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 fish populations span country borders, diluting the incentive for governments to conserve. Climate change will upend the current equilibrium by directly affecting fisheries productivity and by altering the distribution of fish populations as they migrate towards more favorable environments. The later effect could lead to maladaptive overexploitation by stock-losers as it weakens incentives for conservation, but could also increase conservation by stock-gainers. I construct a panel of fishery ranges and show this strategic response in historical data: country-level extraction rates rise as the share of a stock controlled by that country falls, consistent with the theory that controlling a smaller share of a stock reduces incentives for conservation. I then simulate the effects of future climate change on fish ranges and extraction. The strategic response to climate change is close to zero on net, but economically meaningful for individual fisheries: 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 fishery, the strategic response comprises 25% of the total effect of climate change on the fish stock. I also simulate fisheries outcomes under global cooperative management, and find an 87 million ton (77%) increase in escapement. In a more plausible scenario of US-Canada cooperation, escapement increases by 14% and the effects of climate change are 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? At least 67% of commercially valuable fish populations cross two or more Exclusive Economic Zones, and 45% of those are projected to experience significant shifts in habitat due to climate change (Palacios-Abrantes et al., 2020a, 2022). Climate change induced range shifts could alter incentives for conservation.[1] On one hand, range shifts could induce strategic overfishing, move stocks into countries with worse management (see Figure 1), or even move stocks into the internationally open-access high seas.[2] 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).[3]

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 percentage point decrease in the share of a stock under a country's control decreases **escapement** (the quantity of available biomass *not* caught) by 1.5%. 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 and losers. Countries gaining control of the stock will respond by increasing escapement

[1] 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). Fish populations are generally predicted to shift 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; Wernberg et al., 2016; 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). The effects of range shift are even detectable in catch data (Cheung et al., 2013).

[2] Several papers discuss 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.

[3] 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.

by 2.6%, whereas areas losing control of the stock will decrease escapement by 3%. These effects are on the same order of magnitude as the historic effects of warming on fisheries productivity.[4] Naturally, the biophysical effects of climate change are also significant.[5] 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 build a theoretical 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 stock management 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, which I call the **country share**. 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 test these predictions against data and document the relationship between fish stock ranges and extraction from the fishery. I employ the RAM Legacy Stock Assessment Database, a collection of stock assessment results for many of the world's most important fisheries with high-quality stock assessment results (Ricard et al., 2012; RAM, 2024). I identify stocks with data on catch and biomass after 2000, and create an unbalanced panel of these for all available years between 2000 and 2024. All together, there are 326 stocks, representing 168 unique species, from 44 countries. Figure 4 illustrates stocks by country. It

[4] Oceanic warming has decreased fisheries yields by 4.1% from 1930 to 2010 (Free et al., 2019).

[5] 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.

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. For each stock, I identify the designated management region 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). These form the outcomes of my analysis, as predicted by my model.

I combine these outcomes with a panel measure of the share of each population under the manager's control. For each species in the panel, I identify its suitable environmental conditions along 6 environmental variables from AquaMaps (Kaschner et al., 2019): Temperature, Salinity, Dissolved Oxygen, Primary Productivity, Sea Ice Concentration, and Depth.[6] I then use cell-by-year measures of those environmental variables from NOAA and Bio-ORACLE to create annual predictions of suitable ranges (Assis et al., 2024). For each stock in each year, I calculate the suitable area within a 200 nautical mile buffer of the stock shapefile, which identifies the boundary of the stock from the perspective of the managing country.[7] I then find how much of the total suitable area in the buffer falls within the Exclusive Economic Zone of the managing country, and use that as a proxy for the country share. This proxy uses exogenous variation in environmental conditions to identify variation in stock control, and implicitly assumes that fish populations are distributed proportional to suitability within the buffer around their known habitat.

My main empirical contribution is to estimate the effect of the country share on extraction. I use normalized escapement, extraction rate, and catch as my primary outcomes. In

[6]These predictions are imperfect proxies of true habitat ranges, as the AquaMaps method does not account for other factors that could affect the presence of a species (e.g. predator/prey relationships, contiguity, etc). Environmental suitability is also not a perfect measure of species abundance–while I observe the biomass of a species *within* the management area from the RAM database, I do not observe the biomass outside of the management area and cannot base my measure of stock control on that. Nevertheless, the AquaMaps method has been empirically validated as a predictor of population distributions (Ready et al., 2010). Furthermore, the variables that predict suitability are exogenous with respect to fisheries management, as they are purely based on oceanic environmental conditions, whereas range predictions based on catch would be confounded by the exact incentives studied here. Therefore, I view my suitability measure as an exogenous shifter of the realized distribution of the fish population.

[7]A 200 nautical mile buffer ensures that I capture variation in suitability that includes areas outside of the managing country's EEZ.

the cross section, my proxy for the country share is negatively correlated with the extraction rate and catch conditional on biomass and positively correlated with escapement conditional on biomass. In my primary specification, I regress these on my proxy for the country share, controlling for stock and year fixed effects to isolate year-to-year variation in the country share distinct from common shocks to all fisheries in a year or time-invariant features of a fishery. The regression results show that the country share has a significant effect on extraction: a one percentage point decrease in the country share decreases escapement by 1.5%, increases the extraction rate by 2.5%, and increases catch conditional on biomass by 2.3% of their respective averages. The same pattern of results holds for alternative specifications, including first differences, long differences, and trends-on-trends regressions. I also investigate heterogeneity by several characteristics, and find that these strategic responses are strongest under more effective management regimes and appear unaffected by indicators of multinational management.

Finally, I employ my estimated empirical model to simulate fisheries outcomes under several counterfactual environmental and institutional scenarios. First, I predict future fisheries outcomes under climate change. I begin by creating predicted suitability distributions following the same AquaMaps methodology, based on predicted oceanic environmental conditions under various Shared Socioeconomic Pathways (Riahi et al., 2017). I then recompute the country shares, and find that the predicted changes in country shares range from large decreases (-0.19) to large increases (+0.16). However, the vast majority of changes are clustered around zero. The implied effects on escapement range from 29% reductions to 23% increases, though for most stocks the predicted changes are small. While the average effect is small, gross gains and losses are meaningful relative to the historic effects of warming. A majority of EEZs with stocks in my sample are predicted to be property rights winners under climate change, including Russia and Canada.[8] Not all northern EEZs are expected to benefit, however: I predict loses in Alaska, Iceland, and Japan. On net, total escape-

[8]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.

ment is predicted to increase when accounting only for the behavioral response to range shift. I compare these results to the biophysical effects of climate change, where I draw on the Basin Model Hypothesis from MacCall (1990) to predict the future carrying capacity of each species. I follow Gaines et al. (2018) and other papers in the scientific literature in assuming that the carrying capacity of each species will change proportionally with its total suitable range predicted by AquaMaps. I combine the changes in incentives and carrying capacity to estimate a combined effect of climate change, which predicts a 20% increase in escapement and biomass for the average stock. However, omitting the behavioral response to range shift (i.e. projecting future escapement using only the biophysical channel) leads to a 27% misstatement of the combined effect of climate change, for the average stock.

My second counterfactual predicts the impacts of institutional reform by estimating the global gains from collaborative management, assuming every country manages their fisheries consistent with the global optimum. Specifically, I simulate what escapement would be if every country set fisheries policy as if all country shares for all stocks were 1. In that scenario, I find that escapement from the average stock increases by 67% on average. Global escapement from fisheries in my sample increases by 87 million tonnes (77%), since some of the largest fisheries have greater than average improvements in management. In total, the effects of the static transboundary problem is significantly larger than the effects of climate change I estimate in the previous counterfactual. However, under a simulation of a perfect bilateral agreement between the US and Canada, where each country agrees to fully internalize the territory of their neighbor but nothing more, I find that escapement would only increase by 14% from fisheries in those countries. This implies bilateral agreements are far from sufficient to address the global common-pool problem in fisheries.

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 *mal*adaptation. There is a long and growing literature on adaptation to climate, much of which has focused on food systems.[9] The literature views adaptation in these contexts as mitigating the harm for a given scale or frequency of climate change stressor.[10] In my setting that need not be the case–the privately optimal response to range shift could amplify the impacts of the climate change stressor, at least in certain fisheries. Another strand of literature looks at specific adaptive strategies.[11] I look at a particular *mal*adaptive strategy, that both involves endogenous 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.[12] Another strand of literature studies how fishing strategies respond to climate shocks.[13] This paper advances the econometric literature on fisheries adaptation to include the empirically estimated response of fisheries management to climate shocks.

[9] Burke and Emerick (2016) is a notable 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.

[10] 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).

[11] Guo and Costello (2013) looks at value of adaptation on different margins in forestry. 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 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.

[12] 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.

[13] 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. 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.

This paper also contributes to a long literature on the cross jurisdictional management of spillover externalities.[14] This literature has historically exploited variation in jurisdictional coverage to estimate how outcomes respond to management incentives. My paper contributes a new angle to this literature by exploiting variation in the nature of spillovers holding jurisdictional claims fixed.[15] Finally, this paper contributes to the related literature on property rights security and common pool resources.[16] The most similar paper to this one is Liu and Molina (2021), 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 transboundary 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,[17] 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 a fish stock that falls within an EEZ as a proxy for property rights security in an international context. In contrast, this paper takes a dynamic view of property rights security and exploits within fishery variation in the share inside a given EEZ.[18] While my

[14]Lipscomb and Mobarak (2017), perhaps the canonical paper in this literature, 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.

[15]These kinds of species and ecosystem shifts are not unique to fisheries (Pecl et al., 2017).

[16]Although this literature arguably traces back to Gordon (1954) or even before, the most relevant literature begins with Gordon Munro's work on international sharing of fish stocks (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, 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.

[17]See, for example, Costello et al. (2008) and Isaksen and Richter (2019).

[18]Other papers in this literature, such as Costello and Grainger (2018), are conceptually similar in their treatment of the fishery manager as a partially captured regulator who advances the interests of fishermen given their property rights. However, I study property rights security in an international sense rather than as a feature of domestic regulation.

analysis focuses on the global governance of fisheries, this paper also has implications for domestic regulations. In particular, it suggests Territorial Use Rights Fisheries (TURFs), where associations of fishermen are given property rights over a certain area, will be less effective for fisheries subject to range shift[19], and it provides some empirical support for the "blue paradox", where anticipation of conservation causes overfishing.[20]

Methodologically, I contribute to the growing literature using biological and ecological methods in economics. In particular, a subset of that literature has made great use of habitat suitability models to proxy for the presence of a species.[21] The typical approach in this literature has been to treat suitability as static in a given location and use variation in that suitability and/or its interaction with a treatment variable to make inferences about the effects of ecological phenomena. I extend this approach by creating a panel dataset of suitability for 168 different species, exploiting variation in suitability within a given location.

The rest of the paper is organized as follows: Section 2 presents a model of fisheries extraction as a function of the share of a fish population under the jurisdiction of the fishery manager (the country share). Section 3 describes the data I use to empirically validate the model, with special attention to how I construct my measure of the country 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.

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[19] 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.

[20] There is a small, contested literature on the "blue paradox": 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. While my paper does not deal with marine reserves specifically, the economics of spatial closure and spatial spillovers lead to similar incentives (Kaffine and Costello, 2011).

[21] See, for example, Alsan (2015); Flückiger and Ludwig (2020); Taylor (2020); Druckenmiller (2020); Frank and Sudarshan (2024); Frank (2024); Frank et al. (2025)

2 Theory

This section presents a model where a country decides how to extract from a fish stock that is shared with another country.[22] Each country controls the harvest from the population of fish within its own territory.[23] 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:

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

where $G(\cdot)$ is a common growth function with $G'(\cdot) > 0$ and $G''(\cdot) < 0$ and 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 δ.

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

[22] 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).

[23] 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.

This yields the following Bellman equation:

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

The Bellman equation yields the following First Order Condition:

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

The envelope conditions are the following:

$$V_{i,t_{X_i}} = \delta G'(S_{i,t}) \left[\theta_{i,t} V_{i,t+1_{X_i}} + (1-\theta_{i,t}) V_{i,t+1_{X_j}} \right] \tag{5}$$

$$V_{i,t_{X_j}} = \delta G'(S_{j,t}) \left[(1-\theta_{j,t}) V_{i,t+1_{X_i}} + \theta_{j,t} V_{i,t+1_{X_j}} \right] \tag{6}$$

Combining the first order equation and the first envelope condition, we can retrieve that $V_{i,t_{X_i}} = \tilde{p}$. The value of $V_{i,t_{X_j}}$ depends on whether the biomass of the country j' is large enough in period t: if $X_{j,t} > S^*_{j,t}$, then $V_{i,t_{X_j}} = 0$, since the optimal strategy of the country j is to fish its biomass down to the same escapement target regardless of the initial endowment, and so any marginal increase in $X_{j,t+1}$ has no effect on the continuation value of i. This is the relevant case for my empirics, as I do not observe zero catch in my data.[24] Therefore assume $X_{j,t} > S^*_{j,t}$ so that $V_{i,t_{X_j}} = 0$ along the path.

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

$$\theta_{i,t} G'(S^*_{i,t}) = \frac{1}{\delta} \tag{7}$$

This is the familiar "fundamental equation of renewable resources," stating that escapement should equalize the marginal return to fisheries productivity with the marginal return

[24] Without this assumption, the optimal escapement in each period is a slightly more complicated function which tracks both continuation values, but is still increasing in $\theta_{i,t}$ *ceteris paribus*.

to present catch, and does not depend on prices or costs due to the constant marginal profits assumption.

Then the Harvest function is given by

$$H_{i,t}^* = \begin{cases} 0 & \text{if } X_{i,t} \in [0, S_{i,t}^*] \\ X_{i,t} - S_{i,t}^* & \text{if } X_{i,t} > S_{i,t}^* \end{cases} \tag{8}$$

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.[25]

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:

$$ER_{i,t}^* = \begin{cases} 0 & \text{if } X_{i,t} \in [0, S_{i,t}^*] \\ \frac{X_{i,t} - S_{i,t}^*}{X_i} & \text{if } X_{i,t} > S_{i,t}^* \end{cases} \tag{9}$$

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

$$G'(S_{i,t}^*) = \frac{1}{\delta\theta_{i,t}} \tag{10}$$

$$H_{i,t}^* = \theta_{i,t} G(S_i^*) + (1 - \theta_{j,t}) G(S_j^*) - S_{i,t}^* \tag{11}$$

$$ER_{i,t}^* = 1 - \frac{S_i^*}{X_i^*} \tag{12}$$

From here we can derive the first proposition:

Proposition 1 *A lower stock share θ_i implies a lower privately optimal escapement S_i^* and biomass X_i^*, a higher harvest H_i^* conditional on biomass, and an unconditionally higher extraction rate ER_i^*.*

Equation 10 implicitly defines the optimal stock, and reveals that it is increasing in the

[25]Since country j's optimal harvest function takes the same form, country i does not internalize any changes to X_j it makes if $X_j > S_j^*$–these will simply be captured in full by country j.

stock share θ_i because the growth function $G()$ is increasing in X. Equation 8 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 9 and 12 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 loses in the non-cooperative equilibrium.

In a cooperative equilibrium, each country would set

$$G'(S_i^o) = \frac{1}{\delta} \tag{13}$$

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 (Ricard et al., 2012). These measurements apply to a specific managed population of a certain species (for example, Arrowtooth Flounder found in the Gulf of Alaska). I extract the latest available dataset, which includes data until 2024 (RAM, 2024). 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 *Sebastes 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 Country 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 200 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. 200 nautical miles is large relative to the average shapefile size, so this likely results in an overestimated area in consideration. However, 200 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 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). I use Marine Regions to get the shapefile for each EEZ (Claus et al., 2014). 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 country 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.[26] In the case of the Greenstriped Rockfish, the

[26]Figure 12 shows the cross sectional relationship between my country share measure and the extraction rate, and shows that higher country share is correlated with a lower extraction rate.

northward shift of the suitable range of the species between 2000 and 2050 implies that the country 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 country share.

My final dataset is an administrative stock-by-year panel with the catch, biomass and extraction rate as well as the country 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 country 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 country 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 country 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 country share and fisheries extraction. Section 3 described how I construct the country share proxy. Section 2 provided the main theoretical predictions that I will test in this paper, namely that a higher country share leads to lower escapement, a higher extraction rate, and higher catch conditional on biomass.

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 country share is higher. This prediction comes from the manager's optimality condition equation and is the reason the optimal stock is lower when the country share is lower. To deal with differences in the measurement of biomass across stocks, I calculate the normalized escapement in each year, by dividing 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 also include the extraction rate and catch as outcomes. There, I test the theoretical prediction that the extraction rate will be higher when the country share is lower, and the prediction that catch *conditional on biomass* will be higher when the country share is lower. Therefore, I include biomass as a control in all regressions with catch as an outcome. These additional outcomes help account for possible confounders, like the possibility that escapement increases with the stock share simply due to more available biomass. With the extraction rate outcome I show that the *share* of available biomass caught changes, ruling out proportional changes. I also rule out the possibility of a constant catch rule by using catch as an outcome. Like with escapement, I calculate the normalized values of these outcomes by dividing each observation by the stock-level average.

My empirical strategy is to regress my outcomes on the country share, including 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. In the case of catch regressions, I also include a control for biomass. My identification comes from year-to-year variation in the country share of a particular fishery, after removing shocks common to all fisheries within a year. The estimating equation is:

$$\text{Outcome}_{i,t} = \beta \text{Country Share}_{i,t} + \alpha \text{Biomass (in Catch regressions)} + \gamma_i + \lambda_t + \epsilon_{i,t} \quad (14)$$

where γ_i represents the stock fixed effects, λ_t represents the year fixed effects, $\epsilon_{i,t}$ is the error term, and β captures the effect of the country share on escapement. α captures the direct effect of biomass, which is only included in catch regressions. A one percentage point change in the country share implies a change in escapement of $\beta\%$ of the historic average. My model predicts that β should be positive when the outcome is escapement, and negative when the outcome is the extraction rate or catch.

4.1 Robustness

I include cross-sectional regressions to illustrate the cross sectional relationship between the country share and fisheries extraction. For example, Figure 12 shows the stock-level average extraction rate plotted against the average country share. For ease of comparison with different outcome measures, I also include a regression table using the main empirical strategy above, but using logs of the outcomes as 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 country 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 country share. In the case of catch as an outcome I also include the year-on-year change in biomass as a control. I run a similar design using long differences, where I compute the difference in the average outcome and average country share between 2000-2005 and 2015-2020, for each stock. This gives me a dataset of 266 long difference observations, which I use to run the same regressions. Appendix B includes regression tables for these specifications.

Finally, I also regress the trend in each outcome on the trend in the country 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 country share. In Appendix B I include a table of regression results for this specification.

4.2 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 country share. Specifically, I aim to understand whether the effects of the country share on conservation are affected by any of the following:

- **The quality of fisheries management**, as measured by the Environmental Performance Index or the use of Individual Transferable quota.

- **Degree of international sharing**, as measured by indicators for multinational management and highly migratory species, and a measure of the "high seas share."
- **Species growth rates**, as measured by the intrinsic growth rate parameter which does not depend on species biomass.
- **Country interest rates**, as measured by the country-year level lending interest rate.

In Appendix C I discuss specifics on how I generate each of these variables and incorporate them in regressions, and present results.

5 Results

Table 3 shows the cross sectional relationship between country share and my outcomes. Columns (1), (3), and (5), show the relationship between the stock level average country 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. For five of the six columns the coefficient of interest, that of the country share variable, is statistically significant, and in all cases it is directionally consistent with theory. These cross sectional regressions leverage variation in country shares across different stocks. The relatively small effect sizes reflect the fact that there is plenty of other variation in what drives extraction.

Table 4 shows the coefficients of interest for my main specifications. Column (1) shows the effect of the country 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 country share implies greater escapement. The magnitude of the coefficient is also quite large: it implies that if a management area where to increase its country share by 1, it's escapement would increase by 151% of its historic average. While this may seem implausibly large, it should be noted that the variation in country shares is quite small. The within-stock standard deviation in country 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 country shares under climate change are larger, but still not as large as a 1 unit change: The largest predicted gain in country 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 country 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 country share being 0.51, these results would imply that if every stock were managed as if the country 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 country share causes a lower extraction rate. Once again the effect sizes are large but plausible: a one standard deviation increase in the country 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 country 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 country share by 1, it's 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 country 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 Robustness

Table 9 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 country 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 country share on log catch, and is negative, consistent with my predictions.

The appendix includes an additional table of heterogeneity analysis. Table 14 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 country 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 country 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 country share depend on the width of the buffer area around the shapefile of the stock. Figures 67, 68, and 69 show the coefficient plots for escapement, extraction rate, and catch, respectively. As a general pattern, the larger buffer windows are 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 and long differences regressions. Table 10 shows the regression results for all three outcomes in first differences. The coefficients on country share are directionally consistent with the prior results, although it is not statistically significant for escapement as an outcome. Table 11 shows the results for the three outcomes in long differences. Escapement and the extraction rate show statistically significant results with the expected sign. The catch results show the expected sign but are statistically insignificant. Finally, the appendix includes the results of regressing trends in the outcome variables on trends in the country share, in order to confirm that the effects detected are consistent with changes in the climate and not just annual variation in weather. Table 12 shows the regression results, which are consistent in direction and statistical significance with my main results.

5.2 Heterogeneity

In Appendix C I discuss the results of regressions exploring heterogeneity by management quality, international sharing, growth rates, and interest rates. First, my results show that the effects of the country share are stronger for fisheries with more effective fisheries management, as measured by the fisheries management score from the Environmental Performance Index and indicators for the use of Individual Transferable Quota, which are considered the first-best form of management by most economists. This result is intuitive, as more effective management regimes will also be best positioned to recognize and respond to range shifts. However, this also suggests that improvements in management will not necessarily address the immediate impacts of climate change, as some have hoped (Gaines et al., 2018). Second, my results show little difference in the response to the country share for stocks with more international sharing, measured by multinational management indicators, species level migration indicators, or the "high seas share" I calculate along side my country shares. While this suggests existing multinational management arrangements have not helped respond to range shift, it also suggests range shift is not disproportionally more harmful for highly migratory species and/or species shifting to the high seas. Third, consistent with theory, I find that a higher intrinsic growth rate blunts the effect of the country share on fisheries extraction. However, I do not see the expected *amplification* of effects from higher interest rates.

6 Simulations

6.1 Climate Predictions

What do the results above imply for the effects of climate change? If changes in the country 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 country shares of different countries. In this section I predict the changes in country shares by 2050 and simulate what these would imply for global fisheries extraction.

My predictions of global country 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.[27] 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 D shows that results are effectively the same under 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 country 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 country share between the average

[27] While sea levels are predicted to rise in ways that are significant for coastal communities, these changes are small relative to ocean depths.

from 2000 to 2024 and the predicted country shares in 2050. An immediate conclusion of this plot is that the changes in country share are not predicted to occur disproportionately in one direction: while climate change is predicted to reduce some country shares, it is also predicted to increase others. In fact, the the mean change is predicted to be an increase of 0.003 (standard deviation: 0.03). The predicted changes in the country 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 D.

To evaluate the consequences for escapement, I calculate the implied change in escapement by 2050 using the change in the country 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.[28]

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. Unfortunately,

[28]This may be driven partially by the selection of stocks into 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).

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,[29] and has been used in many of the most sophisticated climate forecasts in fisheries.[30] 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 total 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.[31] Therefore, I first estimate the optimal escapement given the 2050 country share for each stock following the methods I describe above. Then I multiply it be 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 biophysical response. Figure 23 shows the distribution of climate change's effects on escapement for both the purely biophysical model and the combined model. Figure 24 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,

[29]See, for example, Southward et al. (1995); Atkinson et al. (1997); Simpson and Walsh (2004); Sullivan et al. (2006); Zador et al. (2011); Pennino et al. (2020).

[30]See, for example, Cheung et al. (2016); García Molinos et al. (2016); Gaines et al. (2018); Free et al. (2020); Sala et al. (2021)

[31]Letting $G(S) = S + rS\left(1 - \frac{S}{K}\right)$ gives optimal escapement $S^* = \frac{K}{2r}\left(1 + r - \frac{1}{\delta\theta}\right)$ where K is the carrying capacity.

although there is substantial heterogeneity across stocks. Figure 26 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. On net, escapement is predicted to increase by 20.3%. However, Figure 27 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. Furthermore, the general pattern of climate change increasing biomass may well be an artifact of my sample of relatively poleward, cold water stocks, which may stand to benefit from warming in the short-to-medium run.

