

# Evaluating Adaptive Management Strategies for Climate-Resilient Fisheries



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The Bren School of Environmental Science & Management produces professionals with unrivaled training in environmental science and management who will devote their unique skills to the diagnosis, assessment, mitigation, prevention, and remedy of the environmental problems of today and the future. A guiding principal of the School is that the analysis of environmental problems requires quantitative training in more than one discipline and an awareness of the physical, biological, social, political, and economic consequences that arise from scientific or technological decisions.

The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

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## ABSTRACT

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Fisheries are a major component of the global economy, providing a livelihood and sustenance for billions of people worldwide. Over half of the global fish catch comes from small, local fisheries, primarily located in developing countries. Despite their immense value, these fisheries lack the appropriate data to use conventional methods for analyzing the health of their fishery. In these situations, known as “data-limited fisheries”, managers often struggle to make informed and sustainable decisions. Furthermore, climate change is now adding to the challenges of fisheries management by driving shifts in the ranges of fish stocks, altering the rates at which fish grow and reproduce, and affecting food and habitat availability. These different impacts can be positive for some species in some locations and negative for others. Failing to recognize these changes and include them in decision-making may lead to poor choices with serious economic and environmental implications. To aid decision making in data-limited fisheries, the Environmental Defense Fund (EDF) developed the Framework for Integrated Stock and Habitat Evaluation (FISHE). FISHE provides scientific guidance for the management of fisheries with minimal resources, however it was not designed to explicitly account for the effects of climate change. This project examined if FISHE would continue to provide sound guidance to data-limited fishery managers given the influences of global climate change on fish. This work gives EDF a location-adaptive process to analyze how FISHE can best be utilized to improve fishery outcomes in the face of global climate change.

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## **SECTION I: EXECUTIVE SUMMARY**

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Fisheries are a major component of the global economy, providing a livelihood and sustenance for billions of people worldwide. Despite their immense value, the majority of global fisheries lack the appropriate data to utilize conventional scientific stock assessment methods. In these situations, known as “data-limited fisheries”, managers must turn to alternative assessment methods and often struggle to make informed and sustainable decisions. To aid decision making in data-limited fisheries, the Environmental Defense Fund (EDF) developed the Framework for Integrated Stock and Habitat Evaluation (FISHE). The goal of this framework is to provide scientific guidance to fisheries managers with minimal resources. FISHE is an 11-step process, and each step contains a variety of tools and resources designed to promote the sustainable management of data-limited fisheries.

With the latest predictions from the Intergovernmental Panel on Climate Change (IPCC), EDF is concerned about the impacts of climate change on the performance of FISHE. Climate change is affecting fisheries by driving range and productivity shifts, increasing physiological stress, and altering food and habitat availability, all of which may result in changes to maximum sustained yield (MSY). These changes could come gradually or abruptly in the form of climate driven shocks to the ecosystem. FISHE does not explicitly account for the ecological impacts of global climate change, and as a result, it is unknown if FISHE will continue to provide sound guidance to data-limited fisheries managers in the face of these changes.

Our team developed a three-step approach to address this problem. We began by comparing the outcomes of FISHE management decisions on model-simulated fish stocks with and without climate change. Given that FISHE performed worse under climate change, we then identified steps in FISHE that were most vulnerable to climate change and could be evaluated quantitatively. We prioritized four steps by qualitatively analyzing the impact of productivity changes on management decisions and evaluating where the exclusion of climate effects would have the most negative management implications. Lastly, we designed experiments to evaluate the degree to which individual and combined management actions could improve the overall outcomes of fisheries given different paces and magnitudes of climate change.

From evaluating single management actions, our results show that the frequency of assessment, accuracy of estimates, and harvest control rules are not individually sufficient for producing good fishery outcomes in the face of climate change. However, when analyzed together, our results reveal there are combinations of these actions that can lower the proportion of undesirable (closed or overfished) outcomes. This framework determines sets

of management actions that produce comparable outcomes and gives managers an ability to weigh the tradeoffs associated with each and select an approach that fits with their goals.

Given that human response has the potential to mitigate the negative effects of climate change, it is critical that FISHE integrates climate-effective management actions. This project provides EDF with a process to analyze how existing and new management actions can improve fishery outcomes to assist managers with appropriating limited resources and enhancing fishery resilience in the face of global climate change.

## **SECTION II: OBJECTIVES**

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Climate change is expected to alter the productivity and distribution of global fisheries. It is unknown if FISHE will continue to provide sound guidance to data-limited fisheries managers in the face of climate change. The goal of this project is to evaluate the performance of FISHE under various climate change scenarios and identify potential vulnerabilities within the framework. The specific project objectives include:

1. Determine if FISHE will continue to perform as expected under moderate to severe climate change scenarios (RCP 4.5, 6.0, and 8.5).
2. Identify the quantitative aspects of FISHE most vulnerable to climate change.
3. Test the sensitivity of the vulnerable aspects of FISHE to climate change using an adaptive management approach.

## **SECTION III: SIGNIFICANCE**

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Global food production will need to more than double (FAO, 1995) to feed the growing global population, which is predicted to reach 8.6 billion by 2030 (UN DESA, 2017). Global fisheries are an important food source, providing 15% of the average per capita animal protein intake to more than 2.9 billion people worldwide (FAO, 2010). Recent estimates indicate marine and inland small-scale fisheries provide over half of the global catch, most of which is directly consumed (FAO, 2010). Fisheries provide economic value, employing 43.5 million people in primary fish production and yielding exports valued at \$85.9 billion (FAO, 2010). Nearly 50% of small-scale fisheries workers are women and more than 95% live in developing countries (FAO, 2010).

Despite their social and economic significance, over 33% of global fisheries are classified as overfished (FAO, 2018). This statistic, however, was derived from only the small fraction of global fisheries that have actually been classified. The vast majority are not classified and are

in need of scientific assessment (Apel *et al.*, 2013). Furthermore, research has shown that most unassessed small-scale fisheries are likely to be overfished (Costello *et al.*, 2012).

In addition to the existing challenges of fisheries management, climate change is now altering marine ecosystems. As a result, global fisheries stand to lose up to 50% of gross revenues in the face of severe climate change and continued overfishing (Cheung and Sumaila, 2010). Recent research suggests that climate change could lead to a significant decline in MSY by 2100 (Gaines *et al.*, 2018). The Food and Agriculture Organization (FAO) predicts total maximum catch from Exclusive Economic Zones (EEZs) could decrease by as much as 16.2% to 25.2% in the absence of climate mitigation (FAO, 2016). Further, research suggests that there is substantial variation in catch potential across the globe. While fisheries may be stabilizing below sustainable levels in some regions, other regions continue to face declining biomass (Worm & Branch, 2012).

However, recent analyses suggest implementing management measures that are adaptive to climate change may increase profit and biomass despite these climate-driven changes (Gaines *et al.*, 2018). These potential benefits come from better management of fisheries that are currently poorly managed. They require new, climate adaptive management strategies incorporating better data on stock-status and ecosystem vulnerability (Worm & Branch, 2012). In addition to curbing projected economic losses, new adaptive strategies could help to offset the negative effects of climate change and bolster the resilience of marine ecosystems.

## **SECTION IV: BACKGROUND**

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### A. Our Client: The Environmental Defense Fund (EDF)

The Environmental Defense Fund (EDF) is a US non-profit environmental advocacy group that tackles global environmental challenges such as climate change, ecosystem restoration, and ocean health (EDF, 2016). Through incentive-based and data-driven programs, EDF's Fisheries Solutions Center works to design tools and develop innovative fisheries management strategies to reverse overfishing. EDF collaborates with conservation groups, governments, fishermen, and other stakeholders to create fisheries management solutions which balance conservation with social and economic needs.

### B. Data-Limited Fisheries

Fisheries managers have to make difficult decisions, balancing the pressure from fishers who rely on certain yields to make a living with the threat of overfishing - and the ensuing social, environmental, and economic losses. Given this delicate balance, it is critical that informed

and thoughtful decisions are made using the best information available about a particular stock.

Conventional fisheries stock assessment methods require large amounts of data that are expensive and time-consuming to collect. As a result, these methods tend to mostly be used for high value, commercially harvested stocks in developed countries (Amorim *et al.*, 2019). Even in the United States, fewer than 50% of federally managed fisheries have been assessed (NMFS, 2012).

Unlike highly developed commercial fisheries, small-scale and less developed fisheries often lack the resources to invest in monitoring and assessment. These unassessed fisheries contribute over 80% to the global fish catch but lack sufficient data to be managed using conventional methods (Costello *et al.*, 2012). Known as “data-limited fisheries”, they must turn to alternative stock assessment methods that require fewer data inputs to guide management actions.

Common approaches to address the challenges of data-limited fisheries management include trend analyses, vulnerability analyses, and extrapolation methods. Trend analyses encompasses a wide range of data types and requirements to analyze changes in stock productivity through time-series analysis (Honey, Moxley, & Fujita, 2010). Simple time-series data on catch statistics, survey-based length or weight reference points, trophic indices, or spawning potential ratios are often used for sequential trend analysis (Honey, Moxley, & Fujita, 2010). Vulnerability analyses use local and expert knowledge to assess the health of and threats to an ecosystem and/or species. An example of a vulnerability analysis is the Comprehensive Assessment of Risks to Ecosystems (CARE). CARE ranks the threats to an ecosystem and/or a single species within data-limited systems, allowing for rapid management decisions (Battista *et al.* 2017). Additionally, managers can extrapolate through local knowledge from fishermen and data from “sister” fisheries that are known to be similar in nature (Honey, Moxley, & Fujita, 2010). With these methods, information from data-rich fisheries is used to infer traits about data-limited fisheries.

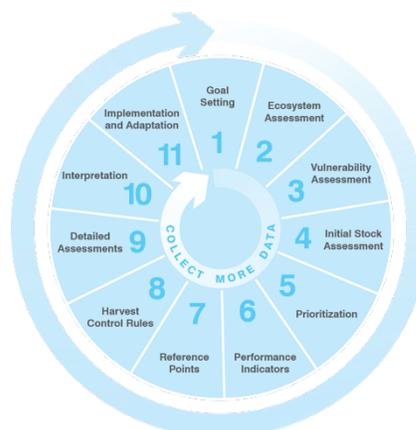
### C. The Framework for Integrated Stock and Habitat Evaluation (FISHE)

To assist in the management of data-limited fisheries, EDF created the Framework for Integrated Stock and Habitat Evaluation (FISHE). FISHE is an 11-step adaptive management framework designed to help fisheries managers conduct simplified stock assessments and evaluate potential management options with minimal inputs. To develop FISHE, EDF compiled a variety of tools and resources that were developed specifically for data-limited fisheries. Because these individual tools and resources are effective in different situations, this approach allows for FISHE to be used and adapted for any type of stock in any geographic

location. FISHE is being used to guide management reforms around the world, including Baja California, the Philippines, and Belize (Karr, 2015).

