Measuring the economic abatement cost of sea turtle bycatch in the Northwest Atlantic Commercial Pelagic Longline Fishery.

Daniel Solís[*], Kathryn Bisack[**], John Walden[**], Paul Richards[***] and Juan Agar[***]

[*] Agribusiness Program, College of Agriculture and Food Sciences, Florida A&M University.

[**] Northeast Fisheries Science Center, National Oceanic and Atmospheric Administration.

[***] Southeast Fisheries Science Center, National Oceanic and Atmospheric Administration.

ABSTRACT

This study estimates the economic cost of reducing the take of sea turtles in the U.S. Northwest Atlantic Commercial Pelagic Longline Fishery. Sea turtles are protected under the Endangered Species Act. The analysis uses an output-oriented stochastic distance frontier methods and drew from a highly unbalanced trip-level panel dataset that had 60 unique vessels that fished between 2006 and 2016. Our results show that mitigating the take of sea turtles is costly. On average, the cost of reducing the take of one sea turtle (or shadow price) equals $36,957. Shadow prices show significant temporal variability and vary by the targeting behavior of the fleets (i.e., tuna vs. swordfish trips). We also find that the technical efficiency of the fishing fleets varies by its targeting behavior. We conclude discussing bycatch management insights from our research.

Keywords: Undesirable outputs; endangered species; commercial fisheries; stochastic frontier; distance function.

JEL: D24; Q22

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INTRODUCTION

One pressing economic, societal and environmental issue affecting commercial fisheries is the production of undesirable outputs. Undesirable outputs are byproducts of production processes that can harm the environment or the economic sustainability of an industry or a geographic area. Most applied economic analyses dealing with undesirable outputs have focused on air and water pollutants such as CO_2, SO_2, waste, noise, etc. In fisheries, undesirable outputs often arise because of economic or regulatory discarding of commercial species and/or the incidentally caught or 'take'[1] of protected species, such as sea turtles and marine mammals[2] (Zhou et al. 2014; Färe et al. 2011; Huang and Leung 2007; Squires et al. 2021). Non-target catch increases harvesting costs because of the added costs of retrieving and removing unwanted catch, replacing lost or damaged gear, and installing bycatch excluder devices. They can also indirectly increase production costs due to the risk of fishery closure (Watson et al. 2006). Additionally, bycatch mortality and its concomitant impact on population sizes can potentially damage the function and structure of ecosystems (Stohs and Heberer, 2011).

In the economic literature, the study of undesirable outputs first centered on who should bear the economic costs imposed by these negative externalities. Pigou's (1932) pioneering work suggested that direct taxes would help mitigate these costs. Coase (1960), on the other hand, argued against the use of taxes and government intervention and instead proposed bargaining between parties to achieve efficient outcomes. These seminal studies led to a wealth of research work on this subject. Cornes and Sandler (1996) offer a good review of this early literature.

Another strand of the economic literature considered the impact of undesirable outputs on the production process. Ethridge (1973) modeled the effects of waste products and byproducts on output and input utilization. Pittman (1981; 1983) underscored the importance of accounting for undesirable outputs when studying economic efficiency and productivity, especially for those industries subject to environmental regulations. Färe et al. (1989) developed a framework for measuring technical efficiency (TE) that penalized the production of undesirable outputs, under the assumption that bad outputs were not freely disposable (e.g., abatement is costly since some

[1] A 'take' under the Endangered Species Act (ESA) is to harass, harm, pursue, hunt, shoot, wound, kill, trap, capture, or collect an ESA listed species, or to attempt to engage in any such conduct.

[2] Sea turtles and marine mammals protected under the Endangered Species Act of 1973, and the Marine Mammal Protection Act of 1972, respectively.

inputs are redirected from producing the desirable outputs to mitigating the production of undesirable ones).

Zhou et al. (2014) reviewed the production economics literature dealing with undesirable outputs and found that most studies concentrated on energy, paper and pulp, and agriculture industries. Our own review of the literature found a limited number of empirical studies accounting for undesirable outputs when estimating production and efficiency models in fisheries. Among these few studies were Färe et al.'s (2006, 2011) work on the United States (U.S.) Georges Bank multi-species otter trawl fishery, Huang and Leung's (2007) article on the Hawaii's long line fishery, Reimer et al.'s (2017) paper on the Alaskan's non-pollock groundfish trawl fishery, and Sheld and Walden's (2018) study on the Northeast U.S. Multispecies Bottom trawlers.

Despite the limited attention to the issue of discarding of undesirable species in the productivity and efficiency literature, it remains a serious environmental and economic concern. Meyer et al. (2017) and Mukherjee and Segerson (2011) show that commercial fishing poses one of the major threats to the marine megafauna and protected species. Furthermore, Färe et al. (2011) warn that ignoring the presence of undesirable outputs when analyzing fishing production processes may inflate production estimates (i.e., productivity, TE, capacity, etc.) due to the omission of environmental costs caused by discarding.

When studying the economic impacts of the incidental take of endangered species, Huang and Leung (2007) argue that production models offer significant advantages over 'regulatory constraint' models. In general, 'regulatory constraint' models derive implicit bycatch abatement valuations based on the forgone benefits from regulatory controls such as area closures for protection of sea turtles (i.e., Curtis and Hicks 2000; Chakravorty and Nemoto 2000). Huang and Leung (2007) argue that 'regulatory constraint' models provide objectionable estimates that are sensitive to the type of regulation imposed. Moreover, these models offer estimates that are only valid for specific time periods precluding intertemporal comparisons. Production models[3], on the other hand, do not require information about specific regulatory policies. Instead, they rely on shadow prices to infer trade-offs between desirable and undesirable outputs. The shadow cost of an undesirable output provides a measure of the cost of reducing (or abating) the take of non-

[3] Production models use mathematical techniques to define the average technological relationship (or the Production Possibilities Frontier (PPF), if a frontier method is used like in this study) between the level of inputs used and the resulting level of outputs for individual firms (fishers in our case) in an industry, accounting for exogenous variables like environment and regulations.

marketable species such as sea turtles and marine mammals (Zhou et al. 2014). If time series data are available, shadow prices can be estimated over time.

