Canadian Journal of Fisheries and Aquatic Sciences

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Journal:	<i>Canadian Journal of Fisheries and Aquatic Sciences</i>
Manuscript ID	cjfas-2018-0122.R2
Manuscript Type:	Article
Date Submitted by the Author:	04-Oct-2018
Complete List of Authors:	Mazur, Mackenzie; University of Maine School of Marine Sciences Li, Bai; University of Maine College of Natural Sciences Forestry and Agriculture, School of Marine Sciences Chang, Jui-Han; University of Maine Chen, Yong; University of Maine,
Keyword:	individual-based model, fisheries management, American lobster, RECRUITMENT < General
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)

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Using an individual-based model to simulate the Gulf of Maine American lobster (*Homarus americanus*) fishery and evaluate the robustness of current management regulations

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Abstract

Individual-based models (IBMs) can capture complex processes with a flexible probabilistic approach, which makes them useful for studying organisms with complex life history and fishery processes such as the American lobster (*Homarus americanus*). This research aims to modify and parameterize an individual-based lobster simulator (IBLS) to simulate the American lobster fishery in the Gulf of Maine. To simulate the fishery, the IBLS was tuned to match the seasonal catch and size composition from the 2015 American lobster stock assessment by adjusting the values of coefficients for select parameters. With appropriate coefficients for the initial abundance, recruitment, and seasonal encounter probability levels, the tuned IBLS accurately simulated the historical landings. Given the uncertainty in future American lobster recruitment, the tuned IBLS was then used to evaluate the effectiveness of current management regulations under different levels of recruitment.

Key words

individual-based model, fisheries management, American lobster, recruitment

1. Introduction

Fishery failures have been common over time and space (Worm et al. 2009), and as a result, there has been a push for better fisheries management. Fisheries management must consider the effects of environmental variability (Hofmann and Powell 1998). In a changing environment, the effectiveness of current fishery management regulations may change. Management regulations may become detrimental to the resource if environmental change is not considered (Hofmann and Powell 1998). Identifying management regulations that are robust to environmental fluctuations is a critical need in fisheries management (Walters and Parma 1995). The distribution and seasonal cycles of marine species may change with changing water temperatures (Mills et al. 2013), which may affect life history parameters, such as recruitment into a fishery.

The current management regulations of American lobster in the Gulf of Maine (GOM) have not been evaluated for effectiveness with variability in recruitment. American lobster recruitment has increased dramatically in the past few decades (ASMFC 2015). However, settlement surveys may indicate a future decline in recruitment (Wahle et al. 2015), and the effects of warming water temperatures on the lobster population are not clear. Lobster landings and abundance in the GOM have increased dramatically and are at historic highs (ASMFC 2015), and American lobster supports one of the most culturally and economically valuable fisheries in the United States, worth more than 666 million USD in 2016 (ACCSP 2018). The importance of the lobster fishery and the uncertainty of the future of the fishery calls for an evaluation of the robustness of current management regulations with a simulation tool. Identifying a simulation tool for the complex American lobster fishery, in which fishery and life history processes vary among individuals, is necessary for such an evaluation.

The complexity of American lobster biological and fisheries processes makes the use of traditional mathematical-formulation-based models difficult (ASMFC 2000). Growth of the American lobster is not continuous, as lobsters grow by molting, which mainly occurs in summer and fall (Factor 1995). Molting frequency is dependent on the size and maturation status of the lobster (Factor 1995; Comeau and Savoie 2001). Additionally, conservation measures used in the GOM fishery, such as minimum and maximum legal sizes, prohibition of the taking of egg-bearing lobsters, and protection of ovigerous females through a V-Notching program, are difficult to consider as separate processes with traditional fishery models (ASMFC 2000). In the GOM lobster fishery, if a lobsterman catches an egg-bearing lobster, he can choose to cut a 'V'-shaped notch in the lobster's tail and release the lobster. Lobsters with a V-Notch are illegal to be caught, because they are proven breeders. Consideration of all these fishery processes as separate is important when evaluating changes in one process but not the others. For example, fishery conservation processes need to be considered as separate to evaluate the effect of minimum size but not maximum size and protection of egg-bearing lobsters.

An individual-based model (IBM) may be an alternative modeling approach used to develop a fishery simulator because it can track the detailed life history and fishery processes of individual lobsters. IBMs describe a population consisting of different individuals and changes in the number of individuals instead of population density and consider the population dynamics under complex processes (Uchmanski and Grimm 1996). With a probabilistic approach, IBMs allow for much more complexity than traditional mathematical-formulation-based models (Uchmanski and Grimm 1996). When mathematical methods are used to model complex processes, unrealistic assumptions are often introduced to attain mathematical solutions; whereas IBMs can assume individuals are different from one another (Judson 1994; Grimm 1999). In

addition to the incorporation of variability among individuals, IBMs can simulate life cycles of individuals that are not usually included in analytical models.

