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ARTICLE

Between a Rock and Soft Bottom: Evaluating the Use of Rod and Reel to Monitor Tautog in Southern Massachusetts

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Abstract
Fishery-independent trawl surveys are commonly used to monitor the status and trends of marine finfish species. Although bottom trawls are powerful sampling tools, they are limited to surveying relatively featureless bottom habitats and, as a result, may not accurately represent the trends in the relative abundance of fish species associated with structured and complex habitats. We evaluated the feasibility of rod and reel as an alternative fishery-independent survey methodology to monitor the abundance of Tautog *Tautoga onitis*, a recreationally and commercially important structure-dwelling reef fish, in the coastal waters of Massachusetts. Results suggest that a rod-and-reel survey is an effective, low-cost approach to monitor the structured habitats inaccessible to trawl gears. Using a generalized linear mixed modeling framework we were able to identify important predictor variables influencing catch rates; variables that would be important in the design of a continued long-term monitoring program and in the standardization of these data as an index of relative abundance. Variables retained in the top model included year, month, depth strata, bottom water temperature, tidal phase, fishing vessel, angler avidity, and random effects that accounted for the repeated measures survey design. Power analyses revealed that the directed rod-and-reel survey had far greater power to detect changes in Tautog abundance than the extant trawl survey, which had very little power to detect even large shifts in abundance. The results of this pilot study suggest that the continued use of rod and reel as a complementary survey tool would be warranted to further compare the trends in Tautog abundance generated using the two different survey methodologies, to reduce uncertainty in the stock assessment, and to improve the information upon which Tautog management is predicated in Massachusetts waters.

Fishery-independent surveys are commonly used to provide unbiased indices of relative abundance for use in stock assessment models, which in turn provide estimates of population status and trends. Designing a survey that can track changes in abundance and age structure, while controlling for extraneous factors that can influence catch

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rates, is paramount (Maunder and Punt 2004). Standardized indices of abundance generated from survey data are assumed to be representative of the underlying population; however, when that assumption is violated, biases in population status can emerge, potentially leading to management measures that are misaligned with management objectives (Maunder and Punt 2004). In the northwest Atlantic Ocean, bottom-trawl surveys are the primary survey tool used to monitor marine finfish species, largely due to their efficiency and ability to provide standardized indices of relative abundance for a wide range of species. However, most bottom trawls are limited to sampling a featureless bottom thereby creating a potential bias when used as an index of abundance for fish species that inhabit the rocky, complex structures inaccessible to bottom-tending mobile gear (Hilborn and Walters 1992; Gregory et al. 1997; Rose and Kulka 1999; Cordue 2007).

In southern Massachusetts, Tautog *Tautoga onitis*, a native species of the wrasse (Labridae) family, supports important commercial and recreational fisheries from late spring through the fall, before their winter migration towards warmer offshore habitats (Cooper 1966). Tautog is a relatively slow-growing, long-lived (25–30 years), and sedentary temperate reef fish that prefers complex, structured habitats (Cooper 1967). During the adult stage, Tautogs are found in and around hard substrates required to support the crustacean communities that comprise much of the Tautog diet (Bigelow and Schroeder 1953). The shelter likely protects them from predators as they are fairly inactive at night and exhibit a torpor-like state throughout much of the winter (Olla et al. 1974, 1975, 1979; Curran 1992).

A synoptic trawl survey carried out by the Massachusetts Division of Marine Fisheries (MDMF) has provided an index of abundance for Tautog since 1978. Abundance from this time series peaked in the 1980s, after which it dramatically declined and has remained low through the present day. In the benchmark stock assessment completed in 2015 (ASMFC 2015), it was estimated that spawning stock biomass (SSB) had declined approximately 70% from the early 1980s leading to an overfished status for most of the previous decade. In the 2016 assessment update, the Tautog stock was assessed with respect to four management units: Massachusetts–Rhode Island; Long Island Sound; New Jersey New York Bight; and Delaware, Maryland, and Virginia. The results from this assessment indicated that although the Massachusetts–Rhode Island (MARI) stock component has not yet rebuilt to the target biomass level, the stock region is no longer overfished based on spawning potential ratio (SPR) biological reference points (ASMFC 2016). One of the potential biases highlighted in the Atlantic States Marine Fisheries Commission assessment (ASMFC 2015) is that none of the trawl-based, fishery-independent surveys were designed to target Tautog, nor are they suitable for sampling the preferred complex habitats. Additionally, the fishery-dependent Marine Recreational Information Program (MRIP), which provides data on the recreational fishery, rarely encounters Tautog, resulting in a paucity of fishery-dependent data.

The question of whether we are accurately characterizing the current population status and recent trends in abundance has been raised due to uncertainties in the assessment and survey time series. The recreational harvest trends reported by MRIP corroborate the trawl-survey trends, but fishery-dependent trends are often conflated with management measures. For example, a decline in recreational harvest could simply be reflective of increasingly restrictive regulations. One hypothesis that has been put forth regarding the Tautog population is that during the years of high trawl-survey catches, the optimal habitat (e.g., rocky ledges and outcroppings) was saturated, leading to a “spillover” effect into suboptimal habitats (e.g., featureless bottom accessible to trawl survey gear). The population at this time had been subjected to decades of commercial fishing; however, recorded commercial landings did not peak until the mid-1980s (ASMFC 2015). If this hypothesis was supported, it suggests that the CPUE from the trawl survey has been exhibiting hyperdepletion (Hilborn and Walters 1992), a phenomenon in which the survey index has declined more rapidly than the true underlying population. For example, this could occur if fish density in the preferred, complex habitat is substantially higher than in the open, featureless bottom, yet remains below the saturation point. Alternatively, density within both the complex and featureless habitats may be low, and the trawl survey may be adequately representing the true population trends. Without a fishery-independent survey method designed to sample Tautog in their preferred habitats, evaluating which of these two explanations is more plausible remains elusive. To address this important knowledge gap, MDMF developed a rod-and-reel pilot study to evaluate the efficacy of this sampling methodology as a potential tool for long-term monitoring of Tautog abundance.

The objective of this study was to evaluate the feasibility of a standardized rod-and-reel survey targeting Tautog in complex habitats and compare our results with data collected from the extant fishery-independent trawl survey. In addition, we used power analysis to evaluate the probability of detecting meaningful changes in the targeted population under different sampling scenarios and compared with the MDMF trawl survey.

