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Food for Thought

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Ecological indicators to monitor offshore wind interactions with fisheries resources

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Abstract

Offshore wind development (OWD) will generate much needed renewable energy, but it will also introduce several stressors to the marine ecosystem. Therefore, there is a need to develop information-rich monitoring programs to assess ecological impacts and inform solutions to mitigate adverse effects. This paper evaluates potential indicators of OWD impacts on fisheries resources that could be considered for monitoring programs, including indices of aggregate biomass, sensitive species, fish size, and trophic dynamics. Short-term (year-to-year) variability and the direction and strength of long-term trends were explored at both the scale of the US Southern New England wind energy area (WEA) and at the scale of the Southern New England region. The majority of candidate OWD indicators exhibited substantial temporal variability at either the WEA scale, the region scale, or both, highlighting the importance of addressing temporal variability in the design and duration of monitoring programs. Recommendations are provided to advance informative monitoring approaches both in the USA and elsewhere where such approaches are urgently needed. Among these is a recommendation for a minimum of 3–5 years of baseline data collection and continued monitoring for the lifetime of the wind project. This will enable an understanding of the temporal structure inherent to the time series of ecological indicators measured so that OWD impacts can be disentangled from those caused by other ecosystem pressures.

Keywords: renewable energy; impact assessment; experimental design; temporal variability; survey design

Introduction

Offshore wind development (OWD) is a central component of society's approach to generating renewable energy as it moves toward reducing its reliance on fossil fuels to combat global climate change. Currently, the USA is on track to develop 30 GW of offshore wind energy capacity by 2030 and an additional 15 GW by 2035 (DOI 2022). The OWD process is in varying stages along the Atlantic, Pacific, and Gulf of Mexico coasts in the USA, but the nation's first utility scale offshore wind farm will be constructed in the Northeast US Continental Shelf (NES) ecosystem (BOEM 2022). In addition to its ample wind resources, the NES ecosystem is also home to critical habitats, protected species, and some of the most productive fisheries on the planet (NOAA 2021, 2022a).

Along with the benefits of renewable energy production, utility scale OWD will also bring an unprecedented suite of stressors to the NES ecosystem, many of which will persist for 30+ years. These include noise, electro-magnetic fields (EMFs), altered patterns of local and regional hydrodynamics, habitat conversion, artificial reef effects (i.e. effects of interactions that form and maintain a reef and its associated community), and fish attraction device (FAD) effects (i.e. attraction of fish to structure for forage, habitat, or refuge) (Hogan et al. 2023). A growing body of peer-reviewed scientific literature suggests that these stressors have important effects on marine ecosystems (Gill et al. 2020, Methratta et al. 2020, Hogan et al. 2023). Well-designed monitoring is key to the co-existence of offshore wind with sustainable fisheries and a healthy marine ecosystem. Such monitoring should be able to detect biologically meaningful changes and provide opportunities to mitigate adverse impacts. Ideally, monitoring plans would sample meaningful biological indices, use experimental designs capable of detecting change, collect data that are comparable among projects and with regional long-term data sets, and provide open and transparent access to information for stakeholders (ROSA 2021). Lacking these fundamental characteristics, the outcome is a scenario in which scientists, managers, and decision-makers are data-rich but information-poor (*sensu* Wilding et al. 2017).

Identifying suitable metrics to assess the impact OWD at the scale of the individual wind project, which can also be compared across wind projects, and inform regional and ecosystem change, is a central challenge facing monitoring programs (ROSA 2021). Useful indicators are those that are scientifically rigorous, measurable, representative of key properties and processes, and are straightforward to interpret when they change (Smit et al. 2021, NOAA 2022b). In the context of offshore wind, useful indicators for monitoring programs would also be sensitive to specific stressors associated with OWD. Candidate indicators are emerging from ongoing research at wind farms worldwide. For example, conversion of habitat from soft bottom to hard structures is associated with increased local abundance of finfish and invertebrates (Reubens et al. 2011, 2013a, van Hal et al. 2017, HDR 2020, Buyse et al. 2022, Wilber et al. 2022a), shifts in size structure (Vandendriessche et al. 2015), changes in fish condition (Reubens et al. 2013b, 2014), and altered trophic dynamics (Mavraki et al. 2020a, Wilber et al. 2022b, Buyse et al. 2023). Noise from impact pile driving can affect physiology, behavior, foraging, communication, mating cues, and migratory patterns (Popper and Hawkins 2019), while operational noise may cause a variety of sublethal effects (Westerberg 1994, Bergström et al. 2013, Mooney et al. 2020, Ströber and Thomsen 2021, Cresci et al. 2023). EMFs associated with OWD cables elicit behavioral responses in EMF sensitive species such as American lobster (*Homarus americanus*) and little skate (*Leucoraja erinacea*) in laboratory settings (Hutchison et al. 2020a). Local and broad scale changes in hydrodynamics around wind farms are expected (Christiansen et al. 2022, Daewel et al. 2022). Although these effects are not yet well understood, there is a potential for effects on larval transport for demersal species (Barbut et al. 2020), on food resources for planktivores (Slavik et al. 2019, van Berkel et al. 2020, Daewel et al. 2022), and on physical water column properties that affect species distributions (Daewel et al. 2022, Dorrell et al. 2022).

Ecological indicators to assess marine ecosystem status have been the focus of over two decades of research in the NES ecosystem with emphasis placed on identifying indicators of fishing pressure and climate change (Brodziak and Link 2002, Methratta and Link 2006, Large et al. 2015, NOAA 2022a). Indicators are an essential component of developing integrated ecosystem assessments (IEAs), an operational approach to ecosystem-based management, comprised of a multi-step process which allows the evaluation of cross-sector trade-offs (Samhouri et al. 2014, NOAA 2022a, RODA 2023). Indicators selected for project-level monitoring could also be considered as candidates for assessment of ecosystem status in an IEA framework, linking together local project scale monitoring with efforts to assess the status of the whole ecosystem (e.g. NOAA 2022a). Additionally, ecological indicators could also be informative for stock assessments of species that are expected to be responsive to OWD through a gain of habitat (e.g. structure oriented species) or a loss of habitat (e.g. soft bottom species).

