ICES Journal of Marine Science, 2025, Vol. 82, Issue 7, fsaf124
https://doi.org/10.1093/icesjms/fsaf124
Received: 12 December 2024; **revised:** 3 July 2025; **accepted:** 4 July 2025
Original Article

International Council for the Exploration of the Sea
Conseil International pour l'Exploration de la Mer

The importance of fleet definition for estimating economic exposure of the summer flounder fishery to offshore wind farms

Meghna N. Marjadi [1,2,*], Andrew W. Jones [1], Anna J. M. Mercer[1], Benjamin Galuardi [3,2], Steven X. Cadrin [2]

[1]Northeast Fisheries Science Center, Narragansett, Rhode Island 02882, USA
[2]Department of Fisheries Oceanography, School for Marine Science and Technology, University of Massachusetts Dartmouth, New Bedford, Massachusetts, 02744, USA
[3]Greater Atlantic Regional Fisheries Office, Gloucester, Massachusetts 01930, USA

*Corresponding author. Department of Fisheries Oceanography, School for Marine Science and Technology, University of Massachusetts Dartmouth, New Bedford, 02744, USA. E-mail: mmarjadi@umassd.edu

Abstract

As offshore wind development continues across the globe, accurate spatial data are required to characterize fishing activity, inform wind farm siting decisions, and estimate economic exposure. We assess the influence of fishing behavior and fleet definition within a multispecies fishery on coarse (logbook-based) footprint biases using a precise (GPS-based) approach. We constructed precise footprints for 838 trips that caught summer flounder (*Paralichthys dentatus*) trips and 1439 trips that caught any species in the Summer Flounder, Scup (*Stenotomus chrysops*), and Black Sea Bass (*Centropristis striata*) Fishery Management Plan from 2016 to 2021. Using the precise footprints as a ground truth, we compared the intersections and estimated economic exposure between coarse footprints (restricted to the 90th, 75th, 50th, and 25th percentiles) for 37 wind farms in the northeast USA. Unrestricted coarse footprints (90th percentile) consistently identified all "true" intersections with wind farms while also overestimating economic exposure. For the multispecies fisheries, restricting footprints between 25th and 50th percentile yielded the most accurate estimates of economic exposure. This contrasts previous work that found the 25th percentile was most accurate for the targeted longfin squid (*Doryteuthis pealeii*) fishery, highlighting the importance of fleet definition in this process. Replicating this approach for other fisheries will allow development of a tool to accurately estimate economic exposure by restricting coarse footprints in the absence of fine-scale data.

Keywords: offshore wind; fishing footprints; fishery dependent data; economic exposure; study fleet

Introduction

Power production from offshore wind is rapidly developing around the world, including across the northeast USA, in an effort to shift energy usage to more renewable sources (Methratta et al. 2020). As of July 2024, the United States Department of Interior has approved projects that will produce 13 gigawatts of energy from offshore wind sources (DOE 2023, DOI 2024). Currently, the majority of proposed offshore wind leases and planning areas are in the northeast USA, where designated lease areas cover 930 777 ha (2.3 million acres) (Methratta et al. 2023). Installation of offshore wind supports national strategies to decrease reliance on fossil fuels, reduce carbon emissions, and mitigate climate change effects. However, proposed wind developments will have impacts for marine ecosystems and will overlap with areas that are already being used by other marine industries, like commercial and recreational fisheries (Willsteed et al. 2017, Gill et al. 2020). In the northeast USA, there is growing concern that offshore wind energy development will impede sustainable seafood production and introduce economic hardship for fishing communities (Scheld et al. 2022, Chaji and Werner 2023). Thus, understanding spatial conflicts and socioeconomic implications of offshore wind for the commercial fishing community have risen to the top as research priorities for offshore wind development (Methratta et al. 2023).

In many cases, offshore wind farms overlap with historical fishing grounds and displace fishing activity (Gray et al. 2016, De Backer et al. 2019, Gill et al. 2020). Although fishing within wind farms is allowed in the USA, the feasibility of doing so will vary based on many factors, including vessel size, gear used, vessel operator experience, and weather conditions (Methratta et al. 2020). For example, bottom-tending mobile gear (e.g. bottom trawls and dredges) may be more challenging to operate near turbine structures than fixed gear (e.g. trap, rod, and reel), because of the risk of hangs (having the gear become stuck). Hangs on turbine scour protection or undersea cable protection could lead to gear loss and be reflected in insurance coverage and gear-specific premiums, which may cause an indirect exclusion from fishing near wind farm structures for some operators (Gill et al. 2020, Methratta et al. 2020). Exclusion from historical fishing areas and activities will likely have broader socioeconomic consequences (e.g. increased transit costs, lower profit margin, loss of markets for some seafood products, loss of jobs, environmental justice), for at least some fisheries and for local communities (NEFSC 2024).

In the USA, offshore wind developers have been tasked with allocating funds to compensate commercial fishers for revenue loss due to offshore wind installation. State agencies and individual developers have used a variety of commercial fishing data and different mapping and trip selection approaches that have produced vastly different estimates of economic exposure. For example, Livermore (2017) used vessel trip reports and Vessel Monitoring System (VMS) data to quantify exposure. An alternative approach using vessel trip reports and observer data was developed by the NOAA Northeast Fisheries Science Center (DePiper 2014, Benjamin et al. 2018). Additionally, some estimations have been based on all purported trips for a specific fishery, while others have only evaluated trips with potential spatial overlaps. Inconsistent methods of economic exposure estimation may hinder accurate and equitable compensation for commercial fishers who are excluded from historical fishing grounds. Thus, there is a need to evaluate a diverse set of approaches and develop an accurate and standardized approach to estimate economic exposure for commercial fishers that operate in areas slated for offshore wind energy development (Hogan et al. 2023, Livermore and Guilfoos 2024).

Using fishing footprints to estimate economic exposure

Evaluating how offshore wind energy development impacts historical fishing operations and seafood production is a research priority in the northeast USA; specifically, this includes research considering spatial overlaps between fishing areas and offshore wind, economic exposure of fishing operations to offshore wind, and impacts on fisheries with different gear types (Methratta et al. 2023). To evaluate spatial overlap between fishing activities and offshore wind farms, we need to understand where and when fishing occurs. Researchers have used a variety of datasets from distinct fisheries monitoring and research programs to build fishing footprints, each with a unique spatial and temporal resolution (Jennings et al. 2012, Eigaard et al. 2017, Amoroso et al. 2018, Scheld et al. 2022, Allen-Jacobson et al. 2023, Livermore and Guilfoos 2024, Samhouri et al. 2024). Fishing footprints can be used to evaluate the number of vessels and the amount of fishing effort exposed to offshore wind development, which can be linked with revenue data to provide estimates of economic losses due to offshore wind development (Benjamin et al. 2018, Allen-Jacobson et al. 2023).

At present, the Northeast Fisheries Science Center (NEFSC) and Greater Atlantic Regional Fisheries Office (GARFO) estimate exposure by using logbooks (Vessel Trip Reports), landings reported by seafood dealers, and data collected from at-sea observer programs (Brooke 2015, Benjamin et al. 2018). Logbooks provide a census of fishing activity (e.g. statistical reporting areas) for federally managed fleets in the region, because commercial fishers are required to submit logbook reports for all trips. Data on fishing effort from logbooks can be linked to associated seafood dealer reports for landings and revenue from individual fishing trips. The spatial resolution of logbook data, however, is coarse, including only the central location of fishing for an entire fishing trip, which can cover tens of square kilometers. Fishery observers, tasked with collecting data primarily used in bycatch estimation, are deployed on a random sample of trips, and they collect more precise information on fishing position (location of individual gear deployments). Observer data, however, are not available for all fisheries or fishing trips. The NEFSC and GARFO have used the available logbook reports and observer data to create coarse fishing footprints with four percentiles of the observed spatial distribution (25th, 50th, 75th, and 90th) that reflect the percentage of trips expected to occur within certain distances of the trip center that was reported in the logbook (DePiper 2014, Benjamin et al. 2018). These revenue density data products are used to estimate economic exposure of fisheries to offshore wind farms, inform siting of offshore wind energy areas, and develop compensation plans for individual wind farms (Kirpatrick et al. 2017). Coarse footprints have been used to assess exposed revenues for fleets defined by species, gear type, and fisheries management plan groupings (Kirpatrick et al. 2017), which may not reflect the complexities of economic exposure for multispecies fisheries.

Coarse locations reported in logbooks are available for all fishing effort in federally managed fisheries in the USA; however, coarse footprints are often based on one recorded location per fishing trip and may not reflect the true spatial extent of hauls that occurred on a trip, which likely varies based on gear and target species (Allen-Jacobson et al. 2023). Allen-Jacobson et al. (2023) used high-resolution data collected by the NEFSC Study Fleet (Palmer 2007, Jones et al. 2022) to evaluate biases in coarse footprint estimates of exposed revenue for the longfin squid (*Doryteuthis pealeii*) fishery. The longfin squid fishery is a targeted bottom-trawl fishery and Allen-Jacobson et al. (2023) assessed trips where longfin squid comprised at least 39% of landings (by weight) and likely represented the majority of trip revenues. For the longfin squid fishery, unrestricted footprints (90th percentile) detected all trips that were exposed to wind farms, but also detected false intersections and underestimated per-trip exposed revenue. As coarse footprints were restricted to lower percentiles, fewer false intersections with wind energy areas were detected while more true intersections were missed. Exposed revenue for the longfin squid fishery was best estimated by coarse footprints that were restricted to the 25th percentile. This is because the low resolution of unrestricted coarse footprints spreads revenue and fishing activity over larger areas than would be represented in footprints based on more fine-scale data (Allen-Jacobson et al. 2023).