While escapement is the primary outcome of interest in this paper due to its theoretical importance and empirical tractability, the most important fisheries outcomes for policy are biomass, catch, and catch values. Here, then, I take my results a step further to calculate the implied effects of climate change on these variables. In order to simulate future biomass, I use the empirical relationship between escapement in one period and biomass in the next. Figure 13 plots normalized biomass against lagged, normalized escapement; it shows a relatively strong, positive, and approximately linear relationship. To allow for some concavity in the growth function, I run a quadratic regression of normalized biomass on lagged normalized escapement, and use those regression results (found in Table 5) to turn escapement predictions into biomass predictions. These generally follow the predicted changes in escapement pretty closely. Figure 28 shows the predicted changes in biomass by EEZ due to the combined effects of climate change. Figure 29 shows the same for percent changes. Both show the same pattern of general increases. On net, biomass increases by 19.8% when accounting for the combined effect of climate change.

To predict catch in these future projections, I calculate catch as the difference between predicted biomass and predicted escapement, bounded below by zero. Figures 30 and 31 show the level and percent changes in catch at the EEZ level. Both show general increases, as expected from the increase in biomass. Overall I predict a 17.7% increase in catch from this approach. I also predict the value of catch, assuming that the price of each species does not change from its latest year in the Sea Around Us ex-vessel price database (Tai et al., 2017). Figures 32 and 33 show the level and percent change in catch value by EEZ. Like catch, they show large increases–catch value increases by 21.2% in my predictions. Again, it must be emphasized that these results don't necessarily apply to the totality of global fisheries, as my dataset covers only a subset of stocks representing around 26% of global catch.

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 country 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 country 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 34 shows the historic and hypothetical cooperative distributions escapement. Under hypothetical cooperation, escapement would be 86.7 million tonnes (76.4%) higher. Figure 35 shows the implications of higher escapement for biomass, using the empirical relationship between escapement and biomass in Figure 13. Table 5 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. Figure 35 shows a biomass distribution that has been shifted meaningfully to the right. Biomass in total would be 98.3 million tonnes (71.3%) tonnes higher.[32] Figures 36 plots the same comparison for catch, and also shows a large shift to the right in the distribution which amounts to an increase of 11 million tonnes in total.

Next, I explore the spatial heterogeneity of these effects. Figure 37 shows the total

[32]The effect on biomass is more muted than on escapement due to the curvature of the growth function.

change in escapement by EEZ, and Figure 38 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 country shares, such as the Mexican Pacific Coast, Brazil, and Greenland. Finally, Figures 39 and 40 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. Finally, Figures 42 and 44 show the percent changes in catch and catch values at the EEZ level. These show general increases, with select EEZ exhibiting enormous changes in percentage terms due to very small starting values. Figures 41 and 44 show changes in level terms. These maps show large increases in escapement and biomass, which become large increases in steady state catch. 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 avenues 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 country 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 country 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 country shares at the EEZ level in the baseline data (no cooperation). Figure 46 maps the change in effective country shares if the US and Canada were to adopt the cooperative agreement I describe. Figure 45 shows the stock level distribution of changes in effective country shares in this counterfactual.

What implications would such collaboration have on fisheries management? Figure 47 shows the stock level distribution of changes in escapement based on the changes in country share and the effect of the country share on escapement estimated above (see Table 4). Figure 48 shows the distribution of percent changes in escapement. Figures 49 and 50 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 51 and 52 map these changes in terms of biomass (in level and percentage terms, respectively), 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. Figures 54 and 56 map the percent changes in catch and catch value, respectively. They show that the same regions that increase escapement would also be predicted to decrease catch on net. However, these catch results do not account for the spillovers to neighboring regions, which are the motivation for the increased conservation to begin with.

Overall, my results imply that cooperation between the US and Canada would increase escapement by 5.44 million tonnes (14%) in total. Steady state biomass would in turn increase by 5.1 million tonnes (12%). Catch would barely decrease on average (-0.9%), but this result masks a large decrease in catch on the Pacific coast of Canada and in the New England region of the United States. The catch decreases come from highly valuable stocks, however, so catch value would decrease by 13.9%. These results apply only for the specific managed stocks in my dataset, however, so this does not account for the spillover benefits that are the real motivation for such cooperation. 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 57 plots the change in country share predicted under climate change against the hypothetical change in effective country 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 country 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 "country share" controlled: using panel variation in the country share, I show that a lower country share causes countries to catch more of the available biomass and decrease escapement. The effects are significant for reasonable variation in the country share: a 1 percentage point decrease in the country share causes a 1.5% decrease in escapement.

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 country shares on average, but there is significant heterogeneity across fisheries. Countries losing control of fish stocks are predicted to decrease their escapement by 3%, and countries gaining control are predicted to increase their escapement by 2.6%. For the average stock, the behavioral response to range-shift is approximately 25% of the total effect of climate change on fish populations.

References

Alsan, M. (2015). The Effect of the TseTse Fly on African Development. *American Economic Review*, 105(1):382–410.

Assis, J., Fernández Bejarano, S. J., Salazar, V. W., Schepers, L., Gouvêa, L., Fragkopoulou, E., Leclercq, F., Vanhoorne, B., Tyberghein, L., Serrão, E. A., Verbruggen, H., and De Clerck, O. (2024). Bio-ORACLE v3.0. Pushing marine data layers to the CMIP6 Earth System Models of climate change research. *Global Ecology and Biogeography*, 33(4):e13813. Publisher: John Wiley & Sons, Ltd.

Atkinson, D. B., Rose, G. A., Murphy, E. F., and Bishop, C. A. (1997). Distribution changes and abundance of northern cod (Gadus morhua), 19811993. *Canadian Journal of Fisheries and Aquatic Sciences*, 54(S1):132–138. Publisher: NRC Research Press.

Bank, W. (2025). Lending interest rate.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*, 124(1):105–159. Publisher: The University of Chicago Press.

Block, S., Emerson, J. W., Esty, D. C., de Sherbinin, A., and Wendling, Z. A. (2024). Environmental performance index. *New Haven, CT: Yale Center for Environmental Law & Policy*.

Bond, J. and McDorman, T. L. (2010). Canada's Pacific Fisheries Agreements: Halibut, Hake, Tuna, and Salmon Outside 200. In VanderZwaag, D. and Russell, D., editors, *Recasting transboundary fisheries management arrangements in light of sustainability principles : Canadian and international perspectives*, volume 8, pages 115–147. Brill, LEIDEN. Journal Abbreviation: LEG ASPEC SUS DEV.

Bradt, J. T. and Aldy, J. E. (2025). Private Benefits from Public Investment in Climate Adaptation and Resilience. *National Bureau of Economic Research Working Paper Series*, No. 33633.

Branch, T. A., DeJoseph, B. M., Ray, L. J., and Wagner, C. A. (2013). Impacts of ocean acidification on marine seafood. *Trends in Ecology & Evolution*, 28(3):178–186. Publisher: Elsevier.

Burke, M. and Emerick, K. (2016). Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.

Burke, M., Zahid, M., Martins, M. C. M., Callahan, C. W., Lee, R., Avirmed, T., Heft-Neal, S., Kiang, M., Hsiang, S. M., and Lobell, D. (2024). Are We Adapting to Climate Change? *National Bureau of Economic Research Working Paper Series*, No. 32985.

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., Rising, J., Rode, A., Seo, H. K., Viaene, A., Yuan, J., and Zhang, A. T. (2022). Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits*. *The Quarterly Journal of Economics*, 137(4):2037–2105.

Champion, C., Hobday, A. J., Zhang, X., and Coleman, M. A. (2022). Climate change alters the temporal persistence of coastal-pelagic fishes off eastern Australia. *ICES Journal of Marine Science*, 79(4):1083–1097.

Cheung, W. W., Jones, M. C., Reygondeau, G., Stock, C. A., Lam, V. W., and Frölicher,

T. L. (2016). Structural uncertainty in projecting global fisheries catches under climate change. *Ecological Modelling*, 325:57–66.

Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R., Zeller, D., and Pauly, D. (2010). Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. *Global Change Biology*, 16(1):24–35. Publisher: John Wiley & Sons, Ltd.

Cheung, W. W. L., Watson, R., and Pauly, D. (2013). Signature of ocean warming in global fisheries catch. *Nature*, 497(7449):365–368.

Claus, S., De Hauwere, N., Vanhoorne, B., Deckers, P., Souza Dias, F., Hernandez, F., and Mees, J. (2014). Marine Regions: Towards a Global Standard for Georeferenced Marine Names and Boundaries. *Marine Geodesy*, 37(2):99–125. Publisher: Taylor & Francis.

Cook, B. (2005). Lobster boat diplomacy: the Canada–US grey zone. *Marine Policy*, 29(5):385–390.

Costello, C. and Collie, S. (2025). Dynamic Climate Adaptation. *Working Paper*.

Costello, C., Gaines, S. D., and Lynham, J. (2008). Can Catch Shares Prevent Fisheries Collapse? *Science*, 321(5896):1678–1681. Publisher: American Association for the Advancement of Science.

Costello, C. and Grainger, C. A. (2018). Property Rights, Regulatory Capture, and Exploitation of Natural Resources. *Journal of the Association of Environmental and Resource Economists*, 5(2):441–479. Publisher: The University of Chicago Press.

Crear, D. P., Curtis, T. H., Hutt, C. P., and Lee, Y.-W. (2023). Climate-influenced shifts in a highly migratory species recreational fishery. *Fisheries Oceanography*, 32(4):327–340. Publisher: John Wiley & Sons, Ltd.

Crutchfield, J. A. and Zellner, A. (2002). *The economics of marine resources and conservation policy : the Pacific halibut case study with commentary*. Pacific halibut case study with commentary. University of Chicago Press, Chicago.

Cullis-Suzuki, S. and Pauly, D. (2010). Failing the high seas: A global evaluation of regional fisheries management organizations. *Marine Policy*, 34(5):1036–1042.

Czich, A. N., Stanley, R., Avery, T., den Heyer, C., and Shackell, N. (2023). Recent and projected climate change–induced expansion of Atlantic halibut in the Northwest Atlantic. *FACETS*, 8:1–14. Publisher: Canadian Science Publishing.

Dahms, C. and Killen, S. S. (2023). Temperature change effects on marine fish range shifts: A meta-analysis of ecological and methodological predictors. *Global Change Biology*, 29(16):4459–4479. Publisher: John Wiley & Sons, Ltd.

DeFilippo, L. B., Thorson, J. T., O'Leary, C. A., Kotwicki, S., Hoff, J., Ianelli, J. N., Kulik, V. V., and Punt, A. E. (2023). Characterizing dominant patterns of spatiotemporal variation for a transboundary groundfish assemblage. *Fisheries Oceanography*, 32(6):541–558. Publisher: John Wiley & Sons, Ltd.

Druckenmiller, H. (2020). Estimating an Economic and Social Value for Healthy Forests: Evidence from Tree Mortality in the American West. *Job Market Paper*.

Dulvy, N. K., Rogers, S. I., Jennings, S., Stelzenmüller, V., Dye, S. R., and Skjoldal, H. R. (2008). Climate change and deepening of the North Sea fish assemblage: a biotic indicator of warming seas. *Journal of Applied Ecology*, 45(4):1029–1039. Publisher: John Wiley & Sons, Ltd.

Englander, G. (2019). Property rights and the protection of global marine resources. *Nature*

Sustainability, 2(10):981–987.

Fabbri, G., Faggian, S., and Freni, G. (2024). On competition for spatially distributed resources in networks. *Theoretical Economics*, 19(2):743–781.

Fang, D., Chen, B., Hubacek, K., Ni, R., Chen, L., Feng, K., and Lin, J. (2019). Clean air for some: Unintended spillover effects of regional air pollution policies. *Science Advances*, 5(4):eaav4707. Publisher: American Association for the Advancement of Science.

Flückiger, M. and Ludwig, M. (2020). Malaria suitability, urbanization and subnational development in sub-Saharan Africa. *Journal of Urban Economics*, 120:103279.

Frank, E. and Sudarshan, A. (2024). The Social Costs of Keystone Species Collapse: Evidence from the Decline of Vultures in India. *American Economic Review*, 114(10):3007–40.

Frank, E. G. (2024). The economic impacts of ecosystem disruptions: Costs from substituting biological pest control. *Science*, 385(6713):eadg0344. Publisher: American Association for the Advancement of Science.

Frank, E. G., Wang, Q., Wang, S., Wang, X., and You, Y. (2025). Campaigning for Extinction: Eradication of Sparrows and the Great Famine in China. *National Bureau of Economic Research Working Paper Series*, No. 34087.

Frawley, T., Provost, M., Bellquist, L., Ben-Aderet, N., Blondin, H., Brodie, S., Buil, M. P., Jacox, M., Bograd, S. J., Hazen, E. L., McGonigal, H., and Ramey, K. (2025). A collaborative climate vulnerability assessment of California marine fishery species. *PLOS Climate*, 4(2):e0000574. Publisher: Public Library of Science.

Free, C. (2023). RAM Legacy Stock Boundary Database Guide.

Free, C. M., Mangin, T., Molinos, J. G., Ojea, E., Burden, M., Costello, C., and Gaines, S. D. (2020). Realistic fisheries management reforms could mitigate the impacts of climate change in most countries. *PLOS ONE*, 15(3):e0224347. Publisher: Public Library of Science.

Free, C. M., Thorson, J. T., Pinsky, M. L., Oken, K. L., Wiedenmann, J., and Jensen, O. P. (2019). Impacts of historical warming on marine fisheries production. *Science*, 363(6430):979–983. Publisher: American Association for the Advancement of Science.

Froese, R. and Pauly, D. (2025). FishBase.

Gaines, S. D., Costello, C., Owashi, B., Mangin, T., Bone, J., Molinos, J. G., Burden, M., Dennis, H., Halpern, B. S., Kappel, C. V., Kleisner, K. M., and Ovando, D. (2018). Improved fisheries management could offset many negative effects of climate change. *Science Advances*, 4(8):eaao1378. Publisher: American Association for the Advancement of Science.

García Molinos, J., Halpern, B., Schoeman, D., Brown, C., Kiessling, W., Moore, P., Pandolfi, J., Poloczanska, E., Richardson, A., and Burrows, M. (2016). Climate velocity and the future global redistribution of marine biodiversity. *Nature Climate Change*, 6(1):83–88.

Gordon, H. S. (1954). The Economic Theory of a Common-Property Resource: The Fishery. *Journal of Political Economy*, 62(2):124–142. Publisher: The University of Chicago Press.

Grainger, C. A. and Costello, C. J. (2014). Capitalizing property rights insecurity in natural resource assets. *Journal of Environmental Economics and Management*, 67(2):224–240.

Gullestad, P., Sundby, S., and Kjesbu, O. S. (2020). Management of transboundary and straddling fish stocks in the Northeast Atlantic in view of climate-induced shifts in spatial distribution. *Fish and Fisheries*, 21(5):1008–1026. Publisher: John Wiley & Sons, Ltd.

Guo, C. and Costello, C. (2013). The value of adaption: Climate change and timberland management. *Journal of Environmental Economics and Management*, 65(3):452–468.

Hanich, Q., Rotjan, R., Aqorau, T., Bailey, M., Campbell, B., Gray, N., Gruby, R., Hampton, J., Ota, Y., Parris, H., Reid, C., Sumaila, U. R., and Swartz, W. (2018). Unraveling the blue paradox: Incomplete analysis yields incorrect conclusions about Phoenix Islands Protected Area closure. *Proceedings of the National Academy of Sciences*, 115(52):E12122–E12123. Publisher: Proceedings of the National Academy of Sciences.

Hannesson, R. (2011). Game Theory and Fisheries. *Annual Review of Resource Economics*, 3(Volume 3, 2011):181–202. Publisher: Annual Reviews Type: Journal Article.

He, G., Wang, S., and Zhang, B. (2020). Watering Down Environmental Regulation in China*. *The Quarterly Journal of Economics*, 135(4):2135–2185.

Heo, S. W., Ito, K., and Kotamarthi, R. (2025). International Spillover Effects of Air Pollution: Evidence from Mortality and Health Data. *The Review of Economics and Statistics*, pages 1–45.

Heutel, G., Miller, N. H., and Molitor, D. (2021). Adaptation and the Mortality Effects of Temperature across U.S. Climate Regions. *The Review of Economics and Statistics*, 103(4):740–753.

Hodapp, D., Roca, I. T., Fiorentino, D., Garilao, C., Kaschner, K., Kesner-Reyes, K., Schneider, B., Segschneider, J., Kocsis, T., Kiessling, W., Brey, T., and Froese, R. (2023). Climate change disrupts core habitats of marine species. *Global Change Biology*, 29(12):3304–3317. Publisher: John Wiley & Sons, Ltd.

Hsiao, A., Moscona, J., and Sastry, K. A. (2024). Food Policy in a Warming World. *Working Paper*.

Hultgren, A., Carleton, T., Delgado, M., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., Jina, A., Kopp, R. E., Malevich, S. B., McCusker, K. E., Mayer, T., Nath, I., Rising, J., Rode, A., and Yuan, J. (2025). Impacts of climate change on global agriculture accounting for adaptation. *Nature*, 642(8068):644–652.

Isaksen, E. T. and Richter, A. (2019). Tragedy, Property Rights, and the Commons: Investigating the Causal Relationship from Institutions to Ecosystem Collapse. *Journal of the Association of Environmental and Resource Economists*, 6(4):741–781. Publisher: The University of Chicago Press.

Kaffine, D. T. and Costello, C. (2011). Unitization of Spatially Connected Renewable Resources. *The B.E. Journal of Economic Analysis & Policy*, 11(1).

Kaschner, K., Kesner-Reyes, K., Garilao, C., Segschneider, J., Ruis-Barile, J., Rees, T., and Froese, R. (2019). AquaMaps: Predicted range maps for aquatic species.

Kesner-Reyes, K., Garilao, C., Kaschner, K., Barile, J., and Froese, R. (2020). AquaMaps: algorithm and data sources for marine organisms.

Kim, K. and Reimer, M. (2025). The Role of Fisheries Diversification in Economic Growth and Stability: Evidence from Alaska's Fishing Economies. *Working Paper*.

Kleisner, K. M., Fogarty, M. J., McGee, S., Hare, J. A., Moret, S., Perretti, C. T., and Saba, V. S. (2017). Marine species distribution shifts on the U.S. Northeast Continental Shelf under continued ocean warming. *Progress in Oceanography*, 153:24–36.

Koss, G. (2025). Network Topology of Fishing Decisions: Simulations of Climate Resilience. *Working Paper*.

Li, Z. (2025). Polluting my downwind neighbor: Evidence of interjurisdictional free riding from air polluter locations in China. *Journal of Environmental Economics and Manage-*

ment, 130:103077.

Lipscomb, M. and Mobarak, A. M. (2017). Decentralization and Pollution Spillovers: Evidence from the Re-drawing of County Borders in Brazil. *The Review of Economic Studies*, 84(1 (298)):464–502. Publisher: [Oxford University Press, The Review of Economic Studies, Ltd.].

Liu, O. R. and Molina, R. (2021). The Persistent Transboundary Problem in Marine Natural Resource Management. *Frontiers in Marine Science*, Volume 8 - 2021.

Lynham, J. (2014). How have catch shares been allocated? *Marine Policy*, 44:42–48.

MacCall, A. (1990). Dynamic geography of marine fish populations.

McDermott, G. R., Meng, K. C., McDonald, G. G., and Costello, C. J. (2018). The blue paradox: Preemptive overfishing in marine reserves. *Proceedings of the National Academy of Sciences*, 116(12):5319–5325. Publisher: Proceedings of the National Academy of Sciences.

McWhinnie, S. F. (2009). The tragedy of the commons in international fisheries: An empirical examination. *Journal of Environmental Economics and Management*, 57(3):321–333.

Melbourne-Thomas, J., Audzijonyte, A., Brasier, M. J., Cresswell, K. A., Fogarty, H. E., Haward, M., Hobday, A. J., Hunt, H. L., Ling, S. D., McCormack, P. C., Mustonen, T., Mustonen, K., Nye, J. A., Oellermann, M., Trebilco, R., van Putten, I., Villanueva, C., Watson, R. A., and Pecl, G. T. (2022). Poleward bound: adapting to climate-driven species redistribution. *Reviews in Fish Biology and Fisheries*, 32(1):231–251.

Miller, K. A. and Munro, G. R. (2004). Climate and Cooperation: A New Perspective on the Management of Shared Fish Stocks. *Marine Resource Economics*, 19(3):367–393. Publisher: The University of Chicago Press.

Moscona, J. and Sastry, K. (2022). Inappropriate Technology: Evidence from Global Agriculture. *SSRN Electronic Journal*.

Moscona, J. and Sastry, K. A. (2023). Does Directed Innovation Mitigate Climate Damage? Evidence from U.S. Agriculture*. *The Quarterly Journal of Economics*, 138(2):637–701.

Munro, G. R. (1979). The Optimal Management of Transboundary Renewable Resources. *The Canadian journal of economics*, 12(3):355–376. Place: Toronto, Ont Publisher: University of Toronto Press.

Munro, G. R. (1990). The Optimal Management of Transboundary Fisheries: Game Theoretic Considerations. *Natural Resource Modeling*, 4(4):403–426. Publisher: John Wiley & Sons, Ltd.

Munro, G. R. (2007). Internationally Shared Fish Stocks, the High Seas, and Property Rights in Fisheries. *Marine Resource Economics*, 22(4):425–443. Publisher: [MRE Foundation, Inc., University of Chicago Press].

Noack, F. and Costello, C. (2022). Credit Markets, Property Rights, and the Commons. *National Bureau of Economic Research Working Paper Series*, No. 29889.

Oremus, K. L. (2019). Climate variability reduces employment in New England fisheries. *Proceedings of the National Academy of Sciences*, 116(52):26444–26449. Publisher: Proceedings of the National Academy of Sciences.

Oremus, K. L., Bone, J., Costello, C., García Molinos, J., Lee, A., Mangin, T., and Salzman, J. (2020). Governance challenges for tropical nations losing fish species due to climate change. *Nature Sustainability*, 3(4):277–280.

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., and van Vuuren, D. P. (2014). A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic Change*, 122(3):387–400.

Palacios-Abrantes, J., Frölicher, T. L., Reygondeau, G., Sumaila, U., Tagliabue, A., Wabnitz, C., and Cheung, W. (2022). Timing and magnitude of climate-driven range shifts in transboundary fish stocks challenge their management. *Global Change Biology*, 28(7):2312–2326. Publisher: John Wiley & Sons, Ltd.

Palacios-Abrantes, J., Reygondeau, G., Wabnitz, C. C. C., and Cheung, W. W. L. (2020a). The transboundary nature of the world's exploited marine species. *Scientific Reports*, 10(1):17668.

Palacios-Abrantes, J., Santos, B. S., Frölicher, T. L., Reygondeau, G., Sumaila, U., Wabnitz, C. C. C., and Cheung, W. W. L. (2025). Climate change drives shifts in straddling fish stocks in the world's ocean. *Science Advances*, 11(31):eadq5976. Publisher: American Association for the Advancement of Science.

Palacios-Abrantes, J., Sumaila, U. R., and Cheung, W. W. L. (2020b). Challenges to transboundary fisheries management in North America under climate change. *Ecology and Society*, 25(4). Publisher: The Resilience Alliance.

Pauly, D. and Cheung, W. W. L. (2018). Sound physiological knowledge and principles in modeling shrinking of fishes under climate change. *Global Change Biology*, 24(1):e15–e26. Publisher: John Wiley & Sons, Ltd.

Pauly, D., Zeller, D., and Palomares, M. L. D. (2020). Sea Around Us Concepts, Design and Data.

Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I.-C., Clark, T. D., Colwell, R. K., Danielsen, F., Evengård, B., Falconi, L., Ferrier, S., Frusher, S., Garcia, R. A., Griffis, R. B., Hobday, A. J., Janion-Scheepers, C., Jarzyna, M. A., Jennings, S., Lenoir, J., Linnetved, H. I., Martin, V. Y., McCormack, P. C., McDonald, J., Mitchell, N. J., Mustonen, T., Pandolfi, J. M., Pettorelli, N., Popova, E., Robinson, S. A., Scheffers, B. R., Shaw, J. D., Sorte, C. J. B., Strugnell, J. M., Sunday, J. M., Tuanmu, M.-N., Vergés, A., Villanueva, C., Wernberg, T., Wapstra, E., and Williams, S. E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science*, 355(6332):eaai9214. Publisher: American Association for the Advancement of Science.

