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Building economic operating models in support of a management strategy evaluation for the Gulf of Maine American Lobster Fishery

US DEPARTMENT OF COMMERCE
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Woods Hole, Massachusetts
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Building economic operating models in support of a management strategy evaluation for the Gulf of Maine American Lobster Fishery

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Editorial Notes

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EXECUTIVE SUMMARY

The project "Building Economic Operating Models in Support of a Management Strategy Evaluation for the Gulf of Maine American Lobster Fishery" ran from October 2021 to September 2022. The project aimed to conduct research to review the literature on bioeconomic studies of the American lobster (*Homarus americanus*) fishery and to build a conceptual model of the key economic dynamics affecting the performance of the lobster fishery in the Gulf of Maine. This report presents: (1) the literature review findings of empirical bioeconomic models related to the American lobster fishery and operating models used in Management Strategy Evaluation (MSE) processes in other lobster fisheries; (2) lobster fishery experts' recommendations on factors and processes that drive the fishery's performance, and (3) a conceptual simulation framework for the American lobster fishery. This report intends to inform those interested in understanding the economic dynamics of the lobster fishery and those seeking to build economic models that characterize the harvest and market dynamics of the fishery.

Key findings from the lobster economic literature:

- The market for lobster is characterized as supply-driven; that is, the variation in supply determines the price, but the price does not determine the fishers' harvesting decisions.
- The supply side of the market has been modeled using a production function that relates landings with a set of inputs, including vessel characteristics, number of traps, number of trips, traps hauled, soak time, bait per trap, fuel consumption, travel distance, available biomass, and time indicators.
- The demand side of the market has been modeled using an inverse demand function that relates lobster price with domestic landings, proxies for disposable income, imports, inventories, and seasonal demand indicators.
- The estimation of production and inverse demand functions have relied on data from federal and state harvesters and dealers datasets, as well as from surveys of individual lobstermen.

Recommendation from lobster fishery experts:

- Relevant factors that affect the harvest sector of the fishery include location and proximity to the biomass, size of business, size of the vessel, license class, captain's experience, available biomass, trap density, technical capacity, bait efficiency, bait quality, labor/number of crew, number of trips, number traps hauled, input prices, output prices, and fishing location. A model for the harvest sector of the fishery must also consider factors that affect fishers' decisions to fish and participate in the fishery, such as tradition, outside opportunities, crew availability, and fisher age, among others. Heterogeneity across vessels and fishers, as well as the interaction of the fishery with other sectors, should be considered.
- Lobster price is highly uncertain, and many factors play a role in determining prices. These factors include shell quality, tourism, international trade, tariffs, international holidays, fisheries certification, trade wars, geopolitical issues, emerging international markets, and international prices of other seafood products.

The high uncertainty around lobster prices raises caution for developing models that characterize the market sector of the fishery.

A conceptual simulation model for the fishery

The conceptual framework of an operating model for the American lobster fishery relies on a set of biological and economic models, depicted in Figure 1. The economic models use outputs from the biological model to estimate vessel-level landings, industry landings, price, and vessel-level profits. The first economic model characterizes the harvest sector of the fishery, employing production and aggregate landing functions. The production function describes individual vessel production technology by relating legal available biomass, capital inputs, labor, effort, and skipper skills to vessel-level landings. The next model characterizes the market sector of the fishery using an inverse demand that relates ex-vessel price with industry landings, domestic inventories, international markets, and known seasonal patterns. The last model calculates vessel-level revenues and profits using inputs from the production, inverse demand, and cost functions.

The operating model has been conceived to simulate the behavior of the fishery. At each time step of the simulation, the biological model estimates legal available biomass, which serves as an input in the production function, to estimate vessel-level landings and aggregated industry level landings. Aggregate landings enter the biological model to calculate the number of lobsters caught at length and fishing mortality in order to estimate total legal available biomass, thus initiating the next fishing cycle step. At each time step, outputs of the production and aggregated landing functions allow estimating monthly prices according to the inverse demand function and vessel-level and industry-level profits. Biological and economic model outputs, at each time step, allow the assessment of stock and fleet performance metrics, such as catch[1] numbers at length, recruitment, exploitation rate, spawning stock biomass, revenue, and profits at the individual vessel and industry level.

At the end of the report, we explore 2 potential modifications to the proposed operating model. Phase II of the model will introduce spatial features to the biological and economic model. The spatial operating model will require introducing a spatial distribution of the stock in the biological model and a spatial effort allocation in the economic model. Phase III may include additional models that characterize vessels' entry-exit and effort allocation behavior. An entry-exit model will endogenously estimate the number of vessels at each time step of the simulation. An effort allocation model will calculate a spatial-temporal effort allocation based on expected profits for each location.

The development and final features of an economic operating model for the American lobster fishery will depend on the intended need of the model and the proposed management alternatives to be evaluated. However, the content of this report provides the background work to build an economic simulation model, a critical component of an MSE, to assess the performance of the American Lobster fishery.

[1] In general, "catch" refers to kept catch and discarded catch, while "landings" represents kept catch. Landing data generated in the harvest model must be adjusted with information regarding discard before entering the biological model.

1. INTRODUCTION: THE AMERICAN LOBSTER FISHERY CHALLENGES AND OPPORTUNITIES

Landings in the American lobster (*Homarus americanus*) fishery have grown about 4-fold in recent decades (ASMFC 2015), and the loss of other invertebrate and groundfish fisheries has left many coastal communities in the region largely dependent on this single-species fishery (Steneck et al. 2011). This increase in the stock has been primarily attributed to increasing temperatures and changing environmental conditions, resulting in a geographic expansion of the stock farther north and into deeper waters previously too cold to be suitable for lobsters (Goode et al. 2019). Changes in the spatial distribution of lobster have brought the fishery to new communities and created a state where fishermen rapidly adapt fishing practices in response to the shifting stock distribution.

Over the past decade, landings in the fishery have fluctuated without trend around record high catches, often making the fishery the most valuable in the United States. However, shifting and potentially declining recruitment patterns make the fishery's future uncertain, with some studies projecting a steep decline in the coming years (Oppenheim et al. 2020). Managers and stakeholders are concerned that the Gulf of Maine fishery may follow the fate of the Southern New England (SNE) fishery, which declined sharply from its own record highs over the past 2 decades due to environmental changes. Management was largely unable to stabilize the population or mediate the economic impacts to the fishery. Under these new challenges, there is a pressing need for managers and stakeholders to have appropriate data and models available to them, ahead of any downturns, in the Gulf of Maine fishery.

Much of the quantitative work needed to model and project the dynamics of the lobster population already exists or is under active development, but economic models tied to fishery dynamics are absent. In an effort to fill this gap, we carried out a 1-year research project to provide a conceptual framework to develop a set of economic models that can aid stakeholders and managers in implementing a Management Strategy Evaluation (MSE) for the American lobster fishery.

The project had the following goals:

1. Review and evaluate the underlying theoretical and empirical bioeconomic models, data, and assumptions employed in known or existing lobster simulation models.
2. Conduct a literature review of more recent modeling approaches, which dovetail with factors such as climate change.
3. Identify available economic and biological data as well as critical gaps where further data needs to be collected.
4. Make recommendations on implementation of an economic operating model that is compatible with the existing biological models to be further developed to support a lobster MSE.
5. Begin empirical estimation of the parameters of the recommended economic model as time allows.

We reviewed the economic literature related to American lobster to achieve the first 2 goals. In many cases, the literature developed empirical models to test hypotheses about the technology of fishing vessels rather than to simulate the fishery. While most of the models we reviewed were not developed to build an operating model, they allowed us to identify factors to consider when modeling the harvest and market sector of the American lobster fishery. We also performed a literature review on worldwide MSE processes in lobster fisheries to identify the core models of the simulation and the relationship among models. This literature review allowed us to identify the different modeling approaches to quantify the climate change impacts within the simulation framework and strategies to model the dynamics of the fishing fleets. Overall, the literature review allowed us to identify the structure of a lobster fishery simulation model and the factors that need to be considered in the simulation.

In addition to the literature review, we hosted 3 workshops with lobster industry stakeholders and scientists whom we asked to identify challenges likely to affect the fishery in the near future. We also asked participants to identify factors that affect fishers' participation and landing behavior and elements that affect the current domestic and international demand for American lobsters. Responses from participants provided information missing in past economic models of the fishery. Participants also identified data gaps likely to constrain our ability to build a simulation model for the fishery (Caballero et al. 2023).

The fourth goal was accomplished by combining findings from the literature reviews and information gathered during the workshop. We summarized the findings by proposing a structure of an operating model for the lobster fishery that interconnects a series of standalone models. The first model characterizes lobster population dynamics. The rest of the models characterize the economics of the fishery by modeling the harvest of individual vessels, the aggregate landings, the fishery's profitability, and the lobster's demand. This report describes how individual models are related to simulate the fishery's performance. The report also identifies the data available to estimate each model and potential augmentation to our proposed operating model. Due to time constraints, we were unable to achieve the last goals.

We structured the remainder of this report as follows: Section 2 describes the modeling approaches found in the literature that characterize the American lobster fishery's supply, demand, and fishery benefits. Section 3 presents experts' recommendations for modeling the dynamics of the lobster fishery. Section 4 presents the operating model's conceptual framework, data availability, and specification of the functions embedded in the model. Section 5 presents the conclusions, where we identify potential extensions to the proposed operating model framework.

2. LITERATURE REVIEW: ECONOMIC MODELS FOR THE LOBSTER FISHERY

The section aims to present a literature review on modeling approaches and relevant variables used to characterize the interplay between supply, demand, price, fishery benefits, and distributional impact on the American lobster fishery. We describe empirical models in the economic literature that have contributed to our knowledge of the dynamics of the American lobster harvest and market sectors. By revising past modeling approaches, we seek to identify building blocks for an operating model to simulate the fishery dynamics. We describe the fishery from a microeconomics perspective rather than from a regional employment and economic growth stance. While it is relevant to understand the impacts of the lobster fishery on employment and economic growth in the regional economy, these fall outside the scope of this document.

2.1 Supply

Lobster supply is usually assumed to be driven by factors other than price (Richardson et al.1986; Holland 2011). Lobstermen decide where, when, and how intensively to fish based on abundance, weather, and input control regulation constraints. Thus, the market for lobster is characterized as supply-driven; that is, the variation in supply determines the price, but the price does not determine harvesting decisions. Lobstermen's harvesting behavior results in a highly variable supply of lobsters within and between years. Within-year variations are generally determined by the molting cycle, much of which is temperature-dependent. When lobsters near the minimum legal carapace size molt, legal lobsters are recruited to the fishery (Cheng and Townsend 1993). The lobster biological cycle determines the largely unchanged seasonal distribution of landings, with most landings occurring from July through October, immediately following the summer molt period (Thunberg 2007). Between-year variations are likely explained by environmental factors such as warming water temperatures (Singer and Holland 2005). For instance, the lobster fishery experienced an unseasonably warm spring in 2012 and an earlier spring molt season leading to a sharp increase in lobster supply and a decline in the ex-vessel price compared to other seasons (Dayton 2018).

Since empirical models assumed supply is exogenously determined by lobster availability and the time of the year rather than the price, supply and demand are not modeled simultaneously (Richardson et al. 1986; Holland 2011). Instead, quantities landed are modeled independently of the price using vessel-level production functions. In contrast, demand models use an inverse demand function where prices are defined as a function of quantity landed while controlling for factors that shift demand.

2.2 Production function

A production function measures the relationship between productive inputs and the quantity of output. Production function estimation has been an important tool for analyzing technology change, assessing responses to new fishery regulations, and measuring vessel-level technical efficiency. In the fisheries economics literature, vessel-level production functions have been estimated to identify likely participants in buyback programs in the limited entry scallop fishery of the Saint Brieuc Bay (Guyader et al. 2004), substitution between regulated and unregulated inputs in the prawn fishery of Australia (Kompas et al. 2004), and economic benefits of replacing controlled access with tradable harvest permits in the Gulf of Mexico commercial reef fish fishery (Weninger and Waters 2003). Squires and Walden (2020) provide a comprehensive review of applications of production function estimation in fisheries.

