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THEMED ISSUE: OFFSHORE WIND INTERACTIONS WITH FISH AND FISHERIES

Evaluating Potential Impacts of Offshore Wind Development on Fishing Operations by Comparing Fine- and Coarse-Scale Fishery-Dependent Data

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Abstract

Climate change will disrupt many aspects of the marine environment, with anticipated effects for half of northeastern U.S. fisheries. To mitigate effects of climate change, the United States has designated 90,650 km^2 (35,000 mi^2) of ocean for offshore wind energy development, but this growing industry could impact fisheries in the region. Hence, there is a need to measure the spatial distribution of fishing operations to support multiple goals, including spatial planning and compensatory mitigation. In the U.S. Northeast, National Oceanic and Atmospheric Administration Fisheries developed fishing footprints previously by using logbooks. However, logbook footprints rely on coarse data: a single location, the center point of fishing trips reported in logbooks. Therefore, we evaluated bias in these logbook footprints by restricting the size of logbook footprints and by generating active-fishing footprints from fine-scale location data collected by a reference fleet operating in the same region. Active-fishing footprints act as a benchmark approximating the "true" fishing footprint and exposure to wind farms. We focused on the longfin inshore squid *Doryteuthis pealeii* fishery, including 336 trips from 2016 to 2019, and 38 wind farms in southern New England and the Middle Atlantic Bight. Compared to the benchmark active-fishing footprints, unrestricted logbook footprints detected all exposed trips. As we restricted the logbook footprints, the logbook analysis failed to detect exposed trips but better approximated the amount of exposed revenue. Finally, unrestricted logbook footprints underestimated the exposed revenue for high-impact wind farms and overestimated the exposed revenue for low-impact wind farms, and this bias declined with logbook footprint restriction. We show how restricting logbook footprints could improve exposure analysis that depends on coarse-scale data when fine-scale data are unavailable. Furthermore, our analysis highlights the limits of coarse-scale data (i.e., logbook footprints). Therefore, we recommend additional incentives for voluntary participation in programs collecting fine-scale data. These incentives should be prioritized because informed, time-sensitive decisions depend on data collected prior to construction of offshore wind farms.

Renewable energy is needed to prevent the worst effects of climate change, and many nations will include offshore wind energy in their portfolio of renewable energy resources. For example, the U.S. Government set a target for offshore wind development as 30 GW of renewable energy by 2030. As of June 2022, these targeted wind areas include 29 leased areas and an additional 13 planned areas that total 9.02 million ha (22.3 million acres) across the Northwest Atlantic shelf from Maine through North Carolina (Methratta et al. 2020). However, these wind development areas (hereafter, "wind farms") overlap with spaces used by other marine industries, including commercial fishing grounds. Therefore, offshore wind development will likely interact with many commercial fishing operations (BOEM 2021).

Cumulative offshore wind development could cause major adverse impacts, including fisheries displacement, changes in fish stocks, and cascading socioeconomic impacts to fishing communities (Hoagland et al. 2015; Haggett et al. 2020). Effects of offshore wind development fall into two categories: direct and indirect effects (Boehlert and Gill 2010). Direct effects include exclusion from fishing grounds near turbine structures, gear loss from entanglement, additional transit time, added safety risks, and potentially higher insurance costs (Mackinson et al. 2006; Alexander et al. 2013; Methratta et al. 2020). Indirect effects include changes to fish abundance and distribution that affect catch and disrupt the fishery-independent surveys that are used to inform quotas (Methratta and Dardick 2019; Gill et al. 2020; Methratta et al. 2020).

The magnitude of direct effects depends in part on the added gear-specific risks of fishing near offshore wind infrastructure (Methratta et al. 2020). Offshore wind infrastructure will increase the dangers and costs incurred when fishing involves the use of mobile gear (e.g., trawls and dredges). In contrast, offshore wind infrastructure could require fewer modifications when fishing involves fixed gear (e.g., traps or rod and reel). For these reasons, insurers could impose gear-specific premiums (Mackinson et al. 2006; Gill et al. 2020), which could effectively restrict fishing at sites near offshore wind infrastructure.

Additionally, individual fishers will need to weigh the risks and benefits of fishing under new conditions (Alexander et al. 2013; Hooper and Austen 2014; Hooper et al. 2015). Risks include those associated with operating within wind farms, navigating through wind farms, and a potentially more complicated emergency response. Potential benefits include high catch, familiarity with the fishing ground, proximity, and possibly increased catch due to artificial reef effects. However, the risks and benefits will differ among individual fishers. For example, wind farms create more risk for larger, less-maneuverable vessels. Wind farms also create more risk for less-experienced captains, regardless of vessel size. When the risks outweigh the benefits, wind turbines will exclude fishermen from these areas and potentially diminish a fisherman's return on investment. Therefore, offshore wind development will disrupt the business landscape, and fishermen will need to adapt historic operations to preserve the viability of existing business models.

Exposure

Economic exposure (hereafter, "exposure") primarily considers direct effects. The Bureau of Ocean Energy Management (BOEM) defined exposure as the "group of fishermen whose fishing activity occurs in or near a [wind farm]" (Kirkpatrick et al. 2017). King (2019) defined exposure as the "maximum potential economic losses [assuming] no fish will be harvested in the [wind farm]. ... [and no changes in] the abundance or availability of fish in the [wind farm]." These two definitions identify two important components of exposure: (1) the number of trips and stakeholders with exposure and (2) the potential revenue lost from trips with exposure.

Two types of data are needed to quantify the components of exposure. First, we need comprehensive descriptions of where and when fishing occurs (i.e., fishing footprints) to count the number of trips and stakeholders with exposure. Researchers build fishing footprints to support multiple goals by using a variety of methods and data sources (Eigaard et al. 2017; Amoroso et al. 2018; Whitmire and Wakefield 2019). Second, records of revenue are needed to quantify the potential economic loss due to offshore wind development (Livermore 2017; Benjamin et al. 2018; King 2019).

To estimate exposure, the ideal data set includes both the full extent of all trips and records of catch or revenue. However, most data sets include a limited number of attributes and fishing locations for a limited spatial and temporal scope. Therefore, it is likely necessary to combine data sources so as to develop a better picture of exposure (Stelzenmüller et al. 2022).

The Northeast Fisheries Science Center (NEFSC) and the Greater Atlantic Regional Fisheries Office (GARFO) estimate exposure using logbooks (i.e., vessel trip reports), data collected by the observer program, and landings. Fishermen report most fishing trips to the Greater Atlantic region in these logbooks, so the data set is near comprehensive for trips in this region. The NEFSC and GARFO report the logbook footprints by delineating four different percentiles (25th, 50th, 75th, and 90th), which reflect the expected percentage of trips that fall within a specific distance from the trip center reported in the logbook (GARFO 2022).

Logbook footprints depend on analyses by DePiper (2014) and Benjamin et al. (2018). First, DePiper (2014) estimated the cumulative distribution function for the distance between the fishing location included in logbooks and the locations of observed hauls, conditional on observed characteristics of that trip (e.g., gear type, trip length, and geographic region). Second, Benjamin et al. (2018) derived the logbook footprint from the predicted spatial variation in fishing effort (DePiper 2014) by using a 500- × 500-m grid and accounting for unfishable areas (e.g., land and no-take zones).