The objective of this study is to measure the economic cost of reducing the take of loggerhead (*Caretta caretta*) and leatherback (*Dermochelys coriacea*) sea turtles in the U.S. Northwest Atlantic Commercial Pelagic Longline Fishery (NWACPLF).[4] In doing so, we implement a multi-output stochastic distance function (MOSDF) that models the joint production of commercially valuable species and the undesirable take (bycatch) of sea turtles.

This study adds to the limited literature on undesirable outputs in the fishing industry by offering an empirical application of MOSDF that explicitly accounts for protected species bycatch. Zhou et al. (2014) note that most fishery production studies dealing with undesirable outputs use non-parametric data envelopment analysis (DEA) and that only a few studies have adopted stochastic frontier analyses (SFA), like the MOSDF method. Orea et al. (2005), Felthoven et al. (2009), and Solís et al. (2014), among others, argue that due to the random nature of fishing processes, stochastic models should be the preferred method since they allow for the presence of 'noise', a limitation in traditional DEA models. In addition, the parametric nature of the SFA generates useful information on the relationship between harvest levels and factors of production and the impact of regulatory and environmental variables. From a management perspective, the analysis produces valuable information about production tradeoffs that fishers face when reducing their take of undesirable species.

The rest of this paper is organized as follows. Next, we present a brief description of the NWACPLF and its bycatch issues. Then, we outline the methods and describe the data and the empirical model, followed by a discussion of the results. The article concludes with a summary of the main findings and management implications.

THE NORTHWEST ATLANTIC COMMERCIAL PELAGIC LONGLINE FISHERY AND BYCATCH BACKGROUND

The U.S. pelagic longline fishery began targeting highly migratory species (HMS) in the Atlantic Ocean in the early 1960's. The fishery primarily targets swordfish (*Xiphias gladius)*, yellowfin

[4] In this study we focus on measuring the producer bycatch abatement costs. Dreze and Stern (1990), clarify that bycatch also affects firms in the value chain, consumers, and the society as a whole. Thus, our estimates can also be interpreted as a lower bound estimate of society's willingness to pay to reduce sea turtle bycatch.

tuna (*Thunnus albacores*), and bigeye tuna (*Thunnus obesus*) but also catches other species such as dolphinfish (*Coryphaena hippurus*), albacore tuna (*Thunnus alalunga*), and pelagic sharks including mako, thresher, porbeagle sharks, and various coastal sharks. Longline vessels target HMS along sea surface temperature fronts (or breaks).

Longliners have a mainline that can extend from five to forty miles in length, with approximately 20 to 30 baited hooks per mile. The longlines can be rigged differently depending on the target species. Modifications include depth of the set, hook type, hook size, bait, and light sticks, which are typically used when targeting swordfish. When targeting swordfish, longlines are deployed at sunset with light sticks and hauled at sunrise to take advantage of swordfish nocturnal near-surface feeding habits (NMFS 1999). Light sticks suspended on the line at certain depths attract baitfish, which can then attract pelagic predators. Day sets are the common practice when targeting tuna (Hsu et al. 2015).

Atlantic HMS are managed under the dual authority of the Magnuson-Stevens Fishery Conservation and Management Act (Magnuson-Stevens Act), and the Atlantic Tunas Convention Act (ATCA). National Oceanic and Atmospheric Administration (NOAA) National Marine Fisheries Service (NMFS) has the primary authority for developing and implementing Atlantic HMS fishery management plans. The U.S. harvests only a small share of the Atlantic-wide HMS catch (NOAA 2018). These data are recorded in NOAA's Fishing Vessel Logbook for HMS database. According to the International Commission for the Conservation of Atlantic Tunas (ICCAT), the U.S. landed 14.6% (1,522 mt) of the total Atlantic swordfish landings in 2016. The U.S. is an active ICCAT member and routinely contributes to the stock assessment conducted by its Standing Committee on Research and Statistics (SCRS). NMFS implements conservation and management measures adopted by ICCAT and other relevant international agreements, consistent with ATCA and the Magnuson-Stevens Act.

The U.S. Atlantic Pelagic Longline fishery is managed using limited access permits, catch shares (i.e., Individual Bluefin Quota Program), gear restrictions, time/area closures, and bycatch avoidance measures (e.g., circle hooks). While this study focuses on the mid-Atlantic Bight (MAB) and Northeast Coastal area (NEC) swordfish and bigeye tuna fishery, there are four other distinct fisheries including the Gulf of Mexico yellowfin tuna fishery, the southern Atlantic (Florida East Coast to Cape Hatteras) swordfish fishery, the U.S. Atlantic Distant Water swordfish fishery, and the Caribbean tuna and swordfish fishery (also see Figure 1 for U.S. statistical reporting areas).

Pelagic longline vessels also frequently interact with protected species such as marine mammals, sea turtles and sea birds; as such, they have been classified as a 'Category I fishery' based on the guidelines of the Marine Mammal Protection Act (MMPA) of 1972. Category I fishery is one that has incidental take levels greater than 50 percent of any MMPA stock's Potential Biological Removal rate per year, the allowable level of human-induced mortality for a marine mammal stock (MMPA 1972, section 1386). An observer program has been in place since 1992 to document finfish bycatch, characterize fleet behavior, and quantify interactions with protected species. Data collection priorities have been to collect catch and effort data of the U.S. Atlantic pelagic longline fleet on HMS along with protected species takes. We used this data (i.e., observed sea turtles takes) with the HMS logbook data to estimate the economic value of preventing sea turtle take in the pelagic longline fishery which uses circle hooks (in place of a J style hook) as its main bycatch avoidance measure.

