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Leveraging data from a private recreational fishing application to begin to understand potential impacts from offshore wind development

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The development of offshore wind energy in the United States necessitates a sound understanding of trade-offs across ocean uses. Location data on private recreational fishing have been a glaring gap in understanding how society uses marine resources, despite its economic importance. In this study, we use a novel data set to start to fill that knowledge gap. We employ a flexible restricted likelihood spatial scan statistic on data from Fish Rules, a smartphone application, which provides georeferenced species-level regulations, to understand whether species-level data of user queries are clustered spatially. Originally developed for epidemiological studies of disease clusters, the flexible scan statistic employed in this study uses a Bernoulli likelihood ratio test to assess the size, number, and significance of clusters in presence/absence data for recreational species. We use a second data set of known fishing locations to validate that the clusters identify private recreational fishing activity. We then discuss the analysis in the context of wind lease areas in the region, highlighting its value in supporting management decision-making. The results suggest that Fish Rules data identify areas with a high likelihood of being private angler fishing locations and can assess differential impacts of offshore wind development on private recreational fishing activities.

Keywords: cluster analysis, offshore wind impacts, recreational fishing, spatial scan statistics.

Introduction

Spatial management is a key strategy employed in marine resource management and encapsulates a wide range of regulations and restrictions on human activities. In fisheries, spatial management includes fully protected conservation areas, gear-restricted areas, and seasonal management such as spawning closures and dynamic protected species closures (e.g. Sciberras *et al.* 2013). Spatial management of resources is also woven throughout the concepts of marine spatial planning and ecosystem-based management (e.g. Arkema *et al.*, 2006; Ehler, 2021).

Offshore wind energy development is an issue that highlights the need for spatially explicit analyses to support management decision-making. In the United States, offshore wind development is managed by the Bureau of Ocean Energy and Management under the Energy Policy Act of 2005 (Public Law 109–58—8 August 2005). Proposed offshore wind projects must undertake a review of the affected environment under the National Environmental Policy Act, including both potential positive and negative economic and social effects of the project (85 FR 43363 § 1502.16). These environmental impact statements are meant to assess all potentially affected human activities, including the likely impacts on commercial and recreational fisheries (Bureau of Ocean Management, 2021a, b). Thus, a legal imperative joins the appeal for sound science in holistically understanding the impacts and trade-offs associated with offshore wind energy development.

All of this necessitates an understanding of where human activities occur in the ocean. Substantial resources have been expended in developing data streams and research aimed at understanding the spatial patterns of commercial fishing, from vessel logbooks and human observers to vessel monitoring systems and automatic identification system data (e.g. Hutton *et al.*, 2004; Scott-Denton *et al.*, 2011; Muench *et al.*, 2017; James *et al.*, 2018; Scheld *et al.*, 2022). Much less investment has been made in understanding where recreational fishers fish (National Research Council, 2006; McCluskey and Lewison, 2008; The National Academies of Sciences, Engineering, and Medicine, 2017). Some US regions require logbooks comparable to commercial fisheries for for-hire and large "party" recreational vessels [e.g. Joint Omnibus Electronic Vessel Trip Reporting Framework Adjustment, 85 Fed. Reg. 71575 (10 November 2020) (to be codified at 50 CFR 648)]. However, the fishing activity from these sectors is often dwarfed by private angler activity, for which the majority of data are collected through surveys that tend to record only generic fishing locations such as inshore vs. offshore (National Research Council, 2006; The National Academies of Sciences, Engineering, and Medicine, 2017; Arlinghaus *et al.*, 2019). This is despite the fact that recreational harvest is larger than commercial harvest in some fisheries (Arlinghaus *et al.*, 2019; Johnston *et al.*, 2022). In addition, recreational fishing can be important to regional and national economies (Fishery and Aquaculture Economics and Policy Division,

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2012; National Marine Fisheries Service, 2022; World Bank, 2012). In the United States, it is estimated that a total of 188 million marine recreational fishing trips were taken in 2019, generating over \$89 billion in sales (National Marine Fisheries Service, 2022) highlighting the importance of this sector in the marine economy, and the need to understand where recreational fishing is occurring in the context of other planned ocean uses such as wind energy development. Impediments to assessing likely impacts on the private recreational fishery develop the potential to overlook a substantial component of the trade-off implicit in the decision of where, and whether, offshore wind development should occur.

An obvious challenge in understanding the activities of private anglers is the cost and complexity of such an endeavour (National Research Council, 2006; The National Academies of Sciences, Engineering, and Medicine, 2017). However, there are a growing number of data sources that were explicitly developed for other purposes that may be used to better understand recreational fishing activities. These include data from satellites (Keramidas *et al*., 2018) and applications for phones and computers (Carter *et al*., 2015; Jiorle *et al*., 2016; Venturelli *et al*., 2017; Kellogg, 2020; Johnston *et al*., 2022). However, because they are data sets of opportunity, these approaches necessitate verification to ensure the data are appropriate for the envisioned alternate use (Venturelli *et al*., 2017; Keramidas *et al*., 2018; Johnston *et al*., 2022). In addition, it is unlikely that a single application will provide all the information necessary to effectively manage recreational fisheries, meaning all available data should be leveraged for management purposes. The value that can be generated from such multi-model and multiple data set analysis is well known (Burnham and Anderson, 2004; Bareinboim and Pearl, 2016).

In this study, we use a novel dataset to begin to understand the spatial distribution of private recreational fishing along the northeast coast of the US. Fish Rules is a smartphone application that uses georeferenced location data to present recreational anglers with the relevant fishing regulations as of the date the app is accessed (https://fishrulesapp.com). We employ a flexible spatial scan statistic to search for clusters where individual species' regulation data have been accessed within portions of the Atlantic Ocean off the coast of the Northeast and Mid-Atlantic United States. To assess whether these clusters have any meaningful linkage to actual fishing activity, we test the cluster's ability to explain recreational charter and party boat fishing locations. The research adds to the existing literature on private angler activity in the marine environment by presenting a novel manner by which to verify the utility of data designed for a purpose other than management of recreational fishing. The data represent the most detailed location information on private recreational fishing activity currently available, underlying the potential importance in both management and science applications. We showcase the method's management utility by assessing the overlap between species clusters that are identified and offshore wind energy lease areas and discuss implications in terms of species-specific recreational fishing impacts.