Choosing the appropriate duration over which monitoring programs should occur is another challenge. While there is scientific need for collecting data to understand impacts of OWD, monitoring programs are expensive and require access to a limited supply of vessels and sampling gear. Therefore, the selection of monitoring program duration must be deliberative, purposeful, and scientifically justifiable. The idea that monitoring programs should be long-term, spanning the lifespan of the wind project through decommissioning, is supported by the longest running OWD monitoring programs in existence which show new and ecologically meaningful changes >10 years after construction (Degraer et al. 2021, Buyse et al. 2023). Furthermore, the NES is a dynamic system under multiple pressures, including climate change (Hare et al. 2016), which is driving a northward range expansion for many marine species due to warming waters (Lucey and Nye 2010, Bell et al. 2015, Walsh et al. 2015, Grieve et al. 2016). This dynamism poses a quandary for conventional before–after OWD monitoring approaches, which focus on the comparison of mean values observed at two time points (i.e. before and after construction) in both impact and control locations (Methratta 2020), because such comparisons neglect the underlying structure of temporal variability. Although issues surrounding spatial variability have been discussed elsewhere (Methratta 2020, 2021), the confounding effects of underlying temporal structure on OWD monitoring studies and their interpretation have received less attention.

The purpose of this paper is to (i) explore year-to-year and long-term temporal trends in 25 ecological indicators of OWD interactions with fisheries resources at the spatial scale of a wind energy area (WEA) and the region where it occurs; (ii) examine whether significant long-term trends at the spatial scale of the WEA are consistent with broad scale regional long-term trends; and (iii) make recommendations for monitoring, including specific recommendations for addressing temporal variability in developing methodological approaches for monitoring OWDs. This study focuses on biotic indicators for which there is peer-reviewed evidence for responsiveness to stressors associated with OWD. The Southern New England (SNE) WEA is used as a case study as it is the putative location of the first utility scale OWD in the USA; however, the conclusions and recommendations provided have utility for marine ecosystems around the world where OWD is planned or underway.

Materials and methods

Data sets, study area, and data analysis

Data from the Northeast Fisheries Science Center's (NEFSC's) bottom trawl survey were used to evaluate ecological indicators expected to be responsive to OWD. The NEFSC bottom trawl survey has sampled the distribution and abundance of fisheries resources in the NES ecosystem during the spring and fall annually since 1963 (Azarovitz 1981, Politis et al. 2014). In addition to measures of abundance, individual fish diets have been sampled as part of the survey since 1973 (Link and Almeida 2000, Smith and Link 2010). Annual estimates were calculated for 25 indices that are representative of ecosystem processes and functions and that are expected to be responsive to stressors associated with OWD (Tables 1–4) (Brodziak and Link 2002, Methratta and Link 2006, Large et al. 2015, NOAA 2022a, b). These included indices of aggregate biomass, sensitive species, fish size, and trophic dynamics.

For each of 25 ecological indicators, survey data were aggregated at the spatial scale of the SNE WEA and at the spatial scale of the SNE region (Fig. 1) for each year. For each of the two spatial scales (SNE WEA and SNE region), data were averaged across seasons to create annual averages for indicators of aggregate biomass, sensitive species, and trophic dynamics from 1980 to 2021 (excluding 2020) and for each size-based indicators from 1992 to 2021 (excluding 2020). No stations were sampled in the SNE region during either spring or fall of 2020 because of the COVID-19 pandemic. The SNE WEA occupies ~3675 km^2 located ~10–40 nautical miles south of the Massachusetts coast. Depths in the SNE WEA range from 27 to 60 m and bottom types are mainly comprised of fine-grained sediments with areas of sand, mud, and mud mixed with gravel (Guida et al. 2017). Between 1980 and 2021, the NEFSC bottom trawl survey sampled 7 ± 2 (mean ± standard deviation) stations per year in the SNE WEA. The SNE region is one of four primary regions of the NES ecosystem defined by NEFSC based on hydrographic variables (Walsh et al. 2015).

Year-to-year variability was explored by calculating three measures of temporal variability: (i) the consecutive disparity index (CD), which is calculated as the natural log of the proportional difference between consecutive years, thereby incorporating temporal autocorrelation associated with the chronological order of values (e.g. Fernandez-Martinez et al. 2018, Fernandez-Martinez and Penuelas 2021, Martin–Vide et al. 2022); (ii) the proportional variability index (PV), which evaluates temporal variability by calculating the av-

Table 1. Aggregate biomass indices: definition, rationale, and stressor associations.

Indicator	Definition	Indicator rationale	Stressor associations	References linking indicator with OWD stressors
Demersal biomass	Annual average demersal species biomass	Aggregate status	FAD effects; Reef effects	Wilhelmsson et al. 2006, Reubens et al. 2011
Elasmobranch biomass	Annual average elasmobrach species biomass	Aggregate status	EMFs	Gill et al. 2012, Hutchison et al. 2018, Gill and Desender 2020, Gill et al. 2020, Kalmaijn 1982
Flatfish biomass	Annual average flatfish species biomass	Aggregate status	Hydrodynamics (larvae); Decreased soft bottom	Hydro: Barbut et al. 2020, van Berkel et al. 2020; Soft bottom: Stenberg et al. 2015, Buyse et al. 2022, Wilber et al. 2022a
Gadid biomass	Annual average gadid species biomass	Aggregate status	Noise; Hydrodynamics (larvae); Increased hard bottom; Reef effects; FAD effects	Noise: Bergstrom et al. 2013, Popper and Hawkins 2019, Westerberg et al. 1994; Hydro: Daewel et al. 2022, van Berkel et al. 2020, Slavik et al. 2019; Hard bottom: Reubens et al. 2013a, 2013b, 2013c; Reef effects: Reubens et al. 2013a, 2013c, Stenberg et al. 2015; FAD: Wilhelmsson et al. 2006, Reubens et al. 2011
Pelagic biomass	Annual average pelagic species biomass	Aggregate status	Noise	van Hal et al. 2017, Jones et al. 2020, 2021, Sole et al. 2022
Pelagic biomass/Demersal biomass	Ratio of pelagic fish biomass to demersal fish biomass	Energy flow, community structure	FAD effects	Leonhard et al. 2011, van Hal et al. 2017
Species diversity	Shannon–Weaver index	Community structure	FAD effects; Reef effects	Stenberg et al. 2015
Total fish biomass	Annual average biomass of most abundant species	Aggregate status	FAD effects	Wilhelmsson et al. 2006, Reubens et al. 2011

Table 2. Sensitive species indices: definition, rationale, and stressor associations.