In this study, we modified, parameterized, and tuned an individual-based lobster simulator (IBLS) so that it can simulate the historical GOM lobster fishery. We used the tuned IBLS to evaluate the robustness of current management regulations under different levels of recruitment. We assessed the status of the fishery under different recruitment levels with ad hoc biological reference points. This study includes 1) the description and parameterization of the IBLS that mimics the dynamics of the life history and fishery processes of individual lobsters 2) calibration of the IBLS, using coefficients for specific parameters in order to predict historical landings and population size composition of lobsters, and 3) application of the simulator to evaluate the robustness of current management regulations under different levels of recruitment. This study also discusses how simulations can highlight uncertainties in input data and model structure.

2. Materials and Methods

The IBLS was developed in Chen et al. (2005) to test the performance of the stock assessment model and further developed in Chang (2015) for management evaluation. An IBM was used to develop the IBLS for the GOM lobster fishery, by expressing numerous components of the model equations as random Bernoulli trials (Chen et al. 2005; Chang 2015) (Fig. 1). Instead of calculating the amount of lobsters that survive a given process, such as natural mortality or fishing mortality, we simulate natural mortality or fishing mortality acting on N_t individual lobsters.

2.1. Model Description

2.1.1. Input

The IBLS requires abundance, recruitment, and other types of data (Table 1). Most of the probabilities and other input data are from the stock assessment data (ASMFC 2015), but fishing effort data are from the Maine Department of Marine Resources (DMR) harvester data, and V-Notching information is from personal communication with managers (Table 1). These are the best available data representing the GOM lobster fishery dynamics.

Some of the probabilities, such as encounter probability, were calculated from the input data. Encounter probability is the probability that a lobster is caught in a trap and is calculated for each season, year, sex, and sizeclass. Encounter probability was calculated as:

$$Enrate_{t,se,si} = \frac{C_{t,se,si}}{C_{t,se,si} + N_{t+1,se,si}} \quad (1)$$

where $C_{t,se,si}$ is the catch on the boat before the illegal lobsters are thrown back, or the total number of lobsters that are caught in time t for sex se and sizeclass si and $N_{t+1,se,si}$ is the abundance in time $t+1$ for sex se and sizeclass si . Catch on boat was calculated as:

$$C_{t,se,si} = \frac{L_{t,se,si}}{S_{t,se,si}^{cons} S_{t,se,si}^{legal}} \quad (2)$$

where $L_{t,se,si}$ is the landings in time t for sex se and sizeclass si , $S_{t,se,si}^{cons}$ is the conservation selectivity in time t for sex se and sizeclass si , and $S_{t,se,si}^{legal}$ is the legal selectivity in time t for sex se and sizeclass si . $C_{t,se,si}$ plus $N_{t+1,se,si}$ is the abundance of the current timestep before fishing mortality, the last process in the IBLS but after natural mortality and growth, plus the lobsters

that are released. The denominator in equation 1 includes lobsters that are released, because in reality, those lobsters could be caught again in a given timestep and need to be included in the total number of lobsters that the catch on boat can be removed from. Encounter probability is then scaled by fishing effort to represent the probability of being caught in the fishery.

2.1.2. State variables and scales

Individual lobsters are characterized by the state variables: size (carapace length (CL) in mm), sex, maturity status, egg status, survival status (if the lobster is alive or dead due to either fishing or natural mortality), and V-Notch presence. The temporal range is from the years 1982 to 2013, because the time range of the most recent American lobster stock assessment model output is from 1982 to 2013 (ASMFC 2015). The spatial extent is the GOM lobster stock area (Fig. 2). The model has four timesteps: winter (January-March), spring (April-June), summer (July-September), and fall (October-December). There are 35 size classes. The largest size class is a plus group including all lobsters larger than or equal to 223 mm CL, and the smallest is 53 mm CL, as this is the smallest size at which a lobster can grow above legal minimum size in one molt. The size class interval of 5 mm CL was chosen because the minimum molting increment is 5 mm CL (ASMFC 2015).

2.1.3. Process overview and scheduling

Individual lobsters are traced throughout the simulation, which includes biological and fishery processes, until the individuals die of natural or fishing mortality. The first part of the IBLS includes the biological processes, such as natural mortality and growth. In each timestep in the IBLS, first, each individual lobster is assessed to see if it is mature; this determines if the lobster is a part of the spawning stock biomass (SSB) and can produce eggs. It then has a

probability of dying from natural mortality such as predation. If the lobster does not die, it has a probability of molting and growing a specific molt increment. Larger lobsters molt less frequently and have smaller molt increments. If it has been two molts since its last V-Notch, it will lose its V-Notch, as the V-Notch will grow out with each molt. After molting, the lobster then has a probability of dying from molting mortality.

