

# Climate Change and the Common-Pool Problem in Fisheries

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## Abstract

How significant is the common-pool problem in global fisheries, and how will it be affected by climate change? Many fisheries are not fully contained in a single country's Exclusive Economic Zone, and therefore face an international common-pool problem. As the ocean warms and acidifies, fishery ranges will shift and alter the distribution of populations across borders. This could lead to maladaptive overexploitation, but could also increase conservation by countries gaining control. I construct a panel of fishery ranges and estimate how fisheries extraction responds to the share of a stock in the given management area. My results show a large increase in extraction in response to a decrease in the share of a stock in a managed area, consistent with the theory that controlling a smaller share of a stock reduces incentives for conservation. I then simulate the effects of climate change on fisheries extraction using these empirically estimated responses. The behavioral response to climate change is close to zero on net, but stock-gainers increase escapement (the quantity of available fish *not* caught) by 1.6 million tons (2.6%) and stock-losers decrease escapement by 1.5 million tons (3%). For the average stock, this behavioral response is 25% of the total effect of climate change. I also simulate fisheries outcomes under global cooperative management, and find a 47.5 million ton (77%) increase in escapement. In a more plausible scenario of US-Canada cooperation, escapement increases by 1.2% and the effect of climate change is slightly dampened.

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# 1 Introduction

How severe is the international common-pool problem in fisheries? How will it be affected by climate change? Many fisheries cross international management boundaries and are targeted by several countries.<sup>1</sup> When countries do not reap the full benefits of conservation, they will extract more from the fishery. In this paper, I leverage variation in fish stock ranges to estimate the effect of international sharing on fisheries extraction. I show that a one standard deviation increase in the share of a stock under a country's control decreases the extraction rate by 72%.

Climate change could alter incentives for conservation by causing fish populations to move.<sup>2</sup> On one hand, range shifts could induce preemptive overfishing, move stocks into countries with worse management (see Figure 1), or even move stocks into the internationally open-access high seas.<sup>3</sup> However, countries expecting to benefit from range shift could increase conservation, and poleward movement of stocks would on average move them towards countries with longer coastlines and larger Exclusive Economic Zones (EEZs) (see Figures 2 and 3).<sup>4</sup> I predict future stock control under different climate scenarios, and apply my estimates of the effect of stock control to simulate the behavioral response to climate change. I find that stock shifts have close to zero effect on average, but create clear winners

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<sup>1</sup>Palacios-Abrantes et al. (2020a) finds that 67% of their sample of commercially valuable fisheries are shared between at least two Exclusive Economic Zones.

<sup>2</sup>As changing climate alters the environmental characteristics of the ocean, many species of fish have and will migrate to seek the environmental conditions they are adapted to (Cheung et al., 2010; Pinsky et al., 2013; Poloczanska et al., 2013; García Molinos et al., 2016; Hodapp et al., 2023). These are generally shifts towards the poles to maintain preferred temperatures (Dahms and Killen, 2023). Several papers in the scientific literature have already identified pronounced range shifts in particular fisheries (Dulvy et al., 2008; Pershing et al., 2015; Kleisner et al., 2017; Yang et al., 2022; Champion et al., 2022; Crear et al., 2023; DeFilippo et al., 2023; Sarre et al., 2024; Frawley et al., 2025).

<sup>3</sup>Several papers have discussed how range shift could worsen management of transboundary stocks, but have not empirically estimated the response (Pinsky et al., 2018; Spijkers et al., 2018; Palacios-Abrantes et al., 2020b; Gullestad et al., 2020; Oremus et al., 2020; Vogel et al., 2023). Palacios-Abrantes et al. (2025) predicts climate change will shift many stocks that straddle EEZs and the high seas further into the high seas.

<sup>4</sup>To my knowledge, the literature has not considered the possible strengthening of international property rights due to range shift. For example, Gaines et al. (2018) is the most sophisticated prediction of the interaction between climate change and management to date, but simply assumes that all shifting stocks would transition to open access if not managed cooperatively.

and losers. Management areas expecting to gain stock share will respond by increasing escapement (the quantity of available biomass *not* caught) by 2.6%, whereas areas expected to lose stock share will decrease escapement by 3%. These effects are on the same order of magnitude as the historic effects of warming on fisheries productivity.<sup>5</sup> Naturally, the biophysical effects of climate change are also significant.<sup>6</sup> Under a simple calibration, I find that, for the average stock, omitting the behavioral response to range shift would miss 27% of the total effect of climate change.

I begin with a model in which a fisheries manager observes the biomass of fish in their management area every period and decides how much to harvest. Their optimal strategy is to set an escapement rule: that is, set a quantity of fish they will *not* catch by equating the marginal profit of catching an additional fish today with the discounted marginal productivity of the fish stock, which accounts for both the marginal profit from the future stock, the discount rate, the growth rate of the stock, and a parameter capturing how much of the total fish stock is in the management area of the fisheries manager. The model predicts that when a fisheries manager does not control the entire stock, their privately optimal escapement rule does not internalize the returns to fisheries productivity that accrue outside of the management area, leading to inefficiently low escapement. This in turn implies greater catch conditional on biomass and an unconditionally higher extraction rate.

Next, I take these predictions to the data and document the relationship between fish stock ranges and extraction from the fishery. The main dataset for this project comes from the RAM Legacy Stock Assessment Database (Ricard et al., 2012). The RAM Database is a collection of stock assessment results for many of the world's most important fisheries with high-quality stock assessment results. I identify stocks with data on catch and biomass after

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<sup>5</sup>From 1930 to 2010, oceanic warming has been estimated to decrease fisheries yields by 4.1% (Free et al., 2019).

<sup>6</sup>Climate change is expected to affect marine ecosystems in several ways. Ocean warming decreases fisheries biomass on average by reducing individual fish sizes and population growth (Pauly and Cheung, 2018). Increased carbon concentrations also have an independent negative impact on fisheries through ocean acidification (Branch et al., 2013). Free et al. (2019) finds variation in the effect of temperature on fisheries productivity.

2000, and create an unbalanced panel of these. Figure 4 shows a map of stocks by country. It shows that the US and Canada together make up a majority of the stocks in the dataset, with Europe and Japan accounting for another significant share. All together, there are 328 stocks, representing 168 unique species, from 44 countries. For each stock, I also identify the relevant area using the shapefiles from the RAM Legacy Stock Boundary Database (Free, 2023). From catch and biomass, I construct escapement as (biomass - catch) and the extraction rate as (catch/biomass). Due to differences in how biomass is measured for each stock, in the core empirical work I use normalized versions of these measures, dividing each observation by the stock level average. In addition to the RAM database, I also bring in variables from other sources. For each country, I assign a fishery management score from the Environmental Performance Index (Block et al., 2024), and for each country-year I assign the lending interest rate from the World Bank. For each stock, I assign whether it is multi-nationally managed, from the RAM database, and whether it is managed with Individual Transferable Quota, based on Lynham (2014) and manual assignment. For each species, I add whether the species is pelagic/highly migratory and the intrinsic growth rate, from FishBase (Froese and Pauly, 2025).

For each species in the panel, I identify its suitable environmental conditions along 7 environmental variables from AquaMaps (Kaschner et al., 2019). I then find annual rasters of those environmental variables from NOAA and Bio-ORACLE (Assis et al., 2024). Based on those values and the environmental preferences of each species, I create annual predictions of suitable ranges. These predictions are imperfect proxies of true habitat ranges, as other variables that affect the presence of a species are not included (e.g. predator/prey relationships, contiguity, etc). Environmental suitability is also not a perfect measure of species abundance—while I know the biomass of a species *within* the management area from the RAM database, I do not know the biomass outside of the management area and cannot base my stock share measure on that. However, the variables that predict suitability are plausibly exogenous with respect to fisheries management, whereas range predictions based

on catch would be confounded by the exact incentives studied here. For each stock in each year, I calculate the suitable range within a wide buffer of the stock shapefile. I then find how much of the total suitable range in the buffer area falls within the Exclusive Economic Zone of the managing country, and use that as a proxy for the stock share.

My main empirical contribution is to estimate the effect of the stock share on extraction. I use normalized escapement, extraction rate, and catch as my primary outcomes. I regress these on my proxy for the stock share, controlling for stock and year fixed effects to isolate year-to-year variation in the stock share distinct from common shocks to all fisheries in a year or time-invariant features of a fishery. The regression results show that the stock share has a significant effect on extraction: a one standard deviation decrease in the share of a fish stock within the management area decreases escapement by 43.7%, increases the extraction rate by 71.9%, and increases catch conditional on biomass by 66.8% of their respective averages. In practice there is much less variation in the stock share within a fishery, so the effect of a one standard deviation within fishery decrease in the stock share is a 1.6% decrease in escapement, a 2.6% increase in the extraction rate, and a 2.4% increase in catch conditional on biomass.

Finally, I extrapolate what these results imply for fisheries under a few counterfactuals. First, I consider what my results predict for future fisheries due to climate change. I begin by creating predicted suitability rasters following the same AquaMaps methodology, based on predicted environmental conditions under various Shared Socioeconomic Pathways. I then recompute the stock shares, and find that the predicted changes in stock shares range from large decreases (-0.19) to large increases (+0.155)—however, the vast majority of changes are clustered around zero. The range of stock share changes imply changes in escapement that range from 28.6% reductions to 23.3% increases, though for most stocks the implied changes are small. A majority of EEZs with stocks in my sample are predicted to be property rights winners under climate change.<sup>7</sup> As a result, total escapement is predicted to increase

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<sup>7</sup>However, it should be noted that my sample includes mostly well managed, poleward fisheries, rather than the poorly managed tropical fisheries which are most likely to be damaged by climate change.

accounting only for the behavioral response. Next, I intend to add the predicted effect of higher temperatures on productivity to calculate the effect of climate change combining the biophysical and behavioral channels.

My second counterfactual considers the global gains from collaborative management, imagining that every country managed their fish stock according to the global optimum. Specifically, I simulate what escapement would be if every country behaved as if all stock shares were 1. In that scenario, I find stock level increases in escapement of 67% on average, with global escapement from fisheries in my sample increasing by 47.5 million tonnes (77%). In total, the effects of the static transboundary problem as significantly larger than the effects of climate change I estimate in the previous counterfactual.

This paper contributes to several literatures in environmental economics. It contributes to the literature on adaptation to climate change by studying a case with potential for *maladaptation*. There is a long and growing literature on adaptation to climate, much of which has focused on food systems.<sup>8</sup> In general, adaptation in these contexts is thought to be a declining responsiveness of the outcome to the relevant weather variables.<sup>9</sup> In my setting that need not be the case—more awareness of the consequences of range shift could lead to more pronounced effects, for example. Another strand of literature looks at specific adaptive strategies.<sup>10</sup> I look at a particular *maladaptive* strategy, that both involves endogenous

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<sup>8</sup>Burke and Emerick (2016) is a notable early example of this literature assessing adaptation in agricultural production to increasing temperatures. Burke et al. (2024) expands that methodology to other domains like mortality, crime, and economic output. Hultgren et al. (2025) predicts the full impact of climate change in agriculture accounting for adaptation.

<sup>9</sup>Many of the seminal papers in this literature show that adaptation flattens the relationship between extreme heat and mortality (Barreca et al., 2016; Heutel et al., 2021; Carleton et al., 2022)

<sup>10</sup>Guo and Costello (2013) looks at the differing values of adaptation on different margins in forestry, finding that “intensive” margin adaptations, like changing crop rotation intervals, have little value whereas “extensive margin” adaptations, like crop choice, have large value. Moscona and Sastry (2022) and Moscona and Sastry (2023) look at innovation in crop varieties as an adaptive strategy with public good components. Bradt and Aldy (2025) examine levees as an adaptive strategy and find that they shift the losses of flooding from protected to unprotected areas. I similarly look at a particular adaptive strategy, and in a setting with potential for spillovers that lead to winners and losers. Two papers in this literature are most similar to this one: Taylor (2025) looks at agricultural adaptation to climate change through irrigation, identifying specific investments that can be made to reduce the private damages of future climate change. Due to common-pool groundwater sources, these responses can be maladaptive in similar ways to the strategies discussed in this paper. However, in my setting the common-pool dynamic is the fundamental force that is changing, and the linked relationship between consumption and growth for a biological renewable resource changes the

policy and comes from a change in the very nature of the externality. There is also a growing literature on climate adaptation in fisheries specifically. One strand of literature focuses on the resilience of fishing and coastal communities to climate change.<sup>11</sup> Another strand of literature studies how fishing strategies respond to climate shocks.<sup>12</sup> This paper advances the econometric literature on fisheries adaptation to include the empirically estimated response of fisheries management to climate shocks.

This paper also contributes to a long literature on the cross jurisdictional management of spillover externalities.<sup>13</sup> This literature has historically exploited variation in jurisdictional coverage to estimate how outcomes respond to management incentives. My paper has the advantage of exploiting variation in the severity of the spillovers holding jurisdictional claims fixed.<sup>14</sup> Finally, this paper contributes to the related literature on property rights security and common pool resources.<sup>15</sup> The most similar paper to this one is Liu and Molina (2021),

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nature of the externalities. Hsiao et al. (2024) studies the response of trade policy to climate shocks in agriculture, and finds that trade restrictions due to domestic political economy can increase the projected losses of climate change. This paper similarly studies endogenous policy responses to climate change, but in a setting where the externalities operate through production rather than trade.

<sup>11</sup>Oremus (2019) shows that temperature variation lowers fishing employment in New England. Reimer et al. (2025) discusses how management can increase adaptability to future climate change. Sethi et al. (2014), Koss (2025), and Kim and Reimer (2025) consider how diversification across fisheries and industries can dampen the effects of climate and other fisheries shocks.

<sup>12</sup>Shrader (2023) studies how fishing decisions respond to forecasts of ENSO phenomenon, and what this implies for the value of forecasts as an adaptation tool. Costello and Collie (2025) presents a model of dynamic climate adaptation where fishermen observe a weather draw from a climate distribution, and then make extraction decisions given the known growth function. The model differentiates between adaptation to the climate distribution and adaptation to a given weather draw. This paper takes a similar perspective on modeling adaptation, letting fishery managers respond annually to new draws of a climate outcome: the share of recruitment biomass they will control next period.

<sup>13</sup>Lipscomb and Mobarak (2017) is perhaps the canonical paper in this literature, that looks at how the management of externalities responds to jurisdictional scale. It finds that county-splits in Brazil lead to greater water pollution, consistent with the hypothesis that managers do not fully internalize the effects of externalities outside their jurisdictions. He et al. (2020) find similar results in China. Fang et al. (2019), Heo et al. (2025), and Li (2025) find the same dynamic for air pollution.

<sup>14</sup>These kinds of species and ecosystem shifts are not unique to fisheries (Pecl et al., 2017). However, the international institutions, economic significance, and data availability make fisheries a natural place to study this more general phenomenon of bioeconomics.

<sup>15</sup>Although this literature arguably traces back to Gordon (1954) or even before, the most relevant literature begins with Gordon Munro's work analyzing the international sharing of fish stocks under the present regime of Exclusive Economic Zones of 200 nautical miles, beyond which there is an internationally open access high sea (Munro, 1979, 1990, 2007; Miller and Munro, 2004). Hannesson (2011) analyzes the game theory of shared fisheries in this kind of environment, and even considers how climate induced changes in sharing can affect conservation. Kaffine and Costello (2011) describes a model of optimal extraction that depends on the share of recruitment accruing to the regulator, much like mine. On the empirical side,

which looks at the severity of the transboundary problem and estimates the cross-sectional relationship between the distribution of a stock across countries and the extraction rates of those fisheries. In this paper I use within fishery variation to isolate the effect of trans-boundary sharing holding all other characteristics of the fishery constant. Another strand of fisheries economics considers the importance of property rights in fishing. Most of these papers estimate the effect of using property rights to allocate catch allowances within a fishery,<sup>16</sup> but a few consider property rights security from an international perspective. Noack and Costello (2022) is the closest in perspective to this paper, as it treats the share of the a fish stock that falls within a management area can be seen as a proxy for property rights security in an international context. However, this paper takes a dynamic view of property rights security, and exploits variation within a fishery in the share that falls within a given EEZ.<sup>17</sup> This paper also has implications for the nature of domestic regulations, however. In particular, it can inform the use of Territorial Use Rights Fisheries (TURFs), where associations of fishermen are given property rights over a certain area. While Wilen et al. (2012) suggests that area-based property rights have advantages over traditional species-based property rights, these must be carefully designed in light of species range shift, since these shifts can effectively weaken the property rights security of a TURF system. This paper is also related to the small, contested literature on the “blue paradox,” the potential overextraction in anticipation of conservation.<sup>18</sup> My paper documents anticipatory overextraction, albeit not in response to conservation per se. However, from the perspective of the fishing industry in a given location, loss of stock share due to climate change may not differ greatly from loss

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McWhinnie (2009) demonstrated that fisheries shared by more countries were more likely to be overfished. Englander (2019) showed that the 200 nautical mile limit matters for conservation, but also that foreign fleets can and do fish significantly right outside of those boundaries.

<sup>16</sup>See, for example, Costello et al. (2008) and Isaksen and Richter (2019).

<sup>17</sup>Other papers in this literature, such as Costello and Grainger (2018), are also conceptually similar in their treatment of the fishery manager as a partially captured regulator who advances the interests of fishermen given their property rights. In this case, however, I study property rights security in an international sense rather than as a feature of domestic regulation.

<sup>18</sup>McDermott et al. (2018) introduces the blue paradox and provides evidence of preemptive overextraction from an area that would later become a marine reserve. However, Hanich et al. (2018) suggests this may be a spurious result due to the choice of control group.

of stock share due to a marine protected area.

The rest of the paper is organized as follows: Section 2 presents a simple model of fisheries extraction as a function of the share of a fish population under the jurisdiction of the fishery manager (the stock share). Section 3 describes the data I use to empirically validate the model, with special attention to how I construct my measure of the stock share. Section 4 describes my empirical strategy and Section 5 presents the results. In Section 6 I present the simulated predictions for various climate change scenarios as well as a hypothetical global collaborative management scenario. Section 7 concludes.

## 2 Theory

This section presents a model where a country decides how to extract from a fish stock that is shared with another country.<sup>19</sup> Each country controls the harvest from the population of fish within its own territory.<sup>20</sup> However, the two populations of fish are connected in terms of reproduction, so the growth of each population depends on the biomass in the other. The fishery manager in country A cares only about maximizing fishing profits in its territory, but the available population will depend in part on the actions of country B.

Let the biomass available to fish in country  $i$  in period  $t$  be  $X_{i,t}$ . Harvest in country  $i$  in period  $t$  is  $H_{i,t} \in [0, X_{i,t}]$ . Let  $S_{i,t} = X_{i,t} - H_{i,t}$  be the escapement from country  $i$  in period  $t$ .

The growth of the biomass in country  $i$  in period  $t + 1$  depends on the escapement in both countries,  $i$  and  $j$ :

$$X_{i,t+1} = \theta_{i,t}G(S_{i,t}) + (1 - \theta_{j,t})G(S_{j,t}) \quad (1)$$

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<sup>19</sup>I am far from the first to write down a model like this one. The particular modification of the fundamental equation of natural resources that I derive was first described in Kaffine and Costello (2011) and most recently extended in Fabbri et al. (2024). My derivation borrows model structure from Weitzman (2002).

<sup>20</sup>Under international law, each country has exclusive jurisdiction over fish found in their Exclusive Economic Zone, an ocean region up to 200 nautical miles from their coast.

where  $G(\cdot)$  is a common growth function with  $G'(\cdot) > 0$  and  $G''(\cdot) < 0$  and  $\theta_{i,t} \in [0, 1]$  is the share of the population originating in  $i$  in period  $t$  that will remain in  $i$  in period  $t + 1$ . I let this value change over time. I will refer to  $\theta_{i,t}$  as the “stock share.”

Let the revenues from fishing be  $pH_{i,t}$ , where  $p$  is the price of fish, and the costs of fishing be  $cH_{i,t}$ , such that the marginal profit is constant at  $\tilde{p}$ .

The goal of fishery manager of  $i$  is to maximize the discounted sum of profits in  $i$ , subject to the growth constraints of the stock and the discount factor  $\delta$ .

$$\max_{H_{i,t}} \sum_{t=0}^{\infty} \delta^t \tilde{p} H_{i,t} \quad \text{s.t.} \quad X_{i,t+1} = \theta_{i,t} G(S_{i,t}) + (1 - \theta_{j,t}) G(S_{j,t}) \quad (2)$$

This yields the following Bellman equation:

$$V_i(X_{i,t}, X_{j,t}) = \max_{H_{it}} \left[ \underbrace{\tilde{p} H_{i,t}}_{\text{Current Profit}} + \delta V_i \left( \underbrace{X_{i,t+1}}_{\theta_i G(S_{i,t}) + (1 - \theta_j) G(S_{j,t})}, \underbrace{X_{j,t+1}}_{(1 - \theta_i) G(S_{i,t}) + \theta_j G(S_{j,t})} \right) \right] \quad (3)$$

The Bellman equation yields the following First Order Condition:

$$\tilde{p} = \delta \left[ V_{i,t+1|X_i} \theta_{i,t} G'(S_{it}^*) + V_{i,t+1|X_j} (1 - \theta_i) G'(S_{i,t}^*) \right] \quad (4)$$

The envelope condition gives:

$$V_{i,t|X_i} = p \quad \& \quad V_{i,t|X_j} = 0 \quad \forall t \quad (5)$$

Then we can solve for the private period  $t$  target escapement:

$$\theta_{i,t} G'(S_{i,t}^*) = \frac{1}{\delta} \quad (6)$$

This is the familiar “fundamental equation of renewable resources,” and does not depend on prices or costs due to the constant marginal profits assumption.

Then the Harvest function is given by

$$H_{i,t}^* = \begin{cases} 0 & \text{if } X_{i,t} \in [0, S_{i,t}^*] \\ X_{i,t} - S_{i,t}^* & \text{if } X_{i,t} > S_{i,t}^* \end{cases} \quad (7)$$

Which states that if the stock is below the optimal escapement it should not be fished, and if the stock is above the optimum escapement it should be fished down to that level.

It is also useful to work with the extraction rate,  $(H_i/X_i)$ , which is the share of the available stock that is caught. The extraction rate is given by:

$$ER_{i,t}^* = \begin{cases} 0 & \text{if } X_{i,t} \in [0, S_{i,t}^*] \\ \frac{X_{i,t} - S_{i,t}^*}{X_i} & \text{if } X_{i,t} > S_{i,t}^* \end{cases} \quad (8)$$

In equilibrium, when both stocks are at their respective optima, we have

$$G'(S_{i,t}^*) = \frac{1}{\delta\theta_{i,t}} \quad (9)$$

$$H_{i,t}^* = \theta_{i,t}G(S_i^*) + (1 - \theta_{j,t})G(S_j^*) - S_{i,t}^* \quad (10)$$

$$ER_{i,t}^* = \frac{\theta_{i,t}G(S_{i,t}^*) + (1 - \theta_j)G(S_{j,t}^*)}{X_{i,t}^*} - 1 \quad (11)$$

From here we can derive the first proposition:

**Proposition 1** *A lower stock share  $\theta_{i,t}$  implies a lower privately optimal escapement  $S_i^*$  and biomass  $X_i^*$ , a higher harvest conditional on biomass, and an unconditionally higher extraction rate.*

Equation 9 implicitly defines the optimal stock, and reveals that it is increasing in the stock share  $\theta_{i,t}$  because the growth function  $G()$  is increasing in  $X$ . Equation 7 shows that, for any given biomass  $X_i$ , the optimal harvest is greater if  $X_i^*$  is smaller. However, this does not imply that a lower stock share leads to greater harvest unconditionally, since it

will involve lower steady state harvest once the lower optimal biomass has been reached. Meanwhile, Equations 8 and 11 show that a lower stock share implies a higher extraction rate both in steady state and along the transition path.

This model also has a straightforward way to characterize the welfare losses in the non-cooperative equilibrium.

In a cooperative equilibrium, each country would set

$$G'(S_i^o) = \frac{1}{\delta} \quad (12)$$

Which does not include  $\theta_{i,t}$  because it is irrelevant to global welfare who the beneficiary of stock growth is.

**Proposition 2** *The privately optimal escapement  $S_i^*$  is strictly lower than the globally optimal escapement  $S_i^o$  if  $\theta_{i,t} < 1$  and the size of the welfare loss is larger the smaller  $\theta_{i,t}$ .*

## 3 Data

### 3.1 Outcomes

The core dataset on fisheries extraction for this project comes from the RAM Legacy Stock Assessment Database, a database of catch, biomass, and other stock assessment results reported by fisheries managers around the world. These measurements apply to a specific managed population of a certain species (for example, Arrowtooth Flounder found in the Gulf of Alaska). For 326 stocks it is possible to construct a panel of both catch and biomass beginning in 2000, from which I can also construct escapement (biomass - catch) and the extraction rate (catch/biomass). However, it must be noted that the measurement of biomass differs across stocks: in some cases it is an estimate of the true underlying biomass, but in other cases it might be a subset like spawning biomass, or biomass of a certain age or size band. As a result, constructing escapement and the extraction rate does not always yield

logical results, and in my main specifications I use a normalized version of each outcome to create comparable values across stocks. Specifically, I divide each observation by the stock level average for that variable so that my outcomes are defined as variations from that average. The stocks in the RAM database typically represent well-managed, data-rich fisheries, predominantly in the developed world. Figure 4 shows the count of stocks in the database found in each Exclusive Economic Zone (EEZ). In the latest year with price data available from The Sea Around Us, the catch from these fisheries was collectively worth over \$15 billion (Tai et al., 2017). This is just 23% of the \$68 billion in catch value in the Sea Around Us Database, and less than 10% of the \$159 billion valuation of catch from all global capture fisheries (Sampson, 2024). Figure 5 maps the average catch value of RAM stocks in each Exclusive Economic Zone (EEZ) using price data from the Sea Around Us Database (Pauly et al., 2020). I match each stock in the RAM Legacy Stock Assessment Database with its shapefile in the RAM Legacy Stock Boundary Database (Free, 2023). For example, Figure 9 shows the management area for *Sebastodes Elungatus*, the Greenstriped Rockfish, which has historically been found off the southern pacific coast of the United States. This shapefile captures the “management area” for that particular stock but does not necessarily capture its range in a given year. In the case of the Greenstriped Rockfish, the managed area ends at the boundary of the US EEZ, whereas the population has historically extended into Mexico.