METHODS

Study site and survey design.— The survey extent for this study was Region 1 of the MDMF bottom-trawl survey, which encompasses Buzzards Bay and Vineyard

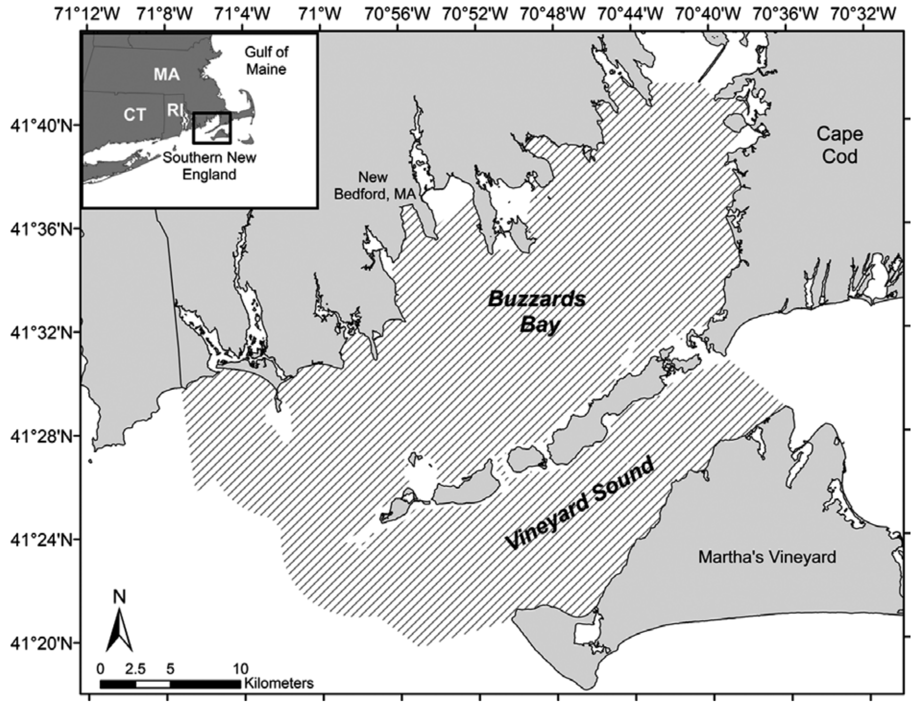

FIGURE 1. Extent of the survey for the rod-and-reel study (textured region), which corresponds to Region 1 of the MDMF trawl survey. The white areas inside the textured region are omitted from the extent of the trawl survey due to shallow, rocky bottom. The inset in the upper left corner shows the broader geographic region for context (MA = Massachusetts, RI = Rhode Island, CT = Connecticut).

Sound, Massachusetts (King et al. 2010; Figure 1). The U.S. Geological Survey sediment and bathymetry data layers (Massachusetts Office of Coastal Zone Management 2015) were merged and overlaid with a 1′ latitude–longitude grid using the ETGeoWizards extension (Tchoukanski 2012) for ArcGIS (ESRI 2012). From this grid, the habitat in each cell was characterized as either "complex" for cells that were composed of at least 50% rock and ledge or "featureless" for cells with less than 50% rock and ledge. Of the 407 grid cells within the study area, 96 were identified as having complex habitat. Each cell in the grid was also assigned to a depth stratum: shallow (0–9 m), intermediate (10–18 m), or deep (19–27 m). Each month, a depth-stratified random sampling design was used to select 48 sampling locations to ensure adequate spatial coverage. The inshore trawl survey, to which we compared and contrasted the rod-and-reel survey, also uses a depth-stratified random sampling design, in which sampling occurs in the spring (May) and fall (September) of each year.

TABLE 1. Summary of sampling effort in terms of number of trips and locations sampled, and the number of Tautog encountered, by month, throughout the rod-and-reel pilot study, 2016–2017.

Month	Number of trips	Number of stations	Number of Tautogs
		2016	
October	6	26	496
November	6	28	437
December	2	8	2
		2017	
April	6	28	7
May	9	46	198
September	6	32	344
October	7	36	351
November	7	37	255

The pilot study was conducted from October 2016 through November 2017, with seasonal sampling throughout the fall (September–December) and spring (April–May; Table 1). We attempted to fish twice per week during those sampling months, typically completing five to six sampling stations per day. Sampling was spread out over a given month due to logistical and weather constraints; however, the timing of the survey was designed to target months during which Tautog are seasonally available. Research angling was conducted from either an MDMF vessel or a chartered fishing vessel. At each sampling station, both vessels identified hard bottom substrate and dense complex terrain using side-scan sonar. By targeting illuminated sonar returns and their resulting shadows, hard structure deemed suitable Tautog habitat was located and anchored on for sampling. Once anchored, latitude, longitude, depth, and wave height were recorded. Additional data corresponding to each sampling event were collected from deployed and in situ data loggers to include bottom water temperature, salinity, dissolved oxygen, tidal phase, and tidal amplitude. The standardized fishing gear was comprised of a 3/0 Daiichi Octopus hook on a dropper loop, baited with half of a green crab *Carcinus maenas* (the most common bait used by commercial Tautog fishers), and an 85–142 g weight.

At each station, fishing was initiated once hooks were dropped to the bottom and continued for 45 min and monitored using a digital stopwatch. All anglers fished continuously for 45 min assuming at least one angler caught a Tautog within the first 30 min; otherwise, sampling concluded after 30 min of fishing effort. All fish caught were retained in a live well until angling was complete, at which point they were identified to species, enumerated, and measured for length (cm). Additional biological sampling of Tautog was performed using a random length-stratified sampling design, sacrificing one fish for each 5-cm length bin per station to obtain weight (kg), sex, maturity, otoliths, and a pelvic fin spine for aging (Elzey and Trull 2016). One pelvic fin spine was removed from all Tautog that were released alive for age analysis.