Logbook footprints depict the extent predicted from a single location—not the true extent of trips. Although logbook footprints have clear limits, in many cases logbooks provide the only record for a trip. Therefore, we need methods to improve estimates of exposure from logbook footprints. To develop these improvements, we first need to quantify the bias in exposure estimated from logbook footprints.

We evaluated bias in logbook footprints by generating active-fishing footprints from high-resolution GPS location data collected by the NEFSC Study Fleet for the full extent of trips. These active-fishing footprints acted as a benchmark approximating the "true" fishing footprint. Furthermore, we restricted logbook footprints to different percentiles to identify a simple method for improving estimates of exposure. We determined the extent of bias by counting the number of trips with exposure using the two sets of footprints: logbook footprints and active-fishing footprints. We also compared the amount of exposed revenue estimated for leased and planned wind farms by using both types of footprints.

Case Study

The NEFSC Study Fleet program engages fishing vessels in collecting detailed information about their fishing operations and catch to address research questions and inform fisheries management (Palmer et al. 2007; Jones et al. 2022). Study Fleet participants come from Maine to North Carolina, and participation varies by year, with 37–42 vessels under contract from 2014 to 2020. Study Fleet vessels collect GPS location data throughout the entire fishing trip, recording their location every minute. Additionally, the Study Fleet vessels manually record the start and end locations of each gear haul. The NEFSC's Cooperative Research Branch identifies active fishing locations by matching the Study Fleet GPS locations to the start and end locations of each haul. Finally, the Cooperative Research Branch confirms that fishing gear was in the water at these active fishing locations by using data collected via depth and temperature loggers.

We selected the longfin inshore squid *Doryteuthis pealeii* fishery as a case study for this research due to the fishery's expected spatial overlap with wind farms (Kuffner 2018) and data availability. Specifically, the longfin inshore squid fishing fleet has abundant data availability from the Study Fleet and logbooks. At the start of the program, Study Fleet vessels harvested little longfin inshore squid as a proportion of total landings by the entire fleet, but this percentage has grown throughout the tenure of the program, reaching over 20% of total landings in 2020 (Jones et al. 2022).

Multiple factors influence the longfin inshore squid fishing footprint and its overlap with wind farms located on predominantly sandy substrate. For example, longfin inshore squid inhabit the outer continental shelf during the winter months and migrate inshore during the late spring, where they form aggregations in mostly sandy habitats (Jacobson 2005). Fishers opportunistically harvest this species with bottom trawl gear and jigs. In 2019, the longfin inshore squid fishery landed more than 12,000 metric tons valued at over US$42 million (NMFS 2019).

METHODS

We selected Study Fleet trips for recent years (i.e., since 2014) with active-fishing GPS location data and with catches dominated by longfin inshore squid (≥39% by weight). We extracted revenue data from a combination of dealer and logbook information. We summed revenue by logbook identifier, monitoring program, and northeastern commercial species code for records of longfin inshore squid. We adjusted revenue to the 2019 gross domestic product by multiplying revenue by the ratio of the nominal year's deflator to the 2019 deflator. We matched trip and revenue data by using the logbook identifier.

Fishing footprints.— We created new fishing footprints by using fine-scale, fishery-dependent data (i.e., active-fishing footprints). We built active-fishing footprints from active fishing locations by creating convex hulls with a 50-m buffer for each haul (Figure 1A) and then merging the convex hulls by trip (Figure 1B; Pebesma 2018; Wickham et al. 2022). We transformed active-fishing footprints from polygons to a grid of cells (i.e., raster; Hijmans et al. 2022) and evenly distributed revenue such that total revenue was the product of the revenue per cell and the total number of cells within the active-fishing footprint.

We selected logbook footprints for each trip in this case study based on the logbook identifier. These logbook footprints, which constitute an NEFSC data product, allocate a proportion of the trip to each cell (Benjamin et al. 2018). Furthermore, the NEFSC restricts these logbook footprints to the 90th percentile, which reflects the expected percentage of trips that fall within a specific distance from the trip center reported in the logbook. However, we wanted to determine whether percentile selection influenced the bias in exposure estimates. Therefore, we restricted the logbook footprints to four different percentile levels (Figure 2; Hijmans et al. 2022; Wickham et al. 2022). To modify rasters of logbook footprints, we identified, ranked, and filtered unique cell values within the raster. Cell values indicated the proportion of the trip predicted per unit area, and these values were homogeneous throughout the area defined by each percentile bin. From low to high, these values corresponded to the 90th, 75th, 50th, and 25th percentiles. Next, we rescaled the cell values,

$$V_{\text{new}} = (N_{\text{bins}} \times N_{\text{cells-bin}})^{-1},$$

such that the new cell value (V_{new}) was a function of the number of percentile bins (N_{bins}) and the number of cells for each percentile bin ($N_{\text{cells-bin}}$).

Exposure.— We evaluated exposure with 38 wind development areas, including 29 leased areas and nine planned areas (Figure 3; BOEM 2022); we refer to these areas collectively as wind farms. We identified lease areas by their lease number, a unique alphanumeric identifier assigned by BOEM. We included multiple planned areas on the U.S. East Coast: the Gulf of Maine planning area, the New York Wind Energy Areas (Fairways North and South), and the six Central Atlantic call areas. We did not include the 16,093 km (10,000 mi) of proposed submarine cable corridors, which will likely interact with fishing operations and are anticipated as part of the 2030 goal. We completed two analyses to evaluate bias in logbook footprints. First, we identified exposed trips by their intersection with wind farms; second, we evaluated the amount of exposed revenue overlapping wind farms.

We identified trips with exposure by checking intersections between fishing footprints and wind farms (Figure 4A). This was a pairwise analysis by fishing trip, with each comparison including one logbook footprint and one active-fishing footprint for the same trip. Next, we counted the number of outcomes in each of four possible categories: (1) neither footprint intersected a wind farm, (2) both footprints intersected a wind farm, (3) only the logbook footprint intersected a wind farm, or (4) only the active-fishing footprint intersected a wind farm. Additionally, we estimated logbook footprint fidelity as the proportion of intersections detected by both footprints and the total number of intersections detected by the active-fishing footprint. Finally, we repeated this analysis with logbook footprints restricted to the 90th, 75th, 50th, and 25th percentiles, with each iteration comparing 12,768 potential intersections (i.e., 336 trips × 38 wind farms).