### 3.2 Stock Share

In order to measure the share of a population that is managed in one of the RAM fisheries, I construct a proxy for each species’ annual habitat range based on the environmental preferences of the species and the environmental characteristics of that year. Following the methodology of AquaMaps, a database of marine species habitats and environmental envelopes, I construct an annual raster of habitat suitability for each species in the stock assessment database based on those environmental envelopes (Kaschner et al., 2019). For

each of six environmental variables, AquaMaps records the minimum and maximum suitable and minimum and maximum preferred level for each species. The six environmental variables are Sea Temperatures, Salinity, Primary Productivity, Depth, Sea Ice Concentration and Dissolved Oxygen Concentration. The AquaMaps method assigns a simple suitability probability based on each variable: If the level is outside of the minimum and maximum suitable range, the probability for that variable is zero. If the level is within the minimum and maximum suitable, the probability for that variable is one. In between the suitable threshold and the preferred threshold, the probability rises or falls linearly between zero and one for that variable. Figure 6 shows a graphical representation of this approach. Finally, all of the relevant probabilities are multiplied together to generate a single raster of environmental suitability probability. Depending on the species' characteristics, only some environmental variables are used: for species with preferred depths below 200 meters, the bottom ocean temperature, bottom salinity, and bottom dissolved oxygen concentrations are used. For other species, sea surface temperatures and surface salinity are used, and dissolved oxygen is not (Kesner-Reyes et al., 2020). The method produces a species specific raster of environmental suitability for a given set of rasters of environmental variables.

I replicate the AquaMaps method annually, using annual Sea Surface Temperatures from NOAA, a static measure of depth from AquaMaps, and decadal values for ocean bottom temperatures, salinity, primary productivity, sea ice concentrations, and dissolved oxygen concentrations from the Bio-ORACLE database (Assis et al., 2024). This gives me a raster of predicted suitability in each grid cell for every species in the stock assessment data and every year from 2000 to 2024. I also construct predicted suitability rasters for 2030, 2040, and 2050 using predicted environmental rasters from Bio-ORACLE. Figure 7 shows the distribution of predicted suitability for Greenstriped Rockfish in 2020.

The species ranges generated with the AquaMaps method must be interpreted with caution for several reasons. Firstly, the AquaMaps method has a tendency to overpredict the suitability of an area for a species regardless of whether the species can actually be found

there. A location can be suitable based on the few environmental predictors covered here, but the species may not be present due to a lack of food sources, ecological niches, or population connectivity. For example, Greenstriped Rockfish is found exclusively on the South pacific coast of North America, but the AquaMaps method might output that the Northeast coast of North America would be a highly suitable location for it based on environmental factors alone. Figure 7 shows exactly that. Therefore, in my empirical analysis, I focus on variation in suitability in areas around each stock’s known range. A second concern with the AquaMaps method is that the suitability probabilities it generates should not be viewed as measures of species abundance. Instead, they are measures of whether a given location is likely to be suitable for that species given the environmental variables. While this complicates the interpretation of static uses of the AquaMaps method, variation in the suitability measure can still capture the movement of stocks. For example, Oremus et al. (2020) uses AquaMaps’ predicted suitability changes to forecast stock shifts in the tropics under climate change. Thirdly, it should be noted that the AquaMaps method was originally created and applied on data using the long-run average of environmental characteristics, rather than the year-to-year variations in environmental characteristics that I use here. Therefore, the ranges I compute should be seen as an imperfect proxy of true species ranges, and not a measure of the distribution of the actual stock. Nevertheless, the AquaMaps method is publicly disclosed and reproducible on public data, and thus constitutes the best proxy available. In particular, it is well suited for my purposes as long as the variation in the predicted suitability probabilities is correlated with the location of the stock because my identification strategy will exploit year-to-year variation in the predicted suitabilities.

Specifically, I exploit year-to-year variation in predicted suitabilities in areas that are known to have the species present. For example Figure 10 shows the predicted suitability for Greenstriped Rockfish in 2000 and 2050 in Southern California. Comparing the two maps, one can see the suitable range is predicted to shift northward due to climate change, precisely in the area the species is known to live. Concretely, I combine the suitability probabilities

that I generate with the AquaMaps method with the known species location from the RAM Legacy Stock Boundary Database. Figure 8 shows an example shapefile for the Southern California population of Greenstriped Rockfish. For each RAM shapefile, I construct a 300 nautical mile buffer area around the shapefile, which I consider the relevant area to look for shifts in suitability. Liu and Molina (2021) treats the RAM shapefiles as a measure of habitat range—for my purposes I use them as a starting point to look at variation around that region. 300 nautical miles is quite large relative to the average shapefile size, so this likely results in an overestimated area in consideration. However, 300 nautical miles guarantees that at least some sizable part of the area considered falls outside of the Exclusive Economic Zone of the country responsible for managing the population in the RAM Stock Assessment Database. I then divide the 300 nautical mile buffer area into two regions: the area that falls inside the Exclusive Economic Zone of the country managing the population in the dataset (the managed area), and the area that falls outside of that, whether it be in another country or in the high seas (the unmanaged area). Figure 9 shows the buffer area, highlighted in two different colors to represent the managed and unmanaged areas. Then I calculate the overlap between the suitable range and each of these areas. Figure 11 shows the overlap between the two areas in the buffer, and predicted suitability for Greenstriped Rockfish in 2000 and 2050. I compute the total suitable range within each area as the sum of the cell-level suitability probabilities. Finally, I calculate my proxy for the stock share as the ratio of the suitable range in the managed area to the total suitable range in the buffer area (inside and outside of the relevant EEZ), which yields a value between 0 and 1.<sup>21</sup> In the case of the Greenstriped Rockfish, the northward shift of the suitable range of the species between 2000 and 2050 implies that the stock share in the US' EEZ will increase significantly. In Appendix A, I walk through the method step by step for Maine Atlantic Halibut, which is predicted to decrease significantly in stock share.

My final dataset is an administrative stock-by-year panel with the catch, biomass and

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<sup>21</sup>Figure 12 shows the cross sectional relationship between my stock share measure and the extraction rate, and shows that higher stock share is correlated with a lower extraction rate.

extraction rate as well as the stock shares calculated using the method described above. Table 2 presents the summary statistics. For empirical exercises, I normalize the catch, biomass, escapement, and extraction rate by dividing each value by the stock-level average to account for the significant differences in scale and measurement between stocks.

### 3.3 Additional Data

To explore heterogeneity in the effects of the stock share, I add several additional variables to my stock-by-year panel. One key aspect of heterogeneity is management methods and efficacy. Specifically, the theoretical model described in Section 2 applies to a fisheries manager capable of controlling annual harvest. If the state capacity of the relevant country is insufficient to optimally set the path of harvest over time, individual fishermen will instead fish according to their private optimum. This open access equilibrium simply equates present benefits and present costs, without any attention to the future growth of the stock. While this means the fishery will be overfished, it also means that the changing stock share should have little effect on outcomes for the fishery. Therefore, I explore heterogeneity in management from a few different sources. The Environmental Performance Index for Fisheries from Block et al. (2024) is a country-level score from 0 to 100 meant to reflect the health and sustainability of fisheries in that country. While it is an equilibrium outcome, I treat it as a measure of baseline fisheries management. Building off of Lynham (2014), I manually identify which of the fisheries in my sample are managed with Individual Transferable Quotas (ITQ). While the vast majority of stocks in the RAM database are managed by some form of Total Allowable Catch, only a few are managed by ITQs, which are known to be the most effective form of management for preventing fisheries decline (Costello et al., 2008; Isaksen and Richter, 2019). The political economy of ITQs can also align the dynamic incentives of fishermen with my model of the fishery manager (Grainger and Costello, 2014; Costello and Grainger, 2018). Finally, I also use the RAM database's categorization of whether a fishery is managed internationally under a Regional Fisheries Management Organization to

test whether this changes the effect of the stock share. I also examine heterogeneity by the intrinsic growth rate of a species and the interest rate of the country. For each species, I add the intrinsic growth rate found on FishBase (Froese and Pauly, 2025). For each country and year, I add the lending interest rate from the World Bank (Bank, 2025).

## 4 Empirical Strategy

The main empirical analysis of this paper is to estimate the relationship between the stock share and fisheries extraction. Section 3 described how I construct the stock share proxy. Section 2 provided the main theoretical predictions that I will test in this paper, namely that a higher stock share leads to lower escapement, a higher extraction rate, and higher catch conditional on biomass.

### 4.1 Escapement

My main outcome is escapement, as a test of the unconditional theoretical prediction that escapement (the quantity of biomass that is *not* caught) will be higher when the stock share is higher. This prediction comes from the manager's optimality condition equation and is the reason the optimal stock is lower when the stock share is lower. To deal with differences in measurement across stocks, I use the normalized escapement in each year, which is given by dividing the escapement in that year (biomass minus catch) by the stock-level average escapement. This normalized measure represents the escapement relative to the mean for that stock. I regress the normalized escapement on the the stock-by-year measure of the stock share plus stock and year fixed effects. The fixed effects remove variation in the outcomes that are common across years for each stock or common across stocks for each year. My identification comes from year-to-year variation in the stock share of a particular fishery,

after removing shocks common to all fisheries within a year. The estimating equation is:

$$\text{Escapement}_{i,t} = \beta \text{Stock Share}_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \quad (13)$$

where  $\gamma_i$  represents the stock fixed effects,  $\lambda_t$  represents the year fixed effects,  $\epsilon_{i,t}$  is the error term, and  $\beta$  captures the effect of the stock share on escapement. The model predicts that  $\beta$  should be positive, as a higher stock share implies lower optimal escapement. In the case of escapement the theory would imply no distinction between steady state and transition, as the optimal strategy in each case is to fish down to the optimal level of escapement. For robustness, I also include a specification with the log of unnormalized escapement as the outcome.

## 4.2 Extraction Rate

Next I include the extraction rate as an outcome. I test the unconditional theoretical prediction that the extraction rate will be higher when the stock share is lower. In this case I regress the normalized extraction rate on the the stock-by-year measure of the stock share and both stock and year fixed effects. Again the fixed effects remove variation in the outcomes that are common across years for each stock or common across stocks for each year. The identifying variation comes from year-to-year fluctuations in the stock share of a particular fishery, after removing shocks common to all fisheries within a year. The estimating equation is therefore the same form as the estimating equation above:

$$\text{Extraction Rate}_{i,t} = \beta \text{Stock Share}_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \quad (14)$$

where  $\gamma_i$  represents the stock fixed effects,  $\lambda_t$  represents the year fixed effects,  $\epsilon_{i,t}$  is the error term, and  $\beta$  captures the effect of the stock share on the extraction rate. The model predicts that  $\beta$  should be negative, as a higher stock share implies a lower extraction rate both in transition and in steady state. For robustness I also include a specification with the

unnormalized extraction rate as the outcome.

### 4.3 Catch

I also consider catch as an outcome. In this case, I must control for biomass, as my theoretical prediction only states that a higher stock share implies lower biomass condition on biomass. I regress normalized catch on the stock-by-year measure of the stock share, while controlling for the normalized biomass, as well as stock and year fixed effects. The fixed effects will remove variation in the outcomes that are common across years for each stock or common across stocks for each year. Then I am isolating year-to-year variation in the stock share and biomass for a given stock, while removing any common shocks across years. The regression equation is:

$$\text{Catch}_{i,t} = \beta \text{Stock Share}_{i,t} + \alpha \text{Biomass}_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \quad (15)$$

where  $\beta$  captures the effect of the stock share and  $\alpha$  captures the effect of biomass.  $\gamma_i$  represents the stock fixed effects,  $\lambda_t$  represents the year fixed effects, and  $\epsilon_{i,t}$  is an error term. From the theoretical model, we expect  $\alpha$  to be positive, as a higher biomass leads to higher catch on all else equal, and  $\beta$  to be negative, as a higher stock share implies a lower catch conditional on biomass. For robustness, I also include a specification with the log of unnormalized catch as the outcome and the log of unnormalized biomass as a control.

### 4.4 Robustness

I also include some cross sectional regressions in Table 3. Columns (1), (3), and (5), show the relationship between the stock level average stock share and the stock level average log escapement (conditional on average log biomass), extraction rate, and catch (conditional on average log biomass), respectively. Columns (2), (4), and (6) repeat these regressions with controls for the species-level intrinsic growth rate and the country-level interest rate, two variables that theory suggests should affect extraction. These tables show the same pattern

of results. For ease of comparison with different outcome measures, I also include a regression table using the empirical strategy from above, but with the same outcome measures used in the cross section, in Appendix B.

For robustness, I repeat the regression specifications described above using different buffer distances to compute my proxy for the stock share; specifically 100, 150, 200, 250, 300, 350 and 400 nautical miles. Coefficient plots for these regressions are included in Appendix B.

I also run first differences regressions as further robustness. In these I regress the year-on-year change in the outcome on year-on-year changes in the stock share. In the case of catch as an outcome I also include the year-on-year change in biomass as a control. A table of those regression results is also included in Appendix B.

Finally, I also include the results of regressing the trend in the outcome on the trend in the stock share. Specifically, I compute the five year trend (up-to and including the year of the observation) for each of my outcomes, the normalized biomass, and the stock share. In Appendix B I include a table of regression results for this specification.

## 4.5 Heterogeneity

In order to explore the heterogeneity of effects, I also run regressions that include an additional variable and the interactions between that variable and the stock share. In these cases, I am interested in the coefficient on the stock share and the coefficient on the interaction term. Specifically, I run additional regressions with the following variables:

- **EPI Score.** I run regressions including the Fishery performance index from the Environmental Performance Index (Block et al., 2024). I include this country-level measure of fisheries performance as a proxy for overall management performance. Higher values of this variable reflect better managed and healthier fish stocks in the managing country as a whole. I include the interaction term to examine whether the effects of the stock share are more significant for better managed fisheries—this prediction is logical because the theoretical model in Section 2 relies on the capability of the fishery

manager to optimally set the dynamic path of extraction. If the fishery is effectively in open access, variation in the stock share should not have the same effects.

- **ITQ Management.** I run regressions including an indicator variable for whether a fishery-year is managed using Individual Transferable Quota. I include this ITQ dummy to measure whether the stock share has differential effects by management mechanism, given that the vast majority of stocks in the same do have some kind of statutory catch limit. Economists view ITQs as the most effective and efficient form of management, but their efficacy and political economy could exacerbate the effects of changing stock shares. Like the logic above, a more effective regulator has a greater ability to act according to their privately optimal incentives for overextraction. Furthermore, ITQ systems that include catch shares (rights to future ITQ allowances) can also align fishermen's incentives with the dynamic incentives of the regulator. Prior research has shown aggregate property rights insecurity can drive ITQ market outcomes, and affect regulatory decisions consistent with regulatory capture by ITQ holders (Grainger and Costello, 2014; Costello and Grainger, 2018). Therefore, ITQ fisheries may be more sensitive to changes in the stock share than other fisheries with catch limits but without property rights to catch.
- **Growth Rates.** I run additional regressions including the intrinsic growth rate of a species found on FishBase (Froese and Pauly, 2025). The theory in Section 2 states that the privately optimal escapement  $S_{i,t}^*$  is found where  $G'(S_{i,t}^*) = \frac{1}{\delta\theta_{i,t}}$ . In a traditional parametrization of  $G()$ , the intrinsic growth rate enters as a multiplier that scales the relationship between the current biomass and the carrying capacity. The larger the intrinsic growth rate, the greater the growth of the biomass at any given value and the greater  $G'()$ . Therefore a greater intrinsic growth rate should increase optimal escapement, and decrease the optimal extraction rate and catch conditional on biomass, holding all else equal. It should also dampen the effect of the stock share on the above

variables.

- **Interest Rates.** I run additional regression including country-year specific lending interest rates from the World Bank (Bank, 2025). Section 2 states that the privately optimal escapement  $S_{i,t}^*$  is found where  $G'(S_{i,t}^*) = \frac{1}{\delta\theta_{i,t}}$ . We can rewrite this condition as  $G'(S_{i,t}^*) = \frac{1+r}{\theta_{i,t}}$ , where  $r$  is the interest rate. This implies that as the interest rate is larger, the effect of the stock share on optimal escapement should be larger as well.
- **Multinational Management.** I run additional regressions including an indicator for multinational management, which reflects whether the relevant RAM stock is covered by a multinational governing body like a Regional Fisheries Management Organization. RFMOs exist to manage internationally shared stocks, albeit particularly on the high seas beyond national jurisdiction. If a RAM stock includes the multinational management indicator, it means that there is some international body responsible for managing aggregate catch of the species in a broad geographic area. This kind of management would ideally suppress the private incentives of individual countries for overextraction, but the efficacy of these international agreements is contested (Cullis-Suzuki and Pauly, 2010). In particular, their voluntary nature might mean that countries participate only when conservation measures align with their domestic incentives, and the agreements have no binding effects. I test whether multinationally managed fisheries are more or less sensitive to changes in stock shares.
- **Highly Migratory.** I run additional regressions including an indicator variable for whether a species is highly migratory or pelagic that is included in the AquaMaps envelopes. Since these species are generally already internationally managed and are likely to straddle EEZs and the high seas, it is possible that these are less affected by changes to the stock share. However, it is also entirely possible that countries do attempt to conserve these species, at least in so far as they expect to reap the rewards

of conservation, and they may behave just like other species.<sup>22</sup>

- **High Seas Share.** I also run a regression specification testing whether the effect of the stock share that I estimate differs based on whether the spillovers accrue to a neighboring Exclusive Economic Zone or on the internationally open-access high seas. Specifically, I include a measure of the high seas share of the stock, following the same stock share construction methodology outlined above but calculating the share of the suitable range within the buffer area that occurs in the high seas. I interact that measure with the national stock share, to detect whether countries respond differently to spillovers in the high seas relative to those in other national jurisdictions. Due to their open access nature, high seas fisheries are generally more overfished than EEZs, and the Regional Fisheries Management Organizations meant to regulate them are generally considered ineffective (Cullis-Suzuki and Pauly, 2010). Palacios-Abrantes et al. (2025) predicts that many transboundary stocks will shift towards the high seas, increasing the importance of them for fisheries outcomes. However, from the perspective of the given country, it is not clear they should view spillovers in the high seas differently than spillovers to other countries. In my model, for example, the relevant parameter is simply what share of recruitment will accrue to the managing country—where the rest of the stock goes is irrelevant.

## 5 Results

Table 3 shows the cross sectional relationship between stock share and my outcomes. For five of the six columns the coefficient of interest, that of the Stock Share variable, is statistically significant, and in all cases it is directionally consistent with theory. These cross sectional regressions leverage variation in stock shares across different stocks. The relatively small effect sizes reflect the fact that there is plenty of other variation in what drives extraction.

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<sup>22</sup>For example, Pons et al. (2018) shows that the management and enforcement of pelagic fishery regulations are worse for regional fisheries management organizations with more member countries.

Table 4 shows the coefficients of interest for my main specifications. Column (1) shows the effect of the stock share on normalized escapement, controlling for stock and year fixed effects. Consistent with the theoretical predictions, it shows a large, statistically significant negative coefficient implying that a larger stock share implies greater escapement. The magnitude of the coefficient is also quite large: it implies that if a management area where to increase its stock share by 1, its escapement would increase by 151% of its historic average. While this may seem implausibly large, it should be noted that the variation in stock shares is quite small. The within-stock standard deviation in stock share is just 0.01, implying a 1.6% increase in escapement. As I'll discuss in more detail in Section 6, the predicted changes in stock shares under climate change are larger, but still not as large as a 1 unit change: The largest predicted gain in stock share in the data, 0.155, would imply a reduction in catch of 23.4% of the historic average, while the largest predicted loss in stock share, -0.19, would imply an increase in catch of 28.7% of the historic average. These effects are quite significant, but not implausibly large. Finally, the average stock share being 0.51, these results would imply that if every stock were managed as if the stock share were 1 (that is, every fishery manager internalized the full effect of recruitment), then escapement would be higher by 73.8% of the historic average.

Column (2) of Table 4 shows the results for the extraction rate. Consistent with the theoretical predictions, it shows a large, statistically significant negative coefficient. This implies that a larger stock share causes a lower extraction rate. Once again the effect sizes are large but plausible: a one standard deviation increase in the stock share would decrease the extraction rate by 72% of its historic average. Using the within-fishery standard deviation, a one standard deviation increase would decrease the extraction rate by 2.6%. Under the predicted climactic changes, the extraction rate effects would range from a 38.4% reduction to a 47.2% increase. Translating that into actual rates using the coefficient and the average extraction rate for each species, the range of climate change effects goes from an increase of 0.09 to a decrease of 0.07. These are significant but plausible changes for those respective

stocks.

Finally, Column (3) of Table 4 report the results for catch. It shows that the stock share has a large, negative, and statistically significant effect on catch once controlling for the available biomass. The magnitude of the affect is quite large: taken literally, it implies that if a given management area were to increase its stock share by 1, its catch would go down by 231% of its historic mean. Again this impossibly large coefficient is consistent with a much more reasonable story: A one standard deviation increase in the stock share (0.29) would imply a reduction in catch of 66.8% of the historic average. A within-fishery standard deviation increase (.01) would only imply a 2.4% reduction in catch. The predicted effects of climate change range from a 35.7% reduction to a 43.8% increase in catch, conditional on biomass.

## 5.1 Heterogeneity

In this section I discuss the results of the regressions I ran including an additional variable and the interaction between that variable and the stock share. In these regressions, there are two coefficients of interest: the coefficient on the stock share and the coefficient on the interaction term.

Table 5 shows the regression results for measures of management heterogeneity. Columns (1), (3) and (5) show the the regression results using the fishery management score from the Environmental Performance Index as a regressor for escapement, extraction rate, and catch as outcomes, respectively. Columns (1) and (3) show that the effect of stock share is driven by countries with high EPI scores, as the interaction term drives the headline result. The same is true for catch in Column (5), albeit the interaction term is not statistically significant. Together, these results support the theory that the stock share effects are driven by countries with effective fisheries management and currently well-preserved stocks. Columns (2), (4) and (6) show the regression results using a dummy for ITQ management as a regressor for for escapement, extraction rate, and catch as outcomes, respectively. In all three columns, both

the stock share coefficient and the interaction term with ITQ management are statistically significant and go in the same direction. I view this as evidence that the effect of the stock share is stronger for fisheries managed by ITQs, consistent with more effective management being better suited for (mal)adaptive responses to climate change. This finding also suggests that more effective management is not necessarily as effective an answer to climate change as some have hoped (see, e.g. Gaines et al. (2018); Free et al. (2020); Melbourne-Thomas et al. (2022)).

Table 6 shows the regression results for measures of other theoretically important heterogeneity. Columns (1), (3) and (5) show the regression results using the intrinsic growth rate of a species as a regressor for escapement, extraction rate, and catch as outcomes, respectively. Every regression shows a large effect of the interaction between the stock share and the growth rate, which is opposite in sign to the stock share coefficient (the interaction is only statistically significant in Columns (3) and (5)). While the coefficients appear large, this does not mean the growth rate actually flips the result, as the growth rate is small. I interpret the opposite sign as evidence that a larger growth rate dampens the effect of the stock share, consistent with bioeconomic theory. That is, as the species growth rate is larger, variation in the stock share matters less for determining the optimal fishing strategy. Columns (2), (4) and (6) show the the regression results using the country-year level interest rate as a regressor, for escapement, extraction rate, and catch, respectively. Counter to the theoretical prediction, the results show that a higher interest rate dampens the effect of stock share. Columns (4) and (6) show large, statistically significant effects of the interaction term that are opposite the sign of the stock share coefficient. Column (2) shows a small and insignificant effect.

## 5.2 Robustness

Table 11 shows the results of regressions with the same specification but slightly different measures of the outcomes meant to be consistent with the measures used in my cross

sectional results. Column (1) shows the effect of stock share on log escapement, which is positive, consistent with my predictions. In this case, Column (2), which uses the unnormalized extraction rate to be consistent with the cross section regressions, is not statistically significant. Finally, Column (3) reports the effect of the stock share on log catch, and is negative, consistent with my predictions.

The appendix includes an additional table of heterogeneity analysis. Table 12 shows the coefficients for regressions that add indicators for multinational management and for highly migratory species, and that add the "high seas share" as an additional variable. None of these dimension of heterogeneity change the headline coefficient, and the interaction terms are not generally statistically significant. I interpret this as evidence that the effects of stock share do not vary meaningfully on these dimensions, all of which capture some notion of the degree of international sharing. That is to say, conditional on the stock share, the other arrangements of international sharing don't appear to matter for fisheries extraction.

The appendix also includes figures showing how the coefficients on stock share depend on the width of the buffer area around the shapefile of the stock. Figures 58, 59, and 60 show the coefficient plots for escapement, extraction rate, and catch, respectively. As a general pattern, the larger buffer windows are less precise and less likely to be statistically significant, consistent with measurement error eroding the result as the buffer area begins to include more and more extraneous area (from the perspective of management).

The appendix also includes the results of first differences regressions. Table 13 shows the regression results for all three outcomes. The coefficients on stock share are directionally consistent with the prior results, although it is not statistically significant for escapement as an outcome. Finally, the appendix includes the results of regressing trends in the outcome variables on trends in the stock share, in order to confirm that the effects detected are consistent with changes in the climate and not just annual variation in weather. Table 14 shows the regression results, which are consistent in direction and statistical significance with my main results.