The 11 steps of FISHE are (Figure 1):

1. Goal Setting
2. Ecosystem Assessment
3. Vulnerability Assessment
4. Initial Stock Assessment
5. Prioritization
6. Performance Indicators
7. Reference Points
8. Harvest Control Rules
9. Detailed Assessments
10. Interpretation
11. Implementation and Adaptation



**Figure 1. FISHE Process.** A diagram of the 11-step FISHE process.

FISHE is an inclusive process, intended to consider the needs of all stakeholders involved. Steps 1 - 8 of FISHE are completed before any data is analyzed or assessed. Rather, these steps are designed to initiate conversations between stakeholder groups and agree upon actions that will be taken once the assessments are performed and the data are returned. With the management framework set, steps 9 - 11 involve the actual stock assessment, interpretation, and implementation of the management decisions previously agreed upon. Table 1 provides a description of each FISHE step in more detail.

**Table 1. FISHE Process Description.** Detailed descriptions of each step of the 11-step FISHE process.

<b>FISHE Step</b>	<b>Description</b>
<b>Step 1: Goal Setting</b>	<ul style="list-style-type: none"> <li>• Goal setting is a stakeholder driven and inclusive process that considers both short-term and long-term goals and acknowledges trade-offs between goals</li> <li>• Goals include considerations of ecological objectives, economic objectives, and cultural objectives</li> </ul>
<b>Step 2: Ecosystem Assessment</b>	<ul style="list-style-type: none"> <li>• Ecosystem assessments involve a qualitative assessment of the status of the marine ecosystem and associated impacts of fishing through local or expert knowledge and simple measurements</li> <li>• Ecosystem assessments can be used to prioritize management measures that address high risk impacts</li> </ul>

<p><b>Step 3: Vulnerability Assessment</b></p>	<ul style="list-style-type: none"> <li>• Vulnerability assessments involve assessing the vulnerability of target stocks to fishing pressure using basic biological and fishery information through a Productivity and Susceptibility Analysis (PSA) model</li> <li>• Vulnerability scores are calculated and used to make an informed decision on how to group species for further assessment and management, if necessary</li> </ul>
<p><b>Step 4: Initial Stock Assessment</b></p>	<ul style="list-style-type: none"> <li>• Initial stock assessments are used to gather a baseline understanding of the current state of target stocks</li> <li>• Methods include examining catch trends or Catch Per Unit Effort (CUPE), MPA Density Ratio, MPA Catch Curve, and the Length-Based Spawning Ratio (SPR)</li> </ul>
<p><b>Step 5: Prioritization</b></p>	<ul style="list-style-type: none"> <li>• Prioritization uses the information from Steps 3 and 4 to organize species by their vulnerability and stock status based on different threat levels</li> <li>• Species are then assigned priority based on threat levels and management goals</li> </ul>
<p><b>Step 6: Performance Indicators</b></p>	<ul style="list-style-type: none"> <li>• Performance Indicators (PI) are measurable aspects of a fishery that can be used to evaluate performance relative to management goals</li> <li>• PI selection dictates the choices that will be made in steps 7-9</li> </ul>
<p><b>Step 7: Reference Points</b></p>	<ul style="list-style-type: none"> <li>• Reference Points (RP) are the theoretical PI values used to compare to the actual PI values of the fishery to measure performance</li> <li>• The target RP is the ideal PI value for the fishery</li> <li>• The limit RP is the worst PI value for the fishery before drastic action is needed</li> </ul>
<p><b>Step 8: Harvest Control Rules</b></p>	<ul style="list-style-type: none"> <li>• Harvest Control Rules (HCR) are simple rules that direct the action to be taken for any resulting PI value</li> <li>• A HCR only specifies <i>what</i> that rule will accomplish, not <i>how</i> that rule will be implemented</li> </ul>
<p><b>Step 9: Detailed Assessments</b></p>	<ul style="list-style-type: none"> <li>• Detailed assessments are completed to estimate the actual PI value of the fishery</li> </ul>

	<ul style="list-style-type: none"> <li>• Methods include Biomass Dynamics models, Depletion-Corrected Average Catch (DCAC), Marine Protected Area-Based Decision Trees, and Catch-MSY</li> </ul>
<b>Step 10: Interpretation</b>	<ul style="list-style-type: none"> <li>• Interpretation involves interpreting the results of step 9, in the context of steps 1-8, to make the appropriate management decisions to meet fishery goals</li> </ul>
<b>Step 11: Implementation and Adaptation</b>	<ul style="list-style-type: none"> <li>• Implementation involves choosing Harvest Control Measures (HCM), which describe <i>how</i> the HCR will be implemented</li> <li>• Adaptation involves the process of re-visiting the fishery goals and re-evaluating the state of the fishery</li> </ul>

The success of FISHE is dependent on its adaptability, as fisheries are dynamic systems that are influenced by a multitude of variables. Constantly changing conditions mean that the FISHE process must be repeated on a regular basis. This gives managers the ability to re-evaluate and adjust decisions based on new observations about fishery conditions and the opportunity to learn from previous management decisions (FISHE, n.d.).

While FISHE was designed to capture the inherently dynamic nature of fisheries, it was not specifically designed to address the expected environmental changes stemming from global climate change. As climate change has already started to impact fish stocks worldwide, it is imperative that FISHE is robust to climate-induced variations and minimizes environmental and economic risk (Gaines *et al.* 2018; FISHE, n.d.).

#### D. Climate Change

The earth system experiences substantial natural variation from seasonal cycles to inter-annual and inter-decadal fluctuations. Anthropogenic activities continue to emit unprecedented amounts of carbon dioxide into the atmosphere leading to higher global mean temperatures. Since 1993, the rate of ocean warming has more than doubled, and the ocean has absorbed more than 90% of the excess heat in the climate system (IPCC, 2019). The changing climate is projected to cause a cascade of physical and chemical changes in the marine environment (Harley *et al.*, 2006). Physical changes to the marine environment include gradual changes such as rising sea levels, intensifying wind fields along the ocean margins, stronger thermal stratification, and shifting precipitation patterns. Of particular concern to fisheries management is the increased frequency of climate shock events such as storms and ENSO conditions (Harley *et al.*, 2006). Elevated levels of atmospheric carbon dioxide will also have important biogeochemical implications. The oceans hold up to 30% of

modern carbon dioxide emissions, which is anticipated to cause a decrease in ocean pH and alter the availability of minerals essential to calcifying organisms (Feely *et al.*, 2004).

The effects of these climate variations on fisheries can be broadly categorized as changing stock productivity or shifting stock distribution (Gaines *et al.*, 2018). Productivity can be influenced by increased physiological stress, altered food availability, decreased reproductive success, changing growth rates, or other ecological interactions. Changes in productivity further impact overall ecosystem productivity. As the marine environment changes, species habitat ranges are gradually shifting to maintain optimal conditions (Szuwalski & Hollowed, 2016). While there is an overall trend toward poleward movement in response to warming, species-level response has not been uniform, demonstrating that the rates and velocities of climate change events plays critical roles in determining the extent of range shifts (Szuwalski & Hollowed, 2016).

Climate change will also affect species differently based on life-history characteristics. Life-history parameters will be altered as the abiotic factors of the environment change, from increasing temperature to decreasing pH. Species with fast life histories have been shown to be more responsive to sea surface temperature changes, both positively and negatively, than those with slow life history traits (Free *et al.*, 2019). In the North Atlantic, benthic invertebrates and diadromous finfish were found to be particularly vulnerable to climate change impacts in an analysis that grouped species together based on life-history characteristics (Hare *et al.*, 2016).

These different categories of climate effects pose unique management challenges. Altering stock productivity influences potential yields and fishery profits, while distributional changes influence who catches fish and where (Gaines *et al.*, 2018). As stock productivity fluctuates, it is imperative that harvest controls be adaptive to respond to changes in abundance. As ranges shift, fish may migrate in and out of country jurisdictions, leaving stocks vulnerable to overharvesting. This could occur as anticipated stock declines may create incentives for overharvesting before the range extends beyond a country's EEZ or through the emergence of unmanaged fisheries from new stocks entering into EEZs (Gaines *et al.*, 2018).

Further, the temporal variation of climate impacts has important implications for management decisions. On short time-scales of 1-5 years, overfishing remains the primary threat to sustainable fish populations (Brander, 2010). Prolonged and heavy fishing pressure reduces the age structure, selects for earlier maturation, reduces diversity and destroys habitat (Free *et al.*, 2019). As a result, overfishing lowers species resilience to changing environmental conditions and can magnify fluctuations due to environmental variability (Brander, 2010; Free *et al.*, 2019). While gradual shifts may not substantially influence fish populations on short time-scales, higher inter-annual variability, particularly the increased

frequency of ENSO events, may have non-linear impacts that can be detrimental to fish populations (Brander, 2010). Research suggests that these gradual shifts in the baseline of the marine environment (i.e. temperature, salinity, pH) are more critical on medium time-scales of 5-25 years (Brander, 2010). Stock recovery and the maintenance of stock abundance are influenced by the growth, reproduction, distribution, and recruitment of marine fish - all of which may be altered by environmental factors.

## E. Uncertainty and Risk

A considerable amount of uncertainty and risk are inherent to both climate change and fisheries management. Climate change projections are highly variable, and the uncertainty surrounding those projections leads to dramatic differences in the expected impacts on fisheries. Understanding the uncertainty and risks involved with each decision is critical to maintaining a sustainable fishery. If not properly considered, there can be lasting and harmful consequences.

Representative Concentration Pathways (RCP) are greenhouse gas concentration trajectories adopted by the IPCC that account for uncertainty in climate change predictions. Each RCP represents a different scenario of future greenhouse gas concentrations and the associated impacts of that concentration. The 4 RCP scenarios include 2.6, 4.5, 6.0, and 8.5, ranging from business-as-usual (RCP8.5) to best-case mitigation (RCP2.6). In fisheries research, it is common practice to model across the 4 RCP scenarios to capture the uncertain effects of climate change from a low to high extreme. However, due to a lack of meaningful global action to address emissions, it is now nearly impossible to achieve the reductions necessary to reach RCP2.6 (Raftery *et al.*, 2017). As a result, more recent research has now dismissed RCP2.6 altogether and instead focused on RCP4.5, 6.0, and 8.5 (Free *et al.*, 2019).

Further uncertainties surround the more fine-scale regional impacts of climate change and their differing effects on specific species and stocks. In addition to climate change, there are many levels of uncertainty within fisheries stock assessments. In data-limited fisheries, this uncertainty is extended due to a lack of adequate information. Varying levels of uncertainty in stock assessments can stem from errors and biases in data collection, errors in model processes within the assessment, and model misspecifications (Szuwalski and Hallowed, 2016). These uncertainties are then exacerbated by the increased variability introduced into the system by climate change.

