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# The spatial correlation between trawl surveys and planned wind energy infrastructure on the US Northeast Continental Shelf

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The development of wind energy on the US Northeast Continental Shelf (NES) may preclude resource-monitoring programmes from continuing in their original study designs. We considered the spatial requirements of energy developers and the spatial autocorrelation of resident species as a means to inform survey mitigation. The spatial requirements of the NES wind industry were considered in respect to the delineation of settled lease areas. We suggest access metrics ranging from 8 to 21 km representing the interquartile range of chord distances across the settled lease areas. Using survey data and concentrating on commercial species with stock assessment requirements, we computed indices of spatial autocorrelation. Tests of spatial autocorrelation using Moran's *I* and join counts statistics were significant ($p < 0.05$) for most species, suggesting a high level of spatial correlation in their distributions. To characterize a scalar extent of spatial correlation, variograms were fit to estimate the physical range of correlated catches. These data suggest most species were spatially correlated well beyond the distance metrics derived from the lease area shapes. Sampling by a range of gears has the potential of producing spatially accurate depictions of species distributions and abundance despite the restrictions wind lease areas may place on sampling designs.

**Keywords:** fish distribution, fisheries, spatial correlation, survey design, wind energy.

## Introduction

In efforts to reduce global greenhouse gas loadings, there is expanding interest in renewable alternatives to fossil fuels. Notable among these efforts is the development of offshore wind energy, owing to the consistent movement of air over ocean domains, thus making offshore wind a relatively reliable source of energy (Li *et al.*, 2020). Large-scale offshore wind construction projects create many and often complex user interactions (Copping *et al.*, 2020). Among these interactions, offshore wind development can have direct effects on the ecosystem (Galparsoro *et al.*, 2022) at the organismal level (e.g. bird kills) or system level effects through habitat modifications (e.g. change in lower trophic level production). In a broader sense, these activities affect maritime commerce and food security (Qu *et al.*, 2021). The development of Wind Energy Areas (WEAs) not only alters patterns of harvest related to food security, but key to the maintenance of food security is the ability to monitor the condition of resource species. We anticipate our ability to monitor resource species will be impacted via constraints on surveys caused by WEAs (Methratta *et al.*, 2020). Evidence from other types of management closure areas suggests that harvesters will continue to exploit mobile species on the perimeters of such areas and we anticipate that harvesters will find ways to operate in WEAs with acceptable safety levels (Schupp *et al.*, 2021). Hence, regulatory agencies will still have a statutory responsibility of providing assessment and management advice for these resources via fishery-independent surveys.

Fishery-independent surveys are conducted by research vessels or contracted commercial fishing vessels. To ensure long-term comparability of relative abundance estimates, all vessels adhere to a rigid sampling protocol, strictly monitor gear performance, and most importantly, take steps to select stations randomly (Latour *et al.*, 2003). Randomization of station selection is important because it allows one to make inferences about the total population, which consists of sampled and unsampled locations. When the sampling design encompasses multiple habitats, refinements of the survey designs can be achieved by dividing the sampling area into strata. Ideally, strata reduce the overall variance of the estimate by having greater similarities in abundance or species compositions within strata than between strata. Taken collectively, these factors have made stratified random designs the de facto standard for fishery-independent surveys around the world (Doubleday, 1981). However, a given realization of a stratified random design can result in very poor estimates if the stratification is inappropriate or if stations are under- or over-allocated to strata (Cochran, 1991). Random stations can exhibit undesirable sampling properties of being either too close together or too far apart. The former is less efficient because nearby samples may not be independent and the latter condition results in an over reliance of a single sample representing a very large area (Gunderson, 1993).

The introduction of WEAs into a sampling framework upsets the delicate balance of stratification and spatial allocation of samples. If the WEA cannot be sampled, the sizes and

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configurations of strata are compromised and station allocations, whatever their basis, must be changed (Gill *et al.*, 2020). Most importantly, the critical design-based attribute, wherein every element in the sampling frame has a non-zero inclusion probability is now invalid. Variances are likely to increase and estimates of the mean will be biased unless it can be shown that samples outside of the WEA can be used to make valid inferences about the conditions inside the WEA. This paper addresses this central problem by using models to characterize the spatial correlations among samples. These correlations can be distilled into practical metrics of distances that define the physical range over which a sample can be assumed to be reasonably similar. In other words, a future survey design might include both design and model-based properties (Dumelle *et al.*, 2022).

The validity of this hybrid design (Brus, 2021) rests on the principle that the correlative properties of samples estimated in the absence of WEAs are still appropriate after the WEA are developed. This is unknowable a priori. Detailed habitat studies have demonstrated differences in benthic invertebrate communities relative to controls following turbine installation, but not all fish species will be affected equally (Franco *et al.*, 2015). Fish that transit WEAs rapidly are less likely to be affected than species with affinity to the altered bottom structure and food resources. Hence, it is important to examine a range of species to help predict the utility of model assisted sampling designs (Di Biase *et al.*, 2022). In this paper, we use the term “adapted surveys” to denote survey designs that augment more traditional designs with information on the spatial autocorrelation properties of fish species. Desirable properties of such future designs are described, but the full sampling properties of such designs are the subject of ongoing research.

Systematic sampling designs have desirable properties of ensuring uniform coverage over the geographic range of the survey domain (Brus and de Gruijter, 1997). Strictly speaking, such designs do not have design-based variances because most of the potential samples have zero inclusion probabilities. Systematic sampling designs might be considered as a subset of spatially balanced designs (Van der Meer, 1997; Benedetti *et al.*, 2017). Recent theoretical advances (Stevens and Olsen, 2004) have led to designs that have both the advantages of systematic coverage and design-based variance estimation. In this paper, we illustrate the spatial properties of samples that could govern the allocation of stations over a geographic domain with a focus on its utility for imputing abundances within areas that cannot be sampled.

One aspect of marine fish and macroinvertebrate ecology that may serve to make adaptive survey designs feasible is that their distributions tend to be spatially autocorrelated. The ecology of fish distribution has received a great deal of recent attention due to distributional responses of fish to climate change (Taheri *et al.*, 2021). The distribution of fish is complex owing to species interactions, both competitive and predatory, life stage effects, and reproductive requirements (Ciannelli *et al.*, 2008). Inference concerning spatial correlation has been made based on catch data to describe distributional clusters in both time and space (Vignaux, 1996). These catch clusters suggest spatial correlation on the order of 20 km in New Zealand hoki (*Macruronus novaezelandiae*). Using models to describe spatial correlation with distance for groundfish species (cod, *Gadus morhua*, haddock, *Melanogramus aeglefinus*), Marquez *et al.* (2021) drew contrasts in the spatial correlation for species by life stage. Not surprisingly, variograms fit to the distribution of tuna and billfish species suggested many large pelagic species have spatial correlations in excess of 100 km (Kleisner *et al.*, 2010). With a rich precedent in the literature of both results and methodological approaches, it should be relatively straightforward to estimate these parameters for a broad spectrum of commercial species that are routinely captured in scientific surveys.