Methods

Step 1: cluster identification

The aim of this research was to assess whether the distribution of points (latitude, longitude) representing anonymous anglers accessing species-specific regulations were spatially uniform or whether the points were clustered in space. Following Kulldorff (1997), a Bernoulli likelihood ratio test, commonly known as a spatial scan statistic, was employed to assess the significance of potential clusters in the binary presence/absence data generated by Fish Rules users. A scan statistic was utilized, as opposed to kriging or kernel density estimation, because of the interest in whether identified clusters are significantly different from the surrounding locations, in terms of species-specific information. In this context, presence meant a view of the Fish Rules application was associated with the species of interest, while absence meant that the view was associated with some other species. The Bernoulli likelihood function was specified as

$$L(Z, p, q) = p^{n_Z} (1-p)^{\mu(Z)-n_Z} q^{n_G-n_Z} (1-q)^{\mu(G)-\mu(Z)-(n_G-n_Z)}. \quad (1)$$

In this specification, G represented the study region, Z represented the spatial zone in (or equivalently the subset of points for) which the cluster was assessed for significance, p was the probability of a species' regulations being viewed within zone Z, q was the probability of that species' regulations being accessed outside of zone Z, $\mu(G)$ was the total number of records within the study region, $\mu(Z)$ was the total number of records within the test zone, n_G was the total number of a specific species' records within the study region, and n_Z was the total number of a specific species' records within the test zone. The null hypothesis was that $p = q$, while the alternative hypothesis was $p > q$, i.e. a species' regulation was proportionally accessed more often within test zone Z than outside of it. Operationally, zone Z was chosen to maximize the likelihood function, and multiple non-overlapping Z windows can be theoretically identified that meet a threshold of statistical significance chosen.

For each candidate test zone Z, commonly described as a window, a likelihood ratio test statistic was calculated as follows:

$$\lambda(Z) = \begin{cases} \dfrac{\left(\frac{n_Z}{\mu(Z)}\right)^{n_Z} \left(1-\frac{n_Z}{\mu(Z)}\right)^{\mu(Z)-n_Z} \frac{n_G-n_Z}{\mu(G)-\mu(Z)}^{n_G-n_Z} \left(1-\frac{n_G-n_Z}{\mu(G)-\mu(Z)}\right)^{\mu(G)-\mu(Z)-(n_G-n_Z)}}{\left(\frac{n_G}{\mu(G)}\right)^{n_G} \left(1-\frac{n_G}{\mu(G)}\right)^{\mu(G)-n_G}}, \\ \quad if \dfrac{n_Z}{\mu(Z)} > \dfrac{n_G-n_Z}{\mu(G)-\mu(Z)} \\ 1, \text{ otherwise.} \end{cases} \quad (2)$$

Although the most common search window employed is circular, this research employed a flexibly shaped search window with a restricted likelihood function as defined by Tango (2008). The flexible search window has been shown to outperform circular windows when faced with clusters departing substantially from a circular pattern (Tango and Takahashi, 2005; Otani and Takahashi, 2021). Given that recreational fishing generally tends to occur within 3 nautical miles of the coast and follow the contour of the shoreline, there was some expectation that not all potential clusters would be circular. In addition, the restricted likelihood flexible scan statistic has been shown to perform well against a broad swath of alternate methods, including the circular, elliptic, upper level set, flexibly shaped, dynamic minimum spanning tree, early stopping dynamic minimum spanning tree, double connection, maximum linkage, and fast subset scan statistics (French *et al.*, 2022).

The restriction on the likelihood function is a filter on the subset of observations to be formally tested for clustering. The aim of the filter was twofold. First, and most importantly, it filtered low-probability areas from being considered within a cluster, as traditional spatial scan statistics tend to overestimate the size of clusters (Tango, 2008). Second, the filtering had the effect of considerably speeding up the algorithm when compared to the original flexibly shaped scan statistic as the search space increases exponentially with the number of observations included in the search window (French *et al.*, 2022).

The filter itself was implemented by only including high-probability groups of observations in the likelihood function comparison, as assessed using a one-tailed test of significance. Following Tango (2008), suppose that the study region was subsetted into M mutually exclusive spatial regions. For our purposes, the subsetting was implemented by aggregating the point data to a 10-min square grid, as is common in the region (e.g. Murawski *et al.*, 2005). The restricted likelihood then only assesses zone Z if all m individual regions in Z have an individual probability of significance less than some cutoff value α_m. Mathematically, the restriction is defined as follows:

$$\prod_{m\in Z} I\left(p_m < \alpha_m\right) = \prod_{m\in Z} I\Bigg(Pr\left(N_m \geqslant n_m + 1 | N_m \sim Bin\left(\mu\left(m\right), \hat{q}\right)\right) + \frac{1}{2} Pr\left(N_m = n_m | N_m \sim Bin\left(\mu\left(m\right), \hat{q}\right)\right) < \alpha_m\Bigg). \tag{3}$$

In Equation (3), $\hat{q}$ represented the probability of success under the null hypothesis, and the product of the indicator function $I(\cdot)$ was zero if at least one of the $m \in Z$ present a mid p-value $> \alpha_m$ and 1 otherwise. The filter was applied by multiplying this product by the likelihood function defined in Equation (1). The mid p-value was used to correct for the discontinuous nature of the Binomial distribution. This research employed $\alpha_m = 0.40$ for two reasons. First, although on the high end of standard thresholds, 0.40 performs well in comparison to Kulldorff's circular spatial scan statistic for identifying the extent of the true underlying data clusters (Tango, 2008). Second, the spatial units of interest in epidemiology are most often geopolitical boundaries delineating meaningful differences in the underlying populations of interest. The 10-min grid employed here, although customarily used in the region, does not have a meaningful interpretation in regard to the underlying data-generating process. As such, the 0.40 threshold combated issues arising from the modifiable areal unit problem, in which the results of a study are dependent on the choice of spatial unit employed (Gehlke and Biehl, 1934; Openshaw, 1984; Wong, 2004). In this case, the relatively high α_m helped ensure that slight permutations in the delineation of the test area would not unduly impact the results of the analysis.

