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research paper

Quantification of "observer effect" in the United States Atlantic pelagic longline fishery

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ABSTRACT.—Fishers in the United States pelagic longline fishery are required to self-report all fishing interactions (captures) on a per-set basis to the National Oceanic and Atmospheric Administration (NOAA) to quantify catch, increase conservation efforts, and allow for an accounting of international quota-managed species. Additionally, trained fisheries observers are deployed on commercial vessels to produce a statistical subset of pelagic longline fisheries data. Generalized additive mixed models were used to compare vessel captain-reported versus observer-collected datasets for fishing occurring in the western North Atlantic Ocean. Results showed a general consistency in logbook reporting for most target species, but potential under-reporting from 1.4× to 5.4× for lesser-valued and bycatch species. These discrepancies among catch rates of targeted species, species of bycatch concern, and species of minimum economic value showed an under-reporting in the logbook versus observer data, indicating the level of accuracy for self-reported data is lower than data collected by pelagic fisheries observers for a number of species. Additional analyses are needed to examine how varying management measures through time may influence reporting accuracy at the species level.

NOAA is charged with federally managing US fisheries at an optimum yield by eliminating overfishing and rebuilding overfished stocks under the 1976 Magnuson-Stevens Act (MSA, 16 U.S.C. §§ 1801 et seq.). All US-flagged pelagic longline (PLL) vessels fishing in the Atlantic Ocean, including the Gulf of Mexico and Caribbean Sea, must submit self-reported logbooks, which contain details on gear configuration and catch composition for each set and trip. These forms contain a list of preprinted, commonly encountered species a pelagic longline vessel might encounter, with the option to handwrite the more obscure species. NOAA selects a subset of vessels to carry a trained observer who is then tasked with recording similar data to the self-reported logbooks, such that the stratum-level (area × calendar quarter) observer

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coverage is at least 8% of the previous year's stratum-level effort for total sets. While self-reported logbooks remain a necessity due to logistical and budgetary limitations, data inaccuracies and omissions may occur at a higher percentage with logbook data compared to observer-reporter data. These data discrepancies can be particularly concerning for bycatch species, as many marine megafauna have a low reproductive output and are vulnerable to overexploitation (Lewison et al. 2004). Both the logbook and observer datasets are used in international highly migratory species (HMS) stock assessments so it is essential to understand what disparities might exist between these two data sets on a species-specific basis.

Systematic differences in reported catch amounts between trips carrying an observer and those that did not have been referred to as an "observer bias" or "observer effect" (Johnson et al. 1999, Faunce and Barbeaux 2011). Referring specifically to the observer and logbook data reports within this analysis, "observer effect" is defined as the mean expected difference in reported set level catch by species, dating from the inception of the NOAA Pelagic Observer Program (POP) in 1992 through 2016. While other studies have applied similar methods to estimate reporting discrepancies between observer and logbook data (*see* Walsh et al. 2002, Faunce and Barbeaux 2011, Torres-Irineo et al. 2014, and Garrison and Stokes 2016), this is the first comparative analysis of catch data from the Atlantic PLL fleet. The observer effect analysis being presented here focused on the commonly encountered species of the Atlantic PLL fleet that are shared between the preprinted logbooks and the observer data sheets. The analysis aims to: (1) assess an observer effect in agency data, (2) assess the relative magnitude of this effect across species, and (3) help to understand the possible causes for dataset discrepancies. A standard assessment method for this analysis between datasets would be beneficial to the many fisheries agencies also collecting data from both logbook and observer programs. A species-specific evaluation of self-reported and observer-collected PLL data could help inform managers on the efficacy of current regulations regarding quotas of target species, bycatch reduction efforts, and overall fisheries management strategies.

Methods

Datasets.—Data on catches from the US Atlantic PLL fishery consisted of (1) self-reported pelagic logbooks (PLP) and (2) the fisheries observer data from the POP. Vessels in the PLL fishery are required to self-report catches (and other details) for each trip on a per-set basis (64 FR 29135, 1999). Each vessel's self-reported data are submitted at the completion of each trip and include information on the overall logistics (e.g., port of departure, number of crew), and each individual set, including any associated fishing activity (e.g., number of hooks, total catch). POP fisheries observers record a variety of similar data on individual catches, in addition to gear parameters, set characteristics, and environmental data. The annual number of observed vessels is proportional to the number of total vessels, with the intent of providing consistent coverage of the total effort within the PLL fleet over time.

In the present study, PLP and POP fisheries observer data from 1992 through 2016 were analyzed, covering a total of 40 species, including several composite species groupings. The majority of species were analyzed over the full 25-year time-period, with the exception of the following species, which were added to logbook forms after 1992: bonito (*Sarda sarda*; 1993–2016), sandbar shark (*Carcharhinus plumbeus*;

1993–2016), escolar (*Lepidocybium flavobrunneum*; 1994–2016), pilot whale (*Globicephala* spp.; 2007–2016), and Risso's dolphin (*Grampus griseus*; 2007–2016).

Dataset Preparation.—A combined set-level dataset was created from variables common to both observer and logbook data. The following environmental and effort variables were considered for potential inclusion in the models: area, time, year, season, hook hours, number of light sticks (illuminated fishing gear attached near baited hooks to attract fish), bait type, and sea surface temperature.

Any records missing data for one of these explanatory variables were removed, as were records falling in areas without consistent overlap in observer and logbook coverage through time. Additionally, sets reported with an observer present were removed from the logbook dataset. The final combined dataset consisted of 25,739 sets from the logbook program and 20,704 sets from the observer program.

