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Perspectives from the water: Utilizing fisher's observations to inform SNE/MA windowpane science and management

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ABSTRACT

Within fisheries, stakeholders often have varying viewpoints regarding natural marine resources, and use different sets information to evaluate their condition. Evaluating a resource with different sets of information can lead to different conclusions. Windowpane flounder (*Scophthalmus aquosus*) are a managed finfish species in the northwest Atlantic whose regulations have the potential to limit harvest opportunities for target species. We analyzed commercial trip and catch information from video data to understand local densities of windowpane flounder in conjunction with fisheries independent surveys. Video monitoring data from three Rhode Island commercial fisher's vessels and fisheries independent trawl survey data were analyzed to understand the geographic distribution of the stock as well as overlap with temporary closed areas. Biomass data from the fisheries-dependent and fisheries-independent surveys were combined with a spatial-temporal model that accounted for differences in catchability among vessels and spatial autocorrelation. A separate analysis of estimated discard rates with observer data was also conducted to determine how the distribution of windowpane discards in Southern New England compared to the distribution of model predicted windowpane abundance. In agreement with the fishermen's observations, the temporary closed areas were not located where the highest densities of windowpane flounder occurred. The temporary closed areas, however, were located where the highest rates of discards occurred and thus where fishing had the greatest impact on the stock. The integration of verified fishery-dependent data with the scientific surveys has the potential to create a single set of information that is trusted by all user groups.

1. Introduction

Within fisheries, stakeholders often have varying view points with regard to natural marine resources and use different sets of information to evaluate their state (Johnson and van Densen, 2007; Verweij et al., 2010; Turner et al., 2016). Fishers generally harvest as efficiently as possible to maximize revenue within the constraints of the regulations (Lordan et al., 2011). They typically have intimate knowledge of the local abundance and distribution of species and choose whether to fish or not fish them based on a range of economic, social and regulatory drivers. In contrast, agencies are focused on managing the entire stock and fishery within the constraints of the law and fisheries management plan objectives. They institute regulations to meet those objectives. Their understanding of what is taking place on the water is shaped by the population level harvest dynamics as they relate to the overall status of the fish population. For well-developed coastal fisheries, managers may have fisheries independent and dependent information to inform decision-making, but the information is typically large scale with a coarse spatial and temporal resolution (Johnson and van Densen, 2007). The deficiency of such data is it lacks the fine scale observations and knowledge of the vessel captains on the water. The two groups can have different perspectives on the fishery and often use different information

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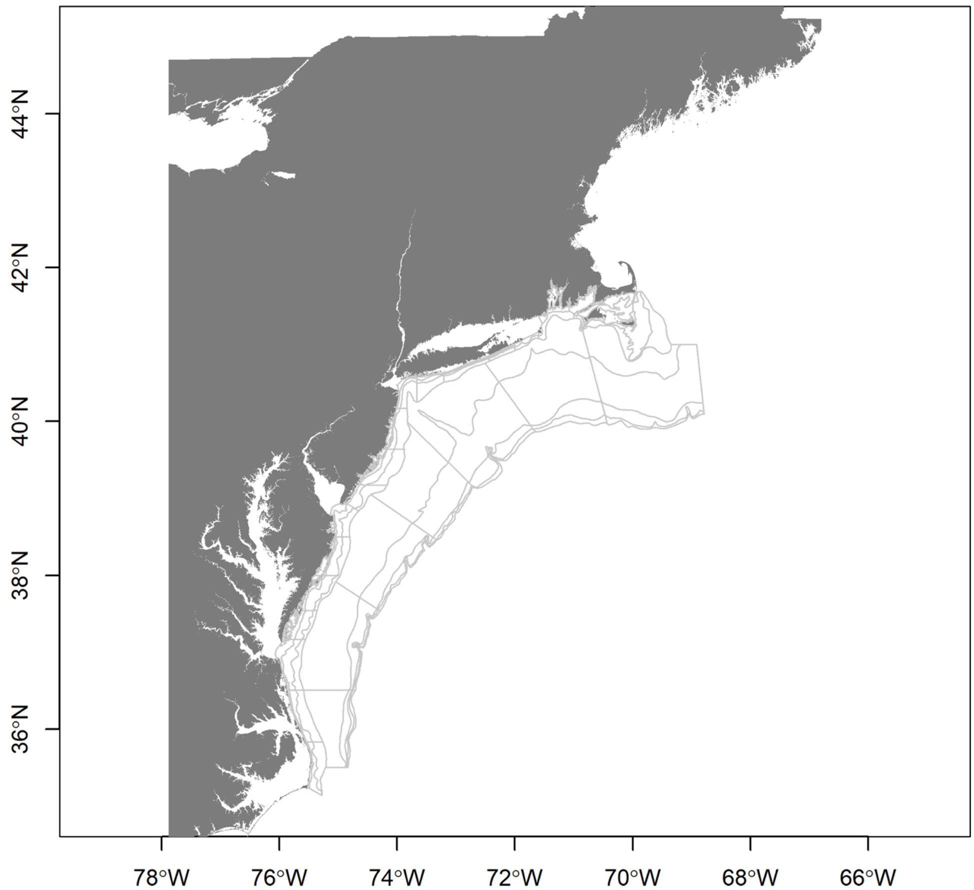

Fig. 1. Strata 1–12 and 61–76 as well as all inshore areas on the Northeast Shelf.

to understand the resource (Johnson and van Densen, 2007; Verweij et al., 2010). Both groups have both more and less knowledge than the other largely due to the different spatial and temporal scales of their information and experience. Managers may know the catch over the entire area and the general distribution and abundance of the population from surveys, but only at coarse scales and for certain seasons. Captains may fish year-round, have intimate knowledge of their local grounds and know what they are choosing not to catch. They may not be as aware, however, of juveniles and/or the broader patterns of fish over the entire population because of the selectivity of regulated gear used and because they often fish in particular areas instead of across the entire stock area. The weight each group places on the different sets of information can lead to contrasting perspectives of the resource as well as differing opinions in how the resource should be managed (Verweij et al., 2010; Turner et al., 2016). One of the basic components that contributes to the ability of fishers and managers to have productive conversations about the resource and regulations is a shared view of the resource itself. Using reliable data, trusted by all user groups to develop products that integrate the different information sources from the range of stakeholders can help reduce the challenges around interpreting stock status and management needs (Mangi et al., 2015).

