Summer Flounder Recreational Demand Model: Overview, Data, and Methods

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1 Introduction

This document describes the data and methods underlying the recreational demand model (RDM) component of the MAFMC's Management Strategy Evaluation (MSE) of the recreational summer flounder (fluke) fishery. As part of a fully integrated bio-economic model,[1] the RDM provides the key link between projected fluke population abundances, regulations, and expected recreational fishing mortality.

The RDM is a unique approach to evaluating the potential impact of alternative fluke management strategies on fishery-wide outcomes because it explicitly models the relationship between policy- or stock-induced changes in trip outcomes and angler behavior. As Fenichel et al (2013) note, angler behavior has important consequences on several aspects of the recreational fishing system, including the cumulative effect on fishing mortality and subsequent impacts to biomass. However, angler behavior is often neglected in the policymaking process (Beard et al. 2011), which may lead to regulations that ineffectively meet management goals. In addition to measuring the likely effect of regulations on angler behavior and recreational fishing mortality, the RDM captures the economic implications of regulations in terms of changes in angler welfare and fishing trip expenditures, allowing for these metrics to be considered in the MSE.

There are three main components of the RDM: an angler behavioral model, a calibration sub-model, and a projection sub-model. Each component is described in detail below. The angler behavioral model uses choice experiment survey data (Sections 2) to estimate angler preferences for harvesting and discarding fluke and other primary species (Sections 3 and 4). These estimates parameterize the calibration and projection sub-models and are also used to calculate behavioral and welfare responses to regulations (Section 5). The calibration sub-model, discussed in Section 6, emulates coast-wide fishing activity in a baseline year using trip-level data and serves as a baseline to which we compare alternative management scenarios. The link between projected stock structures and angler catch is described in Section 7. The projection sub-model, described in Section 8, simulates the fishery conditional on a projected stock structure and management scenario and computes expected impacts to angler effort, angler welfare, the local economy, and recreational fishing mortality. Section 8.1 discusses the economic metrics captured by the RDM and Section 8.2 provides information about how alternative operating model assumptions enter

[1] For an overview of the integrated bio-economic model, please see the August 2022 Council meeting briefing book materials at: https://www.mafmc.org/briefing/august-2022.

the RDM. We also the evaluate the out-of-sample predictive power of the RDM and provide these results in Section 8.3.

2 Choice experiment survey

Choice experiments (CEs) are a common stated-preference approach to non-market valuation and provide a means to estimate the value of goods and attributes that are not traded explicitly in a market and therefore lack prices to signal value (Adamowicz et al. 1998). Like other types of stated preferences methods, CEs rely on individuals' responses to hypothetical questions and are particularly useful when revealed preference, i.e., observational data on actual human behavior is inadequate or non-existent. In the case of the summer flounder MSE, the CE approach allowed us to derive the marginal value of harvesting and discarding fluke and therefore estimate the economic implications of current and previously unobserved management scenarios that might affect angler harvest and discards.

In a typical CE, respondents are presented with two or more hypothetical multi-attribute goods and asked to compare and choose their most preferred good. It is common for one attribute to represent the "price" of the good, defined in monetary (e.g., annual tax or one-time trip cost) or non-monetary units that can be monetized (e.g., travel distance) that provide a budget constraint to individuals' purchasing decisions. Individuals are assumed to choose a good only when its benefit outweighs its cost and it provides maximum utility overall all available goods in a given choice scenario. The resulting data on individual purchasing decisions can be used to evaluate consumer preferences for, behavioral response to, and welfare impacts of marginal changes in attribute levels (Louiviere et al. 2000). In recreational fishing contexts, there have been numerous applications of CEs and other types of stated preference surveys seeking to evaluate the influence of catch and non-catch related attributes on angler choices (Hunt et al. 2019).

Our CE data come from an angler survey administered in 2010 as a follow-up to the Access Point Angler Intercept Survey (APAIS), an in-person survey that collects information from anglers at publicly accessible fishing sites as they complete their fishing trips. The APAIS is one of several surveys used by the Marine Recreational Information Program (MRIP) to produce catch and effort estimates for recreational marine species across the United States. Anglers who participated in the APAIS in coastal states from Maine to North Carolina during

2010 were asked to participate in the voluntary follow-up CE survey. Those willing to participate were sent CE survey materials via mail or email shortly after the intercept interview. A total of 10,244 choice experiment surveys were distributed, of which 3,234 were returned for an overall response rate of 31.5%.

The survey instrument contained three sections. Section (A) collected information about respondents' fishing experiences in the past year and species preferences, as well as the factors that influence their decision to fish. Section (B) contained a set of choice experiment questions (Figure 1). In these questions, respondents were presented with three hypothetical multi-attribute fishing trip options. Trip A and Trip B varied and contained different species-specific bag and size limits, catch and keep of fluke and other primary species, and total trip costs. Trip A provided a range for numbers of fluke caught and kept rather than single value as in Trip B. Trip C was an option to go fishing for other species and was added as an attempt to capture target species substitution. Respondents were asked to compare and choose their favorite among the three trip options or opt to not saltwater fish. Lastly, section (C) gathered demographic information including gender, birth year, education, ethnicity, and income. Given regional differences in species availability, survey versions were developed for four sub-regions: (i) coastal states from Maine through New York, (ii) New Jersey, (iii) Delaware and Maryland, and (iv) Virginia and North Carolina. The four survey versions differed in the species other than fluke and black sea bass included in Sections A and B.[2]

2.1 Experimental design

For each regional version of the survey, multiple sub-versions that differed in levels of the trip attributes shown within and across choice questions were administered. Trip attribute levels were chosen based on historical catch and trip expenditure data and corroborated with focus group feedback. They were then randomized across choice questions using an experimental design that sought to maximize the statistical efficiency of the ensuing model parameters. Each experimental design was specified to produce a total 128 choice questions. Because 128 is too many questions

[2] In terms of the CE attributes in Section B, the Maine to New York version included fluke, black sea bass, and scup; the New Jersey version included fluke, black sea bass, scup, and weakfish; the Delaware and Maryland version included fluke, black sea bass, and weakfish; and the Virginia and North Carolina version included fluke, black sea bass, weakfish, and red drum.

for a single respondent to answer, questions were randomly allocated into 16 subsets such that each respondent was presented with eight choice questions.

SECTION B: SALTWATER FISHING TRIPS

The following questions help us understand tradeoffs made by anglers when they go fishing.
Compare Trip A, Trip B, and Trip C in the table below, then **answer** questions **1A** and **1B**.
Compare only the trips on this page. Do **not** compare these trips to trips on other pages in this survey.

Trip Features		Trip A	Trip B	Trip C
Summer Flounder (Fluke)	Regulations	1 Fluke, 16" or larger	3 Fluke, 18" or larger	Go fishing for striped bass or bluefish
	Fish Caught	3 to 13 Fluke, 22" TL	1 Fluke, 15" TL	
	Fish Kept	1 Fluke	0 Fluke	
Black Sea Bass	Regulations	20 Bl. S. Bass, 14" or larger	30 Bl. S. Bass, 9" or larger	
	Fish Caught	30 Bl. S. Bass, 12" TL	10 Bl. S. Bass, 9" TL	
	Fish Kept	0 Black Sea Bass	10 Black Sea Bass	
Scup (Porgy)	Regulations	20 Scup, 12.5" or larger	5 Scup, 13" or larger	
	Fish Caught	3 Scup, 16" TL or larger	40 Scup, 6" TL or smaller	
	Fish Kept	3 Scup	0 Scup	
Weakfish	Regulations	0 Weakfish of any size	5 Weakfish, 12" or larger	
	Fish Caught	7 Weakfish, 15" TL	1 Weakfish, 18" TL	
	Fish Kept	0 Weakfish	1 Weakfish	
Total Trip Cost		$160	$160	$45

Definitions:
- **Regulations:** The legal minimum size restriction and bag limit for this trip.
- **Fish caught:** The number of fish caught on this trip and the total length (TL) of those fish.
- **Fish kept:** The number of fish you can legally keep on this trip.
- **Total trip cost:** ***Your portion*** of the costs associated with this trip, including bait, ice, fishing equipment purchase or rental, daily license fees, boat rental fees, boat fuel, trip fees, and round trip transportation costs associated with traveling to and from the fishing location. Travel costs may include vehicle fuel, car rental, tolls, airfare, and parking.