Statistical Analysis.—General Additive Mixed Models (GAMMs) were selected to allow modeling of nonparametric penalized smooth functions of predictor variables [e.g., sea surface temperature (sst), year, hook hours], which can more accurately capture the relationship of these quantities with reported catch (Hastie and Tibshirani 1986). GAMMs were fitted by fast restricted maximum likelihood using the R programming language (R Core Team 2022) package mgcv (Wood 2011) bam function (Wood et al. 2015, 2017, Li and Wood 2020) for analyses of reported catch differences between data sources. Separate models were fitted to set level data by species, with the aim of capturing any nuisance variation arising from environmental and effort variables not directly related to the observer effect. To account for overdispersion, partially due to the excessive number of zeros present in the data, a negative binomial response structure with a log-link function was employed.

Type (categorical/continuous) and levels of each potential predictor variable were defined prior to model selection as follows:

- *Area*: Represents the 11 geographic regions (Cramer and Adams 1998) of the western North Atlantic, Gulf of Mexico and Greater Caribbean, as defined via latitude and longitude by NOAA for the US domestic HMS fisheries (Fig. 1).
- *Season*: Assigned sets to 1 of 4 seasons: March–May as "spring"; June–August as "summer"; September–November as "fall"; and December–February as "winter."
- *Haul Year*: Calendar year in which set was retrieved. Included as both separate continuous smooth terms with trends estimated separately for observer and logbook sets and as a categorical random effect to address correlation of observations in time and prevent data in any given year from having an outsized influence on the results.
- *Sea Surface Temperature* (*sst*): Modeled as a continuous smooth term to capture potential nonlinearity.
- *Hook Hours*: Time (in hours) elapsed from the deployment of the last hook during the set and the first hook removed during the haul back multiplied by the number of hooks deployed. Any sets with "negative" soak times, or soak durations exceeding 50 hours were removed from subsequent analyses.

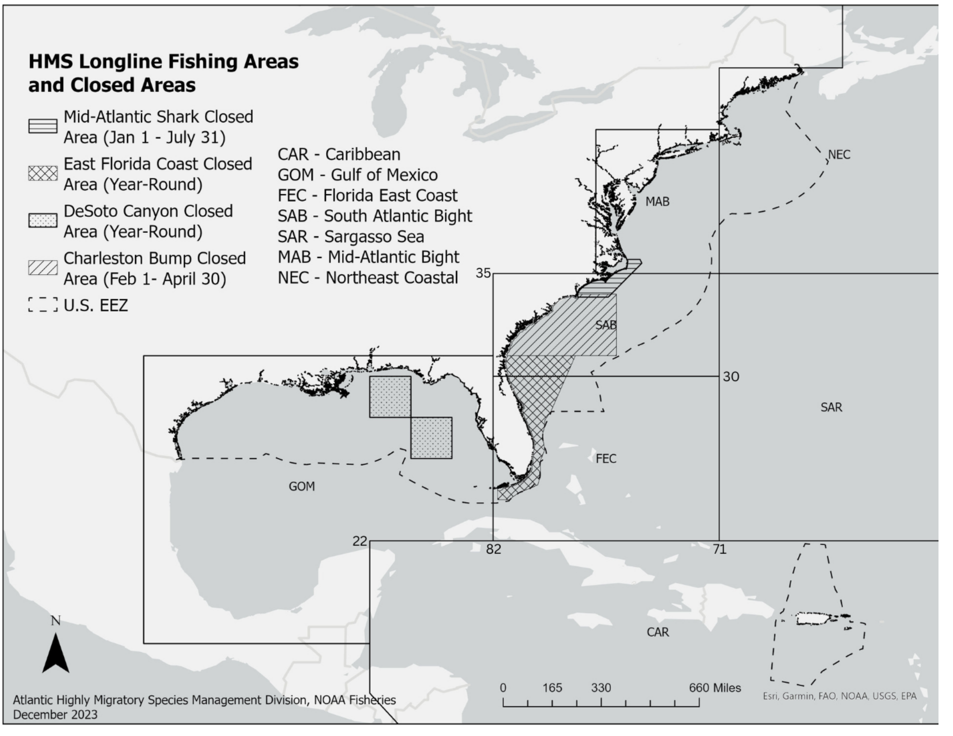

Figure 1. Map of NOAA geographic statistical areas used for the pelagic longline fishery.

- *Targeted Species*: A method used by the POP to determine the intended targeted species (swordfish, tuna, mix), the proportion of hooks to light sticks is used, with a higher proportion of light sticks (>0.75) used when targeting swordfish, and a lower proportion of light sticks used when targeting tuna (<0.25). Light stick proportions were defined according to the following ranges <0.25 | >0.25 and <0.50 | >0.50 and <0.75 | >0.75.
- *Vessel ID*: Each vessel's unique identifier, included as a random effect.
- *Observer Presence*: A binary value of 1 (observer present) or 0 (observer absent) to test the hypothesis that the amount of reported catch is associated with the presence of an observer (in addition to other covariates).

To account for potential correlation between reports from the same vessel and unrepresentative observer deployments to certain vessels, a vessel random effect—defined as each individual vessel identification number—was included in the model. This helped ensure that certain vessels did not have an outsized influence on the estimation of model parameters simply by having many reported sets, as opposed to treating each set as an independent unit. A random effect for individual trips was considered as well but proved too computationally costly for model convergence.

Akaike's Information Criterion (AIC) was used to identify an appropriate set of predictor variables and interactions to include in the final models. For the sake of interpretability and fitting constraints, up to two-way interactions of main effects were considered for inclusion in a backward stepwise selection approach, with log

Table 1. List of coastal and pelagic shark species.