Electronic monitoring (EM) is a tool to collect fisheries-dependent data while at sea (Bradley et al., 2019). The system typically includes video cameras to record what was caught and discarded as well as position data to record where the tow took place (van Helmond et al., 2020). Numerous EM programs have been successfully implemented internationally for both catch compliance and scientific data collection (Stanley et al., 2009; Hold et al., 2015; Needle et al., 2014; van Helmond et al., 2020). On the Northeast US Shelf, two EM programs are underway to examine the larger application in both the mid water fleet and the groundfishing fleet. In the groundfishing fleet, the EM program has been in place since 2016 as a partial replacement of the required observer program (observer coverage has varied from 14% to 32% on groundfish trips over the last decade (NEFMC, 2019). The groundfish EM program covers the At-Sea-Monitoring component of observers, focusing on counting and measuring the discards of regulated groundfish and some captains have elected to have the cameras running on every tow. All regulated discards are then counted and measured producing a data set that is accurate, verifiable and trusted by both managers and fishers.

One commonly discarded groundfish species in certain parts of Southern New England is windowpane flounder, *Scophthalmus aquosus* (NEFSC, 2008). Windowpane are a thin flatfish on the US East coast that has an onshore/offshore seasonal migration (Collette and Klein-MacPhee, 2002). The stock supported a small fishery that declined in the early 1990s and commercial catch was prohibited by regulations in 2010 (Stokesbury et al., 2019). The current stock assessment used for management is an empirical assessment based on an index of abundance from a fishery independent trawl survey and possession is prohibited, resulting in all catch becoming discards (NEFSC, 2008). Because of concerns for low biomass of windowpane, managers instituted accountability management areas (AM) that come into effect if discard numbers exceed a regulatory threshold (NEFMC, 2012). The AM area location was developed based on discard information from observers, but was not situated where the windowpane fishery had previously operated or where the fishers believed the highest abundances occurred.

In 2015, windowpane discards crossed the threshold level creating the potential for triggering the AM areas in 2017. One of the participants in the EM program who regularly fishes in and around the AM area found they were catching significant numbers of windowpane outside of the AM area. The Captain knew all his discards had been recorded and verified on video and asked his state marine fisheries agency (Rhode Island Department of Environmental Management) how catch

Table 1
Fisheries independent and dependent surveys combined in the analysis. The mean across years of the total kilograms (kg) of windowpane caught each year.

Survey	Sample years	Max years	Timing	Coverage	KG	Mean tows/year
NEFSC	2010–2018	1963–present	Day/night	Northeast Shelf EEZ	120.2	207
NEAMAP	2010–2018	2008–present	Day	SNE and MA inshore	123.8	140[a]
RI DEM	2010–2018	1979–present	Day	RI state waters	9.7	44
BIWF	2013–2018	2013–present	Day	BIWF area	92.1	41
EM	2017–2018	2017–present	Day	BI Sound and RI Sound	10,975.4	197

[a] NEAMAP completed 150 tows in every year except 2017.

information from the EM program varied spatially and how it compared to other available data.

The goal of this work is to integrate multiple data streams covering both vessel captains and manager information to determine the spatial distribution of windowpane flounder in the Southern New England/Mid-Atlantic (SNE/MA) area that could potentially provide a single view of the location of windowpane flounder for all stakeholders.

A number of fisheries independent trawl surveys sample within the study area as well as EM data from three vessels that fish around the AM area. The different surveys (fishery independent and dependent) have different spatial footprints and gear configurations and were integrated with a spatial-temporal model that can account for annual changes in abundance and distribution while accounting for differences in catchability among surveys. Spatial-temporal models have increased in use as they can utilize data from multiple vessels/surveys by treating the vessels/surveys as random effects, attribute the variance in species presence and abundance to environmental conditions, and predict abundance over unsampled areas while accounting for spatial autocorrelation (Thorson et al., 2015; Thorson, 2019). While other methods have been used to integrate several surveys into a single abundance index (Conn, 2010), they generally fail to specifically account for the spatial and temporal changes in distribution that is fundamental. Spatial-temporal models have previously been used to examine multiple species within the Northeast shelf, including summer flounder (Perretti and Thorson, 2019) and northern shrimp (Cao et al., 2017). With these model predictions, we provided an example of how fisher and manager data can be combined to test fishers' hypotheses. More specifically, we examined a fisher-driven research question on how windowpane spatial abundance patterns correspond to management measures, specifically the AM areas.

2. Material and methods

We examined the spatial distribution of the southern stock of windowpane flounder with a particular focus on the overlap between the AM restricted area and the occurrence of windowpane. The study has two major components. (1) Fisheries independent and dependent data were combined with a spatial-temporal model in the R package VAST (Thorson, 2019) to determine the location of the stock. (2) The location and current utility of the AM areas were examined by estimating a proxy for the distribution and intensity of windowpane fishing mortality with fishery dependent observer coverage. Data from the south side of Cape Cod, MA to Cape Hatteras, NC were included with the major focus near Block Island, RI (Fig. 1).