Based on analyses of the targeted longfin squid fishery, restricting coarse footprints may improve exposure analysis in the absence of fine-scale data; however, the utility of restricting footprints may vary among fleets depending on target species and gear type. Fleet definitions also differ for more targeted fisheries. For example, fleets that target multiple species (e.g. mixed groundfish, summer flounder) may have wider spatial distributions compared to fleets that target a single species (e.g. longfin squid), which may have smaller or patchier spatial distributions (Allen-Jacobson et al. 2023). Additionally, for multispecies fisheries, revenue will be distributed across more species than targeted fisheries, which means that exposed revenue for multispecies fisheries may be underestimated if only target species revenues are considered. Therefore, more research is needed to better understand biases in fleet definitions and coarse footprints for multispecies fisheries. Comparing fine-scale data and coarse data on fishing locations for other fisheries will also facilitate understanding of how logbook data can be used to accurately estimate economic exposure across fleets, including those lacking fine-scale data.

Table 1. Terms and definitions for this paper

Term	Definition
Summer flounder trips	Trips that landed summer flounder, which are defined as trips that have any (>0 pounds) summer flounder kept catch.
FMP trips	Trips that landed species included in the summer flounder, scup, and black sea bass fishery management plan and include any kept catch (>0 pounds) from at least one relevant species.
Coarse footprints	Fishing footprints that are derived from Vessel Trip Report (logbook) logbook data.
Precise footprints	Fishing footprints that were created using fine-scale GPS and haul-by-haul data from the NEFSC Study Fleet.
True positive	Both the coarse and precise footprint intersect with a wind farm.
False positive	The coarse footprint intersects with a wind farm but the precise footprint does not.
True negative	Neither the coarse nor the precise footprint intersects with a wind farm.
False negative	The precise footprint intersects with a wind farm but the coarse footprint does not.

Our objective was to quantify biases in coarse fishing footprints and their estimates of economic exposure for a multispecies fishery. The mid-Atlantic large-mesh trawl fishery targets multiple demersal species, including summer flounder or “fluke” (*Paralichthys dentatus*), which is the focus of this research. Summer flounder is the most commercially valuable flatfish in the mid-Atlantic region and supports productive recreational and commercial fisheries (Collette and Klein-Macphee 2002). Vessels fishing for summer flounder often coincidentally catch several other species, including scup (*Stenotomus chrysops*) and black sea bass (*Centropristis striata*). Thus, the Fishery Management Plan (FMP) used by the Mid-Atlantic Fishery Management Council is inclusive of all three species. In 2022, the commercial fisheries in the USA landed 4634 metric tons of summer flounder valued at over $26 million, 5492 metric tons of scup valued at over $10 million, and 2336 metric tons of black sea bass valued at over $14 million (NOAA 2024). We chose the summer flounder fishery because it is a multispecies fishery, which operates in a distinct manner from the more targeted longfin squid fishery, making it a well-suited comparison. Additionally, spatial data for summer flounder fishery were well represented in our fine-scale (Study Fleet) and coarse-scale (logbook) datasets. To test whether optimal footprint calculation methods varied by fishery, we applied the analytical approach used by Allen-Jacobson et al. (2023) to compare precise fishing footprints (based on fine-scale data) to coarse fishing footprints (based on logbook data) for longfin squid and estimate economic exposure of these fisheries to wind farms. To better understand exposed revenue for the multispecies summer flounder fishery and FMP, we considered species-specific and all multispecies revenues. Comparing our results for more diversified fisheries (summer flounder and the summer flounder, black sea bass, and scup FMP) to each other and to those for the single-species fishery (longfin squid) allows a better understanding of how fleet definition and fishery type influence fishing footprint definition and revenue exposures.

Materials and methods

We used fine-scale GPS data from the NEFSC Study Fleet to create precise fishing footprints for vessels targeting summer flounder and for vessels targeting other species in the FMP between 2016 and 2021 (Table 1). Since 2014, the NEFSC Study Fleet has engaged 37–42 vessels annually with participants from Maine to North Carolina, USA. Study Fleet vessels collect detailed data on fishing operations and catch from each haul, which supports fisheries science and management efforts (Palmer 2007, Jones et al. 2022, 2025). During their fishing trips, Study Fleet vessels collect Global Positioning System (GPS) locations every minute, and captains manually record the start and end locations of each gear haul, making the dataset well suited for constructing precise fishing footprints. We used the Catch and Accounting Monitoring System (CAMS) to retrieve total landings, trips, and vessels for the summer flounder fishery and to then calculate Study Fleet coverage from 2006 to 2023 (Supplementary Table S1 and Fig. S1). CAMS is a collaborative effort between the NEFSC and GARFO to provide a comprehensive source of landings for all catch in the Greater Atlantic region of the USA. Between 2006 and 2023, overall landings for summer flounder decreased while the number of participating Study Fleet vessels increased, which led to higher rates of coverage by Study Fleet-affiliated vessels in more recent years. Based on our assessment of Study Fleet coverage, we selected fishing trips from years for which Study Fleet vessels harvested at least 10% of landings for the entire commercial summer flounder fishery (2016–2023). From 2016 to 2023, Study Fleet summer flounder landings represented 10%–15% of all commercial summer flounder landings (Supplementary Materials: Fig. S1). When conducting this research, complete Study Fleet GPS and revenue data were not yet available for 2022 or 2023 due to data processing lags, so only data from 2016 to 2021 were included in our study.

We completed two analyses using different subsets of fishing trips that harvested summer flounder with the goal of testing how each fleet definition influenced our estimations of intersections with wind farms and revenue exposure. Our selection criteria are based on existing management definitions for multispecies fisheries, where fleets are defined by permit, positive catch of target species, gear, and region (McAfee 2024). One of the goals of this research was to better understand how the characterization of a fishery influenced economic exposure results. For the summer flounder fishery, we first selected trips that the Study Fleet captains designated as targeting summer flounder in their reporting. Upon doing this, we found that many trips had zero revenue or pounds of kept summer flounder catch and that we were missing a fair amount of summer flounder revenue that was caught on trips that were not designated as targeting summer flounder. This is due to the multispecies and opportunistic nature of summer flounder fishing trips, which often target other species (primarily black sea bass and scup). Thus, to accurately account for summer flounder fishing effort and revenue, we selected all Study Fleet trips with at least 1 pound of summer flounder kept catch. This approach is consistent with the requirement of a summer flounder permit to retain them and used for defining fleets in our region for bycatch monitoring and standardized catch rates. We considered selecting a landings threshold, but wanted to be as inclusive as possible of trips with exposed summer flounder revenue. Thus, the first analysis included all trips that had summer flounder kept catch (hereafter, “summer flounder trips”).

Summer flounder trips were defined as large-mesh otter trawl (> 5 inches) trips that targeted and landed summer flounder.

To account for the multispecies nature of the summer flounder fishery, we also selected trips based on the associated FMP. The second analysis included trips that had kept catch for any species included in the summer flounder, scup, and black sea bass FMP (hereafter, "FMP trips"). FMP trips were defined as targeting the FMP by large mesh trawls (>5 inches) with greater than 0 pounds kept catch for at least one of the FMP species. For both analyses, we selected all NEFSC Study Fleet trips that occurred between 2016 and 2021, had fine-scale GPS location data, and met the gear and catch criteria. We used the most recent 5 years of data to best reflect the current state of the fishery and mirror data requirements in compensation claim instructions, which request the most recent 3–5 years of data. As summer flounder are included in the FMP, we expected summer flounder trips to overlap with FMP trips, which would allow us to better evaluate how different definitions of the multispecies fishery (summer flounder or FMP) may influence the biases in estimates of economic exposure to wind farms.

We calculated trip-specific revenues based on logbook and dealer information extracted from NOAA databases. For the summer flounder trips, we calculated summer flounder revenue by summing revenue by logbook trip identification codes, monitoring program, and northeastern commercial species code for records of summer flounder, following methods developed by Allen-Jacobson et al. (2023). We also calculated total species revenue for each summer flounder targeted trip by summing revenue across all reported species codes with kept catch for that trip. Similarly, for the FMP trips, we calculated FMP revenue by summing revenue by logbook trip identification codes, monitoring program, and the northeastern commercial species codes for records of all three FMP species. We also calculated the per-trip total species revenue for all FMP trips. We adjusted revenue to reflect the 2022 Gross Domestic Product, as that was the most recent deflator available from the Federal Reserve Economic Database (FRED) at the time of writing. For each trip, we multiplied revenue by the ratio of the nominal year's value to the 2022 deflator.

Fishing footprints

We used fine-scale GPS data to create precise fishing footprints following Allen-Jacobson et al. (2023). Specifically, we used fishing location data to construct convex hulls with a 50-m buffer for each recorded fishing haul. Hauls were then merged by trip to create a "precise fishing footprint" (PFF) for each trip (Supplementary Fig. S2). To estimate exposed revenue, we transformed precise fishing footprint polygons into grids of cells (rasters) and then evenly distributed total trip revenues across the fishing footprint cells. This means that total trip revenue would be the sum of the revenue per cell for all cells in the precise fishing footprint.

We used logbook identifiers to match logbook footprints (coarse fishing footprints) to each of the selected trips. Coarse logbook footprints were developed by the NEFSC using logbook fishing locations, validated against observer-based haul locations to produce a modeled representation of fishing activity (DePiper 2014, Benjamin et al. 2018). Covariates based on fishing gear and trip length were produced and then applied to the logbook-based positions and transformed to a gridded representation of fishing activity intensity. These grids can then be applied to trip-based values for a coarse representation of spatial valuation. To better understand the trade-offs of percentile restriction inherent in the coarse logbook footprints, we restricted logbook footprints to four different percentile levels (90th, 75th, 50th, and 25th) to assess biases across a range of possible restrictions that could be used. We applied the methods developed by Allen-Jacobson et al. (2023) to modify rasters and assign revenues based on restricted percentiles. GARFO reports logbook footprints that are restricted to the 90th percentile, for which 25% of the revenue is distributed to each percentile level. We modified the standard logbook footprints by restricting them to the 75th, 50th, and 25th percentiles. As percentile was restricted, revenue was distributed across a smaller footprint with 33%, 50%, or 100% of the revenue distributed across each percentile level when footprints were restricted to the 75th, 50th, and 25th percentiles. Thus, revenue was more concentrated in the center of the coarse footprints.