Next, we selected all wind farms that intersected a fishing footprint (logbook or active-fishing footprint) and all fishing footprints that intersected a wind farm (Figure 4B). This analysis did not include wind farms that did not intersect fishing footprints or fishing trips that did not intersect one of the 38 leased or planned wind farms. For each trip in the analysis, we estimated exposure as the amount of revenue assigned to the portion of the footprint overlapping the wind farm. Next, we built cumulative logbook and active-fishing footprints cropped to each wind farm. Finally, we summed the amount of exposed revenue by trip for each cumulative logbook footprint (E_{LF}) and active-fishing footprint (E_{AFF}) cropped to each wind farm. We compared these estimates by taking the difference (D):

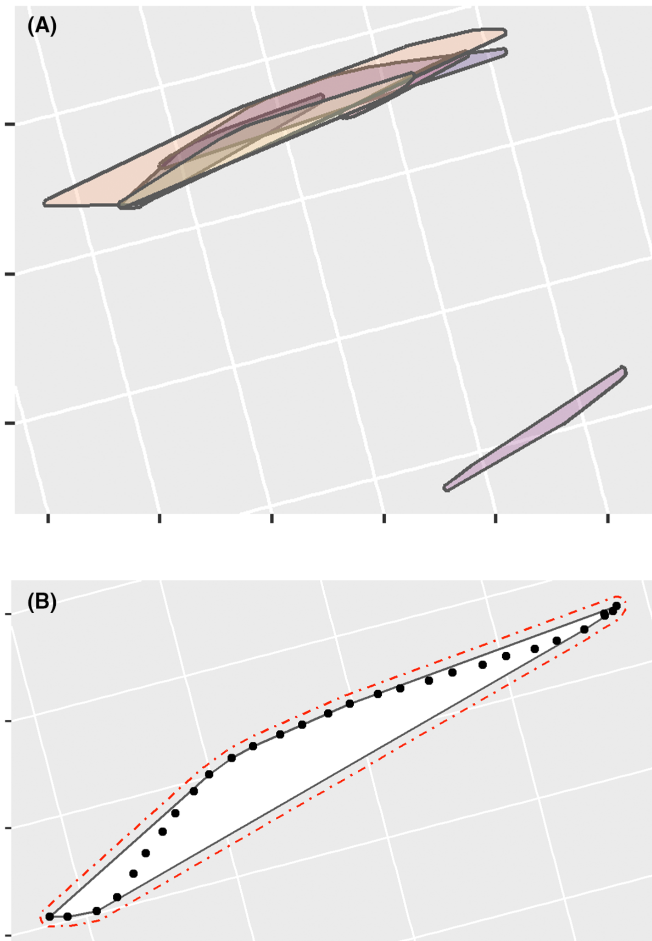

FIGURE 1. Creating active-fishing footprints. **(A)** For each haul, we wrapped a convex hull (solid black line) around active fishing locations (black circles) and added a 50-m buffer (dash–dotted red line). **(B)** We then created an active-fishing footprint by merging all convex hulls for each trip. In this example, the haul (panel A) includes 30 GPS points and the trip (panel B) includes six hauls.

$$D = E_{\mathrm{LF}} - E_{\mathrm{AFF}}.$$

Since we consider the active-fishing footprint to be a benchmark for "true" effects, we compared high-impact wind farms (i.e., those having a relatively large E_{AFF}) with low-impact wind farms (i.e., those having a relatively low E_{AFF}). Specifically, we determined whether D predictably varied with E_{AFF} by using a linear model.

RESULTS

The final data set included data from 16 vessels and 336 trips occurring from 2016 through 2019 (Figure 3). The following statistics describe the set of fishing trips included in this case study (averages indicated the median). Fishing effort averaged 4 gear hauls/trip, with a range of 1 to 37 gear hauls/trip. Gear hauls averaged 104 GPS locations, with a range of 1 to 322 GPS locations. Trips averaged \$4,348.48 in total revenue, with a range of \$1.75 to \$122,241.70. The wind development areas averaged 342.6 km^2 (132.3 mi^2), with the smallest wind farm being 0.8 km^2 (0.3 mi^2) and the largest wind farm being 60,015.5 km^2 (23,172.1 mi^2).

Detecting Exposure

The analyses of logbook and active-fishing footprints concurred when neither footprint intersected a wind farm or when both footprints intersected a wind farm. Neither footprint intersected a wind farm, regardless of footprint type, for the majority of fishing trips included in this study (Figure 5). Both footprints intersected a wind farm for 25, 24, 21, and 17 trips when we restricted the logbook footprints to the 90th, 75th, 50th, or 25th percentile, respectively (Figure 5).

Analyses of logbook and active-fishing footprints did not concur when only one type of footprint intersected a wind farm. Furthermore, active-fishing footprints more closely reflect reality. Therefore, we interpreted intersections as false positives if only the logbook footprint intersected the wind farm. In contrast, we interpreted intersections as false negatives if only the active-fishing footprint intersected the wind farm.

The number of false positives declined with restricted logbook footprints: 1,417, 334, 33, and 5 trips for logbook footprints that were restricted to the 90th, 75th, 50th, and 25th percentiles, respectively (Figure 5). In contrast, the number of false negatives increased with restricted logbook footprints: 0, 1, 4, and 8 trips for logbook footprints that were restricted to the 90th, 75th, 50th, and 25th percentiles, respectively (Figure 5). Finally, logbook footprint fidelity declined with increasing restriction: when restricted to the 90th, 75th, 50th, and 25th percentiles, logbook footprints captured 100, 96, 84, and 68% of intersections, respectively, between wind farms and active-fishing footprints.

Quantifying Exposure

The logbook footprint analysis detected the largest number of exposed trips (Figure 6A), the most total revenue (Figure 6B), and the least revenue per trip (Figure 6C) when we restricted logbook footprints to the 90th percentile. However, we observed that revenue per trip varied inversely with the number of exposed trips and total revenue when we compared all analyses with both footprint types. This pattern occurred because many larger, unrestricted footprints partially overlapped wind farms and the overlap was exclusively with their low-revenue outer band. Relatedly, the restricted logbook footprint and active-fishing footprint analyses detected fewer