The significance of the test statistic was assessed through Monte Carlo simulations. This was done by drawing replicate samples using the population-level statistics under the null hypothesis. The analyis drew 9999 replicate data sets per species to assess statistical significance. For each replicate data set $\mu(Z)$ observations from the population were randomly relabeled as inside of zone Z and the number of positive views for the species of interest in the new subsample, n_Z^*, were calculated with the results then substituted into Equation (2) to calculate $\lambda(Z^*)$. The null hypothesis was rejected at significance level α_1 if the original likelihood ratio test statistic fell within the α_1 highest draws of $\lambda(Z^*)$ calculated from the simulations. The cluster window searched a maximum of 100 nearest neighbours. These hundred 10-min squares represented an upper bound on the spatial footprint of a cluster, and clusters with smaller number of cells could be identified. The upper bound was set at hundred 10-min squares as it heuristically seems on the bounds of what would be useful in a management context, and broadly speaking should circumscribe similar recreational marine fishing opportunities.

Step 2: cluster validation

The clusters from step 1 identified areas in which the regulations of an individual species were accessed more frequently than would be expected if uniformly distributed in space. Ultimately, the aim is to use the Fish Rules data to make inferences about fishing locations. Therefore, in the second step, the relationship between the clusters and an independent data set of species harvested at known fishing locations was assessed as described below. Of particular note is that the approach employed did not hinge on the equality of the Fish Rules and independent fishing location data set distributions. Rather, the approach tested whether the Fish Rules clusters could identify areas that represented elevated harvest rates in the independent data sets. If a species from the independent data set was harvested more often inside a cluster than outside of a cluster, it would link the regulation views to known hotspots of recreational harvest for that species. This, in turn, would suggest that fishers are likely accessing the regulations either for fish already caught or expected fishing activity at a location, both of which are useful in a management context.

This linkage was investigated by testing whether the harvest rates of a species within the cluster were higher than outside of the cluster. This question revolves around whether there was a higher probability of harvesting a species inside the cluster than outside of the cluster: i.e. the dominance of the distribution of harvest rates within the cluster. We therefore use a test of first-order stochastic dominance to assess whether the rate of harvest for a species within the associated Fish Rules data clusters was significantly higher than the rate of harvest outside of the clusters. The Kolmogorov–Smirnov type test developed by Barrett and Donald (2003) was used to test for first-order stochastic dominance of the rate of harvest of individual species within the clusters. Given the continuous cumulative distribution functions F and H over samples of random variable z from two different populations, first-order stochastic dominance of H over F is defined as $H(z) \leq F(z)\ \forall\ z$. This means that for any arbitrary cutoff along the common support Z, the distribution function H has more probability mass above the cutoff than F.

The test itself focused on the distance between the two distribution functions, $d^* = \sup_{z\in Z}[H(z) - F(z)]$. Barrett and Donald (2003) provide the following empirical analogy for this test statistic:

$$\hat{d} = \left(\frac{NM}{N+M}\right)^{1/2} \sup_{z\in Z}\left[\hat{H}_N(z) - \hat{F}_M(z)\right], \tag{4}$$

with the corresponding empirical distributions $\hat{H}_N = \frac{1}{N}\sum_{i=1}^{N} I(X_i \leq z)$ and $\hat{F}_M = \frac{1}{M}\sum_{j=1}^{M} I(Y_j \leq z)$ of sample sizes M and N. The approach from Whang (2019) was implemented through the recentered bootstrap methodology

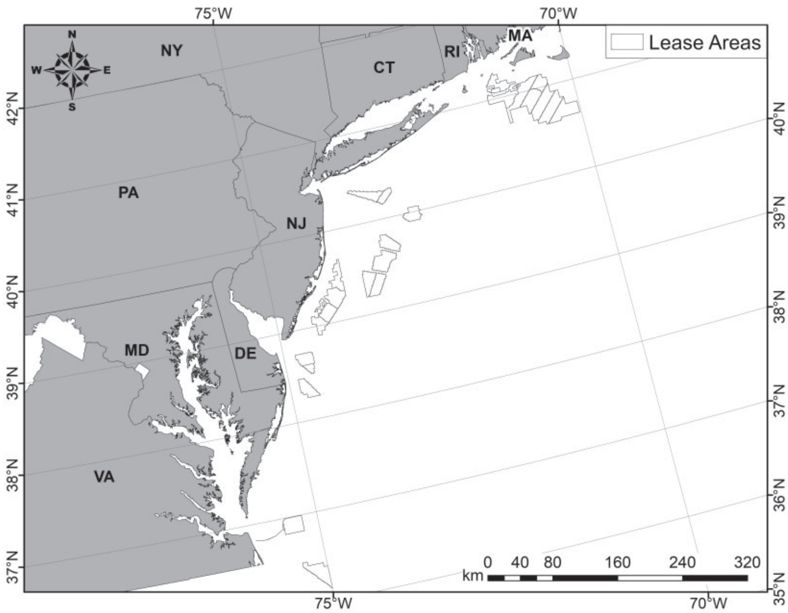

Figure 1. The location of the 26 wind lease areas anticipated to be developed within the Greater Atlantic Region, as they were defined in December 2022.

