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 climate change reshape it? Most fish populations cross national borders, diluting the incentive for governments to conserve. Climate change will upend the current equilibrium by altering biological productivity and by shifting species' geographic ranges. These range shifts reallocate control across countries, potentially inducing maladaptive overexploitation by "stock-losers" and stronger conservation by "stock-gainers." I use species distribution modeling methods to construct a historical panel that tracks fishery ranges over time and document a strategic response: extraction from a transboundary stock increases as the managing country's share of the fishery declines. I then use my estimates to simulate the consequences of future range shifts under climate change. The behavioral responses to range shift net out to close to zero, but are economically meaningful for individual fisheries: stock-gainers increase conservation by 1.7 million tons (2.8%) and stock-losers decrease conservation by 1.5 million tons (3.2%) due to range shift. For the average fishery, this strategic response comprises 29% of the total effect of climate change on the fish stock. Under first-best global cooperation, conservation increases by 89 million tons (79%). Under a more plausible U.S.–Canada agreement, conservation increases by 14% and the behavioral response to climate change is dampened by 66%.

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1 Introduction

How severe is the international common-pool problem in fisheries? How will it be affected by climate change? Many environmental problems involve cross-country spillovers and face changing dynamics under climate change. In marine fisheries, at least 67% of fish populations cross two or more Exclusive Economic Zones (EEZs)–the areas up to 200 nautical miles from a country's coast wherein it has jurisdiction over marine resources–and 45% of those are projected to experience significant shifts in range due to climate change (Palacios-Abrantes et al., 2020a, 2022).[1] Climate change-induced range shifts could alter incentives for conservation: On one hand, range shifts could induce strategic overfishing, move stocks into countries with worse fisheries outcomes (see Figure 1), or even move stocks into the internationally open-access high seas.[2] On the other, range shift could *increase* conservation from countries that now internalize greater rewards, with poleward movements directing fisheries toward countries with longer coastlines and larger EEZs on average (see Figure 1).[3]

In this paper, I leverage historical variation in fishery ranges to estimate the effect of the transboundary problem on fisheries conservation. I show that a one percentage point decrease in the share of a fishery under a country's control decreases **escapement** (the quantity of available biomass *not* caught) by 1.6%. I use my estimates to simulate the behavioral response to different climate scenarios. I find that range shift has close to zero effect on

[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 it simply assumes that all shifting stocks will transition to open access if not managed cooperatively.

average due to offsetting effects: by 2050 stocks with increasing control over the fishery will increase escapement by 2.8%, whereas stocks losing control will decrease escapement by 3.2%. These effects are on the same order of magnitude as the historic effect of warming on fisheries productivity, which has been estimated to reduce fishing yields by 4.1% from 1930 to 2010 (Free et al., 2019). Naturally, accounting for the biophysical effects of climate change is also essential.[4] Under a simple calibration, I find that omitting the behavioral response to range shift would miss 32% of the total effect of climate change on escapement for the average stock. I also find large static losses due to fragmented governance, and that international cooperation could significantly mitigate the effects of range shift.

I begin by building 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. Optimal escapement equates the marginal profit of catch today with the discounted marginal productivity of the fish stock, which depends on the marginal profit of catch tomorrow, the discount rate, the growth rate of the stock, and a parameter that captures how much of the fish stock will remain 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 predicts 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 control and extraction from the fishery. This requires data on extraction outcomes and a measure of the country share. For outcomes, I employ the RAM Legacy Stock Assessment Database, a collection of stock assessment results for many of the world's most important

[4] 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).

fisheries with high-quality stock assessment results (Ricard et al., 2012).[5] 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 (RAM, 2024). All together, there are 326 stocks, representing 163 unique species, from 23 countries in my panel.[6] For each stock, I identify the designated management region using the shapefiles from the RAM Legacy Stock Boundary Database (Free, 2023). For each stock-year, I construct escapement (biomass − catch) and the extraction rate (catch/biomass), which form the outcomes of my analysis.

I combine these outcomes with a novel panel measure of the share of each population under the manager's control which I construct following species distribution modeling techniques. For each species in the panel, I withdraw the suitable conditions along a few key environmental variables from AquaMaps (Kaschner et al., 2019): temperature, salinity, primary productivity, sea ice concentration, dissolved oxygen, and depth. Then, I use cell-by-year measures of those environmental variables based on satellite data, ocean monitors, and environmental modeling to create annual predictions of suitable ranges. The measure captures exogenous shifts in the realized distribution of the fish population. For each stock in each year, I identify 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] Finally, I calculate 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.

My main empirical contribution is to estimate the effect of the country share on escapement, the extraction rate, and catch conditional on biomass. In the cross section, my proxy for the country share is positively correlated with escapement and negatively correlated with the extraction rate and catch (conditional on biomass). In my primary specification, I regress these on my country share measure, controlling for stock and year fixed effects to iso-

[5]Each stock in this data represents a species in a location (e.g. Atlantic Halibut off the coast of Maine).

[6]Figure 2 illustrates the number of stocks in my dataset by EEZ and country. It shows that the US and Canada together make up a majority of the stocks, with Europe and Japan accounting for another significant share.

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

late 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 1.6%, increases the extraction rate by 2.7%, and increases catch conditional on biomass by 2.5% 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 multinational management.

Finally, I deploy my estimated empirical responses to simulate fisheries outcomes under counterfactual environmental and institutional scenarios. First, I predict future fisheries outcomes under climate change. I follow the same AquaMaps methodology to create predicted suitability distributions under predicted oceanic environmental conditions for different 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), with a majority of changes clustered around zero. The implied effects on escapement vary from 30% reductions to 26% increases, though for most stocks the predicted changes are small. Although the average effect is small, the gross gains and losses are significant in relation to the historic effects of warming. Most EEZs with stocks in my sample are predicted to gain stock control under climate change, especially Russia and Canada. Not all northern EEZs are expected to benefit, however: I predict losses in Alaska, Iceland, and Japan. On net, total escapement from these fisheries is predicted to slightly increase when accounting only for the behavioral response to range shift.[8]

To benchmark the significance of these results, I compare them to the biophysical effects of climate change. Specifically, I exploit the Basin Model Hypothesis from MacCall (1990) to predict the future carrying capacity of each species. I follow Gaines et al. (2018) and other

[8]It should also 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.

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 32% misstatement of the combined effect of climate change for the average stock, although this is not systematically biased upwards or downwards.

My second simulation predicts the impacts of institutional reform by estimating the global gains from collaborative management, assuming every country manages their fisheries consistent with a global social planner. Specifically, I simulate what escapement would be if every stock where managed as if its country share were 1 (that is, each country fully internalized spillovers). In that scenario, I find that escapement from the average stock increases by 67%. Global escapement from fisheries in my sample increases by 89 million tonnes (79%), since some of the largest fisheries have greater than average improvements in management. In total, the potential gains from solving the static transboundary problems are significantly larger than the predicted effects of climate change. This hypothetical global agreement also precludes any behavioral response to range shift. However, under a simulation of a 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, comparable in magnitude to the effects of climate change. I also find that this bilateral agreement dampens the behavioral response to range shift by two-thirds.

1.1 Related Literature

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.

This paper also contributes to a long literature on the cross-jurisdictional management of

[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]A few papers look at adaptation with spillovers. Moscona and Sastry (2022) and Moscona and Sastry (2023) study innovation in crop varieties as an adaptive strategy and a public good. 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 El Niño 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.

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]

This paper also 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 analysis focuses on the global governance of fisheries, this paper also has implications for domestic regulations. In particu-

[14] Lipscomb and Mobarak (2017), perhaps the canonical paper in this literature, 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), 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, 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 Exclusive Economic Zones exert binding pressures on fishing locations.

[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.

lar, 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 163 different species, exploiting temporal 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 my data, 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. Section 6 presents the simulated predictions for various climatic and institutional scenarios. Section 7 concludes.

[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] It motivates focus on escapement as the most relevant outcome, and shows how optimal policy in each period is to set an escapement target that depends on the country share in that period. This motivates my empirical design, which estimates the effect of the country share on escapement.

Each country controls the harvest from the population of fish within its own territory. However, the two populations of fish are connected in terms of reproduction, so the growth of each population depends on the escapement in the other.[23] 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, and vice versa.

The biomass available to fish in country i in period t is $X_{i,t}$. 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 $t+1$.[24]

I will refer to $\theta_{i,t}$ as the "country share," which is *not* the (endogenous) share of biomass $(\frac{X_{i,t}}{X_{i,t}+X_{j,t}})$ but rather an exogenous parameter determined by ecological conditions.

[22] I am not the first to build 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] For example, Ramesh et al. (2019) demonstrates the close biomass linkages between countries due to currents and larval dispersal.

[24] In Appendix A, I consider a more general growth function that depends on both countries' escapement jointly.

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 $\tilde{p}$.[25]

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.

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

This yields the following Bellman equation:

$$V_i(X_{i,t}, X_{j,t}) = \max_{H_{i,t} \in [0, X_{i,t}]} \left[\underbrace{\tilde{p} H_{i,t}}_{\text{Current Profit}} + \delta V_i(\underbrace{X_{i,t+1}}_{\theta_{i,t} G(S_{i,t}) + (1-\theta_{j,t}) G(S_{j,t})}, \underbrace{X_{j,t+1}}_{(1-\theta_{i,t}) G(S_{i,t}) + \theta_{j,t} G(S_{j,t})}) \right] \tag{3}$$

The Bellman equation yields the following First Order Condition:

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

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.[26] Therefore

[25]In Appendix A, I consider a case where harvest costs depend on the available biomass.

[26]I consider the case where country j is not at an interior solution in Appendix A

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 to present catch, and does not depend on prices or costs due to the constant marginal profits assumption.[27] for more detail.

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.[28]

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:

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

[27] Adding costs does not overturn the qualitative result that the escapement target increases with θ, but can add complications. Specifically, adding harvest costs can add additional forces for present marginal profits and/or the future returns to fisheries productivity. See Appendix A

[28] 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.

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 country 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 country 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 country 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 country share implies a higher extraction rate both in steady state and along the transition path.

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

In a cooperative equilibrium, each country would set

$$G'(S^o_i) = \frac{1}{\delta} \tag{13}$$

Which does not include $\theta_{i,t}$ because it is irrelevant to global welfare (profits) who the beneficiary of stock growth is. This yields the second proposition:

Proposition 2 *The privately optimal escapement S^*_i is strictly lower than the globally optimal escapement S^o_i 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 2 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 (SAU) database, the catch from these fisheries was collectively worth over $15 billion (Tai et al., 2017). This is 23% of the $68 billion in catch value in the SAU database, and less than 10% of the $159 billion valuation of catch from all global capture fisheries (Sampson, 2024). 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 5 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. I begin by calculating the distribution of predicted suitability for each species in each year of my dataset. I then use the share of predicted suitable area around a fish stock's known habitat which falls inside a countries exclusive economic zone as a proxy for the country share.

Following the methodology of AquaMaps, a database of fish species habitats and environmental prefrences, 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, which form "environmental envelopes."[29] The AquaMaps method assigns a simple suitability probability based on each variable: If the level is outside of the minimum and maximum preferred 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 3 shows a graphical representation of this approach by graphing the six environmental envelopes for an example species. Finally, all of the relevant probabilities are multiplied together to generate a single raster of environmental suitability probability.

[29] The six environmental variables are Sea Temperatures, Salinity, Primary Productivity, Depth, Sea Ice Concentration and Dissolved Oxygen Concentration.

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 4 shows the distribution of predicted suitability for Greenstriped Rockfish in 2000 and 2050 following this approach.

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. 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. Furthermore, the method has been shown to predict population distributions (Ready et al., 2010). 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 4 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 5 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 5 also 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 6 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.[30] In the case of the Greenstriped Rockfish, the 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 B, I walk through the method step by step for Maine Atlantic Halibut, which is predicted to lose significant 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.

[30]Figure 7 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.

4 Empirical Strategy

The main empirical contribution 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, namely that a higher country share leads to lower escapement, a higher extraction rate, and higher catch conditional on biomass. In this section I will test these predictions and quantify their significance for global cooperation and climate change.

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 country share simply due to more available biomass. With the extraction rate outcome I show that the *share* of available biomass caught changes, ruling out some mechanical increase in escapement solely due to higher biomass. 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. This requires that the variation in my country share proxy captures real, exogenous variation in the fish population, and that outcomes for different stocks would evolve in parallel in the absence of changes in the country share. 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. This has been studied previous, notably in McWhinnie (2009) and Liu and Molina (2021), and provides a logical sense check for whether my estimates are related to the static transboundary problem. For example, Figure 7 shows the stock-level average extraction rate plotted against the country share decile, and shows that my measure does in fact correlate negatively with extraction rates. 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 C.

This is not the baseline panel specification due to the presence of zeros in my data challenging the interpretation Chen and Roth (2024).

To examine robustness to the construction of the country share, I repeat the regression specifications described above using different buffer distances to compute my proxy for the country share; specifically 150, 200, 250, 300 and 350 nautical miles. Coefficient plots for these regressions are included in Appendix C.

I also run first differences regressions as a robustness check for serial correlation. My country share measure is highly serially correlated, so I use first differences to isolate variation that comes only from year-to-year changes in the country share. 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 approach deals with serial correlation differently, by isolating only the long run variation in the country share. This gives me a dataset of 266 long difference observations, which I use to regress changes in the outcomes on changes in the country share. Appendix C includes regression tables for these specifications.

Finally, I also regress the trend in each outcome on the trend in the country share. This helps confirm that the relationship between my outcomes and the country share are not driven by outlying observation. 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 C 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 efficacy of fisheries management**, as measured by the Global Fishing Index, the use of Individual Transferable quota, and indicators of Illegal, Unregulated and Unreported Fishing. My theory applies to a fishery manager with sufficient knowledge and institutional capability to observe biomass and set binding catch constraints. Therefore, I explore whether more effective fisheries management regimes have stronger responses to range shift.

- **Degree of international sharing**, as measured by an indicators for multinational management and a measure of the "high seas share." It is possible that greater international sharing exacerbates the strategic responses to range shift because even small shifts might imply greater reallocation. On the other hand, stocks with more international sharing may already be quite close to open access, or alternatively may already have effective international management regimes. In either of those cases, range shift may be *less* consequential.

- **Migratory Behavior**, as measured by an indicator for whether a species is pelagic (open ocean) or highly migratory and a continuous measure of species home range. Like above, more migratory species may already have international management institutions, or may already suffer from effective open access. If so, these could depress the effect of range shift.

- **Species growth rates**, as measured by the intrinsic growth rate parameter which does not depend on species biomass. My theory predicts that escapement should respond to the country share, but the magnitude of the response is mediated by the curvature of the growth function. I investigate whether this is empirically supported.

- **Country interest rates**, as measured by the country-year level lending interest rate. My theory predicts that the interest rate should magnify the effect of the country share, holding all else fixed. However, interest rates may also be correlated with other economic or institutional confounders.