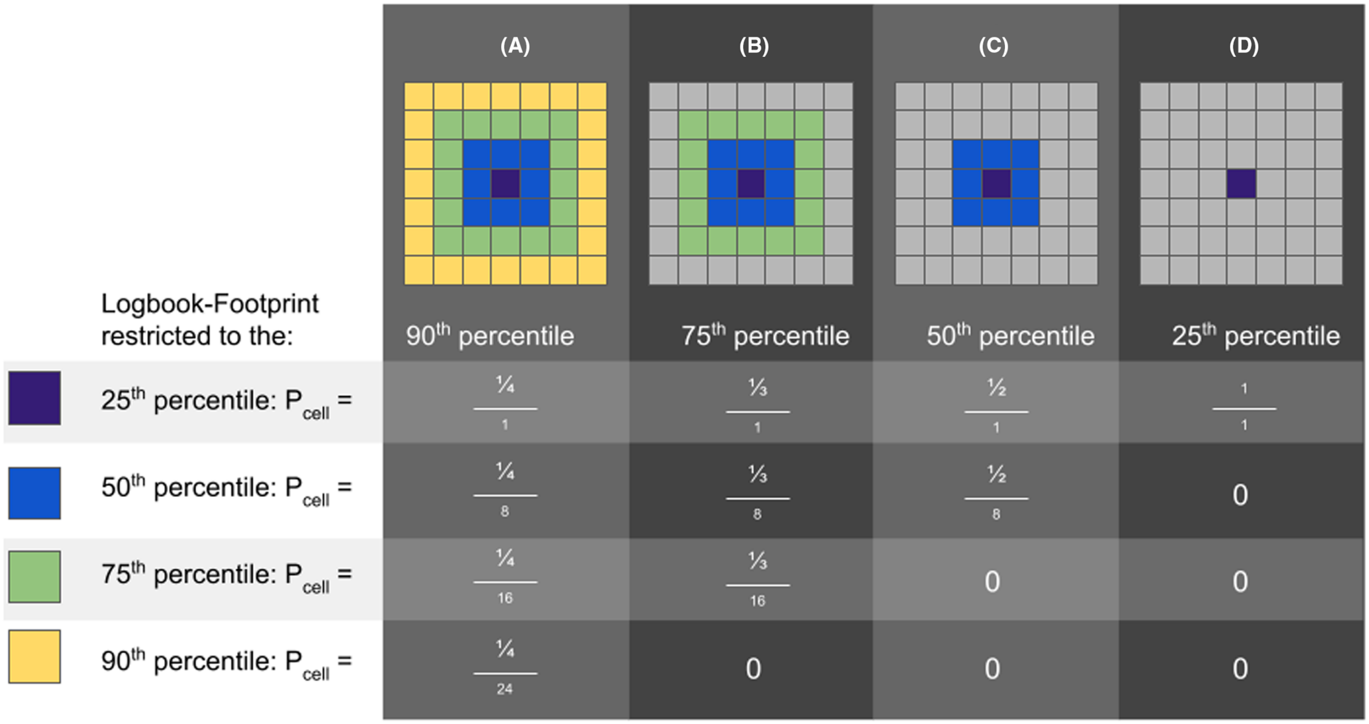

FIGURE 2. Restricting logbook footprints. **(A)** The Greater Atlantic Regional Fisheries Office and the Northeast Fisheries Science Center report logbook footprints restricted to the 90th percentile, which reflects the expected percentage of trips that fall within a specific distance from the trip center reported in the logbook. We modified these logbook footprints by further restricting them to the **(B)** 75th percentile, **(C)** 50th percentile, and **(D)** 25th percentile. In these modified logbook footprints, we recalculated cell-specific probabilities. For the 90th percentile, the standard report attributes 25% of the revenue to each percentile level, so cell-specific probabilities are 0.25 divided by the number of cells in that percentile level. In this schematic, there are 1, 8, 16, and 24 cells for the 25th, 50th, 75th, and 90th percentiles. In the modified rasters, we distributed all revenue throughout a smaller footprint, so we attributed 33, 50, or 100% of the revenue to each percentile level when we restricted the logbook footprints to the 75th, 50th, or 25th percentile.

exposed trips (Figure 6A), less total revenue (Figure 6B), and more exposed revenue per trip (Figure 6C).

Cumulative logbook and active-fishing footprints differed qualitatively. Figure 7 illustrates an example wind farm (OCS-A 0500). The cumulative active-fishing footprint for this example wind farm was heterogeneous, with hot spots of high revenue (Figure 7A). In contrast, the cumulative logbook footprint restricted to the 90th percentile for this wind farm suggested a relatively homogeneous distribution of low revenue per cell (Figure 7B). The total number of trips intersecting the wind farm was greater for the cumulative logbook footprint (69 trips) than for the cumulative active-fishing footprint (6 trips). However, the total amount of revenue was less for the cumulative logbook footprint ($45,503) than for the cumulative active-fishing footprint ($77,203). Figure 7 also shows the cumulative logbook footprint restricted to the 25th percentile; this restricted cumulative logbook footprint (Figure 7C) more closely resembled the cumulative active-fishing footprint (Figure 7A), and revenue was heterogeneous in both cumulative footprints, with a revenue hot spot in the northwest corner of the wind farm. Furthermore, the number of trips with exposure was more similar (5 trips for the logbook footprint versus 6 trips for the active-fishing footprint), and the amount of exposed revenue was more similar ($60,400 for the logbook footprint versus $77,203 for the active-fishing footprint; Figure 7C).

We repeated this analysis for all 36 wind farms that overlapped a logbook footprint or an active-fishing footprint. We found that the magnitude of the exposure difference (D) varied with E_{AFF}, with logbook footprints underestimating exposure (E_{AFF}) at high-impact wind farms and overestimating exposure (E_{AFF}) at low-impact wind farms (Figure 8A). Furthermore, D diminished for more restricted logbook footprints (Figure 8B–D).

DISCUSSION

Traditional fishery monitoring systems do not collect fine-scale data. However, we might require precise information about fishing locations to evaluate spatial overlap

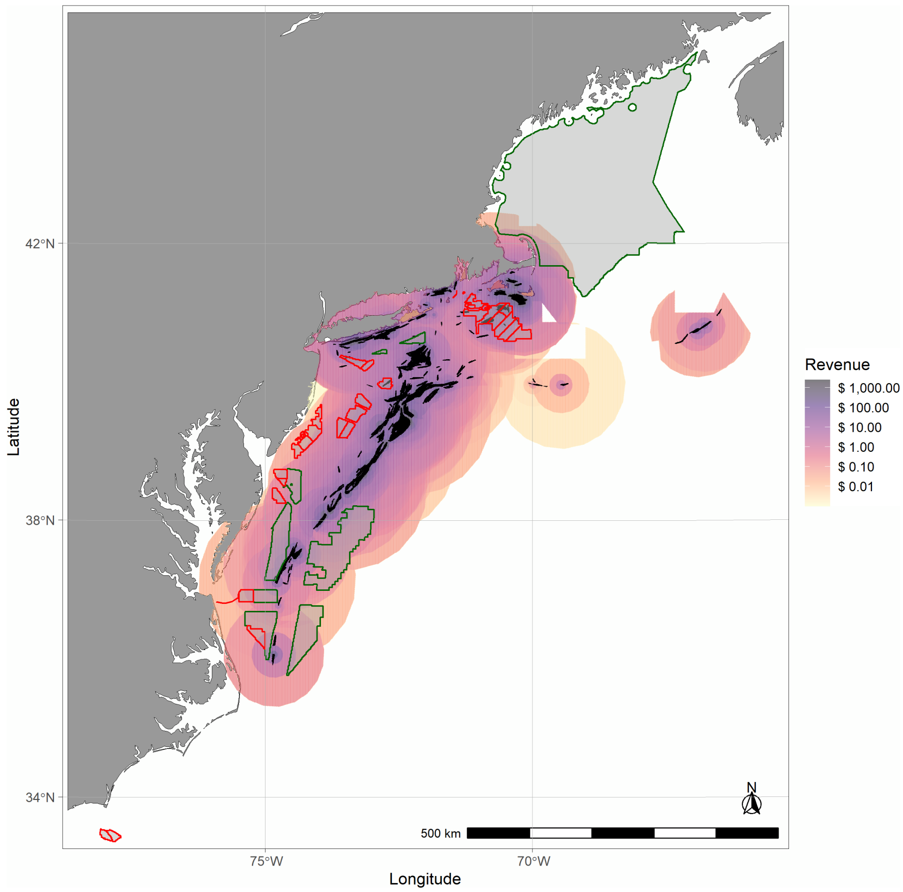

FIGURE 3. Map illustrating U.S. East Coast wind farms, unrestricted logbook footprints, and active-fishing footprints included in this study. All leased areas are outlined in red, and all planned areas are outlined in dark green. Logbook footprints depict the predicted revenue (on a log scale) per 500- × 500-m grid cell. Solid black polygons indicate active-fishing footprints. The total revenue represented on this map is US$19,767,483.

between commercial fishing and planned offshore wind energy development. Hence, this research sought to use fine-scale fishery data collected through a cooperative research program, the NEFSC Study Fleet, to refine coarse-scale analyses of offshore wind impacts on fishing operations.