1A Choose your favorite trip. (Please mark only **one** trip with a ☑ or a ☒.)

Trip A ☐
Trip B ☐
Trip C ☐
I would not go saltwater fishing ☐

Figure 1. Example choice experiment question from the New Jersey survey version.

2.2 Choice experiment sample

A total of 3,234 people completed or partially completed the mail or web version of the survey. Of these respondents, 2,941 answered at least one of the eight choice experiment questions. We removed from the sample respondents who universally choose the zero-cost, “Do not go saltwater fishing” option or the pelagic trip (Trip C) as their favorite trip following recommended best practices in Johnston et al. (2017).[3] We also excluded from the analysis respondents who indicated that the survey was not completed by the person to whom it was addressed. The remaining sample consisted of 2,448 anglers.

Table 1 displays some demographic characteristics of sample anglers by region. Sample anglers were predominantly male (90-93% across regions) and Caucasian (94-96% across regions). The average age was just under 53. Roughly one quarter to one third of the sample in each region attained a bachelor's degree or higher. Between 60% and 70% of the sample in each region had household incomes ranging from $20,000 to $100,000, while between 26% and 30% had household incomes above $100,000. Lastly, the average number of days spent fishing during the previous calendar year (2009) varied from 20 to 28 across regions, with New Jersey anglers fishing considerably more frequently in the past year than anglers in other regions.

Table 1. Demographic characteristics of choice experiment sample.

Characteristic	ME-NY	NJ	DE/MD	VA/NC
% male	92.7	93.2	91.0	90.0
% Caucasian	95.6	95.7	94.5	94.5
Mean age	52.8	52.8	52.9	52.2
Education				
% with high school graduate or GED	33.1	42.4	43.7	28.8
% with some college but no degree or associate's degree	34.7	30.5	28.0	36.8
% with bachelor's degree or higher	32.1	27.0	28.2	34.2
Household income				
% less than $20,000	6.9	2.0	7.1	4.6
% between $20,000 and $100,000	62.7	69.5	67.0	69.0
% over $100,000	30.3	28.4	25.7	26.3
Mean # fishing trips taken during 2009	21.1	27.7	18.6	20.1

Sample anglers were recruited from the APAIS, which occurs at publicly accessible fishing sites only. Anglers fishing from private access points were therefore excluded from the sampling design. To understand the extent to which each fishing mode is represented in our

[3] Key parameter estimates from choice models that included these participants were similar in sign, significance, and magnitude to those presented in this document.

sample and how the distribution of fishing effort by mode aligns with the distribution of fishing effort in the population, Table 2 compares MRIP estimates of fishing effort for primary species by mode to the distribution of fishing effort indicated by our sample.[4] Compared to the population, shore trips were underrepresented in the sample while party and charter boat trips were overrepresented. The percent of private boat trips in the sample closely matches the population and in both cases and accounts for the lion's share of all trips. So while the sample did not mirror the population distribution of fishing effort by mode in 2009, it did encompass directed effort from all four fishing modes.

Table 2. Percent of trips taken for primary species by mode during 2009.

	MRIP	CE sample
ME-NY		
Shore	40.3	16.7
Party boat	2.0	24.0
Charter boat	1.5	4.0
Private boat	56.2	55.3
NJ		
Shore	34.9	22.6
Party boat	2.1	21.8
Charter boat	1.3	3.9
Private boat	61.6	51.7
DE/MD		
Shore	37.8	28.6
Party boat	1.3	11.6
Charter boat	0.9	4.4
Private boat	60.0	55.4
VA/NC		
Shore	46.4	30.6
Party boat	0.1	3.6
Charter boat	0.2	3.5
Private boat	53.3	62.4

Notes: Primary species include fluke and black sea and other species that varied by survey version: the ME-NY survey also included scup, the NJ version also included scup and weakfish, the DE/MD version also included weakfish, and the VA/NC also included weakfish and red drum. The MRIP columns shows percentages of all trips taken for the primary species, while the CE sample column shows percentages of all trips taken for the primary species as indicated by sample respondents.

[4] The survey asked anglers how many trips they took in 2009 for fluke, black sea bass, and either scup, weakfish, and/or red drum depending on the survey version.

3 Behavioral model framework

We analyzed our CE data using random utility models (McFadden 1973) , which decompose the overall utility angler n receives from trip alternative j $(j = A, B, C, or\ no\ trip)$ into two components: V_{nj}, a function that relates observed fishing trip attributes x_{nj} to utility, and ε_{nj}, a random component capturing the influence of all unobserved factors on utility. Angler utility can be expressed as

$$\begin{aligned} U_{nj} &= V_{nj} + \varepsilon_{nj} \\ &= \beta_n' x_{nj} + \varepsilon_{nj}, \end{aligned} \tag{1}$$

where β_n' is a vector of preference parameters measuring the part-worth contribution of trip attributes x to angler n's utility, and ε_{nj} is an independent and identically distributed Type I extreme value error term. Under the random utility framework, an angler will select alternative i if it provides maximum utility over all alternatives available to him or her in a given choice occasion, i.e.

$$U_{ni} > U_{nj}\ \forall\ j \neq i. \tag{2}$$

We estimated panel mixed logit models, which allow for unobserved preference heterogeneity—a recommended best-practice for stated preference analysis (Johnston et al. 2017)—through estimation of parameter distributions for the attributes specified as random. Allowing preferences to vary across individuals is the primary advantage of the mixed logit over the basic multinomial logit (MNL) model, which assumes that individuals have the same preferences. Panel mixed logit estimation also resolves some behavioral limitations of the MNL model, including the independence of irrelevant alternatives property and the assumption that unobserved factors that influence decisions are uncorrelated over repeated choice situations (Hensher and Greene 2003). The probability that angler n chooses alternative i is obtained by integrating the logit formula over the density of β (Train 2003):

$$P_{ni} = \int \frac{e^{\beta' x_{ni}}}{\sum_{j=1}^{J} e^{\beta' x_{nj}}} f(\beta) d\beta. \tag{3}$$

These probabilities are approximated via simulation in which repeated draws of β are taken from $f(\beta|\theta)$, where θ refers to the mean and covariance of this distribution. For each draw, the logit formula is calculated for all choice scenarios (up to eight) faced by individual n. Then, the product of these calculations is taken, giving the joint probability of observing individual n's sequence of choices. The average of these calculations over all draws is the simulated choice probability, $\check{P}_{ni}$. The estimated parameters are the values of θ that maximize the simulated log likelihood function,

$$LL = \sum_{n=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{J} d_{ntj} \ln(\check{P}_{ntj}), \tag{4}$$

where $d_{njt} = 1$ if individual n chose alternative j in choice scenario t and zero otherwise.

We specified the utility associated with fishing trip alternatives A and B as a linear additive function of the number of fish kept and released by species and the trip cost. For Trip A, the midpoint of the range of fluke catch depicted in the choice experiment was used to calculate numbers of fluke kept and released. The utility associated with Trip C, a fishing trip for other species, was specified as a function of the trip cost and a constant term (*fish for other species*) that measures the utility of a pelagic trip relative to the utility from the other alternatives. The utility associated with the non-fishing, “I would not go saltwater fishing” alternative (alternative D), was specified as a function of a constant term (*do not fish*) that captures preferences for not fishing. To allow for diminishing marginal utility of catch (Lee et al. 2017), keep and release attributes entered the model as their square root. The estimated models assumed that all non-cost parameters were normally distributed, while the cost parameter was treated as fixed to facilitate welfare calculations (Revelt and Train 2000).

4 Behavioral model results

Results from the panel mixed logit model, estimated separately for each regional survey sub-version, are shown in Table 3. Mean parameters measure the relative importance of each trip attribute on overall angler utility, while standard deviation parameters measure the extent to which preferences vary across the sampled population.

The estimated mean parameters were generally of the expected sign. Across the regional models, the mean parameters on *trip cost*, the marginal utility of price, were negative and significant and intuitively suggest that higher trip costs reduce angler utility. Mean parameters on all keep variables were positive, significant, and higher in magnitude than their corresponding release parameter. This means that each species is predominantly targeted for consumption rather than sport, which aligns with input from recreational fishery stakeholders. The magnitude of the summer flounder keep parameters relative to other primary species' keep parameters suggests that anglers value keeping fluke more than they value keeping black sea bass, scup, weakfish, or red drum.