If it survives or did not molt, it has a probability of being caught in the fishery (encounter probability). Once caught, if it is of illegal size or has a V-Notch, it is released back to the population. There is no mortality when lobsters are released back to the population. If it has eggs, it has a probability of being V-Notched by a lobsterman and then released back to the population. Once V-Notched, it is released back to the population and protected from harvest for two molts. The released lobster can be harvested in the next timestep if it is legal to be caught. If a lobsterman does not V-Notch an egg-bearing lobster, the lobsterman still releases the lobster back to the population, because it is illegal to land lobsters with eggs. If the lobster did not die from fishing mortality, it survives to the next timestep.

The lobsters that survive to the next timestep plus the recruits into the fishery are the number of lobsters that go through the life history and fishery processes in the next timestep. Each individual lobster entering the IBLS goes through all the processes again and again until it dies due to natural mortality or is caught in the fishery. Two recruitment events occur in the summer and fall, when molting occurs. At the end of each discrete timestep, the state variables are updated and recorded. The internal process of the IBLS is programed in C++ (Chang 2015) and the input and output data are handled and analyzed in the R programming environment (R Core Team 2017).

2.1.4. Initialization

The initial size composition ($p_{si,1982}^{se}$) and abundance (N_{1982}^{se}) for each sex is specified, so that the number of lobsters for each sex se in size class si in the first assessment timestep (i.e., winter in 1982) is:

$$N_{si,1982}^{se} = p_{si,1982}^{se} N_{1982}^{se} \tag{3}$$

The fishery was initially occupied with 93.2 million lobsters with an initial sex ratio of 0.546. There was a burn in period of five years to get the amount of lobsters with a V-Notch to the levels of that in 1982.

2.1.5. Submodels

2.1.5.1 Recruitment

For the historical simulation and calibration parts of the study, historical recruitment was used. For evaluating the current management regulations under different levels of recruitment, we used three different recruitment levels: low, intermediate, and high. Under the assumption that estimated historical recruitment from the stock assessment has some errors, recruitment was drawn from a normal distribution with a given mean and a coefficient of variation (CV) of 10%. The means of the low and high recruitment levels were the average of the five lowest and highest historical recruitment values, respectively. The intermediate recruitment level mean was the average of all the historical recruitment values.

2.1.5.2. Maturity

The proportion of females that are mature, which make up the SSB, at a certain CL is defined with a logistic equation:

$$P_{matcl} = \frac{1}{1 + e^{27.243 - 0.3CL}}$$

(4)

The size of 50% maturity is estimated to be around 91 mm CL (ASMFC 2015).

2.1.5.3. *Weight-length relationship*

The weight-length relationship used in the IBLS to calculate stock biomass for males is described as:

$$W_L = 5.21 \times 10^{-7} CL^{3.07814}$$

(5)

For females it is described as:

$$W_L = 8.67 \times 10^{-7} CL^{2.97157}$$

(6)

where CL is carapace length in mm for each lobster (ASMFC 2015).

2.1.6. *Output*

The output from each simulation is carefully documented. The output data can be aggregated into fishery indicators such as year-, season-, and size-specific abundance, biomass, and catch. Biomass can be estimated by summing the weights of individual lobsters after weight is determined from the weight-length models (ASMFC 2015). Total biomass, $B_y^{\text{total},se}$, and legal biomass, $B_y^{\text{legal},se}$, in year y for sex se are estimated as:

$$B_y^{total,se} = \sum_{si} N_{si,y}^{se} w_{si}^{se} \quad (7)$$

$$B_y^{legal,se} = \sum_{si} N_{si,y}^{se} p_{si,y}^{se} w_{si}^{se} \quad (8)$$

where w_{si}^{se} is the weight of the lobster in size si , and $p_{si,y}^{se}$ is a switch (0 for size classes not of legal size, and 1 for legal size classes).