## 6 Counterfactuals

### 6.1 Climate Predictions

What do the results above imply for the effects of climate change? If changes in the stock share lead to meaningful endogenous extraction responses, then it is possible that this behavioral response to range-shift will be a significant consequence of climate change in the fishing industry. However, this depends highly on how climate change will affect the stock shares of different countries. In this section I document the predicted change in the stock shares and discuss what these would imply for global fisheries extraction.

The predictions of global stock shares follow the methods discussed in Section 3 exactly, using predicted 2030, 2040, and 2050 values for all environmental variables except depth, which is left unchanged.<sup>23</sup> By default, I use the environmental predictions for SSP2-4.5, a climate scenario “middle of the road” that bases future projections on a continuation of historic trends. Appendix C shows results for SSP1-1.9 and SSP5-8.5, which represent a lower and upper bound on plausible warming, respectively. Figure 14 shows a density graph of the stock share for each decade in my dataset. It shows relatively little predicted change between the historic distribution and the distributions in 2030, 2040 and 2050. Figure 15 plots the change in the stock share between the average from 2000 to 2024 and the predicted stock shares in 2050. An immediate conclusion of this plot is that the changes in stock share are not predicted to occur disproportionately in one direction: while climate change is predicted to reduce some stock shares, it is also predicted to increase others. In fact, the mean change is predicted to be an increase of 0.003 (standard deviation: 0.03). The predicted changes in the stock share are uncorrelated with the catch, catch value, or biomass size of the fishery. This general pattern is unchanged by the particular climate scenario used, which I explore in more detail in Appendix C.

To evaluate the consequences for escapement, I calculate the implied change in escape-

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<sup>23</sup>While sea levels are predicted to rise in ways that are significant for coastal communities, these changes are small relative to ocean depths.

ment by 2050 using the change in the stock share from the historic average to its 2050 value, and interacting that with stock level averages and the coefficients from Table ???. Figure 16 shows the distribution predicted changes in escapement from that exercise. It shows a wide range of effects, with most clustered around zero. Summing up across all of the predicted escapement effects gives a net increase in escapement of around 100,000 tonnes, which is trivial compared to the average total escapement of 113,000,000. Figure 21 maps the total change in escapement for stocks in my sample by EEZ. It shows some significant winners and some significant losers. However, Figure 22 maps the percent change in escapement for those same stocks by EEZ, and shows that the most significant changes in percentage terms will be increases in escapement. This is a feature of averaging to the EEZ level: Figure 17 shows the density plot of percent change in escapement at the stock level, and shows no particular pattern for increases and decreases.

These increases in escapement should be understood to correspond directly to increases in the biomass: Figure 13 shows the close relationship between escapement in one period and biomass in the next. Using those relationships, Figure 23 shows the predicted change total biomass by EEZ in 2050 based only on the relationship between stock share and fisheries extraction. Figure 24 shows the implied percent changes in biomass by EEZ. For several EEZs these changes are quantitatively significant, although the average effect is small. Once again, the stock-level density shows no particular pattern: the average change in biomass is small and close to zero. Overall, most EEZs with fisheries in my sample are climate change winners on net, with an increase in stock share leading to greater conservation. In many cases these increases in conservation may be as large, if not larger, than the biophysical effect of climate change on biomass. However, this may well be an artifact of my sample, as it disproportionately covers poleward stocks in the developed world, and does not include the large number of fish stocks around the tropics that are predicted to be the greatest climate losers (Oremus et al., 2020).

Thus far, I have discussed the effect of climate-induced range shift as if it were the only

effect of climate change on fisheries. Naturally, that is not the case: climate change will also affect fisheries biomass due to warmer temperatures and greater acidity in the ocean (Branch et al., 2013; Free et al., 2019). Next, I set out to calculate how significant the behavioral response to range shift will be relative to these direct biophysical effects. There is substantial uncertainty over these biophysical effects, and no perfect methodology available to forecast them. Therefore, I borrow a straightforward method that has been used to make climate predictions in the fisheries science literature, which assumes that the carrying capacity of a stock is proportional to its suitability-weighted range. This prediction comes out of the Basin Model Hypothesis first described in MacCall (1990). This relationship has been empirically validated in several species,<sup>24</sup> and has been used in many of the most sophisticated climate forecasts in fisheries.<sup>25</sup> I follow the methodology of Gaines et al. (2018) in using the species distribution maps from AquaMaps in the historic period and in 2050 as my endpoints. I assume that the carrying capacity of each species will change proportionally with the change in suitable range. That is, if a species range is predicted to double, I assume the carrying capacity will double as well for all stocks of that species. Although this is unlikely to be accurate for all stocks, it is an actionable prediction with a basis in the scientific literature. Under a standard bioeconomic model, the  $S^*$  which satisfies the equilibrium condition  $G'(S^*) = \frac{1}{\delta\theta}$  will be proportional to the carrying capacity.<sup>26</sup> Therefore, I first estimate the optimal escapement given the 2050 stock share for each stock following the methods I describe above. Then I multiply it by the proportional change in biomass to arrive at the escapement under the combined effects of climate change. To estimate only the biophysical effect, I simply multiply the average historic escapement by the proportional change in biomass.

Now I can describe how the behavioral response to climate change relates to the biophys-

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<sup>24</sup>See, for example, Southward et al. (1995); Atkinson et al. (1997); Simpson and Walsh (2004); Sullivan et al. (2006); Zador et al. (2011); Pennington et al. (2020).

<sup>25</sup>See, for example, Cheung et al. (2016); García Molinos et al. (2016); Gaines et al. (2018); Free et al. (2020); Sala et al. (2021)

<sup>26</sup>Letting  $G(S) = S + rS(1 - \frac{S}{K})$  gives optimal escapement  $S^* = \frac{K}{2r}(1 + r - \frac{1}{\delta\theta})$  where  $K$  is the carrying capacity.

ical response. Figure 25 shows the distribution of climate change’s effects on escapement for both the purely biophysical model and the combined model. Figure 26 plots the difference between the biophysical and the combined model. For the average stock, using only the biophysical model would miss approximately 27% of the full effect of climate change, although there is substantial heterogeneity across stocks. Figure 28 maps the percent change in escapement due to the combined effects of climate change by EEZ. Comparing it to Figure 22, we see general increases in escapement due to the dominance of the biophysical channel. However, Figure 29 plots the error in the Biophysical-Only prediction of escapement in 2050. It shows significant errors for several EEZs from only using the biophysical prediction.

## 6.2 Cooperative Equilibrium

What would global fisheries look like in a cooperative equilibrium, where countries internalize the effects they have on each other? Here, I set the stock share to 1, and see how the extraction rate, escapement, and biomass would differ from their historic averages. Specifically, I find the difference between 1 and the historic average stock share, and then multiply that difference by the escapement regression coefficient from Column (2) of Table 4 and the stock level average escapement. The result is the hypothetical average escapement *if* the fishery manager internalized the effects of their fishing on its neighbors as well.

Figure 32 shows the historic and hypothetical cooperative distributions escapement. Under hypothetical cooperation, escapement would be 86.7 million tonnes (76.4%) higher. Figure 33 shows the implications of higher escapement for biomass, using the empirical relationship between escapement and biomass in Figure 13. Table 7 shows the coefficients for a regression of biomass on lagged escapement and lagged escapement squared, which I use for predicting biomass under alternative escapement scenarios. It also shows a biomass distribution that has been shifted meaningfully to the right. Biomass in total would be 60.4 million tonnes (43.8%) tonnes higher.<sup>27</sup>

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<sup>27</sup>The effect on biomass is more muted than on escapement due to the curvature of the growth function.

Next, I explore the spatial heterogeneity of these effects. Figure 34 shows the total change in escapement by EEZ, and Figure 35 shows the percent change in escapement by EEZ. Both show that there are significant increases in escapement, although there is also meaningful heterogeneity across EEZs. The largest changes in percentage terms come from EEZs with low average stock shares, such as the Mexican Pacific Coast, Brazil, and Greenland. Finally, Figures 36 and 37 show the total change and percent change in biomass, respectively, using only the change in escapement from the particular stock region. These show the same pattern of significant changes with large heterogeneity, in the same places. These maps show enormous decreases in the extraction rate and increases in escapement and biomass. These results indicate that the global cost of the transboundary problem is quite significant, and much larger than the expected effects of property rights reallocation under climate change.

### 6.3 US-Canada Cooperation

However, the fully cooperative equilibrium above is highly unrealistic. Even if all neighboring countries could agree to internalize their spillovers on each other, fishing on the internationally open-access high seas would still mean that not all of the returns to conservation would be internalized by fisheries managers. Short of a benevolent and omnipotent world government, this is not a plausible counterfactual. In this section I discuss a much more realistic counterfactual: cooperation between the US and Canada. The US and Canada have some history of cooperating on fisheries management going back to the 1924 Halibut Treaty which is still the basis of the modern International Pacific Halibut Commission (Crutchfield and Zellner, 2002). This is one of several fisheries conservation agreements Canada has in the pacific, mostly with the United States (Bond and McDorman, 2010). Relations are more fraught in the Atlantic, where the US and Canada have disputes over the management and jurisdiction of important commercial stocks like American Lobster (Cook, 2005). The US and Canada also have many other international agreements and sites of cooperation, which facilitate a hypothetical fisheries agreement by creating frameworks of cooperation and av-

venues for side payments. Finally, the US and Canada are the two best represented countries in my dataset (149 stocks total), making the specifics of the counterfactual less likely to depend on only a few stocks.

In this counterfactual, I suppose that both the US and Canada agree to behave in fisheries management as if they had a joint Exclusive Economic Zone. Operationally, that means that my stock share computation method treats the US EEZ as Canadian stock control for the purpose of Canadian stocks, and vice versa. Mechanically this must increase the measured stock shares, but the precise magnitudes will vary by stock based on the location and shape of the stock shapefile and the distribution of the suitable range. In particular, this approach will continue to treat suitable range in the high seas as an uninternalized spillover from the point of view of the fisheries manager. Figure 18 shows the average stock shares at the EEZ level in the baseline data (no cooperation). Figure 39 maps the change in effective stock shares if the US and Canada were to adopt the cooperative agreement I describe. Figure 38 shows the stock level distribution of changes in effective stock shares in this counterfactual.

What implications would such collaboration have on fisheries management? Figure 40 shows the stock level distribution of changes in escapement based on the changes in stock share and the effect of the stock share on escapement estimated above (see Table 4). Figure 42 shows the distribution of percent changes in escapement. Figures 41 and 43 maps these changes at the EEZ level. It shows that the Canadian Pacific coast and the US Atlantic coast both show significant increases in escapement (by 35% and 30%, respectively). This aligns naturally with the location and distribution of those stock: Many stocks on the Canadian Pacific coast extend either into the Pacific coast of the continental US or into the Gulf of Alaska. Similarly, many stocks in the Gulf of Maine spill over into the Bay of Fundy and the coast of Nova Scotia. Figures 45 and 47 map these changes in terms of biomass, and show a muted version of the same effect: biomass increases by anywhere from 1% in the US West Coast to 21% in the Canadian West Coast.

Overall, my results imply that cooperation between the US and Canada would increase

escapement by 5.44 million tonnes (12%) in total. Steady state biomass would in turn increase by 3.32 million tonnes (7%). These results are based on the historical values in my dataset, and do not include the potential effects of climate change. However, US-Canada cooperation could also help address stock shift under climate change. Figure 48 plots the change in stock share predicted under climate change against the hypothetical change in effective stock share under climate change *if* the US and Canada had a cooperative agreement. For many stocks this change does not matter, as the other country in the agreement is not the relevant shifting area, but for several stocks the cooperative agreement significantly reduces the changes in stock share implied by climate change.

## 7 Conclusion

In this paper I study how fisheries extraction responds to changes in the share of a population found within a management area. The core empirical result is that extraction in a management area does respond to the “stock share” controlled: using panel variation in the stock share, I show that a lower stock share causes higher catch conditional on biomass, consistent with overextraction due to property rights insecurity. The effects are quite large for reasonable variation in the stock share.

As climate change alters the environmental conditions of the ocean, many species are predicted to undergo changes to their habitat ranges which could change the relative shares controlled by different countries. This paper investigates the implications of climate-induced range shift for fisheries extraction. I find that climate change is predicted to have relatively small effects on stock shares on average, but there is significant heterogeneity across fisheries. For the average stock, the behavioral response to range-shift is approximately 25% of the effect of climate change.

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## 8 Tables

Table 1: Distance to Equator Regressions

|                      | <i>Dependent variable:</i> |                                  |                      |
|----------------------|----------------------------|----------------------------------|----------------------|
|                      | Avg. Coastline Length (km) | Avg. EEZ Area (km <sup>2</sup> ) | Avg. EPI Score       |
|                      | (1)                        | (2)                              | (3)                  |
| Degrees from Equator | 57.408***<br>(7.081)       | 7,190.809***<br>(317.310)        | -0.010***<br>(0.001) |
| Constant             | 13,084.570***<br>(736.944) | 1,519,061.000***<br>(33,021.610) | 20.172***<br>(0.146) |
| Observations         | 721                        | 721                              | 721                  |
| R <sup>2</sup>       | 0.084                      | 0.417                            | 0.065                |

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Results from regressing the average value of each measure within latitude on the distance from the equator in degrees. Column (1) shows the average coastline length for countries at that latitude. Column (2) shows the average EEZ area for countries at that latitude. Column (3) shows the average fishery management score from the Environmental Performance Index for countries at that latitude.

Table 2: Summary Statistics

| Variable                | Value      |
|-------------------------|------------|
| Unique Years            | 24.00      |
| Unique Stock IDs        | 326.00     |
| Unique Scientific Names | 163.00     |
| Stock Share (mean)      | 0.53       |
| Stock Share (sd)        | 0.29       |
| Extraction Rate (mean)  | 0.17       |
| Extraction Rate (sd)    | 0.17       |
| Escapement (mean)       | 399185.23  |
| Escapement (sd)         | 1056573.39 |
| Biomass (mean)          | 482240.50  |
| Biomass (sd)            | 1313272.89 |
| Catch (mean)            | 83055.27   |
| Catch (sd)              | 385919.45  |

Summary statistics for main panel dataset.

Table 3: Cross Section Regressions

|                     | Dependent variable: |                     |                      |                      |                      |                     |
|---------------------|---------------------|---------------------|----------------------|----------------------|----------------------|---------------------|
|                     | Log Mean Escapement |                     | Extraction Rate      |                      | Log Mean Catch       |                     |
|                     | (1)                 | (2)                 | (3)                  | (4)                  | (5)                  | (6)                 |
| Mean Stock Share    | 0.021*<br>(0.011)   | 0.008<br>(0.015)    | -0.128***<br>(0.028) | -0.099***<br>(0.032) | -0.217***<br>(0.058) | -0.185**<br>(0.082) |
| Log Mean Biomass    | 0.107***<br>(0.001) | 0.105***<br>(0.002) |                      |                      | 0.134***<br>(0.007)  | 0.132***<br>(0.009) |
| Growth Rate         |                     | -0.050**<br>(0.020) |                      | 0.273***<br>(0.042)  |                      | 0.466***<br>(0.108) |
| Mean Interest Rate  |                     | -0.093<br>(0.067)   |                      | 0.308**<br>(0.142)   |                      | 0.071<br>(0.363)    |
| Constant            | 1.162***<br>(0.017) | 1.214***<br>(0.022) | 0.239***<br>(0.017)  | 0.076**<br>(0.030)   | 0.726***<br>(0.088)  | 0.524***<br>(0.123) |
| Observations        | 326                 | 206                 | 326                  | 206                  | 323                  | 204                 |
| R <sup>2</sup>      | 0.953               | 0.957               | 0.062                | 0.253                | 0.570                | 0.570               |
| Residual Std. Error | 0.059 (df = 323)    | 0.057 (df = 201)    | 0.146 (df = 324)     | 0.122 (df = 202)     | 0.301 (df = 320)     | 0.310 (df = 199)    |

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Results from cross sectional regression of average outcomes on average stock shares (each observation is one stock). Odd columns also include controls for species level intrinsic growth rates and average country-year level interest rates. A positive coefficient on the Stock Share for Escapement implies that a larger quantity of fish is not caught in fisheries where the managing authority controls a greater share of the fish population. A negative coefficient on the Stock Share for the Extraction Rate and Catch (conditional on Biomass) implies that larger quantities of fish are caught when the managing authority controls a smaller share of the fish population.

Table 4: Panel Regressions

|                | <i>Dependent variable:</i> |                       |                      |
|----------------|----------------------------|-----------------------|----------------------|
|                | Norm. Escapement           | Norm. Extraction Rate | Norm. Catch          |
|                | (1)                        | (2)                   | (3)                  |
| Stock Share    | 1.506***<br>(0.554)        | -2.481***<br>(0.743)  | -2.306***<br>(0.669) |
| Norm. Biomass  |                            |                       | 0.556***<br>(0.020)  |
| Stock FE       | Yes                        | Yes                   | Yes                  |
| Year FE        | Yes                        | Yes                   | Yes                  |
| Observations   | 4,884                      | 4,875                 | 4,884                |
| R <sup>2</sup> | 0.002                      | 0.002                 | 0.150                |

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Results for regressing outcomes on my proxy for share of the total stock found in the managing country's exclusive economic zone. Regressions include fixed effects for the management stock and year. Sample years 2000–2024. Standard errors are clustered at the stock level. A positive coefficient on the Stock Share for Escapement implies that a larger quantity of fish is not caught in years where the managing authority controls a greater share of the fish population. A negative coefficient on the Stock Share for the Extraction Rate and Catch (conditional on Biomass) implies that larger quantities of fish are caught when the managing authority controls a smaller share of the fish population.

Table 5: Management Heterogeneity Regressions

|                       | <i>Dependent variable:</i> |                       |                         |                      |                         |                      |                         |                         |     |
|-----------------------|----------------------------|-----------------------|-------------------------|----------------------|-------------------------|----------------------|-------------------------|-------------------------|-----|
|                       | Norm. Escapement           | Norm. Extraction Rate | Norm. Catch             | (1)                  | (2)                     | (3)                  | (4)                     | (5)                     | (6) |
| Stock Share           | -5.113<br>(3.381)          | 1.452***<br>(0.555)   | 8.451*<br>(4.508)       | -2.415***<br>(0.745) | 1.510<br>(4.043)        | -2.415***<br>(0.671) | 1.510<br>(4.043)        | -2.252***<br>(0.671)    |     |
| Norm. Biomass         |                            |                       |                         |                      |                         |                      | 0.526***<br>(0.020)     | 0.556***<br>(0.020)     |     |
| EPI Score             | -0.166<br>(257,774.300)    |                       | -0.103<br>(348,956.600) |                      | -0.103<br>(348,956.600) |                      | -0.010<br>(308,178.900) | -0.010<br>(308,178.900) |     |
| Stock Share×EPI Score | 0.404**<br>(0.204)         |                       | -0.671**<br>(0.272)     |                      | -0.671**<br>(0.272)     |                      | -0.233<br>(0.244)       | -0.233<br>(0.244)       |     |
| ITQs                  |                            | -0.952**<br>(0.453)   |                         | 1.745***<br>(0.607)  |                         | 1.745***<br>(0.607)  |                         | 1.517***<br>(0.547)     |     |
| Stock Share×ITQs      |                            | 1.000**<br>(0.500)    |                         | -2.052***<br>(0.672) |                         | -2.052***<br>(0.672) |                         | -1.815***<br>(0.604)    |     |
| Stock FE              | Yes                        | Yes                   | Yes                     | Yes                  | Yes                     | Yes                  | Yes                     | Yes                     |     |
| Year FE               | Yes                        | Yes                   | Yes                     | Yes                  | Yes                     | Yes                  | Yes                     | Yes                     |     |
| Observations          | 4,864                      | 4,845                 | 4,855                   | 4,836                | 4,864                   | 4,845                | 4,864                   | 4,845                   |     |
| R <sup>2</sup>        | 0.002                      | 0.003                 | 0.004                   | 0.005                | 0.137                   | 0.137                | 0.137                   | 0.151                   |     |

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

Note:

Regression results for heterogeneity regressions involving management proxies. Odd columns show the results interacting the stock share with the fishery management score from the Environmental Performance Index. Odd columns show results interacting the stock share with a stock-year indicator for management with Individual Transferable Quota. Results show that the headline effect of the stock share is magnified by better management, measured through either the EPI score or the use of ITQs.

Table 6: Rate Heterogeneity Regressions

|                           | <i>Dependent variable:</i> |                     |                      |                      |                      |                      |
|---------------------------|----------------------------|---------------------|----------------------|----------------------|----------------------|----------------------|
|                           | Norm. Escapement           | Norm.               | Extraction Rate      | Norm.                | Catch                |                      |
|                           | (1)                        | (2)                 | (3)                  | (4)                  | (5)                  | (6)                  |
| Stock Share               | 3.024**<br>(1.368)         | 1.888***<br>(0.513) | -5.555***<br>(1.768) | -2.777***<br>(0.794) | -4.090***<br>(1.579) | -2.562***<br>(0.706) |
| Norm. Biomass             |                            |                     |                      |                      | 0.561***<br>(0.020)  | 0.548***<br>(0.025)  |
| Stock Share×Growth Rate   |                            |                     |                      |                      | 9.244**<br>(3.950)   |                      |
| Interest Rate             |                            |                     |                      | 0.290<br>(0.361)     | -1.032*<br>(0.559)   | -1.312***<br>(0.496) |
| Stock Share×Interest Rate |                            |                     |                      | 0.010<br>(0.764)     | 3.040**<br>(1.184)   | 4.106***<br>(1.050)  |
| Stock FE                  | Yes                        | Yes                 | Yes                  | Yes                  | Yes                  | Yes                  |
| Year FE                   | Yes                        | Yes                 | Yes                  | Yes                  | Yes                  | Yes                  |
| Observations              | 4,330                      | 4,021               | 4,330                | 4,012                | 4,330                | 4,021                |
| R <sup>2</sup>            | 0.002                      | 0.004               | 0.002                | 0.005                | 0.163                | 0.121                |

*Note:*

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

Regression results for additional heterogeneity regressions. Odd columns show the results interacting the stock share with the species level intrinsic growth rate. Odd columns show results interacting the stock share with the country-year level interest rate. Both variables appear to dampen the effect of the stock share, as the interaction term is opposite in sign to the uninteracted stock share coefficient in most cases. However, these results are only statistically significant for two of the three outcomes.

Table 7: Biomass Prediction Regression

| <i>Dependent variable:</i> |                      |
|----------------------------|----------------------|
| Normalized Biomass         |                      |
| Lag Norm. Escapement       | 0.921***<br>(0.015)  |
| Lag Norm. Escapement Sq    | -0.091***<br>(0.005) |
| Intercept                  | 0.186***<br>(0.011)  |
| Observations               | 4,558                |
| R <sup>2</sup>             | 0.607                |
| Residual Std. Error        | 0.209 (df = 4555)    |

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Results for regression of normalized biomass on lagged escapement and lagged escapement squared. I use this regression to predict biomass given my escapement results. The quadratic form allows for a non-linear relationship between lagged escapement and biomass, as one would expect from a concave growth function.