The signs and significance of the release parameters varied by species and region. For example, only in the VA/NC model was the mean parameter on $\sqrt{SF\ released}$ positive and significant, suggesting that anglers in this region value catching and releasing summer flounder. Additionally, in two of the three regional models, the parameter on $\sqrt{WF\ released}$ was positive and significant. Catching and releasing scup reduces utility for anglers in New Jersey according to the parameter on $\sqrt{scup\ released}$. Perhaps these anglers perceive catching and having to release scup as a nuisance when fishing for larger and more valuable target species.

Baseline levels of non-fishing utilities, captured by the parameters on *do not fish*, were negative and significant. This mean that, when given the option, anglers derive more utility from fishing than not fishing. In contrast, the parameters on *fish for other species* suggest that anglers place a relatively high value on trips for striped bass and bluefish (or striped bass, bluefish, cobia, and Spanish mackerel in the VA/NC model). This follows from Trip C being most frequently selected as the favorite trip and aligns with the fact that striped bass are the most heavily targeted recreational species in the region. Lastly, with the exception of $\sqrt{BSB\ released}$ in the ME-NY and NJ models, the significance of standard deviations parameters confirms that preferences for keeping and releasing fish vary across the population, i.e., that marginal changes in catch will affect different anglers differently.

Table 3. Estimated utility parameters from mixed logit models.

	ME-NY		NJ		DE/MD		VA/NC	
Mean parameters	*Estimate*	*St. Err.*	*Estimate*	*St. Err.*	*Estimate*	*St. Err.*	*Estimate*	*St. Err.*
trip cost	-0.012***	0.000	-0.008***	0.000	-0.009***	0.000	-0.007***	0.000
$\sqrt{\text{SF kept}}$	0.535***	0.061	0.721***	0.064	0.776***	0.048	0.507***	0.031
$\sqrt{\text{SF released}}$	-0.068	0.045	0.007	0.041	0.043	0.033	0.105***	0.021
$\sqrt{\text{BSB kept}}$	0.273***	0.033	0.175***	0.032	0.239***	0.027	0.178***	0.018
$\sqrt{\text{BSB released}}$	-0.021	0.024	0.010	0.024	-0.009	0.019	0.025**	0.013
$\sqrt{\text{scup kept}}$	0.078***	0.020	0.096***	0.021				
$\sqrt{\text{scup released}}$	-0.015	0.015	-0.033**	0.016				
$\sqrt{\text{WF kept}}$			0.367***	0.055	0.360***	0.042	0.231***	0.029
$\sqrt{\text{WF released}}$			0.096**	0.043	0.061*	0.035	0.034	0.023
$\sqrt{\text{RD kept}}$							0.428***	0.036
$\sqrt{\text{RD released}}$							0.081***	0.023
do not fish	-2.398***	0.233	-1.877***	0.257	-2.838***	0.231	-3.573***	0.231
fish for other species	1.272***	0.172	1.049***	0.198	0.606***	0.151	0.493***	0.116
St. dev. parameters								
$\sqrt{\text{SF kept}}$	0.692***	0.079	0.630***	0.079	0.516***	0.061	0.457***	0.043
$\sqrt{\text{SF released}}$	0.358***	0.058	0.125	0.104	0.258***	0.047	0.230***	0.034
$\sqrt{\text{BSB kept}}$	0.245***	0.048	0.283***	0.048	0.311***	0.037	0.189***	0.031
$\sqrt{\text{BSB released}}$	0.080	0.058	0.053	0.051	0.139***	0.029	0.087***	0.031
$\sqrt{\text{scup kept}}$	0.096*	0.058	0.128***	0.040		0.000		0.000
$\sqrt{\text{scup released}}$	0.077***	0.028	0.120***	0.027		0.000		0.000
$\sqrt{\text{WF kept}}$			0.220**	0.111	0.251***	0.094	0.283***	0.058
$\sqrt{\text{WF released}}$			0.223***	0.081	0.220***	0.052	0.142***	0.046
$\sqrt{\text{RD kept}}$				0.000		0.000	0.472***	0.062
$\sqrt{\text{RD released}}$				0.000		0.000	0.324***	0.033
do not fish	2.193***	0.198	1.969***	0.173	2.246***	0.164	2.676***	0.181
fish for other species	1.652***	0.129	1.799***	0.144	1.752***	0.114	1.839***	0.090
No. anglers	443		357		581		1067	
No. choices	3451		2764		4494		8332	
LL	-3221.809		-2797.016		-4227.267		-8051.496	
LL(0)	-3753.301		-3203.314		-4814.363		-9215.204	
Pseudo R^2	0.327		0.270		0.321		0.303	
AIC/n	1.877		2.039		1.889		1.938	
BIC/n	1.914		2.095		1.918		1.959	

Notes: *,**, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively. SF = summer flounder, BSB = black sea bass, WF = weakfish, RD = red drum.

5 Simulation modeling overview

To assess the effect of alternative fluke management measures and stock conditions on fishing effort, angler welfare, the local economy, and fishing mortality, we integrate the utility parameters in Table 3 with historical catch, effort, and trip expenditure data to create the recreational demand model (RDM). The RDM measures behavioral and economic responses to changes in fishing conditions through simulation of individual choice occasions, i.e., sets of fishing and non-fishing opportunities for hypothetical decision makers. Similar models have been developed for Northeast U.S. recreational fluke (Holzer and McConnell 2017) and striped bass (Carr-Harris and Steinback 2020) fisheries, and for managing the recreational Gulf of Maine cod and haddock fishery (Lee et al. 2017).

The RDM is multipart algorithm that simulates individual choice occasions mirroring those depicted in the CE survey. Each simulated choice occasion consists of three multi-attribute options: a fluke trip, a pelagic trip, and an option of not going saltwater fishing. The algorithm assigns to each choice occasion attribute levels based on historical and projected catch and effort data and utility parameters from the angler behavioral model. It then calculates the expected utility of each multi-attribute option, from which it derives the probability an angler would select that option and the associated consumer surplus. Expected utilities are calculated twice: first, in the baseline scenario in which harvest, discards, and trip cost per choice occasion reflect fishery conditions in the baseline year; and then again in subsequent projection scenarios when harvest and discards per choice occasion reflect alternative management measures and projected stock conditions. Differences in expected utilities between baseline and projection scenarios form the basis for determining the impact of alternative management and stock conditions on fishing effort, angler welfare, the local economy, and fishing mortality.

6 Calibration sub-model

The first of the two-part simulation algorithm, visually depicted in Appendix Figure 1, involves calibrating the recreational demand model to a baseline year. In essence, we attempted to replicate observed state-level outcomes, i.e., harvest and discards, using trip-level data. We calibrate the model to 2019 because it was the most recent year in which input recreational data was unaffected by COVID-related sampling limitations and because management measures remained relatively consistent across all states from 2019-2021.

The calibration sub-model begins by assigning choice occasions a trip costs drawn at random from state-level distributions. Cost distributions were created from recent trip expenditure survey data (Lovell et al. 2020) and weighted in proportion to the estimated number of directed fluke trips taken from shore, private boats, and for-hire boats in each state in 2019.

Choice occasion are then assigned numbers of fish caught by species drawn at random from baseline-year catch-per-trip distributions. According to MRIP data, directed trips for fluke also tend to catch black sea bass, as the correlation in catch-per-trip between the two species is positive and significant across the study area. This is likely due to the two species cohabitating similar fishing grounds and sharing a bottom-dwelling nature that makes them susceptible to similar fishing gears. We account for this correlation through copula modeling. Copulas are functions that describe the dependency among random variables and allow us to simulate correlated multivariate catch data that enter the demand model. We fit negative binomial distributions to each catch series (Terceiro 2003) and enter the estimated mean and dispersion parameters into a t-copula function. With this function we simulate catch data with a correlation structure approximating the observed correlation between the two series. This copula modeling approach provides the flexibility to generate multivariate catch-per-trip data with any specified correlation structure and distributional parameterization. Catch-per-trip of other species included in the model is assumed independent and these distributions are fitted (negative binomial) to MRIP catch data.[5]

The calibration sub-model then allocates catch as harvest and discards. To do so, it draws a value d_{fs} from $D \sim U[0,1]$ for every fish species f caught in state s on a given choice occasion. Fish are harvested (discarded) if d_{fs} is higher (lower) than d^*_{fs}, where d^*_{fs} is the value for which simulated harvest-per-choice occasion of species f in state s approximates the MRIP-based estimate of harvest-per-trip in the baseline year.[6] These d^*_{fs} values, identified outside the simulation algorithm, are the value of the catch-at-length cumulative distribution function evaluated at the minimum size limit. We implemented this method because harvest is the key determinant of the probability a choice occasion results in a fluke trip, and these probabilities in aggregate determine the number of choice occasions entering the ensuing projection sub-model.