Conceptually, a vessel-level production function typically takes the following form:

$$q_{it} = f(K, L, E, S; N), \tag{1}$$

where q_{it} denotes vessel-level output for vessel i at time t; K, L, E, S *and* N denote physical capital, labor, effort, skipper skill, and natural capital, which is exogenously determined (Squires and Walden 2020). The same production function is typically specified for all vessels. However, some inputs vary by vessel, such as physical capital, effort, labor, and skipper skill. Natural capital can vary depending on the length of t. Thus, the same production function characterizes the production technology across many vessels.

Production functions empirically estimated for the American lobster fishery include vessel characteristics such as length, tonnage, and horsepower as a proxy for physical capital (Dow 1975; Dayton 2018) as well as capital investment (Dayton et al. 2014). Vessel characteristics are time-invariant inputs. Natural capital (e.g., available biomass) is a non-vessel-specific time-varying input (Holland 2011); time and location indicators have been included to account for differences in resource stock abundance across seasons and space (Holland 2011; Dayton 2018). Indicator variables are vessel-specific time-varying inputs, given that a vessel chooses when and where to harvest lobsters. Proxies for labor—an input—include vessel owner labor, measured by hours spent on fishing activities, and crew size (Dayton 2018; Dayton 2014).

Effort[2]—a composite input—has included inputs such as number of traps set in the water, number of trips, number of traps hauled, trap soak time, bait per trap, fuel consumption, and distance traveled (Dow et al. 1975; Fullenbaum and Bell 1974; Dayton 2018; Holland 2011; Gates 2000); these are all considered vessel-specific time-varying inputs. Non-vessel-specific time-varying inputs related to effort include the aggregated number of traps (Holland 2011). Proxies for skipper skills include years of experience, age, and technical ability (Dayton 2018). Other studies also included non-vessel-specific time-varying environmental variables, such as seawater temperature (Fullenbaum and Bell 1974).

Estimated production functions for the American lobster fishery show that natural capital, as measured by available biomass, is positively correlated with output (Fullenbaum and Bell 1974; Holland 2011a). Dow et al. (1975) estimates a single production function, assumes the number of homogeneous vessels is a good proxy for fishing effort, and finds that production—quantity landed—is greater for larger and newer vessels along with increasing the number of traps and trips. Dayton (2018) shows that lobster vessels exhibit different production technologies and degree of inefficiencies. Output elasticities show vessels under 34 ft can achieve higher production by increasing the number of trips in a quarter, while larger vessels greater than 40 ft. should tend more traps with more crew (Dayton et al. 2014). Dayton (2018) also examined the impact of the input skipper skills on landings across vessel classes and found technical expertise parameters such as age and years of experience are significant only for small vessels. In addition, temporal and spatial indicator variables, time of fishing, and zone/ port were statistically significant explanatory variables in the production function (Holland 2011; Dayton et al. 2014). Holland (2011) also looked at vessel-level production in relation to bait use and found that increasing the amount of herring bait per trap would likely increase revenue per trap haul more than the cost of the increase in bait at current prices.

Data used in the empirical production function studies mentioned here used individual vessel survey data merged with landing data to estimate production functions for the lobster fishery. For instance, Holland (2011) uses a port sampling catch and effort survey running since 1966, collected by the Maine Department of Marine Resources, merged with a cost survey carried out by the National Marine Fisheries Service (NMFS). Similarly, Dayton (2018) uses confidential firm-level data and survey responses from a sample of 1,007 fishers in 2011 to obtain effort and cost information; the data were then merged with federal dealer-reported landings transactions in order to obtain catch information. Finally, estimated production functions for the lobster fishery include annual (Dow et al. 1975), quarterly (Dayton 2018), monthly (Lehuta et al. 2014), and daily (Holland 2011a; 2011b) time steps t. Data availability determined the temporal scale at which production inputs related to landings.

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[2] Effort has also been specified as an output, which is then used as an input in a 2-stage production process. See Anderson LG (1976).

2.3 Demand

While the lobster economics literature has assumed that lobster supply is independent of price, the demand and price relationship has been explicitly modeled with an inverse demand function, which relates lobster prices to quantities landed and factors known to affect the demand for lobster. An estimated inverse demand function can be considered an abstraction of the market. In general, the inverse demand function relates prices to a set of inputs, following a general form:

$$p_t = f(Q_t, Y_t, D_t), \tag{2}$$

where, p_t denotes the price of lobster at time t. Q_t, Y_t, and D_t denote measures of landing and its characteristics, personal income, and demand shifters, respectively.

The early literature estimated the inverse demand functions for 2 market levels: the wholesale market and the ex-vessel market (Richardson and Gates 1986; Wang and Kellogg 1988). Richardson and Gates (1986) estimated monthly price equations—wholesale and ex-vessels—as a function of annual yield and average lobster weight. In this case, the inverse demand function takes the form of $p_t = \alpha + \beta_1 q_t + \beta_2 Y_t + \beta_3 D_t + \varepsilon_t$, with income and demand shifter variables; where $\boldsymbol{\epsilon_t}$denotes the random disturbance, $\beta's$ are parameters estimated by the authors.

Wang and Kellog (1988) estimated the wholesale price as a function of lobster size, domestic landings, and income measured by disposable income. The authors also included imports, inventories, and seasonal demand indicators to account for consumption patterns as demand shifters. The authors assumed the inverse demand function for the ex-vessel market is derived from the wholesale market. Thus, they included the wholesale price in the specification for the ex-vessel price function. Wang and Kellog (1988) specification took the following form:

$$p_e = \alpha + \beta_1 p_w + \beta_2 Q_{US} + \varepsilon_t, \tag{3}$$

where p_e and p_w denote ex-vessel and wholesale prices, respectively, and Q_{US} denotes U.S. landings. Using this specification, the authors show that wholesalers transfer to the lobstermen, on average, 52% of the changes in the wholesale price.

Estimation of the inverse demand function has also taken the form of a system of equations for prices based on landings characteristics. Richardson et al. (1986) estimate a system of price equations for 5 size classes to predict size-specific price responses to changes to minimum legal size. The authors argue that size-specific price equations are necessary since distributional lobster channels have evolved to allocate lobster of different sizes into different markets. The authors also argue that changes in minimum size regulation will change the relative number of different size classes. Price differences have also been found based on shell conditions and quality. For instance, soft shell lobster receives a lower price than hard shell lobster due to lower meat yield (Thunberg 2007).

Holland (2011) estimated a log-log specification to model monthly average ex-vessel price as a function of landings, U.S. quarterly per capita personal income, the U.S.-Canadian exchange rate, and the percentage change in U.S. gross domestic product (GDP); the author found all explanatory variables significant at the 1% level. Dayton (2018) estimated a similar specification where the ex-vessel price is a function of domestic landings, GDP (as a proxy for consumer income), seasonal variables, frozen and live imports from Canada, and lagged inventories. Dayton's results show that imports from Canada and lagged inventories are negatively correlated with domestic prices, implying that both may contribute to the over-supply against market demand, pushing prices down (Dayton 2018).

Across all inverse demand specifications, the lobster price has been found inversely related to domestic quantity landed and positively related to proxies for personal income, suggesting lobster is a luxury good (Holland 2011a). The literature has found a negative correlation between price and the U.S.-Canada exchange rate, inventories, and imports from Canada. Price has followed a seasonal pattern that mirrors landings, increasing during the winter—when available landings are low— and declining during the late summer/early fall as landings increase (Thunberg 2007). Lobster size and quality also appear to be determinants of price (Richardson et al. 1986; Steinback et al. 2008; Thunberg 2007). Modeling the relation between lobster characteristics and lobster price is an area of further research, especially considering that warm temperatures might increase the susceptibility to lobster shell disease (Tanaka et al. 2017).

The estimation of an inverse demand function (equation 2) for the studies mentioned here required data from different sources. Price data were obtained from NMFS dealer data or derived from the value of sales and quantity data from other NMFS datasets. Cheng and Townsend (1993) obtained 1981-1988 landings data in reports from the NMFS Office of Data and Information Management. The NOAA Office of Science and Technology databases have data that are more recent. Import data came from the National Fishery Statistics Program, the NMFS, the NOAA Office of Science and Technology database, and the Department of Oceans and Fisheries Canada. Information on exchange rates, per capita income, and changes in GDP came from macroeconomic statistic sources such as those from the Federal Reserve Bank of St. Louis (Dayton 2018). Finally, the estimation required standardizing the temporal scale of data such that price and quantity relationships were measured at the same temporal scale, monthly or annual.

2.4 Fishery benefits

The benefits of fishing operations at a vessel level *i*, have been calculated as net revenues and/or net profits (Dow et al. 1975; Holland 2011b; Lehuta et al. 2014). To calculate net revenues, authors use the following:

$$R_{it} = p_t q_{it} - Cost_{it}, \tag{4}$$

where p_t denotes the price, q_{it} denotes vessel-level landings, and R_{it} denotes total revenues. $Cost_{it}$ represents a cost function for lobster vessels *i*, including operating, fixed, and opportunity costs. Operating costs generally include fuel, bait, crew wages, repairs, gear, and other miscellaneous expenses (Kitts et al. 2022). Fixed costs included insurance, principal and interest payment, license fees, property taxes, vessel and gear depreciation, and dockage fees (Kitts et al. 2022). Few studies have also included the opportunity cost of labor (instead of crew wages) and capital. The opportunity cost of labor measures the value of earnings that a vessel owner and the crew would obtain in an alternative occupation. Proxies for the opportunity cost of labor included aggregated statistics such as per capita income (Thunberg 2007), median hourly wage (Holland 2011b), or the minimum wage multiplied by the averages of trips, hours, and days per crew member (Milon et al. 1999). The opportunity cost of capital provides a measure of whether capital would be better used in alternative investments, typically measured by the market interest rate. There is consistent evidence that after accounting for fixed costs and opportunity costs, on average, lobster vessels have been operating with a negative net profit (Dayton et al. 2014; Thunberg 2007).

Calculating costs requires information on the total amount of inputs used and their prices. For instance, the cost of bait is calculated as the product of the bait's price, bait per trap, and number of trap hauls in time *t* (Holland 2011). The standard procedure to calculate fishery benefits was to aggregate revenues and profits across all vessels. Due to the lack of cost data for the entire fleet across all years, net revenue was typically calculated by the product of the net revenue of a representative vessel and the total number of vessels (Holland 2011a; Lehuta et al. 2014). This calculation assumes that all vessels are homogeneous and that difference between their revenue, $p_t q_t$, and their cost function, $Cost_t$, averages out across the different classes of vessels. Richardson and Gates (1986) used survey data that differentiates costs across types of vessels and approximated total fishery benefits by aggregating net revenues across all vessel classes.

Richardson and Gates (1986) calculated the changes in consumer and producer surplus due to changes in harvest regulations. While the authors did not provide a mechanism by which surplus was calculated, economic theory suggests that one needs to estimate the demand function, such as equation 2, to calculate the quantity demanded at different prices. The demand curve allows calculating changes in consumer surplus by measuring, in monetary terms, changes in consumers' expenditures. Likewise, a surplus function allows estimating changes in producer surplus by measuring the changes in vessels' revenues as prices change.

The lobster fishery affects aggregate income, sales, and regional employment. For instance, Steinback et al. (2008) used IMPLAN, an input-output model, along with information from a bioeconomic simulation of the fishery to calculate the contribution of vessels' expenditure to the regional economy. Their analysis relied on the assumption that fishers' expenditures to operate their vessels have a cascading effect on local business providers creating a series of industry-to-industry multipliers and consumption spending cycles that affect all sectors of the economy. Measuring impacts on the broader economy requires cost data beyond those needed to estimate a production function, such as the cost of repair, maintenance, and professional and administrative expenses.

The description of economic models of the American lobster fishery is based on literature from as early as the 1970s. While this literature review allows us to identify different factors that play a role in the past configuration of lobster economics, we are aware that some of those may not characterize the current economic dynamics of the fishery. To fill out the gap, in the next section, we used expert feedback to identify factors that play an essential role in the current economics of the fishery and that must be considered in future efforts to characterize the fishery.