2.1. Fishery surveys

Four fisheries independent and one fisheries dependent data sets were used to determine the distribution of windowpane in SNE (Table 1). The data sets differed in spatial and temporal scales, but all overlapped and when taken together provided comprehensive coverage of the study area. We examined the years from 2010 to 2018 and investigated the southern stock of windowpane flounder spatially within the Northeast Fisheries Science Center (NEFSC) trawl survey offshore strata 1-12, 61-76 and all waters landward as specified in the stock assessment (Hendrickson, 2008) (Fig. 1). The time period was selected as it provided a reasonable amount of time to cover variability of windowpane while reflecting the current abundance and distribution of windowpane. Starting in 2010 also ensured the federal trawl survey data were consistent as this is after the survey conversion in 2009 (Miller et al., 2010) and after regulation prohibited the catch of Windowpane flounder. The NEFSC federal trawl survey occurs biannually along the US Northeast shelf since the 1960s. It conducts roughly 300–350 tows per season during day and night operations with a bottom trawl covering federal waters (see Sosebee and Cadrin, 2006 for details). The survey changed vessels and gear in 2009 (NEFSC, 2007). We only used data from after the change and did not include any gear or vessel conversions (Miller et al., 2010). The North East Area Monitoring Program (NEAMAP) conducts a bottom trawl survey from Cape Hatteras, NC to Cape Cod, MA covering the inshore waters that overlap both the federal survey and many state surveys (Bonzek et al., 2015). Rhode Island Department of Environmental Management (RIDEM) conducts a biannual bottom trawl survey covering all RI state waters including areas around Block Island. The Block Island wind farm (BIWF) has a designated bottom trawl survey to evaluate impacts of the construction and operation of the wind farm (Lipsky et al., 2016; Wilber et al., 2018). The BIWF survey had data from 2013 to 2018. Three commercial fishing vessels that utilize EM were included in the study to both get as complete a picture as possible of windowpane abundance and distribution, and to ensure fisher collected and agency collected data were integrated in the study. Windowpane flounder are not actively targeted while fishing given the prohibition of landing them, but are not actively avoided due to their partial spatial overlap with harvestable species of economic importance. As with many of the groundfish species, there is some habitat overlap between windowpane flounder and the economically important species. That said, given the lack of targeting or avoiding, the variability inherent in fishing and the only partial overlap in habitat, the process generating the sample locations (where to fish) was assumed to be independent of the process generating the sample abundances (windowpane distribution). Commercial discards of windowpane, therefore, were considered a random sample of the population (Diggle et al., 2010). EM data were available in 2017 and 2018 during their spring, ground fishing season. The EM program was part of the groundfish fishery and therefore EM data was not available for all boats during other parts of the year as vessels moved to different fisheries in other seasons.

The commercial vessels captured windowpane from 16 cm to 41 cm (majority between 23 and 36 cm) with a single 6 cm and a single 7 cm fish recorded while the fishery independent surveys captured fish in all size classes. To ensure the data were comparable across surveys, we developed a size cut off by calculating the first percentile of the cumulative distribution of length frequencies from the commercial vessels. The commercial gear had a steep selectivity and the first percentile was a good balance between including as much information as possible while eliminating rare size classes. Analyses were limited to the spring season (Jan–May) and included only fish that were $\geq$22 cm across all data sets.

2.1.1. Electronic monitoring

The three commercial fishing vessels in the study were part of an EM program. The vessels employed multiple cameras, GPS and sensors to ensure cameras were running during all fishing activities. After each tow, catch was sorted on deck in full view of the cameras. Kept catch was processed as usual by the crew. Regulated discards, those species listed in the Northeast multispecies fishery management plan, were individually placed on a measuring board under a camera by the crew and then sent overboard. Video was analyzed onshore and species and length for each individual that was a regulatory discard was recorded. Length was converted to weight with the NEFSC length-weight relationship (Wigley et al., 2003). Position of the vessel and length of each tow were also recorded with the EM system. Two of the vessels had the cameras running on all trips and tows and one vessel ran the cameras only when they would have normally been randomly selected to have an observer on board.

2.2. Modeling

Tow level data for surveys were integrated within a spatial-delta, generalized linear mixed model using the VAST package in the software R (Thorson, 2019). The delta model accounts for zero-inflated observations in sampled data by combing two models. The method first models presence/absence data with a logit link function and then models the biomass of occurrences (tows in which windowpane were caught) with a Gamma error distribution. Spatial-Gaussian Markov random fields estimate the density of windowpane as a function of latitude and longitude to account for the spatial aspect of the samples. The random fields specify the distribution of density at all locations resulting in a smooth density field. The variations in the density field, areas with high and low concentrations, represent the combined effects of unobserved ecological factors such as habitat associations and predator-prey relationships on distribution and density (Thorson et al., 2015). The multiple vessels/surveys are accounted for as random effects within the model. In the presence/absence model

$$p_{i,1} = \beta_{t,1} + L_{\omega_1}\omega_{s,1} + L_{\varepsilon_1}\varepsilon_{s,t,1} + L\eta_v + \gamma_{t,p}\chi_{s,t,p} + \lambda Q_k \quad (1)$$

$$p_{i,2} = \beta_{t,2} + \text{offset} + L_{\omega_2}\omega_{s,2} + L_{\varepsilon_2}\varepsilon_{s,t,2} + L\eta_v + \gamma_{t,p}\chi_{s,t,p} + \lambda Q_k \quad (2)$$

The probability of presence/absence ($p_{i,1}$) is equal to an intercept term representing the annual relative biomass, plus the spatial term ω_s (patterns in distribution that persist through time), the spatial-temporal term $\varepsilon_{s,t}$ (spatial patterns in distribution that vary with time) and the two loading matrices L_ω and L_ε representing the covariance of the spatial and spatial-temporal terms. Environmental covariates can be included through the χ term and the catchability term Q_k accounts for catchability components separate from the random effect vessel term η_v (differences among surveys). The vessel term was included as a vessel-year effect to estimate both the variability among vessels/surveys and the variability within a vessel/survey over different years (Thorson and Ward, 2014). The catchability term was included to account for differences in catch rate related to the sampling time of day. Photoperiod impacts fish behavior which affects their susceptibility to fishing gear (Casey and Myers, 1998). Windowpane are caught more readily on night tows, which only occurred on the NEFSC survey. The solar zenith angle was calculated for each sample based on the time, date and location of the tow and included in the model as a continuous variable to account for day/night differences (Jacobson et al., 2011, 2015). The biomass of occurrence component of the delta model ($p_{i,2}$) contained the same elements as the presence/absence component, but included a Gamma error structure as well as the swept area of each tow as an offset term to aid in standardizing the sampling areas of each data set.

The model estimates the density of windowpane flounder at a user defined number of knots that are spatially fixed in time. Based on the number of sample points and initial runs, the final model was run with 200 knots. The number of knots was a balance between providing the highest resolution of model estimates as possible with the density of the actual sample data points. The location of the knots are determined by the K-means clustering algorithm that distributes the knots based on the sampling intensity of the observed data (Thorson et al., 2015). Each knot represents a specific amount of area enabling the density estimates to scale to a relative index of abundance over the sampling area.

2.3. Fishing discards/mortality

As the second component of the study, we developed a proxy for the distribution and intensity of windowpane fishing mortality to evaluate fishing in the context of the windowpane stock distribution. The second analysis was conducted with an additional data sources, fishery dependent observer coverage, that was not included in the spatial-temporal model above to ensure the two analyses were independent. Spatially explicit windowpane flounder discards were estimated by ten-minute square, roughly following the method used to develop the initial AM areas (NEFMC, 2012). The goal was to identify the distribution of windowpane discards from the observer data and examine how they aligned with the distribution of windowpane in SNE from the spatial-temporal analysis.