The use of 'circle' hooks (size 16/0 or greater) was mandated in August 2004 (69 Federal Register 40734, July 6, 2004) based upon experimental studies conducted during 2001-2003 in the Northeast Distant Water (NED) fishing area (Watson et al. 2005). Circle hooks' shape and smaller openings reduce the likelihood of sea turtles and marine mammals ingesting hooks or being caught. When hooking does occur, they are superficial and primarily in the mouth, which reduces internal injury and allows for a safer release. Switching to circle hooks and mackerel bait (from squid bait) helped reduce the incidental capture of loggerhead sea turtles by 71%-90% and leatherback sea turtles by 51%-66% (Watson et al., 2005). These measures continue to be in place today (NOAA 2018).

NOAA's HMS logbook data shows that between 2006 and 2015, there were 114 longline vessels in the U.S. Atlantic, which in aggregate earned $32.41 million in revenues per annum. Roughly, 45% of these vessels earned 30% of the revenues in the NEC and MAB area. Between 2006 and 2015, 445 loggerhead and 353 leatherback sea turtles were bycaught in the U.S. Atlantic (Figure 2). Approximately 40% of the loggerhead and 33% of the leatherback caught in the U.S. Atlantic, took place in the NEC and MAB regions.

METHODS

We implement a MOSDF model to estimate the cost of sea turtle bycatch abatement accounting for temporal and geographic differences, and vessel heterogeneity.[5] In general, a MOSDF measures the maximum amount by which an output vector can be proportionally expanded with a given input vector. The maximum feasible output vector maps the 'best practice' frontier for the industry. This best practice frontier depicts the boundary of the production possibility set. MOSDF models are well suited for the study of production processes that account for the presence of multiple desirable outputs in fisheries (Solís et al. 2014), and it can also be adapted to accommodate for the incidence of undesirable outputs, such as the bycatch of sea turtles (Färe et al. 1993). MOSDF is advantageous for analyzing production processes in commercial fisheries because it does not assume that all deviations from the frontier are solely explained by inefficiency, but also allows for stochastic or random events. In addition, the parametric nature of the MOSDF generates valuable information on the relationship between outputs (harvest) levels and inputs (factors of production) and regulatory and environmental variables (Van Nguyen et al. 2021).

Following Orea et al. (2005) and Coelli and Perelman (1999) a translog output distance function can be rewritten as:

$$lnD_{oi} = \beta_0 + \sum_{m=1}^{M} \beta_m lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} lny_{mi} lny_{ni} + \sum_{k=1}^{K} \beta_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{km} lnx_{ki} lny_{mi} + \sum_{j}^{J} \theta_j G_j + \sum_{h}^{H} \theta_h lnC_h + \omega T + \rho T^2 \quad (1)$$

where D_{oi} denotes the output distance function measure, y_{mi} and x_{ki} are, respectively, the production level of output *m* (including desirable and undesirable outputs) and the quantity of input *k* used by vessel *i*, G_j is a vector of *j* dummy variables, and C_h is a vector of *h* control variables.

To satisfy the necessary conditions for a well-behaved output distance function, the function is normalized by an arbitrary output, and symmetry is imposed by setting $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$ (Coelli and Perelman 1999). After imposing these restrictions, the method estimates the

[5] A directional distance function procedure was also attempted; however, the results were not satisfactory. An anonymous review also suggested the use of fixed effect models to capture 'fixed' skipper and/or vessel effects. However, the due to highly unbalanced nature of our data, we were not able to implement alternative panel data techniques.

distance from each observation to the frontier as inefficiency (*i.e.*, $ln\mathrm{D}_{oi} = -u_i$) and adds a random noise variable (v_i) into the model:

$$-lny_{1i} = \beta_0 + \sum_{m=2}^{M} \beta_m ln\frac{y_{mi}}{y_{1i}} + \frac{1}{2}\sum_{m=2}^{M}\sum_{n=2}^{M} \beta_{mn} ln\frac{y_{mi}}{y_{1i}} ln\frac{y_{ni}}{y_{1i}} + \sum_{k=1}^{K} \beta_k lnx_{ki} +$$
$$\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=2}^{M} \beta_{km} lnx_{ki} ln\frac{y_{mi}}{y_{1i}} + \sum_{j}^{J} \theta_{hj} G_j + \sum_{h}^{H} \theta_h lnC_h + +\omega T +$$
$$\rho T^2 + v_i + u_i \qquad (2)$$

where v_i, is assumed to be an independent and identically distributed normal random variable with 0 mean and constant variance, iid [N~$(0,\sigma_v^2)$]. v_i is intended to capture random events, and its variance, σ_v^2, is a measure of the importance of random shocks in determining variation in output. Conversely, the inefficiency term u_i is non-negative and it is assumed to follow a half-normal distribution. Differences across vessels in the u_i are intended to capture differences in skill or efficiency (Alvarez and Schmidt 2006). To facilitate the interpretation of the parameters, the left side of the equation is set to ln y_1 rather than -ln y_1 as suggested by Coelli and Perelman (1999).

To estimate TE scores in this model we followed Jondrow et al. (1982):

$$TE_i = D_{oi} = \exp(\mathrm{E}(-u_i)|v_i - u_i) \qquad (3)$$

To estimate marginal (bycatch) abatement cost, the MOSDF needs to satisfy the weak disposability assumption for the undesirable output since reducing bycatch imposes a cost in the form of a reduction in the production of desirable outputs when all inputs are held constant. The weak disposability assumption is consistent with existing regulations that require a reduction in sea turtle takes. Take reduction is related to the opportunity cost of the desirable output due to the consumption of scarce inputs. Imposing linear homogeneity in outputs ensures that the weak disposability assumption is met (Huang and Leung 2007).

Since a MOSDF measures the optimum value that brings the output set to the frontier holding inputs constant, we also ensure that the MOSDF is non-increasing in undesirable output(s) and non-decreasing in desirable outputs. Following Fare and Grosskopf (2004), we impose restrictions on the signs of the derivative to obtain non-positive shadow prices for the undesirable outputs.

Following Huang and Leung (2007) we estimate, the shadow price of a sea turtle (p_n) relative to a desirable output (p_m) as:

$$p_n = \frac{\partial Doi(x,y,u,t)/\partial u_n}{\partial Doi(x,y,u,t)/\partial u_m} \times p_m \tag{4}$$

The estimated shadow price reflects the trade-off between these two outputs (Chambers et al. 1998).