The strategies used to allocate offshore WEAs take into account maritime access, so consequently, wind developments are large in the aggregate, but individual WEAs tend to be sized on scales that are more reasonable. The primary factor used to site WEAs, both in offshore and terrestrial environments, is the distribution of wind speed and air density (Rediske *et al.*, 2021). Furthermore, a wide range of spatial planning issues are considered, especially maritime transport access (Caceoğlu *et al.*, 2022). Fundamental differences in the space of operation requirements between terrestrial and maritime transport, i.e. trucks vs. ships, ultimately limit the size of lease areas because transit by a wide range of ship types and classes must occur between the boundaries of adjacent WEAs. Though the intention is to insure safe seafood harvest within WEAs (Perry and Heyman, 2020), spacing between structures of 1–2 km or less may preclude operation of large fishing vessels using active gear in these areas.

The goal of this study was to examine the spatial autocorrelation of populations of commercially harvested and assessed fish and macroinvertebrates in the US Northeast Continental Shelf (NES) ecosystem in context to the dimensionality of individual and accessible WEAs. The physical dimensions of the wind lease areas, distinguished from interest and call areas, were analysed to determine the range of sizes from navigable edge to distances across the area. Species with assessments that include the use of bottom trawl data were analysed using historical data to determine the tendency for distribution to be spatially autocorrelated and to affix a distance measure to that correlation using spatial statistics. Our goal was to generalize the tradeoffs between station spacing and the spatial correlation among trawl species catch; hence, providing a tool to evaluate survey mitigation strategies.

## Methods

### Study system

This study was based on survey observations and WEA activities in the NES. Survey observations refer to the long-term bottom trawl-monitoring programme for fish and macroinvertebrates used to guide fisheries and ecosystem management. WEA activities refer to the emergent development of wind power in the form of wind turbines within the ecosystem. The Northeast Fisheries Science Center bottom trawl survey (Desprespatanjo *et al.*, 1988) is conducted annually in the spring and autumn seasons, and consists of ∼300 or more stations sampled per season. This random stratified survey started in 1963 in autumn and 1968 in spring, and samples areas off the coast of North Carolina to Nova Scotia; the full spatial extent of station locations are shown in Supplementary Figure S1 in the Supplementary Material. The study domain was sometimes expanded with extended station coverage south of Cape Hatteras (south of 35°N). We constrained the analysis of the trawl data to the core strata of the survey shown in Supplementary Figure S1. Over time, a

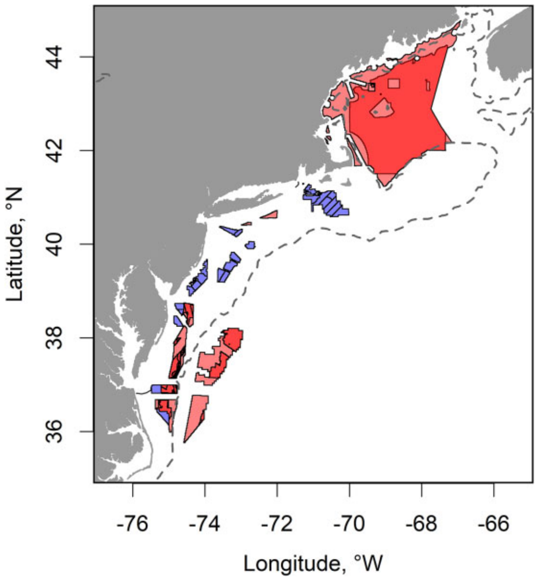

**Figure 1.** The US Northeast Shelf with decided lease areas (blue) and interest areas (red) being considered for wind energy development. The dashed line marks the 100-m depth contour.

number of changes in trawl gear, vessels, and trawl doors occurred. Each of these changes was accompanied by field experiments to adjust new observations to the historical time series (Desprespatanjo *et al.*, 1988). The largest change occurred in 2008 when the survey changed to a much larger vessel (FSV Bigelow). The effects of this shift were fully calibrated as described in Miller *et al.* (2010). The transition to the Bigelow further reduced the spatial domain of the survey because shallower inshore stations could no longer be safely sampled. Survey activities were disrupted by the COVID-19 epidemic in 2020, so we restricted our analyses to years prior to 2020.

The NES is also a leading region for the development of offshore wind energy in the United States, with many wind lease areas already identified. Procedurally, the development of lease areas is preceded by the identification of call and interest areas that may eventually provide the basis for lease areas. The boundaries for these areas are rapidly changing and as of the writing of this paper, based on data for March 2023, there are nearly 30 call and interest areas, with some overlapping areas, and 26 lease areas (Figure 1). As can be seen in the map, call and interest areas tend to be larger than what eventually emerge as a lease area. Multiple factors go into the designation of a lease area, but currently, lease areas have at least one side that is open to navigation. The current lease areas are listed in Table 1 along with their areal coverage in square kilometers. The areas range from ∼9 to 586 km$^2$; however, the shapes vary from rectangular to triangular. To characterize the size of the lease areas, we calculated a family of chord distances across an area based on all combinations of vertices of the outline shape. Depending on the complexity of the lease area shape, the number of chords ranged from 72 to 43056. The distribution of the chord distances was summarized with the median and lower and upper quartiles. The means of these statistics, 8, 14, and 21 km, were use as benchmark distances to evaluate the spatial statistics calculated from the bottom trawl survey.

## Measures of spatial correlation in the survey catch

We characterized the spatial correlation pattern in the survey catches (abundance or catch in numbers) of each fish and macroinvertebrate species for each year and season (spring and autumn), restricting the analysis to managed species that utilize the bottom trawl survey data for their assessments (Table 2). In a practical sense, some species are well represented in the survey and the data serve as a major part of the assessment; whereas, some species are rare occurrences in the survey and thus, the survey plays a minor role. To test for spatial autocorrelation, we calculated Moran's Index (Moran's *I*) of global autocorrelation (Gittleman and Kot, 1990) using the "ape" package in R (version 5.7). For each species, we computed Moran's *I* by year and season and summarized the statistic as the proportion of years with significant values (significance at $p = 0.05$). Significant and positive tests led to rejection of the null hypothesis that the underlying distribution was random and supported the hypothesis of spatial clustering. We also examined spatial correlation among the absence and presence data for each species using join count tests (Sokal and Oden, 1978). Absence or presence was coded into each data record as a factor and the test statistic was calculated using the "spdep" package in R (version 1.2–8). The statistic tested for spatial autocorrelation between absences and presences in the data; we concentrated on the results of presence tests.