In Appendix D 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.[31]. 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. Specifically, it implies that a 1 percentage point increase in the country share increases escapement by 1.57% of its historic average. As I discuss in more detail in Section 6, the predicted changes in country shares under climate change are mostly small but range from significant increases to significant decreases. The largest predicted gain in country share, 0.166, would

[31]For cross sectional regressions, I condition on biomass even when escapement is an outcome to account for stock-level differences in magnitude

imply an increase in escapement of 26.1% of the historic average, while the largest predicted loss in country share, -0.19, would imply a decrease in escapement of 29.8% of the historic average. These effects are quite significant, but not implausibly large–the standard deviation of escapement is 39% of the historic average. Finally, the average country share being 0.53, these results would imply that if every stock were managed as if the country share were 1 (that is, every fishery manager internalized the global benefits of their conservation), then escapement would be higher by 73.7% of the historic average, under a simple linear extrapolation.

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 lower country share causes a higher extraction rate. A 1 percentage point decrease in the country share would increase the extraction rate by 2.68% of the historic average. Under the predicted climatic changes, the extraction rate effects would range from a 44.6% reduction to a 50.8% increase. Translating that into actual extraction rates (the fraction of available biomass that is caught) using the coefficient and the average extraction rate for each species, the range of climate change effects goes from an increase of 0.085 to a decrease of 0.075, relative to an average of 0.17. 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. It implies that a 1 percentage point decrease in the country share would increase catch by 2.47% of its historic average, conditional on biomass. The predicted effects of climate change range from a 41.2% reduction to a 46.9% 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 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 30, 31, and 32 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 D 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 indicators for above average fisheries management and the use of Individual Transferable Quota, which are considered the first-best form of management by most economists. Meanwhile, measures of low-management capacity, such as high Illegal, Unregulated and Unreported fishing, also depress the effect of the country share. 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 efficacy 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.[32] By default, I use the environmental predictions for SSP2-4.5, a "middle of the road" climate scenario that bases future projections on a continuation of historic trends.[33] Under this projection, the average cell in the ocean will have warmed by 1.15°C from 2000 to 2050. Figure 8 plots the change in the country share between the average 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 E.

To evaluate the consequences for escapement, I calculate the implied change in escapement by 2050 multiplying the change in the country share from the historic average to its 2050 value with the coefficients from Table 4 to get the predicted changes in percentage terms. I then multiply by the historic average to calculate level changes. Summing up across all of the predicted escapement effects gives a net increase in escapement of around 215,000 tonnes, which is small compared to the average total escapement of 113,000,000. Figure 9 maps the percent change in escapement for those same stocks by EEZ, and shows that most EEZs will increase escapement, and a few will increase it significantly. This is a feature of

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

[33]Appendix E 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.

averaging to the EEZ level, as the stock level percent changes follow the same distribution as the changes in the country shares, which show no particular pattern for increases and decreases.[34]

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, 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,[35] and has been used in many of the most sophisticated climate forecasts in fisheries.[36] 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.[37] Therefore,

[34]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).

[35]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).

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

[37]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.

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. The purely biophysical model predicts the change in escapement and biomass based on projected changes in the suitable area. The combined model then adds my predicted behavioral response by countries to changes in the country share. Figure 10 plots the difference between the biophysical and the combined model. For the average stock, using only the biophysical model would miss approximately 31.6% of the full effect of climate change, although there is substantial heterogeneity across stocks. Figure 12 maps the percent changes in escapement by EEZ due to the combined effects of climate change. Compared with Figure 9, we see general increases in escapement due to the dominance of the biophysical channel. On net, escapement is predicted to increase by 20.4%. However, Figure 13 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, which align with the Behavioral-Only results from above: the Biophysical-Only prediction understates the increases in Russia and Canada, but overstates the increases in Japan and Alaska, for example.[38]

Although escapement is the main 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.

[38] The general pattern of climate change increasing biomass may also 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.

Figure 11 plots normalized biomass against lagged, normalized escapement; it shows a relatively strong, positive, and slightly concave 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. The estimated relationship is close to linear, so changes in biomass are close to proportional to changes in escapement. Figure 12 includes a panel for the predicted percent changes in biomass by EEZ due to the combined effects of climate change. On net, biomass increases by 20.6% 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. Figure 12 shows the percent changes in catch and catch value at the EEZ level. It show general increases, as expected from the increase in biomass. Overall I predict a 21.7% increase in catch from this approach. In predicting the value of catch, I assume that the price of each species does not change from its latest year in the SAU database (Tai et al., 2017). The figure again shows large increases–I predict catch value increases by 27.9% in total for stocks in my sample under the combined effects of climate change.

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 and the high seas. It should be noted this often implies changes in the country share that are far out of sample, and should therefore be taken as a back of the envelope calculation of an upper bound on the gains to global cooperation.

Figure 14 shows the historic and hypothetical cooperative distributions of escapement, biomass and catch. Under hypothetical cooperation, escapement would be 89.4 million tonnes (78.7%) higher. Using the empirical relationship between escapement and biomass estimated in Table 5, I predict stock-level biomass based on the predicted stock-level escapement. The figure shows the biomass distribution that would shift meaningfully to the right: Biomass in total would be 70.8 million tonnes (51.4%) tonnes higher.[39] Finally, I predict the new steady state catch as the difference between biomass and escapement for each stock. The figure shows a large decrease in catch in order to satisfy the increased escapement under cooperation: Catch would have to decline by 7.7 million tonnes (31.7%) from the stocks in my sample. However, this decrease refers only to the decrease in catch from the managed stocks in my dataset–it does not account for the spillovers onto stocks outside my data which motivates the conservation to begin with.

Next, I explore the spatial heterogeneity of these effects. Figure 15 shows the percent changes in escapement, biomass, catch, and catch value by EEZ. It shows significant increases in escapement, although there is also meaningful heterogeneity across EEZs. The largest increases come from EEZs with low average country shares, such as the Mexican Pacific Coast, Brazil, and Greenland. Changes in biomass are calculated using the relationship between biomass and escapement estimated in Table 5. These show the same pattern of significant changes with large heterogeneity, in the same places. Finally, the figure shows large percentage decreases in catch and catch values at the EEZ level. Catch value calculations also assume no adjustment to prices. These maps show that large increases in escapement and biomass would require large decreases in steady-state catch from the stocks in my sample. However, these catch reductions account *only* for the requisite catch reductions in the studied stock area. As noted above, this omits the increases in catch elsewhere due to con-

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

servation spillovers. For several stocks this implies it would be optimal to have a moratorium on fishing in that location in order to reap the benefits of spillovers on neighbors. Again, these are extrapolations of my estimates far out of sample, and should be interpreted as an upper bound on the consequences of cooperation. Nevertheless, these results indicate that the global cost of the transboundary problem is quite significant, and much larger than the expected effects of climate change. This full cooperation hypothetical also implicitly rules out any behavioral response to range shift.

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 outcome. In this section I discuss a much more realistic scenario: 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, which is itself shifting rapidly due to climate change (Cook, 2005; Le Bris et al., 2018). 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 simulation, 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. This mechanically increases 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 16 shows the stock-level distribution of changes in effective country shares if the US and Canada were to adopt the cooperative agreement I describe: the average effective country share would increase by 0.12. Figure 17 maps the average change in effective country shares at the EEZ level.

What implications would such collaboration have on fisheries management? Figure 18 maps the predicted changes in outcomes at the EEZ level. The first panel shows that the Canadian Pacific coast and the US Atlantic coast both show significant increases in escapement (by 43.6% and 28.8%, respectively). This aligns naturally with the location and distribution of those stocks: 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. The second panel maps the percent changes in biomass and show a muted version of the same effect: biomass increases by anywhere from 1% in the US West Coast to 21% in the Canadian West Coast. Panels 3 and 4 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. Changes in catch value also do not account for any changes in prices.

Overall, my results imply that cooperation between the US and Canada would increase escapement by 5.25 million tonnes (13.5%) in total. Steady state biomass would in turn increase by 4.5 million tonnes (10.7%). Catch would barely decrease on average (-3%), 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 19.8%. 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 19 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. The unaffected stocks, shows in blue, are stocks where the relevant counterparty for the US or Canada isn't the other member of the hypothetical agreement. For those stocks, the changes under climate change are unaffected by the agreement. For the affected stocks, shown in red, the agreement would generally imply smaller changes in the country share, as indicated by the slope of the red line being below 45 degrees. Figure 20 plots the distribution of escapement responses to range shift (using the Behavioral-Only model) for US and Canadian stocks, with or without the bilateral agreement. It shows a significant compression in the distribution of escapement changes, with a disproportionate reduction in the share of stocks with predicted declines in escapement. The change in escapement for the average stock rises from 0.5% to 1% due to the adoption of the bilateral agreement. On net, the predicted behavioral response to range shift for US-Canada stocks is a 551,000 (1.4%) decline in escapement in the baseline compared to a 185,000 (0.5%) decline in the agreement scenario. This suggests that in the particular setting of the US and Canada, a bilateral agreement could reduce the behavioral response to climate change by nearly two-thirds.

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 1.6% 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 3.2%, and countries gaining control are predicted to increase their escapement by 2.8%. For the average stock, the behavioral response to range-shift is approximately 29% of the total effect of climate change on fish populations.

Nevertheless, I find that the effects of climate change are small relative to the global losses due to the transboundary problem. A speculative global optimum could increase escapement by as much as 79% and completely eliminate the strategic response to range shift. A more plausible scope of cooperation, a bilateral agreement between the US and Canada, could increase escapement by 14% and reduce the behavioral response of range shift by 66%. This suggests that while bilateral agreement may not fully solve the transboundary problem, it can meaningfully dampen the strategic consequences of range shift.

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8 Tables

Table 1: Distance to Equator Regressions

	Dependent variable:		
	Avg. Coast Length (km)	Avg. EEZ Area (km^2)	Avg. EPI Score
	(1)	(2)	(3)
Degrees from Equator	57.41***	7,190.81***	−0.01***
	(7.08)	(317.31)	(0.001)
Constant	13,084.57***	1,519,061.00***	20.17***
	(736.94)	(33,021.61)	(0.15)
Observations	721	721	721
R^2	0.08	0.42	0.06
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. Each observation represents one degree latitude. 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 fisheries score from the Environmental Performance Index for countries at that latitude.

Table 2: Summary Statistics

Variable	Value	Units
Unique Years	24	Years
Unique Stock IDs	326	Stocks
Unique Scientific Names	163	Species
Country Share (mean)	0.54	Proportion
Country Share (sd)	0.29	
Extraction Rate (mean)	0.17	Proportion
Extraction Rate (sd)	0.17	
Escapement (mean)	399,185	Tonnes
Escapement (sd)	1,056,573	
Biomass (mean)	482,240	Tonnes
Biomass (sd)	1,313,273	
Catch (mean)	83,055	Tonnes
Catch (sd)	385,919	

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	0.023**	0.009	−0.126***	−0.095***	−0.208***	−0.166**
	(0.011)	(0.015)	(0.027)	(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***		0.467***
		(0.020)		(0.043)		(0.108)
Mean Interest Rate		−0.092		0.313**		0.101
		(0.066)		(0.142)		(0.364)
Constant	1.161***	1.213***	0.238***	0.074**	0.721***	0.512***
	(0.017)	(0.022)	(0.017)	(0.030)	(0.088)	(0.124)
Observations	326	206	326	206	323	204
R^2	0.953	0.957	0.061	0.251	0.569	0.568

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	1.570^{***}	-2.679^{***}	-2.474^{***}
	(0.541)	(0.724)	(0.653)
Norm. Biomass			0.557^{***}
			(0.020)
Stock FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,884	4,875	4,884
R^2	0.002	0.003	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)
Intercept	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: Distance to Equator and Fisheries Management

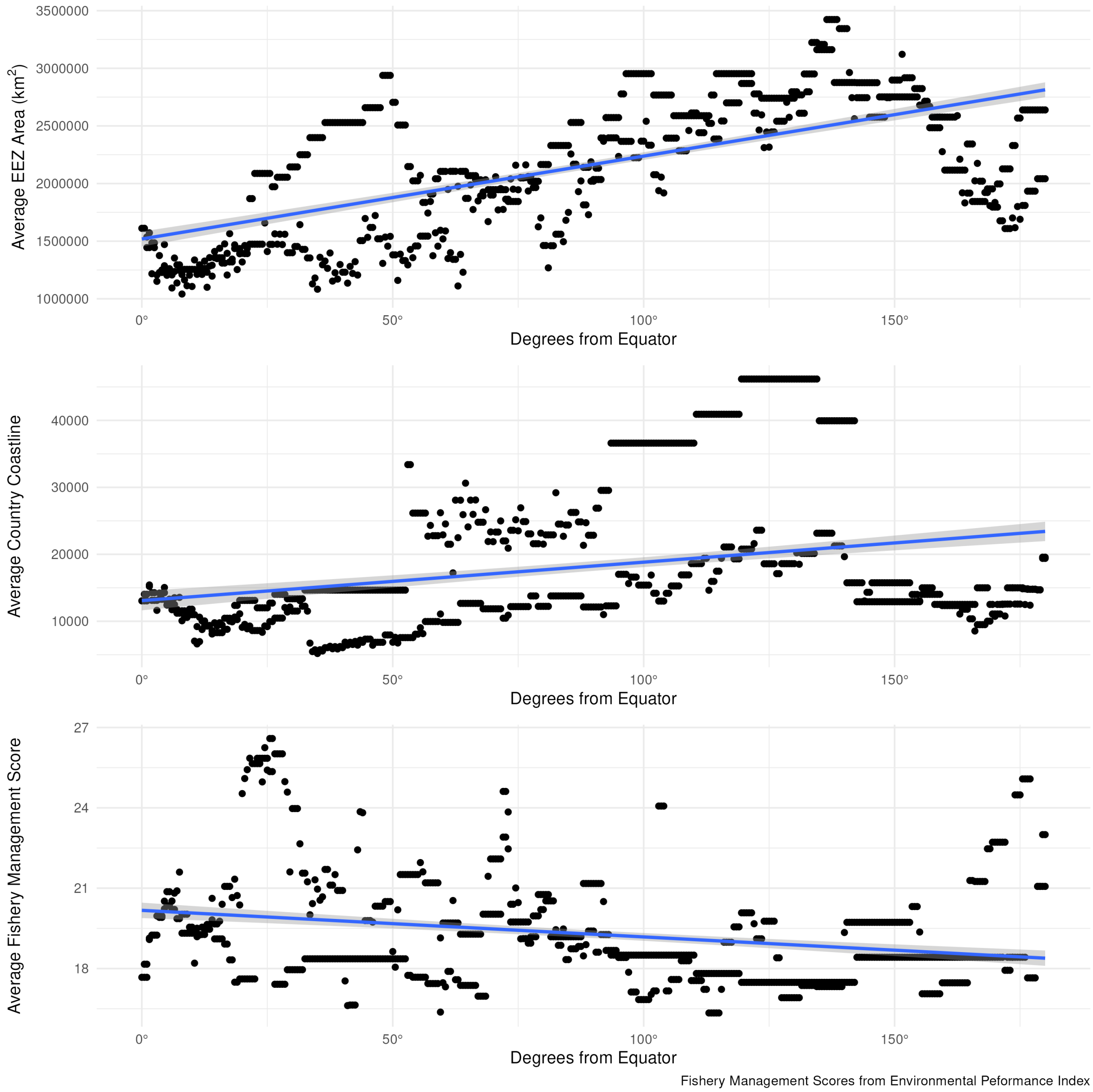
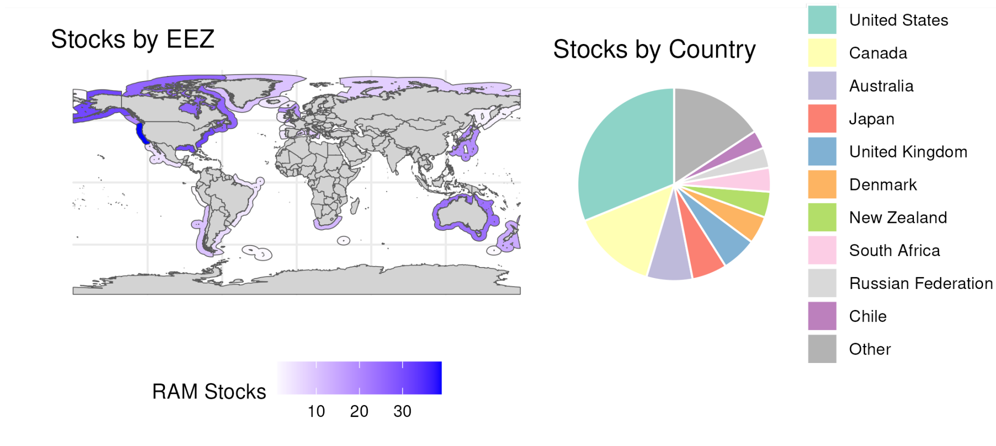