DATA AND EMPIRICAL MODEL

Detailed trip-level data on harvest composition, fishing gear and effort, fishing grounds, crew size, and vessel characteristics between 2006 and 2016 were obtained from NMFS. Sea turtle bycatch data was acquired from the Pelagic Observer Program (POP), which reports turtle takes from the MAB and NEC regions. After merging these two data sets, we obtained a highly unbalanced panel dataset of 302 trips taken by 60 unique vessels. This database captures the activity of approximately 40% of the fleet operating in the MAB and NEC regions. Figure 3 shows the sampled fleet size and the number of trips taken between 2006 and 2015.

The empirical model had three desirable outputs (species or species' groups): swordfish (y_1); tuna (all species, y_2); and other marketable species (y_3); one undesirable output: total number of sea turtle takes (y_4)[6]; and five inputs: crew size (x_1); total number of hooks (x_2); vessel length (x_3), which is used as a proxy for fixed capital; soak time in hours (x_4); and number of sets per trips (x_5). Similar empirical specifications can be found in Solís et al. (2015), Felthoven *et al.* (2009), Huang and Leung (2007) and Orea *et al.* (2005), among others. Figures 4 and 5 show commercial landings, and loggerhead and leatherback takes over time, respectively. Observed sea turtle takes fluctuate from a low of 6 in 2014 to a high of 61 in 2008. Garrison and Stokes (2020) describe the cyclic pattern in sea turtle bycatch rate for the NWACPLF.

To control for fishing conditions, we included stock (spawning biomass) indices for the major species[7], swordfish and tuna (bigeye, bluefin and yellowfin; this data were provided by

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[6] Since bycatch is a rare event, both species of sea turtles (loggerhead and leatherback) were pooled into one variable and a monotonic transformation was applied by adding a small constant (0.001) to each observation.

[7] See Alvarez (2021) for a good discussion on the use of fish stock on production frontier analyses.

NMFS), sea surface temperature (SST) for average location of the trip[8], and quarterly dummy variables (Jin et al., 2002; Hsu et al. 2015; Agar et al. 2017). Figure 6 shows stock indices over time.

To account for ecological differences between the NEC and MAB fishing grounds we included a geographical dummy variable, which was set equal to one if the vessel operated in the NEC region. Time trends, in both the linear and quadratic forms, were introduced to account for technical change.[9] Table 1 reports summary statistics of the data used in the analysis.

RESULTS AND DISCUSSION

Model performance and characteristics of the technology

Table 2 presents the parameter estimates of the stochastic *translog* MOSDF model.[10] All but one of the first-order input and output parameters were statistically significant and all the parameters displayed the expected signs consistent with economic theory. The null hypothesis that technical inefficiency did not exist (H_o: $\lambda = 0$) was rejected at the 1% level suggesting that the stochastic production frontier specification was preferable to the conventional production function specification. The standard errors for u and v were statistically significant indicating that skill and random shocks are important factors explaining the underlying technology. The estimated value of λ, the ratio of the standard errors for u and v ($\lambda = \sigma_\mu/\sigma_v$), was equal to 1.725, indicating that catch (revenue) differences across vessels can be better explained by fishing skill (or TE) rather than by random shocks (or luck).

As expected, output levels were positively correlated with crew size, number of sets per trip, soak time and number of hooks. The vessel length coefficient was positive but not statistically significant. The empirical model controlled for abundance levels, fishing area, seasonality (quarters), and annual variability. Fish abundance coefficients were, as expected, positive for both tuna and swordfish stocks but only statistically significant for tuna. These results suggest that an increase in fish abundance causes an upward shift of the production possibility frontier which is

[8] SST data was obtained from the NASA's PODACC project (https://podaac.jpl.nasa.gov/).

[9] An anonymous reviewer suggested the use of a dummy variable to capture the relationship between set depth and sea turtle bycatch. Unfortunately, our data is not rich enough at the set level to utilize a production frontier. Thus, we defined the unit of time as the fishing trip, which aggregates both the soak time and number of sets to be inputs in production model. However, this is an important point for the development of conservation policies that deserves further research.

[10] The *translog* functional form was selected over other specification based on generalized likelihood ratio test.

consistent with previous research (Jin et al. 2002; Solís et al. 2020; among others). As in Hsu *et al.* (2015), SST coefficient was statistically significant and negatively correlated with catch levels, suggesting the catch rates are higher in cooler waters.

The NEC regional dummy variable was positive but not statistically significant indicating comparable productivity levels between the two fishing grounds. The statistical significance of quarterly dummies suggests that productivity levels increase in the late winter and fall. The time trend was positive but not statistically significant. Figure 7 displays the evolution of TE scores. The average level of TE for the studied sample was approximately 0.722, suggesting that, on average, the fleet operated at 72% of their potential. In other words, if the fleet was fully efficient (i.e., operating on its best practice frontier) then it could increase its production by 28% with the existing inputs. Figure 8 shows the Kernel density distribution of TE by trip types (tuna and swordfish trips). The distribution of TE scores for those vessels targeting tuna was significantly higher and narrower than for those targeting swordfish. TE averages were similar between the two fishing grounds.

Shadow price of the undesirable output

The shadow price for sea turtles (p_n) was calculated, as shown in Equation 4, by multiplying the marginal rates of transformation between sea turtle bycatch reduction and tuna harvest ($\frac{\partial D(x,u,t)/\partial u_n}{\partial D(x,u,t)/\partial u_m}$), by the price of tuna or (p_m) in our case. We used a weighted tuna price (weighted average of all tuna species) because tuna species accounted for over 59% of the total revenues generated by the fleet. Swordfish and the other (marketable) species accounted for the remaining 35% and 6% of the revenues, respectively (Table 3).