2.5 Missing considerations in the literature

Inverse demand functions have been estimated for the ex-vessel market. Indicator variables for months, or quarters, were included in the econometric estimation to account for the intra-seasonal price variation. However, the intra-seasonal variation is assumed constant across years. This assumption is particularly problematic if one suspects that the underlying factor determining the seasonality of landing may change over time, such as the intra-annual molting cycle. To fully consider the relationship between price and landing quantities across multiple years, we need to consider that environmental variables may affect the monthly distribution of landings over the years. However, this will require carefully specifying an inverse demand relationship that includes variables beyond fixed seasonal dummies.

The Canadian and U.S. lobster markets are fully integrated in that prices on both sides of the border are directly related to landings in both countries (Dayton et al. 2014). The trade relationship between both countries has evolved, switching from a unidirectional relationship with

Canadian imports supplementing domestic landings to a bilateral relationship that benefits both countries (Thunberg 2007)**.** The role that the U.S.-Canada lobster trade plays in the domestic relationship between price and landings has been modeled by accounting for the exchange rate between the 2 countries (Holland 2011b; Lehuta et al. 2014). This approach assumes that currencies' prices fully determine the amount of trade that occurs between both countries. However, the exchange rate alone may fail to explain the role trade plays in smoothing out variability in domestic and Canadian landings and the observed seasonality of Canadian lobster supply to domestic markets (Dayton et al. 2014; Dayton 2018). More work needs to be done to fully characterize the trade relationship between both countries and its implications for the domestic price determination and forecast in the short and long term.

Further, one also needs to consider the interaction between the lobster fishery and other species, which may affect a vessels' cost. For instance, gear modification requirements and access restrictions have been implemented in the lobster fishery to reduce the risk of entanglement for North Atlantic right whales (*Eubalaena glacialis*) in order to reduce mortality (Bisack and Magnusson 2021). Profit functions (i.e., production and cost) and market models need to consider the link between the American lobster and Atlantic herring (*Clupea harengus*) bait market since harvesting behavior, costs, and revenue in the lobster and herring fisheries are likely intertwined (Lehuta et al. 2014; Stoll et al. 2022). Since herring accounts for nearly 90% of bait used in lobster traps, one may suspect that changes in the regulation of the herring fishery, such as a Total Allowable Catch (TAC) reduction, would create shortage concerns that directly affect lobster input prices.

Another underdeveloped area of research is the lack of models that differentiate between sources of demand and product differentiation. The lobster market has an ex-vessel market, wholesale market, and retail market like any other fishery; it also has a subsidiary market driven by the demand of domestic wholesalers for Canadian lobster. Lobster prices may be differentiated in the wholesale market by quality and size. This suggests different demand curves may be required. Botsford et al. (1986) assumes ex-vessel and wholesale demand as being derived from retail demand. Richardson and Gates (1986) estimated a system of 3 demand functions to model both ex-vessel and wholesale markets simultaneously: wholesalers' demand for domestic landings at dockside and lobster imported from Canada if domestic landings are insufficient. There is also a demand for wholesalers from retailers, and consumers' demand on retailers; product quality and size may differ across these markets. Wang and Kellogg (1988) introduced size as a right-hand-side variable in their lobster demand model. Dayton et al. (2014) differentiates price, once lobsters have been sorted and graded in the wholesale market. Our observation is, there is a shortcoming in the literature that explores the role of product differentiation as a determinant of ex-vessel price. Further, estimating explicit demand curves may be of interest when measuring the distributional effect that regulation may have on harvesters and wholesalers and whether and how the impacts are passed on to consumers.

All models described above lack spatial considerations in the landings and price determination. Richarson and Gates (1986) model inshore and offshore harvesting sector independently, and Dayton (2014; 2018) and Dow (1975) included distance traveled as an explanatory variable in the production function. If lobster distribution across space is not homogeneous (Chang et al. 2010), the spatial distribution of effort will affect the expected quantity harvested at the different locations. Distance traveled variables may fail to account for this spatial effect if the model is not spatially stratified. An estimated production function that does not characterize the relationship between space and abundance may fail to forecast future landings if environmental and spatial variables change over time, affecting both effort allocation and expected landings. The inverse demand function may also need to include spatial considerations if the harvest is sold at different locations with different prices. Considering the timing and spatial cues, international markets, supply chain, and product differentiation, lobster economics modeling presents challenges and opportunities that may be worth investigating.

3. EXPERT RECOMMENDATIONS: ECONOMIC MODELS FOR THE LOBSTER FISHERY

The literature review in section 2 describes modeling approaches and information on relevant processes and factors used to characterize the American lobster fishery. Due to the dynamic nature of the fishery, past literature may fail to account for contemporary events likely to drive the management challenges in the incoming years. To identify current key challenges of the harvesting and market sector of the fishery, we hosted a series of workshops with stakeholders from the lobster fishery. During the workshops, we asked the participants to identify factors that influence lobster economics as well as challenges and opportunities in developing a simulation model for the fishery. A full workshop proceeding is available in a separate document (Caballero et. al 2023). In this section, we describe relevant factors identified during the workshop to consider for developing a set of models that characterize landings, price, demand, and fishery benefits.

3.1 Factors that determine harvests

We dedicated one of the workshops to presenting the literature findings on harvest models for the lobster fishery and asked the participants to list inputs that determine the vessel-level landings. Our goal was to identify which inputs are necessary to include in a lobster vessel production function beyond those already found in the literature. Participants listed the following inputs as determinants of vessel level landings: location and proximity to the biomass, size of the business, size of the vessel, license class, captain's experience, available biomass, trap density, technical capacity, bait efficiency, bait quality, labor/number of crew, tradition, number of trips, number of traps hauled, input prices, output prices, and fishing location. Of those, size of the vessel, captain's experience, available biomass, trap density, labor, number of trips, number of traps hauled, and fishing location have been incorporated in the literature as described in section 2. In contrast, the literature has excluded all other inputs. Some of the inputs not included in the literature may be highly correlated with inputs that were included, thus not providing additional information on vessels' production technology. For instance, the size of a business and technical capacity are likely to be correlated with inputs such as vessel characteristics and number of traps.

Some inputs could add new and essential information to vessel production technology, including bait type, bait quality, and traditions. Bait type and quality arise as an essential factor of production given the challenges to finding substitutes for herring, a key source of bait for the lobster fishery and in low supply due to the recent reduction in herring catch limits. Tradition as a determinant for landings refers to fishers following their historical patterns when deciding when, where, and how to fish without responding to economic incentives. On one hand, proxies for bait quality can be added if one can identify bait sources and differentiate quality across different bait sources. Measures for tradition as attributes of production are difficult to quantify but can be included as state-dependent variables, as in the fishing location or fishery participation literature (Holland and Sutinen 2000; Bockstael and Opaluch 1983).

In addition to listing inputs, workshop participants also stated that vessel-level production technologies are highly diverse. Participants suggested that one needs to consider vessel heterogeneity when estimating a production function. Vessel production technology varies by license type, state vs. federal permits, infrastructure and access to market differences, fishing dependence between island and mainland fishers, cultural differences, motivation for fishing, and short-term and long-term goals. Characterizing all differences across lobstermen is challenging; however, 5 vessel categories are sufficient to capture heterogeneity, according to participants with experience modeling the lobster industry. The classification should be based on vessel characteristics and observed effort.

3.2 Factors that determine the lobster price

As described in section 2, an inverse demand function uses domestic landings, personal income, imports from Canada, inventories, and seasonality indicators as determinants of prices. According to the workshop participants, in addition to these inputs, other determinants of lobster prices may include shell quality (hardness), prices of substitutes (different species of lobster or other crustaceans, such as crab), and tourism. The domestic price for lobster is also affected by international demand and supply of lobster beyond Canada. Participants suggested considering the influence of tariffs, international holidays, trade wars, geopolitical issues, emerging international markets, competition with other exporters, and international prices of other seafood products.

Some of the missing inputs are difficult to quantify, such as explanatory variables on an inverse demand function (e.g., trade wars, geopolitical issues, views of environmental groups, emerging international markets). Accounting for these factors requires creating a proxy or indicator variables that signal their temporal effect on price. Collecting data on substitutes, tariffs, and international prices require first determining lobster substitutes and major importers of American lobster; a domestic and international market analysis may be needed to identify such products and countries. While past literature has recognized the role of lobster size and shell quality as a determinant of price (Thunberg 2007), the lack of available data has prevented other authors from including a measure of quality when estimating an inverse demand function. Accounting for factors that affect lobster's price and demand creates challenges in collection of appropriate data for the analysis.

An additional challenge to modeling the price of lobster is the high degree of uncertainty in factors that affect the domestic and international supply of and demand for lobster. Some sources of uncertainty in lobster prices include the increasing competition from other international lobster fisheries, the mismatch between international holiday supply and demand, changes in tariffs, geopolitical issues, fisheries certification, emerging markets, and changes in transportation and fuel costs. During the workshop, participants empathized that price is highly variable—in some instances, the price of live lobster changes overnight—due to changes in both the supply and demand for lobster. Participants also raised concerns about the ability to build price models that characterize uncertainty in the lobster market. When building a lobster price model, one needs to identify whether changes in these factors correlate with price changes to determine which factors provide information on general price patterns. Some of the factors mentioned above may not provide systematic information on observed price changes; in such cases, those factors could be considered disturbances in the stable relationship between price and its determinants. An operating model should be built knowing that we cannot capture every influence affecting lobster's price. In summary, participants recognized the challenges of modeling lobster prices and showed skepticism in our ability to build a model to characterize general patterns of lobster prices.

3.3 Other factors that affect the fishery

Participants of the workshops identified climate and environmental variables as factors that need to be examined while modeling the fishery's biological, harvest, and market sectors. Relevant information on increased storm events, changes in spatial distribution and size structure, and intra-annual volatility due to heatwaves should be considered as future drives of stock abundance. In addition, participants recommended considering the impact of regulation on the performance of the fishery, including regulations related to area restrictions due to offshore wind development or North Atlantic right whale protection rules, gear restrictions, licensing rules, bait source restrictions, and restrictions in trade dynamics between the U.S. and Canada, the U.S. and China, and the U.S. and the E.U. Finally, we should also consider the impact of demographic changes, infrastructure, and different coastal development patterns across fishing communities.

In addition to factors that affect the harvest and the market sector of the fishery, participants mentioned factors that affect fishing behavior beyond harvesting. Examples include whether participation in the fishery is influenced by outside opportunities, license availability, crew availability, capital age, and finance access. Modeling fishery participation is important to understand human behavior, including latency, in the fishery. According to workshop participants, where to go fishing depends on factors such as closures, proximity to biomass, fuel price volatility, offshore wind development, and traditions. Thus, an economic operating model for a fishery may include models other than harvest and market models. Such models will characterize the entry-exit behavior of fishers, temporal allocation of effort, and fishing location choices.

Challenges to developing an operating model for the fishery arise from several fronts. First, one needs to define the functional form for the harvest and market models; the literature presented in section 2 provides some guidance to address this challenge. Second, one needs to identify available data to measure inputs to characterize the harvesting and market sectors. During the workshop, participants foresaw difficulties estimating the harvest model due to the lack of information on vessel characteristics, lobstermen's experience, and availability of bait data. Lack of access to Canadian data on landings and inventories will likely prevent measuring essential factors in an inverse demand function. The low spatial and temporal resolution of both biological and economic data is likely to constrain the spatial and temporal scale and the compatibility across models in the operating model.

4. RECOMMENDATIONS: A CONCEPTUAL SIMULATION MODEL FOR THE FISHERY

Based on findings from the economics literature and stakeholders' feedback, we propose a conceptual framework of an operating model to support the development of an MSE for the American lobster fishery. The framework relies on biological and economic models. Each model takes a series of exogenous and endogenous inputs to produce outputs that serve as inputs on other models. This framework is intended to serve as the first phase of building an operational economic model. The following section describes how the framework can be augmented during Phase II to account for other models, the stock's spatial structure, or the fishing fleet's spatial dynamics. First, we present the framework by describing the general features of the models and their connections.