## 9 Figures

Figure 1: EPI Score and Distance to Equator

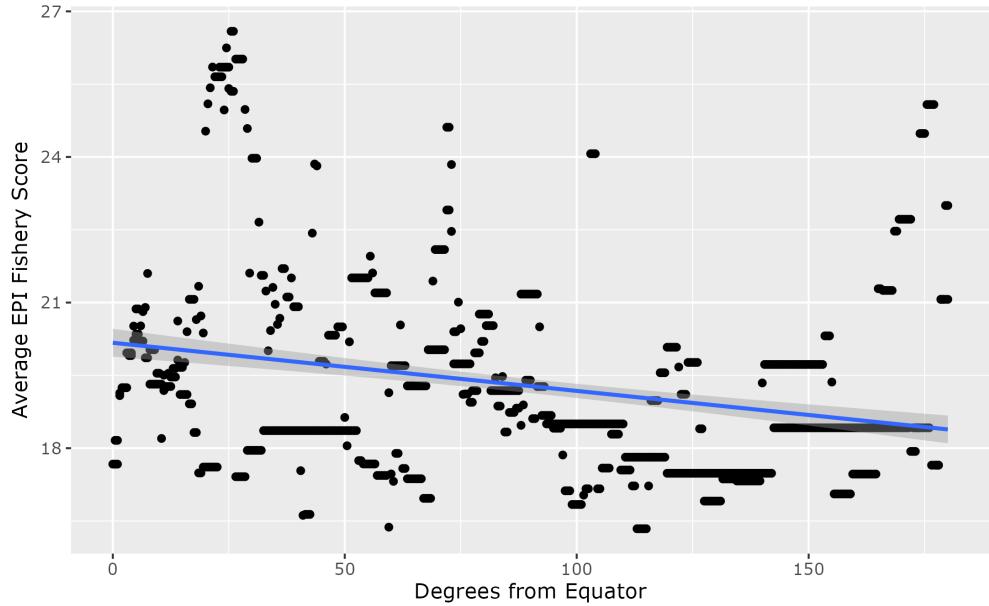


Figure 2: Coastline and Distance to Equator

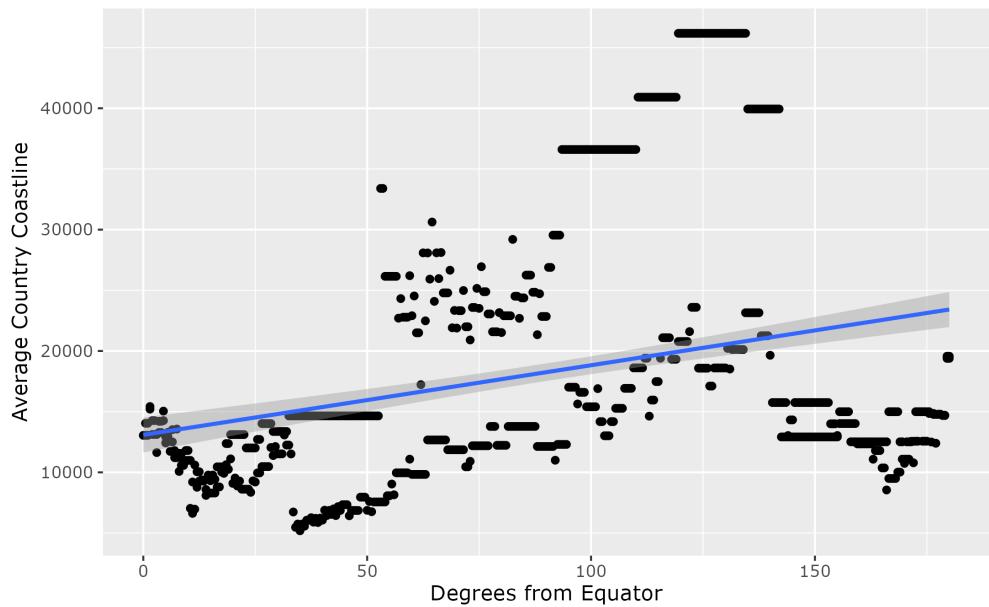


Figure 3: EEZ Area and Distance to Equator

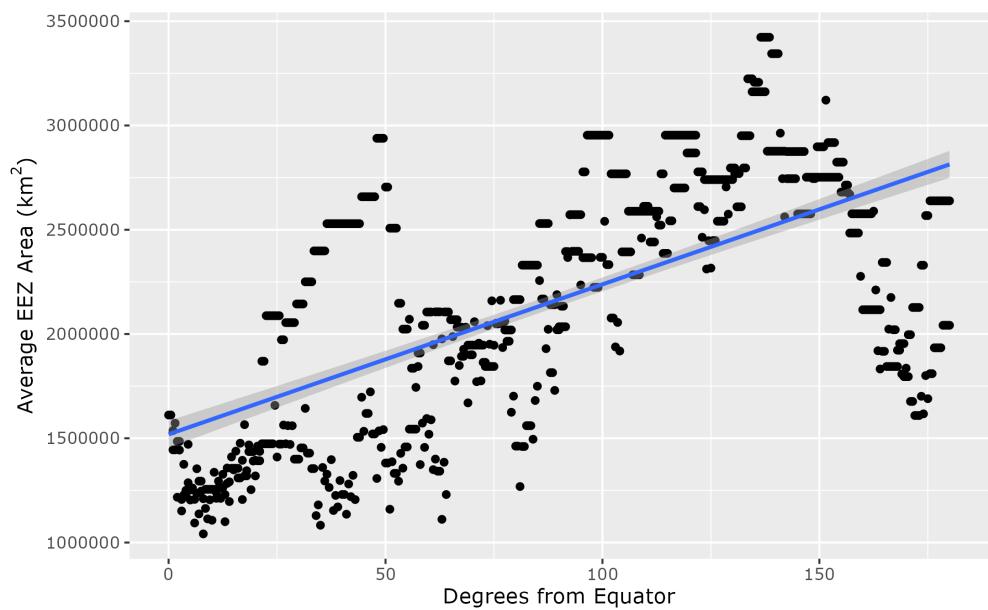


Figure 4: Map of RAM Stocks

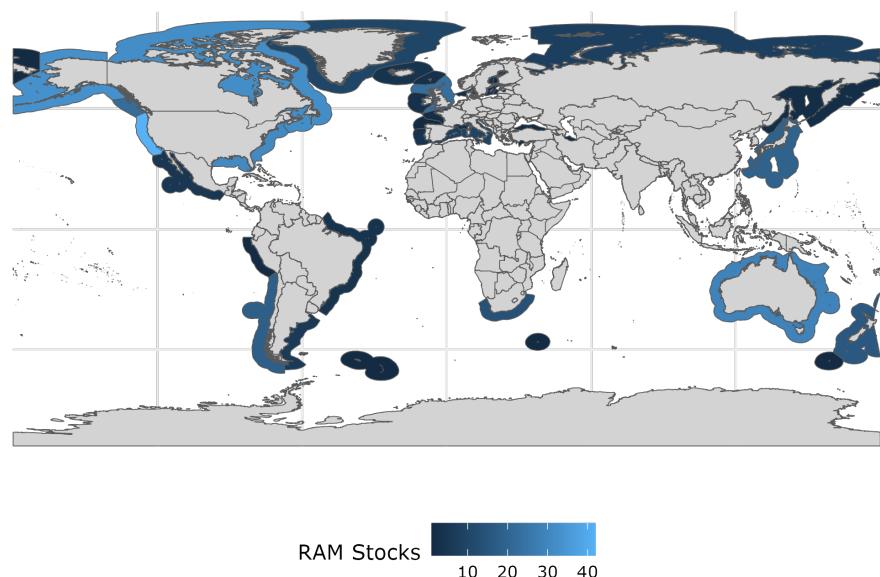


Figure 5: Map of Average Catch Values

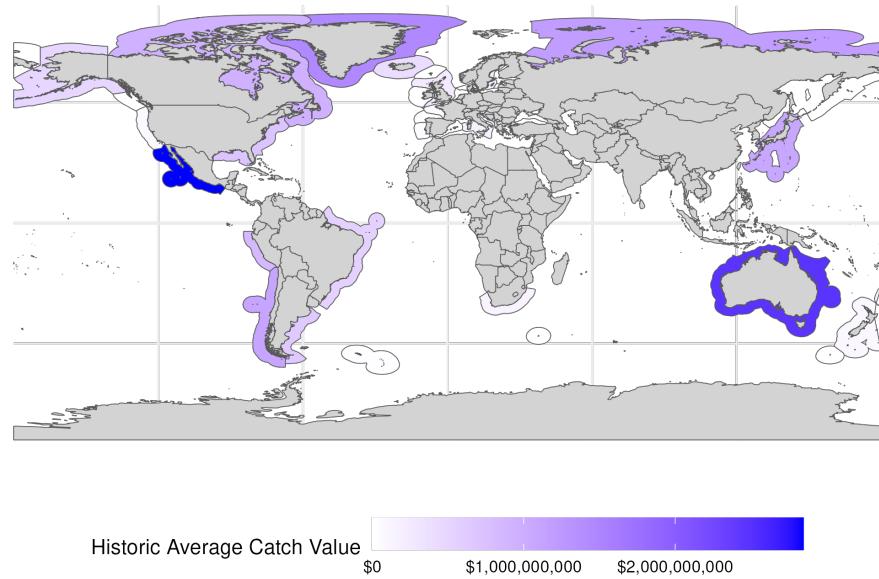


Figure 6: Temperature Envelope for Greenstriped Rockfish

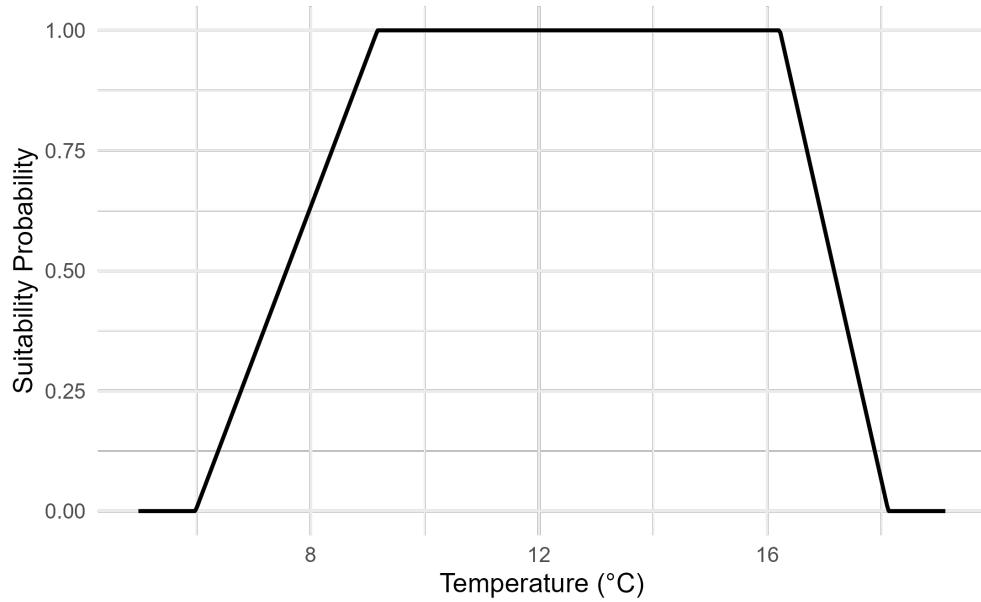


Figure 7: Greenstriped Rockfish Suitability in 2020

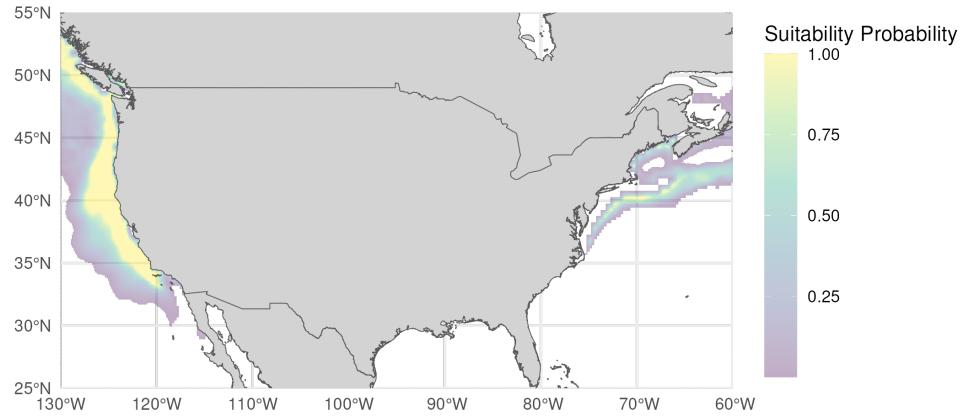


Figure 8: Greenstriped Rockfish RAM Shapefile

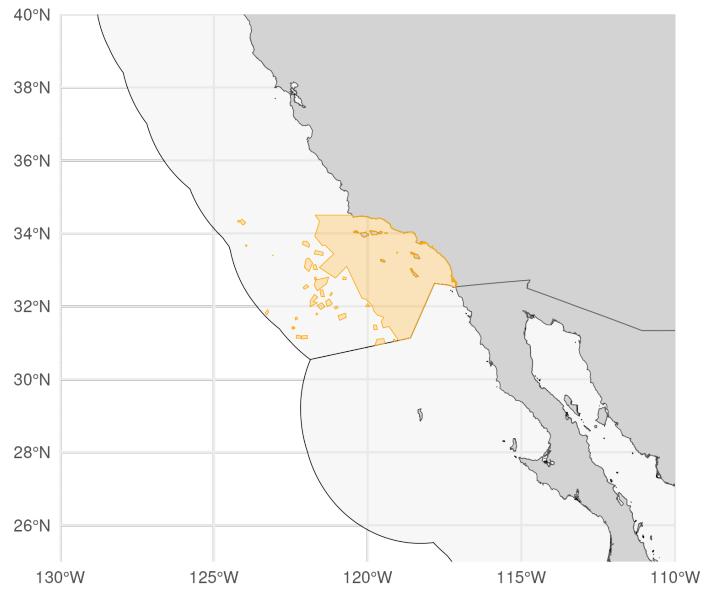


Figure 9: Greenstriped Rockfish Management Areas

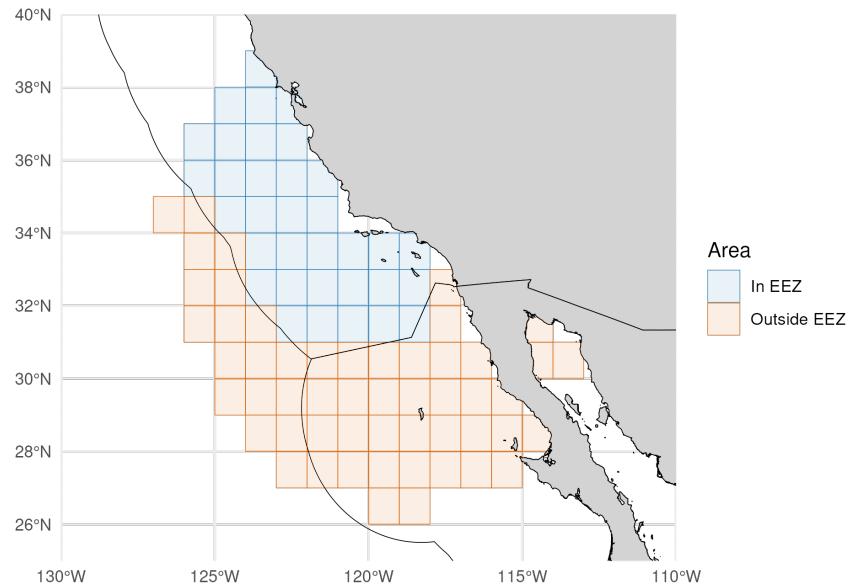


Figure 10: Greenstriped Rockfish Suitability

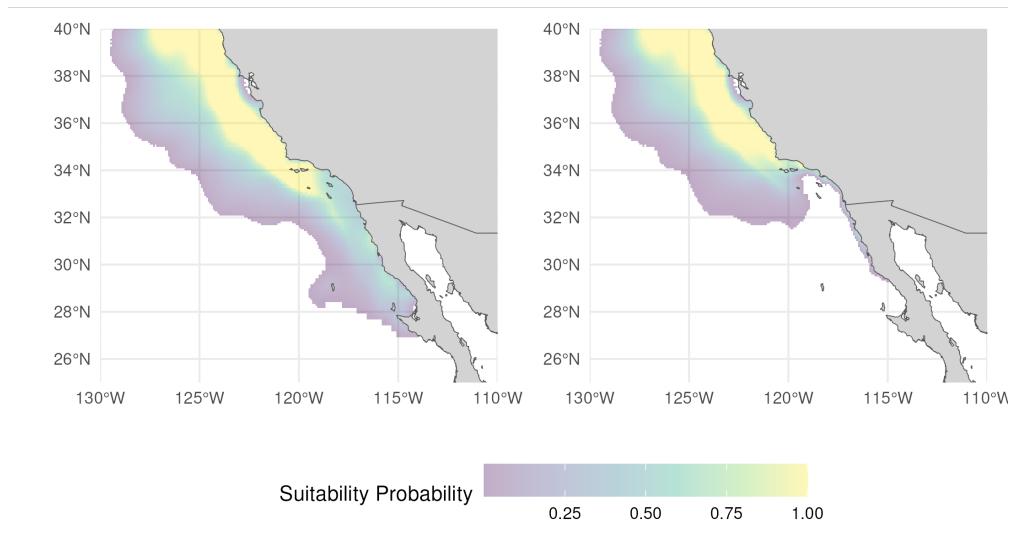


Figure 11: Greenstriped Rockfish Management and Suitability

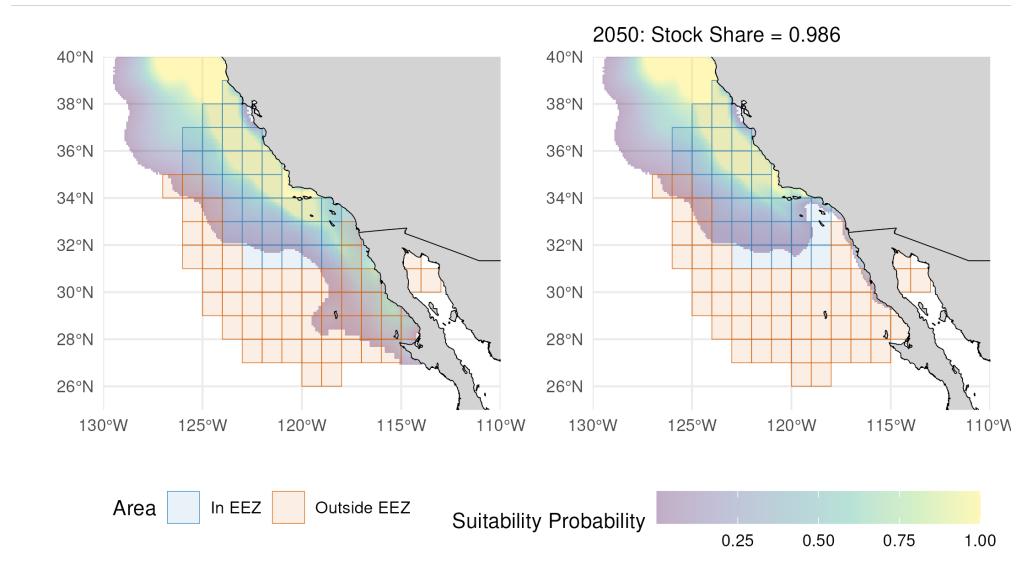


Figure 12: Avg. Extraction Rate Vs Avg. Stock Share

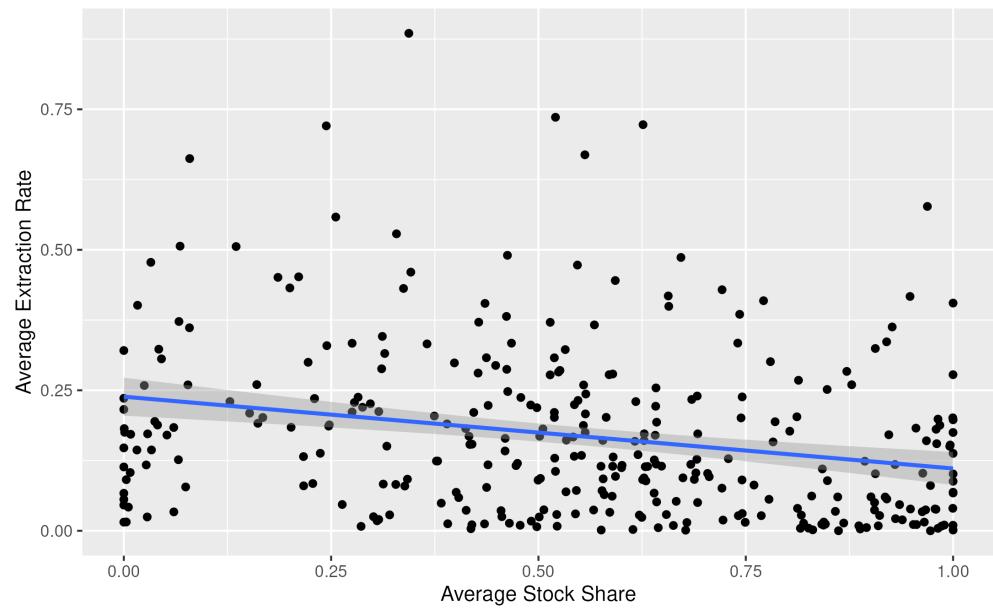


Figure 13: Normalized Escapement Vs Normalized Biomass

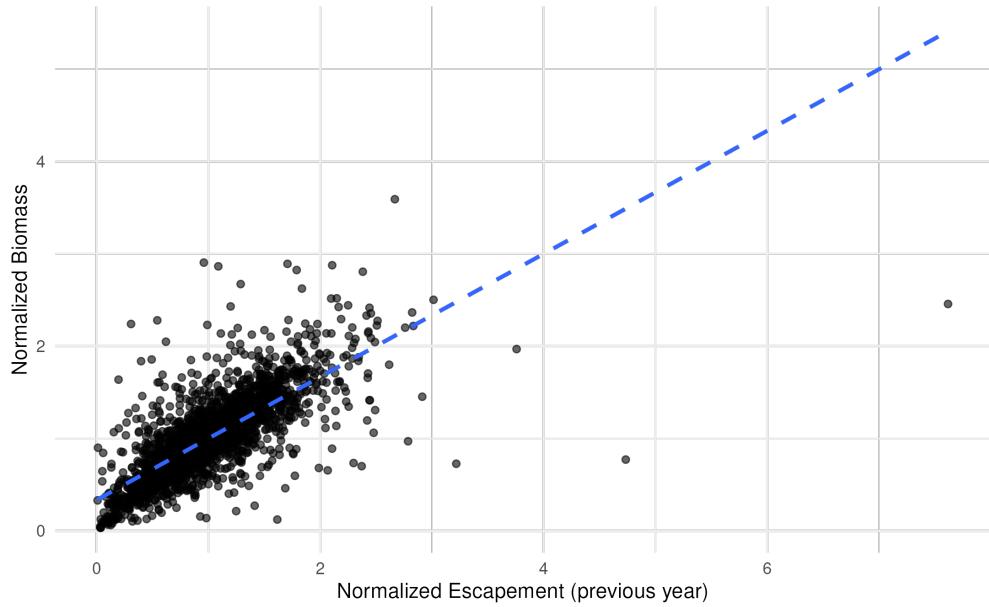


Figure 14: Stock Share Density by Decade

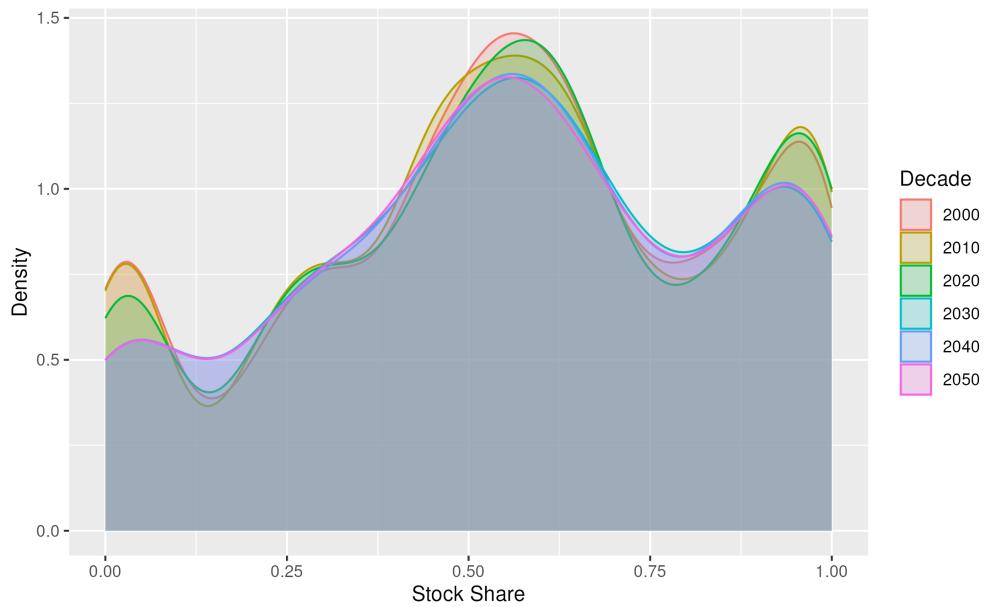


Figure 15: Stock Share Change by 2050

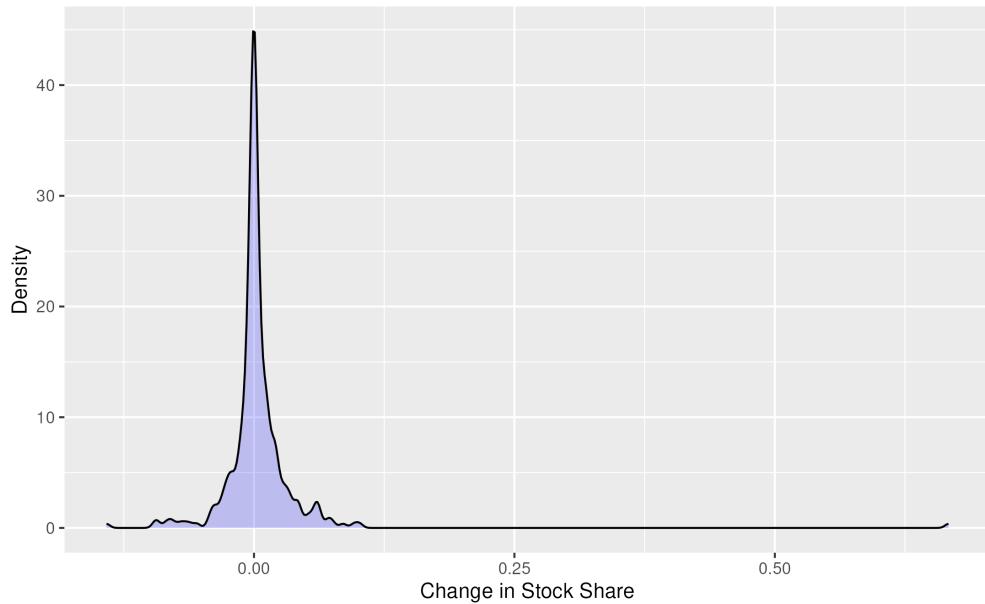


Figure 16: Escapement Changes by 2050 (Behavioral Only)

