NEFSC's Recreation Demand Model (RDM) Decision Support Tool: Overview, Data, and Methods

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Outline of presentation

Overview

Discrete choice model of fishing decisions

- random utility modeling
- survey data
- econometric analysis

Fishery simulation

- algorithm overview
- input data
- model calibration and prediction
- model output

Overview

RDM comprised of two main components:

1. Discrete choice model of fishing decisions
   - Estimate structural parameters representing the importance of trip attributes (e.g., harvest, trip cost) on anglers' decisions to fish
   - Structural parameters allow us to compute the expected "utility" an angler would derive from a fishing trip with specified attributes, as well as several other important trip-level outcomes
2. Fishery simulation
   - Use structural parameters + best available fishery data to simulate trips under both current conditions and alternative conditions in which some aspects are manipulated (e.g., regulations, length dist'n of the stock)
   - Compute trip-level outcomes under both scenarios and aggregate over all trips

Discrete choice

There are many situations in which a decision-maker must choose between a discrete number of alternatives:

- Which mode of travel a commuter takes to get to work
- Which car to buy
- Which job to take
- Whether to commercial fish or not, and if so at which location
- Whether to recreational fish or not

Understanding why choices were made is important to those interested in influencing or evaluating behavior (marketers, managers, etc.)

Random utility theory (RUT)*

Under RUT, discrete choices are modeled under the assumption of utility-maximizing behavior

- A decision-maker receives some "utility" from each of the alternatives
- The amount of utility can depend of characteristics of the alternative, characteristics of the decision-maker, and unobserved characteristics
- The decision-maker chooses the alternative that provides the greatest overall utility

*More details on random utility theory and modeling can be found in Train (2003) - *Discrete Choice Methods with Simulation*. Available free at https://eml.berkeley.edu/books/choice2.html

Random utility model specification

From the perspective of the decision-maker:

- Decision-maker n faces a choice between J alternatives
- Each alternative j provides utility U_{nj} (where $j = 1, ..., J$)
- Decision-maker n chooses alternative i if it provides the greatest utility over all the alternatives: $U_{ni} > U_{nj} \; \forall \; j \neq i$
- However, we (the analysts) do not observe U_{nj}
  - We observe the chosen alternative, some attributes of the alternative, some attributes of the decision-maker

Random utility model specification

We decompose the utility the decision-maker derives from each alternative into two components:

- $V(\mathbf{x}_{nj})$: observable component, known as representative utility
- ϵ_{nj}: unobservable component

$$U_{nj} = V(\mathbf{x}_{nj}) + \epsilon_{nj}$$

- $\mathbf{x}_{nj}$ can include characteristics of the alternatives and the decision-maker
- ϵ_{nj} is everything else that affects utility but not included in V_{nj}

Random utility model specification

- If we specify V_{nj} as a linear function, total utility is:

$$U_{nj} = \beta' \mathbf{x}_{nj} + \epsilon_{nj} \tag{1}$$

  where β' is a vector of structural parameters that tell us how observable attributes relate to overall utility; they measure the marginal utility of the attributes or characteristics

- We don't know with certainty which alternative provides maximum utility (as utility depends on ϵ_{nj}), so we can only make probabilistic statements about choice

- Choice probabilities play an important role in RUT

Logit choice probabilities

- The probability that decision maker n chooses alternative i is:

$$\begin{aligned} P_{ni} &= Prob(U_{ni} > U_{nj}\ \forall\ j \neq i) \\ &= Prob(\beta'\mathbf{x}_{ni} + \epsilon_{ni} > \beta'\mathbf{x}_{nj} + \epsilon_{nj}\ \forall\ j \neq i) \\ &= Prob(\epsilon_{nj} < \beta'\mathbf{x}_{ni} - \beta'\mathbf{x}_{nj} + \epsilon_{ni}\ \forall\ j \neq i) \\ & \ldots \\ &= \frac{e^{\beta'\mathbf{x}_{ni}}}{\sum_j e^{\beta'\mathbf{x}_{nj}}} \end{aligned} \tag{2}$$

- Maximum likelihood estimation involves finding the structural parameters β' that make the choice probabilities consistent with observed choices
  - P_{ni} close to 1 for alternatives that were chosen; P_{ni} close to 0 for alternatives that were not chosen

Discrete choice data

Stated preference mail/web survey of recreational anglers licensed in MA-VA conducted in 2022

- Pre-tested to ensure that questions could be interpreted and answered as intended
- 6,000 saltwater fishing licensees sampled; 2,317 completed surveys returned (38.7%)
- Collected demographic and fishing-related information, as well as stated preference information from a discrete choice experiment (DCE)

Angler discrete choice experiment (DCE)

- Designed to elicit the structural parameters (β') of anglers' decision-making process
  - i.e., the marginal utilities of the most salient features of a recreational fishing trip: harvest, discards, and costs
- Asked survey respondents to choose between three alternatives, each characterized by attributes and costs that differ across alternatives
  - Essentially created choice situations that anglers might face

Angler discrete choice experiment

- Attribute levels based on survey pre-testing, MRIP data on catch-per-trip, and recent fishing trip expenditure data collected along the East Coast
- Attribute level combinations and option groupings selected based on an efficient experimental design
- 30 versions of the survey, each containing a different set of 6 choice questions

SECTION B: SALTWATER FISHING TRIPS

Suppose that you have the choice between two recreational saltwater fishing trips (**Trip A** or **Trip B**) and not going recreational saltwater fishing (**Trip C**). Below the table, indicate which of these three options would be your first choice.

REGULATIONS
You are legally allowed to keep: 2 Fluke, 18" or longer 22 Black Sea Bass, 12.5" or longer 20 scup, 9" or longer

	TRIP FEATURES	Trip A	Trip B	Trip C
CATCH	TOTAL NUMBER OF FISH YOU CATCH This number includes both undersized and legal size fish.	6 Fluke	1 Fluke	Do something other than saltwater fishing.
	NUMBER OF LEGAL-SIZE FISH YOU CAN KEEP These fish are at least legal minimum size.	2 Fluke	1 Fluke	
	TOTAL NUMBER OF OTHER FISH YOU CATCH Other fish you catch.	30 Black Sea Bass 0 scup	0 Black Sea Bass 60 scup	
	NUMBER OF OTHER LEGAL-SIZE FISH YOU CAN KEEP Other fish you catch on this trip that can be legally kept.	22 Black Sea Bass 0 scup	0 Black Sea Bass 10 scup	
TRIP DETAILS	TOTAL TRIP COST Your share of the fishing-related, transportation, and other expenses. This cost would not cover anyone else on the trip.	$160	$10	

If you were presented with these three options, which one would you choose? →

(Choose only one option.)

Trip A	Trip B	Trip C
○	○	○

Example choice question

Mixed logit model

- We estimate a variant of the logit model, the mixed logit model
- Overcomes three limitations of the logit model:
  - Unobserved (or random) preference variation of the population of decision-makers
  - Unrestricted substitution patterns
  - Correlations in unobserved factors over time (better application to panel data)
- To do this it assumes a distribution of coefficients $f(\beta|\theta)$, rather than use a set of fixed set of coefficients for the population, β
- Utility of alternative j under the mixed logit model is:

$$U_{njt} = \beta_n' \mathbf{x}_{njt} + \epsilon_{njt} \tag{3}$$

Model specification

- We specify the utility of the alternatives in the DCE as:

$$U_{njt} = \beta_1\sqrt{\text{SF kept}} + \beta_2\sqrt{\text{BSB kept}} + \beta_3(\sqrt{\text{SF kept}} \times \sqrt{\text{BSB kept}})$$
$$+ \beta_4\sqrt{\text{SF released}} + \beta_5\sqrt{\text{BSB released}} + \beta_6\sqrt{\text{scup catch}} + \beta_7\text{trip cost}$$
$$+ \beta_8\text{opt-out} + \beta_9(\text{opt-out} \times \text{age}) + \beta_{10}(\text{opt-out} \times \text{avidity}) + \epsilon_{njt}$$

