## Abstract


Title of Dissertation: EXPANDING THE FISHERIES MANAGEMENT TACKLE BOX: A MULTIPLE-MODEL APPROACH TO SUPPORT BETTER DECISIONS

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Marine fisheries provide critical ecosystem services but face an array of stressors like climate change and overfishing. Managing fisheries is challenging due to limited information and the need to make complex tradeoffs among ecological and social objectives. Decision processes that include integrated social-ecological models and equitable stakeholder engagement are increasingly recognized as approaches to improve the likelihood of achieving management goals compared to those that rely solely on stock assessment models with limited stakeholder input. Additionally, advanced technologies offer new opportunities to understand marine ecosystem dynamics, including human behavior. This research adds two examples of underutilized tools: multi-criteria decision analysis (MCDA) and agent-based models (ABMs). In the first case, I compared management recommendations for the Chesapeake Bay oyster fishery arising from A) stakeholder engagement using group negotiations and B) preferences elicited from individuals using an MCDA approach. The recommendations were consistent across methods, suggesting that group effects did not bias group negotiation outcomes. The second case investigated New

England groundfish reporting behavior based on stock dynamics, quota markets, and fishery observer coverage. First, having an observer onboard was found to significantly reduce the probability and magnitude of reporting error (ie., an observer effect) using a linear mixed effects model of data from vessel trip reports and remote vessel monitoring systems. Next, an ABM was used to explore emergent responses to policy changes - varying levels of observer coverage and the strength of the observer effects - on fish catch, reporting error, and profit outcomes, given fisher interactions and responses to fish population dynamics. Scenarios with strong observer effects resulted in increasing marginal improvements in reporting accuracy at high levels of observer coverage. MCDA and ABM can contribute to a multiple-model approach by allowing fisheries managers to integrate diverse stakeholder perspectives and use additional data sources that could lead to better fishery outcomes.

# EXPANDING THE FISHERIES MANAGEMENT TACKLE BOX: A MULTIPLE-MODEL APPROACH TO SUPPORT BETTER DECISIONS

by

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## List of Abbreviations

ABM - Agent-Based Model

ACL – Annual Catch Limit

FMP – Fishery Management Plan

GARFO – Greater Atlantic Regional Fisheries Office

ITQ – Individual Transferrable Quota

LMM – Linear Mixed Model

MCDA – Multi-Criteria Decision Analysis

MSE –Mean Squared Error

NEFSC – Northeast Fisheries Science Center

NMFS – NOAA's National Marine Fisheries Service

NOAA – National Oceanic and Atmospheric Administration

OF – OysterFutures

PSC – Percent Sector Contribution

TAC – Total Allowable Catch

VMS – Vessel Monitoring System

VTR – Vessel Trip Report

# Chapter 1: Introduction and Literature Review

Marine fisheries provide critical ecosystem services, like biodiversity and food web stability (Houk et al., 2018), and they help to fulfill essential human needs like jobs and food security (fisheries provided 1.7 million jobs and 8 billion pounds of seafood in the US in 2020; [NMFS, 2020a]). However, the sustainability of the flow of marine ecosystem benefits is in jeopardy: over a third of global (FAO, 2016) and a fifth of US (NMFS, 2020b) fisheries are overfished due to overharvesting, climate change, habitat destruction, and pollution. The good news is that innovations in science, economics, and collaborative management have added to a growing list of management success stories in the last couple of decades. There are myriad examples of fisheries recoveries, but a few from the US include Atlantic sea scallops (NMFS, 2020b), Alaskan pollock (Bailey, 2021), and North Atlantic swordfish (NMFS, 2020b). All three species were severely overfished in the mid- to late-20th century, but by the 1990s, advances in science and management provided a path to recovery.

Improvements in monitoring, stock assessments, and bioeconomic and environmental modeling have aided managers in developing and implementing successful plans. However, a perpetual challenge for resource managers is that users often behave in unexpected ways, so the focus on marine social sciences has expanded to better understand and predict human behavior (Bennett, 2019; Fulton et al., 2011; Salgueiro-Otero and Ojea, 2020). For example, Salas and Gaertner (2004) argued that ignoring adaptive user responses has led to fisheries management failures in the past, and they recommended innovative, integrated ecosystem models that draw from multiple information sources.

Thus, the social sciences play an increasingly important role in fisheries management by providing insights into the economic, social, and cultural factors that influence the fishing practices of individuals as well as the overall well-being of fishing communities. Fisheries managers are required to consider the economic and social impacts of management measures (e.g., Magnuson Stevens Act, 2014), and economists analyze the economic factors that affect fishers, fishing communities, and fish populations and facilitate developing beneficial policies (Andersen et al., 2008; Wilen et al., 2002). Cultural anthropologists and sociologists also contribute to a better understanding of the social and cultural dynamics of fisheries and fishing communities, and they work towards developing more effective and sustainable management strategies that are responsive to local needs and values (Clay et al., 2014). Moreover, social scientists help engage stakeholders in fisheries' collaborative management processes, including cooperative data collection and group decision-making (Linke and Bruckmeier, 2015; Pinto da Silva and Kitts, 2006). Though many benefits have come from the use of social sciences' resources and tools in fisheries management, this dissertation makes the case that there are additional opportunities to apply behavioral and decision sciences to fisheries management by adding case examples of underutilized, interdisciplinary models in the fishery management "tackle box."

Decision-science-based tools could advance the ecosystem-based management approach that the National Oceanic and Atmospheric Administration (NOAA) has made a priority (Harvey et al., 2021; Kasperski et al., 2021; Pikitch, 2004). This first chapter outlines the group and individual decision-making contexts that underlie each case study in the dissertation, followed by a description of the case and a brief introduction to the models. The following chapters share examples of underutilized tools that could be used to continue integrating social and decision sciences with fisheries models. Integrated tools provide a better understanding of the fishing community's needs (DePiper et al., 2021; Kasperski et al., 2021), and the cases presented in this dissertation may be valuable in helping Eastern oysters (*Crassostrea virginica*) and Atlantic cod (*Gadus morhua*) to join the list of success stories.

## Comparing Multi-Criteria Decision Analysis to Group Negotiations in Fisheries Co-Management

### *Group-Decision-Making Context: Collaborative Management*

The value of engaging stakeholders in understanding, assessing, mitigating, and managing ecological and economic tradeoffs in fisheries management has grown in recent years, and a suite of tools and methods that facilitate this collaborative management (also known as co-management) have been developed (Ansell and Gash, 2018; Cooper et al., 2006; Crawford et al., 2004; Pomeroy and Berkes, 1997). Co-management "refers to a range of arrangements, with different degrees of power sharing, for joint decision-making by the state and communities (or user groups) about a set of resources or an area" (Berkes, 2009). It can promote equitable, inclusive representation among diverse stakeholders, as opposed to government agents controlling the management process (Quimby and Levine, 2018). Some co-management processes, such as the one presented in Chapter 2, provide a logical framework for breaking complex problems into independent component goals and performance measures that reduce the difficulty or cognitive burden of making decisions (Belton, 2002; Keeney, 1982; Keeney and Raiffa, 1976). Co-management also can improve the probability of achieving management goals by leveraging the diverse experiences, preferences, and knowledge of stakeholders and bolstering perceptions of legitimacy (Arnstein, 2019; Carlsson and Berkes, 2005; Karr et al., 2017). Research suggests that when stakeholders believe the management process is inclusive and fair (i.e., legitimate), they are more likely to accept management decisions and less likely to oppose relevant policies through political channels (Cash et al., 2003; Kuperan and Sutinen, 1998; Sandström et al., 2014), but there have also been cases where some actors only collaborated to advance their own interests (Bodin, 2017).

***Individual Decision-Making Context: Preferences***

OysterFutures (OF) was a project designed to bring representatives of diverse stakeholder groups together to reach a consensus (at least 75% agreement) about recommendations for Chesapeake Bay oyster management through collaborative modeling and facilitated discussions (OysterFutures Stakeholder Workgroup, 2018). In a series of nine meetings over two years, 16 stakeholders (nine from the fishing industry, five from non-governmental organizations, and one each from the U.S. federal and Maryland state government) and a team of facilitators and academic researchers developed a vision for oyster resource management in the region and approved a set of specific management options to improve fishing regulations, enhance water quality, and expand suitable oyster habitat. This stakeholder group is also the study group in Chapter 2, which compares an individual preference-based multi-criteria decision analysis to the OF results.

The final OF recommendations package included a set of unranked options which was unanimously approved, but the individual options within it had varying support. Chapter 2 evaluates the degree to which OF recommendations aligned with individual stakeholder preferences, particularly whether and how minority views were represented in the final recommendations.  In OF, it was up to each individual to evaluate the tradeoffs among benefits (e.g., water quality improvements, harvest revenues, habitat for other species) and decide whether to support a particular option or set of options—decisions that carry a cognitive burden. To mitigate the cognitive burden, people are known to use heuristics, or mental shortcuts, in situations where time is limited, information is incomplete or ambiguous, or when a person is facing a complex decision (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981). The heuristics can make replication or transparency of the decision a challenge.

There are at least three common heuristics that could have impacted OF participants' decision-making: availability bias, confirmation bias, and the framing effect (Wilkinson and Klaes, 2012). Availability bias refers to the ease with which someone can recall an example and how this affects that person's perceived probability of occurrence. In confirmation bias, people seek out information that confirms their beliefs and ignore information that runs counter to those beliefs. The framing effect describes how decisions can change based on how information is presented or framed. To reduce the complexity of a problem and the potential effects of heuristics, a multi-criteria decision analysis (MCDA) was employed in Chapter 2.

Semi-structured interviews were conducted to elicit and quantify individual preferences by objective to explore whether individual preferences were consistent with apparent preferences expressed in support for the outcomes of the group negotiation process. Seeking individual preferences avoids the group effects of peer pressure or "groupthink" that is common in group negotiation and which can stifle individuals' expression of novel or conflicting opinions as people tend to seek group cohesion (Janis, 2008). Group effects are a type of peer pressure or social influence to take certain actions or adopt specific beliefs to be accepted in one's peer group (Mani et al., 2013).

***The Case: Chesapeake Oysters***

Maryland Chesapeake Bay eastern oysters (*Crassostrea virginica*) are filter feeders that provide a range of ecosystem services, including supporting a commercial fishing industry, improving water quality by extracting particles from the water column, serving as habitat for other species, and providing a cultural connection to Chesapeake fishing heritage (Kellogg et al., 2014; Newell, 1988; North et al., 2010; Wilberg et al., 2011). However, these benefits have been sharply curtailed because the population has declined over 99% since the 19th century, with over 90% of this decline occurring after 1980 due to water quality degradation and overharvesting (Damiano and Wilberg, 2019; Rothschild et al., 1994). In response to the oyster population decline, oyster restoration efforts driven by the 2014 Chesapeake Bay Watershed Agreement (Chesapeake Bay Program, 2014) are well underway. The Agreement calls for federal, state, and non-profit investments in 10 major oyster reef construction projects, including the largest such project in the world in the Great Wicomico and Piankatank Rivers (Solyst, 2021). Efforts to review and improve fishery regulations are led by the Maryland Department of Natural Resources. The states work closely with NOAA's National Marine Fisheries Service (NMFS), which is responsible for federal investments in habitat restoration. Additionally, there are several private conservation organizations and other organizations and individuals that are heavily involved in oyster restoration (Chesapeake Bay Program, 2014).

The challenge for oyster managers in Maryland is striking an effective balance between ecosystem restoration, economic (revenue and employment) goals, and short- and long-term outcomes. Ecological uncertainties and lack of trust among stakeholder groups add additional complexity to management. For example, stakeholders do not agree on several critical aspects of system functioning, such as effects of high recruitment years and variability of disease intensity. Yet stakeholders also share the objective of producing a suite of ecological, economic, and social benefits from oyster management, though they may differ in the weight they attach to each type of benefit (e.g., Paolisso and Dery, 2010). Their interest in working together to achieve oyster restoration despite different perspectives provided an opportunity to test group and individual-based approaches to decision-making by comparing OF to an MCDA-based approach.

***The Model: Multi-Criteria Decision Analysis***

MCDA is a decision-making support tool used to systematically compare the performance of alternative management policies across multiple objectives (Belton, 2002; Keeney and Raiffa, 1976; Stewart et al., 2010). The performance of each policy alternative is measured by combining the ratings of multiple user-defined criteria weighted by stakeholder preferences or importance levels. It is a structured approach to analyzing tradeoffs between different criteria, such as fishery revenue and other in-situ ecosystem services (Jaini and Utyuzhnikov, 2017). MCDA is structured to focus attention on the desired policy performance rather than the policies themselves as a way to reduce the effect of individual cognitive biases and group social dynamics.

**Observer Effects: Linear Mixed Models Indicated Reduced Disagreement Between Data Sources in the New England Groundfish Fishery**

and

**How Much Fishery Observer Monitoring Is Sufficient? Scenario Testing Using an Agent-Based Model of New England Groundfish**

***Group Decision-Making Context: US Federal Fisheries Management***

US law requires NMFS to "prevent overfishing while achieving, on a continuing basis, the optimum yield from each fishery […] based upon the best scientific information available" (50 U.S.C § 600; Magnuson-Stevens Act Provisions, 2021). Achieving optimum yield (OY) requires managing fishing effort to optimize tradeoffs between fish stock abundance and economic output—a “wicked problem” given the social, economic, and ecological complexity and uncertainty of fisheries (DeFries and Nagendra, 2017; Jentoft and Chuenpagdee, 2009). In addition to conservation and science requirements, the groundbreaking Magnuson-Stevens Fishery Conservation and Management Act (1976) mandates management cost-efficiency, equitable impacts and benefits across users, stakeholder collaboration, and other lofty goals. The law set up regional councils to ensure that fisheries are managed in a way that balances the conservation and economic objectives of all stakeholders. The Fishery Management Council framework provides a platform for sharing science, local or traditional ecological knowledge, and stakeholder input through a decision-making process that includes industry, government and non-governmental organizations, and other stakeholders in developing fishery management plans based on the best available science (Public Law 94-265). Currently, fishery management councils are shifting away from relying on single-species stock assessment and bioeconomic models to a more holistic ecosystem-based management approach for designing regulatory recommendations (DePiper et al., 2021; Harvey et al., 2021). Additional multidisciplinary models presented in this dissertation, such as the agent-based model (ABM) of the New England groundfish fishery and the MCDA of Chesapeake oyster management, could complement existing management decision support tools by adding new perspectives and insights regarding the fishery system and what stakeholders value.

Stock assessments are the critical foundation of marine fisheries management, but they are typically insufficient to evaluate management options, particularly when success is defined by social and economic stability as well as ecological sustainability; management strategy evaluation (MSE) has arisen in response to this need for more holistic assessment (Bunnefeld et al., 2011; Goethel et al., 2019; Punt et al., 2016). MSE is a framework used in fisheries management to test the effectiveness of different management strategies, such as catch limits or gear regulations, in achieving specific management goals. In Chapters 3 and 4, this dissertation draws on MSE principles by applying novel simulation techniques to an ABM.

***Individual Decision-Making Context: Compliance***

Although not always a prominent component of stock assessment and fishery management plan development (Randall, 2004; Shaw, Reena, 2005), regulatory compliance is essential to achieving management objectives. Compliance also can be an equity issue because violators can place honest harvesters at a competitive disadvantage. Depending on the jurisdiction and fishery, state or federal law enforcement officials are responsible for ensuring compliance with the regulations. Enforcement is the most expensive component of fishery management in the US, representing around 57% of the costs of fishery management (Mangin et al., 2018). While other regions use observers as enforcement assets (Porter, 2010), there have only been two cases in the Northeast where observer data was used as evidence (GARFO, pers. comms.). As such, boosting compliance voluntarily or by using fishery observer data in law enforcement potentially offers an opportunity to improve conservation outcomes while reducing the overall costs of management (Porter, 2010).

Since the Becker's (1976) "*Crime and Punishment: An Economic Approach*," enforcement literature highlights that increased risk of detection and sanctions deters some individuals from deviating from regulatory compliance. However, the pure deterrence model, in which an economically rational actor weighs potential economic benefits against the severity of sanctions and the likelihood of detection, only partly explains empirical compliance behavior (Cash et al., 2003; Shaw, 2005; Sutinen and Kuperan, 1999). In fact, fishers comply far more often than expected economic benefits suggest that a rational actor would. For example, in the

Northeast multispecies groundfish fishery which is the subject of Chapters 3 and 4, King and Sutinen (2010) found that only about 12%–24% of the catch was illegal despite illegal fishing's expected revenue being about five times that of the expected penalty. They also found that infractions were largely accidental, and most of the illegal harvest was attributed to a minority of fishermen who were chronic violators.

The enriched theory of compliance model developed by Sutinen and Kuperan (1999) incorporates morality and social influence to better explain compliance behavior. Fishermen tend to follow a moral code. For example, in the Chesapeake crab fishery, watermen recognize illegal catch as immoral and describe it as a "greed" that threatens sustainable harvests for the entire fishery (Paolisso, 2007). Nonetheless, intrinsic motivation to follow the rules is variable among individuals and correlates with their perceptions of the legitimacy of the regulations (Boonstra and Österblom, 2014; Crawford et al., 2004; Kuperan and Sutinen, 1998; Nielsen, 2003).

Social influence is another important factor in compliance with fishery regulations. Reputations are important social capital in typically small fishing communities, and fishing communities have been known to "self-enforce" regulations through physical violence and gear destruction (Acheson et al., 2015). Tyran and Feld (2006) noted that people are conditionally cooperative, meaning they comply when they assume that others are also going to comply but will defect when they expect others to do so. Both intrinsic morality and extrinsic social influences are components of compliance decisions, along with potential economic gains (Kuperan and Sutinen, 1998). Despite the unobservable components of motivations for non-compliance, Chapter 3 explores whether observer coverage influences reporting accuracy in the groundfish fishery, and Chapter 4 simulates cumulative reporting error at multiple levels of observer coverage.

### ***The Case: New England Groundfish***

To call the Atlantic cod (*Gadus morhua*) an iconic species is an understatement, especially to New Englanders. The "sacred cod" was a critical export for colonial America, playing a significant role in funding the American Revolutionary War (Magra, 2006), and its likeness still hangs over the Massachusetts House of Representatives. Yet perhaps it has been loved too much—largely due to overfishing, the population has fallen 80%–90% since the 1980s despite multiple attempts at recovery plans (Meng et al., 2016). Atlantic cod landings peaked in the US in 1980 and fell by over 98% by 2018 (NMFS, 2021a). Cod are among 13 groundfish species managed through the Northeast Multispecies Fishery Management Plan (FMP). The first FMP in 1977 included catch quotas, gear restrictions, trip limits, and area closures. In 1982, minimum size limits replaced quotas to control fishing mortality (GARFO, 2022).

Today, cod are caught and managed in the multispecies groundfish complex, where most fishers combine species-specific fishing rights into fishing cooperative groups called sectors. Each sector is then responsible for managing its own catch quota, and members are jointly liable for overages (GARFO, 2022). By allocating catch quotas to sectors, the system aims to provide more flexibility and economic benefits to fishermen while also promoting sustainable fishing practices, but it has also led to consolidation of the fishery into fewer firms (Holland et al., 2013). Although fishers in the groundfish fishery now target haddock (*Melanogrammus aeglefinus*) or other species and avoid cod due to its high-cost quota, cod is often unavoidable bycatch. Cod are "choke" stocks that can shut the groundfish fishery down if their total allowable catch is exceeded (Hatcher, 2022). Quota prices are negotiated among fishers based on supply and demand and have been fairly constant recently, but they can be highly variable based on the relationship between buyer and seller and if traded in a bundle of different types of quotas. When stock abundance is low, the supply of annual catch limits (ACLs) is also low, and prices tend to be higher (Hatcher, 2022). Cod and haddock stocks are assessed separately in the Gulf of Maine and Georges Bank (NMFS, 2021a), and since the cod decline has been more acute in the Gulf of Maine than Georges Bank stock areas, the quota prices for incidental catch of cod are more expensive there. This dynamic incentivizes (illegal) discarding of cod at sea or reporting the catch in the area with the lowest cost of quota (regardless of where it was caught) so that fishers can continue fishing non-cod stocks (Palmer and Wigley, 2009).

Stock area misallocation, or the reporting of catch location other than the actual catch location, is identified as a significant source of measurement error in stock assessments (Palmer, 2017; USCG, 2021) because several groundfish species are managed using multiple stock areas under the umbrella of an individual transferable quota system. As noted above, different area-specific quota values for the same species create an economic incentive to report the catch from the lower-cost area. Misallocation is difficult to detect when the fish are landed, but it comes in (at least) two forms. First, vessels are legally required to record catch on a fishing tow from the area in which that catch is brought on board, allowing vessels to fish for many hours in one stock area, move into a different area, and then legally report that catch in the area where gear is retrieved, known as "fishing the line" (GARFO, 2022). Second, because the area fished is entirely self-reported, it is also possible for fishers to illegally misreport, by recording catch from areas where they fished little or not at all (Palmer, 2017; Palmer and Wigley, 2009; USCG, 2021). Absent an onboard observer, the stock area from which fish are caught is entirely self-reported. Chapters 3 and 4 explore the implications of this reporting system.

***The Models: A Linear Mixed Model & an Agent-Based Model***

The Vessel Monitoring System (VMS) provides hourly locations of groundfish vessels, and Palmer and Wigley (2009) used those data to determine vessel speeds. Further, they identified the range of fishing speeds associated with each gear type in the fishery in order to identify the spatial distribution of apparent fishing effort. The NEFSC compared the proportion of time spent traveling at fishing speed in each area to the catch allocation associated with each area to infer potential misallocation. Similar VMS-based analyses have been produced from other fisheries in the US North Pacific (Watson and Haynie, 2016), Indonesia (Utama et al., 2021), and Ireland (Gerritsen and Lordan, 2011). In each study, the VMS-based estimated catch was found to be relatively robust to potential biases and, in the New England groundfish case, VMS-based estimates aligned more closely with observer data than vessel trip reports (Palmer, 2017).

In Chapter 3 an empirical linear mixed effects model is used to compare the reported proportion of catches by area in vessel trip reports (VTRs) to the NMFS-produced proportion of apparent fishing effort by area from VMS data. A linear mixed model (LMM) was selected to analyze the comparison data due to its clustered structure, which has different numbers of observations for each permit. LMMs are also often used in fisheries science to standardize catch-per-unit-effort unbalanced panel data (e.g., Baum and Blanchard, 2010; Helser et al., 2004).

The goal of Chapter 3 was to test the presence of an observer effect on the probability and magnitude of misallocation of catches across stock areas, as determined. The observer effect in fisheries describes a change in fishing behavior when carrying a fisheries observer (Benoît and Allard, 2009; Gilman et al., 2017). Fisheries observers are trained to collect data on fishing activities, including the amount and types of fish caught, the fishing gear used, and the location and time of fishing. However, fishermen may change their fishing practices, alter their fishing locations, or misreport their catch in an attempt to avoid certain species interactions, particularly in relation to protected species or high-quota cost species (Benoît and Allard, 2009; Demarest, in prep.). For example, groundfish trips are thought to avoid fishing in certain areas that they believe will result in higher cod catches when an observer is present, which makes observer data less representative of unobserved trips (Demarest, in prep.). Bias may also be introduced into observer data when a captain denies an observer for safety or other reasons (GARFO, pers. comms.). The observer effect from the LMM was then fed into an ABM of the New England groundfish fishery in Chapter 4.

ABMs are computer simulation models used to study the behavior of heterogeneous agents' interactions with their environment and one another (Railsback and Volker, 2012). They are increasingly being used to explore the (often unanticipated) potential social and economic outcomes of management actions that emerge from complex system feedback and heterogeneous agents' interactions (Bailey et al., 2019; Burgess et al., 2018; Carrella et al., 2020). The short-term goal of the ABM described here was to evaluate the effect of observer coverage on the prevalence of misallocation and explore whether the relationship was linear across observer coverage rates. ABMs can capture the heterogeneity of agents in a fishery and the patchiness of the seascape. In this model, the stocks were distributed proportionally to sampling in the NMFS survey trawls, and the agents were assigned log-normally distributed catch-rates and normally distributed fuel efficiencies. ABMs also can capture the complexity of agent interactions, feedback, and adaptations. Ultimately, ABMs can be used to test different management scenarios, such as changes in fishing regulations. Here, the ABM tests varying levels of observer coverage and emergent changes to overall error in catch reports.

Improved reporting accuracy was expected to help achieve the long-term management goals set out in the Magnuson-Stevens Act, namely the recovery and long-term sustainability of New England groundfish stocks and fishing communities. Specifically, the recently approved management measures in Amendment 23 (GARFO, 2022) called for up to 100% observer coverage after over a decade of less than 40% coverage. Current management regulations require an uncertainty buffer for ACLs of 5%–7% unless 100% of trips are monitored to account for the uncertainty in catch records and as a precautionary approach to avoid overfishing the stock. However, the uncertainty buffer can be removed if all trips are observed according to the new regulations.

This ABM was used to simulate fisher behavior under alternative levels of monitoring to test whether the relationships between reported catch errors and observer coverage were linear across the potential range of observer coverage. Potential outcomes across a range of monitoring coverage levels were explored, and the hypothesis that marginal benefits (reductions in misallocation per unit increase in observer coverage) diminish above 90% observer coverage was tested.

## Discussion and Conclusions

The concluding chapter of this dissertation compiles key findings, caveats, and limitations of the preceding research chapters as well as outlines the opportunities of the research to contribute to a multidisciplinary, multiple model approach. As the fields of fisheries science and management continue to expand from single-species to ecosystem-based fisheries management, new cross-disciplinary and ecosystem-based perspectives can result in more robust management approaches and reduce the chances of unintended consequences that can lead to fishery collapse (Harvey et al., 2021; Pikitch, 2004).

In addition to summarizing the preceding chapters, Chapter 5 explores where fisheries management may be headed in the future. New "big data" technologies, such as uncrewed systems, artificial intelligence, and blockchain, provide platforms for new types of observations and assessment at potentially lower costs (Mustapha et al., 2021; Tsolakis et al., 2022). These new technologies could reduce uncertainty in stock dynamics and management outcomes, which is increasingly important as environmental stressors, especially climate change, increase risk to fisheries and resource managers must rethink their approach to decision-making and consider every tool in the management "tackle box."

## Chapter 2: Comparing Multi-Criteria Decision Analysis to Group Negotiations in Fisheries Co-Management[1]

### Abstract

Chesapeake Bay oyster ( *Crassostrea virginica* ) management is often contentious due to differences in stakeholders' support for alternative strategies that aim to reverse historic declines in oyster harvests and abundance. The OysterFutures (OF) research program brought 16 stakeholders from the fishing industry, non-governmental organizations, and state and federal management agencies together to generate a consensus package of management recommendations for the Choptank River basin (a tributary of the Chesapeake Bay). In this study, we looked for group effects on results by testing the consistency of the OF group-negotiated management recommendations with individual preferences, as evaluated through individual interviews and multi-criteria decision analysis methods (MCDA). We further tested the sensitivity of option rankings to stakeholder group composition, preference elicitation method, and MCDA analytic choices. We developed metrics of cost-effectiveness and elicited time preferences for outcomes, which were only used implicitly in the negotiated OF process. We found that group effects appeared minimal since the OF-derived set of preferred options generally ranked highly in the MCDA analysis. However, some of the recommended options were not found to be among the most cost-effective. The consistency of findings using individual vs group-derived preferences suggests that methods to elicit individual preferences outside of group meetings might complement and streamline consensus-seeking engagement processes by

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quickly identifying areas of agreement and disagreement to reduce the substantial time commitments of in-person meetings.

**Introduction**

Competing ecological, economic, and social fisheries management objectives often require fisheries managers to evaluate tradeoffs among objectives that stakeholders value differently, leading to conflict. For example, in the Chesapeake Bay, controversy has arisen because Maryland fisheries managers have restricted fishing effort in some productive shellfish areas by creating sanctuaries (Walburn, 2020) to promote self-sustaining oyster populations and ecosystem benefits including water quality and aquatic habitat. However, such restrictions are seen by some fishers and others as limiting regional economic benefits, including maintaining jobs (Freitag et al., 2018; Walburn, 2020).

To transparently engage stakeholders and assess, mitigate, and manage tradeoffs, a suite of tools and methods have been developed known as collaborative management, or co-management (Ansell and Gash, 2018; Cooper et al., 2006; Pomeroy and Berkes, 1997). Co-management "refers to a range of arrangements, with different degrees of power sharing, for joint decision-making by the state and communities (or user groups) about a set of resources or an area" (Berkes, 2009). Co-management can promote equitable, inclusive representation among diverse stakeholders, instead of government agents controlling the entire management process (Quimby and Levine, 2018). Further, when co-management processes apply decision support techniques, they provide a logical framework for breaking complex problems into independent component goals and performance measures, that reduce the difficulty or cognitive burden of such decisions (Belton, 2002; Keeney, 1982; Keeney and Raiffa, 1976).

In addition to being more inclusive than top-down control frameworks, co-management improves probability of achieving management goals by leveraging the diverse experience, preferences, and knowledge of stakeholders, and bolstering perceptions of legitimacy (Arnstein, 2019; Basurto et al., 2013; Hilborn, 2007; Pascoe et al., 2017). Several case studies suggests that the co-management approach improves the likelihood of meeting management goals by enhancing the confidence and support of the stakeholder community and compliance with regulations (e.g., Bodin, 2017; Cooper et al., 2006; Defeo and Castilla, 2006; Emerson et al., 2012; Ostrom, 2009, 2007, 1990)**.** Further, research suggests that when stakeholders believe the management process is inclusive and fair (i.e., legitimate), they are more likely to accept the management decisions and less likely to oppose the policy through political channels (Cash et al., 2003; Cooper et al., 2006; Sandström et al., 2014).

This study compares two co-management approaches – multi-criteria decision analysis (MCDA) and model-supported group negotiations – both of which provide decision support platforms for enhanced stakeholder engagement and shared decision-making. In MCDA, explicit weight is given to heterogeneous outcomes based on stakeholder preferences, so the benefits and tradeoffs of complex decisions can be explored and quantified (Adem Esmail and Geneletti, 2018; Belton, 2002; Innes and Pascoe, 2010; Pascoe et al., 2017, 2017). In contrast, group negotiations do not typically require quantitative measures of preferences, but the method used in the case study asked participants to express willingness to accept alternative management options (or components of options) on a 4-point ranked scale. Any options that received low scores by any participant, were then discussed to see if concerns could be resolved.