Indicator	Definition	Indicator rationale	Stressor associations	References linking indicator with OWD stressors
Black sea bass biomass	Annual average black species biomass	Reef associated species	Noise; Increased hard bottom; FAD	Noise: Stanley et al. 2020, Debusschere et al. 2016; Increased hard bottom & FAD: Wilber et al. 2022a, HDR 2020
Ctenophore index	Annual average % of spiny dogfish diets composed of Ctenophores	Sensitive species; Planktonic species	Hydrodynamics	Smith et al. 2016, Wang et al. 2018, Daewel et al. 2022
Little skate biomass	Annual average little skate biomass	Sensitive species	EMFs	Kalmaijn 1982, Gill et al. 2012, Hutchison et al. 2018, 2020a,b, Gill and Desender 2020
Longfin squid biomass	Annual average longfin species biomass	Sensitive species	Noise	Jones et al. 2020, 2021, Sole et al. 2022

erage proportional variability among all possible combinations of values in a time series, thereby reducing the effects of temporal autocorrelation (e.g. Heath and Borowsky 2013, Fernandez-Martinez et al. 2018); and (iii) the coefficient of variation (CV), which calculates temporal variability as proportional deviation of the standard deviation of the time series from its mean (e.g. Fernandez-Martinez et al. 2018). A CD of ≥50% would indicate that there was on average a ≥50% change between consecutive years in the time series; a PV of ≥50% would show that there was on average a ≥50% difference between all pair-wise combinations of years; and a CV of ≥50% would demonstrate that the standard deviation of the time series was at least half the value of the mean. The presence of long-term directional temporal trends was evaluated with a Mann–Kendall test, a non-parametric approach for evaluating significant trends (Hollander and Wolfe 1973, Cotter 2009). Concurrence or non-concurrence in the directionality of long-term trends at the WEA and region scales was determined by comparison of model results.

Aggregate biomass and sensitive species indices

The most abundant species in the SNE WEA were identified as species occurring in ≥4 tows and contributing >0.65 kg/tow during the most recent 11 years of the bottom trawl survey (2010–2019 and 2021; $N = 73$ stations). The most recent 11-year time block was used to identify abundant species to ensure all relevant species were included in the analyses. Species meeting these criteria were included in an evaluation of temporal trends for indices of aggregate biomass, sensitive species, size, and trophic dynamics.

Table 3. Size-based indices: definition, rationale, and stressor associations.

Indicator	Definition	Indicator rationale	Stressor associations	References linking indicator with OWD stressors
Finfish condition	Annual average Fulton finfish condition index	Fish condition	Increased hard bottom; Decreased soft bottom; Reef effects	Hard bottom: Reubens et al. 2014; Soft bottom: Wilber et al. 2022b; Reef effects: Reubens et al. 2014
Finfish length	Annual average finfish length	Size distribution	Increase hard bottom; Decreased soft bottom; Reef effects; Reduced fishing pressure	Hard bottom: Vandendriessche et al. 2015, Reubens et al. 2014; Soft bottom: Wilber et al. 2022a; Reef effects: Reubens et al. 2014; Reduced fishing pressure: Roach et al. 2018
Finfish weight	Annual average finfish weight	Size distribution	Increased hard bottom; Decreased soft bottom; Reef effects	Hard bottom: Vandendriessche et al. 2015, Reubens et al. 2014; Soft bottom: Wilber et al. 2022b; Reef effects: Reubens et al. 2014
Small/large fish ratio	Ratio of small fish biomass to large fish biomass	Index of fish productivity	Increased hard bottom; Hydrodynamics; Reef effects	Hard bottom: Reubens et al. 2014; Hydro: Shields et al. 2011, Slavik et al. 2019, Barbut et al. 2020, Daewel et al. 2022; Reef effects: Reubens et al. 2014

Table 4. Trophic dynamic indices: definition, rationale, and stressor associations.

Indicator	Definition	Indicator rationale	Stressor associations	References linking indicator with OWD stressors
Benthivore biomass	Annual average benthivore biomass	Energy flow, community structure	Increased hard bottom; Decreased soft bottom; Reef effects; FAD effects	Hard bottom: Mavraki et al. 2021; Soft bottom: Wilber et al. 2022a, Stenberg et al. 2015; Reef effects: Buyse et al. 2023; FAD: Buyse et al. 2022, 2023, Vandendriessche et al. 2015
Benthivore consumption	Benthivore per capita annual consumption	Energy flow, community structure	Increased hard bottom; Decreased soft bottom; Reef effects; EMFs (decapod consumers)	Hard bottom: Mavraki et al. 2021; Soft bottom: Mavraki et al. 2021, Buyse et al. 2022, Wilber et al. 2022b; Reef effects: Buyse et al. 2023, Scott et al. 2018, Thatcher et al. 2023
Diet diversity	Shannon-Weaver index of diversity of prey in predator stomachs	Change in prey field, energy flow, number of trophic links	Increased hard bottom; Decreased soft bottom; Reef effects	Hard bottom: Mavraki et al. 2020a,b, 2021, ter Hofstede et al. 2022, Reubens et al. 2011, 2013b; Soft bottom: Wilber et al. 2022b; Reef effects: Reubens et al. 2011; 2013
Forage species biomass	Annual average forage species biomass	Energy flow, community structure	Hydrodynamics; Reef effects; FAD effects	Hydro: Floeter et al. 2017, van Berkel et al. 2020; Shields et al. 2011; Reef effects: van Hal et al. 2017, Leonhard et al. 2011; FAD: van Hal et al. 2017, Leonhard et al. 2011, Mavraki et al. 2021, Wilhelmsson et al. 2006
Piscivore biomass	Annual average piscivore biomass	Energy flow, community structure	Increased hard bottom; Reef effects	Mavraki et al. 2021, Wilber et al. 2022a
Piscivore consumption	Piscivore per capita annual consumption	Energy flow, community structure	Reef effects	Wilber et al. 2022b
Planktivore biomass	Annual average planktivore biomass	Energy flow, community structure	Hydrodynamics; Reef effects; FAD effects	Hydro: Floeter et al. 2017, van Berkel et al. 2020, Shields et al. 2011; Reef effects: van Hal et al. 2017, Leonhard et al. 2011, Mavraki et al. 2021; FAD: van Hal et al. 2017, Leonhard et al. 2011, Mavraki et al. 2021, Wilhelmsson et al. 2006
Planktivore consumption	Planktivore per capita annual consumption	Energy flow, community structure	Increased hard bottom; Reef effects	Mavraki et al. 2021
Trophic level (TL) ratio	TL ratio of (Planktivore + Benthivore) / (Deapodivore + Piscivore)	Energy flow, community structure	Increased hard bottom; Reef effects	Mavraki et al. 2021 and Wilber et al. 2022b