Discards were estimated with the standard NEFSC methodology (Cochran, 1977; Wigley et al., 2007) using the ratio of discarded windowpane to total kept catch of all species (d/k) from on-board observers with slight modifications. Discards are typically estimated at the vessel trip level aggregating across all the gear types used on a trip. To increase the precision of the discards by location, estimates were calculated at the haul level as trips often fished multiple statistical fishing areas and some vessels used multiple gear types on a single trip. Gear stratification is an important factor in estimating discards. Discard rates for one gear type do not necessarily apply to other gears types based on how the gear operate (e.g. pots vs. gillnets). Exploratory analysis indicated that parsing the gear into four general gear classification of: *Bottom Trawl*, *Dredge, Sink*, *Gillnet*, and *All Others* captured the major distinctions of gear specific windowpane discards. Observer data spanning 2010 through 2017 were used. Estimates were calculated for Jan-May to align with the period used for the fisheries independent surveys.

Total discards by gear type for each ten-minute square were calculated with the following method:

$$r_{\mathrm{jh}} = \frac{\sum_{i=1}^{n_h} d_{\mathrm{jih}}}{\sum_{i=1}^{n_h} k_{\mathrm{ih}}}$$

$$\widehat{D_{\mathrm{jh}}} = K_h r_{\mathrm{jh}}$$

where

$\widehat{D_{\mathrm{jh}}}$ is the total estimated discarded pounds for species j from gear type h
K_h is the total kept pounds of all species from gear type h
r_{jh} is the discard ratio for species j with gear type h
d_{jih} is discards of species j from observed trip i for gear type h
k_{ih} is the kept pounds of all species on observed trip i for gear type h
n_h is the number of observed trips with gear type h

Discards were estimated for Jan–May at the gear level for each ten-minute square. Discards were not summed across gear types in each ten-minute square as that requires applying the Cochran ratio estimator. This requires a number of trips observed and trips fished per strata. Since trips span multiple ten-minute squares, and can have multiple gear types, this was not possible. Furthermore, d/k was calculated at the haul level due to the location information available.

3. Results

The sampling stations covered the entire SNE/MA area with NEAMAP covering the inshore areas, NEFSC covering the offshore areas and

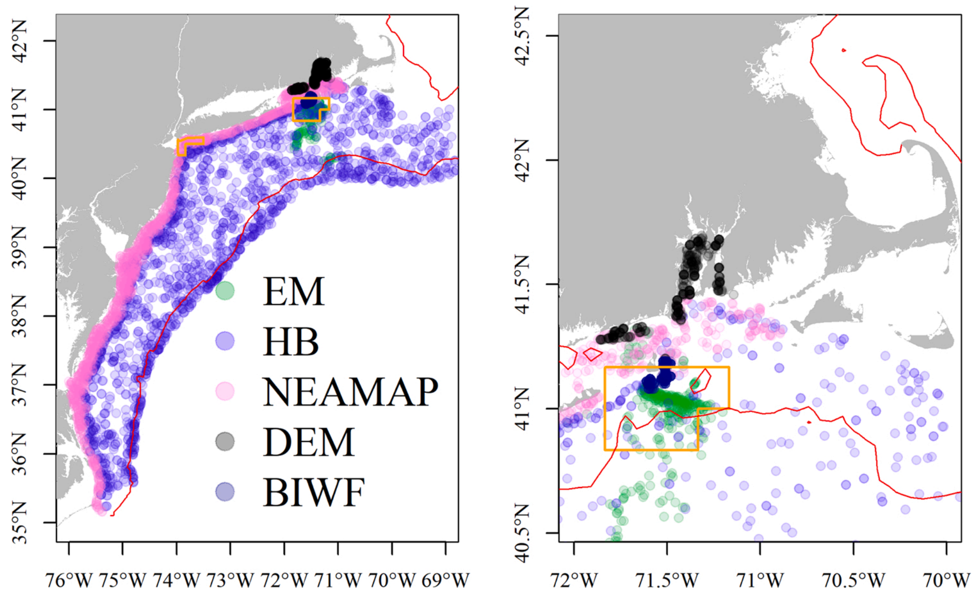

Fig. 2. Distribution of tows for the different data inputs on the Northeast Shelf with a focused map in Southern New England. The boxes outlined in orange are the AM areas. Red line is the 100 m contour for the entire shelf and 50 m contour in Southern New England.