MCDA and structured group negotiations are considered complements or alternatives to monetary economic valuation methods (e.g., cost-benefit analysis) because they are able to include broad and diverse stakeholder concerns, rather than being limited to outcomes that can be represented in monetary units. Another advantage of these approaches, relative to valuation, is the opportunity for participants to revise initial preferences through group discussions that reveal salient details and perspectives of all stakeholders (Belton, 2002). MCDA is similar to economic valuation, because it typically uses quantitative measures to represent stakeholder preferences and utility functions, as part of a process for identifying preferred management alternatives. However, the preferences in MCDA differ from those embedded in monetary valuation because they only represent those of engaged stakeholders, rather than the views of the general public. Further, the preferences elicited are relative to achieving case study goals, and do not reflect willingness to make tradeoffs among all potential goods and services (i.e., willingness to pay), as would be represented by monetary values. Both of these aspects of MCDA suggest that the decisions made could be socially inefficient by failing to represent aggregate social preferences and by creating opportunity costs, or the lost benefits from failing to allocate resources where they create the most benefits (e.g., Hahn and Sunstein, 2002).

Still, MCDA is a tool used in natural resources management and other areas, ranging from health care to land use planning, to make decision processes accessible and transparent. It provides the opportunity to directly consider the preferences of those stakeholders who will bear the largest burdens of decisions and whose perspectives may be more salient and relevant to managers than those of the general public (Saarikoski et al., 2016). Thus, the concerns regarding MCDA inefficiencies relative to cost-benefit analysis may be largely inconsequential, given that the decisions that they support are rarely conducted using cost-benefit analysis.

Benefits of MCDA include the ability to reduce individual biases in and ease the cognitive burden of decision-making. By considering different types of outcomes (e.g., economic and ecological) separately and at the individual stakeholder level, MCDA promotes careful consideration of tradeoffs. Further, because MCDA typically uses individual surveys to elicit preferences (before and/or after group discussion), it avoids the group effects of peer pressure or 'groupthink' that is common in group negotiation. Groupthink stifles individuals' expression of novel or conflicting opinions, as people tend to seek group cohesion (Janis, 2008). Group effects are a type of peer pressure, or social influence to take certain actions or adopt specific beliefs in order to be accepted in one's peer group (Mani et al., 2013). In the OF example, one stakeholder dropped objections after referencing the interests of overall group cohesion, and some participants accepted the position of their peer group when they struggled with decisions. The MCDA approach presented here mitigates group dynamics by eliciting preferences individually. Peer effects can become a problem when individuals, who are representing a group of external stakeholders, make concessions that are not acceptable to the group they represent.

Moreover, if preference, objectives, and model outputs are not systematically considered, individuals tend to focus on model outputs that support options that provide personal benefits (Holland, 2008). MCDA reduces the influence of this bias by separating preference elicitation from output evaluation. Similarly, the difficulty of implicitly weighting multiple criteria when assessing acceptability of management options is well established and tends to promote the use of heuristics in which participants rely on a subset of the information presented (Borrero, 2017; Montibeller and Franco, 2010). Heuristics are defined with examples above in Chapter 1.

Although MCDA has been applied in fisheries management outside the U.S. (e.g., de Juan et al., 2017; Estévez and Gelcich, 2015; Innes and Pascoe, 2010; Silva et al., 2010; Stewart et al., 2010) and in land management in the U.S. (e.g., Martin and Mazzotta, 2018; Mendoza and Martins, 2006; Schafer and Gallemore, 2016), it is rarely employed in U.S. fishery management

(Mardle and Pascoe, 1999). Instead, group negotiations are common in U.S. fisheries management, for example in federal fishery management council processes (see *Fishery Conservation and Management Act of 1976*, 1976). This study adds to the MCDA literature by evaluating a case of a U.S. state-managed fishery: Maryland Chesapeake Bay oysters (*Crassostrea virginica*). It explores the feasibility of relatively simple, transparent co-management tools for improving the efficiency and inclusivity of the management process relative to traditional top-down, opaque fisheries management processes (Cash et al., 2003; Goethel et al., 2019).

***Oyster History and Management in Maryland***

Maryland has grappled with oyster fishery management since at least the 19th century (Kennedy and Breisch, 1983). In response to an influx of oyster dredgers from outside the state in the mid-1800s, Maryland created a State Oyster Police Force to curtail “oyster pirates.” Yet, management actions, including the oyster police, could not prevent the 98% decline since peak production in the late nineteenth century when the Chesapeake Bay “was the greatest oyster-producing region of the world” (Kennedy and Breisch, 1983; Wennersten, 1981). The decline was attributed, in part, to disease and water quality degradation, but overfishing and associated habitat loss were found to be the most significant contributors (Rothschild et al., 1994; Wilberg et al., 2011). Recent oyster management efforts are intended to reduce fishing mortality using seasonal and day-of-week closures, fishing restrictions in certain areas, and trip limits (MD DNR, 2019a), while also restoring some of the nearly 70% of oyster habitat area that was lost between 1980 and 2009 (MD DNR, 2019b; Wilberg et al., 2011).

Oyster restoration is important to enhance water quality and increase aquatic habitats, so Maryland committed to restoring oyster populations in five Chesapeake Bay tributaries by 2025 through the 2014 Chesapeake Bay Watershed Agreement. Successful restoration was defined as establishing "a sustainable oyster population that ultimately will provide increased levels of ecosystem services,"(Chesapeake Bay Program, 2014). The Maryland Oyster Restoration Interagency Workgroup has responsibility for achieving the goals of the Agreement and reported in 2019 to have constructed 788 acres of oyster reefs since 2014 at a cost of $57.02 million in five tributaries of the Chesapeake Bay (MD DNR, 2019b), which is just over half of the goal of restoring 1,439 acres by 2025. One Maryland project, the Harris Creek Restoration Project was the largest oyster restoration project in the world when it was completed in 2015, and the Piankatank River in Virginia took that distinction when it was completed in 2021 (Solyst, 2021).

The challenge for oyster managers in Maryland is striking an effective balance between ecosystem restoration and economic (revenue and employment) goals and between long- and short-term outcomes. Ecological uncertainties and lack of trust among stakeholder groups add additional complexity to management. For example, stakeholders do not agree on some critical aspects of system functioning, such as effects of high recruitment years and variability of disease intensity. Yet, stakeholders also share values for producing a suite of ecological, economic, and social benefits from oyster management, but may differ in the weight they put on each type of benefit (e.g., Paolisso and Dery, 2010).

***OysterFutures (OF) - A Case Study in Group Negotiations***

OysterFutures (OF) was a research program that tested the "Consensus Solutions" process of negotiation (OysterFutures Stakeholder Workgroup, 2018) with collaborative modeling to develop recommendations for oyster fishing regulations and restoration policies in the Choptank basin of the Chesapeake Bay (Ihde et al., 2011; Irwin et al., 2011; Miller et al., 2010). In a series of nine meetings over two years, 16 stakeholders - nine from industry, five from non-governmental organizations, and one each from federal and state government - developed a vision for oyster resource management in the region and approved a set of specific management options to improve fishing regulations, enhance water quality, and expand suitable oyster habitat. Some of the features used to empower participants were the use of neutral facilitators and academic scientists and a 60% industry representation on the stakeholder workgroup. When combined with a 75% consensus agreement threshold, the 60% representation meant that industry views were dominant, but not decisive, in selecting management options.

The academic collaborators of the OF developed a spatially-explicit computer model that was reviewed by participants to forecast the performance of management options 25 years into the future. After reviewing model outputs, the OF group decided that the management status quo was not an acceptable option (OysterFutures Stakeholder Workgroup, 2018), a condition that is thought to motivate successful negotiations (Weible et al., 2012). Through the negotiation process, stakeholders achieved consensus on a package of management recommendation to MD DNR (OysterFutures Stakeholder Workgroup, 2018).

The OF group negotiation involved modeling more than 100 sets of potential management options. Stakeholders narrowed them to 25 sets by reviewing dashboards of simulated annual performance indicators. After evaluating the model outputs and discussing their knowledge of the system, stakeholders verbally rated the acceptability of each management option. In addition to producing consensus recommendations, the group negotiation process resulted in greater cohesion and reliance on stakeholders for advice (Goelz et al., 2020b; Goelz, 2019). The group negotiation process in OysterFutures produced consensus management recommendations, but the degree to which the recommendations aligned with individual stakeholder preferences was not clear, particularly how minority views (anyone not in agreement with the 75% consensus threshold for including an option) were represented in the final recommendations.

## Materials and Methods

In order to generate rankings or numeric scores representing benefits of the management options based on individual preferences, we used three main steps. We first used results from OF to create a benefits hierarchy representing measurable high-level objectives and sub-objectives. Second, we interviewed OF stakeholders, except two non-respondents, privately to elicit preferences for management objectives represented in the hierarchy and established preference weights. Third, we combined preference weights with OF simulation model outputs to score management options. Those scores were then used within an MCDA to rank management outcomes by preferences. The MCDA benefit scores were also compared to proposed MD DNR spending to evaluate the cost-effectiveness of each management option. The interviews were also used to explore participant satisfaction with the OF process to consider whether MCDA could ameliorate any concerns about effective and efficient co-management.

### *Building on OysterFutures with MCDA*

To evaluate MCDA as a potential complement or alternative to OF, this analysis leveraged both the workgroup assembled by the OF team and the outputs from the OF model. A key difference in approaches is the way that the workgroup members were engaged in evaluating the management options. In OF, stakeholders were asked to give each management options an acceptability rating of “acceptable,” “minor reservations,” “major reservations,” or “Not Acceptable,” through hand raising in the group setting. They were provided with a dashboard of median results of 14 indicators for the final 25 management options across model forecasts of 5, 10, 15, 20, and 25 years. It was largely up to individuals to determine how to use the dashboard and supplemental graphs and tables of information to assess each option. In the MCDA process, stakeholders evaluate and score management objectives rather than simulated outcomes until the final review at the end of the process.

The full MCDA approach to establishing benefit scores for each management option consists of the following steps (Keeney, 1982; Keeney and Raiffa, 1976):

1. Convene a representative stakeholder group,
2. Identify a shared vision and objectives to achieve that vision,
3. Deliberate on options or actions to achieve the objectives,
4. Develop performance indicators for evaluating the options,
5. Elicit preference weights for the performance indicators,
6. Construct a model to assess the benefits of options using preference-weighted indicators,
7. Discuss the resulting rankings of management options with stakeholders, and
8. Return to steps 3-7 as needed.

This MCDA study restructured OF information to fit steps 1-4 and conducted novel work for steps 5 and 6. To expand on OF, we used interviews to elicit individual preference weights (step 5) and scored and ranked each management option as a function of performance indicators and the preference weights (step 6). Steps 7 and 8 were not conducted because group meetings had ceased by the time this analysis was conducted.

In the interviews of Step 5, the preferences elicited were those that emerged after the OF engagement. After years of interacting with other user groups during the OF process, stakeholders likely shifted from original positions (Goelz et al., 2020b). Therefore, this MCDA analysis cannot be completely separated from the effects created as a result of the consensus group negotiations. Nonetheless, a full MCDA process would have provided some of the same opportunities for group interactions but the comparison between OF and MCDA is limited by the overlap of early process step.

The OF ecological, economic, and management process vision themes were considered the top-level objectives, and OF-generated management objectives were nested within them in non-overlapping categories to create the MCDA objectives hierarchy (Table 1). Over telephone interviews approved by University of Maryland Institutional Review Board Project 955830-4, the interviewer elicited preferences for each vision theme and objective in the hierarchy (Table 1, columns 1-2). Responses were calibrated to weight associated performance indicators (Table 1, Column 3) to generate a benefit measure.

The MCDA applied the results of the OF simulation models to score the effectiveness of management options for achieving four primary objectives – employment, revenues, water quality, and habitat – associated with quantitative performance indicators. Other objectives, such as management accessibility and cultural heritage, were important to stakeholders (see Table 2) but did not have quantitative performance indicators, and thus excluded from the analysis.

**Table 1**

*Oyster management objectives hierarchy.*

| OF Vision Theme | Objective | Performance Indicator |
|---|---|---|
| Supports a healthy and productive ecosystem | Supports biodiversity | -- |
| | Improves water quality | Nitrogen removed |
| | Increases oyster bar habitat | Habitat volume increase |
| Supports an economically viable fishery | Increases full-time employment opportunities | Number of active licenses with at least 100 trips |
| | Increases revenues for fishery participants | Average revenue at 10 years |
| | Reduces season-to-season variation in oyster harvests | -- |
| | Maintains cultural heritage | -- |
| | Improves opportunities for young people to enter the fishery | -- |
| Gives me opportunities to provide input into management decisions | Ensures fishing regulations are clear and simple | -- |
| | Gives watermen flexibility to choose their gear | -- |
| | Does not further reduce fishing access to oyster bars | -- |
| | Raises additional bushel taxes and fees to fund shell addition | -- |

**Table 2**

*Objectives importance scores based on stakeholder interviews.*

| **Objective -** "It is important to me that oysters are managed in a way that…" | Mean Score[2] | SD |
|---|---|---|
| increases oyster abundance. | 7.0 | - |
| supports a healthy and productive ecosystem. | 6.8 | 0.4 |
| gives me opportunities to provide input into management decisions. | 6.4 | 1.1 |
| increases oyster bar habitat. | 6.4 | 0.9 |
| improves water quality (as measured by nitrogen removal). | 6.3 | 1.2 |
| supports an economically viable fishery. | 6.1 | 1.4 |
| maintains cultural heritage. | 6.1 | 1.2 |
| ensures fishing regulations are clear and simple. | 6.1 | 1.4 |
| supports biodiversity. | 6.0 | 1.2 |
| increases full-time employment opportunities. | 5.8 | 1.4 |
| improves opportunities for young to people enter the fishery. | 5.8 | 1.6 |
| increases revenues for fishery participants. | 5.6 | 1.3 |
| reduces season-to-season variation in oyster harvests. | 5.3 | 1.3 |
| raises additional bushel taxes and fees to fund shell addition. | 4.7 | 1.9 |
| does NOT further reduce fishing access to oyster bars. | 4.4 | 2.2 |
| gives watermen flexibility to choose their gear. | 4.4 | 1.5 |

[2] Rated on a scale from 1 to 7, with 1 being "Not at all important" and 7 being "Extremely important."

***Benefits Assessment Methods***

Benefit scores for each management option were calculated using a weighted sum model, one of many MCDA benefits assessment approaches (Triantaphyllou, 2000; Triantaphyllou and Baig, 2005). The simple weighted sum model has the advantage of being intuitive to stakeholders viewing results, but it assumes additive utility across benefit types and requires that performance indicators be largely independent, numerical or ordinal, and comparable after units are transformed into normalized or standardized units (Triantaphyllou and Baig, 2005). It can be difficult to achieve independence among indicators, but a parsimonious set of indicators was used to minimize overlap. Another assumption is that indicators are compensatory, or that desirable outcomes can make up for undesirable outcomes, and the option with the largest cumulative benefit score is best (Martin and Mazzotta, 2018).

We evaluated relative benefits by normalizing scores and applying local scaling to create unitless and compensatory measures. Benefits of each management option are meant to be indicators of well-being, but do not represent economic benefits. Economic benefits are measured when participants characterize their strength of preferences in terms of willingness to make tradeoffs among other goods and services, typically represented by willingness to pay for changes. Instead in this approach, preference weights take on the role of values. $B_j$ are the sum of standardized performance indicators, $a_{ij}$, weighted by stakeholder group (or subgroup) mean preference weights, $\underline{w_i}$, as follows:

$$B_j = \sum_{i=1}^{n} a_{ij}\underline{w_i} \qquad \text{Equation 1}$$

The *base model* represented in Equation 1, includes $a_{ij}$ that were standardized using local scaling (Martin and Mazzotta, 2018; Poyhonen and Hamalainen, 1999) as shown in Equation 2. Alternative models are created by using global scaling of model performance metrics and logged benefits across the performance range to represent diminishing marginal returns, as described under sensitivity analysis. Local scaling provides unitless values between 0 and 100 that represent the ratio of the difference between the nominal performance indicator value and the least-preferred outcome relative to the range of outcomes in the dataset used (Table 3). That is, the locally-scaled performance indicator for each management option is as follows:

$$a_{ij} = \frac{p_{ij} - min\ (p_i)}{max\ (p_i) - min\ (p_i)}\ 100 \qquad \text{Equation 2}$$

Where $p_{ij}$ is the *i*th nominal performance indicator value of the *j*th management option, and $min\ (p_i)$ and $max\ (p_i)$ are the minimum and maximum simulated performance indicator values across all $j$. All performance indicators were scaled such that low values were the least desirable and high values were the most desirable. For example, average annual revenue outcomes after 10 years ranged from $3.4M in the status quo simulation to $8.9M in top performing simulation, so the standardized performance indicator of the former is 0 and the latter is 100 with other simulations falling in between. There are other approaches to standardizing performance indicators, for example, global scaling is a common alternative. While local scaling is based on the range of observed values, global scaling relies on the entire range of possible or theoretical best and worst outcomes (Martin and Mazzotta, 2018). In the global scaling sensitivity run, Equation 2 was modified so that the 25-year best model outcome replaced $max\ (p_i)$ and the 25-year worst model outcome (for when habitat and nitrogen were removed) or 0 (for when employment and revenue represented a theoretical fishery closure) replaced $min\ (p_i)$.

**Table 3**

*Management outcomes*

Performance indicators and Criteria Scaled 0-100 for years 7-10 after action.

| | Performance Measures (OysterFutures Nominal Values) | | | | Criteria (Locally-Scaled Values) | | | |
|---|---|---|---|---|---|---|---|---|
| **Option** | **Habitat (1000 bu)** | **Revenue (1000 $)** | **Number Full Time** | **N removed (lbs)** | **Habitat** | **Revenue** | **Employment** | **N removed** |
| A. | 11,184 | 3,879 | 60 | 168,990 | 0 | 8 | 2 | 0 |
| 2. | 11,188 | 3,753 | 58 | 170,003 | 0 | 6 | 0 | 2 |
| 3. | 11,209 | 3,437 | 61 | 175,318 | 1 | 0 | 3 | 15 |
| 13a. | 11,293 | 4,765 | 74 | 173,028 | 4 | 24 | 17 | 9 |
| 13b. | 11,516 | 6,022 | 92 | 176,892 | 12 | 47 | 38 | 18 |
| 16a. | 11,294 | 4,760 | 74 | 171,938 | 4 | 24 | 18 | 7 |
| 16b. | 11,506 | 5,123 | 80 | 173,347 | 11 | 31 | 24 | 10 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 17a. | 12,020 | 3,929 | 60 | 169,142 | 29 | 9 | 2 | 0 |
| 17b. | 13,972 | 4,267 | 66 | 170,008 | 98 | 15 | 9 | 2 |
| 18. | 11,799 | 4,662 | 73 | 169,193 | 21 | 22 | 16 | 0 |
| 18a. | 11,279 | 4,754 | 75 | 170,171 | 3 | 24 | 19 | 3 |
| 18b. | 11,478 | 5,557 | 87 | 171,592 | 10 | 39 | 32 | 6 |
| 19. | 12,679 | 4,866 | 72 | 197,611 | 52 | 26 | 16 | 67 |
| 23. | 11,193 | 3,886 | 60 | 169,256 | 0 | 8 | 2 | 1 |
| 26a. | 11,312 | 6,445 | 99 | 173,697 | 4 | 55 | 46 | 11 |
| 26b. | 11,541 | 8,721 | 133 | 177,010 | 12 | 96 | 84 | 19 |
| 16b+19. | 12,992 | 6,208 | 93 | 200,144 | 63 | 50 | 39 | 73 |
| 16b+19+3. | 13,015 | 5,503 | 93 | 207,511 | 64 | 38 | 39 | 90 |
| 26a+19+3. | 12,831 | 6,759 | 113 | 209,302 | 58 | 60 | 61 | 94 |
| 26b+19+3. | 13,061 | 8,940 | 147 | 211,801 | 66 | 100 | 100 | 100 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 26a+16a+19. | 12,917 | 7,412 | 113 | 204,574 | 61 | 72 | 61 | 83 |
| 26a+17a+19+23+ 3. | 13,694 | 6,837 | 115 | 209,847 | 88 | 62 | 63 | 95 |

Sensitivity study – spat set

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| B. | 12,044 | 4,718 | 73 | 170,989 | 30 | 23 | 16 | 5 |
| C. | 14,043 | 7,216 | 115 | 176,512 | 100 | 69 | 64 | 18 |
| D. | 11,809 | 5,422 | 84 | 170,349 | 22 | 36 | 29 | 3 |

Preferences regarding the importance of each objective were elicited through interviews of OF participants and used to assign weights to each performance indicator. Respondents used a semantic differential (Osgood, 1964) scale of 1-7 (1 = "not at all important" to 7 = "extremely important") to assign a level of importance to the management objectives. The interviewer asked each respondent to score a series of 16 statements: "It is important to me that oysters are managed in a way that…" followed by outcomes that were presented in a random order, such as "…increases oyster abundance" (see full list in Table 2). Several studies have suggested that this direct weighting method is preferred by respondents and provides more consistent weights than other common weight elicitation methods such as point allocation, ranking methods, the analytic hierarchy process, or equal weighting (Bottomley et al., 2000; Jia et al., 1998; Triantaphyllou, 2000; Triantaphyllou and Baig, 2005).

Each primary objective was associated with a single performance indicator (see Table 1), so preference scores were directly applicable as weights on performance outcomes, and there was no need for additional sets of weights, as required for a more complex objectives hierarchy (Marttunen et al., 2018). Respondent k's preference weight for ith objective, $w_{ik}$ , was derived by scaling the reported importance value, $v_{ik}$ (1-7), across all primary objective importance values, $V_k$ (4-28), to generate a preference weights of 5% to 70% representing relative importance of a given objective among the set of 4 objectives (Equation 3).

$$w_{ik} = \frac{v_{ik}}{V_k} \qquad \text{Equation 3}$$

For the base model, we applied non-hierarchical direct weighting (Marttunen et al., 2018) using the $w_{ik}$ produced from Equation 3. The effects of hierarchical preference weights – objectives weights scaled by vision theme weights - were tested by applying Equation 3 one level of the objectives hierarchy at a time, with global preference weights being the product of the "conditional weights" down the hierarchy (Lund, 1994; Marttunen et al., 2018; Stillwell et al., 1987) and applied to Equation 1.

In addition to non-hierarchical and hierarchical weighting, we elicited a subset of preference swing weights from interview participants. Swing weighting explicitly incorporates the magnitude of change, or the range of values being considered (Fischer, 1995; Parnell and Trainor, 2009). In this case, we asked respondents to rank the four primary objective benefits in order of importance, after being given the maximum magnitude of the range of simulation model outcomes. The four primary objectives and magnitudes were:

- Enhance full-time employment by 150%
- Increase average revenue by 150%
- Improve water quality by 25%
- Increase oyster shell habitat by 25%.

Respondents were asked to assign a score of 100 to the most important objective (given the expected maximum effect), and score remaining objectives on a 0-100 scale, relative to the most important benefits (Von Winterfeldt and Edwards, 1986). For example, after identifying the second most important swing, we asked, "If we assign the most important change a score of 100, what would you score the second most important on a scale of 0 to 100?" The swings weights were thus a test of whether the magnitude of effect influenced preferences weights. It also provided an opportunity to compare consistency of weights when using semantic differential versus point allocation.

Swing weights, $r_{ik}$, were calculated by scaling the scores provided by interviewees per objective, $s_{ik}$, by the sum across all four objectives $S_k$:

$$r_{ik} = \frac{s_{ik}}{S_k} \qquad \text{Equation 4}$$

In addition to preference weights of objectives, the interviewer asked respondents to score the importance of management yielding benefits within 1, 2, 5, 10, and 25 years to elicit stakeholders' time preferences. The change in the performance metric of oyster harvest amount can be selected for any year when calculating management objective benefits, so the reportedly most important time frame was used to select the model output for benefit scoring (Equation 1).

The final section of the interview included questions to characterize participants. They were asked to self-identify their job type (industry, government, and non-governmental organizations). They were also asked open-ended questions about the OF negotiated process, including questions on what information they used to make decisions to accept or reject management alternatives, whether they felt OF was likely to meet its objectives, and how the process could be improved in the future.

***Sensitivity Analyses of Management Option Rankings***

Sensitivity analyses were used to test the potential influence of several assumptions and modeling choices on the final benefit scores of the management options using Equation 1. We conducted six sensitivity analyses (Table 4) to test effects of using alternative methods including stakeholder workgroup composition, non-respondent preferences, performance indicator scaling (i.e., global or log scaling), and preference weight elicitation.

**Table 4**

*MCDA rankings of management options*

| Option[3] | Benefit Scores BASE | NON-RESPONDENT[4] | GLOBAL[3] | EQUAL USER GROUPS[3] | HIERARCHY[3] | SWING[3] | LOG |
|---|---|---|---|---|---|---|---|
| 26b+19+3 | 90.95 | 100.43 | 45.85 | 90.31 | 90.82 | 90.37 | 90.95 |
| 26a+17a+19+23+3 | 77.65 | 83.81 | 43.40 | 78.69 | 77.78 | 78.07 | 82.39 |
| 26a+16a+19 | 69.32 | 76.31 | 38.29 | 69.50 | 69.32 | 69.37 | 73.66 |
| 26a+19+3 | 68.63 | 74.54 | **37.46** | 69.15 | 68.66 | 68.57 | 73.48 |
| C | 62.59 | 69.16 | **41.41** | 62.37 | 62.66 | 63.20 | 67.00 |
| 16b+19+3 | 58.53 | 62.42 | 34.65 | 59.89 | 58.68 | 58.95 | 64.04 |
| 16b+19 | 56.75 | 61.77 | 34.43 | 57.60 | 56.85 | 57.23 | 62.21 |
| 26b | 51.08 | 59.76 | 29.18 | 48.42 | 50.72 | 49.92 | 52.63 |
| 19 | 40.96 | 43.75 | **28.05** | 42.35 | 41.12 | 41.65 | 45.20 |
| 17b | 32.04 | 33.80 | **30.92** | 33.46 | 32.34 | 33.56 | 35.00 |
| 13b | 28.12 | **32.43** | 21.08 | 27.14 | 27.98 | 27.71 | 33.62 |
| 26a | 27.99 | **32.94** | 20.58 | 26.48 | 27.78 | 27.33 | 33.37 |
| D | 21.97 | 25.30 | 20.31 | 21.28 | 21.90 | 21.89 | 27.23 |
| 18b | 21.09 | 24.59 | 18.84 | 20.13 | 20.97 | 20.75 | 26.49 |
| 16b | 18.62 | 21.45 | **17.96** | **18.04** | **18.55** | **18.44** | 23.58 |
| B | 18.57 | 20.80 | **19.85** | **18.50** | **18.59** | **18.83** | 22.75 |
| 18 | 14.91 | 17.00 | 17.89 | 14.64 | 14.90 | 15.03 | 19.01 |

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[3] Glossary of OysterFutures Management Options contains descriptions.

[4] The scores that changed rankings relative to the base model are **bolded**.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 13a | 13.24 | 15.46 | 15.41 | 12.75 | 13.17 | 13.06 | 17.52 |
| 16a | 12.73 | 14.93 | 15.30 | 12.18 | 12.65 | 12.53 | 17.05 |
| 18a | 11.70 | 13.86 | **15.00** | 11.05 | 11.61 | 11.46 | 16.07 |
| 17a | 10.44 | 11.37 | **17.05** | 10.79 | 10.52 | 10.93 | 11.96 |
| 3 | 4.85 | 4.89 | 12.06 | 5.06 | 4.86 | 4.80 | 5.33 |
| 23 | 2.59 | 3.34 | 11.60 | 2.43 | 2.57 | 2.60 | 3.96 |
| A | 2.30 | 3.04 | 11.49 | 2.14 | 2.28 | 2.31 | 3.65 |
| 2 | 1.99 | 2.53 | 11.33 | 1.94 | 1.98 | 2.03 | 2.80 |

Methods to this point described the base case (BASE) of our assumptions and methods. Two OF participants, both fishers, were unavailable for the preference weighting interviews, so the first sensitivity analysis tested the choice to use mean preferences of commercial fishers to represent the missing respondents and the effect of capping the weights at 70%. Instead of the fisher group mean weights, we used an extreme value of 100% weight on fishing revenues to replace the missing values in the NON-RESPONDENT scenario. In the GLOBAL sensitivity analysis, global scaling was applied instead of local scaling, as described above.

The preference weights in the base model run were the mean of preferences of OF, in which industry had more representatives (9) than non-profit groups (5) or managers (2). To test the influence of industry's majority representation in the working group, EQUAL USER GROUPS were simulated in a sensitivity analysis using an equal weighting of the mean preferences of each stakeholder group. As additional tests, industry only and non-profit only user groups were simulated.

The HIERARCHY and SWING scenarios applied the hierarchical preference weighting and swing weight elicitation techniques, respectively, described above under Equation 3.

In the final sensitivity test, we evaluated the standardized performance indicators on natural log scales to simulate relatively high marginal utility at lower values that diminish over the range in the LOG scenario. The effect of diminishing marginal utility reflects evidence that people experience reductions in the benefit of each additional unit of a good or service, all else equal (Taylor et al., 2014).