in order to calculate p-values. The null hypothesis indicates that $H \ngeq_{FSD} F$. This method of bootstrapping simulated the distribution of the test statistic under the null hypothesis as follows. Define sample 1 as $\eta = \{X_1, \cdots, X_N\}$ and sample 2 as $\psi = \{Y_1, \cdots, Y_M\}$. Draw a sample with replacement of size N from η to calculate estimate $\hat{H}^*_N = \frac{1}{N}\sum_{i=1}^{N} I(X^*_i \le z)$, and of size M from ψ to calculate estimate $\hat{F}^*_M = \frac{1}{M}\sum_{j=1}^{M} I(Y^*_j \le z)$. For first-order stochastic dominance, the test statistic can be estimated as:

$$\hat{d}^* = \left(\frac{NM}{N+M}\right)^{1/2} \sup_{z\in Z} \times \left[\left(\hat{H}^*{}_N(z) - \hat{H}_N(z)\right) - \left(\hat{F}^*_M(z) - \hat{F}_M(z)\right)\right], \tag{5}$$

where z was approximated by a grid. The grid size was set to the number of unique values in the pooled samples, and $\hat{d}^*$ was recalculated using 9999 replicates to estimate the empirical distribution of the test statistic under the null hypothesis. The p-value is then the percentage of the bootstrap estimates of $\hat{d}^*$ that are greater than the original test statistic $\hat{d}$ as calculated in Equation (4). Being a single-tailed test, the null hypothesis was rejected at significance level α_2 if the bootstrapped p-value is smaller than α_2.

Step 3: practical example of management utility

As a practical example, the species clusters identified in step 1 and validated in step 2 were compared against 26 wind lease areas off the coast of the northeast United States where offshore wind development is slated to occur. Figure 1 maps the location of all 26 wind lease areas within the region. The extent to which each wind lease area spatially overlapped a species cluster can be used to assess likely private angler fishing activities within the area. In a managerial context, this likelihood can be used to identify user groups likely to be impacted by offshore wind development and to understand differential impacts across these user groups.

All analyses were conducted in the R programming environment (R Core Team, 2019). The flexible scan statistic employed the rflexscan package (Otani and Takahashi, 2021), while the first-order stochastic dominance test employed MATLAB code published in Whang (2019), and ported to R by the authors. All geospatial analysis was undertaken using the sf package (Pebesma, 2018).

Data

The research undertaken employs two sets of data. The cluster analysis outlined in step 1 used anonymized information gathered from the Fish Rules smartphone application. Fish Rules captures location information in order to display relevant recreational fishing regulations for marine waters within the US Exclusive Economic Zone. The location is used to identify regulations, and can be either geolocated automatically by the user's computer or cell phone, or manually entered by the user. Regulations can thus be accessed either on the water or from land, and location can be manually sourced or geolocated automatically. Fish Rules was designed explicitly to allow recreational fishers that the ability to quickly identify the species they had caught and the regulations to understand whether that fish can be kept. However, in reality, potential uses could include planning fishing trips or motivations with more tenuous linkages to actual or anticipated fishing activities, such as mere curiosity. The ambiguity around usage is one of the motivating factors for our research. The regulations are species-specific, and include information such as season, bag limit, size limits, gear restrictions, and area closures for both state and federal waters. The data cover Fish Rules usage during the years 2020 and 2021. Of note is that these years fall squarely within the COVID-19 pandemic, which had documented impacts on recreational fishing patterns (Midway *et al*., 2021). Although data limitations did not offer an opportunity to assess alternate years, it will be important for future work to understand the impact of the pandemic on the results presented.

We focus on the Greater Atlantic Region, which extends from North Carolina in the south to the Canadian border in the north. NOAA's Greater Atlantic Regional Fisheries Office works collaboratively with state and other regional partners to administer federal fisheries resources in this region, and thus the region delineates an important recreational fisheries management unit. For the purpose of this research, we focus primarily on species with high federal reporting coverage, as this federal reporting is core to our validation approach employed in step 2 of the analysis. The list of species assessed includes striped bass (*Morone saxatilis*), Atlantic cod (*Gadus morhua*), summer flounder (*Paralichthys dentatus*), haddock (*Melanogrammus aeglefinus*), scup (*Stenotomus chrysops*), red drum (*Sciaenops ocellatus*), black sea bass (*Centropristis striata*), tautog (*Tautoga onitis*), bluefish (*Pomatomus saltatrix*), windowpane flounder (*Scophthalmus aquosus*), winter flounder (*Pseudopleuronectes americanus*), yellowtail flounder (*Limanda ferruginea*), and weakfish (*Cynoscion regalis*). Although striped bass, weakfish, and red drum are not federally managed species, we include them in the analysis due to their historic importance as target species for recreational anglers. The Fish Rules data include the latitude and longitude at which species-specific regulations were viewed within the app. The app also indicates whether the latitude and longitude was derived from global positioning software within the phone or user-inputted location. For the purpose of this research, we did not differentiate between the two location attributions, as we are interested in understanding whether the location data credibly identifies fishing locations, regardless of the input method. Broadly speaking, for management purposes, we are interested in both where individuals expect to fish for a species, a leading indicator for a trip and identification of expected catch, and where a species is encountered, a realized catch. We are thus interested in the ability of the pooled data to credibly identify private recreational fishing locations for management purposes. As such, we only utilize data whose latitude and longitude fall within marine waters. For summary purposes, we aggregate the number of times regulations were accessed to the daily level by species (Table 1).

The second dataset utilized is party and charter recreational fishing vessel trip reports (VTRs). Federally permitted charter and party boats in the United States are required to submit these VTR logbooks to NOAA Fisheries, and the VTRs represent the legal record of a fishing trip. Charter and party trips differ from private angler trips in that the choice of where and when to fish is made by a captain instead of the angler themselves, and the incentives between a captain and paying customers might differ. In addition, many charter and party boats are larger and more powerful than a standard private recreational vessel, allowing them to access areas that might be unavailable to the average fisher. The VTRs include the coordinates representing the majority of fishing effort on that trip, along with the number and type of species harvested on the trip. Although the VTR request numbers of fish harvested, there is some measurement error in which pounds instead of numbers are sometimes recorded. However, this should not unduly impact our analysis, as the reporting would not systematically differ across species. For our purposes, we estimate the daily harvest of each species, as a percentage of all species harvested that day. These harvest rates are then used in the cluster validation described in step 2 above. The data are presented in Table 2, in numbers of fish, for ease of interpretation.