We used a Kriging interpolation procedure to estimate the distance over which catch was correlated for each species. For species by year and season, we fit a variogram and used the range from the fit as an estimate of the linear distance of catch correlation. We first specified the variogram as the logarithm of catch plus one (to account for zero catch) using the "gstat" package in R (version 2.0–9). We then used the variogram fitting procedure, also in "gstat", that fit Kappa and selected the best fit variogram model (Pebesma, 2004). For some species and years, there were range estimates from the variogram fits that were off scale and had to be considered outliers. These values were identified using the boxplot command in R base graphics; they were excluded from the data summaries. The range estimates were characterized as means and quantile summaries (10–90% quantiles, 25–75% quantiles, and median) by species and season.

## Putative interaction of sample grid size and range correlation

The effect of putative grid size and correlation distance were considered simultaneously by mapping grids at two spacings and evaluating the effect of the grids by overlaying circles with varying diameters based on different correlation lengths. We considered two grid spacings, 0.333 and 0.5°, with the former at approximately the same spacing as the trawl stations in the current bottom trawl survey and resulting in ∼290 stations in a seasonal survey. The latter represents a relaxation of survey station spacing and would likely result in ∼120 trawl stations over the survey area. However, we believe a relaxed survey may be necessitated if spatial access is restricted by WEA development. For each of the spacing scenarios, circles were added at the grid locations with diameters of 10, 20, 30, and 40 km meant to simulate the extent of species catch correlation. The intention here is to generalize the tradeoffs between station spacing and the spatial correlation among trawl species catch; hence, developing a set of tools to

**Table 1.** List of US Northeast Shelf wind energy lease areas shown in Figure 1 with their areas, and medians (50%) and quartile intervals (25 and 75%) of the chord lengths of the lease area shapes.

| | | Chord length | | |
|---|---|---|---|---|
| Project | Area km$^2$ | 25% km | 50% km | 75% km |
| Bay State Wind LLC | 586 | 11 | 19 | 31 |
| Vineyard Northeast LLC | 536 | 9 | 16 | 25 |
| Beacon Wind LLC | 522 | 12 | 17 | 26 |
| SouthCoast Wind Energy LLC | 516 | 12 | 17 | 26 |
| Community Offshore Wind, LLC | 510 | 11 | 18 | 23 |
| Avangrid Renewables, LLC | 495 | 9 | 17 | 27 |
| Virginia Electric and Power Company | 457 | 8 | 15 | 23 |
| Sunrise Wind, LLC | 445 | 9 | 15 | 24 |
| Atlantic Shores Offshore Wind Projects 1 & 2, LLC’s | 413 | 9 | 16 | 21 |
| Park City Wind LLC | 411 | 10 | 16 | 22 |
| Orsted North America Inc. | 344 | 5 | 10 | 14 |
| Attentive Energy LLC | 341 | 9 | 14 | 19 |
| Invenergy Wind Offshore LLC | 340 | 10 | 14 | 20 |
| Revolution Wind, LLC | 339 | 8 | 13 | 19 |
| Atlantic Shores Offshore Wind, LLC | 328 | 8 | 15 | 25 |
| US Wind Inc. | 323 | 9 | 14 | 19 |
| Atlantic Shores Offshore Wind Bight, LLC | 321 | 9 | 15 | 20 |
| Empire Offshore Wind, LLC | 321 | 9 | 16 | 25 |
| Ocean Wind LLC | 306 | 7 | 13 | 18 |
| Bluepoint Wind, LLC | 289 | 8 | 14 | 18 |
| GSOE I, LLC | 284 | 8 | 14 | 17 |
| Vineyard Wind 1 LLC | 264 | 7 | 14 | 17 |
| Mid-Atlantic Offshore Wind LLC | 174 | 7 | 10 | 14 |
| Skipjack Offshore Energy, LLC | 107 | 5 | 8 | 11 |
| South Fork Wind, LLC | 55 | 3 | 5 | 7 |
| Cmlth of Virginia, Dept. of Mines, Minerals, and Energy | 9 | 5 | 16 | 29 |
| Mean | 347 | 8 | 14 | 21 |

**Table 2.** List of species that to some measure rely on bottom trawl survey data in their assessment process, SVSPP code is the primary database code used in the trawl database and is provided to facilitate species identification in other figures.

| Common name | Scientific name | SVSPP Code | Common name | Scientific name | SVSPP Code |
|---|---|---|---|---|---|
| Spiny dogfish | *Squalus acanthias* | 15 | Witch flounder | *Glyptocephalus cynoglossus* | 107 |
| Barndoor skate | *Dipturis laevis* | 22 | Windowpane flounder | *Scophthalmus aquosus* | 108 |
| Winter skate | *Leucoraja ocellata* | 23 | Atlantic mackerel | *Scomber scombrus* | 121 |
| Clearnose skate | *Raja eglanteria* | 24 | Butterfish | *Peprilus triacanthus* | 131 |
| Rosette skate | *Leucoraja garmani* | 25 | Bluefish | *Pomatomus saltatrix* | 135 |
| Little skate | *Leucoraja erinacea* | 26 | Black sea bass | *Centropristis striata* | 141 |
| Smooth skate | *Malacoraja senta* | 27 | Scup | *Stenotomus chrysops* | 143 |
| Thorny skate | *Amblyraja radiata* | 28 | Golden tilefish | *Lopholatilus chamaeleonticeps* | 151 |
| Atlantic herring | *Clupea harengus* | 32 | Acadian redfish | *Sebastes fasciatus* | 155 |
| Alewife | *Alosa pseudoharengus* | 33 | Atlantic wolffish | *Anarhichas lupus* | 192 |
| Blueback herring | *Alosa aestivalis* | 34 | Ocean pout | *Zoarces americanus* | 193 |
| American shad | *Alosa sapidissima* | 35 | Monkfish | *Lophius americanus* | 197 |
| Silver hake | *Merluccius bilinearis* | 72 | American lobster | *Homarus americanus* | 301 |
| Atlantic cod | *Gadus morhua* | 73 | Northern shrimp | *Pandalus borealis* | 306 |
| Haddock | *Melanogrammus aeglefinus* | 74 | Deep sea red crab | *Chaceon quinquedens* | 310 |
| Pollock | *Pollachius virens* | 75 | Jonah crab | *Cancer borealis* | 312 |
| White hake | *Urophycis tenuis* | 76 | Atlantic sturgeon | *Acipenser oxyrinchus oxyrinchus* | 380 |
| Red hake | *Urophycis chuss* | 77 | Atlantic sea scallops | *Placopecten magellanicus* | 401 |
| Cusk | *Brosme brosme* | 84 | Atlantic surfclam | *Spisula solidissima* | 403 |
| Atlantic halibut | *Hippoglossus hippoglossus* | 101 | Ocean quahog | *Arctica islandica* | 409 |
| American plaice | *Hippoglossoides platessoides* | 102 | Illex squid | *Illex* spp. | 502 |
| Summer flounder | *Paralichthys dentatus* | 103 | Longfin squid | *Doryteuthis (Amerigo) pealeii* | 503 |
| Yellowtail flounder | *Limanda ferruginea* | 105 | Blueline tilefish | *Caulolatilus microps* | 621 |
| Winter flounder | *Pseudopleuronectes americanus* | 106 | | | |