[5] Catch-per-trip data for all species included in the simulation are based on recreational fishing trips that caught or primarily targeted fluke.

[6] Fluke fishing is assumed to stop once the bag limit is reached, i.e., there are no additional discards after a choice occasion reaches the limit.

Approximating MRIP-based estimates of harvest in the baseline years therefore ensures that the calibration sub-model generates an appropriate number of choice occasions. The whole process up to this point is repeated 10 times, providing multiple draws per choice occasion that reflect angler expectations about catch and trip cost.

Having a vector of attributes x_{ni} anchored on 2019 catch and recent trip expenditure data, we then assign to each choice occasion n a draw from the distribution of estimated utility parameters in Table 3 and calculate the utility of option i as $\beta_n' x_{ni}$. Expected utility is taken as $\beta_n' x_{ni}$ averaged over the 10 draws of catch and costs and is used to calculate choice probabilities conditional on β_n:

$$p_{ni} = \frac{e^{\beta_n' x_{ni}}}{\sum_{j=1}^{J} e^{\beta_n' x_{nj}}}. \tag{5}$$

The calibration model generates N_s^0 choice occasion for each state s, where the sum of the conditional probabilities of taking a fluke trip over the N_s^0 choice occasions equals the MRIP-based estimate of total directed fluke trips in state s during 2019. The number of choice occasions N_s^0 remains fixed throughout subsequent projection sub-model iterations. Expected total harvest and discards is computed as the sum of probability-weighted harvest and discards over the N_s^0 choice occasions.

Output from the calibration sub-model and MRIP-based estimates of harvest in 2019 are displayed in Table 4. Calibration statistics come from re-running the model 30 times, generating and drawing from new fluke and black sea bass catch-per-trip and utility parameter distributions at each iteration. MRIP point estimates and variance statistics are based on the weighting, clustering, and stratification of the survey design. Given the relative importance of harvest and the general insignificance of discards on angler utility, Table 4 compares simulated and MRIP-based estimates of harvest on directed summer flounder trips in numbers of fish for each state and species and omits discards.[7]

The calibration sub-model was designed to approximate estimated actual harvest, and thus simulated harvest for each species-state combination approximates the MRIP-based

[7] Catch statistics were only calculated in the model for state-species combinations in which a species' catch attributes entered the corresponding regional utility model.

estimates. Given that expected harvest is a key determinant of the probability of taking a fluke trip, this bolsters confidence that the calibration model generates an appropriate number of choice occasions for the ensuing projection sub-model.

Table 4. Harvest in numbers of fish on directed fluke trips from the calibration sub-model and MRIP. 95% confidence intervals in brackets.

State	Calibration sub-model	MRIP 2019
	Summer flounder harvest	
Massachusetts	54,896 [54615, 55177]	55,386 [23325, 87447]
Rhode Island	220,799 [219764, 221834]	213,592 [51594, 375590]
Connecticut	92,581 [91951, 93211]	89,843 [54911, 124776]
New York	563,376 [559579, 567173]	561,173 [318178, 804167]
New Jersey	1,075,530 [1069815, 1081245]	1,108,158 [736178, 1480138]
Delaware	89,045 [88593, 89497]	91,025 [56129, 125921]
Maryland	77,650 [77195, 78105]	79,371 [25346, 133396]
Virginia	150,361 [149794, 150928]	149,785 [66148, 233423]
North Carolina	33,391 [33280, 33502]	34,895 [13536, 56253]
	Black sea bass harvest	
Massachusetts	52,917 [52587, 53247]	54,178 [20329, 88028]
Rhode Island	207,900 [206767, 209032]	214,471 [118736, 310206]
Connecticut	157,294 [156091, 15849]	153,564 [84144, 222985]
New York	567,622 [562454, 572790]	556,955 [349796, 764115]
New Jersey	123,443 [121616, 125270]	123,860 [65887, 181833]
Delaware	13,672 [13469, 13875]	14,348 [4518, 24178]
Maryland	12,515 [12311, 12718]	13,272 [2407, 24136]
Virginia	32,112 [31675, 32549]	31,597 [-11867, 75062]
North Carolina	0	0
	Scup harvest	
Massachusetts	31,467 [31247, 31687]	31,515 [9304, 53726]
Rhode Island	368,228 [365533, 370923]	366,744 [72937, 660551]
Connecticut	355,442 [352371, 35851]	439,359 [-65705, 944423]
New York	1,074,804 [1067309, 1082300]	1,085,926 [687,805, 1,484,048]
New Jersey	3,452 [3090, 3815]	2,458 [-524, 5440]
	Weakfish harvest	
New Jersey	33,540 [32687, 34393]	32,668 [-10985, 76322]
Delaware	3,162 [3107, 3216]	3,185 [52, 6317]
Maryland	0	20 [-19, 60]
Virginia	6,903 [6790, 7015]	6,765 [158, 13372]
North Carolina	350 [344, 355]	682 [-594, 1958]
	Red drum harvest	
Virginia	0	0
North Carolina	0	0

7 Population-based adjustments to recreational catch

Built into the RDM is an explicit relationship between the projected fluke population abundance and size distribution with the numbers and sizes of fluke caught by recreational anglers. For example, we assume that greater numbers of fluke in the ocean will lead to greater catch-per-trip, holding all else constant. Similarly, if the size distribution of fluke changes, so too will the size distribution of fish encountered by anglers. To account for these two links, we incorporated into the RDM two approaches based on angler targeting behavior.

We determined state-level angler targeting behavior for fluke by computing recreational selectivity-at-length, or the proportion of the fluke population by length class caught by anglers. This metric required a recreational catch-at-length and population numbers-at-length distribution, the former of which we created using historical catch data adjusted by the d^{*}_{fs} values identified in the calibration sub-model model. The original catch-at-length distribution is:

$$f(m_s) = \frac{c_{ms}}{\sum_1^L c_{ls}} \; \forall \, m \in 1 \ldots L, \qquad (6)$$

where $\sum_1^L c_{ls}$ the MRIP-based estimate of total fluke catch and c_{ms} is the sum of fluke harvested and discarded within a length bin for state s.[8]

If $f(m_s)$ accurately represented the true catch-at-length distribution, we could for each simulated trip's draw of catch up to the bag limit, draw from $f(m_s)$, impose a size limit, and compute total harvest and discards overall all trips. However, we compared results from this method against MRIP estimates in a baseline year and found considerable differences in harvest and discards. The differences occurred because $f(m_s)$ does not represent the true catch-at-length distribution and is derived from available catch data that perhaps over- or under-samples fluke harvest- or discards-at-lengths. Left unaccounted for, this discrepancy would in some cases project shifts in harvest that move in a direction opposite to what we would expect under a given change in size limits. To ensure that hypothetical changes in size limits affect harvest in ways

[8] Numbers of fluke harvested by length are computed by multiplying estimated proportions of harvest-at-length, derived from 2018 and 2019 MRIP estimates, by the MRIP-based of estimate of total harvest in 2019. Numbers of fluke discarded by length are computed similarly; however, we calculate proportions fluke discarded-at-length in 2018 and 2019 using raw MRIP data supplemented by volunteer angler logbook data on discard lengths. The resulting proportions fluke discarded-at-length are multiplied by the MRIP-based estimate of total discards in 2019 to arrive at 2019 fluke discards-at-length.

that follow *a priori* expectations (e.g., decreasing the minimum size limit relative to 2019 and holding all else constant will lead to increased harvest) we adjusted $f(m_s)$ based on the d^*_{fs} values for fluke attained in the calibration sub-model.