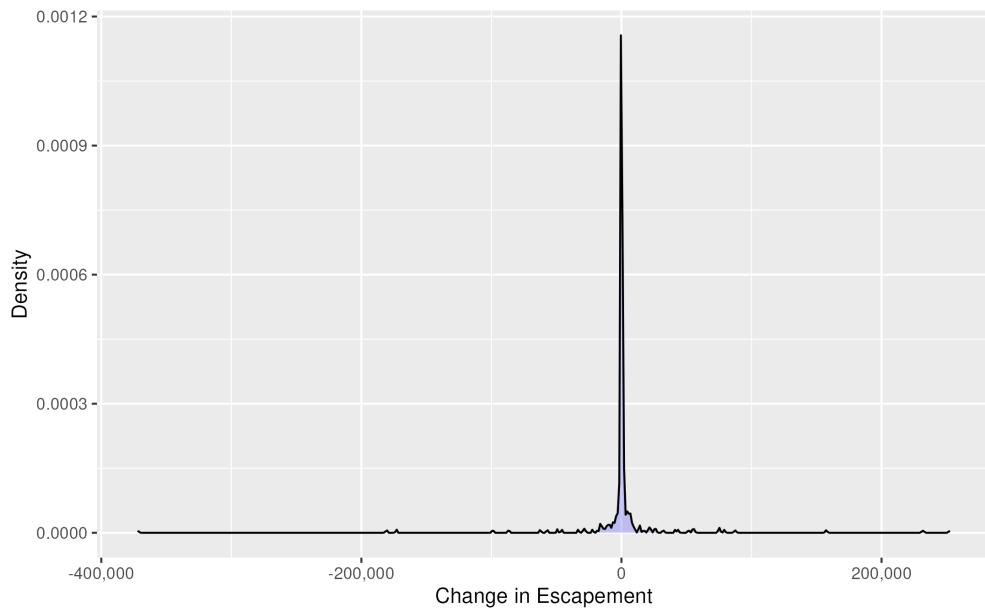


Figure 17: Escapement Percent Changes by 2050 (Behavioral Only)

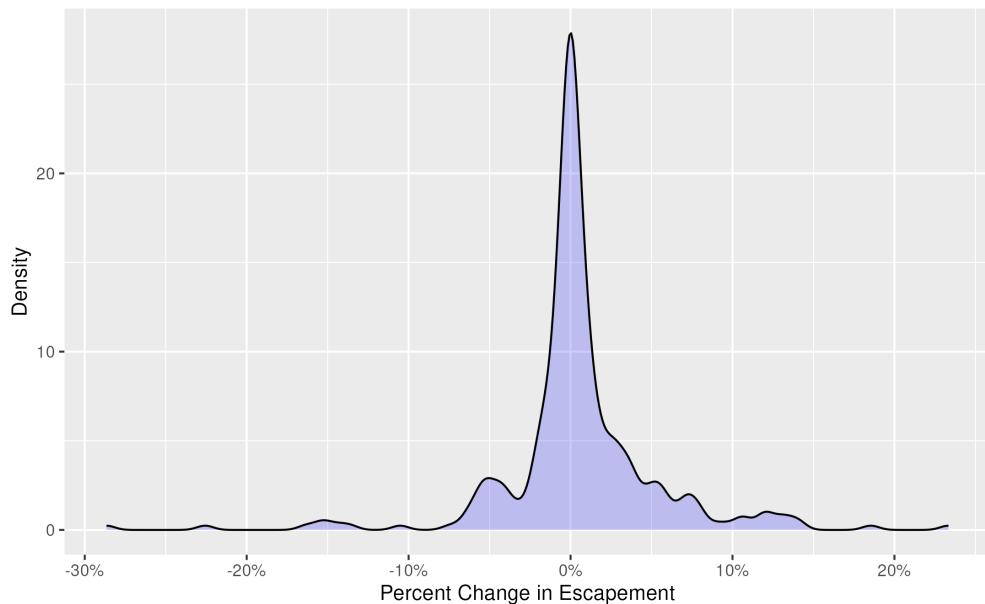


Figure 18: Average Stock Share by EEZ

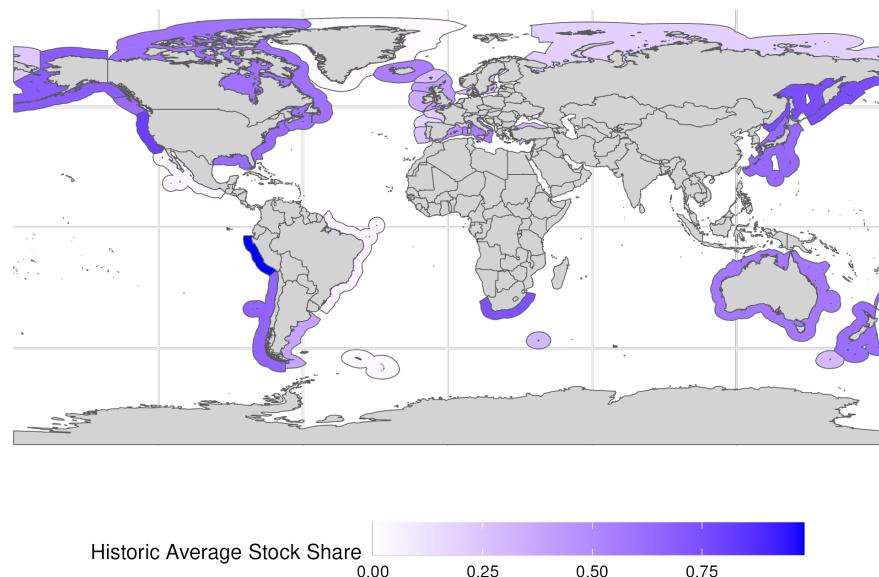


Figure 19: 2050 Average Change in Stock by EEZ

2050 Prediction Under SSP245

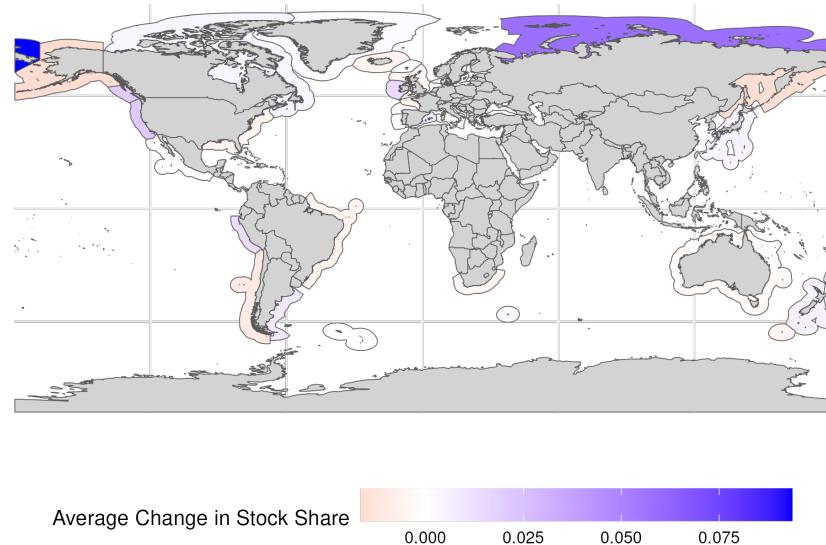


Figure 20: Total Escapement by EEZ (Historic Average)

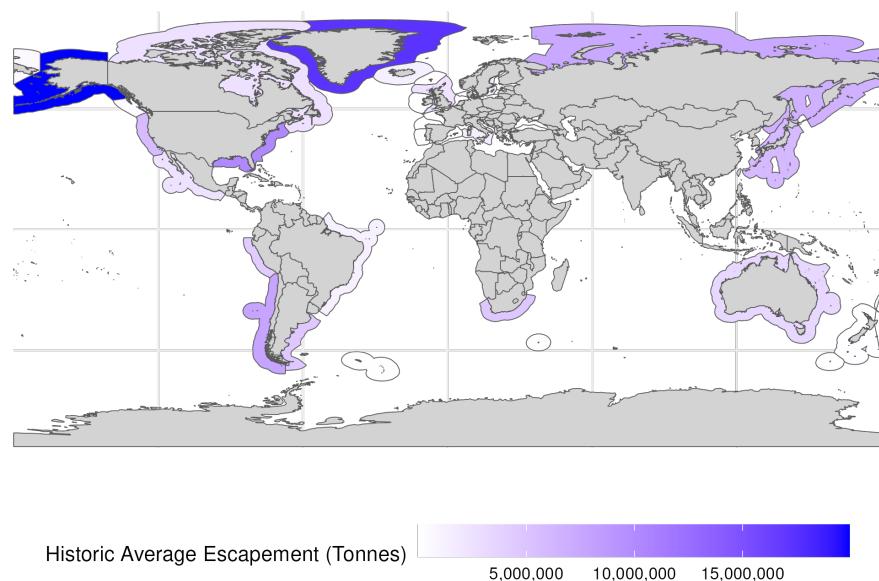


Figure 21: 2050 Total Change in Escapement by EEZ (Behavioral Only)

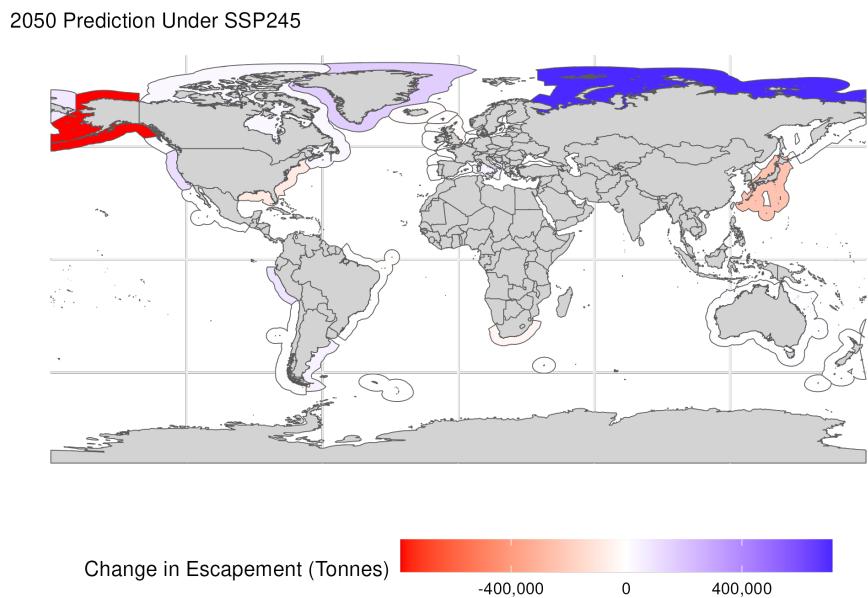


Figure 22: 2050 Percent Change in Escapement by EEZ (Behavioral Only)

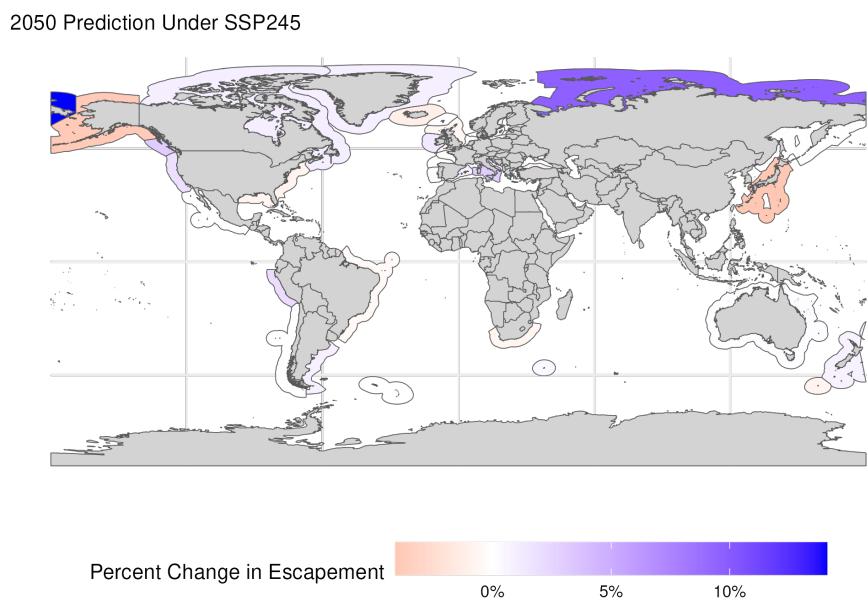


Figure 23: 2050 Total Change in Biomass by EEZ (Behavioral Only)

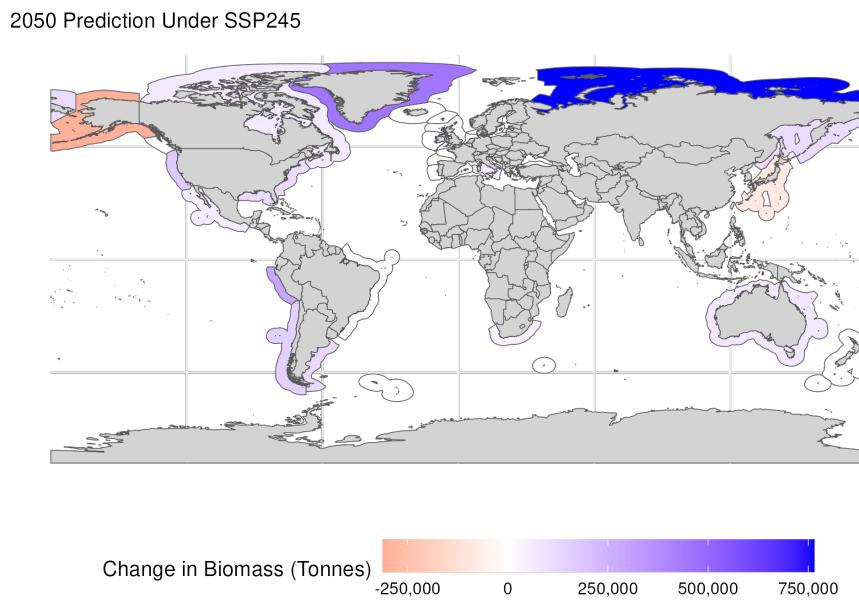


Figure 24: 2050 Percent Change in Biomass by EEZ (Behavioral Only)

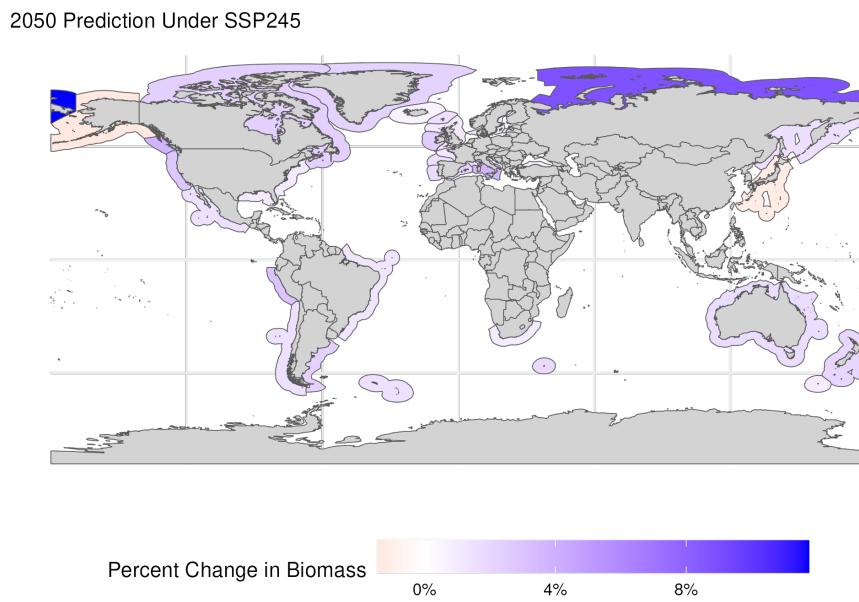


Figure 25: 2050 Change in Escapement (Biophysical Vs Combined)

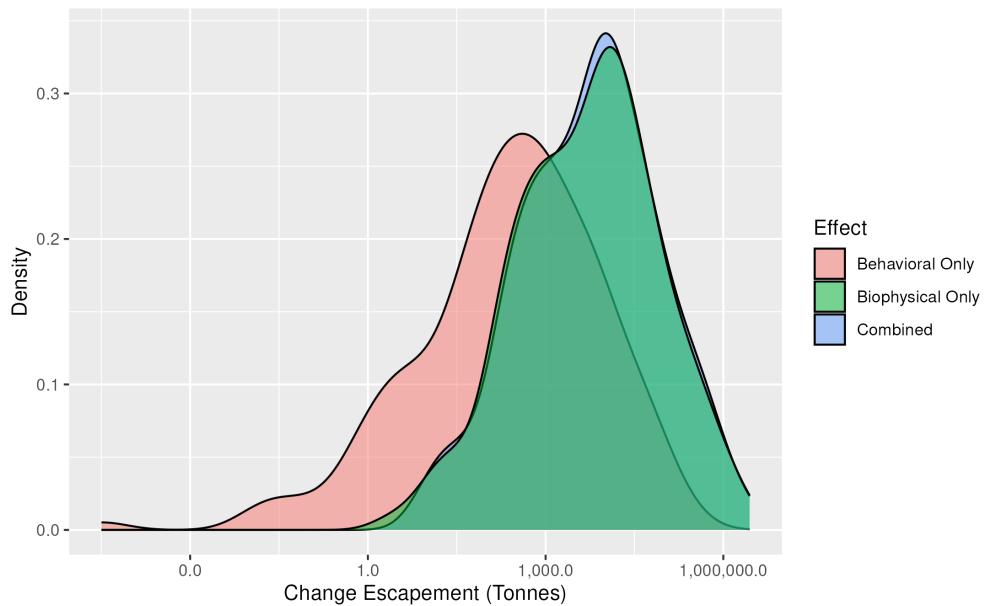


Figure 26: Error in Biophysical-Only Escapement Prediction

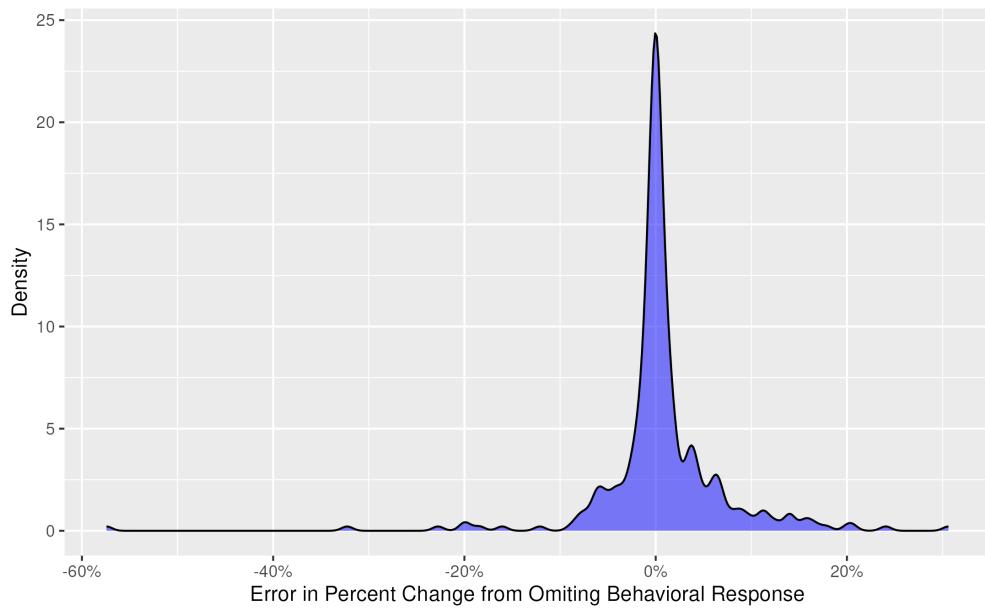


Figure 27: 2050 Total Change in Escapement by EEZ (Combined Effects)

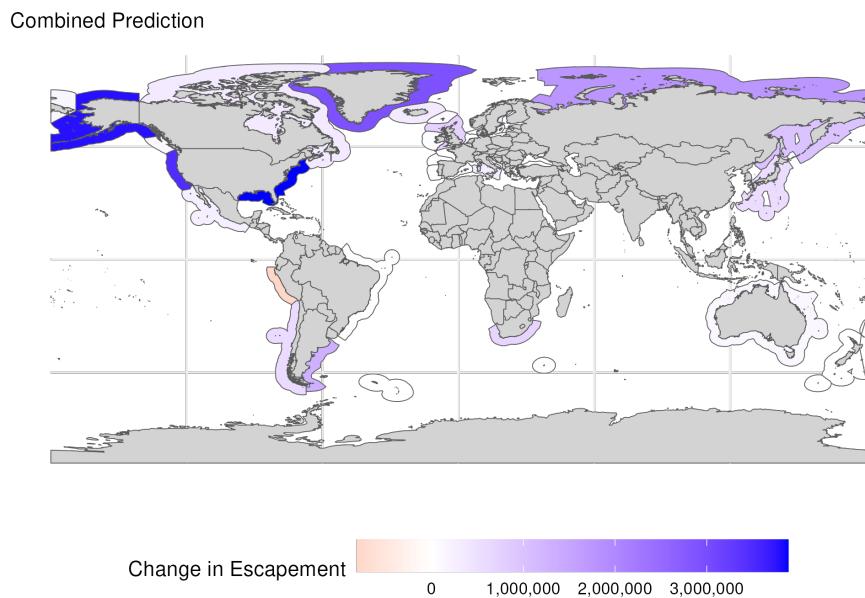


Figure 28: 2050 Percent Change in Escapement by EEZ (Combined Effects)

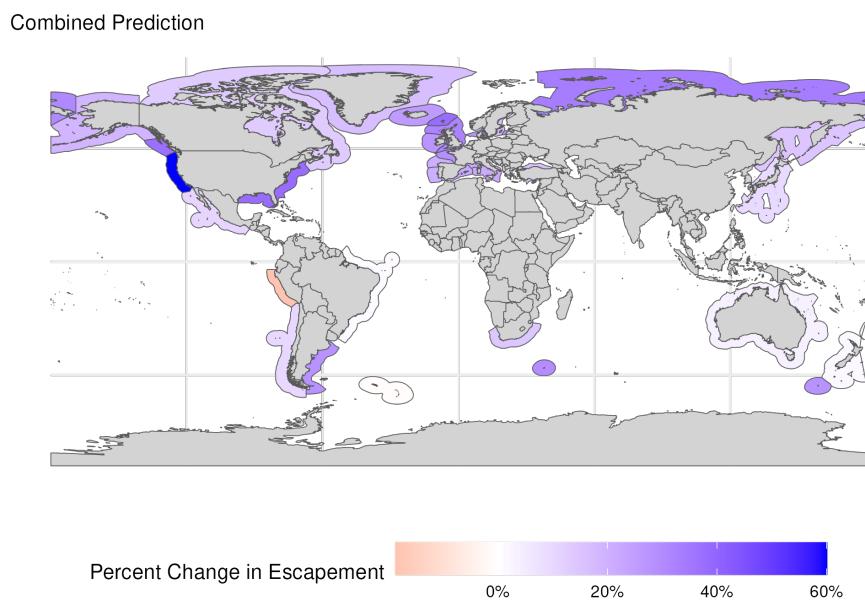


Figure 29: Error in Biophysical-Only Escapement Prediction by EEZ

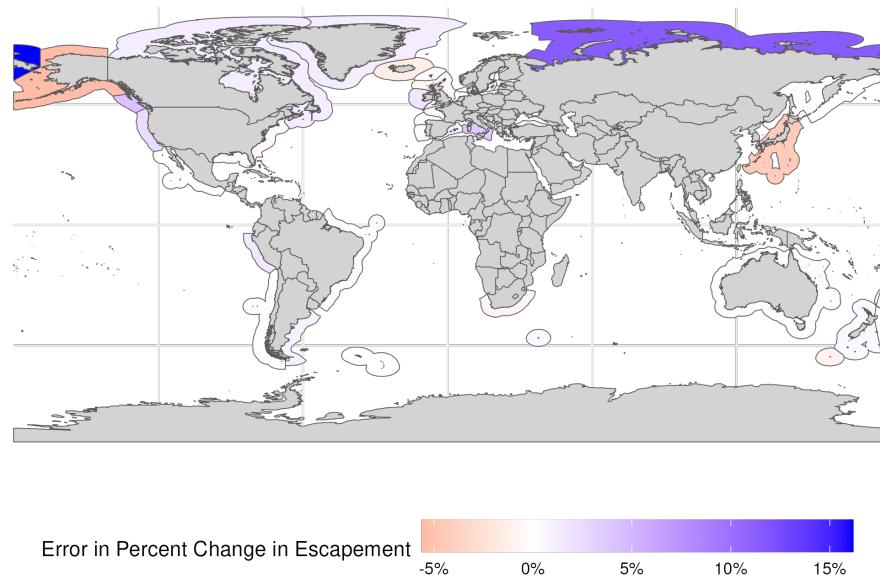


Figure 30: 2050 Total Change in Biomass by EEZ (Combined Effects)

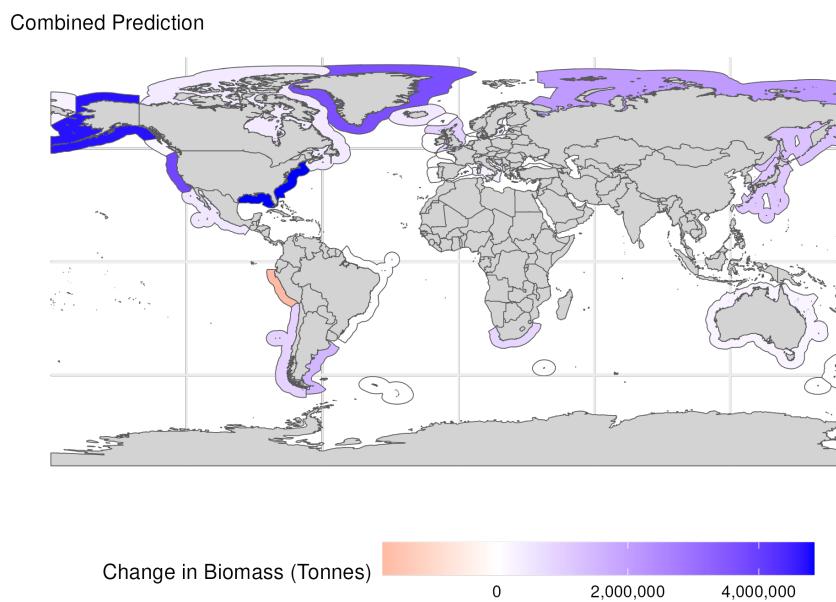


Figure 31: 2050 Percent Change in Biomass by EEZ (Combined Effects)