Then we identify data available to estimate the economic models and propose functional forms for the harvest and market models.

4.1 Operating model framework

Figure 1 depicts the operating model's conceptual framework. The Economic part of the model comprises 5 models; each relies on estimating a set of functions to convert inputs into outputs. For the purpose of this report, we describe only the economic models, which rely on the input biomass—produced as output in the biological model—to calculate vessel-level harvest and revenues and industry-level landings and prices.

The first and the second economic model characterizes the harvest sector of the fishery, employing production and aggregate landing functions. The production function describes individual vessel production technology by relating legal available biomass, capital inputs, labor, effort, and skipper skills to vessel-level landings, q_{it} where i denotes an individual vessel and t represents the time step. Estimating the production function requires vessel-level information on the catch, effort, crew size, and characteristics of the vessel and skipper. In the following subsection, we describe in detail the features of this model. The aggregate landing function calculates the aggregate level of landing across all vessels, denoted with Q_t, using vessel-level landings estimated from the production function. If we assume all vessels are homogeneous, such that all vessels have the same production function, the aggregate landing function can take the following functional form: $Q_t = \eta q_{it}$ where η denotes the total number of vessels in the fishery. Alternatively, one can estimate vessel-level landings by vessel classes, use landings by categories, and exogenous information on the number of vessels by class to estimate aggregated landings across heterogeneous vessels.

The next model characterizes the market sector of the fishery using an inverse demand function, $p_t = f(Q_t, Y_t, D_t)$. The function models the relation between quantity landed and ex-vessel price while accounting for factors that drive American lobsters' direct and derived demand. Such factors may include domestic inventories, international markets, and known seasonal patterns (Dayton 2018; Holland 2011; Richardson and Gates 1986; Wang and Kellogg 1988).

The fourth model, called the profit function, calculates vessel-level revenues and profits using inputs from the production, inverse demand, and cost functions. Revenues are calculated by combining vessel-level quantity landed and market price estimates, as predicted by the production and the inverse demand functions, ($R_{it} = p(q_t)q_{it}$). The cost function model uses variable and fixed inputs and their prices to calculate total production costs. The production cost is calculated at each time step, using variable costs, including fuel, bait, and crew. Finally, vessel-level profits, are calculated using a profit function that combines revenues and costs: $\pi_{it} = p_t q_{it} - c_{it}$.

The fourth model is intended to calculate the industry-level revenue and profits by aggregating vessel-level revenues across all vessels. Two approaches are available for aggregation. The first involves calculating a representative vessel's landings and net revenue values, assuming that all vessels share the same production and cost structure. In this case, industry revenues are calculated as the product of the representative revenue and the total number of vessels. The second approach involves including vessel characteristics in the production function to calculate landings for several representative vessels. Assuming that the number of vessels varies by category, one can estimate the industry landings and revenue as the sum of the aggregate landings by vessel classification, such that $NR_t = \sum_{v=1}^{V} \sum_{i \in v}^{I} NR_{i \in v,t}$ where v denotes vessel class, such as $v \in \{Small, Medium, Large\}$.

4.2 Fishery simulation

The purpose of the operating model is to simulate the fishery system using the linkages across models, as shown in Figure 1. At the beginning of each time step of the simulation, the biological model estimates the numbers of lobsters at length post-recruitment and pre-exploitation, as well as total legal available biomass, N_t. Legal available biomass, along with fishing inputs E_{it}[3], serve as inputs in the production function to estimate the landings of the individual vessel i. Aggregated vessel-level landings are used to calculate the industry level of landings Q_t.[4] Aggregate landings enter the biological model to calculate catch number at length, number at length post-exploitation, fishing mortality, and spawning stock biomass. Once calculated, these variables are used to determine the next time step and total legal available biomass, thus initiating the next step fishing cycle. Outputs of the production and aggregated landings functions allow estimating monthly prices according to the inverse demand function and vessel-level and industry-level profits.

At every time step, outputs of the biological and economic models allow assessing stock and fleet performance metrics such as catch at numbers, recruitment, exploitation rate, spawning stock biomass, revenue, and profits at the individual vessel and industry level. Furthermore, the collection of outputs across all time steps of the simulation allows the creation of time series, which can be synthesized by taking the average over time, reporting lower values, or final output values. Time-trajectory of key outputs across different simulation scenarios—different parameter values—can allow us to evaluate trade-offs between long-term catch and fishing mortality, revenue variability, and average catch, among others. The ability to quantify and understand trade-offs will benefit stakeholders and decision-makers in evaluating the performance of different management strategies.

4.3 A harvest production function, data availability, and specification

Estimating a production function at the vessel level requires information on the catch, effort, and vessel characteristics. Table 1 lists available federal and state data sources. Vessels with only a federal lobster permit and no other federal fishery permits are not required to report landings to NOAA Fisheries. Vessels with a federal lobster permit and other federal fisheries permit that requires reporting Vessel Trip Reporting (VTRs) are required to report the harvest of lobster and all other species to NOAA Fisheries for each fishing trip[5]. NOAA Greater Atlantic Regional Office (GARFO) currently administers the fishing VTR reporting system. The data is recorded in the Vessel Logbook Database[6], which contains trip-level information such as vessel permit number, date, gear used, statistical area, species caught, amount discarded, and landing port.

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[3] The simulation using the operating model from phase I takes effort as an exogenous variable. Based on past observations, several simulation scenarios can be performed assuming different levels of effort (such as business as usual, low, or high), a practice found in the literature (Ives et al. 2013; Dichmont et al. 2008). Phase II of the operating model may include an additional module that determines effort endogenously using an effort allocation function using linear programming (Bellanger et al. 2018; Ono et al. 2018).

[4] This step requires an estimate of the total number of vessels. In phase I of the operating model, this information is exogenous to the simulation and can take several values based on past observations. In phase II, an additional module can be used to determine the total number of vessels using an entry-exit model that determines whether a vessel decided to stay or exit the fishery after a fishing season.

[5] https://www.fisheries.noaa.gov/species/american-lobster#commercial

[6] https://www.fisheries.noaa.gov/inport/item/11489

The NMFS dealer database provides lobster landings information. The database contains primary data reported by federally permitted seafood dealers in the Northeast[7], allowing for tracking lobster landings sold to federally licensed dealers. The data collection started in 1961 to monitor and track commercial fisheries landings and was voluntary from 1961-1994, with a subset of reports containing catch and effort data. The reporting became mandatory after 1994 but no longer contained effort data. Some relevant entries in the database for modeling a production function include dealer ID, vessel permit, statistical area code, and catch.

Alternative to federal sources, individual states collect lobster landing information. The Maine Department of Marine Resources (DMR) provides 2 databases: a harvest logbook and a dealer report. Since 2008, Maine fishers have been categorized by their license type and fishing zone. A random 10% of fishers from each license type and zone combination are selected to report their logbook for a full year. The logbook dataset contains harvesters' state permit ID, area fished, and landings (ASMFC 2020). Unfortunately, one cannot construct a time series of landings of an individual vessel since vessels chosen to report on a given year are excluded from the random draw for the following year. Additional trip-level landing information in Maine is available from the Maine DMR dealer report. Since 1967, 10 dealers have been randomly selected from a list of potential buying stations each month. Once selected, fishers selling their catch at the dealer are interviewed for catch and effort information. The data available in this dataset includes dealer ID, vessel ID, landing date, harvester ID, port landed, effort, and landings[8].

The New Hampshire Fish and Game Department harvester data provided annual landings by vessel prior to 1985. From 1986-2005, a random sample reported trip-level harvest and effort data, and after 2006, all harvesters with more than 1,000 pounds in the previous year were required to report harvest and effort (ASMFC 2020). The Massachusetts Division of Marine Fisheries (DMF) harvesters' database contains monthly landing data. Before 2008, all commercial harvesters with a lobster permit were required to provide monthly information on gear, effort, catch, area, and principal landing port. After 2008, a random selection of 10% of harvesters reported trip-level data; the sample increased to 20% in 2009 and 100% in 2010.

Since 1999, Rhode Island has had a mandatory commercial lobster catch and effort logbook-reporting program. Likewise, Connecticut has had a mandatory monthly logbook system that provides catch from 1979-present. The database provides detailed daily catch data by species, area, and gear, as well as the port of landing, traps hauled, set over days, and hours trawled. In New York, Lobster permit holders have been required to fill out state VTRs since 2008 (ASMFC 2020).

In addition to federal and state landing information, the Gulf of Maine Research Institute (GMRI), in collaboration with the Maine Lobstermen's Association, collected quarterly landing data for 2005 and 2010 via telephone or online survey. The survey includes the voluntary landing information from 1156 and 1001 fishers, respectively. The survey targeted Maine, New Hampshire, Massachusetts, and Rhode Island vessels that harvest in the lobster management area 1, LMA 1 (Dayton et al. 2014).

Estimating a production function requires information on production inputs. Physical capital inputs require information on vessel characteristics and capital investment. Information on fishing permits and vessel characteristics is available in the GARFO Vessel Permit System dataset. The dataset includes information on vessels, owners, permitted fisheries, gear types, hailing port, the main vessel landing location, length, gross tonnage, engine horsepower, and year the vessel

[7] https://www.fisheries.noaa.gov/inport/item/17366

[8] https://www.maine.gov/dmr/commercial-fishing/landings/reporting-forms.html

was built, among other information[9]. The dataset tracks a vessel's permit status, including when a permit has been canceled. Lobster commercial fishing license datasets by state provide information on vessel characteristics for vessels that do not have a federal permit. Time series information on capital investment is scant. The Northeast Commercial Fishing Vessel Cost Survey[10] contains fixed, variable, and labor costs from a sample of vessels for 3 years: 2011, 2012, and 2015 (Zou et al. 2021). The survey data contains detailed information on vessel improvements, business vehicles, repair, and maintenance costs. The GMRI survey contains quarterly information on vessel characteristics and investment in lobster business for 2005 and 2010 (Singer and Holland 2005; Dayton et al. 2014).

The 2020 American Lobster Benchmark Stock Assessment and Peer Review Report provides time series information on spawning stock abundance, recruitment abundance, and effective exploitation by stock, size, and sex (ASMFC 2020). The assessment also presents aggregate annual information on landings, number of traps, and number of trips by year, stock, and state. The annual series started in 1981 and ended in 2018 with data points for 2 quarters, fall and spring. Past studies have used this information to estimate the legal available biomass on a monthly basis by interpolating quarterly information on biomass, recruitment, and observed landings (Holland 2011a).

Dealers and harvesters' databases contain information to estimate vessel-level effort. The NMFS dealer database contains voluntary information on effort prior to 1994. The Maine DMR dealer database records the number of traps hauled and average soak times at the trip level. The Massachusetts DMF harvester database contains effort data (number of trips) monthly prior to 2008 and on a trip-by-trip basis after 2010. The New Hampshire Fish and Game Department harvester data provides effort information from a random sample from 1986-2005 and comprehensive data from 2006. Logbook programs from Rhode Island and Connecticut contain trip-level data on traps hauled. The GMRI surveys contain quarterly effort data, including the number of traps, trap configuration, the number of traps hauled per day, soak time, time spent on each fishing trip, days per week spent fishing, and steam time to fishing grounds. In addition, the survey contains information on quarterly fuel use and steam time, which, combined with average speed, can allow estimating a distance traveled variable (Dayton 2018).

Since 2001, the Maine DMR dealer report has included bait per trap; however, this information is only available for a random sample of 10 dealers that vary month by month and covers only the months from April to December. Additionally, the Maine DMR has conducted the Maine Lobster Sea Sampling Survey (LSSS) as a voluntary observer program since 1985. The data collected in the LSSS included information on the location of fishing activities, environmental conditions, catch, and the number of traps hauled. Since 2001, the survey has included information about the quantity and types of bait. Three sampling trips are completed for each lobster management zone from May through November, with at least 1 sampling trip in each statistical area from December through April (Boenish and Chen 2018). The program is entirely voluntary. GMRI surveys described above collected quarterly information on the type, amount, and cost of bait for 2005 and 2010.