## SECTION V: METHODOLOGY

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### A. Overview

A qualitative analysis of the FISHE framework was conducted to identify which steps include processes that are potentially vulnerable to climate impacts. Four main steps (Reference Points, Harvest Control Rules, Detailed Assessment, and Implementation and Adaptation) were identified to prioritize in our analysis. A model was developed to test the influence of different management actions on fishery outcomes over different paces of climate change. The model included three components: a biological model to track the fishery over time, a climate change model to track changing productivity and ranges, and a management model to simulate implementation of FISHE. Data to test the model was generated by selecting a range of values for each model input that would occur in nature. Each of the four steps of FISHE were integrated into the model and tested in isolation to understand their individual influences. We tested the effect of error in detailed assessment, the amount of reduction in fishing mortality from harvest control rules, the frequency of assessment, and tracking productivity changes by updating reference points. These four tests were run over a period of 100 years across a range of initial biomasses, growth rates, and paces of climate change. Additionally, all interactions of these factors were analyzed to explore tradeoffs between combinations of actions. Three types of climate impacts were analyzed: gradual changes in productivity, gradual range shifts, and shock events resulting in larger productivity changes in a single year.

### B. Literature Review

The team performed an extensive literature review to gain an understanding of how climate change is expected to affect fisheries, common data-limited assessment methodologies, and existing studies with research objectives similar to our own. Additionally, this literature review included an in-depth look at the FISHE framework through interviews and case studies.

### C. Qualitative Evaluation of FISHE

The FISHE framework contains 11 steps and offers multiple methods for completing each step based on the data and resources available. Analysis of all the steps and all the methods contained in FISHE was not feasible within the timeframe of the project. The qualitative evaluation of the FISHE framework was completed to prioritize steps for analysis in the model.

A preliminary evaluation identified steps where the absence of climate considerations may have important implications based on our understanding of how climate will influence the biology of fish. These steps were further narrowed down to select those for which the information presented in the framework could be examined in a quantitative model. Finally,

our advisory team (2020) suggested that the steps be compared to a general three-step approach for resource management: 1) Identify the state of the resource; 2) make a decision about how to respond; and 3) determine how often this process will be repeated. The initial analysis prioritized the steps that most closely followed this framework: Detailed Assessment, Harvest Control Rules, and Implementation and Adaptation. Reference Points was included based on a hypothesis that updating reference points to account for productivity changes would have a strong influence on fishery outcomes.

## D. Model

A model was developed to analyze the impacts of different management actions over a range of climate impacts. The model consisted of three components: a biological model, a climate model, and a management model.

### *Biological Model*

The underlying fish stock was tracked through a dynamic Pella Tomlinson surplus production model (Equation 1). Surplus is calculated as net change in total biomass:

$$\text{Equation 1: } SP_{i,t} = B_{i,t+1} - B_{i,t} + C_{i,t}$$

where surplus production for stock  $i$  over time  $t$  ( $SP_{i,t}$ ) is the difference between the biomass of stock  $i$  in time  $t+1$  and time  $t$  ( $B_{i,t+1}$  and  $B_{i,t}$ , respectively) and the catch of stock  $i$  between time  $t$  and time  $t+1$  ( $C_{i,t}$ ). The Pella Tomlinson model includes a shape parameter ( $p$ ) which allows it to replicate either a Fox or Schaefer production model (Equation 2) (Free *et al.* 2019):

$$\text{Equation 2: } SP_{i,t} = \left(\frac{r_{i,t}}{p}\right) \times B_{i,t} \times \left(1 - \left(\frac{B_{i,t}}{K_{i,t}}\right)^p\right)$$

where  $r_{i,t-1}$  is the intrinsic growth rate of stock  $i$  in time  $t$  and  $K_{i,t}$  is the carrying capacity of stock  $i$  in time  $t$ . The time variable is included to reflect the changes to stock productivity and ranges from climate change over time. The shape parameter used in the model maximizes productivity at 40% of carrying capacity ( $p = 0.2$ ), which is the meta-analytic mean for fish (Free *et al.* 2019). The model calculates biomass of stock  $i$  in each time step as a function of the previous biomass, the growth, and the catch for the 100-years of the simulation (Equation 3):

$$\text{Equation 3: } B_{i,t} = B_{i,t-1} + \left[\left(\frac{r_{i,t-1}}{p}\right) \times B_{i,t-1} \times \left(1 - \left(\frac{B_{i,t-1}}{K_{i,t-1}}\right)^p\right)\right] - c_{i,t-1}$$

where catch is calculated for stock  $i$  using fishing mortality and biomass in time  $t$  (Equation 4):

$$\text{Equation 4: } c_{i,t} = f_{i,t} \times B_{i,t}$$

#### *Climate Model*

Three kinds of climate influences were tracked in the model: gradual productivity changes, gradual range shifts, and shock events. Gradual productivity changes to stock  $i$  were represented as a compounding annual decrease or increase in productivity (Equation 5):

$$\text{Equation 5: } r_{i,t} = r_{i,t-1} + (r_s \times r_{i,t-1})$$

where  $r_s$  is a slope term representing the percent change in productivity per year.

In the same way gradual range shifts for stock  $i$  were included in the model as a compounding annual increase or decrease in carrying capacity (Equation 6):

$$\text{Equation 6: } K_{i,t} = K_{i,t-1} + (K_s \times K_{i,t-1})$$

where the  $K_s$  term is a slope term representing a percent change in range per year. We assume that changes to a species range are proportional to a change in the carrying capacity (Gaines *et al* 2018). For example, if the species range decreases by 15%, we assume the carrying capacity declines by 15%. Gradual productivity changes and gradual range shifts were not evaluated in the same model.

Shock events were represented in the same manner as gradual productivity changes, through a change to the  $r_{i,t}$  term. Rather than a gradual slope, however, shock events were applied as single-year productivity decreases that did not carry over to the following year.

#### *Management Model*

The management aspect of the model reflects the decisions being made using the FISHE process and depend on the chosen performance indicators. The performance indicators are selected based on the goals of the fishery and used to track progress in meeting those goals. This analysis was conducted assuming the management goal is maximum sustainable yield (MSY), a common practice in fisheries management. In this model, the performance indicator is the ratio of fishing mortality for stock  $i$  ( $f_i$ ) to the fishing mortality that would provide maximum sustainable yield for stock  $i$  ( $f_{MSY,i}$ ), hereafter called the f-ratio (Equation 7):

$$\text{Equation 7: } f - \text{ratio} = \frac{f_i}{f_{MSY,i}}$$

Initial fishing mortality was calculated assuming the initial biomass is the result of an equilibrium where catch is equal to surplus production (Equation 8):

$$\text{Equation 8: } f_{\text{initial},i} = \left( \frac{r_{0,i}}{p} \right) \times \left( 1 - \left( \frac{B_{0,i}}{K_i} \right)^p \right)$$

where  $r_{0,i}$  is the intrinsic growth rate of stock  $i$  before any climate influences and  $B_{0,i}$  is the initial biomass of stock  $i$  at the start of the simulation. The fishing mortality rate that produces MSY is calculated using the growth rate and the shape parameter (Equation 9):

$$\text{Equation 9: } f_{\text{MSY},i} = r_{i,t} \times \frac{1}{(1+p)}$$

where  $r_{i,t}$  is the growth rate of species  $i$  in time  $t$ . As climate change alters productivity,  $f_{\text{MSY},i}$  for stock  $i$  will also change.

After selecting and calculating reference points, the management model contains three additional parts: sampling error, assessment intervals, and a management decision.

#### *Sampling Error*

The sampling error reflects the uncertainty around estimating the status of the stock using the chosen performance indicators. The model tracks the true  $f$ -ratio and updates it every year based on the changes in productivity ( $r$ ). A second variable is used to track the fisheries manager's perceptions of the  $f$ -ratio (hereafter called the perceived  $f$ -ratio). In the initial tests, the perceived  $f$ -ratio does not account for the changes in biological productivity from gradual climate change or shock events (Equation 10):

$$\text{Equation 10: } \textit{perceived } f - \textit{ratio} = \frac{f_{i,t}}{f_{\text{MSY},i,1}}$$

where  $f_{i,t}$  is the fishing mortality rate of stock  $i$  in time  $t$  and  $f_{\text{MSY},i,1}$  is the fishing mortality rate that would produce MSY in Year 1, using the initial growth rate of species  $i$ . For later experiments two versions of tracking productivity were tested. The first updated  $f_{\text{MSY}}$  in every time step based on changes in underlying productivity from gradual climate change and shock events (Equation 11):

$$\text{Equation 11: } \textit{perceived } f - \textit{ratio} = \frac{f_{i,t}}{f_{\text{MSY},i,t}}$$

where  $f_{\text{MSY}}$  for stock  $i$  is based on productivity ( $r$ ) in time  $t$ .

The management decision is made based on an estimate of the perceived f-ratio with error that is randomly drawn from a lognormal distribution using the `rlnorm` function in R (Equation 12):

$$\text{Equation 12: } f - \text{ratio} - \text{error} = \text{rlorm}(\mu, \sigma)$$

where the mean ( $\mu$ ) is the log transformed perceived f-ratio (Equation 13) and the standard deviation ( $\sigma$ ) is the log transformed coefficient of variation (Equation 14):

$$\text{Equation 13: } \mu = \log(\text{perceived } f - \text{ratio})$$

$$\text{Equation 14: } \sigma = \sqrt{\log(cv^2 + 1)}$$

The coefficient of variation ( $cv$ ) is the amount of error being tested.

#### *Assessment Intervals*

Assessment intervals dictate when management decisions are made. Management actions are carried through until the next assessment. An assessment is always conducted in Year 1 and then varied depending on the frequency being tested. For example, for a five-year assessment interval, an initial assessment is completed in Year 1 and the management action is carried through until the next assessment in Year 5. The management decision made in Year 5 is carried through until Year 10, and so on until Year 100.

#### *Management Decision*

The management decision is based on an observation of the chosen performance indicator (f-ratio with error) compared to the reference points. A target reference point represents the ideal amount of fishing pressure while the limit reference point is the maximum allowable fishing pressure. The initial analysis set the target f-ratio to one, meaning fishing mortality would be exactly the rate that produces MSY. The limit f-ratio was placed at two, meaning fishing mortality would be twice as high as the rate that would produce MSY. Fisheries managers would take a different management action depending on where their observation with sampling error places them relative to the target and limit (Figure 2).

<b>IF:</b>	<b>THEN:</b>
Reference Point > Limit	Stop Fishing
Target < Reference Point < Limit	Reduce fishing pressure by the harvest control rule
Target = Reference Point	Maintain same fishing pressure
Target > Reference Point	Increase Fishing Pressure

**Figure 2. Management Decision Framework.** Example of the general management decision framework utilized in the FISHE process.