This research shows how the spatial scale of fishery data influences the predicted effects of offshore wind energy development on fishing operations. Existing federal fishery monitoring efforts were designed to manage fisheries; they were not designed to manage offshore wind or to manage fisheries interactions. For example, most fishery data provide stock-level accounting of fishery extractions for stock assessment and management purposes. Nevertheless, fishery-dependent data can be helpful for understanding interactions.

Restricted Logbook and Active-Fishing Footprints

We assumed that the active-fishing footprint approximated the "true" exposure for each trip. Logbook footprints that were restricted to the 90th percentile detected all trips with "true" exposure (i.e., no false negatives). However, the unrestricted logbook footprint analysis included the greatest number of false positives. Furthermore, we detected fewer false positives but more false negatives when we restricted the logbook footprint to lower percentiles. Therefore, modifying the logbook footprint had trade-offs: more false negatives and fewer false positives.

We think that there is value in a tool that captures all trips with exposure, so we recommend using the logbook footprint at the 90th percentile to identify at-risk trips. In contrast, restricted logbook footprints could miss at-risk trips; therefore, we do not recommend restricting the logbook footprints when the goal is to generate a comprehensive list of at-risk trips. As a next step, analysts can use additional tools, such as the active-fishing footprint, to complement the logbook footprint analysis, narrow the field of impacted fishing trips, and better triangulate the effects. This triangulation will depend on data availability.

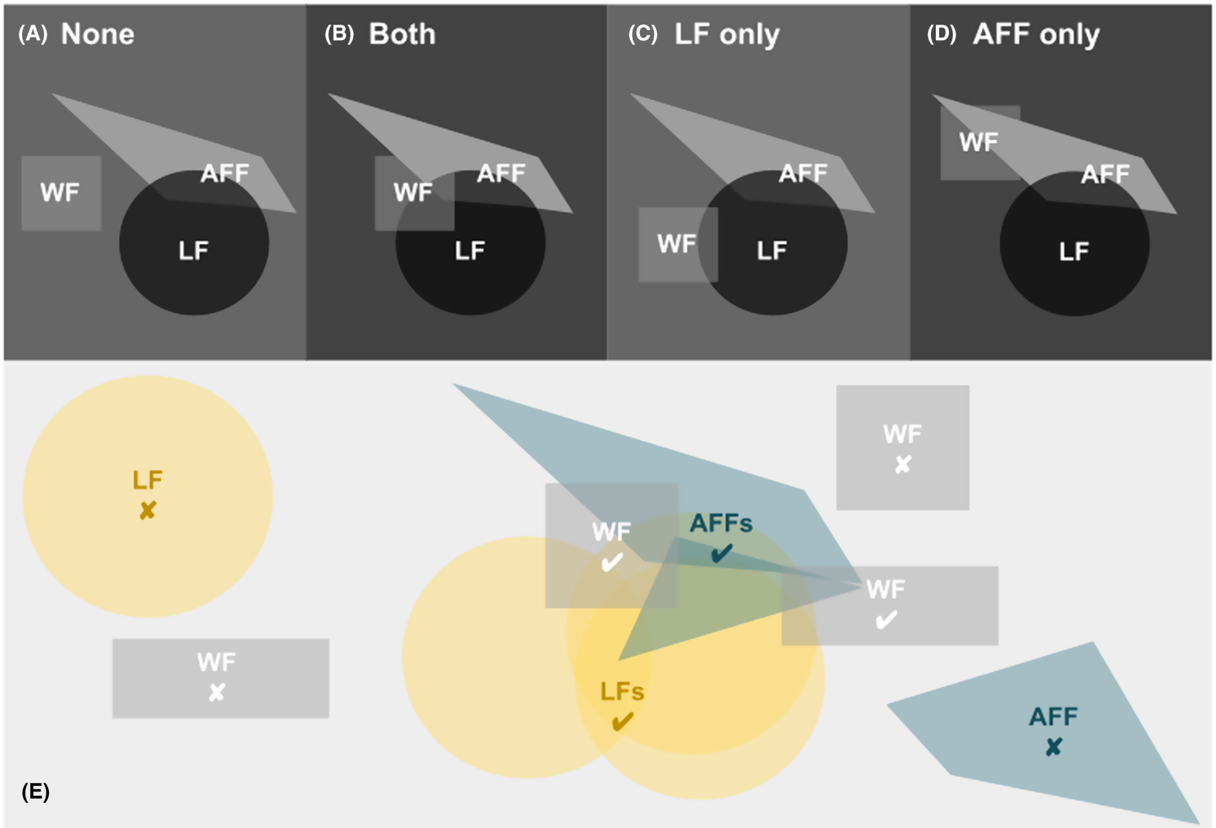

FIGURE 4. Exposed trips and revenue. We completed two analyses to evaluate bias in logbook footprints (LFs). First **(A–D)**, we tested intersections with wind farms (WFs) for a pair of footprints for each trip: the LF and the active-fishing footprint (AFF). From this test, there were four possible outcomes: **(A)** neither footprint intersected a WF, **(B)** both footprints intersected a WF, **(C)** only the LF intersected a WF, or **(D)** only the AFF intersected a WF. **(E)** Second, we evaluated the impact of each WF (gray rectangles) by building cumulative footprints for LFs (yellow circles) and AFFs (blue polygons). This analysis included WFs that intersected footprints, and it included footprints that intersected WFs (check = included; x = not included).

By restricting the percentiles, we create smaller fishing footprints, which has two implications for exposure analysis. First, smaller footprints are less likely to intersect wind farms. Second, revenue is more concentrated within a smaller footprint because in all cases, we distributed all revenue throughout the logbook footprint. Both of these factors influence the cumulative footprint, which we used to estimate the amount of exposed revenue. At the 90th-percentile level, logbook footprints underestimated the amount of exposed revenue compared to that estimated from active-fishing footprints. Exposure is defined as the potential *maximum* impact of offshore wind development on fishing operations. Therefore, we do not recommend using unrestricted logbook footprints to estimate the amount of exposed revenue. Instead, higher-resolution data would more accurately estimate the amount of exposed revenue. When additional data are unavailable, restricting the logbook footprints could improve estimates of exposed revenue.

Ultimately, we think that coarse- and fine-scale data can support different goals. It is possible that coarse-scale data (e.g., logbook footprints) can support mitigation of fishery impacts for individual wind farms and can be used to identify general trends in the impact of offshore wind energy on fishing operations regionwide. However, we likely need fine-scale data to more precisely quantify trip-level impacts. For example, active-fishing footprints or other fine-scale techniques could accurately inform compensation needs. Therefore, it is imperative to support mechanisms that facilitate the collection of fine-scale data to improve trip-level analyses.