We completed analyses in R (R Core Team 2023) and used the "terra" (Hijmans et al. 2024), "raster" (Hijmans et al. 2025), "dplyr" (Wickham et al. 2023), and "ggplot" (Wickham 2016) packages to complete analyses and create figures.

Evaluating exposure to wind areas

We evaluated fishing exposure to offshore wind for 37 wind development areas (8 planning areas and 29 leased areas), which ranged in area from 2.34 km^2 to 14 251 km^2 with a median area of 328.52 km^2, as defined in November 2023 (BOEM 2023). Since our goal was to assess all possible intersections of fishing footprints with offshore wind, we included all planned and leased wind energy areas across the US East Coast. We also included planned and installed submarine transmission cables extending between offshore wind turbines and from offshore wind farms to shore. We evaluated biases in coarse footprints assessment of exposure to offshore wind areas for summer flounder and FMP-targeted trips by comparing (1) intersections of coarse and precise footprints and (2) exposed revenue across percentile restrictions and fleet definitions.

First, we compared intersections of coarse and precise fishing footprints with wind farms across coarse footprint percentiles for summer flounder and FMP trips. For each trip, we evaluated how coarse and precise footprints overlapped with each other and with wind farms for each of the four percentile restrictions (90th, 75th, 50th, and 25th). We classified intersections into four possible outcomes, which we organized into a confusion matrix: (1) neither footprint intersected with a wind farm (True Negative, TN), (2) both footprints intersected with a wind farm (True Positive, TP), (3) only the coarse footprint intersected with a wind farm (False Positive, FP), (4) only the precise footprint intersected with a wind farm (False Negative, FN). We then used a binary classification metric (F1 score) to measure differences in coarse and precise fishing footprint agreement for summer flounder trips and FMP trips and find the "optimal" percentile restriction to assess intersections with wind farms.

F1 scores can be used to compare an estimated classification from a model to a ground truth (Goodwin et al. 2022). F1 scores range from 0 to 1, with 1 representing the best classification ability for the model. In the context of our study, we assumed that precise fishing footprints and their intersections were "true" representations of fishing activity, and we used F1

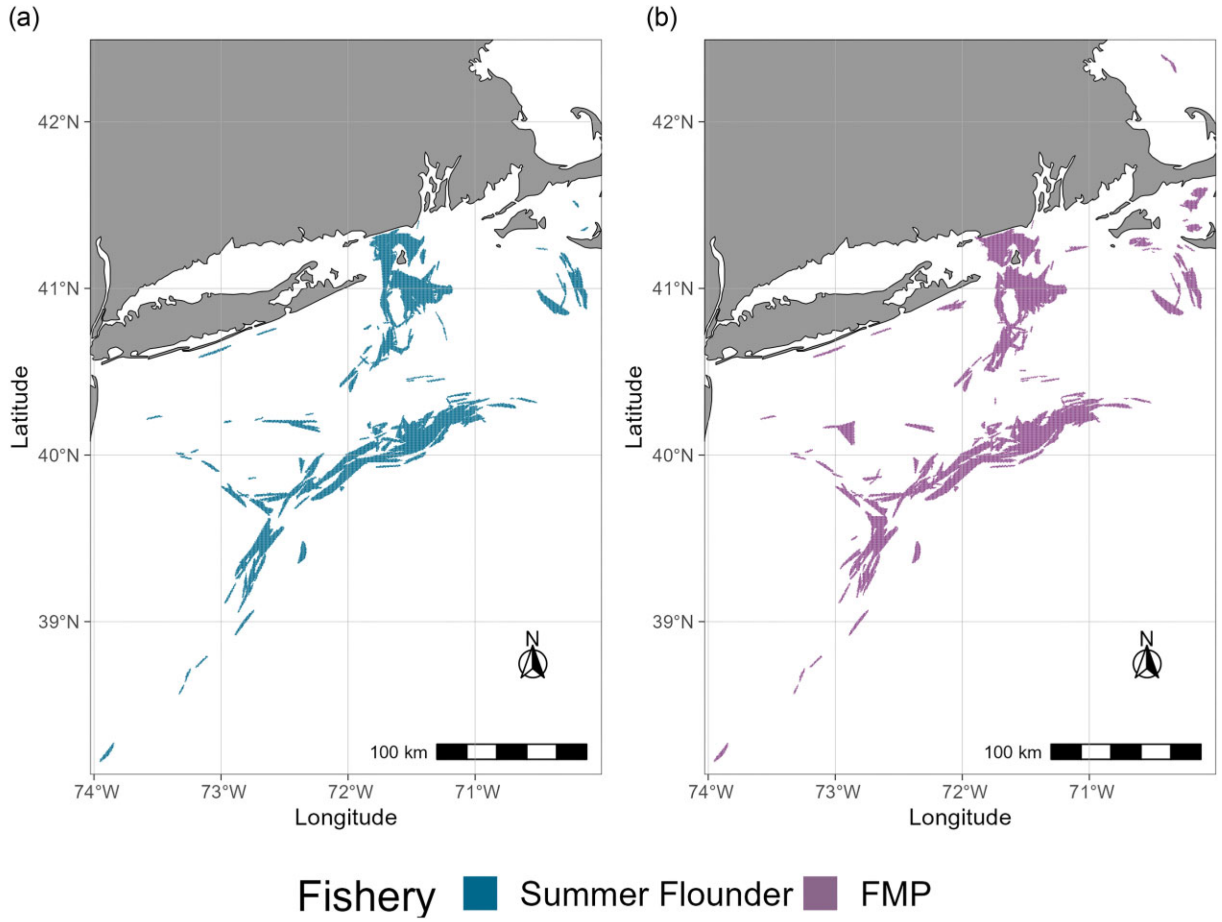

Figure 1. Precise footprints for (a) summer flounder targeted trips and (b) FMP-targeted trips.

scores to compare them to "modeled" coarse fishing footprints intersections. F1 scores use weighted average of precision and recall to evaluate model performance. Precision evaluates the correctness of positive model classifications and can be used to evaluate a model's ability to provide relevant results. Recall indicates how many positive cases are predicted correctly when all the positive cases in the data are considered. For our study, higher recall would suggest more instances that coarse footprints and precise footprints agreed in their intersection with wind farms. Finally, F1 scores combine precision and recall into a single composite metric to rate overall performance and agreement for categorization of both true positives and true negatives. F1 scores are calculated as:

$$Precision = \frac{True\ Positive}{True\ Positive + \ False\ Positive}$$
$$Recall \ = \frac{True\ Positive}{True\ Positive + \ False\ Negative}$$
$$F1 \ = \ 2 \times \ \frac{Precision \ \times Recall}{Precision \ + \ Recall}.$$

To facilitate comparisons of biases across fleet classification, we calculated F1 scores for each percentile (90th, 75th, 50th, 25th) for both summer flounder and FMP trips. We also used results reported by Allen-Jacobson et al. (2023) to calculate an F1 score for longfin inshore squid trips.

Second, for trips that intersected with wind farms, we compared exposed revenue estimates for summer flounder and FMP trips across percentiles for both target species and total species revenue. Following Allen-Jacobson et al. (2023), we estimated economic exposure for each intersecting trip by calculating the amount of revenue assigned to the portion of the precise or coarse footprint that overlapped with the wind farm. For summer flounder trips we calculated exposed revenue for summer flounder and for all kept species. For FMP-targeted trips we calculated exposed revenue for FMP species and for all kept species (all species revenue). We considered exposed revenue for all intersecting trips (total exposed revenue) and calculated an average per-trip exposed revenue (per-trip exposed revenue).

We defined the "optimal" percentile restrictions as those that best matched estimates of exposure and intersections produced by precise footprints. In the context of our study, the "optimal" percentile restriction for identifying intersections would be the percentile with highest F1 score, while the "optimal" percentile restriction for estimating revenue exposure would be the percentile that produced an estimate of economic exposure that best matched the precise footprint estimate.

Results

We analyzed 838 trips which caught summer flounder completed by 17 vessels between April 2016 and September 2021 representing \$1 739 880 in summer flounder revenue and \$2 948 640 total multispecies revenue (Fig. 1a). Fishing effort ranged from 1 to 22 trawl hauls per trip with a mean of 2 (SD: 1.8) hauls per trip, with 75 (SD 46.4)

Table 2. Summary of data, landings, and revenue for summer flounder and FMP-targeted trips.