Statistical analyses.— We applied a series of generalized linear mixed models (GLMMs) to identify important variables influencing catch per angler (CPA). Generalized linear models (GLMs) are commonly used to standardize fishery-dependent data for use as an index of abundance, but can also be used to standardize fishery-independent surveys if variables influencing catch rates, other than changes in abundance, cannot be explicitly controlled for through the survey design (Maunder and Punt 2004). Discrete count data (e.g., angler catch) are common in fisheries studies and are often modeled assuming a Poisson or negative binomial error structure (White and Bennetts 1996; Ver Hoef and Boveng 2007); however, ecological phenomena can produce a greater number of zeros than is expected under either of the aforementioned distributions. To address zero-inflation arising from both structural and sampling zeros and to avoid potential bias in the parameter estimation, we modeled CPA using zero-inflated negative binomial (ZINB) mixed models (Zuur et al. 2009; Harrison 2014; Brooks et al. 2017). Mixed models were used, as opposed to the general ZINB, because the survey design led to repeated measures on the same individual, sampling location, and fishing day. Observations can be correlated in space and time, thus violating the assumption of independence among observations (VanLeeuwen et al. 1996). Using random effects in a mixed-modeling framework can effectively account for this correlation while quantifying the amount of variability among the factors that were repeatedly measured (Bolker et al. 2009; Irwin et al. 2013).

We estimated fixed effects associated with year (i), month (j), vessel (k), depth strata (l), fishing depth (m), bottom temperature (n), tidal phase (o) and amplitude (p), and angler avidity (q) and random effects to account for angler (r), spatial (s), and ephemeral temporal (t) variability (i.e., fishing day). Consideration was given to the inclusion of nontarget species catch as a covariate in the models to account for gear saturation and potential competition; however, doing so may be inappropriate as species that exhibit similar patterns of recruitment or mortality may obscure some of the interannual variability in the target species (Maunder and Punt 2004; Harms et al. 2010), the signal that would be one of the primary objectives of this monitoring program. All continuous covariates were standardized before model fitting to improve convergence; the R package glmmTMB (Magnusson et al. 2016) was used to implement the ZINB mixed models.

The general probability function for the zero-inflated negative binomial mixed models (Zuur et al. 2009) is as follows:

$$f(y_{i-t}=0)=\pi_{i-t}+(1-\pi_{i-t})\cdot\left(\frac{\kappa}{\mu_{i-t}+\kappa}\right)^{\kappa}$$

and

$$f(y_{i-t}|y_{i-t}>0)=(1-\pi_{i-t})\cdot fNB(y),$$

where $y_{i\text{–}t}$ is observed CPA, $\pi_{i\text{–}t}$ is the estimated parameter from the logistic regression, and

$$\begin{aligned} fNB(y) &= f(y_{i-t};\kappa,\mu_{i-t}|y_{i-t}\geq 0)\\ &= \frac{\Gamma(y_{i-t}+\kappa)}{\Gamma(\kappa)\Gamma(y_{i-t}+1)}\cdot\left(\frac{\kappa}{\mu_{i-t}+\kappa}\right)^{\kappa}\cdot\left(1-\frac{\kappa}{\mu_{i-t}+\kappa}\right)^{y_{i-t}}. \end{aligned}$$

Distribution parameters from each model component can be modeled using canonical link functions (McCullagh and Nelder 1989). The logistic regression component was modeled using the logit-link function as an intercept only model as well as with water temperature (T) as a covariate (equation 1),

$$\text{logit}_e(\pi_{i-t})=\upsilon+\delta T, \tag{1}$$

while the negative binomial model included combinations of covariates identified a priori as potential factors influencing Tautog catch rates (Table 2),

$$\log_e(\mu_{i-t})=\alpha+\Theta X_{i-q}+\gamma W_{r-t}.$$

In the negative binomial component, $\mu_{i\text{–}t}$ is the mean of the distribution (for levels i through t of the predictor variables) and κ is the estimated dispersion parameter. We used a log-link function such that the linear predictor is a function of random variables treated as fixed X and

TABLE 2. Description of continuous and categorical covariates evaluated in the model selection process.

Variable	Description
	Fixed effects
Year	Categorical: temporal variable related to interannual changes in abundance
Month	Categorical: temporal variable to control for intraannual variability in catch rates associated with migration and spawning
Vessel	Categorical: variable to control for potential vessel effects on catch rates (charter vessel and MDMF vessel)
Temperature	Continuous: bottom water temperature (°C) obtained at every sampling location using an Onset Hobo data logger
Depth stratum	Categorical: stratum associated with average depth within the 1′ latitude–longitude grid cell for each sampling location (shallow: 0–9 m, intermediate: 10–20 m, deep: 21–30 m)
Fishing depth	Continuous: the depth (m) of the actual fishing location
Tidal phase	Categorical: M2 gravitational tidal phase broken down into 3-h increments to represent high tide, high transitioning to low tide, low tide, and low to high tide
Tidal amplitude	Continuous: a deviation from the mean tidal amplitude (m)
Angler avidity	Ordinal: a qualitative self-assigned rating between 1 and 10 indicating an angler's level of fishing expertise relative to Tautog; 1 = no experience, 5 = moderate skill level, and 10 = expert
	Random effects
Trip	Categorical: variable to quantify ephemeral temporal variability associated with the fishing day; 5–6 stations were typically sampled on a given fishing day
Station	Categorical: spatial variable to control for potential autocorrelation in catch rates due to the sampling location; multiple anglers fish at the same station on a given day and stations could be repeatedly sampled throughout the survey
Angler	Categorical: individual angler identifier was used to quantify the effect of angler skill that could influence catch rates; individual anglers participated to varying degrees at multiple sampling locations throughout the survey

random effects W. Regression coefficients for the fixed Θ and random effects γ were estimated by the model. The random intercept from the negative binomial component of the model (α) represents the reference level for each of the categorical explanatory variables included in the models, and as a result, interpreting the intercept directly is impractical. The coefficients associated with a specific level of a categorical variable represent the mean CPA relative to the reference level (Arab et al. 2008). All random effects were assumed to come from a Gaussian distribution with a mean of zero and an estimated variance parameter (σ^2).

Model selection was performed to identify the most parsimonious model out of our candidate set (eight models in total; see Table 3) to explain variability in Tautog CPA. The candidate set of models represented combinations of variables believed to have an effect on Tautog abundance and catchability. An information theoretic approach, using Akaike information criterion (AIC; Akaike 1973), was used to compare models by evaluating the inclusion of fixed effects using a maximum-likelihood estimation framework, while keeping the random effects constant as they represented complexity in the survey design. When comparing models, models within two ΔAIC units of the top model were assumed equivalent (Burnham and Anderson 2002:49–97).