We did this by first using $f(m_s)$ to compute the relative probability of catching a length-m fluke among fluke shorter than, and equal to or longer than the 2019 minimum size limit in state s, respectively:

$$f_{\underline{l}}(m_s) = \frac{f(m_s)}{\sum_{l=1}^{min.size-1} f(l_s)} \forall\ m \in 1 \ldots min.size - 1, \tag{7}$$

$$f_{\bar{l}}(m_s) = \frac{f(m_s)}{\sum_{l=min.size}^{L} f(l_s)} \forall\, m \in min.size \ldots L. \tag{8}$$

We then distributed d^*_{fs} and $(1 - d^*_{fs})$ across the relative probability weights assigned to the corresponding sizes by the unadjusted catch-at-length size distribution to create $F(l_s)^*$:

$$F(l_s)^* = \begin{cases} \sum_{l=1}^{m} f_{\underline{l}}(m_s)\, d^*_{fs} & : m < min.size\ limit \\ d^*_{fs} & : m = min.size\ limit \\ \sum_{l=min.size+1}^{m} f_{\bar{l}}(m_s)\,(1 - d^*_{fs}) & : m > min.size\ limit \end{cases} \tag{9}$$

The resulting probability distribution $f(l_s)^*$ preserved the value of the catch-at-length cumulative distribution function evaluated at the minimum size limit which explains harvest in the baseline year (d^*_{fs}) and redistributed the remaining probability in proportion to the original catch-at-length probability distribution. Using $f(l_s)^*$, we computed an adjusted catch-at-length distribution:

$$f(m_s)^* = \sum_{1}^{L} c_{ls}\, f(l_s)^* = \frac{c^*_{ls}}{\sum_{1}^{L} c_{ls}}\ \forall\ c \in 1 \ldots L, \tag{10}$$

We then used c^*_{ls}, the adjusted catch of length-l fluke, and median population numbers-at-age in the baseline year, N_a, from the Monte Carlo Markov Chain resampling procedure implemented in the fluke age-structured assessment program (NEFSC 2019) to compute recreational selectivity-at-length. After converting median population numbers-at-age to numbers-at-length using commercial trawl survey age-length indices, we followed Lee et al. (2017) and rearranged the Schaefer (1954) catch equation to solve for recreational selectivity of length-l fluke in state s:

$$q_{ls} = \frac{c^*_{ls}}{N_l}. \tag{11}$$

Having computed q_{ls} for a representative year, c^*_{ls} can be computed for any stock structure $\widetilde{N}_l$. Rearranging Equation (11) and dividing c^*_{ls} by total catch gives the probability of catching a length-l fluke conditional on the projected stock structure $\widetilde{N}_l$:

$$\widetilde{f(c_s)}^* = \frac{q_{ls}\widetilde{N}_l}{\sum_l^L q_{ls}\widetilde{N}_l} = \frac{\tilde{c}^*_{ls}}{\sum_l^L \tilde{c}^*_{ls}}. \tag{12}$$

Assuming constant q_{ls}, Equation (12) shows the relationship between any projected size distribution of fluke in the ocean and the size distribution of fluke caught by recreational anglers.

In addition to population-adjusted recreational catch-at-length distributions by state, Equation (12) provides total expected recreational catch by state, $\sum_l^L \tilde{c}^*_{ls}$, which we use to generate population-adjusted fluke catch-per-trip distributions. For each state s we scale the estimated mean parameters from the baseline-year fluke catch-per-trip distributions by $\sum_l^L \tilde{c}^*_{ls}/\sum_1^L c_{ls}$, where $\sum_1^L c_{ls}$ is the MRIP-based estimate of total fluke catch in the baseline year. The adjusted mean catch-per-trip parameters therefore reflect expected trip-level changes in fluke catch brought on by changes in population abundance. We also adjust the dispersion parameter of the projected fluke catch-per-trip distributions such that their coefficients of variation remain at baseline-year levels. These adjusted marginal catch-per-trip parameters are combined with baseline-year black sea bass marginal parameters and integrated into the estimated copula function to create new, population-adjusted joint catch-per-trip distributions from which we draw in the projection sub-model.

8 Projection sub-model

After adjusting the catch-per-trip and catch-at-length distributions based on projected numbers-at-length, the projection sub-model proceeds by re-simulating outcomes under the alternative management scenarios for each of the N_s^0 choice occasions. The projection sub-model, depicted in Figure A2, begins by assigning to each choice occasion β_n', trip costs, and numbers of scup, red drum, or weakfish harvest and discards from the calibration sub-model. It then draws fluke and black sea bass catch-per-trip values from the population-adjusted catch-per-trip distribution. Fluke harvest and discards per choice occasion are determined by drawing lengths from $\widetilde{f(c_s)}^*$ and checking them against the alternative size and bag limit. Black sea bass catch, also drawn from the population-adjusted catch-per-trip distribution, is allocated to a harvest or discard bin based on the d_{fs}^* approach from the calibration sub-model. The process up to this point is repeated 10 times and utilities are calculated at each iteration. Expected utility is taken as the average utility over the 10 draws and choice occasion probabilities are calculated using Equation (5). As in the calibration sub-model, projected total numbers of directed fluke trips is the sum of the probability of taking a fluke trip over the N_s^0 choice occasions and expected total harvest and discards is the sum of probability-weighted harvest and discards over the N_s^0 choice occasions.

8.1 Economic impacts

We measured both market and non-market values of changes in fishery conditions. The market value of recreational marine fishing is in part generated by angler trip expenditures filtering though the regional economy. Angler expenditures spur direct, indirect, and induced effects, which together represent the total contribution of marine angler expenditures on the regional economy. Direct effects occur as angler spend money at retail and service industries in support of their trip. In turn, angler spending produces indirect effects as retail and service industries pay operating expenses and purchase supplies from wholesalers and manufacturers. The cycle of secondary industry-to-industry spending continues until all indirect effects occur outside the region. Induced effects occur as employees in direct and indirect sectors make household consumption purchases from retailers and services industries. We measure the total contribution of marine angler expenditures on the regional economy using economic multipliers from the Northeast U.S. marine fishing input-output model (Lovell et al. 2020). Specifically, we measure the effect of changes in aggregate angler expenditures on (i) the gross value of sales by affected businesses, (ii) labor income, (iii) contribution to region GDP, and (iv) employment in recreational fishing-related industries. The first three metrics are measures in dollars, whereas the latter is measured in numbers of jobs. We compute these metrics on a state-by-state basis and assume that spending on durable fishing equipment, i.e., equipment that is not purchased on a trip-by-trip basis like boats, insurance, rods, or reels, which also contributes to the local economy, remains constant. When fishing conditions become more attractive to anglers, perhaps due to a relaxation of regulations, our model will predict an increase in overall angler expenditures that stems from an overall increase in directed fishing trips. Aggregate angler expenditures are computed in the projection sub-model as the probability-weighted sum of trip costs across choice occasions.

The non-market value of changes in recreational fluke fishery conditions occurs through trip-level changes in expected harvest and discards, attributes of which lack explicit markets that directly reveal their value. We measure these angler welfare impacts by computing the change in consumer surplus (CS), or the difference in expected utility in dollar terms between the baseline management scenario (scenario 0) and the alternative management scenario (scenario 1) (Hoyos 2010), i.e.,

$$\Delta E(CS_n) = \frac{\ln\left(\sum_{j=1}^{J} e^{V_{nj}^{1}}\right) - \ln\left(\sum_{j=1}^{J} e^{V_{nj}^{0}}\right)}{-\beta_{trip\ cost}} \tag{13}$$

where V_{nj}^{1} and V_{nj}^{o} are expected utilities in the baseline and alternative scenarios and $\beta_{trip\ cost}$ is the marginal utility of price. Positive $\Delta E(CS_n)$ signifies angler welfare loss and is the amount of money needed to offset decreased angler utility from scenario 1 relative to scenario 0, thus maintaining scenario 0 utility. Conversely, negative $\Delta E(CS_n)$ signifies angler welfare gain and is the amount of money anglers would be willing to forego in scenario 1 to maintain scenario 0 utility. To ease the interpretation of our results, we multiply $\Delta E(CS_n)$ by -1 so that positive (negative) values of $\Delta E(CS_n)$ signify angler welfare gains (losses).

8.2 Alternative operating model assumptions

Two alternative operating model assumptions were considered in the MSE based on stakeholder and technical working group input that represent hypotheses about particular aspects of uncertainty in the summer flounder fishery. The first was that MRIP point estimates of recreational summer flounder effort are biased upward. We incorporated this scenario in the RDM by calibrating the model to the lower bounds of the 95% confidence intervals on MRIP estimates of effort, rather than the point estimates. Additionally, recreational selectivity-at-length in the baseline year was re-calculated from Equation 11 using (i) initial (2019) numbers-at-age data that was scaled down in proportion to the scaling of the MRIP effort data and (ii) MRIP catch estimates evaluated the lower 95% confidence interval.