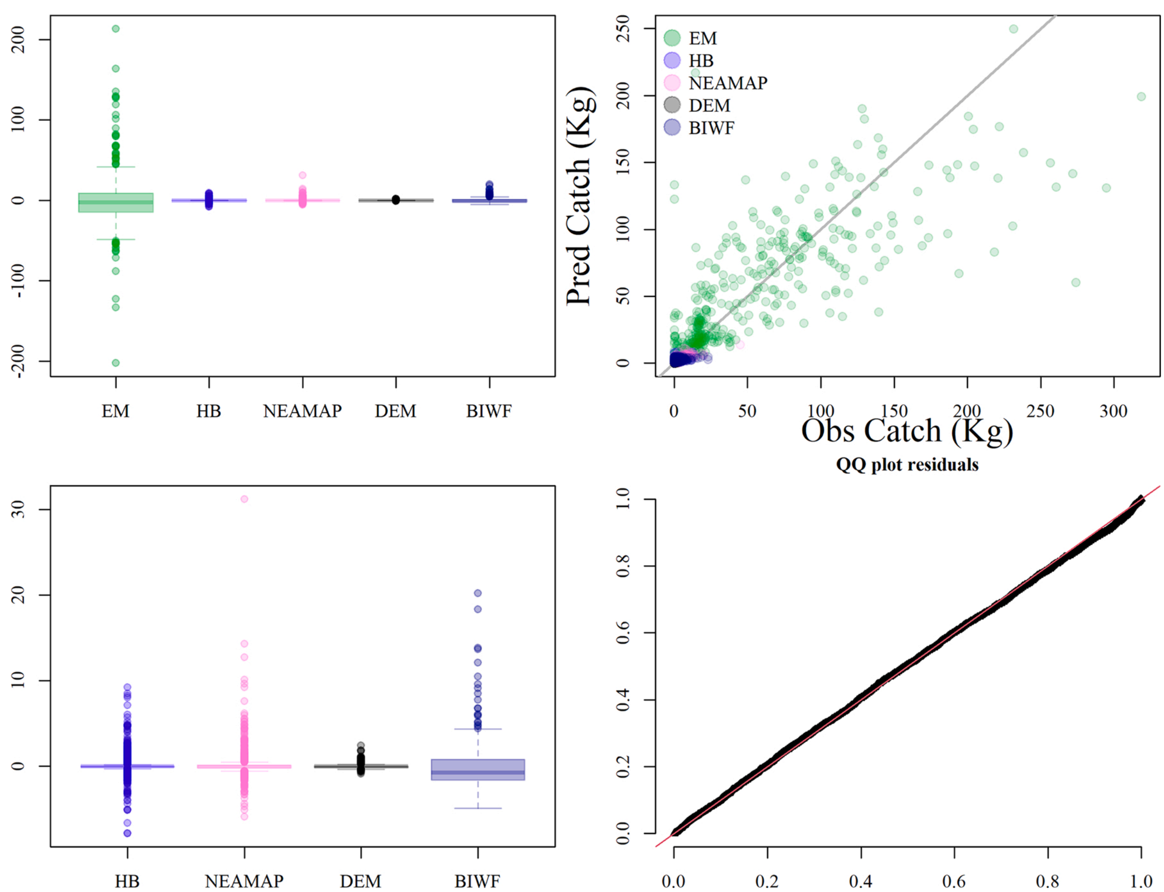

Fig. 3. Boxplot and scatter plot of VAST model residuals by survey, described as observed minus the predicted kilograms per tow. The solid diagonal line in the scatter plot is a 1:1 line. (Bottom row) Boxplot of observed weight per tow minus the predicted weight per tow from the VAST model by survey with the EM results removed to show scale and a QQ plot of observed vs predicted.

a high concentration of points around Rhode Island waters and Southern New England (Fig. 2). The surveys overlapped in space and time enabling the model to combine surveys and estimate the random vessel effect among them.

The spatial-delta generalized linear mixed model converged and fit the data well. The QQ plot approximated the theoretical distribution well (Fig. 3) and while some of the residuals are large, particularly for some of the EM tows, the residuals are unbiased with a few outliers

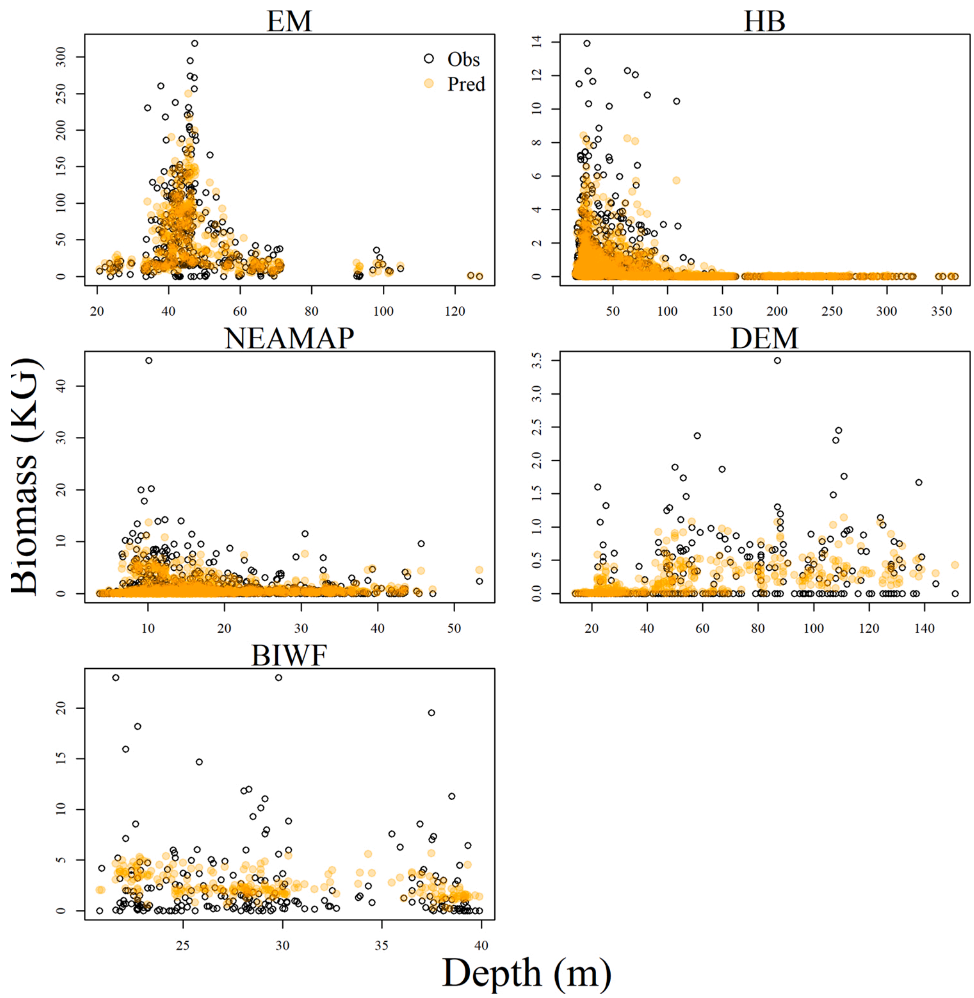

Fig. 4. Observed and predicted unstandardized biomass for each vessel/survey by depth. EM – Electronic monitoring commercial vessels, HB – Henry Bigelow, Northeast Fisheries Science Center, NEAMAP – Northeast Area Monitoring and Assessment Program, DEM – Rhode Island Department of Environmental Management, BIWF – Block Island Wind Farm.

(Fig. 3).

As an additional model diagnostic, the predicted and observed values were compared by depth and temperature to ensure the observed patterns were present in the predicted values. The predicted biomass values at each depth and temperature zone matched the observed values well (Figs. 4 and 5). The patterns were similar without any gaps that might suggest the model failed to represent the observed values. The output indicated the model estimates were able to capture the spatial, depth and temperature aspects of the observed data.

The predicted values for the BIWF survey were relatively constant compared to the observed data. The BIWF survey had a relatively small spatial footprint corresponding to relatively few knots from which the model made predictions. Therefore estimates were generally similar across the depth and temperature range. The model would need a much higher resolution of knots to capture the small spatial area around the BIWF. Overall the BIWF survey did not cover much of a depth range and the results were reasonable.