Pennino, M. G., Coll, M., Albo-Puigserver, M., Fernández-Corredor, E., Steenbeek, J., Giráldez, A., González, M., Esteban, A., and Bellido, J. M. (2020). Current and Future Influence of Environmental Factors on Small Pelagic Fish Distributions in the Northwestern Mediterranean Sea. *Frontiers in Marine Science*, Volume 7 - 2020.

Pershing, A. J., Alexander, M. A., Hernandez, C. M., Kerr, L. A., Le Bris, A., Mills, K. E., Nye, J. A., Record, N. R., Scannell, H. A., Scott, J. D., Sherwood, G. D., and Thomas, A. C. (2015). Slow adaptation in the face of rapid warming leads to collapse of the Gulf of Maine cod fishery. *Science*, 350(6262):809–812. Publisher: American Association for the Advancement of Science.

Pinsky, M. L., Reygondeau, G., Caddell, R., Palacios-Abrantes, J., Spijkers, J., and Cheung, W. W. L. (2018). Preparing ocean governance for species on the move. *Science*, 360(6394):1189–1191. Publisher: American Association for the Advancement of Science.

Pinsky, M. L., Worm, B., Fogarty, M. J., Sarmiento, J. L., and Levin, S. A. (2013). Marine Taxa Track Local Climate Velocities. *Science*, 341(6151):1239–1242. Publisher: American

Association for the Advancement of Science.

Poloczanska, E. S., Brown, C. J., Sydeman, W. J., Kiessling, W., Schoeman, D. S., Moore, P. J., Brander, K., Bruno, J. F., Buckley, L. B., Burrows, M. T., Duarte, C. M., Halpern, B. S., Holding, J., Kappel, C. V., O'Connor, M. I., Pandolfi, J. M., Parmesan, C., Schwing, F., Thompson, S. A., and Richardson, A. J. (2013). Global imprint of climate change on marine life. *Nature Climate Change*, 3(10):919–925.

Pons, M., Melnychuk, M. C., and Hilborn, R. (2018). Management effectiveness of large pelagic fisheries in the high seas. *Fish and Fisheries*, 19(2):260–270. Publisher: John Wiley & Sons, Ltd.

RAM (2024). RAM Legacy Stock Assessment Database.

Ready, J., Kaschner, K., South, A. B., Eastwood, P. D., Rees, T., Rius, J., Agbayani, E., Kullander, S., and Froese, R. (2010). Predicting the distributions of marine organisms at the global scale. *Ecological Modelling*, 221(3):467–478.

Reimer, M. N., Rogers, A., and Sanchirico, J. N. (2025). Managing for adaptive capacity in climate-ready fisheries. *Marine Policy*, 174:106601.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L. A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J. C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., and Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, 42:153–168.

Ricard, D., Minto, C., Jensen, O. P., and Baum, J. K. (2012). Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database. *Fish and Fisheries*, 13(4):380–398. Publisher: John Wiley & Sons, Ltd.

Sala, E., Mayorga, J., Bradley, D., Cabral, R. B., Atwood, T. B., Auber, A., Cheung, W., Costello, C., Ferretti, F., Friedlander, A. M., Gaines, S. D., Garilao, C., Goodell, W., Halpern, B. S., Hinson, A., Kaschner, K., Kesner-Reyes, K., Leprieur, F., McGowan, J., Morgan, L. E., Mouillot, D., Palacios-Abrantes, J., Possingham, H. P., Rechberger, K. D., Worm, B., and Lubchenco, J. (2021). Protecting the global ocean for biodiversity, food and climate. *Nature*, 592(7854):397–402.

Sampson, S. (2024). FAO Report: Global fisheries and aquaculture production reaches a new record high.

Sarre, A., Demarcq, H., Keenlyside, N., Krakstad, J.-O., El Ayoubi, S., Jeyid, A. M., Faye, S., Mbaye, A., Sidibeh, M., and Brehmer, P. (2024). Climate change impacts on small pelagic fish distribution in Northwest Africa: trends, shifts, and risk for food security. *Scientific Reports*, 14(1):12684.

Sethi, S. A., Reimer, M., and Knapp, G. (2014). Alaskan fishing community revenues and the stabilizing role of fishing portfolios. *Marine Policy*, 48:134–141.

Shrader, J. (2023). Improving Climate Damage Estimates by Accounting for Adaptation.

Simpson, M. R. and Walsh, S. J. (2004). Changes in the spatial structure of Grand Bank yellowtail flounder: testing MacCall's basin hypothesis. *Proceedings of the Fifth International*

Symposium on Flatfish Ecology, Part II, 51(3):199–210.

Southward, A., Hawkins, S., and Burrows, M. (1995). Seventy years' observations of changes in distribution and abundance of zooplankton and intertidal organisms in the western English Channel in relation to rising sea temperature. *Effects of Rising Temperature on the Ecology and Physiology of Aquatic Organisms*, 20(1):127–155.

Spijkers, J., Morrison, T. H., Blasiak, R., Cumming, G. S., Osborne, M., Watson, J., and Österblom, H. (2018). Marine fisheries and future ocean conflict. *Fish and Fisheries*, 19(5):798–806. Publisher: John Wiley & Sons, Ltd.

Sullivan, M. C., Cowen, R. K., Able, K. W., and Fahay, M. P. (2006). Applying the basin model: Assessing habitat suitability of young-of-the-year demersal fishes on the New York Bight continental shelf. *Continental Shelf Research*, 26(14):1551–1570.

Tai, T. C., Cashion, T., Lam, V. W. Y., Swartz, W., and Sumaila, U. R. (2017). Ex-vessel Fish Price Database: Disaggregating Prices for Low-Priced Species from Reduction Fisheries. *Frontiers in Marine Science*, 4.

Taylor, C. (2025). Irrigation and Climate Change: Long-run Adaptation and its Externalities. *Working Paper*.

Taylor, C. A. (2020). Cicadian Rhythm: Insecticides, Infant Health and Long-term Outcomes. *CEEP Working Paper Series*.

Vogel, J. M., Longo, C., Spijkers, J., Palacios-Abrantes, J., Mason, J., Wabnitz, C. C., Cheung, W., Sumaila, U. R., Munro, G., Glaser, S., Bell, J., Tian, Y., Shackell, N. L., Selig, E. R., Le Billon, P., Watson, J. R., Hendrix, C., Pinsky, M. L., van Putten, I., Karr, K., Papaioannou, E. A., and Fujita, R. (2023). Drivers of conflict and resilience in shifting transboundary fisheries. *Marine Policy*, 155:105740.

Weitzman, M. L. (2002). Landing Fees vs Harvest Quotas with Uncertain Fish Stocks. *Journal of Environmental Economics and Management*, 43(2):325–338.

Wernberg, T., Bennett, S., Babcock, R. C., de Bettignies, T., Cure, K., Depczynski, M., Dufois, F., Fromont, J., Fulton, C. J., Hovey, R. K., Harvey, E. S., Holmes, T. H., Kendrick, G. A., Radford, B., Santana-Garcon, J., Saunders, B. J., Smale, D. A., Thomsen, M. S., Tuckett, C. A., Tuya, F., Vanderklift, M. A., and Wilson, S. (2016). Climate-driven regime shift of a temperate marine ecosystem. *Science*, 353(6295):169–172. Publisher: American Association for the Advancement of Science.

Wilen, J. E., Cancino, J., and Uchida, H. (2012). The Economics of Territorial Use Rights Fisheries, or TURFs. *Review of Environmental Economics and Policy*, 6(2):237–257. Publisher: The University of Chicago Press.

Yang, T., Liu, X., and Han, Z. (2022). Predicting the Effects of Climate Change on the Suitable Habitat of Japanese Spanish Mackerel (Scomberomorus niphonius) Based on the Species Distribution Model. *Frontiers in Marine Science*, 9.

Zador, S., Aydin, K., and Cope, J. (2011). Fine-scale analysis of arrowtooth flounder Atheresthes stomias catch rates reveals spatial trends in abundance. *Marine Ecology Progress Series*, 438:229–239.

8 Tables

Table 1: Distance to Equator Regressions

	Dependent variable:		
	Avg. Coastline Length (km)	Avg. EEZ Area (km^2)	Avg. EPI Score
	(1)	(2)	(3)
Degrees from Equator	57.408***	7,190.809***	−0.010***
	(7.081)	(317.310)	(0.001)
Constant	13,084.570***	1,519,061.000***	20.172***
	(736.944)	(33,021.610)	(0.146)
Observations	721	721	721
R^2	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
Country Share (mean)	0.53
Country 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 Country Share	0.021*	0.008	−0.128***	−0.099***	−0.217***	−0.185**
	(0.011)	(0.015)	(0.028)	(0.032)	(0.058)	(0.082)
Log Mean Biomass	0.107***	0.105***			0.134***	0.132***
	(0.001)	(0.002)			(0.007)	(0.009)
Growth Rate		−0.050**		0.273***		0.466***
		(0.020)		(0.042)		(0.108)
Mean Interest Rate		−0.093		0.308**		0.071
		(0.067)		(0.142)		(0.363)
Constant	1.162***	1.214***	0.239***	0.076**	0.726***	0.524***
	(0.017)	(0.022)	(0.017)	(0.030)	(0.088)	(0.123)
Observations	326	206	326	206	323	204
R^2	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 country 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 Country 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 Country 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

	Dependent variable:		
	Norm. Escapement	Norm. Extraction Rate	Norm. Catch
	(1)	(2)	(3)
Country Share	1.506^{***}	-2.481^{***}	-2.306^{***}
	(0.554)	(0.743)	(0.669)
Norm. Biomass			0.556^{***}
			(0.020)
Stock FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,884	4,875	4,884
R^2	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 Country 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 Country 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: Biomass Prediction Regression

	Dependent variable:
	Normalized Biomass
Lag Norm. Escapement	0.928***
	(0.026)
Lag Norm. Escapement Sq.	−0.092***
	(0.011)
Constant	0.180***
	(0.015)
Observations	4,556
R^2	0.612
Residual Std. Error	0.208 (df = 4553)
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