- Expected to be positive; expected to be negative
- "opt-out" $= 1$ if option 3 was chosen, zero otherwise
- "avidity" is the number of fishing trips the respondent took in the past 12 months

Utility parameter estimates from mixed logit model

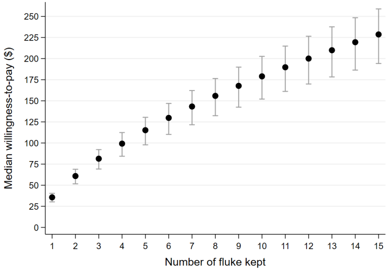
Attribute	Mean parameter	St. dev. parameter
$\sqrt{\text{SF kept}}$	0.827***	1.267***
	(0.070)	(0.057)
$\sqrt{\text{BSB kept}}$	0.353***	0.129**
	(0.048)	(0.071)
$\sqrt{\text{SF kept}} \times \sqrt{\text{BSB kept}}$	−0.056*	0.196***
	(0.031)	(0.024)
$\sqrt{\text{SF released}}$	0.065***	0.325***
	(0.022)	(0.050)
$\sqrt{\text{BSB released}}$	0.074***	0.055
	(0.013)	(0.034)
$\sqrt{\text{scup catch}}$	0.018*	0.024
	(0.009)	(0.025)
cost	−0.012***	
	(0.000)	
opt-out alternative:		
constant	−2.056***	1.977***
	(0.297)	(0.109)
avidity	−0.010**	
	(0.005)	
age	0.010**	
	(0.005)	
No. anglers	1,437	
No. choices	8,522	
LL	-7297	
McFadden's pseudo R^2	0.221	
AIC	14,629	

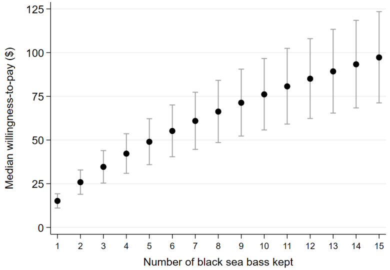
Note: Standard errors in parentheses. Variables under the opt-alternative are interacted with a dummy variable that takes the value of one if the "Do something other than fishing" alternative is chosen and zero otherwise. "Avidity" is the number of fishing trips taken in the past year.
* $p<0.10$, ** $p<0.05$, *** $p<0.010$.

Economic values

- What can we do with these estimates?
- For one, we can infer angler willingness-to-pay values:

$$WTP_{\#\text{ SF kept}} = \frac{\partial U}{\partial \text{SF kept}} \Big/ \frac{\partial U}{\partial \text{trip cost}} = \frac{\beta_{\text{SF kept}} + \beta_{\text{SF \& BSB kept}}\sqrt{\#\text{ BSB kept}}}{-2\beta_{\text{trip cost}}\sqrt{\#\text{ SF kept}}}$$



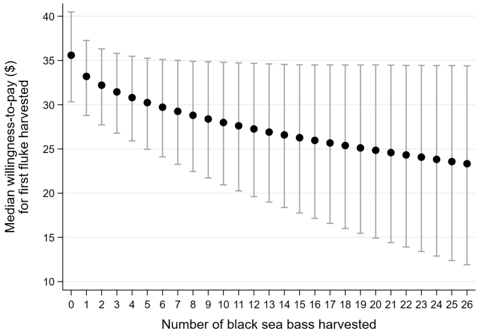


Median willingness-to-pay for increases in harvest of fluke only (left) and black sea bass only (right)

Economic values

Negative parameter on the $\sqrt{\text{SF kept}} \times \sqrt{\text{BSB kept}}$ in the discrete choice model indicates that fluke and black sea bass are substitute species

- The value anglers place on keeping fluke decreases as the number of black sea bass also kept increases (and vice versa)



Median willingness-to-pay for harvest of the first fluke caught with increases in black sea bass harvest

Counterfactual simulation

- A more practical benefit of the structural econometric modeling approach is that it allows us to conduct counterfactual simulations and assess their effect on overall angler welfare and other attributes in $\mathbf{x}_{nj}$ (e.g., harvest)
- We ask: what would choices be under alternative fishery scenarios?
- We compare outcomes under a baseline fishery scenario to an alternative fishery scenario in which some attributes are manipulated

Simulating individual choices and outcomes

- Suppose we have structural parameters β_n' and data x_{nj} for all alternatives in J (e.g., fishing trip alternative and no-trip alternative)

- We use choice probabilities to simulate choices in expectation:

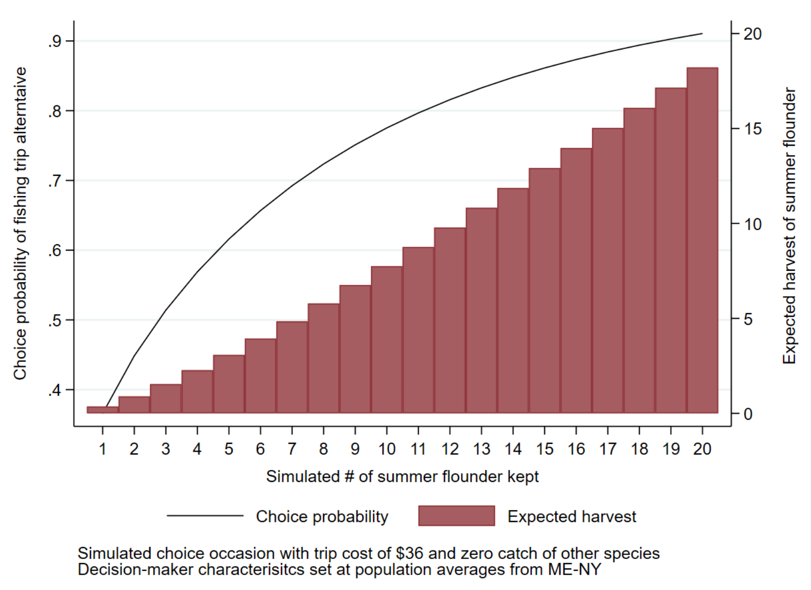
$$E(Y_{ni}) = P_{ni} = \frac{e^{\beta_n' \mathbf{x}_{ni}}}{\sum_{j=1}^{J} e^{\beta_n' \mathbf{x}_{nj}}} \tag{4}$$

  where $Y_{ni} = 1$ if n chooses i

- The expected value of x_{ni} (e.g., harvest) on the choice occasion is the observed outcome multiplied by the probability that n chooses i:

$$E(x_{ni}) = x_{ni} P_{ni} \tag{5}$$

Choice probabilities change with changes in attributes



Simulating *changes* in individual choices and outcomes

- The change in a decision maker's expected choice due to a change in choice setting is:

$$\Delta E(Y_{ni}) = P^1_{ni} - P^0_{ni} = \frac{e^{\beta' \mathbf{x}^1_{ni}}}{\sum_{j=1}^{J^1} e^{\beta' \mathbf{x}^1_{nj}}} - \frac{e^{\beta' \mathbf{x}^0_{ni}}}{\sum_{j=1}^{J^0} e^{\beta' \mathbf{x}^0_{nj}}} \tag{6}$$

  where superscripts 0 and 1 indicate alternatives in a baseline and alternative fishery scenarios

- While the change in a decision-maker's expected outcome due to a change in choice setting is:

$$\Delta E(x_{ni}) = x^1_{ni} P^1_{ni} - x^0_{ni} P^0_{ni} \tag{7}$$

- We must simulate choices under both scenarios!

Simulating changes in aggregate choices and outcomes

- The change in the total number of decision-makers expected to choose alternative i due to a change in choice setting is:

$$\Delta E(A_i) = \sum_{n=1}^{N} P_{ni}^{1} - \sum_{n=1}^{N} P_{ni}^{0} \tag{8}$$

- Similar intuition behind computing aggregate changes in $\mathbf{x}_{ni}$
- We must simulate choices under both scenarios!