To assess the statistical power from our survey design to detect changes in Tautog abundance, we performed a series of power analyses using the stratified mean CPA. Using the extensive spatial and temporal sampling carried out during this 18-month pilot study, we were able to evaluate the power to detect changes under the pilot study design and explore whether sampling effort could be reduced (e.g., sampling only in the spring or fall) without diminishing our ability to detect meaningful changes. In addition, we compared the power from the rod-and-reel survey to that of the MDMF trawl survey using trawl data (stratified mean number per tow and associated SEs) from the same years and study region as the pilot rod-and-reel survey. Power analyses were performed using the "powertrend" function from the fishmethods R package (Nelson 2014).

RESULTS

From 2016 through 2017, 2,090 individual Tautog were caught at 241 sampling locations over the course of 49 d by 41 anglers (Table 1). Tautog ranged in size from 16 to

63 cm, with the vast majority of fish under the legal size-limit of 40.6 cm (Figure 2). Tautog were caught on 537 of 978 angler fishing events for an overall angler success rate of approximately 55%, and of the 241 locations sampled, 169 produced Tautog for a percent occurrence of approximately 70%. The survey was stratified by depth and month; therefore, each sampling location had the potential to be sampled multiple times. Of the 96 potential sampling locations identified, 94 were sampled at least once throughout the survey and on rare occasions individual locations were sampled up to six times. Tautog was by far the most commonly encountered species (83%); however, bycatch included Black Sea Bass *Centropristis striata* (13%), Striped Sea Robin *Prionotus evolans* (2%), Scup *Stenotomus chrysops* (2%), and a few rare species, each making up less than 1% of the catch totals: Smooth Dogfish *Mustelus canis*, Cunner *Tautogolabrus adspersus*, Gray Triggerfish *Balistes capriscus*, and Oyster Toadfish *Opsanus tau*.

Model selection suggested that three models were indistinguishable using an information-theoretic approach, meaning that two models were within two ΔAIC units from the top model (Table 3). We chose to present the results from the top model (Table 4), acknowledging, however, that for different research objectives, model averaging may be appropriate. The top model, from our candidate set, included bottom water temperature T as a covariate in the logistic regression,

$$\text{logit}_e(\pi_n) = \upsilon + \delta T_n,$$

where π is the probability of a zero catch, υ is the random intercept, and δ the regression coefficient associated with water temperature. The negative binomial regression was estimated as

$$\log_e(\mu_{ijklnpqrst}) = \alpha + \beta X_{ijklnpq} + \gamma W_{rst},$$

where $\mu_{ijklnpqrst}$ is the linear predictor modeled on the log scale, α is a random intercept representing the reference level for all categorical variables (i.e., year, month, vessel, depth stratum, and tidal phase) with fixed effects for year (*i*), month (*j*), vessel (*k*), depth stratum (*l*), bottom water temperature (*n*), tidal phase (*p*), and angler avidity (*q*). All random effects, i.e., individual angler (*r*), station location (*s*), and trip (*t*), were also included in the model. The estimated dispersion parameter κ was 7.1. Predicted values and variance estimates are therefore calculated as a mixture of the model components:

$$E(Y_{ijklnpqrst}) = \mu_{ijklnpqrst} \cdot (1 - \pi_n),$$

and

$$\text{var}(Y_{ijklnpqrst}) = (1 - \pi_n) \cdot \left(\mu_{ijklnpqrst} + \frac{\mu^2_{ijklnpqrst}}{\kappa} \right) + \mu^2_{ijklnpqrst} \cdot (\pi_n^2 + \pi_n).$$

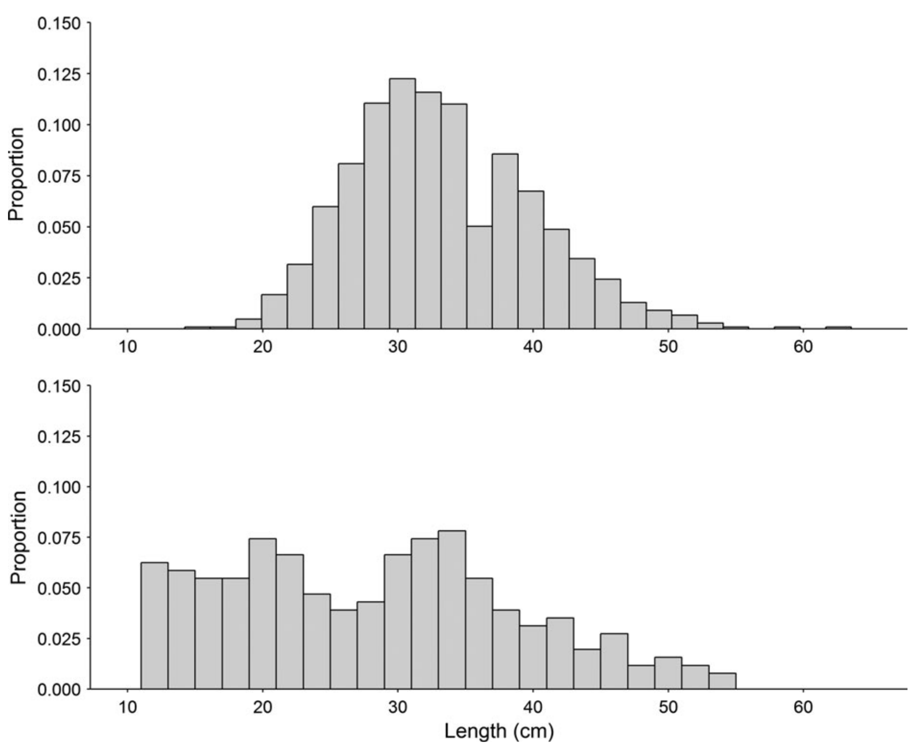

FIGURE 2. Length frequency distributions of Tautogs captured throughout the 2016–2017 rod-and-reel pilot study (top panel; N = 2,090) and the trawl survey (bottom panel; N = 263) during the same time period (from fall 2016 to fall 2017), represented as a proportion at each length category.