The second assumption considered the expected northward shift of fluke biomass over time (Perretti and Thorson 2019) that may differentially affect recreational catch in different regions. To model these expectations, we first predicted future percentages of fluke biomass in three regions (Massachusetts to New York, New Jersey, and Delaware to North Carolina) using historical interpolated fluke biomass data downloaded from the Area Analysis Tool in the NOAA Fisheries Distribution Mapping and Analysis Portal (NOAA Fisheries, 2022). These data were derived from the NMFS Northeast U.S. fall trawl survey dataset and predictions were based on the most recent 10 years of available data. Percent total biomass by region was modeled as a function of a linear time trend and predicted values were obtained for the out-of-sample years. The left panel in Figure 2 shows the regional delineations, while the right panel shows observed and predicted percentages of interpolated fluke biomass by region.

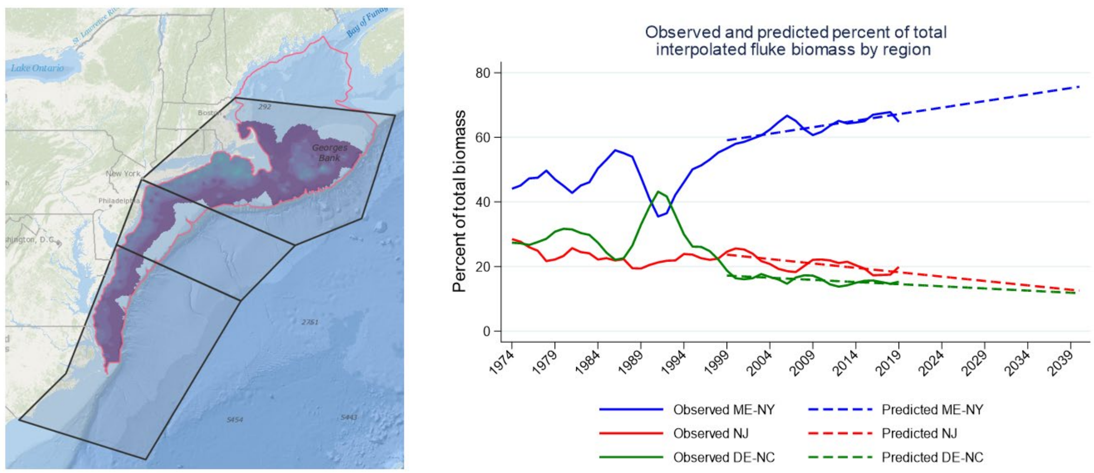

Figure 2. Left: regional delineations of interpolated biomass data. Right: observed and predicted percent of total biomass by region.

Predicted changes in the distribution of fluke biomass across the region entered the RDM through changes in mean catch-per-trip. For each year of the projection time horizon, we calculated state-level total catch relative to 2019 assuming differentiated biomass accessibility across states. After adjusting and rearranging and Equation (12) to reflect this assumption, total expected catch during projection year y for state s was calculated as:

$$\tilde{C}_{lsy} = \sum_{l}^{L} q_{ls}\tilde{p}_{sy}N_l. \qquad (14)$$

where $\tilde{p}_{sy}$ was the predicted percent of total fluke biomass available to state s in projection year y. Note that in this formulation there is no distinction in availability across length classes. The ratio $\tilde{C}_{lsy}/C_{ls}$, where C_{ls} is total fluke catch in the baseline year for state s, was then computed for each year of the projection time horizon. During projection simulations, state-level mean parameters characterizing the catch-per-trip distribution were multiplied by $\tilde{C}_{lsy}/C_{ls}$, thus capturing a potential recreational catch response to the northward shifting biomass distribution.

This scenario results in a progressive increase in recreational summer flounder catch in the northern states with a concurrent decrease in catch in New Jersey and the southern region.

8.3 Out-of-sample predictions

We assessed the predictive accuracy of the RDM by comparing out-of-sample model forecasts of total fluke catch and harvest to MRIP-based estimates. After calibrating the model to 2019, forecasts were made for 2015, 2016, 2017, 2018, 2020, and 2021 conditional on state-specific recreational fishing regulations and distributions of stock sizes from the summer flounder management track 2021 assessment model in those years. We performed 30 iterations of the RDM to produce confidence bounds around the mean estimates. MRIP- and RDM-based estimates are shown in Figure 3.

Of important note is that 2020 and 2021 were both years in which COVID-19 induced substantial changes in recreational activities, including fishing behavior (e.g. Midway et al. 2021). Despite the massive disruption of a pandemic, the RDM does reasonably well at predicting fluke catch and harvest in 2018, 2020, and 2021, as mean projections fall within 95% confidence intervals of the MRIP estimates. However, the model consistently under-predicts total fluke catch and harvest in 2015, 2016, and 2017, as mean projections fall outside or just inside the MRIP confidence intervals. Given the good performance of the model during known behavioral shifts due to the COVID pandemic, the discrepancies in 2015, 2016, and 2017 could be an artifact of the MRIP's transition from the Coastal Household Telephone Survey (CHTS) to the Fishing Effort Survey (FES) in 2018 and the resulting calibration of its entire time series of catch and effort estimates through 2017.[9] Official MRIP estimates through 2017 are now based on calibrated CHTS data, while official MRIP estimates for 2018 and after are based on the FES data only. By conditioning the RDM to FES-based estimates in 2019 and comparing our projections to re-calibrated CHTS-based estimates in 2015 through 2017, we may be

[9] Prior to 2018, the CHTS collected data about recreational fishing effort through a random digit dialing sampling approach. Due largely to a decline in the use of landlines over time, between 2007 and 2017 the MRIP developed the FES, a mail survey that is sent to randomly sampled residential households in coastal states. Compared to the CHTS, the FES was found to be more representative sample of angler population and less susceptible to non-response and non-coverage bias. The FES was peered review in 2014 and certified as a scientifically sound replacement for the CHTS in 2015. For more information see https://www.fisheries.noaa.gov/recreational-fishing-data/effort-survey-improvements.

confounding model performance with differences in MRIP estimates driven by the alternative data collection methods used to generate the estimates.[10]

In an attempt to eliminate the possible effect of alternative MRIP data collection methods on our assessment of the RDM's predicative performance, we calibrated the RDM to 2017 (rather than 2019) and projected outcomes for 2015 and 2016. These three years share the same underlying data generating process by which recreational fishery statistics are estimated and so provide a consistent baseline to assess the predictive accuracy of the RDM for the period prior to the changes in the MRIP methodology. Comparisons of coast-wide output from the 2017-calibrated RDM to MRIP estimates are shown in Figure 4.

Figure 4 shows that calibrating the RDM to 2017 leads to more accurate predictions of total fluke harvest and catch in 2015 and 2016. While the model over-predicts coast-wide harvest in both years, mean estimates fall well within the MRIP-based confidence intervals. The RDM over-predicts total fluke catch in 2015 and under-predicts total fluke catch in 2016 but predicted means are similar to the MRIP-based point estimates. Furthermore, the predicted 95% confidence intervals for total catch in both years are nested within the MRIP-based confidence intervals.

Results in Figures 3 and 4 suggest the RDM is capable of making projections that fall within MRIP-based ranges of estimated outcomes. However, they also suggest that the baseline year used to calibrate the RDM is important and can affect the accuracy of model predictions. As a best practice when making projections for management purposes, the RDM should be calibrated to the most recent year of data and projections should be limited to a short, one- or two-year time horizon.

[10] Recreational harvest weight for all species in the Mid-Atlantic region dropped by roughly 50% from 2017 to a historic low in 2018 (NOAA Fisheries 2022), which may also be indicative of the alternative survey instruments used to generate these estimates.