Consumer surplus

- It is often of interest to measure how a particular market shock (e.g., policy, environmental condition) affects the economic well-being of the affected consumers
  - What is the monetary value of the harm to anglers caused by degraded water-quality (perhaps from an oil spill)?
  - What is the monetary value of the benefit to anglers caused by better fishing conditions? (e.g., more fish, relaxation of regulations)
- The logit model provides an expression for consumer surplus (CS) that is easy to calculate
  - An individual's CS is the utility, in dollar terms, that the individual receives in the choice occasion
  - The maximum $ an individual would pay for good with specified attributes, over and above what was actually paid

Consumer surplus

- If we assume utility is linear in income, then the expected CS that an individual receives from a given choice scenario is:

$$E(CS_n) = \frac{1}{\alpha_n} \ln\left(\sum_{j=1}^{J} e^{\beta' \mathbf{x}_{nj}}\right) + C \tag{9}$$

where α_n is the marginal utility of income ($-\beta_{trip\_cost}$) and C is an unknown constant

- The change in consumer surplus resulting from a change in the choice setting is:

$$\Delta E(CS_n) = \frac{1}{\alpha_n}\left[\ln\left(\sum_{j=1}^{J^1} e^{\beta' \mathbf{x}^1_{nj}}\right) - \ln\left(\sum_{j=1}^{J^0} e^{\beta' \mathbf{x}^0_{nj}}\right)\right] \tag{10}$$

where superscripts 0 and 1 denote the choice occasion under the baseline and alternative scenario

- Aggregate (fishery-wide) change in consumer surplus is the sum of $\Delta E(CS_n)$ across all decision-makers

Components of the RDM

So far we have discussed Part 1:

1. Discrete choice model of fishing decisions
   - Estimate structural parameters representing the importance of trip attributes (e.g., harvest, trip cost) on anglers' decisions to fish
   - Structural parameters allow us to compute the expected "utility" an angler would derive from a fishing trip with specified attributes, as well as several other important trip-level outcomes
2. Fishery simulation
   - Use structural parameters + best available fishery data to simulate trips under both current conditions and alternative conditions in which some aspects are manipulated (e.g., regulations, length dist'n of the stock)
   - Compute trip-level outcomes under both scenarios and aggregate over all trips

Components of the RDM

Now for Part 2:

1. Discrete choice model of fishing decisions
   - Estimate structural parameters representing the importance of trip attributes (e.g., harvest, trip cost) on anglers' decisions to fish
   - Structural parameters allow us to compute the expected "utility" an angler would derive from a fishing trip with specified attributes, as well as several other important trip-level outcomes
2. Fishery simulation
   - Use structural parameters + best available fishery data to simulate trips under both current conditions and alternative conditions in which some aspects are manipulated (e.g., regulations, length dist'n of the stock)
   - Compute trip-level outcomes under both scenarios and aggregate over all trips

Fishery simulation

- The rest of the RDM entails simulating $\mathbf{x}^0_{nj}$ and $\mathbf{x}^1_{nj}$, i.e, variables that appeared in the choice experiment and characterize trip-level outcomes under baseline (Scenario 0) and alternative (Scenario 1) fishery conditions

- Why? Allows us to calculate changes in (or absolute levels of) demand, harvest/discards, and angler welfare:

$$\Delta\text{demand for fishing}_n = P^1_{ni} - P^0_{ni} = \frac{e^{\beta' \mathbf{x}^1_{ni}}}{\sum_{j=1}^{J^1} e^{\beta' \mathbf{x}^1_{nj}}} - \frac{e^{\beta' \mathbf{x}^0_{ni}}}{\sum_{j=1}^{J^0} e^{\beta' \mathbf{x}^0_{nj}}}$$

$$\Delta\text{harvest/discards}_n = x^1_{ni} P^1_{ni} - x^0_{ni} P^0_{ni}$$

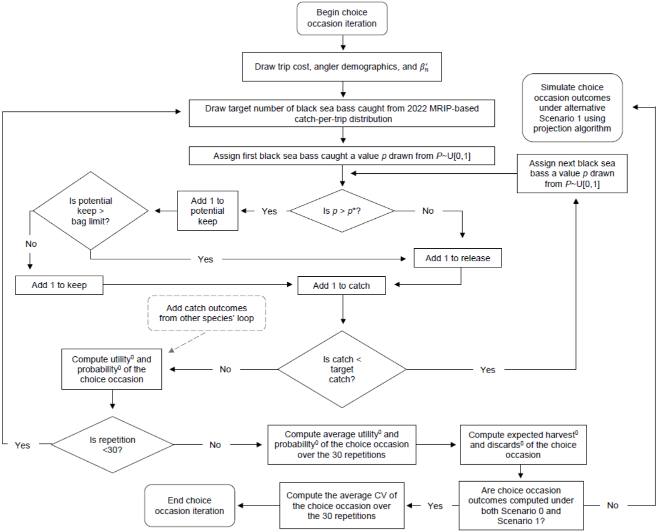
$$\Delta\text{welfare}_n = \frac{1}{\alpha_n}[\ln(\textstyle\sum_{j=1}^{J^1} e^{\beta' \mathbf{x}^1_{nj}}) - \ln(\sum_{j=1}^{J^0} e^{\beta' \mathbf{x}^0_{nj}})]$$

Fishery simulation

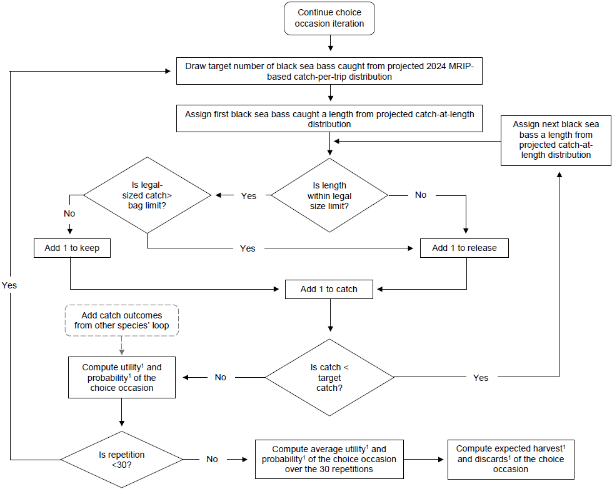
Multi-part algorithm with three main components:

- Simulate "choice occasions" under baseline (2022) fishery conditions
- Calibration: determine how many choice occasions to simulate, ensure their outcomes are similar to observed trip outcomes in 2022
- Simulate choice occasions under alternative (2024) fishery conditions
  - Methods and data used to simulate choices occasions differ slightly between the baseline and alternative
  - The entire algorithm is repeated 100 times, each time generating new data to account for statistical uncertainty in input data (MRIP catch-per-trip and directed fishing effort, projected numbers-at-age)

Simulating individual choice occasions in the baseline (2022) scenario



Simulating individual choice occasions in the alternative (2024) scenario

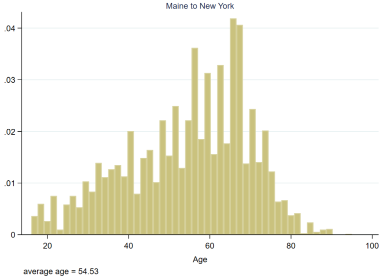


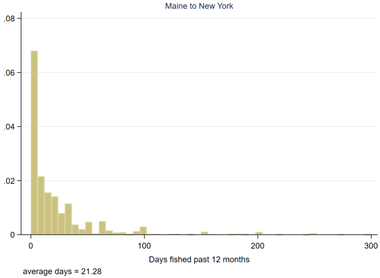
Simulating individual choice occasions in the baseline (2022) scenario