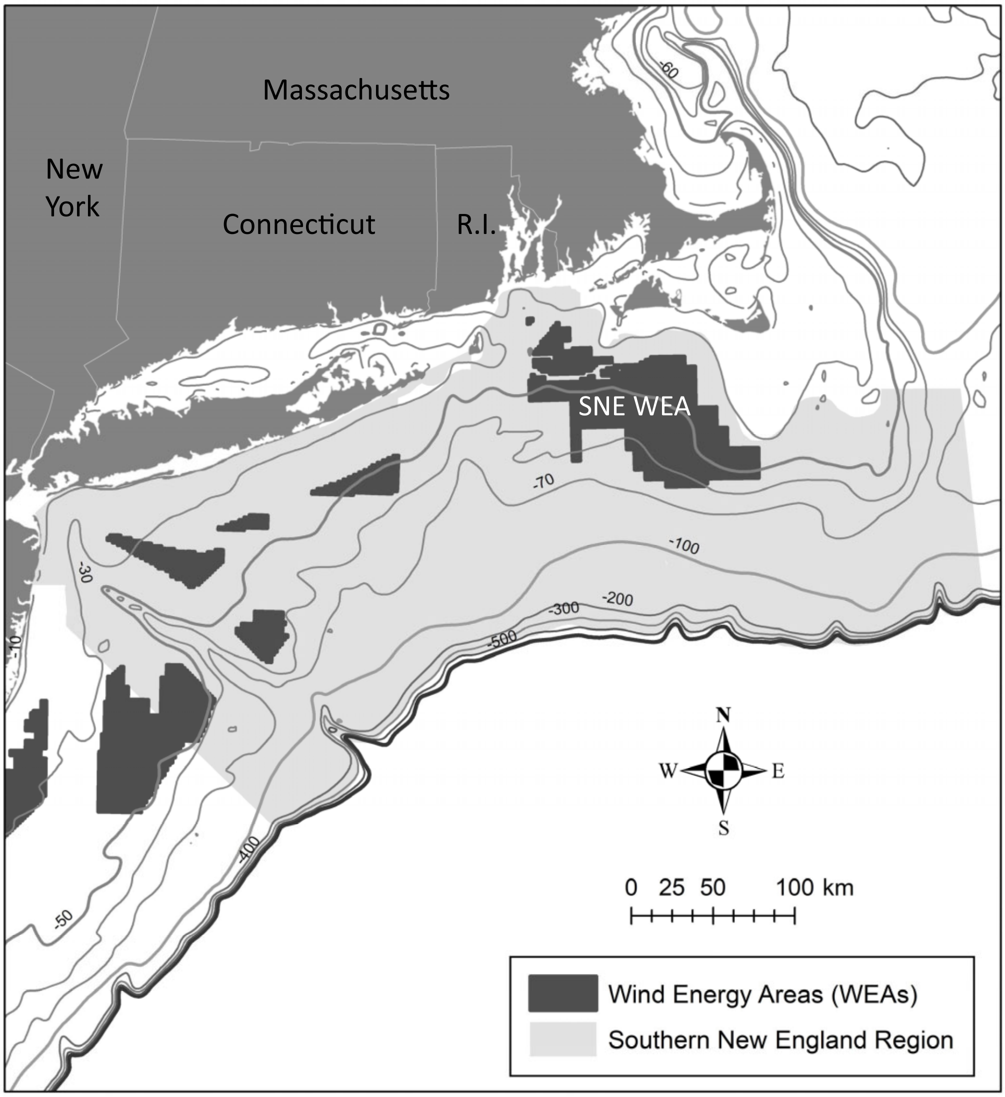

Figure 1. Map of Southern New England wind energy area (SNE WEA) within the SNE region with bathymetry contours (m).

Average yearly catch biomass (kg/tow/yr) within the SNE WEA was calculated for eight aggregate biomass indices and four sensitive species or species groups. Tables 1 and 2 provide the rationale and stressors associated with aggregate biomass and sensitive species indices. The Ctenophore index was calculated as the average annual percentage of spiny dogfish diets composed of Ctenophores (Link and Ford 2006). Species diversity was calculated using Shannon's index of species diversity (H): $H = -\Sigma pi \times ln(pi)$, where p is the proportion of individuals of species i.

Size-based indices

Size-based indices included the average annual per capita length (cm) and weight (kg) of individual fish, and fish condition which was calculated using Fulton's condition index (weight/length^3) (Bolger and Connelly 1989) (Table 3). In addition, a size-based indicator of fish productivity was calculated as the yearly ratio of small fish to large fish. Categorical size classes based on fish length as defined in the NEFSC bottom trawl database were used (see Smith and Smith 2020 for size ranges for each species). The seven species included in this index were chosen to match the species used to calculate this index in the Mid-Atlantic State of the Ecosystem Report (SOE) (NOAA 2022a). These species were: black sea bass (*Centropristis striata*), red hake (*Urophycis chuss*), silver hake (*Merluccius bilinearis*), summer flounder (*Paralichthys dentatus*), windowpane (*Scophthalmus aquosus*), winter flounder (*Pseudopleuronectes americanus*), and yellowtail flounder (*Pleuronectes ferruginea*). Three other species were included in the calculation of this index in the SOE report (NOAA 2022a), but were not included here because they did not occur at SNE WEA stations.