***Cost-Effectiveness Analysis***

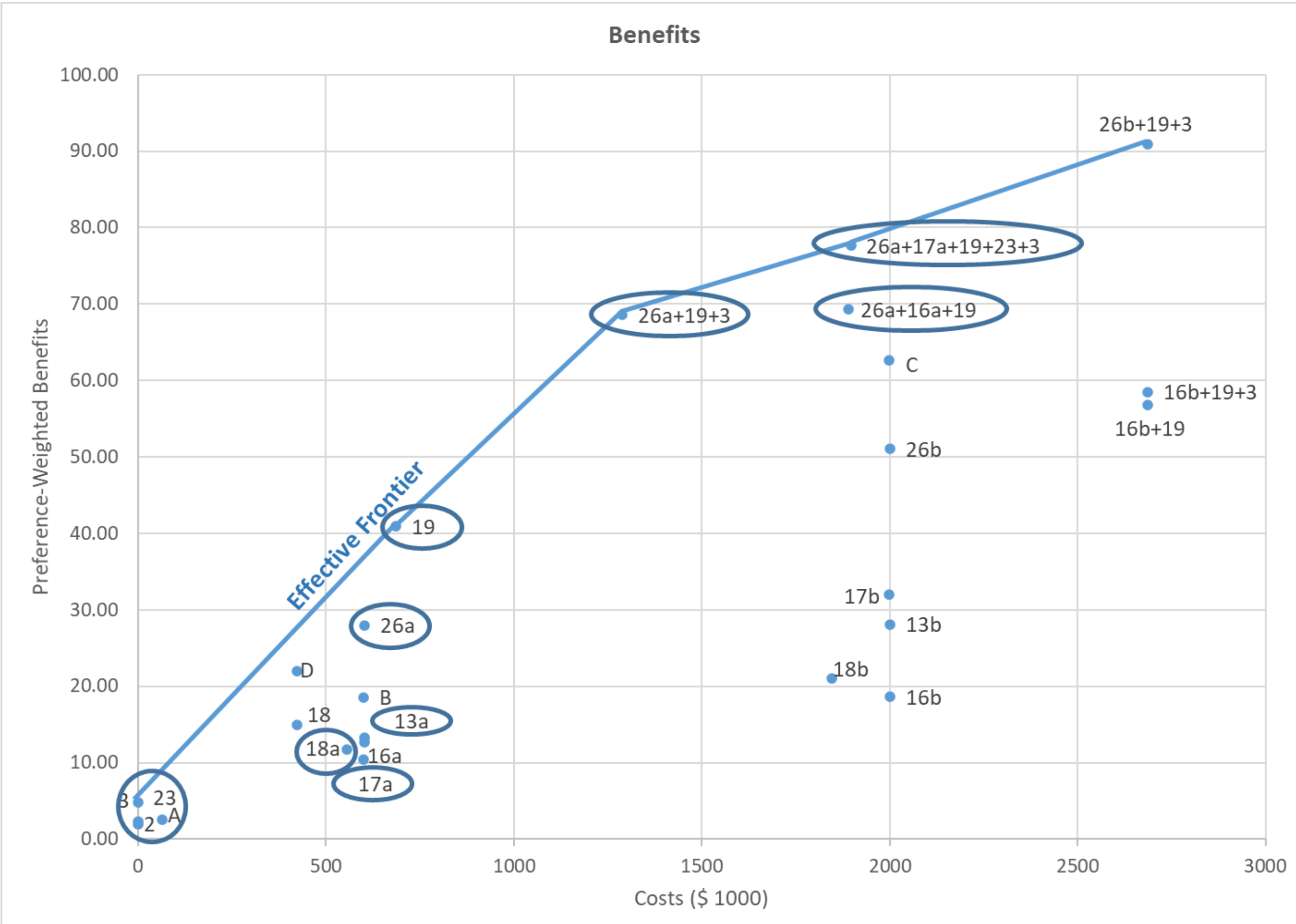
Management investments were frequently discussed during OF, and stakeholders requested a cost-effectiveness analysis (CEA) across management options to identify the most effective use of limited public resources. MD DNR costs for each management option were estimated by the OF research team and MD DNR, except the cost of increased compliance was unavailable and therefore excluded. Using benefit scores ($B_j$) from Equation 1, we evaluated cost-effectiveness ratios (CER) and plotted benefits and costs in Figure 1. An effective frontier, "i.e., a set of potentially cost-effective options" (Suen and Goldhaber-Fiebert, 2016), was approximated graphically in Figure 1 by connecting the highest level of preferred outcomes across multiple costs to represent the highest expected benefits score at each level of investment. The effective frontier represented the greatest benefit across options at several annual costs which represent average annual investments over 25 years up to a maximum of $2.7 million.

***OysterFutures Comparison***

Benefit scores (from Equation 1) were used to rank options and compare whether rank corresponded to inclusion in the set of final recommendations from OF. We also compared cost-effectiveness of the options, i.e., proximity to the effective frontier (Figure 1). This test revealed whether results were sensitive to the two different co-management approaches, as might be caused by the influence of group dynamics, cognitive interpretation of model results, or other factors.

**Figure 1**

*Effectiveness of oyster management options*




## Results

### *Interview Responses*

The interviews revealed some similarities in preference scoring among all stakeholders but also key differences, (Table 2). One management objective received unanimous agreement as "extremely important" which was "…increases oyster abundance." There was also general agreement on the importance of ecological and engagement objectives. The rest of the top five most important management objectives based on average stakeholder scores included "…

supports a healthy and productive ecosystem," "… gives me opportunities to provide input into management decisions," "… increases oyster bar habitat," and "… improves water quality (as measured by N Removal)."

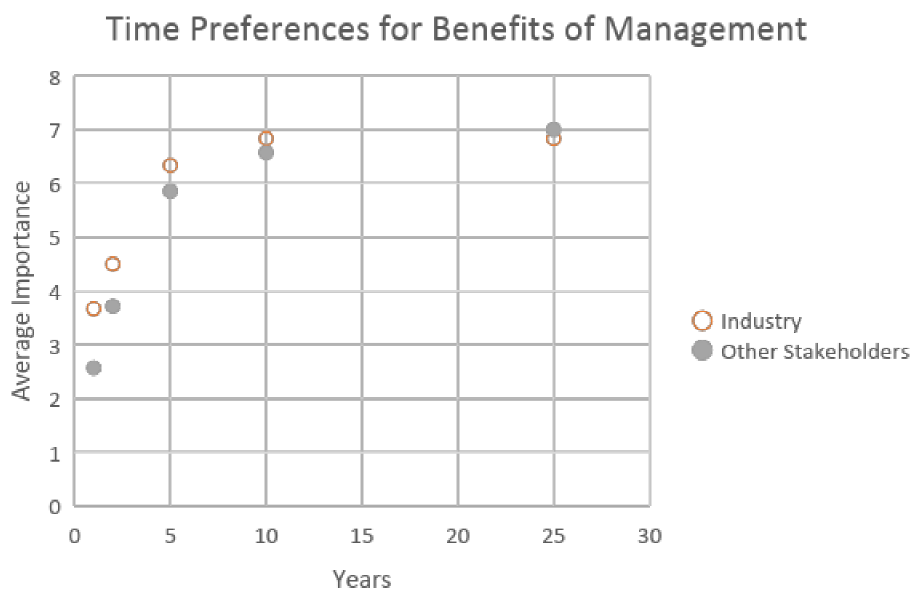
There were also some areas where stakeholder groups diverged. On average, industry representatives gave roughly equal weight to the four primary objectives used in this study (employment, revenues, water quality and habitat), while the other stakeholders gave somewhat more uneven scores with higher values on the water quality and habitat benefits than the employment and revenue benefits (Table 5). The balanced preferences of industry stakeholders also were reported at the higher-level vision themes; all but one industry representative assigned equal weights to "healthy and productive ecosystem" and "economically viable fishery." Objectives related to fishing, such as access to fishing location and gear, were among the least important, on average, across non-industry stakeholders.

Preference weights elicited through hierarchical direct weighting (H) and swing weighting (S) were similar to those elicited through non-hierarchical direct (N) weighting (Table 5). The swing weights tested preference weights by including the maximum magnitude of change represented in the modeled outcomes across all management options. The similarity between direct and swing weights, therefore, suggests that stakeholders were indifferent to the inclusion of the magnitude of improvement in individual outcomes when considering which outcomes were most important. Results suggested that most stakeholders were firm in their preference weights, regardless of the additional information about the magnitude of change.

Time preferences were similar across stakeholder groups. Industry respondents expressed a slightly higher preference for benefits in the short-term (< 10 years) relative to other respondents (Figure 2). However, all respondents said it was extremely important to see progress toward the management objectives by the 10-year mark and that persisted to 25 years. Separately, in the open-ended questions, most respondents indicated that they primarily examined timeframes of about 10 years when evaluating model output for each option.

**Figure 2**

*Stakeholder group time preferences  for restoration benefits.*




During the open-ended question segment of interviews, industry representatives highlighted the interconnectedness of the four objectives developed for this study, which may explain why they assigned roughly equal preference weights to employment, revenue, habitat, and water quality. For example, one waterman (in the Chesapeake Bay, commercial fishers are called ‘watermen’) said, “nobody wants better water quality more than a waterman.” Other industry representatives expressed that their livelihoods are entirely dependent on a healthy Bay ecosystem. Sustainability and fairness were also cited as key goals; one fisher stated that to find a “more sustainable way to manage the resource that is fair for all the stakeholders and is made sustainable through economic incentives… [we have] got to get away from driving the system with shell addition." In this ecosystem, shell is the best substrate for oyster settlement and growth (where new shell is produced). However, with dredging and siltation, oyster shell often is removed or sinks, so constant addition is required for new oyster growth.

**Table 5**

*Preference weights by objective for stakeholder groups*

Elicited through Non-hierarchical (N) and Hierarchical (H) Direct Weighting and Swing Weighting (S).

| | Employment | Revenue | Water Quality | Habitat |
|---|---|---|---|---|
| Industry (N) | 27% | 26% | 23% | 24% |
| Others (N) | 21% | 20% | 29% | 30% |
| Industry (H) | 26% | 24% | 24% | 25% |
| Others (H) | 21% | 22% | 28% | 29% |
| Industry (S) | 25% | 27% | 24% | 24% |
| Others(S) | 18% | 20% | 28% | 33% |

Conversely, some members of the panel separated and prioritized objectives. During interviews, some environmental group representatives stressed that long-term economic benefits were not possible unless environmental sustainability was ensured, reflecting their perceptions of the precedence of environmental benefits. Despite these differences, all stakeholders were largely in agreement about the need to restore oysters, rebuild habitat, and improve water quality (Table 2).

***MCDA, Sensitivity Analyses, and CEA Results***

After ranking the management options by their benefits scores (Table 6), four management options emerged as having substantially higher benefits than other options. All four were combinations of management actions that included completing ongoing interagency restoration projects (#19) and investing in spat-on-shell every year in the Middle Choptank (#26). The first and fourth-ranked options also included full compliance (#3) with size and area regulations.

We found that the most cost-effective investments of those simulated were completing Little Choptank and Tred Avon restoration projects (CER = 59.7, #19), and combining these restoration projects with adding spat every year in the Middle Choptank and enhanced enforcement (CER = 53.3, #26). In Figure 1, some OF recommendations (circled) are on or near the effective frontier, while others were not found to be as cost-effective.

Relative benefits and associated rankings were generally not sensitive to the assumptions that were explored in sensitivity analyses (Table 4). In particular, the top three ranked management options did not change in any of the sensitivity runs. In several sensitivity analyses – Non-Respondent, Equal User Group, Hierarchy, and Swing – two options in the middle of the ranked list changed by one rank. Somewhat unexpectedly, having a majority of industry (60%) on the panel had little influence on the rankings of the options compared to an equal weighting of all stakeholder groups. Moreover, the top nine benefit-ranked options were identical whether the simulated, exclusive panels were only industry or only environmental organization stakeholders.

For the remaining sensitivity analyses, the rankings of management options also remained consistent across the three preference weighting methods. Weights that were elicited through swing weighting (S) were within 3% of the weights that were elicited directly through hierarchical (H) or non-hierarchical (N) methods (Table 5). The rankings in the sensitivity run with logarithmically-scaled performance indicators were identical to the base model with standard scaling (Equation 1). Global scaling had the largest, although still minimal, effect on results: four options moved up two or three positions (Table 4).

**Table 6**

*Benefits and cost-effectiveness ratio (CER) rankings and OysterFutures recommendations*

| **Option** (**Bold** = OF Recommendation, ~~Strike~~ = OF Rejection) | CER Ranking[5] | OF Recom.[6] |
|---|---|---|
| 26b+19+3. Spat MC $2M, restore, compliance | 14 | |
| 26a+17a+19+23+3. Spat MC, Shell BC, restore, reef balls, compliance | 6 | H3 |
| 26a+16a+19. Spat MC $600K, 2-yr R LC, restore | 2 | H1 |
| 26a+19+3. Spat MC $600K, restore, compliance | 7 | H2 |
| C. Shell every yr in BC, $2M (#17b) | 10 | |
| 16b+19+3. 2-yr R LC, restore, compliance | 9 | |
| 16b+19. 2-yr R LC, full restoration | 15 | |
| 26b. Spat every yr in MC, $2M | 12 | |
| 19. Complete LC & TA restoration | 1 | E3 |
| 17b. Shell every yr in BC, $2M | 19 | |
| 13b. 2-yr R, MC sanc, $2M – spat | 20 | |

[5] Summary descriptions of the options are in Table 3.

[6] OF recommended options are grouped by letter and described further in the OF final report. Blanks indicate options were not included in the final package of recommendations.

| | | |
|---|---|---|
| 26a. Spat every yr in MC, $600K | 4 | F |
| D. Open LC tribs, shell 3rd yr (#18) | 3 | |
| 18b. Open LC tribs, spat 3rd yr, $2M | 21 | |
| 16b. 2-yr R, LC tribs, $2M – spat | 22 | |
| B. Shell every yr in BC, $600K (#17a) | 11 | |
| 18. Open LC tribs, shell 3rd yr | 8 | |
| 13a. 2-yr R, MC sanc, $600K – spat | 13 | D |
| 16a. 2-yr R, LC tribs, $600K – spat | 16 | |
| 18a. Open LC tribs, spat 3rd yr, $600K | 17 | E2 |
| 17a. Shell every yr in BC, $600K | 18 | E1 |
| 3. SQ, full compliance | NA | B |
| 23. Reef balls in MC sanc | 5 | E4 |
| A. Status quo (SQ) | NA | |
| 2. SQ, full compliance with size | NA | B |

The weighted sum model was parsimonious by design to efficiently provide information to stakeholders, and the base model was found to be robust to alternative specifications tested in the sensitivity analysis (e.g., direct weighting and linear value functions). The finding was consistent with other empirical decision science studies that suggest simpler models perform as well or better than more complex models in aiding stakeholder evaluation (Dargin et al., 2019; Helgeson et al., 2020; Marttunen et al., 2018).

***OysterFutures Comparison***

Despite some differences, results (options included in the final OF package or highly ranked in MCDA and CEA analyses) were relatively consistent across the three co-management approaches (Table 6). The OF recommendations were not quantitatively ranked, therefore a direct comparison of rankings between approaches was not possible. Of the 100+ management options considered at various points during OF and the top 25 evaluated in this MCDA, 14 options were considered individually in the last round of acceptability ratings before the final OF vote on a package of recommendations. The five options with the highest MCDA benefits scores and the six options with the highest CER were all included in the OF package of recommendations (Table 6). Additionally, the three options that were rejected in the final OF ratings ranked low in MCDA and CEA.

While outcomes of the group negotiations and the MCDA were largely consistent, there were noteworthy differences, particularly for the options that expanded or improved available fishing grounds (Table 6). The full package of recommendations from OF included opening the Middle Choptank sanctuary to 2-year rotational harvest (CER = 22.0, #13a), open Little Choptank tributaries to hand tonging (CER = 21.0, #18a), and add shell to Broad Creek (CER = 17.4, #17a). With CER ≤ 22, those three options did not appear to deliver benefits as cost-effectively as other management options recommended by OF, where the average CER was 49.0 (Figure 1).

## Discussion

Both the negotiated OF process and this MCDA elevate the role of stakeholders in the collaborative management process, and such co-management increases legitimacy of management decisions, which tends to improve compliance and raises the likelihood of successful outcomes (Cash et al., 2003; Raakjær Nielsen, 2003). We tested whether the OF results might have introduced group effects and found that the use of two co-management approaches, group negotiation and MCDA, did not elicit markedly different outcomes from the same stakeholder group. Among options for MD DNR to meet their mandate for co-management, group negotiation and MCDA offer similar benefits for stakeholders assessing a set of management options using multiple criteria. Both approaches reduce the cognitive burden for participants by breaking the problem into smaller parts for assessment (Estévez et al., 2013; Estévez and Gelcich, 2015; Keeney and Raiffa, 1976), provide an opportunity for stakeholders to consider and express preferences and expected outcomes, and benefit from collective learning.

In addition to co-management benefits from either approach, we found MCDA may have some advantages to group negotiations such as transparently evaluating tradeoffs among objectives by eliciting quantitative preferences for each objective. The transparency can make decision-making more efficient by easing communications and reducing misunderstanding of preferences (Addison et al., 2013; Reichert et al., 2015). MCDA and group negotiations offer frameworks for formally evaluating tradeoffs among objectives and explicitly integrating stakeholder preferences into increasingly common fisheries management structures, such as management strategy evaluation (Punt et al., 2016). Another common approach to evaluating preferences is stated preference choice experiments, in which respondents are asked to select one of several choice sets, each composed of different combinations of attribute levels and costs. Results can be used to estimate the marginal value of each attribute. Each preference elicitation approach is subject to biases, but choice experiments are especially prone to simplification heuristics, in which respondents ignore certain attributes and focus on a subset (Tervonen et al., 2017). However, by including costs in each choice set, choice experiments make the costs more salient than this MCDA which does not ask respondents to consider costs when weighting benefits. Total costs to the government agency of management options were considered later in the process when cost-effectiveness was evaluated.

Another challenge with negotiations is ensuring equity among stakeholders. Personalities, social networks, and power dynamics can influence representation in the negotiated processes in ways that are difficult to reconstruct. The skilled OF facilitators ensured input from all participants through open discussions and public ratings of options. However, the threshold of 75% consensus potentially disincentivized minority viewpoints from being raised; at least one OF stakeholder acknowledged holding comments because it made no difference in the outcomes. Alternatively, the MCDA individual interviews gave all participants equal, structured opportunities to share preferences and add their individual perspectives with no influence of peer pressure to represent a particular position (Davies et al., 2013; Wainger et al., 2017). Our observations of the collaborative OF process were that engagement increased understanding of alternative stakeholder perspectives, which is consistent with engagement processes involving Chesapeake Bay stakeholders (Goelz et al., 2020a; Paolisso and Dery, 2010; Wainger et al., 2017).

***Streamlining Co-management***

Participants had overwhelmingly positive comments about OF, but one complaint was the length of time required to produce recommendations. OF reached consensus on an acceptable package of recommendations after two years of regular group meetings, simulation model development, collective learning, and negotiations. The OF un-ranked package of recommendations received unanimous support as it included a range of options preferred across stakeholder groups. The final package carried the weight of the whole group's consensus, but prioritization within the package would have required additional analysis like the MCDA presented here. At the end of the OF process, there was little interest in negotiating rankings for each option, despite the state management representative's suggestion that prioritization would be helpful given budget constraints.

The iterative development of the new OF simulation model took about 18 months (M. Wilberg, personal communication, March 20, 2021), and the group negotiations and endorsement of recommendations took over six months. Stakeholders said that articulation of preferences was sometimes challenging because they had to simultaneously consider and explain scores for multiple benefits and tradeoffs. No quantitative method of combining benefits across multiple objectives across multiple time scales and comparing multiple options was used. To simplify and potentially expedite the group decision-making, MCDA offers an explicit, structured approach to ranking options using relative preference weighting and standardized performance indicators. MCDA reveals specific differences in preferences, so group negotiations can focus discussion on the most decision-relevant areas and move more quickly through areas of agreement. As a result of this efficiency, MCDA could potentially speed the time to identifying and ranking recommendations in future management processes. Because this study used some results from OF, and interviewed stakeholders after the group negotiated process, it does not provide an independent test of MCDA. A full MCDA would be needed to test the potential time savings of an independent MCDA, relative to a negotiated co-management process.

**Conclusions**

After comparing the outputs of alternative decision processes: 1) MCDA with CEA and 2) Consensus solutions negotiations with collaborative modeling, we conclude that both processes have been effective at identifying stakeholder preferences for management of part of Maryland's oyster fishery. Despite concerns that the negotiation process could have introduced group effects, such as diminishing minority voices, we find no evidence of group effects based on individual elicitation of preferences. However, the ability to use MCDA results to rank cost-effectiveness of management options added a new dimension to the information produced and managers said such information would be useful to support decisions. The novel CEA information created with MCDA identified that some of the options selected through the negotiation process had substantially lower cost-effectiveness than other options. MCDA provides quantitative decision support input that may reduce the cognitive burden of comparing options by parsing model results and individual stakeholder preferences and explicitly evaluating tradeoffs in Equation 1.

Another major finding addressed concerns that the majority of the stakeholder group (60%) were from industry. When simulating equal representation across stakeholder groups, we found that the small advantage for a particular stakeholder group had only marginal impacts on the order of low-ranking recommendations. The balanced preferences of industry representatives across objectives meant that their absolute representation did not substantially sway the results.

Finally, the similarity of OF management recommendations, benefit rankings, and cost-effectiveness suggested a robustness of co-management approaches, but we acknowledge that this abbreviated MCDA process was built on the OF process, and a full MCDA could have yielded different results. Recognizing that each approach has benefits for collective learning, inclusivity, and trust building, perhaps some combination of negotiated, MCDA, and CEA approaches might improve the final recommendation advice to managers. In the right sequence, combining approaches could reduce time commitments needed to reach consensus by more quickly identifying areas of conflicting priorities through MCDA, then using group negotiations to find a compromise or resolution.

# Chapter 3: Observer Effects: Linear Mixed Models Indicated Reduced Disagreement Between Data Sources in the New England Groundfish Fishery


## Abstract

Inaccurate reporting of catch by location is believed to introduce error into area-specific stock assessments used to set annual catch limits in the New England groundfish fishery, so managers are increasing observer coverage to improve data quality and enhance stock recovery. Although it is rare for observer data to be used by law enforcement, there is growing evidence that fishers change behavior on observed trips. This study tested the hypothesis that observer presence is negatively correlated with the probability and the amount of misallocation of catch across cod stock areas. This hypothesis was evaluated using a linear mixed model including observer presence, fishing year, and quarter as fixed effects and permits nested within fishing sectors as the random effects to evaluate the probability and magnitude of disagreement between vessel trip reports and estimates of fishing effort by area based on VMS. Data from Gulf of Maine and Georges Bank fishing areas and from 2010 to 2019 time period were employed. Vessel length and a categorical variable for convicted seafood fraudster Carlos Rafael were considered but were not included in the best model. The probability of a suspect unobserved trip was 54.8%, 95% CI [48.7%, 60.8%], but on observed trips, it fell to 38.2% [29.0%, 48.6%] on observed trips. The proportion of catch misallocated from Gulf of Maine to Georges Bank was estimated to be 27% [23%, 32%], but dropped by an average of 8% [5%, 10%] on trips with an observer. Thus, despite the lack of deterrence effects from a law enforcement standpoint, results indicate that the accuracy of landings data and associated stock assessments could improve as monitoring increases, supporting improved quota estimates and potentially reducing the likelihood of overfished stocks.

## Introduction

Largely due to overfishing, New England cod populations have fallen 80%–90% since the 1980s, despite multiple unsuccessful recovery plans (Meng et al., 2016). One substantial management change occurred in 2010, when Amendment 16 to the Northeast Multispecies Fisheries Management Plan shifted recovery efforts from input controls (e.g., limiting days at sea) to output controls (e.g., the sector management program; [Murphy et al., 2018]). The sector management program allows trading of fishing rights within the constraints of a total allowable catch (TAC). When the TAC is potentially limiting for a particular stock, it drives the lease price higher for that stock (Hatcher, 2022). This system created incentives to avoid or discard species due to high-cost quota lease prices of low-quota, overfished stocks. For example, during the 2010s, 2015 featured the largest economic incentive to attribute Gulf of Maine cod (*Gadus morhua*) landings to Georges Bank after prices spiked in response to a 75% reduction in the Gulf of Maine quota (Figures 3 & 4). This study builds on a Northeast Fisheries Science Center (NEFSC) evaluation of potential misallocation (described below) to evaluate the correlation between fishery observer presence and the probability and magnitude of apparent reporting error for cod landings between 2010 and 2019.

The sector management system allows groups of fishermen to pool quotas associated with their permits, and they take joint and several liability for staying within their allocated quota. The system allowed sectors flexibility for utilizing quota and fisher autonomy, but it also required additional monitoring and reporting requirements to ensure that fishing activity was properly tracked and managed (Clay et al., 2014). Fishery observer coverage has varied over the years but is expected to increase given recent NMFS regulations that call for up to 100% observer coverage.

**Figure 3**

*Gulf of Maine cod quota lease price difference ($/pound) from Georges Bank*

Quota lease price between 2010 and 2020.

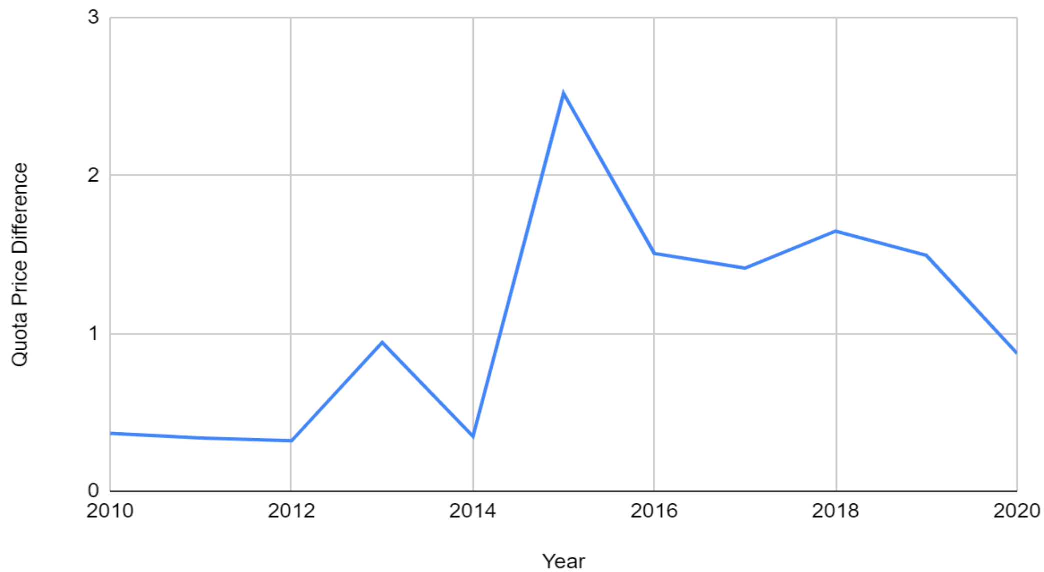


**Figure 4**

*Gulf of Maine and Georges Bank cod and haddock annual catch limits and landings*

Gulf of Maine (GOM, left column) and Georges Bank (GB, right column) cod (Gadus morhua, top row) and haddock (Melanogrammus aeglefinus, bottom row) catches (blue lines) and sector annual catch limit (Sub-ACL) (red lines) between 2010 and 2022 (note: 2022 is a partial year).

**Table 7**

*Summary of the New England groundfish fishery.*

Active permits in New England groundfish sectors and number of trips, cod landings, and fishing time from single- and multi-area trips that landed cod.

| | | Trips Landing Cod | | | | | |
|---|---|---|---|---|---|---|---|
| **Year** | **Active Permits** | **Single-Area Trips** | **Multi-Area Trips** | **Single-Area Cod Landings (lbs)** | **Multi-Area Cod Landings (lbs)** | **Single-Area Fishing Time (Hours)** | **Multi-Area Fishing Time (Hours)** |
| 2010 | 305 | 8,456 | 901 | 10,033,639 | 3,048,202 | 102,893 | 69,306 |
| 2011 | 302 | 8,084 | 1,109 | 9,321,604 | 6,010,753 | 82,047 | 93,332 |
| 2012 | 303 | 8,475 | 1,006 | 5,769,130 | 3,603,001 | 87,839 | 101,306 |
| 2013 | 245 | 5,586 | 969 | 2,504,524 | 2,017,341 | 84,654 | 94,271 |
| 2014 | 230 | 4,888 | 891 | 2,455,032 | 2,349,233 | 84,078 | 87,142 |
| 2015 | 213 | 3,170 | 753 | 1,235,601 | 1,717,886 | 70,409 | 68,452 |
| 2016 | 210 | 3,104 | 687 | 1,188,400 | 1,251,427 | 53,991 | 60,963 |
| 2017 | 200 | 2,949 | 610 | 748,438 | 656,641 | 48,945 | 52,303 |
| 2018 | 179 | 3,313 | 579 | 1,030,937 | 864,158 | 48,822 | 46,050 |
| 2019 | 168 | 3,148 | 584 | 992,330 | 1,001,151 | 53,899 | 43,744 |
| 2020 | 173 | 2,894 | 562 | 746,795 | 596,929 | 60,588 | 47,312 |
| 2021 | 132 | 2,719 | 591 | 484,175 | 606,841 | 44,391 | 51,771 |

The number of vessels that have been active in the sector system has fallen by over half since sectors were first implemented in 2010. In the first three years, over 300 vessels participated, but by 2021, there were just 132 active vessels (GARFO, Table 7). Relatedly, annual hours fished and the total number of trips that landed cod also fell between 2010 and 2021 (Table 7).

***Catch Reporting Error***

In the New England groundfish fishery, inaccurate trip reporting is thought to introduce systematic error into stock assessments, thus necessitating a management "uncertainty buffer," which introduces economic inefficiency into the management process (NMFS, 2021a). Stock area misallocation is a significant source of error (Palmer, 2017; Palmer and Wigley, 2009; USCG, 2021) because several groundfish species are managed using multiple stock areas under an umbrella of an individual transferable quota system. Different, area-specific quota values for the same species create an economic incentive to inaccurately report the stock area from which fish are caught. Absent an observer onboard, the stock area from which fish are caught is entirely self-reported. Misallocation of stock area comes in (at least) two forms. First, vessels are legally required to record only the area in which that catch is brought on board, regardless of where fishing effort took place (GARFO, 2022). Second, it is possible to self-report catches from areas where they fished little or not at all (Palmer, 2017; Palmer and Wigley, 2009; USCG, 2021).