Information on labor and skipper skills is scant. The Maine DMR harvester database and the GMRI annual survey contain information on crew size. Only the GMRI survey collected yearly information on fishers' age and years of experience that serve as a proxy for skipper skills.

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[9] https://www.fisheries.noaa.gov/inport/item/16840
[10] https://www.fisheries.noaa.gov/inport/item/26888.

To estimate a production function, the dataset must combine different data sources to create a set of variables that characterizes production output and inputs for a series of observed production events. An event can be defined as the occurrence of lobster landings by vessel i during time t. To simulate the economics of the fishery, a monthly time step provides enough temporal variation to accommodate the biological dynamics of lobster and variability in the fishing patterns of the fleet. Monthly time steps will require aggregating trip level information by vessel when trip-by-trip data is available, such as in the NMFS dealer database or the Maine DMR dealer and harvesters report.

We need to identify the vessel of interest to estimate the production function. Historically, there are 3 fleets harvesting lobster: the SNE fleet (traditionally an inshore fishery), the Gulf of Maine fishery (primarily an inshore fishery), and the Georges Bank fishery (traditionally an offshore fishery). One approach is to consider vessels from the 3 fleets as units of interest for estimating the production function. Alternatively, one could concentrate exclusively on the fishing behavior of the Gulf of Maine lobster fishery fleet, which accounts for over 90% of the U.S. landings (ASMFC 2020). The vessel sample selection also requires considering the simulated lobster stock in the biological model. Suppose the biological model simulates the dynamics of the SNE and the Gulf of Maine-Georges Bank (GOMGBK) fleets. In that case, the sample of vessels must include the inshore and offshore fleet targeting lobster from Southern New England to Maine.

The spatial scale of the production function will be constrained by the scale of the spatial information on landings; some datasets contain information on the port of landing while others contain statistical areas of harvest. Due to the lack of fine spatial scale data, port or statistical area, indicators can serve as coarse spatial information to account for the heterogeneity of harvest across space.

Based on the available data we can specify a production function with the following flexible functional form:

$$\ln(q_{it}) = \alpha + \sum_{n=1}^{N} \beta_n \ln(x_{nit}) + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N} \delta_{nk} \ln\big(x_{nit} \cdot \ln(x_{kit}) \quad + \sum_{m=1}^{12} \lambda_m d_{mit} + \sum_{p=1}^{P} \gamma_p I_{pit} + \varepsilon_{it} \quad (5)$$

where q_{it} denotes landings of vessel i at month t. The quantity of input n for vessel i at time t is specified as x_{nit}. The total number of inputs n includes proxies for physical capital (vessel characteristics and capital investment), natural capital (available biomass), labor (crew size), effort (number of trips, number of traps, traps hauled, soak time, bait per trap, and distance traveled), and skills (age and years of experience). Allow d_{mt} and I_{pt} to denote indicator variables for time and location of fishing which are intended to capture the spatial and temporal differences in productivity in the fishery. The former indicates the month and the latter the port of landing as a proxy for location. Table 2 summarizes the list of inputs required to estimate a production function according to the literature and experts' opinions. The parameters of the production function, α, β_n, δ_{nk}, λ_m, and γ_p are unknown and need to be statistically estimated using a linear regression if there is no correlation between the right-hand side variables the error termϵ_{it}.

Equation 5 is known as the translog production function in the economics literature. It is a flexible functional form because it models complex features of the production. The function is linear, but it serves as an approximation to some unknown nonlinear production function. The production specification using this form allows estimating input production shares, also known as output elasticity of an input, which is the percentage change in output (landing) for a 1% change in a given input. Further, the estimated parameters of the function allow estimating the substitutability among inputs, which in turn can be used to understand the input intensities likely to arise from changes in the relative price of inputs or the establishment of inputs controls. This specification follows the estimation of the production function for the American lobster fishery found in the literature (Holland 2011a; Dayton et al. 2014; Dayton 2018).

4.4 A market demand model specification, data availability, and recommendations

Following Holland (2011), we propose to estimate the inverse demand function using a log-log specification of the following form:

$$\ln(p_t) = \alpha + \sum_{n=1}^{N} \beta_n \ln(x_{nt}) + \frac{1}{2}\sum\nolimits_{n=1}^{N} \sum_{k=1}^{N} \delta_{nk}\, ln(x_{nt}) ln(x_{kt}) + \sum_{m=1}^{M} \lambda_m d_{mt} + \varepsilon_{it} \qquad (6)$$

where p_t indicates lobster monthly price, x_t denotes a vector of explanatory variables including monthly landings, U.S. per capita income —as a proxy for disposable income—the exchange rate between the U.S. and key importers of American lobster such as Canada, China, and European Union, and average lobster size and shell quality, if available. The variable d_{mt} is a set seasonal indicator denoting months with traditionally high lobster demand, such as the Chinese New Year. Finally, ϵ_{it} represents the impacts of other factors in the monthly price that do not follow a given pattern and are not correlated, x_n and d_m; factors such as changes in tariffs, geopolitical issues, and the view of the environment[11]. Parameters α, β_n, δ_{nk}, and λ_m are unknown and need to be statistically estimated. Before estimating equation 6, one needs to consider whether the seasonal indicators, d_{mt}, are highly correlated with all other explanatory variables; for instance, the landing variable may already capture seasonal demand effects. If independent variables are highly correlated, one must consider whether to include all suggested variables in the inverse demand function.

The estimation of an inverse demand function, equation 6, requires monthly price data, which can be calculated from the value of sales from NMFS federal dealer datasets. Information on exchange rates and per capita income can be collected from macroeconomic statistical sources, such as those from the Federal Reserve Bank of St. Louis, as in Dayton (2018), or from the Organisation for Economic Co-Operation and Development (OECD) databases[12]. Before the estimation, one needs to consider standardizing the temporal scale of all data through interpolation, such that the price and quantity relationship is measured at the same temporal scale (i.e., a monthly basis).

An alternative and parsimonious approach to model price are time series techniques that rely solely on past monthly price data. This approach has been applied to wild and farmed salmon prices in the U.S. wholesale market (Gu and Anderson 1995), Japanese wild salmon (Vukina and Anderson 1994), and the Canadian lobster fishery (Gordon 2020). These approaches, commonly known as autoregressive models, specify the current monthly price as a function of prices from previous months. An autoregressive model for the lobster fishery can be defined as follows:

$$p_t = \alpha + \beta_1 p_{t-1} + \beta_2 p_{t-2} + \cdots + \beta_n p_{t-n} + \varepsilon_t. \qquad (7)$$

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[11] If we can obtain data on these factors, we must perform a correlation test to justify the independent assumption.

[12] https://stats.oecd.org/index.aspx?queryidp169

The specification indicates that the monthly price at time t is a function of the values of the lobster price at months $t-1$, $t-2$, …, $t-n$. In its simplest form, we can estimate the autoregressive model assuming that ϵ_t is independent and identically distributed with mean zero and constant variance $\sigma^2{}_{\varepsilon}$. Additionally, one can include previous values of the disturbance ϵ_t as part of the specification, such as:

$$p_t = \alpha + \beta_1 p_{t-1} + \beta_2 p_{t-2} + \cdots + \beta_n p_{t-n} + \delta_1 \varepsilon_{t-1} + \delta_2 \varepsilon_{t-2} + \cdots + \delta_m \varepsilon_{t-m} + \varepsilon_t \quad (8)$$

where ϵ_{t-m} denotes the forecast error in period $t-m$ where m indicates the time lag; a specification such as equation 8 is known as a moving average model. Under this specification, p_t can be considered a weighted moving average of past price observations and forecast errors.

The estimation of equations 7 and 8 does not require information on landings or economic conditions surrounding the demand for lobster. Time series techniques, however, have one major shortcoming likely relevant to the simulation of the American lobster fishery. Autoregressive and moving average models are usually employed to estimate short-term price fluctuation. However, an operating model that characterizes the market sector of the fishery needs to simulate lobster price's trajectory over many time steps; forecasting prediction is likely to increase as simulation time steps increase. In a simulation setting, a time series technique will not use new information from the harvest model to improve the estimation of simulated prices; the estimate relies solely on the behavior of past price observations without accounting for changes in the market that affect prices. As stated during the lobster economics workshop, lobster prices are highly uncertain; past trends provide little information on future price behavior. While the inverse demand function and time series techniques are 2 options to estimate the market model of the lobster fishery, more needs to be done to identify alternative modeling approaches that characterize the uniqueness of the fishery and that account for the uncertainty in the lobster market.

According to Punt et al. (2016), operating models must account for at least 3 types of uncertainty: process, parameter, and model uncertainty. Process uncertainty refers to uncertainties that come from variations in the system itself (e.g., warming temperatures affecting recruitment or population abundance). Parameter uncertainty refers to operating models built based on data subject measurement error. Model uncertainty represents the lack of understanding of the whole dynamics of the system that the operating model is characterizing.

The proposed operating model accounts for process uncertainty by including the impact of environmental variables in the biological model. The uncertainty spreads through the system due to the feedback process between the biological model and the economic models. Suppose we have predictions on key environmental variables, such as sea surface and bottom temperatures. We can then use the operating model to simulate the fishery's performance under the different temperature scenarios to evaluate the uncertainty in recruitment and fishery benefits associated with different temperature trajectories.

4.5 Accounting for uncertainty

To account for parameter uncertainty, we first need to identify what data is likely to suffer from observational error, bias, and other uncertainties and the function likely to be affected. Once identified, we need to partition the data into several samples and estimate parameters of the affected function, such as production function, for all subsets of samples. This exercise will allow us to identify which estimated parameters are robust; those whose values are sensitive to different samples are likely to suffer from parameter uncertainty. Thus, when using the operating model to perform simulations, we need to perform several simulations with random values of the parameters from a known probability distribution, as in Punt et al. (2012), to account for the inherent uncertainty associated with the parameter.

As recognized during the lobster economic workshop, our framework will likely suffer structural uncertainty, especially in the market model. The framework we propose is intended to represent the real lobster fishery system according to our findings from the literature. However, our framework is only one possible way to characterize the fishery and is unlikely to capture all the processes affecting the fishery's biology and economics. To test for structural uncertainty, especially in the market model, we suggest running separate simulations, one where the price is determined endogenously using an inverse demand and another where the price is obtained from a random draw of known distribution. Suppose there is no significant difference between the outputs of both simulations. In that case, we can argue that the model mischaracterizes the market relationships and does not do better than a random process. Alternatively, we recommend performing simulation using a stochastic term in each function and evaluating the distribution of simulation outputs under the assumption that the distribution provides a range of potential values. Punt et al. (2016) provide alternative approaches to account for different sources of uncertainty to the operational model we propose here.

5. CONCLUSIONS

The final goal of this report is to provide a conceptual framework, shown in Figure 1, for a potential operating model for the American lobster fishery. The operating model is built from the interconnection of standalone models that characterize the biology of lobster, the harvest and market sector of the fishery, and the profitability of the fishing fleet. Each model can be estimated independently using a series of functions. However, outputs produced by each model enter as input into another model, creating a series of feedback responses between biological and economic sectors that drive the fishery's performance. The interconnection and feedback between models allow for simulating the biological and economic performance of the lobster fishery under different sets of values for model parameters. The ability to simulate the fishery opens the possibility of initiating an MSE for the American lobster fishery.

We gave careful consideration to each model of the conceptual framework. The models are built based on economic theory and past empirical evidence, as found in the literature reviewed in section 2. We have chosen inputs based on economic lobster literature findings and lobster industry experts' recommendations. Further, we identified the functional form for the economic models following common approaches in the lobster literature and application beyond the lobster fishery. We have identified data sources to estimate the functions to build the harvest and market model of the operating model.

The conceptual framework in Figure 1 can be considered Phase I to develop an operating model to support an MSE process in the lobster fishery. The framework can be augmented to address current shortcomings or to accommodate potential management tools of interest to lobster managers. For instance, the current framework lacks spatial consideration. The biological model considers a single stock distributed into a single location targeted by a single fleet. The harvest estimates individual vessel landings without taking fishing location as an input in the production. Thus, the current framework will fail to evaluate the impact of spatial management policies in the lobster fishery, such as area closures due to concerns about protected species.