Table 3 presents the estimated average shadow price of a sea turtle (i.e., the cost, in U.S. dollars, per sea turtle take) by year and for the entire study period (2006-2015). These estimated values display significant temporal variability, ranging from \$11,818 in 2008 to \$106,916 in 2014 (all values are in 2016 U.S. dollars). It is important to highlight that in 2014 only six sea turtles were reported as incidental catch, a value significantly lower than the annual-average of thirty turtle takes reported in the sample. This temporal variation in the shadow prices can be explained by: 1) changes in the ratio of sea turtle bycatch to tuna harvest; and, 2) the price of tuna. In general, lower turtle catch rates are associated with higher shadow prices, which is reflected by the estimated Pearson correlation between turtle bycatch and shadow prices of -0.735. High tuna prices make it costlier to reduce sea turtle bycatch, *ceteris paribus*.

The average shadow price of a sea turtle for the 10-year period was equal to $36,957, which translates to an average conditional 'per trip' cost of $19,532.[11] As indicated earlier, our estimates exhibit significant temporal variability as shown by their large standard deviation ±$26,861. These results are in line with previous studies. For instance, in the Hawaii's longline fishery, Huang and Leung (2007), and Curtis and Hicks (2000) reported sea turtle shadow prices of $35,736 and $41,624, respectively.[12] These two studies based their shadow price estimates as forgone gross revenues using non-parametric methods. Similarly, Chakravorty and Nemoto (2000), using a forgone profit framework, estimated a shadow price of $14,000 for sea turtles in Hawaii. This last estimate is markedly lower because profit models explicitly account for production costs.

We also estimated the average trip-level sea turtle shadow price by target species (i.e., tuna vs. swordfish trips). In the NW Atlantic region, longlines target swordfish at night and tuna during the day. Because fishers' targeting behavior, influences the catch composition and input use (e.g., number of light sticks used per set and the average set time) shadow prices are expected to vary too. Our estimates confirm that shadow prices vary by the species targeted. On average, vessels targeting swordfish have slightly lower bycatch abatement costs ($37,571) than those targeting tuna ($39,625).[13] This difference is statistically significant based on a t-test with a p-value < 0.001. These results suggest that cost-effective bycatch reducing management proposals should encourage vessels targeting swordfish to reduce their take of sea turtles.

Last, we estimated shadow prices by fishing ground. Between 2006 and 2015, 104 sea turtles were incidentally caught in the MAB and another 191 in the NEC. Despite of the difference in the total number of takes, shadow prices were similar in these two areas ($35,754 in the MAB and $37,521 in the NEC). The difference between these two values were found not statistically significant, indicating that the average cost of reducing the sea turtle bycatch does not vary by fishing ground.

[11] This value was estimated using conditional survival probabilities per event (see Montgomery et al., 1994).

[12] These values were transformed from the original studies into 2016 U.S. dollars to make them comparable with our results.

[13] It is important to indicate, that we used the market price of tuna the estimation of equation 4 for both cases, vessels targeting tuna and swordfish, to make the estimates comparable.

CONCLUDING REMARKS

We estimated the shadow price of reducing the take of sea turtles in the U.S. NWACPLF using a multi-output stochastic distance function. The shadow price of an undesirable output provides a reliable proxy of the forgone revenues due to bycatch mitigation. Our study adds to the literature by accounting for temporal, geographic differences and vessel heterogeneity in the estimation bycatch abatement costs, a limitation found in previous studies that used 'regulatory constraint' models. The parametric nature of the model also generates valuable information on the relationship between harvest levels and factors of production and the impact of regulatory and environmental variables.

We find that reducing the take of sea turtles in the NWACPLF is costly. The longline fleet cannot decrease turtle mortality without losing revenue. The 10-year average shadow price for a sea turtle was \$36,957, which represents an average conditional cost 'per trip' of \$19,532. These estimates are high considering that the average revenue per trip was \$24,322. The model can also produce shadow prices that vary by trip characteristics (e.g., targeted species, location, season, etc.) which can be used to tailor different avoidance and bycatch mitigation management policies. For instance, vessels targeting tuna were found to have, on average, higher shadow prices than those targeting swordfish indicating that bycatch abatement was more expensive for tuna vessels. Therefore, if managers are interested in lowering bycatch abatement costs, then they should consider management proposals that encourage reducing 'sea turtle takes' in the swordfish fishery. Shadow prices can also be used to inform about policy tradeoffs dealing with time-area closure proposals.

Although shadow prices can offer valuable insight, the complexity and scope of sea turtle bycatch issues may require a combination of approaches. Squires et al (2021) identifies four main approaches: (1) private solutions, including voluntary, moral suasion, and intrinsic motivation such as nesting protection projects (Gjertson et al. , 2014; Moore et al. 2009); (2) 'command-and-control' regulation such as gear modifications (e.g. Watson et al. 2005) and bycatch hotspot modeling (FAO, 2009; Ecocast[14]); (3) incentive-based; and (4) hybrid of 'command and control' and incentive-based regulation using liability laws. Clearly, the design of sound sea turtle conservation and protection policies requires examining biological, economic, social, and equity factors simultaneously (Kitts et al., 2021; Bisack and Magnusson, 2016; Squires et al. 2021).

[14] https://coastwatch.pfeg.noaa.gov/ecocast/map_product.html

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Table 1. Observed trip-level statistics of variables used in the empirical model

Variable (Units)	Mean	Std. Dev.	Min	Max
Swordfish (lbs.) (y_1)	2,038	3,418	0.1	30,106
Tuna (lbs.) (y_2)	3,389	3,622	0.1	22,006
Other (lbs.) (y_3)	1,034	1,255	0.1	6,553
Loggerheads (No.) (y_4)	0.60	1.57	0.0	15
Leatherback (No.) (y_4)	0.36	0.96	0.0	9
Crew (No.) (x_1)	3.96	0.79	2.0	6
Length (foot) (x_3)	57.30	11.75	39.0	85
Set (No.) (x_5)	6.00	5.75	1.0	24
Soak time (hrs.) (x_4)	20.00	5.81	6.0	46
Hooks (No.) (x_2)	4,787	3,489	320.0	18,502