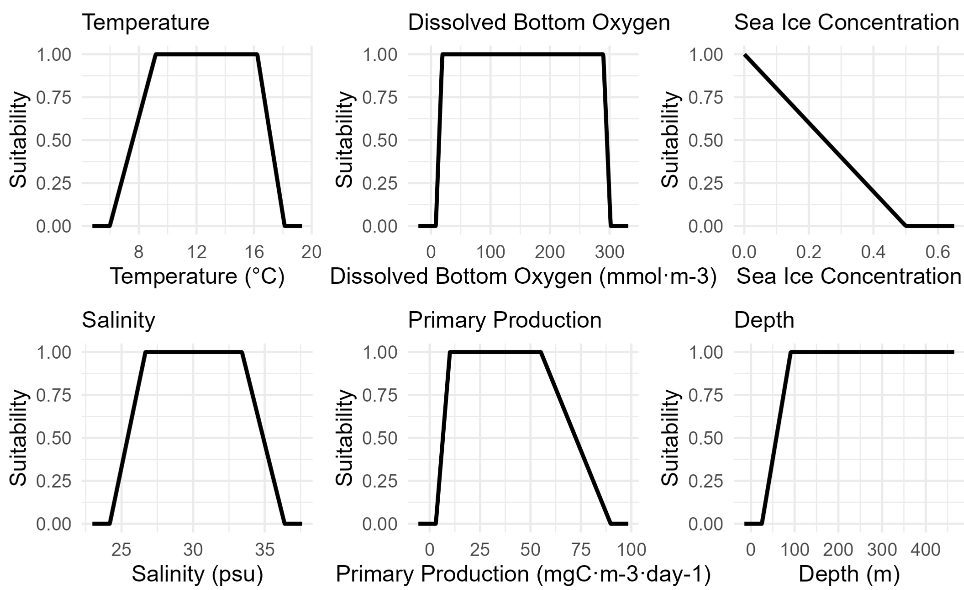
Figure plots average Exclusive Economic Zone area (km^2), coastline length (km) and Fisheries Score (from the Environmental Performance Index) at each latitude against its distance from the equator. It suggests that moving towards the poles increases international property rights security but is also correlated with worse fisheries outcomes.

Figure 2: RAM Stock Locations



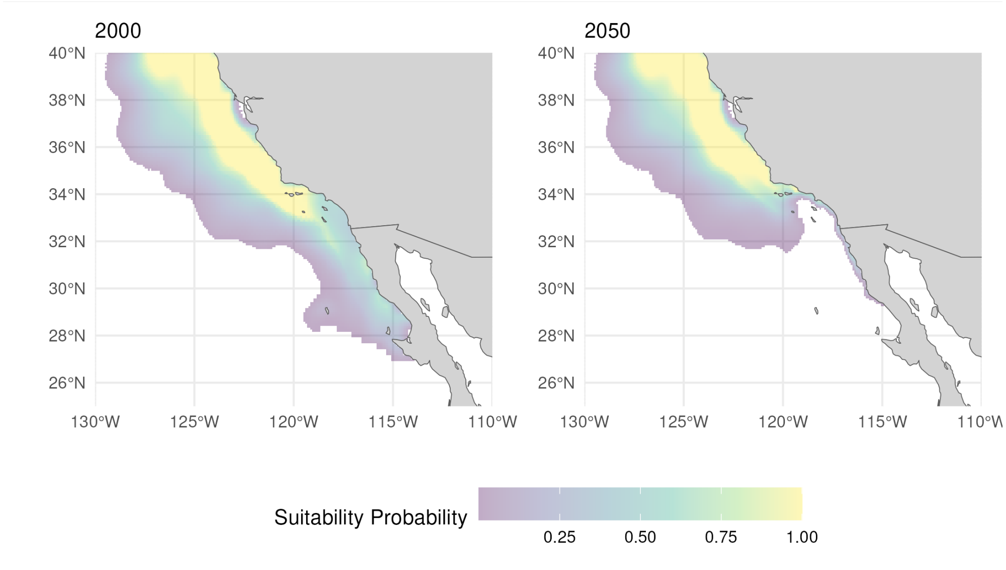
The figure on the left maps the number of stocks in my sample in each EEZ. The figure on the right shows the share of stocks in each of the top ten countries and an ”other” category for the remainder.

Figure 3: Environmental Envelopes for Greenstriped Rockfish



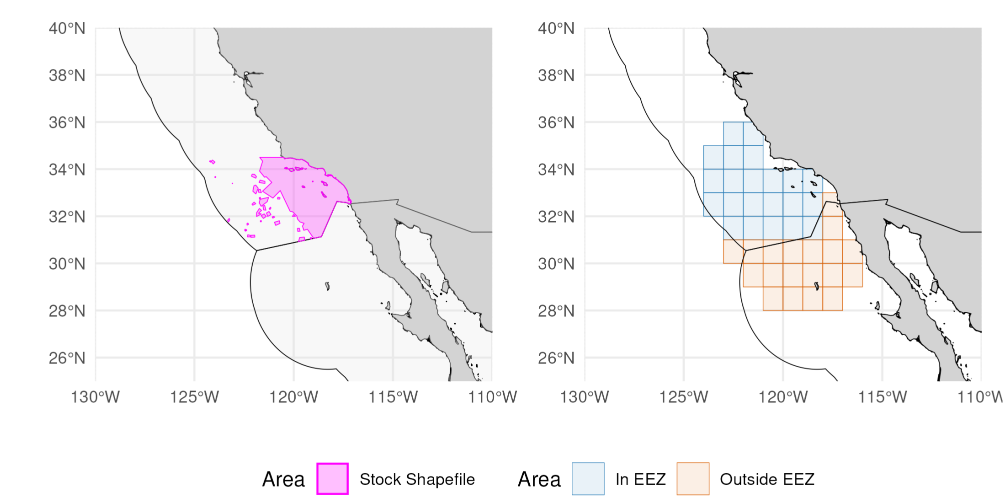
Example environmental envelopes for Greenstripped Rockfish. Each panel shows the predicted suitability for the species for each value of the environmental variable. The overall suitability at a grid cell is the product of each of the six individual probabilities.

Figure 4: Greenstriped Rockfish Suitability



Example suitable ranges calculated based on species-level environmental preferences and annual environmental variables, for Greenstripped Rockfish in 2000 and 2050.

Figure 5: Greenstriped Rockfish Management Areas



The first panel shows an shapefile from the RAM Legacy Shapefile Database, for the Pacific coast Greenstripped Rockfish stock. The second shows an example of a 200 nautical mile buffer around that shapefile. The buffer area is categorized as falling within the EEZ (in blue) and outside the EEZ (in orange).

Figure 6: Greenstriped Rockfish Management and Suitability

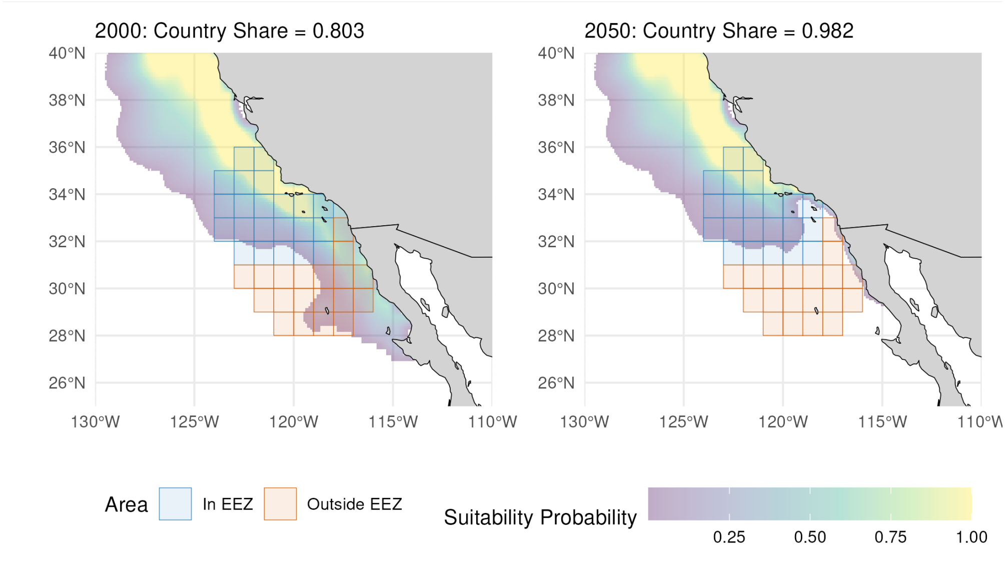
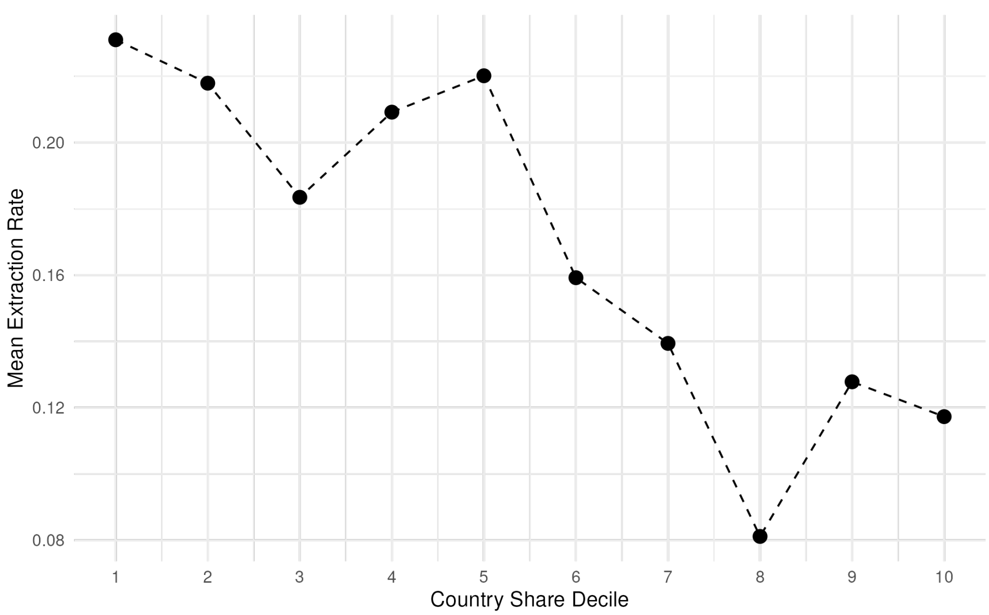


Figure illustrates the calculation of the country share using 2000 and 2050 Greenstripped Rockfish as an example. The country share is calculated as the share of suitable habitat found inside the buffer area that falls inside the EEZ area.

Figure 7: Avg. Extraction Rate Vs Country Share Decile



Binscatter comparing the average extraction rate for each decile of the country share variable. The figure shows a large negative relationship between the country share decile and the average extraction rate.

Figure 8: Country Share Change by 2050

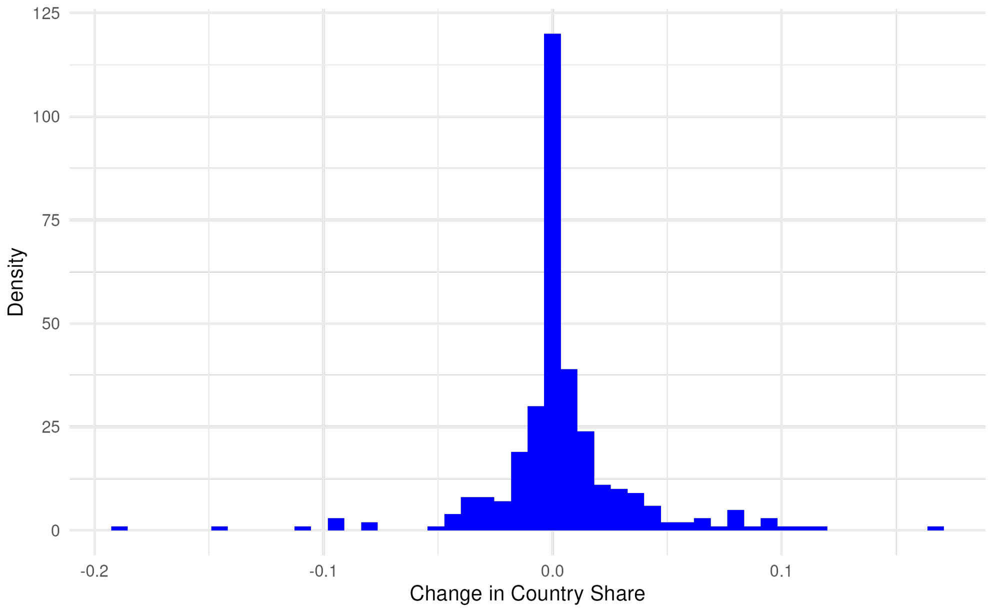
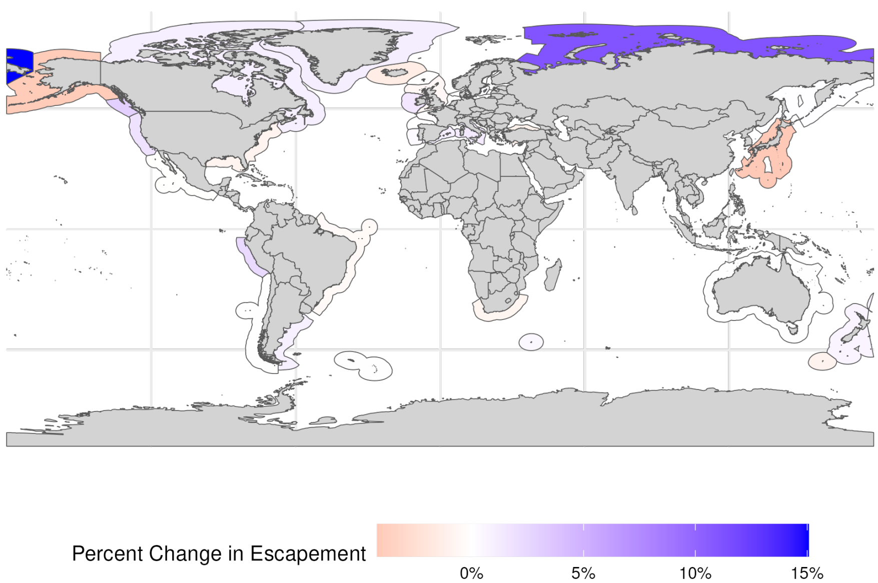


Figure shows the stock-level predicted changes in country shares between the historic average and the 2050 projection.