A spatial operating model will require introducing a spatial distribution of the stock in the biological model so that abundance differs across space. The biological model will produce an N_{jt} variable indicating the level of abundance at location j at time t. Given that abundance varies across space, location must be considered as an input in the production function so that the level of landings will vary across space. Individual vessel landings will have to account for all fishing location choices visited by vessel i, so that $q_{it} = \sum_j q_{ijt}$ where j indicates location and q_{it} indicates landings of vessel i at time t of visiting locations $j = (1,2,\ldots,j)$. Aggregate landings need to consider the number of vessels and the locations visited by each vessel. The fishing location needs to be introduced as an input in the cost function since distance travel influences the operating cost of fishing. Vessel-level profits must be aggregated across space as vessels visit multiple fishing locations. In a simulation setting, one can evaluate closure impacts by removing fishing location choices and estimate the lobster abundance and vessel-level harvest and profits when fishing locations are constrained to only specific sites. An open question remains on how to generate vessel-level effort allocation across space under different closure scenarios. While adding a spatial structure and process adds realism to the operating model, it will also increase the computational cost of estimating each model and building a tractable simulation process. The computational cost is likely to increase as the spatial dimension of the model increases.

During the workshops, lobster industry experts pointed out that fishery participation decisions, such as entry-exit and effort allocation behavior, are significant drivers of the fishery's performance. Phase III of the operating model could address this shortcoming by building 2 models that endogenously calculate vessel-level effort and decision to remain or exit the fishery, given a set of endogenous and exogenous inputs. An effort allocation model will use expected cost and revenues, or catch, in an optimization model to calculate the effort allocated at each time step. Under a spatially explicit model, the effort allocation model will calculate the level of effort across different locations based on expected profits for each location. The effort allocation model will produce the amount of effort as output—potentially measured as the number of trips, number of traps, and soak time, which will enter as an input in the production function in the harvest model.

An entry-exit model will endogenously estimate the number of vessels at each time step of the simulation. The model will require inputs calculated endogenously, such as expected revenues and cost, and exogenous inputs, such as outside opportunities, crew availability, age of the fisher, expectations about upcoming economic conditions, and other relevant variables. Once a vessel-level entry-exit model is estimated, we can calculate the probability that a vessel with given characteristics and expectations will exit the fishery. By performing this operation across different vessels, we can estimate the number of vessels likely to leave the fishery at every time step. The output of this model will be used as an input in the aggregate landing function to estimate industry-level landings and prices. To add an entry-exit model to the current operating model framework, we need to consider the time scale at which entry-exit decisions occur. The current framework seeks to simulate the fishery at monthly time steps; however, vessels' entry-exit divisions are likely to occur at more extended time frames. We must consider an entry-exit model that operates between seasons, using simulation results from time steps within seasons.

Phases II and III of the operating model require different data types than Phase I. In particular, Phase II requires spatially explicit harvest data to estimate the harvest model. Estimating behavioral models for Phase III requires collecting data on fishers' participation behavior, outside opportunities, and other factors that affect fishers' decisions to remain or exit the fishery. This type of information is not available in the current data sets listed in Table 1; thus, Phase III will require additional data collection efforts. In summary, more work needs to be done to identify spatially explicit and fishery participation data availability, to build operating models for Phases II and III.

This report proposes a basic operating model framework that is feasible to build with readily available databases. The extent to which the model needs to be augmented in different directions depends on the intended use and the model's ability to test alternative management strategies of interest to American lobster managers. Building Phase I of the operating model will serve as a basis for future developments and provide an initial tool for lobster managers to initiate an MSE process. Shortcomings of the proposed framework can be addressed by augmenting the model to phases II and III. Furthermore, we acknowledge that many other challenges will arise when building the basic framework; some challenges are only apparent when collecting data and estimating each of the functions in the models. For now, we argue that the basic framework has several attributes that make it worth considering when building an initial operating model of the fishery. The framework is consistent with past models of the lobster fishery, it aligns with the structure of operating models for other fisheries, it can track the biological and economic performance of the fishery, it is feasible to estimate with the available data sources, and it can be generalizable to accommodate other relevant features of the lobster fishery.

TABLES

Table 1. Summary of American lobster landings, price, and available cost data sources.

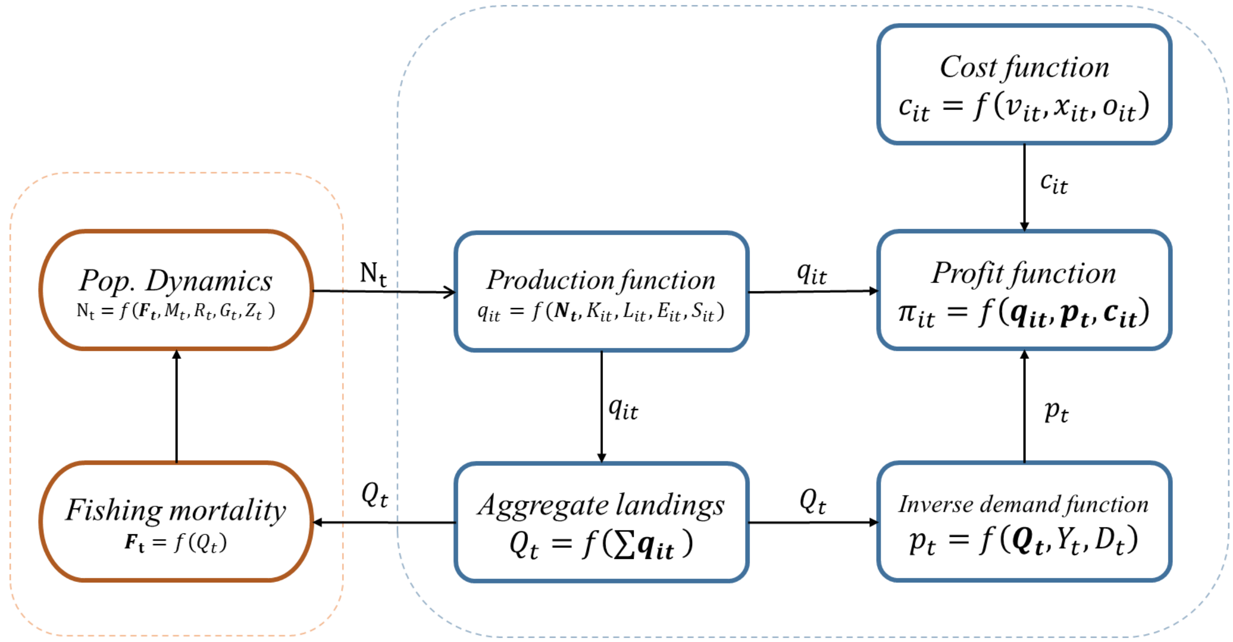
Data Source	Spatial Resolution	Temporal resolution	Key fields	Begin year	End year
NMFS[13] dealer database	Statistical Area Code	Trip level	Vessel Permit, Date, Area, Catch	1961	Current
DMR[14] harvester logbook	Management zone	Trip level	Harvester name, State permit ID, Date # number of crew, Gear type, Gear quantity, Total gear in water, Area fished, Landing (pounds), Port	2008	Current
DMR dealer reporting	Port	Trip level	Dealer ID, Date, Average price, Harvester ID, Vessel ID, Landing, Effort (traps hauled and average soak times)	1967	Current
NH[15] Fish and Game Dept Harvester data	Area	- Annual prior to 1985 - Monthly 1986-2005 - Trip level after 2006	Month and day fished, Number of gear fished, Area fished, Average set over days/pot, Weight of harvest, Gear		Current
MA DMF[16] Harvesters Database	- Coarse prior to 1990 - Statistical Area after 1993	- Monthly prior to 2008 - Trip level after 2008	Number and type of gear, Effort (set-over days, number of trips per month, etc.), Landing, Areas fished, Ports of landing	1967	Current
NEFSC SSB[17] Cost survey	Primary port	Annual for 3 years, 2010, 2011, and 2014	Vessel ID, Vessel characteristics, Operating and fixed costs, Total Revenue	2011	2014
The New England Lobster Socioeconomic Survey	Management Area	Annual	Demographics, Vessel characteristics, Effort, Operating cost, Revenue, Alternative opportunities	2005	2005
The Gulf of Maine Lobster Socioeconomic Study	LMA 1	Quarter	Vessel characteristics, Business financing, Effort, Landings, Revenue, Expenses	2010	2010
Maine Lobster Sea Sampling Survey	Near shore Maine	Trip level	Catch, Effort, Price, Gear characteristics, Bait quantity and type	1985	Current

[13] National Marine Fisheries Service (NMFS)
[14] Department of Maine Resources (DMR)
[15] New Hampshire (NH)
[16] Massachusetts Department of Marine Fisheries (MA DMF)
[17] Northeast Fisheries Science Center (NEFSC) Social Sciences Branch (SSB)

Table 2. Classification of inputs for the American lobster fishery production fishery.

Factor of production	Vessel-specific		Non-vessel-specific
	Time variant	Time invariant	Time variant
Physical capital	Capital investment	Vessel characteristics (length, tonnage, horsepower)	
Natural capital	Time indicators Location indicators		Available biomass; Environmental variables
Labor	Crew size		
Effort	Number of trips Number of traps Distance traveled Soak time Traps hauled Bait per trap Bait quality Fuel consumption		Aggregated number of traps
Skills	Year of experience Age of fishermen Technical ability		

FIGURE



Notes: Variables in bold are endogenous to the simulation; all others are exogenous.

Variables notation

Population dynamics
N_t: Legal available biomass
F_t: Fishing mortality
M_t: Natural mortality
R_t: Recruitment
G_t: Growth
Z_t: Environmental variables

Production and Aggregate landing functions
q_{it}: Landings
N_t: Natural capital/Available biomass
K_{it}: Physical capital
L_{it}: Labor
E_{it}: Effort
S_t: Skipper experience
Q_t: Aggregate catch

Inverse demand and profit functions
p_t: Ex – vessel price
Y_t: Disposable income
D_t: Demand shifters
π_{it}: Profit

Cost function
v_{it}: operating costs
x_{it}: fixed costs
o_{it}: Opportunity cost

Figure 1. Conceptual operating model for the American lobster (*Homarus americanus*) fishery.

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APPENDIX I: REVIEW OF MANAGEMENT STRATEGY EVALUATIONS

The purpose of this section is to provide an overview of the general features of the Management Strategy Evaluation (MSE) approach, applications to lobster fisheries around the world, and applications that explicitly incorporate economic components and climate change in the design. This review seeks to identify consideration for the future development of an MSE for the American lobster (*Homarus americanus*) fishery.

MSE general characteristics

We provide a brief description of the MSE approach, its core elements based on the information found in Holland (2010), Punt et al. (2016), and ICES (2020). Commonly, an MSE is defined as the mechanism to evaluate candidate management strategies, which could realistically be implemented with management objectives that are quantifiable by employing performance metrics. The robustness of each candidate management strategy is tested by comparing the outcomes of the MSE under different planning scenarios. Such plausible hypotheses about future scenarios in the biology, environment, and fishery of the management system are included as uncertainties around the model, parameters, observation, implementation, or processes[18]. The goal of an MSE is not to identify optimal management strategies but to provide information to identify strategies with performance metrics consistent with management objectives (Holland et al. 2005).

At the simplest level, the MSE involves simulating 2 sets of models: the operating model and the management procedure model. The operating model represents a realization of the natural world. It includes 3 sets of models: the observation model, the biology and fishery model, and the implementation model. The management procedure model translates the perception of the real world through data onto decision rules. It is divided into estimation models and decision models. The components of the MSE process are depicted in Figure A1. Computer simulation allows representing both models to mimic an entire management cycle, project the system's evolution into the future, and test whether a management strategy is robust to different sources of uncertainty.