Table 2. Parameter estimates of the output distance function

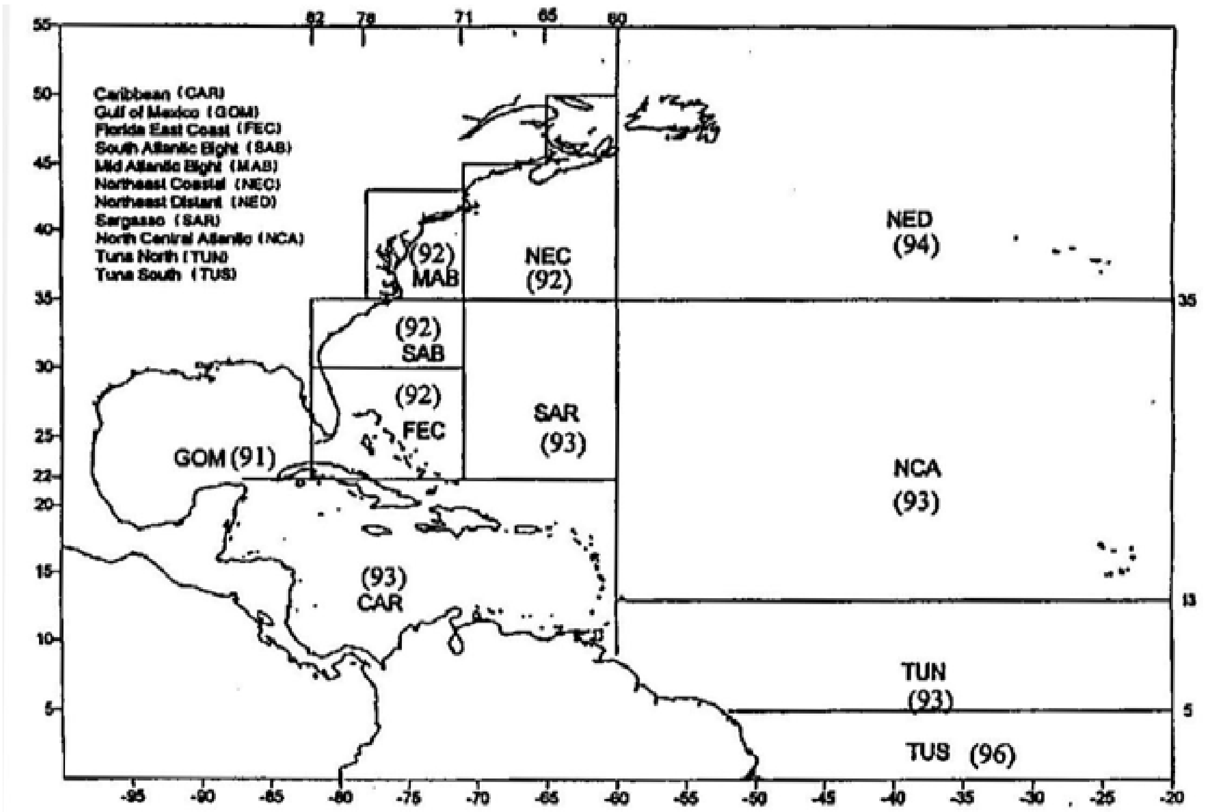
Parameter	Coefficient	Parameter	Coefficient
y_2	-0.266***	x_{34}	-0.0546***
y_3	-0.173***	x_{45}	0.070*
y_4	-0.073***	y_2x_1	0.003
y_{22}	-0.322***	y_2x_2	0.029*
y_{33}	-0.031***	y_2x_3	-0.046*
y_{44}	-0.014**	y_2x_4	-0.038***
y_{23}	0.250	y_2x_5	-0.019
y_{24}	0.058*	y_3x_1	-0.036***
y_{44}	-0.427	y_3x_2	-0.002
x_1	0.469***	y_3x_3	0.099***
x_2	0.179*	y_3x_4	0.0701*
x_3	0.061	y_3x_5	0.0028
x_4	0.029**	y_4x_1	-0.045
x_5	0.497***	y_4x_2	-0.074*
x_{11}	1.481	y_4x_3	0.083
x_{22}	-0.888	y_4x_4	0.087
x_{33}	0.246*	y_4x_5	0.166
x_{44}	0.186*	NEC	0.267
x_{55}	-0.060	Stock (Tuna)	0.071***
x_{12}	0.032***	Stock (Swordfish)	0.052
x_{13}	-0.580	SST	-0.245**
x_{14}	0.070*	Q_1	0.347**
x_{15}	0.003	Q_2	0.115
x_{23}	0.029*	Q_4	0.218*
x_{24}	-0.545	t	0.015
x_{25}	-0.202	t^2	0.004
x_{34}	0.042*		
Constant	5.536***		
Sigma-u	0.698***		
Sigma-v	0.405***		
Λ	1.725***		
Log-Likelihood	-232.5		
N	302		

*P < 0.10; **P < 0.05; ***P < 0.01.
Note: y_1 (swordfish) is absent from the estimates because it was used to impose homogeneity.