**Table 3.** The number of years in which there were sufficient data to estimate a variogram range (Range, which is also the number of years Moran's *I* test was estimated) for each study species.

| | Spring | | | | Autumn | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Join Count | | | | Join Count | |
| SVSPP | Range | Outliers | Absence | Presence | Range | Outliers | Absence | Presence |
| 15 | 52 | 49 | 52 | 52 | 57 | 51 | 57 | 57 |
| 22 | 44 | 40 | 44 | 38 | 50 | 47 | 50 | 44 |
| 23 | 52 | 52 | 52 | 52 | 57 | 57 | 57 | 57 |
| 24 | 48 | 47 | 48 | 48 | 52 | 51 | 52 | 51 |
| 25 | 51 | 42 | 51 | 46 | 57 | 52 | 57 | 55 |
| 26 | 52 | 50 | 52 | 52 | 57 | 55 | 57 | 57 |
| 27 | 52 | 48 | 52 | 52 | 57 | 52 | 57 | 57 |
| 28 | 52 | 50 | 52 | 52 | 57 | 54 | 57 | 57 |
| 32 | 52 | 43 | 52 | 52 | 57 | 54 | 57 | 57 |
| 33 | 52 | 46 | 52 | 52 | 57 | 51 | 57 | 57 |
| 34 | 52 | 46 | 52 | 52 | 55 | 48 | 55 | 52 |
| 35 | 52 | 42 | 52 | 52 | 57 | 50 | 57 | 57 |
| 72 | 52 | 47 | 52 | 52 | 57 | 47 | 57 | 57 |
| 73 | 52 | 50 | 52 | 52 | 57 | 56 | 57 | 57 |
| 74 | 52 | 46 | 52 | 52 | 57 | 55 | 57 | 57 |
| 75 | 52 | 43 | 52 | 52 | 57 | 50 | 57 | 57 |
| 76 | 52 | 50 | 52 | 52 | 57 | 53 | 57 | 57 |
| 77 | 52 | 49 | 52 | 52 | 57 | 49 | 57 | 57 |
| 84 | 52 | 51 | 52 | 52 | 57 | 56 | 57 | 57 |
| 101 | 52 | 45 | 52 | 51 | 56 | 45 | 56 | 54 |
| 102 | 52 | 49 | 52 | 52 | 57 | 46 | 57 | 57 |
| 103 | 52 | 45 | 52 | 52 | 57 | 50 | 57 | 56 |
| 105 | 52 | 51 | 52 | 52 | 57 | 53 | 57 | 57 |
| 106 | 52 | 48 | 52 | 52 | 57 | 55 | 57 | 57 |
| 107 | 52 | 50 | 52 | 52 | 57 | 52 | 57 | 57 |
| 108 | 52 | 51 | 52 | 52 | 57 | 57 | 57 | 57 |
| 121 | 52 | 47 | 52 | 52 | 57 | 51 | 57 | 56 |
| 131 | 52 | 44 | 52 | 52 | 57 | 47 | 57 | 57 |
| 135 | 40 | 39 | 40 | 34 | 54 | 49 | 54 | 52 |
| 141 | 52 | 48 | 52 | 52 | 56 | 46 | 56 | 55 |
| 143 | 52 | 45 | 52 | 52 | 57 | 49 | 57 | 57 |
| 151 | 35 | 29 | 35 | 26 | 31 | 26 | 31 | 14 |
| 155 | 52 | 52 | 52 | 52 | 57 | 54 | 57 | 57 |
| 192 | 52 | 44 | 52 | 50 | 56 | 50 | 56 | 54 |
| 193 | 52 | 48 | 52 | 52 | 57 | 51 | 57 | 57 |
| 197 | 52 | 47 | 52 | 52 | 57 | 51 | 57 | 57 |
| 301 | 52 | 46 | 52 | 52 | 57 | 53 | 57 | 57 |
| 306 | 31 | 28 | 31 | 31 | 40 | 40 | 40 | 39 |
| 310 | 41 | 35 | 41 | 41 | 51 | 46 | 51 | 45 |
| 312 | 49 | 44 | 49 | 44 | 49 | 44 | 49 | 48 |
| 380 | 32 | 26 | 32 | 18 | 10 | 9 | 10 | 4 |
| 401 | 52 | 48 | 52 | 52 | 57 | 56 | 57 | 57 |
| 403 | 14 | 13 | 14 | 9 | 11 | 10 | 11 | 4 |
| 409 | 7 | 6 | 7 | 5 | 3 | 3 | 3 | 2 |
| 502 | 52 | 46 | 52 | 52 | 57 | 53 | 57 | 57 |
| 503 | 52 | 48 | 52 | 52 | 57 | 49 | 57 | 56 |
| 621 | 8 | 7 | 8 | 5 | 10 | 10 | 10 | 6 |

The number of years of range data after outlier removals (Outliers). Number of years a Join Count estimate of absences and presents could be estimated (Absence and Presence, respectively). Shading added to emphasize range in values.

evaluate survey adaptation and mitigation of encroachment issues. To add further context, these putative grids were overlaid on the currently established lease areas to illustrate the feasibility of rudimentary gridded survey designs.

## Results

### Performance statistics for species

Measures of spatial correlation for each species were estimated over all the years and seasons of the bottom trawl survey time series. The combined total for both seasonal surveys was 109 years and for 47 taxa resulting in 5123 statistical estimates (Table 2). In the spring, only 35 of the 47 species had sufficient data to calculate the indices in all 52 years of the spring time series; that figure is even lower in the autumn where 32 species had sufficient data in the 57-year time series (Table 3). Data availability issues primarily affected Atlantic surfclam (*Spisula solidissima*), Ocean quahog (*Arctica islandica*), and Blueline tilefish (*Caulolatilus microps*), none of which are effectively sampled by the bottom