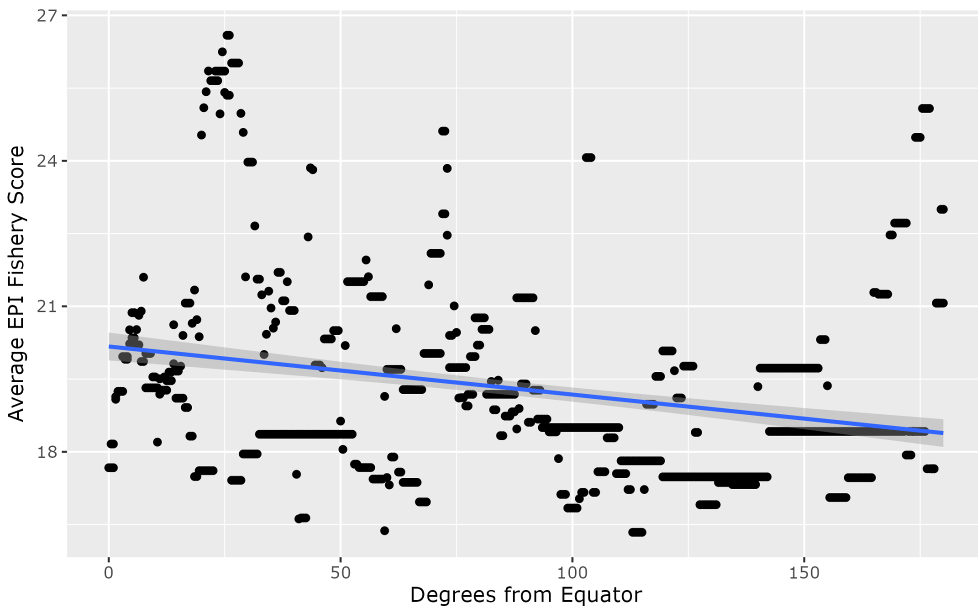


Figure 2: Coastline and Distance to Equator

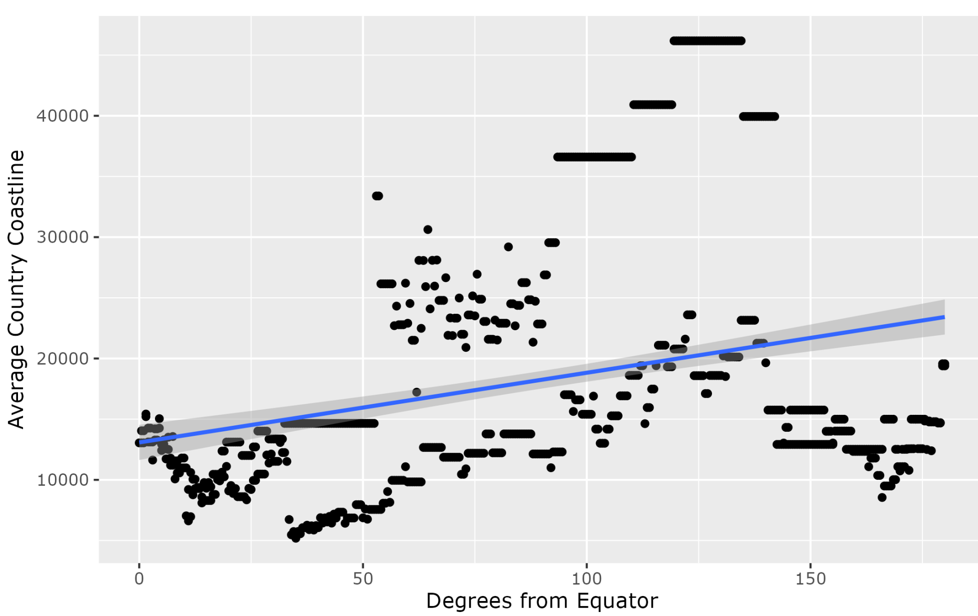


Figure 3: EEZ Area and Distance to Equator

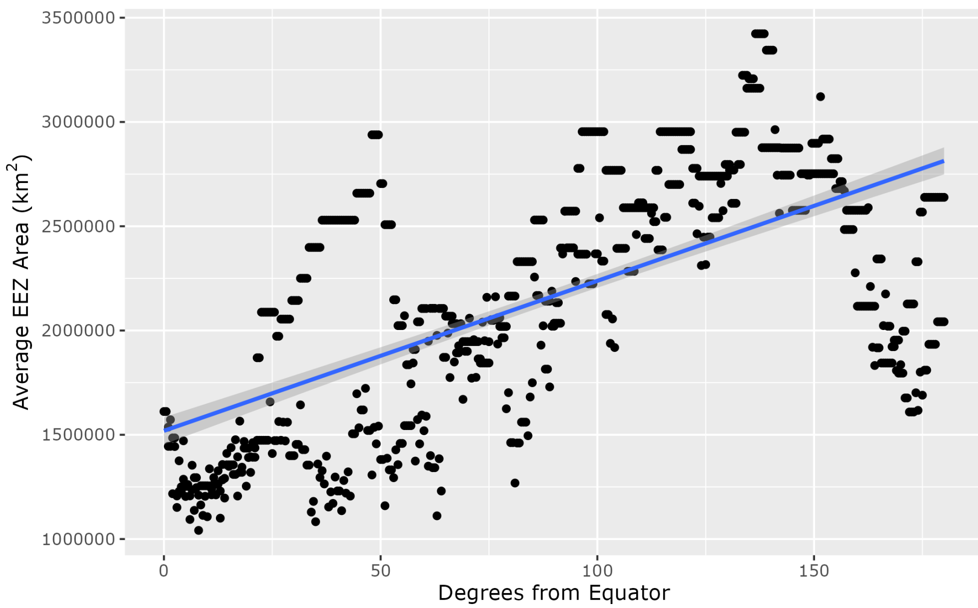


Figure 4: Map of RAM Stocks

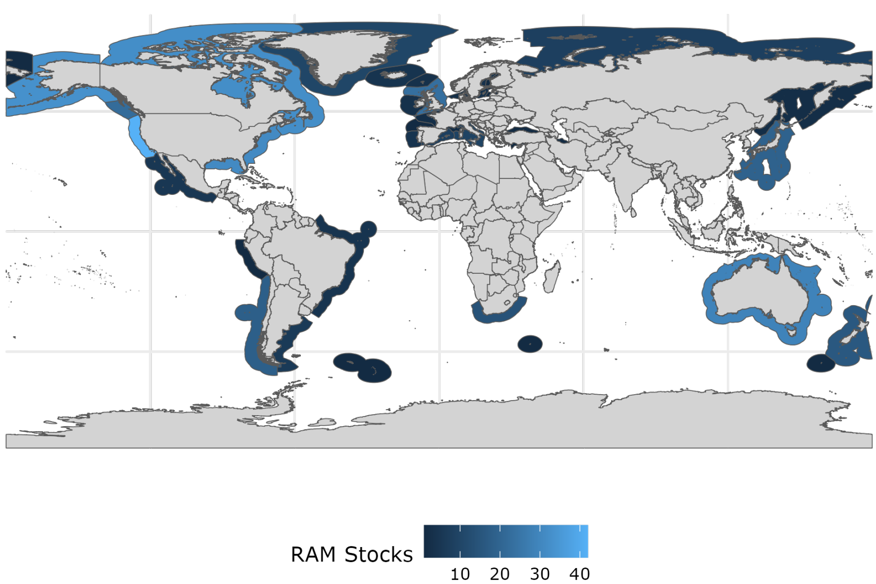


Figure 5: Map of Average Catch Values

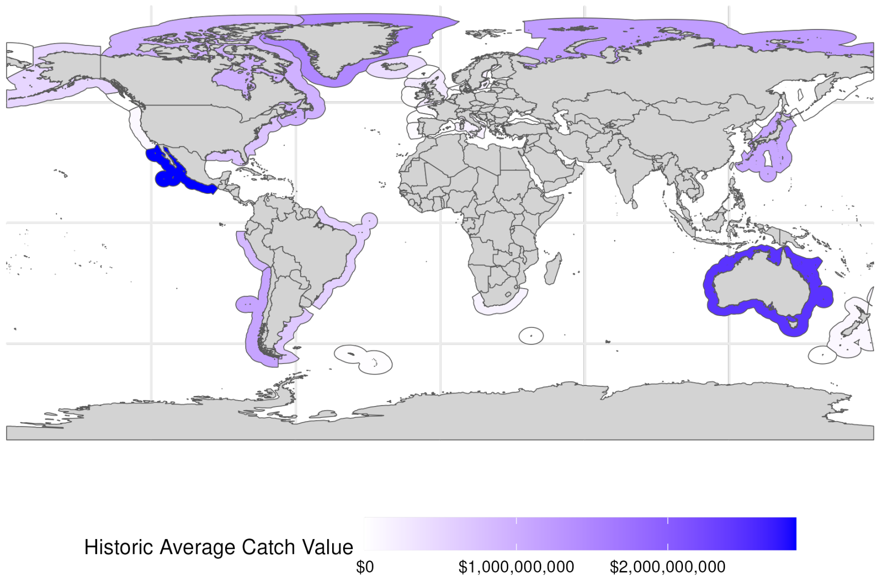


Figure 6: Temperature Envelope for Greenstriped Rockfish

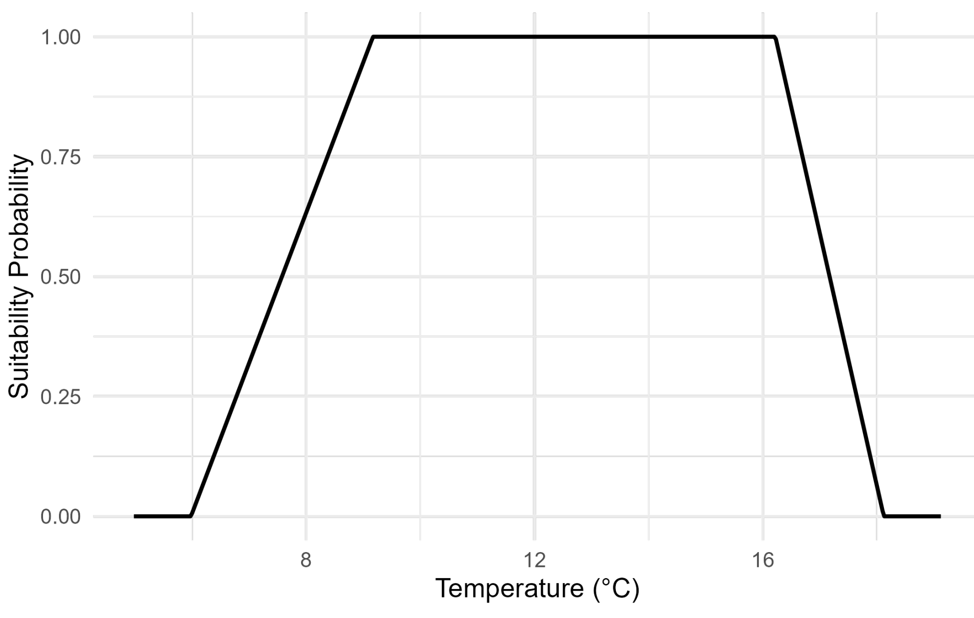


Figure 7: Greenstriped Rockfish Suitability in 2020

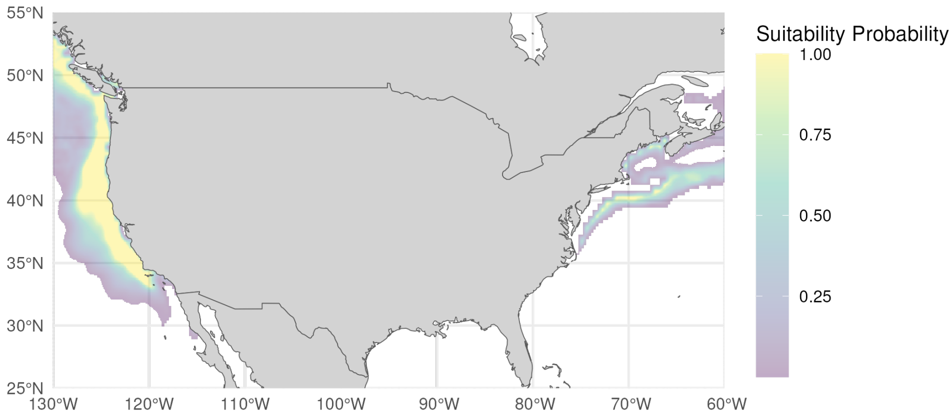


Figure 8: Greenstriped Rockfish RAM Shapefile

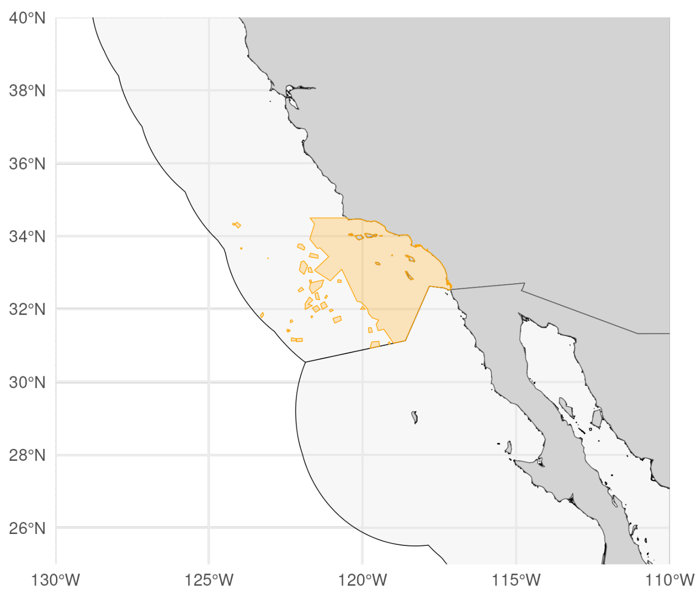


Figure 9: Greenstriped Rockfish Management Areas

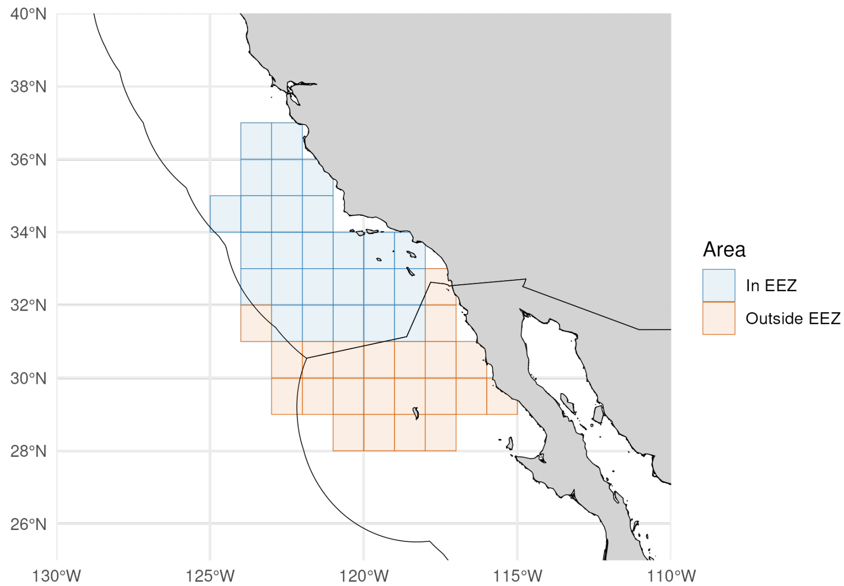


Figure 10: Greenstriped Rockfish Suitability

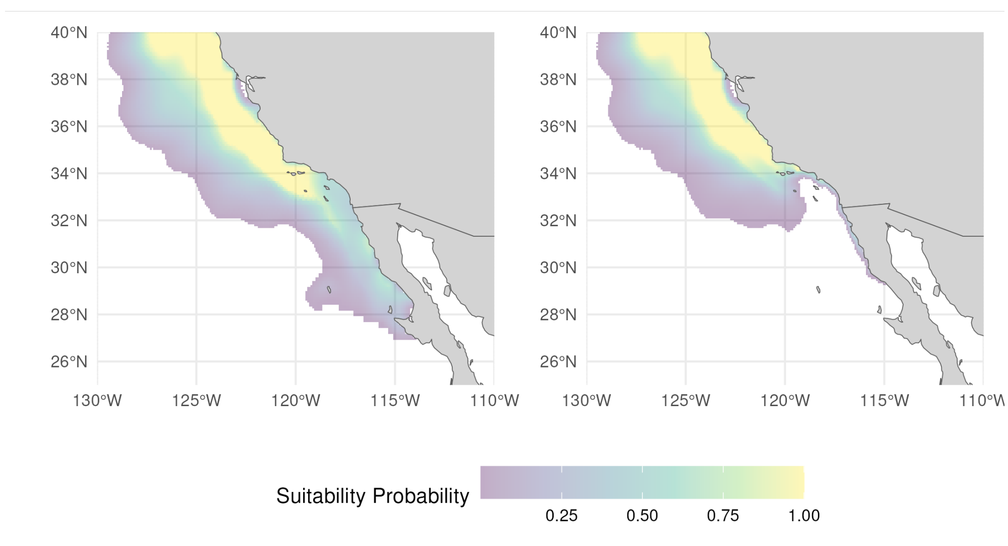


Figure 11: Greenstriped Rockfish Management and Suitability

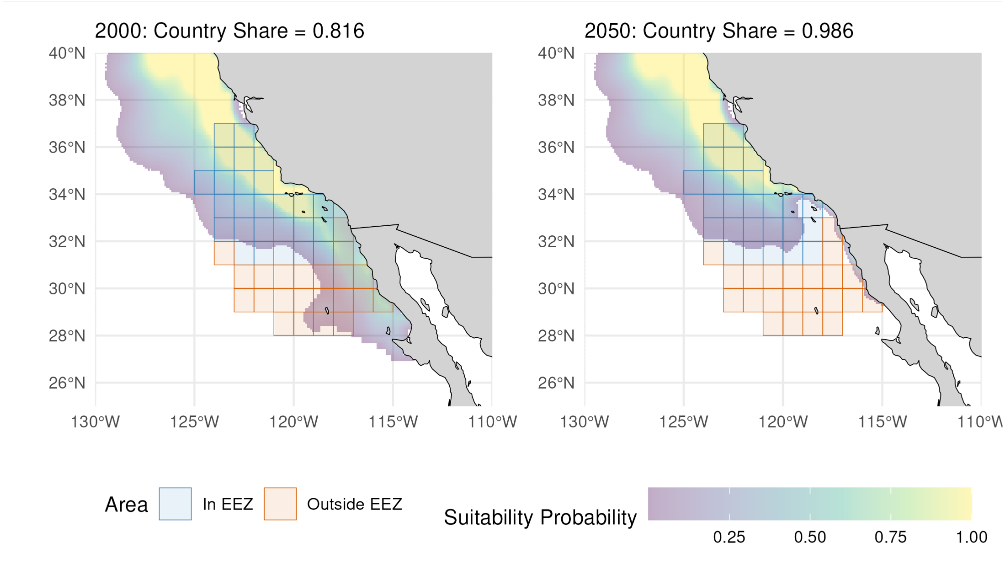


Figure 12: Avg. Extraction Rate Vs Avg. Country Share

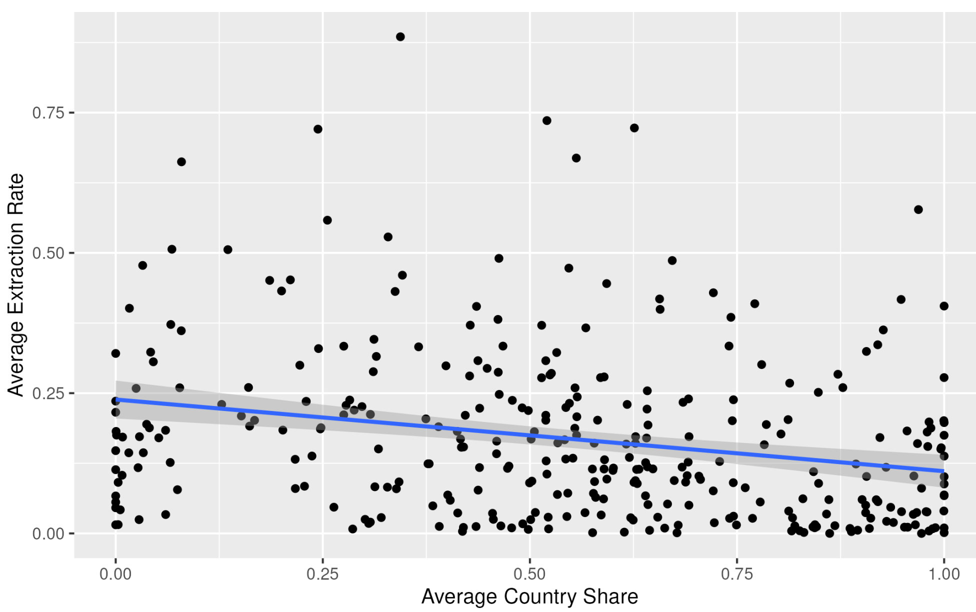


Figure 13: Normalized Escapement Vs Normalized Biomass

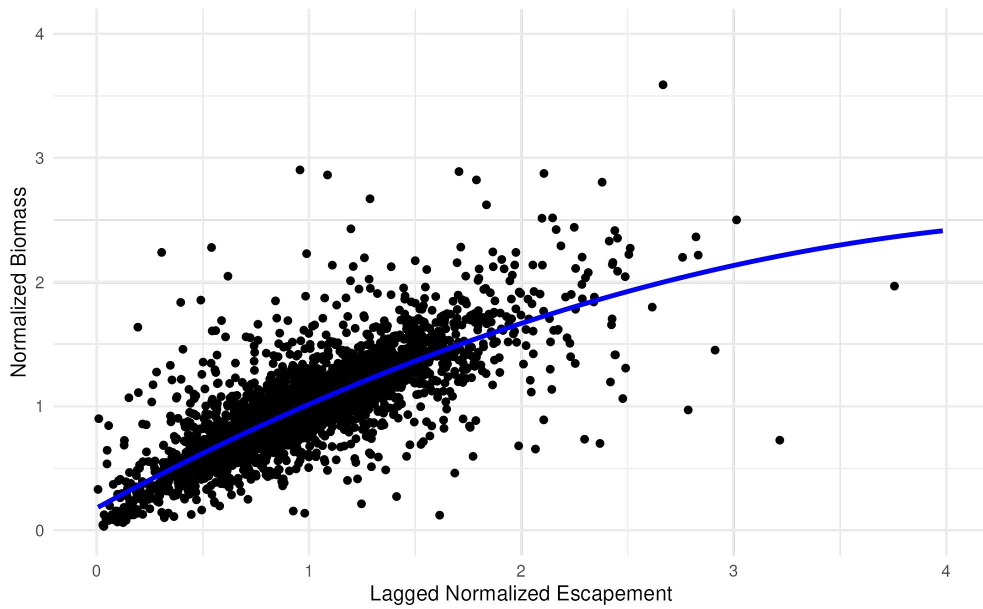


Figure 14: Country Share Density by Decade

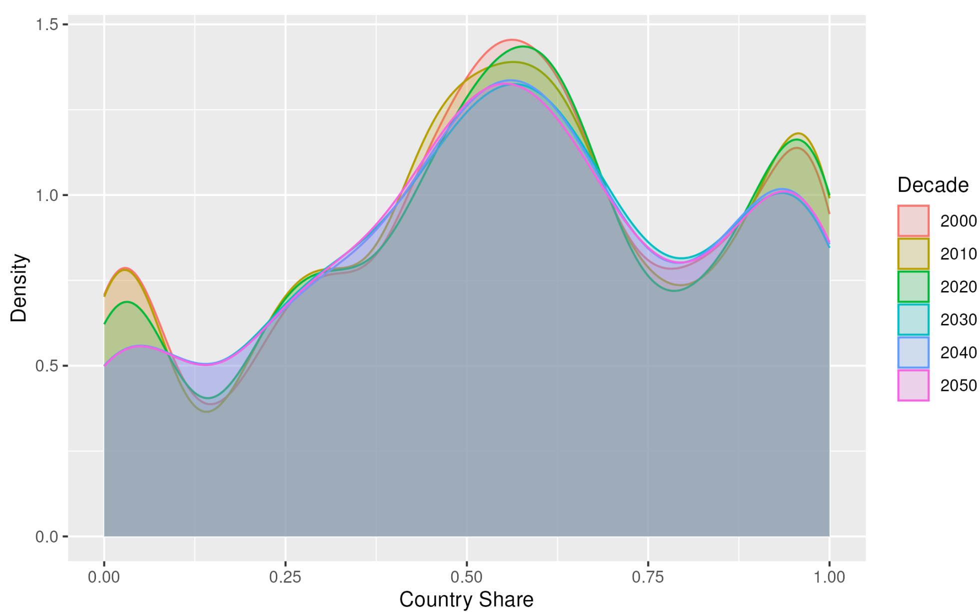


Figure 15: Country Share Change by 2050

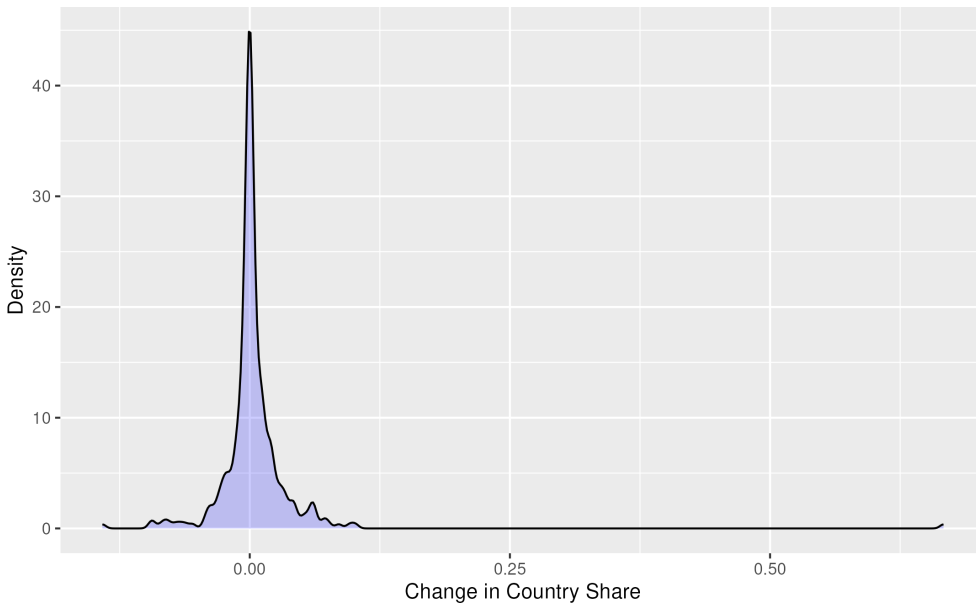


Figure 16: Escapement Changes by 2050 (Behavioral Only)

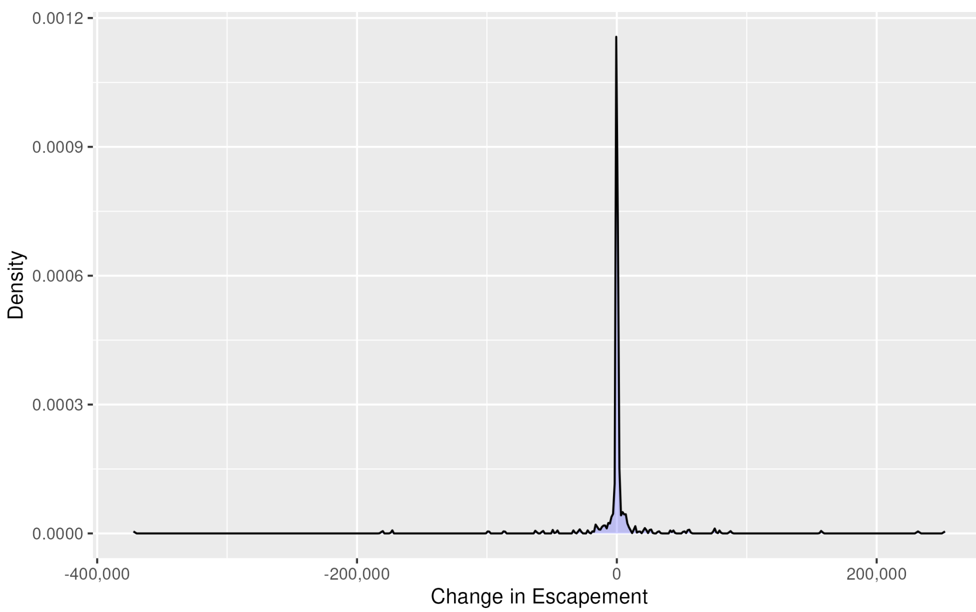


Figure 17: Escapement Percent Changes by 2050 (Behavioral Only)

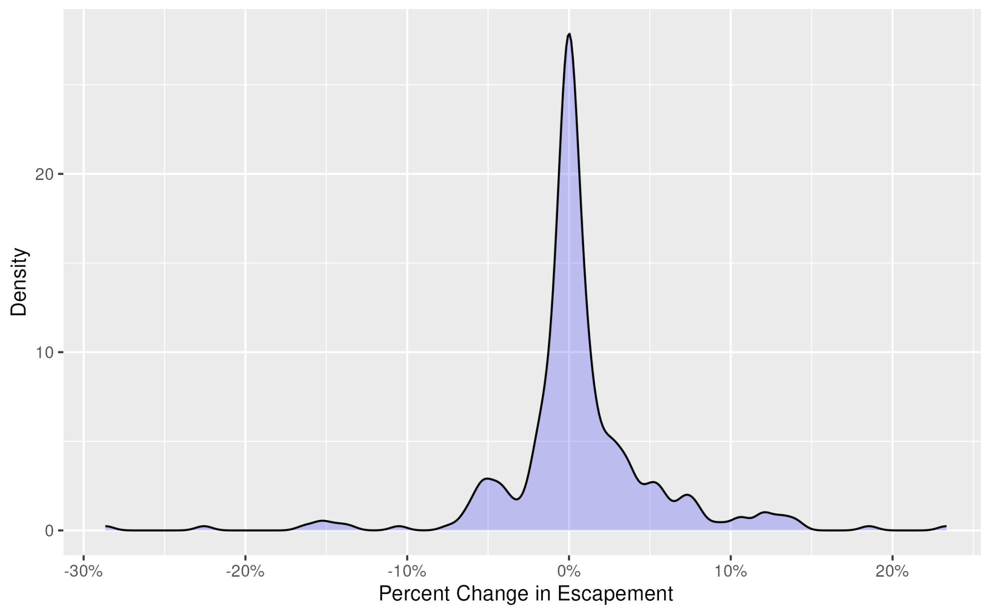


Figure 18: Average Country Share by EEZ

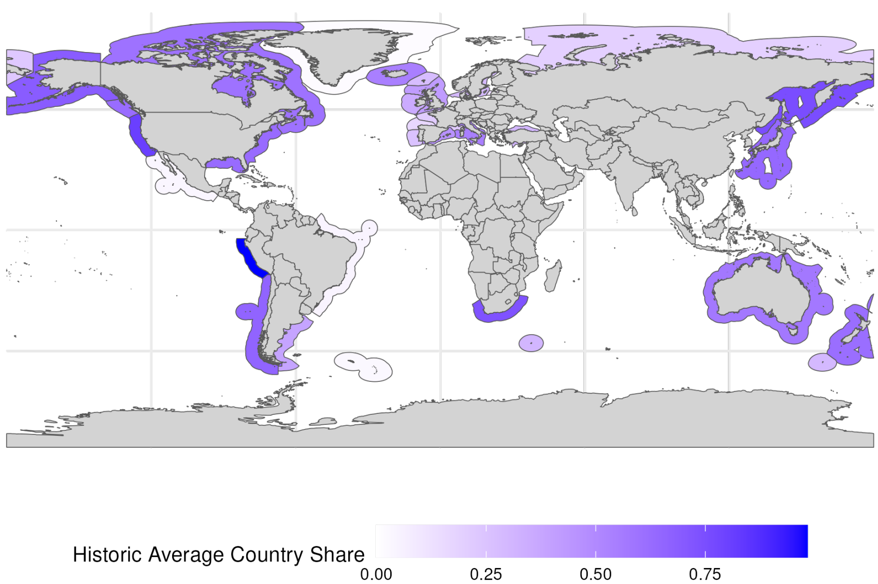


Figure 19: 2050 Average Change in Stock by EEZ

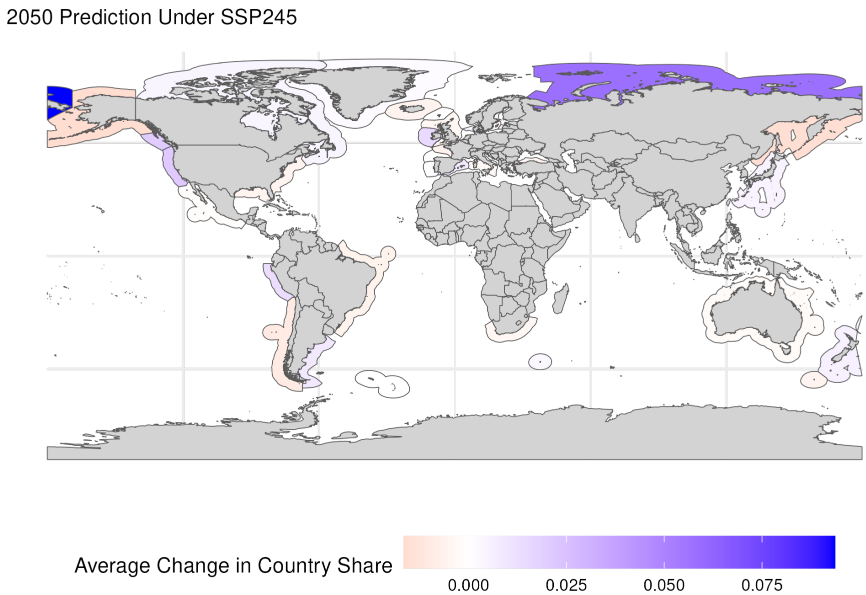


Figure 20: Total Escapement by EEZ (Historic Average)

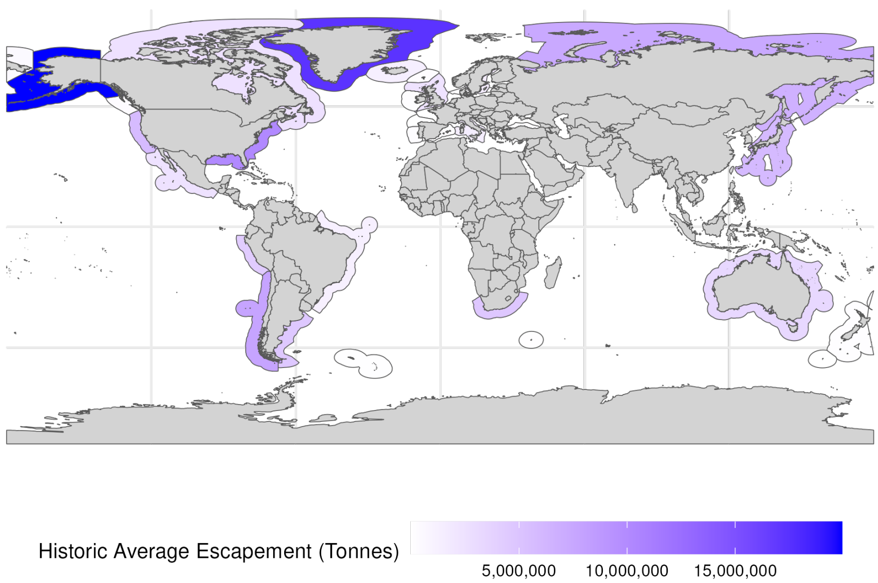


Figure 21: 2050 Total Change in Escapement by EEZ (Behavioral Only)

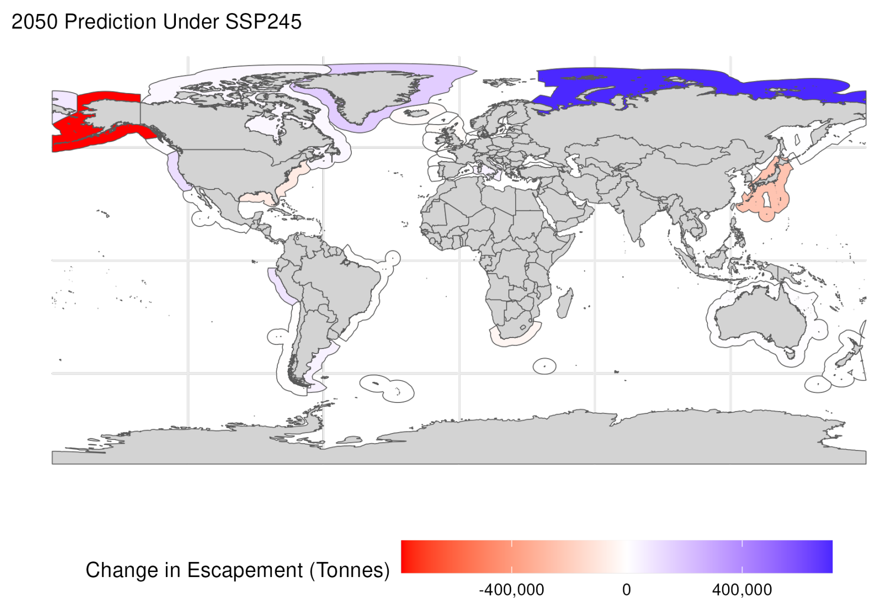


Figure 22: 2050 Percent Change in Escapement by EEZ (Behavioral Only)

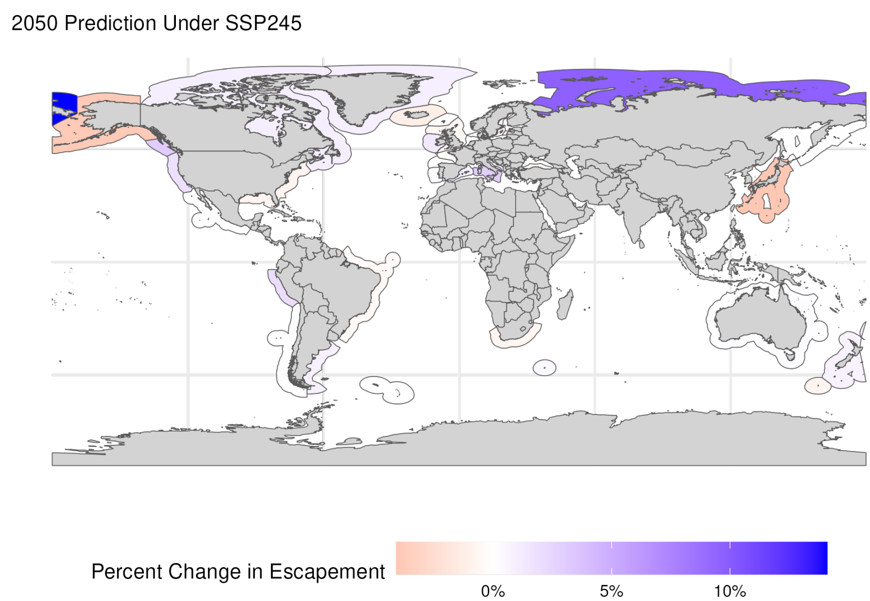


Figure 23: 2050 Change in Escapement (Biophysical Vs Combined)