Table 3. Total revenue by year and species

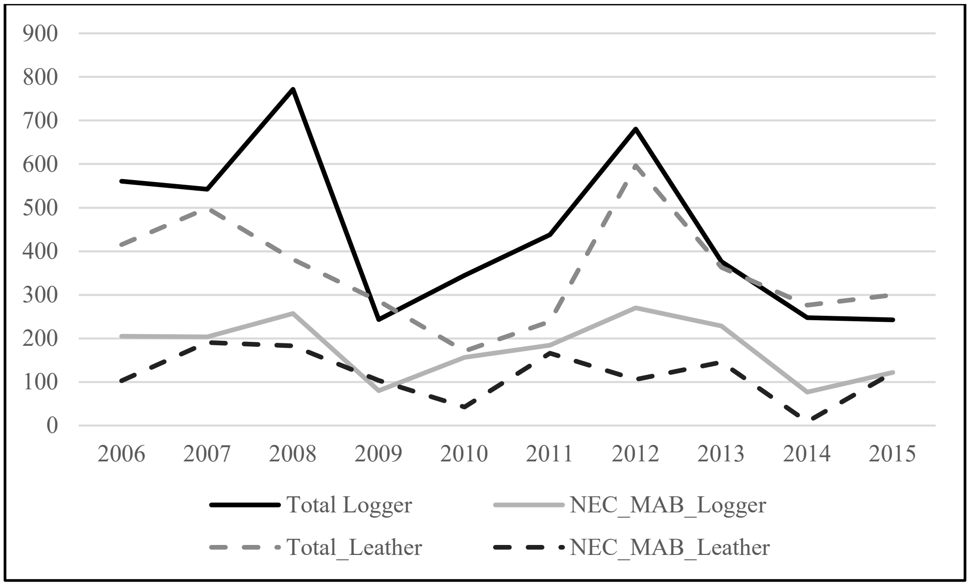
Year	Swordfish	Tuna (all species)	Other	No. Turtles Captured	Total Revenue	Overall Shadow Price Sea Turtle
2006	139,890	236,133	19,157	22	395,180	20,369
2007	236,874	248,464	21,298	30	506,636	19,150
2008	356,273	235,190	33,881	60	625,344	11,818
2009	279,252	354,849	57,508	18	691,609	43,570
2010	239,546	577,021	47,214	22	863,781	44,522
2011	286,657	531,217	53,219	28	871,093	35,277
2012	207,594	533,786	48,567	32	789,947	27,993
2013	357,241	547,048	74,544	48	978,833	23,124
2014	145,040	534,125	66,552	6	745,717	106,916
2015	229,905	581,051	66,009	27	876,965	36,830
Average	**247,827**	**437,888**	**48,795**	**29.3**	**734,511**	**36,957**

Figure 1. The geographic zones are referred to as Caribbean (CAR), Gulf of Mexico (GOM), Florida east coast (FEC), South Atlantic Bight (SAB), Mid-Atlantic Bight (MAB), northeast coastal (NEC), northeast distant (NED), Sargasso Sea (SAR), north central Atlantic (NCA), tuna north (TUN), and tuna south (TUS).



Source: Cramer and Adams (2000).

Figure 2. NEC/MAB loggerhead and leatherback bycatch estimates (2006-2015).



Source: Fairfield et al. (2006) to Garrison and Stokes (2020)

Figure 3. Number of vessels and trips by year.

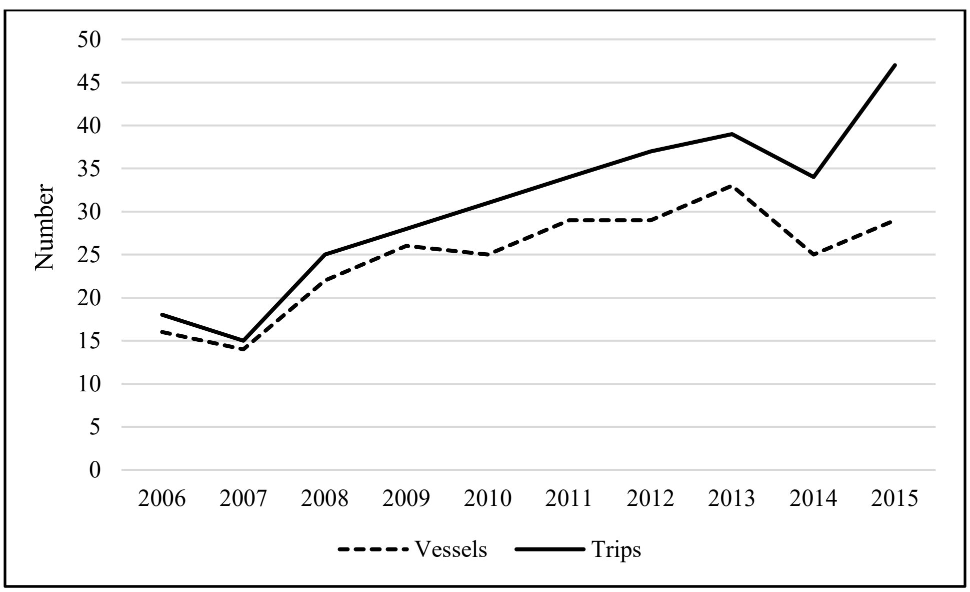


Figure 4. Production of desirable outputs by year

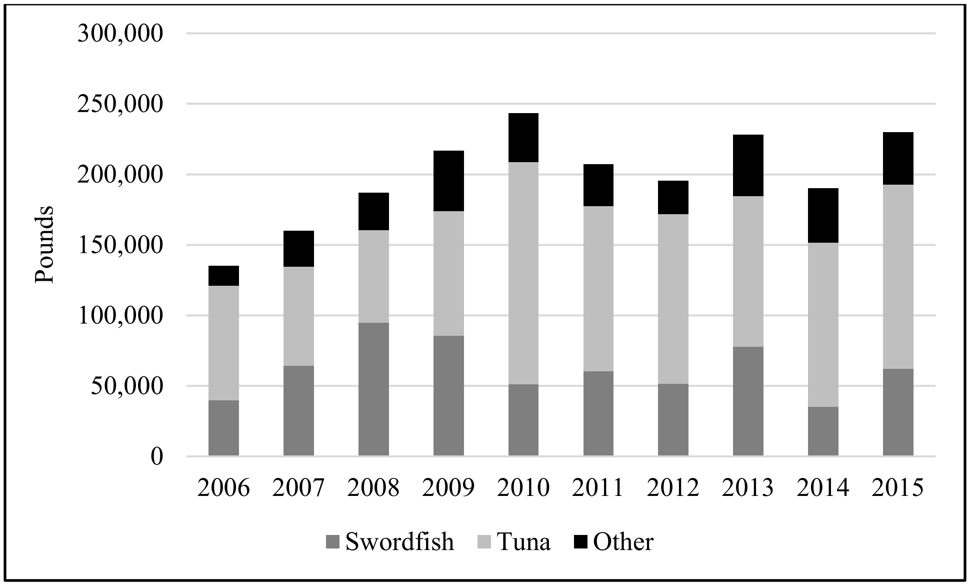


Figure 5. Sea turtle takes by year.