TABLE 3. Summary of the candidate models evaluated, listed in rank order, with an "x" placed under each variable that was included in the model. Under fixed effects, covariates were abbreviated as follows: Y = year, M = month, V = vessel, T = water temperature, S = depth stratum, F = fishing depth, Tp = tidal phase, Ta = tidal amplitude, Av = angler avidity. For the random effects, all three random effects (angler, location, and trip) were included in all models. ZI represents the zero-inflated model component, with T indicating when water temperature was included as a covariate in the logistic regression. The AIC and ΔAIC values are also reported.

	Fixed effects									Random effects			ZI		
Rank	Y	M	V	T	S	F	Tp	Ta	Av	Ang	Loc	Trip	T	AIC	ΔAIC
1	x	x	x	x	x		x		x	x	x	x	x	3038.5	0
2	x	x	x	x	x	x	x	x	x	x	x	x	x	3039.7	1.2
3	x	x	x	x	x			x	x	x	x	x	x	3040.1	1.6
4	x	x	x	x	x				x	x	x	x	x	3044.0	5.5
5	x	x	x	x		x	x		x	x	x	x	x	3045.1	6.6
6	x	x	x	x	x	x	x	x	x	x	x	x		3049.7	11.2
7	x	x	x	x	x					x	x	x	x	3053.1	14.6
8	x	x	x	x						x	x	x	x	3061.4	22.9

Mean CPA was highest in October, followed by September and November (Figure 3). Temperature was marginally important in predicting presence–absence of Tautog ($P = 0.09$) and also significant as a covariate in the negative binomial regression, indicating that mean CPA increased with increasing temperatures. The CPA was lower when fishing occurred from the MDMF vessel than from the charter vessel, reflecting the skill of the contracted charter fisher, but is likely also an artifact of the relatively few trips conducted from a MDMF vessel and the catch rates associated with those trips. Fishing depth was not retained in the model, but depth stratum was, and mean CPA was highest in the intermediate depths followed by the deep stratum and then the shallow stations. Tidal phase seemed only marginally important and highly variable, but there is some evidence that slack low and incoming tides were associated with higher CPA than slack high and outgoing tides. Lastly, there was a positive relationship between mean CPA and angler avidity.

TABLE 4. Parameter estimates associated with the model with the lowest AIC value. The reference level for the model intercept represents the following as the reference level: year 2016, month of April, charter vessel, shallow depth stratum, and high tidal phase.

Variable	Factor level	Estimate	SE
	Logistic model		
Intercept		−4.997	2.420
Temperature		−3.525	2.073
	Negative binomial model		
Fixed effects			
Intercept		−1.147	0.875
Year	2017	−0.577	0.252
Month	May	1.766	0.804
	Sep	1.063	1.012
	Oct	0.881	0.935
	Nov	1.553	0.839
	Dec	−1.706	1.190
Vessel	MDMF	−1.598	0.534
Strata	Mid	0.724	0.218
	Deep	0.336	0.279
Temperature		0.917	0.259
Tidal phase	High–Low	−0.113	0.150
	Low	−0.147	0.154
	Low–High	0.240	0.143
Angler avidity		0.178	0.046
Random effects			
Angler (σ^2)		0.013	
Station (σ^2)		0.722	
Trip (σ^2)		0.288	

Although this survey was conducted in a relatively small geographic area, we observed tremendous variability in catch rates among sampling locations. Given the high variability, the top model was able to predict catch rates reasonably well (Figure 4). Some of this variability is illustrated in the random effects for station ($\sigma^2 = 0.72$), fishing day ($\sigma^2 = 0.29$), and to a lesser degree, angler ($\sigma^2 = 0.01$; Figure 5). There was very little variability among anglers and fishing day, but there was substantially greater variability among sampling locations (Figure 5). The sampling locations that were above and below average appeared randomly distributed throughout the bay and did not show signs of clustering, suggesting that Tautog abundance varies across small spatial scales (Figure 6). This observation that localized densities can vary even among neighboring rock piles has been noted anecdotally.

The rod-and-reel survey had a reasonable level of statistical power to detect changes in the Tautog population, with a slightly greater ability to detect a decline in