The estimated vessel-year effects from the mixed effects component of the model provided a relative scaling between the different data sources (Fig. 6). The surveys exhibited within year variability, but had some general clustering by survey. NEAMAP, the Henry Bigelow (HB) that conducts the NEFSC survey and the RI DEM survey had similar vessel-year effects. The commercial EM vessels were variable and separate from the surveys and the BIWF survey had large variability.

The main output of the spatial-delta, mixed effects model was the distribution of southern windowpane flounder in SNE/MA (Fig. 7). The model estimated the density at each of the 200 knots in each of the nine years (2010–2018) and expanded the density over an extrapolation grid. This study was interested in the general distribution of windowpane over the last decade and not on the annual variability. To get an overall distribution, we scaled the density estimates in each year to one to weight each year the same and then calculated the mean density at each point across all nine years. The output was the mean proportional density of windowpane flounder across SNE/MA for individuals 22 cm and greater from 2010-2018.

Windowpane distribution over the time period indicated that the species was more prominent north of Delaware Bay with higher densities occurring offshore of New Jersey and along the south coast of Long Island, NY. The highest densities were found offshore of southern Rhode Island and Massachusetts. While there was a high density of windowpane flounder just to the east of the AM area, the estimated densities of windowpane flounder within the AM area were low (Fig. 7).

The model was run with and without the EM data to examine the influence of the commercial data on the estimated distribution of Windowpane flounder. The EM data set had a relatively small footprint, but was situated in the focal location around the AM area. The largest difference when running the model with and without the EM data was a change in the distribution of the knots (Fig. S1). The knots are fixed locations through time where the model estimates density and thus the density and distribution of the knots defines the spatial resolution of

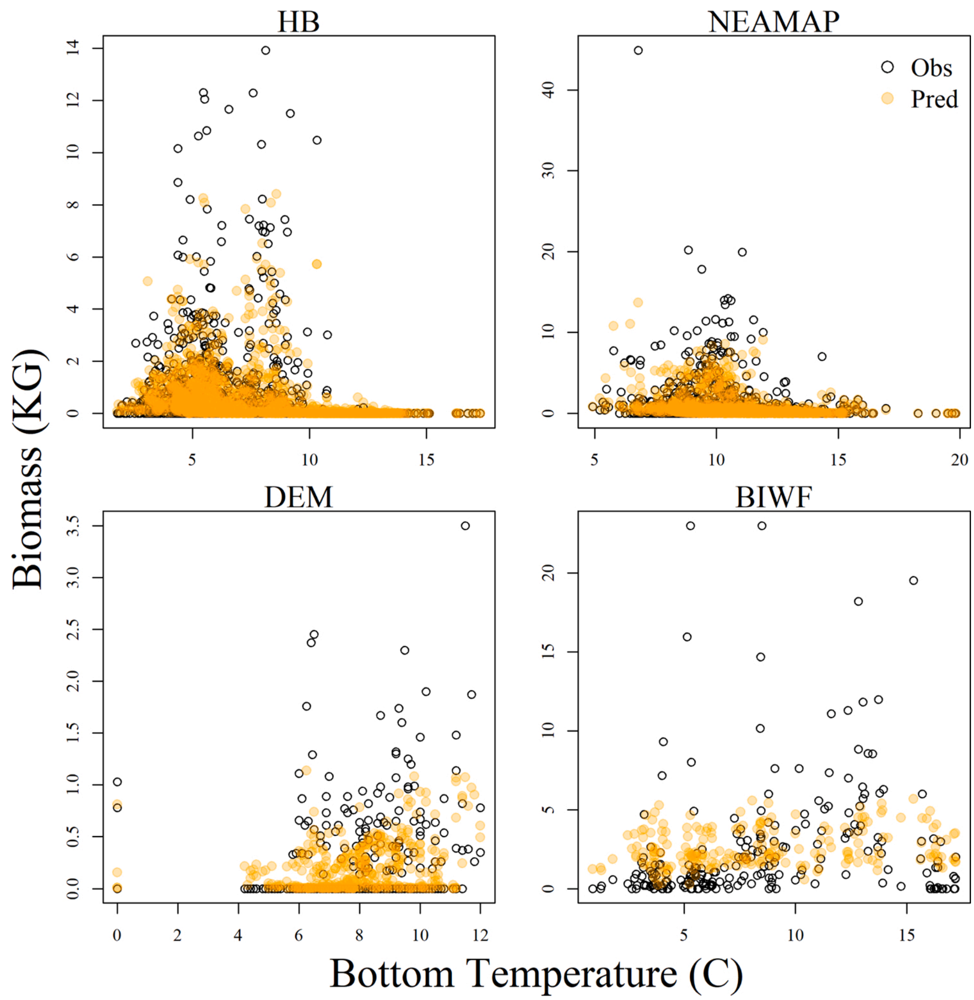

Fig. 5. Observed and predicted unstandardized biomass for each vessel/survey by observed bottom temperature (commercial vessels (EM) data did not have temperature information). HB – Henry Bigelow, Northeast Fisheries Science Center, NEAMAP – Northeast Area Monitoring and Assessment Program, DEM – Rhode Island Department of Environmental Management, BIWF – Block Island Wind Farm.

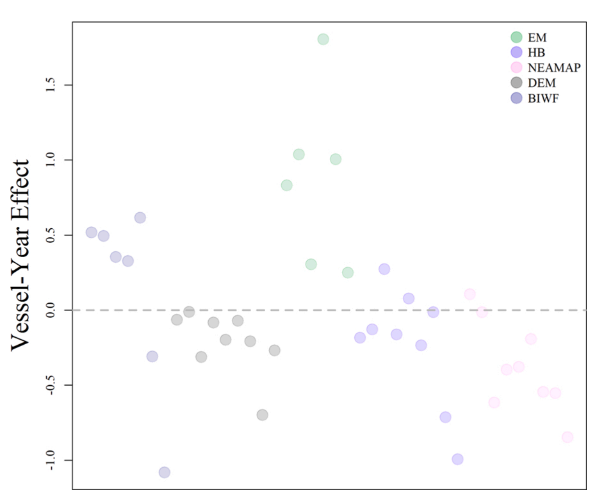

Fig. 6. Vessel-year effects modeled as random effects within the VAST model.

estimates in an area. The knot locations are determined by a K-means clustering algorithm that is a function of the sampling intensity (Thorson et al., 2015). Where there are more samples spatially, the knots will be closer together. The inclusion of the EM data almost doubled the number of knots in the AM area, substantially increasing the spatial resolution of estimated windowpane density in the focal area. The inclusion of the EM data does not make a dramatic difference to the overall distribution of windowpane on the northeast shelf (Fig. S2). The high density areas remain roughly the same, but the inclusion of the EM data actually slightly reduces the density of windowpane within the AM area.