1. Draw β_n' from the estimated distribution, and trip cost and angler demographics from distributions based on recent data collected in the northeast U.S.
2. Draw target number of fish caught by species from 2022 MRIP-based catch-per-trip distribution
3. Determine whether each fish caught is kept or released
4. Add a "no-trip" alternative, then compute the utilities ($\beta_n' x_{nj}$) and probabilities of the alternatives using Equation (4)
5. Repeat steps 1-4 30 times per choice occasion, each time drawing from new MRIP-based distribution of catch-per-trip to reflect sampling uncertainty in the program's estimates of catch-per-trip
6. Compute the expected utility as the average utility and probability of the choice occasion over the 30 repetitions
7. Compute expected harvests and discards of the choice occasion

Simulating individual choice occasions in the baseline (2022) scenario

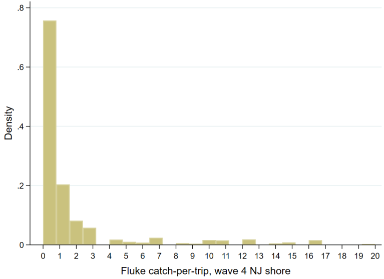
1. Draw β_n' from the estimated distribution, and trip cost and angler demographics from distributions based on recent data collected in the northeast
    - Total trip costs by state and fishing mode come from NOAA's 2016-2017 National Marine Recreational Fishing Expenditures on Fishing Trips Survey, adjusted for inflation
    - Angler ages and avidities come from unpublished survey-weighted data from NOAA's 2019-2020 National Marine Recreational Fishing Expenditures on Durable Goods Survey (Sabrina Lovell), four regions (ME-NY, NJ, DE-MD, VA-NC)

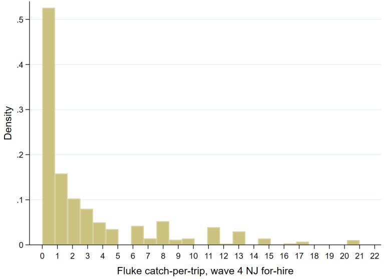




Simulating individual choice occasions in the baseline (2022) scenario

2. Draw target number of fish caught by species from 2022 MRIP-based catch-per-trip distribution
   - Catch-per-trip distributions generated at the state-wave-mode level





Simulating individual choice occasions in the baseline (2022) scenario

3. Determine whether each fish caught is kept or released
   - For each fish caught, draw a random value p between 0 and 1. If $p > p^*$ and bag limit has not been reached, add one to keep. If $p < p^*$ and/or bag limit has been reached, add one to release
   - p^* is determined outside the model and is the proportion of trip-level catch that was released in 2022, conditional on 2022 catch-per-trip and bag limits
   - This step ensures that harvest-per-choice occasion, the key determinant of utility, accurately reflects baseline conditions

Simulating individual choice occasions in the baseline (2022) scenario

4. Add a "no-trip" alternative, then compute the utilities and probabilities of the alternatives using Equation (4):
   - $\beta_n' \mathbf{x}_{ni}^0$ and $P_{ni}^0 = \frac{e^{\beta' \mathbf{x}_{ni}^0}}{\sum_{j=1}^{J^0} e^{\beta' \mathbf{x}_{nj}^0}}$
5. Repeat steps 1-4 30 times per choice occasion, each time drawing from new MRIP-based distribution of catch-per-trip to reflect sampling uncertainty in the program's estimates of catch-per-trip
6. Compute the expected utility as the average utility and probability of the choice occasion over the 30 repetitions:
   - $\overline{\beta' \mathbf{x}_{ni}^0} = \frac{\sum_{d=1}^{30} (\beta' \mathbf{x}_{nid}^0)}{30}$ and $\overline{P_{ni}^0} = \frac{\sum_{d=1}^{30} (P_{nid}^0)}{30}$
7. Compute expected harvests and discards of the choice occasion:
   - $\overline{P_{ni}^0} \times \overline{x_{ni}}$

Model calibration

- Before simulating choice occasions in the alternative (2024) scenario, we must calibrate the model
- Calibration involves (a) ensuring simulated baseline-year trip outcomes reflect observed baseline-year trip outcomes and (b) choosing the number of choice occasions to simulate
  - We do (a) in step 3
- Together, these steps ensure that the simulated size of the market for recreational fishing and the quality of the “good” being evaluated (i.e., trips) reflect observed baseline-year market conditions

Model calibration

- All aggregate model outputs are the sum of output across n individual choice occasions
  - How do we determine the number of choice occasions to simulate (N)?
- MRIP provides an estimate of the number of times a decision-maker chose to go fishing in the baseline year, $\sum_{t=1}^{T} E(Y_{ti}^{MRIP\ 2022})$ (i.e., fishing trips)
- We simulate a number of choice occasions such that the sum of their individual probabilities approximates the MRIP estimate of directed trips for fluke, sea bass, and scup in the baseline year:

$$\sum_{n=1}^{N} P_{ni}^{0} = \sum_{t=1}^{T} E(Y_{ti}^{MRIP\ 2022})$$

- N held constant when simulating alternative fishery conditions (Scenario 1), but individual choice probabilities and their sum will change according to the change in fishery conditions relative to the baseline

Model calibration

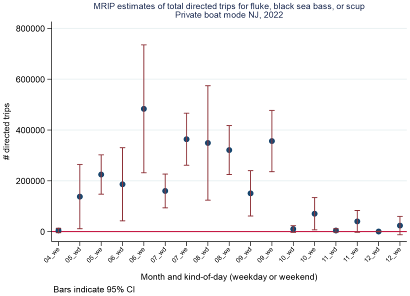
Additional notes about calibration:

- MRIP estimates of directed trips contain sampling uncertainty based on the stratified random sampling approach used to reach the population of angler-trips

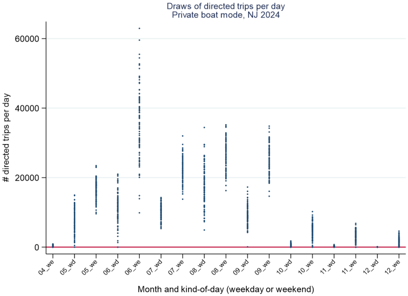
- We incorporate this uncertainty in the model by re-calibrating to a random draw of directed trips in each of the 100 iterations
  - For each iteration x, draw a random number of total directed trips from the MRIP-based truncated normal distribution of directed trips $T \sim G(\mu, \sigma, a, b)$, where μ and σ are the mean and standard deviation and $a = 0$ and $b = \infty$ are the truncation intervals
  - Select N_x choice occasions such that $\sum_{n=1}^{N_x} P_{ni}^0 = T$

Directed trips

- Distribution of directed trips generated at the state, month, mode, and kind-of-day level then divided by the number of days within these strata in 2022 to get trips-per-day in 2022



MRIP estimates of **total** directed trips by month and kind-of-day, NJ private boat mode 2022



Model draws of directed trips **per day** by month and kind-of-day, NJ private boat mode 2022

Calibration statistics - 2022 New Jersey harvest (numbers)

Species	Mode	MRIP data	Model	% difference
BSB	for-hire	90,311 (17,639)	90,269 (17,678)	0.052 (1.389)
BSB	private boat	1,417,877 (179,490)	1,418,313 (180,073)	-0.029 (0.916)
BSB	shore	0	0	
SCUP	for-hire	65,943 (16,653)	66,015 (16,662)	-0.097 (1.043)
SCUP	private boat	144,547 (19,504)	144,543 (19,777)	0.018 (1.095)
SCUP	shore	0	0	
SF	for-hire	47,886 (7,524)	47,907 (7,534)	-0.046 (0.857)
SF	private boat	1,284,445 (106,731)	1,285,438 (108,297)	-0.072 (0.925)
SF	shore	243,533 (41,148)	243,618 (41,221)	-0.046 (1.382)

Note: Means with standard deviations below in parenthesis. MRIP statistics describe the product of directed trips and mean harvest-per-trip over 100 random draws from the estimated distributions of directed trips and harvest-per-trip. Model statistics describe the results of 100 iterations of the model. Percent difference is computed as [(MRIP-model)/MRIP]$\times$100.