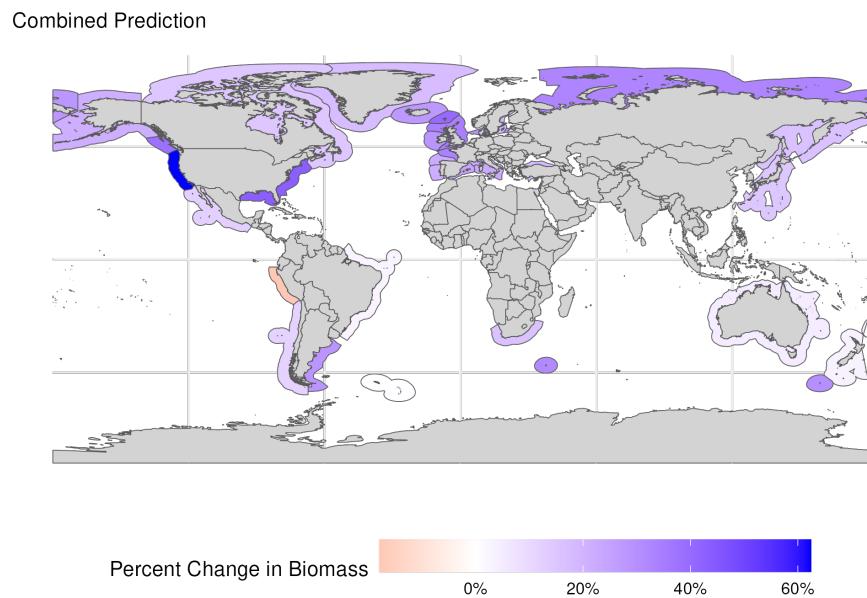


Figure 32: Historic and Cooperative Escapement Distributions

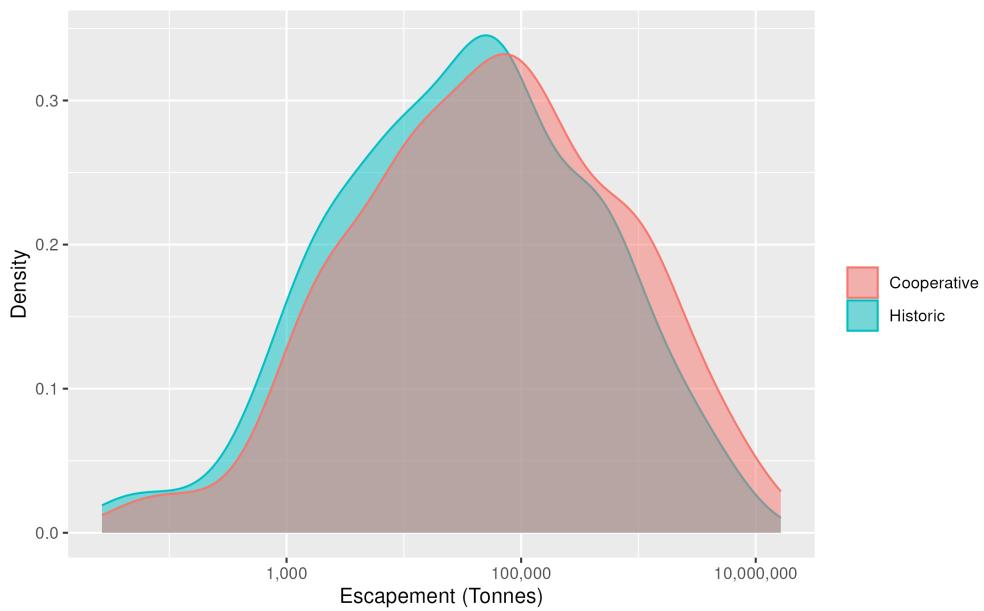


Figure 33: Historic and Cooperative Biomass Distributions

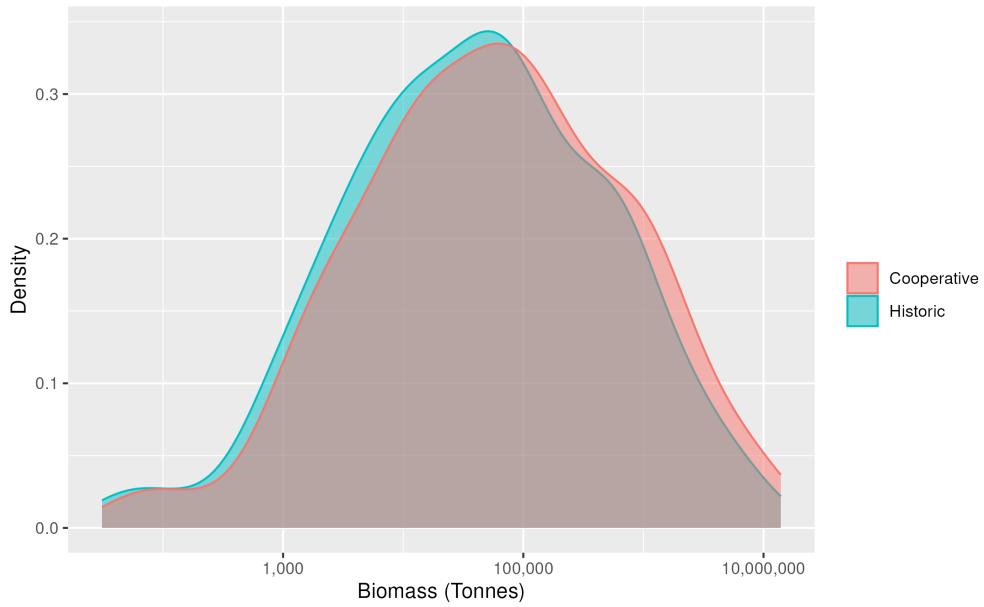


Figure 34: Cooperative Escapement Changes by EEZ

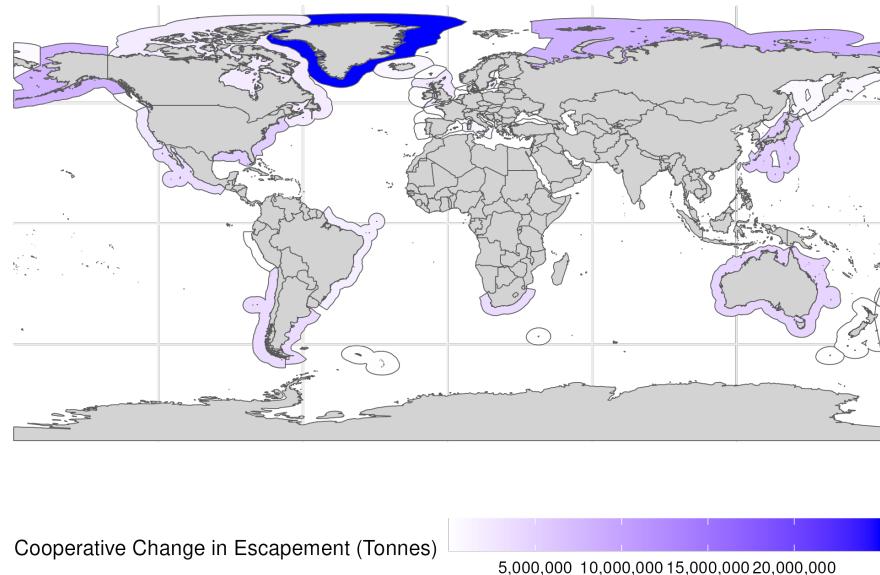


Figure 35: Cooperative Percent Change in Escapement by EEZ

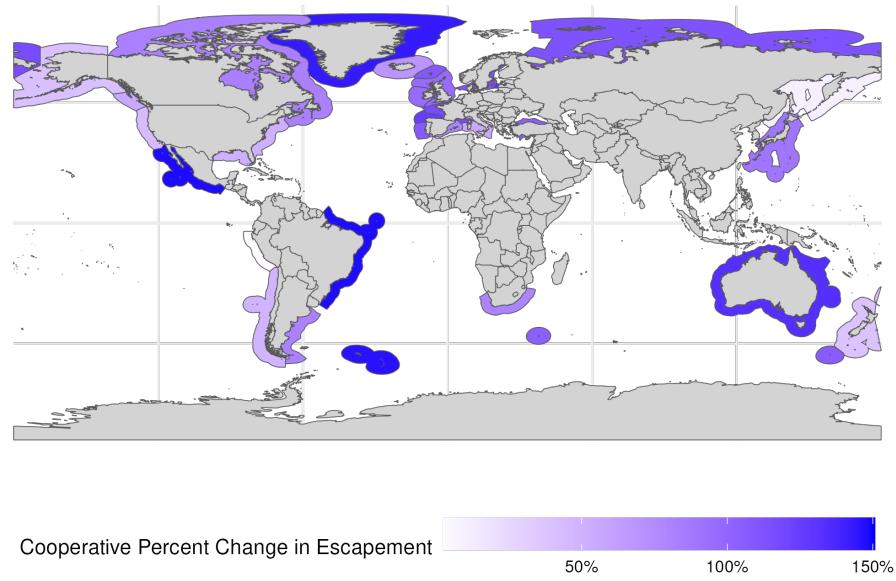


Figure 36: Cooperative Biomass Changes by EEZ

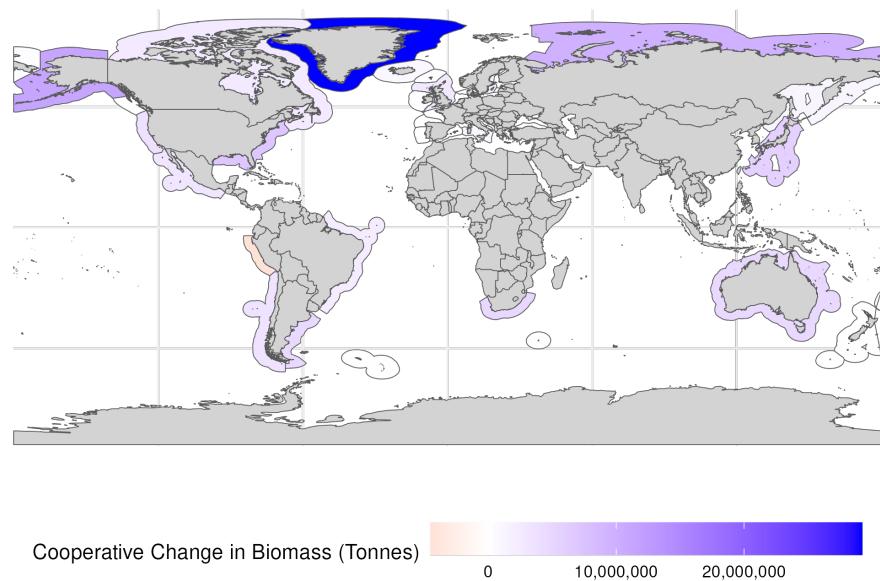


Figure 37: Cooperative Percent Change in Biomass by EEZ

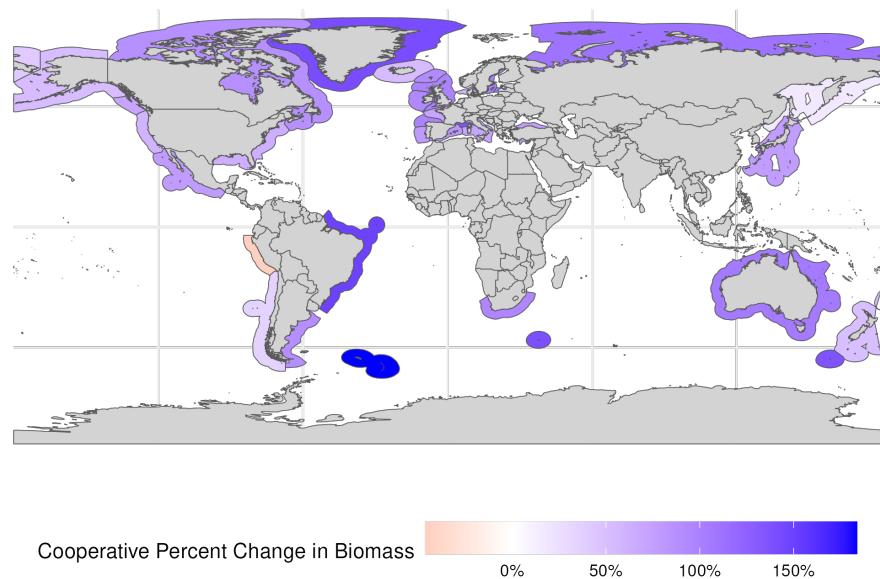


Figure 38: Change in Effective Stock Share Under US-Canada Agreement

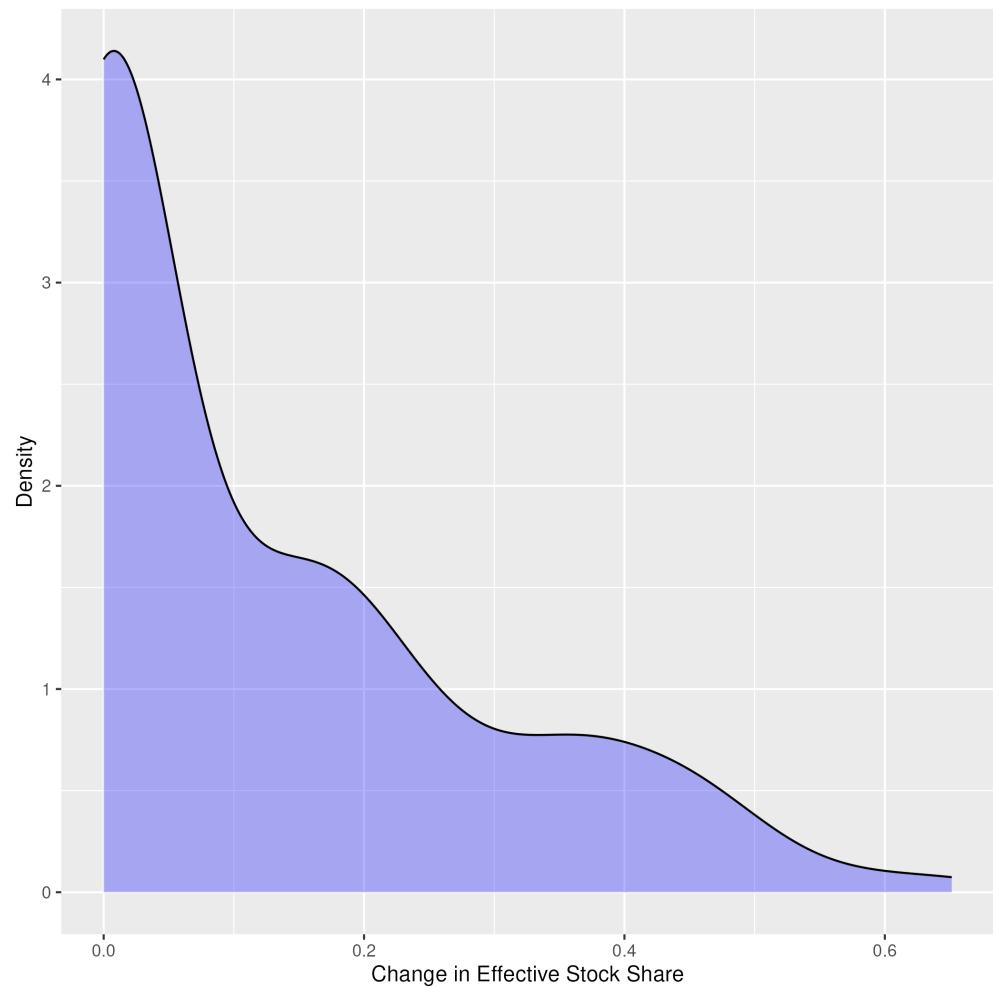


Figure 39: Change in Effective Stock Share Under US-Canada Agreement by EEZ

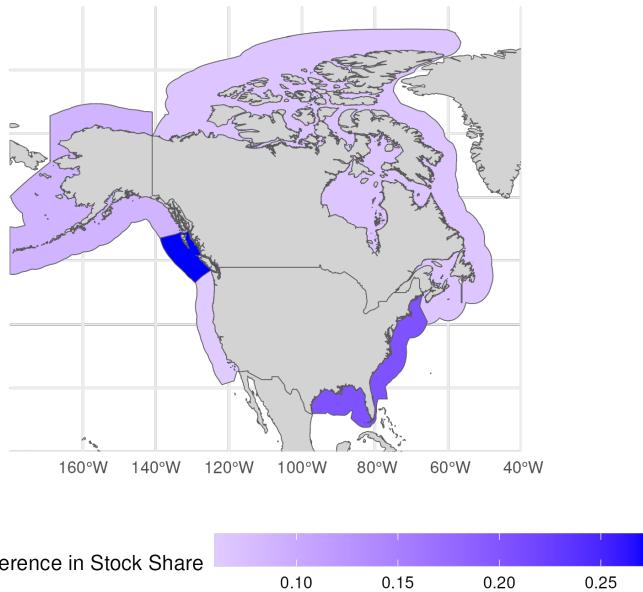


Figure 40: Change in Escapement Under US-Canada Agreement

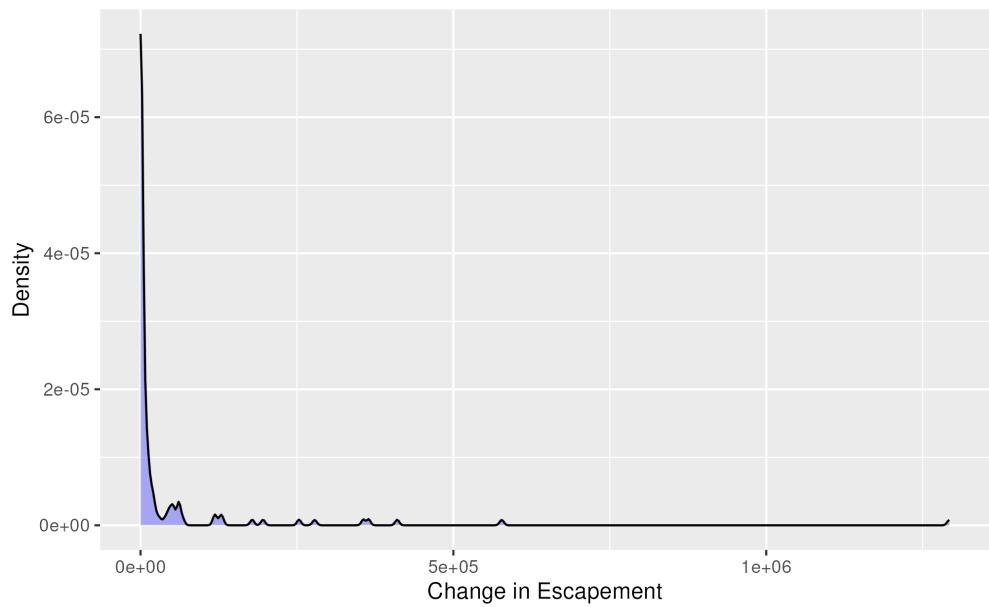


Figure 41: Change in Escapement Share Under US-Canada Agreement by EEZ

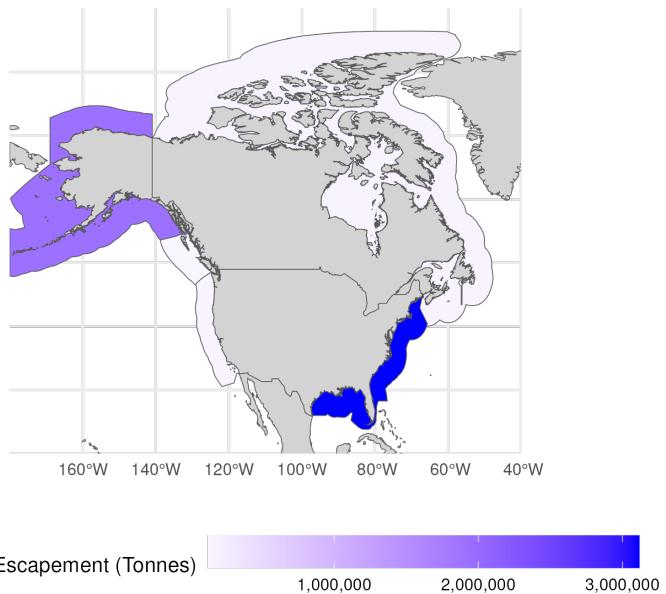


Figure 42: Percent Change in Escapement Under US-Canada Agreement

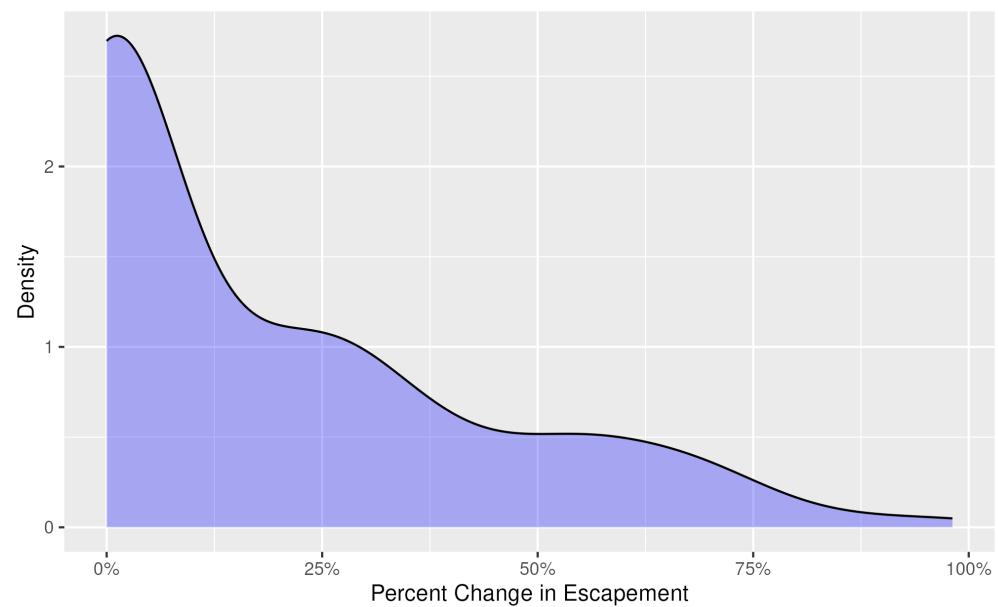


Figure 43: Percent Change in Escapement Share Under US-Canada Agreement by EEZ

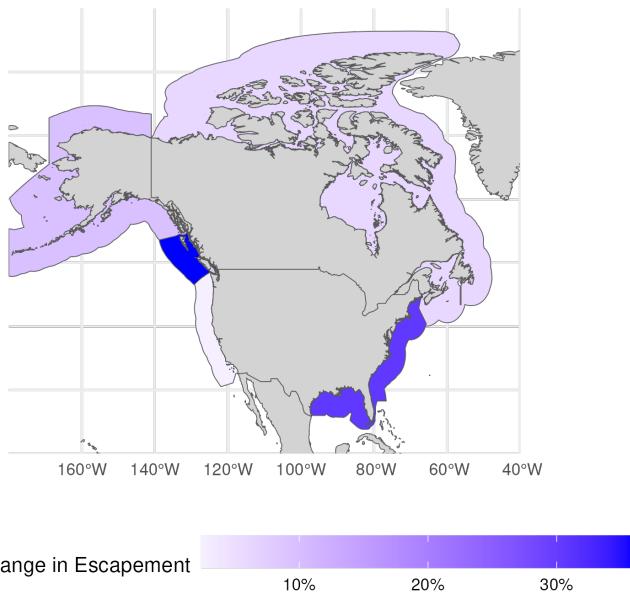


Figure 44: Change in Biomass Under US-Canada Agreement

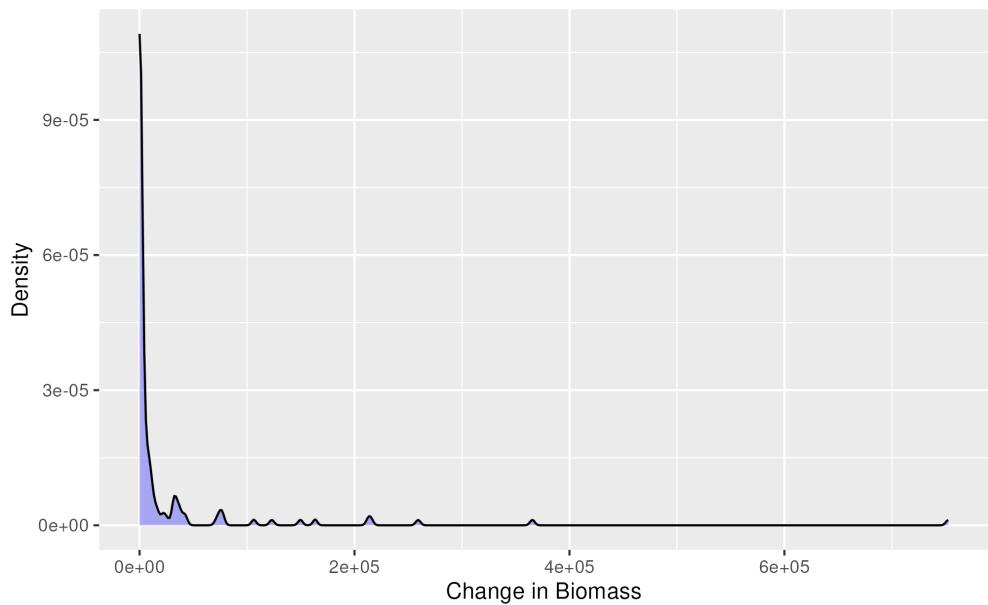


Figure 45: Change in Biomass Share Under US-Canada Agreement by EEZ

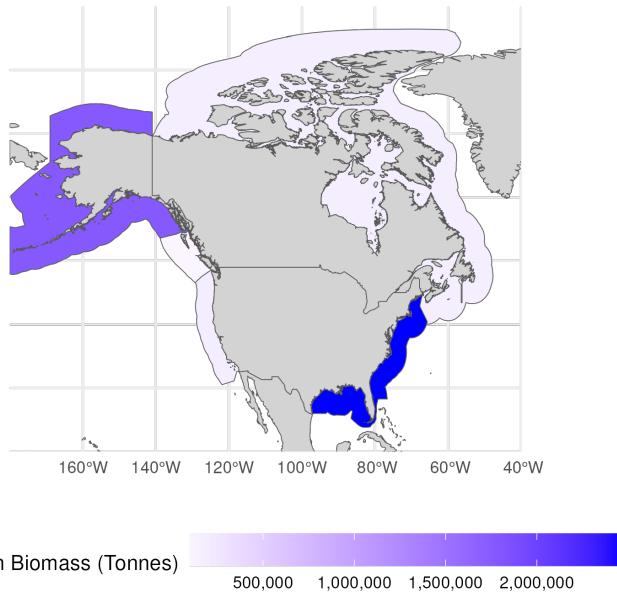


Figure 46: Percent Change in Biomass Under US-Canada Agreement

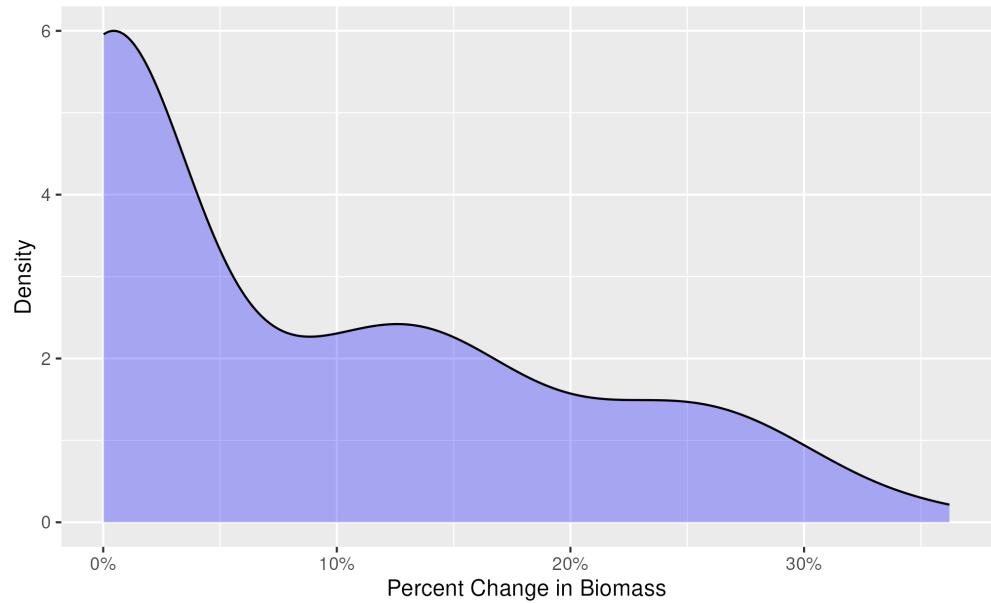


Figure 47: Percent Change in Biomass Share Under US-Canada Agreement by EEZ

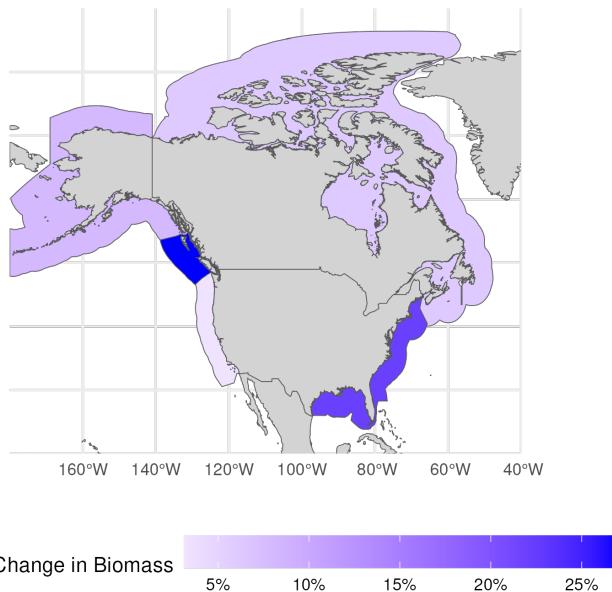
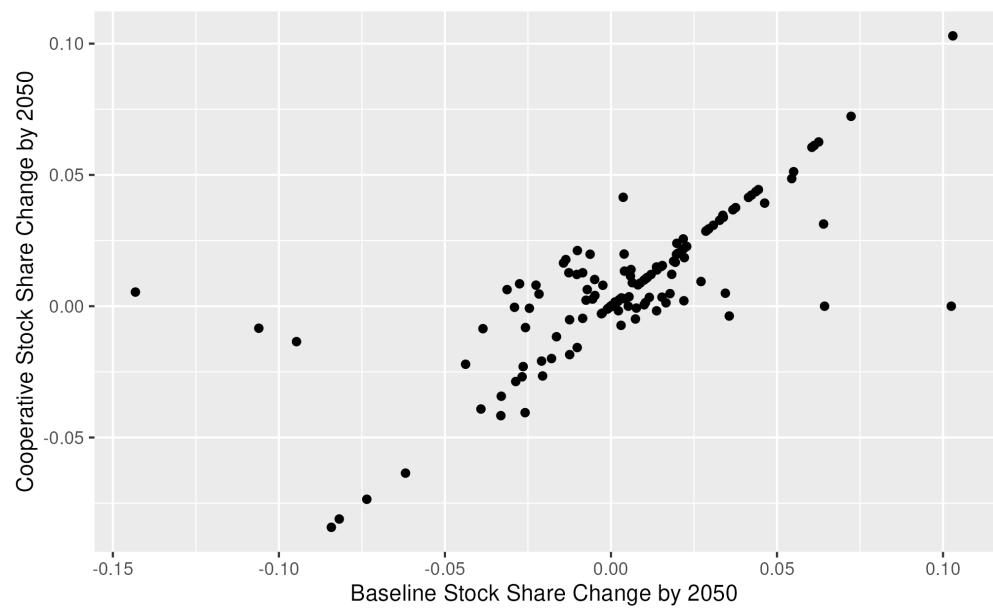


Figure 48: Climate-Induced Stock Share Changes, With and Without US-Canada Agreement



# A Stock Share Measure

## A.1 Stock Share Construction

In this section, I describe the full process of generating my stock share measure using the American Atlantic Halibut fishery as an example. The goal is to produce a proxy for the share of the fish population originating in a given country that will remain in the country next period. This is my empirical measure corresponding to  $\theta_i$  in the theoretical model in Section 2.

The first step in the process is to generate annual suitability rasters for each species based on their particular environmental preferences. Therefore, I begin with the species-level environmental preferences for the relevant species, *Hippoglossus Hippoglossus*, which can be found in Table 8.

Table 8: Atlantic Halibut Environmental Preferences

| Parameter  | Used | Min   | Min Pref | Max Pref | Max     |
|--|------|-------|----------|----------|---------|
| Depth (m)  | 1    | 50.00 | 313.00   | 864.00   | 2000.00 |
| Temperature (°C)   | 1    | -0.92 | 2.23     | 10.86    | 18.98   |
| Salinity (psu)   | 1    | 5.21  | 28.51    | 34.96    | 37.77   |
| Primary Production ( $\text{mgC}\cdot\text{m}^3\cdot\text{day}^{-1}$ ) | 1    | 1.65  | 3.77     | 13.71    | 42.40   |
| Sea Ice Concentration (0–1 frac.)                                      | 1    | -0.98 | 0.00     | 0.06     | 0.58    |
| Dissolved Bottom Oxygen ( $\text{mmol}\cdot\text{m}^{-3}$ )            | 0    | 1.33  | 170.27   | 310.10   | 408.48  |
| Distance to Land (km)  | 0    | 0.00  | 9.00     | 305.00   | 685.00  |

Because the minimum depth is less than 200 meters, I use the surface values for Temperature and Salinity, and do not use Dissolved Oxygen to form environmental envelopes. Distance to Land preferences are never used. Depth suitability is set to 1 if the depth of a grid cell is greater than the minimum preferred depth, and to 0 if the depth is less than the minimum depth; for values in between the suitability rises linearly from 0 to 1. For the other four variables, I construct a grid cell-level of suitability for each variable in each year based on where the value falls relative to the minimum, minimum preferred, maximum preferred, and maximum. Figure 49 shows an example of how suitability is calculated for a generic environmental variable: suitability is zero if the value is less than the minimum or greater than the maximum, 1 if the value is between the minimum preferred and maximum preferred, transitions linearly between 0 and 1 between the minimum and minimum preferred, and transitions linearly between 1 and 0 for between the maximum preferred and maximum.

Figure 49: Generic Environmental Envelope

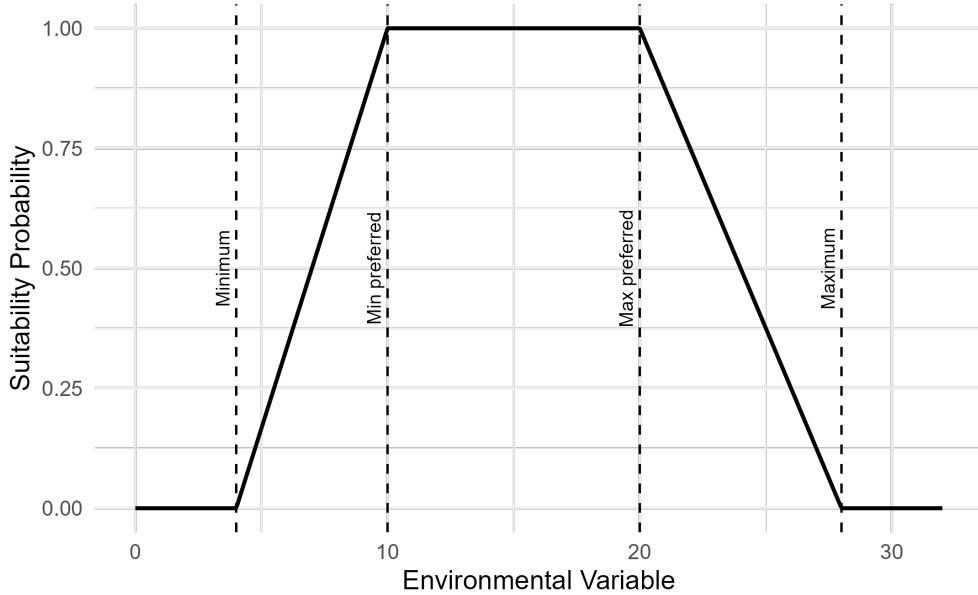
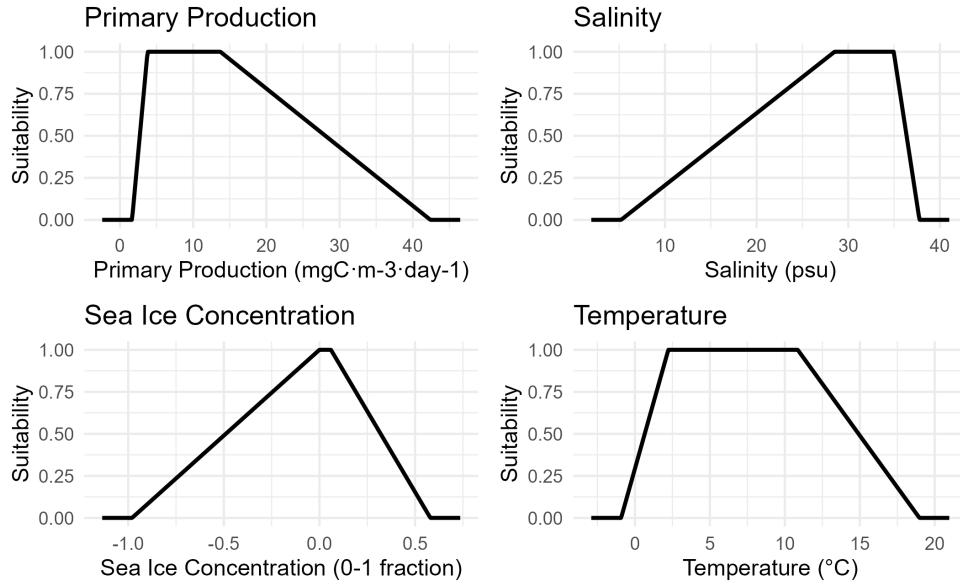


Figure 50 shows the four environmental envelopes used for Atlantic Halibut.

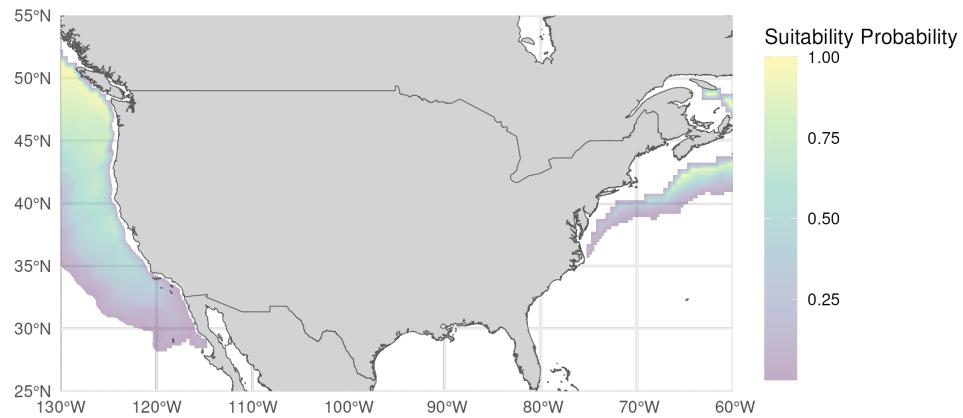
Figure 50: Environmental Envelopes for Atlantic Halibut