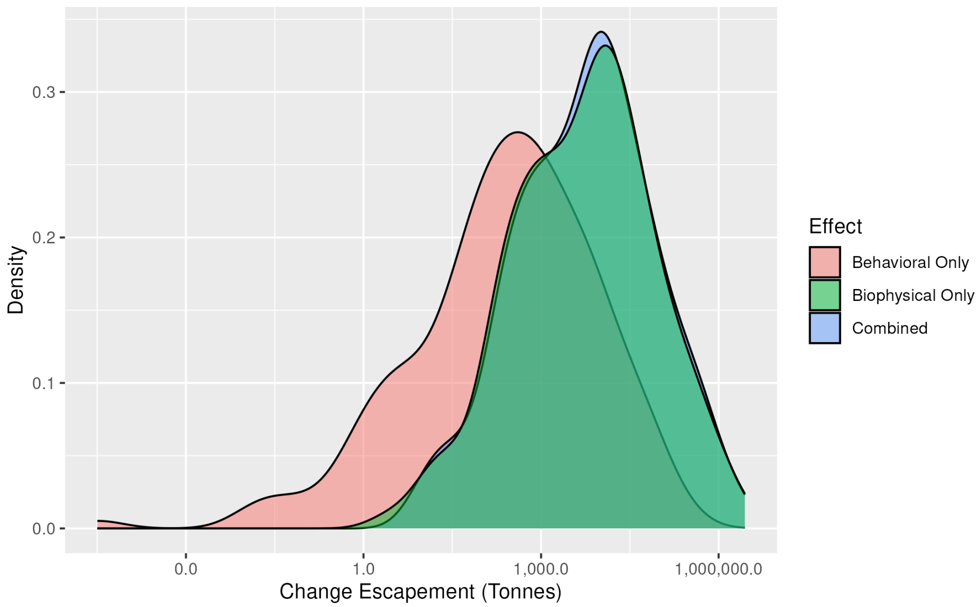


Figure 24: Error in Biophysical-Only Escapement Prediction

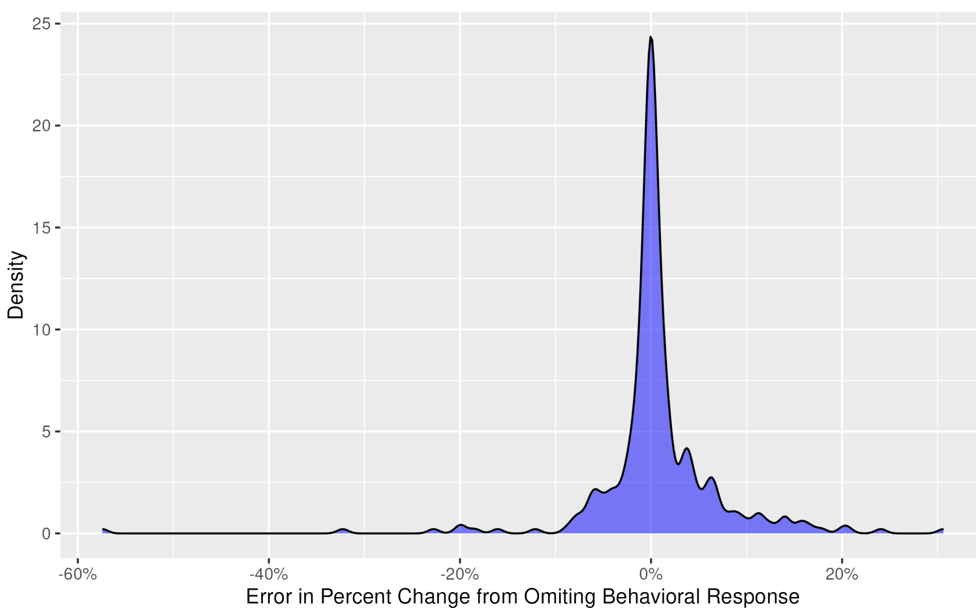


Figure 25: 2050 Total Change in Escapement by EEZ (Combined Effects)

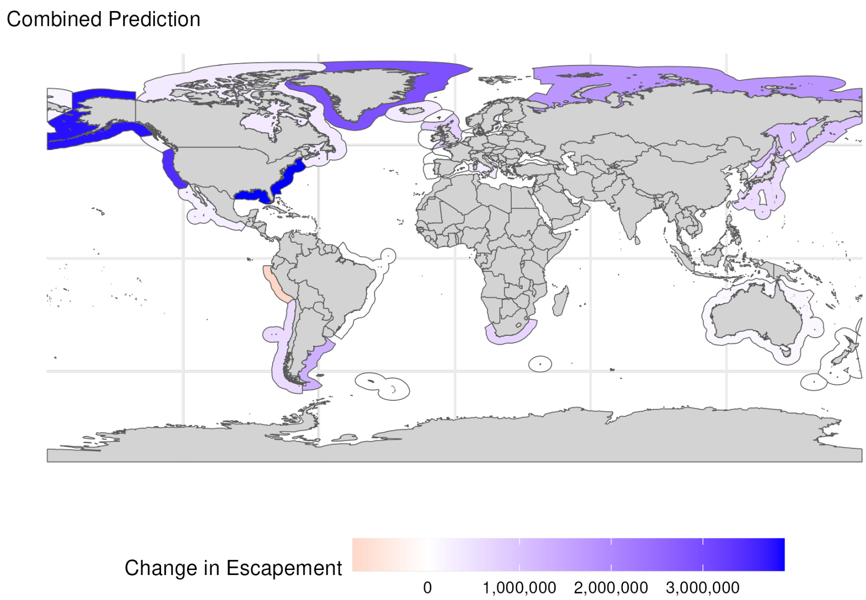


Figure 26: 2050 Percent Change in Escapement by EEZ (Combined Effects)

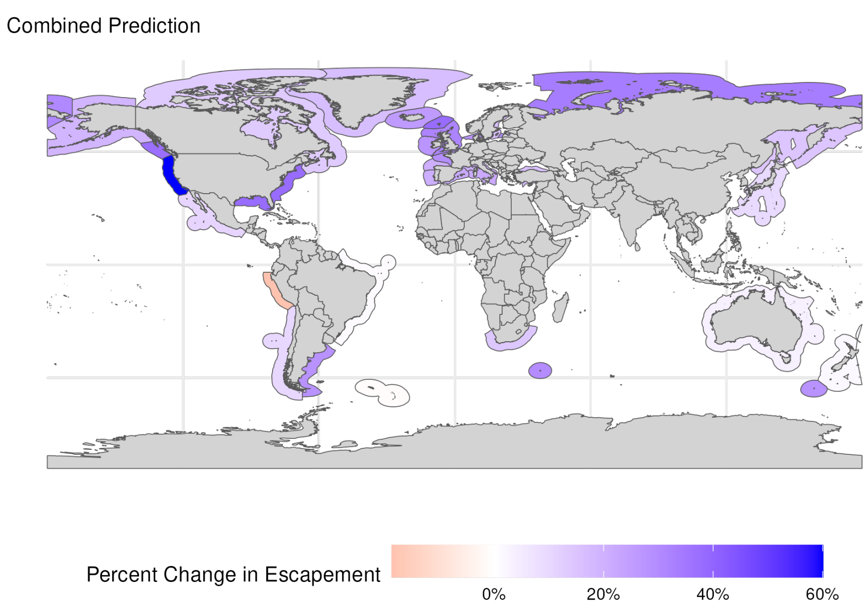


Figure 27: Error in Biophysical-Only Escapement Prediction by EEZ

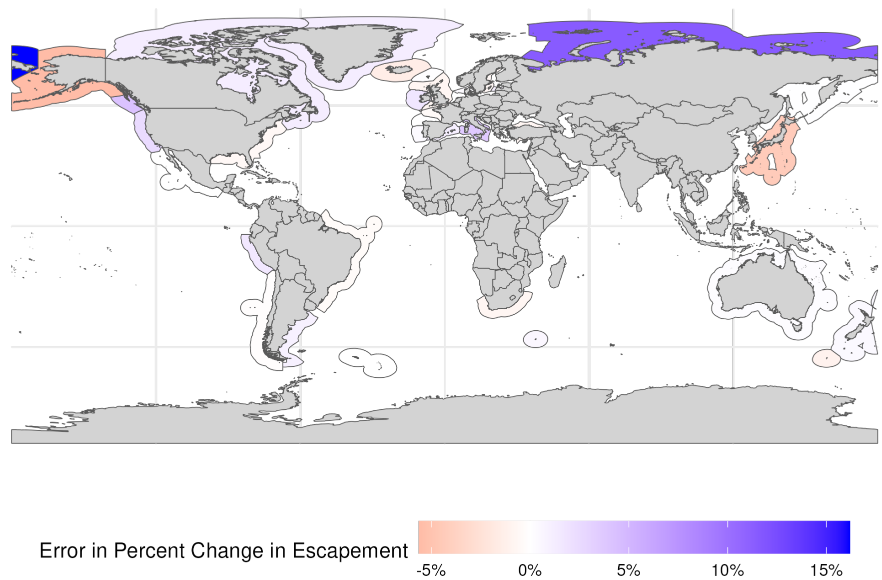


Figure 28: 2050 Total Change in Biomass by EEZ (Combined Effects)

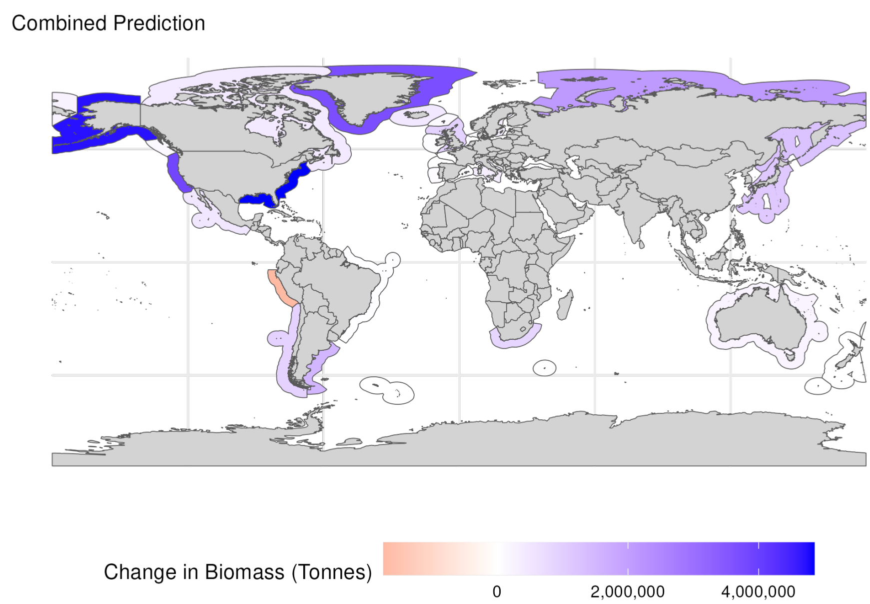


Figure 29: 2050 Percent Change in Biomass by EEZ (Combined Effects)

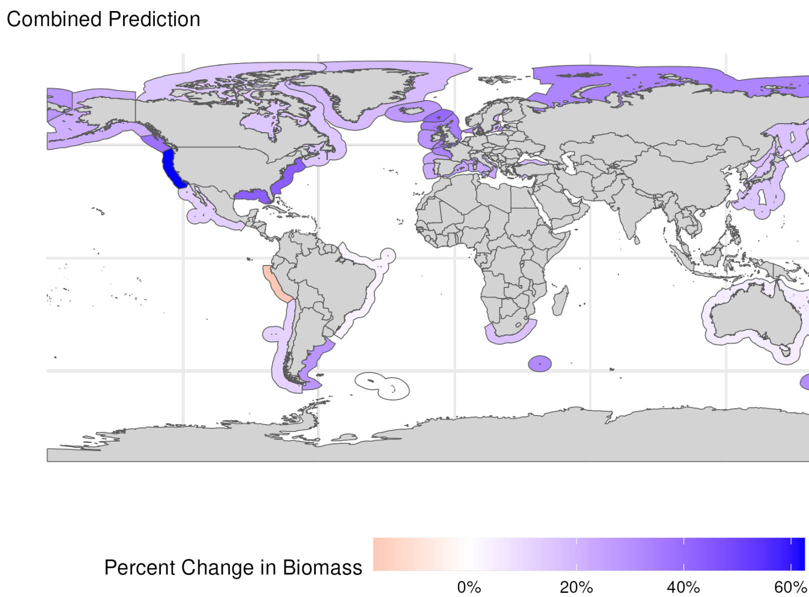


Figure 30: 2050 Total Change in Catch by EEZ (Combined Effects)

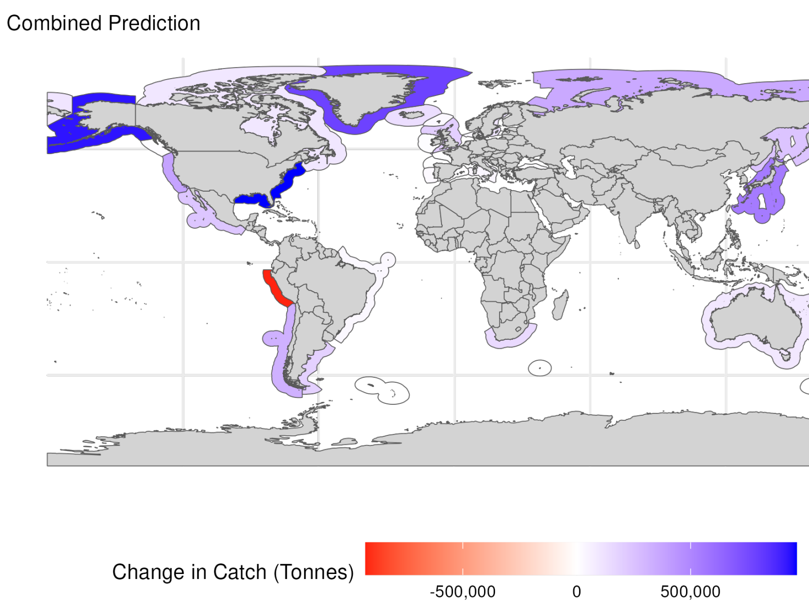


Figure 31: 2050 Percent Change in Catch by EEZ (Combined Effects)

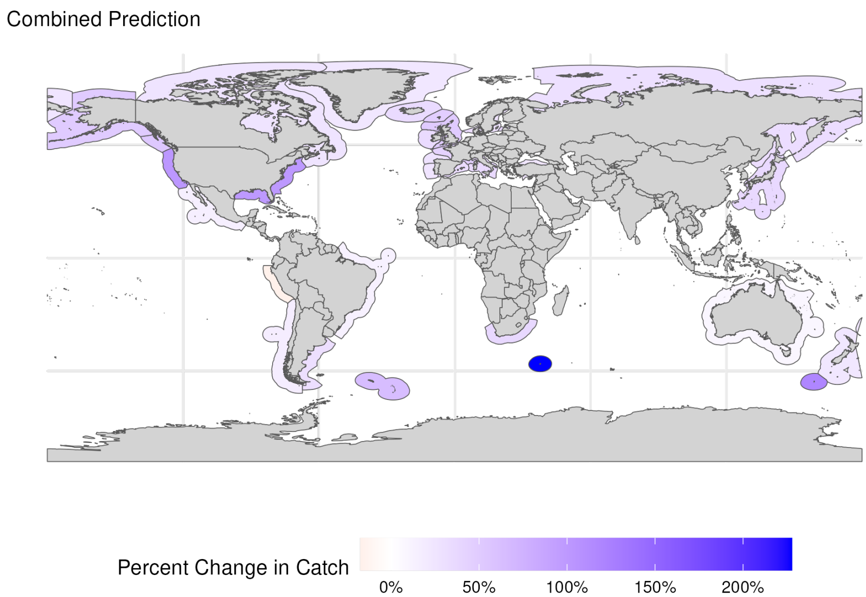


Figure 32: 2050 Total Change in Catch Value by EEZ (Combined Effects)

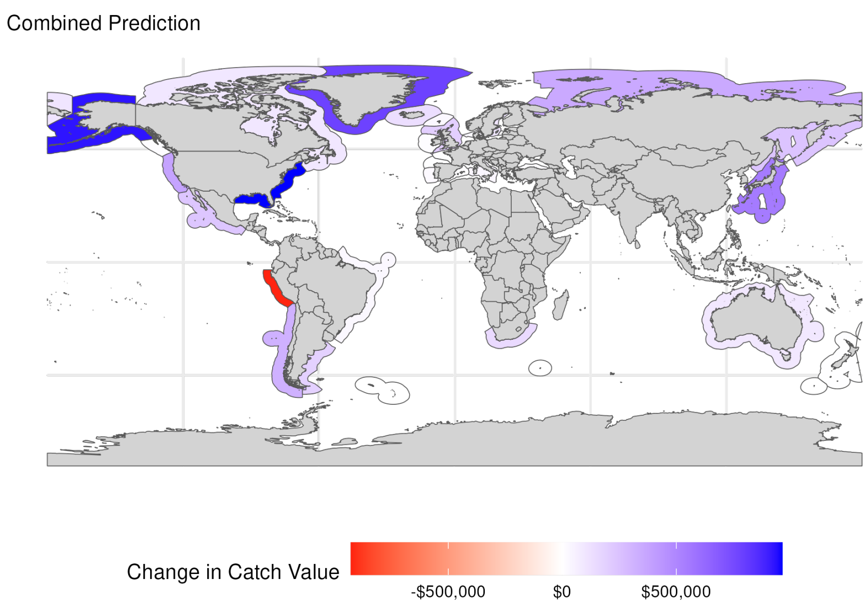


Figure 33: 2050 Percent Change in Catch Value by EEZ (Combined Effects)