Coastal sharks	Pelagic sharks
Bignose *Carcharhinus altimus*	Blue *Prionace glauca*
Blacktip *Carcharhinus limbatus*	Shortfin mako *Isurus oxyrinchus*
Dusky *Carcharhinus obscurus*	Longfin mako *Isurus paucus*
Great hammerhead *Sphyrna mokarran*	Oceanic whitetip *Carcharhinus longimanus*
Scalloped hammerhead *Sphyrna lewini*	Porbeagle *Lamna nasus*
Smooth hammerhead *Sphyrna zygaena*	Bigeye thresher *Alopias superciliosus*
Night *Carcharhinus signatus*	Common thresher *Alopias vulpinus*
Sandbar *Carcharhinus plumbeus*	
Silky *Carcharhinus falciformis*	
Spinner *Carcharhinus brevipinna*	
Tiger *Galeocerdo cuvier*	

hook hours, year random effect, vessel random effect, and observer effect kept in all models. This process was carried out for a range of species to identify consistently important variables and interactions, until ultimately settling on the final model. If data were not sufficient to allow estimation of all levels of an interaction for a given species, or if a particular model did not converge, interactions were subsequently dropped until the model converged. Basis dimensions (k) of thin plate spline terms were set sufficiently high such that there were no substantial gains in effective degree of freedom (edf), ensuring relationships between predictors and response were appropriately captured. To test for differences in reported catch between the two data sources in consideration of the other covariates, significance of the observer effect in each model was evaluated using the Bayesian estimated covariance matrix of parameter estimates (Wood 2017). Percent deviance explained was examined to indicate how well the terms included in the model captured variability in set level reported catch.

Species Analyzed.—

Finfish and Sharks (*Coastal and Pelagic*).—Swordfish, tunas, and other finfishes were placed into one of two disposition categories: kept or discarded catch. For discards, being alive or dead at time of discard was irrelevant. Kept species that were examined within this category included: swordfish (*Xiphias gladius*), Atlantic bluefin tuna (*Thunnus thynnus*; plotted as a bycatch species as well), yellowfin tuna (*Thunnus albacares*), bigeye tuna (*Thunnus obesus*), albacore (*Thunnus alalunga*), blackfin tuna (*Thunnus atlanticus*), skipjack tuna (*Katsuwonus pelamis*), escolar, common dolphinfish (*Coryphaena hippurus*), and wahoo (*Acanthocybium solandri*). The observer effect by species was analyzed over the entire 25-year study period.

Due to the common misidentification of certain shark species, the 18 species included within the analysis were grouped as either coastal shark species (11) or pelagic shark species group (7; Table 1). Each shark group (coastal or pelagic) was then analyzed separately over the 25-yr period under the same two disposition categories of kept or discarded.

Billfishes.—With the implementation of the 1988 Atlantic Billfish Fishery Management Plan (53 FR 37765), all billfishes were prohibited from sale or possession by the US PLL fishery. Given the retention prohibition for billfishes, the analysis only focused on whether an observer effect was present for discards. The following four istiophorid billfish species were analyzed: blue marlin (*Makaira nigricans*), white marlin (*Kajikia albida*), sailfish (*Istiophorus platypterus*), and roundscale spearfish (*Tetrapturus georgii*), with roundscale spearfish and white marlin being combined into a single category due to common misidentification.

Sea Turtles and Marine Mammals.—Loggerheads (*Caretta caretta*) and leatherbacks (*Dermocheys coriacea*) were the only preprinted sea turtle options for captains to self-report on the 2016 Atlantic HMS Logbook Set Form, and for marine mammals, the only preprinted options were pilot whales (combined short-finned *Globicephala macrorhynchus* and long-finned *Globicephala melas*) and Risso's dolphin. With sample sizes of reported interactions from the logbook program for both sea turtles and marine mammals being so low, model fitting was not feasible, resulting in their exclusion from the model-based analyses. Instead, species were summarized according to counts of total observer captures (per 100,000 sets) vs total logbook captures (per 100,000 sets) over all sets and disposition categories (uninjured, injured, and dead). Unlike the model-based comparisons, all variables were not required to be present for the comparative results, so all recorded sets from both programs (270,705 logbook sets and 21,336 observer program sets) were analyzed as opposed to only those sets with complete information.

Results

In addition to the observer effect, and year and vessel random effects, the final model consisted of parametric terms for area, season, light stick proportion, and interactions of area × season and area × light stick proportion. Smooth terms consisted of sea surface temperature (sst) by area, season, and light stick proportion, log hook hours by area and season, and separate smooths for haul year by observer presence. The full model is presented in Equation 1,

$$\log(\lambda_i) = \beta_0 + \beta_1\text{area}_i + \beta_2\text{season}_i + \beta_3\text{light sticks}_i + \beta_4\text{area}_i \times \text{season}_i + \beta_5\text{season}_i \times \text{light sticks}_i + \beta_6\text{observer}_i + s(\text{year} \mid \text{observer}_i) + s(\text{sst}_i \mid \text{area}_i) + s(\text{sst}_i \mid \text{season}_i) + s(\text{sst}_i \mid \text{light sticks}_i) + s(\log(\text{hook hours}_i) \mid \text{area}_i) + s(\log(\text{hook hours}_i) \mid \text{season}_i) + Y_i + V_i \quad \text{(Eq. 1)}$$

where λ_i equals the expected number of captures reported (either kept, discarded, or total) on set i, β represents estimated parametric coefficients, s represents smooth functions, and Y_i and V_i represent the year and vessel random effects, respectively. For the majority of species, these models resulted in between approximately 40% and 60% deviance explained. Model R code and detailed model summaries are available as supplementary material.