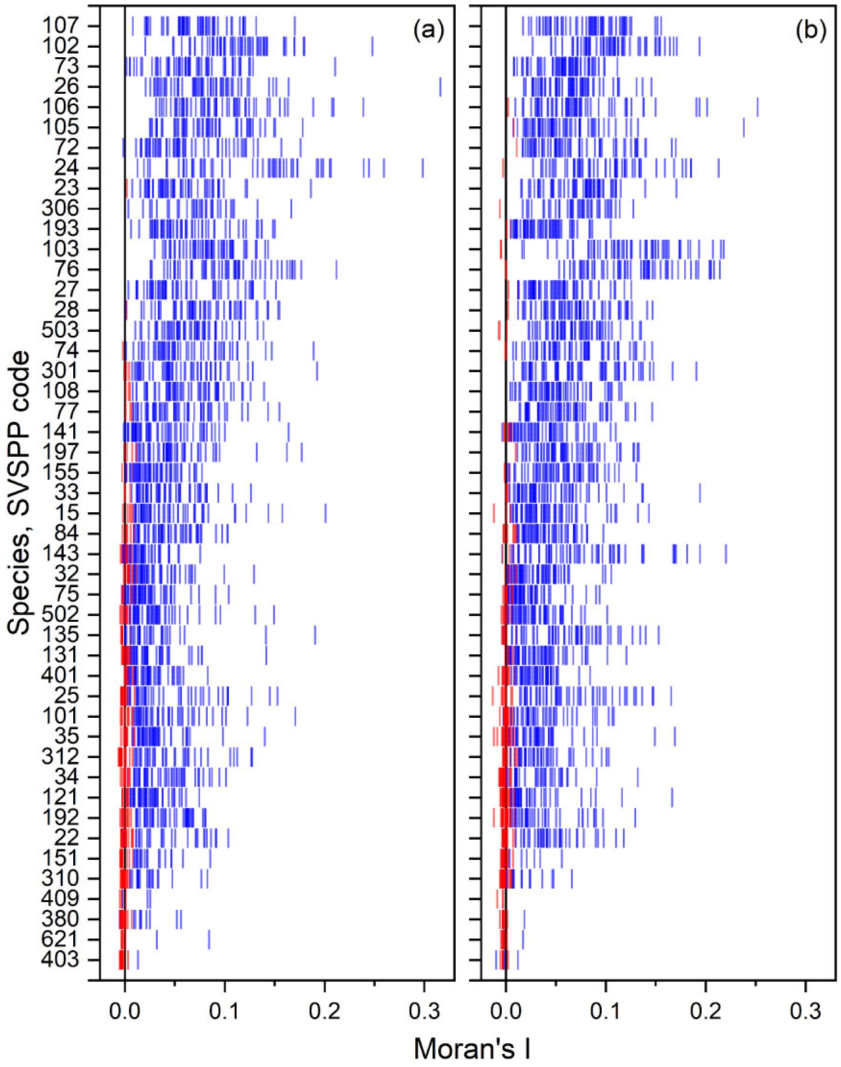

**Figure 2.** The distribution of annual Moran's *I* test statistics sorted by species based on the mean of spring and autumn significant positive test results for spring (a) and autumn (b). Blue symbols indicate significant tests; red symbols indicate non-significant tests.

trawl gear. It is worth noting that surfclam is the subject of another dedicated survey. Of those season and species combinations, ~9% of the data were eliminated as outliers with values generally ranging between 0 to 11 years eliminated for a given taxon.

## Moran's *I*

For most species, Moran's *I* was significant and positive in value in the majority of survey years, indicating a tendency for the distribution of species to be spatially autocorrelated. In most years, there were sufficient data to calculate Moran's *I*, notably there were low numbers of years for Atlantic surfclam, ocean quahog, and blueline tilefish (Table 3). Overall, in spring, only 8% of the Moran *I* statistics were negative in sign, and of those negative tests, only 8% were significant (Figure 2a). The balance of the test statistics were positive in sign and among these tests, 93% were significant. The statistics were patterned similarly in the autumn where 9% of the tests were negative, of which 4% were significant tests, whereas among positive test statistics, 94% were significant (Figure 2b). The preponderance of significant positive test statistics in both seasons suggest most species distribute with positive spatial autocorrelation; however, noting that for some species the sample size is inadequate to come to any conclusion.

## Join count test

The join count test for spatial autocorrelation among presence locations for the survey species indicated a tendency towards spatial autocorrelation. In spring, 93% of the join tests for presence spatial autocorrelation were significant (Figure 3a). The non-significant tests were distributed over a number of species. Of the taxa with a high proportion of non-significant tests (Deep sea red crab, ocean quahog, blueline tilefish, Atlantic sturgeon, and Atlantic surfclam), only red crab had test statistics for most years of the time series. In autumn, the percentage of significant tests was the same as in spring, 93% (Figure 3b). Similar to the spring, those species with a high proportion of non-significant tests are the same as the spring with the addition of Golden Tilefish and the only taxon with a test statistic in most years was red crab. Using a contrasting approach to Moran's *I*, the join count statistics also indicate