2.2. Model calibration:

With these probabilities and input data, the base case, or historical fishery, was simulated. Additionally, catch and size composition data were aggregated from the American lobster stock assessment, and these data were used to tune the IBLs. The historical fishery simulation is systematically calibrated, or tuned to minimize the objective function to fit the observed data (from the stock assessment) using all possible combinations of coefficients for specific parameters with equal weight on both catch and size composition. A range of values of coefficients are chosen for initial abundance, recruitment, and the season specific encounter probabilities. The historical fishery was simulated from 1982 to 2013 with every possible combination of coefficients. The coefficients that minimize the objective function, the coefficient of variation of the root mean square error (CVRMSE) between the observed (from the stock assessment) and simulated catch and size composition, were chosen (Table 2). Tuning the IBLs with coefficients is necessary to find the optimal parameter values given the data, so that the observed historical fishery can be simulated. With the calibrated IBLs, we then observe

trends in the outputs such as catch and abundance. The calibrated IBLS can then be used to evaluate management regulations.

2.3 Application:

To illustrate the some of capabilities of the simulator, we evaluated the current management regulations under different levels of recruitment: low, intermediate, and high. The different recruitment levels were projected from the years of 2014-2023. Averages of the encounter rates of the most recent five years were used for each of the projection years. The status of the fishery was assessed using ad hoc biological reference points that were used in the most recent lobster stock assessment (ASMFC 2015). The target reference points were the 25th percentile of historical exploitation rate and the 75th percentile of historical reference abundance, and the limit reference points were the 75th percentile of historical exploitation rate and the 25th percentile of historical reference abundance. Reference abundance and exploitation rate are calculated with lobsters greater than 78 mm CL (ASMFC 2015).

By comparing the reference abundance, exploitation rate, and the landings of the different scenarios, we can ask: 1) how would the fishery and lobster population be different if recruitment were to change? and 2) are current management regulations robust to variability in recruitment? The simulations were run 50 times for each of the three scenarios: 1) low recruitment, 2) intermediate recruitment, and 3) high recruitment.

3. Results

3.1. Calibration:

Applying coefficients to the parameters had dramatic effects. The parameter coefficients that produced the smallest objective function (Table 2) increased recruitment and decreased

initial abundance. These coefficients also increased the winter and spring encounter probabilities and decreased the summer and fall encounter probabilities, as the encounter probabilities can vary by season. The objective function seeks to minimize the sum of the CVRMSE of observed and predicted catch and size composition by timestep. The error indicator, e.g. CVRMSE, is 0.92 with the coefficients and 1.11 without the coefficients.

With these values of coefficients, the tuned IBLS accurately captured the historical annual and seasonal landings (Fig. 3 and 4). Before tuning, the simulated annual landings were lower than the observed landings (Fig. 3). Without the coefficients, the simulated seasonal landings were lower than the observed landings in the spring and summer, however higher in the winter and fall (Fig. 4).

The IBLS simulates fewer small lobsters and more large lobsters in all seasons for both sexes, but more so in the winter and spring (Fig. 5 and 6). Also, in the summer and fall, the IBLS simulates more male lobsters just above the legal minimum size (Fig. 6). Before tuning, the simulated size composition matched the size composition from the stock assessment better (Fig. 5 and 6). The biggest differences in size composition before and after tuning were in the winter and spring (Fig. 5 and 6).

3.2 Application:

With high recruitment, reference abundance remained steady and well above the abundance target reference point (124,000,000) from 2014-2023 (Fig. 7). With intermediate recruitment, reference abundance declines below the abundance target reference point but stays above the abundance limit reference point (60,700,000) (Fig. 7). With low recruitment, reference abundance declines below the limit reference point (Fig. 7). The rate of decline is larger with low

recruitment, and the rate of decline decreases over time in both the low and intermediate recruitment scenarios (Fig. 7).

Exploitation rate remains steady and above the exploitation rate limit (0.352) with high recruitment (Fig. 8). With intermediate recruitment, exploitation rate declined to around the limit and then increased (Fig. 8). With low recruitment, exploitation rate declined to below the target (0.332) and then increased to just above the target (Fig. 8). Exploitation rates were similar across all recruitment levels until the fifth year of the projection (Fig. 8).

With high recruitment, landings only slightly declined (Fig. 9). With intermediate recruitment, landings declined to about half of the amount in the first year of the projection (Fig. 9). Landings declined even more with low recruitment and at a faster rate (Fig. 9). With both intermediate and low recruitment, the landings leveled off around year six of the projection (Fig. 9).

4. Discussion

In this study, an individual-based simulation tool, which can be used to evaluate fisheries management, is described, modified, parameterized, tuned, and applied. In this section, we discuss the lessons learned from calibrating the IBLS, the management implications for the American lobster fishery, and the applicability of this simulator in other crustacean fisheries.