Figure 9: 2050 Percent Change in Escapement by EEZ (Behavioral Only)



Map shows the percent change in escapement from stocks in each EEZ implied by changes in the country shares by 2050. This does *not* account for any biophysical effects of climate change.

Figure 10: Error in Biophysical-Only Escapement Prediction

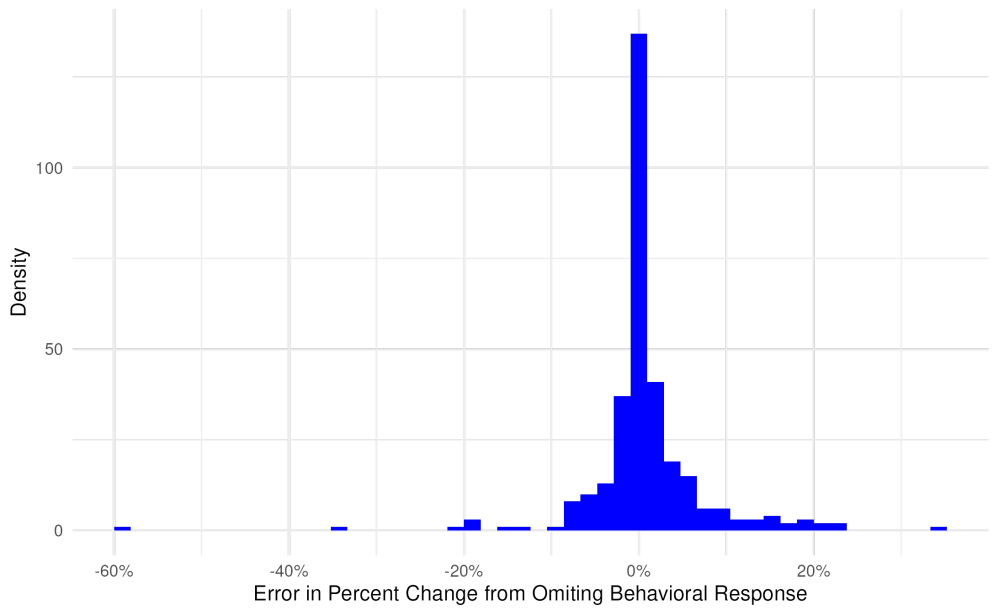
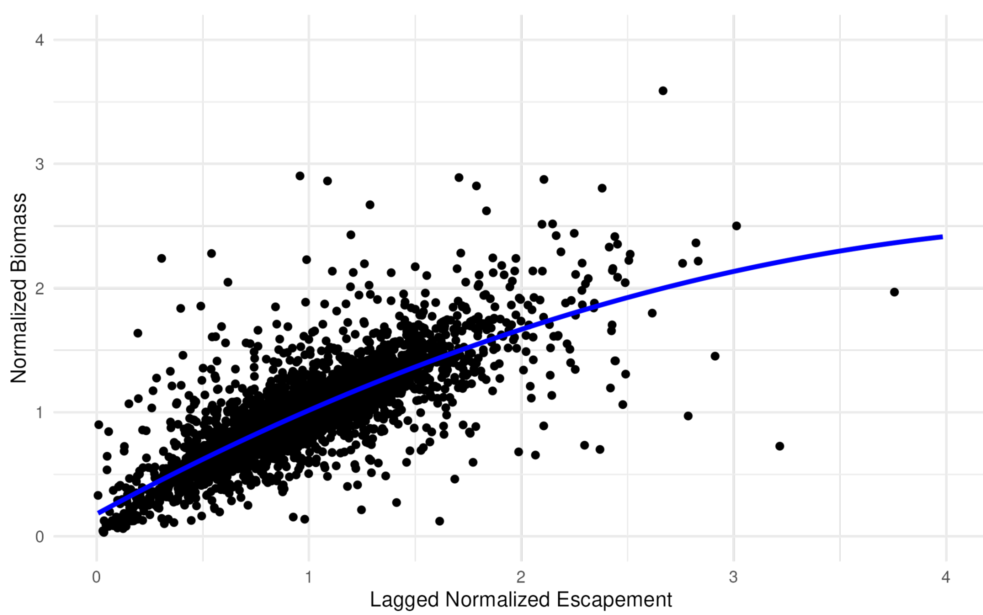


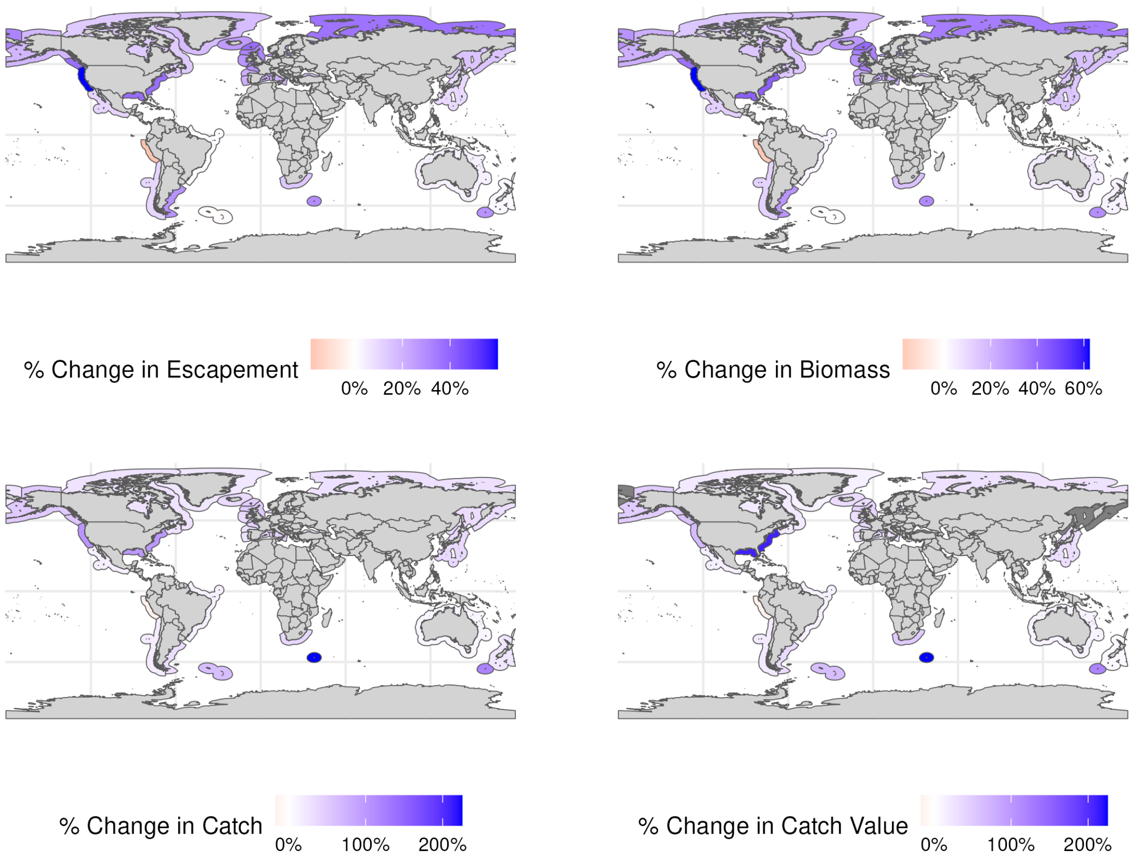
Figure shows the distribution of errors made when omitting the behavioral response to climate change when calculating the percent change in escapement. That is, it plots the difference between the combined prediction of percent change in escapement and the biophysical-only prediction of percent change in escapement.

Figure 11: Normalized Escapement Vs Normalized Biomass



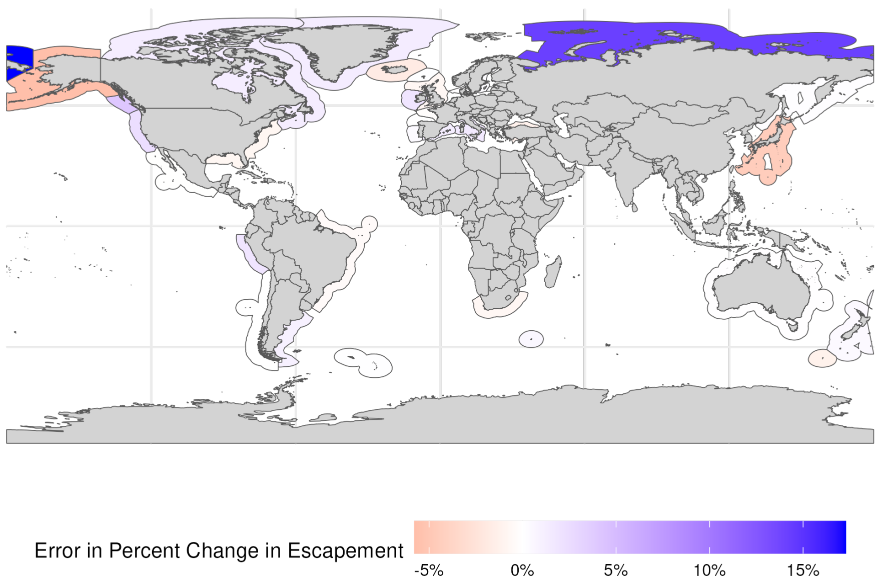
Scatterplot showing the relationship between normalized escapement and normalized biomass.

Figure 12: Percent Changes in Outcomes by EEZ by 2050 (Combined Effects)



Maps showing the percent change in escapement, biomass, catch, and catch value from stocks in each EEZ, using the combined effects of biophysical changes and the behavioral response to range shift.

Figure 13: Error in Biophysical-Only Escapement Prediction by EEZ



Map shows the error in the predicted percent change in escapement from stocks in each EEZ when using a biophysical-only prediction.

Figure 14: Historic and Cooperative Escapement Distributions

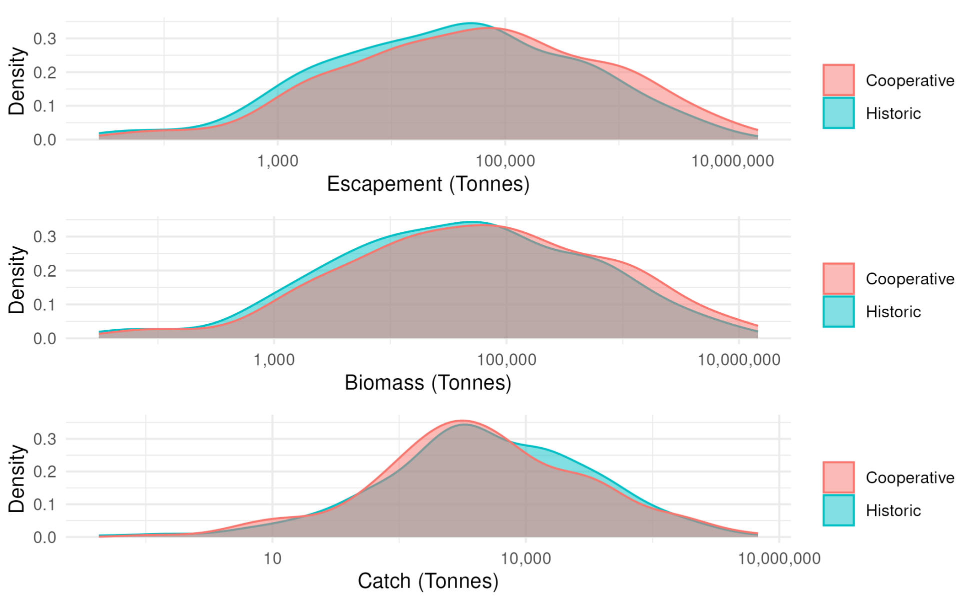
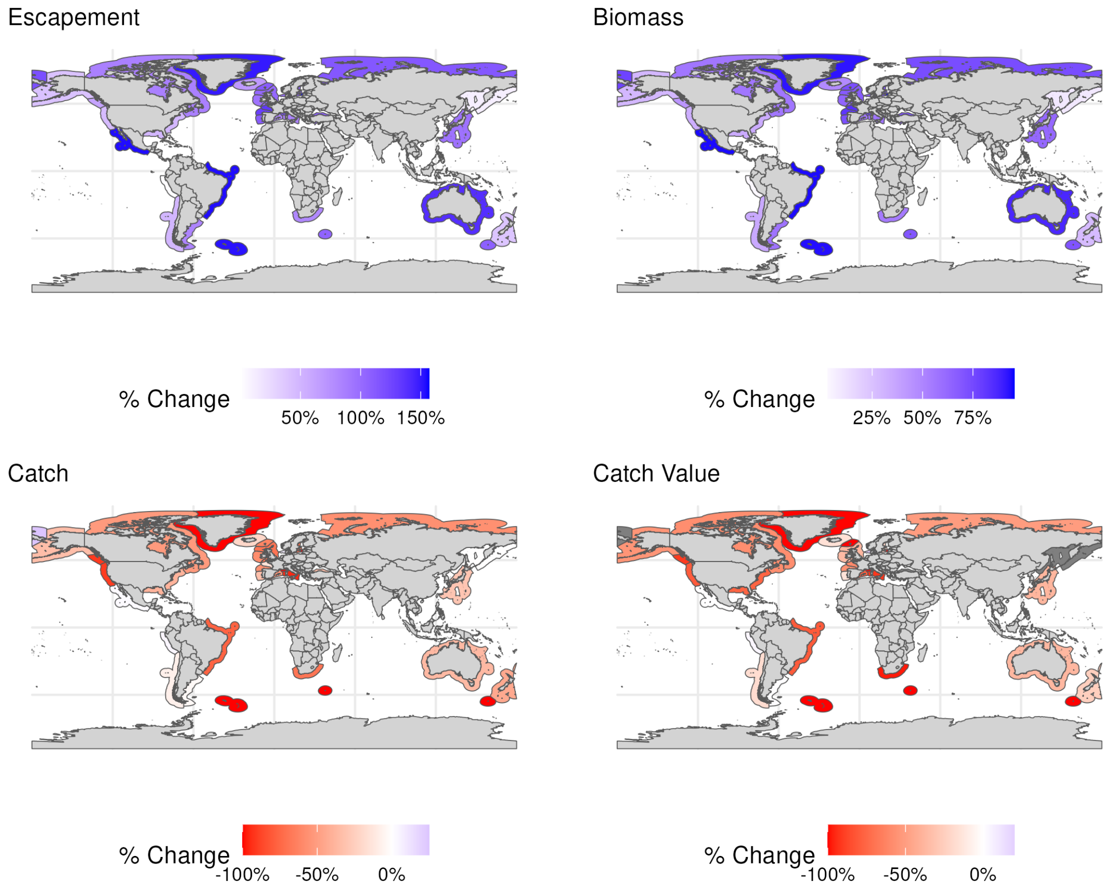


Figure plots the historical distributions of escapement, biomass and catch alongside their predicted distributions under global cooperative management. All are plotted on log scales.