	Range	Median	Mean (SD)
Summer flounder targeted trips (838)			
Hauls per trip	1–22	2	2 (1.8)
GPS points per haul	1–396	70	75 (46.4)
Landings			
Summer flounder (mt)	0.001–7	0.05	0.2 (0.6)
Summer flounder (%)	0–100	3	15 (28)
All species (mt)	0.03–10	2.13	2.5 (1.7)
Revenue			
Summer flounder ($)	$7–$45 817	$502	$1 805 ($4 797)
Summer flounder (%)	1–100	27	37 (28)
All species ($)	$133–$47 054	$2 165	$3 394 ($5 168)
FMP targeted trips (1439)			
Hauls per trip	1–22	2	2 (1.6)
GPS points per haul	1–396	70	72 (39.2)
Landings			
Summer flounder (mt)	0–8	0.05	0.2 (0.6)
Summer flounder (%)	0–100	2	13 (25)
Black sea bass (mt)	0–2	0.00	0.02 (0.09)
Black sea bass (%)	0–100	0	2 (7)
Scup (mt)	0–6	0.01	0.13 (0.42)
Scup (%)	0–100	1	7 (18)
FMP (mt)	0–9	0.11	0.32 (0.72)
FMP (%)	0–100	6	22 (35)
All species (mt)	0–32	2	3 (2.3)
Revenue			
Summer flounder	$0–$46 817	$480	$1 440 ($3 975)
Summer flounder (%)	0–100	27	36 (31)
Black sea bass	$0–7 672	$3	$128 ($567)
Black sea bass (%)	0–100	0	5 (11)
Scup	$0–21 449	$20	$173 ($831)
Scup (%)	0–100	1	6 (14)
FMP	$2–$46 959	$674	$1 741 ($4 215)
FMP (%)	0–100	40	47 (31)
All species	$13–$47 054	$2 035	$2 914 ($4 205)

Statistics represent per-trip summaries.

GPS points per haul (Table 2). Summer flounder comprised a mean of 15% (SD 28%) of total landings per trip. Revenue from summer flounder ranged from $7 to $45 817 (mean: $1805, SD: $4797) per-trip, which represented a mean of 37% (SD 28%) of total trip revenue (Table 2 and Supplementary Figs S3–S4). Many other species contributed to revenue from summer flounder trips, with little skate (*Leucoraja erinacea*), haddock (*Melanogrammus aeglefinus*), and tautog (*Tautoga onitis*) contributing the most, after summer flounder (Supplementary Figs S5–S7).

We assessed 1 439 FMP trips that occurred between February 2016 and September 2021 and were completed by 17 vessels, representing $2 810 903 in FMP species revenue and $4 722 340 in all species revenue (Fig. 1b). As expected, many of the FMP trips were also included in our summer flounder analysis (838, 58%), with some additional FMP trips (601, 43%) occurring south of Cape Cod, MA. Fishing effort and GPS coverage for FMP trips were very similar to summer flounder trips (Table 2). Per trip revenue from FMP species (summer flounder, scup, and black sea bass) ranged from $2 to $46 959, with a mean of $1 741 (SD $4 215). On average, FMP species represented 47% (SD: 31) of total trip revenues. Of the FMP species, summer flounder generally represented more revenue on each trip (median: 27%; mean: 36%; SD: 31%) compared to scup (median: 1%; mean: 6%; SD: 14%)

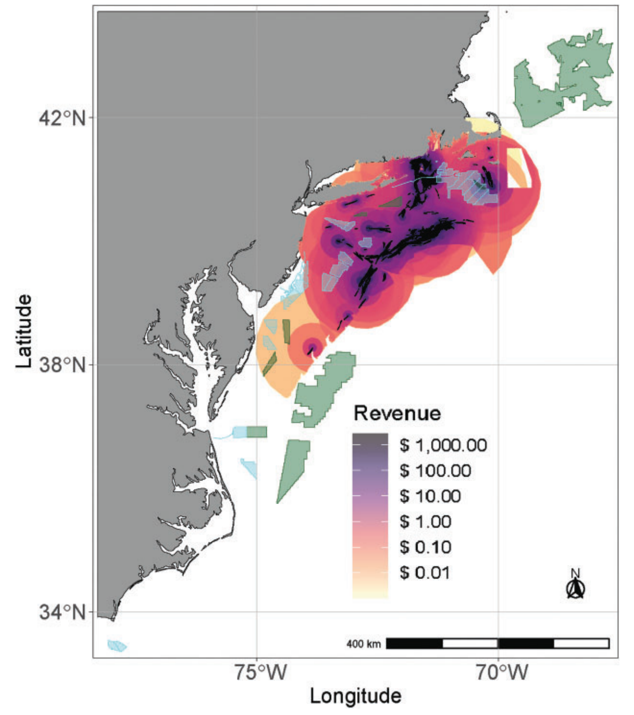

Figure 2. Precise (black polygons) and coarse (colored circles) footprints for 838 summer flounder targeted trips and revenue. Leased wind farms are indicated in teal and planning areas are indicated in green. The polygon (with blank space) on the upper right of the figure reflects a fishing closure area.

and black sea bass (median: 0.1%; mean: 5%; SD: 11%) (Table 2).

Estimating footprint intersections with wind energy areas

Based on precise fishing footprints, 120 of the 838 summer flounder trips (14%) and 200 of the 1439 FMP trips (14%) intersected with wind areas. We used a confusion matrix to evaluate coarse and precise fishing footprint intersections with all 37 wind farms (Fig. 2, Figure 3), resulting in 31 006 possible intersections for summer flounder trips (838 trips ✖ 37 wind farms) and 53 243 possible intersections for FMP trips (1439 trips ✖ 37 wind farms). Overall, the majority (94.3%–99.5%) of footprints at all restrictions did not intersect with wind farms. Considering all possible intersections, 0.4% (120) of precise footprints for summer flounder trips and FMP trips (200) intersected with wind farms (Table 3, Fig. 4). For both FMP and summer flounder trips, unrestricted coarse footprints (90th percentile) captured all precise footprint intersections with wind farms, but also predicted many false intersections (summer flounder: 5.3% (1 655), FMP: 4.5%; Table 3, Fig. 4). Logbook fidelity (the ability of coarse footprints to capture precise fishing footprint intersections with wind energy areas) decreased with percentile restriction for both summer flounder (90th: 100%; 75th: 95%; 50th: 66%; 25th: 44%) and the FMP (90th: 100%; 75th: 95%; 50th: 72%; 25th: 48%).

For both summer flounder and FMP trips, true and false positives were highest when logbook footprints were restricted to the 90th percentile and both declined with percentile restriction (Fig. 4). True negatives and false negatives

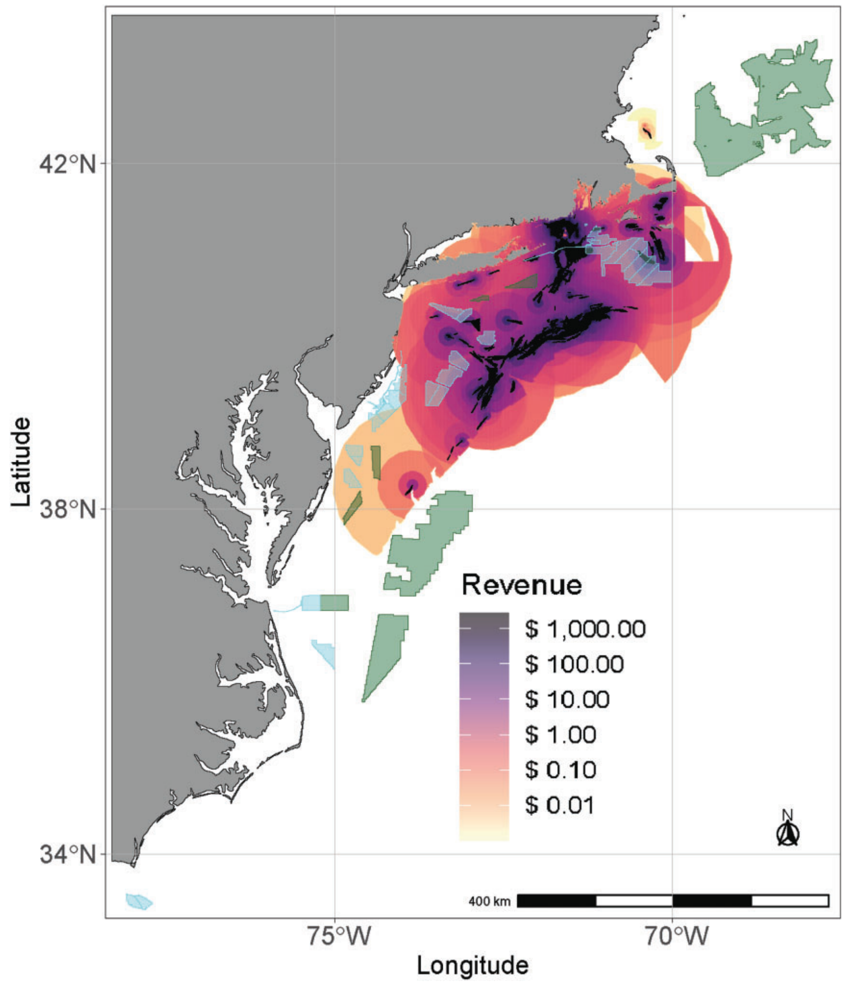

Figure 3. Precise (black polygons) and coarse (colored circles) footprints for 1439 FMP-targeted trips and revenue. Leased wind farms are indicated in teal and planning areas are indicated in green. The polygon (with blank space) on the upper right of the figure reflects a fishing closure area.