4.1. Lessons from calibrating the IBLS

One of the main goals posed by the present study was to tune the IBLS by identifying appropriate values of coefficients for the IBLS parameters. Because fisheries are complex, variable, and difficult to observe, there is substantial uncertainty in fisheries models (Hill et al. 2007). Complex fisheries result in complex models and many assumptions, and data are

310 frequently inadequate for evaluating complex models (Hill et al. 2007). Calibrating a model
311 includes tuning the model by determining a set of parameters that fit the model to its data and
312 can provide insights into the uncertainty of input data, model parameters, and model structure.
313 Results from a simulation model are based on many initial parameter estimates, which are not
314 known exactly. Overall, tuning simulators can highlight uncertainties in the input data and the
315 model structure. Coefficients can be applied to inputs that are not as certain, and once the
316 simulator is tuned, the more the coefficients deviate from 1, the more uncertainty can be
317 expected from that input or the model structure.

318 In this study, there are discrepancies between results obtained before and after calibrating the
319 IBLS. The large coefficients represent either inaccuracies of the input data or the IBLS structure.
320 Interestingly, the simulated size composition matched the historical size composition better
321 before tuning the model, which may be a result of the model catching more small lobsters to
322 better fit the historical landings. Additionally, structural differences between the assessment
323 model and the simulator may result in bias (Hill et al. 2007). Potential bias may be apparent in
324 the size composition of male lobsters in the summer and fall. The IBLS simulates more male
325 lobsters just above the legal minimum size in these seasons, which may be a result of the IBLS
326 simulating overall less catch of male lobsters to match the catch from the stock assessment.
327 Tuning the IBLS highlights some uncertainties in the lobster stock assessment. The GOM lobster
328 stock assessment model underestimated the amount of large lobsters (ASMFC 2015), and the
329 tuned simulations produced more large lobsters than in the stock assessment output data,
330 especially in the winter and spring, which is when migration to offshore waters occurs. In the
331 IBLS, lobsters cannot migrate, so the large lobsters are kept within the system unless they die.

Moving forward, the ASMFC will combine the GOM lobster stock with the Georges Bank lobster stock because of the migration of large lobsters between the two stocks (ASMFC 2015).

Tuning the IBLS addresses the uncertainty in the fishing effort and other parameters as well. Fishing effort is estimated from harvester data as trap haul set over days. Simulated landings are sometimes underestimated with no coefficients which indicate that this may not be the best estimate of fishing effort. The effort data used in this study were obtained from fishing vessels that only target lobster. However, misreporting by lobstermen is possible, and logbooks are only filled out by ten percent of Maine lobstermen, which may not be representative of the fishery. Additional factors, such as lobsterman skill and bait, may also play a role.

As a result, the simulated annual, spring, and summer landings before calibration were all lower than the landings from the stock assessment, which indicates that the trap haul set over days from the harvester data may be an underestimation of fishing effort. The simulated landings in the winter and fall are higher than the landings from the stock assessment, which suggests that in those seasons, the harvester data may be an overestimation of fishing effort. The values of coefficients for the encounter probabilities had a much higher magnitude in the winter and spring than in the summer and fall, indicating that the harvester data are more reliable in the summer and fall than in the winter and spring. The same amount of trap haul set over days applied in the summer and fall can result in a larger catch than that in the winter and spring due to the differences in spatial distribution of lobster (Chang et al. 2010).

However, the lack of fit to the observed catch and size composition may be an effect of inappropriate model structure and assumptions instead of the data input. For example, the IBLS is structured so that lobsters are only allowed to be caught once in a timestep, when in reality, they could be caught and released several times in a timestep. This affects the encounter rate

calculation, hence another reason to tune the encounter probabilities. Also, the lobsters and fishing effort are assumed to be distributed evenly across the area, which is not realistic. Lobsters are also assumed not to migrate out or into the stock. Additionally, natural mortality is assumed to occur before growth and fishing.

2. Management implications for the American lobster fishery

The simulations in this study indicate that the robustness of Maine lobster fishery management regulations is dependent upon recruitment. However, the recruitment levels in these simulations are much different from each other, because they are based off the historical recruitment, which has a wide range of values. Future studies should include different levels of recruitment that are closer in magnitude.

Nevertheless, according to the simulations, even if recruitment declines to a third of the current recruitment, abundance will still be above the limit abundance. Also, if recruitment were to decline to a tenth of the current recruitment, then exploitation rate would decline to below the target, which indicates that current management regulations allow for a reduction in exploitation rate with low recruitment. Current management regulations allow for a reduction in exploitation rate with intermediate recruitment as well. Additionally, although catch declines dramatically with low recruitment, it only declines to a level like the historical catch in the mid 1990's.

The tuned IBLS replicates the historic data well, and therefore, can be used to evaluate management regulations in the GOM lobster fishery. Simulators for fisheries management combine the best available data and can evaluate a variety of management scenarios (Grant et al. 1981). The simulator in this study can be a useful tool for management of the American lobster

fishery and other lobster and crab fisheries by evaluating management strategies with consideration of varying biological factors.