Calibration statistics - 2022 New Jersey total catch (numbers)

Species	Mode	MRIP data	Model	% difference
BSB	for-hire	575,068 (109,392)	576,120 (109,520)	-0.188 (0.734)
BSB	private boat	10,082,888 (977,873)	10,100,000 (974,356)	-0.293 (0.597)
BSB	shore	1,529,022 (232,338)	1,530,386 (231,529)	-0.105 (1.045)
SCUP	for-hire	127,516 (34,485)	127,646 (34,400)	-0.117 (0.953)
SCUP	private boat	289,921 (32,674)	290,018 (33,068)	-0.028 (1.506)
SCUP	shore	0	0	
SF	for-hire	257,679 (41,914)	258,184 (41,885)	-0.203 (0.409)
SF	private boat	9,321,574 (737,855)	9,345,688 (746,681)	-0.253 (0.439)
SF	shore	3,911,835 (448,416)	3,915,086 (452,354)	-0.074 (0.544)

Note: Means with standard deviations below in parenthesis. MRIP statistics describe the product of directed trips and mean catch-per-trip over 100 random draws from the estimated distributions of directed trips and catch-per-trip. Model statistics describe the results of 100 iterations of the model. Percent difference is computed as [(MRIP-model)/MRIP]$\times$100.

Simulating choice occasions in the *alternative* (2024) scenario

- After generating baseline trip-level outcomes ($\mathbf{x}^0_{ni}$) and calibrating, we generate trip-level outcomes in the alternative 2024 scenario ($\mathbf{x}^1_{ni}$)
- What differs in the alternative 2024 scenario that affect $\mathbf{x}^1_{ni}$?
  - Catch-per-trip
  - Catch-at-length
  - Regulations

Catch-per-trip in 2024

- As we did to compute baseline scenario trip outcomes, we need to generate catch-per-trip distributions for the alternative (2024) scenario

- After consulting with the TC/MC, we will compute 2024 catch-per-trip by state-wave-mode using the average of the most recent two years of MRIP data
    - 2023 and 2022 MRIP data for wave 2, 3, and 4
    - 2022 and 2021 MRIP data for wave 5 and 6

Catch-at-length in 2024

- To allow for counterfactual simulation of alternative size limits, we need to determine the lengths of fish caught in 2024
- Therefore, unlike what we did to compute 2022 harvest- and release-per-choice occasion, we:
  - Draw a length from the **catch-at-length distribution** for each fish caught
  - Check the length of the fish against the size limit
  - Allocate as harvested if within the size limit and under the bag limit, or discarded if not
- Requires generating a catch-at-length distribution for 2024

Computing 2024 catch-at-length

- Use MRIP and volunteer angler survey (VAS) data from 2022 to compute 2024 catch-at-length
- Data aggregated to the region level and for all modes combined to account for regional differences in catch sizes and small sample sizes
  - Fluke and sea bass data aggregated to three regions: North (MA-NY), NJ, South (DE-NC)
  - Scup data aggregated to two regions: North (MA-NY), South (NJ-NC)

Computing 2024 catch-at-length

Catch-at-length distributions are computed as follows:

a. Generate proportions harvested-at-length in 2022 (MRIP)
b. Generate proportions released-at-length in 2022 (MRIP & VAS)
c. Multiply (a) by total harvest in 2022 to get #'s harvested-at-length
d. Multiply (b) by total release in 2022 to get #'s released-at-length
e. Add (c) to (d) to get total catch-at-length (C_l)
f. Fit (e) to gamma distribution
g. Adjust fitted catch-at-length distribution to account for projected 2024 length distribution of the fish stock

Fluke release size data

Number of measured released fluke by state and data source

source	MA	RI	CT	NY	NJ	DE	MD	VA	NC
ALS VAS	3	43	10	736	1302	0	0	0	0
CT VAS	0	0	696	0	0	0	0	0	0
MA VAS	31	0	0	0	0	0	0	0	0
NJ VAS	0	0	0	0	406	0	0	0	0
RI VAS	0	25	0	0	0	0	0	0	0
MRIP	1	269	92	471	262	225	303	17	0
Total	35	337	798	1207	1970	225	303	17	0
Region total	2377				1970	545			

Black sea bass release size data

Number of measured released black sea bass by state and data source

source	MA	RI	CT	NY	NJ	DE	MD	VA	NC
ALS VAS	12	26	14	98	108	0	0	0	0
CT VAS	0	0	2469	0	0	0	0	0	0
MA VAS	166	0	0	0	0	0	0	0	0
NJ VAS	0	0	0	0	177	0	0	0	0
RI VAS	0	158	0	0	0	0	0	0	0
MRIP	725	962	704	545	166	466	1014	2618	0
Total	903	1146	3187	643	451	466	1014	2618	0
Region total	5879				451	4098			

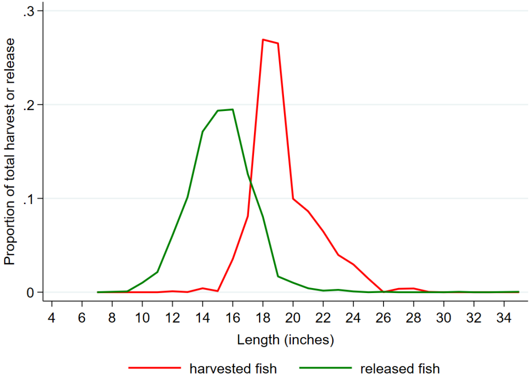
Scup release size data

Number of measured released scup by state and data source

source	MA	RI	CT	NY	NJ	DE	MD	VA	NC
ALS VAS	1	4	0	8	5	0	0	0	0
CT VAS	0	0	2136	0	0	0	0	0	0
MA VAS	95	0	0	0	0	0	0	0	0
RI VAS	0	246	0	0	0	0	0	0	0
MRIP	867	134	420	432	49	5	0	6	0
Total	963	384	2556	440	54	5	0	6	0
Region total	4343				65				

Harvest & release proportions-at-length (fluke)

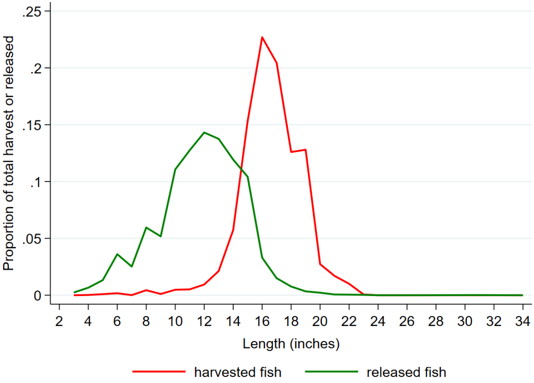
a. Generate proportions harvested-at-length in 2022 (MRIP)
b. Generate proportions released-at-length in 2022 (MRIP & VAS)



Fluke harvest- and release-at-length proportions MA-NY, 2022

Harvest & release proportions-at-length (black sea bass)

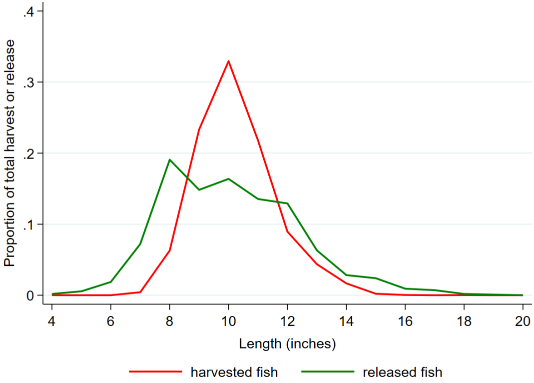
- (a) Generate proportions harvested-at-length in 2022 (MRIP)
- (b) Generate proportions released-at-length in 2022 (MRIP & VAS)



Black sea bass harvest- and release-at-length proportions MA-NY, 2022

Harvest & release proportions-at-length (scup)