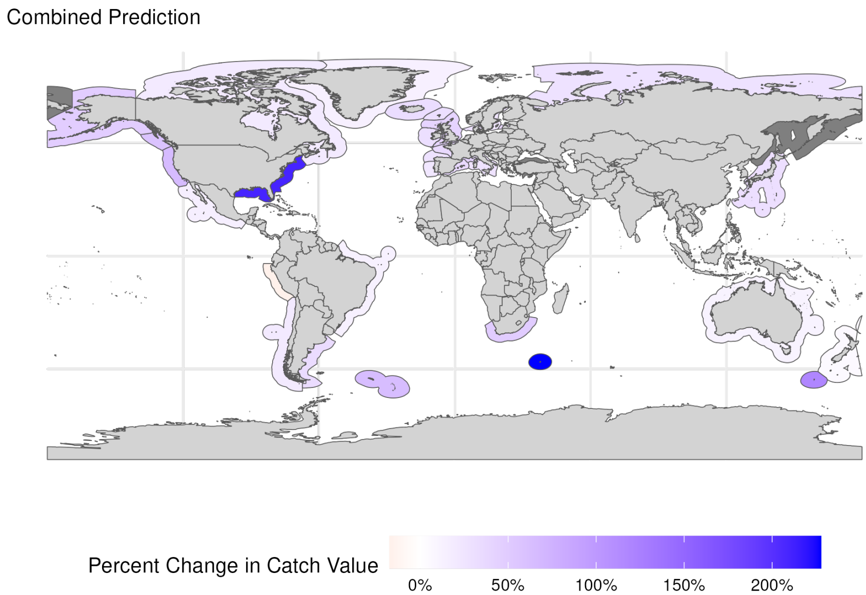


Figure 34: Historic and Cooperative Escapement Distributions

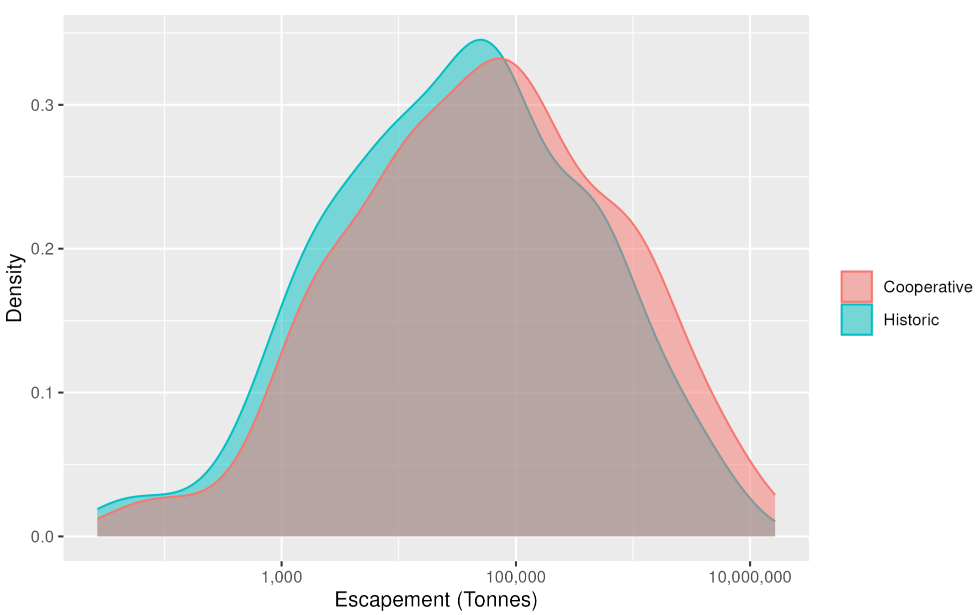


Figure 35: Historic and Cooperative Biomass Distributions

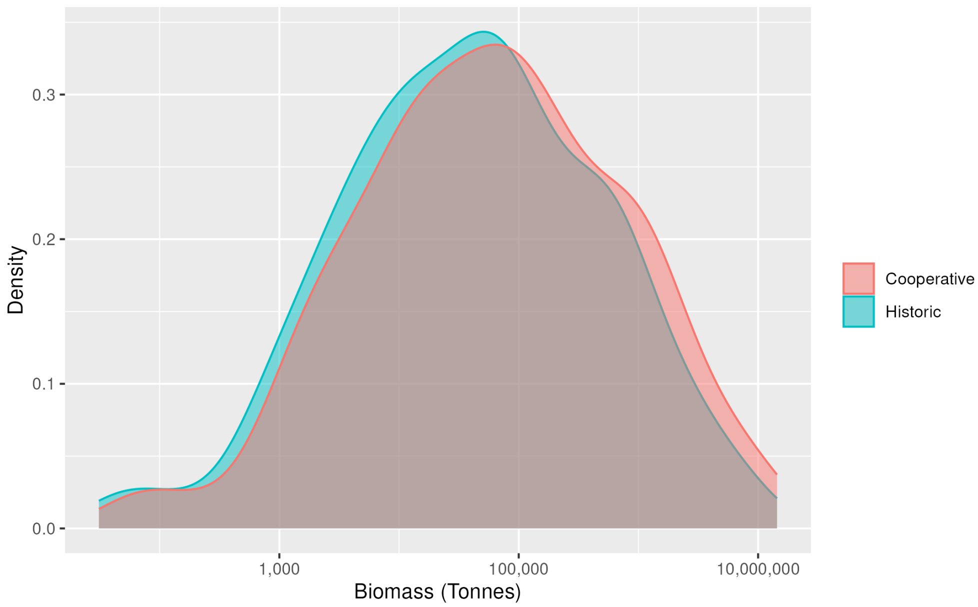


Figure 36: Historic and Cooperative Catch Distributions

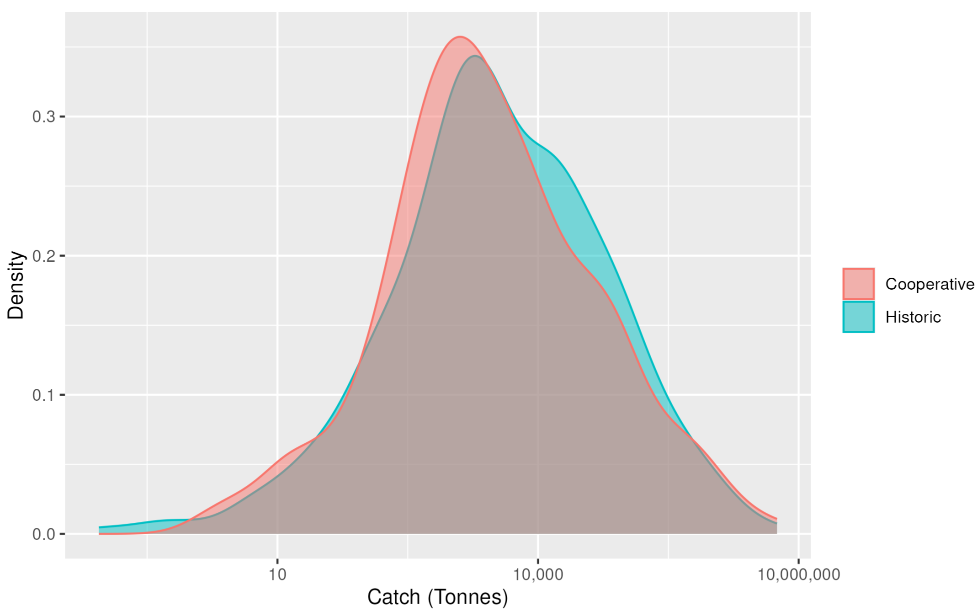


Figure 37: Change in Escapement Under Global Cooperation by EEZ

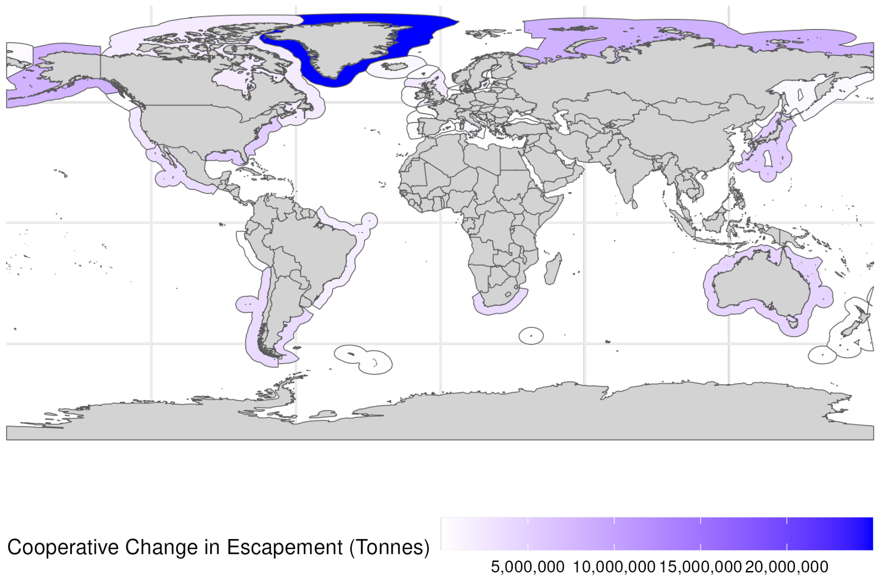


Figure 38: Percent Change in Escapement Under Global Cooperation by EEZ

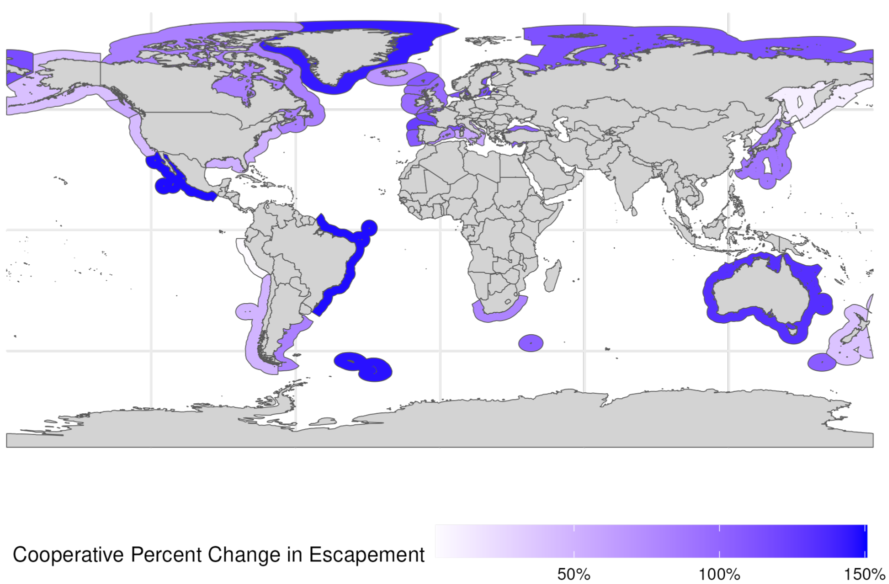


Figure 39: Change in Biomass Under Global Cooperation by EEZ

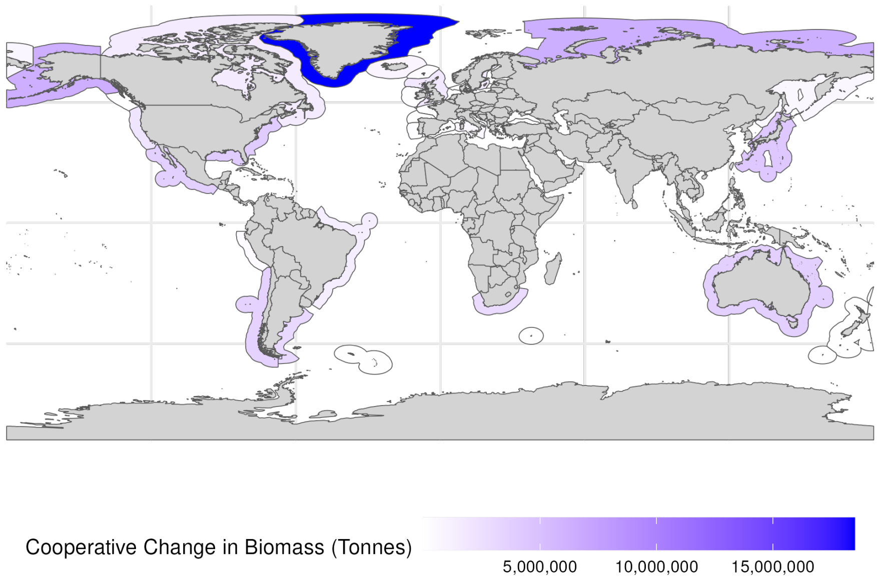


Figure 40: Percent Change in Biomass Under Global Cooperation by EEZ

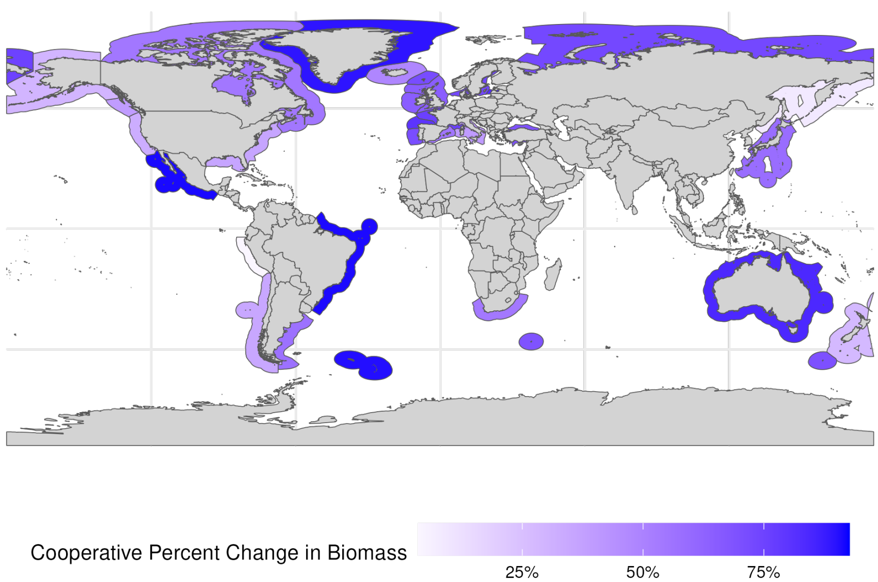


Figure 41: Change in Catch Under Global Cooperation by EEZ

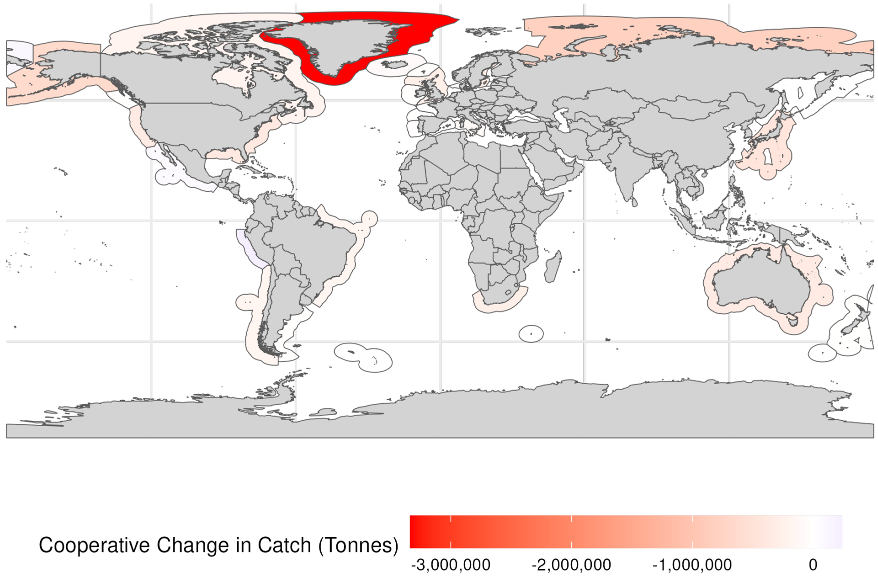


Figure 42: Percent Change in Catch Under Global Cooperation by EEZ

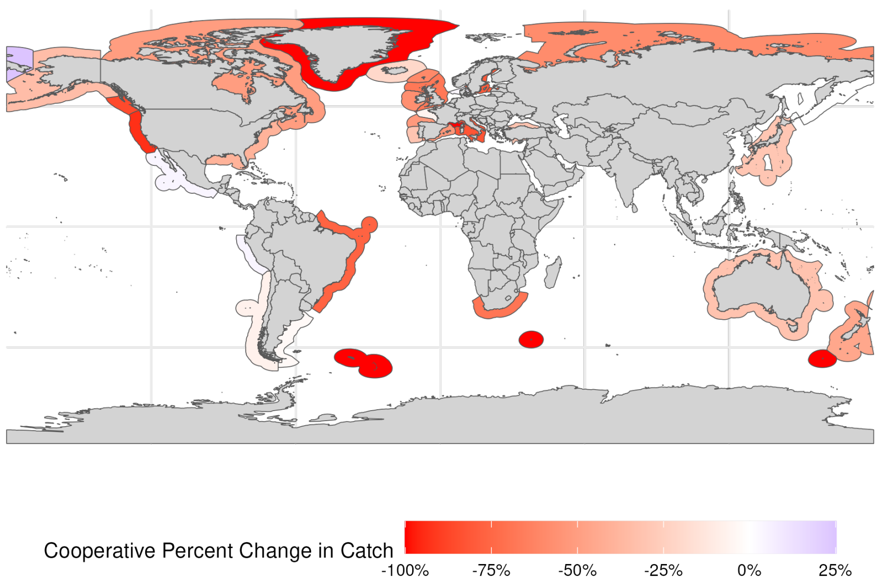


Figure 43: Change in Catch Value Under Global Cooperation by EEZ

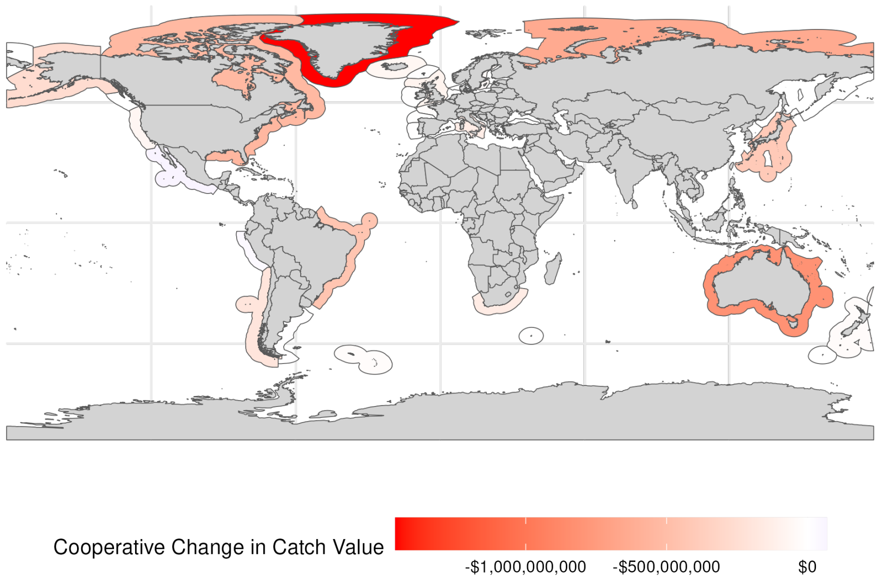


Figure 44: Percent Change in Catch Value Under Global Cooperation by EEZ

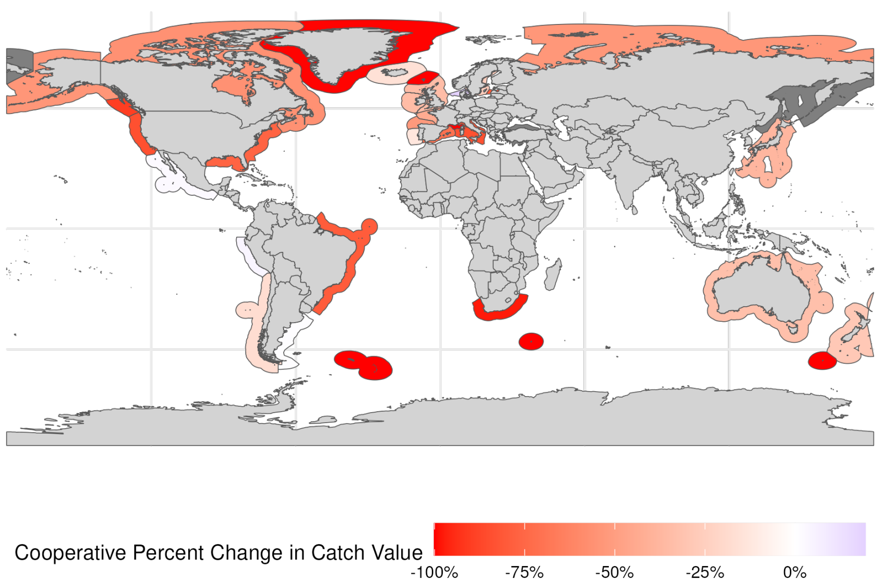


Figure 45: Change in Effective Country Share Under US-Canada Agreement

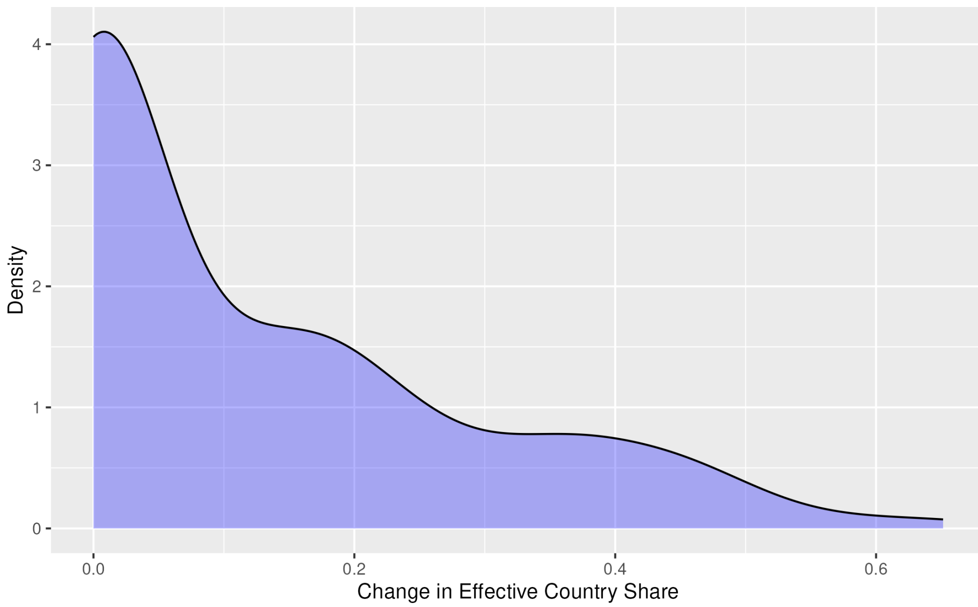


Figure 46: Change in Effective Country Share Under US-Canada Agreement by EEZ

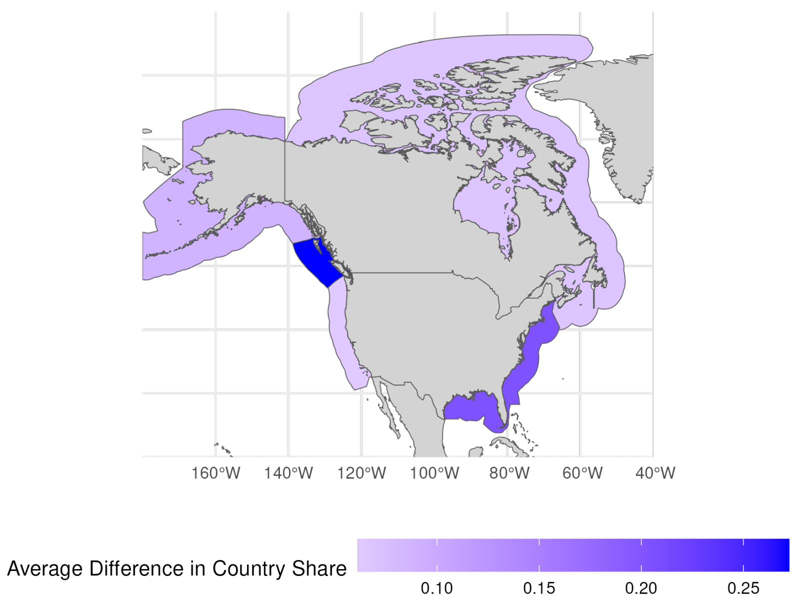


Figure 47: Change in Escapement Under US-Canada Agreement

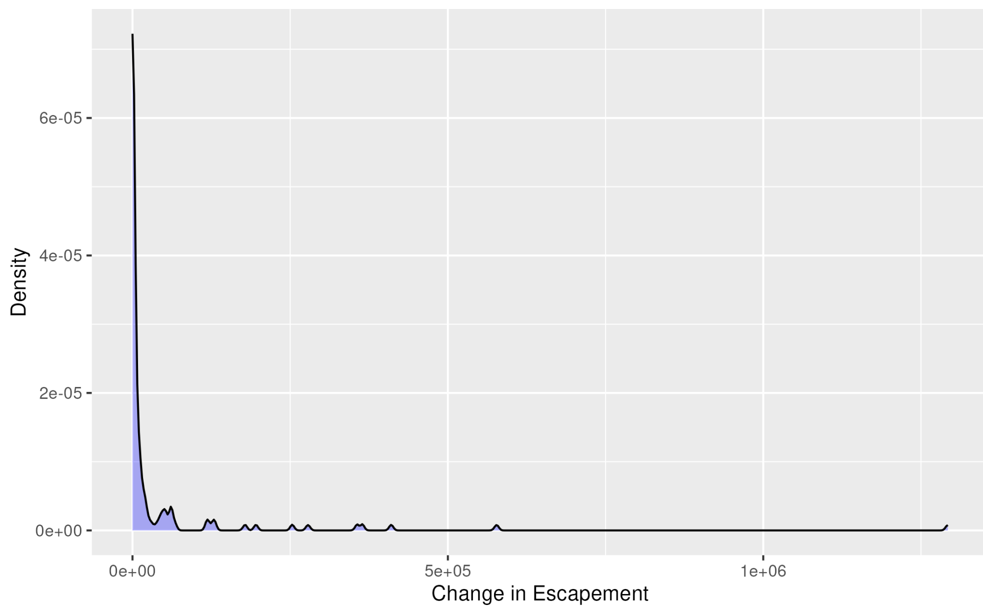


Figure 48: Percent Change in Escapement Under US-Canada Agreement

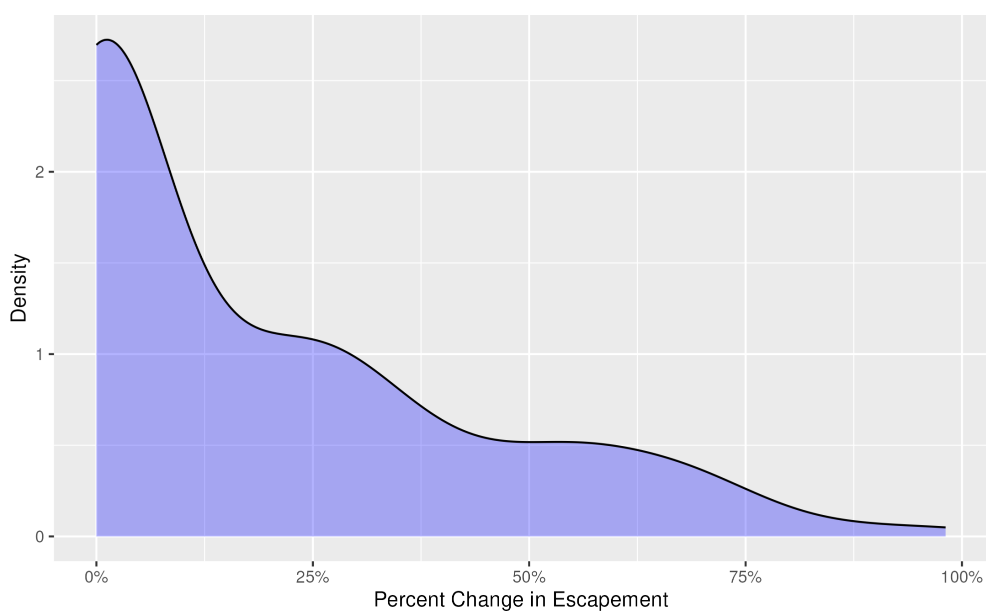


Figure 49: Change in Escapement Share Under US-Canada Agreement by EEZ

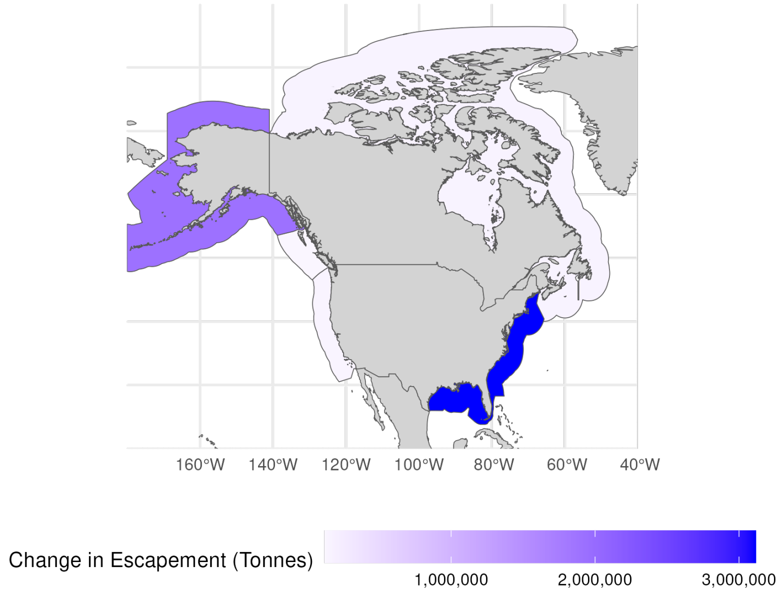


Figure 50: Percent Change in Escapement Share Under US-Canada Agreement by EEZ

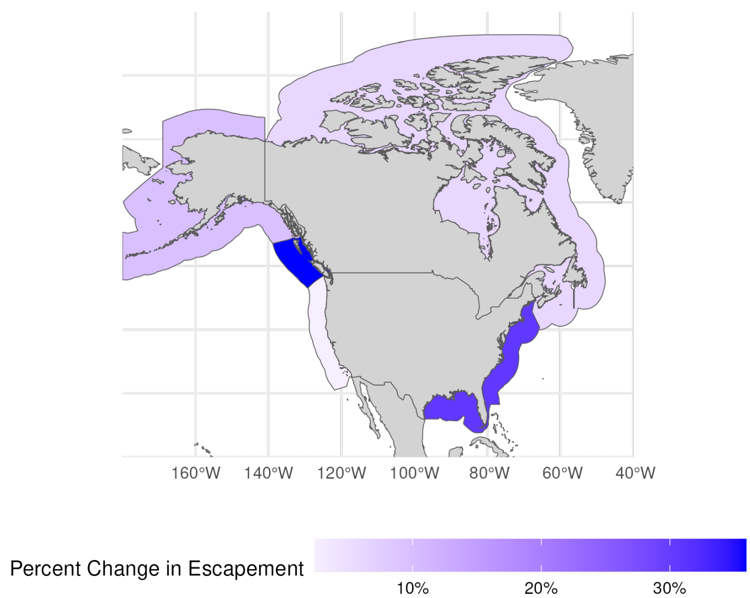


Figure 51: Change in Biomass Under US-Canada Agreement by EEZ

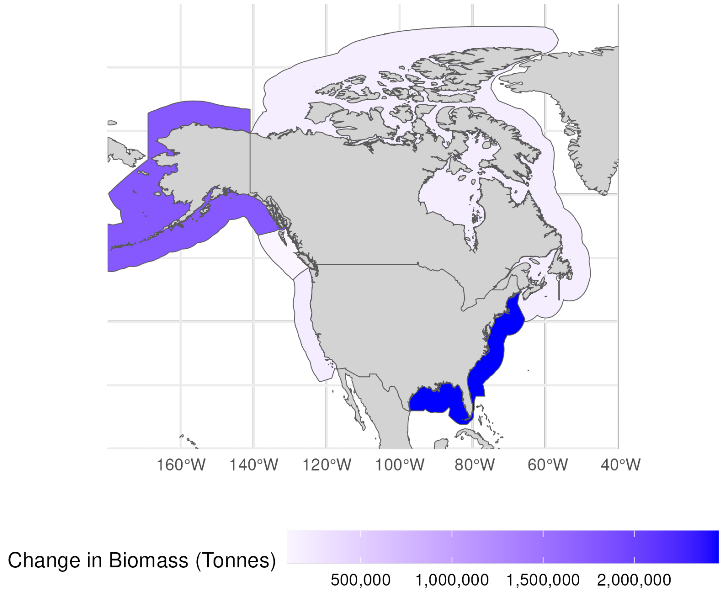


Figure 52: Percent Change in Biomass Under US-Canada Agreement by EEZ

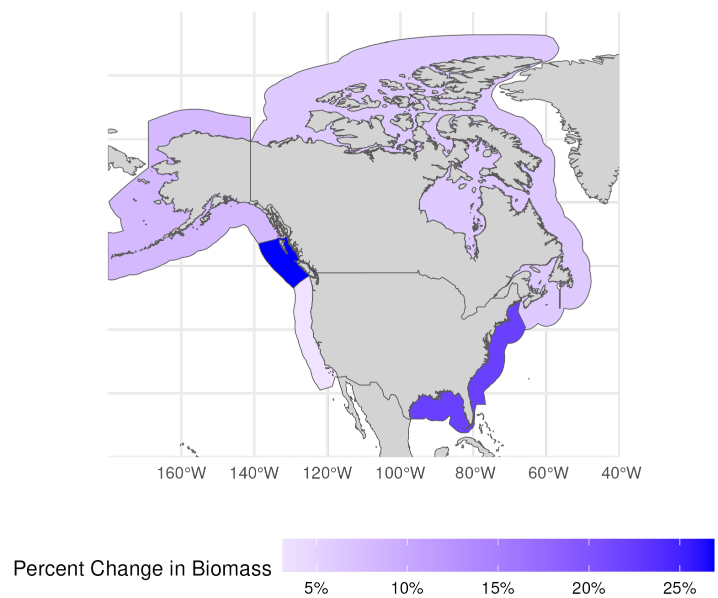


Figure 53: Change in Catch Under US-Canada Agreement by EEZ

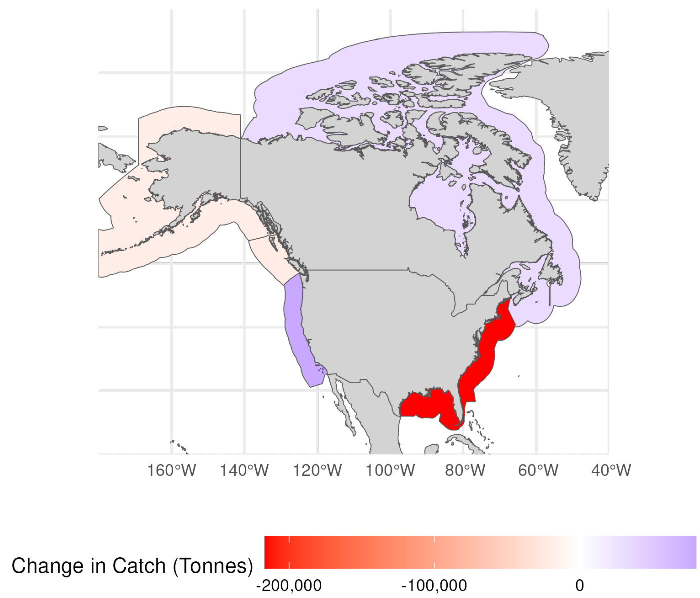


Figure 54: Percent Change in Catch Under US-Canada Agreement by EEZ

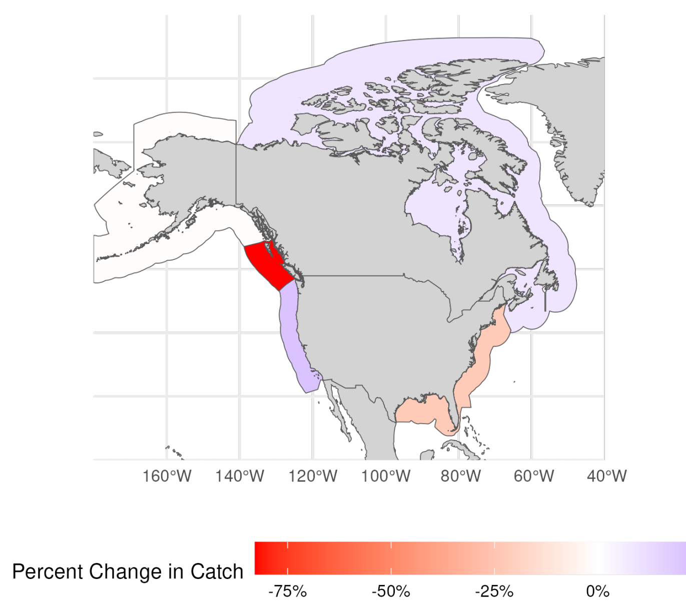


Figure 55: Change in Catch Value Under US-Canada Agreement by EEZ

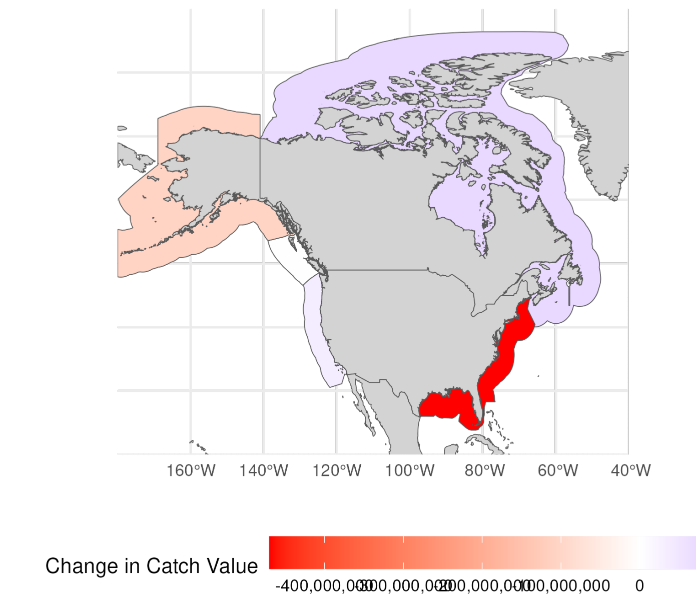


Figure 56: Percent Change in Catch Value Under US-Canada Agreement by EEZ

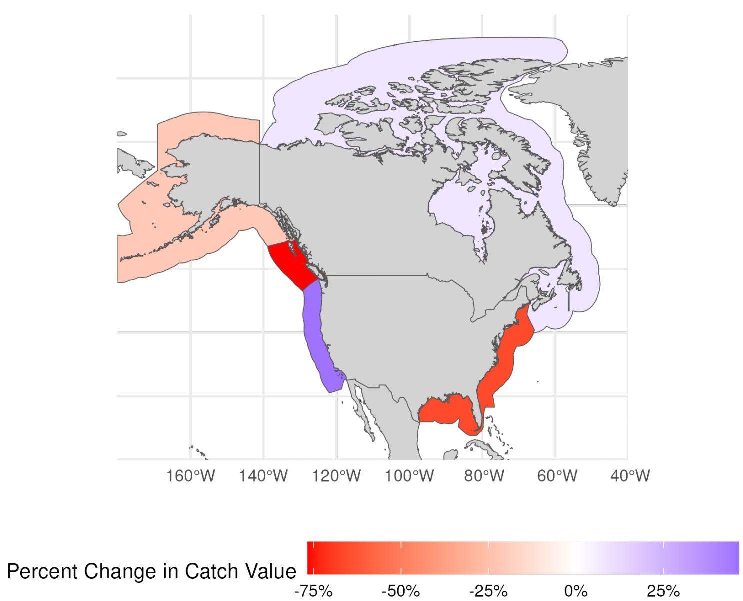
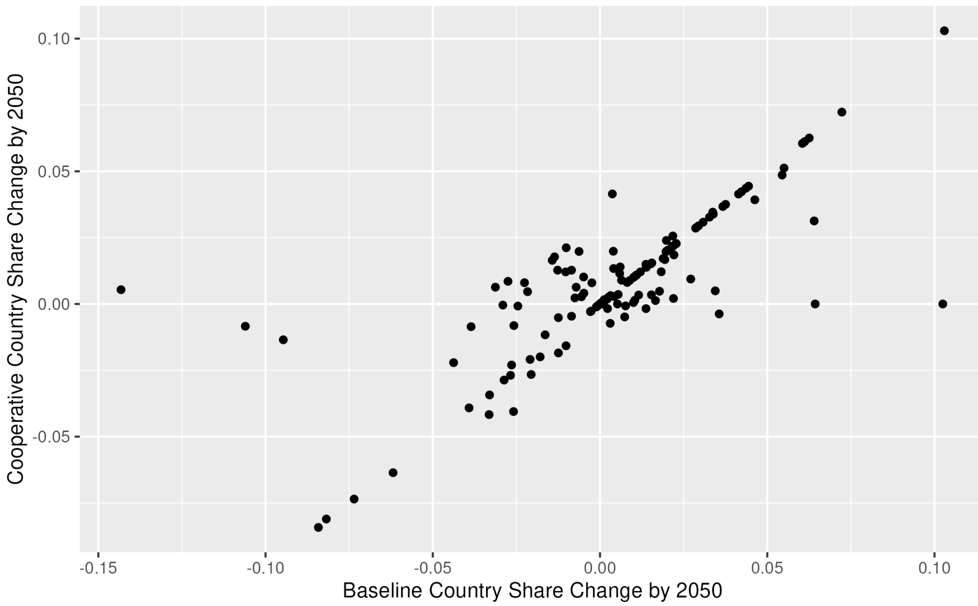


Figure 57: Climate-Induced Country Share Changes, With and Without US-Canada Agreement



A Country Share Measure

A.1 Country Share Construction

In this section, I describe the full process of generating my country 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 θ_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 6.