Figure 15: Percent Changes in Outcomes Under Global Cooperation by EEZ



Maps showing the percent changes in escapement, biomass, catch, and catch value from stocks in each EEZ, under global cooperative management.

Figure 16: Change in Effective Country Share Under US-Canada Agreement

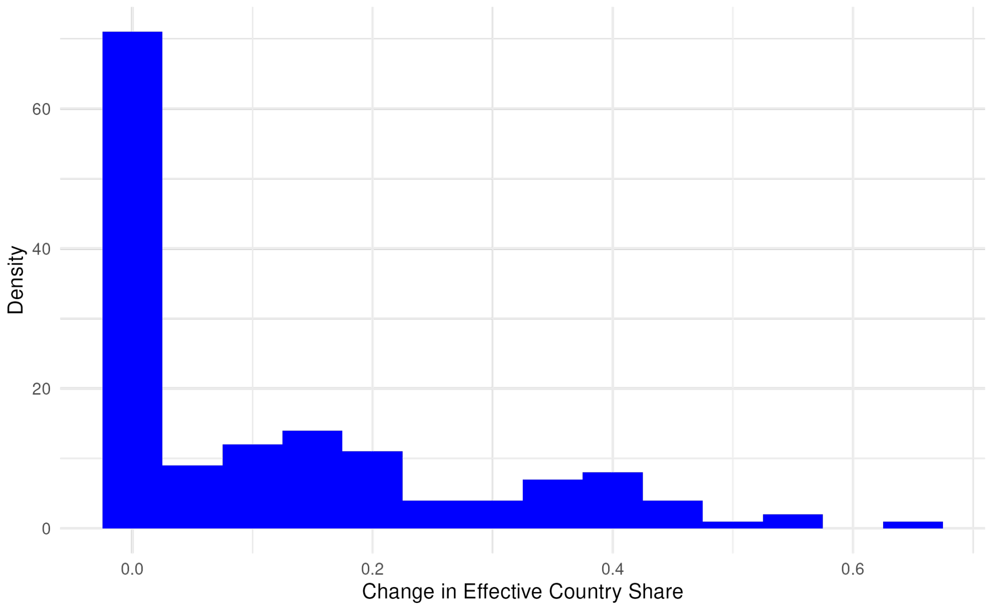
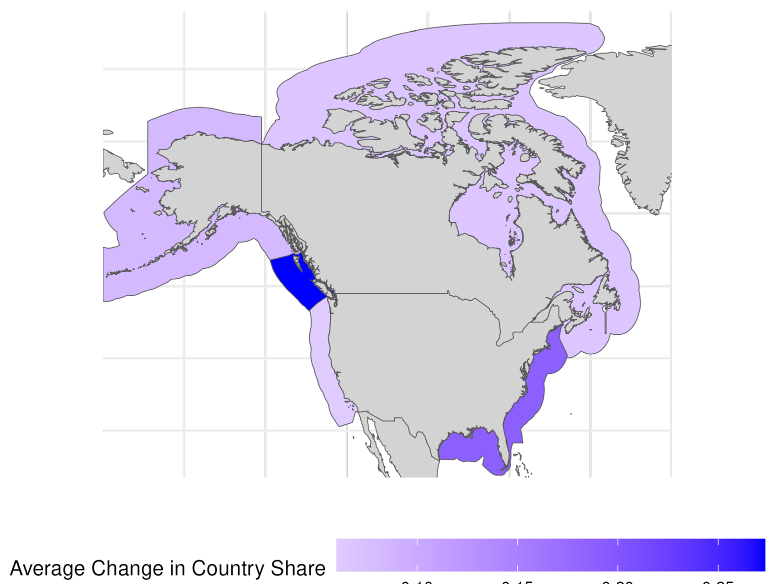


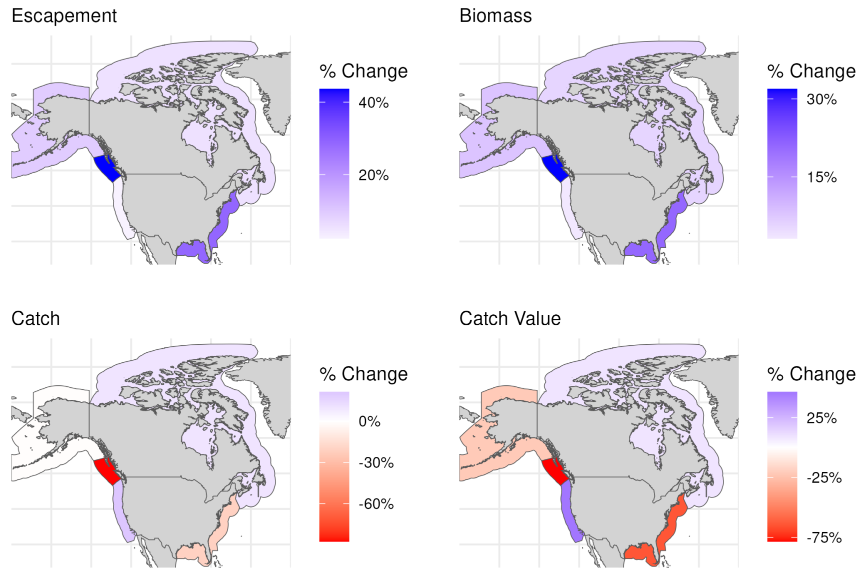
Figure plots the stock-level changes in the "effective country share" under a US-Canada agreement to fully internalize each other's EEZs.

Figure 17: Change in Effective Country Share Under US-Canada Agreement by EEZ



Map shows the EEZ level changes in the "effective country share" for the average stock under a US-Canada agreement to fully internalize each other's EEZs.

Figure 18: Percent Changes in Outcomes Under US-Canada Agreement by EEZ



Maps showing the EEZ level percent changes in escapement, biomass, catch, and catch value under full US-Canada cooperation.

Figure 19: Country Share Changes, With & Without US-Canada Agreement

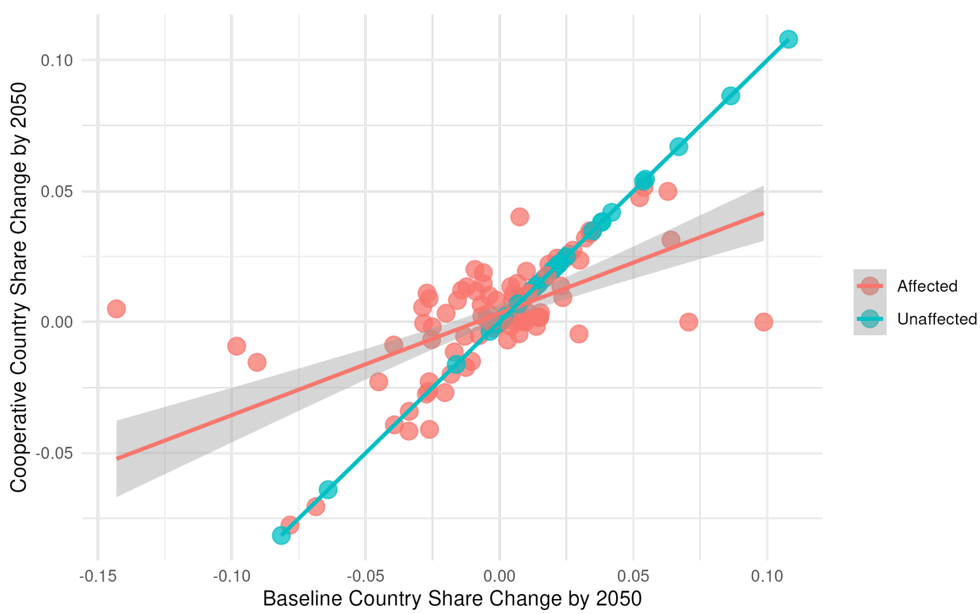


Figure plots the predicted changes by 2050 in country shares in the baseline case versus a US-Canada agreement case. Stocks in blue are unaffected by the cooperative arrangement, whereas stocks in orange show a pattern of smaller changes due to climate change in the cooperative scenario.

Figure 20: US-Canada Percent Changes in Escapement (Behavioral Only)

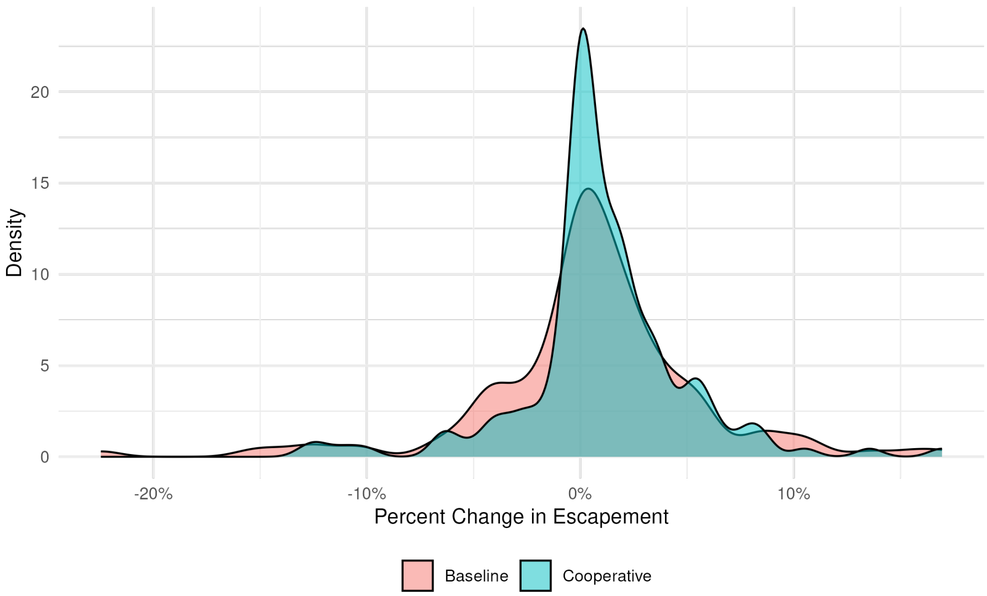


Figure plots the stock-level predicted percent changes in escapement due to range shift in the baseline case versus a US-Canada agreement case. It shows a rightward shift in the distribution, implying fewer escapement reductions due to range shift in the cooperative scenario.

A Theory Appendix

In this section, I consider several alternative modeling decisions and how they affect the main result that *"A lower country 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^*."* The section is structured around frequently asked questions, and each section will begin with the model from Section 2 as the base case.

A.1 Why does optimal escapement not depend on the path of $\theta_{i,t}$ over time?

To see this result, it is helpful to add some structure to the path of $\theta_{i,t}$. Let $\theta_{i,t}$ and $\theta_{j,t}$ be exogenous and evolve as finite-state Markov chains with Poisson jump structure: in each period, with probability λ they jumps to a different state, and with probability $1-\lambda$ they remain the same. Let the state be represented by $z_t = (X_{i,t}, X_{j,t}, \theta_{i,t}, \theta_{j,t})$. Then we can write the Bellman equation as

$$V_i(z_t) = \max_{H_{i,t}\in[0,X_{i,t}]} [\tilde{p}H_{i,t} + \delta E_t[V_i(z_t)]] \tag{15}$$

Taking the first order condition gives

$$\tilde{p} = \delta G'(S_{i,t}) \left[\theta_{i,t} E_t[V_{iX_i}(z_t) + (1-\theta_{j,t}) E_t[V_{iX_j}(z_t)]\right] \tag{16}$$

The envelope conditions are

$$V_{i,t_{X_i}} = \delta G'(S_{i,t}) \left[\theta_{i,t} E_t[V_{iX_i}(z_t) + (1-\theta_{j,t}) E_t[V_{iX_j}(z_t)]\right] \tag{17}$$

$$V_{i,t_{X_j}} = \delta G'(S_{j,t}) \left[(1-\theta_{i,t}) E_t[V_{iX_i}(z_t) + \theta_{j,t} E_t[V_{iX_j}(z_t)]\right] \tag{18}$$

Regardless of $\theta_{i,t+1}$, we can simplify this to $V_{i,t_{X_i}} = \tilde{p}$, as the marginal unit of $X_{i,t+1}$ can always be harvested next period for a marginal profit of $\tilde{p}$. This pins down the marginal value of the own country's biomass in equilibrium, regardless of the path of $\theta_{i,t}$.

The same logic pins down $V_{i,t_{X_j}} = 0$ if country j is in an interior solution, as any marginal unit of $X_{j,t+1}$ is harvested by country j down to it's target, yielding country i no marginal continuation value.

Thus these can be plugged back into the FOC to derive that

$$\tilde{p} = \delta G'(S_{i,t})[\theta_{i,t}\tilde{p} + (1-\theta_{j,t}) \cdot 0] \tag{19}$$

Which can be rearranged to retrieve the main result: $\theta_{i,t} G'(S_{i,t}^*) = \frac{1}{\delta}$

A.2 What happens if the counterparty's biomass is below their optimal escapement so they do not have an interior solution?

In the baseline model, I assume that country j is at an interior solution, meaning it's next period biomass is known to be above its optimal escapement: $X_{j,t+1} > S_{j,t+1}^*$. In that case,

$V_{iX_{j,t+1}} = 0$, because any marginal increase in the biomass in country j will just be consumed by country j, and country i will expect the same escapement regardless. However, what if this is not the case?