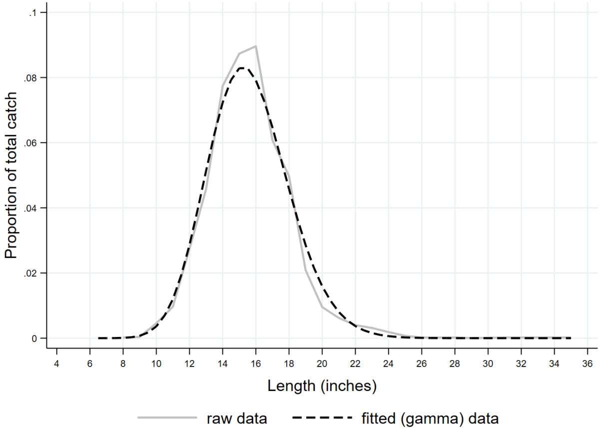
- a. Generate proportions harvested-at-length in 2022 (MRIP)
- b. Generate proportions released-at-length in 2022 (MRIP & VAS)



Scup harvest- and release-at-length proportions MA-NY, 2022

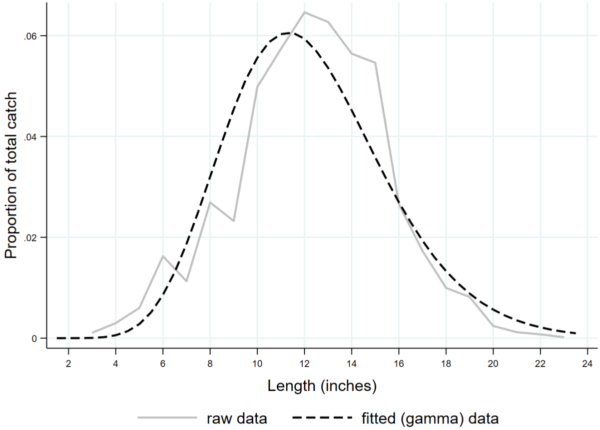
Proportions catch-at-length (fluke)

c. Multiply (a) by total harvest in 2022 to get #'s harvested-at-length
d. Multiply (b) by total release in 2022 to get #'s released-at-length
e. Add (c) to (d) to get total catch-at-length (C_l)
f. Fit (e) to gamma distribution



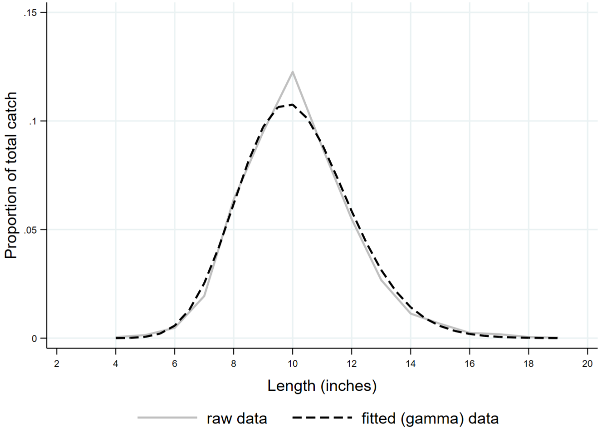
Proportions catch-at-length (black sea bass)

- (c) Multiply (a) by total harvest in 2022 to get #'s harvested-at-length
- (d) Multiply (b) by total release in 2022 to get #'s released-at-length
- (e) Add (c) to (d) to get total catch-at-length (C_l)
- (f) Fit (e) to gamma distribution

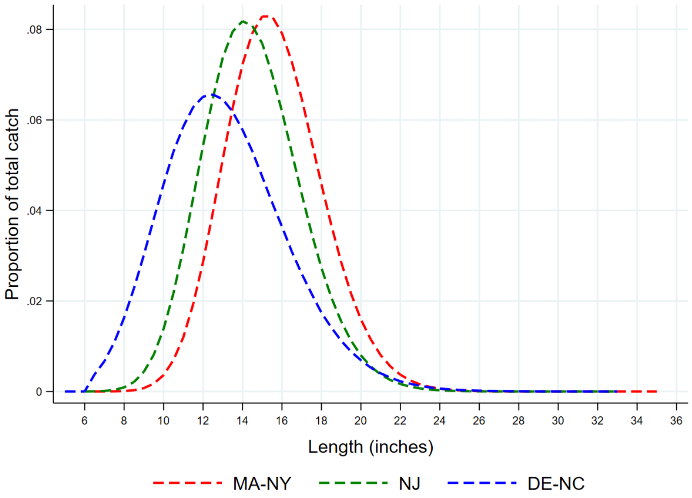


Proportions catch-at-length (scup)

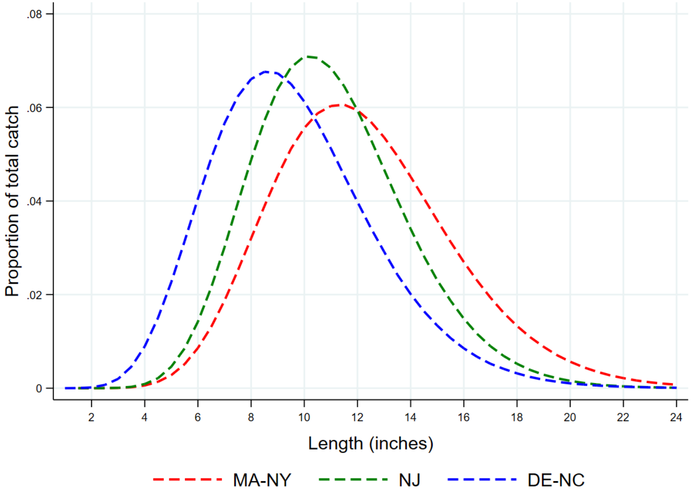
- (c) Multiply (a) by total harvest in 2022 to get #'s harvested-at-length
- (d) Multiply (b) by total release in 2022 to get #'s released-at-length
- (e) Add (c) to (d) to get total catch-at-length (C_l)
- (f) Fit (e) to gamma distribution



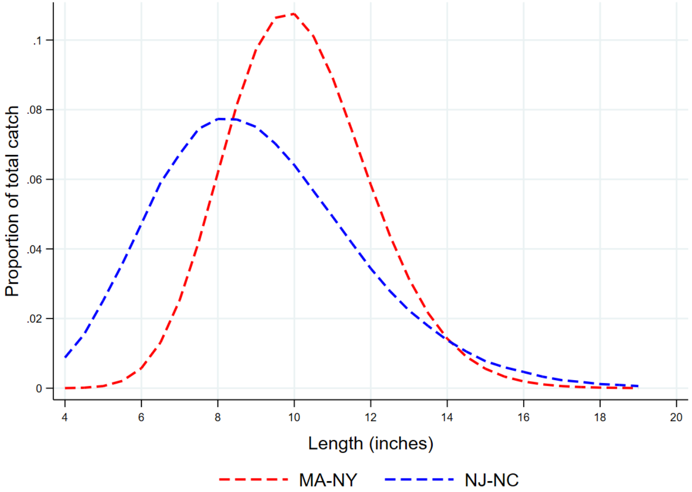
Fitted proportions fluke catch-at-length 2022 by region



Fitted proportions black sea bass catch-at-length 2022 by region



Fitted proportions scup catch-at-length 2022 by region



Accounting for the projected length distribution of the stock

- We assume angler selectivity of length-l fish depends on the availability of length-l fish in the ocean
- 2024 catch-at-length is adjusted to reflect the projected 2024 length distribution of the fish stock
- Example: more larger fish in the ocean in 2024 relative to the baseline year $\rightarrow$ more larger fish caught by anglers in 2024