Within the operating model, the biology and fishery model captures the underlying dynamics of the stock population, the exploitation sector, and the relevant ecosystem features of the system, which includes variables such as mortality, movement, recruitment, growth, catchability, prices, cost, and habitat. The observational model extracts information through data collection and passes it to the management procedure models, which may include data such as catch indexes, survey biomass, and age/length composition. The implementation model translates the decided regulatory measures (such as Total Allowable Catches [TACs]) into actual removals, which serve as inputs in the biological and fishery model. As part of the management procedure models, the estimation model assesses stock status based on available data from the observation model using information such as fishing mortality, stock status, and reference point. The decision model is used to calculate the removals based on the outcomes of the estimation model using rules commonly known as harvest control rules (HCRs). The simulation occurs as these models constitute a loop in which the outcomes of the management procedure feed back into the operating model to create new inputs, creating the system's dynamics for several years, or seasons, into the future.

[18] Punt et al. 2016 provides a definition for each source of uncertainty.

MSE application to the lobster fisheries

MSEs are used extensively to select management strategies for implementation in actual fisheries. Applications found in the literature for lobster species, including rock lobster (*Jasus lalandii*) in the South African fisheries (Johnston and Butterworth 2005) and rock lobster (*Jasus edwardsii*) in New Zealand (Bentley et al. 2005; Breen and Kim 2006; Holland et al. 2005) and Australian fisheries (McGarvey et al. 2016; Punt et al. 2012; 2013; Punt and Hobday 2009). In some cases, MSEs for lobster fisheries have been motivated by observed biological or environmental changes. For instance, operational management procedures were evaluated in the South African rock lobster fishery to formulate TAC recommendations while accounting for uncertainties in somatic growth and recruitment — assumed to be the leading cause of declining biomass in the late 1990s (Johnston and Butterworth 2005). Likewise, a decrease in biomass of rock lobster off western Victoria, Australia—due to changes in ocean currents and water temperature—led to the development of an MSE that considers future trends in parameters of the operating model, including recruitment, natural mortality, growth, and catchability (Punt et al. 2013).

Another motivation was simply the evaluation of candidate management strategies. The Otago and Southland lobster fishery in New Zealand had 2 quota management areas (QMAs). By 2005, the management decision rules to determine TAC for both relied on the catch per unit effort (CPUE) of a single management area. Holland et al. (2005) implemented an MSE to evaluate the performance of alternative management structures where decision rules were based on a weighted-average CPUE from both areas and where both locations are combined into a single management unit. Punt and Hobday (2009) implemented an MSE on the lobster fishery off Victoria, Australia, to compare 3 management strategies which differ in whether assessments were conducted, and TACs implemented, at different spatial scales (i.e. management zone or by region within the management zones). Comparison between 2 catch-based harvest rules for setting TACs—discrete versus linear controls—motivated the implementation of an MSE in a South Australian lobster fishery (Punt and Hobday 2009). Methodologically, the latter MSE is different from the rest in that it lacks an estimation model, that is, it does not use a population model to estimate biomass; rather, it sets harvest rules directly from catch data. On the contrary, all other lobster MSE applications apply a stocks assessment and estimation model to obtain inputs for the harvest control rule and decision model (Figure A1).

The lobster MSE population dynamics models share the same features in all applications; there are sex-structured models with separate recruitment, mortality, and growth parameters. Additionally, all the models are size-structured with size-specific parameters, such as selectivity at size, fecundity at size, and minimum legal size, among others. The transition between size classes takes the form of a sex- and size-specific transition probability matrix (Punt et al. 2013), a fixed proportion (McGarvey et al. 2016), or a simulated value from a distribution with mean and standard deviations of observed values (Breen and Kim 2006). The temporal scale of population dynamics follows an annual time step with 2 seasons; the exception is Punt et al. (2012), which breaks down each season into monthly time steps. The spatial scale considers a single homogeneous area and 2 or more spatial units. Holland et al. (2005) consider 2 management areas, each with its population dynamics and an underlying unidirectional dispersion pattern. Punt and Hobday (2009) model 6 spatial units with different maturity and growth parameters but homogeneous recruitment and natural mortality values.

In the operating model, the fishery sector is represented throughout a fishery mortality parameter in the population dynamic model. In some cases, the fishery mortality parameter is a function of size-selectivity (Holland, et al. 2005), gear-selectivity (Punt and Hobday 2009), and a size-specific catchability coefficient (Punt and Hobday 2009), and is generally restricted by minimum legal size regulations. Fishery mortality includes commercial catch only or both commercial and recreational catch parameters. Catches are calculated under a wide range of assumptions. For instance, the MSE for the New Zealand lobster fishery assumes that commercial catches can be directly calculated through a moving CPUE average over a recent season, plus an error process, while non-commercial catches are assumed to be proportional to biomass (Breen and Kim 2006). Similarly, McGarvey et al. (2016) assume that a fixed proportion of the most recent catch defined by the harvest control rules determines commercial catch. A different assumption is that commercial catches follow a random distribution with expectation values around the distribution of most recent season values. Commercial and non-commercial catches take a spatial dimension in the MSE for the rock lobster off Victoria, Australia. There, catches are allocated to spatial units in proportion to the exploitable biomass within each unit while accounting for the historical distribution of catches. Further, the recreational catch was assumed to be proportional to the commercial catch in expectation but to be lognormal distributed about the expected value (Punt and Hobday 2009).

The data collection and estimation model are similar across lobster MSE implementations. Generally, catch rate, catch size-composition, or catch length-frequencies are used to estimate operational models. In most cases, estimation and decision models rely on a stock assessment process to compare catch rates with stock status. Then, limited reference points or target CPUE procedures are applied to determine TACs via some harvest control rule algorithm; Punt et al. (2013) include recovery and a rebuilding plan. Most applications add parameter uncertainty to the MSEs by assuming that biological parameters followed a given probability distribution, allowing for stochastic variation in parameter values. Holland et al. (2005) introduced model uncertainty by modeling different stock structures and interactions among stocks. Other sources of uncertainty in the lobster MSEs included the randomness in data available for assessment purposes (Holland et al. 2005), variability in catches, and trends in catchability coefficients (Punt et al. 2012).

As customary for MSE applications, all lobster MSEs presented a series of performance statistics to evaluate candidate management strategies concerning management objectives. Performance metrics quantified a broad range of values related to yield, abundance, risk, stability, and economic indicators. Yield indicators took the form of annual catches, average yearly catches, minimum catches over the entire simulation period, the distribution of catch indicating percentiles, and, in one case, the size composition of catch (Holland et al. 2005). Abundance indicators included biomass measurements on an annual basis or at the end of the simulation period. All applications to Australian lobster fisheries also had yearly average egg production (McGarvey et al. 2016; Punt et al. 2012, 2013; Punt and Hobday 2009). The stability of the abundance and catch indicators are measured using the variability of the indicators over time or annual percentage changes. Safety indicators included the number of years in which the biomass or catch fell below a reference vulnerable value calculated over some reference period (Breen and Kim 2006); the probability that stock and egg production at the end of the simulation period exceeds a reference and a target value (Punt et al. 2012, 2013; Punt and Hobday 2009); and the probability that a management scenario would be expected to produce a higher or lower average catch than under base case management (Holland et al. 2005). Finally, only 2 applications included economic indicators, such as cumulative annual profits and the net present value of profits (Holland et al. 2005; McGarvey et al. 2016). In general, best performance metrics are associated with higher average catch, lower variation in the catch, and lower probabilities of declines in exploitable biomass.

Economic considerations in MSE applications

Of the MSE application listed above, only Holland et al. (2005) and McGarvey et al. (2016) explicitly modeled economic elements of the fishery. The MSE for rock lobster in Southern New Zealand integrated a suboperating economic model that transformed catches and CPUE from a biological operating model into revenue, effort, and cost for 4 fleets. The authors calculate the present values of net revenues for all fleets while overcoming disparities between the temporal scale of data from the biological and economic models. The biological model provides seasonal catch data, and the subeconomic model disaggregates it into monthly data to combine it with monthly price information. Seasonal CPUE is used along with an estimated number of vessels to calculate fleet-level effort and harvest cost for each fleet. Similar to Holland et al. (2005), the MSE for the rock lobster fishery in South Australia uses a suboperating model to calculate revenue and cost at each time step along with the net present value of profits. Likewise, the cost is generated as a function of the catchability coefficient, exploitable biomass, and relative vulnerability (McGarvey et al. 2016). In both cases, the present value of the net revenue over the entire simulation period is used as a performance statistic to rank the candidate management strategies.

Although not a direct MSE, Richardson and Gates (1986) present an evaluation of candidate management strategies using elements of an MSE and explicitly accounting for economic features of the American lobster fishery. The authors evaluate 2 alternative policies, an increase in minimum legal size and a reduction in fishing mortality. The approach contains operating models—biological and economic—but it lacks management procedure models (estimation and decision models). As is typical with MSEs, the evaluation relies on performance metrics that characterize changes in yield, harvesting sector profitability, and welfare benefits to both consumers and producers. The evaluation follows a simulation approach; however, it does not provide a time trajectory of performance metrics and instead simulates 2 equilibrium states, one before the implementation of the policy and another after.

An important contribution of the Richardson and Gates (1986) approach is that the prices (both ex-vessel and wholesale) and costs are endogenously determined within the economic operational model using yield estimates produced by the biological model. On the one hand, the biological model determines each alternative’s impacts on catch and catch characteristics, such as average weight. On the other hand, the economic model translates changes in catch and catch characteristics directly into ex-vessel and wholesale prices and indirectly into economic profitability and social surplus. A shortcoming of this model is that it does not introduce uncertainty in the strategies evaluation. The model provides a deterministic analysis and cannot test the robustness of performance metrics to assumptions made by the authors. While MSE applications to the rock lobster and American lobster fisheries provide examples of how economic elements are used to evaluate alternative management strategies, other applications provide other relevant insights.

While many MSE applications exist that introduce economic elements in the simulation, for convenience, we only review the following: the Bay of Biscay sole fishery (Bellanger et al. 2018), the Spanish demersal mixed-fisheries operating in the Iberian waters (Garcia et al. 2017), the groundfish fishery in the Bering Sea and Aleutian Island (Ono et al. 2018), the multi-species, multi-fleet prawn fishery in Australia (Dichmont et al. 2008; Dichmont et al. 2012; Ives et al.

2013). These applications show that MSEs allow modeling distributional consequences of alternative strategies, short-term and long-term fleet behavior, and managers' strategic behavior.

Quite commonly, an operating model that characterizes the effort allocation of the fishing fleet accompanies the biological operating model. Effort allocation models are helpful when the harvest control rules from the decision model produce a TAC for mixed-stock fishery (Ono et al. 2018) or multiple fishing locations (Dichmont et al. 2008; Dichmont et al. 2012). A simple approach to calculate effort allocation is to use historical catch data (Ives et al. 2013) or transition probabilities based on the history of past effort allocation (Dichmont et al. 2008). More complex modeling involves a linear programming approach where effort is allocated to maximize expected profits while meeting management and technological constraints (Bellanger et al. 2018; Ono et al. 2018).This last approach requires information on prices and harvest costs, typically obtained from surveys and projected exogenously to use in the simulation. Alternatively, price data can be directly integrated into the economic operating model as a price formation model using expected landings (Garcia et al. 2017).

Short-term fleet behavioral models take place within the simulation of a time step. Long-term behavioral models account for the fleet decision-making process at the end of a season. Long-term behavior modeling is intended to determine the adjustment of the fleet capacity throughout the entire simulation period. For instance, for the Bay of Biscay sole fishery MSE application, at the end of each time step, a vessel decides whether to exit the fishery before the next simulation step based on a proxy for expected earnings, expected cost, and parameters that represent capital malleability[19]. This exit decision allows endogenously determining the distribution of catch share over the next time period (Bellanger et al. 2018). In the demersal mixed fisheries simulation, the long-term behavioral model is presented as a "capital operational model" that describes the investment of fishers in new vessels or technologies through changes in capacity and catchability parameters (Garcia et al. 2017). Including long-term fleets' dynamics on an MSE is of particular interest if one pursues to evaluate how the alternative management strategies' impacts propagate to fishing communities.