The management decision is made in the beginning of the assessment year and the change in fishing pressure is applied to the fishing mortality rate in that year. For example, if the  $f$ -ratio with error places the fishery in between the target and limit, fishing mortality would be calculated as a function of the harvest control rule (Equation 15):

$$\text{Equation 15: } f_{i,t} = (1 - hcr) \times f_{i,t-1}$$

where  $f_{i,t}$  is the new fishing mortality rate for stock  $i$  in time  $t$ , the  $hcr$  is the amount by which fishing pressure will be reduced (i.e. 0.10), and  $f_{i,t-1}$  is the previous fishing mortality rate of stock  $i$ . For example, if the harvest control rule is to reduce fishing pressure by 10%, then the new fishing mortality rate is 90% of the previous fishing mortality rate.

## E. Model Inputs and Data Generation

The FISHE framework was designed to be applied to a broad diversity of fisheries in many geographic locations. As such, the model was designed to incorporate a range of each parameter to represent the various situations in which FISHE might be applied (see Table 2).

**Table 2. Parameters.** Gives the range of values for each model.

Parameter	Description	Range of Values
$B_0$	Initial biomass	1500, 4000, 6000 <sup>1</sup>
$r$	Intrinsic growth rate	0.1 to 0.8 <sup>2</sup>
$K$	Carrying capacity	10,000
$p$	Shape parameter	0.2 <sup>2</sup>
$r_s$	Percent change in growth per year	-0.01767 to 0.01433 <sup>2</sup>
$K_s$	Percent change in range per year	-0.045 to -0.001 <sup>3</sup>
$ai$	Assessment interval	1, 5, 10, 15, 20, 100
$e$	Error	0.1, 0.3, 0.5
$hcr$	Harvest control rule	0.05 to 0.50

Sources: 1. Ye 2011; 2. Free et al 2019; 3. Gaines et al 2018

### *Biological Model*

Biological model parameters include initial biomass ( $B_0$ ), intrinsic growth rate ( $r$ ), and carrying capacity ( $K$ ). Three initial biomasses were chosen to represent the different status of fisheries prior to implementation of FISHE. Classifications for fishery status were determined using the Food and Agriculture Organization's definitions of overfished (15% of carrying capacity), fully fished (40% of carrying capacity), and healthy (60% of carrying capacity) fisheries (Ye 2011). A range of intrinsic growth rates was chosen to represent different life history traits from slow growing species to fast growing species. A single carrying capacity was selected and applied across all the species. The carrying capacity was used to calculate relative starting biomasses and could be adjusted for a specific species in a future analysis.

### *Climate Model*

The climate model inputs were two slope values  $r_s$  and  $K_s$ , representing a compounding annual change in productivity and species ranges, respectively. The lower bound (30% decline) and upper bound (33% increase) of productivity changes per degree ( $^{\circ}\text{C}$ ) of sea surface temperature change were gathered from Free et al 2019. The pace of climate change ( $^{\circ}\text{C}/\text{year}$ ) was taken from two different Representative Concentration Pathways (RCP) and scaled to match the length of our simulation (100 years). Under RCP 4.5, a single degree of temperature change occurs over 33 years (Hoegh-Guldberg et al 2014), and there would be

an approximately 3°C change over 100 years. For RCP 8.5, one degree of warming occurs every 20 years (Hoegh-Guldberg *et al* 2014) for a total of 5°C over 100 years. The  $r_s$  and associated productivity changes under the two RCPs are given in Table 3.

**Table 3. Productivity Changes.** The change in productivity per degree Celsius (°C) of sea surface temperature (SST) change associated with the slope term ( $r_s$ ) used in the model under Representative Concentration Pathways (RCPs) 8.5 and 4.5.

$r_s$	Productivity Change (RCP 8.5) <sup>1</sup>	Productivity Change (RCP 4.5) <sup>2</sup>
- 0.01767	- 30%	-45%
-0.01567	- 27%	-40%
-0.01367	-24%	-37%
-0.01167	- 21%	-32%
-0.00967	-18%	-27%
-0.00767	-15%	-22%
-0.00567	-11%	-17%
-0.00376	-7%	-11%
-0.00167	-3%	-5%
+0.00033	+1%	+1%
+0.00233	+5%	+8%
+0.00433	+9%	+15%
+0.00633	+13%	+23%
+0.00833	+18%	+31%
+0.01033	+23%	+40%
+0.01233	+28%	+50%
+0.01433	+33%	+60%

<sup>1</sup> Based on 5 °C warming over 100 years

<sup>2</sup> Based on 3 °C warming over 100 years

Source: Hoegh-Guldberg *et al* 2014

Species range shifts are also dependent on the pace of climate change (Gaines *et al* 2018). Due to the high uncertainty about how far species ranges will shift under any given pace of climate change and the dependence on geographic location, we explored a wide range of potential shifts. On the lower boundary we used a narrow range shift of 5% over 100 years and the upper boundary represents a significant shift of 95% over 100 years.

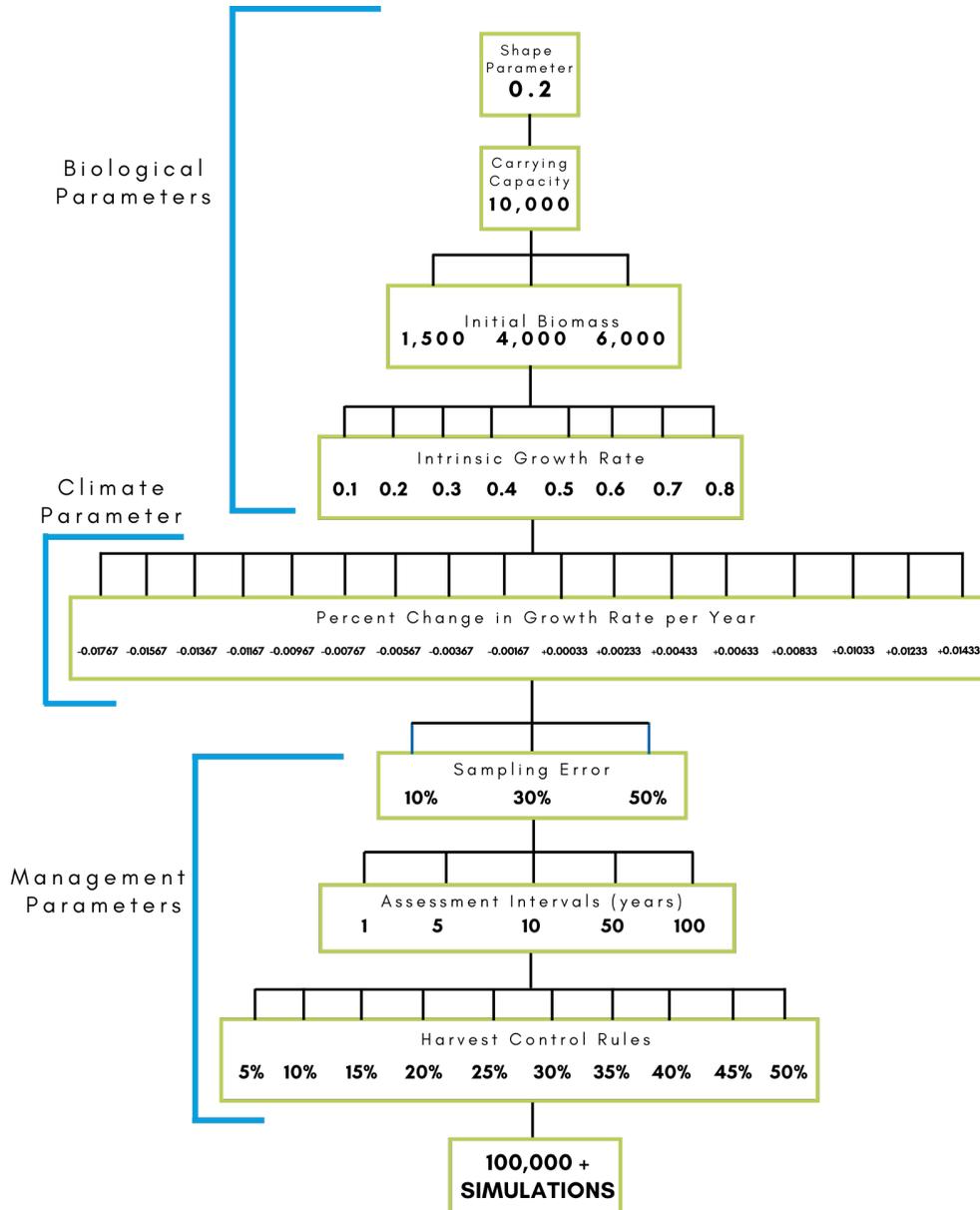
### Management Model

The management model includes three different inputs: assessment intervals, error, and harvest control rules (HCRs). Assessing every year represents perfect implementation of FISHE as an adaptive management tool. However, from interviews with EDF reassessment every year is rare. Intervals of 5, 10, 15, and 20 years were chosen to mimic more realistic

frequencies of implementation. Assessing once every 100 years represents a fishery that implements FISHE once but never repeats the process. Three levels of error were chosen to represent the three tiers of data availability in FISHE. Tier 1 represents less than one year of data from a single data stream, which corresponds to the highest error (0.5) tested in the model. Tier 2 fisheries have at least one year of data from a single source, which is the moderate error scenario (0.3) in the model. A Tier 3 fishery has more than one year of data from more than one data stream and corresponds to the lowest error scenario (0.1) tested in the model. A range of harvest control rules were tested from a 5% reduction in fishing pressure through a 50% reduction in fishing pressure if the f-ratio with error fell between the target and limit reference points.

#### *Data Generation*

Every combination of parameters was fed through the model to generate the data to analyze the influence of different management actions on fishery outcomes. A flow-chart generating one combination of data for a single model run is illustrated in Figure 3.



**Figure 3. Model Run Example.** Illustrates a single pathway through the model starting with the two static biological parameters and then selecting one value from every box of climate and management parameters. All combinations of inputs were run through the model for a total of 61,200 combinations.

## F. Model Outputs

The model tracked eight outputs in every year of the 100-year simulation (Table 4). The growth rate ( $r$ ) or carrying capacity ( $K$ ), the fishing mortality rate at MSY ( $f_{msy}$ ), and the true  $f$ -ratio are updated every year based on the changes to productivity or ranges from climate change. In assessment years, the perceived  $f$ -ratio is updated and a new  $f$ -ratio is drawn with random error. Based on the management decision made in the assessment, the fishing mortality rate ( $f$ ) is updated and then held constant until the next assessment year. These outputs were used to analyze biomass in the final year of simulation and compare outcomes across the different scenarios.