Trophic dynamic indices

A total of nine trophic indices were evaluated to explore candidate indices that may be responsive to changes in prey availability and energy uptake driven by OWD (Table 4). First, trophic guilds were identified using stomach content analysis and supporting information from Smith and Link (2010). Stomach content data used in analyses were collected during the NEFSC bottom trawl survey stations which were conducted in the SNE WEA during 2010–2019 and 2021 ($N = 73$

Table 5. The most abundant species in the SNE WEA sampled during 2010-2021. Summary statistics are provided in the online supplemental material (Table S1).

Common name	Scientific name	Trophic Guild
Alewife	*Alosa pseudoharengus*	Planktivore
Atlantic Herring	*Clupea harengus*	Planktivore
Atlantic Mackerel	*Scomber scombrus*	Planktivore
Barndoor Skate	*Dipturus laevis*	Benthivore
Black Sea Bass	*Centropristis striata*	Benthivore
Bluefish	*Pomatomus saltatrix*	Piscivore
Butterfish	*Peprilus triacanthus*	Planktivore
Fouspot Flounder	*Paralichthys oblongus*	Benthivore
Goosefish	*Lophius americanus*	Piscivore
Haddock	*Melanogrammus aeglefinus*	Benthivore
Little Skate	*Leucoraja erinacea*	Benthivore
Longfin Squid	*Doryteuthis pealeii*	Piscivore
Longhorn Sculpin	*Myoxocephalus octodecemspinosus*	Benthivore
Northern Searobin	*Prionotus carolinus*	Benthivore
Red Hake	*Urophycis chuss*	Benthivore
Round Herring	*Spratelloides gracilis*	Planktivore
Sea Scallop	*Placopecten magellanicus*	Planktivore
Scup	*Stenotomus chrysops*	Benthivore
Silver Hake	*Merluccius bilinearis*	Benthivore
Smooth Dogfish	*Mustelus canis*	Benthivore
Spiny Dogish	*Squalus acanthias*	Piscivore
Spotted Hake	*Urophycis regia*	Benthivore
Striped Searobin	*Prionotus evolans*	Benthivore
Summer Flounder	*Paralichthys dentatus*	Piscivore
Windowpane	*Scophthalmus aquosus*	Benthivore
Winter Flounder	*Pseudopleuronectes americanus*	Benthivore
Winter Skate	*Leucoraja ocellata*	Benthivore
Yellowtail Flounder	*Limanda ferruginea*	Benthivore

stations). Diet composition was calculated using the methods of Buckel et al. (1999). Trophic groups were identified with hierarchical agglomerative cluster analysis. Euclidean distance and the complete agglomeration method were used. The amount of variation explained with the observed number of clusters was examined using canonical discriminant analysis. Species with >20 stomachs were included in the cluster analysis. For species with <50 stomachs whose entire diet breadth may not be captured by the dataset, trophic guild assignment was verified by comparing results with the trophic relationships presented in Smith and Link (2010) and Malek et al. (2016). Average yearly catch biomass (kg/tow/yr) and the annual per capita rate of consumption for each feeding guild within the SNE WEA were calculated. Per capita consumption rates were estimated for each trophic guild with the evacuation rate methods of Eggers (1977) and Elliot and Persson (1978). Equations and demonstrations of these methods are reported in Smith and Smith (2020). In addition to the aggregate catch biomass and consumption rates for each trophic guild, additional trophic metrics included forage species catch biomass, prey diversity (i.e. Shannon's index of diversity of the proportional prey contents of individual predators), and the trophic level ratio (i.e. the ratio of lower to higher trophic levels) (Table 4).

Results

Aggregate biomass indices

Twenty-eight species occurred in ≥4 stations and contributed >0.65 kg/tow annually between 2010–2019 and 2021 (Table 5). These species were included in calculations for indices of aggregate biomass, size, and trophic dynamics.

Large year-to-year variability for several aggregate biomass indicators was demonstrated by the indices of temporal variability. At the WEA scale, 7/8 (88%) indicators had a CD of ≥50% meaning that there was on average ≥50% change between consecutive years (Figs 2 and 3). Five of eight indicators (63%) had a PV of ≥50% showing that there was on average a ≥50% difference between all pair-wise combinations of years. Seven of eight indicators (88%) had a CV of ≥50% demonstrating that the standard error of the time series was at least half the value of the mean for those indicators. Across all three measures of temporal variability, gadid biomass, pelagic fish biomass, and the pelagic: demersal fish ratio exhibited the highest year-to-year variability. At the region scale, one of eight (13%) aggregate biomass indicators (pelagic: demersal ratio) had a CD, PV, and CV that exceeded 50% (Fig. 4). Six of eight (75%) indicators had a PV or a CV ≥25%. At the region scale, the pelagic:demersal ratio had the highest measures of year-to-year variability. Species diversity showed the least year-to-year variability at both the WEA and region scales of all aggregate biomass indicators evaluated.

Long-term temporal trends in aggregate biomass indicators at both the WEA and region scale were evidenced by the Mann–Kendall test results (Table 6). At the WEA scale, there was a long-term increasing trend for gadid biomass. At the region scale, there were long-term decreasing trends for 7/8 (88%) indicators, including demersal biomass, elasmobranch biomass, flatfish biomass, gadid biomass, pelagic biomass, pelagic: demersal ratio, and total fish biomass, (Table 6).