The Australian Prawn fisheries MSE application presents a unique approach to incorporating an economic model. In this application, the MSE goal is to compare alternative management strategies that maximize the fishery's net present value (NPV). Before the implementation of the simulation, the authors obtain the maximum economic yield (MEY) by choosing the level of effort that maximizes profits over the entire simulation period using abundance projection and assuming that stock-recruitment relationships remain constant over the entire time horizon. Parameters of the maximization problems are calculated directly from economic surveys. The optimal effort time trajectory serves as the target effort indicator (i.e., harvest control rule) in the decision model (Dichmont et al. 2012). A caveat with this approach is that one has to assume that projections of abundance are correct and that the optimal level of effort that maximizes MEY is robust to uncertainties within the simulation.

Lastly, Richardson and Gates (1986) illustrate that an economic operating model can be used to calculate changes in social welfare measures, such as consumer and producer surplus. In particular, one needs to use ex-vessel and wholesale prices and quantities relations to estimate demand and supply equations. Such equations allow measuring nominal social surplus and NPV after applying a discount factor. Changes in surplus allow evaluating changes in social benefits and distributional impacts of alternative management strategies among consumers and producers.

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[19] Malleability is defined as the ability of the initial investment to be reversible in terms of vessel resale value for capital when exiting the fishery.

The above MSE applications illustrate that introducing economic analysis in evaluating management strategies increases realism to operating and management procedure models likely to improve the characterization of the fishery and the management system in question. Further, economic variables may allow for rating alternative management strategies beyond biological performance metrics. In some cases, economic metrics may overturn the ranking of management strategies evaluated solely under biological considerations (Holland 2010). Comparison of biological and economic performance statistics allows for evaluating tradeoffs between conservation and fishery benefits goals.

The reviewed MSE applications evaluated alternative strategies based on economic performance metrics such as nominal trajectories of profits, the net present value of profits, or variability of profits. However, none of these applications uses such measures to develop a metric of economic risk, such as the probability that the fleets' profits fall below threshold levels (similar to abundance reference points) that will compromise the future of the fleet. This type of threshold level exists in the American lobster stock assessment for the Gulf of Maine-Georges Bank (GOM-GBK) stock, where an abundance below the 25th percentile on the annual abundance estimate during the high abundance regime, 212 million lobsters, is assumed to lead to degradation of the economic conditions of the lobster fishery (ASMFC 2020). More work is needed to identify fishery target reference points compatible with conservation goals and based on economic metrics drawn from an MSE implementation.

Climate change modeling in the MSE applications

Evidence shows that climate change is an essential driver of change in marine and fisheries environments through changes in productivity, life history, and distribution of fish stocks (Doney et al. 2012). MSE has been used to evaluate the impacts climate variations have on the performance of alternative management strategies using one of two approaches: the mechanistic approach and the empirical approach (Punt et al. 2014). On the one hand, the mechanistic approach relies on establishing a direct relationship between environmental variables and elements of the population dynamics in the operating model and the use of outputs of global climate models to incorporate them into projection models. The empirical approach does not rely on directly inputting environmental variables; rather, it imposes trends in the values of some parameters under the hypothesis that such parameters will be impacted by environmental variation. This last approach does not require any further changes in the structure of the operating and management procedure models; it only requires performing the simulations using a range of values on the biological parameters under the assumption that climate change impacts drive those values.

Applications of the mechanistic approach include MSEs for the walleye pollock (*Gadus chalcogrammus)* fishery in the Gulf of Alaska (A'mar et al. 2009a), the Bering Sea walleye pollock fishery (Ianelli et al. 2011), the jackass morwong (*Nemadactylus macropterus*) fishery in Southeastern Australia (Wayte 2013)**,** and the U.S. west coast sablefish (*Anoplopoma fimbria*) fishery (Haltuch et al. 2019), among others. In all these cases, the first step was to link environmental variables to elements of the biological operating model supported by the literature. A'mar et al. (2009b) use a linear combination of climate indices for precipitation, wind-mixing energy (WME), and sea surface temperature (SST) as explanatory variables to predict the age-1 abundance of walleye pollock. Another example includes a spatially structured metapopulation model that captures the dynamics of the interaction between prawn populations and the fisheries that target the species; a river discharge variable is included as a driver of school prawn movement and growth (Ives et al. 2013).

The second step of the mechanism approach requires using outputs of global climate models in the MSE simulations to project the impacts that environmental variables have on the values of the biological parameters of the population dynamics. Haltuch et al. (2019) use near-shore sea-level projections from the Intergovernmental Panel on Climate Change (IPCC) Coupled Model Inter-comparison Project Phase 5 (CMIP5) to produce multidecadal recruitment projections from sablefish on the U.S. West Coast to explore the robustness of current HCRs. Likewise, A'mar et al. (2009b) use precipitation, WME, and SST predictions from 6 IPCC general circulation models to project age-1 abundance while including a recruitment process error. Note that this step requires the modelers to assume that large-scale climate forces, as measured by global climate models, drive changes at the spatial scale at which population dynamics occur.

Implementing the mechanistic approach requires biological research and modeling studies that state the structural link between climate and fish population process, as well as a long track of data collection that validates such relationships. The extent to which climate impacts are included on an MSE depends on the structure of the operating model. For instance, a model without spatial structure restricts the analysis from considering the effects of environmental change on growth, survival, mortality, and recruitment. On the other hand, age and spatial-structured population dynamics models allow accounting for impacts of environmental variation on spatial distribution and dispersal dynamics at different life stages. Finally, this approach also requires that the stated relationship between environmental variables and elements of fish dynamics holds in the future as climate conditions fall beyond historical observations (Haltuch et al. 2019).

As stated above, the mechanistic approach is motivated by the existence of ecological principles based on empirical evidence on the relationship between environmental variables and fish population dynamic parameters. When data does not exist to support the evidence of such a relationship, one can evaluate the impacts of climate change within an MSE framework by allowing parameters of the operating model to change to reflect potential climate impacts. For instance, the regimen shift in the inter-annual climate variability in the North Pacific and its relations with fluctuation in fish abundance and population dynamics are poorly understood and difficult to forecast. However, the impact that a future regimen shift in recruitment may have on the performance of management strategies was evaluated using the MSE approach by changing the average level of recruitment over time (A'mar et al. 2009b). In such cases, the direct mechanism by which the regimen shift occurs is not directly introduced in the operating model but imposed in the simulation. Similarly, one can introduce an algorithm in the MSE that performs a sequential statistical test for regimen shift, change in mean values over time to identify a regimen shift endogenously, disregarding the environmental relationships that drive the shift (Szuwalski and Punt 2013).

In contrast with the mechanistic approach, the outcomes from an empirical approach cannot be treated as future trajectories of relevant biological variables but as hypothetical scenarios (Punt et al. 2014). The empirical approach can be applied to any MSE by introducing uncertainty to one or more parameters and evaluating the performance of alternative management strategies under the assumption that climate change drives such uncertainties. The primary value of this approach is to explore the extent to which management strategies are likely to be robust to changing parameters in the operating model rather than environmental variability.

Conclusions

This literature review aims to describe the MSE approach, MSE application to lobster fisheries, and strategies to include climate change impacts on fisheries within the MSE approach.

According to the literature, an MSE application relies on operating models to characterize the dynamics of the fishery. In particular, biological and economic operating models are needed to account for the population dynamics of the resources and the dynamics of the fishing fleet and provide metrics to evaluate the biological and economic impacts of alternative strategies. The MSE literature applied to lobster fisheries suggests that a biological operating model should include sex and size-structure population dynamics models with separate recruitment, mortality, and growth parameters. The transition between sizes is typically defined as transition probabilities, fixed proportions, or draws from probabilistic distributions. The biological and economic operating model's connection is usually represented with a fishery mortality parameter. Simple approaches calculate catches as moving averages over recent periods or as a fixed proportion of most recent catches. Complex approaches to account for fleet dynamics relate catch to fleet's effort. A simple approach to calculate effort is to use historical catch data, and a complex approach involves a constrained optimization model to maximize profits subject to management and technological constraints.

MSE applications also provide advice to account for climate change when evaluating alternative management strategies. A simple approach requires simulating the biological system under a range of values of key biological parameters, such as recruitment, assumed to be impacted by climate change. A complex approach requires introducing environmental variables in the biological operating model. Climate change impacts are evaluated using outputs of climate models to create a projection of key environmental variables and use them in the simulation.

This literature review is intended to guide the structure of an operating model for the American lobster fishery and to identify approaches to characterize the fishery's biology, economics, and climate features. As described above, the complexity of operational models arises as one introduces more realistic features to the models. When developing an MSE for the American lobster fishery, one needs to consider that adding complexity to the operating model may increase the MSE approach's realism and undermine the simulation's tractability. One needs to account for this trade-off when building an operating model that characterize the dynamics of the fishery.

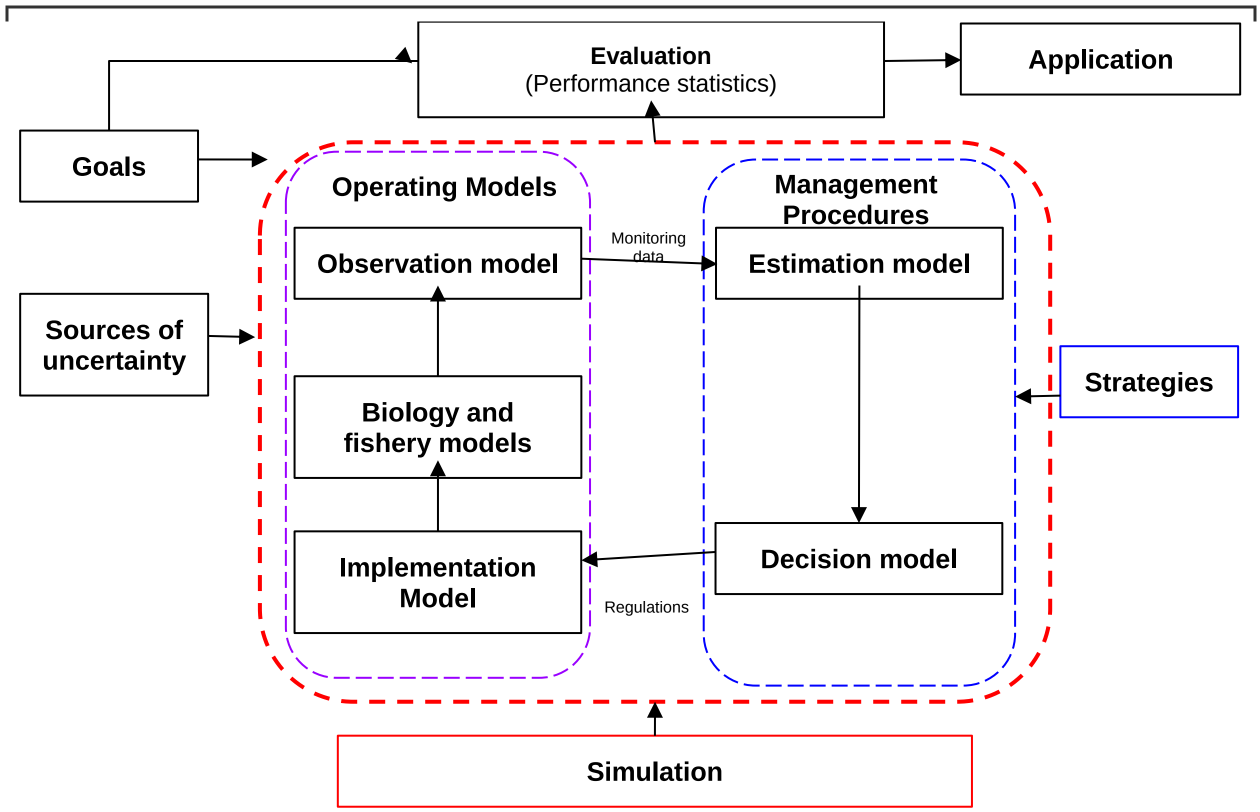

Figure A1. The conceptual Management Strategy Evaluation (MSE) process (based on Punt et al. 2016).

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