)	• Occupies shallow harbours and pelagic and demersal waters of the continental shelf. • Juveniles usually inhabit estuaries, bays, and shallow continental shelf waters. • Adults occur in bays and coastal waters, including estuaries and form schools near the seabed on the continental shelf. Schools are found at the surface, in mid-water and on the bottom and are often associated with reefs and rough bottom. • Feed on plankton and on bottom invertebrates. • Tropical environment (40°N - 47°S)		To about 80 cm FL	Widespread in central and northern New Zealand from Kermadec Islands to off Canterbury with records from Chatham Island and Foveaux Strait. Norfolk Island. Other overseas records are uncertain.	A few to 240 m

Sources: Biology and Ecology (Froese and Pauly 2020; McMillan et al. 2019); Preferred Temperature (Froese and Pauly 2020); Size, Distribution and Depth (McMillan et al. 2019)

Appendix Table 4. 3. Average annual sea surface temperature of fished areas in NZ (1990 to 2018)

Method/Species	Mean	SD
Flatfish		
Bottom Trawl	14.83	2.77
Midwater Trawl	11.76	2.76
Set Net	15.75	2.58
Jack Mackerel		
Bottom Trawl	14.92	2.7
Midwater Trawl	13.89	2.44
Set Net	16.27	2.24
Trevally		
Bottom Trawl	16.53	1.78
Midwater Trawl	16.07	1.6
Set Net	16.51	1.9

Data Source: COBE-SST2

Appendix Table 4. 4. Akaike Information Criterion, R^2, and Marginal Product of SST at means (in grams per ha) for each species and fishing method