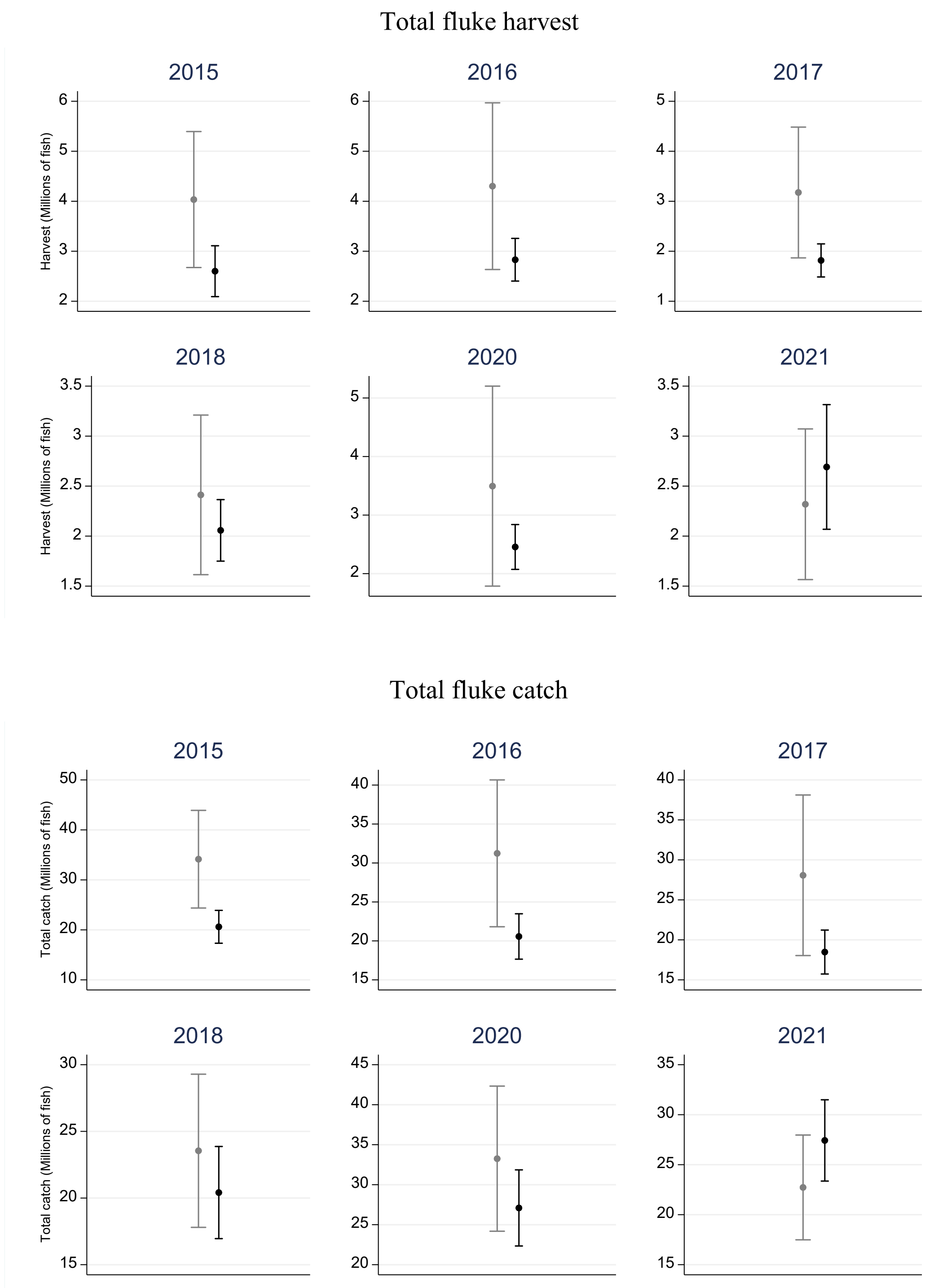

Figure 3. MRIP vs. model projections of coast-wide fluke catch (top) and harvest (bottom) in numbers of fish and 95% confidence intervals. Model calibrated to baseline year 2019. Gray = MRIP, black = model.

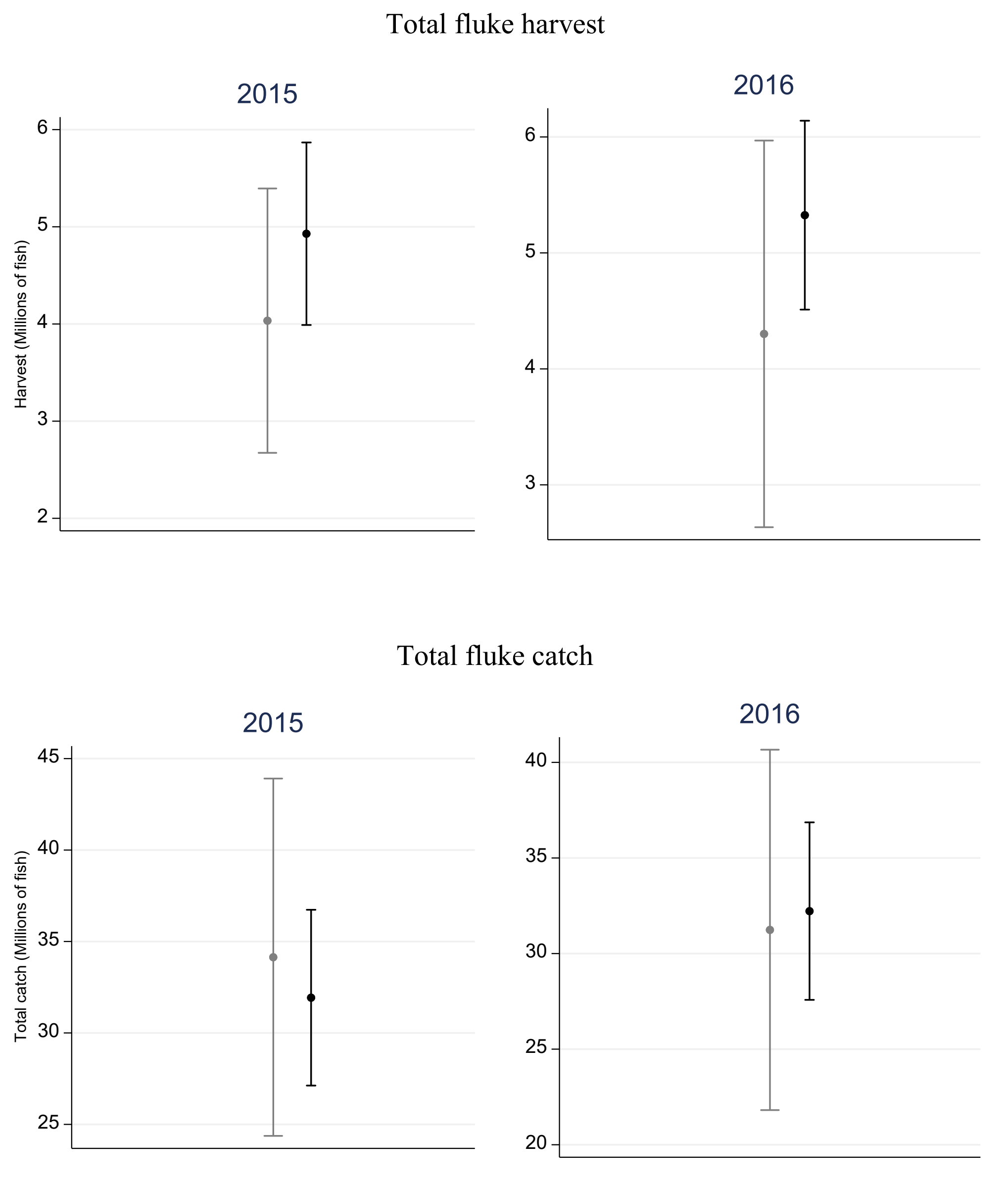

Figure 4. MRIP vs. model projections of coast-wide fluke catch (top) and harvest (bottom) in numbers of fish and 95% confidence intervals. Model calibrated to baseline year 2017. Gray = MRIP, black = model.

9 Summary

To recap, the RDM uses estimated preference parameters from the angler behavioral model to estimate changes in angler welfare and effort (fishing trips) conditional on expected harvest and discards. These estimates parameterize the ensuing calibration- and projection sub-models. Along with the behavioral parameters, the calibration sub-model uses historical catch, effort, and trip cost data to simulate fishing trips that emulate fishery conditions in the baseline year (2019). The calibration sub-model generates a number of fishing trips that enter and remain fixed in the subsequent projection sub-model.