**Table 4. Model Outputs.** Lists the variables and description for model outputs.

Parameter	Description
B	Biomass
C	Catch
$r^1$	Growth rate
$K^1$	Carrying capacity
$f$	Fishing mortality rate
$f_{msy}$	Fishing mortality rate at maximum sustainable yield
$f$ -ratio	Ratio of fishing mortality to fishing mortality at maximum sustainable yield
$f$ -ratio-p	Ratio of fishing mortality to fishing mortality at maximum sustainable yield perceived by the fisheries manager
$f$ -ratio-err	Perceived ratio of fishing mortality to fishing mortality at maximum sustainable yield drawn randomly from lognormal sampling error

<sup>1</sup> Either the growth rate ( $r$ ) or carrying capacity ( $K$ ) were tracked in the outputs, depending on the type of climate influence being tested in the model run.

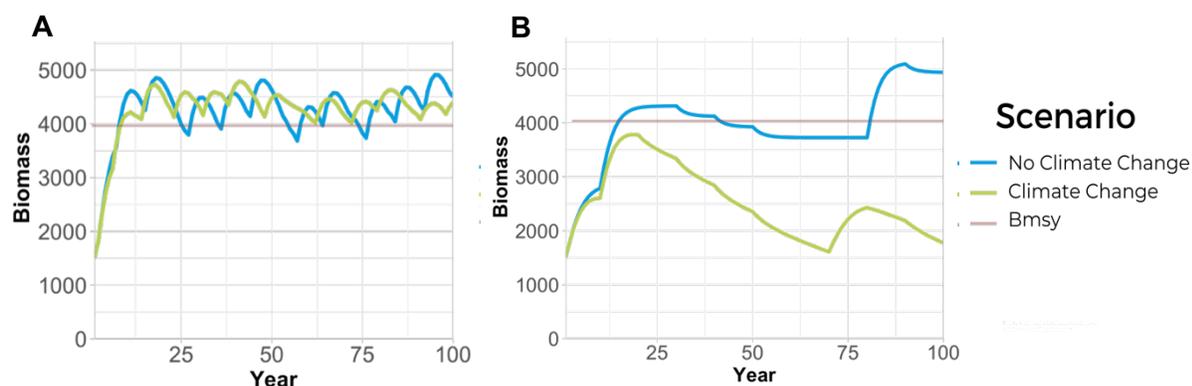
## SECTION VI: RESULTS

### A. Overview

First, our results explore the effectiveness of the FISHE framework with and without climate change. The individual management actions in the model (sampling error, assessment intervals, harvest control rules, and tracking productivity) are then isolated to understand the individual influence of each action on fishery outcomes. Once these independent effects are explored, we combined actions to examine tradeoffs that achieve similar outcomes using a case study format.

### B. No Climate Change vs. Climate Change

The FISHE framework is designed to be an adaptive management tool and ideal management using FISHE would repeat the process every year. When FISHE is implemented annually there is not a dramatic difference between the fishery's performance over the 100-year time period under moderate climate change and no climate change. One specific simulation to illustrate this general trend is shown in Figure 4A. Moderate climate change corresponds to either a 22% or a 15% decrease in productivity per °C under RCP 4.5 or 8.5, respectively (Table 3). However, FISHE is not often implemented annually and more realistic management using the framework occurs on 5- to 20-year timescales. Fishery biomass over time in moderate climate change and no climate change using a 10-year assessment interval had more significant variation. One specific simulation to illustrate this trend is shown in Figure 4B.



**Figure 4. FISHE Management Comparison.** Fishery biomass is tracked over a 100-year time period without climate change (blue line) and with moderate climate change (green line). A biomass at maximum sustainable yield is shown in red. Figure 3A compares a fishery where the FISHE framework is implemented every year and Figure 3B compares a fishery that assesses every 10 years. All scenarios use a 30% harvest control rule, 10% sampling error, a growth rate of 0.4, and an initial biomass of 1500.

### C. Management Actions

The following results examine the effect of each individual management action on fishery outcomes. Outcomes are calculated as a proportion of closed or overfished fisheries. A closed fishery represents a management decision to stop fishing because the observed reference point with error was greater than the limit value (i.e. the perceived f-ratio was greater than 2), representing severe overfishing. An overfished, but open, fishery represents a simulation in which the biomass drops below 10% of the carrying capacity by year 100.

#### Sampling Error

The effects of sampling error were tested across the full range of climate scenarios, harvest control rules, assessment intervals, starting biomasses, and growth rates. This process was repeated five times for a total of 122,400 simulations at each level of error. Any changes to



**Figure 5. Sampling Error Outcome Comparison.** Displays the proportion of closed or overfished fisheries in Year 100 of the simulation for the levels of sampling error. Closed fisheries, shown in green, are closed due a management decision to stop fishing, while overfished fisheries, shown in blue, are those with less than 10% of the carrying capacity at the end of the simulation.

underlying productivity of the species from climate change were not accounted for in these simulations. At the highest sampling error (0.5), a total of 39.8% of fisheries had undesirable outcomes in year 100 of the simulation with 10.9% being overfished and 28.9% closed. With a moderate sampling error (0.3), a total of 27.3% of fisheries were closed or overfished in year 100 (16.9% overfished and 10.3% closed). Simulations with the lowest sampling error (0.1) had a

total of 24.3% closed and overfished fisheries in year 100, with 23.5% overfished and 0.8% closed. Overall, the proportion of closed or overfished fisheries declines as sampling error improves (Figure 5). While there is only a slight improvement in the total proportion of closed/overfished fisheries between the moderate and low sampling error scenarios, the proportion of closed fisheries continued to decline (Figure 5).

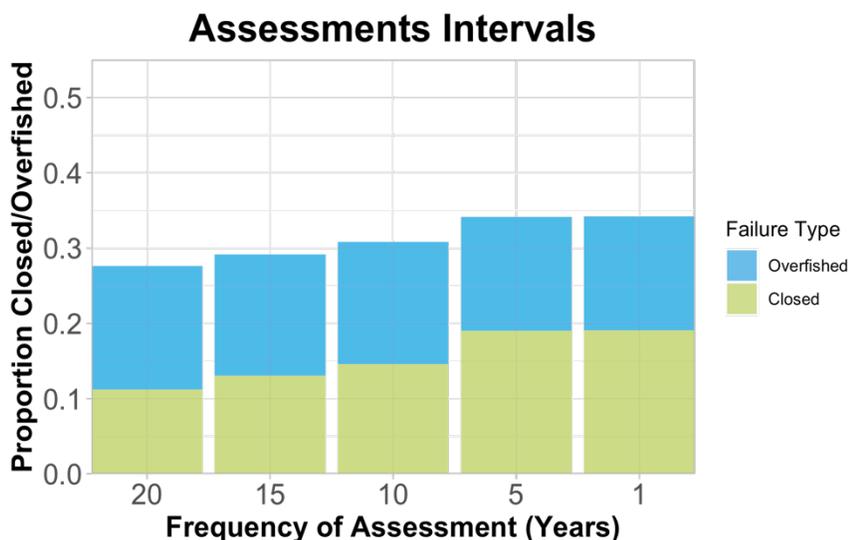
### Assessment Intervals

Assessment intervals were likewise evaluated across the full range of combinations of parameters and the model runs were repeated five times. A total of 61,200 simulations were run at the 20-, 15-, 10-, and 5-year assessment intervals, and 48,960 simulations were run for the one-year assessment interval. Simulations assumed that managers were not accounting for any

changes to the productivity of the species from climate change. When a fishery was assessed on 20-year intervals it had the lowest total of undesirable outcomes at 27.6%, with 16.39% being overfished and 11.21% closed (Figure 6). On 15-year intervals 16.11% of fisheries were overfished in year 100 and 13.06% of fisheries were closed, for a total of 29.17% (Figure 6). With 10-year assessment intervals 30.83% of fisheries had bad outcomes, with 16.25% and 15.48% overfished and closed, respectively (Figure 6). Both 5-year and 1-year assessments had very similar outcomes with 34.17% of fisheries on 5-year assessment intervals and 34.19% of fisheries of annual assessments being closed or overfished in year 100 (Figure 6). The breakdown of overfished and closed fisheries was also comparable in the two simulations. Overfished fisheries made up 15.13% and 15.11% of the 5-year and 1-year assessments, respectively, while 19.04% and 19.08% were closed in 5-year and annual intervals, respectively.

### Harvest Control Rules

Harvest control rules (HCRs) were evaluated across all combinations of input parameters and repeated five times for a total of 36,720 simulations per HCR. Percent reduction indicates the amount of the cutback if the observed reference point with error falls between the target and limit values. In these simulations the fisheries managers are not updating their reference points based on changes to productivity from climate change. Higher cutbacks resulted in a lower overall proportion of simulations ending as closed or overfished (Figure 7). While the proportion of the cases with overfishing decrease with higher cutbacks, they change far less



**Figure 6. Assessment Interval Outcome Comparison.** Displays the proportion of closed or overfished fisheries in Year 100 of the simulation for the different assessment intervals. Closed fisheries, shown in green, are closed due a management decision to stop fishing, while overfished fisheries, shown in blue, are those with less than 10% of the carrying capacity at the end of the simulation.

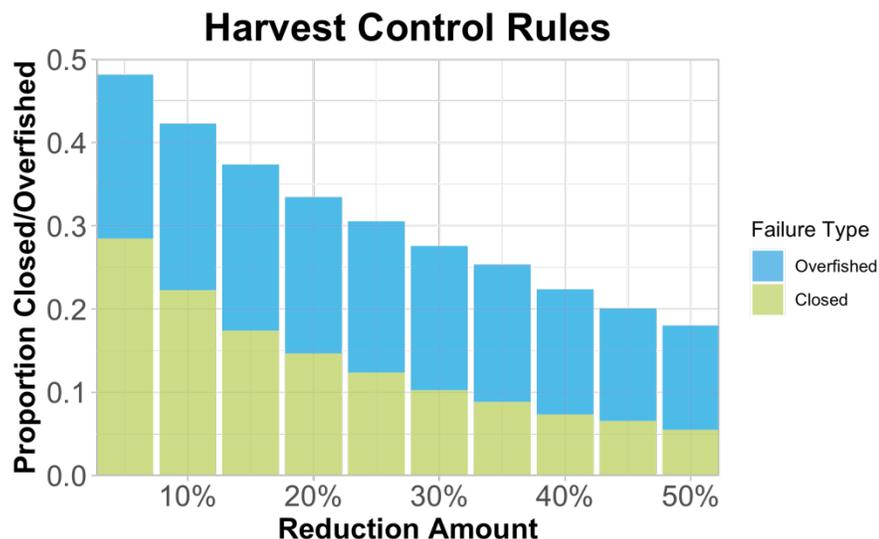
between the lowest cutback (19.69%) and the highest cutback (12.49%), than do the proportion of fisheries that are closed (28.44% and 5.5%, respectively; Figure 7).