Reporting error is particularly problematic in stock areas where the catch is near the limit, as is the case for Gulf of Maine cod (Figure 4). In the multi-species New England groundfish fishery, constraining stocks, or those near the limit that can "choke" fishing for other target species, are associated with increased quota lease prices that provides incentive to misallocate. Compliance with reporting requirements can be costly for fishers because accurate catch reporting accelerates the rate at which quota for certain fish stocks becomes scarce, theoretically increasing either the costs of leasing additional quota or the costs of avoiding those fish (or both) (Lee, in prep.). Therefore, in addition to improving the quality of data and stock assessments, compliance with catch and fishing area reporting requirements is a fairness issue because violators can put compliant harvesters at a competitive disadvantage. However, enforcement of accurate location reporting is nearly impossible due to the vastness of the area, so observer coverage or video monitoring is necessary to determine the extent of reporting error and potentially reduce it (Ardini et al., 2020; USCG, 2021).

***Observer Effects***

Fishery observers in New England are hired by contracting companies and funded by the industry or NOAA to collect unbiased data to inform scientific research and stock assessments. They have no formal role in law enforcement in New England, but they are responsible for monitoring and recording information about fishing effort (e.g., gear and location), fish catches, and bycatch (de Bianchi, 2013). Fishery observers are deployed by NOAA on a stratified random sample of groundfish trips to estimate discards and collect data on bycatch of non-targeted species. Discard rates from observed trips are scaled to unobserved trips and combined with landings to assess whether catch limits have been reached. However, there is evidence that fishers behave differently when a fishery observer is onboard compared to unobserved trips; this is known as the observer effect (Benoît and Allard, 2009; Demarest, in prep.) and entails differences in fishing location and trip length. To address the potential bias in discard rates due to the observer effect, recently approved management measures in Amendment 23 (NMFS, 2021b) call for both 100% observer coverage, contingent on federal funds, after over a decade of sub-40% coverage as well as reduction of the management uncertainty buffer if all trips are observed.

According to the observer effect, observers have been shown to affect fishing behavior, such as location selection and length of time fishing (Benoît and Allard, 2009; Demarest, in prep.). Although the observer effect may seem obvious, Porter (2010) found that less than 30% of law enforcement officers in the Northeast agreed that “Although observers are not involved in enforcement, their presence aboard a vessel affects fishery practices in ways that reduce violations of fishery regulations.” In other words, the law enforcement officers in the region do not believe in the observer effect.

Observers have no enforcement responsibilities in the study region. Their only role is to record catch and fishing effort information, and there is a reluctance to involve observers in enforcement given their already-dangerous task of objectively recording fishing activities and being subject to frequent resistance from certain fishers. However, observers are trained in enforcement and required to report illegal activity in other regions like the North Pacific, though it is exceedingly rare for a prosecution to rely on observer data (Porter, 2010). Only twice in the New England region (GARFO, pers. comms.) has observer information been used to prosecute a case, and this rarity may limit the deterrence effect of observers. Despite the potential importance of the observer effect for the New England cod fishery, analysis of the VTR and VMS data for evidence of an observer effect has not yet been conducted.

The purpose of this chapter is to estimate the magnitude of the observer effect on reporting behavior. Specifically, the chapter tests the null hypothesis that the presence of an observer has no effect on the probability of apparent misallocation as well as the amount of cod reported as Georges Bank that were actually caught during fishing activities in the Gulf of Maine.

## Methods

### *Data Sources and Preparation*

The NEFSC provided the 2010–2019 dataset (n = 161,989) for this study, which included vessel monitoring system (VMS) effort and vessel trip reports (VTR) catch proportions by area; total landings in pounds; observer presence; a flag for suspect trips (described below); fishing date, gear, and vessel length at the trip; and species. VTRs include self-reported catch and trip information (e.g., landings, fishing location, gear, etc.) and are required for all groundfish trips. Separately, the Northeast Fisheries Observer Program (NEFOP) assigns fishery observers to a stratified random sample of trips through the Pre-trip Notification System to monitor catch, discards, and protected species interactions (GARFO, 2022).

In addition to carrying an observer when randomly selected, all groundfish trips require hourly VMS positions, that can be converted to average vessel speeds (i.e., distance traveled between pings/hours between pings). However, vessels not traveling in a straight line could lead to underestimates of fishing activity (Mills et al., 2007; Watson and Haynie 2016). To determine vessel speeds associated with fishing activities, Palmer and Wigley (2009) used high-frequency GPS on vessels through cooperative research projects to identify gear-specific fishing speeds (trawl gear 2-4 knots, gillnets 0.1-1.3 knots, longlines 0.1-1.3 knots). A full explanation of NEFSC VMS analysis methodology is available (Palmer, 2017; Palmer and Demarest, 2018; Palmer and Wigley, 2009), but using fishing speed estimates, the NEFSC was able to infer fishing activities (time traveling at fishing speed) by area for all groundfish trips. VMS-based proportions of time fishing (the ratio of time traveling at fishing speed in a particular area relative to total time traveling at fishing speed on the trip) per area were compared to the catch composition (i.e., proportion of species from each area) that was self-reported in the VTRs.

Separately, NEFOP data were compared to validate each catch allocation method by Palmer and Wigley (2009). All sources are likely to introduce some form of error, but the NEFOP measurement and reporting techniques are standardized to minimize error and are considered the most accurate data available to document likely catch areas. Palmer (2017) compared the consistency of VMS-inferred and VTR-self-reported fishing activities to NEFOP data and found that VMS-inferred fishing locations were in complete agreement with observer data 65.5% of the time, while VTR data were in complete agreement with NEFOP just 14.4% of the time..

The NEFSC comparison of VMS-inferred effort across areas to VTR catch area composition provided the basis for the linear mixed models presented here. Model response variables were 1) ***PropDiff***, or the difference between proportion of fishing effort in each area from VMS-based analysis and the proportion of the catch of that species in that area reported in the VTRs; and 2) the binary ***'Suspect'*** trips, which were flagged in apparent cases of misallocation. A trip is considered 'suspect' for a given species-area combination if ***PropDiff*** is greater than either the VTR-reported catch proportion/1.25 or the VMS-inferred fishing time proportion/1.25 (Figure 5). NEFSC selected 1.25 as a threshold based on visual inspection of several factors to reduce false positives. Based on these definitions, the number of suspect trips were 3562, or 55% of the multiarea trips that landed cod.

This study focuses on misallocation between stock areas, so only the four following multi-stock species were included: Atlantic cod, haddock, winter flounder (*Pseudopleuronectes americanus*), and yellowtail flounder (*Limanda ferruginea*) (Figure 6). Single-stock species—namely windowpane flounder (*Scophthalmus aquosus*), silver hake (*Merluccius bilinearis*), and red hake (*Urophycis chuss*)—were removed. Monkfish *Lophius americanus* are managed through a different fishery management plan, so those records were also removed. Moreover, under-reporting across stock areas was not expected for single-area trips, so those records were not included. This assumption could be violated on trips that had 100% misallocation – fished in one area and reported in another. Given the significant economic incentive to strategically report Gulf of Maine cod as Georges Bank cod, this study focused only on multi-area trips that landed Gulf of Maine cod (Table 7).

Because this study evaluated data reporting errors spanning the period before and after the arrest of “the Codfather,” Carlos Rafael, a self-described “pirate” convicted in 2016 of mislabeling large quantities of seafood, it includes an explanatory variable for the permits associated with Mr. Rafael and his wife between 2010 and 2016. It was hypothesized that his vessels would be significantly more likely to be flagged as suspect for area misallocating.

**Figure 5**

*Scatter plot of Gulf of Maine cod suspect trips*

The proportion of the time fished (VMS Time Proportion) and the proportion of the catch reported (VTR Catch Proportion) in the Gulf of Maine for Atlantic cod (n = 6,450). Red dots are considered 'suspect,' and green dots are not. The 1:1 black line represents perfect correlation between fishing time and catch proportion.

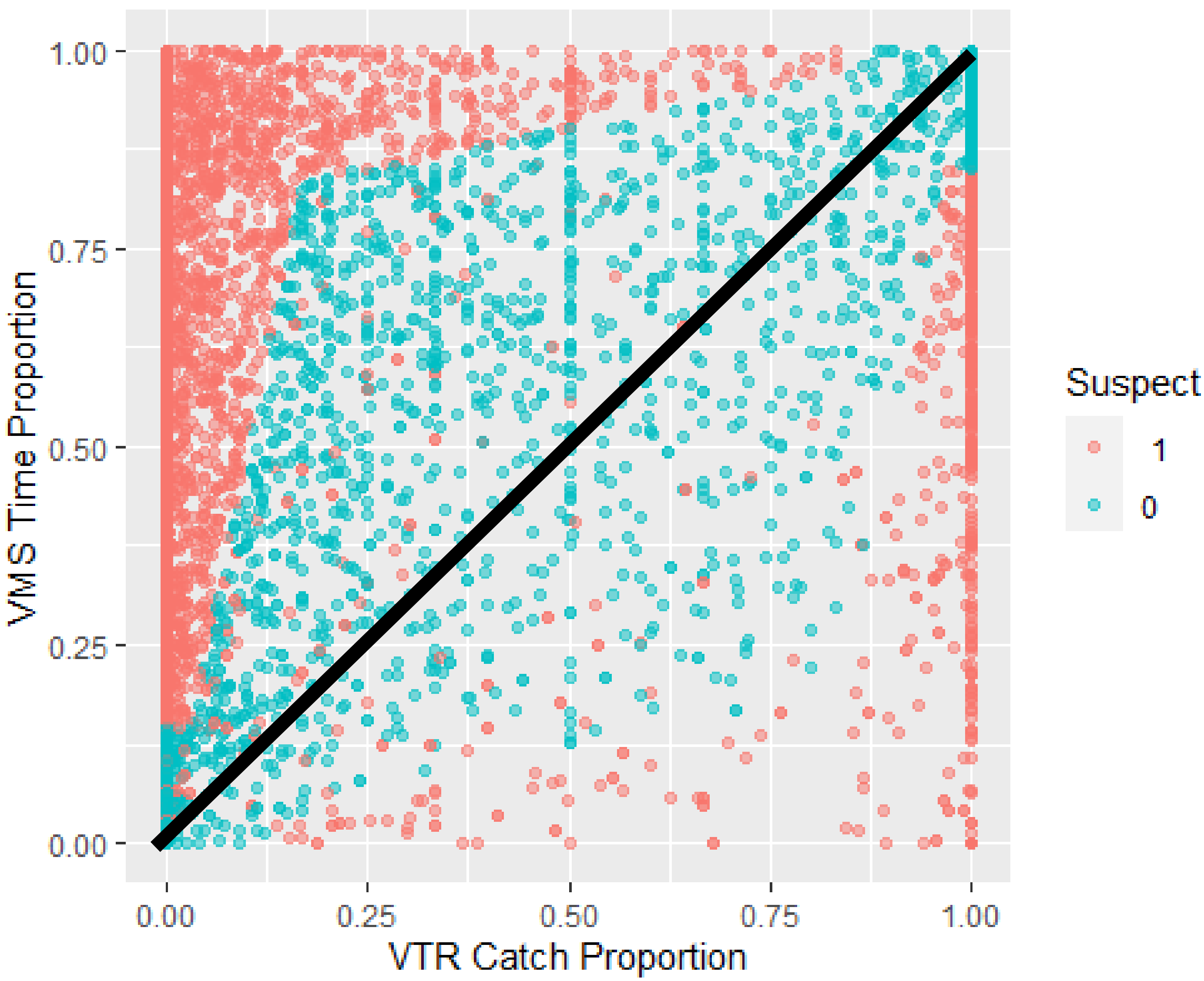
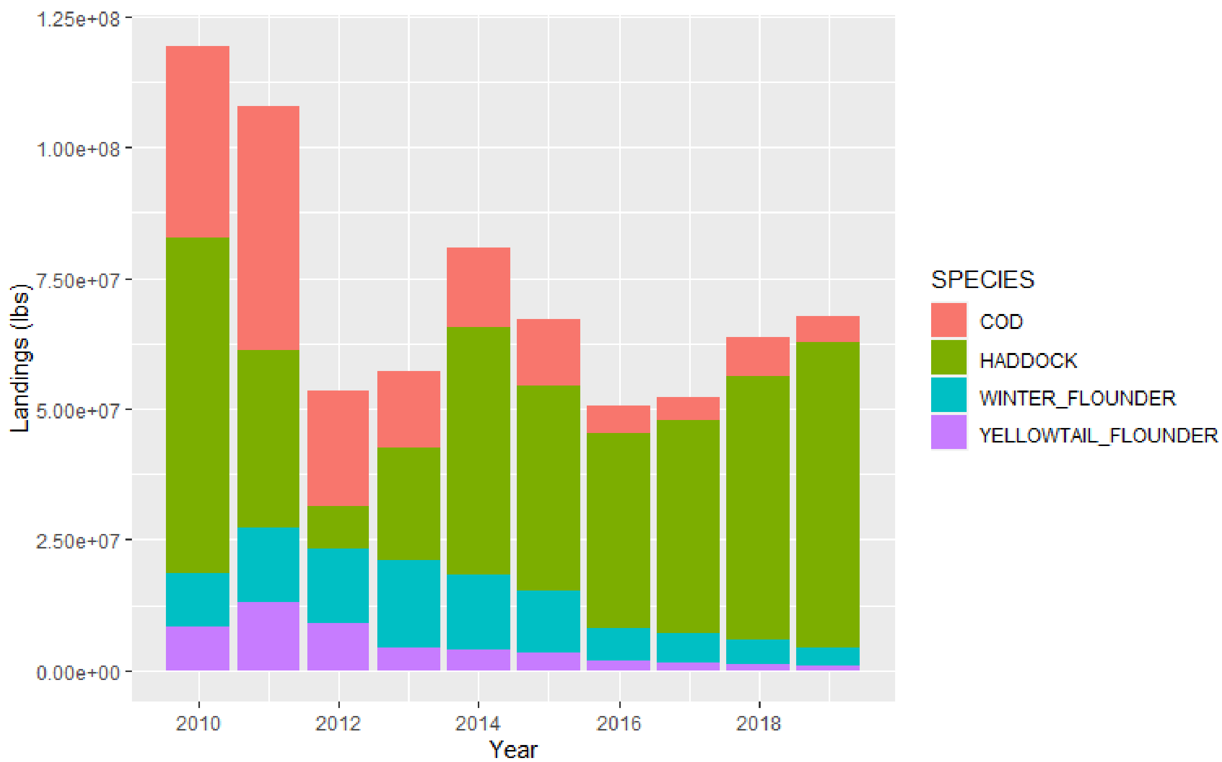


**Figure 6**

*2010 to 2019 landings of the four multi-area New England groundfish stocks.*




### *Mixed Effects Models*

Linear mixed models explicitly account for correlation across repeated and unbalanced measures clustered by individuals (Helser et al., 2004; Thorson and Minto, 2015). In this case, reporting behaviors are correlated across trips by individual fishers (and potentially within sectors), so permit ID and sector ID were treated as random effects. Other explanatory variables considered (i.e., categorical variables for observer presence, fishing year**,** fishing quarter, vessel length, and Carlos Rafael vessels) were treated as fixed effects in the linear mixed effects model constructed in R 4.2.1.

The generic mixed effects model was

$$y = X\beta + \mathrm{Z}b + \varepsilon \qquad \text{Equation 5}$$

where $y$ are n x 1 vectors of response variable *PropDiff*. $X$ is a (n x p) matrix of first-column 1s followed by p-1 fixed-effect explanatory variables. $\beta$ is an n x 1 vector of fixed-effect coefficients. $Z$ is the $n$ x $q$ matrix of random effects for each permit, and $b$ is the $q$ x 1 random-effect coefficients for each permit. $\varepsilon$ is an $n$ x 1 vector of normally distributed errors.

For the dependent variable *Suspect* (binary, following a binomial distribution) given observer presence, we started with a saturated model that included all the fixed effects listed above. Fishing quarter (p = 0.07), the Carlos Rafael permit categorical variable (p = 0.48), and vessel length (p = 0.06) were removed during backward stepwise regression (fixed effects with p-values > 0.05 were eliminated). For trip i of permit j, the final binomial logit model with a link function of the log-odds of a trip being suspect is a function of observer presence and fishing year:

$$\mathrm{P}\{\mathrm{suspect} = 1\}_{ij} = b_{0j} + \beta_1 year + b_{1j} observer + \varepsilon_{ij}$$

$$b_{0j} = \gamma_{00} + u_{oj}$$

$$b_{1j} = \gamma_{10} + u_{1j}$$

Equation 6

where the permit-specific intercepts $b_{0j}$ are the sum of the average intercept $\gamma_{00}$ and the random intercept $u_{oj}$. The permit-specific observer effects are the sum of the average observer effect $\gamma_{10}$ and a random effect $u_{1j}$. The year effect, $\beta_1$, is fixed across permits. For the binomial logit model, coefficients represent log-odds, so a transformation - exp(ln(odds)) / (1 + exp(ln(odds))) - is necessary to estimate probabilities.

For the dependent variable of proportion difference (continuous variable), backward stepwise regression was also used to formulate the final model. The Carlos Rafael flag ($p = 0.51$) and vessel length ($p = 0.66$) were again removed, but the fishing quarter remained. Thus, the proportion difference refers to the VMS-based proportion of time fishing in the Gulf of Maine minus the VTR-based catch proportion of Gulf of Maine cod model is as follows:

$$PropDiff_{ij} = b_{0j} + \beta_1 year + \beta_2 FQ + b_{1j} observer + \varepsilon_{ij}$$

$$b_{0j} = \gamma_{00} + u_{oj}$$

$$b_{1j} = \gamma_{10} + u_{1j}$$

Equation 7

To evaluate the influence of specific permits on model results, Cook's distance was calculated for each permit to assess how the fitted values in the model change with removal of that permit. One permit had a relatively high Cook's distance of 0.52. For reference, the second highest Cook's distance was 0.10. Hence, this warranted in-depth analysis of the observations associated with that permit. Upon review, there was no reason to exclude the data associated with that permit: the levels of observer coverage (27%), suspect flags (46%), and average VMS-VTR proportions difference (22%) were in line with average values. In a sensitivity run, the permit was removed to evaluate the effect the on results.

In another sensitivity run, the effect of trips with low catches or little time spent fishing was tested by dropping trips that reported < 500 lbs. of cod landings (lowest 10% of trips) or spent less than 5% of time in the Gulf of Maine. At low catch levels, relatively few fish can substantially change the composition, so there is greater probability that a difference in proportions was noise in the data instead of misallocation.

**Results**

The analysis is divided into two parts. The first explores the probability of substantial disagreement between the VTR-reported and VMS-estimated proportions (i.e., trips identified as 'suspect,' above; see Figure 5). The second part addresses the following question for trips with a higher VMS estimate of Gulf of Maine cod landings than reported in the VTRs: how does the proportion of disagreement vary with the presence of an observer?

Both the number of 'suspect' trips and proportion of disagreement vary over time. It appears that between 2010 and 2019 the proportion difference (VMS-estimate - VTR-reported Gulf of Maine proportions) increased while the proportion of suspect trips remained relatively constant (Figure 7). The data also include error due to variation in catch rates and other sources. The cumulative distribution function (Figure 8) indicates that a small proportion of observations (20%) had overreporting (VTR Gulf of Maine cod reported landings greater than the VMS-inferred landings [values less than 0 on the x-axis]). These results are inconsistent with the economic incentive to underreport and suggest the magnitude of error in the specification of misallocation. However, the magnitude of apparent economically advantageous underreporting of Gulf of Maine cod (number of points above the black line in Figure 5 and cumulative probability of x-values to the right of 0 in Figure 8) appeared to be much larger than apparent overreporting.

Ignoring other factors, the average rate of suspect trips was 17% higher on unobserved trips between 2010 and 2019 (Figure 9). Moreover, on a density plot (Figure 10), the average misallocation (dashed vertical line) shifts to the right toward complete disagreement when no observer is present. The shift is also evident in histograms (Figure 11) of the proportion difference between VMS and VTR estimates for trips flagged as suspect (below) or not (above). Finally, a scatterplot (Figure 12) displays cod landings in pounds and proportion difference to evaluate the presence of an obvious correlation between the two variables, but points clustered above zero on the y-axis indicated a tendency to underreport across a range of landings.

The binomial model of Equation 6 and proportion difference model of Equation 7 indicated that the presence of an observer was significant in reducing the divergence between the proportion of catch coming from an area and the time spent fishing in that area.

The results from the binomial logit model (Equation 6, Table 8) indicated that the presence of an observer was significantly ($p < 0.05$) and negatively correlated with the probability of suspect reporting (Table 8). Hence, model results were consistent with hypotheses that observed trips were less likely to have errors in catch reporting. The probability of an unobserved trip being suspect was 54.8%, 95% CI [48.7%, 60.8%], but on observed trips, the probability fell to 38.2% [29.0%, 48.6%].

**Table 8**

*Results of the binomial logit models (Equation 6)*

Observer year as fixed effect, permit as second-level and sectors as third-level random effects (Nested Model); only the permit random effect variable (Full Model); and only the observer fixed effect. Bold indicates $p < 0.05$.

| | Binary - Full Nested Model | | | Binary - Full Model, No Sector ID | | | Binary - Reduced Model, Only Observer | | |
|---|---|---|---|---|---|---|---|---|---|
| *Predictors* | *Odds Ratios* | *CI* | *p* | *Odds Ratios* | *CI* | *p* | *Odds Ratios* | *CI* | *p* |
| (Intercept) | 1.21 | 0.95 – 1.55 | 0.116 | 1.1 | 0.85 – 1.43 | 0.454 | 1.05 | 0.86 – 1.28 | 0.64 |
| observer [1] | 0.51 | 0.43 – 0.61 | **<0.001** | 0.53 | 0.44 – 0.63 | **<0.001** | 0.49 | 0.43 – 0.55 | **<0.001** |
| Year [2011] | 0.97 | 0.78 – 1.20 | 0.766 | 0.99 | 0.80 – 1.22 | 0.94 | | | |
| Year [2012] | 0.79 | 0.63 – 0.99 | **0.037** | 0.79 | 0.63 – 0.98 | **0.035** | | | |
| Year [2013] | 0.98 | 0.78 – 1.21 | 0.828 | 0.96 | 0.78 – 1.20 | 0.743 | | | |
| Year [2014] | 0.65 | 0.52 – 0.82 | **<0.001** | 0.66 | 0.52 – 0.83 | **<0.001** | | | |
| Year [2015] | 1.47 | 1.14 – 1.89 | **0.003** | 1.49 | 1.18 – 1.87 | **0.001** | | | |
| Year [2016] | 0.87 | 0.67 – 1.13 | 0.295 | 0.85 | 0.66 – 1.08 | 0.191 | | | |
| Year [2017] | 0.74 | 0.56 – 0.97 | **0.031** | 0.74 | 0.57 – 0.95 | **0.02** | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Year [2018] | 1.11 | 0.85 – 1.45 | 0.452 | 1.15 | 0.90 – 1.48 | 0.27 | |
| Year [2019] | 0.77 | 0.58 – 1.02 | 0.07 | 0.81 | 0.62 – 1.06 | 0.128 | |
| **Random Effects** | | | | | | | |
| σ2 | 3.29 | | | 3.29 | | | 3.29 |
| τ00 | 0.99 SECTOR_ID:PERMIT | | | 1.00 PERMIT | | | 0.90 PERMIT |
| τ11 | 0.13 SECTOR_ID:PERMIT.observer1 | | | 0.13 PERMIT.observer1 | | | |
| ρ01 | -0.57 SECTOR_ID:PERMIT | | | -0.63 PERMIT | | | |
| ICC | 0.22 | | | 0.22 | | | 0.21 |
| N | 16 SECTOR_ID<br>137 PERMIT | | | 137 PERMIT | | | 137 PERMIT |
| Observations | 6450 | | | 6450 | | | 6450 |
| Marginal R2 / Conditional R2 | 0.030 / 0.243 | | | 0.029 / 0.242 | | | 0.022 / 0.232 |
| Parameters | 14 | | | 14 | | | 3 |

| | | | |
|---|---|---|---|
| AIC | 8200.4 | 8227 | 8279.2 |
| BIC | 8295.2 | 8321.8 | 8299.5 |
| logLik | -4086.2 | -4099.5 | -4136.6 |
| Deviance | 8172.4 | 8199 | 8273.2 |

**Table 9**

*Results of the proportion difference models (Equation 7)*

**O**bserver, year, and fishing quarter as fixed effects and permit as second-level and sectors as third-level random effects (Nested Model); only the permit random effect variable (Full Model);

| | **% Difference - Full Nested Model** | | | **% Difference - Full Model, No Sector ID** | | | **% Difference - Reduced Model, Only Observer** | | |
|---|---|---|---|---|---|---|---|---|---|
| *Predictors* | *Estimates* | *CI* | *p* | *Estimates* | *CI* | *p* | *Estimates* | *CI* | *p* |
| (Intercept) | 0.27 | 0.23 – 0.32 | **<0.001** | 0.26 | 0.21 – 0.31 | **<0.001** | 0.35 | 0.32 – 0.39 | **<0.001** |
| observer [1] | -0.08 | -0.10 – -0.05 | **<0.001** | -0.07 | -0.10 – -0.05 | **<0.001** | -0.09 | -0.11 – -0.06 | **<0.001** |
| Year [2011] | 0.03 | -0.00 – 0.06 | 0.065 | 0.03 | 0.00 – 0.06 | **0.041** | | | |
| Year [2012] | 0 | -0.04 – 0.03 | 0.821 | 0 | -0.04 – 0.03 | 0.859 | | | |
| Year [2013] | 0.06 | 0.03 – 0.09 | **<0.001** | 0.05 | 0.02 – 0.08 | **0.001** | | | |
| Year [2014] | -0.04 | -0.07 – -0.00 | **0.025** | -0.04 | -0.07 – -0.00 | **0.024** | | | |
| Year [2015] | 0.11 | 0.08 – 0.14 | **<0.001** | 0.1 | 0.07 – 0.13 | **<0.001** | | | |
| Year [2016] | 0.11 | 0.07 – 0.14 | **<0.001** | 0.09 | 0.06 – 0.13 | **<0.001** | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Year [2017] | 0.1 | 0.06 – 0.14 | **<0.001** | 0.09 | 0.05 – 0.12 | **<0.001** | | | |
| Year [2018] | 0.15 | 0.12 – 0.19 | **<0.001** | 0.15 | 0.12 – 0.18 | **<0.001** | | | |
| Year [2019] | 0.09 | 0.05 – 0.13 | **<0.001** | 0.09 | 0.05 – 0.12 | **<0.001** | | | |
| FQ [2] | -0.04 | -0.07 – -0.02 | **<0.001** | -0.04 | -0.06 – -0.02 | **<0.001** | | | |
| FQ [3] | 0.02 | 0.00 – 0.04 | **0.036** | 0.03 | 0.01 – 0.05 | **0.013** | | | |
| FQ [4] | 0.07 | 0.05 – 0.09 | **<0.001** | 0.07 | 0.05 – 0.09 | **<0.001** | | | |
| **Random Effects** | | | | | | | | | |
| σ2 | 0.06 | | | 0.06 | | | 0.06 | | |
| τ00 | 0.04 SECTOR_ID:PERMIT | | | 0.04 PERMIT | | | 0.04 SECTOR_ID:PERMIT | | |
| τ11 | 0.01 SECTOR_ID:PERMIT.observer1 | | | 0.01 PERMIT.observer1 | | | 0.01 SECTOR_ID:PERMIT.observer1 | | |
| ρ01 | -0.77 SECTOR_ID:PERMIT | | | -0.87 PERMIT | | | -0.88 SECTOR_ID:PERMIT | | |
| ICC | 0.38 | | | 0.37 | | | 0.35 | | |
| N | 15 SECTOR_ID | | | 121 PERMIT | | | 15 SECTOR_ID | | |
| | 121 PERMIT | | | | | | 121 PERMIT | | |
| Observations | 4981 | | | 4981 | | | 4981 | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Marginal R2 / Conditional R2 | 0.065 / 0.423 | | | 0.062 / 0.406 | | | 0.012 / 0.357 | | |
| Parameters | 18 | | | 18 | | | 6 | | |
| AIC | 529.28 | | | 581.5 | | | 801.58 | | |
| BIC | 646.52 | | | 698.74 | | | 840.66 | | |
| logLik | -246.64 | | | -272.75 | | | -394.79 | | |
| Deviance | 493.28 | | | 545.5 | | | 789.58 | | |

**Figure 7**

*Annual proportions of suspect trips and VMS-VTR differential*

Annual proportions of trips identified from empirical data as suspect and the proportion difference (VMS proportion of fishing time - VTR proportion of catch) between allocations of time fished and catch proportion.

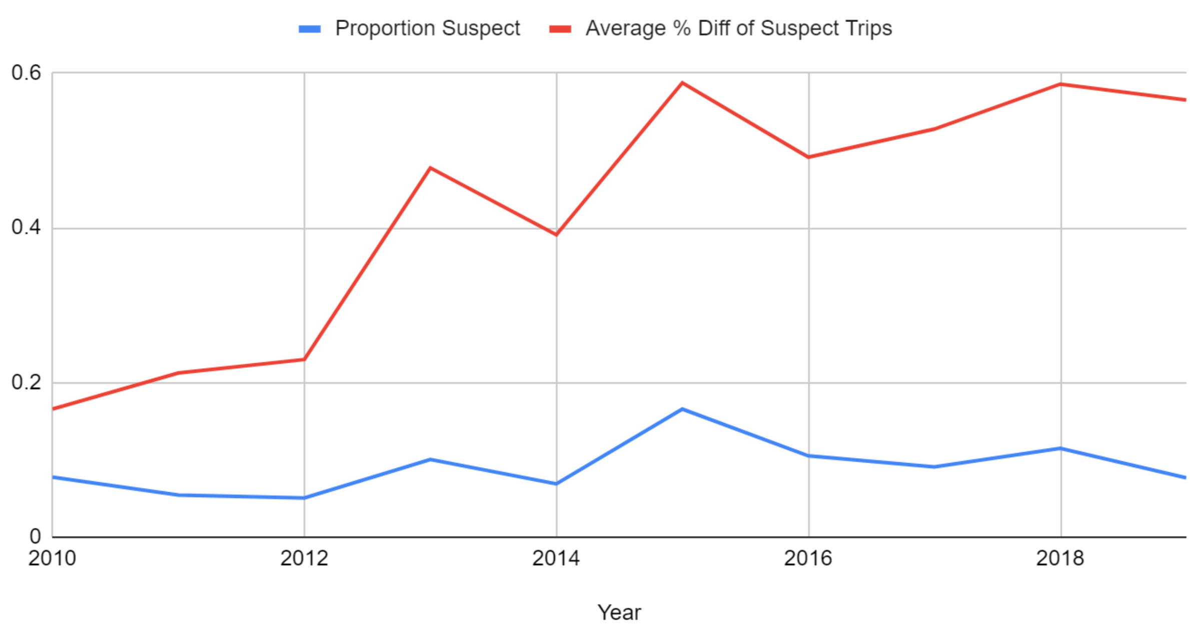


**Figure 8**

*Proportion difference cumulative distribution function*

Gulf of Maine Cod Multiarea Trips VMS proportion of fishing time - VTR proportion of catch.