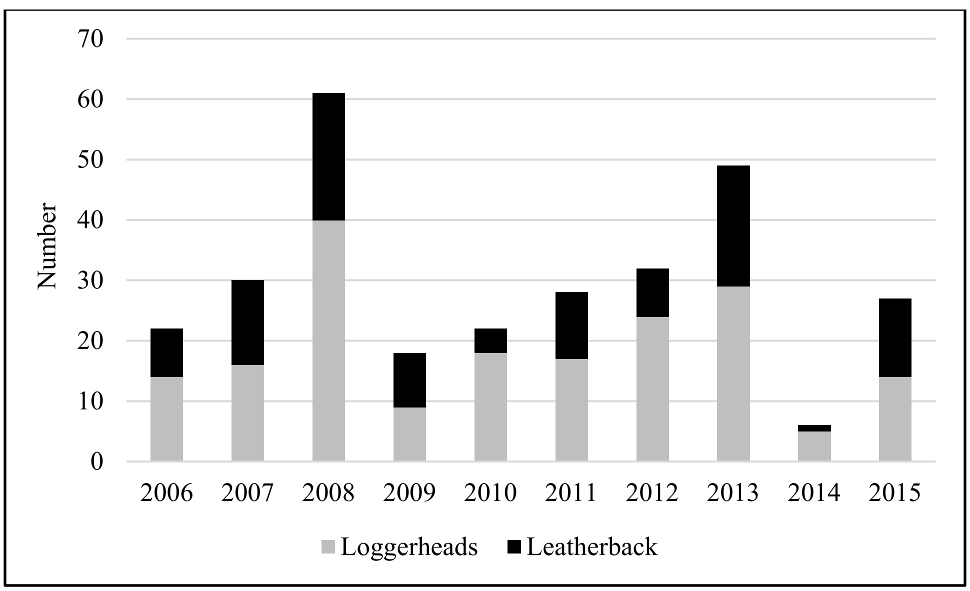


Figure 6. Spawning biomass estimates by year.

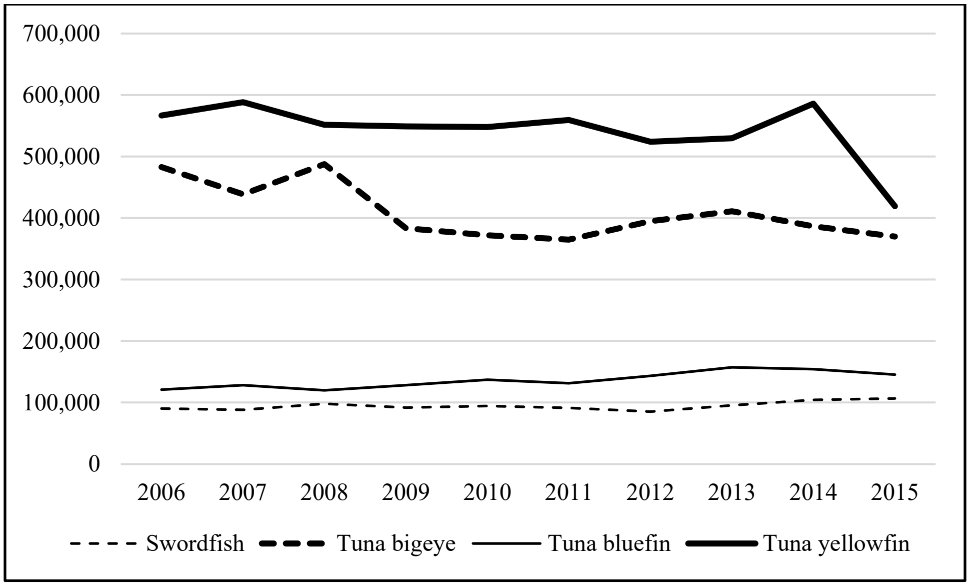


Figure 7. Technical Efficiency Scores (2006-2015).

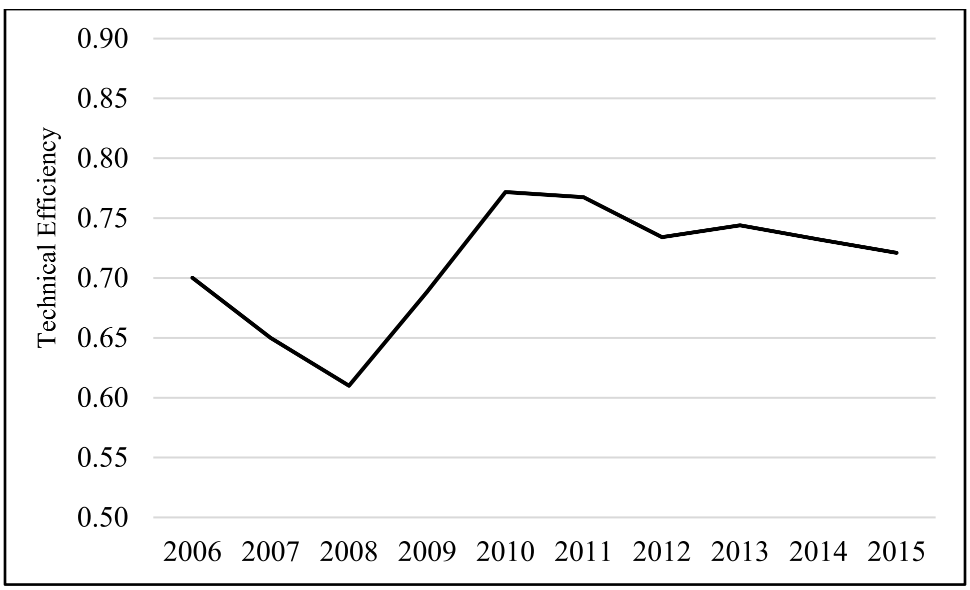


Figure 8. Kernel density distribution of TE by trip type.