Results

Table 3 presents the results of the spatial scan statistic. Of note is that the spatial scan statistic for two species tested (yellowtail flounder and weakfish) returned p-values that were larger than any conventional level of significance, meaning no clusters exist for those species. In all, the flexible restricted likelihood spatial scan statistic identified 24 clusters across 11 species. Maps of the location of each of these clusters can be found in Appendix 1 online. The total area of the clusters runs from just under 144 square km for red drum to just over 7100 square km for summer flounder.

Table 4 presents the results of the first-order stochastic dominance test for whether the Fish Rules clusters identify areas that represent elevated harvest rates in the independent data sets of known fishing locations, when compared to fishing locations outside of the clusters. Elevated harvest rates inside a cluster would link the regulation views to known hotspots of recreational harvest for that species and indicate that the Fish Rules clusters likely represent private recreational fishing locations. In order to control for seasonal availability of species regionally, we test stochastic dominance for days on which the species was harvested within the cluster. Thus, Table 4 presents the number of daily observations available, and the test uses double that number of observations, one set of observations inside the cluster and one set of observations outside of the cluster. We also follow the literature and define a significant spatial scan statistic if the corresponding corrected p-value presented in Table 3 is <0.05 (Tango, 2008; Otani and Takahashi, 2021; French *et al.*, 2022), and only those clusters are tested for first-order stochastic dominance. We process the daily harvest totals from 2020 to 2021 separately, to account for interannual fluctuations in regulations, species distributions, and other drivers that can affect where and when recreational fishing occurs. Of interest is that, using $\alpha_2 = 0.1$, the rate of harvest for the species inside the clusters first-order stochastically dominates the rate of harvest for the species outside the cluster for all species and years except striped bass in 2020 (p-value $= 0.013$), haddock in 2021 (p-value $= 0.036$), and bluefish in 2021 (p-value $= 0.099$). This means that for 17 of 20 species-year combinations tested, there is a higher probability of harvesting the species inside the cluster than outside of the cluster.

We present the proportion of each wind energy area that overlaps a species cluster in Table 5, with a visual example of the analysis undertaken in Figure 2. The mapped overlap of species clusters with individual lease areas are presented in the Appendix 1 online. From Table 5, OCS-A 0486 and OCS-A 0512 wind energy areas overlap the most clusters, at 6, followed by OCS-A 0487, OCS-A 0500, OCS-A 0534, and OCS-A 0549, which each overlap five clusters.

Table 6 shows a complimentary analysis: the percentage of each individual cluster that falls within the wind energy areas. Seventeen wind lease areas overlap the four black sea bass private recreational fishing clusters, which is the highest number of overlaps for any one species. However, 44% of tautog cluster 2 (559 square km), 27% of haddock cluster 3 (909 square km), and 21% of the Atlantic cod cluster 1 (1018 square km) fall within offshore wind energy areas. More

Table 1. Descriptive statistics of daily view data generated by users on the Fish Rules application for the 13 species assessed within this research.

Species name	Total	Average	Median	Max	Min	*SD*
Black sea bass	747	2.8	2	14	1	2.33
Striped bass	638	2.9	1	20	1	3.39
Summer flounder	574	2.7	2	15	1	2.38
Tautog	452	2.4	2	13	1	1.99
Bluefish	386	2.1	1	11	1	1.74
Atlantic cod	351	1.9	1	8	1	1.44
Winter flounder	305	2.1	1	10	1	1.69
Scup	249	1.7	1	6	1	1.07
Red drum	211	1.8	1	6	1	1.22
Haddock	207	1.7	1	8	1	1.22
Weakfish	180	1.6	1	5	1	0.92
Yellowtail flounder	156	1.4	1	6	1	0.83
Windowpane flounder	139	1.4	1	4	1	0.74

Table 2. Descriptive statistics of recreational harvest as reported by federally permitted party and charter vessels in VTRs.

Species name	Total	Average	Median	Max	Min	*SD*
Scup	1 552 596	3 346.10	3 126	14 937	0	2 448.14
Black sea bass	899 505	1 694.00	1 590	8 357	0	1 417.93
Haddock	455 347	975.00	848	4 274	1	710.70
Bluefish	131 725	287.60	220	1 508	0	280.92
Summer flounder	110 937	292.70	222	1 111	0	293.02
Tautog	67 102	141.90	25	2 617	0	254.16
Striped bass	33 764	69.00	53	389	0	63.18
Atlantic cod	24 888	43.90	18	461	0	67.41
Winter flounder	3 108	11.00	6	93	0	13.66
Weakfish	888	5.60	3	39	0	7.17
Windowpane flounder	288	6.10	0	48	0	10.15
Red drum	126	1.40	0	12	0	2.47
Yellowtail flounder	125	3.80	2	40	1	6.83

Data are presented in daily numbers of fish harvested.

Table 3. Flexible restricted likelihood spatial scan statistic significance levels and cluster area for species presenting significant results.

Species name	Corrected *p*-value	Cluster area (km^2)
Bluefish	0.0322	2316.49
Red drum	0.0001	3571.61
Red drum	0.0001	143.78
Scup	0.0016	3434.56
Scup	0.0026	4467.60
Atlantic cod	0.0003	4933.51
Atlantic cod	0.0003	2553.29
Atlantic cod	0.0956	2709.88
Haddock	0.0003	2786.77
Haddock	0.0092	2606.49
Haddock	0.0386	3355.76
Summer flounder	0.0003	7134.04
Summer flounder	0.0120	2908.31
Summer flounder	0.0414	2863.58
Tautog	0.0002	3554.69
Tautog	0.0477	1257.73
Windowpane flounder	0.0115	2953.90
Winter flounder	0.0004	3851.82
Black sea bass	0.0004	4087.79
Black sea bass	0.0004	4938.24
Black sea bass	0.0004	2862.97
Black sea bass	0.0004	5797.10
Striped bass	0.0002	2504.76
Striped bass	0.0072	799.85

p-values corrected for multiple tests using the Holm–Bonferroni method.
Note: Yellowtail flounder and weakfish were found to have no significant clusters in the data.