Proportion difference > 0 indicates overreporting of cod in the Gulf of Maine.

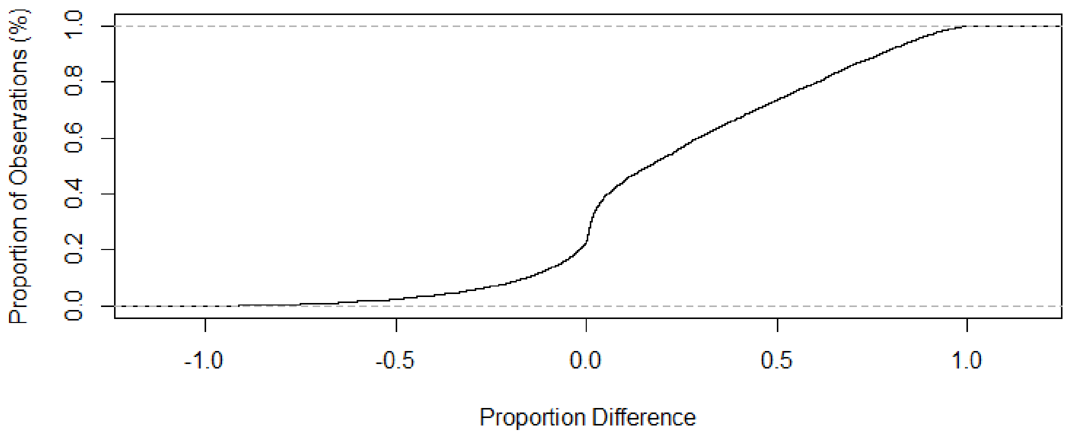


**Figure 9**

*Suspect trips with and without observers*

Proportion of Multi-Area Gulf of Maine cod (n = 6,450) ‘Suspect’ unobserved (x = 0) and observed (x = 1) trips.

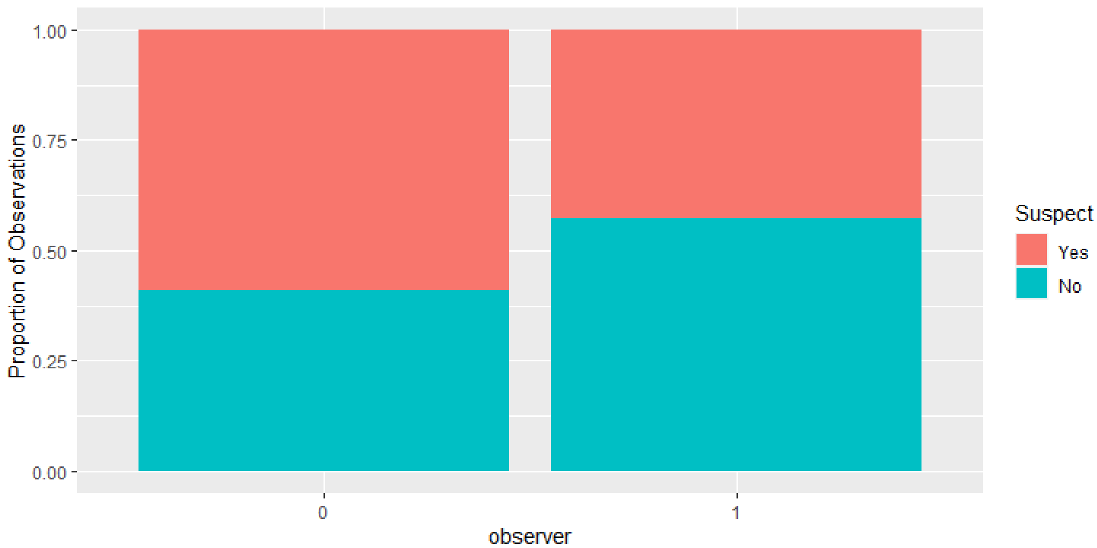


**Figure 10**

*Density plot of estimated reporting error for observed and unobserved trips*

VMS % of time in area - VTR % of catch from area for trips with apparent under-reporting (n = 4,981) with (n = 1,058) and without (n = 3,923) an observer. Vertical lines indicate the mean proportion difference.

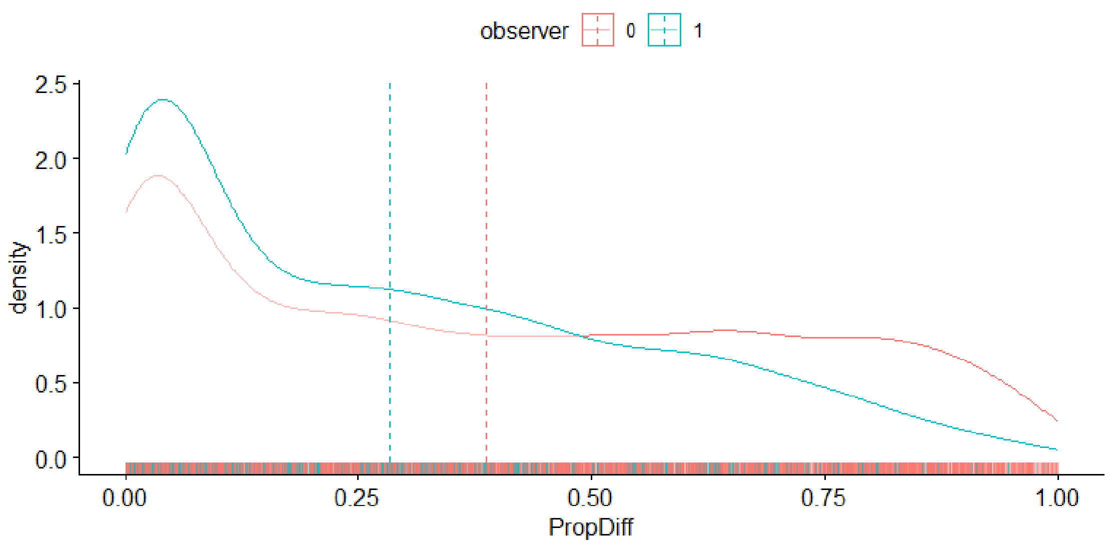


**Figure 11**

*Histograms of proportion difference for non-suspect and suspect trips*

VMS proportion of fishing time - VTR proportion of catch for multi-area Gulf of Maine cod trips for non-suspect (top, n = 2,888) and suspect (bottom, n = 3,562) trips.

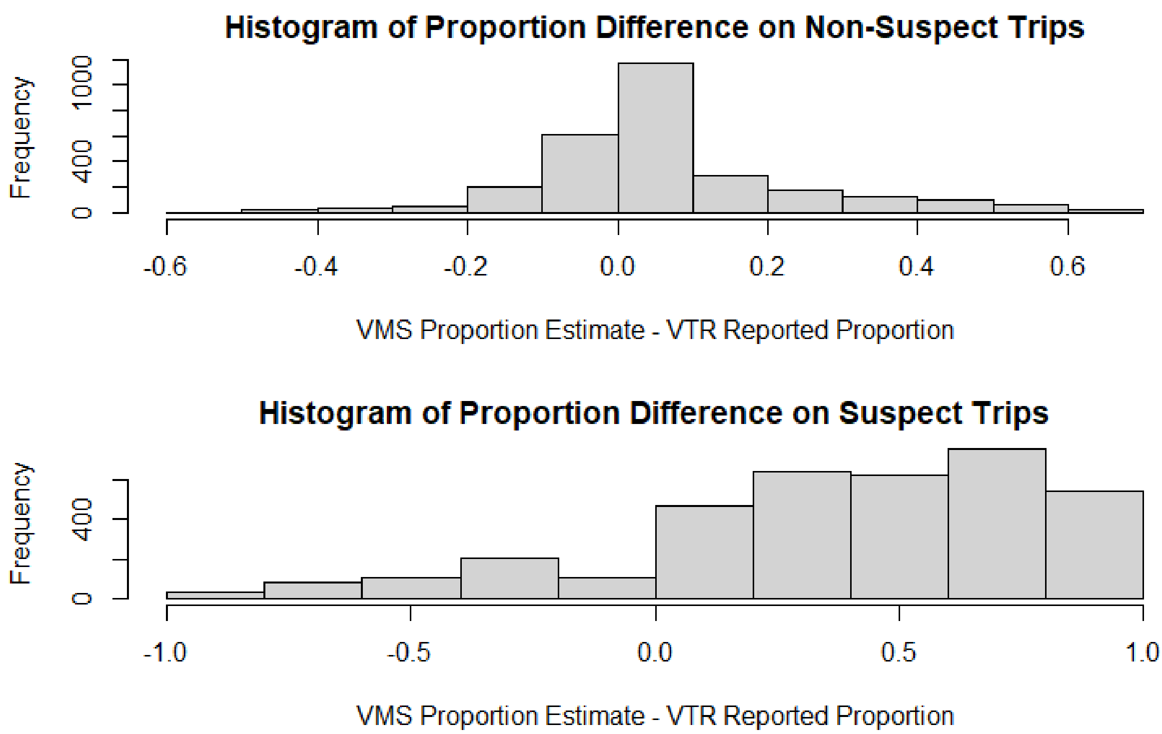
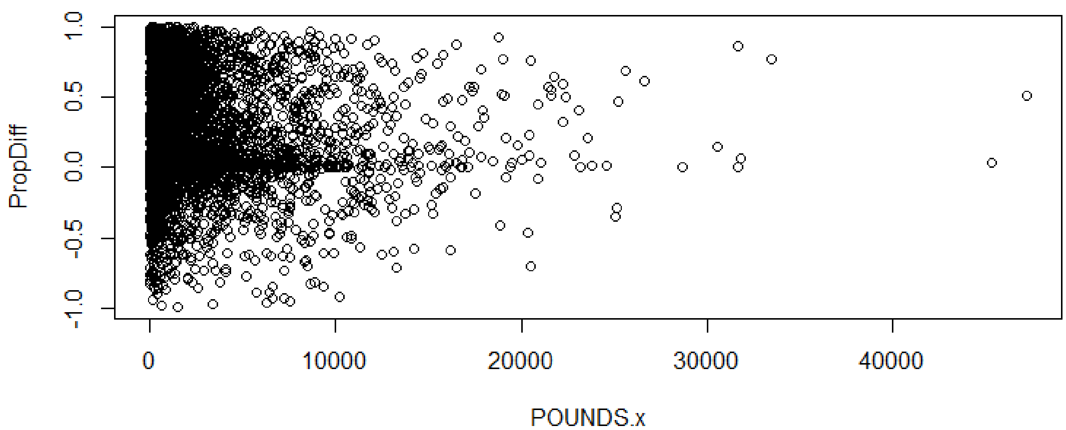


**Figure 12**

*Proportion difference between VMS and VTR proportions by landings*




The difference in proportion of landings across areas in multiarea trips was significantly smaller on trips with an observer relative to trips without an observer (Table 9). That means that apparent reporting errors are smaller, on average, when an observer is present. The proportion of catch misallocated from Gulf of Maine to Georges Bank was estimated to be 27% [95% CI 23%, 32%] on average for trips without observers but dropped by an average of 8% [95% CI 5%, 10%] to 19% misallocation with an observer present.

In both models, the permit random effects nested within sectors had lower AIC values than models that excluded sectors or models with observer presence as the only fixed effect, as measured by AIC, BIC, and Log Likelihood (Tables 8 & 9). The intercept of the nested binomial logit model was not significantly different than 1 ($p = 0.116$), so the suspect flag on a multi-area trip was essentially a coin toss with a 95% confidence interval between 49% and 61%.

Sensitivity tests were consistent with the negative correlation between apparent misallocation and observer coverage. Both models were robust to the sensitivity analyses. Removing the trips with < 500 lbs of cod did not change the significance of the results that the presence of an observer significantly reduced the probability of a trip having substantial difference between the VMS and VTR estimates and the magnitude of the difference (Table 10). Similarly, the observer effect was significant with or without the highly influential permit value (Table 11).

**Table 10**

*Nested models without low catch records*

Results after excluding observations with < 500 lbs. of cod landed and < 5% of time spent in the Gulf of Maine, according to the VMS analysis.

| | **Binomial Logit (Nested)** | | | **Proportion Difference (Nested)** | | |
|---|---|---|---|---|---|---|
| *Predictors* | *Odds Ratios* | *CI* | *p* | *Estimates* | *CI* | *p* |
| (Intercept) | 1.83 | 1.41 – 2.37 | **<0.001** | 0.08 | 0.03 – 0.12 | **0.003** |
| observer [1] | 0.47 | 0.39 – 0.57 | **<0.001** | -0.12 | -0.15 – -0.08 | **<0.001** |
| Year [2011] | 0.88 | 0.69 – 1.12 | 0.306 | 0.05 | 0.01 – 0.08 | **0.008** |
| Year [2012] | 0.75 | 0.57 – 1.00 | **0.046** | 0.04 | -0.00 – 0.08 | 0.05 |
| Year [2013] | 1.34 | 1.01 – 1.78 | **0.046** | 0.25 | 0.21 – 0.29 | **<0.001** |
| Year [2014] | 0.8 | 0.59 – 1.08 | 0.148 | 0.18 | 0.13 – 0.22 | **<0.001** |
| Year [2015] | 2.34 | 1.67 – 3.28 | **<0.001** | 0.34 | 0.29 – 0.38 | **<0.001** |
| Year [2016] | 0.98 | 0.69 – 1.41 | 0.926 | 0.25 | 0.20 – 0.30 | **<0.001** |

| | | | | | | |
|---|---|---|---|---|---|---|
| Year [2017] | 0.74 | 0.50 – 1.07 | 0.111 | 0.27 | 0.21 – 0.32 | **<0.001** |
| Year [2018] | 2.26 | 1.57 – 3.24 | **<0.001** | 0.37 | 0.32 – 0.42 | **<0.001** |
| Year [2019] | 1.32 | 0.89 – 1.97 | 0.167 | 0.33 | 0.27 – 0.38 | **<0.001** |
| FQ [2] | | | | 0 | -0.04 – 0.03 | 0.931 |
| FQ [3] | | | | 0.06 | 0.03 – 0.09 | **<0.001** |
| FQ [4] | | | | 0.09 | 0.05 – 0.12 | **<0.001** |
| **Random Effects** | | | | | | |
| σ2 | 3.29 | | | 0.1 | | |
| τ00 | 0.66 SECTOR_ID:PERMIT | | | 0.02 SECTOR_ID:PERMIT | | |
| τ11 | 0.14 SECTOR_ID:PERMIT.observer1 | | | 0.01 SECTOR_ID:PERMIT.observer1 | | |
| ρ01 | -0.93 SECTOR_ID:PERMIT | | | -0.59 SECTOR_ID:PERMIT | | |
| ICC | 0.15 | | | 0.19 | | |
| N | 15 SECTOR_ID | | | 15 SECTOR_ID | | |
| | 109 PERMIT | | | 109 PERMIT | | |
| Observations | 3786 | | | 3786 | | |
| Marginal R2 / Conditional R2 | 0.067 / 0.203 | | | 0.173 / 0.327 | | |

**Table 11**

*Nested models without influential permit.*

To examine the influence of a permit with a relatively high Cook's distance, that permit was excluded and the nested models were estimated without it.

| | Binomial Logit (Nested) | | | Proportion Difference (Nested) | | |
|---|---|---|---|---|---|---|
| *Predictors* | *Odds Ratios* | *CI* | *p* | *Estimates* | *CI* | *p* |
| (Intercept) | 1.4 | 1.02 – 1.93 | **0.037** | 0.28 | 0.24 – 0.33 | **<0.001** |
| observer [1 | 0.42 | 0.34 – 0.53 | **<0.001** | -0.07 | -0.10 – -0.05 | **<0.001** |
| Year [2011 | 1.29 | 0.96 – 1.73 | 0.087 | 0.03 | -0.01 – 0.06 | 0.129 |
| Year [2012 | 0.91 | 0.67 – 1.23 | 0.539 | -0.01 | -0.04 – 0.03 | 0.682 |
| Year [2013 | 1.28 | 0.96 – 1.69 | 0.093 | 0.05 | 0.02 – 0.08 | **0.003** |
| Year [2014 | 0.74 | 0.55 – 0.99 | **0.044** | -0.04 | -0.08 – -0.01 | **0.008** |
| Year [2015 | 1.67 | 1.22 – 2.30 | **0.002** | 0.08 | 0.04 – 0.11 | **<0.001** |
| Year [2016 | 1.23 | 0.87 – 1.74 | 0.245 | 0.09 | 0.05 – 0.13 | **<0.001** |
| Year [2017 | 0.78 | 0.54 – 1.12 | 0.174 | 0.07 | 0.03 – 0.11 | **0.001** |
| Year [2018 | 1.48 | 1.04 – 2.09 | **0.028** | 0.12 | 0.09 – 0.16 | **<0.001** |
| Year [2019 | 1 | 0.69 – 1.45 | 0.996 | 0.06 | 0.02 – 0.11 | **0.002** |
| FQ [2 | | | | -0.04 | -0.06 – -0.01 | **0.002** |
| FQ [3 | | | | 0.02 | 0.00 – 0.05 | **0.04** |
| FQ [4 | | | | 0.07 | 0.05 – 0.09 | **<0.001** |
| **Random Effects** | | | | | | |
| σ2 | 3.29 | | | 0.06 | | |
| τ00 | 1.42 SECTOR_ID:PERMIT | | | 0.04 SECTOR_ID:PERMIT | | |
| τ11 | 0.30 SECTOR_ID:PERMIT.observer1 | | | 0.01 SECTOR_ID:PERMIT.observer1 | | |
| ρ01 | -0.59 SECTOR_ID:PERMIT | | | -0.82 SECTOR_ID:PERMIT | | |

| | | |
|---|---|---|
| ICC | 0.29 | 0.39 |
| N | 15 SECTOR_ID | 15 SECTOR_ID |
| | 120 PERMIT | 120 PERMIT |
| Observations | 4638 | 4638 |
| Marginal R2 / Conditional R2 | 0.041 / 0.317 | 0.054 / 0.420 |

**Discussion**

This study builds on previous literature by examining whether the presence of an observer on a particular trip explains the variability in differences in area composition of VTR-reported landings and VMS-inferred fishing activities. By applying a linear mixed modeling approach to evaluate differences between VMS-inferred fishing behavior and self-reported catch, it appears that both the probability that a permit holder misallocated a substantial portion of their catch of Gulf of Maine cod and the scale of the misallocation across areas was significantly reduced with the addition of an observer, after accounting for year fixed effects and permit-level random effects. These results appear to be robust to the inclusion of low catch or low effort records as well as highly influential permit observations.

The linear mixed models used the NEFSC comparison of VMS and VTR data that included process error. The algorithm is flagging uneven effort and reporting, but given that fish are dispersed unevenly, it is an indicator of misallocation, but not a precise measure. The final ratio of 1.25, representing the ratio of the proportions of time spent to catch reported, was chosen to distinguish highly unlikely ratios while still allowing considerable deviation from the 1:1 ratio. However, given that the ratio was established with best professional judgement, it is prone to error and will likely flag legal activity as suspect when the ship is "fishing the line" (e.g., allocating substantial fishing effort in the Gulf of Maine but hauling back to and legally reporting in Georges Bank) or when ships happen to be highly successful or unsuccessful in one area.

This approach led to a small number of 'suspect' trips that apparently overreported Gulf of Maine cod that, if accurate, would run counter to economic incentives. These 'suspect' trips could be due to misallocation, mistakes (costly mistakes in the case of overreporting Gulf of Maine cod), or algorithm inaccuracy. However, the distribution of suspect trips was asymmetrical with over 80% of suspect trips appearing to underreport cod in the Gulf of Maine (Figure 11), consistent with the economic incentive to do so. Although the underreporting results suggests that the algorithm is likely to generate some false positives, the much larger proportion of suspect trips that overreport, suggest that the algorithm functions reasonably well to identify area misallocation, intentional or not.

Year effects appear more important in the proportion difference model than the binomial logit model. For the latter, the probability of a suspect flag is relatively stable across years; just four years had a significant effect at the $p = 0.05$ level: 2012, 2014, 2015, and 2017. However, the 95% confidence intervals of the 2012 and 2017 estimates almost included the odds ratio of 1. The other two years were anomalous. Emergency measures were implemented in 2014, including a 200-lb limit on cod landings and a ban on multi-area, unobserved trips (79 FR 77946, 2014), that reduced the opportunity for broad stock area misallocation. Thus, the probability of misallocation was found to be significantly lower than in 2010. In the following year of 2015, although emergency measures were eased, the annual catch limit available to sectors dropped from 810 MT to 201 MT, representing a drop of nearly 75%. Quota lease prices—and the associated economic incentive to misallocate—spiked (see Figure 3), so it is not surprising that the probability to misallocate was significantly higher in 2015.

At the same time, the proportion of apparent misallocation of Gulf of Maine cod on suspect trips was significantly higher than in 2010 in every year from 2013 to 2019 (Table 9). One possible explanation for this finding is that fishers shifted more of their effort to multi-area maneuvers that allow legal misallocation. A possible explanation for the time trend is that fishers who were intentionally and illegally misreporting (the illegal portion of misallocation) may have become bolder over time if they had not gotten caught.

The categorical variable assigned to observations from permits associated with the major mislabeling criminal syndicate headed by Carlos Rafael was not significant. Because Rafael mislabeled the species he fished, there was no need to further misallocate the area from which the fish came. The scheme allowed the Rafael operation to avoid high-cost quota by mislabeling species but not the area misallocation that this study was designed to quantify. Separately, the size of the vessel did not appear to be a significant factor in either model.

The final model was chosen using stepwise regression techniques. Stepwise regression risks can create an omitted variable problem if one or more relevant variables that are correlated with the independent variable are removed; this problem can lead to biased estimates and affect the predictive power of the model (Dunkler et al., 2014). However, the year variable should capture the changes in annual catch limits, associated economic incentives to misallocate, and other potential sources of model variance, so the risk of omitted variable bias was assumed to be low.

Future research into a correlation between quota prices and observer coverage may be relevant to discussions about the overall cost and benefits of adjusting observer coverage.

Additional observer coverage would likely lead to increased demand for Gulf of Maine cod quota and elevate the lease prices or reduced fishing in the Gulf of Maine. Hatcher (2022) found that, as might be expected, the bidding up of choke species quota prices resulted in a decrease in the price of quotas for other species. Given that this is a multi-species fishery, the net change in quota expenditures and rent generated across all species as observer coverage changes are key research questions.

This study applies a previously published analysis (Palmer, 2017; Palmer and Demarest, 2018; Palmer and Wigley, 2009) using VMS location information to infer vessel speed and that associates fishing speeds with allocation of fishing effort to different areas. The challenge is translating effort allocation to catch proportions, an analysis that requires the simplifying assumption of constant catchability (catch per unit of time) across fishing locations. Given heterogeneous habitat, oceanographic conditions, and other environmental factors, stocks are distributed unevenly, so catch rates likely vary geographically. However, when compared to self-reported data on VTRs, VMS-based landings estimates were more in line with observer data (Palmer, 2017; Palmer and Wigley, 2009). While it is likely that some of the VTRs flagged as suspect were accurate, it is also likely that the opposite is true, and the approach was selected to avoid bias in either direction. The ‘suspect’ designation was conservatively specified to identify only the largest discrepancies between reported and inferred catches to avoid bias toward false positives (Demarest, pers. comms.). As a result, just 7.5% of total landings across the NEFSC data set (including single area) were flagged as suspect. For reference, this rate is roughly half of the King and Sutinen (2010) estimates that 12%–24% of landings were illegally harvested in this fishery.

## Conclusion

Although it is not possible to provide conclusive estimates of changes in the probability or magnitude of cod stock area misallocation, the results presented here provide evidence that observers affect reporting behavior in the New England cod fishery. These findings are consistent with the presence of the observer effect that states that people often change their behavior when they are being observed. Managers and law enforcement may be able to better leverage the observer effect to ensure that quality data support the stock assessment models used to set sustainable allowable catches. With all of the potential sources of error in stock assessments, increased monitoring offers some ability to increase the accuracy of catch data. The next chapter explores the cost-effectiveness of various types of observer coverage, including the level of observer coverage that would be necessary to reduce misallocation to below 5%.

# Chapter 4: How Much Fishery Observer Monitoring Is Sufficient? Scenario Testing Using an Agent-Based Model of New England Groundfish


## Abstract

Reporting error is a problem in the New England groundfish fishery and can lead to biased population estimates and suboptimal annual catch limits. To reduce reporting error, managers are increasing fishery observer coverage, but there is debate on the level of coverage necessary. An agent-based model (ABM) was used to simulate a range of observer coverage levels and the potential outcomes of each level. ABMs allow managers to test for potential emergent outcomes from the complex actions and interactions of heterogeneous agents in coupled human–environmental systems and can be particularly useful when spatial dynamics are important. The ABM described here combines simple population dynamics models of Gulf of Maine and Georges Banks haddock and cod with an adaptive fishing fleet of individual decision-making agents to test for changes in fishing and reporting behavior under different levels of fishery observer coverage. Testing across coverage levels was a timely management question given new regulations that call for up to 100% coverage. Calibration results suggested recent stock assessments may have overestimated the stock of Georges Bank haddock. Simulation outcomes indicated that benefits were limited to reducing error to 3% if observed trips continue to contain significant reporting errors. However, the observer effect yielded substantial benefits to the stocks if reporting error was eliminated on observed trips, so observer protocols and additional collaboration with law enforcement could add value to additional observer coverage.

## Introduction

Human behavior is a key contributor of uncertainty in fishery science and management, yet coupled social ecological systems (SES) models remain rare in fisheries management processes compared to ecosystem and stock assessment models (Fulton et al., 2011; Liu et al., 2007; Ostrom, 2009, 2007). Fisheries science literature and management efforts largely focus on reducing scientific uncertainty surrounding stock dynamics and identifying optimum economic yield. However, human behavior is known to deviate from rational choices in recognized ways known as cognitive biases, such as bounded rationality ( i.e.,“ rational choice that takes into account the cognitive limitations of the decision-maker – limitations of both knowledge and computational capacity” [Simon, 1987]). In the ABM, simulated fishers have access to a limited number of potential fishing locations. Bounded rationality and other complicated choice patterns (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981), that can lead resource users to behave differently than expected and complicate model averaging of behavior across the group (Fulton et al., 2011; Heckbert et al., 2010; Nielsen et al., 2017; Schlüter et al., 2012). This chapter adds to growing fisheries agent-based modeling (ABM) research used to explore cumulative interactions of autonomous agents (e.g., Bailey et al., 2019; Burgess et al., 2018; Carrella et al., 2020) by simulating the observer effect in the New England groundfish fishery.

ABMs are increasingly being used to explore potential social and economic outcomes of management actions that emerge from complex system feedback and the interactions of heterogeneous agents (Magliocca and Ellis, 2013; Smajgl and Barreteau, 2017). Coupled SES models like the ABM presented in this chapter can offer additional multidisciplinary perspectives to managers. Agent-based models are particularly appropriate for fisheries management because of their ability to represent fisher heterogeneity, spatial patchiness of fish stocks, and adaptive behavior of fishers (Railsback and Grimm, 2012). In the ABM developed here, profit-seeking agents with limited knowledge of potential revenue were combined with spatially explicit fish population dynamics models to simulate the decision to fish, site selection, and reporting behavior. Feedback between fishing effort, the observer effect described in Chapter 3 (i.e., fishers behaving differently when an observer is present; [Bellanger et al., 2019]), fish population density, and anticipated profitability were explored.

***The Fishery***

New England groundfish, primarily cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), winter flounder (Pseudopleuronectes americanus), and yellowtail flounder (Limanda ferruginea), are managed collectively through policy recommendations from the New England Fishery Management Council (NEFMC) to the National Marine Fisheries Service (NMFS) which is responsible for approval, implementation, and enforcement. The sector management system for New England groundfish is similar to an individual transferable quota (ITQ) system, which sets annual catch limits (ACLs) and allocates portions of the ACLs to quota holders. Quota holders are then able to fish or lease out their quota to other fishers. In addition to ACLs, commercial groundfish management measures include area and seasonal closures, gear restrictions, and days-at-sea restrictions for harvesters that opt out of the quota system (NMFS, 2021). The NEFMC sets the ACLs based on NMFS stock assessments, stakeholder input, and an evaluation of risk to the sustainability of the stocks. Despite decades of management efforts, including limits on days-at-sea, fishing areas, and the introduction of the sector management system, cod remain overfished in both the Gulf of Maine and Georges Bank stocks (Labaree, 2012, NMFS, 2021).

The management of New England multispecies groundfish uses substantial reporting and ongoing monitoring to assess when the ACL is likely to be reached and to avoid exceeding it. Current management regulations also require an uncertainty buffer for annual catch limits of 5%–7% below stock-assessment-based total allowable catch unless 100% of trips are monitored, reducing the amount of fish that each fisher can harvest or lease to others. If a sector exceeds its quota during a fishing year, it must either lease additional quota from another sector or lose access during the following year (GARFO, 2022). The catches of some stocks approach their ACL more often than others. For example, Gulf of Maine cod are considered a "choke" species because they are caught in pursuit of other groundfish, but cod can cause fishers to reduce effort or even close the fishery if their quota is exceeded. Therefore, fishers avoid "choke" stocks, and the level of avoidance is thought to vary between observed and unobserved trips (Hatcher, 2022; Mortensen et al., 2018). Assuming fishers take less care to avoid cod on unobserved trips, a difference in average proportions of the choke stock reported would be expected on observed trips.