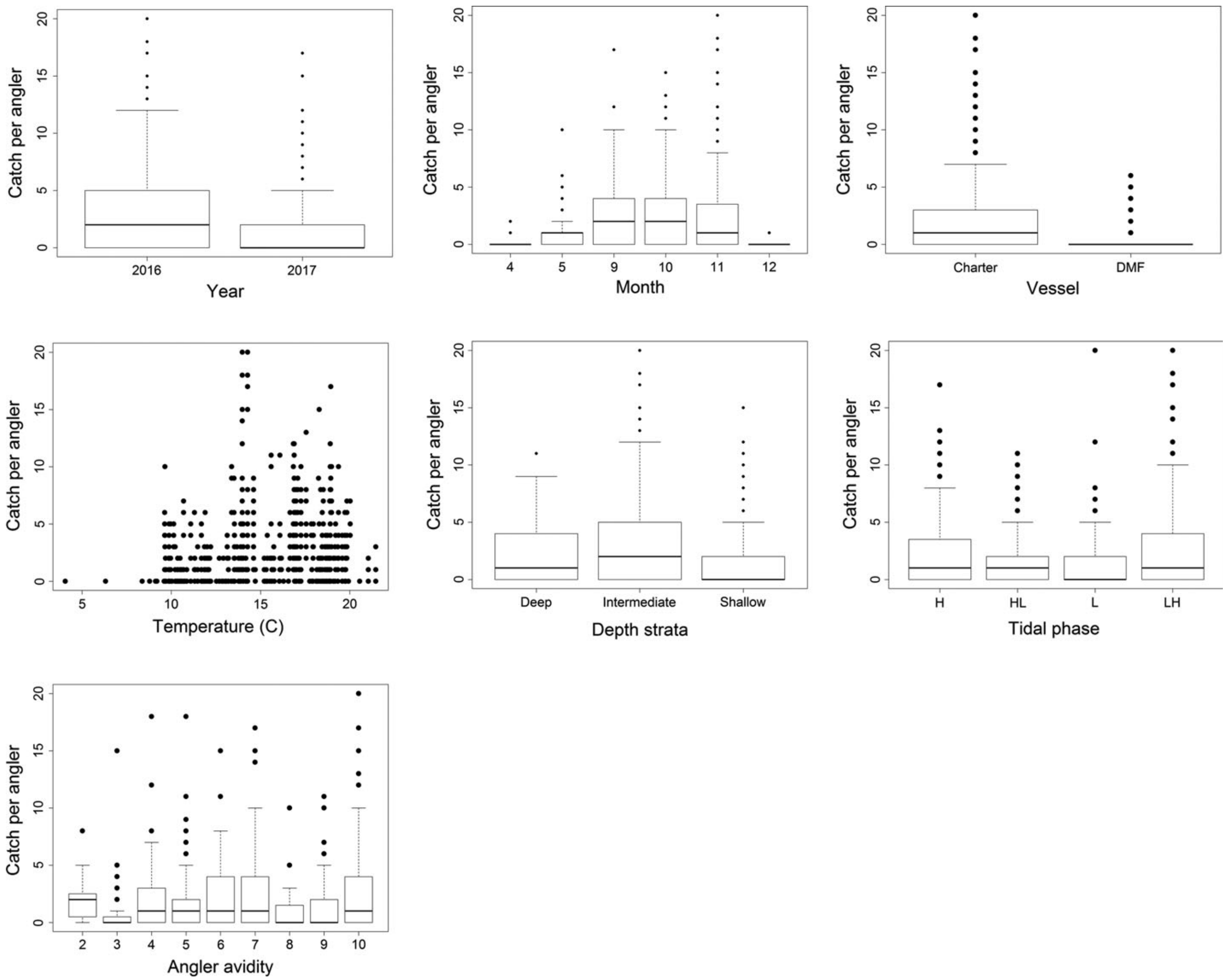

FIGURE 3. Predicted angler CPA plotted against fixed effects covariates. The boxplots, shown for categorical predictor variables, show the median predicted catch per angler with a dark black line; the upper and lower limits of the box represent the third and first quartile, and the whiskers extending up to 1.5 times indicate the interquartile range. Data extending beyond 1.5 times the interquartile range are depicted as solid points.

abundance than an increase (Figure 7). We estimated about a 20–40% chance of detecting a 20% increase or decrease in the population. These results suggest that reducing our sampling to only 2 months during the fall (using the 2017 data only, as we did not sample in the spring of 2016) did not substantially influence our ability to detect meaningful trends. Because the purpose of this study was to evaluate whether a rod-and-reel survey could provide better information on Tautog trends than the MDMF trawl survey, we compared our results with the estimated power from the trawl survey. The trawl survey had less than a 10% chance of detecting up to a 50% increase or decrease in the population in both 2016 and 2017 (Figure 7).

DISCUSSION

This pilot study illustrated that the use of rod and reel is a capable method of effectively sampling Tautog in complex habitats that are inaccessible to bottom trawls, and this may offer a more powerful alternative to trawl-based indices of abundance. Rod-and-reel surveys are relatively cost effective and easy to implement from a variety of platforms (e.g., small vessels without specialized equipment). Given that Tautog are relatively sedentary with inter- and intraannual site fidelity (Olla et al. 1979), improved monitoring and management of Tautog in state waters is likely to have direct benefits to local anglers. Based on the power analyses, the ability to detect meaningful changes in the abundance of Tautog would increase

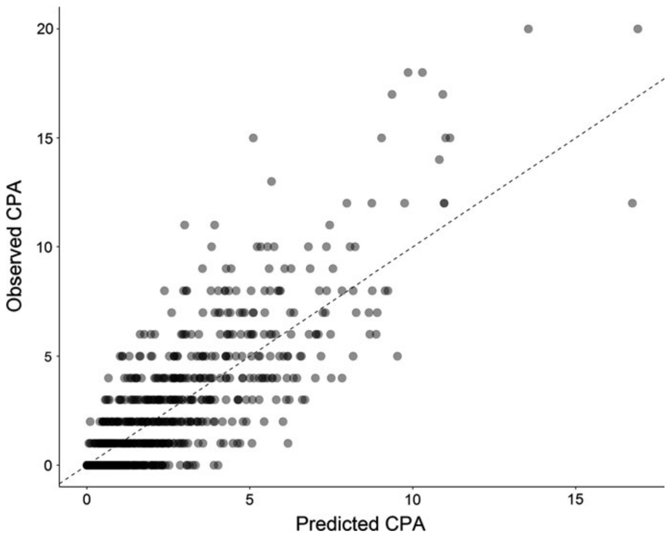

FIGURE 4. Observed versus predicted catch per angler (CPA) to illustrate model fit that approximates a 1:1 relationship (dashed line).

substantially by implementing a rod-and-reel survey to generate an annual index of relative abundance.

Our results suggest that a fishery-independent rod-and-reel survey shows promise as a viable monitoring tool; however, it is not without challenges and limitations. Tautog catch rates illustrated spatial and temporal variability. During the spring, no Tautog were encountered until the water temperatures approached 10°C. As the water warmed, catch rates slowly began to increase, and fish became distributed throughout the study region as they migrated inshore to spawn. During the fall, catch rates were generally higher but also more variable as fish staged for their winter migration into deeper waters. Appropriate standardization to address factors influencing catch rates other than changes in abundance represents one of the primary challenges to using a rod-and-reel survey as an index of relative abundance. Standardization attempts to adjust for factors that influence catch rates through time other than changes in abundance (Maunder and Punt 2004). In this study, the variables identified in our top models as being influential with regard to catch rates are largely factors that can be controlled through the design of a future survey, thus minimizing post hoc standardization. Trawl gear is an effective survey tool because trawls can be easily standardized and readily produce density estimates. Standardizing rod-and-reel gear can be more challenging for a suite of reasons. In our study, we standardized fishing time to 45 min; however, in some cases individual angler effort deviated from the standard time interval for reasons that included hang-ups on the bottom, hook loss, fishing rig replacement, and, in one instance, reel malfunction. Effort standardization could be improved upon by implementing individual hook timers similar to the design used by Harms et al. (2010) and refining the effort estimate to include only the time that the hook is in the water (e.g., Haggarty and King 2006).