Prior to the projection sub-model routine, the RDM takes projected numbers-at-length in year t from the operating model, $\widetilde{N}_{lt}$, and adjusts the catch-per-trip and catch-at-length distributions via Equation (12). Conditional on these population-adjusted trip-level distributions and a given management scenario, the projection sub-model re-simulates the fishery and computes expected angler effort, angler welfare, impacts to the local economy, and total harvest and discards. Predicted total harvest and discards feed back into the operating model, which subsequently produces $\widetilde{N}_{lt+1}$, the input for the RDM in year $t+1$. This recursive cycle continues for each year of the time horizon and over multiple iterations.

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Appendix

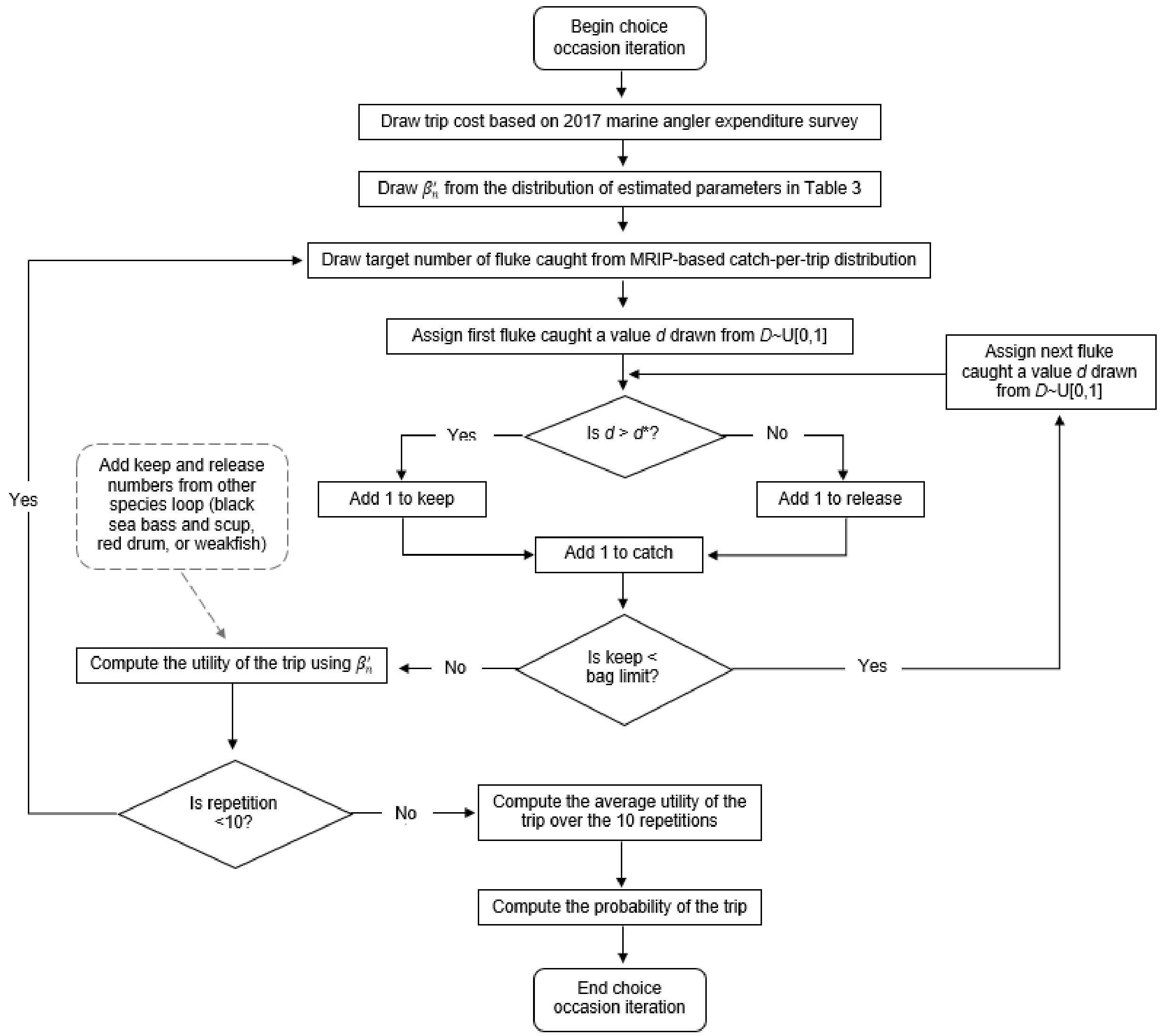

Figure A1. Calibration sub-model algorithm. Only the loop for summer flounder is shown in detail.

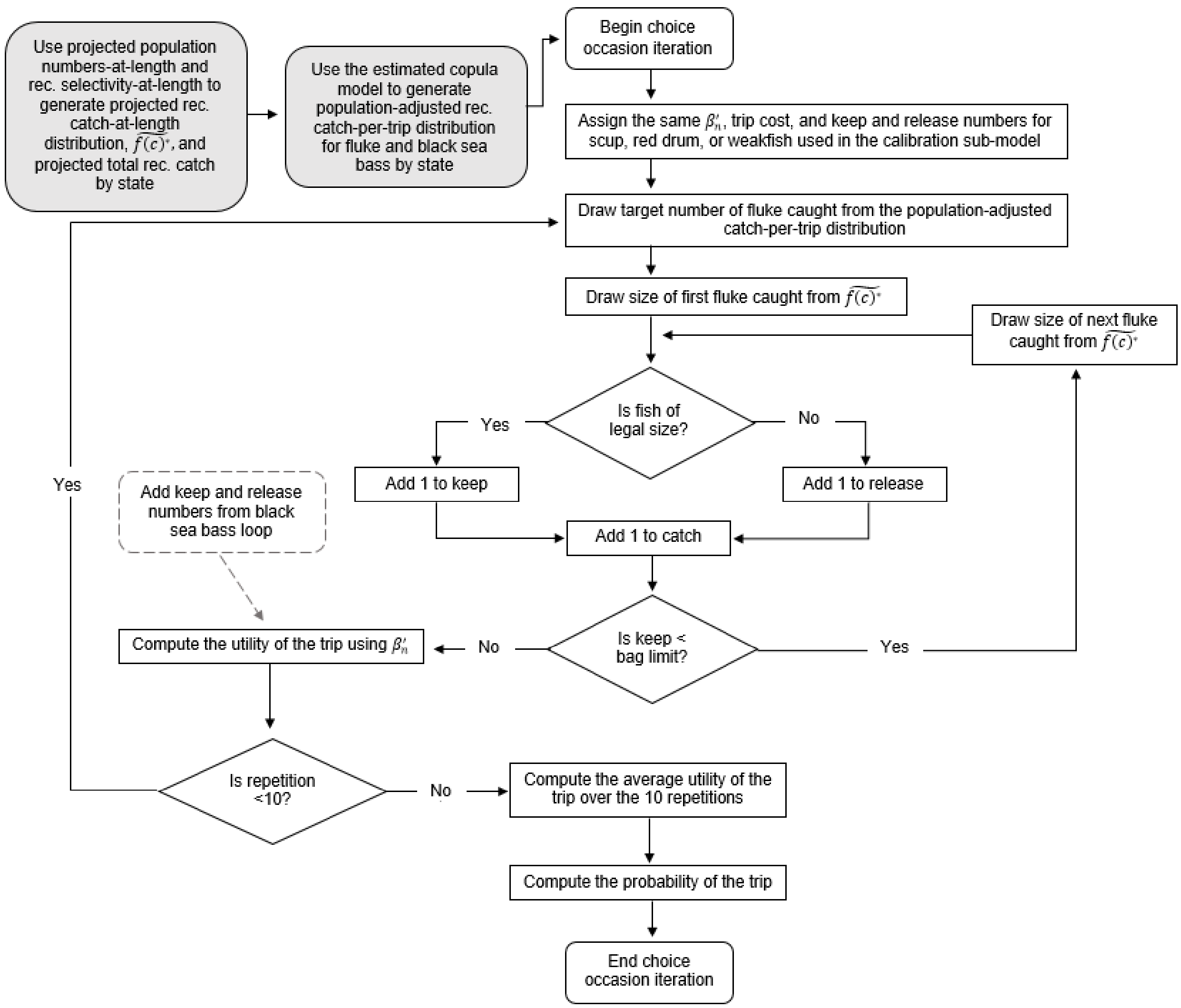

Figure A2. Projection sub-model algorithm. Only the loop for summer flounder is shown in detail.