With all of the relevant environmental envelopes, I then create an annual raster of habitat suitability based on annual rasters of each environmental variable. Sea Surface temperatures come from NOAA, Depth (static) comes from AquaMaps, and the rest of the variables come from Bio-ORACLE (Assis et al., 2024). I then generate annual, global maps like in Figure 51. The figure shows the predicted suitability of each grid cell for Atlantic Halibut in 2020.

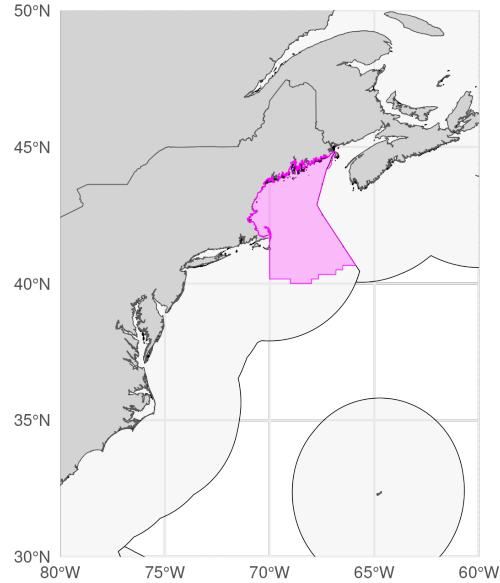
The predicted ranges are massive overpredictions—one can easily see it shows suitable ranges for Atlantic Halibut outside of the Atlantic.

Figure 51: Atlantic Halibut Suitability in 2020



To deal with the overprediction problem, I focus on habitat suitability in ranges around areas known to contain the species. Since my outcomes come from the RAM Stock Assessment Database, I use the relevant shapefiles for each stock as a starting place for determining the range of the stock. These shapefiles define the management area from the perspective of the fishery managers and, therefore, are generally nested in national boundaries. Figure 52 shows the shapefile for the US stock of Atlantic Halibut, found in the Gulf of Maine.

Figure 52: Shapefile for US Atlantic Halibut Stock



With the RAM shapefile, I then identify the relevant EEZ for management based on what EEZ shapefile most overlaps with the RAM shapefile. This lets me distinguish between the US East Coast and the US West Coast even if the RAM dataset would only tell me that the primary country is the US, for example. I also restrict my attention to the area around the RAM shapefile. First I create a raster identifying the shapefile and 300 nautical miles around it. The 300 nautical mile buffer ensures that at least some significant area falls outside of the managing country's EEZ. I then divide that large buffer region into two parts, the managed area and the unmanaged area. Figure 53 shows this for the US Atlantic Halibut stock. The blue area is the area that falls inside the US EEZ, whereas the red area is the area that falls outside. I focus my attention on variation in suitability found in this range.

Figure 53: Atlantic Halibut Management Areas

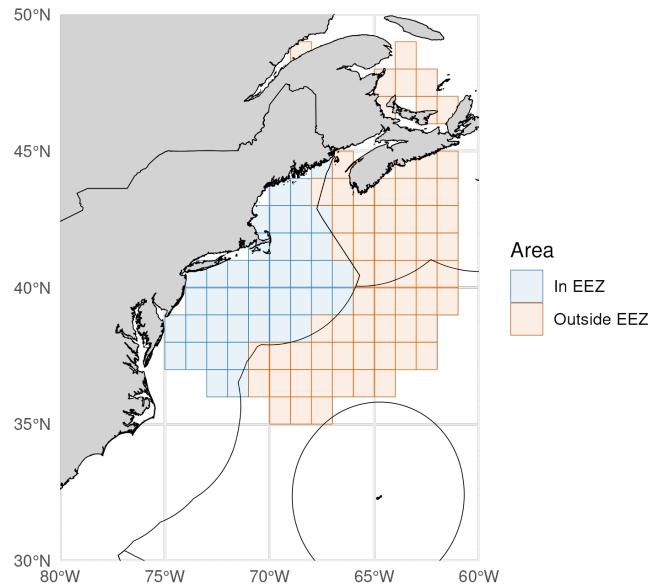
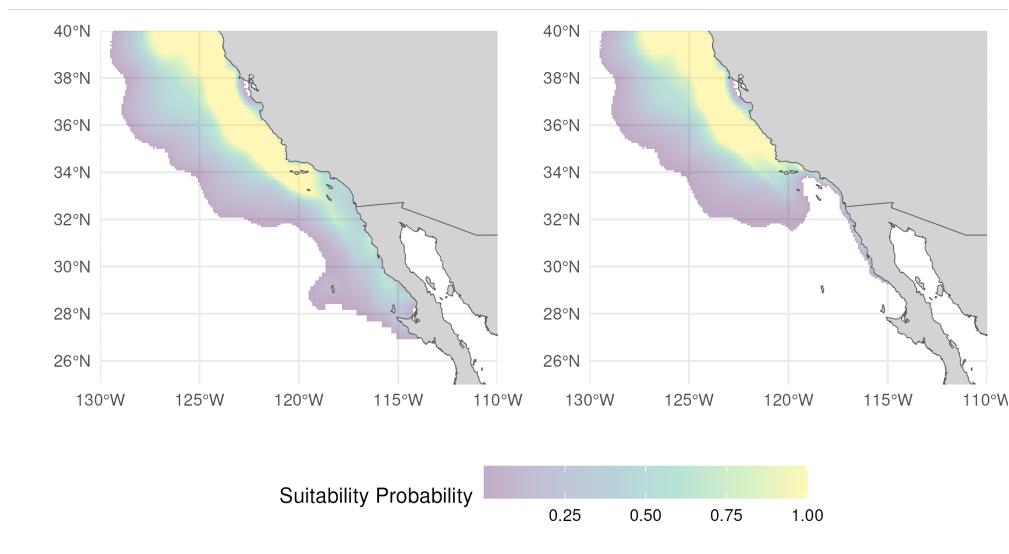


Figure 54 shows the predicted suitability for Atlantic Halibut in the area around the RAM shapefile for 2000 and 2050. Zooming in on this area where the species is known to be found highlights the actual anticipated effects of climate change. Comparison of the two maps shows a clear northward shift, with the suitability mass moving more into Canadian waters. This aligns with the scientific literature on the shift in the range of Atlantic halibut, which has identified movement from the US to Canada (Czich et al., 2023).

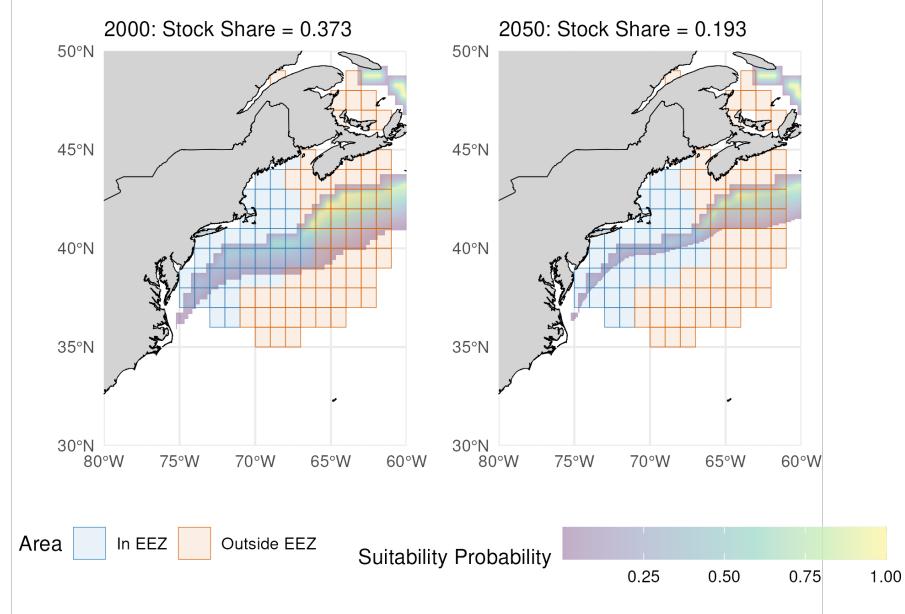
Figure 54: Atlantic Halibut Suitability in 2000 and 2050



Finally, I put the habitat suitability and the management areas together. Figure 55 shows

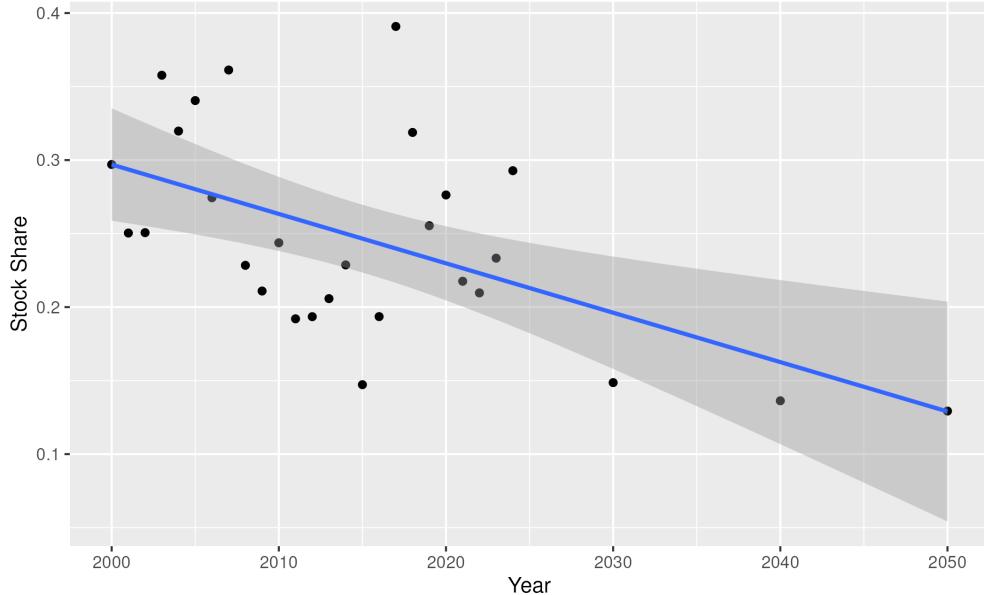
both the predicted suitability and the management areas for 2000 and 2050. To compute the stock share I then calculate the share of the total predicted suitability in the entire buffer area (the sum predicted suitability over red and blue grid cells) that falls inside the management area (just the blue grid cells). This gives a stock share of 0.380 in 2000 and a stock share of 0.197 in 2050, indicating that the share of the relevant stock that is found in the US's EEZ is predicted to decline significantly from its historic highs due to climate change.

Figure 55: Atlantic Halibut Management and Suitability



Repeating this process for every year between 2000 and 2024, and again for projections in 2030, 2040 and 2050, gives me a stock share variable I can add to my panel. It is variation in that variable within a given fishery that I use to identify the effect of the stock share on extraction outcomes. Figure 56 shows the calculated values for the US' Atlantic Halibut stock share for each year in my data. It shows a trend of declining stock share, with significant variation within the historic data.

Figure 56: US Atlantic Halibut Stock Share Over Time



## A.2 Stock Share Validation

In this section I discuss the empirical exercises I do to validate my measure of the stock share.

### A.2.1 State Variation

First, I construct a state-year level measure of suitability for each of the 168 species in the RAM stock assessment databases. I do this by combining the species-year environmental suitability rasters I generated (explained in Section 3) with a raster of the US EEZ matched to the nearest state. That gives me a grid cell level measure of suitability, which I can attribute to a specific state. For each state-species-year, I calculate the predicted suitable habitat for the species.