Table 4. Tests for first-order stochastic dominance for species harvested inside vs. outside of their relevant clusters.

Species name	Year	*p*-value	Daily observations
Striped bass	2020	0.0125	111
Striped bass	2021	0.7468	145
Cod	2020	0.8566	146
Cod	2021	0.9290	140
Summer flounder	2020	0.9336	165
Summer flounder	2021	0.8252	183
Haddock	2020	0.5381	100
Haddock	2021	0.0359	100
Scup	2020	0.9018	178
Scup	2021	0.8951	220
Red drum	2020	0.7792	16
Red drum	2021	0.6923	9
Black sea bass	2020	0.9403	218
Black sea bass	2021	0.4979	256
Tautog	2020	0.8449	82
Tautog	2021	0.4942	112
Bluefish	2020	0.7671	72
Bluefish	2021	0.0990	55
Winter flounder	2020	0.9799	79
Winter flounder	2021	0.9898	115

Variable tested is the ratio of species harvested vs. all species harvested daily. Failure to reject the null hypothesis indicates harvest rates within the cluster are higher than outside of the cluster.
Note: Windowpane flounder could not be assessed due to a lack of charter and party trip data.

Table 5. Percentage of each wind energy area overlapping a species cluster, with nonzero quantities in bold.

	Atlantic cod	Black sea bass	Bluefish	Haddock	Red drum	Scup	Striped bass	Summer flounder	Tautog	Windowpane flounder	Winter flounder
OCS-A 0482	0.00	**45.13**	**45.39**	0.00	0.00	0.00	0.00	**61.73**	0.00	0.00	0.00
OCS-A 0483	0.00	**47.78**	0.00	0.00	**55.06**	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0486	**43.87**	**23.10**	0.00	**68.84**	0.00	**34.17**	0.00	**1.14**	**23.10**	0.00	0.00
OCS-A 0487	**82.46**	**17.37**	0.00	**71.16**	0.00	**11.30**	0.00	0.00	**17.54**	0.00	0.00
OCS-A 0490	0.00	**53.31**	**11.85**	0.00	0.00	0.00	0.00	**56.84**	0.00	0.00	0.00
OCS-A 0497	0.00	**14.76**	0.00	0.00	**93.65**	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0498	0.00	**23.78**	0.00	0.00	0.00	**1.38**	0.00	**82.26**	**88.42**	0.00	0.00
OCS-A 0499	0.00	**13.26**	0.00	0.00	0.00	**74.46**	0.00	**15.59**	**13.26**	0.00	0.00
OCS-A 0500	**51.59**	**0.22**	0.00	**51.37**	0.00	0.00	0.00	**0.22**	**19.38**	0.00	0.00
OCS-A 0501	**51.95**	**63.63**	0.00	0.00	0.00	0.00	0.00	**51.95**	0.00	0.00	0.00
OCS-A 0512	0.00	**10.01**	0.00	0.00	0.00	**31.29**	**0.21**	**31.08**	0.00	**31.37**	**22.07**
OCS-A 0517	**100.00**	0.00	0.00	**100.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0519	0.00	**44.70**	**45.07**	0.00	0.00	0.00	0.00	**99.63**	0.00	0.00	0.00
OCS-A 0520	**0.79**	**35.45**	0.00	0.00	0.00	0.00	0.00	**0.79**	0.00	0.00	0.00
OCS-A 0521	0.00	**3.88**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0532	0.00	**61.60**	0.00	0.00	0.00	0.00	0.00	**28.66**	**68.07**	0.00	0.00
OCS-A 0534	**0.71**	**0.78**	0.00	**0.53**	0.00	0.00	0.00	**0.18**	**33.72**	0.00	0.00
OCS-A 0539	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**24.56**	0.00
OCS-A 0549	0.00	**34.76**	0.00	0.00	0.00	**47.45**	0.00	**9.26**	0.00	**8.74**	**0.51**

A high percentage overlap indicates high probability that the wind lease area falls within important private vessel recreational fishing areas for the species identified.
Note: One red drum cluster, one Atlantic cod cluster, one striped bass, and two haddock clusters did not overlap with any wind area.

granularly, roughly 22% of tautog cluster 2 falls within area OCS-A 0498 alone. This indicates that private angler trips for tautog, haddock, and cod are most exposed to impacts from offshore wind development.

Discussion

The analyses presented in this study indicate that Fish Rules data can be used to credibly identify areas that have a high likelihood of being private angler fishing locations. The cluster analysis highlights that the data are not spatially uniform, in that spatial clusters can be identified within marine waters. Eleven of the 13 species tested indicated spatial clusters. Assessing the exact mechanism driving the lack of clustering for yellowtail flounder and weakfish is beyond the scope of this manuscript. However, some hypotheses include a limited recreational fishery for yellowtail and weakfish having been held to a one fish per day bag limit since 2009; meaning encounters of these two species are driven primarily by chance instead of angler intent, leading to a diffuse and relatively uniform distribution of Fish Rules access for these species.

Further, linking these clusters to known fishing locations from charter and party trips, we show that the harvest rate of the same species within the clusters first-order stochastically dominates the harvest outside of the clusters. This is true for all but three species/year combinations tested. The first-order stochastic dominance of the striped bass cluster in 2020 and the haddock cluster in 2021 were rejected at the 0.05 level, though both failed to reject the null in the alternate year. In addition, the null hypothesis for the bluefish cluster was rejected at the 0.10 level in 2021, though the test failed to reject the null in 2020 at any customary level employed. These results could suggest that the clusters are ephemeral, subject to changes in species distributions, management measures, and other drivers that affect where, when, and what fishers are targeting. The clusters themselves should therefore be assessed on an ongoing basis for continued validity.