Table 3. Summary of agreement between coarse and precise footprint intersections with wind farms for each coarse footprint percentile (90th, 75th, 50th, 25th) along with recall (Re.), precision (Pr.), and F1 score (F1) metrics

Percentile restrictions	*Types of intersections with wind farms*								*Performance metrics*		
	True positives		*False positives*		*True negatives*		*False negatives*				
	%	*(#)*	*%*	*(#)*	*%*	*(#)*	*%*	*(#)*	*Re.*	*Pr.*	*F1*
Summer flounder											
90th	0.4%	(120)	5.3%	(1655)	94.3%	(29 231)	0%	(0)	1.00	0.07	0.13
75th	0.4%	(114)	0.8%	(239)	98.8%	(30 647)	<0.1%	(6)	0.95	0.32	0.48
50th	0.3%	(79)	0.2%	(53)	99.4%	(30 833)	0.1%	(41)	0.66	0.60	0.63
25th	0.2%	(53)	0.1%	(16)	99.6%	(30 870)	0.2%	(67)	0.44	0.77	0.56
FMP											
90th	0.4%	(200)	4.5%	(2386)	95.1%	(50 657)	0%	(0)	1.00	0.08	0.14
75th	0.4%	(189)	0.9%	(462)	98.8%	(52 581)	<0.1%	(11)	0.95	0.29	0.44
50th	0.3%	(143)	0.2%	(125)	99.4%	(52 918)	0.1%	(57)	0.72	0.53	0.61
25th	0.2%	(95)	0.1%	(50)	99.5%	(52 993)	0.2%	(105)	0.48	0.66	0.55

increased as the percentile was restricted for both fisheries. Precision increased as coarse footprints were restricted for both summer flounder and FMP trips, indicating that coarse fishing footprints predicted positive intersections more correctly as they were restricted (Fig. 5a). As coarse footprints were restricted, many fewer false positives were detected. Conversely, recall decreased as coarse footprints were restricted for both summer flounder and FMP trips, which reflects the reduction in true positives detected as footprints were restricted (Fig. 5b). For both summer flounder and FMP trips, F1 scores were lowest when coarse footprints were unrestricted (summer flounder F1 = 0.13; FMP F1 = 0.14) and highest when coarse footprints were restricted to the 50th percentile (summer flounder F1 = 0.63; FMP F1 = 0.61) (Fig. 5c). Precision and recall metrics for the longfin squid fishery followed the same patterns as the summer flounder and FMP trips. How-

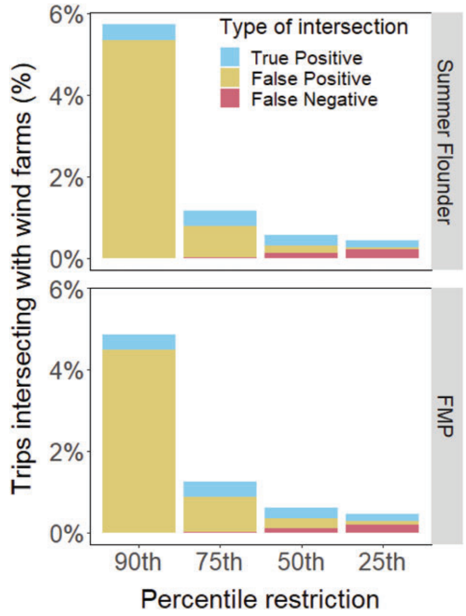

Figure 4. Intersections with wind energy areas for coarse and precise footprints for summer flounder targeted and fishery management plan (FMP) targeted trips. This plot includes the results of our confusion matrix, specifically the % of total possible intersections (Summer flounder: 838 trips ✖ 37 wind farms, 31 006 possible intersections; FMP: 1439 trips ✖ 37 wind farms, 52, 243 possible intersections) for three possible intersection types. "True positive" indicates that both the coarse and precise footprint intersected with wind farms. "False positive" indicates that only the coarse footprint intersects with wind farms. "False negative" indicates that only the precise footprint intersected with wind farms. Percentiles (90th, 75th, 50th, 25th) represent restrictions of the coarse footprint. This plot does not include footprints that did not intersect with any wind farms ("True negatives"), which are included in Table 3.

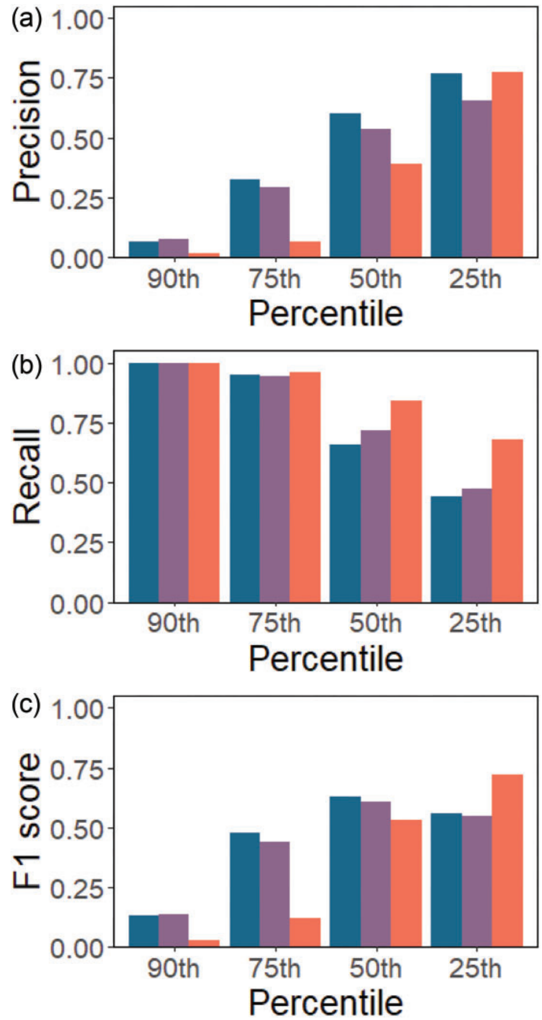

Figure 5. Precision (a), recall (b), and F1 scores (c) to evaluate coarse footprint and precise footprint agreement on intersections with wind farms for longfin squid, summer flounder, and FMP (Summer Flounder, Scup, and Black Sea Bass) trips. Percentile indicates the restriction of coarse footprints (25th, 50th, 75th, 90th).

ever, for longfin squid coarse footprints restricted to the 25th percentile (Fig. 5c) produced the highest F1 score (0.72).

Estimating exposed revenue

Summer flounder trips

For trips that caught summer flounder, we found that 120 precise footprints intersected with wind farms and exposed 0.71% of summer flounder revenue and 1.12% of revenue for all kept species (Fig. 6a; Table 4). When considering individual trips, on average 5.68% ($103, SE: $4.77) of summer flounder revenue and 8.09% ($275, SE: $8.5) of total species revenue were exposed for each intersecting precise fishing footprint (Fig. 6b; Table 4). Unrestricted coarse footprints (90th percentile) estimated higher total exposed revenue (2.56% of total revenue) than precise footprints (summer flounder: 2.56% ($44 566); all kept species: $75 364). However, unrestricted coarse footprints also estimated lower per-trip exposed revenue than precise footprints (summer flounder: 1.25% ($25, SE: $0.1); all kept species: 1.34% ($42, SE: $0.1); Fig. 6b]. Coarse footprint estimates of total exposed revenue were closest to precise footprint estimates when coarse footprints were restricted to the 25th percentile (summer flounder: 0.99%; all kept species: 1.10%); however, coarse footprints restricted to the 25th percentile also overestimated average exposed revenue per trip [summer flounder: 13.77% ($249, SE: $13.5); all species: 13.90% ($472, SE: $20.8)] when compared to precise footprints. For summer flounder revenue, coarse footprint estimates of exposed revenue per trip best matched precise footprint estimates at the midpoint of the 50th [summer flounder: 8.59% ($155, SE: $5.0)] and 75th [4.88% ($88; SE: $1.0)] percentiles (Fig. 6b). For total species revenue, coarse footprint estimates of exposed revenue per trip best matched precise footprint estimates at the 50th percentile (all kept species: 7.92%, $269, SE: $6.6; Fig. 6b).

FMP trips

FMP precise footprints had 200 intersections with wind farms, which exposed 0.72% of FMP species revenue and 1.12% of all kept species revenue (Table 4, Fig. 4). As with summer flounder trips, unrestricted FMP coarse footprints (90th percentile) estimated the highest total exposed revenue (FMP species: 2.14%; all kept species: 2.10%; Fig. 6c) and the lowest per-trip exposed revenue (FMP species: 1.34%; all species: 1.31%; Fig. 6d). Coarse footprint estimates of total exposed revenue best matched precise footprint estimates when restricted to the 25th percentile for FMP species revenue (0.90%) and the 50th percentile for all kept species revenue (1.14%). Per-trip exposed revenue for FMP trips was high-