Back-transformation of the model estimated observer effect parameters according to Equation 2 yielded percentage values to quantify the estimated effect of observer presence on the reported catch, with sets without an observer serving as the reference group.

$$\%\ \text{Difference} = 100 * (\exp(\beta_6) - 1) \quad \text{(Eq. 2)}$$

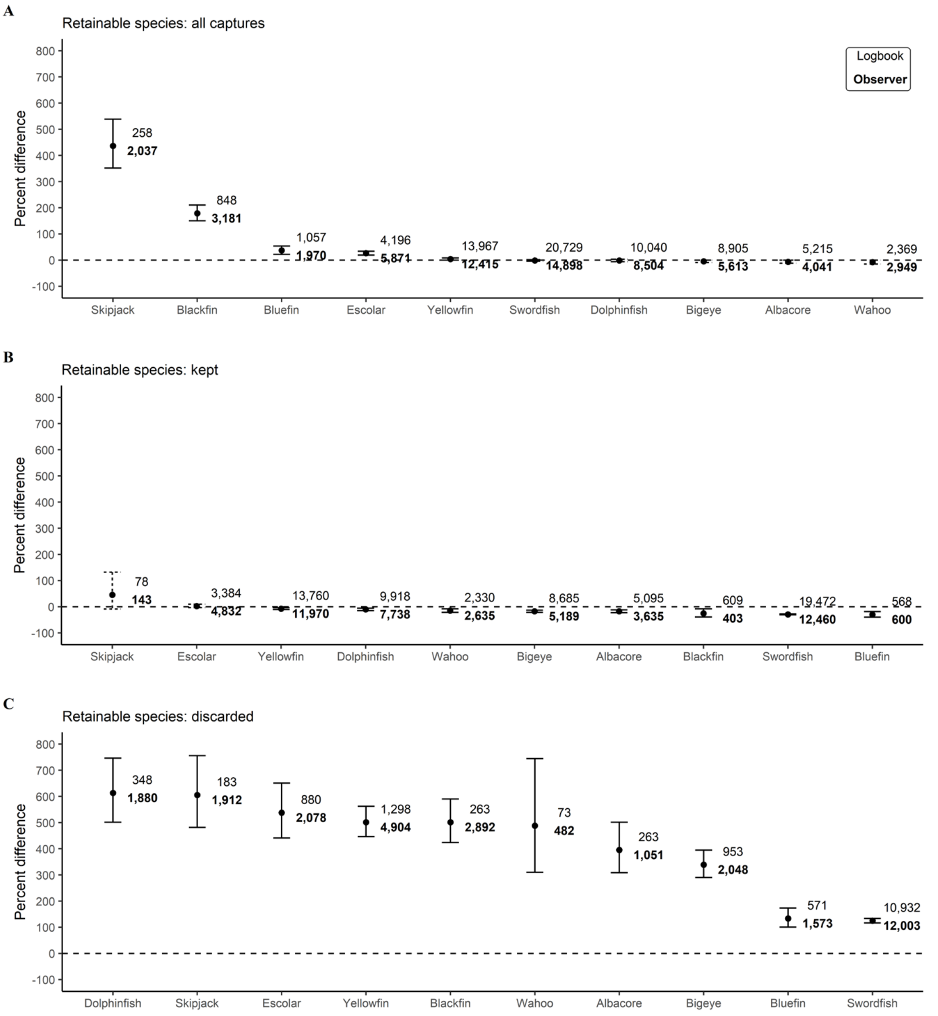

Figure 2. Model estimated mean observer effect between 1992 and 2016 as a percentage relative to logbook baseline, ranked in descending order, with sets for (A) retainable species, (B) retainable species kept, and (C) retainable species discarded. Numbers denote sample size (number of sets) of each category (logbook vs observer) included in the model. Error bars represent Wald 95% confidence intervals.

These quantities are presented for retainable and bycatch species respectively over 1992–2016 and are ranked in order of greatest to least estimated under-reporting with all disposition categories (kept and discarded; alive and dead) summed into a single variable (Figs. 2 and 3). Wald 95% confidence intervals based on standard normal quantiles were constructed around these percentages, with lower confidence bounds above zero indicating evidence of greater catch reported in the presence of an observer and upper confidence bounds below zero indicating evidence of lesser catch reported in the presence of an observer at $\alpha = 0.05$. Time-series plots of the estimated observer effect between 1992 and 2016 (including all disposition categories) were produced for retainable (Figs. 4 and 5) and bycatch (Fig. 6) species by calculating