Table 6: 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 (mgC·m^3·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 (mmol·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 58 shows an example of how suitability is calculated for a generic environmental variable: suitability is zero if the value is less that 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 58: Generic Environmental Envelope

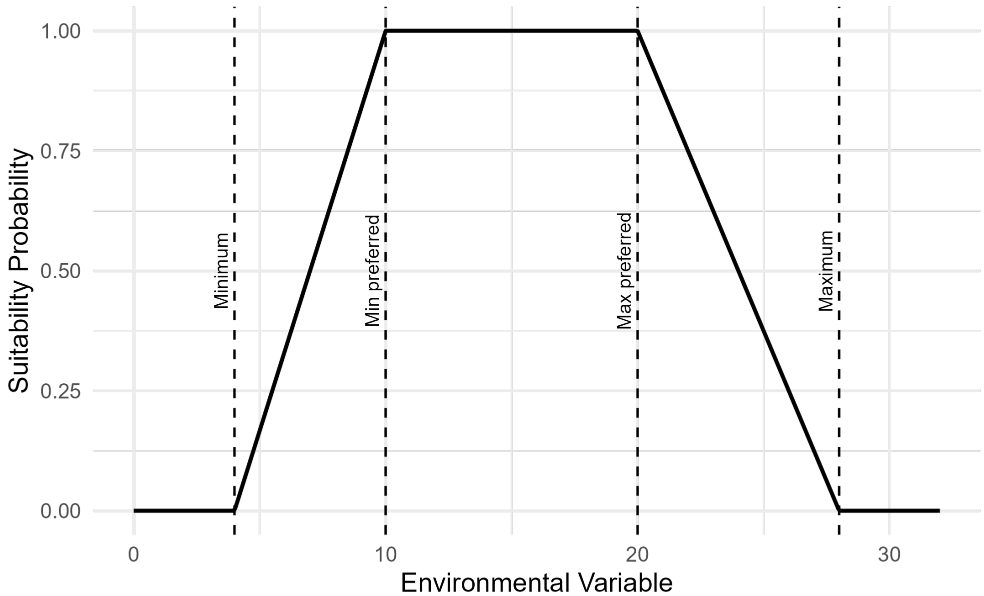
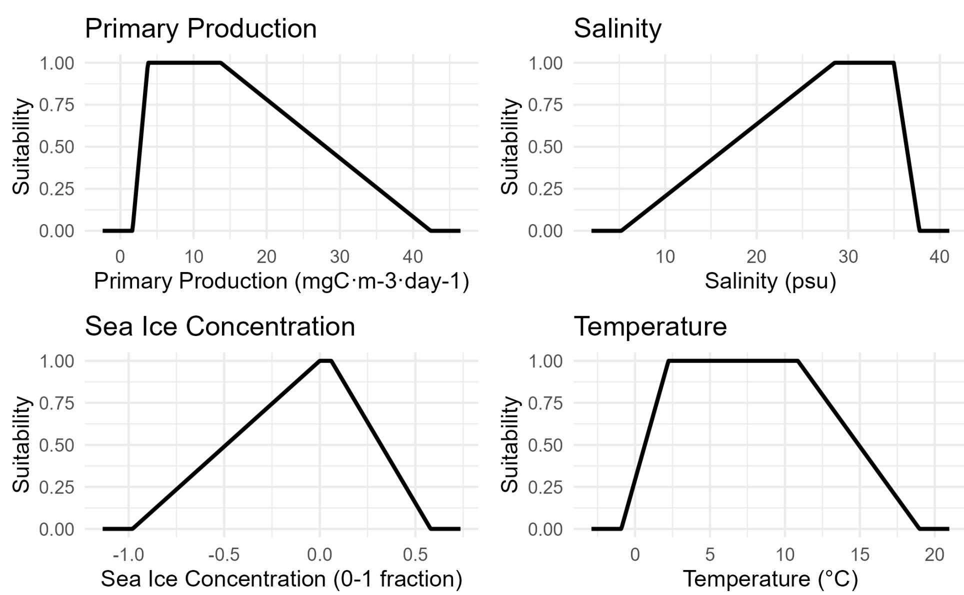


Figure 59 shows the four environmental envelopes used for Atlantic Halibut.

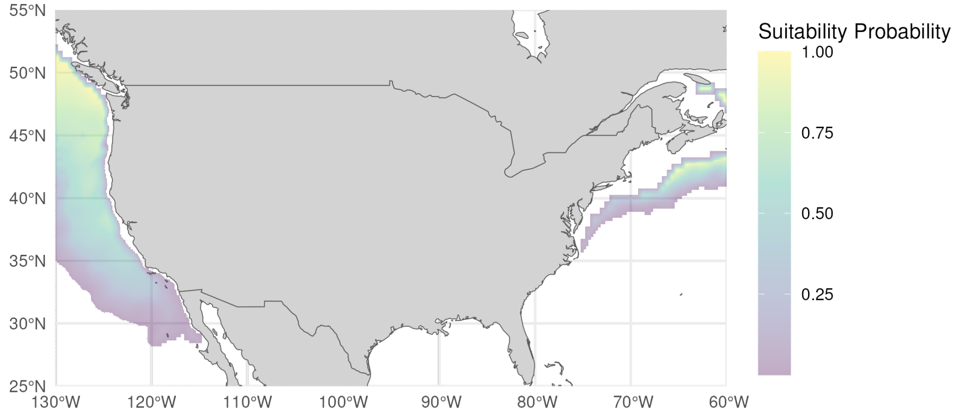
Figure 59: Environmental Envelopes for Atlantic Halibut



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 60. The figure shows the predicted suitability of each grid cell for Atlantic Halibut in 2020.

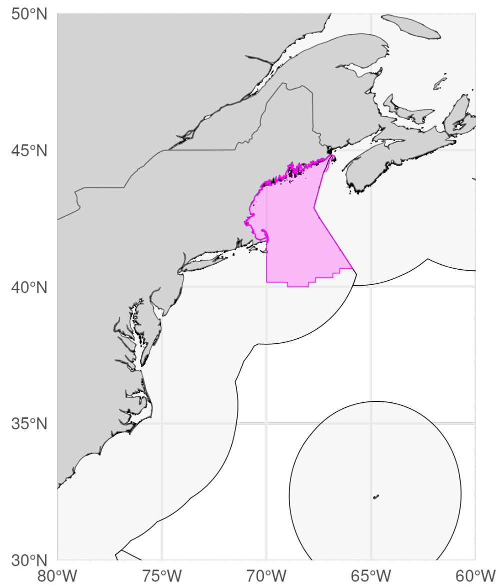
The predicted ranges are massive overpredictions–one can easily see it shows suitable ranges for Atlantic Halibut outside of the Atlantic.

Figure 60: 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 61 shows the shapefile for the US stock of Atlantic Halibut, found in the Gulf of Maine.

Figure 61: 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 62 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 62: Atlantic Halibut Management Areas

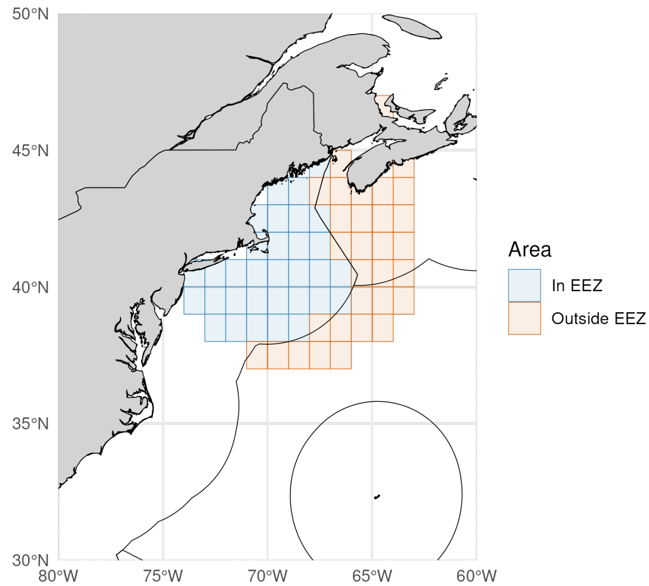
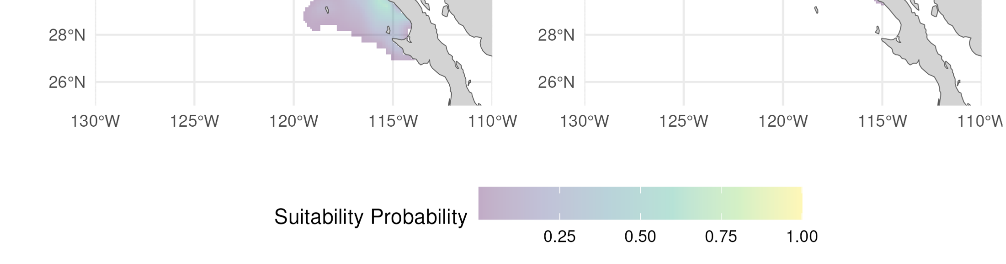


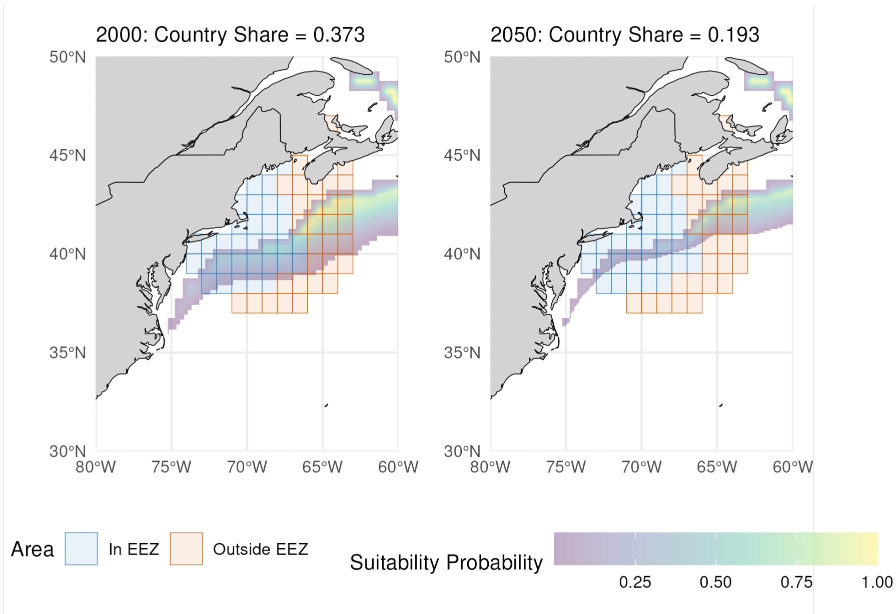
Figure 63 shows the predicted suitability for Atlantic Halibut in the area around the RAM shapefile for 2000 and 2050. Zooming in on this area where the species is known to be found highlights the actual anticipated effects of climate change. Comparison of the two maps shows a clear northward shift, 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 63: Atlantic Halibut Suitability in 2000 and 2050



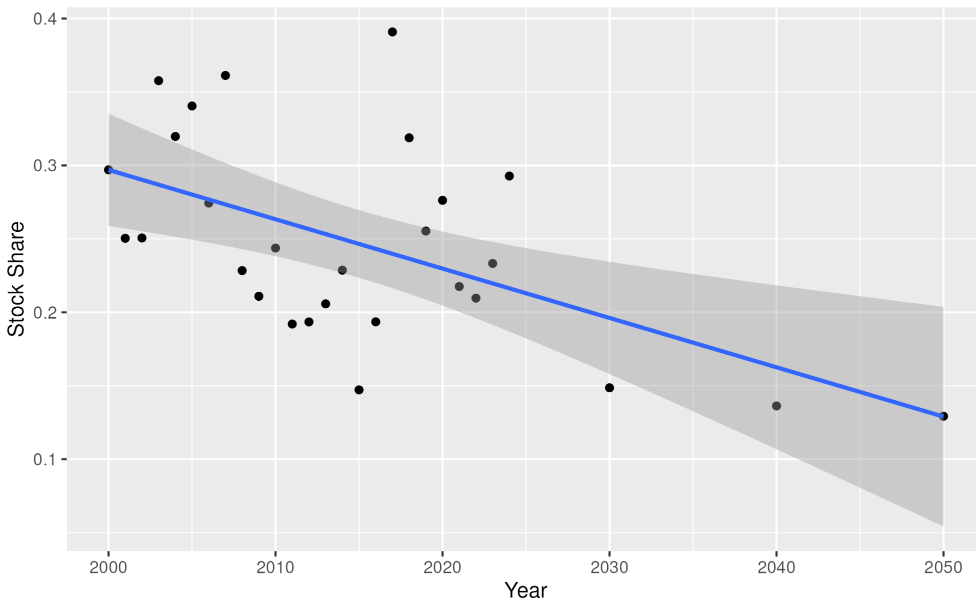
Finally, I put the habitat suitability and the management areas together. Figure 64 shows both the predicted suitability and the management areas for 2000 and 2050. To compute the country share I then calculate the share of the total predicted suitability in the entire buffer area (the sum predicted suitability over red and blue grid cells) that falls inside the management area (just the blue grid cells). This gives a country share of 0.380 in 2000 and a country 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 64: 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 country 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 country share on extraction outcomes. Figure 65 shows the calculated values for the US' Atlantic Halibut country share for each year in my data. It shows a trend of declining country share, with significant variation within the historic data.