The simulator used in this study can be adapted to serve as an operating model within a management strategy evaluation (MSE) context. MSE is an emerging approach that can improve fisheries management, because it is an adaptable framework for modeling a fishery management system, instead of just the fish stock (Cochrane et al. 1998; Smith et al. 2008). MSE uses a simulator as a realization of the truth and can be used to identify management strategies that will fail at meeting objectives before deciding the final management measures (Harwood and Stokes 2003). However, to work towards a complete MSE, future studies should identify management objectives for the GOM lobster fishery with information from stakeholders. Failure in fisheries management is often due to lack of clearly defined management objectives. Future MSE work should involve lobstermen early in the process. MSEs allow precautionary management to be implemented thoroughly and scientifically (Harwood and Stokes 2003).

Not only can the simulator evaluate management strategies, but it can also be used identify what factors influenced the current lobster abundance and landings. In the GOM lobster fishery, fishermen and scientists believe that both conservation measures and environmental factors have led to the changes in the Maine lobster fishery and population (Acheson and Steneck 1997; Acheson and Gardner 2010). Future studies should use simulations to help identify to what degree conservation measures and biological factors have influenced the fishery.

However, before the simulator can be used to test management scenarios, it is important that the assumptions of the simulator be understood. Because the conclusions may be incorrect if some of the numerous restraining assumptions were changed, the best performing management scenarios should be viewed with consideration of these assumptions. Some of these assumptions

include: population dynamics do not vary over space, no migration between stocks, natural mortality is constant, and size at maturity is constant. For the most part, the simulator is based on similar assumptions and the same equations as those in the stock assessment. Natural mortality and maturity equations used in the simulator are assumed to be known in the stock assessment, which is usually not true.

Additionally, an important assumption of this simulator is that the behavior of the lobstermen is a response to present management. The response of lobstermen to new management measures are not considered, although it is important for policy performance (Sanchirico and Wilen 2001). Parameterization of the lobstermen's response to new management measures is difficult. In the stock assessment, no stock-recruitment relationship is assumed, which is why the simulator has multiple options for simulating recruitment. Future work with the simulator should focus on sensitivity analyses to evaluate the robustness of the results by varying these assumptions.

In this study, recruitment is not affected by changes in SSB that result from changes in management because there is no relationship between recruitment and SSB. The stock-recruitment relationship, which is often important in identifying the effects of long-term management scenarios, is difficult to quantify for American lobster. In general, the stock-recruitment relationship and how environmental variability and biological factors impact this relationship is unclear (Punt et al. 2014). Although the simulator is based on single-species population dynamics, it can consider some effects of ecosystem variability when simulating recruitment. Rather than trying to identify a single best recruitment estimation method, uncertainty in recruitment can explicitly and formally accounted for by incorporating a wide range of biologically plausible recruitment scenarios into the tuned IBLs. Other fishery simulators have included a range of structures for recruitment relationships (Punt and Smith

1999). Recruitment can be designated as a function of SSB and bottom water temperature. Otherwise, recruitment can be drawn from theoretical distributions derived from historical recruitment that correspond to high and low SSBs.

Not only should future studies on simulations of the Maine lobster fishery focus on recruitment estimation but also on growth and fishing behavior changes. The GOM is experiencing rapid water temperature changes (Mills et al. 2013; Le Bris et al. 2018) and an aging Maine lobster fleet (Johnson and Mazur 2018). Temperature changes may influence lobster population dynamics, as temperature has a large effect on the life history of American lobster, especially on recruitment and growth (Aiken & Waddy 1986). This can be incorporated into the simulator by creating a relationship between temperature and recruitment and temperature and growth matrices. An aging lobster fishing fleet may also impact the effectiveness of existing management, because fishing behavior may begin to change, as different generations of fishermen may have different perceptions of the resource (Nemec 1972; Silva 2016). For example, the percentage of compliance of V-Notching may change over time. These changes could be incorporated by testing scenarios with different V-Notching ratios. Incorporation of other information, such as temperature changes and lobster fishing fleet dynamics, may potentially improve the calibration of the IBLS. Incorporating temperature into the development of a SSB and recruitment relationship may improve the calibration of the IBLS and projection of the population. In addition, changing growth may result in changes in the effectiveness of existing size-related management.

4.3. Applicability of the IBLS in other crustacean fisheries

IBMs are useful alternatives to statistical models for crustacean management. Although statistical models work well for crustacean population dynamics, IBMs can also accurately

simulate crustacean fisheries and can even be used to validate statistical model results. IBMs can be used to supplement stock assessments and to inform fisheries management. As the IBLS is flexible, it can be modified for the use of a simulator in other crustacean fisheries as well. Numerous biological and management scenarios can be simulated with small alterations of the parameters.