### Tracking Productivity

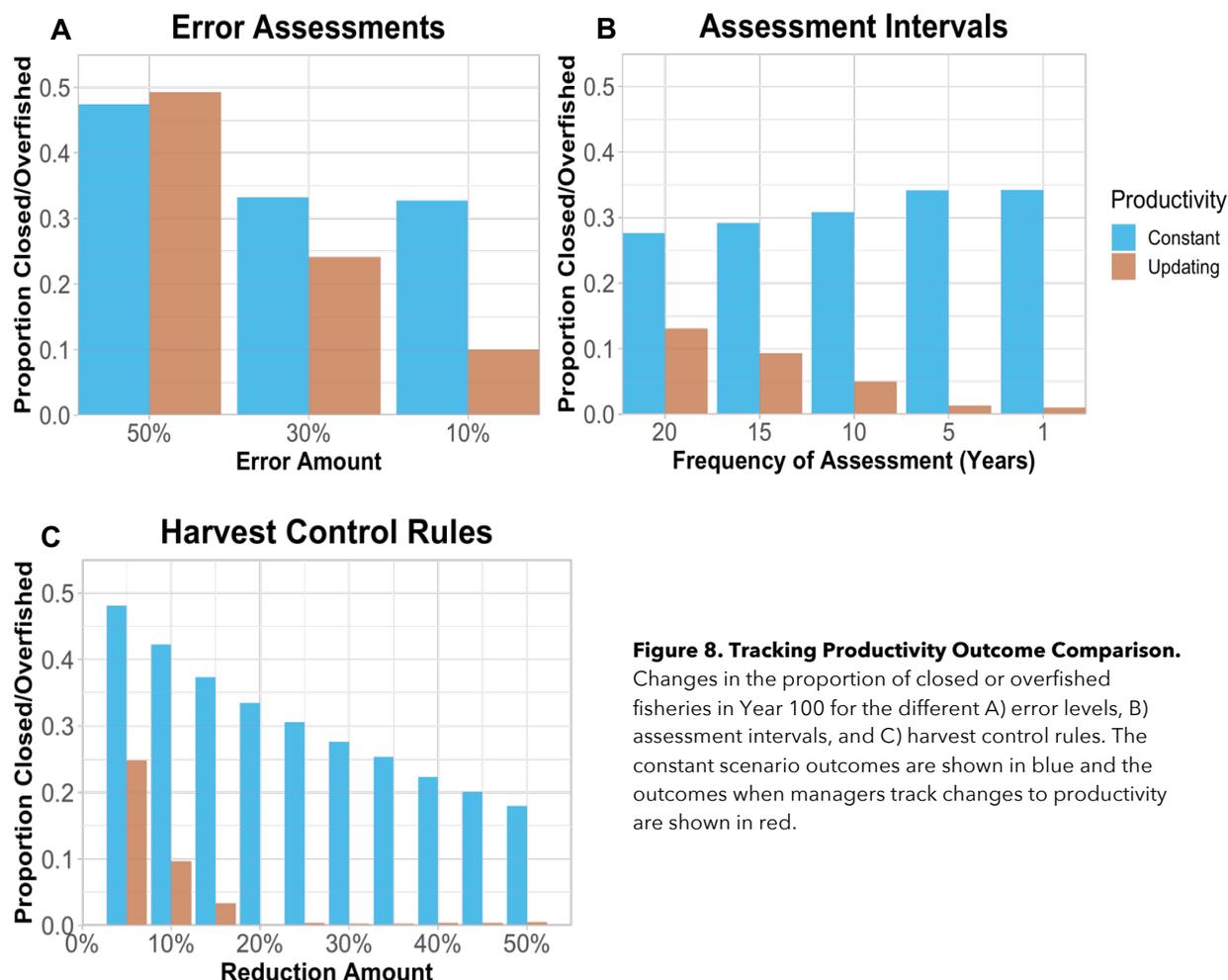
Tracking productivity simulated fisheries managers who had a means of updating their estimates of the reference point in assessment years based on changes in underlying productivity from

gradual climate change. The same three actions explored above (sampling error, assessment intervals, and harvest control rules) were re-run across all the combinations of inputs. A total of 816 simulations were run at each level of sampling error and for each harvest control rule. A total of 1,224 simulations were run at each assessment interval. In general, across all three actions, the proportion of closed or overfished fisheries in year 100 was lower when productivity changes were accounted for (Figure 8).

While at the highest level of sampling error (0.5) the proportion of bad outcomes is higher than in the previous scenario, is not significantly different given the amount of error involved. However, for both the moderate and low error scenarios (0.3 and 0.1, respectively), the total proportion of simulations ending as closed or overfished is lower than the previous scenario, with the low error scenario exhibiting the largest difference in the overall proportion of bad outcomes (Figure 8A). While the total proportion is lower (10.0% compared to 24.3%), the proportion of those outcomes that are closed is higher when productivity changes are tracked compared to when they are not (9.93% and 0.89%, respectively). When productivity is tracked, only a single run ended with an overfished fishery in year 100 at each of the error levels.



**Figure 7. Harvest Control Rule Outcome Comparison.** Displays the proportion of closed or overfished fisheries in Year 100 of the simulation for the different harvest control rules. Reduction amount is the percent cutback in fishing mortality. Closed fisheries, shown in green, are closed due a management decision to stop fishing, while overfished fisheries, shown in blue, are those with less than 10% of the carrying capacity at the end of the simulation.



**Figure 8. Tracking Productivity Outcome Comparison.** Changes in the proportion of closed or overfished fisheries in Year 100 for the different A) error levels, B) assessment intervals, and C) harvest control rules. The constant scenario outcomes are shown in blue and the outcomes when managers track changes to productivity are shown in red.

When underlying changes in productivity are tracked, the trend seen under the constant scenario for assessment intervals is reversed. The 20-year interval had the highest overall proportion of closed or overfished fisheries in year 100 (13.07%) which continued to decline as the frequency of assessment increased. The 10-, 5- and 1-year intervals all had total proportions below 5% (4.98%, 1.31%, and 0.98%, respectively). Further, the number of runs ending with an overfished fishery in year 100, were comparable between the 15-, 10-, 5-, and 1-year assessment intervals. At every interval, the proportion of bad outcomes was substantially lower than the previous constant productivity scenario, with 1- and 5-year assessments showing the largest change (Figure 8B).

Similarly, tracking productivity resulted in a lower overall proportion of bad outcomes. At lowest HCR (5%), tracking productivity lowered the total proportion of closed or overfished fisheries in year 100 by about half (from 48.13% to 24.87%). The change between the constant and updating scenarios for the other HCRs was greater than 50%. The largest

change in overall proportion of bad outcomes under the tracking productivity scenario is made when moving from a 5% cutback to a 10% cutback (from 24.87% to 9.69%). As all HCRs had below one percent of runs end as overfished, these changes come from a lower number of closed fisheries in year 100. When reducing by 20% or more, none of the runs ended with closed fisheries in year 100 (Figure 8C).

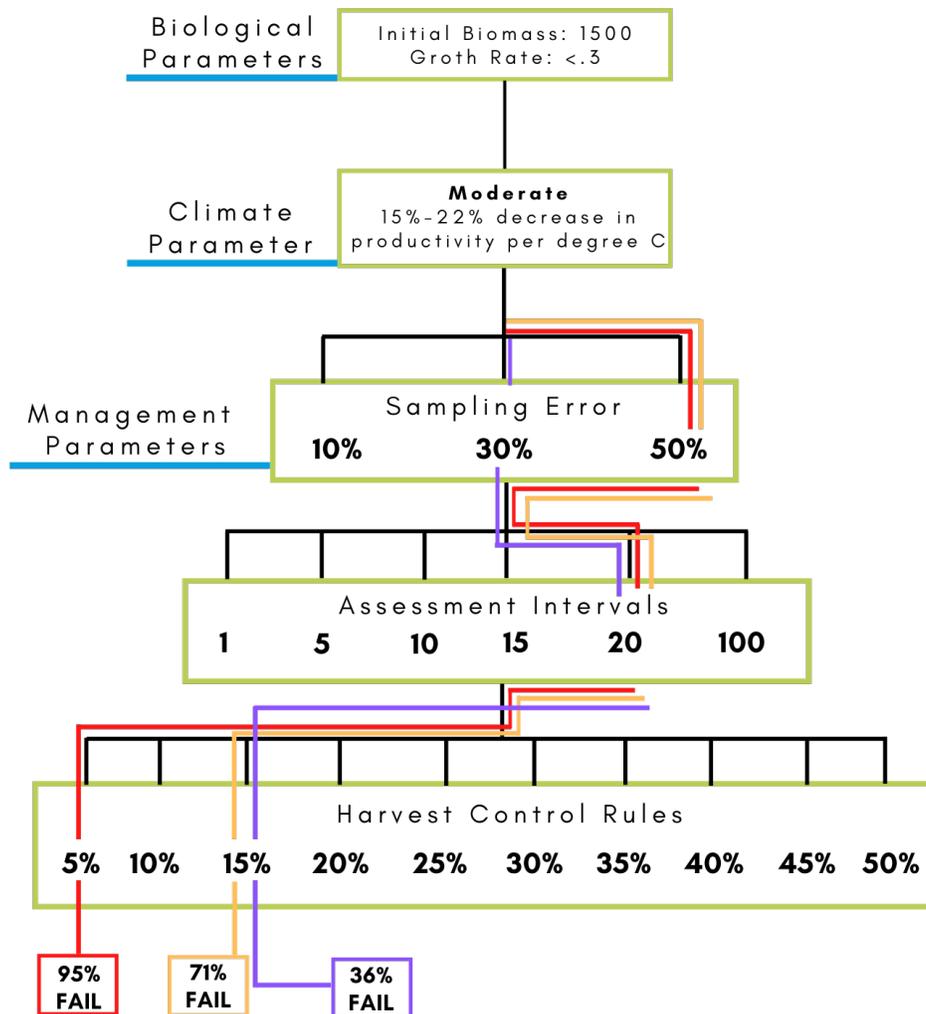
These results indicate that as a single action, tracking productivity has the greatest improvement in fishery outcomes compared to reducing sampling error, increasing the frequency of assessment, or increasing the cutback of the HCR. However, tracking underlying productivity changes is challenging in any real-world scenario. The initial growth rate of a species is rarely known, let alone how quickly the growth rate is changing due to various climate impacts. For this reason, the following case study focuses on the other three management actions, which can be easily used and implemented by fisheries managing use FISHE.