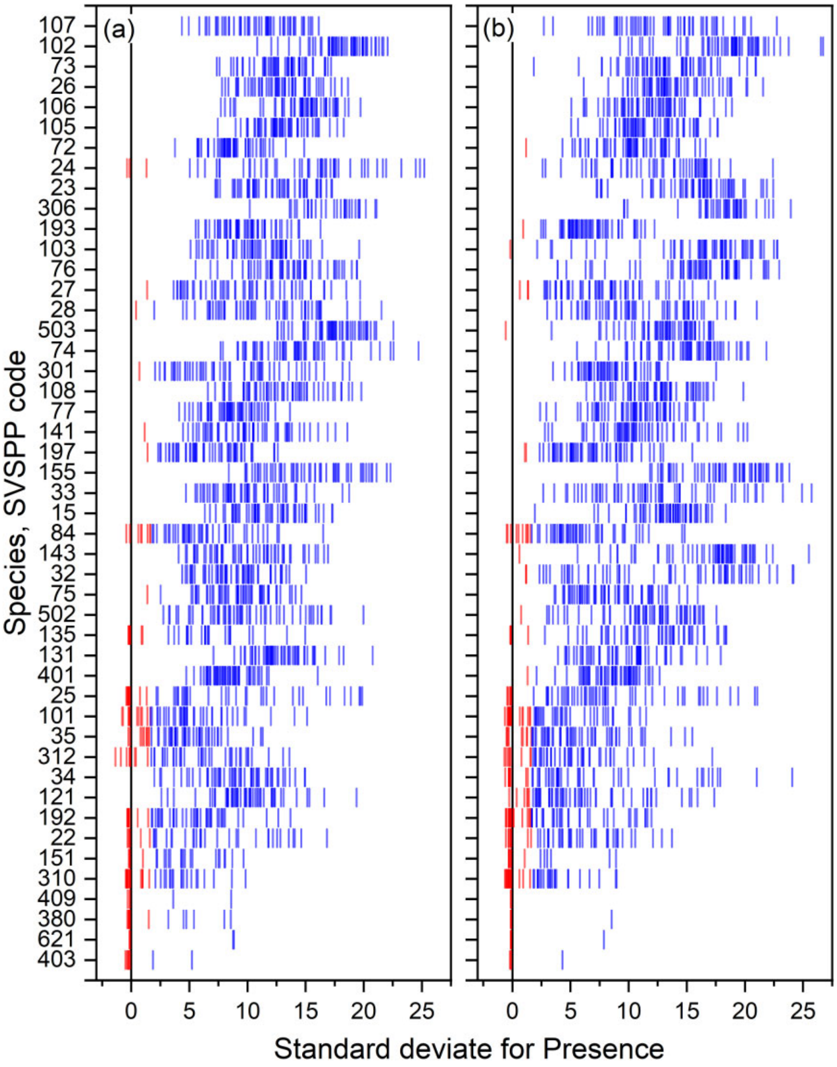

**Figure 3.** The distribution of join count test of spatial correlate of presence locations, sorted by species based on the mean of spring and autumn significant positive test results (from Figure 2) for spring (a) and autumn (b). Blue symbols indicate significant tests; red symbols indicate non-significant tests.

a high degree of spatial autocorrelation among species distributions.

## Variogram range

Estimates of variogram range generally exceeded the measures of access to the lease areas based on the distribution of lease area chord distances. The mean of the range estimates over the study period by species spanned values from 46 to 702 km (Figure 4). The rank ordering of the means suggest the smallest ranges were realized for sea scallops (*Placopecten magellanicus*) at 58 and 48 km for the spring and autumn survey, respectively. The highest ranges were observed for ocean quahog at 85 and 702 km for the spring and autumn survey, respectively. Over all taxa, all mean range estimates exceeded the upper quartile of chord lengths of 21 km by at least a factor of two. The lower extent of the confidence intervals of range estimates were <21 km for three taxa including blueline tilefish in the spring and Atlantic surfclam and ocean quahog in the autumn. These data generally had right-hand skewness in their distribution, hence, the mean tended to be much greater than the median. To address this issue, the range data were also presented as quantiles and median scores. In the spring, the medians of range spanned 18 to 284 km, which is markedly less than suggested by the mean of the ranges (Figure 5). Though the medians met or exceeded the chord distance benchmarks, many species had 10–90 and 25–75% quantile ranges that were less than these reference distances. A similar result was realized with the autumn data, with the median spanning values from 17 to 306 km and many species with quantile ranges below the reference distances (Figure 6). The performance of some species was not equivalent between seasons. For example, the lowest autumn median was observed in Atlantic surfclam; however, in spring, surfclam had a median of 52 km, noting that this species is not well sampled by the survey gear. In other taxa, some of which were specifically targeted by the trawl gear, seasonal medians were consistent; for example, the spring median for Atlantic cod (*Gadus morhua*) was 88 km vs. an autumn median of 100 km.

## Putative interaction of sample grid size and range correlation

The interactive effects of sample grid spacing and the likely spatial coverage of samples suggested some general principles that may be helpful in the consideration of a wide variety of

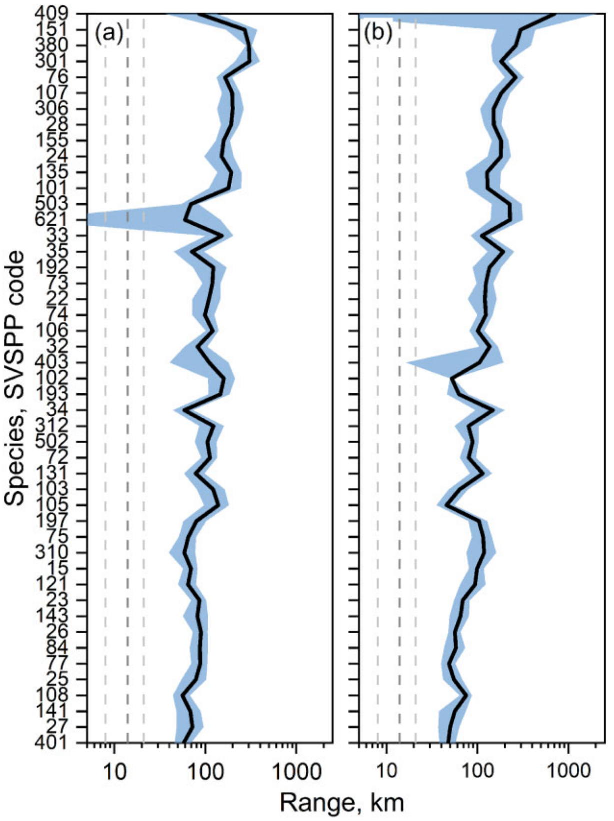

**Figure 4.** Mean variogram ranges (black line) and 95% *CI* (blue) by species sorted by mean range for spring (a) and autumn (b). Range references of 8, 14, and 21 km (mean of quartile statistics of lease area chord distances) are added as dashed lines.

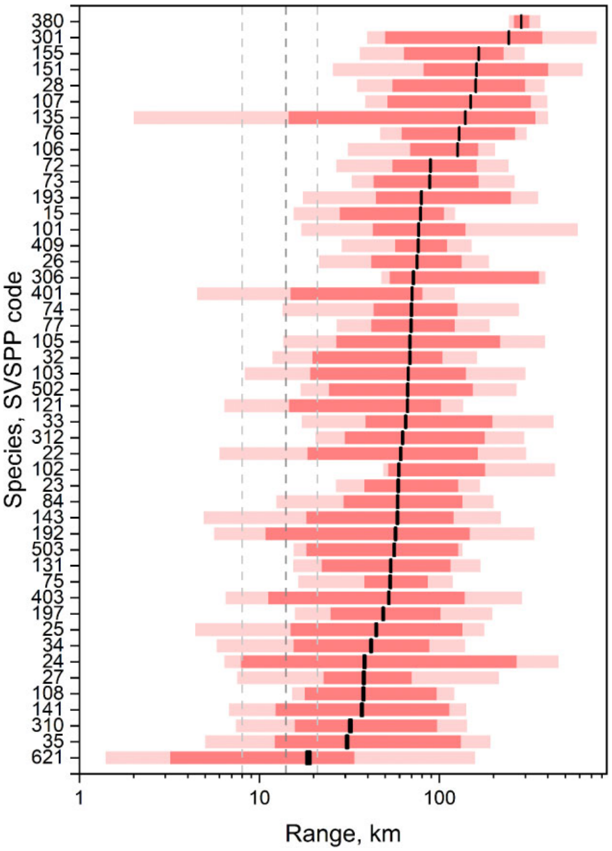

**Figure 5.** Spring variogram ranges plotted over 10–90% quantiles (light red), 25–75% quantiles (dark red), and medians (black line) sorted by range median. Range references of 8, 14, and 21 km (mean of quartile statistics of lease area chord distances) are added as dashed lines.