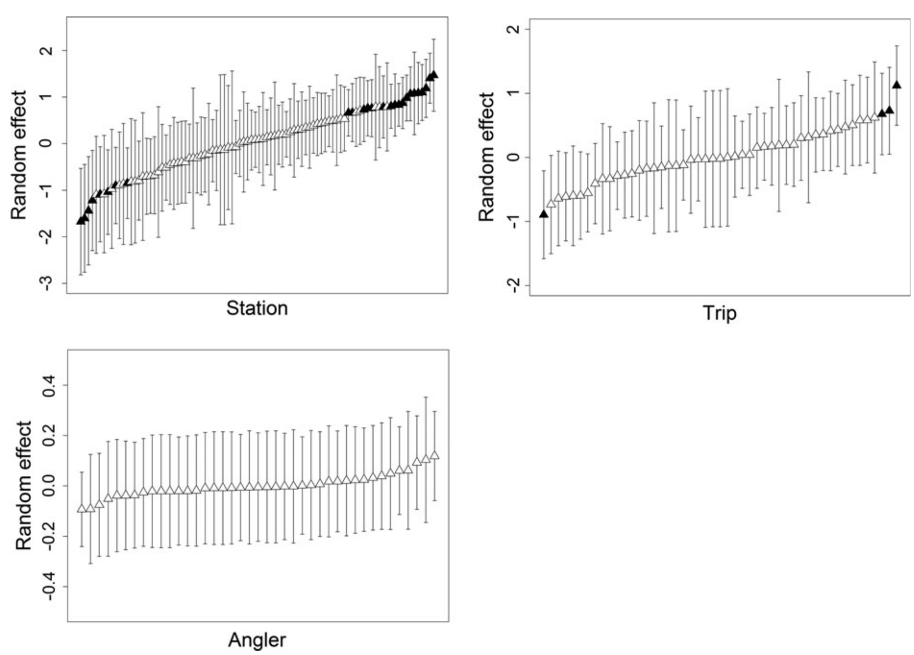

FIGURE 5. Caterpillar plots showing the distribution of the individual factor levels within the three random effects included in the model relative to the mean value for that factor. The triangles represent the best linear unbiased predictor for a given level, and the vertical bars represent two SDs. Positive values suggest that the factor level is above average, and negative values below average. The black triangles indicate factor levels for which the estimates ±2 SD do not include zero, thus are considered significantly different from the mean effect.

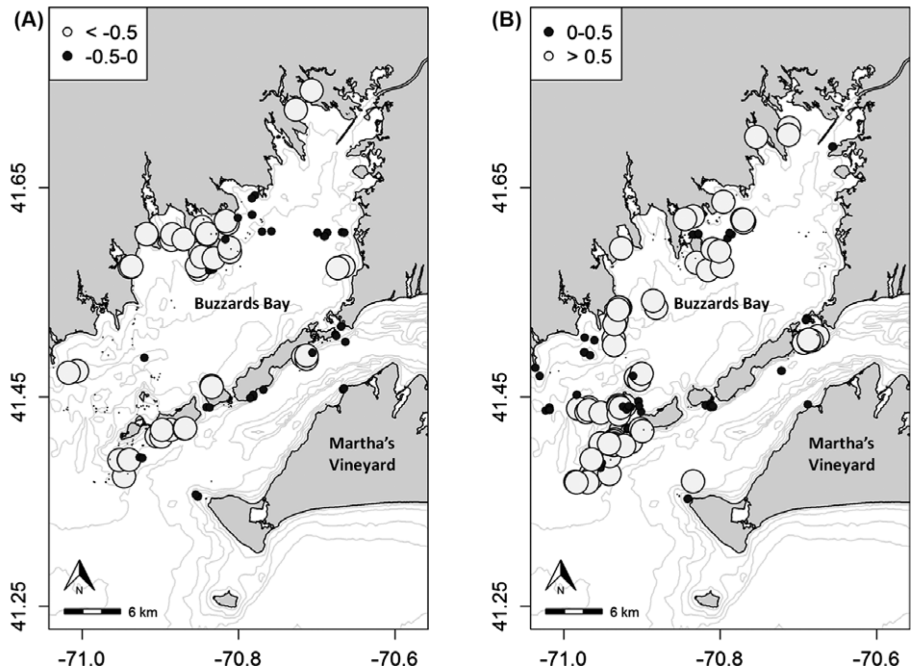

FIGURE 6. Location and relative magnitude of the sampling location random effects. **(A)** The large light-gray circles represent large negative random effects (i.e., below-average locations with regard to Tautog CPA), and the small black circles indicate relatively small negative random effects. **(B)** The large light-gray circles represent large positive station effects (i.e., above-average locations in terms of Tautog CPA), and the small black circles indicate small positive random effects.

Catch per angler was chosen as the preferred response metric to capture the fine-scale variability in catch rates. We initially predicted that variability in angler catches would largely be attributed to angler skill; however, our observations and modeling results suggested that, although angler skill level explained some of the variability in catch rates, the fine-scale habitat differences seemed even more important (e.g., fishing directly over a rock cluster versus adjacent to one). Angler catches at a given sampling event varied considerably, suggesting that pseudoreplication was not an issue and that aggregating across angler catches would artificially decrease the catch rate variability and increase the statistical power. We have presented a comparison of power between the rod-and-reel and trawl surveys, but this comparison is not a direct one due to differences in selectivities. We evaluated whether the low power of the trawl survey was caused in part by the inclusion of the smaller, potentially more variable size-classes. We found that the low power of the trawl survey to detect changes in the Tautog population was more an artifact of low sample size than the differences in size selection.

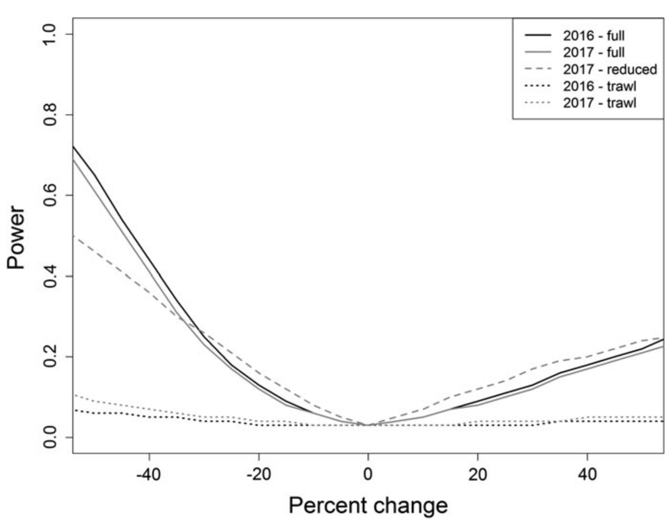

FIGURE 7. The power curves illustrate the probability (*y*-axis) of detecting a given percent change in Tautog abundance (*x*-axis). This figure depicts five power curves: two for the full pilot study sampling effort in 2016 (black solid line) and 2017 (gray solid line), one for the estimate from reduced sampling in the months of September and October in 2017 (dashed gray line), and two from the synoptic MDMF trawl survey in 2016 (black dotted line) and 2017 (gray dotted line).