The value of the fishing rights to cod varies over time due to supply and demand conditions (Figure 13), and prices are particularly high in years where the fishery approaches the ACL (Figures 14). During the period of analysis (2015-2019), prices of the quota-limited Gulf of Maine cod were relatively higher than for other species-area combinations (Figure 15). This difference between quota lease prices of the same species across areas provides an economic incentive to report them as having been caught in the lower-cost area. This cost-savings opportunity incentivizes potential misallocation (reporting catch location inaccurately) across stocks, and it also means that some fish caught in an area do not count toward the ACL for that area, increasing the potential for overfishing.

Accurate reporting is assumed to enhance the modeling and sustainable management of fish stocks. However, regulations only require reporting of the haul-back area, so legal reporting error is possible when a fishing set covers multiple areas (GARFO, 2022). However, some error is also likely to come from illegal misallocation (USCG, 2021). Previous studies by the US Coast Guard and NEFSC found large errors for certain stocks, particularly Eastern Georges Bank and Gulf of Maine cod and Gulf of Maine haddock, but the studies suggested that the error may be attributable to a small number of vessels and ventured

**Figure 13**

*Annual Gulf of Maine (GOM) cod catches and catch limits.*

The portion of the annual catch limit allocated to sectors (Sub-ACL), between 2010 and 2022 (NMFS). The difference between the two lines represents quota available at the end of the year.

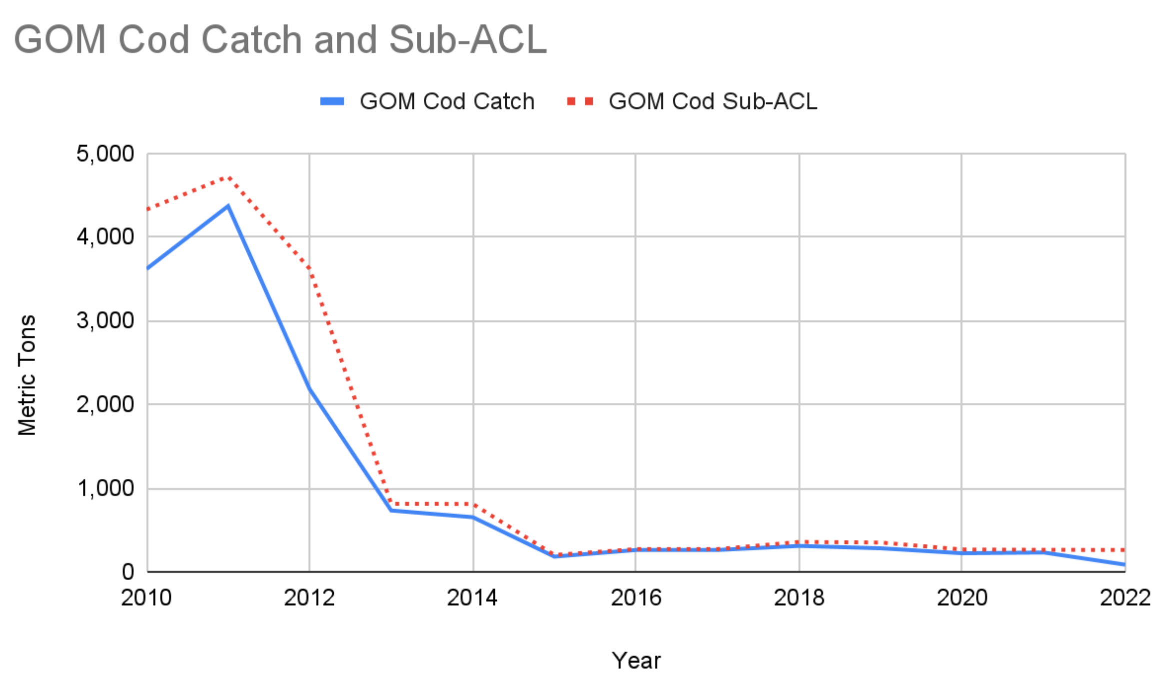


**Figure 14**

*Average annual quota lease prices and proportion of ACL caught (2010-2018)*

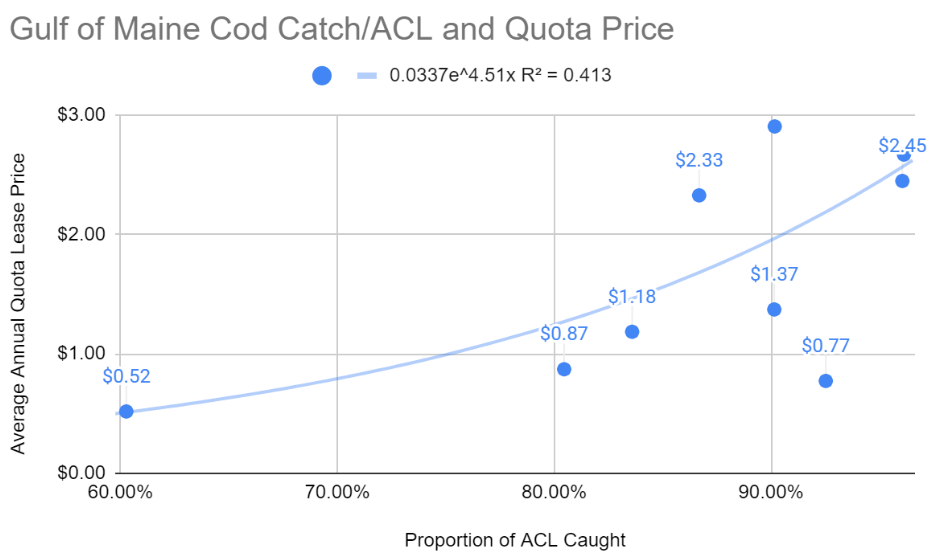
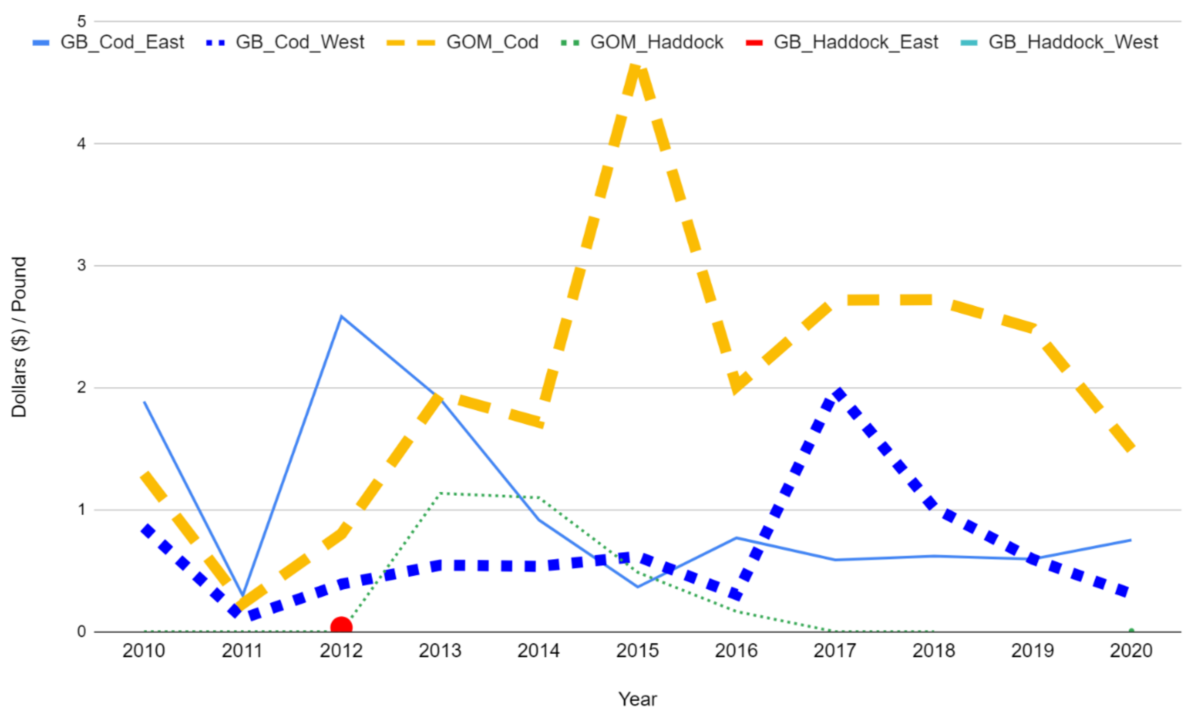


**Figure 15**

*Quota lease prices (US dollars per pound)*

Gulf of Maine and Georges Bank cod and haddock **estimated lease prices** between 2010 and 2020 (Demarest, pers. comms.). Gulf of Maine cod were the highest priced quota during the study period, 2015-2020.




***Research Need***

Accurate reporting reduces stock assessment model error and enhances sustainable management of fish stocks. However, regulations only require reporting of the haul-back area, so legal misallocation is possible when a fishing set covers multiple areas (GARFO, 2022). However, some error is also likely to come from illegal misreporting (USCG, 2021). Previous studies by the US Coast Guard and NEFSC found large errors for certain stocks, particularly Eastern Georges Bank and Gulf of Maine cod and Gulf of Maine haddock. However, the studies suggested that the reporting error may be attributable to a small number of vessels and suggested that expanded catch monitoring could mitigate the impact of reporting error (Palmer, 2017; Palmer and Demarest, 2018; Palmer and Wigley, 2009; USCG, 2021).

The goals of the ABM are to 1) gain insight into the emergent, collective fisher behavior, stock recovery, and profitability, 2) evaluate alternative management strategies regarding observer coverage and reporting requirements/enforcement, 3) test illustrative models of discarding. Improved accuracy of reporting should improve stock assessment models, which could then help achieve the long-term management goals set out in the Magnuson-Stevens Act. More specifically, this model was used to simulate multiple levels of observer coverage and associated changes in the fishing and reporting decisions of heterogeneous fishers, their catch and revenues, and the general trajectory (net growth or depletion) of stock sizes. Potential outcomes across a range of monitoring coverage levels were explored to test the null hypothesis that marginal benefits (reductions in misallocation per unit increase in observer coverage) do not diminish above 90% observer coverage.

## Methods

### *The Model*

This ABM was initialized using NMFS stock assessment, trawl survey, and quota allocation data, and the daily loop combined four key sub-models: fish stock dynamics, fishing location selection, fisher interactions, and reporting decisions.

#### Fish Stock Dynamics Submodel

A simple fish stock dynamic model was run in each patch on a daily time step. The initial stock sizes for Gulf of Maine and Georges Bank cod and haddock were set based on NMFS stock assessment annual biomass estimates which were spatially distributed proportional to NMFS 2015-2019 bottom trawl surveys. Initial stocks of groundfish other than cod and haddock were represented proportional to cod and haddock using NMFS landings records. Given the low population levels, carrying capacity was not expected to impact growth and ignored. For the daily stock dynamics submodel of each patch, biomass $B$ of species $s$ in patch $p$ at time $t$ was:

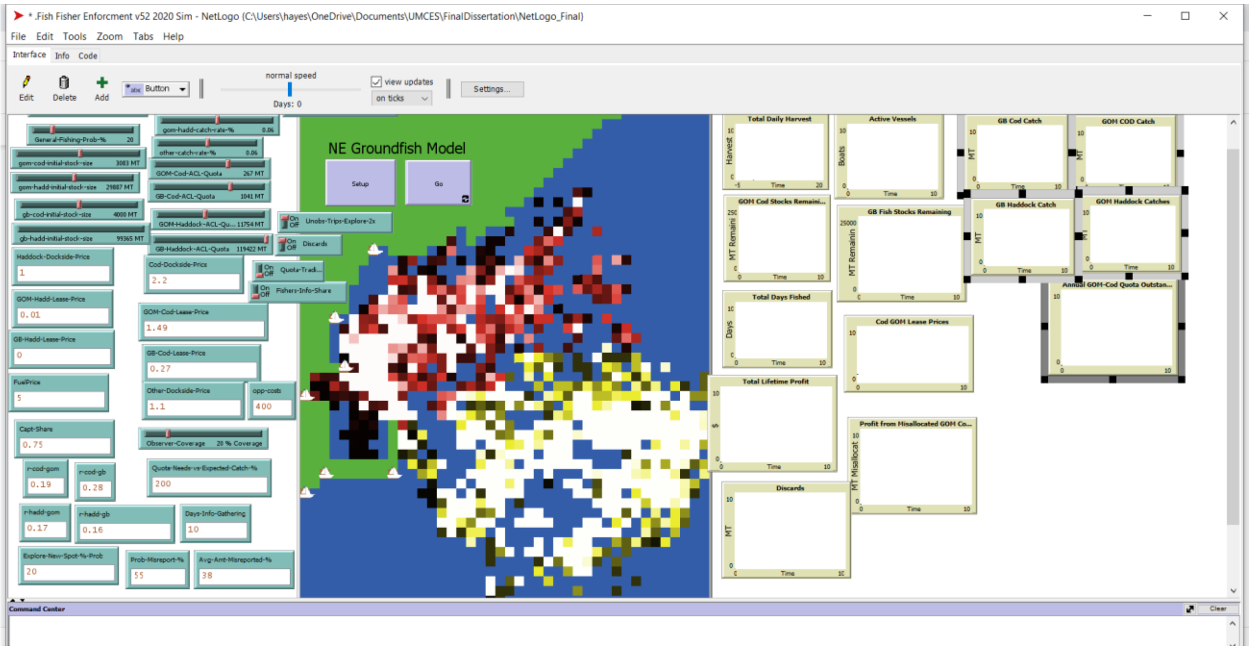
$$B_{t+1\ sp} = B_{tsp} - \sum q_{sp} B_{tsp} + \frac{r_{sp}}{365} B_{tsp} \qquad \text{Equation 8}$$

in which catches (catch rate $q$ proportion of the biomass) of all fishers present were removed and the stock grew by the average daily growth rate $r$. Both rates were calibrated using methods described below. The Gulf of Maine (red) and Georges Bank (yellow-green) starting conditions of fish stocks were illustrated with a color range indicating density (from dark [low] to light [high]; Figure 16).

**Figure 16**

*The northeast groundfish ABM simulation environment*

Red scale patches represent Gulf of Maine stocks and yellow scale patches represent Georges Bank stocks, with black and white patches being the lowest and highest populations, respectively. Green patches are land, and brown patches are ports.




### Fishing Location Selection Submodel

The fisher conceptual daily loop (Figure 17) began with fishers (n = 253) evaluating whether to fish based on 1) a general fishing probability constraint, 2) quota availability, and 3) profitability. Fishing was constrained by a calibration parameter (General-Fishing-Prob-%, described below) that scaled model fishing days to empirical data provided by NMFS. This scaling represented factors in fishing decisions not included in the model (e.g., vessel maintenance or weather). Additionally, the availability of quota (initially allocated or through trading) was required to consider starting a fishing trip. Thus, with probability General-Fishing-Prob-%, each fisher with access to quota identified the patch $p$ of the highest expected profitability, $\pi$, from a subset of known (initial random 10, subsequently visited, or neighbor-reported) locations such that

$$\mathrm{E}(\pi_p) = \sum_{s=1}^{3}(d_{ts} - a_{ts})E(l_{tsp}) \quad - c_p \mid B = \max(observed, reported)$$

Equation 9

where dockside price $d$ and fixed quota prices $a$ were provided by NMFS, expected landings $E(l)$ = biomass × catch rate ($q$) and daily fishing costs $c_p$ (distance, fuel costs and fuel efficiency [Murphy et al., 2018]) were estimated within the model, but in the base scenario, the empirical quota prices were held constant. Catch rates specific to each fisher-species-area combination were assigned from a lognormal, random distribution to represent heterogeneity in skill. Fisher-specific fuel efficiency was normally distributed with an average of 1.6 km per gallon of fuel (Toft et al., 2011).

If the highest $E(\pi)$ exceeded opportunity costs (assumed to be the average fishing wages, about $400 daily, in New England [U.S. Bureau of Labor Statistics]), the fisher traveled to location $x$ to and caught $q$ proportion of the biomass of each species. Fishers were initially allocated a limited quota based on real GARFO data, but they traded quota with one another. A given species/area quota lease reserve price is based on expectations of net revenue per unit of leased quota plus the dockside value (Hatcher, 2022; Lee et al., 2014) and fishers are willing to lease out their quota to other fishers willing to pay a higher reserve price.

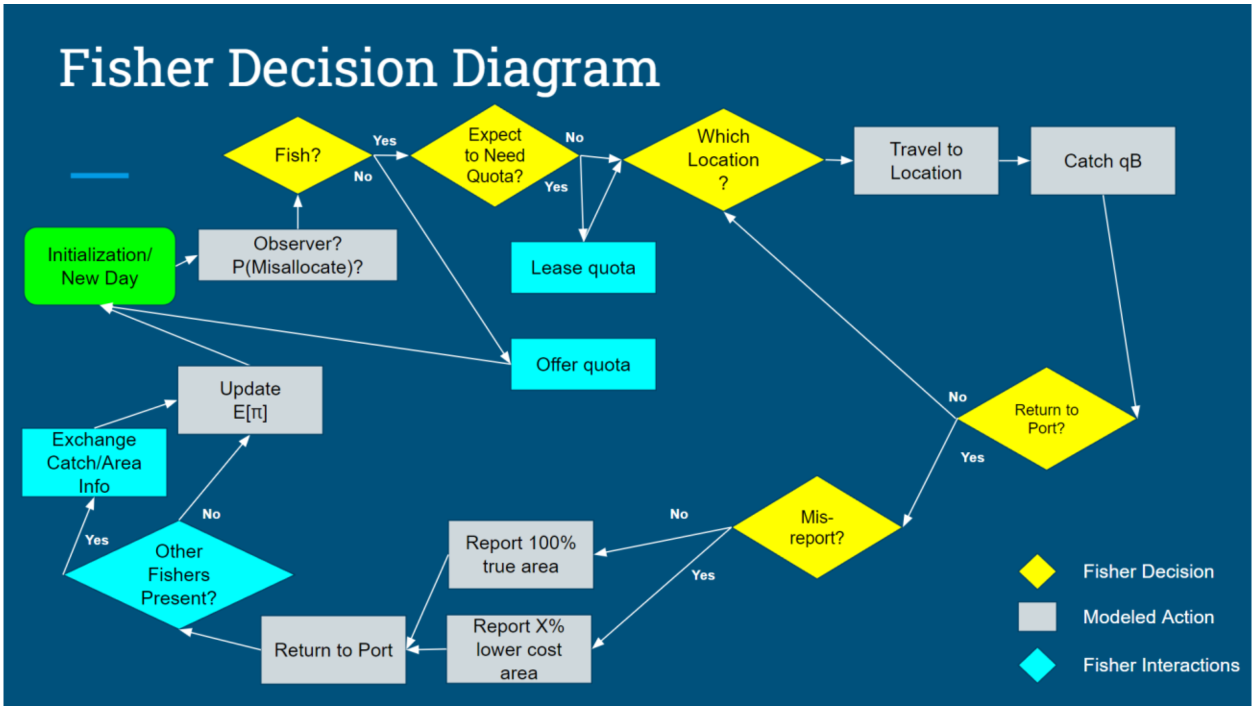
Using an explore-exploit-imitate decision model, the simulated fishers select a fishing target area from either 1) a best-known location (from personal experience or learned from another fisher in the same port and sector) with 80% probability or 2) a random new location within a given radius with 20% probability (Bailey et al., 2019; Carrella et al., 2020; Madsen et al., 2021). Separately, fishers tend to avoid congestion at any particular fishing site (Soulié and

Thébaud, 2006; Tidd et al., 2011), and so the simulated fishers avoid any site that already has over two fishers present.

**Figure 17**

*Fisher decision diagram representing the ABM daily loop.*

Adapted from Bailey et al. (2019)




**Fisher Interactions Submodel**

At port, the fishers interacted with other fishers at the same port by trading quota (Hatcher, 2022; Little et al., 2009) and exchanging information (Gutierrez et al., 2017) in some scenarios. The quota trading sub-model consisted of each fisher evaluating their reserve price for species 1 of n $species_s$-$area_g$ combinations, which was a function of expected net revenue from landings of other species at patch $x$ and the dockside price (derived from [Hatcher, 2022]):

$$Reserve\ Price_{\ s=1} = \frac{\sum_{s=2}^{n}[d_{ts} - a_{tsg}\,]l_{tsg} - c_{tx}}{l_{s=1}} + \ p_{s=1} \qquad \text{Equation 10}$$

Equation 10 includes a strong assumption of substitutability across species, but the analytic focus was on Gulf of Maine cod, so the information was limited for other species. In addition to quota trading, in the base scenario, fishers shared information about their best fishing locations. The fishers updated their knowledge as new areas are explored and shared information about best fishing locations with other fishers at the same port at the same time.

**Reporting Decision Submodel**

After fishers were randomly assigned an observer with probability *Observer-Coverage*, they were assigned a willingness to misallocate Gulf of Maine cod and haddock as Georges Bank cod and haddock with probabilities of Prob-Misallocate-% (55% if no observer) or Prob-Misallocate-w-Obs-% (38% if observer present) in the base model (Chapter 3). Prob-Misallocate-w-Obs-% was set to 0% in the strong observer effect scenario, where the presence of observers completely eliminates the chance of misallocation. In both cases, if willing to misallocate, the fisher misallocated 27% or 19%, depending on whether they have an observer onboard (Chapter 3). All three scenarios are summarized in Table 13.

***Overview, Design Concepts, Details (ODD) Protocol***

The rest of the model description provides details about the model using the ODD (Overview, Design concepts, Details) protocol to describe individual- and agent-based models (Grimm et al., 2010, 2006; Müller et al., 2013).

**Overview.** In the ABM, simulated fishers applied bounded rationality, or the expectation of profit based on past experience rather than complete information, to decide whether and where to fish based on both highest known density of target species and the ability to report the source area accurately based on economic incentives and the presence of a fishery observer. The model world programmed in Netlogo Ver 6.3.0 (Wilensky, U., 1999) represented New England fishing grounds. After selecting the site, the fisher traveled to the location and caught a fisher- and species-specific portion of the stock of cod, haddock, and other fish. Stock levels at any time step are estimated based on Equation 9.

***Purpose***. Some management measures introduced incentives to inaccurately report the location of catches or discard fish at sea (Hilborn, 2007), so the latest amendment to the fishery management plan (Amendment 23) called for increased monitoring via human observer or video monitoring, up to 100% "to improve the accuracy of collected catch data (landings and discards) and catch accounting," contingent on federal funding (50 C.F.R. § 648).

The purpose of this model was to simulate multiple levels of observer coverage and the strength of the observer effect (i.e., the probability of misallocation given an observer present) and associated changes in the fishing and reporting decisions of heterogeneous fishers, their catch and revenues, and the general trajectory (net growth or depletion) of stock sizes.

***Entities, state variables and scales***. Each 15-pixel grid cell or patch (Figure 16) represented 10 $km^2$ in the model world, which roughly equates to the following groundfish fishing area: 40–45 degrees N Latitude - (556 km; mid-New Jersey to Canadian Border) & 66–71 degrees W Longitude (413 km; approximately Boston to St. John NS). The actual and reported harvest and discards, remaining fish stocks, total profit, and days fished were tracked over the model simulation. The ABM simulated fishers, Gulf of Maine cod and haddock, and Georges Bank cod and haddock, as well as a generic stock of other groundfish. Each patch's stock was depleted as fish were removed by the agents but then grew based on a log-normally distributed average growth rate (inclusive of natural mortality) derived from the stock assessments and calibration. Brown patches in the model world represented major ports, such as New Bedford and Gloucester, MA, and green patches represented other land masses.

***Process overview and scheduling***. For each of the first 10 days (each day is a Netlogo "tick") of the simulation, every fisher built information about one random patch per day within the area for which they held quota. Each subsequent day, fishers updated their knowledge about patch stock sizes based on experience and considered the most profitable location based on previous experience or information from neighbors. Using that location to set catch and profit expectations and their reserve price as well as neighbors' reserve prices, the agent decided whether to fish or lease out their quota.

If the agent decided to fish, an ε-Greedy algorithm was employed in which there is an 80% probability that the agent fished the known best location and a 20% probability that the agent fished at a new, random location. These probabilities were set based on Carrella et al. (2019), who explored several decision algorithms and found that ε-Greedy performed well relative to logbook data from the US West Coast groundfish fishery.

**Design concepts**. ***Emergence.*** Key behavioral, economic, and ecological outcomes emerged from feedbacks between the submodels and were tracked in the ABM to evaluate the model as well as provide fishery managers with relevant information.

***Adaptation***. Fishers adapedt to changes in fish abundance and quota prices when deciding whether and where to fish. They also adapted behavior when an observer was present, either using the coefficients from the binomial logit model in Chapter 3 or in a scenario with strong observer effect that reduced misallocation to 0% on observed trips.

***Objectives***. Given that cod quota prices vary by stock area (Figure 15), there is often an economic incentive to avoid or discard cod or allocate landings to an area with a lower quota price. The incentive is typically to avoid Gulf of Maine cod as quota prices tend to be near or above dockside prices, meaning net revenue for cod tends to be near or below zero (Figure 15).

Proportions of recent landings were consistent with this assumption; most of the landings were of haddock, with cod making up a very small portion of the catch as fishers actively avoid it (Figure 6).

***Learning***. Initially, a harvester collected information about 10 random patches in the area for which they had quota allocation. After those 10 simulated days, each fisher visits the patch with the highest haddock density with 80% probability or randomly selects a new patch to explore with 20% probability. If the new bar has a higher population density, that becomes the new target with 80% probability. Because any other fisher could visit the best known fishing location and deplete the stock, fishers updated their expectations and target locations daily based on experience. Fishers also shared information with one another about the best fishing locations by randomly selecting a neighbor at port.

***Prediction***. Agents predicted likely profits at several locations based on previous experience, initial information gathering, visiting other locations, or other fishers.

***Sensing***. Fishers sensed the stock density at locations they visit or scout out during the initial 10-day learning period. They can also sense when an observer is present and are conditional cooperators (Frey and Torgler, 2007), meaning they are less likely to misallocate the origin of their landings and reduce the amount misallocated conditional on observer presence at probabilities outlined in Chapter 3.

***Interaction***. Fishers interact with stocks of fish by visiting the patch where they are located and removing a proportion (q) of the fish in that location. Agents interact with one another at their home port by potentially trading quotas and sharing information about fish density by location. In some scenarios, the fishers shared information at the dock, despite also having the behavior of avoiding congestion per patch, potentially putting fishers in the position of having to make substitutions for their best patch. This altruistic behavior was a test of potential impacts of fisher interactions.

***Stochasticity***. VTRs indicate that fishers are at sea no more than about 100 days per year, likely due to a variety of factors including days off, participation in other fisheries, weather, maintenance, and so on. Thus, agents have a probability of fishing on any given day, and that value was calibrated as described below. Individual patch growth rates are randomly assigned from a lognormal distribution with an average derived from recent stock assessments and model calibration.

***Observation***. Key outputs from the ABM that are used for model evaluation and relevant to managers are the proportion of landings that are misallocated across stock areas, Gulf of Maine and Georges Bank stock sizes, lease prices, total profit, and days of fishing.

**Details**. ***Initialization***. Each species-stock total biomass matched estimates from NOAA's most recent stock assessments and were apportioned to each patch based on stratified random sampling in the fishery-independent Northeast Fisheries Science Center Trawl Survey during 2015–2019. The stock of other fish were distributed proportionally to cod and haddock using historic catch proportions. Fishers were individually simulated agents with heterogeneous characteristics including catch rate (q: skill - log-normally distributed), quota allocation for species-area combinations (percent sector contributions, based on NOAA data), and fuel efficiency, randomly assigned from a normal distribution with average of 1.6 km/gallon (24 km/hour steaming and 15 gallons/hour = 1.6 km/gallon; [Toft et al., 2011]). The probability of trips being assigned an observer varied across scenarios. Model results were compared with the costs associated with each level of observer coverage from Ardini et al. (2020).

***Input Data***. NOAA potential sector contributions (PSCs), Total Allowable Catch (TAC) data, vessel trip reports (VTRs), vessel monitoring system (VMS) data, and stock assessments were used to initialize and tune the model.

- PSC data include the annual proportion (%) or harvest (lbs) allocated to each individual fisher. These data were used to create the fisher agents.
- NOAA provided the most recent (2021) stock assessments, including the biological reference points of maximum sustainable yield (MSY), standing stock biomass (current and at MSY), and fishing rate (current and at MSY).
- NOAA VTRs indicate landings by species, stock area, gear, date, and permit. Trip length and days at sea were constrained to align with these data.
- VMS provided spatial tracking data for vessels, and the system also requires initial plans to be filed and trip end "hails" that include landings. VMS data were used in Chapter 3 to evaluate the observer effect coefficient.
- Fishing regulations are available on the GARFO website.

***Sub-models***. The fisher daily loop combines four key sub-models: fish stock dynamics, fishing location selection, fisher interactions, and reporting decisions (described above).

***Calibration, Validation, and Simulations***. Some model parameters were calculated from government sources, while others were calibrated (Table 12). The probability of fishing on a given day (General-Fishing-Prob-%) was calibrated with empirical data (number of fishing days [NMFS]) using a parameter sweep, or simulating a range of parameter values in specified increments, in BehaviorSpace (Wilensky, 1999). Next, population growth rates and catch rates were simultaneously calibrated using BehaviorSpace parameter sweep. Standing stock biomass was calibrated first using a genetic algorithm, described below. All parameters are defined in Table 12. Note that several parameters have more than one source.