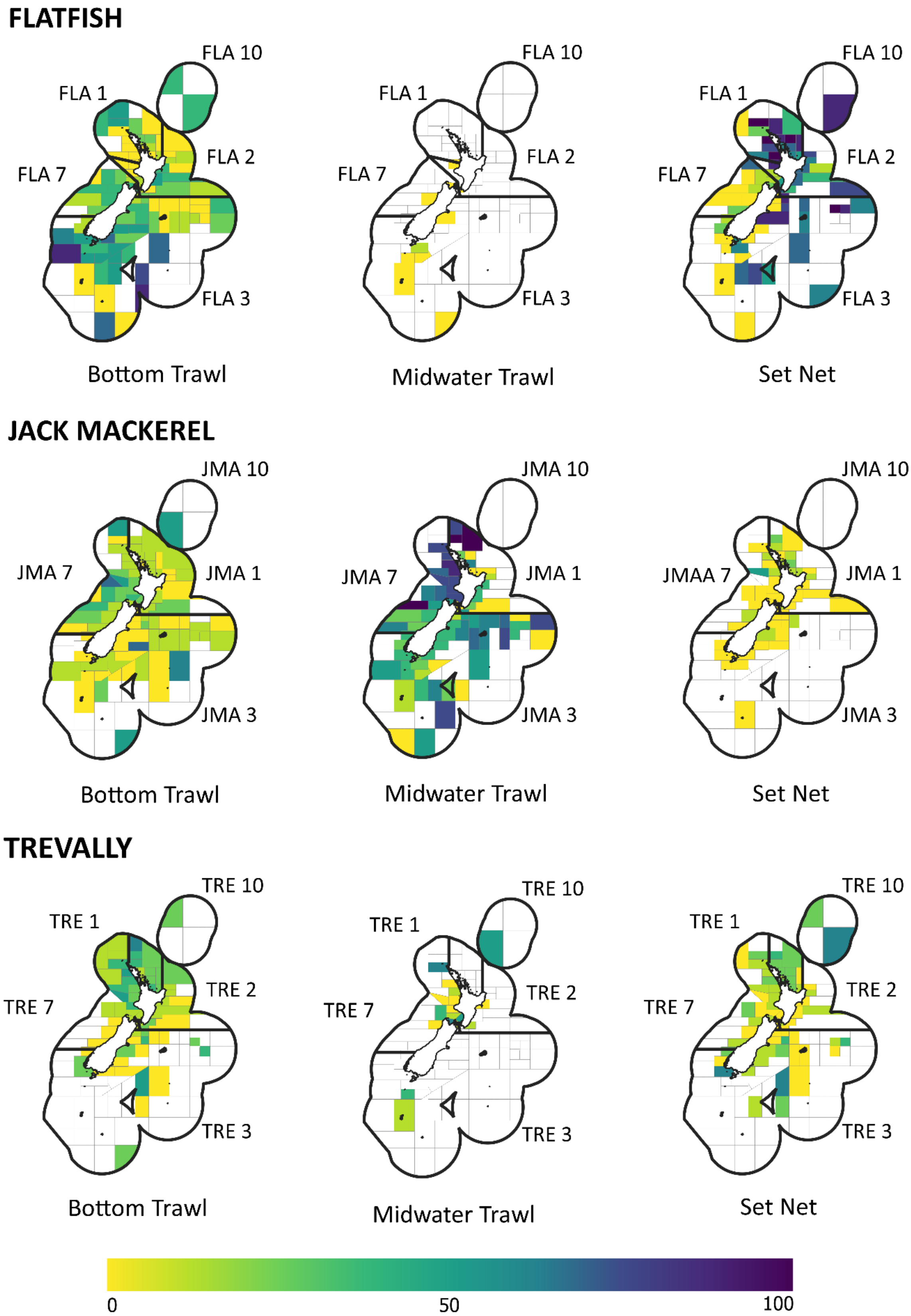
Species/ Fishing Method	n	RTO				YEAR				YEAR STAT				STAT AREA			
		R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp
LOGARITHMIC																	
Flatfish																	
Bottom Trawl	1392	0.89	-5187	1.17		0.89	-5191	1.15		0.95	-6297	1.05		0.95	-6281	1.01	
Midwater Trawl	21																
Set Net	1235	0.85	-671	3.38		0.85	-672	3.41		0.93	-1540	3.89		0.93	-1515	3.98	
Jack Mackerel																	
Bottom Trawl	1472	0.95	-4150	1.70		0.95	-4171	1.72		0.96	-4441	1.81		0.96	-4433	1.78	
Midwater Trawl	906	0.96	305	15.96		0.96	299	15.62		0.96	216	16.33		0.96	241	16.38	
Set Net	638	0.96	-6704	0.02		0.96	-6709	0.02		0.97	-6791	0.03		0.97	-6785	0.03	
Trevally																	
Bottom Trawl	1019	0.84	-4215	1.02		0.84	-4237	0.95		0.91	-4834	0.96		0.90	-4746	0.91	
Midwater Trawl	57																
Set Net	966	0.92	-4753	0.49		0.92	-4757	0.49		0.96	-5327	0.31		0.96	-5328	0.31	
QUADRATIC																	
Flatfish																	
Bottom Trawl	1392	0.93	-5928	-5.64	9.80	0.93	-5940	-5.72	9.74	0.96	-6544	-4.61	10.01	0.96	-6518	-4.60	9.93
Midwater Trawl	21																
Set Net	1235	0.86	-713	-8.77	12.26	0.86	-713	-8.84	12.24	0.94	-1690	-13.47	11.61	0.93	-1677	-14.69	11.43
Jack Mackerel																	
Bottom Trawl	1472	0.95	-4228	-3.16	11.91	0.95	-4246	-3.04	12.00	0.96	-4510	-2.89	12.17	0.96	-4497	-2.70	12.26
Midwater Trawl	906	0.96	236	49.491		0.96	232	48.360		0.96	150	47.84		0.96	155	45.461	
Set Net	638	0.97	-6800			0.97	-6803			0.97	-6853			0.97	-6850		
Trevally																	
Bottom Trawl	1019	0.85	-4253			0.85	-4272			0.92	-4862			0.91	-4802		
Midwater Trawl	57																
Set Net	966	0.93	-4848	-2.61	11.28	0.93	-4849	-2.47	11.46	0.96	-5440	-2.38	10.65	0.96	-5442	-2.42	10.54

Appendix Table 4. 5. Akaike Information Criterion, R^2, and Marginal Product of SST at means (in grams per ha) for each species, fishing method, and QMA assuming logarithmic relationship between SST and carrying capacity