Exposure, a Component of Economic Impact

Our analysis does not address many important factors (e.g., other direct effects or indirect effects). For example, our analysis assumes that wind farms will displace all fishing, even though wind farms could become multi-use areas where industry can harvest fish and wind energy (Schupp

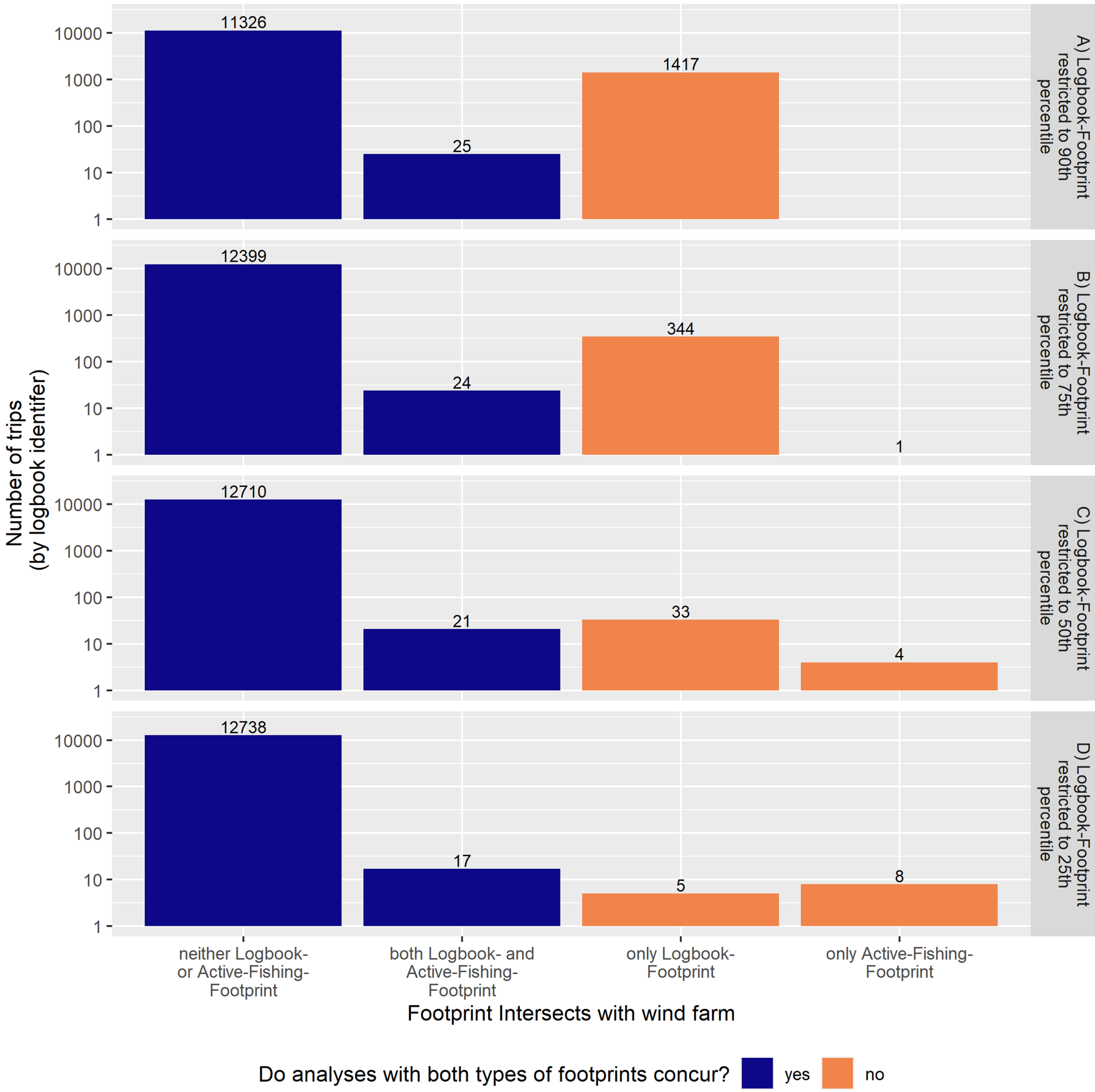

FIGURE 5. Exposed trips. Each bar shows the number of trips (abscissa) within each outcome (ordinate) when checking whether a pair of footprints (logbook footprint and active-fishing footprint) intersected a wind farm. The four possibilities were that (1) neither footprint intersected a wind farm, (2) both footprints intersected a wind farm, (3) only the logbook footprint intersected a wind farm (false positive), or (4) only the active-fishing footprint intersected a wind farm (false negative). The first two outcomes show agreement between the logbook footprint and active-fishing footprint analyses, while the second two outcomes show disagreement between the analyses. Each panel shows the analysis repeated for the logbook footprint restricted to the **(A)** 90th percentile, **(B)** 75th percentile, **(C)** 50th percentile, and **(D)** 25th percentile.

et al. 2021). However, our analysis attempts to quantify one component of the system: exposure. Exposed revenue is the revenue lost because a wind farm overlaps a fishing ground, which is one component of economic impact:

$$\text{Impact} = \text{Recoup} - \text{Exposure} - \text{New costs} - \text{Indirect costs}.$$

New costs include increases to insurance, time, and fuel to transit longer distances around wind farms and

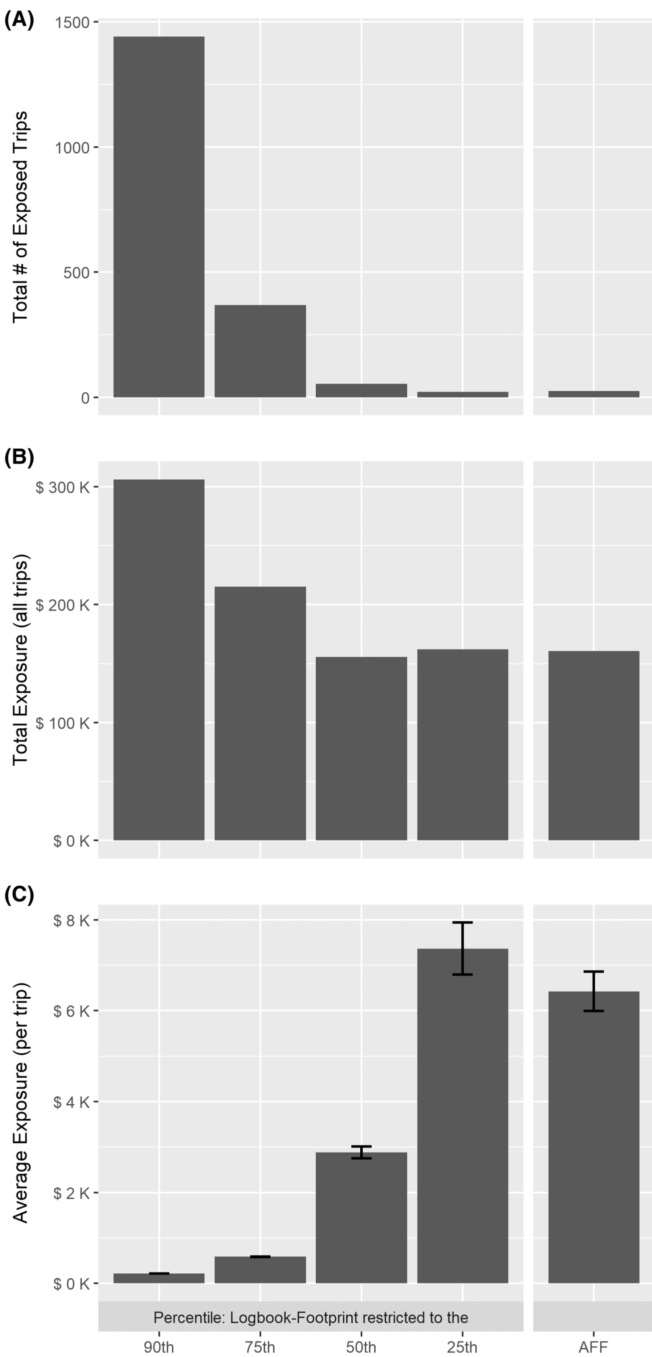

FIGURE 6. Comparing estimates of exposure using fine- and coarse-scale fishery-dependent data. Total exposure includes **(A)** the number of exposed trips and **(B)** the total revenue summed across all exposed trips. Total exposure declines with logbook footprint restriction and approaches the number of trips detected using the active-fishing footprint (AFF) analysis. **(C)** In contrast, average exposure increases with logbook footprint restriction and approaches the average exposure estimated from the AFF analysis. Average exposure is the mean exposure for all trips; error bars indicate SE.