Two approaches were used to calibrate the fish catch and population variables. In addition to the parameter sweep described above, parameter combinations were simulated in 100 searches using the genetic algorithm in BehaviorSearch (Stonedahl, F. and Wilensky, U., 2010). Evolutionary or genetic algorithms (GAs) use machine learning inspired by natural selection to solve calibration/optimization problems in ABMs across a wide range of disciplines, including biomedical research, materials engineering, and knowledge dissemination (Cockrell and An, 2021; Greig and Arranz, 2021; Jang et al., 2019; Seretis et al., 2018). The standard GA starts with a population of candidate parameter combinations, so-called "chromosomes," which undergo a process of “natural selection” whereby the fitness of each “gene” is tested (Figure 18). High-performing genes are passed on to the new generation of candidate solutions while others “mutate.”

This GA selection process allows for more efficient exploration of the parameter space than other techniques, such as a parameter sweep looking at all parameter combinations. This efficiency allowed a third calibration parameter (standing stock biomass) within the time available to conduct the analyses, in addition to the two calibration parameters of the parameter sweep (catch rate and growth rate). However, the genetic algorithm appeared to consistently overestimate catch rates, so a final parameter sweep with 100 iterations in Netlogo’s simulation experiment tool BehaviorSpace (Figure 19) were evaluated to minimize mean square error for days fished and average catch rates (Railsback and Grimm, 2012).

**Figure 18**

*BehaviorSearch interface*

Tool used for optimizing model parameters with a genetic algorithm (Stonedahl, F. & Wilensky, U., 2010)

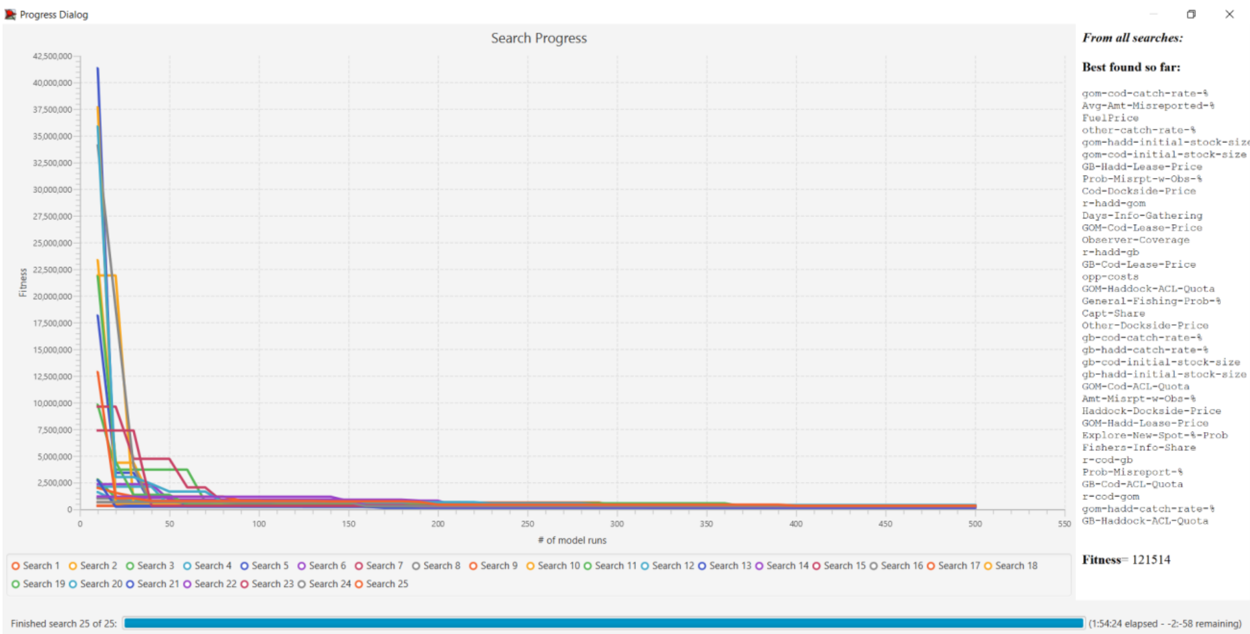
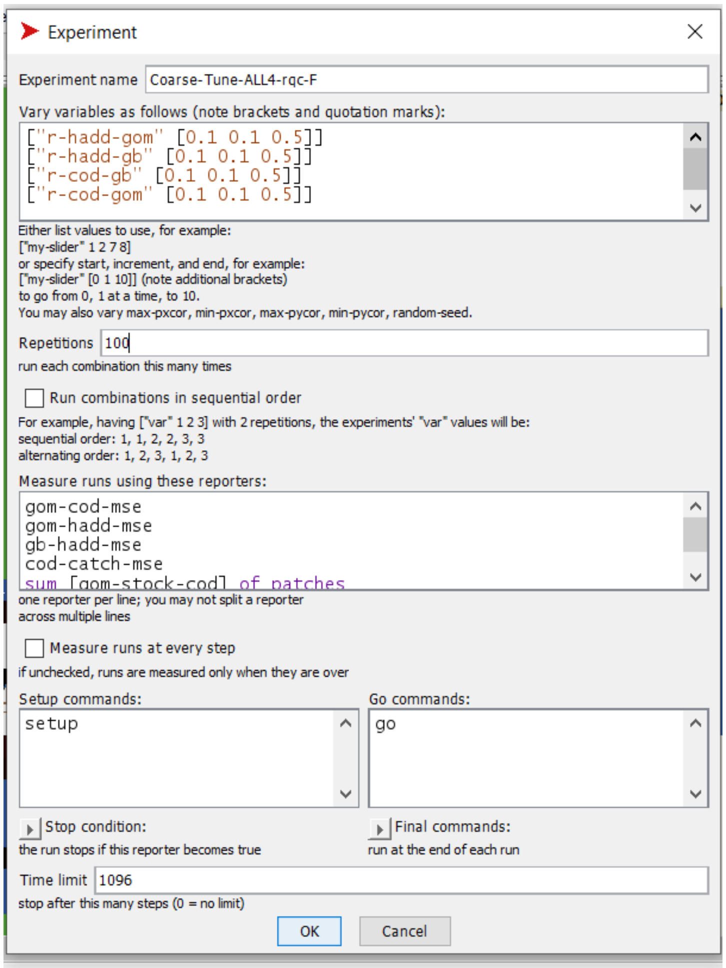


**Figure 19**

*BehaviorSpace interface*

Netlogo has a tool to conduct a parameter sweep that was used for calibration and to conduct simulations for scenario testing (Wilensky, U., 1999).



**Scenarios.** Once the model was calibrated, simulation experiments tested changes in outcomes across a range of observer coverage levels in three scenarios (Table 13): misallocating behavior described in Chapter 3 (Base), a scenario where all observed trips had no errors in reporting (Strong Observer Effect), and a scenario that introduced discarding on unobserved trips when fishing limits were exceeded (Discards).

In all three scenarios, observer coverage was simulated in 10% increments between 0% and 100% (the potential level of coverage, assuming federal funding) to generate model estimates of catch reporting error, number of days fished, and average net revenue per day. The proportion of misallocated landings is the key performance criteria for testing the hypothesis. To compare potential reduction in misallocating at various levels of observer coverage to the costs of coverage, the Ardini et al. (2020) linear estimate of $681 per day was inflated to $841 (in 2023 dollars) per day of observer coverage.

## Results

***Model Calibration Results*** The model included a 32% probability that any particular fisher would pursue an otherwise profitable trip, which is consistent with the vast majority of permits (> 90%) fishing fewer than 120 days per year (Figure 20). Potential reasons for this are proposed in the discussion below.

**Figure 20**

*Agent-based model fit using BehaviorSpace: simulated and empirical trips*

2015–2019 trips (NMFS) and calibrated simulation model trips with 10% error bars given General-Fishing-Prob-% = 0.32..

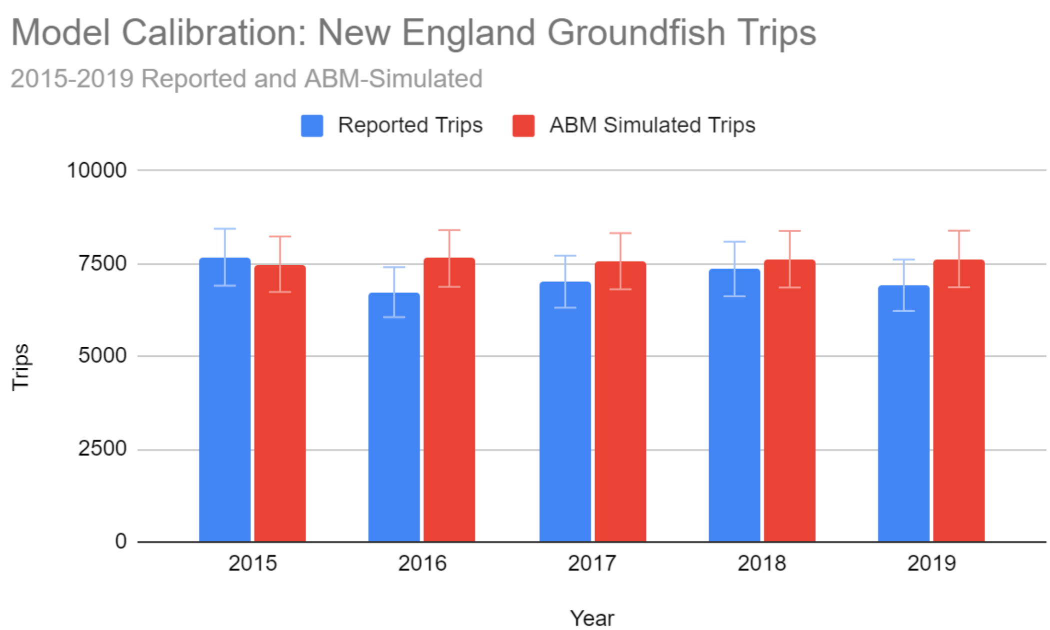


**Table 12**

*Agent-based model parameters and sources*

The value, meaning, and calibration method of parameters used in model simulations.

**System Parameters**

| Stock Area | Species | Parameter | Value | Meaning | Calibration Method or (Source) |
|---|---|---|---|---|---|
| Gulf of Maine | Cod | r | 0.19 | Annual population growth rate | Genetic Algorithm, (NMFS 2021) |
| | | q | 0.004 | Catch Rate | Parameter Sweep |
| | | SSB | 3,083 | Initial Stock Size (MT) | (NMFS 2021) |
| | | Q | 267 | Catch Limit (MT) | (GARFO) |
| | | d | $2.20 | Dockside Price ($/lb) | (NMFS) |
| | | a | $1.49 | Quota Price ($/lb) | (NMFS) |
| | Haddock | r | 0.17 | Annual population growth rate | Genetic Algorithm, (NMFS 2021) |
| | | q | 0.002 | Catch Rate | Parameter Sweep |
| | | SSB | 29,887 | Initial Stock Size (MT) | (NMFS 2021) |
| | | Q | 11,754 | Catch Limit (MT) | (GARFO) |
| | | d | $1.00 | Dockside Price ($/lb) | (NMFS) |
| | | a | $0.01 | Quota Price ($/lb) | (NMFS) |
| Georges Bank | Cod | r | 0.28 | Annual population growth rate | Genetic Algorithm, (NMFS 2021) |
| | | q | 0.006 | Catch Rate | Parameter Sweep |
| | | SSB | 4000 | Initial Stock Size (MT) | Genetic Algorithm |
| | | Q | 1,041 | Catch Limit (MT) | (GARFO) |
| | | d | $2.20 | Dockside Price ($/lb) | (NMFS) |

| | | | | |
|---|---|---|---|---|
| | a | $0.27 | Quota Price ($/lb) | (NMFS) |
| Haddock | r | 0.16 | Annual population growth rate | Genetic Algorithm |
| | q | 0.006 | Catch Rate | Parameter Sweep |
| | SSB | 25,000 | Initial Stock Size (MT) | Genetic Algorithm |
| | Q | 119,410 | Catch Limit (MT) | (GARFO) |
| | d | $1.00 | Dockside Price ($/lb) | (NMFS) |
| | a | $0.00 | Quota Price ($/lb) | (NMFS) |
| Other | r | 0.2 | Annual population growth rate | Genetic Algorithm |
| | q | 0.006 | Catch Rate | Genetic Algorithm |
| | SSB | 61,970 | Initial Stock Size (MT) | Proportional to Cod & Haddock |
| | d | $1.10 | Dockside Price ($/lb) | (NMFS) |

## Behavioral Probabilities

| | | | | |
|---|---|---|---|---|
| | General-Fishing-Prob-% | 32% | Probability that Fisher will make profitable fishing trip | Min. MSE - Number of Days at Sea |
| | Observer Coverage | 26% | Probability Trip is assigned an observer | (NMFS) |
| Unobserved Trips | Prob-Misallocation-% | 55% | Probability of an Unobserved Trip with Misallocation | Hayes, C. Dissertation. Chapter 3 |
| | Avg-Amt-Misallocation-% | 27% | Average Misallocation on Unobserved Trips with Misallocation | Hayes, C. Dissertation. Chapter 3 |
| | Explore-New-Spot-%-Prob | 40% | Probability of Exploring New Fishing Location | (Carrella et al. 2020) |
| Observed Trips | Prob-Misallocation-w-Obs-% | 38% | Probability of an Observed Trip Misallocating | Hayes, C. Dissertation. Chapter 3 |
| | Amt-Misallocation-w-Obs-% | 19% | Average Misallocation on Observed Trips with Misallocation | Hayes, C. Dissertation. Chapter 3 |
| | Explore-New-Spot-%-Prob | 20% | Probability of Exploring New Fishing Location | (Carrella et al. 2020) |

Population growth rates between 2015 and 2020 were estimated to be 0.19 (Gulf of Maine cod), 0.17 (Gulf of Maine haddock), 0.28 (Georges Bank cod), and 0.16 (Georges Bank haddock). Figure 21 illustrates the distribution of growth rates for Georges Bank cod as an example. Apart from Georges Bank haddock, which had a growth rate that appears to have dropped to near or below zero as the massive 2013 cohort aged out, these estimates are consistent with the estimates from the NMFS stock assessments (Table 12). Catch rates were estimated by parameter sweep in BehaviorSpace. The initial stock sizes of Gulf of Maine stocks were similar to NMFS estimates, but Georges Bank haddock stock size estimate (25,000 MT) was substantially lower than the NMFS assessment (99,365 MT), and there was no Georges Bank cod population estimate available for comparison. Minimizing squared error of cod across years led to variation in the quality of model fits. Simulated catches of cod in the Gulf of Maine (MSE = 2,842) and Georges Bank (MSE = 156,800) fit better than haddock (MSE = 1,626,168 and 1,309,860, respectively [Figure 22]). The pattern of increasing Gulf of Maine haddock landings over time seemed to be particularly difficult for the model to match.

**Figure 21**

*Calibrated Georges Bank cod growth rate distribution*

Frequency of cod growth rates in best fit (2015-1019 simulated - empirical catch data)

BehaviorSearch genetic algorithm simulations.

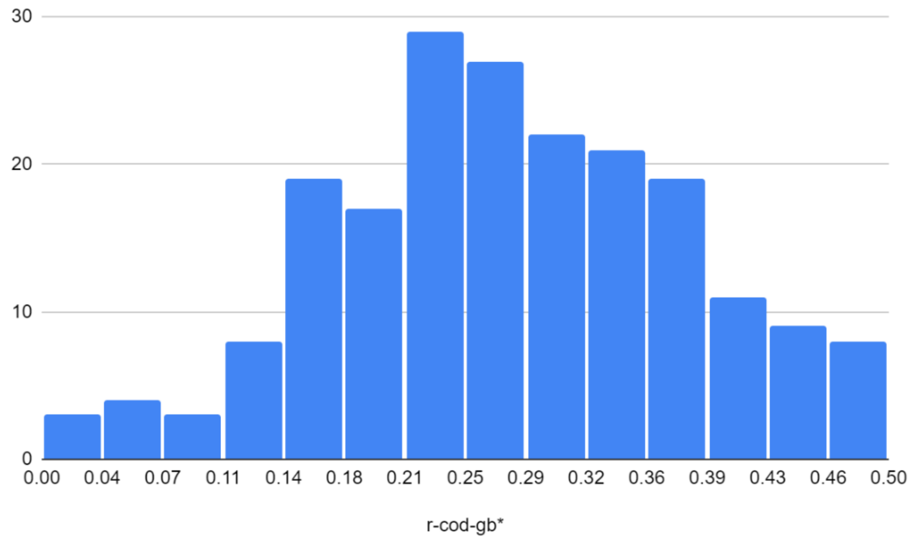
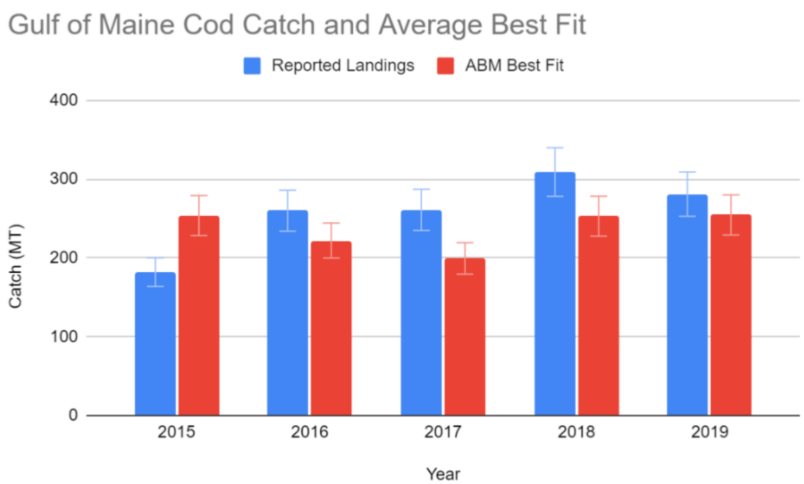
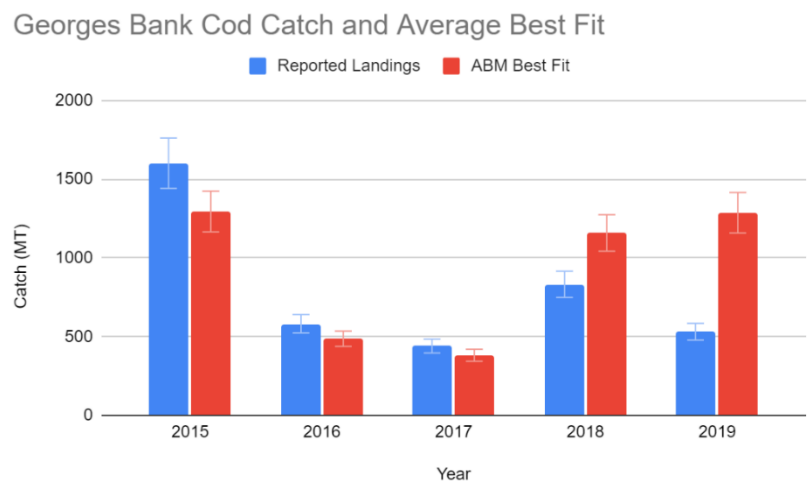


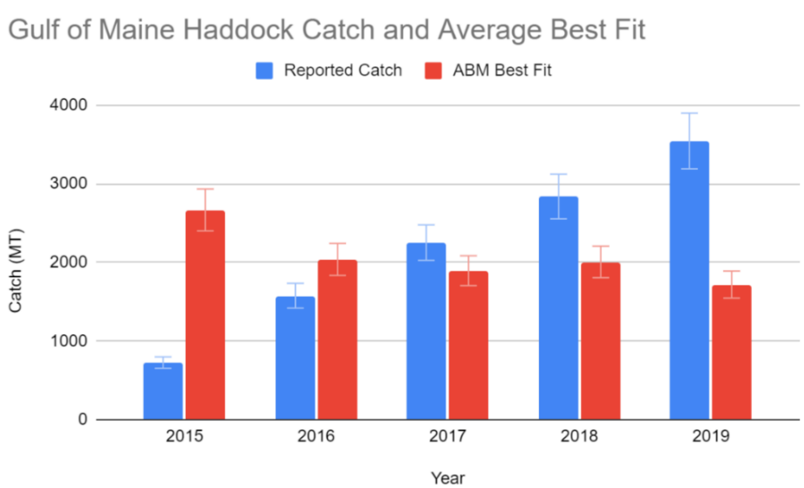

**Figure 22**

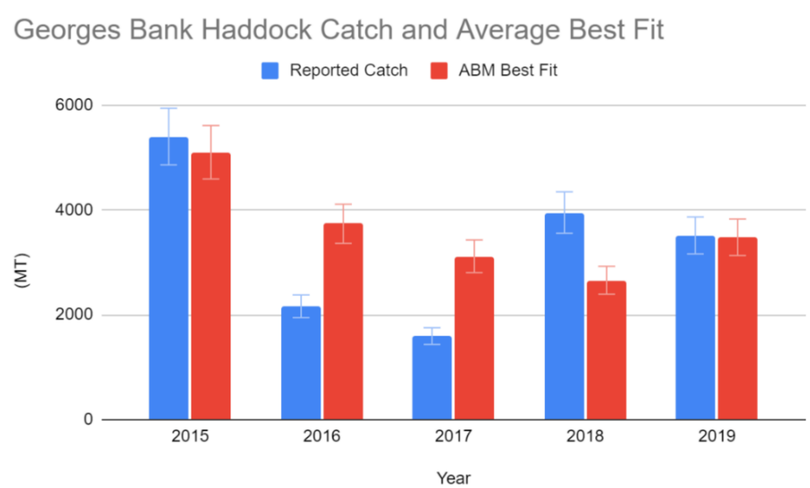
*Parameter sweep calibration results: landings and model results by area and species*

Gulf of Maine and Georges Bank cod and haddock 2015–2019 landings (NMFS) and simulated landings with 10% error bars.


Gulf of Maine Cod Catch and Average Best Fit
Reported Landings
ABM Best Fit
Catch (MT)
400
300
200
100
0
2015
2016
2017
2018
2019
Year


Georges Bank Cod Catch and Average Best Fit
Reported Landings
ABM Best Fit
Catch (MT)
2000
1500
1000
500
0
2015
2016
2017
2018
2019
Year


Gulf of Maine Haddock Catch and Average Best Fit
Reported Catch
ABM Best Fit
Catch (MT)
4000
3000
2000
1000
0
2015
2016
2017
2018
2019
Year


Georges Bank Haddock Catch and Average Best Fit
Reported Catch
ABM Best Fit
(MT)
6000
4000
2000
0
2015
2016
2017
2018
2019
Year

***Simulation Results.*** In the base scenario, fisher misallocation behavior was based on the probability of multi-area trip misallocation (55% on unobserved trips and 38% on observed trips) and the average proportion of catch misallocated on those trips (27% on unobserved trips and 19% on observed trips) derived in Chapter 3 (Table 13). In an alternative, illustrative, and hypothetical scenario, there was no misallocation on observed trips. Observer coverage reduced misallocation of Gulf of Maine cod from 34 MT (9% of the catch) to 11 MT (3% of the catch) in the base scenario and from 34 MT to 0 MT in the illustrative scenario with no misallocating on observed trips (Figure 23). The base model curve (blue) is linear, suggesting that there are no diminishing marginal returns at high levels of observer coverage, consistent with the null hypothesis. In contrast, the illustrative scenario of strong observer effect (orange), shows some increasing marginal returns (decreasing reporting error) with increasing observer coverage, particularly between 90% and 100% observer coverage.

**Table 13**

*Scenarios tested with the calibrated ABM*

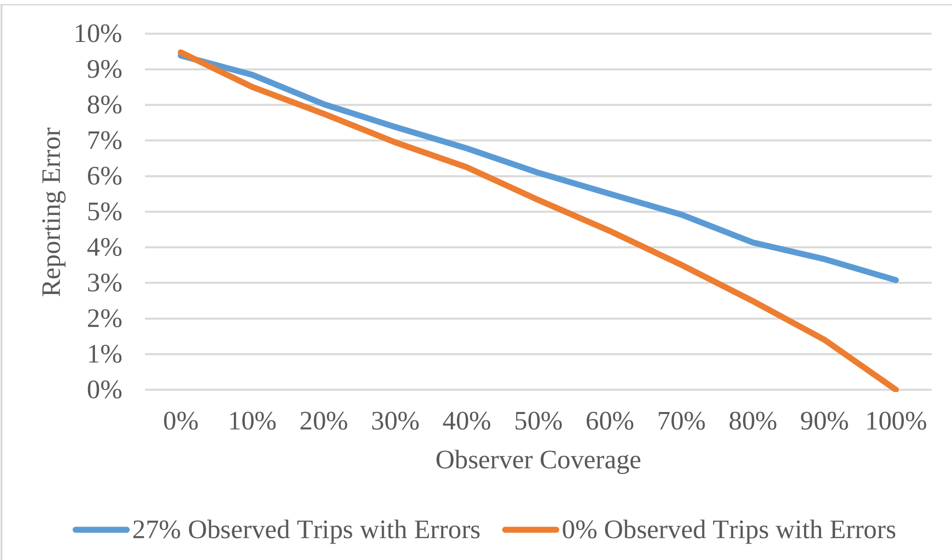
**ABM Scenarios**

| **Scenario** | **Description** | **Unobserved Trip Misallocation Probability** | **Observed Trip Misallocation Probability** | **Unobserved Trip Misallocation Proportion** | **Observed Trip Misallocation Proportion** | **Discards** |
|---|---|---|---|---|---|---|
| Base | Observer Effects from Chapter 3 | 55% | 27% | 38% | 19% | No |
| Strong Observer Effect (SOE) | No misallocation if observed | 55% | 0% | 38% | 19% | No |
| Discards | Discard quota overage | 55% | 0% | 38% | 19% | Yes |

**Figure 23**

*Agent-based model results: misallocation*

Gulf of Maine cod misallocations (% of Landings) with and without misallocation on observed trips in 400 single-year simulations.




The reason for this behavior appears to be that the number of trips decreased with higher levels of observer coverage as marginally profitable fishers who could not profitably fish without misreporting increasingly stayed at port (Table 14). Less fishing at high levels of observer coverage led to the marginal profit per day fished increasing (Table 14, Figure 24), as the total days fell more quickly than total landings as observer coverage approached 100%.

**Table 14**

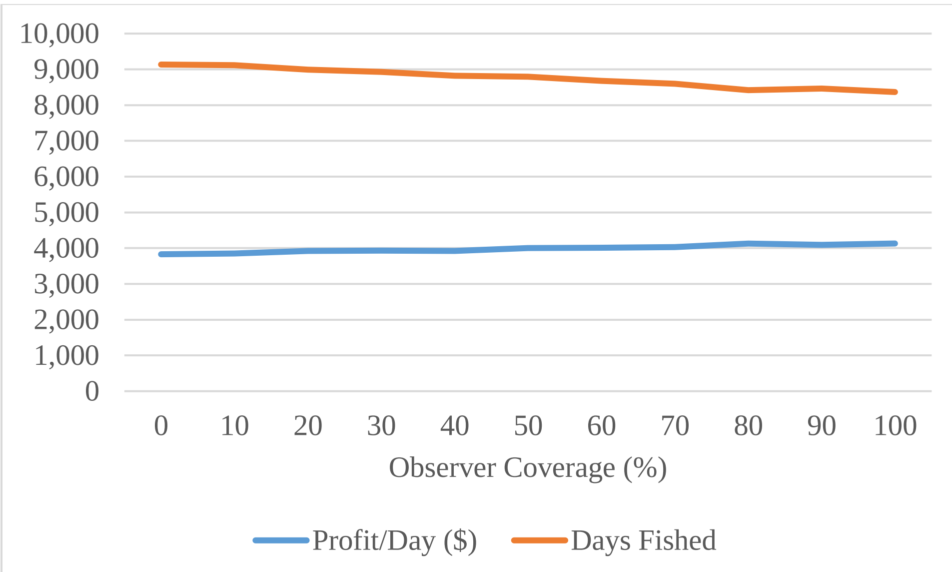
*Key outcomes for Gulf of Maine cod (GMC) from ABM scenarios*

| Scenario | Base | Strong Observer Effect | Discards |
|---|---|---|---|
| **0% Observer Coverage** | | | |
| GMC Misallocation (MT) | 34 | 34 | 408 |
| GMC Misallocation (%) | 9.4% | 9.5% | 159% |
| GMC Annual Stock Change | 4.5% | 4.7% | -5.2% |
| Average Daily Profit ($) | $3,828 | $3,880 | $4,916 |
| **50% Observer Coverage** | | | |
| GMC Misallocation (MT) | 22 | 19 | 371 |
| GMC Misallocation (%) | 6.1% | 5.3% | 143% |
| GMC Annual Stock Change | 4.9% | 5.3% | -4.0% |
| Average Daily Profit ($) | $4,001 | $4,147 | $5,258 |
| **90% Observer Coverage** | | | |
| GMC Misallocation (MT) | 13 | 5 | 165 |
| GMC Misallocation (%) | 3.7% | 1.4% | 61% |
| GMC Annual Stock Change | 5.2% | 6.1% | 3.0% |
| Average Daily Profit ($) | $4,090 | $4,739 | $5,256 |
| **100% Observer Coverage** | | | |
| GMC Misallocation (MT) | 11 | 0 | 0 |
| GMC Misallocation (%) | 3.1% | 0.0% | 0.0% |
| GMC Annual Stock Change | 5.4% | 6.8% | 6.8% |
| Average Daily Profit ($) | $4,130 | $5,197 | $5,256 |

**Figure 24**

*Agent-based model results: Average profit per sea day and average days fished per year by observer coverage level*

*Averages of 400 simulations shown.*




The fish population dynamics sub-model was very basic, but across the simulations, Gulf of Maine stocks tended to fall at low levels of observer coverage and grow at coverage levels above 50% observer coverage (Figure 25). In the discards scenario, discarding was introduced as another option for the agents to avoid costs associated with landing Gulf of Maine cod. The agents that were willing to misallocate at the start of the trip discarded any catch above their remaining quota allocation (Figure 26). At observer coverage levels below 80%, more cod were discarded than landed (i.e., the error exceeded 100%) even if the observer effect was strong.