3.1. Fishing discards/mortality

In general, estimated discards from the observer data were highly skewed with most tows and therefore most ten-minute squares having very low or zero estimates of windowpane discards (Fig. 8). Even where discards were common, the proportion of windowpane discards in the catch tended to be low. Windowpane flounder in SNE/MA were caught most frequently in commercial bottom trawls with some additional windowpane caught in dredge gear (Fig. 8). The other gears had minimal amounts of windowpane catch and were not plotted. Roughly ten times more windowpane were caught in trawl gear compared to dredge, however, it cannot be concluded if this was because of the gear, the location of fishing, the method of fishing or the target species. While the d/k ratio was generally low, particular areas exhibited high levels of harvest resulting in large quantities of windowpane discards focused around Block Island, RI in SNE. The eastern portion of the AM area had the highest area of windowpane discards. Windowpane discards from dredge gear were highest in the New York Bight area, but were substantially lower than the bottom trawl discards around the Block Island

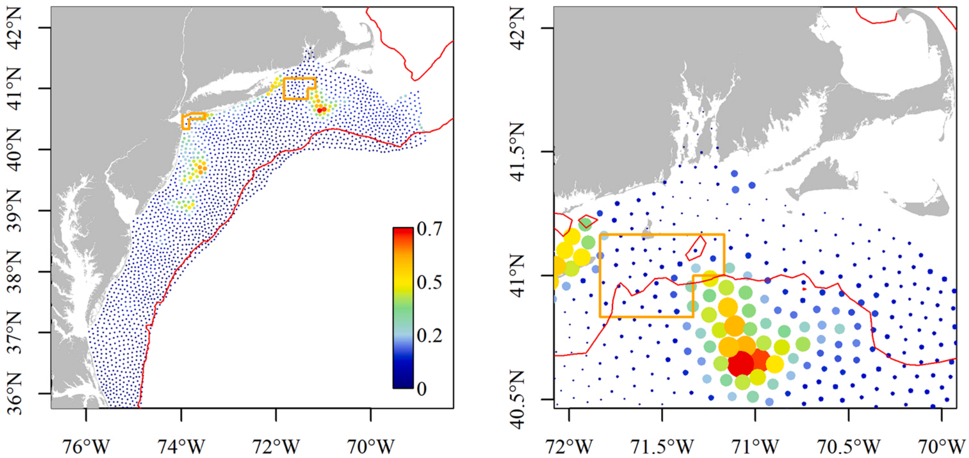

Fig. 7. Mean density of windowpane flounder (≥22 cm) over all years across the northeast shelf with a focused map in Southern New England. The boxes outlined in orange are the AM areas. Red line is the 100 m contour for the entire shelf and 50 m contour in Southern New England.

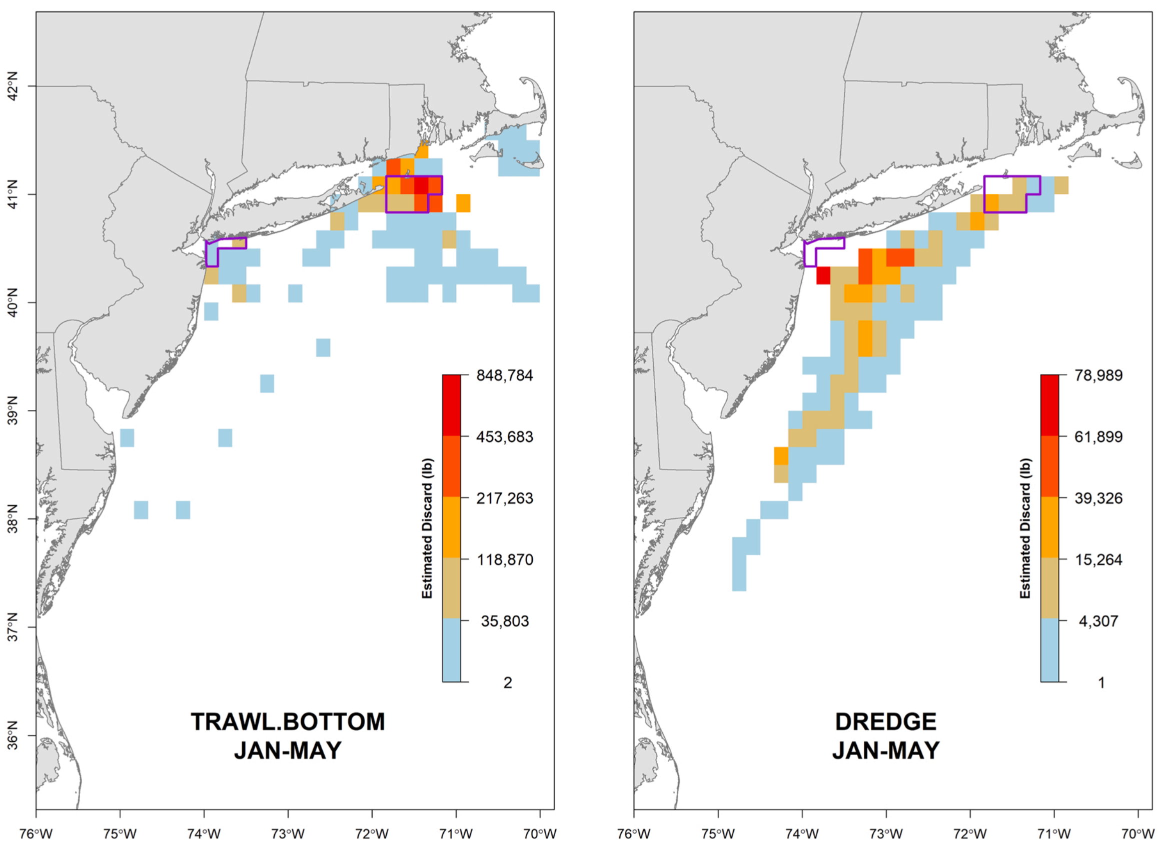

Fig. 8. Estimated discard for 2010–2017, combined, by time period and gear. Cells with zero windowpane discards are not shown. (At least 10 observed hauls and three unique vessels are present in each cell.)