The IBLS can be especially useful for any lobster or crab fishery, as they have similar life history and fishery processes to American lobster. With an IBM approach, a variety of biological and fishery processes is included in the simulator. Crustacean life history processes, such as molting, molting mortality, and bearing eggs, are included. The individual-based approach can capture the non-continuous molting processes that vary among individuals.

The results from the present study are encouraging for the simulation of crustacean fisheries; however, additional explorations are needed. The simulator can integrate enhanced knowledge about the fishery and changes in some model assumptions, such as changes in size at maturity or natural mortality over time. The IBLS also has functionality that allows uncertainties in recruitment to be addressed, which should be used in future studies.

Management measures common in crustacean fisheries, such as legal sizes and protection of egg-bearing individuals, are included in the simulator. IBMs are useful, because they can treat each of the many complex management measures as separate processes, rather than just one combined selectivity. This differs from models that incorporate traditional fisheries management, in which total allowable catches (TACs) or fishing effort levels are the only management measures included. An important feature of the IBLS is that it does not have fishing mortality as a parameter, instead it is estimated. Using encounter probabilities as a proxy for fishing effort is important for the American lobster fishery, which does not have harvest control rules; so in

testing management regulations, there should be no predetermined fishing mortality. Additionally, V-Notching is not practiced in all lobster fisheries. This simulator can be used as a tool to test this conservation measure in other fisheries. In the simulator, the compliance of V-Notching can be set at different rates, which is important to consider for a management measure that cannot be fully enforced as it occurs on the boat. Maximum size is another management measure not used in all lobster fisheries and can be tested with the simulator as well. In the IBLS, the number of fisheries and management measures is not a limitation. Many different management measures can be simulated alone and in combinations within the simulator, such as a marine protected area (MPA), TAC, and different legal sizes. A combination of numerous management measures is more realistic. The seasonality of the simulator also allows evaluation of seasonal management measures.

New knowledge can be easily integrated and updated in the simulator without recompiling the code. Economic variables, such as price and price decreasing with landings, can also be incorporated into the fishery dynamics. Many bioeconomic models have been developed for crustacean fisheries and could be linked with the simulator (Clarke et al. 1992; Maynou et al. 2006; Holland 2011; Chang 2015). Currently, the IBLS is only parameterized for one area, but this is not fixed. Additional areas can be designated according to the data available. With the necessary data, IBMs have the flexibility to include multiple areas (Grimm 1999). Adaptive management simulations are also a valuable ability of the simulator, as management can be simulated as more conservative or less conservative when the fishery or fish population passes a reference point. Another innovation in this model has been the inclusion of the ability to select different compliance rates for conservation measures. Another advantage that IBMs have over statistical models is the process-based design. This allows for easier communication to

stakeholders about how the model works. A flowchart, such as in Fig. 1, may be easier for stakeholders to understand than mathematical equations.

Lobster fishery management can have effects that extend past the species and into the ecosystem. Future studies should address potential missing ecosystem processes in the simulator. Because of modelling limitations, not all effects of fisheries management can be examined with a single simulation tool. In many cases, adding extra details into the model to address these limitations may not be essential; as Walters et al. (1997) describe we should not “go to too much detailed models without stopping to ask whether the extra is necessary”. The results from simulations will become less useful if additional uncertainties are integrated (Grant et al. 1981; Somers and Wang 1997). This may cause managers to not implement management measures that would have positive influences on the fishery (Grant et al. 1981). Adding multiple areas would require all the input data for each area and migration of lobsters between areas, which often is not available or difficult to quantify. Spatially-explicit models are often not developed because of the sensitivity of fishery dynamics to migration coefficients and the difficulty of estimating the coefficients (Pelletier and Mahevas 2005). Because there is usually not enough detailed data compared to model complexity, parameter estimation for spatially-explicit models is difficult (Pelletier and Mahevas 2005). Here, a trade-off between parsimony and complexity must be made.

In this study, an individual-based approach captures the necessary details of the life history and fishery processes of the American lobster. With the simulation tool that has been modified, parameterized, and calibrated in this study, the GOM American lobster fishery can be simulated. The process of tuning the IBLs highlights the uncertainty in the input data and model structure. This study begins to evaluate the robustness of current management regulations with variability

in recruitment, but the simulator has potential to explore more questions. This simulator can be used to evaluate the robustness of management regulations not only in the GOM lobster fishery but can also be modified for use in other lobster and crab fisheries.