Second, I show that the predicted suitable habitat for the species predicts catch of that species in that state in that year. Figure 57 shows the relationship between the suitable range measure and catch in the cross section. Table 9 shows a regression of catch on suitable habitat, controlling for State-Species and Year fixed effects. It shows a statistically significant positive relationship with high explanatory power. I interpret this as favorable evidence that my suitability measure is predicting variation in the available biomass. State level evidence is nice for this, because it allows to use variation in suitability across areas that won't have a confounding behavioral response.

Figure 57: State Catch Vs Suitability

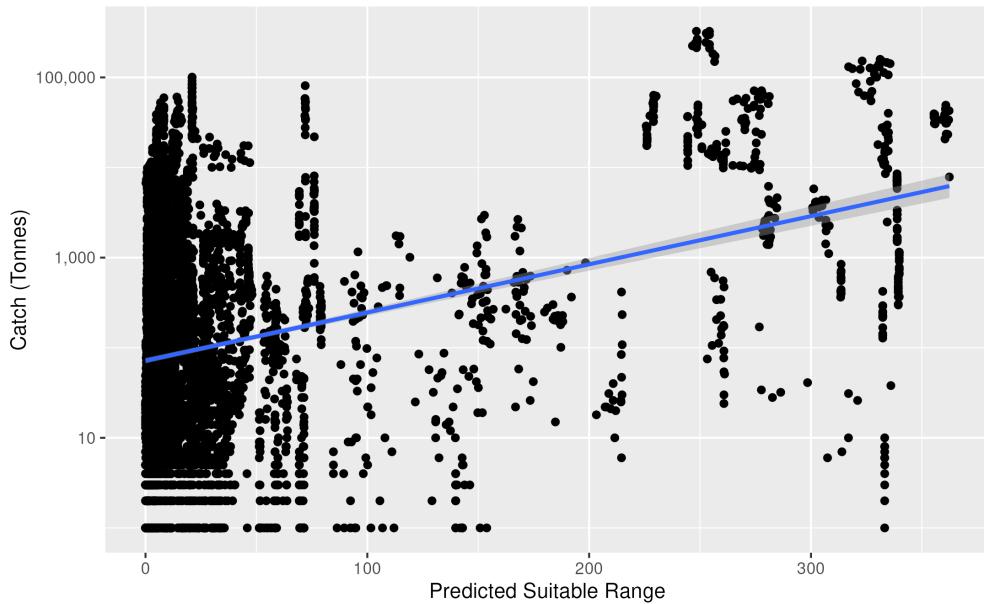


Table 9: Regressing State Catch on Suitability

| <i>Dependent variable:</i> |                       |
|----------------------------|-----------------------|
|                            | Catch (Tonnes)        |
| Suitable Habitat           | 54.902*<br>(29.450)   |
| State-Species FE           | Yes                   |
| Year FE                    | Yes                   |
| Observations               | 6,806                 |
| R <sup>2</sup>             | 0.930                 |
| Residual Std. Error        | 4,865.306 (df = 6364) |

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Results of regressing state-species-year level catch on estimated suitable habitat in the most proximate areas of the US Exclusive Economic Zone. Results show that my suitability proxy does predict variation in catch within-country, where preemptive and adversarial responses are less likely.

### A.2.2 Recruitment

My stock share measure is supposed to be an empirical proxy of  $\theta$  in my model from Section 2. In that model,  $\theta$  specifically captures what share of recruitment from period  $t$  escapement a country expects to receive in period  $t + 1$ . Therefore, another way of validating the stock share measure is to show that it predicts recruitment. In Table 10 I show the results of regressing normalized biomass on the lags of normalized escapement, stock share, and the interaction between the two. The table shows that a higher stock share leads to greater biomass next period, conditional on escapement, consistent with its theoretical role.

Table 10: Regressing Biomass on Lagged Escapement and Stock Share

| <i>Dependent variable:</i>       |                     |
|----------------------------------|---------------------|
| Normalized Biomass               |                     |
| Lag Norm. Escapement             | 0.696***<br>(0.020) |
| Lag Stock Share                  | 0.883***<br>(0.335) |
| Lag Stock Share×Norm. Escapement | -0.037<br>(0.036)   |
| Stock FE                         | Yes                 |
| Year FE                          | Yes                 |
| Observations                     | 4,558               |
| R <sup>2</sup>                   | 0.599               |

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Results of regressing biomass on lagged escapement and lagged stock share. Positive coefficient on lagged escapement confirms that higher escapement in the prior period increases current biomass. Positive coefficient on lagged stock share confirms that higher stock share in the prior period increases current biomass.

## B Robustness

### B.1 Additional Outcomes

Table 11: Log Panel Regressions

|                | <i>Dependent variable:</i> |                      |
|----------------|----------------------------|----------------------|
|                | Log Escapement             | Log Catch            |
|                | (1)                        | (2)                  |
| Stock Share    | 1.487**<br>(0.647)         | -3.312***<br>(0.985) |
| Log Biomass    |                            | 0.777***<br>(0.027)  |
| Stock FE       | Yes                        | Yes                  |
| Year FE        | Yes                        | Yes                  |
| Observations   | 4,884                      | 4,884                |
| R <sup>2</sup> | 0.001                      | 0.160                |

*Note:* \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Regression results for panel regressions using log(Escapement) and log(Catch) as outcomes for robustness. Regressions use stock and year fixed effects. Standard errors are clustered at the stock level. Sample years are 2000-2024. Results are consistent with my main specification, showing that higher stock shares increase escapement and decrease catch conditional on biomass.

Table 12: Other Heterogeneity Regressions

|                           | <i>Dependent variable:</i> |                     |                     |                       |                      |                      |                      |                      |                      |
|---------------------------|----------------------------|---------------------|---------------------|-----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                           | Norm. Escapement           |                     |                     | Norm. Extraction Rate |                      |                      | Norm. Catch          |                      |                      |
|                           | (1)                        | (2)                 | (3)                 | (4)                   | (5)                  | (6)                  | (7)                  | (8)                  | (9)                  |
| Stock Share               | 1.695***<br>(0.620)        | 1.611***<br>(0.566) | 1.714***<br>(0.574) | -3.022***<br>(0.831)  | -2.256***<br>(0.759) | -2.487***<br>(0.743) | -3.371***<br>(0.747) | -2.215***<br>(0.683) | -2.315***<br>(0.669) |
| Norm. Biomass             |                            |                     |                     |                       |                      |                      | 0.556***<br>(0.020)  | 0.556***<br>(0.020)  | 0.556***<br>(0.020)  |
| Stock Share×Multinational |                            |                     |                     |                       | 2.682<br>(1.843)     |                      |                      | 5.278***<br>(1.657)  |                      |
| Stock Share×Migratory     |                            |                     |                     |                       | -2.499<br>(2.745)    |                      |                      | -2.144<br>(3.311)    |                      |
| High Seas Share           |                            |                     |                     |                       | 0.189<br>(0.444)     |                      | -0.212<br>(0.583)    |                      | -0.306<br>(0.525)    |
| Stock Share×HS Share      |                            |                     |                     |                       | -4.100<br>(2.996)    |                      |                      |                      |                      |

|                | Yes   |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Stock FE       | Yes   |
| Year FE        | Yes   |
| Observations   | 4,884 | 4,884 | 4,884 | 4,875 | 4,875 | 4,875 | 4,884 | 4,884 | 4,884 |
| R <sup>2</sup> | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 | 0.002 | 0.152 | 0.150 | 0.150 |

*Note:*

\* p&lt;0.1; \*\* p&lt;0.05; \*\*\* p&lt;0.01

Regression results for additional heterogeneity regressions. Columns (1), (4) and (7) show results interacting the stock share with a stock-level indicator for multinational management. Columns (2), (5) and (8) show results interacting the stock share with a species-level indicator for highly migratory behavior. Columns (3), (6) and (9) show results interacting the stock share with the high seas share. None show any consistent difference between the baseline stock share effect and the effect on stocks with more multinational sharing.

Table 13: First Differences Regressions

|                        | <i>Dependent variable:</i> |                                |                      |
|------------------------|----------------------------|--------------------------------|----------------------|
|                        | $\Delta$ Norm. Escapement  | $\Delta$ Norm. Extraction Rate | $\Delta$ Norm. Catch |
|                        | (1)                        | (2)                            | (3)                  |
| $\Delta$ Stock Share   | 0.215<br>(0.366)           | -2.297***<br>(0.709)           | -1.677***<br>(0.648) |
| $\Delta$ Norm. Biomass |                            |                                | 0.347***<br>(0.031)  |
| Constant               | 0.002<br>(0.004)           | -0.034***<br>(0.008)           | -0.030***<br>(0.007) |
| Observations           | 4,232                      | 4,225                          | 4,232                |
| R <sup>2</sup>         | 0.0001                     | 0.002                          | 0.029                |

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Regression results for first difference regressions of changes in outcomes on changes in the stock share. Standard errors are clustered at the stock level. Sample years are 2000-2024. Results are generally consistent with my main specification, with columns (2) and (3) showing that increases in the stock share cause decreases in the extraction rate and catch conditional on biomass. Column (1) shows a positive, but statistically insignificant coefficient. Its sign is consistent with my main results.

Table 14: Trends-on-Trends Regressions

|                   | <i>Dependent variable:</i> |                              |                      |
|-------------------|----------------------------|------------------------------|----------------------|
|                   | Escapement Trend<br>(1)    | Extraction Rate Trend<br>(2) | Catch Trend<br>(3)   |
| Stock Share Trend | 1.101*<br>(0.590)          | -3.179***<br>(0.969)         | -2.369***<br>(0.875) |
| Biomass Trend     |                            |                              | 0.574***<br>(0.028)  |
| Stock FE          | Yes                        | Yes                          | Yes                  |
| Year FE           | Yes                        | Yes                          | Yes                  |
| Observations      | 3,587                      | 3,582                        | 3,587                |
| R <sup>2</sup>    | 0.001                      | 0.003                        | 0.112                |

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Regression results for regressions of trends in outcomes on trends in the stock share. Regressions use stock and year fixed effects. Sample years are 2000-2024. Results are generally consistent with my main specification, showing that an increasing trend in the stock share causes an increasing trend in escapement, and decreasing trends in the extraction rate and catch conditional on biomass.

## B.2 Alternative Buffer Distances

Figure 58: Escapement on Stock Share with Various Buffer Distances

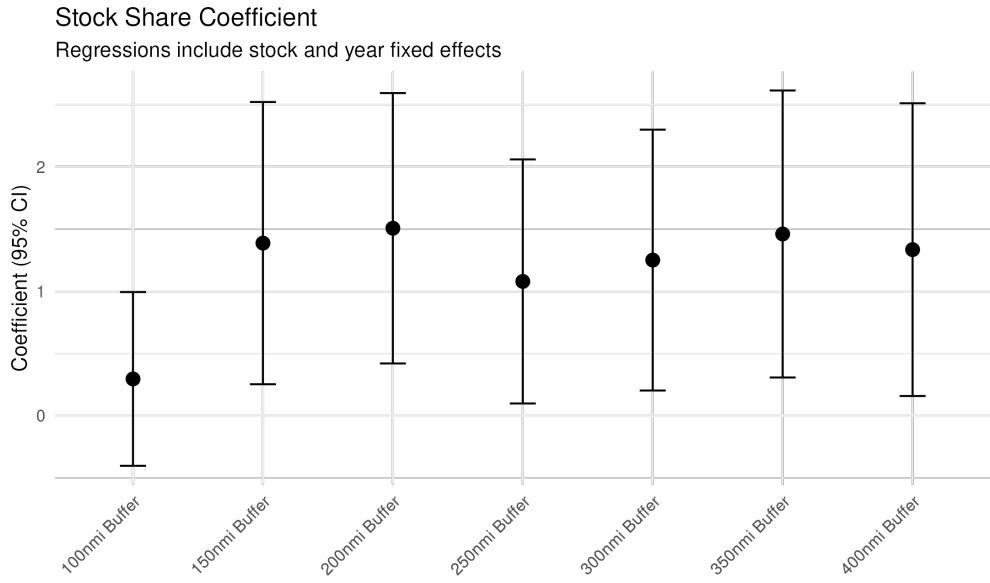


Figure 59: Extraction Rate on Stock Share with Various Buffer Distances

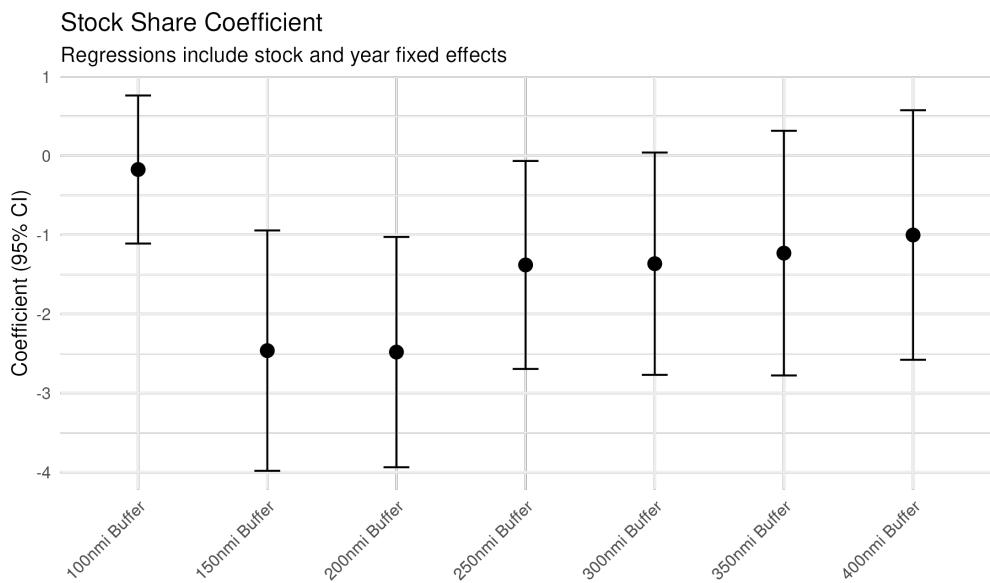
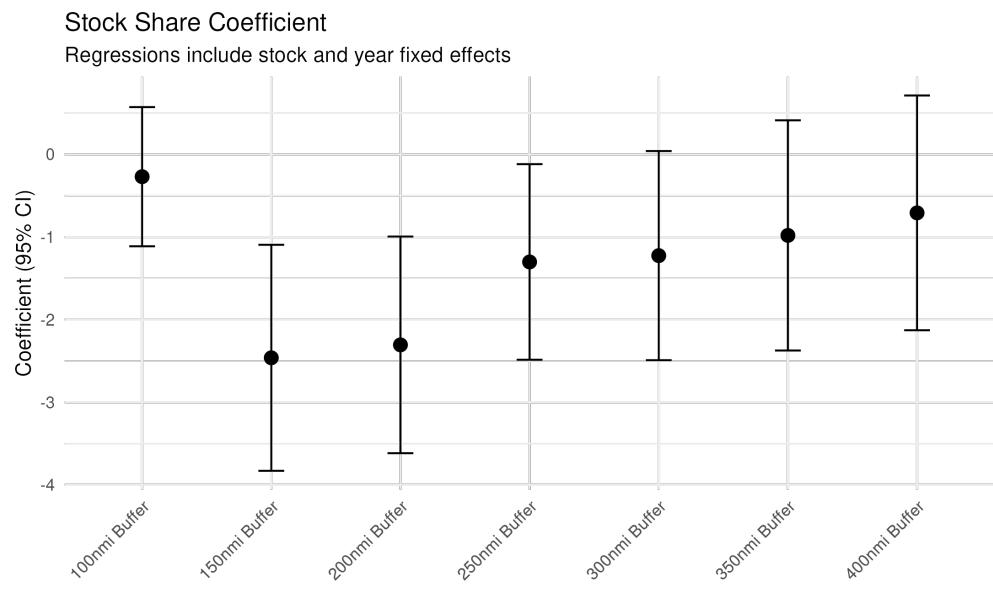


Figure 60: Catch on Stock Share with Various Buffer Distances



## C Climate Scenarios

In this section I present differing results by climate scenario, for three different Shared Socioeconomic Pathways (SSPs): SSP1-1.9, SSP2-4.5, and SSP5-8.5. These scenarios combine socioeconomic narratives with greenhouse gas emissions trajectories, designed to facilitate integrated assessment and climate model projections (O'Neill et al., 2014). For example, SSP1-1.9 depicts a world where rapid decarbonization limits warming to around 1.5 °C by 2100. SSP2-4.5 represents a “middle-of-the-road” pathway, where socioeconomic and technological trends broadly follow historical patterns, leading to intermediate forcing levels and warming of roughly 2–3 °C. The baseline results I show in the paper come from SSP2-4.5. Finally, SSP5-8.5 assumes rapid fossil-fueled development with limited climate policy, yielding very high end-of-century forcing and warming outcomes. These scenarios thus differ in their socioeconomic assumptions, emissions pathways, and associated climate outcomes. For my purposes, I take the environmental projections associated with each scenario from Bio-ORACLE (Assis et al., 2024). I use the environmental projections to predict the effects of climate change on each fishery’s stock share in that scenario.

The most notable result of this climate scenario analysis is that the general pattern of results does not depend on the specifics of the climate scenario. In the relatively less warming scenario, SSP1-1.9, the predictions are similar to the more extreme scenario, SSP5-8.5, but simply more muted. Places predicted to lose stock share still lose, just less dramatically, and all of the follow on effects of that are dampened. This follows naturally from the effects of climate on the stock share in the different scenarios: Figure 61 shows the distribution of changes in stock shares in each scenario. It shows the same general shape (centered around zero with wide tails) for each scenario, with wider and flatter distributions as the scenarios involve more warming.

Figure 61: Stock Share Changes by Scenario

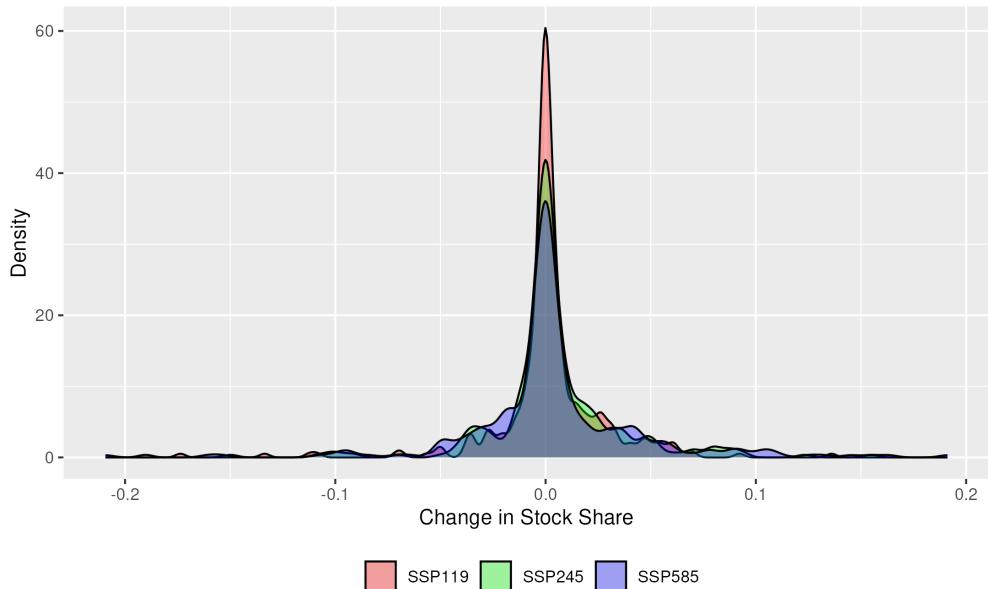


Figure 62: Total Change in Escapement by EEZ Under SSP119

2050 Prediction Under SSP119

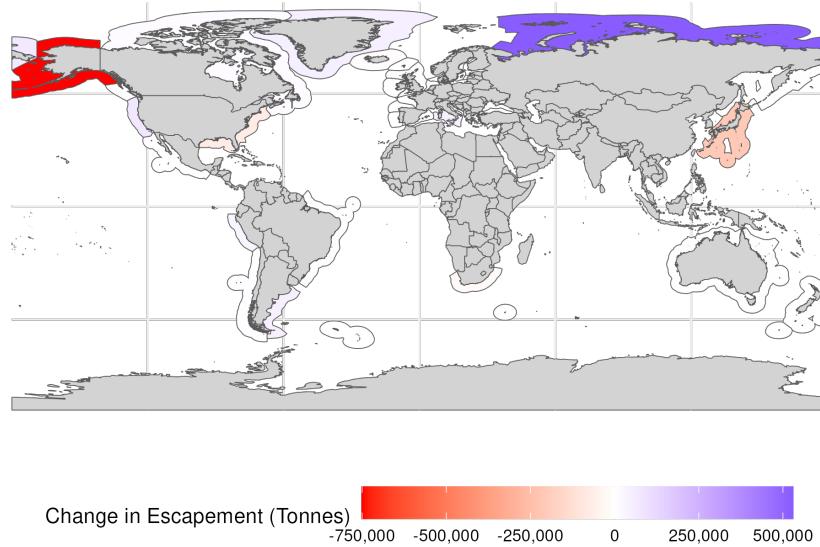


Figure 63: Percent Change in Escapement by EEZ Under SSP119

2050 Prediction Under SSP119

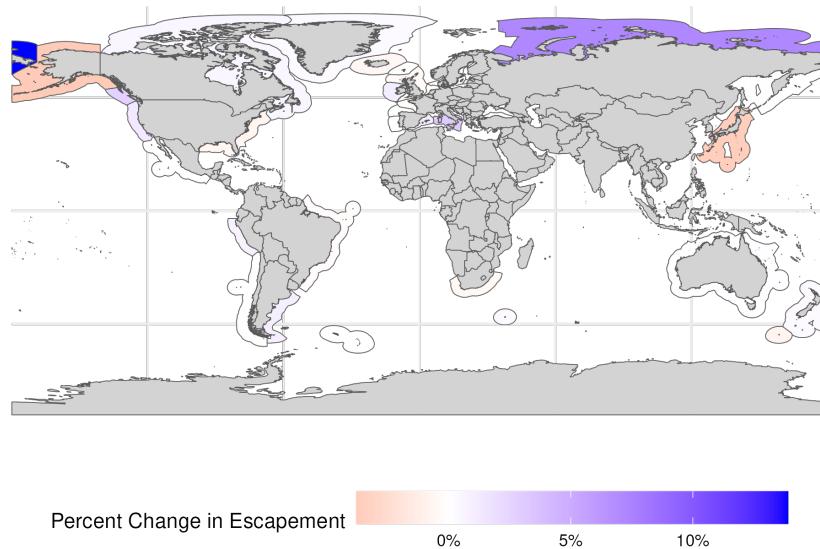
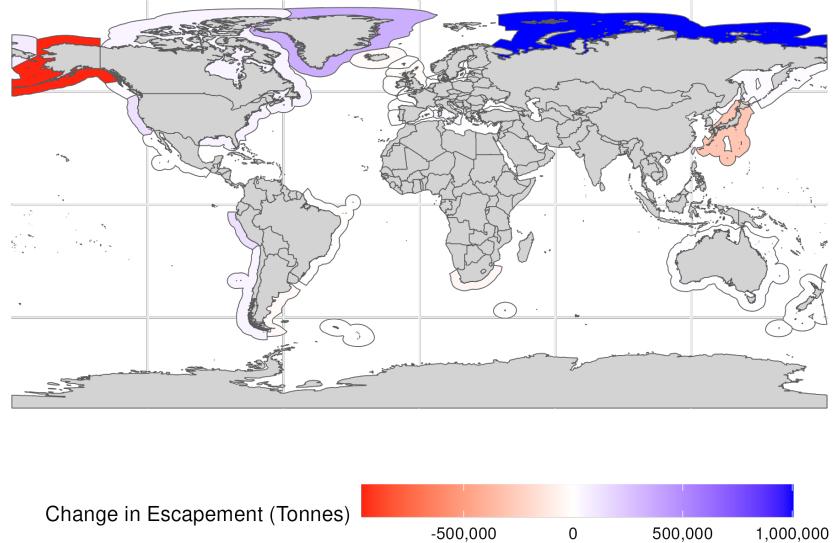


Figure 64: Total Change in Escapement by EEZ Under SSP585

2050 Prediction Under SSP585

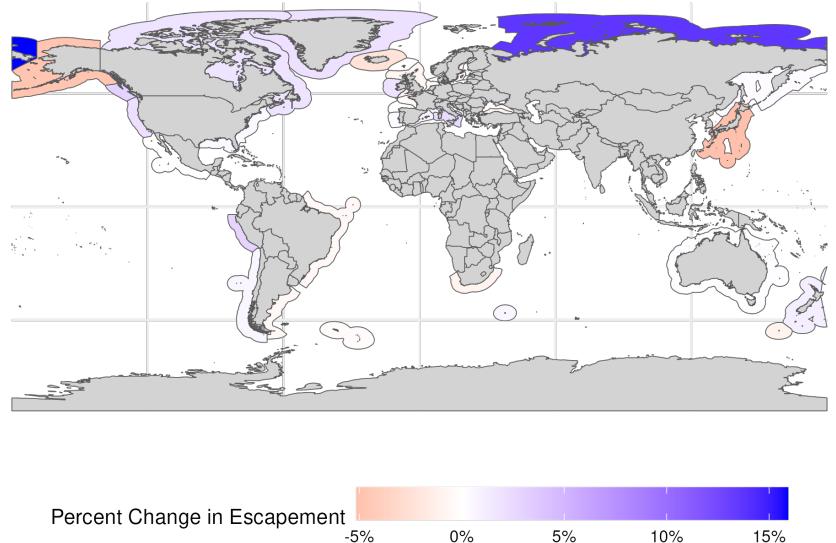


Change in Escapement (Tonnes)

-500,000 0 500,000 1,000,000

Figure 65: Percent Change in Escapement by Under SSP585

2050 Prediction Under SSP585



Percent Change in Escapement

-5% 0% 5% 10% 15%