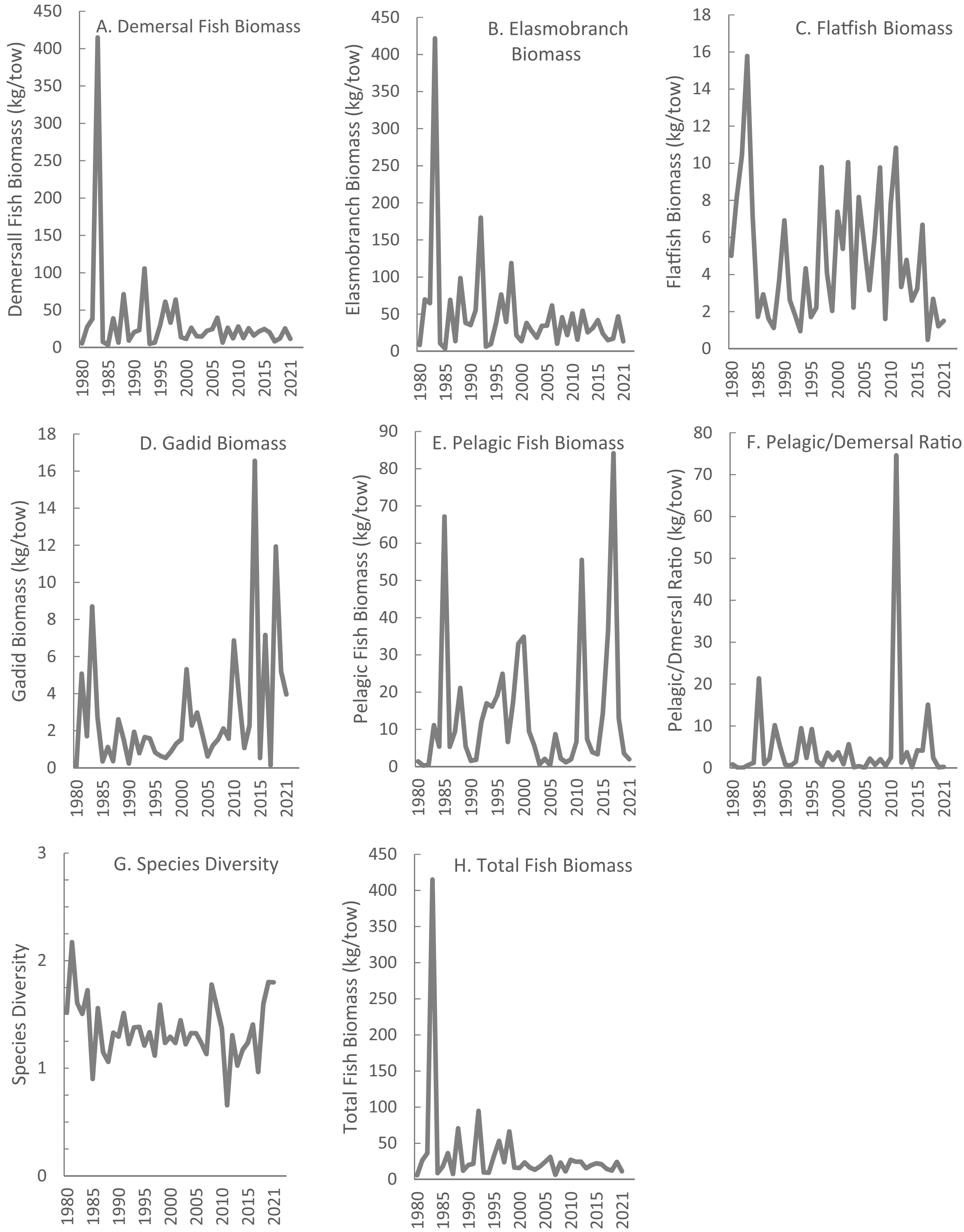

Figure 2. Aggregate biomass indicator time series at the scale of the Southern New England WEA. (A) Demersal Fish Biomass (kg/tow); (B) Elasmobranch Biomass (kg/tow); (C) Flatfish Biomass (kg/tow); (D) Gadid Biomass (kg/tow); (E) Pelagic Fish Biomass (kg/tow); (F) Pelagic/Demersal Ratio; (G) Species Diversity; (H) Total Fish Biomass (kg/tow).

Sensitive species indices

High year-to-year variability was found for the sensitive species indices. At the WEA scale, 3/4 (75%) of indicators had a CD and a CV ≥50%; 2/4 (50%) indicators had a PV ≥50% (Figs 3 and 5). At the region scale, 1/4 (25%) indicators had a CD and a PV ≥50%; 2/4 (50%) had a CV ≥50% (Fig. 4). Notably all but 1 sensitive species indicator (75%) had a CD, PV, and a CV >25% at the region scale. Black sea bass and little skate biomass had the greatest year-to-year variability at the region scale. At the WEA scale, black sea bass biomass, little skate biomass, and longfin squid biomass had the highest year-to-year variability.