Our results indicate that the spatial location of recreational fishing regulations viewed within Fish Rules corresponded to areas with abnormally high rates of harvest for the species investigated. Although critical, this is only a first step in understanding how the Fish Rules data can be used to inform ocean use management. For example, it is unclear how representative Fish Rules data are for the population fishing off of the Northeast and Mid-Atlantic United States (Venturelli *et al.*, 2017; Johnston *et al.*, 2022), an issue that future research will aim to explore. Further, behavioural models of recreational demand are the gold standard in assessing the ramifications of changing ocean uses through revealed preferences (Bateman and Kling, 2020; Lupi *et al.*, 2020). Future research will investigate how to use Fish Rules data in this capacity, if possible.

Nevertheless, the research presented here can be used to identify user groups who could be impacted by spatial management decisions, but for whom data have been largely unavailable. In the context of offshore wind development, we showcase how the spatial clusters for individual species can help identify the type of private recreational fishing occurring, and thus user groups likely active, within wind lease areas.

For example, Table 5 identifies six wind energy areas that overlap five or more clusters: OCS-A 0486, OCS-A 0512, OCS-A 0487, OCS-A 0500, OCS-A 0534, and OCS-A 0549. This suggests that the development of these particular wind

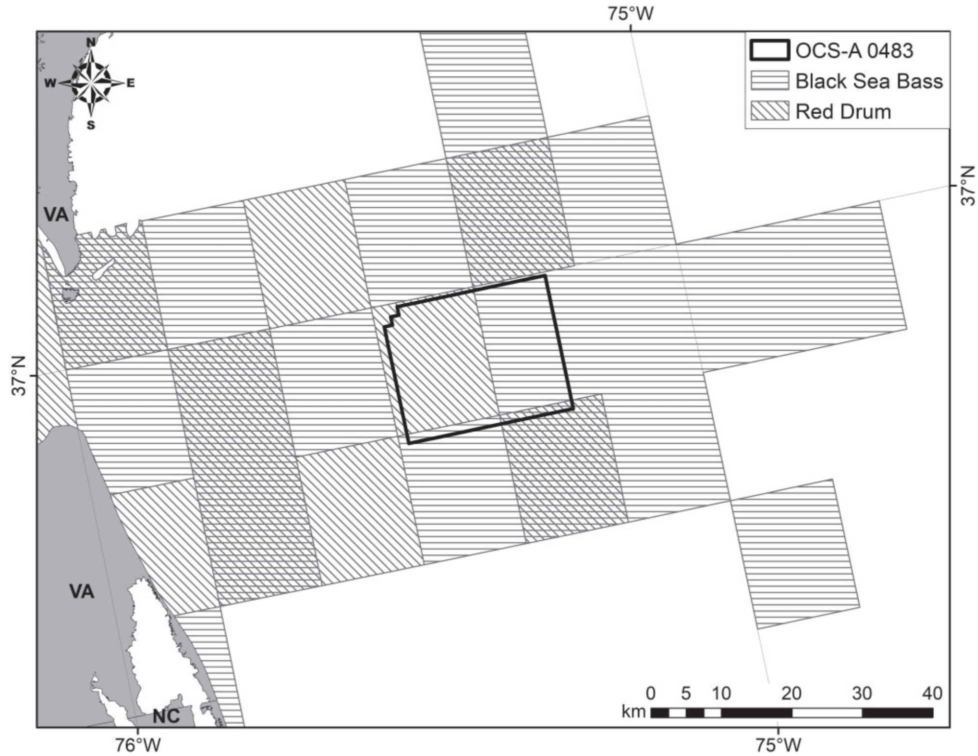

Figure 2. The overlap of black sea bass and red drum clusters with offshore wind lease area OCS-A 0483.

energy areas is likely to impact recreational fishing for numerous species. However, there is heterogeneity in how much any one wind energy area overlaps a species cluster. For example, OCS-A 0517 falls 100% within Atlantic cod and haddock clusters, while < 4% of OCS-A 0521 falls within the black sea bass clusters, the only species with which it overlaps.

In addition, there are likely to be differential biological impacts of offshore wind development across species. Black sea bass and cod prefer structured bottom habitat, and thus are likely to be drawn to wind energy areas, which can increase catch rates for recreational fishers (Wilber *et al.*, 2022). Conversely, summer flounder prefer sand habitat, and although existing research suggests little impact to this species or its fishery from wind energy development (Wilber *et al.*, 2018, 2022), the scale of planned wind development is unprecedented and could lead to non-linear impacts on sand-dependent species.

Beyond biological impacts, there are potential direct impacts to fishers due to the management of offshore wind farms. For example, if these wind energy areas are managed as fishery exclusion zones, from Table 6 it becomes clear that fishing for tautog, Atlantic cod, and haddock are most highly exposed to the current slate of offshore wind lease areas. This co-occurrence of haddock and Atlantic cod would be expected, as they are managed jointly to account for the fact that they are caught together recreationally (National Oceanic and Atmospheric Administration, 2022). Although historically the majority of cod and haddock recreational catch occurred in the Gulf of Maine, in 2020 and 2021 the possession limit was just one cod per individual and the season for cod was < 2 months long, which effectively marginalized the recreational fishing for cod and haddock in the Gulf of Maine and explains the clusters for these species in southern New England (National Oceanic and Atmospheric Administration, 2020). This suggests that recreational management measures can also play an important role in a fishery's exposure to offshore wind, and underlines the need for a holistic ecosystem-based approach to the management of natural resources. However, it also highlights the need to reassess clusters on an ongoing basis to understand longer term impacts on private recreational fishing from wind farm development. Given that the analysis only represents two years of activity, it is impossible to say how static private recreational fishing activity is spatially, which would have obvious ramifications on the impacts of offshore wind development on this user group. However, the fact that this question can be addressed by the approach as outlined provides a major step forward in the ability to assess potential impacts.