resource monitoring approaches. We selected a sampling grid at a spacing of 0.333° that approximates the station density of the current bottom trawl survey. With this grid spacing, if capture at a grid location has a spatial correlation of at least 20 km, the grid results in overlapping effectiveness of neighbouring samples. This statement is supported by comparing the coverages over a 0.333° grid given spatial correlation distances of 10, 20, 30, and 40 km (Figure 7a). With a sampling grid spaced at 0.5°, the spatial correlation assumed for species would have to be closer to 30 km to achieve a similar level of sample coverage and station overlap (Figure 7b). Given the range estimates for the species considered in this study, either grid spacing would seem to offer a viable alternative for data collection by trawl gear or other types of survey telemetry. Hence, for a putative sampling grid of 0.333°, there is sufficient spacing suggested by the lease areas designated thus far to locate extra-lease area sampling within each grid member (Figure 7c). This is also true for a sample grid of 0.5°, affording even greater flexibility for the location of survey stations. This rudimentary exercise suggests the potential feasibility for a grid design with the requirement of one sample per grid square, either assigned in a fixed location or with some degree of randomization.

## Discussion

The range or distance of survey catch correlation as characterized with variogram model fits suggests spatial correlation far exceeds the general dimensions of offshore WEAs for species dependent on bottom trawl data for assessment purposes. This suggests that sampling in proximity to the WEAs may be a suitable substitute indicative of the WEA habitat for species with high spatial autocorrelation. Underlying this general conclusion is the idea that species have patch size dynamics associated with their distribution (Jentsch and White, 2019). These patch-sizes can be relatively small or localized to fine scale physical structures (Deza and Anderson, 2010), or exist over relatively large ocean domains (Filous *et al.*, 2022). Our estimates of spatial autocorrelation suggest a range of patch sizes for the study species of tens to over 100 km, which may be limited by the extents of the survey area itself. If other regions were included in the sampling range, many taxa presented here may have a larger range of spatial correlation. For example, it is likely that haddock would have a much larger range of correlation due to their distribution in Canadian waters if the Scotian Shelf were included as part of the study area. Though the basis of our conclusions concerning spatial correlation may, if anything, be conservative, they would appear to be more than adequate to address the issues raised in the analysis concerning the spatial scales of wind field sample exclusion and species catch correlation.

We anticipate two spatial scales of habitat alteration caused by WEA development. At the local scale of tens to hundreds of metres, benthic habitat modification is expected at the base of turbines, in the scour protection zone, and surrounding sediments. Altered patterns of sediment organic content, benthic community composition, and finfish community structure

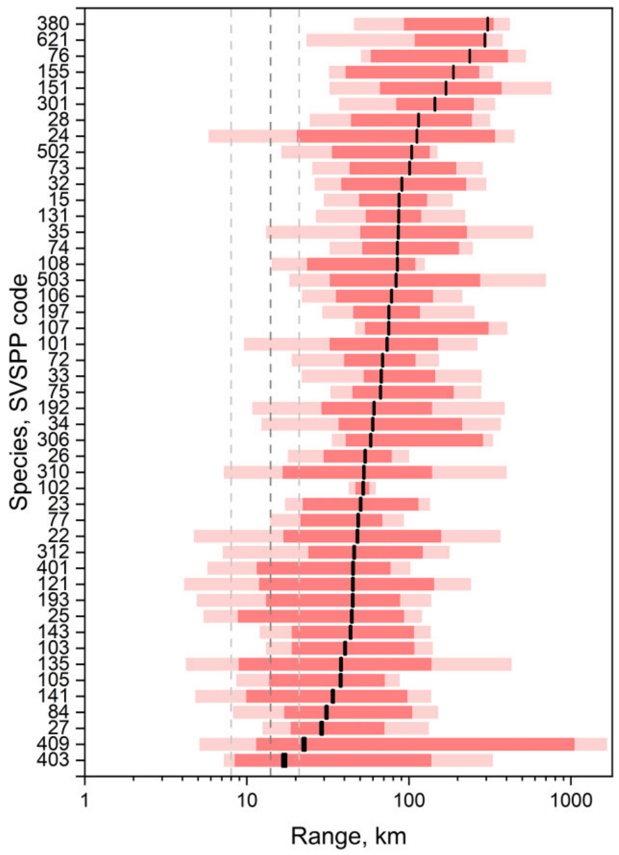

**Figure 6.** Autumn variogram ranges plotted over 10–90% quantiles (light red), 25–75% quantiles (dark red), and medians (black line) sorted by range median. Range references of 8, 14, and 21 km (mean of quartile statistics of lease area chord distances) are added as dashed lines.

have been observed at this scale in Europe where installations have been in place for many years (Coates *et al.*, 2014; Degraer *et al.*, 2020; Buyse *et al.*, 2022; Coolen *et al.*, 2022). Effects of electromagnetic fields (EMFs), chemical contaminants, construction and operational noise, substrate vibration, particle motion, and entrainment within offshore cooling substations also emerge at this scale (Kirchgeorg *et al.*, 2018; Hutchison *et al.*, 2020; Mooney *et al.*, 2020; Tougaard *et al.*, 2020; Hawkins *et al.*, 2021). It is important to remember that many frequently caught species orient to structures like a wind tower foundation. Black Sea Bass (*Centropristis striata*) are known to orient to other structures in the NES environment (wrecks and artificial reefs). To characterize these sorts of changes, specific assessments are needed to address the newly created habitat. Gears such as bottom trawls have limited utility in monitoring these habitats; instead, point observations such as video or those made using scuba would be required.

Mesoscale effects in the water column caused by turbulence associated with the structures as well as interactions between atmospheric wind wake and physical oceanography processes are also anticipated (Dorrell *et al.*, 2022). These interactions may affect primary productivity, transparency, thermal distribution, larval distribution, etc. and would operate over scales of tens of kilometres, thus extending beyond the boundaries of wind energy projects (Christiansen *et al.*, 2022; Daewel *et al.*, 2022). These latter effects form the basis for any rationale to apply the findings made in this study; since the range of spatial correlation exceeds the chord distances of WEA access, sampling by any gear should have relevance beyond the constraints created by any wind field sample exclusions.