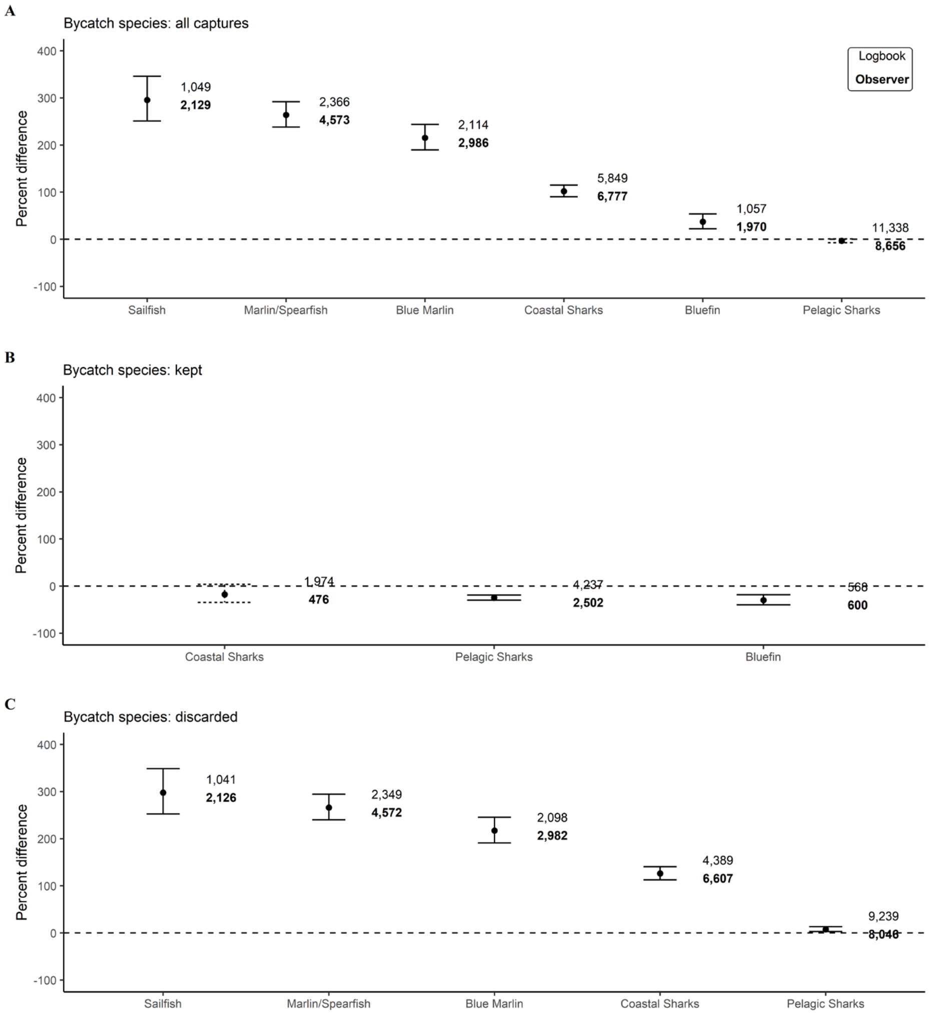

Figure 3. Model estimated mean observer effect between 1992 and 2016 as a percentage relative to logbook baseline, ranked in descending order, with sets for (A) bycatch species, (B) bycatch species kept, and (C) bycatch species discarded. Numbers denote sample size (number of sets) of each category (logbook vs observer) included in the model. Error bars represent Wald 95% confidence intervals.

differences with 95% confidence intervals (Marra and Wood 2012) between the model estimated smooths for haul year by observer presence and shifting the back-transformed differences by the estimated coefficient for the observer main effect to display the expected multiplicative differences over time in set level reported catch with an observer onboard relative to the logbook baseline. As the observer effect may vary over time, the overall mean observer effects from Table 2 are displayed on these figures as dotted lines, representing long-term average reporting biases.

With all retention categories combined for target and incidental species, there was evidence of under-reporting (percent difference > 0) for skipjack tuna, blackfin tuna, bluefin tuna, and escolar (Fig. 2, top panel). Ranking the examined species according

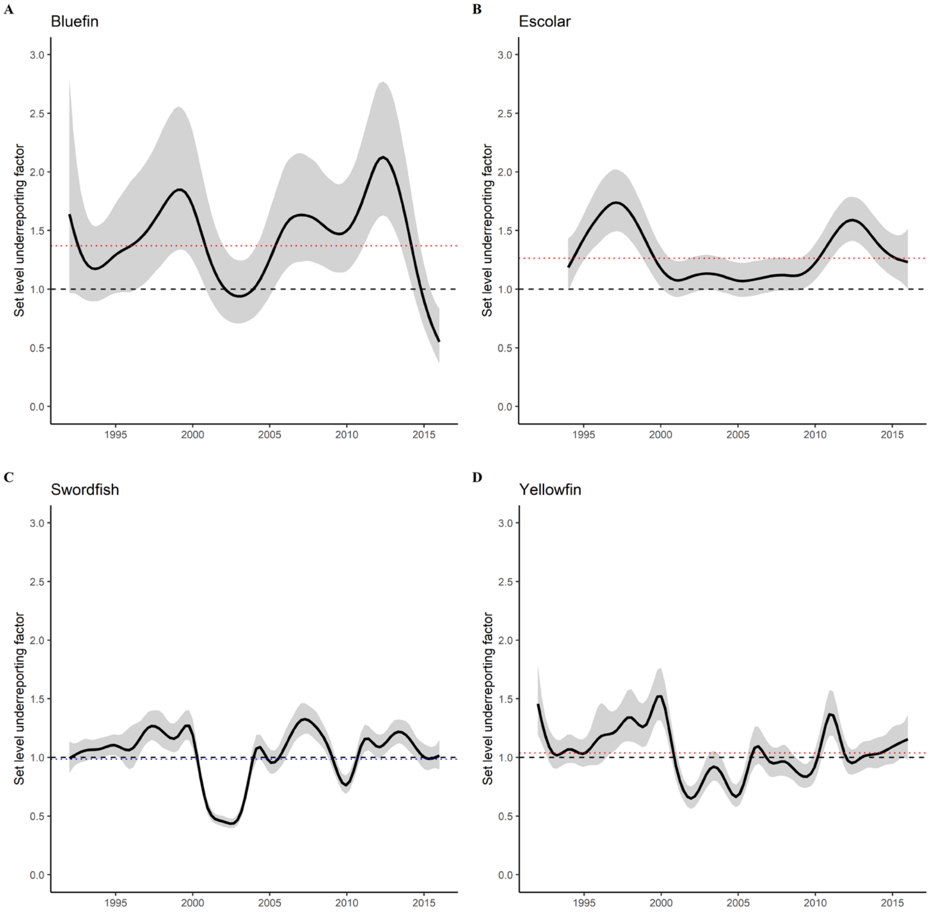

Figure 4. Model estimated observer effect for retainable species: (A) bluefin tuna, (B) escolar, (C) swordfish, and (D) yellowfin tuna, 1992–2016. Solid lines (± 95% CI) represent expected magnitude difference in set level reported captures with observer present relative to logbook baseline (dashed line at 1.0). The dotted line represents estimated long-term mean difference over the study period.