Accounting for the projected length distribution of the stock

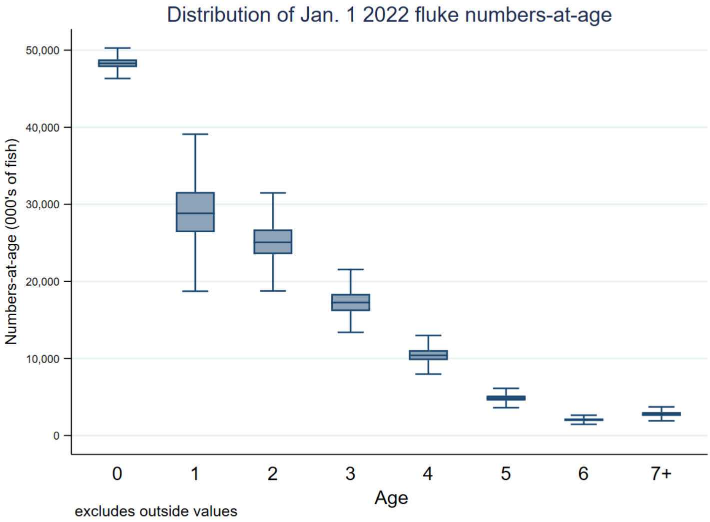
- First we compute recreational selectivity-at-length in 2022, i.e., proportion of length-l fish in the ocean that were caught:

$$q_l = \frac{C_{l,2022}}{N_{l,2022}}$$

  where $C_{l,2022}$ is total catch of length-l fish and $N_{l,2022}$ is the number of length-l fish in the ocean in 2022

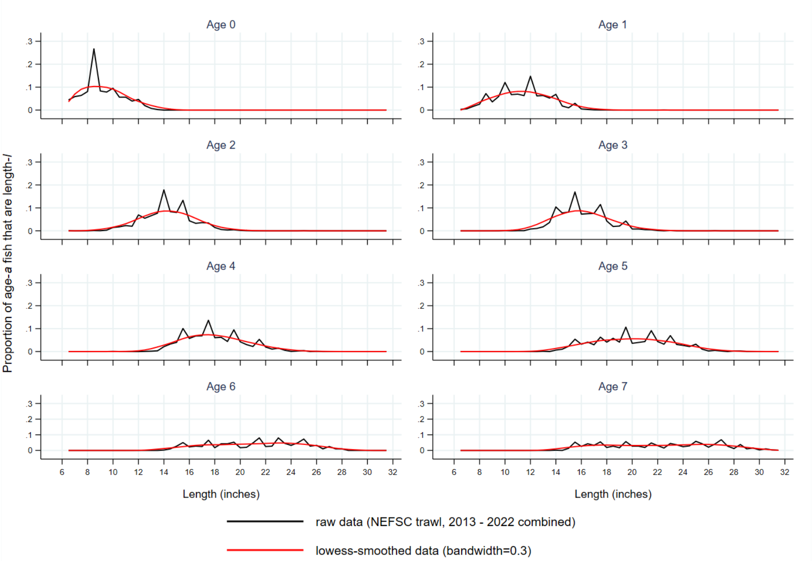
- To obtain $N_{l,2022}$, we translate projected numbers-at-age in 2022 ($N_{a,2022}$) from ages to lengths using age length keys
  - 1,000 draws of ASAP MCMC year $t+1$ $N_{a,2022}$ for fluke and scup from Mark Terceiro (NEFSC), black sea bass data not yet available

Fluke numbers-at-age 2022 ($N_{a,2022}$)

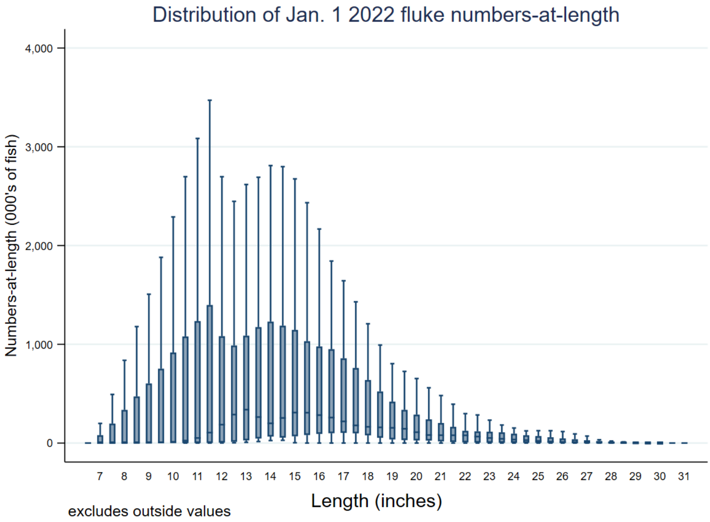


Fluke age-length keys

- NEFSC trawl survey data from 2013-2022 used to translate ages to lengths

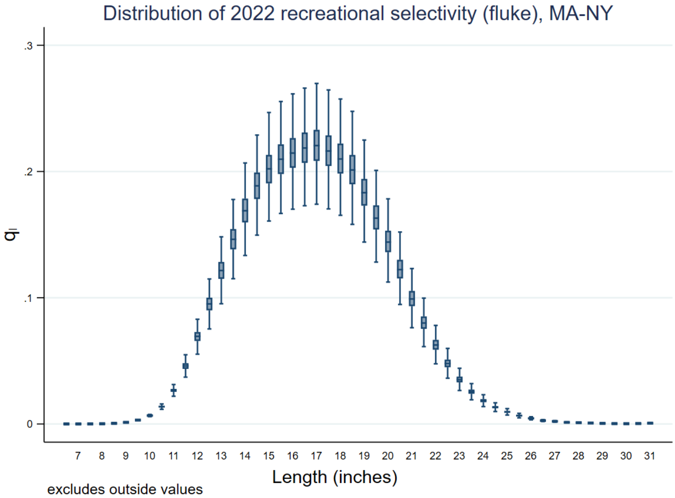


Fluke numbers-at-length 2022 ($N_{l,2022}$)

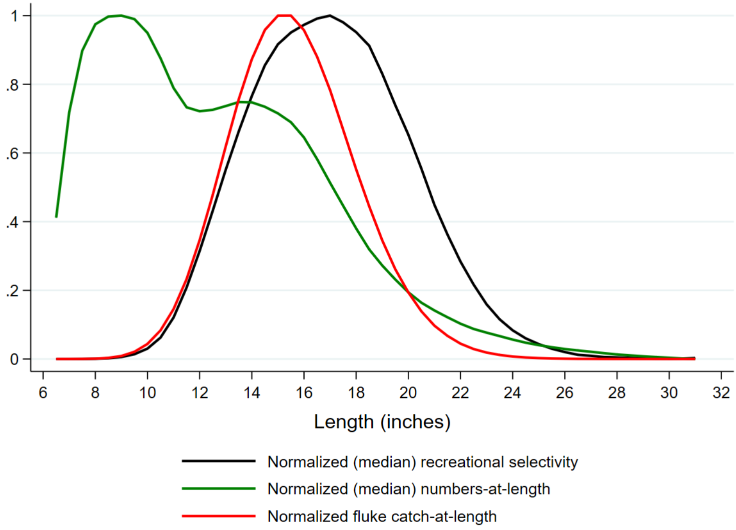


Fluke recreational selectivity ($q_l = \frac{C_{l,2022}}{N_{l,2022}}$)

One draw of $C_{l,2022}$ and 1,000 draws of $N_{l,2022}$ gives us 1,000 draws of q_l