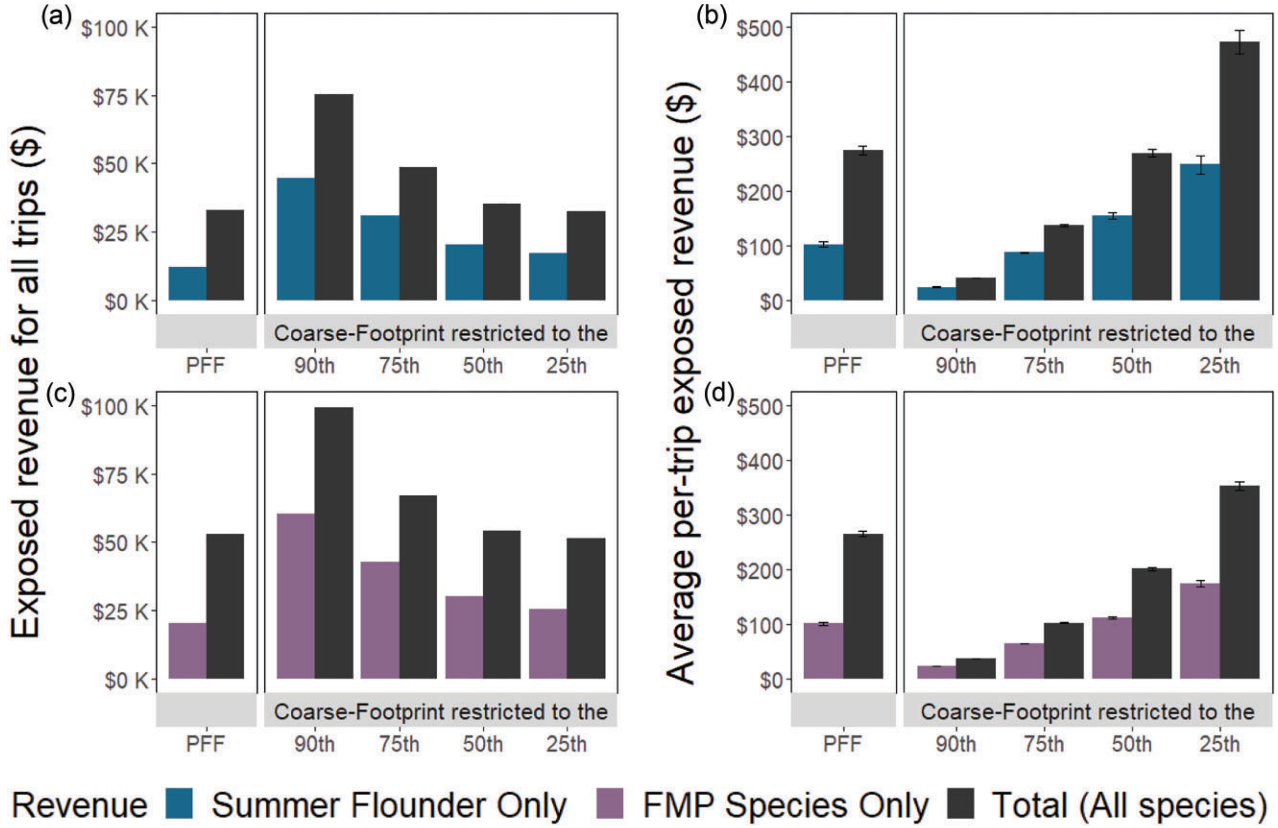

Figure 6. Total and per-trip exposed revenue for the summer flounder targeted (a, b) and FMP-targeted trips (c, d). "PFF" refers to exposed revenue calculated based on the precise fishing footprint. "Summer Flounder Only" refers to exposed revenue from summer flounder catch. "FMP Species Only" refers to exposed revenue from all three species in the Fishery Management Plan (Summer Flounder, Scup, and Black Sea Bass). "Total (All species)" refers to exposed revenue from all species landed.

Table 4. Summary of exposed revenue for precise footprints and coarse footprints that intersected wind farms at each coarse footprint percentile (90th, 75th, 50th, 25th).

			Exposed revenue				
Analysis	Percentile restriction	Exposed trips (#)	Total exposed ($)	Percent of total revenue (%)	Mean per-trip	SE ($)	Percent of per-trip revenue exposed (%)
Summer flounder trips							
Summer flounder only	90th	1 775	$44 566	2.56%	$25	$0.08	1.39%
	75th	353	$31 112	1.79%	$88	$1.04	4.88%
	50th	132	$20 475	1.18%	$155	$5.02	8.59%
	25th	69	$17 154	0.99%	$249	$16.25	13.77%
	PFF	120	$12 310	0.71%	$103	$4.77	5.68%
All species	90th	1 775	$75 364	2.56%	$42	$0.10	1.25%
	75th	353	$48 447	1.64%	$137	$1.36	4.04%
	50th	132	$35 497	1.20%	$269	$6.55	7.92%
	25th	69	$32 543	1.10%	$472	$20.83	13.90%
	PFF	120	$32 945	1.12%	$275	$8.48	8.09%
FMP trips							
FMP species only	90th	2 586	$60 172	2.14%	$23	$0.05	1.34%
	75th	651	$42 764	1.52%	$66	$0.48	3.77%
	50th	268	$30 055	1.07%	$112	$1.96	6.44%
	25th	145	$25 373	0.90%	$175	$5.83	10.05%
	PFF	200	$20 324	0.72%	$102	$2.53	5.84%
All species	90th	2 586	$98 966	2.10%	$38	$0.06	1.31%
	75th	651	$66 945	1.42%	$103	$0.61	3.53%
	50th	268	$53 947	1.14%	$201	$2.63	6.91%
	25th	145	$51 214	1.08%	$353	$7.74	12.12%
	PFF	200	$53 068	1.12%	$265	$4.49	9.11%

est when coarse footprints were restricted to the 25th percentile (FMP species: 10.05%; all kept species: 12.12%). Precise footprint per-trip exposed revenue (FMP species: 5.84%; all kept species: 9.11%) best matched per-trip exposed revenue for coarse footprints restricted to the 50th percentile for FMP species (6.44%) and between the 50th (6.91%) and 25th (12.12%) percentiles for all kept species.

Discussion

As offshore wind development evolves, evaluating spatial overlap between commercial fisheries and offshore wind farms is necessary to assess economic and practical implications for fishing communities and the seafood supply chain. Ideally, precise spatial data, including catch and revenue information, would be available for all fishing trips to assess where fishing is occurring in relation to offshore wind areas. However, since precise information on fishing locations is not collected for many fishing trips and some entire fisheries, there is a need to estimate offshore wind impacts using coarse footprints. Coarse fishing footprint data are available for many more fishing trips, but may provide biased estimates of fishing locations and revenue exposure depending on the fishery and gear type. Fine-scale data can be used to refine coarse footprints and provide more robust estimates of fishing locations and economic exposure, as has been demonstrated for the targeted small-mesh longfin squid fishery (Allen-Jacobson et al. 2023). In this study, we used fine-scale data collected by the NEFSC Study Fleet to evaluate tradeoffs in coarse footprint construction methods for the summer flounder fishery and FMP with the goal of better understanding biases in coarse footprints for a multispecies fishery that used large mesh trawls.

Our results demonstrate the importance of spatial scale and fleet definitions when using fishery-dependent data to estimate economic impacts of offshore wind on fisheries. Coarse data collected for fisheries management purposes was not designed to evaluate offshore wind development and fisheries interactions, but these data can be refined based on fine-scale datasets and trends in specific fisheries. Although coarse footprints effectively detected all fishing trips that intersected with wind areas, they also detected many false positives and overestimated total exposed revenue while underestimating per-trip exposed revenue. Restricting footprints may reduce false positives but may also result in missing intersections and, consequently, underestimate economic exposure. This general trend was consistent across assessed fishery types (summer flounder, summer flounder FMP, and longfin squid), though the optimal coarse footprint restriction differed by fishery. Based on our analysis, marine resource managers working to site offshore wind farms to minimize socioeconomic impacts should consider these trade-offs when using coarse footprints to estimate offshore wind impacts. Ultimately, the optimal restriction of a coarse fishing footprint may be dependent on specific project goals; for example, one might use unrestricted footprints to assess the presence/absence of fishing and use restricted footprints to estimate economic exposure.

Biases in unrestricted coarse footprints

We assumed that intersections between wind development areas and precise footprints represented "true" exposure for each trip. When coarse footprints were restricted to the 90th percentile (unrestricted footprints), they detected all trips with "true" exposure for summer flounder trips and FMP trips. At the same time, unrestricted footprints detected the most false positive intersections. As coarse footprints were restricted to smaller percentiles, true positives decreased while false negatives increased. These results corroborate those found with longfin inshore squid (Allen-Jacobson et al. 2023), and further suggest that restricting coarse footprints comes with a trade-off between more false negatives and fewer false positives for both targeted and multispecies fisheries.

When the goal is to assess all at-risk trips and their geographic attributes, unrestricted coarse footprints should be used since restricted footprints have the potential to miss at-risk trips. If the goal is to assess the general trends in the numbers and locations of trips that may be at risk, F1 scores could be a useful tool to pick an optimal coarse footprint percentile restriction. The F1 scores assessed trade-offs between true and false positives and varied between fisheries. For summer flounder and FMP trips the highest F1 score occurred when coarse footprints were restricted to the 50th percentile, while for longfin squid, the highest F1 score occurred when coarse footprints were restricted to the 25th percentile. This difference in optimal restriction may reflect differences in species distribution, fishing behavior, and gear types. Summer flounder and FMP trips were limited to large mesh trawls, while longfin squid trips tend to use small mesh trawls. Summer flounder and FMP trips may more consistently cover larger spatial areas than longfin squid trips due to differences in species distribution, which is reflected in the optimal coarse footprint restrictions. If we had considered fixed gears commonly used on black sea bass trips (e.g. fish pots), we would expect to see similar restrictions, or greater, to the longfin fishery. This is an important consideration in our fleet definition, as summer flounder are managed within a multispecies, multi-gear FMP.

We found that unrestricted footprints underestimated per-trip exposed revenue for summer flounder and FMP trips. As coarse footprints are restricted, revenue is concentrated into smaller areas, and more revenue is exposed in detected intersections. When considering exposure for individual trips and vessels, using unrestricted footprints may underestimate exposed revenue and reduce vessel operator access to compensation. For mixed-species fisheries like summer flounder, considering species- and FMP-specific revenues greatly reduced estimates of economic exposure. If the goal is to estimate overall economic exposure for a set of trips or a specific vessel, one should use total species revenue rather than species- or FMP-specific revenue.

Based on F1 scores and our exposed revenue analysis, restricting coarse footprints to the 50th percentile may provide the optimal spread to balance detection of true and false positives and accurately estimate total and per-trip exposed revenue for both summer flounder and FMP trips. For the more targeted longfin squid fishery, restricting coarse footprints to the 25th percentile produced the most accurate exposed revenue estimates and best balanced true and false positive detections. Restricting footprints based on fishery-specific F1 scores and our assessments of exposed revenue may support more balanced estimations of intersections with wind areas and economic exposure. Restricting coarse footprints and including all landed species provided more realistic estimates of exposed revenues for individual trips when compared to using unrestricted coarse footprints and species or FMP-specific revenues. Species-specific revenues may not accurately represent trip revenue exposure for multispecies fisheries like the summer flounder fishery or groundfish fishery.