Species/ Fishing Method	QMA	n	RTO				YEAR				YEAR_STAT AREA				STAT AREA			
			R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp
Flatfish																		
Bottom Trawl	1	358	0.85	-2617	0.12		0.85	-2616	0.12		0.86	-2646	0.14		0.86	-2646	0.13	
Bottom Trawl	2	268	0.93	-1722	0.42		0.93	-1721	0.41		0.95	-1835	0.50		0.95	-1837	0.50	
Bottom Trawl	3	536	0.87	-1859	1.60		0.87	-1866	1.49		0.94	-2272	1.09		0.94	-2246	0.93	
Bottom Trawl	7	227	0.97	-867	2.42		0.97	-866	2.38		0.97	-881	2.03		0.97	-883	2.03	
Set Net	1	511	0.85	170	6.85		0.85	171	6.92		0.93	-205	7.77		0.93	-178	8.17	
Set Net	2	229	0.87	-1902	0.14		0.87	-1906	0.13		0.91	-2003	0.17		0.91	-1999	0.17	
Set Net	3	308	0.77	-2323	0.16		0.77	-2334	0.15		0.81	-2383	0.14		0.80	-2364	0.15	
Set Net	7	174																
Jack Mackerel																		
Bottom Trawl	1	454	0.74	-2679	0.30		0.75	-2684	0.32		0.85	-2919	0.24		0.85	-2921	0.24	
Bottom Trawl	2																	
Bottom Trawl	3	555	0.90	-2941	0.73		0.90	-2941	0.73		0.91	-3013	0.75		0.91	-3013	0.74	
Bottom Trawl	7	460	0.96	-848	3.91		0.96	-853	3.96		0.97	-917	4.08		0.97	-919	4.06	
Midwater Trawl	1	121																
Midwater Trawl	2																	
Midwater Trawl	3	442	0.92	-156	8.30		0.92	-155	8.17		0.93	-206	8.11		0.93	-203	8.01	
Midwater Trawl	7	343	0.97	341	27.47		0.97	335	26.26		0.97	309	28.94		0.97	314	29.46	
Set Net	1	292	0.98	-3113	0.04		0.98	-3114	0.04		0.98	-3128	0.04		0.98	-3130	0.04	
Set Net	2																	
Set Net	3	105																
Set Net	7	241	0.98	-2872	0.01		0.98	-2870	0.01		0.98	-2880	0.01		0.98	-2876	0.01	
Trevally																		
Bottom Trawl	1	268	0.90	-1101	1.21		0.90	-1110	1.09		0.92	-1157	1.11		0.90	-1120	1.19	
Bottom Trawl	2	206	0.93	-1306	0.60		0.94	-1315	0.55		0.96	-1393	0.77		0.95	-1385	0.79	
Bottom Trawl	3	82																
Bottom Trawl	7	449	0.87	-1861	1.41		0.87	-1871	1.29		0.91	-2032	1.13		0.90	-1995	1.07	
Set Net	1	271	0.92	-1994	0.18		0.92	-1997	0.17		0.95	-2119	0.17		0.95	-2120	0.17	
Set Net	2	138																
Set Net	3	100																
Set Net	7	433	0.94	-1874	0.95		0.94	-1874	0.95		0.96	-2055	0.60		0.96	-2056	0.62	

Appendix Table 4. 6. Akaike Information Criterion, R^2, and Marginal Product of SST at means (in grams per ha) for each species, fishing method, and QMA assuming quadratic relationship between SST and carrying capacity

Species/ Fishing Method	QMA	N	RTO				YEAR				YEAR_STAT AREA				STAT AREA			
			R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp	R^2	AIC	MP_{SST}	Opt. Temp
Flatfish																		
Bottom Trawl	1	358	0.89	-2737	-1.75	10.20	0.89	-2735	-1.75	10.20	0.90	-2745	-1.84	10.14	0.90	-2745	-1.85	10.11
Bottom Trawl	2	268	0.96	-1875	-3.81	9.80	0.96	-1876	-3.83	9.76	0.97	-1918	-2.86	10.43	0.96	-1919	-2.90	10.34
Bottom Trawl	3	536	0.91	-2073	-9.81	7.71	0.92	-2079	-9.80	7.65	0.94	-2315	-5.98	8.19	0.94	-2281	-5.47	8.15
Bottom Trawl	7	227	0.97	-876	-4.89	12.05	0.97	-877	-5.67	11.67	0.98	-912	-11.75	9.85	0.98	-912	-11.22	9.96
Set Net	1	511	0.86	149	-39.72	11.84	0.86	151	-40.23	11.76	0.94	-264	-48.55	11.50	0.94	-248	-48.88	11.74
Set Net	2	229	0.89	-1950			0.89	-1948			0.92	-2014			0.92	-2006		
Set Net	3	308	0.77	-2321			0.77	-2332			0.81	-2382			0.80	-2362		
Set Net	7	174																
Jack Mackerel																		
Bottom Trawl	1	454	0.89	-3078	-4.11	9.74	0.89	-3078	-4.17	9.68	0.91	-3164	-4.62	9.72	0.91	-3152	-4.48	9.71
Bottom Trawl	2																	
Bottom Trawl	3	555	0.90	-2965	-0.37	11.00	0.90	-2965	-0.40	10.92	0.92	-3049	-0.67	10.42	0.92	-3046	-0.65	10.44
Bottom Trawl	7	460	0.96	-873	-13.94	11.39	0.96	-876	-13.29	11.51	0.97	-937	-11.47	11.89	0.97	-939	-11.57	11.85
Midwater Trawl	1	121																
Midwater Trawl	2																	
Midwater Trawl	3	442	0.95	-355			0.95	-354			0.95	-403			0.95	-405		
Midwater Trawl	7	343	0.97	317			0.97	312			0.97	297			0.97	300		
Set Net	1	292	0.98	-3128			0.98	-3129			0.98	-3139			0.98	-3141		
Set Net	2																	
Set Net	3	105																
Set Net	7	241	0.98	-2882			0.98	-2879			0.98	-2887			0.98	-2887		
Trevally																		
Bottom Trawl	1	268	0.91	-1124	10.26	4.39	0.91	-1130	9.41	4.40	0.92	-1169			0.91	-1143	10.23	4.43
Bottom Trawl	2	206	0.94	-1324	-2.62	11.24	0.94	-1339	-2.97	10.81	0.96	-1392			0.95	-1383	0.73	20.39
Bottom Trawl	3	82																
Bottom Trawl	7	449	0.89	-1943			0.89	-1953			0.92	-2062			0.91	-2038		
Set Net	1	271	0.92	-1993			0.92	-1995			0.95	-2117			0.95	-2119		
Set Net	2	138																
Set Net	3	100																
Set Net	7	433	0.94	-1917	-4.04	11.60	0.94	-1915	-4.07	11.57	0.96	-2108	-4.20	10.71	0.96	-2110	-4.27	10.62