#### D. Case Study

A case study format was used to explore how combining the above management actions could lead to improved fishery outcomes. Data used in the case study were generated using every combination of model inputs for a total of 367,200 model runs, which equates to 60 runs for any given combination of inputs. In each phase of the case study there are three individual actions available to the fishery manager: 1) Invest in collecting more diverse data to reduce sampling error (i.e. move from a high error level to the moderate error level); 2) Invest in more frequent assessments (i.e. moving from a 20-year assessment interval to a 15-year assessment interval); and 3) Implementing a more aggressive HCR (i.e. moving from a 5% cutback to a 10% cutback). This case study used a slow growing species ( $0.1 < r_0 < 0.3$ ) that is already severely depleted ( $B_0 = 1500$ ) in a moderate climate scenario. Moderate climate change corresponds to either a 22% or a 15% decrease in productivity per °C under RCP 4.5 or 8.5, respectively (Table 3). This scenario also assumes changes in species productivity from climate influences are not being accounted for in management decisions. At the beginning of the case study, we assume managers begin by implementing a low HCR (5% cutback), have a high level of sampling error (0.5), and reassess relatively infrequently (20-year intervals). This combination of infrequent assessment, a low cutback, and high error leads to approximately 95% of the runs ending with a closed or overfished fishery (Figure 9, Red).

First, we looked at how the proportion of closed and overfished fisheries would change if the manager only improves upon one of the three actions: reducing sampling error, more frequent assessments, or a more aggressive harvest control rule. By moving from a high error level to a moderate error level, the overall closed and overfished outcomes is reduced to 86.67%. More frequent assessments on 10-year intervals actually worsens the probability of

ending with a closed or overfished fishery to 100 percent. This is likely because the increased frequency is not enough to offset the poor combination of high error and a low HCR. Increasing the HCR from 5% to 15%, yielded the best reduction in bad outcomes, down to 71.67% (Figure 9, Yellow).



**Figure 9. Case Study Example Scenarios.** Three scenarios of management actions using the FISHE Framework. The outcomes, or X% fail, corresponds to the proportion of simulations under these conditions that either A) Close due to a management decision, or B) are overfished by year 100.

At the beginning of the next step, the fishery manager is starting with a high error, 20-year assessment interval, and now a 15% HCR. The manager now examines how to further improve outcomes using the same three possible actions. This time, investing in diversifying the data streams to reduce sampling error from high to moderate has the largest impact on

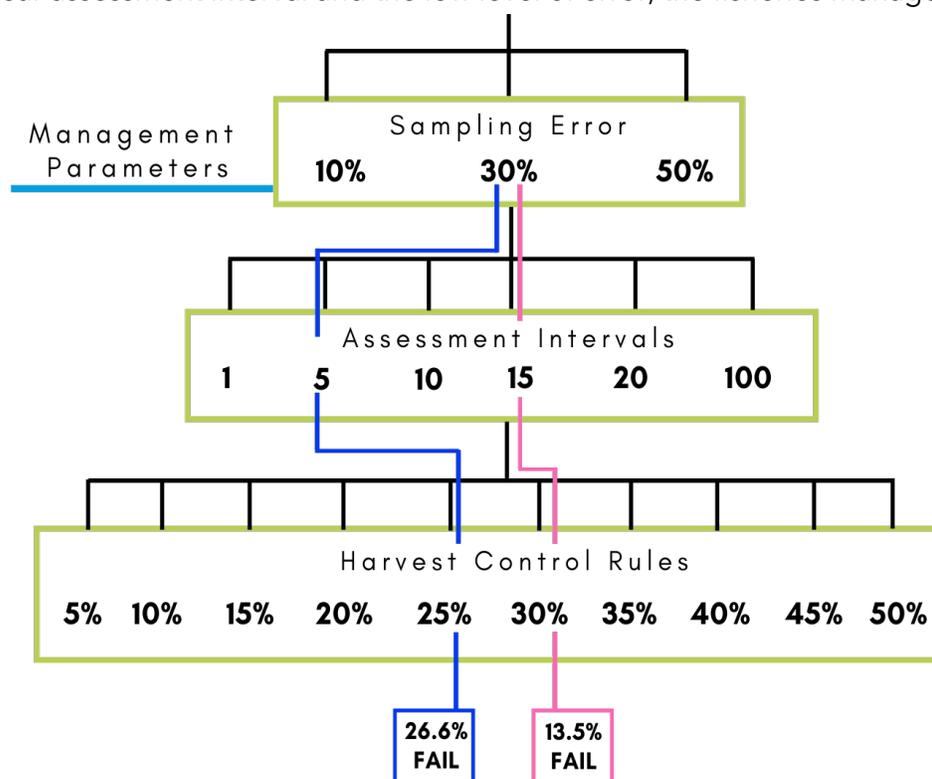
improving overall outcomes. The proportion of closed and overfished fisheries in year 100 is reduced from the previous 71.67% to 36.67%, compared to 58.33% from instituting a 20% cutback, and 81.67% from increasing the assessment interval to 15 years (Figure 9, Purple).

The combination of increasing the harvest control rule to 15% and reducing the sampling error down to a moderate level (0.3), lowers the overall proportion of bad outcomes from the initial 95% down to 36.67%. While this is a significant improvement it might not be as good as the managers would like. By further investing in reducing sampling error to the low level (0.1), the proportion of closed and overfished fisheries in year 100 reduces to nearly zero. Maintaining the 20-year assessment interval and the low level of error, the fisheries manager

could actually decrease the HCR back down to 10% and still have a proportion of bad outcomes that is about 5%. However, this could be expensive or for other reasons, not practical for a given fishery.

Examining other combinations of actions yields a few additional options that provide relatively comparable outcomes. At the moderate sampling error,

increasing the assessment interval to every 15 years and the HCR to 30% can still reduce the proportion of bad outcomes to 13.56% (Figure 10, Pink). Or keeping a moderate sampling error, increasing the frequency to every 5 years with a slightly lower HCR of 25% would reduce the proportion of bad outcomes to 26.67% (Figure 10, Blue).



**Figure 10. Alternative Combinations of Management Decisions.** When it is not possible to reduce sampling error further, there are other combinations of management actions that still perform fairly well under moderate climate change. This is an example of a trade-off, as these options may be less effective as reducing error further, but they are likely less expensive.

## SECTION VII: DISCUSSION

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Studies on the influence of climate change on fisheries have found that human responses have the ability to increase abundance of fish biomass, reduce overfished stock recovery time, and raise profits (Free *et al* 2019; Gaines *et al* 2018; Costello *et al* 2016). While many of these studies were completed for data-rich fisheries, our results indicate the same conclusions may be true in data-limited situations. By simulating fishery outcomes by prioritizing alternate management actions, we show there are multiple combinations of actions that can make fisheries more climate resilient.

Taken individually, these results indicate that the single best option to improve fishery outcomes is to track changes in underlying productivity. However, in practice this is challenging, particularly for data-limited fisheries. It requires not only an understanding of the biological growth rate of the target species, but also an estimate of the decline in productivity and a projection for the pace of climate change in a given area. The best alternative single action is implementing a drastic HCR, however, this would likely have significant economic implications and in many cases may not be feasible. A drastic HCR creates years with dramatic declines in catch whenever it is implemented. However, as seen through the case study, combinations of these actions can lower the proportion of closed or overfished fisheries. The purpose of the case study is not to determine which set of actions is best or what level of closed and overfished fisheries is acceptable, rather, it illustrates how multiple combinations of actions can achieve comparable outcomes. Costs and benefits of different sets of management actions are context dependent and this research provides a framework for exploring the tradeoffs between different sets of actions which can lead to similar overall outcomes.

While most of our results are focused on the negative impacts of climate change, positive effects were also analyzed. Specifically, our model took inputs ranging from 1% to 60% increases in growth rate per degree increase in temperature (RCP 4.5 and 8.5). While EDF is primarily concerned with negative effects of warming, positive effects were included after recent research found that historical warming trends have actually benefited the productivity of several species. Those benefiting species were those existing at the cooler ends of their thermal niches (Free *et al.* 2019), primarily in temperate waters.

The FISHE framework is primarily used in tropical regions where climate effects are overwhelmingly negative. Cheung *et al.*, 2010 found that climate change may lead to large-scale redistribution of global catch potential, with an average of 30-70% increase in high-latitude regions and a drop in 40% in the tropics from present day to 2055. Regions near the equator will see the largest decline in catch potential (apart from the Antarctic), while temperate regions, such as the North Atlantic, generally see an increase in catch potential

through mid-century. Free *et al* (2019) also noted that if warming were to continue, an increase in productivity would begin to decline as temperatures reached the warmer end of the organism's thermal niche. This is supported by a FAO report (2018), which found that the North Atlantic and other temperate regions would see a decline in productivity in the latter half of the century under RCP 8.5.

Our results showed that with strategic adaptive management and improved data collection, it is possible to sustain fisheries under moderate climate scenarios (RCP 4.5 - RCP 6.0). However, the optimism of many studies on the future of global fisheries is contingent on the pace and magnitude of climate change (Gaines *et al* 2018, Free *et al* 2019). Free *et. al* (2020) looks at regional effects of climate change under three different RCPs and found that under the most severe climate scenario (RCP 8.5), 51 countries will likely see reductions in productivity at a magnitude of a 50-100% decline in MSY. Notably, all 18 nations in West Africa (south of Senegal and north of Angola) are expected to experience losses in MSY greater than 85%. The Indo-Pacific and South America were also found to experience dramatic losses in MSY. These findings are cause for even greater concern, as these regions are also areas which currently lack the resources required to enact the monitoring programs needed to quantify changes in fish distribution and productivity.

Our results corroborate these findings by showing that under severe climate change, very few combinations of management actions we explored were able to produce a majority of good outcomes. Severe climate change in this study is based on RCP 8.5 (a 5°C warming over 100 years) and defined as an 18-30% decline in productivity per degree (°C) of sea surface temperature change (Table 3).

A few key analytic constraints imply that the negative impacts of climate change on fisheries may be overestimated in this analysis. Due to time constraints, the model does not currently account for the effort required to catch the number of fish specified in each year. As the biomass of fish decreases fishers will be forced to exit the fishery. This provides some degree of natural decline in fishing pressure that cannot be accounted for in this model, leading to perhaps an overestimate of negative outcomes. The inclusion of effort would also be critical for analyzing the economic potential between different sets of management decisions. Further, once a fishery was closed due a management decision it was never reopened for the remainder of the simulation. The FISHE framework currently does not provide a recommendation for a quantitative threshold to re-open a fishery and this decision is left to the discretion of fishery managers. However, by not re-opening fisheries, the proportion of closed fisheries in year 100 is likely higher than it would be otherwise. Determining a quantitative mechanism for re-opening also has economic implications and would be an important addition to the model for analyzing yields over time.

Our approach represents a wide-range of potential climate impacts based on their fundamental influence on the physiology of the fish stock. While this limits the model by generalizing all climate impacts into affecting species growth rates, a more complex underlying model could be used instead. For example, using an age-structured model could allow for increased specificity around if a climate influence would affect recruitment vs. adult natural mortality. However, by using a simplified model, we have created a method for evaluating climate effects on fisheries that is particularly useful in data-limited contexts. The model does not require specific knowledge about the exact climate influences or precise predictions of the pace of climate change, which makes it broadly applicable to different geographic locations and useful despite high levels of uncertainty surrounding climate predictions.