to their model-estimated observer effect parameters for combined retentions and discards in order of largest (most under-reported) to smallest (most over reported; Table 2), skipjack tuna was observed to be the most under-reported species, with an estimated 5.4 times more individuals reported per set in the presence of an observer (95% CI: 4.51–6.38) on PLL vessels. Four species analyzed had evidence of over-reporting at $\alpha = 0.05$ for combined retentions and discards: wahoo, with an estimated observer effect parameter of 0.92× (95% CI: 0.85–1.00), albacore tuna (0.94×, 95% CI: 0.88–1.00), bigeye tuna (0.95×, 95% CI: 0.90–1.00), and bonito (0.57×, 95% CI: 0.37–0.88), meaning the estimated observer-reported catch per set for bonito was 57% of that expected to be reported without an observer. For billfishes and sharks, the comparison showed under-reporting was likely in logbook reported catch for every examined taxon (or grouping of species) with the exception of pelagic sharks (Fig. 3). The greatest disparities occurred for the three billfish species (sailfish: 3.96×,

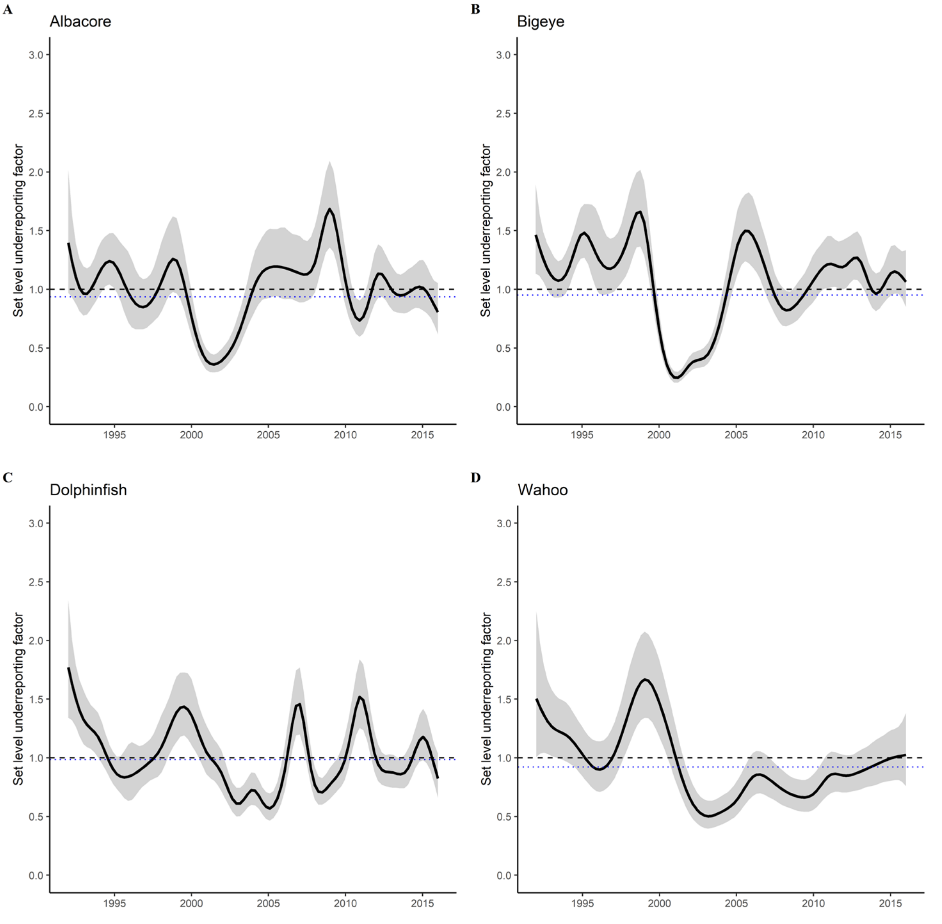

Figure 5. Model estimated observer effect for retainable species: (A) albacore, (B) bigeye tuna, (C) common dolphinfish, and (D) wahoo, 1992–2016. Solid lines (± 95% CI) represent expected magnitude difference in set level reported captures with observer present relative to logbook baseline (dashed line at 1.0). The dotted line represents estimated long-term mean difference over the study period.

95% CI: 3.51–4.46; spearfish: 3.64×, 95% CI: 3.38–3.92; blue marlin: 3.15×, 95% CI: 2.89–3.44).