replacing gear that is lost or damaged by wind developers. Indirect costs, for example, include negative effects on the target species. These costs can be offset by the potential revenue added by concentrating effort in new fishing grounds (i.e., recouped costs). Note that this is the individual vessel impact, not the total fishery or community impact; also, the ability to recoup costs could change through time.

Exposure analysis depends on historic fishing and revenue, which creates two limitations. First, existing fisheries data might or might not accurately depict spatial characterizations of future fishing (Battista et al. 2013). Importantly, accuracy increases with data availability, and some stakeholders have better records of landings. Second, exposure analysis cannot quantify and explicitly is not quantifying other components of economic impact. Our analysis aims to quantify only one part of the equation, exposure, which we think is a necessary and practical first step to evaluating potential impacts. Subsequent analyses should estimate other components of this equation to generate a more complete description of impacts.

Scope and Next Steps

These conclusions may be limited to the group of Study Fleet vessels participating in the longfin inshore squid fishery. Indeed, the Study Fleet includes a nonrandom selection of trips, which limits interpretations of the data set. Still, Study Fleet vessels harvested about 20% of longfin inshore squid as a proportion of total landings by the entire fleet for the years included in this study. To evaluate possible differences, researchers could repeat this analysis with any fishery that collects fine-scale data, including other fisheries that (1) participate in the Study Fleet, (2) participate in electronic monitoring, or (3) collect Automatic Identification System (AIS) or vessel monitoring system (VMS) data. The following two examples outline subsequent analyses that could broaden the scope of these conclusions.

First, Study Fleet participants report fishing locations that are automatically generated from their GPS location data (i.e., without reporting errors). Although other fleets might report locations in logbooks with little error, we will likely need to modify our analysis for fleets that report locations with large errors. Therefore, we need to determine whether restrictions should account for differences in reporting errors. Subsequent analyses could repeat this analysis with electronic monitoring data, which include fine-scale active fishing locations that are independent of the logbook locations. We expect that restriction will improve estimates with accurate logbook locations.

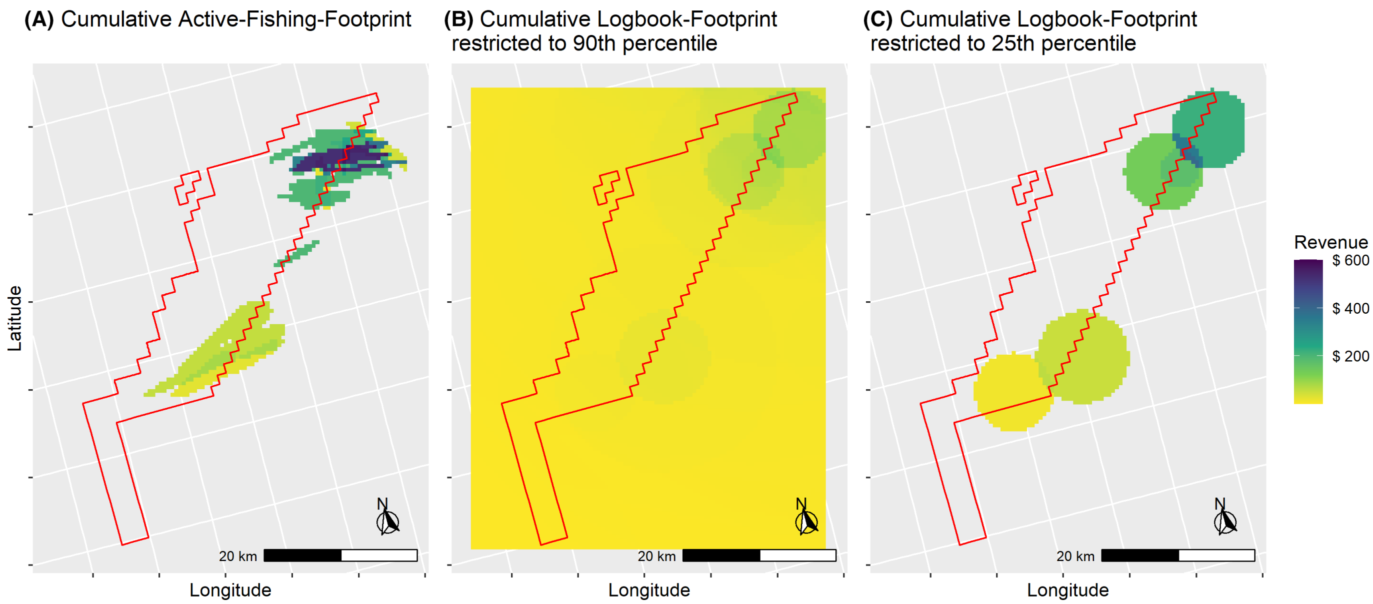

FIGURE 7. Cumulative footprints for an example wind farm (OCS-A 0500). Each plot shows a cumulative fishing footprint cropped to the wind farm: **(A)** cumulative active-fishing footprint, **(B)** cumulative logbook footprint restricted to the 90th percentile, and **(C)** cumulative logbook footprint restricted to the 25th percentile. The active-fishing footprint identifies 6 trips and US$77,200 of revenue with exposure to this wind farm. The logbook footprint restricted to the 90th percentile identifies 69 trips and $45,500 of revenue with exposure to the wind farm. The logbook footprint restricted to the 25th percentile identifies 5 trips and $60,400 of revenue with exposure to the wind farm. Note that each panel uses the same arithmetic scale for revenue; on this scale, the revenue is relatively homogeneous in panel B versus panels A and C. In contrast, Figure 3 displays revenue on a log scale with narrower limits, highlighting the heterogeneity in the total cumulative logbook footprint restricted to the 90th percentile.