Figure 65: US Atlantic Halibut Country Share Over Time



A.2 Country Share Validation

In this section I discuss the empirical exercises I do to validate my measure of the country 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 66 shows the relationship between the suitable range measure and catch in the cross section. Table 7 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 66: State Catch Vs Suitability

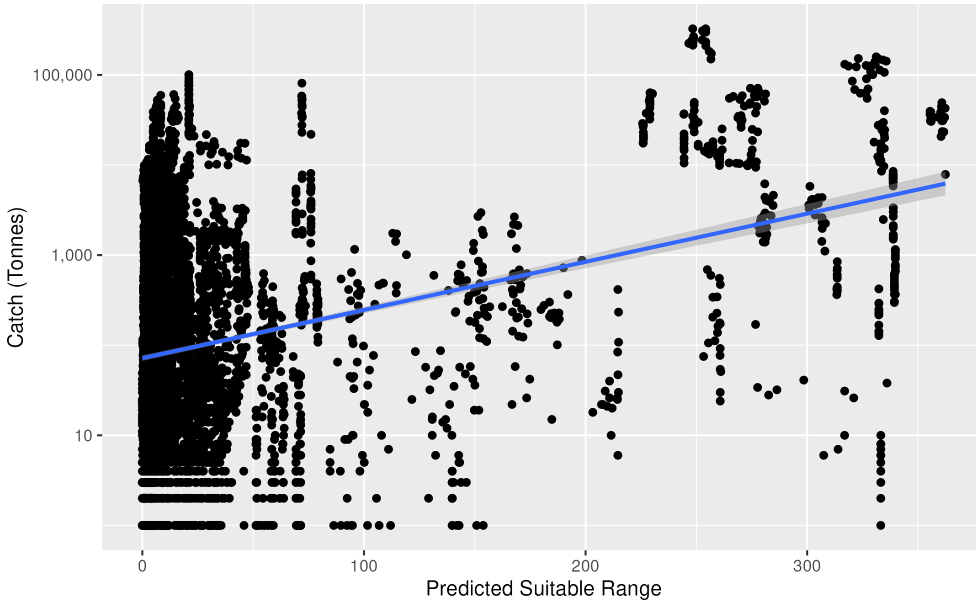


Table 7: Regressing State Catch on Suitability

	Dependent variable:
	Catch (Tonnes)
Suitable Habitat	54.902*
	(29.450)
State-Species FE	Yes
Year FE	Yes
Observations	6,806
R^2	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 country share measure is supposed to be an empirical proxy of θ in my model from Section 2. In that model, θ 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 country share measure is to show that it predicts recruitment. In Table 8 I show the results of regressing normalized biomass on the lags of normalized escapement, country share, and the interaction between the two. The table shows that a higher country share leads to greater biomass next period, conditional on escapement, consistent with its theoretical role.

Table 8: Regressing Biomass on Lagged Escapement and Country Share

	Dependent variable:
	Normalized Biomass
Lag Norm. Escapement	0.696***
	(0.020)
Lag Country Share	0.883***
	(0.335)
Lag Country Share×Norm. Escapement	−0.037
	(0.036)
Stock FE	Yes
Year FE	Yes
Observations	4,558
R^2	0.599
Note:	*p<0.1; **p<0.05; ***p<0.01

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

B Robustness

B.1 Additional Outcomes

Table 9: Log Panel Regressions

	Dependent variable:	
	Log Escapement	Log Catch
	(1)	(2)
Country Share	1.487^{**}	-3.312^{***}
	(0.647)	(0.985)
Log Biomass		0.777^{***}
		(0.027)
Stock FE	Yes	Yes
Year FE	Yes	Yes
Observations	4,884	4,884
R^2	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 country shares increase escapement and decrease catch conditional on biomass.

Table 10: First Differences Regressions

	Dependent variable:		
	Δ Norm. Escapement	Δ Norm. Extraction Rate	Δ Norm. Catch
	(1)	(2)	(3)
Δ Country Share	0.215	-2.297^{***}	-1.677^{***}
	(0.366)	(0.709)	(0.648)
Δ Norm. Biomass			0.347^{***}
			(0.031)
Constant	0.002	-0.034^{***}	-0.030^{***}
	(0.004)	(0.008)	(0.007)
Observations	4,232	4,225	4,232
R^2	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 country 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 country 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 11: Long Differences Regressions

	Dependent variable:		
	Δ Norm. Escapement	Δ Norm. Extraction Rate	Δ Norm. Catch
	(1)	(2)	(3)
Δ Country Share	4.194^{*}	-3.226^{*}	-1.919
	(2.174)	(1.874)	(1.777)
Δ Norm. Biomass			0.565^{***}
			(0.067)
Constant	0.011	-0.320^{***}	-0.295^{***}
	(0.057)	(0.049)	(0.046)
Observations	172	172	172
R^2	0.021	0.017	0.298
Residual Std. Error	0.737 (df = 170)	0.635 (df = 170)	0.594 (df = 169)
Note:			*p<0.1; **p<0.05; ***p<0.01

Regression results for long difference regressions of changes in average outcomes on changes in the average country share. Standard errors are clustered at the stock level (2000-2005 vs 2015-2020). Results are generally consistent with my main specification, with columns (1) and (2) showing that increases in the country share cause increases in escapement and decreases in the extraction rate, respectively. Column (3) shows a negative, but statistically insignificant coefficient, consistent with the main results.

Table 12: Trends-on-Trends Regressions

	Dependent variable:		
	Escapement Trend	Extraction Rate Trend	Catch Trend
	(1)	(2)	(3)
Country Share Trend	1.101^{*}	-3.179^{***}	-2.369^{***}
	(0.590)	(0.969)	(0.875)
Biomass Trend			0.574^{***}
			(0.028)
Stock FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,587	3,582	3,587
R^2	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 country 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 country 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 67: Escapement on Country Share with Various Buffer Distances

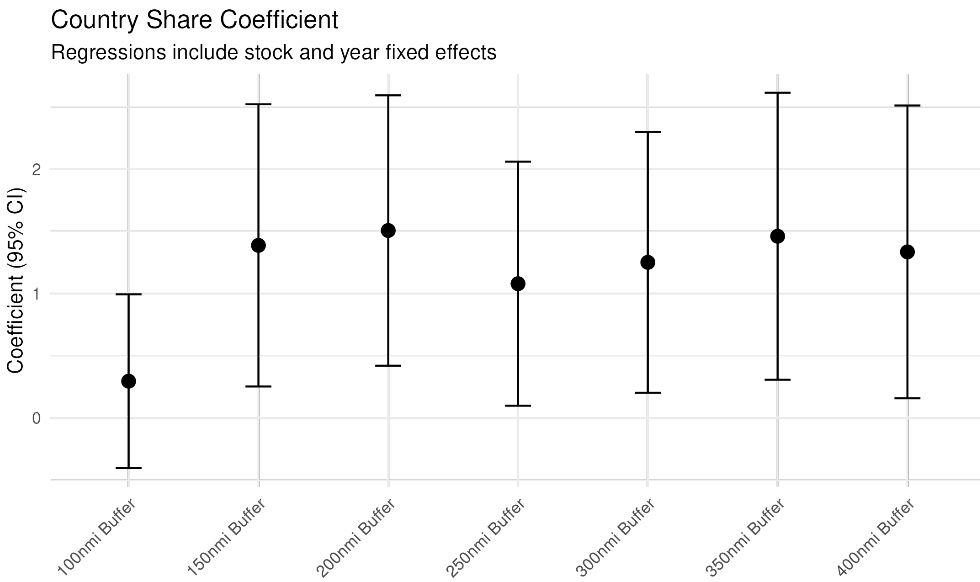


Figure 68: Extraction Rate on Country Share with Various Buffer Distances

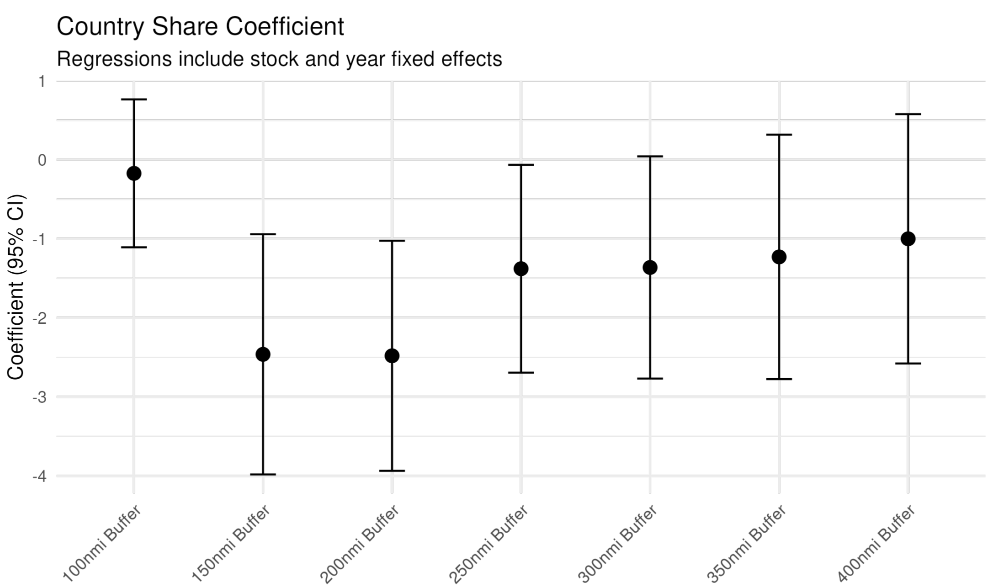
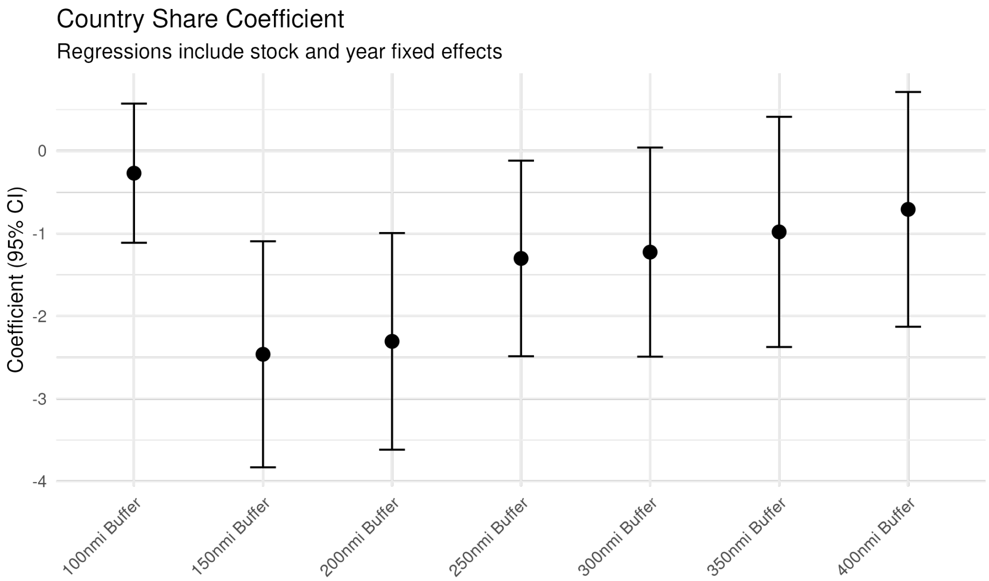


Figure 69: Catch on Country Share with Various Buffer Distances



C Heterogeneity

In this section, I run regressions that include an additional variable and the interactions between that variable and the country share. In these cases, I am interested in the coefficient on the country share and the coefficient on the interaction term.

C.1 Variables

The specific variables I use to explore heterogeneity are the following:

- **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 country 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 country 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 country 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 country 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 country share than other fisheries with catch limits but without property rights to catch.

- **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 country 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 country 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.[33]

- **High Seas Share**. I also run a regression specification testing whether the effect of the country 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 country 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 country 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.

- **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 country 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

[33] 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.

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 country share on optimal escapement should be larger as well.

C.2 Empirical Strategy

In order to incorporate these variables, I run the following regressions:

$$\begin{aligned}\text{Outcome}_{i,t} =& \beta\text{Country Share}_{i,t} + \lambda\text{Variable}_{i,t} + \gamma\text{Country Share} \times \text{Variable} \\ & + \alpha\text{Biomass (in Catch Regressions)} + \text{Stock FE}_i + \text{Year FE}_t + \text{Error}_{i,t} \quad (15)\end{aligned}$$

In these regressions, there are two coefficients of interest: the coefficient on the country share β and the coefficient on the interaction term γ. I always include stock and year fixed effects. I include a control for normalized biomass in catch regressions. The expected signs of β and γ depend on the particular outcome and heterogeneity variable. I examine whether the inclusion of the heterogeneity variable meaningfully changes the coefficient on the country share β, indicating that the effect I estimate in the baseline model is actually driven by specific observations. I also examine whether the interaction term γ has the same or opposite sign as the headline result, indicating that the heterogeneity variable either amplifies or dampens the effect of the country share.

C.3 Results

Here I describe the regression results including an additional variable and the interaction between that variable and the country share.

Table 13 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 country 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 country 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 country 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 country 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 15 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 country share and the growth rate, which is opposite in sign to the country 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 country share, consistent with bioeconomic theory. That is, as the species growth rate is larger, variation in the country 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 country share. Columns (4) and (6) show large, statistically significant effects of the interaction term that are opposite the sign of the country share coefficient. Column (2) shows a small and insignificant effect.

C.4 Tables

Table 13: Management Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	−5.113	1.452***	8.451*	−2.415***	1.510	−2.252***
	(3.381)	(0.555)	(4.508)	(0.745)	(4.043)	(0.671)
Norm. Biomass					0.526***	0.556***
					(0.020)	(0.020)
EPI Score	−0.166		−0.103		−0.010	
	(257,774.300)		(348,956.600)		(308,178.900)	
Country Share×EPI Score	0.404**		−0.671**		−0.233	
	(0.204)		(0.272)		(0.244)	
ITQs		−0.952**		1.745***		1.517***
		(0.453)		(0.607)		(0.547)
Country Share×ITQs		1.000**		−2.052***		−1.815***
		(0.500)		(0.672)		(0.604)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,864	4,845	4,855	4,836	4,864	4,845
R^2	0.002	0.003	0.004	0.005	0.137	0.151
Note:						*p<0.1; **p<0.05; ***p<0.01

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

Table 14: International Heterogeneity Regressions

	Dependent variable:								
	Norm. Escapement			Norm. Extraction Rate			Norm. Catch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country Share	1.695***	1.611***	1.714***	−3.022***	−2.256***	−2.487***	−3.371***	−2.215***	−2.315***
	(0.620)	(0.566)	(0.574)	(0.831)	(0.759)	(0.743)	(0.747)	(0.683)	(0.669)
Norm. Biomass							0.556***	0.556***	0.556***
							(0.020)	(0.020)	(0.020)
Country Share×Multinational	−0.937			2.682			5.278***		
	(1.376)			(1.843)			(1.657)		
Country Share×Migratory		−2.499			−5.333			−2.144	
		(2.745)			(3.678)			(3.311)	
High Seas Share			0.189			−0.212			−0.306
			(0.444)			(0.583)			(0.525)
Country Share×HS Share			−4.100						
			(2.996)						
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,884	4,884	4,884	4,875	4,875	4,875	4,884	4,884	4,884
R^2	0.002	0.002	0.002	0.003	0.003	0.002	0.152	0.150	0.150

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

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

Table 15: Rate Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	3.024**	1.888***	−5.555***	−2.777***	−4.090***	−2.562***
	(1.368)	(0.513)	(1.768)	(0.794)	(1.579)	(0.706)
Norm. Biomass					0.561***	0.548***
					(0.020)	(0.025)
Country Share×Growth Rate	−4.717		11.917***		9.244**	
	(3.424)		(4.425)		(3.950)	
Interest Rate		0.290		−1.032*		−1.312***
		(0.361)		(0.559)		(0.496)
Country Share×Interest Rate		0.010		3.040**		4.106***
		(0.764)		(1.184)		(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^2	0.002	0.004	0.002	0.005	0.163	0.121
Note:						*p<0.1; **p<0.05; ***p<0.01

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

D 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 country 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 country 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 country share in the different scenarios: Figure 70 shows the distribution of changes in country 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 70: Country Share Changes by Scenario

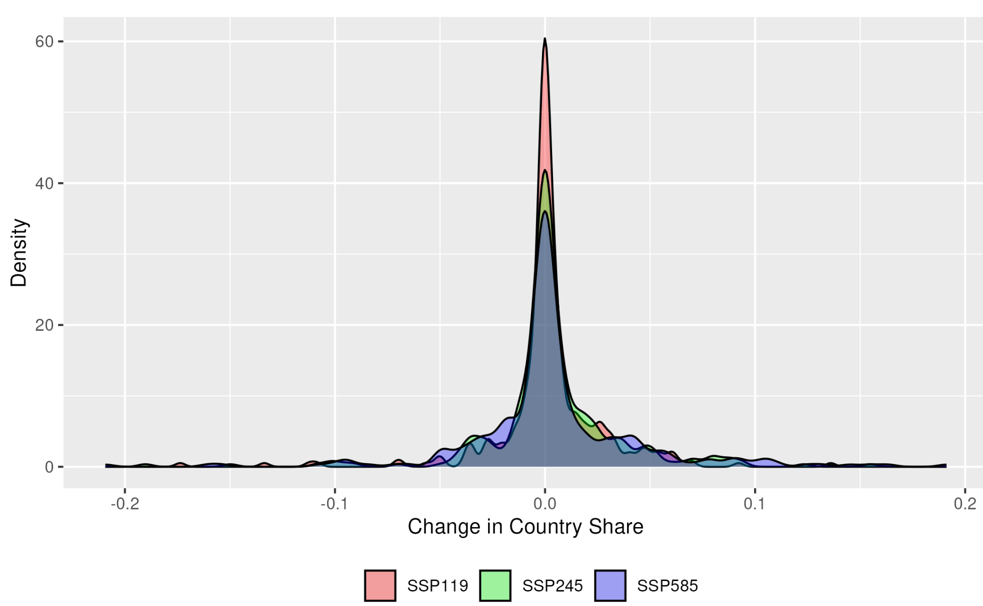


Figure 71: Total Change in Escapement by EEZ Under SSP119

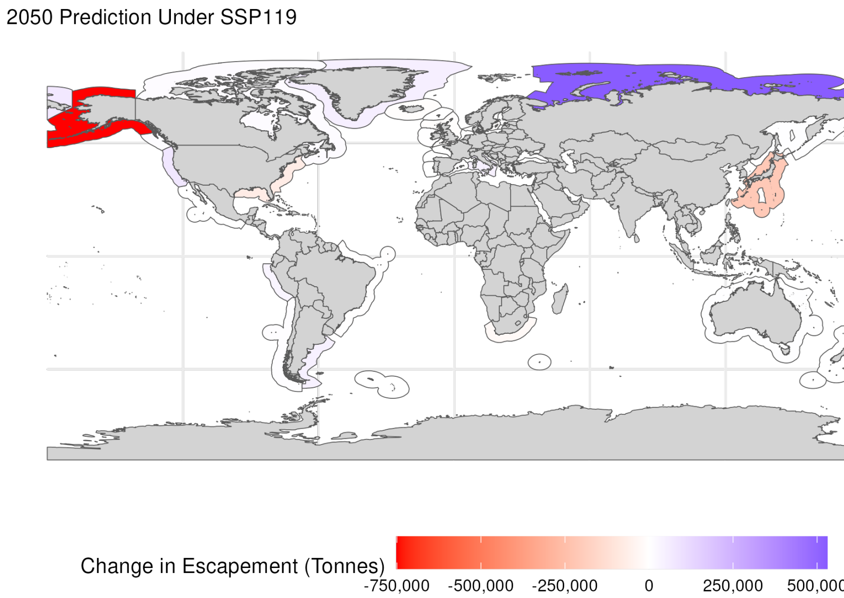


Figure 72: Percent Change in Escapement by EEZ Under SSP119

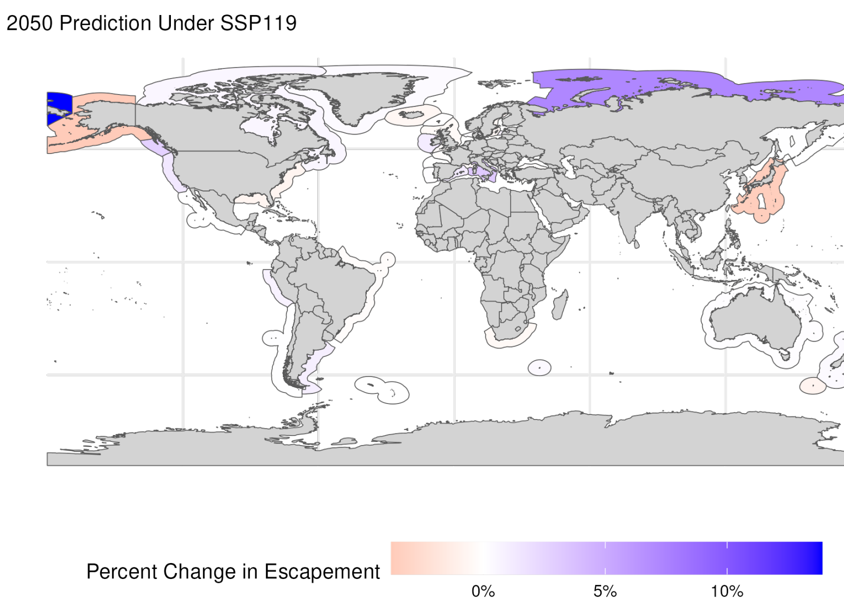


Figure 73: Total Change in Escapement by EEZ Under SSP585

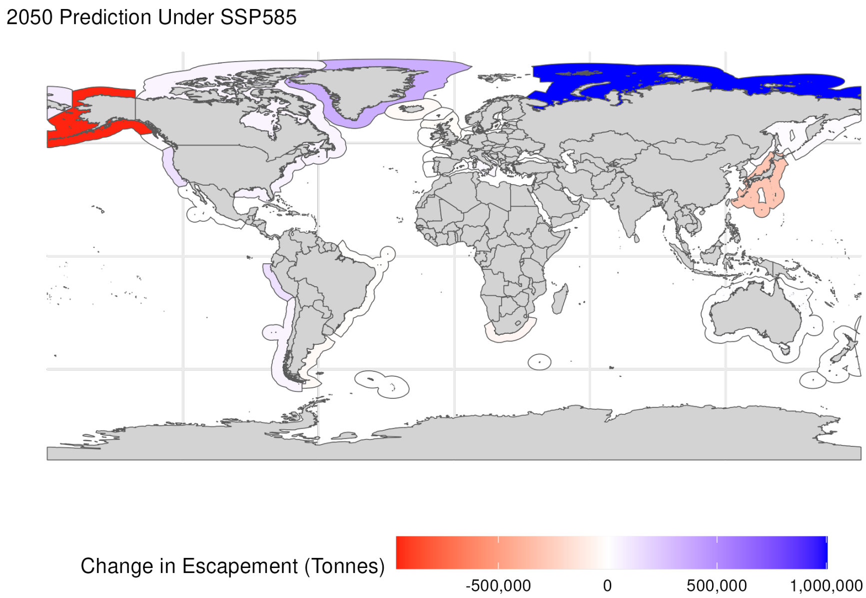


Figure 74: Percent Change in Escapement by Under SSP585