Selectivity of both the rod and reel and trawl surveys is assumed to be asymptotic as the hook size is consistent with that of the recreational and commercial fisheries; however, the length frequency data suggest that the trawl survey has greater selectivity for the smaller fish (<20 cm; Figure 2). Given the apparent differences in selectivity between the two surveys, the trawl survey could be used to provide an index of young of the year and age-1 Tautog abundance, while the rod-and-reel survey could index fish ages 2 and older. Understanding survey gear selectivity is an important consideration for stock assessments when a survey is incorporated as an index of relative abundance. Directed research to further evaluate selectivity associated with different hook sizes would be valuable to solidify our assumption of asymptotic selectivity and define the ascending limb of the selectivity curve (e.g., Punt et al. 1996).

Gear saturation is another important consideration given the finite capture capacity of hook-and-line sampling gear, because it can potentially degrade the proportionality between the relative index and true abundance when abundance is above the saturation threshold. Given our sampling design, gear saturation would have been perceived if each hook drop readily resulted in capture. In this pilot study, hook saturation never presented as a problem, but this could be a concern in the future if Tautog abundance increases. Although density estimates are difficult to obtain using rod and reel, CPA can be used as an informative measure of relative abundance to monitor trends in a population through time (Haggarty and King 2006).

In this survey we targeted the preferred Tautog habitats, but given our hypotheses it is also valuable to understand how catch rates in the suboptimal habitat change through time. The MDMF trawl survey is expected to continue into the future and therefore will be able to provide this additional information. Targeting the featureless bottom with the rod-and-reel survey would be inefficient and likely provide little useful data, and targeting only the complex habitat could result in hyperstability (Hilborn and Walters 1992), the situation where the index could remain stable as the true population declined. For these reasons, we suggest that tracking Tautog population dynamics through time could be best achieved by using the combined information from both the trawl and rod-and-reel surveys, as these data sources are viewed as complementary rather than mutually exclusive.

The top model indicated that depth stratum was an important variable, but not fishing depth. We acknowledge the possible confounding of these variables; however, we were interested in evaluating a model that retained both variables as well as models that included only one or the other. Due to the flexibility of fishing within the 1′ square associated with each sampling location, there was an occasional disconnect between fishing depth and the depth stratum that a given sampling location was assigned to. Even so, depth stratification was important in the models; this was likely due in part to the geographical location of the sampling events and not solely the influence of depth. The deep sampling locations were largely clustered in the southwestern region of our survey extent, while the shallow strata were clustered closer to shore. In the power analysis, CPA was stratified by depth and month, but we also evaluated power with the omission of depth stratification. We found that depth stratum reduced our statistical power at times, suggesting that the stratification scheme could be refined to better reflect variability in the monitored population. We are exploring the use of a simulation to further refine the stratification and random selection of sampling locations, should this survey be adopted as a long-term monitoring tool.

In the Massachusetts–Rhode Island region, recreational fishing accounts for upwards of 90% of the Tautog landings. With the expanding human population and advances in fishing technologies, it is expected that recreational angling has the capacity to deplete exploited stocks in a manner similar to commercial fishing (Post et al. 2002; Arlinghaus 2006). In particular, species that form predictable aggregations, both geographically and temporally, are exceptionally vulnerable to overexploitation (e.g., Sadovy and Domeier 2005; Cheung et al. 2007; Sadovy de Mitcheson et al. 2013; Grüss et al. 2014). Tautog, being a reef fish, exhibits aggregating behavior in structured habitats throughout coastal waters, particularly during the fall months before winter migration. This aggregating behavior, although not linked to spawning events, does result in predictable high-density aggregations at specific times of the year. As such, there is concern regarding their vulnerability to overexploitation; therefore, the ability to monitor trends in abundance is paramount for conservation. Our results demonstrate that the MDMF trawl survey has very low power to detect even substantial changes in Tautog abundance and therefore has limited ability to monitor fine-scale population fluctuations that are relevant for timely management. In addition, the rod-and-reel survey could be used to identify persistent high-density aggregations, which in turn could help determine spatial management approaches (e.g., directed fine-scale closures if stock abundance declines or stock status changes).

We have framed this study largely around habitats defined either as optimal or suboptimal based on previous research (Olla et al. 1974, 1975, 1979), yet there remains much to learn about fine-scale habitat use. Ontogenetic shifts in home range have been described, where adults make larger foraging excursions than do juveniles (Olla et al. 1974), and although there appears to be a strong adherence to a homesite, Tautogs will leave those sites in search of more amenable habitat if conditions become suboptimal (Olla et al. 1979). Density is likely a contributing factor in the decline of homesite suitability (e.g. basin model: MacCall 1990), as food and space can become limiting. Further research investigating habitat characteristics amenable to Tautogs would be warranted to better understand how they are using different habitat types, to refine the survey stratification, and to also identify important habitat needs for conservation measures.

In summary, the use of a fishery-independent, rod-and-reel survey shows promise as an effective monitoring tool, complementary to the inshore trawl survey, to monitor trends in Tautog abundance in the coastal waters of Massachusetts. The development of a survey to explicitly sample the preferred, complex habitats is warranted given uncertainties in the current assessment and limitations of the fishery-independent survey data in Massachusetts waters. Due to the relative sedentary behavior and site fidelity of Tautogs, investments in improved monitoring and management of the MARI stock component is anticipated to have direct benefits to the anglers in this region. The methods and models we have proposed could be used in the development of a standardized index for use in future stock assessment. Until we gain a better understanding of habitat use and the influence that it has on survey catch rates, it would be prudent to use multiple and complementary survey gears to characterize this Tautog population and ensure management actions are appropriate.

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