Fluke $C_{l,2022}$, $N_{l,2022}$, and q_l, northern region



Accounting for the projected length distribution of the stock

- With q_l computed for the baseline year by region/species, we can calculate $\tilde{C}_l$ for any stock structure $\tilde{N}_l$:

$$\tilde{C}_l = q_l \tilde{N}_l$$

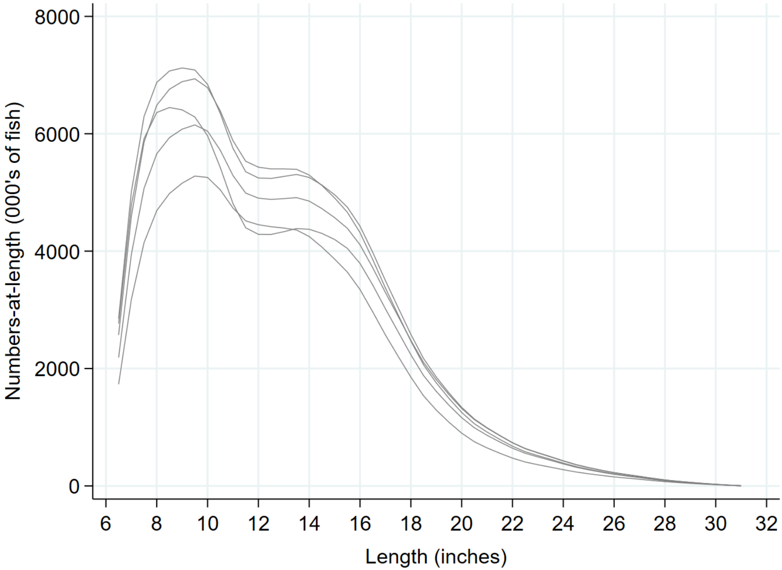
- The projected population-adjusted probability of catching a length-l fish in 2024 is then:

$$Prob[C_l, length = l] = \frac{\tilde{C}_l}{\sum_l^L \tilde{C}_l} = \frac{q_l N_{l,2024}}{\sum_l^L q_l N_{l,2024}}$$

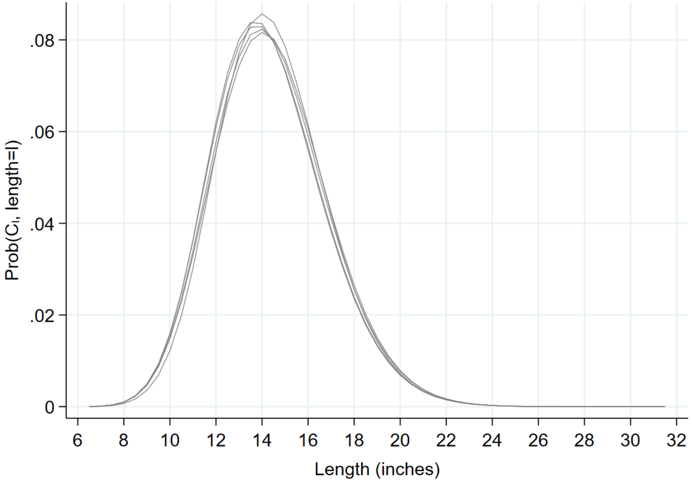
where $N_{l,2024}$ for fluke and scup are the AGEPRO projection numbers from Mark Terceiro (black sea bass projections not yet available)

- For each of the 100 iterations of the model, draw without replacement a random $N_{l,2024}$ and compute $Prob[C_l, length = l]$

Five random draws of projected 2024 fluke numbers-at-length ($N_{l,2024}$)



Five random draws of projected 2024 fluke catch-at-length probability distribution ($Prob[C_l, length = l]$), northern region



Probability at or above 17 inches for the five draws: 15.4%, 16.7%, 15.7%, 16.8%, 17.4%

Accounting for mismatch between observed and simulated harvest

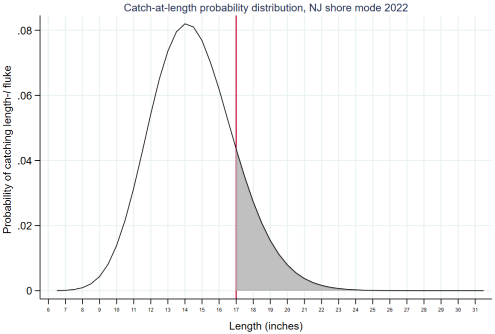
- One final adjustment to account for discrepancies between catch-at-length-based versus MRIP-based estimate of the proportion of fish above and below the minimum size limit

- Recap: to simulate harvest and release-per-choice occasion in the **baseline 2022 scenario**, we determine a value p^* for each state, mode, and species
  - p^* is the proportion of trip-level catch that was released in 2022, conditional on 2022 MRIP catch-per-trip and bag limits
  - $1 - p^*$ is the proportion of trip-level catch that was harvested in 2022, conditional on 2022 MRIP catch-per-trip and bag limits
  - Simulated trip-level catch in baseline scenario is deemed harvested or released based on p^*

- However, to simulate harvest and release-per-choice occasion in the **alternative 2024 scenario**, we draw fish lengths from the catch-at-length distribution and check them against the size limit

Accounting for mismatch between observed and simulated harvest

- In most cases, the proportion of legal-sized fish based on the 2022 catch-at-length distribution differs from $1 - p^*$
  - Example: $1 - p^*$ for fluke among shore trips in NJ = 7.3%, meaning we observed that 7.3% of trip-level catch in 2022 was harvested. We assume that these fish are of legal-size.
  - However, $Prob[C_l, length \geq 17"]$ from 2022 catch-at-length distribution is 17.7% (shown below)



Pr(legal-sized catch) based on catch-at-length (gray area) = 17.7%
Pr(legal-sized catch) based on simulation= 7.3%

Accounting for mismatch between observed and simulated harvest

- Were we to simulate choice occasions in the baseline and alternative scenario holding everything constant and **not** account for these discrepancies, then harvest, fishing effort, and angler welfare would erroneously differ between scenarios
- We account for the mismatch when simulating trip-level harvest/release in **2024** by re-allocating a proportion of harvested fish as releases, or vice versa, depending on the direction of the mismatch
- In the previous example, a portion of legal-sized, "harvested" fish must be re-allocated as releases when simulating **2024** trip-level outcomes for NJ shore mode under a 17" min. size limit
- We assume harvest/release re-allocation proportions remain constant under different min. size limits

Accounting for mismatch between observed and simulated harvest

- Two potential reasons why mismatches occur:
  - Angler harvest/release behavior: voluntary release of legal-sized fish and harvest of sub-legal-sized fish
  - Running the RDM at the fishing mode-level, at which catch length data become sparse and so we aggregate catch-at-length data for all modes
- Re-allocation procedure accounts for both

Converting harvest and release numbers to weights

- After simulating numbers of harvest and releases under the alternative scenario, we must convert numbers to weights
- We use length-weight equations derived from various sources:
  - Fluke l-w equation from Mark Terceiro, 2015-2019 both sexes combined
  - Black sea bass l-w equation from Kiersten Curti, 2012-2021 both sexes combined by region (NY north, NJ south) and semester (Jan.-May, June-Dec.)
  - Scup l-w equation from Wigley et al. (2003)*, 1992-1999 both sexes combined by season (autumn, winter/spring)

*Susan E. Wigley, Holly M. McBride, and Nancy J. McHugh. 2003. "Length-Weight Relationships for 74 Fish Species Collected during NEFSC Research Vessel Bottom Trawl Surveys, 1992-99". *NOAA Technical Memorandum NMFS-NE-171*.

Wrapping up

- Model users can adjust 2024 bag and size limits for each state and mode at the daily level
- Outcomes of individual choice occasions (harvest, discards, trips, welfare) summed across states/regions
- RDM is run 100 times, each time drawing from a new distribution of directed trips, catch-per-trip, and population numbers-at-length (for fluke and scup) $\rightarrow$ results in 100 outcomes
  - Final output will include median values of the 100 outcomes and confidence intervals based on percentiles of the distribution, which capture the various sources of uncertainty baked into the model

Current status of the 2024 RDM

- In the process of finalizing and pre-testing the simulation model using NJ as a prototype
- Working with folks at Azure cloud computing to create user-interface and allow for parallel processing, which will dramatically reduce computing time
  - Current run time for NJ $\approx$ 1.5 hours for 100 iterations

Conclusion

- Structural econometric model provides key information about what drives anglers to fish
- Allows for a tractable assessment of the effect of counterfactual regulations on fishery outcomes
- Unlike previous approaches for predicting harvest, the RDM accounts for angler behavioral responses and allows for consideration of both biological and economic outcomes in management decisions

Questions?

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