Though the green sea turtle *Chelonia mydas,* hawksbill sea turtle *Eretmochelys imbricata,* and Kemp's Ridley sea turtle *Lepidochelys kempii* have been caught by PLL vessels according to observer data (142 total interactions), encounters are a rarity, representing roughly 0.002% of the longline catch from 1992 to 2016 (even including unidentified turtle species interactions). Of all 21,336 observer sets from 1992 to 2016, there were 2187 leatherback and loggerhead sea turtle encounters, or 1182 logbook interactions vs 10,250 observer interactions per 100,000 sets (Table 3). The largest discrepancy between the datasets occurred between individuals deemed injured. For marine mammal interactions (short-finned pilot whales, long-finned pilot whales, and Risso's dolphin), zero interactions were reported in the logbook dataset while 397 were reported when an observer was present, or 1862 per 100,000 sets (Table 3).

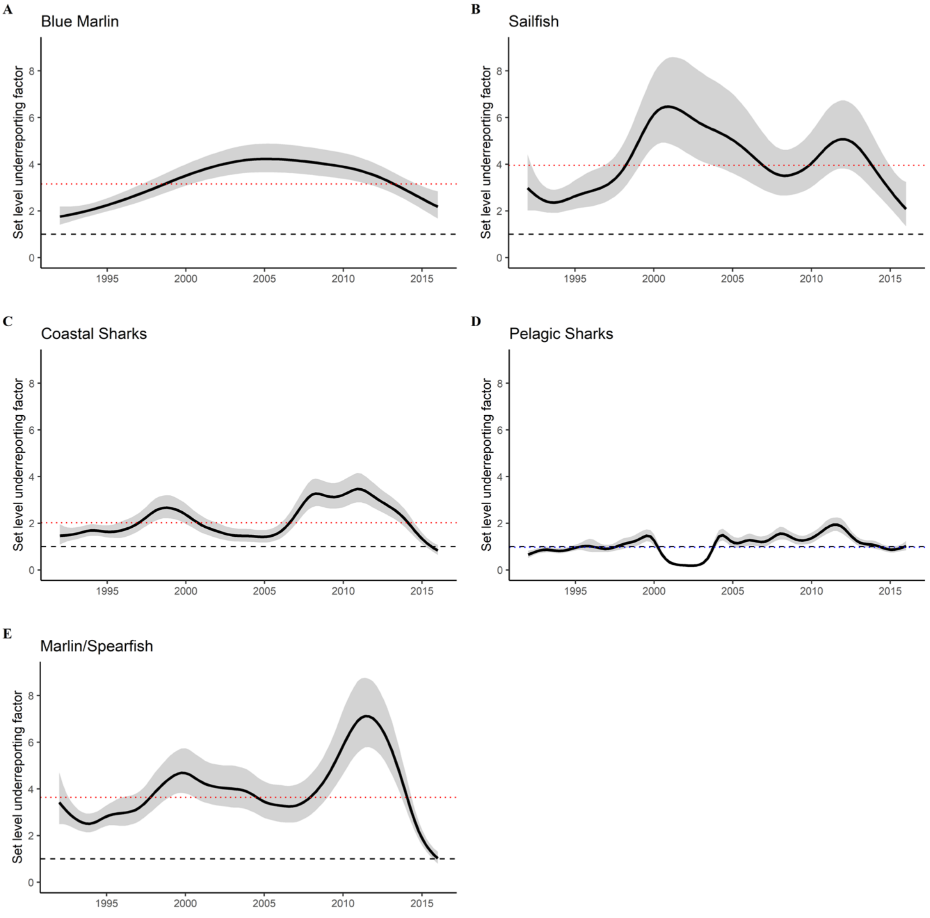

Figure 6. Model estimated observer effect for bycatch species: (A) blue marlin, (B) sailfish, (C) coastal sharks, (D) pelagic sharks, and (E) white marlin/roundscale spearfish/unidentified marlin/spearfish, 1992–2016. Solid lines (± 95% CI) represent expected magnitude difference in set level reported captures with observer present relative to logbook baseline (dashed line at 1.0). The dotted line represents estimated long-term mean difference over the study period.

Discussion

The analyses of each species or grouping of species led to the same result for a majority of bycatch species and retainable species discarded: an apparent under-reporting in the logbook data versus the observer data, and the level of accuracy for self-reported data—in general—is lower than data collected by pelagic fisheries observers. Despite this quantitatively confirmed under-reporting, there is still utility to the logbook data set regarding catch trends for retainable species and time series analyses, especially since placing an observer on every commercial fishing trip is both logistically and economically impossible. While the aim of this paper was to compare differences by species on an annual level, all else equal, there is opportunity to focus on specific species of interest in the future to further explore the impact of the results presented here on finer scales of space and time.

Table 2. Observer effect (expected catch per set reported in presence of observer relative to logbook baseline) for combined retentions and discards by species in order of magnitude from largest to smallest, with 95% confidence intervals. * Denotes significant difference at α = 0.05 (i.e., 95% confidence interval does not overlap 1.0).

Species	Observer Effect (relative to logbook)	95% Confidence Interval
Skipjack tuna (SKJ)	5.37*	4.51 – 6.38
Sailfish (SAI)	3.96*	3.51 – 4.46
W marlin/R spearfish (WHX)	3.64*	3.38 – 3.92
Blue marlin (BUM)	3.15*	2.89 – 3.44
Blackfin tuna (BLK)	2.79*	2.50 – 3.10
Coastal sharks	2.02*	1.90 – 2.15
Bluefin tuna (BFT)	1.37*	1.22 – 1.54
Escolar (GEM)	1.26*	1.19 – 1.34
Yellowfin tuna (YFT)	1.04*	1.00 – 1.08
Swordfish (SWO)	0.99	0.96 – 1.01
Dolphinfish (DOL)	0.98	0.94 – 1.03
Pelagic sharks	0.97	0.93 – 1.01
Bigeye tuna (BET)	0.95*	0.90 – 1.00
Albacore (ALB)	0.94*	0.88 – 1.00
Wahoo (WAH)	0.92*	0.85 – 1.00
Bonito (BON)	0.57*	0.37 – 0.88