Appendix Figure 4. 1. Average share of species to total catch (%)

Chapter 5 Conclusion

This thesis aims to establish the relationship between sea surface temperature and commercial fisheries catch using a bioeconomic framework pioneered by Barbier and Strand (1998). The three substantive chapters in this thesis investigate several fish species and fishing methods and cover different geographical areas. We also test for different relationships between SST and the carrying capacity of the fishery. The findings and implications of the essays are summarized as below.

The relationship between SST and the catch of yellowfin and skipjack tuna catch by three types of purse seine sets in the Eastern Pacific Ocean (EPO) is investigated in Chapter 2. We show that yellowfin and skipjack tuna catch is increasing with SST and the magnitude of the marginal product of SST (MP_{SST}) varies across species, type of set, and location of catch and effort. This result suggests the need for sector- and species- specific predictions. The MP_{SST} is positive for all types of sets for both tuna species if we assume linear and logarithmic relationships between SST and the carrying capacity. These results change for a quadratic relationship, where the MP_{SST} is positive for yellowfin tuna but is sometime negative for skipjack depending on the types of sets considered. As the ocean warms, higher latitudes become more suitable habitats for the tuna species that already dominate the area's catch.

In Chapter 3, we show that countries within the Eastern Pacific Ocean gain from the redistribution of tuna due to ocean warming. We show that catch of skipjack and yellowfin tuna in the EEZ of countries increases with the SST. This result supports the conclusion from fisheries science studies that tuna disperse towards the eastern part of the Pacific Ocean as the ocean warms. The highest marginal revenue product, when adjusted for population, is reported for countries with the highest dependency on marine resources.

Chapter 4 focuses on commercial fisheries in Aotearoa New Zealand. We establish the relationship between SST and the catch of flatfishes, trevally, and jack mackerel caught using bottom trawl, midwater trawl, and set nets. We show that there is an increase in catch for all three fish species if we assume a logarithmic relationship between SST and the carrying capacity of the fishery. The MP_{SST} are positive for all species and gears if we assume a logarithmic relationship. By assuming a quadratic relationship between SST and carrying capacity, we also show that there is a threshold above which catch starts to decrease as SST increases. The computed optimal level of SST are close to the lower bound of the average annual SST of New Zealand.

We demonstrate that analyses of the link between SST and catch using an economic framework produce results consistent with results of models in fisheries science. Future studies should therefore consider species, gear-, and location-specific analyses so that the impact of ocean warming can be more fully understood. We emphasise that our results may not be applicable everywhere, as these results are specific to the species, fishing gear, location, and period covered.

Any program to manage fisheries in response to ocean warming must be explicitly designed for the target species and area and should consider the different fishing methods used. Governments and regional bodies may employ measures to allow fishers to adapt to the impacts of climate change. Training on business skills and product development should be provided to build capacity and improve the resilience of fishers. Governments should create additional livelihood opportunities for areas adversely affected by fish redistribution. It is also vital to improve the awareness and understanding of climate change vulnerabilities and adaptation pathways in the fisheries sector.

Fisheries management plans and other policies must be revised to integrate climate change mitigation and adaptation actions at the regional blocks and national levels.

The design of the policies must allow greater flexibility to respond to changes in fish distribution and fisher practices.

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