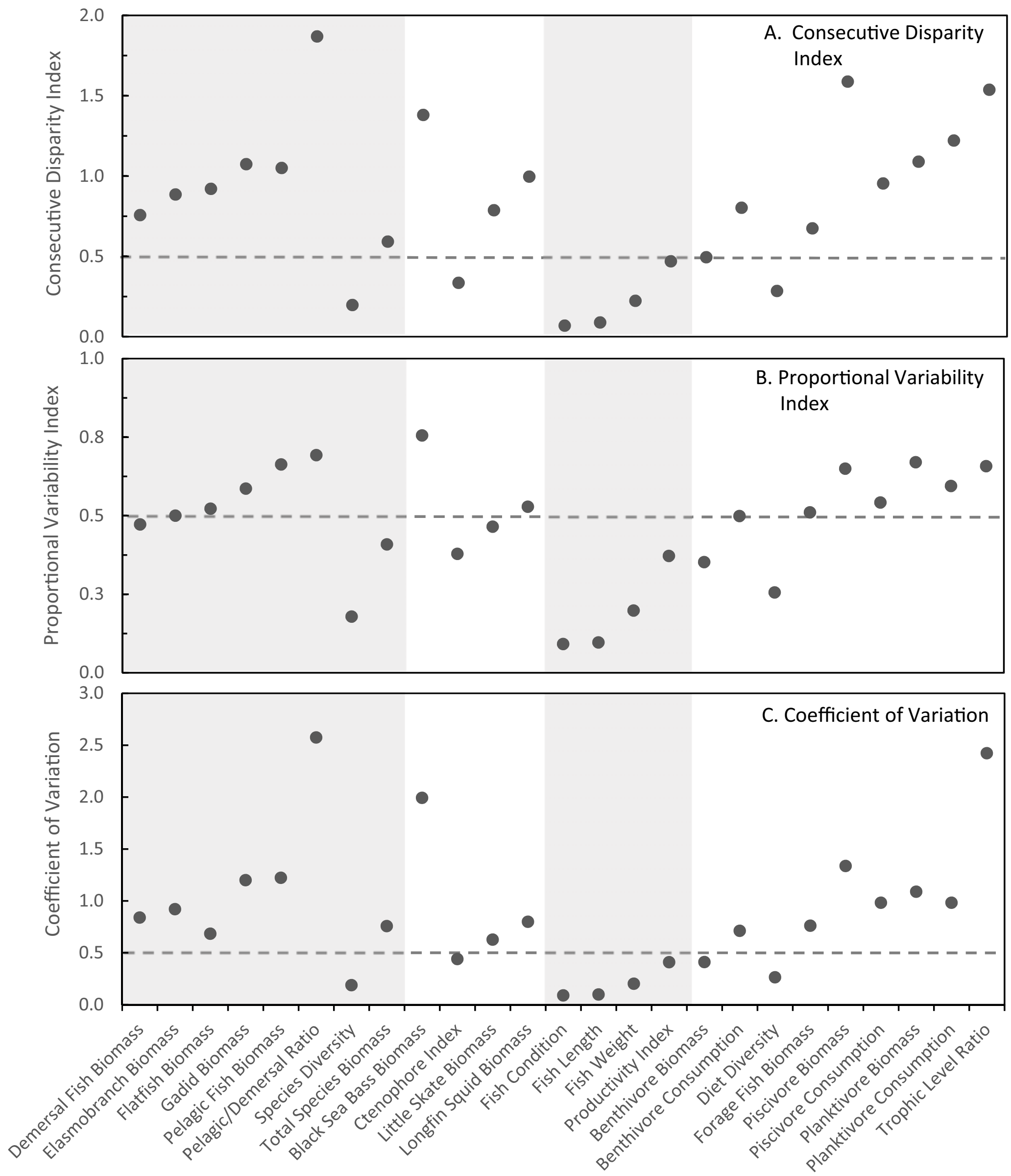

Figure 3. Indices of year-to-year variability at the scale of the SNE wind energy area. (A) consecutive disparity (CD) index; (B) proportional variability (PV) index; (C) coefficient of variation (CV). The dashed line on each figure indicates the position of 50% for each index. Shading indicates indicator groupings: aggregate biomass, sensitive species, size, and trophic dynamics.

At both the WEA and region scales, long-term increasing trends were found for both black sea bass biomass and the Ctenophore index as shown by the significant results of the Mann–Kendall test (Table 6). There were no long-term trends for either little skate biomass or longfin squid at either spatial scale.

Size-based indices

Fish productivity was the most temporally variable of the size-based indicators. At the WEA scale, the CD, PV, and CV for fish productivity ranged from 35% to 47%, whereas at the region scale, these measures ranged from 23% to 27% (Figs 3 and 4). At the WEA scale, the year-to-year variability measures for length, weight, and condition ranged from 6% to 22% (Figs 3 and 6). At the region scale, the year-to-year variability measures for fish length, weight, and condition ranged from 3% to 10% (Figs 4 and 6). The Mann–Kendall test found a significant long-term increasing trend for fish condition at both the WEA and region scales, and a significant decreasing trend in fish length at the region scale only (Table 6). There was no long-term trend for either fish weight or the productivity index.

Trophic dynamic indices

Four primary feeding guilds were identified in the SNE WEA: planktivores, piscivores, and two groups of benthivores: those that mainly consume decapods and amphipods, and those that mainly consume annelids and amphipods (Fig. 7). The diets of individual species within each guild are provided with the online supplemental material (Table S2, Figure S1). Canonical discriminant analysis indicated that four clusters explained 83% of the variation. Planktivore diets were mainly