While this analysis incorporated only four main management actions from the FISHE framework, we have created a process by which any of the steps within FISHE can be translated and analyzed in a modeling environment. This framework is flexible enough to provide insights into the trends of fishery outcomes based on any starting stock size, growth rate, and existing management actions. This process can also be leveraged to test new methods for enhancing the climate resilience of fisheries. For example, the model could be used to test the effect of implementing a more complex set of reference points where there are two HCRs depending on if the fishery falls closer to the target or closer to the limit. Analyzing the change in overall outcomes dependent on initial stock size, life-history, or climate change pace can suggest under what circumstances this method might be effective. Further, the framework could be used to test the implications of making generalized estimates of productivity change or anticipating increased El Niño events. With this approach, additional questions can be addressed, such as: can assuming a simple rate of decline in productivity be enough to capture the benefit shown by the tracking productivity results? How accurate does that general estimate need to be? Does implementing a more drastic HCR every five years cushion a fishery from potential major productivity declines from El Niño events?

Recent research highlights that including human response when analyzing the impacts of climate change on fisheries is critical as the actions of fisheries managers have the potential to either exacerbate or mitigate the effects of climate change (Free *et al* in prep/in press, Holsman *et al* 2019, Gaines *et al* 2018). The Environmental Defense Fund uses the FISHE framework to assist with fisheries management in some of the regions where climate impacts are expected to be the most severe. Given that human response has the potential to offset the negative effects of climate change, it is critical that the FISHE framework integrates climate-effective management actions. Based on our results, there are a number of combinations of actions which already exist in the FISHE framework that produce fairly good overall outcomes. However, it appears that even frequent assessment, low error, and

aggressive HCRs might not be enough for resilient fisheries in severe climate change. We recommend EDF begin by pursuing additional analysis of the potential new actions (general productivity estimates and preemptive shock event cutbacks), which we have outlined above. This project provides EDF with a process to accomplish this and to test any number of new and existing management actions in the FISHE framework to boost the climate resilience of data-poor fisheries.

## SECTION VIII: REFERENCES

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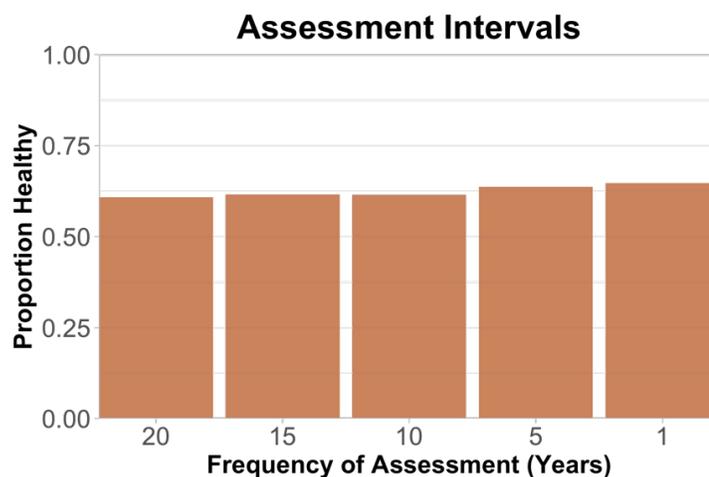
## SECTION IX: APPENDIX

After submitting the final report to the Bren School of Environmental Science & Management, our team continued to work on improving our analysis based on feedback from the Environmental Defense Fund. We focused on two main areas of improvement, 1) the model’s response to a fishery exceeding the “limit” reference point, and thus initiating a closure, and 2) testing if a regional proxy for tracking productivity may be an effective precautionary step for data-limited fisheries unable to accurately track productivity changes stemming from global climate change.

### A. No Full Closures

The purpose of our model is to simulate a fishery over time while using FISHE to guide all management decisions. Our first iteration of the model assumed that if the fishing pressure was beyond the limit reference point (f-ratio greater than 2), then the fishery would close indefinitely. This set-up led to a model limitation resulting in higher frequency of assessments having higher proportions of closed and overfished fisheries, which is counter to what we had anticipated based on our literature review.

A second iteration of the model was developed to address this limitation through simulating a more realistic response to fisheries that are over the limit. In this second version, the model maintains a small level of fishing activity until the next assessment year. For example, for a fishery that samples annually found to be over the limit in year  $y$ , the model will cut back the catch in year  $y$  by 95%. This cutback lasts a single year and the fishing pressure ( $f$ ) in year  $y+1$  will be the same as year  $y$ . This change resulted in the previous trend reversing to be in the anticipated direction, though the effect was still not as dramatic as anticipated based on similar studies.



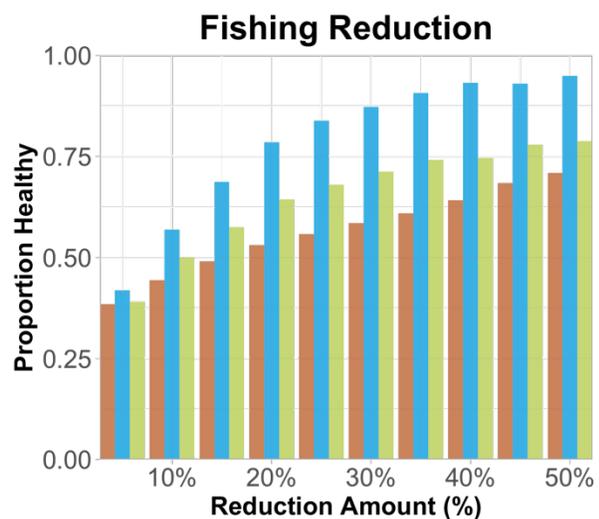
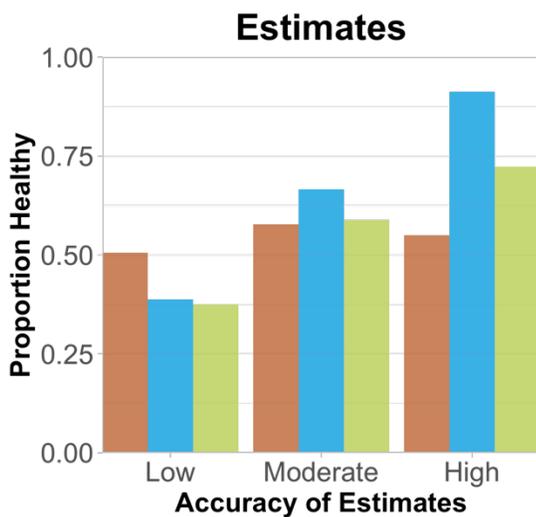
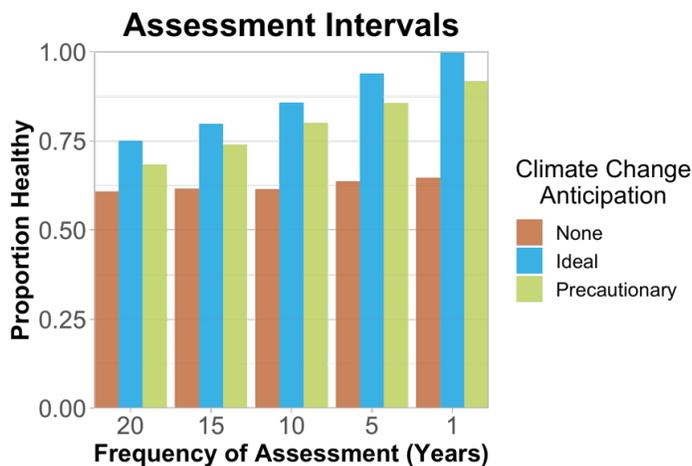
**Figure 11. No Closure.** While this trend is subtle the second iteration of our model gives more logical assessment interval results. Fisheries that are assessed more frequently have a high proportion of remaining in a “healthy” range than those assessed less frequently.

## B. Taking a Precautionary Approach to Climate Change

Our results indicate that regardless of the management action, anticipating the effects of climate change by tracking the underlying productivity of a fishery improves outcomes more effectively than any other action. However, understanding how fish are responding to climate change is challenging in any real-world scenario, especially data-limited ones. Thus, it seems unrealistic to expect a fishery guided by FISHE to accurately track and act upon underlying productivity changes due to global climate change.

Due to this challenge, our team worked to determine if FISHE could be adapted to capture the benefits from anticipating productivity changes. To test this, we created a proxy for tracking productivity, which represents an estimate made by the fishery manager of how climate change will affect the fishery's productivity. We tested a range of assumed declines (from 0.5% to 1.5%) per year. We found when tested against the full range of negative climate

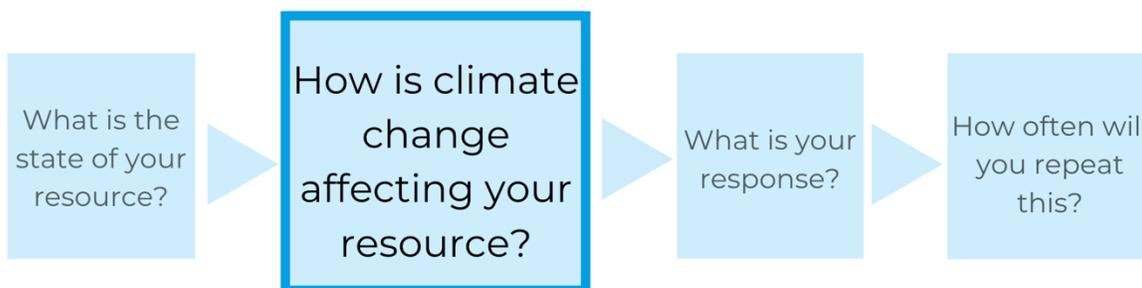
change scenarios, assuming a 1% decline in productivity per year achieved over 85% of the benefits seen from being able to perfect track underlying productive of a fishery.



**Figure 12. Productivity Proxy.** These graphs illustrate that assuming a 1% decline in productivity per year can yield better outcomes in the face of climate change than when no precautionary actions are take.

### C. Recommendations

We recommend that EDF incorporate an additional management question into FISHE: How is climate change affecting your resource? Different geographies will experience different levels of climate effects. As a result, the severity of those effects will vary for any given region. Taking a precautionary approach, fisheries managers can institute a climate change anticipation "proxy" - an assumed change in the growth of the fish stock - that is scaled to the expected severity of climate change in their region.



Climate change is affecting how fast fish grow and where they can be found, but how quickly and severely these impacts are occurring is uncertain and varies across species and regions. However, by incorporating a new step into FISHE, managers have the opportunity to consider the context-specific impacts of climate change. This knowledge can then be taken into account as unique precautionary management strategies are developed, and thus, promote more effective approaches to managing data-limited fisheries in the face of global climate change.