The identify $V_{iX_{i,t+1}} = \tilde{p}$ still holds, as it comes from combining the FOC and envelope condition on X_i. However, since $V_{iXj,t+1} \neq 0$, we must define the next period shadow-value ratio:

$$\alpha_{t+1} \equiv \frac{V_{iX_{j,t+1}}}{V_{iX_{i,t+1}}} = \frac{V_{iX_{j,t+1}}}{\tilde{p}} \tag{20}$$

Then we can rewrite the FOC to get an generalized escapement rule:

$$(\theta_{i,t} + (1-\theta_{i,t})\alpha_{t+1})G'(S^*_{i,t}) = \frac{1}{\delta} \tag{21}$$

Relative to the baseline case, we now multiply the derivative of the growth function by $\theta_{i,t} + (1-\theta_{i,t})\alpha_{t+1}$ instead of just $\theta_{i,t}$ reflecting the value of recruitment that accrues to the counterparty country. If $\alpha_{t+1} = 1$, meaning recruitment accruing to country j is equally valuable to country i as recruitment accruing to it, then we return to the global optimum where $G'(S^*_{i,t}) = \frac{1}{\delta}$. In general, α_{t+1} depends on the future values of α, bounded by the condition that $\theta_j G'(S_j) > \frac{1}{\delta}$ such that there is no interior solution. So long as $\alpha < 1$, then the basic result that an increase in the country share θ_i increases escapement S_i holds. This leaves the theoretical possibility that, if the value of recruitment accruing to country j is greater than the value recruitment accruing to country i from country i's perspective, then a lower country share can *increase* optimal escapement. However, I view this as a fringe case, as there are appear to be few fisheries in non-interior solutions in practice.

A.3 How does the result change if you account for harvesting costs?

In this subsection I consider the addition of harvesting costs that depend on biomass but not on effort. That is, I let the marginal cost of harvesting vary based on the quantity of fish, say due to higher catchability in periods with high biomass, but I do not let the marginal cost of harvesting vary within the period as more harvest occurs.

Suppose now that there is a per-unit harvesting cost that depends on biomass $X_{i,t}$. Then call the period-t marginal net profit per harvested unit $\mu_i(X_{i,t})$. Everything else remains just as in the baseline case.

Then the Bellman Equation can be written:

$$\max_{H_{i,t}\in[0,X_{i,t}]} [\mu_i(X_{i,t})H_{i,t} + \delta V_i(X_{i,t+1}, X_{j,t+1}] \tag{22}$$

This has the following FOC:

$$\mu_i(X_{i,t}) = \delta G'(S_{i,t}) \left[\theta_{i,t}V_{iX_{i,t+1}} + (1-\theta_{i,t})V_{iX_{j,t+1}}\right] \tag{23}$$

As in the baseline, $V_{iX_{j,t+1}} = 0$ as long as country j is in an interior solution. The same envelope condition gives $V_{iX_{j,t}} = \mu_i(X_{i,t})$, which is now state-dependent.

Then we can generalize the main result to the following condition:

$$\theta_{i,t}G'(S^*_{i,t}) = \frac{\mu_i(X_{i,t})}{\delta\mu_i(X_{i,t+1})} \tag{24}$$

In a steady state, this equation collapses to the same baseline condition $\theta_i G'(S^*_i) = \frac{1}{\delta}$. Off steady state the ratio of marginal net profits tilts the specific escapement target, but does not change the basic result that increases in θ_i increase the escapement target.

A.4 How does the result change under alternative growth functions?

One natural concern is that the result rests on the assumption that the fish population grows separately and *then* mixes according to country shares. However in this subsection I show that the baseline result holds even for an arbitrary growth function that depends on escapement from both countries.

Specifically, suppose the growth function of country i is given by the following:

$$X_{i,t+1} = \theta_{i,t}G(S_{i,t}, S_{j,t}) \tag{25}$$

Where $\theta_{i,t}$ represents the share of total recruitment from the joint fishery that accrues to country i in period t, the new analogue for the country share.

Now the fishery manager's objective function is

$$\max_{H_{i,t}\in[0,X_{i,t}]} \sum_t \delta^t \tilde{p} H_{i,t} \quad \text{s.t.} \quad X_{i,t+1} = \theta_{i,t}G(S_{i,t}, S_{j,t}) \tag{26}$$

The Bellman equation becomes

$$V_i(X_{i,t}, X_{j,t}) = \max_{H_{i,t}\in[0,X_{i,t}]} [\tilde{p}H_{i,t} + \delta E_t[V_i(X_{i,t+1}, X_{j,t+1}]] \tag{27}$$

And the FOC becomes

$$\tilde{p} = \delta G_{S_i}(S_{i,t}, S_{j,t})[\theta_{i,t}E_t[V_{iX_i}] + \theta_{j,t}E_t[V_{iX_j}]] \tag{28}$$

With the same logic as the baseline case, $V_{iX_i} = \tilde{p}$ along the equilibrium path as a marginal unit of $X_{i,t+1}$ can always be harvested immediately at marginal profit $\tilde{p}$. Similarly, in the empirically relevant interior case where $X_{j,t} > S^*_j$, $V_{iX_j} = 0$ as country j harvests down to its target in every period and country i captures no profit from the marginal unit of $j's$ stock.

Then we derive a similar condition as in our baseline for the non-cooperative private optimum, where a larger country share θ_i implies greater escapement:

$$\theta_{i,t}G_{S_i}(S^*_{i,t}, S^*_{j,t}) = \frac{1}{\delta} \tag{29}$$

B Country Share Measure

B.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 21 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 21: Generic Environmental Envelope

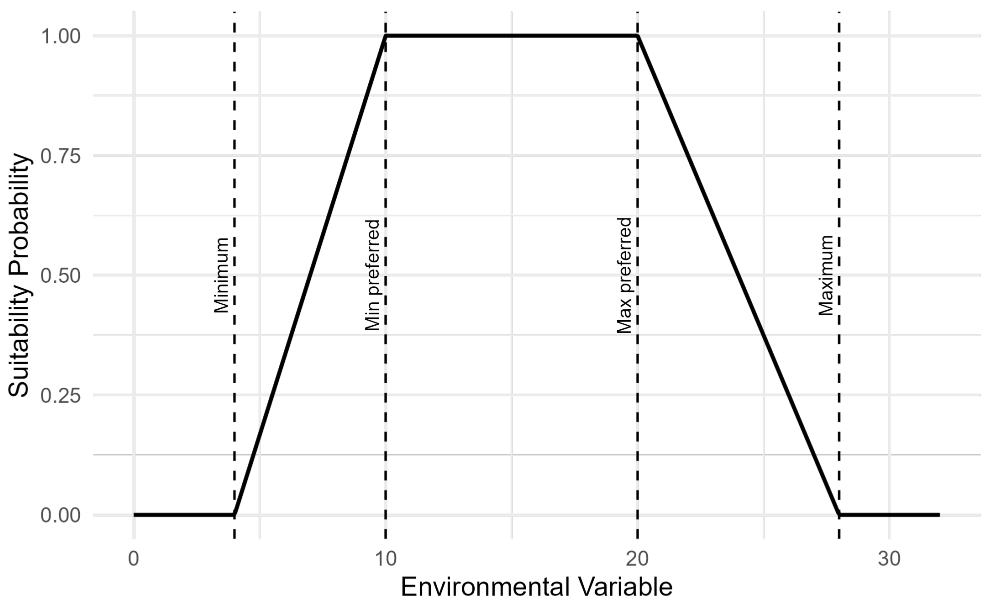
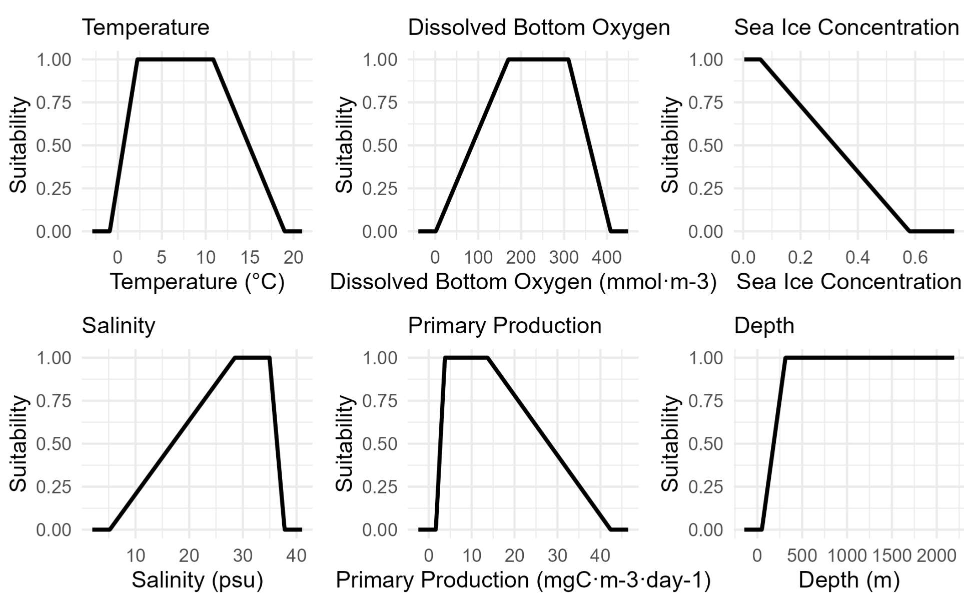


Figure 22 shows the six environmental envelopes used for Atlantic Halibut, based on the environmental preferences found in Table 6.

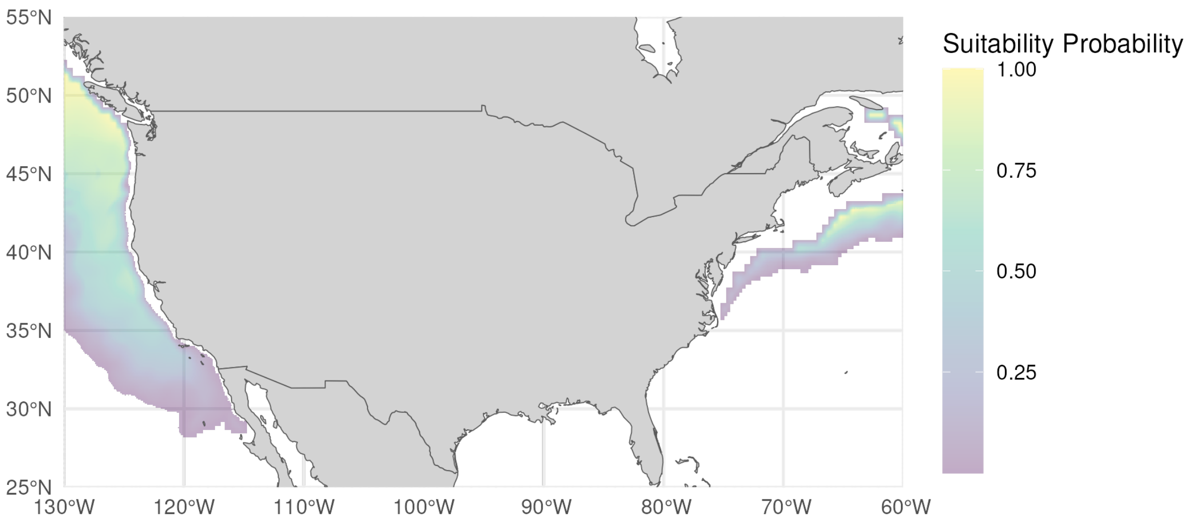
Figure 22: Environmental Envelopes for Atlantic Halibut



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

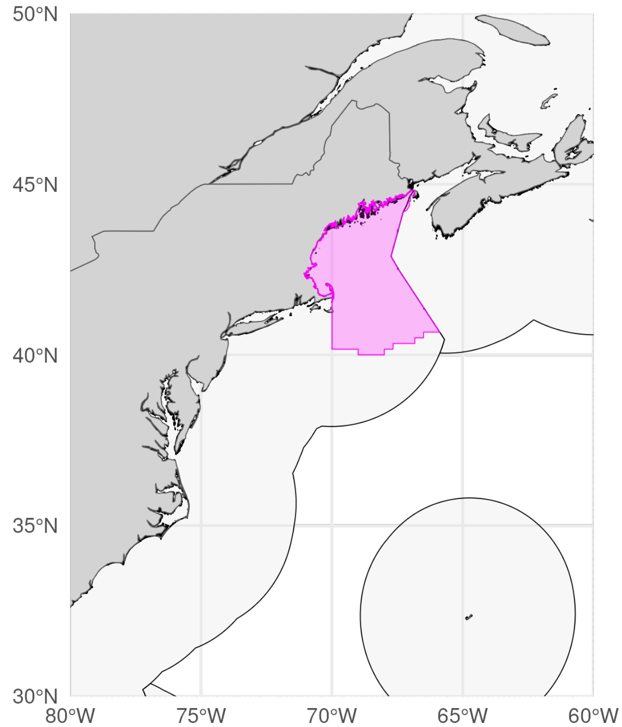
23. The figure shows the predicted suitability of each grid cell for Atlantic Halibut in 2020. The predicted ranges are massive overpredictions–one can easily see it shows suitable ranges for Atlantic Halibut outside of the Atlantic.

Figure 23: 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 24 shows the shapefile for the US stock of Atlantic Halibut, found in the Gulf of Maine.

Figure 24: 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 25 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 25: Atlantic Halibut Management Areas

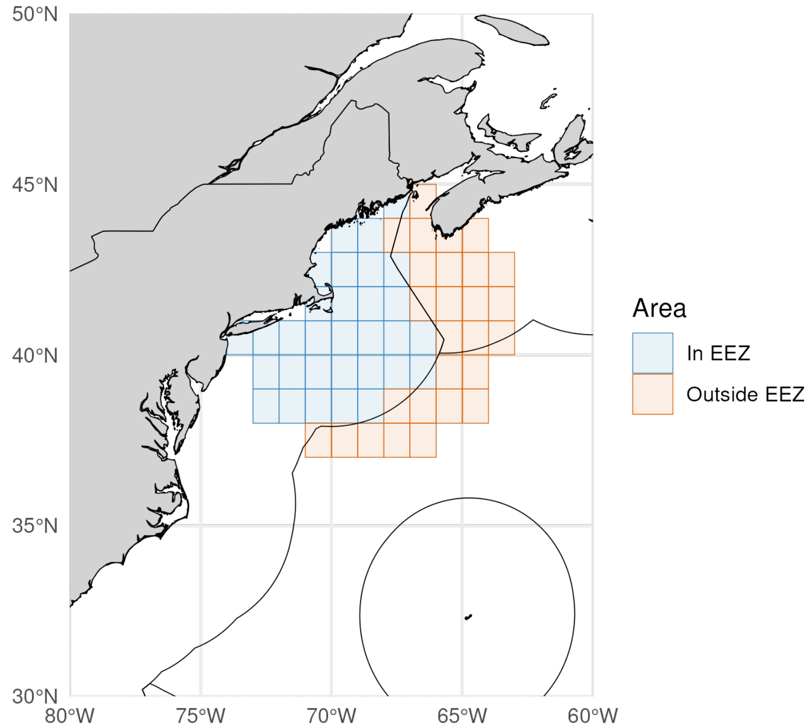
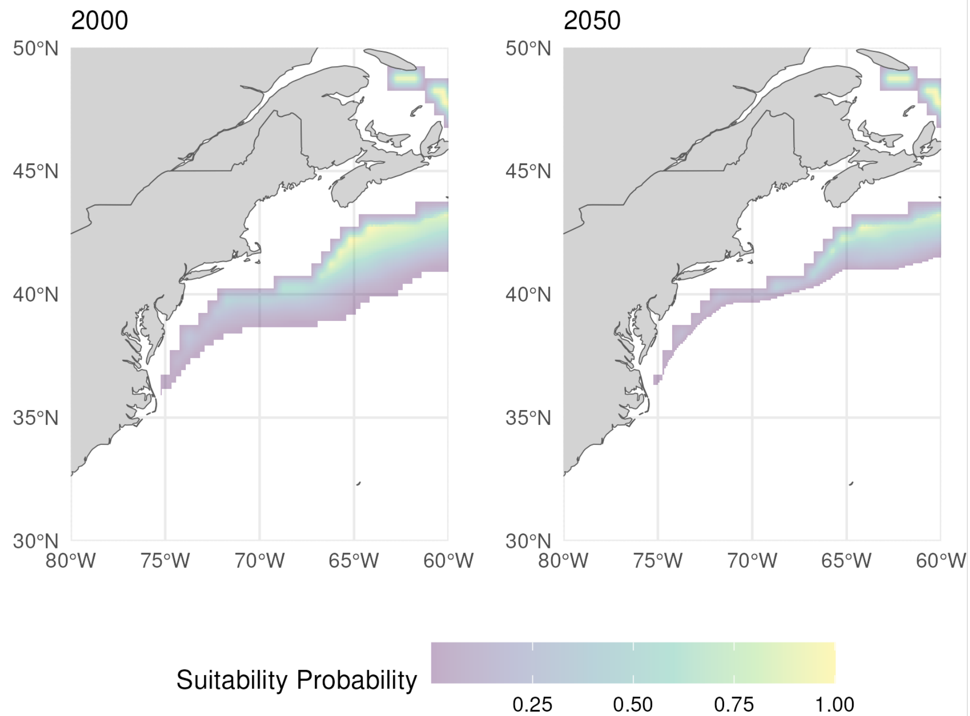