AM area.

4. Discussion

Different perspectives on the status and utility of a natural resource can create challenges for successful management (Johnson and van Densen, 2007; Verweij et al., 2010; Lordan et al., 2011; Turner et al., 2016). An initial step to reduce these challenges is to ensure that reliable data, trusted by all stakeholders are used to make decisions (Johnson and van Densen, 2007). In this project we attempted to bring together data collected by both commercial fishing vessels and scientific surveys to create a single picture of the southern stock of windowpane flounder.

The spatial-temporal model effectively estimated the spatial distribution of windowpane by combining the fisheries independent and dependent data sets. The spatial and temporal overlap among the data sets were essential for the model to parse differences in the sample station biomass as either differences among vessels/surveys or true density differences (Thorson and Ward, 2014). The vessel-year effects (random-effects across the vessels) were variable, but accounted for the differences among vessels/surveys. As found in previous studies, the variability of a vessel across years could be greater than the variability among vessels (Thorson and Ward, 2014). The NEAMAP and NEFSC

(HB) surveys had similar values and both utilize the same gear with similar tow methodologies (Bonzek et al., 2015; NEFSC, 2007). The Block Island wind farm survey had the most variability among years and had the smallest spatial footprint of any of the data sets. The BIWF survey was developed to monitor the fish assemblages during and after the construction of the wind turbines and sampled both control and construction locations. The variability could reflect the small spatial sample within the larger spatial-temporal dynamics of the stock as well as the particulars of the sample design along with construction (Lange et al., 2010; Lipsky et al., 2016; Michel et al., 2007).

The spatio-temporal model provided further information on the general biology of windowpane flounder. The temperature and depth range for windowpane showed some broad agreement with previous studies indicating they are generally found in water <100 m and water temperatures <10 °C (NMFS, 1999; Stokesbury et al., 2019). Stokesbury et al. (2019) observed most individuals at temperatures <7 °C, but sampled further north on a different stock of Windowpane which may explain the difference in temperature, however, the authors found windowpane flounder at very similar depth distribution (all individuals collected were from 25 m to 100 m). The different data sets in this study indicated some more area-specific patterns, which are partially related to the geographic and depth range covered by each individual vessel/survey.

The inclusion of the EM data ensured that the fishing captains' information was directly included in the process. What the captains saw on the water every day fed directly into the analysis so they could be sure their observations were part of the science that can inform management measures. The EM information was also a verified data product containing both the detailed magnitude and location of tows. It was run on 100% of trips for most boats and was fully reviewed, thus reducing the biases, questions and caveats that often accompany self-reported and even observer collected fisheries-dependent data. The EM information, therefore, was trusted by both captains and scientists enabling it to be directly integrated into the scientific process. Windowpane flounder fit into a group of bycatch species that are neither targeted nor actively avoided and therefore their occurrence in the catch was considered a random sample (Diggle et al., 2010). The assumption of a random sample simplified the analysis in the spatial-temporal model allowing the EM data to be directly included as an additional data set (Grüss and Thorson, 2019). For species that are actively targeted, additional modifications are required (Grüss et al., 2019; Xu et al., 2019; Zhou et al., 2019).

The results of this study concurred with the fishing captains understanding of the resource that the largest concentrations of windowpane flounder were outside of the AM restricted area. Speaking with one EM captain, his years of experience on the water indicated that the AM area was located on the western edge of a concentration of windowpane and the concentration extended east quite a ways. The western edge of windowpane could expand and contract in different years, but was around the eastern edge of the AM area. He also said that there was not much fishing in the area of high density these days and that when he use to target windowpane, he generally fished in shallower water, though that was multiple decades ago.

The location of the AM areas were not designed or implemented to enclose the highest densities of windowpane; they were instituted due to the declining abundance of windowpane flounder (NEFMC, 2012) and were positioned where the greatest catch of windowpane flounder was taking place in an effort to reduce fishing mortality on the stock. The discard estimates from the observer data show that there is relatively little catch of windowpane in the high-density areas due to their being low fishing effort in these areas. To place the AM restricted area around the high-density areas would have done little to impact fishing mortality under current fishing practices, and thus would not have been an effective management strategy for this stock. While it is clear that the AM areas do not protect the highest concentrations of windowpane, they are located where they will do the most to reduce interactions between the fishing fleet and windowpane. From the perspective of a commercial fishing captain who knows the local fishing grounds well, the AM areas could seem entirely out of place. Particularly if the rational for why and how the AM areas were created was not communicated to the captains well or got lost in the flood of information being pushed to the captains. However, because the windowpane stock is currently assessed using an index based method (commonly called an empirical assessment) that is only accounting for abundance trends, rather than an analytical assessment that estimates the biological characteristics of the stock along with accounting for abundance trends, the management program instituted makes sense. This is because it targets the area of highest fishing discards, which is the only other piece of information available to the managers apart from the index-based abundance trend. In the current assessment structure, because there is no analytical feedback between the stock size and the fishery removals, from a management perspective, the AMs are generally sited correctly to achieve the goals of the management effort.

Using different sets of information at different spatial and temporal scales can lead to conflicting perspectives of a resource and challenges in management. Electronic monitoring can provide a range of information such as discard numbers, location and compliance, but it also provides a means to directly input industry observations into the scientific process. Catch numbers collected with video and independently verified provide trusted data. Combining the EM data with the scientific surveys into a single resource can enable user groups to have more faith in the information, bring groups closer to a single world view of the resource, and enable them to proactively work together for sustainable management.

Author contributions

Richard J. Bell: helped develop the project, conducted modeling, interacted with the vessel captains, wrote manuscript. Conor McManus: helped develop the project, conducted modeling, interacted with the vessel captains, wrote manuscript, provided data. Jason McNamee: helped develop the project, interacted with the vessel captains, wrote manuscript. James Gartland: wrote manuscript, provided data. Ben Galuardi: conducted modeling, wrote manuscript, provided data. Chris McGuire: helped develop the project, interacted with the vessel captains, wrote manuscript, provided data.

Declaration of competing interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.fishres.2021.106090.

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