Economic exposure and compensation

Precise estimates of per-trip and vessel-specific exposed revenue are increasingly important as developers begin offering compensation to commercial fishers who are affected by offshore wind farms (Lennon 2024, Zuckoff 2024). Although compensation processes differ between developers, these programs generally require applicants to submit data proving that they have recently fished within specific wind farm areas, as well as revenue data for those fishing trips. Revenue data might include an estimate of exposed revenue or the operation's total revenue. Logbook-based data are an accepted form of spatial data for these claims. For commercial fishers submitting claims to offshore wind companies, unrestricted coarse footprints may overestimate intersections with wind energy areas while also underestimating economic exposure for individual trips, which could result in reduced or inaccurate compensation. Restricting footprints based on fishery biases may provide more representative estimates of lost revenues for both developers and affected commercial fishers so that total compensation settlements can cover the claims. As commercial fishers go through the compensation process, it will be important to document the process and evaluate how offered compensation matches expectations based on available data and perceived economic impacts. Future research may consider evaluating coarse footprints for additional fishery types, using more widely collected fine-scale data (e.g. vessel monitoring system data), or considering other methods of constructing precise fishing footprints to produce more accurate fishing footprints. For example, since our primary goal in this paper was to make a comparison between a targeted fishery (Allen-Jacobson et al. 2023) and a multispecies fishery, we chose to use convex hulls to maintain consistency between the two studies. As depicted in Figs. 2 and 3, the convex hulls are much smaller than the coarse footprints and additional precision may not be required for the purpose of evaluating intersections between fishing trips and offshore wind areas. More precise "linestrings" may be useful for other applications, like estimating overlaps with aquaculture. Future studies may consider comparing methods of constructing precise footprints, including "linestrings" and convex hulls, to better assess biases.

It is important to note that our research only considered exposed revenue from reported landings for fishing footprints that overlapped with proposed and leased offshore wind farms. Economic exposure represents one facet of overall economic impacts for commercial fisheries (Chaji and Werner 2023). For example, we have not considered how vessels may change transit routes to accommodate wind areas, which may result in increased fuel usage (Samoteskul et al. 2014). We have also not considered other indirect impacts of offshore wind on fisheries operations, like higher insurance costs (Hall and Lazarus 2015, Hooper et al. 2015). Additionally, this analysis does not consider broader impacts on shoreside support businesses and communities (Chaji and Werner 2023).

Collaboration with the fishing community was a key component of this research, from collection of high-resolution catch and effort data through Study Fleet to review and interpretation of results. Communication mechanisms with commercial fishers included individual phone calls, one-page research summaries, in-person presentations, and in-person conversations. Each form of communication yielded unique feedback and insights that were used in the interpretation of results. Further, as compensation programs have moved forward, the data processing and summarization methods developed through this research have been used to provide commercial fishers with quantitative evidence of fishing within and around offshore wind farms. Several compensation programs are ongoing and are likely to reveal the value of having high-resolution catch and effort data for individual fishing vessels. Developing useful data products for collaborating fishers is critical for maintaining motivation and engagement in data collection activities.

Expanding to other fine-scale datasets

Our study relied on fine-scale data from the NEFSC Study Fleet, which partners with commercial fishers to generate time series of research-quality self-reported data. The Study Fleet program partners with vessels, rather than sampling across the fleets, and may not reflect the diversity of fishing occurring in the northeast USA. Our studies analyzed some of the fleets with the best coverage in the Study Fleet. Other fine-scale spatial datasets—including the Vessel Monitoring System (VMS) and Automatic Identification System (AIS)—may be useful to produce precise footprints for a broader range of vessels, but they also have limitations. VMS tracking is required for a large proportion of federally managed fisheries and thus covers more vessels than Study Fleet; however, VMS polling frequency is every 30–60 minutes and these data are not freely available due to their confidential nature. AIS data are publicly available and include one location every 2 seconds–3 minutes, thus providing finer spatial data than VMS. However, AIS is only required for vessels that are longer than 19.81 m (65 ft.) and the system can be turned off by the vessel operator once vessels are >19.31 km (12 miles) from shore. Further, Study Fleet data includes descriptions of fishing behavior—like the start and end of each haul—which allows researchers to create specific footprints to reflect when fishing is occurring. AIS and VMS data cannot be readily used to identify fishing activity since they are not annotated and do not distinguish between fishing and other activities, including transit, processing, preparing, or repairing gear. Additionally, each of these fishing activities will vary by fishery. Research is underway to utilize deep learning techniques to parse un-annotated AIS data based on available fishing behavior data (including vessel position, haul start and end, and vessel speed) from fisheries observers for the New England scallop fishery (Livermore and Guilfoos 2024).

Fishing behavior varies by fishing gear and fishery type, and researchers may consider using annotated Study Fleet data along with deep learning techniques to predict fishing activity for other fisheries using other fine-scale datasets that lack fishing behavior information (AIS, VMS). Using more broadly available fine-scale data would allow researchers to construct more precise fishing footprints for a larger proportion of active vessels and build a more realistic picture of spatial patterns and exposed trips.

Conclusions

Previous studies suggested fine-scale data could be used to investigate the accuracy of fishing footprints and test the generality of prior findings that restricting lower-resolution coarse fishing footprints improved their accuracy. Using a second, and behaviorally distinct fishery, we found that restricted logbook footprints were the most accurate, and had the highest F1 score. Because these coarse logbook footprints are currently being used to evaluate impacts of offshore wind development, we suggest restricting them or evaluating whether restricted footprints would increase their accuracy. Our results underscore the importance of collecting fine-scale data to evaluate spatial patterns for commercial fishing. Fisheries monitoring systems, such as Vessel Trip Reports, were developed to support fisheries management and enforcement, not to make precise spatial determinations.

Our results also demonstrate that fleet definition influenced our evaluation of economic exposure for the multispecies summer flounder fishery. When considering the economic exposure of species that are part of a multispecies fishery, evaluations conducted at the FMP level may produce more realistic estimations of fishery impacts than considerations of a single species. Additionally, we found that inclusion of total species revenue for a trip is more important in calculations of economic exposure for multispecies fisheries compared to more targeted fisheries. Managers may consider these results when reevaluating methods for defining the summer flounder fishery or other multispecies fisheries.

As ocean use priorities change, there is an opportunity to reevaluate fisheries-dependent data collection efforts and introduce new protocols to meet new data needs. Implementing broader fine-scale data collection programs requires additional resources and considerations of data confidentiality, but can provide many benefits. In addition to their utility in evaluating offshore wind impacts, fine-scale spatial data supports construction of more accurate fishing footprints, which can be used for other research priorities. For example, they may be used to evaluate changes in species spatial distributions related to climate change, changes in ocean use, effects of proposed marine protected areas, and other spatial management actions. For commercial fishers, collection of fine-scale spatial data may also support compensation claims as offshore wind developments are constructed and become operational.

Acknowledgments

This work utilized code developed by Lianne Allen-Jacobson to complete the analysis and create figures. Andrew Lipsky, Doug Christel, and Angela Silva provided guidance as the project was completed. We are also grateful to the Study Fleet vessels captains and NOAA NEFSC support staff for collecting and organizing the data that informed this research. Laura Solinger reviewed a draft of the manuscript. The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its sub-agencies.

Author contributions

Meghna N. Marjadi (Conceptualization [equal], Data curation [equal], Formal analysis [lead], Methodology [lead], Project administration [equal], Writing – original draft [lead], Writing – review & editing [lead]), Andrew W. Jones (Conceptualization [equal], Data curation [equal], Formal analysis [supporting], Methodology [supporting], Project administration [equal], Supervision [equal], Visualization [equal], Writing – original draft [supporting], Writing – review & editing [supporting]), Anna J. M. Mercer (Conceptualization [equal], Formal analysis [supporting], Project administration [lead], Supervision [equal], Writing – original draft [supporting], Writing – review & editing [supporting]), Benjamin Galuardi (Data curation [equal], Formal analysis [supporting], Methodology [supporting], Writing – original draft [supporting], Writing – review & editing [supporting]), and Steven X. Cadrin (Conceptualization [equal], Formal analysis [supporting], Project administration [equal], Supervision [equal], Writing – original draft [supporting], Writing – review & editing [supporting])

Supplementary data

Supplementary data is available at *ICES Journal of Marine Science* online.

Conflict of interest: None declared.

Funding

This research was supported by NOAA Cooperative Institute for the North Atlantic Region (Grant No. NA19OAR4320074).

Data availability

We used data collected by the Northeast Fisheries Science Center study fleet and by commercial vessels. These spatial data and related code are confidential and cannot be shared publicly, except as aggregated in this publication.

References

Allen-Jacobson LM, Jones AW, Mercer AJ *et al.* Evaluating potential impacts of offshore wind development on fishing operations by comparing fine- and coarse-scale fishery-dependent data. *Mar Coast Fish* 2023;**15**:1–14. https://doi.org/10.1002/mcf2.10233

Amoroso RO, Pitcher CR, Rijnsdorp AD., *et al.* Bottom trawl fishing footprints on the world's continental shelves. *Proc Natl Acad Sci* 2018;**115**:E10275–82. https://doi.org/10.1073/pnas.1802379115

Benjamin S, Lee M-YA, DePiper GS. *Visualizing Fishing Data as Rasters (Nos. 18–12; Northeast Fisheries Science Center Reference Document)*. Woods Hole, Massachusetts, USA: National Marine Fisheries Service; Northeast Fisheries Science Center, 2018. https://doi.org/10.25923/c14d-g218

BOEM, (Bureau of Ocean Energy Management). *Outer Continental Shelf Renewable Energy Leases (No. OREP-2023-2001)*. BOEM, Office of Renewable Energy Programs, 2023. https://catalog.data.gov/dataset/outer-continental-shelf-active-renewable-energy-leases (21 July 2025, date last accessed).