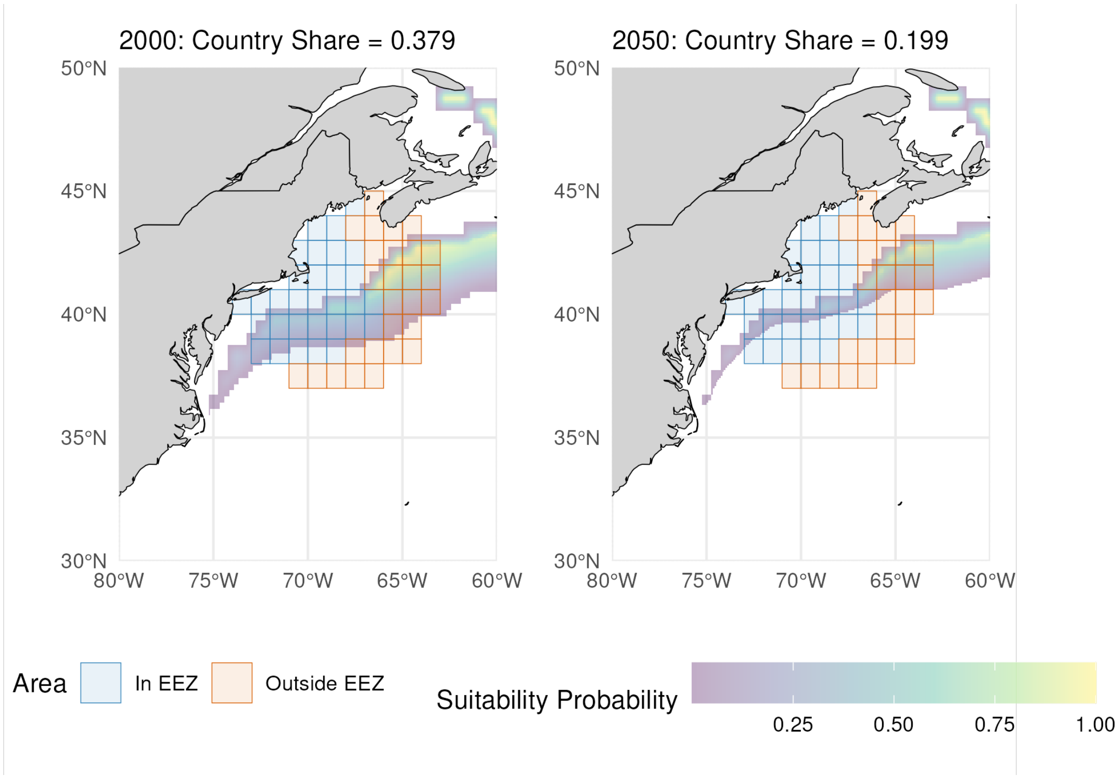
Figure 26 shows the predicted suitability for Atlantic Halibut in the area around the RAM shapefile for 2000 and 2050. Zooming in on this area where the species is known to be found highlights the actual anticipated effects of climate change. Comparison of the two maps shows a clear northward shift, 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 26: Atlantic Halibut Suitability in 2000 and 2050



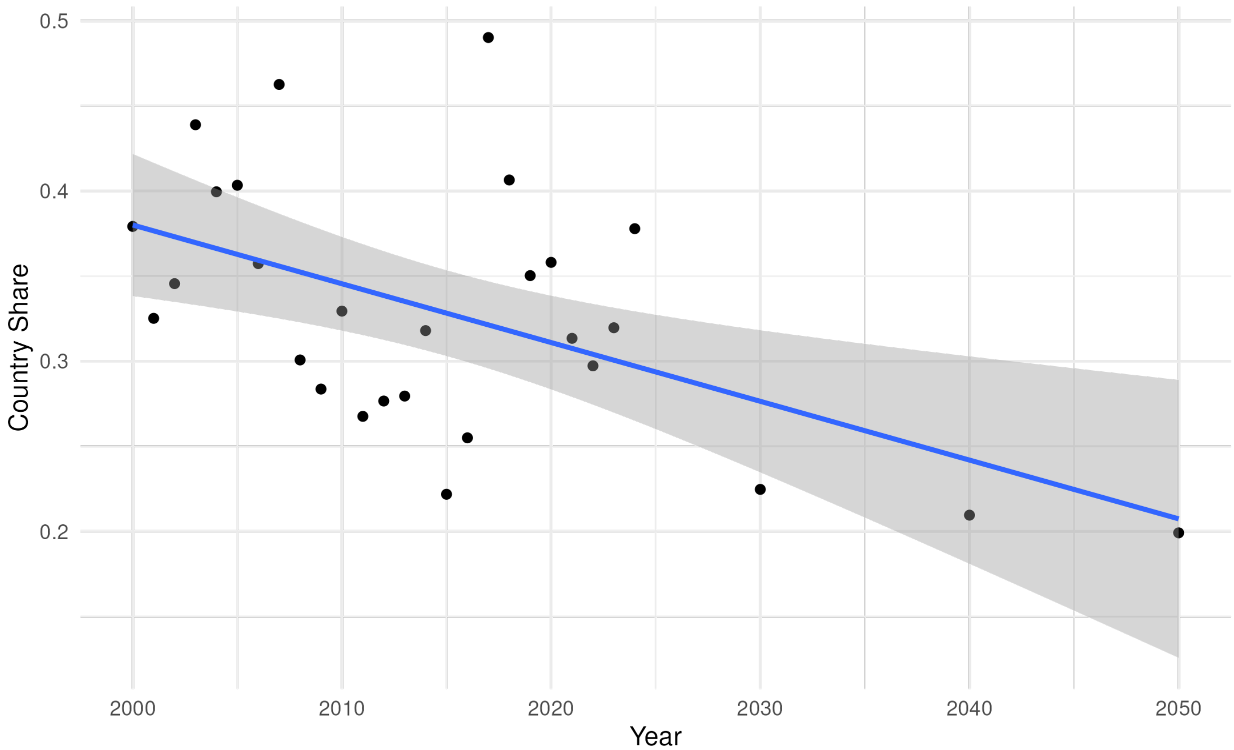
Finally, I put the habitat suitability and the management areas together. Figure 27 shows both the predicted suitability and the management areas for 2000 and 2050. To compute the country share I then calculate the share of the total predicted suitability in the entire buffer area (the sum predicted 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 27: 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 28 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 28: US Atlantic Halibut Country Share Over Time



B.2 Country Share Validation

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

B.2.1 State Variation

First, I construct a state-year level measure of suitability for each of the 163 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 29 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 29: State Catch Vs Suitability

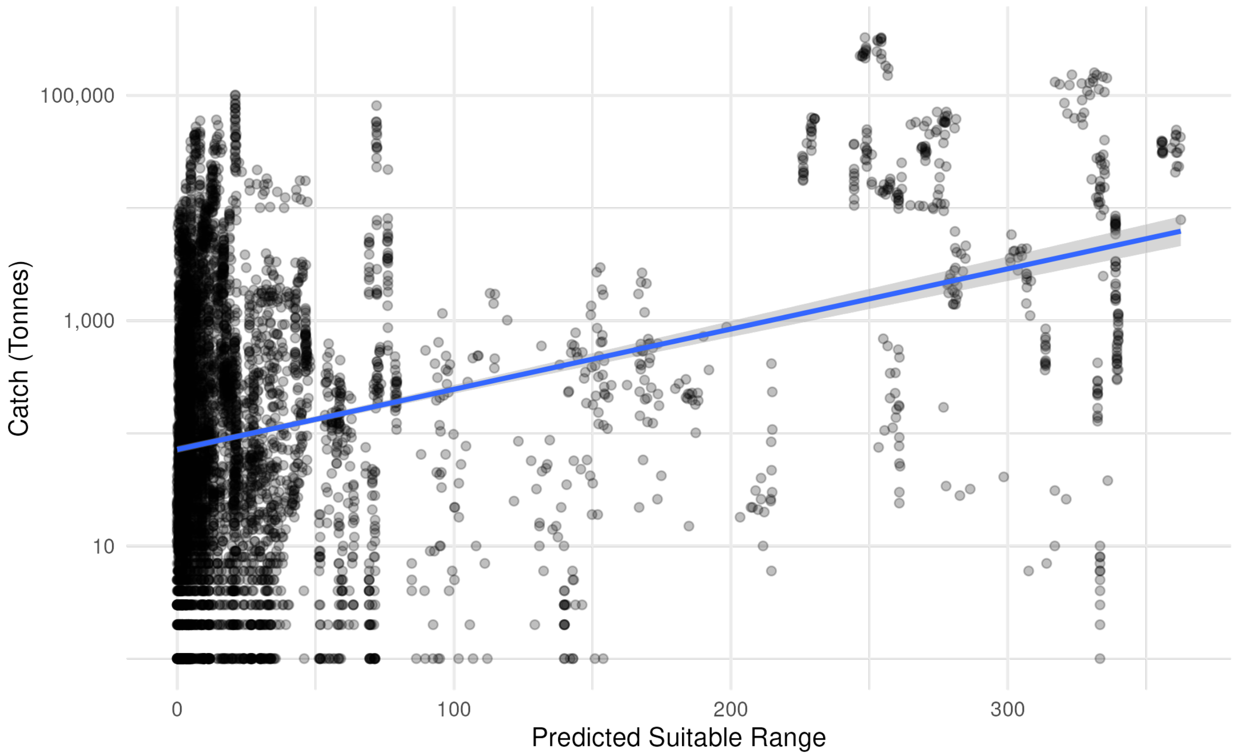


Table 7: Regressing State Catch on Suitability

	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.

B.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 $t+1$. Recruitment refers to the biomass available to fish due to last period's escapement. 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	0.702***
	(0.020)
Lag Country Share	0.920***
	(0.327)
Lag Country Share×Norm. Escapement	−0.047
	(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.

C Robustness

C.1 Additional Outcomes

Table 9: Log Panel Regressions

	Dependent variable:	
	Log Escapement	Log Catch
	(1)	(2)
Country Share	1.600**	−3.469***
	(0.631)	(0.961)
Log Biomass		0.778***
		(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	0.160	-2.211^{***}	-1.564^{**}
	(0.355)	(0.689)	(0.629)
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	0.00005	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	4.019^{*}	-3.060^{*}	-1.929
	(2.079)	(1.792)	(1.698)
Δ Norm. Biomass			0.566^{***}
			(0.067)
Constant	0.012	-0.321^{***}	-0.295^{***}
	(0.057)	(0.049)	(0.046)
Observations	172	172	172
R^2	0.022	0.017	0.298
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 (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	0.967*	$-$3.355***	$-$2.640***
	(0.572)	(0.939)	(0.847)
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	0.004	0.113
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.