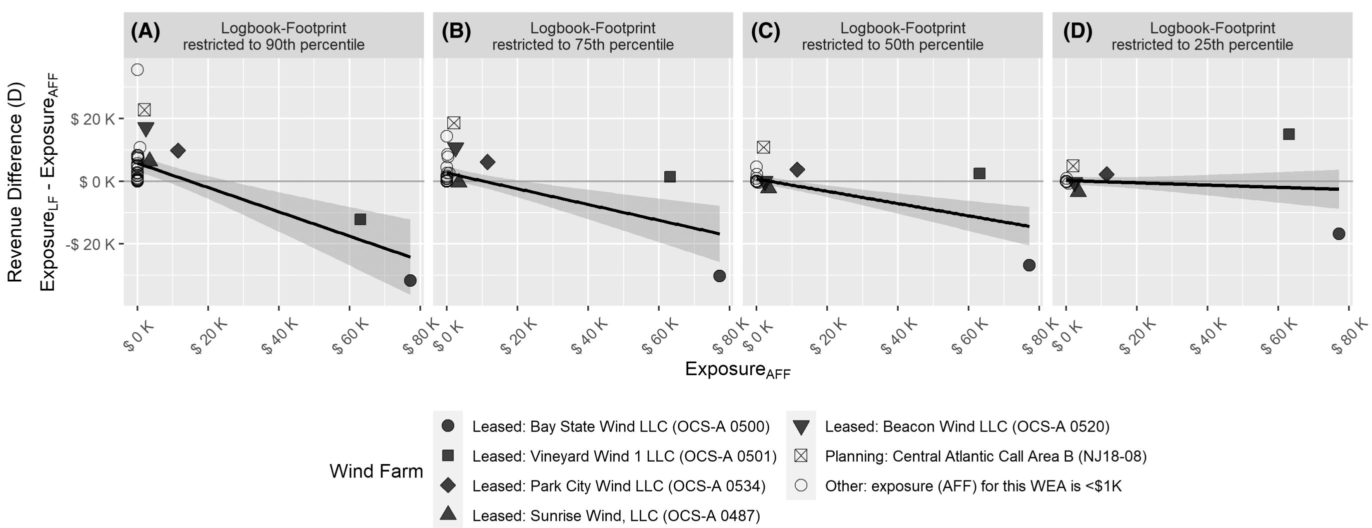

FIGURE 8. Differences between analyses (D) depend on the magnitude of impact and logbook footprint restriction. The solid black line (with 95% confidence interval) shows the relationship between exposure estimated from the active-fishing footprint (E_{AFF}; ordinate) and the difference between exposure estimated using the logbook footprint (E_{LF}) and E_{AFF} (i.e., $D = E_{LF} - E_{AFF}$; abscissa). Each shape represents exposure created by a single wind farm (WEA = wind energy area); open circles indicate all wind farms with low exposure ($E_{AFF} <$ US$1,000). If D is greater than zero, then the logbook footprint overestimates exposure; if D is less than zero, then the logbook footprint underestimates exposure. Each panel shows the analysis repeated for the logbook footprint restricted to the **(A)** 90th percentile, **(B)** 75th percentile, **(C)** 50th percentile, and **(D)** 25th percentile.

Second, fishing behaviors vary by target species and gear type. However, this analysis is limited to the longfin inshore squid fishery, which is an opportunistic fishery that is executed by a fleet of primarily bottom trawl vessels. These traits determine the fishery's gear-specific risk, fishing footprint, and, subsequently, the outcome of the analysis. Therefore, we need to determine the ideal fishery- or gear-specific restrictions for logbook footprints by repeating this analysis with additional fisheries that collect fine-scale data.

We expect that restriction will improve estimates when concentrated fishing occurs near the single logbook location. For example, vessels that target aggregating species, such as the Silver Hake *Merluccius bilinearis*, Scup *Stenotomus chrysops*, and Butterfish *Peprilus triacanthus*, as well as vessels that target sedentary shellfish species, such as the Atlantic sea scallop *Placopecten magellanicus* and ocean quahog *Arctica islandica*, are more likely to fish in concentrated areas within a fishing trip. In contrast, we expect that restriction will not improve estimates when diffuse fishing occurs far from the single logbook location. For example, vessels targeting more widely distributed species or participating in multispecies fisheries, such as the groundfish fishery, are more likely to fish a wider spatial range within one fishing trip.

Other Fine-Scale Data Sets

We must consider other fine-scale data sets to broaden the utility of active-fishing footprints. Other fine-scale data sets include electronic monitoring, VMS, AIS, or plotter data. For fleets that currently lack fine-scale data, we advocate for targeted incentives to increase the voluntary collection of fine-scale data, ideally with description of fishing behavior. These data sets could differ from Study Fleet data in two major ways. First, ping frequency varies among data sets. Therefore, subsequent analyses should determine how ping frequency affects footprints and exposure analysis. Second, most data sets do not describe fishing behavior—that is, they do not distinguish between active fishing and other activities, such as transit, scoping, gear prepping, etc. Thus, subsequent research should develop tools to determine fishing behavior (e.g., speed windows, cluster analysis, and deep learning). For example, we could use Study Fleet data to predict annotations (e.g., fishing versus nonfishing locations) in unannotated but more comprehensive GPS location data sets (e.g., VMS and AIS). Furthermore, analyses should determine whether ping frequency affects the accuracy of different annotation tools.

For example, VMSs collect data via a satellite surveillance system that reports vessel location every 30–60 min with high accuracy. Indeed, Stelzenmüller et al. (2022) used VMSs to delineate fishing footprints in European waters. Furthermore, VMS data are reported at a higher frequency in the United States than in Europe: 1 poll per 60 min in the U.S. Northeast and 1 poll per 30 min in Alaskan waters versus 1 poll per 120 min in European waters (Palmer and Demarest 2018). Vessels using VMSs catch a majority of annual landings of federally managed species; nevertheless, VMS data do not capture the catch of all species and may not be representative of all operations within each fishery.

Furthermore, VMS data are subject to strict confidentiality requirements and are not easily available. In contrast, AIS data are publicly available and have a higher spatial resolution: poll rates range from 1 poll per 2 s to 1 poll per 3 min depending on speed and class (MarineTraffic 2022). However, use of AIS is only required for vessels longer than 19.81 m (65 ft) and AIS units can be turned off outside of 19.31 km (12 mi) from shore. Therefore, AIS data have finer spatial resolution than VMS or logbook data, but their utility may also be limited. Future research should determine whether we can use AIS and VMS data to build active-fishing footprints.

CONCLUSIONS

Data access and merging of data streams create large hurdles for this type of project. Additionally, confidentiality agreements limit access, which makes combining and sharing information difficult. To ameliorate these hurdles and process data efficiently, we recommend creating a shared trip identifier among regional data sets. This is underway within the National Marine Fisheries Service, but the timeline for completion of that effort is uncertain.

We provide an approach to more accurately estimate fishing footprints, which influences how we interpret lower-resolution data for the entire fleet in the context of offshore wind development. We found that the resolution of fishery-dependent data could affect spatially explicit changes in fishing behavior. Therefore, we recommend that multiple groups consider the value and need for finer-scale, industry-based data collection efforts like the Study Fleet; these groups include offshore wind managers, decision makers, and research funders investing in planning or mitigation science. These efforts have the potential to be purpose-built to meet the needs of data end users. Scaling up such programs is also possible but would require additional resources, additional incentives for voluntary participation, and data sharing and data trust agreements.

Regulators must consider many imminent decisions related to offshore wind, and informed decisions depend on pre-construction data. Therefore, these incentives are time sensitive and should be prioritized to support multiple goals, including prelease planning, mitigation, and compensation processes and optimizing the collection of fishery-dependent data.

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