**Figure 25**

*Agent-Based model results: Gulf of Maine cod biomass change by observer coverage level*

*Gulf of Maine cod stock size (MT) annual population change (growth and fishing mortality) in 400 simulations averaged across all scenarios.*

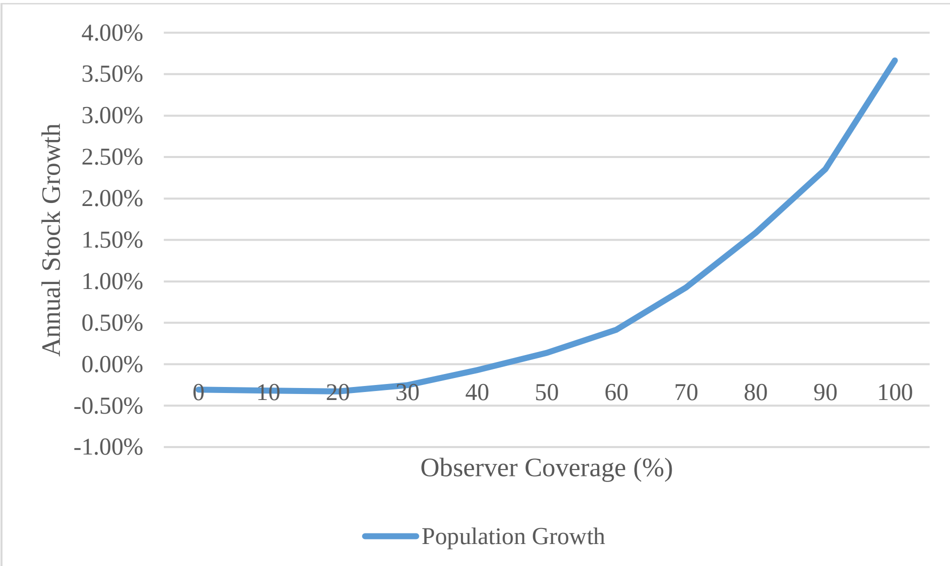
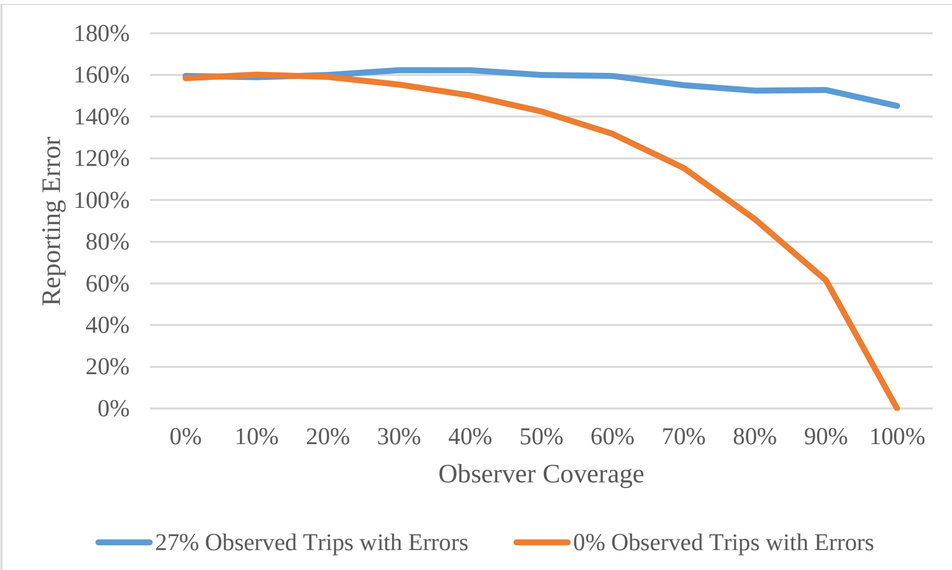


**Figure 26**

*Agent-based model results: Gulf of Maine cod discards (% of Landings) with and without misallocation by observer coverage*

Discards on observed trips for two scenarios of normal and strong observer effect. Results are averages of 400 single-year simulations.




***Sensitivity Testing.*** The model appeared to be robust to the assumptions tested in the sensitivity analyses (Table 15). The scales of some parameters were varied to test the effect on model results. Removing the constraint of the general fishing probability increased days fished but had little effect (< 1%, on average) on the proportion of Gulf of Maine cod misallocation. In a separate but similar dynamic, adjusting the opportunity costs of groundfish fishing (forgone income from alternative fisheries or occupations) by 25% and 250% also had a minimal (< 1%, on average) impact on the proportion misallocated. Finally, information sharing among fishers led to more productive fishing, but the proportion misallocated also changed by less than 1%.

**Table 15**

*ABM sensitivity testing.*

The effect of information sharing, the probability of potentially fishing, and opportunity costs on misallocation and fishing effort were tested.

| Sensitivity Analyses | | Condition | GMC Misallocation (MT) | GMC Misallocation (%) | Days Fished |
|---|---|---|---|---|---|
| Fishers-Info-Sharing | Fishers share best fishing location | On | 25 | 7% | 10,738 |
| | | Off | 17 | 6% | 7,770 |
| General-Fishing-Prob-% | Initial constraint allowing fishing effort | 32% | 20 | 6% | 8,118 |
| | | 100% | 21 | 6% | 10,390 |
| Opportunity Costs | Profit expectation needed to fish | $100 | 21 | 6% | 9,513 |
| | | $400 | 21 | 6% | 9,272 |
| | | $1,000 | 20 | 6% | 8,978 |

## Discussion

The next step in ABM development would involve stakeholder engagement to validate assumptions, identify additional performance metrics, and simulate additional management scenarios. After stakeholder input, the ABM of the New England groundfish fishery presented here could complement existing stock assessment models in the US federal fisheries management process. In this example, the ABM could provide insight into the accuracy of catch data to inform the appropriate observer coverage target and associated level of federal funding. While the simulations are not meant to be good predictors of outcomes, they provide insight about the influence of observers and discards on reporting accuracy and the general direction of stock dynamics and profitability.

Quota prices were fixed in the ABM which is likely to cause simulated fishers to drop out of the fishery slower than if quota prices were allowed to vary with supply and demand. As fishers leave the fishery, the quota price would be expected to drop due to falling demand, allowing more fishers to continue fishing profitably. In future research, the ABM will be used to explore individual decision-making and compliance behavior in the context of social pressure within given sectors' joint liability and inequality aversion (Bellanger et al., 2019). It can also be used to simulate changes in quota prices as a result of system dynamics.

The calibration itself presented an interesting finding. The catch rates for Georges Bank stocks were particularly challenging to calibrate; the machine learning technique and parameter sweep approach produced estimates that differed by an order of magnitude. However, when simultaneously calibrating the standing stock biomass parameter in addition to the growth and catch rates, the calibrated parameters from the two approaches converged on initial stock sizes. The uncertainty surrounding standing stock biomass is not surprising given that the most recent stock assessment of Georges Bank cod was unable to produce standing stock biomass estimates (NMFS, 2021), and the haddock assessment is currently being reconsidered and is expected to be revised downward (NMFS pers. Comms.).

Although Chapter 3's findings indicate a significant observer effect, a substantial (identified as 'suspect' in the NEFSC analysis) amount of apparent misallocation takes place on observed trips. However, accurate reporting resulted in an increasing population of Gulf of Maine cod. Policy changes like requiring reporting of all fishing activity by location (instead of the current requirement to only report where fishing gear is hauled back) and strengthening the deterrence effect by using observer data to identify illegal misreporting could reduce misallocation on observed trips. I looked at how a stronger "observer effect" could improve marginal benefits (accuracy of reporting, stock recovery, and profitability) of observer coverage (Table 14).

The findings presented here focus on the observer effect on reporting behavior, but they do not address how improved catch accuracy (i.e., the reduction in reporting error) impacts stock assessments and would make annual catch limits more likely to effectively enhance stock recovery. This study focused on misallocation across stock areas, but it appears that discards, which were assumed dead (i.e., removed from the biomass) in the simulation, may have a much more profound effect on catch reporting error and stock recovery than misallocation as shown in Figure 26. Currently, discards are extrapolated from observed trips to estimate discards on all trips. Since fishing behavior differs between observed and unobserved trips (Chapter 3, Demarest, in prep.), there is likely a bias of unknown magnitude in discard estimates. Therefore, another benefit of observing more trips is reducing the bias in discard estimates, which would provide more accurate catch accounting for stock assessments, quota monitoring, and potential fishery closure.

Finally, the policy treatments also have varying costs associated with them. The cost to supply observers is estimated to be $681 per day, or $841 in 2023 dollars (inflated from Ardini et al., 2020). There are just over 10,000 days fished annually, so assuming linear costs, observer coverage is roughly $840,000 per 10% increase in coverage. This study only focused on one species in one stock area, so other benefits of observer coverage would need to be considered when evaluating the cost-effectiveness of marginal increases in observer coverage.

## Chapter 5: Discussion and Conclusions

*Research Trends*

This dissertation was inspired by three observations from the literature and two decades of personal fisheries science and management experience. First, the literature increasingly recognizes social sciences as offering valuable perspectives that complement species-specific stock assessments and ecosystem models (Bennett, 2019; Fulton et al., 2011; Kasperski et al., 2021). Second, and relatedly, stakeholders' perspectives are valuable in understanding tradeoffs in ecosystem management and designing policy instruments (Keeney and Raiffa, 1976; Lester et al., 2013), and collaborative management increases buy-in, legitimacy, and chances of success (Goelz et al., 2020a; Gutierrez et al., 2011; Ihde et al., 2011; Sandström et al., 2014). Third, advanced technologies such as "big data" from satellite-based sensors (e.g., VMS), video monitoring platforms, and artificial intelligence offer a new horizon for fisheries management if appropriate tools are in place to use the data to reduce uncertainty and drive science-based management (Bradley et al., 2019; Mills et al., 2007; Mustapha et al., 2021).

Thus, these three research trends have underpinned this dissertation. Chapter 2 applied decision sciences to compare two approaches to developing recommendations for Chesapeake oyster management. Chapter 3 used VMS data (remote observations) to test the significance of a fishery observer presence on reporting behavior in the New England groundfish linear mixed model. The coefficients from this model feed into an agent-based model (ABM) in Chapter 4, which was calibrated using a genetic algorithm (a type of machine learning). This concluding chapter starts by highlighting the expected and unexpected key findings of each of those chapters. Then, it delves into the overarching conclusions about these three areas for future research and what they might mean for the direction of fisheries management.

*Chapter 2 Further Discussion*

Chapter 2 compared two alternative decision processes for managing Chesapeake Bay oysters: 1) multi-criteria decision analysis (MCDA) with cost-effectiveness analysis (CEA), where preferences were elicited with semi-structured interviews; and 2) consensus solutions negotiations with collaborative modeling, in which preferences were elicited during in-person meetings. Given the potential for group effects, the degree to which the final recommendations from the group negotiations (#2) aligned with individual preferences was not clear. For example, one possible group effect is groupthink, "a mode of thinking that people engage in when they are deeply involved in a cohesive in-group, when the members' strivings for unanimity override their motivation to realistically appraise alternative courses of action" (Janis, 1972). The analysis in Chapter 2 intended to reveal whether individual preference elicitation would lead to different recommendations than the group negotiations. It was found that the resulting recommendations of the two approaches were similar, suggesting that group effects were not a major factor in the final management recommendations.

There were also concerns about the majority representation of industry representatives, an agreed-upon condition for joining the negotiations. To test the impact of the decision to allow industry participants 60% of the seats at the negotiating table, an equal representation scenario was simulated. In the simulation, industry, non-profit group, and government representative preferences were given equal weight; the results presented only marginal changes to the order of low-ranking recommendations and no impact on the top rankings.

The major finding of equal representativeness across individuals' preferences and subgroups' influences likely depended on a combination of skilled facilitators and group cohesion that was built during the negotiations process over a substantial amount of time (Goelz et al., 2020a). With the application of MCDA in Chapter 2, every participant had equal influence in the final model. Individual preferences were combined in a weighted average analytical model, which can potentially provide a more time-efficient path for identifying a balanced model of preferences compared to multiple group negotiation meetings. There were also other benefits unique to the novel MCDA-CEA. The CEA provided alternative options rankings, as requested by managers, instead of the consensus package of unranked recommendations provided by group negotiations. The MCDA-CEA translated the benefits of each option into comparable benefits index units, which were necessary to identify options that had substantially lower cost-effectiveness than other options.

There were also limitations to the MCDA-CEA approach. This particular MCDA process was abbreviated and leveraged the existing group negotiations process, which limited interpretations of how MCDA might perform as a stand-alone approach, because the trust-building and collective learning of the group negotiations influenced the preferences of the participants. Were it conducted separately, the MCDA may have yielded different results. The relationships built during the group negotiation process built social capital (Pretty, 2003) and cohesion (Goelz et al., 2020b) that could potentially improve prospects for long-term resource management. MCDA typically calls for initial group discussions about goals, objectives, and performance indicators and reconvenes stakeholders to discuss model results before finalizing the rankings of recommendations, but the MCDA described in Chapter 2 leveraged the parallel group negotiations process rather than holding independent meetings.

Each approach has advantages and disadvantages, and a combination of facilitated group negotiations, MCDA, and CEA approaches might improve advice to managers more than any of the approaches on their own. In fact, combining approaches could reduce the time commitments needed to reach a consensus by more quickly identifying areas of conflicting priorities through MCDA, ranking the options based on CEA, and then using group negotiations to find a compromise or resolution.

*Chapter 3 Further Discussion*

While Chapter 2 focused on comparing different management processes, Chapter 3 was a more traditional statistical hypothesis test of whether the presence of a fishing observer was significantly correlated with reporting behavior through the observer effect. In this case, I tested whether the presence of a fishery observer (i.e., the observer effect) significantly reduced the probability of misreporting and the amount of cod reported as Georges Bank during fishing activities in the Gulf of Maine. The observer effect may seem obvious, and observers have been shown to impact fishing behavior in other ways, such as location selection and fishing time (Benoit and Allard 2009, Demarest, in prep.). However, observers are not required to report illegal activity in the Northeastern US as they must do in some other regions. Less than 30% of enforcement agents in the region agreed that the presence of observers reduces violations of fishery regulations (Porter, 2010).

Collecting data on illegal activities through surveys or interviews can be challenging due to self-reporting bias, or the tendency to misrepresent behaviors due to recall error (not accurately remembering past events) or underreporting illegal or reputation-damaging behaviors (Gavin et al., 2010). Chapter 3 uses the Northeast Fisheries Science Center assessment of fishing time and location estimates from the VMS observations to infer divergence between proportions of apparent fishing activities (based on vessels traveling at fishing speeds) and proportions in the self-reported catch data.

The results presented in Chapter 3 suggested rejecting the null hypothesis that there is no correlation between observer presence and misallocation probability. The model coefficient was significant, which suggests that observers indeed reduce the amount of misallocating. Nonetheless, the 95% confidence interval of the probability of misallocation on an *observed* trip was 29.0% to 48.6%, suggesting that reporting error remains substantial even with observers.

There are at least three ways to potentially reduce reporting errors: increase observer coverage, strengthen the observer effect, and eliminate regulatory misallocation. If observer data were more often used to prosecute intentional misallocating, a deterrence effect may incentivize more accurate reporting (Porter, 2010). Additionally, regulatory changes could improve the accuracy of area reporting. One option would be to require fishing activity be reported in each area fished, which would eliminate legal misallocation. Current regulations only require the haul-back location to be recorded. A related change could be a prohibition on "fishing the line" or crossing area lines during a two. Finally, targeting observer coverage based on expected misallocation (vessels with high levels of suspect trips) would likely be politically unpopular, but could be a cost-effective use of observers.

*Chapter 4 Further Discussion*

In Chapter 4, the hypothesis was that marginal benefits (reductions in misallocation per unit increase in observer coverage) would diminish above 90% observer coverage, but it appeared to be a linear relationship in the base model. Moreover, there appear to be *increasing* marginal benefits at high levels of observer coverage in strong observer effect scenarios (e.g., 0% error on observed trips). In those cases, there was a greater decrease in reporting error between 90% and 100% observer coverage than at 10% changes at lower average observer coverage levels. This result is consistent with King and Sutinen (2010), who found that a small proportion of fishers are responsible for the majority of all types of noncompliance (e.g., with gear restrictions or closed areas). It only takes a few individuals misallocating to have a significant effect on the overall reporting error, so just a few unobserved trips have a disproportionate impact on the overall error. Hence, in the scenario with a strong observer effect (i.e., no misallocation on observed trips), the simulated marginal increase in observer coverage from 90% to 100% coverage had a greater impact on misallocation than marginal increases at lower coverage levels.

Chapter 4 describes how parameters were varied systematically in the parameter sweep and through a genetic algorithm to find parameters that minimize mean square error (the difference between annual simulated catches and historic catches) (Badham et al., 2017; Grimm et al., 2005). The genetic algorithm model was able to replicate Georges Bank cod and Gulf of Maine stock population growth rates within 2% of the growth rates inferred from the NMFS stock assessments. However, according to NMFS (2022), the Georges Bank haddock growth rate appears to have dropped below zero since 2017 as a massive 2013 cohort has aged out. Still, the genetic algorithm optimization estimated the growth rate at 0.16, which is consistent with other stock growth rates and was used in the base ABM.

The relatively close alignment between the genetic algorithm results and NMFS stock assessment estimates across most parameter values gave some confidence in the growth rate and initial stock size parameters, so they were fixed in the stock dynamics sub-model of the ABM. At the same time, behavioral parameters were varied in the sensitivity analyses and simulation experiments.

While there were many modeling choices and assumptions that impacted model behavior, the model appeared to be robust to the assumptions tested in the sensitivity analyses. The scales of some parameters were varied to test the effect on model results. Removing the constraint of the general fishing probability increased days fished but had little effect (< 1%, on average) on the proportion of Gulf of Maine cod misallocation. In a separate but similar dynamic, adjusting the opportunity costs of groundfish fishing (forgone income from alternative fisheries or occupations) by 25% and 250% also had a minimal (< 1%, on average) impact on the proportion misallocated. Finally, information sharing among fishers led to more productive fishing, but the proportion misallocated also changed by less than 1%.

Other modeling choices such as the population dynamics sub-model were fundamental to the model, and while the effects were expected to be small, they were not readily testable. The NMFS assessments were largely age-structured models, but a simpler surplus production model was selected for the ABM based on the assumption that the size structure of the catch and the number of individual fish were not important factors in misallocation behavior. Constant growth rates do not account for the variability in recruitment, which is particularly important in large age classes of haddock. However, the ABM simulations represent a single year, and recruitment dynamics should therefore have minimal impacts across scenarios or observer coverage levels. Additionally, the ABM populations did not follow a logarithmic growth curve (i.e., growth slowing as it approached carrying capacity) given the assumption that all populations were well below carrying capacity, and density-dependence was not likely to impact growth at current population levels. Additionally, the ABM did not restrict fishing in closed areas, which would have impacted the spatial distribution of fishing effort and fishing costs. Restricting closed areas in the ABM would have concentrated more effort in open areas and depleted them more quickly, and future model iterations could then test the impact of closed areas. Another simplifying assumption of the model was that travel costs and crew shares were the only costs in the profit sub-models, although there are many other variable costs (e.g., bait, ice, groceries) and fixed costs like the boat (Werner et al., 2020; Wieland, 2007). Additional costs would likely have led to fewer trips and perhaps reduced the magnitude of misallocated landings, but the general fishing probability calibration parameter had a similar effect of constraining fishing effort.

A cost-benefit analysis was not possible without monetizing the benefits of reductions in the Gulf of Maine cod reporting error. However, a basic cost-effectiveness analysis is possible if we assume that more accurate catch reports are beneficial and improve the chances of meeting management goals. The cost to supply observers on boats is estimated to be $841/boat-day in 2023 dollars (inflated from [Ardini et al., 2020]). There have been just over 10,000 days at sea in each of the recent five years, so 100% coverage would cost nearly $8.4 million. While there may be economies of scale, this cannot be confirmed because there is no historical cost data for high levels of coverage. In the base ABM model, there is a roughly linear 0.6% reduction in misallocation per each additional 10% of observer coverage (~$1 million). However, the relationship between observer coverage and misallocation in the scenario with the strongest observer effect (no misallocation on observed trips) appears to be slightly parabolic. The improvement from 0% to 10% observer coverage is slightly greater than the improvement from 10% to 20% observer coverage. Each additional 10% of observer coverage above 20% yields greater marginal improvements, with the biggest marginal improvement being from 90% to 100%. Taken together, given that the observer effect is strengthened to the point of completely eliminating misallocation on observed trips, the most cost-effective observer coverage level approaches 100%.

*Conclusions*

This dissertation addressed specific research questions in each chapter, but the larger questions regard how marine fisheries management can more effectively sustain fish stocks and the communities that rely on them. This research draws from and adds to the body of science that supports collaborative and integrated management approaches in order to understand and manage complex fisheries issues. The preceding chapters provide new applications of decision sciences to support evidence-based decision-making. ABM modeling choices could be evaluated in future research, but the most pressing need is a structured stakeholder workshop to discuss the model assumptions and identify other scenarios. While the ABM in Chapter 4 was informed by iterative discussions with NMFS scientists and managers as well as fishing sector managers, a broader and more structured discussion would identify model shortcomings and opportunities for improvement and other model uses. Other areas for future research include investigating discards with more complex decision rules. The discarding scenarios presented in Chapter 4 were considered for comparison, but they had no restrictions on discards.

Cascading environmental stressors, particularly related to climate change, require fisheries science to evolve and adapt to continue to meet both management objectives as well as societal expectations. For example, more collaborative management is needed to meet the changing needs of society, which Jane Lubchenco (1998) described as a "New Social Contract for Science." Co-management can promote inclusivity and effective fisheries management by incorporating local knowledge and perspectives into decision-making, and it also increases the legitimacy of management decisions, which tends to improve compliance and raises the likelihood of successful outcomes (Cash et al., 2003; Raakjær Nielsen, 2003).

Ecosystem-based approaches to fisheries management—a recognized goal for fishery managers in the US (DePiper et al., 2021)—explicitly integrate human behavior and values into multi-species modeling (Pikitch, 2004). For example, the National Marine Fisheries Service

> strives to adopt an ecosystem-based approach throughout its broad ocean and coastal stewardship, science, and service programs. Ecosystem-based management aims to maintain ecosystems in a healthy, productive, and resilient condition so they can provide the services humans want and need. (NMFS, 2023)

To understand human wants and needs, economic and social sciences should continue to be integrated into fisheries modeling.

In addition to integrating stakeholders and social sciences into traditional approaches, fisheries management also has opportunities to improve the assessment of fisheries using new data sources. More real-time data is available to reduce uncertainty and adaptively manage fishing activities at higher spatial and temporal resolutions. For example, electronic monitoring that uses cameras and remote sensing technologies is an alternative to using fishery observers to collect data on catch, discards, and bycatch. Depending on the reviewing protocol for video footage (audit vs. census), video monitoring can cost less than fishery observers while also producing higher quality data (Demarest, in prep.). Autonomous systems can also collect fishery data and support real-time analysis to obtain timely and accurate information on fish stocks and fishing activities, allowing for more effective and timely management decisions (Linden, 2021). Machine learning and artificial intelligence can help parameterize more complex models, as done in Chapter 4. Blockchain and emerging traceability systems can assist in tracking seafood from point of capture to point of sale, thereby improving transparency and reducing misrepresentation of where the fish were caught (Howson, 2020; Tsolakis et al., 2022).

Advanced technologies have the potential to improve fisheries management and ensure the long-term sustainability of fisheries if they can be appropriately harnessed by the slow-moving governing bodies that manage the resources. While this dissertation covers a wide range of topics, its goal was to highlight a few rarely used tools to assess and manage fisheries. Each fish stock and fishing community has a unique set of challenges, and this dissertation does not assert that any of the approaches presented here are the right tool for any given fishery. The purpose is to stimulate ideas about how fisheries managers can design new frameworks for collaborating with stakeholders, integrating social and natural sciences, and harnessing the power of advanced technologies to sustain fish stocks and fishing communities.

## Appendix A

PseudoCode: New England Groundfish Fishing Observer Agent-Based Model
Chris Hayes

- Fishers are a breed of turtles, nested within cooperatives called Sectors
- Patches represent fishing grounds, ports, and land; Patch = 10km squared = 15 pixels
- Cod
- Model world represents New England coastline, Gulf of Maine (GOM), and Georges Bank (GB); it represents roughly 556 x 413km; 40-45 N, 71-66 W.

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;Setup - Details below in Initial Distributions;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

1. Patches updated:
   a. 2015-2019 Trawl Survey spatial pattern used to allocate recent stock estimates (NEFSC)
   b. Major fishing ports (brown) and land area (green) identified
2. Harvesters updated:
   a. Quota, catch rate (q), and fuel efficiency assigned to known fishers with quota (GARFO)

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;Daily Loop Code;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

1. For first 10 days, fishers [build knowledge]:
   a. update best-spot if randomly selected patch (one per day) within radius (100 kms for GOM fishers) has more haddock/other than previous best-spot
2. After 10 days, fishers evaluate whether and where to fish:
   a. if total species-area reported catch <= total species-catch quota…
   b. AND trip not constrained - random 59% (max of 150 days/year) - due to weather, maintenance, etc….AND expected to be profitable, evaluate profitability of best-spot given quota prices
   c. Assign observer with random probability [observer-coverage]
   d. Update GOM cod quota reserve price: $p_{cod\text{-}dock}$ + [$NR_{hadd+other}$ / $Catch_{cod}$] (Hatcher 2022) [update-reserve-prices]
   e. If quota expected to be needed AND reserve price > neighbor's reserve price, lease quota from neighbor [quota-trade]
   f. If expected net revenue [ 0.75(qB * (dockside price - quota price)) - travel costs)] > opportunity costs, [trip-execution]
      i. Random 20% of the time travel new random target within radius (30km for GOM fishers, 60km for GB fishers),
      ii. Other 80% of the time, travel to best known location
      iii. Update best spot to current location, if applicable

iv. Harvest q proportion of stock present and update trip length [catch-update]
v. Update remaining stock size to reflect depletion [ stock-remaining-update]
vi. Update trip-length, and if trip-length > random N(3,2), [return to dock]

g. Return to dock

3. Target nearest port, and evaluate profit [profit-update]
   a. If no observer onboard,
   b. AND Cod-lease-price > GB-Cod-lease-price
   c. AND random 0-99 < Prob(misallocation | no observer; from Ch. 2)
   d. Shift X proportion (randomly generated between 0 and 100%) in report of GOM Cod Catch to GB Cod Catch reported.
   e. Set profit based on REPORTED catch
4. Move to nearest dock
5. Update annual catches, lifetime profit
6. Reset trackers:
   a. Catch, reported landings, trip profit, travel distance
7. Fish Population Growth
   a. Each patch adds (r/365)B
8. On days 365, 730, and 1095, Reset available quota and annual landings
9. Report MSE - AVG ((ModelSSB - StockAssessmentSSB) ^ 2)

;;;;;;;;;;;;;;;;;;;;;;;;;; Initial Distributions (Trawl Surveys), Ports/Land Designations, and Fisher

<u>read-spatial-stock-distribtion</u>

1. Convert Trawl Lat/Long to model x/y patches, and given initial total stock size from NMFS assessment, set each patch cod and haddock stocks ∝ trawl catch for the patch.
2. Set color scale red for GOM, yellow for GB
3. Set ‘other’ stock = sum of cod+haddock

<u>read-turtles-from-csv</u>

1. Create one new simulated fisher for each active vessel with quota from NMFS GARFO at random ports, each with:
   a. GB/GOM Cod/Haddock quota
   b. Target Area [0 = both areas, 1 = GOM only, 2 = GB only]
   c. q - heterogeneous catch rate log-normal distribution, mean set in interface
   d. Fuel efficiency - log-normal distribution, mean = 1.6 km/gal (Palmer and Wigley 2009; Toft et al. 2011)
   e. Sector

## Appendix B Glossary

### Glossary of Oyster Futures Management Options

**A:** Status quo regulations continue, 5% non-compliance with size laws, 1% Sanctuary harvest, and bushel price of $47.22]

**2**: Status quo regulations continue, 0% non-compliance with size laws, 1% Sanctuary harvest, and bushel price of $47.22]

**3:** Status quo regulations continue, 0% non-compliance with size laws, 0% Sanctuary harvest, and bushel price of $47.22]

**13a:** 2-yr hand tong rotation in Middle Choptank sanctuary (cost ~$600K/year), paired with planting spat on shell in the closed years.

**13b:** 2-yr hand tong rotation in Middle Choptank sanctuary (cost ~$2M/year), paired with planting spat on shell in the closed years.

**16a:** 2-yr hand tong rotation in Little Choptank tributaries (cost ~$600K/yr), paired with planting spat on shell in the closed years.

**16b:** 2-yr hand tong rotation in Little Choptank tributaries (cost ~$2M/year), paired with planting spat on shell in the closed years

**17a:** Add shell to selected bars every year in Broad Creek (cost ~$600K/year).

**17b:** Add shell to selected bars every year in Broad Creek (cost ~$2M/year)

**18:** Open tributaries in the Little Choptank River to hand tonging, and provide added shell every 3 years (cost ~$460K/year).

**18a:** Open tributaries in the Little Choptank River to hand tonging, and provide added shell every 3 years (cost ~$600K/year).

**18b:** Open tributaries in the Little Choptank River to hand tonging, and provide added shell every 3 years (cost ~$2M/year).

**19:** Complete Little Choptank and Tred Avon restoration (6" and 12" substrate per restoration plan.)

**23:** Place reefballs (placed near/around the bridge, channel markers, etc.) in the Middle Choptank region (reef balls, 1 foot apart, 1 time, cost ~$2M) not in conflict with fishing activities. Work with watermen for placement options. [Note: private funding will be used for implementation of this Option]

**26a:** Add spat every year in the Middle Choptank (cost ~$600K/year).

**26b:** Add spat every year in the Middle Choptank (cost ~$2M/year).

Sensitivity study – spat set 3.4x higher on clean shell

**B:** #17a with spat set 3.4x higher on clean shell

**C:** #17b with spat set 3.4x higher on clean shell

**D:** #18 with spat set 3.4x higher on clean shell

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