Acknowledgements

The authors thank K. Tanaka for helpful advice during the development of this project; B. Shank for the stock assessment data and guidance; K. Reardon, C. Wilson, and R. Watts for the harvester data and helpful comments; and S. Cousins for permission to use and help with using the University of Maine supercomputer. This work was made possible thanks to funding from Sea Grant, the University of Maine, and the National Marine Fisheries Service.

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636

637 **Figure Captions**

638 Figure 1. Flowchart of the individual-based American lobster simulator. Each lobster has a
639 conditional probability of going through each process, as the probability at each process depends
640 on what processes the lobster previously went through. The diagram was modified from Chen et
641 al. (2005) and Chang (2015).

642 Figure 2. The Gulf of Maine lobster stock area.

643 Figure 3. The observed (black dots), simulated with coefficients (dashed blue line), and
644 simulated without coefficients (grey line) annual landings over time.

645 Figure 4. The observed (black dots), simulated with coefficients (dashed blue lines), and
646 simulated without coefficients (grey lines) seasonal landings over time.

Figure 5. The observed (black dots), simulated with coefficients (dashed blue lines), and simulated without coefficients (grey lines) average size composition of female lobsters in the winter, spring, summer, and fall.

Figure 6. The observed (black dots), simulated with coefficients (dashed blue lines), and simulated without coefficients (grey lines) average size composition of male lobsters in the winter, spring, summer, and fall.

Figure 7. Reference abundance (>78 mm CL) from 2014- 2023 with low, intermediate, and high recruitment. The horizontal dotted green line represents the target abundance reference point (124,000,000). The horizontal dotted red line represents the limit abundance reference point (60,700,000).

Figure 8. Exploitation rate from 2014- 2023 with low, intermediate, and high recruitment. The horizontal dotted green line represents the target exploitation rate reference point (0.332). The horizontal dotted red line represents the limit exploitation rate reference point (0.352).

Figure 9. Percent change in landings from 2014- 2023 with low, intermediate, and high recruitment.

Tables

Table 1. Input data for the individual-based American lobster simulator. The most recent American lobster stock assessment is the Atlantic States Marine Fisheries Commission (ASMFC 2015) source. Personal communication was done with Maine lobstermen and Maine Department of Marine Resources staff. Harvester data is from the Maine DMR.

Inputs	Values	Source
Initial abundance	93,200,000	ASMFC 2015
Initial size composition	Differs among sizes	ASMFC 2015
Initial sex ratio	0.546	ASMFC 2015
Recruitment	Differs among years in summer and fall; 0 in winter and summer	ASMFC 2015
Recruit size composition	Differs among sizes	ASMFC 2015
Natural mortality probability	0.025 each timestep	ASMFC 2015
Molting probability	Differs among sizes	ASMFC 2015
Probability of growth increments per molt	Differs among sizes	ASMFC 2015
Maximum interval in between molts	7	Personal communication
Time between first molt and second molt if there is a double molt in a year	1	ASMFC 2015
Maximum molt increment	20	ASMFC 2015

(mm)

Number of molts a V-Notch lasts	2	Personal communication
Molting mortality probability	0.05	ASMFC 2015
Fishing effort (trap haul set over days)	Average of 1,085,440 in winter, 4,512,963 in spring, 25,485,938 in summer, and 8,606,713 in fall	Harvester data
Landings	Differs among sizes, sexes, seasons, and years	ASMFC 2015
Conservation selectivity	Differs among sizes, sexes, seasons, and years	ASMFC 2015
Legal selectivity	Differs among sizes, sexes, seasons, and years	ASMFC 2015
Abundance	Differs among sizes, sexes, seasons, and years	ASMFC 2015
Maximum legal size (mm CL)	128	ASMFC 2015
Minimum legal size (mm CL)	1982-1987: 81, 1988: 82, 1989-2013: 83	ASMFC 2015
Number of timesteps until a mature female lobster can have eggs after she molts	4	Personal communication

Maximum number of timesteps a mature female lobster can keep her eggs	4	Personal communication
Probability of a lobster caught with eggs being V-Notched by a lobsterman	0.9	Personal communication

Table 2. The optimal coefficients for the parameters that were tuned in the individual-based American lobster simulator. These coefficients produced the smallest objective function.

Parameter(s)	Coefficient value
Initial abundance	0.7
Recruitment	1.2
Encounter probabilities	
Winter	1.9
Spring	2.9
Summer	0.7
Fall	0.7

Figure 1. Flowchart of the individual-based American lobster simulator. Each lobster has a conditional probability of going through each process, as the probability at each process depends on what processes the lobster previously went through. The diagram was modified from Chen et al. (2005) and Chang (2015).

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237x237mm (72 x 72 DPI)

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