Brooke SG. Federal fishery Observer programs in the United States: over 40 years of independent data collection. *Mar Fish Rev* 2015;**76**:1–38. https://doi.org/10.7755/MFR.76.3.1

Chaji M, Werner S. Economic impacts of offshore wind farms on fishing industries: perspectives, methods, and knowledge gaps. *Mar Coast Fish* 2023;**15**:e10237. https://doi.org/10.1002/mcf2.10237

Collette BB, Klein-Macphee G. *Bigelow and Schroeder's Fishes of the Gulf of Maine*. Washington DC, USA: Smithsonian University Press, 2002.

De Backer A, Polet H, Sys K *et al.* Fishing activities in and around Belgian offshore wind farms: trends in effort and landings over the period 2006–2017. In: *Environmental Impacts of Offshore Wind Farms in the Belgian Part of the North Sea: Marking a Decade of Monitoring, Research and Innovation* Brussels:Royal Belgian Institute of Natural Sciences, 2019. 31–46.

DePiper GS. Statistically assessing the precision of self-reported VTR fishing locations. NOAA Technical Memorandum NMFS-NE-229 2014. https://doi.org/10.7289/V53F4MJN (21 July 2025, date last accessed).

DOE, (Department of Energy). *Advancing Offshore Wind Energy in the United States. U.S. Department of Energy Strategic Contribu-*

tions toward 30 Gigawatts and Beyond. (No. GO-102023-5888). United States Department of Energy. 2023. https://www.energy.gov/sites/default/files/2023-03/advancing-offshore-wind-energy-full-report.pdf (21 July 2025, date last accessed).
DOI, U. S. D. of I. Biden-Harris Administration Approves Ninth Offshore Wind Project [Press release]. 2024. https://www.doi.gov/pressreleases/biden-harris-administration-approves-ninth-offshore-wind-project (21 July 2025, date last accessed).
Eigaard OR, Bastardie F, Hintzen NT., *et al.* The footprint of bottom trawling in European waters: distribution, intensity, and seabed integrity. *ICES J Mar Sci* 2017;**74**:847–65. https://doi.org/10.1093/icesjms/fsw194
Gill A, Degraer S, Lipsky A., *et al.* Setting the context for offshore wind development effects on fish and fisheries. *Oceanography* 2020;**33**:118–27. https://doi.org/10.5670/oceanog.2020.411
Goodwin M, Halvorsen KT, Jiao L., *et al.* Unlocking the potential of deep learning for marine ecology: overview, applications, and outlook. *ICES J Mar Sci* 2022;**79**:319–36. https://doi.org/10.1093/icesjms/fsab255
Gray M, Stromberg PL, Rodmell D. *Changes to Fishing Practices around the UK as a Result of the Development of Offshore Wind Farms—phase 1 (revised)*. London: The Crown Estate, 2016.
Hall DM, Lazarus ED. Deep waters: lessons from community meetings about offshore wind resource development in the U.S. *Mar Policy* 2015;**57**:9–17. https://doi.org/10.1016/j.marpol.2015.03.004
Hijmans R, raster: Geographic Data Analysis and Modeling [Computer software]. R package version 3.6-32. 2025, https://github.com/rspatial/raster (21 July 2025, date last accessed).
Hijmans RJ, Bivand R, Cordano E *et al.*. terra: Spatial Data Analysis (Version 1.7-83) [Computer software]. 2024. https://cran.r-project.org/web/packages/terra/index.html (21 July 2025, date last accessed).
Hogan F, Hooker B, Jensen B *et al.*. Fisheries and Offshore Wind Interactions: Synthesis of Science (Technical Memorandum No. 291; NOAA Technical Memorandum NMFS-NE, pp. 1–383). NMFS (National Marine Fisheries Service); NEFSC (Northeast Fisheries Science Center). 2023. https://doi.org/10.25923/tcjt-3a69 (21 July 2025, date last accessed).
Hooper T, Ashley M, Austen M. Perceptions of fishers and developers on the co-location of offshore wind farms and decapod fisheries in the UK. *Mar Policy* 2015;**61**:16–22. https://doi.org/10.1016/j.marpol.2015.06.031
Jennings S, Lee J, Hiddink JG. Assessing fishery footprints and the trade-offs between landings value, habitat sensitivity, and fishing impacts to inform marine spatial planning and an ecosystem approach. *ICES J Mar Sci* 2012;**69**:1053–63. https://doi.org/10.1093/icesjms/fss050
Jones AW, Burchard KA, Mercer AM *et al.*. Learning from the study fleet: maintenance of a large-scale reference fleet for northeast U.S. Fisheries. *Front Mar Sci* 2022;**9**:869560. https://doi.org/10.3389/fmars.2022.869560
Jones AW, Mercer AJ, Duarte DG *et al.*. Combining sources of high-resolution fishery-dependent data from the northeast United States to develop a catch rate time series. *ICES J Mar Sci* 2025;**82**:fsaf032. https://doi.org/10.1093/icesjms/fsaf032
Kirpatrick AJ, Benjamin S, DePiper GS *et al.*. *Socio-Economic Impact of Outer Continental Shelf Wind Energy Development on Fisheries in the U.S. Atlantic, Volume II- Appendices (Nos. 2017–012; OCS Study BOEM, p. 191)*. Washington D.C.: U.S. Department of the Interior, Bureau of Ocean Energy Management, Atlantic OCS Region, 2017. https://espis.boem.gov/final%20reports/5581.pdf
Lennon AE. Offshore wind compensation programs open for Mass. Fishermen—The New Bedford Light. The New Bedford Light. 2024. https://newbedfordlight.org/offshore-wind-compensation-programs-open-for-mass-fishermen/ (21 July 2025, date last accessed).
Livermore J. Spatiotemporal and Economic Analysis of Vessel Monitoring System Data within Wind Energy Areas in the Greater North Atlantic. Providence (RI). Rhode Island Department of Environmental Management Division of Marine Fisheries. 2017. http://www.dem.ri.gov/programs/bnatres/fishwild/pdf/RIDEM_VMS_Report_2017.pdf (21 July 2025, date last accessed).
Livermore J, Guilfoos T. Scallop fishing activity characterization in Southern New England: offshore wind demands and fisheries-dependent methods. *PLoS One* 2024;**19**:e0313197. https://doi.org/10.1371/journal.pone.0313197
McAfee B. 2024 discard estimation, precision, and sample size analysis for 14 federally managed species groups in the waters off the northeastern United States. 2024. https://repository.library.noaa.gov/view/noaa/60888 (21 July 2025, date last accessed).
Methratta ET, Hawkins A, Hooker BR *et al.*. Offshore wind development in the Northeast US Shelf large marine ecosystem: ecological, Human, and fishery management dimensions. *Oceanography* 2020;**33**:16–27. https://doi.org/10.5670/oceanog.2020.402
Methratta ET, Silva A, Lipsky A *et al.*. Science priorities for offshore wind and Fisheries research in the northeast U.S. Continental shelf ecosystem: perspectives from scientists at the National Marine Fisheries Service. *Mar Coast Fish* 2023;**15**:e10242. https://doi.org/10.1002/mcf2.10242
Fisheries Science Center (US) (NEFSC), Northeast. *2024 State of the Ecosystem: Mid-Atlantic*. Northeast Fisheries Science Center (U.S.), 2024. https://doi.org/10.25923/vz5a-d111 (21 July 2025, date last accessed).
NOAA. NOAA fisheries office of science and technology, commercial landings query. 2024. http://www.fisheries.noaa.gov/foss (21 July 2025, date last accessed).
Palmer MC. An evaluation of the northeast region's study fleet pilot program and electronic logbook system phases I and II (NOAA Technical Memorandum NMFS-NE) [204].Northeast Fisheries Science Center (U.S.). 2007https://repository.library.noaa.gov/view/noaa/3913 (21 July 2025, date last accessed).
R Core Team. *R: a Language and Environment for Statistical Computing. [Computer software]*. R Foundation for Statistical Computing. 2023. https://www.R-project.org/ (21 July 2025, date last accessed).
Samhouri JF, Feist BE, Jacox M *et al.*. Stay or go? Geographic variation in risks due to climate change for fishing fleets that adapt in-place or adapt on-the-move. *PLoS Clim* 2024;**3**:e0000285. https://doi.org/10.1371/journal.pclm.0000285
Samoteskul K, Firestone J, Corbett J *et al.*. Changing vessel routes could significantly reduce the cost of future offshore wind projects. *J Environ Manage* 2014;**141**:146–54. https://doi.org/10.1016/j.jenvman.2014.03.026
Scheld AM, Beckensteiner J, Munroe DM *et al.*. The Atlantic surfclam fishery and offshore wind energy development: 2. Assessing economic impacts. *ICES J Mar Sci* 2022;**79**:1801–14. https://doi.org/10.1093/icesjms/fsac109
Wickham H. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag. 2016. https://ggplot2.tidyverse.org (21 July 2025, date last accessed).
Wickham H, François R, Henry L *et al.* dplyr: a Grammar of Data Manipulation (R package Version 1.1.4) [Computer software]. 2023. https://cran.r-project.org/web/packages/dplyr/index.html (21 July 2025, date last accessed).
Willsteed E, Gill AB, Birchenough SNR *et al.*. Assessing the cumulative environmental effects of marine renewable energy developments: establishing common ground. *Sci Total Environ* 2017;**577**:19–32. https://doi.org/10.1016/j.scitotenv.2016.10.152
Zuckoff E. Fishermen Can Now Get Paid If Vineyard Wind Hurts Business. CAI. 2024. https://www.capeandislands.org/local-news/2024-03-05/fishermen-can-now-get-paid-if-vineyard-wind-hurts-business/ (21 July 2025, date last accessed).

Handling Editor: Raul Prellezo