A portion of the logbook dataset (>200,000 sets, about 80%) was excluded from the analysis because of quality control issues, i.e., missing data for one or more of the modeled variables, or because an observer was present. Between 1992 and 2016, more than 600 distinct vessels reported at least one PLL set in the logbook data, but less than 300 distinct vessels were observed. In 2000, a large portion of these small day boats left the fishery entirely as a result of the East Florida Coast time area closure. As a small representation of the fleet and logbook data, it is worth noting the possibility that the discrepancy between vessels reporting and vessels observed is not as impactful in the full data set. However, we do not have reason to expect this would introduce a directional bias in the results and does not detract from meaningful comparisons among species.

Further analyses of vessels selected for observer coverage, including specific techniques and/or variables associated with higher recordings of self-reported logbook data, may provide future insight into increasing accuracy across the fleet. While misreporting would have a minimal impact on the indices of abundance if the bias is consistent in magnitude and direction; discards, on the other hand, are absolutes and hence positive or negative bias will lead to biased estimates of the

Table 3. Uninjured, injured, and dead sea turtle and marine mammal interactions per 100,000 sets (Logbook and POP). Note that "Pilot Whales" includes both Globicephala species encountered in the fishery.

Status	Source	Loggerhead sea turtle	Leatherback sea turtle	Pilot whales	Risso's dolphin
Uninjured	Logbook	477	311	0	0
	Observer	9	9	1	0
Injured	Logbook	1,335	1,061	0	0
	Observer	4,884	5,259	1,411	380
Dead	Logbook	6	8	0	0
	Observer	33	56	37	33
Total	Logbook	1,818	1,380	0	0
	Observer	4,926	5,324	1,449	413

total removals from the population. Similarly biased estimates will mean that any measures designed to reduce discards will be difficult or impossible to measure. It is possible that captains who omit data fields might also be less likely to accurately report catch data, or captains in general may tend to under-report sets with no catch, so the "observer effect" might be even greater than is reported here, providing rationale for future opportunities to analyze logbook reporting accuracy. Additionally, a "negative observer effect," meaning more catch reported in the absence of an observer, could be a result of discrepancies in species identification, especially for similar looking species, such as small tunas or a number of coastal and pelagic sharks.

For self-reported data, attempts to verify species-level identifications on non-observed trips have led to the implementation of electronic monitoring systems (EM, i.e., video surveillance) on US Atlantic PLL vessels (79 FR 71594, 2014). Although originally intended for Atlantic bluefin tuna, EM offers additional options to verify self-reported catch and bycatch data without the high cost of deploying an observer. EMS have improved reporting accuracy in other fisheries such as the Australian Eastern Tuna and Billfish Fishery (Emery et al. 2019), though questions remain as to the ability of these systems to quantify species counts as completely and accurately as human observers in the Atlantic PLL fleet (Alhale and Dettloff 2020). As these monitoring systems are implemented and improved over time, logbook data should be reviewed for the effects of changes in self-reporting rates that could affect abundance estimates.

From 1992 until 2016, two major occurrences dramatically altered the US Atlantic PLL industry: closure of the Florida Straits in 2000 (65 FR 47213) and mandatory use of circle hooks in 2004 (69 FR 40733). It is also worth noting that in 1992, there were a total of 339 permitted PLL vessels, but that number decreased to 151 vessels by 2016. As this analysis quantified overall mean discrepancies through 2016, future analyses could similarly assess self-reporting, keeping in mind the implementation of the Individual Bluefin Quota Program (IBQ) in 2017 and the temporary reduction in observer coverage in 2020 as a result of COVID-19.

There is also opportunity to utilize these results in a further developed study associated with certain species, protected areas and time-areas closures such as the DeSoto Canyon closure in the Gulf of Mexico. Through an increased accuracy in logbook data, improved management of area-regulated closures, and potentially even opening a discussion for higher-accuracy-reporting vessels to be granted temporary access to restricted areas is plausible.

Additional drivers may be related to patterns in reporting accuracy. For example, there is strong potential for under-reporting legally retainable species with low market value (e.g., skipjack and blackfin tuna). For species of particular bycatch concern (e.g., sea turtles), there is an incentive to minimize self-reported interactions to avoid penalties or increased regulations. Alternatively, commonly caught species such as the pelagic stingray (*Pteroplatytrygon violacea*) or lancetfish (*Alepisaurus* spp.) have the potential for under-reporting due to minimal economic benefit. A third category for misreporting includes species like escolar, which historically had been considered of lesser or no value and thus discarded but have now become part of the "normal" retained incidental catch (Levesque 2010). Given that mandatory dealer reporting of landings can be matched with logbooks, there is a potential for a higher level of accuracy in self-reporting in recent years for these newly retained species in the fishery. Finally, there are "incidentally caught" species such as blackfin tuna or skipjack tuna which are legally retainable but more commonly discarded due to their minimum market value.

While logbook catch reporting appears to be consistent for target species, the present analyses suggest a potential under-reporting for catches of nontarget and bycatch species. For some species, this under-reporting may be substantial, if unintentional. As fisheries management transitions into an ecosystem-based framework, catches and catch trends will be needed for modeling efforts, which logbook data may not be able to solely and accurately provide for nontarget species. Agencies and other organizations developing ecosystem models for large pelagic species may need to examine multiple data sources to ensure accurate modeling results.

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