In addition, the behavioural responses of recreational fishers themselves have the potential to mitigate at least some of the impacts associated with offshore wind development. This is particularly true for species such as striped bass and winter flounder that present little total exposure to offshore wind development. However, tautog cluster 2 highlights the fact that offshore wind has at least the potential to displace a substantial portion of the active fishing area for that species off the coast of New Jersey. In addition, the offshore areas assessed in this study are a subset of the total offshore wind development anticipated for the region. Although other areas are at earlier stages of planning and thus not ripe for analysis, this fact raises the prospect that cumulative effects across wind areas could be substantial and much broader when a full assessment is possible. The analyses presented herein thus generate baseline information by which to contextualize any changes in fishing behaviour, and begin to understand the realized impacts of offshore wind development on private recreational fishing.

Table 6. Percentage of each species cluster overlapping a wind energy area.

	Atlantic cod 1	Black sea bass 1	Black sea bass 2	Black sea bass 3	Black sea bass 4	Bluefish 1	Haddock 3	Red drum 1	Scup 1	Scup 2	Striped bass 1	Summer Flounder 1	Summer Flounder 2	Summer Flounder 3	Tautog 1	Tautog 2	Windowpane flounder 1	Winter flounder 1
OCS-A 0482	0.00	0.00	0.00	4.47	0.00	5.56	0.00	0.00	0.00	0.00	0.00	2.46	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0483	0.00	0.00	0.00	0.00	3.77	0.00	0.00	7.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0486	3.02	0.00	1.59	0.00	0.00	0.00	6.96	0.00	3.37	0.00	0.00	0.00	0.13	0.00	2.20	0.00	0.00	0.00
OCS-A 0487	7.44	0.00	1.57	0.00	0.00	0.00	9.44	0.00	1.46	0.00	0.00	0.00	0.00	0.00	2.20	0.00	0.00	0.00
OCS-A 0490	0.00	0.00	0.00	6.01	0.03	1.65	0.00	0.00	0.00	0.00	0.00	2.57	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0497	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0498	0.00	0.00	0.00	2.54	0.00	0.00	0.00	0.00	0.00	0.09	0.00	3.53	0.00	0.00	0.00	21.50	0.00	0.00
OCS-A 0499	0.00	0.00	0.00	1.92	0.00	0.00	0.00	0.00	0.00	6.89	0.00	0.90	0.00	0.00	0.00	4.36	0.00	0.00
OCS-A 0500	6.13	0.00	0.03	0.00	0.00	0.00	8.97	0.00	0.00	0.00	0.00	0.00	0.04	0.00	3.20	0.00	0.00	0.00
OCS-A 0501	2.78	0.00	3.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.72	0.00	0.00	0.00	0.00	0.00
OCS-A 0512	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.25	0.03	0.00	0.00	3.49	0.00	0.00	3.41	1.84
OCS-A 0517	1.12	0.00	0.00	0.00	0.00	0.00	1.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0519	0.00	0.00	0.00	1.66	0.00	2.07	0.00	0.00	0.00	0.00	0.00	1.49	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0520	0.08	0.00	3.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00
OCS-A 0521	0.00	0.00	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OCS-A 0532	0.00	0.00	0.00	7.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.38	0.00	0.00	0.00	18.62	0.00	0.00
OCS-A 0534	0.06	0.00	0.06	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.02	0.00	3.90	0.00	0.00	0.00
OCS-A 0539	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.24	0.00
OCS-A 0549	0.00	2.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.49	0.00	0.43	0.00	0.00	0.00	0.00	0.97	0.04

A high percentage overlap indicates higher exposure of important private vessel recreational fishing areas for the species identified to wind energy development impacts.
Note: One red drum cluster, one Atlantic cod cluster, one striped bass, and two haddock clusters did not overlap with any wind area.

From above, it is clear that the potential impacts of offshore wind to recreational fishing are species and lease area specific, and that cumulative effects are key to understanding the breadth of impacts accrued. What is more, the interaction of fishery and offshore wind management decisions are real and should be considered when setting regulations for either. The analysis presented here fills a current gap on offshore private recreational fishing, and has clear implications for understanding differential impacts across user groups and assessing all potential impacts of offshore wind development on human activities, as required by US law (Bureau of Ocean Management, 2021a,b). The approach outlined here identifies likely private recreational fishing activity, a fishing mode that has historically lacked any data from which to assess even exposure of management actions, in wind lease areas.

Conclusion

The research presented here begins to fill a major gap in the understanding of the temporal and spatial distribution of private recreational anglers' effort in targeting and harvesting managed living marine resources (i.e. important fisheries species). The demand for ocean resources is growing, with the potential for substantial disruption to historical activities and user conflict (e.g. Jouffray *et al.*, 2020). The first step in developing sound ocean use management is an understanding of where current activities are engaged. Given the cost and time of developing new data streams, the only realistic alternative is to leverage existing data. In this study, we have shown that Fish Rules data can credibly represent private recreational fishing locations for multiple species landed off the Mid-Atlantic and Northeast coast of the United States. As such, this research contributes a novel, low-cost, non-invasive approach to quantifying species-specific spatial and temporal patterns of private angler recreational use of marine resources.

Further, we use offshore wind lease areas in the same region as a case study that highlights the utility of our approach in a management context. The clusters identify likely important fishing grounds for private anglers within wind lease areas, by species, a critical step in scoping the universe of individuals likely to be impacted by wind energy development, as required by US regulations (Bureau of Ocean Management, 2021a, b).

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Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Author contributions

GSD developed the methodology and implemented the statistical tests. DC implemented the spatial analyses and produced the figures. DAA, RB, and NR collected and curated the Fish

Rules data. All authors contributed to conceptualization, interpretation of results, and writing.

Conflict of interest

Fish Rules is a wholly owned subsidiary of FishBrain AB, the employer of DAA, RB, and NR.

Data availability

The data underlying this study were provided by FishBrain AB by permission. Data will be shared on request to the corresponding author with permission of FishBrain AB.

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