Given the spacing of wind energy towers, we know that the bottom trawl survey vessels currently in use, such as the FSV Henry B. Bigelow, will be unable to operate within WEAs (Hare *et al.*, 2022). Smaller trawl survey vessels operated by state and federal agencies or other groups may be able to continue to sample within the areas, but it is unclear if and how considerations beyond tower spacing, such as cable placements, might affect access. For example, there is still a large debate about the impact of cabling and cable armouring on the ability of smaller trawl vessels to operate in the areas. Cable tracks are expected to take multiple routes through the wind field to create efficiencies for transmission to the main energy grid (Srinil, 2016). These irregular cable patterns limit the areas of potentially trawlable habitat within the WEAs and add further risk of interaction between sampling vessels and wind energy infrastructure. Additionally, many safety and insurance details for the vessels that might undertake this work are yet to be settled (Hogan, 2023). Thus, it is quite possible that trawl survey vessels will effectively be excluded from these areas. This adds further emphasis to the question of whether a sampling design for active gear can be envisioned completely outside the wind field areas.

An active gear like a bottom trawl has an important advantage over other types of fisheries survey methods in providing biological sample data that are critical to stock assessments. Ideally, stock assessments utilize models that incorporate age compositions and other biological attributes of the populations (e.g. average weight, maturity). Such models tend to be superior to models that rely on coarser measures of relative abundance and exclude age- or size-based information. Hence, both scientific and commercial sampling should collect size and age data from individual specimens (NRC, 2000). There are efforts to increase the accuracy of analytical assessments with the inclusion of data to calibrate natural mortality using auxiliary data of consumption by predator species, again data dependent on the collection of specimens for stomach contents analysis (Dorn and Barnes, 2022). Without these data, we run the risk of having stock assessments regress to index level assessments with reduced ability to set appropriate biological reference points. Though we can see where new telemetry methods such as active and passive sound measurements, environmental DNA, and manned and unmanned video recordings, among others, may provide information on biomass levels and population trajectories, they lack the ability to address the data deficiencies created by the absence of specimen data (Sheaves *et al.*, 2020; Stoeckle *et al.*, 2021). We would advocate for the consideration of hybrid survey designs that can maintain the existing time series of indicators and specimen data and be augmented by other methods.

Use of passive gear (e.g. traps, gill nets) or telemetric gear to monitor populations introduces other complications because the measurements are not strictly comparable to active gear such as trawls. In the absence of calibration experiments, it is impossible to determine if changes in relative abundance are due to true changes or simply different catchabilities among gears. Passive gear relies on volitional movements of fish as well as probabilities of entanglement and behavioural traits (likelihood of entering a closed space, etc.). Remote sensing gear rely on detection probabilities and ability to identify

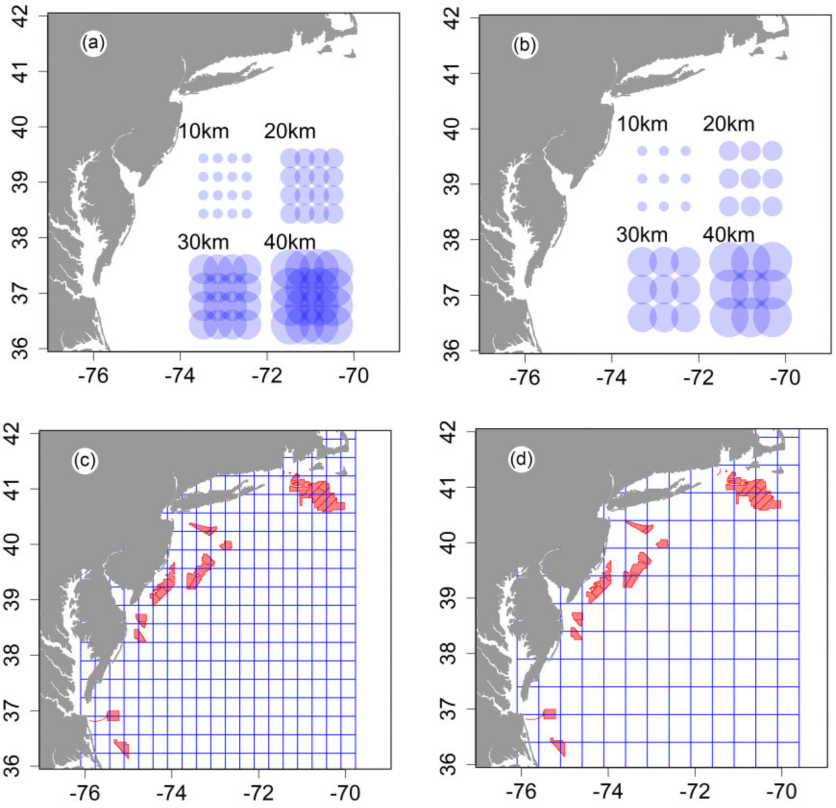

**Figure 7.** Putative sample grid spacing and influence or coverage circles based on spacing of 0.333° with circles of 10, 20, 30, and 40 km diameter (a) and based on spacing of 0.5° (b). A putative 0.333° grid with lease areas shown in red (c) and a putative 0.5° grid (d).

individuals to the species level. Without calibration experiments, the use of alternative gear in WEAs will not have the same basis of inference as trawls and the consistency of future with past observations cannot be ensured. Applying the same logic, future observations that are informed by samples around the perimeter of wind areas will have greater uncertainty. The effects of this uncertainty on the overall survey data have not been quantified, but should be considered in future research.

The NES is among the most rapidly warming ecosystems worldwide (Pershing *et al.*, 2015) and has experienced regime level change in temperature (Friedland *et al.*, 2020), in part due to basin-scale shifts in North Atlantic gyre circulation (Gonçalves Neto *et al.*, 2021). Our knowledge of these environmental changes was formed with the *in-situ* observations made during ecosystem surveys (Gawarkiewicz *et al.*, 2019) that will have to be adapted to new sampling designs with the installation of wind energy turbines. We have also seen regime level change in lower (Morse *et al.*, 2017) and upper (Methratta and Link, 2006) trophic level productivity and distribution. Likewise, surveys that measure these parameters will also have to adapt. To continue to understand what is occurring in our environment, it would be desirable, or perhaps necessary, to continue a comparative time series of the trawl survey that formed the basis of this report. What was apparent prior to the realization of climate change in our oceans was the anticipatory needs for time series data (McGowan, 1990); the landscape that defined these needs over three decades ago has not changed and perhaps has grown more critical. Hopefully, the data reported here will find utility in the development of strategies to meet survey goals.

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## Supplementary data

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

## Conflict of interest

The authors declare no conflicts of interest.

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## Author contributions

KF conceived of the project and developed initial data analysis. All authors contributed to manuscript drafting and edits.

## Data availability

The data used to describe the wind energy areas in the NES were obtained from the Bureau of Ocean Energy Management (BOEM). https://www.boem.gov/renewable-energy/mapping-and-data/renewable-energy-gis-data. The data from the Northeast Fisheries Science Center bottom trawl survey is available via the World Wide Web, spring data https://www.fisheries.noaa.gov/inport/item/22561 and fall data https://www.fisheries.noaa.gov/inport/item/22560.

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