C.2 Alternative Buffer Distances

Figure 30: Escapement on Country Share with Various Buffer Distances

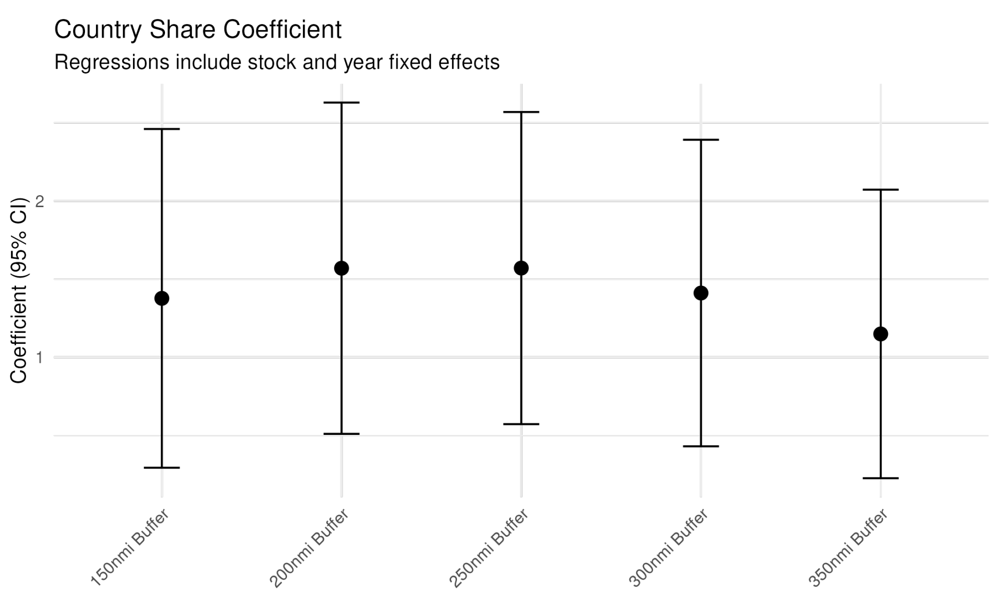


Figure 31: Extraction Rate on Country Share with Various Buffer Distances

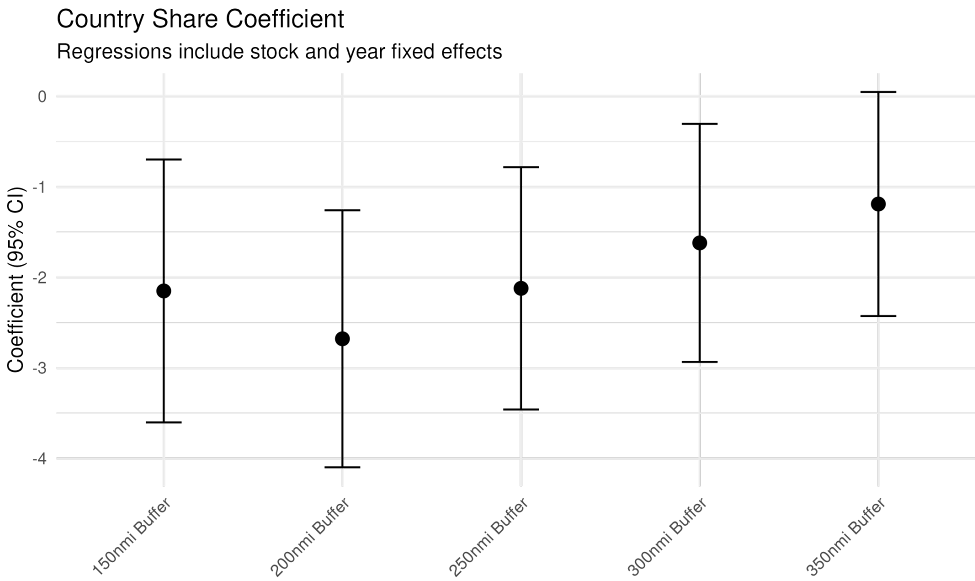
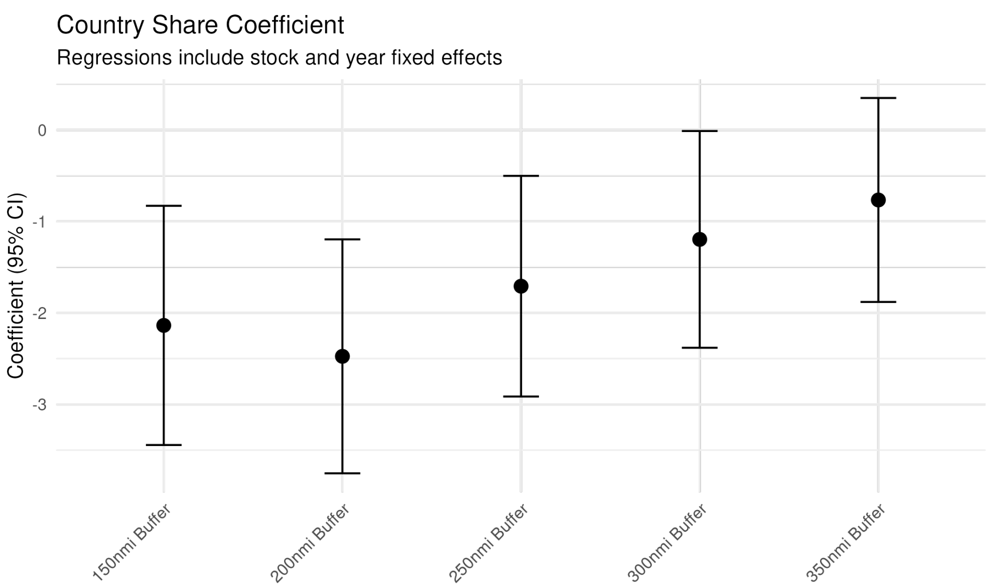


Figure 32: Catch on Country Share with Various Buffer Distances



D 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.

D.1 Variables

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

- **Above Average GFI Score**. I run regressions that include an indicator variable for whether a country has above average fishery management, as scored by the Global Fishing Index (Barley et al., 2021). The Global Fishing Index collects several measurements of management capacity and quality, and assigns each country a letter grade from F to A. Earning a C or above qualifies as above average, and I use this to construct a binary variable. A one in this measure reflects better management of fisheries for the 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. Building off of Lynham (2014), I manually identify which of the fisheries in my sample are managed with Individual Transferable Quotas (ITQ), which assign tradeable rights to certain quantities of catch. 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 viewed as 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). 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.

- **IUU Fishing Activity**. I run regressions that include measures of IUU fishing activity at the country level. Specifically, I use two indicators of port and coastal management quality from the IUU fishing Index (Macfadyen and Hosch, 2023): "Compliance with RFMO port state obligations" and "Views of MCS practitioners on port compliance incidents," which I call the RFMO IUU Score and the MSC IUU Score respectively. RFMO observers come from Regional Fisheries Management Organizations. MSC observers come from the Marine Stewardship Council, a non-profit organization that certifies fisheries as sustainable for consumer marketing. These scores come from outside observers and refer specifically to the management quality in the relevant country's coast and ports (not e.g. it's responsibility as a flag state on the high seas). I view this as another measure of management capacity, though in this case I expect that higher values of these IUU risk scores should dampen the effect of the country share as less capable fisheries managers should also exhibit smaller responses.

- **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 (RFMO). This indicator comes from the RAM stock assessment database. 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.

- **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 outside of any EEZ. 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.

- **Highly Migratory**. I run additional regressions including an indicator variable for whether a species is highly migratory or pelagic (open ocean) that is included in the AquaMaps database on species characteristics (drawn from FishBase). 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. In a similar vein, these species may already be treated as effectively open access, so variation in the country share could play no role in conservation. However, it is also 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.[40]

- **Home Range**. I run additional regressions including the predicted home range of a species from Bradley et al. (2024). In this paper, a fish's "home range" is defined as the area that the animal regularly uses during its normal life–the spatial envelope within which it moves, forages, and carries out daily behavior. This is an alternative notion of range to simply using the binary classification above, but should obey similar economic principles: species with larger home ranges may be less affected by variation in the country share if there is either 1) already effective international management OR 2) already a perception that these species are effectively open access. If neither is true, management may respond to the country share like normal.

- **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 level lending interest rates from the World Bank (Bank, 2025). Section 2 states that the privately optimal escapement $S^*_{i,t}$ is found where $G'(S^*_{i,t}) = \frac{1}{\delta\theta_{i,t}}$. We can rewrite this condition as $G'(S^*_{i,t}) = \frac{1+r}{\theta_{i,t}}$, where r is the interest rate. This implies that as the interest rate is larger, the effect of the country share on optimal escapement should be larger as well.

D.2 Empirical Strategy

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

$$\begin{aligned}\text{Outcome}_{i,t} =& \beta\text{Country Share}_{i,t} + \lambda\text{Variable}_{i,t} + \gamma\text{Country Share} \times \text{Variable} \\ &+ \alpha\text{Biomass (in Catch Regressions)} + \text{Stock FE}_i + \text{Year FE}_t + \text{Error}_{i,t} \quad (30)\end{aligned}$$

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

[40] 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.

or opposite sign as the headline result, indicating that the heterogeneity variable either amplifies or dampens the effect of the country share.

D.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 an indicator for high quality fisheries management in the Global Fishing Index as a regressor for escapement, extraction rate, and catch as outcomes, respectively. They show that the effect of country share is driven by countries with high management scores, as the large, statistically significant interaction terms drive the headline results. 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 result is corroborated by Table 14, which shows results for regressions including interactions with measures of IUU fishing risk. It shows that countries with high risk (ineffective management) are less responsive to the country share. 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 regression results using measures of international sharing. Columns (1), (3) and (5) show the results of interactions of the country share with an indicator for whether a species is multinationally managed. Columns (2), (4) and (6) show results interacting the country share with the high seas share. Neither set of results shows any consistent difference between the baseline results and the alternate specification. The same pattern is evident in Table 16, which shows regression results using measures of fish ranges. Columns (1), (3) and (5) show the results of interactions of the country share with an indicator for whether a species is highly migratory or pelagic. Columns (2), (4) and (6) show results interacting the country share with estimated home range of a species, which captures the typical extent of movement for an individual of that species within a day. Again, I do not see any significant differences between the baseline results and the alternate specification. I take the results of these two tables to indicate that the management of stocks with greater international sharing does not respond any differently to range shift.

Table 18 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 optimal escapement, as the steeper growth function reduces the necessary variation in escapement to address variation in the target condition. 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. In contrast 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. I suspect this counter-theoretical result is driven by selection bias, as higher interest rate countries may also have worse management.

D.4 Tables

Table 13: Management Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	−0.521	1.517***	1.071	−2.619***	0.913	−2.426***
	(0.992)	(0.542)	(1.322)	(0.727)	(1.185)	(0.654)
Norm. Biomass					0.528***	0.556***
					(0.020)	(0.020)
Country Share×Above Average GFI	2.926**		−5.336***		−4.766***	
	(1.176)		(1.568)		(1.406)	
ITQs		−1.014**		1.733***		1.495***
		(0.476)		(0.638)		(0.574)
Country Share×ITQs		1.058**		−2.017***		−1.770***
		(0.521)		(0.699)		(0.629)
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	0.003	0.003	0.006	0.005	0.140	0.152
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 an indicator for above average management quality in the Global Fishing Index. Even 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 GFI score or the use of ITQs. Odd regressions indicate that the headline results are driven by countries with above average management.

Table 14: IUU Fishing Risk Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	4.010***	1.815	−4.343***	−5.370***	−4.296***	−6.726***
	(1.068)	(1.127)	(1.425)	(1.513)	(1.279)	(1.363)
Norm. Biomass					0.527***	0.536***
					(0.020)	(0.021)
RFMO IUU Score	−2.133***		1.414		1.589*	
	(0.802)		(1.071)		(0.960)	
Country Share×RFMO IUU Score		−0.127		1.829*		3.075***
		(0.732)		(0.982)		(0.885)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,864	4,537	4,855	4,528	4,864	4,537
R^2	0.003	0.002	0.004	0.005	0.138	0.142

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

Regression results for heterogeneity regressions involving Illegal, Unregulated and Unreported fishing risks. Odd columns show the results interacting the country share with IUU risk score based on RFMO observers. Even columns show results interacting the country share with with IUU risk score based on MSC observers. Results indicate that the effect of the country share is weaker for countries with higher IUU risk, which represents weaker fisheries management, although the interaction terms are not statistically significant for all outcomes.

Table 15: International Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	1.855***	1.780***	−3.246***	−2.712***	−3.552***	−2.322***
	(0.610)	(0.561)	(0.817)	(0.752)	(0.735)	(0.678)
Norm. Biomass					0.557***	0.556***
					(0.020)	(0.020)
Country Share×Multinational	−1.322		2.632		4.995***	
	(1.310)		(1.755)		(1.578)	
High Seas Share		0.213		−0.236		−0.205
		(0.441)		(0.591)		(0.532)
Country Share×HS Share		−4.211		0.512		−3.311
		(3.048)		(4.085)		(3.677)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,884	4,884	4,875	4,875	4,884	4,884
R^2	0.002	0.002	0.004	0.003	0.152	0.150
Note:	*p<0.1; **p<0.05; ***p<0.01					

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

Table 16: Migration Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	1.702***	1.681***	−2.518***	−1.820**	−2.418***	−0.927
	(0.552)	(0.582)	(0.740)	(0.750)	(0.667)	(0.665)
Norm. Biomass					0.557***	0.544***
					(0.020)	(0.021)
Country Share×Migratory	−3.075		−3.724		−1.312	
	(2.646)		(3.546)		(3.191)	
Home Range		−0.005		−0.0004		−0.001
		(3,282.575)		(4,234.224)		(3,746.549)
Country Share×Home Range		0.014		0.004		0.005
		(0.012)		(0.015)		(0.013)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,884	3,757	4,875	3,757	4,884	3,757
R^2	0.002	0.003	0.003	0.002	0.150	0.158
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 17: Regression results for regressions exploring heterogeneity in international sharing. Columns (1), (3) and (5) show results interacting the country share witha species-level indicator for highly migratory behavior. Columns (2), (4) and (6) show results interacting the country share with the predicted home range. None show any consistent difference between the baseline country share effect and the effect on more migratory stocks.

Table 18: Rate Heterogeneity Regressions

	Dependent variable:					
	Norm. Escapement		Norm. Extraction Rate		Norm. Catch	
	(1)	(2)	(3)	(4)	(5)	(6)
Country Share	2.918**	1.944***	−5.086***	−2.994***	−3.852**	−2.745***
	(1.345)	(0.499)	(1.738)	(0.773)	(1.552)	(0.688)
Norm. Biomass					0.561***	0.549***
					(0.020)	(0.025)
Country Share×Growth Rate	−4.429		10.401**		8.397**	
	(3.421)		(4.422)		(3.946)	
Interest Rate		0.247		−1.043*		−1.335***
		(0.364)		(0.564)		(0.501)
Country Share×Interest Rate		0.138		2.977**		4.048***
		(0.755)		(1.170)		(1.038)
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	0.005	0.002	0.005	0.163	0.122
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.

E 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 33 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 34 shows the EEZ level changes in escapement predicted under the two alternate SSPs (accounting only for the behavioral channel). The expected changes closely resemble those for the middle of the road climate scenario shown in Table **??**, with only slightly different magnitudes. Therefore, I view my estimates as relatively invariant to the choice of climate scenario.

Figure 33: Country Share Changes by Scenario

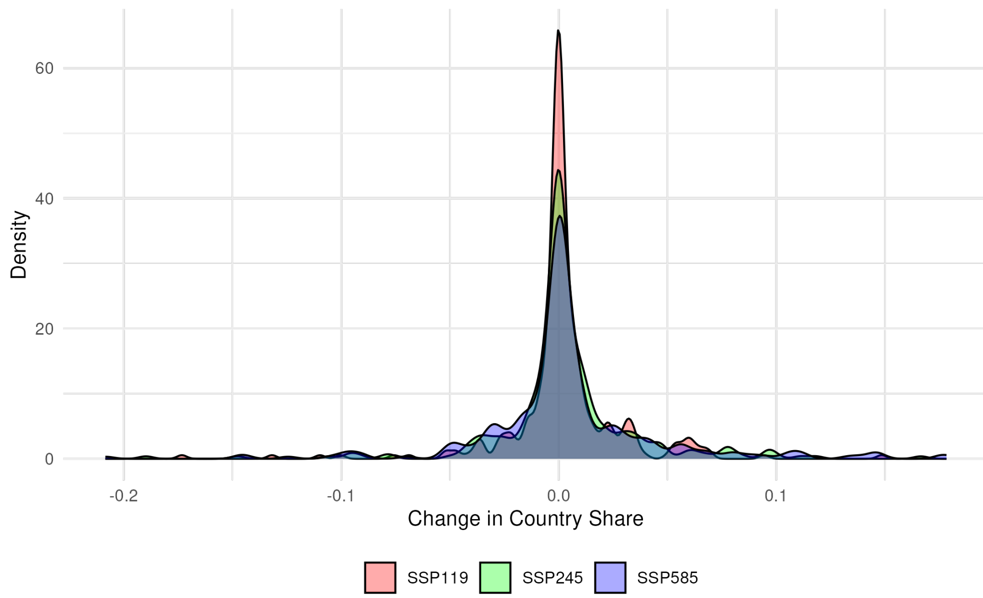


Figure 34: Percent Change in Escapement by EEZ by Climate Scenario