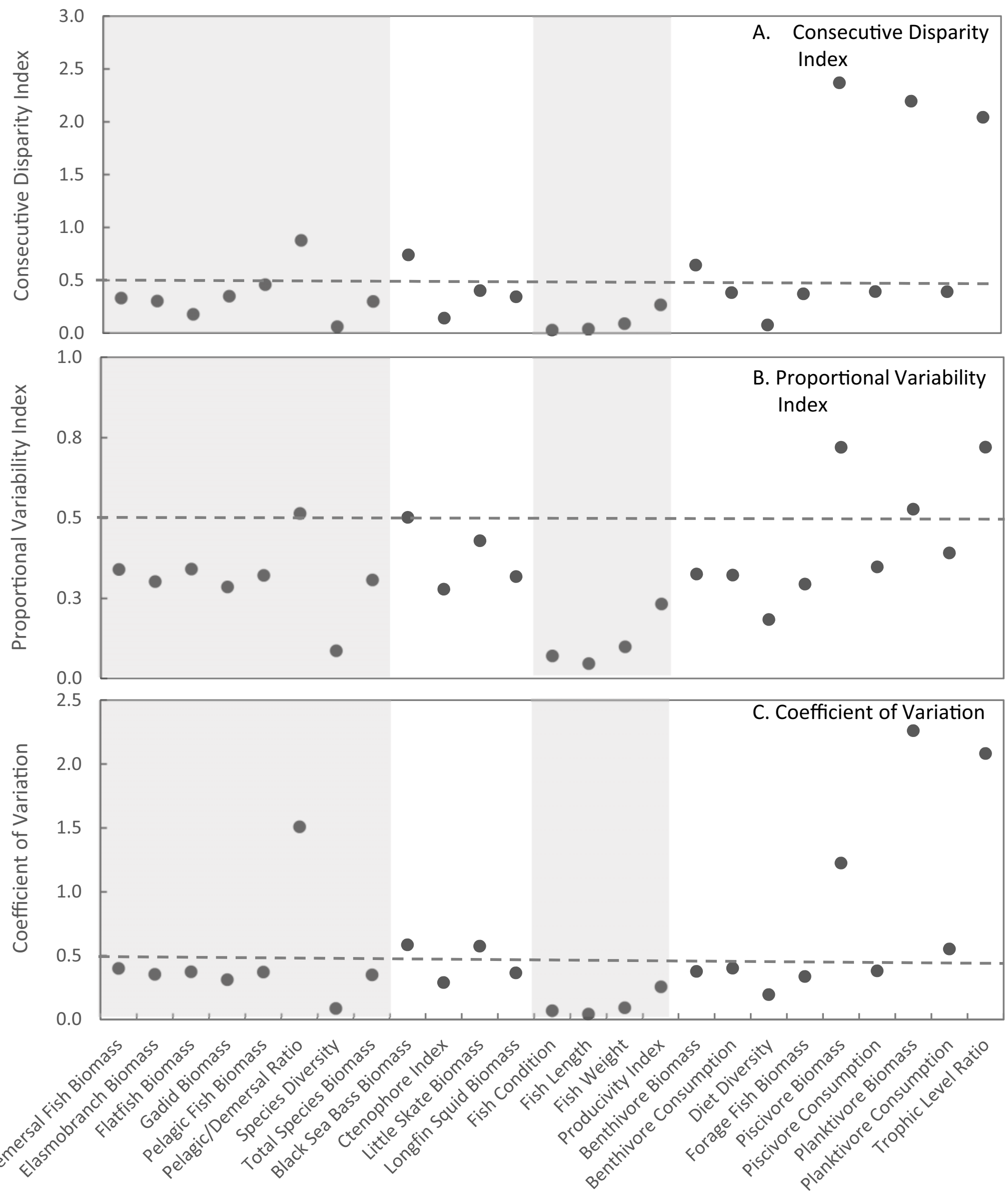

Figure 4. Indices of year-to-year variability at the scale of the SNE region. (A) consecutive disparity (CD) index; (B) proportional variability (PV) index; (C) coefficient of variation (CV). The dashed line on each figure indicates the position of 50% for each index. Shading indicates indicator groupings: aggregate biomass, sensitive species, size, and trophic dynamics.

composed of copepods and animal remains which are likely partially digested zooplankton. Benthivore diets were diverse. For Amphipod/Annelid consumers, those two prey taxa combined represented 58%–67% of the diet. For the Decapod/Amphipod consumer group, decapods and amphipods combined represented 32%–93% of the diet. Other prey consumed by this group included Mysidacea and other small crustaceans. Piscivores consumed finfish in the families of Gadidae, Clupidea, Cottidae, Rajidae as well as other fish species in addition to cephalopods (4%–16% of diet).

The indices of temporal variability showed substantial year-to-year variability for all trophic indices (Figs 3 and 4.). At the WEA scale, 7/9 (78%) indicators had a CD, PV, and a CV of ≥50% (Fig. 3). The indicators with the greatest year-to-year variability at the WEA scale were piscivore biomass, planktivore biomass, planktivore consumption, and trophic level ratio (Figs 3 and 8). At the region scale, 3/9 (33%) indicators had a CD ≥50%, 3/9 (33%) had a PV ≥50%, and 4/9 (44%) had a CV ≥50%. At both scales, across all trophic dynamic indicators except one (diet diversity), measures of temporal variability were ≥25%. The indicators with the greatest year-to-year variability at the region scale were piscivore biomass, planktivore biomass, and trophic level ratio. Diet diversity had the lowest year-to-year variability of all of the trophic indicators at both the WEA and region scales (Figs 3 and 4). Mann–Kendall test results showed significant decreasing long-term trends for four trophic indicators at the region scale (diet diversity and consumption by benthivores, piscivores, and planktivores) (Table 6). Significant long-term decreasing trends for piscivore consumption and diet diversity were also observed at the WEA scale. A significant increasing trend in benthivore biomass was found at the WEA scale only.

Table 6. Results of Mann–Kendall test for significant long-term trends at the scale of the SNE wind energy area (WEA) and the scale of the SNE region.

Indicator	Wind energy area			Region		
	tau	*P*	Direction	tau	*P*	Direction
Aggregate biomass indices						
Demersal biomass	– 0.061	ns	n/a	– 0.445	****	decrease
Elasmobranch biomass	– 0.117	ns	n/a	– 0.463	****	decrease
Flatfish biomass	– 0.093	ns	n/a	– 0.463	****	decrease
Gadid biomass	0.207	*	increase	– 0.296	**	decrease
Pelagic biomass	0.085	ns	n/a	– 0.231	*	decrease
Pelagic:demersal ratio	0.054	ns	n/a	– 0.231	*	decrease
Species diversity	– 0.078	ns	n/a	0.015	ns	n/a
Total fish biomass	– 0.088	ns	n/a	– 0.491	****	decrease
Sensitive species indices						
Black sea bass biomass	0.528	****	increase	0.456	***	increase
Ctenophore index	0.554	***	increase	0.616	****	increase
Little skate biomass	0.148	ns	n/a	– 0.138	ns	n/a
Longfin squid biomass	0.035	ns	n/a	– 0.129	ns	n/a
Size-based indices						
Fish condition index	0.345	**	increase	0.356	**	increase
Fish length	– 0.192	ns	n/a	– 0.292	*	decrease
Fish weight	– 0.020	ns	n/a	0.094	ns	n/a
Productivity index	– 0.224	ns	n/a	0.159	ns	n/a
Trophic dynamic indices						
Benthivore biomass	0.340	**	increase	– 0.214	ns	n/a
Benthivore consumption	0.054	ns	n/a	– 0.407	**	decrease
Diet diversity	– 0.256	*	decrease	– 0.697	****	decrease
Forage fish biomass	– 0.108	ns	n/a	– 0.035	ns	n/a
Piscivore biomass	– 0.054	ns	n/a	0.044	ns	n/a
Piscivore consumption	– 0.286	*	decrease	– 0.379	**	decrease
Planktivore biomass	– 0.138	ns	n/a	– 0.039	ns	n/a
Planktivore consumption	– 0.158	ns	n/a	– 0.421	**	decrease
Trophic level ratio	0.143	ns	n/a	– 0.241	ns	n/a

Shading indicates significant results. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$, ****$P < 0.0001$; ns = not significant; n/a = not applicable.

There were no long-term trends for forage fish biomass, piscivore biomass, planktivore biomass, or trophic level ratio at either spatial scale.

Summary of comparisons between WEA scale and regional scale long-term trends

Overall, there was a total of seven indices that exhibited significant long-term temporal trends at the WEA scale and 15 indices with significant long-term trends at the scale of the region (Table 6). The trends for six indices were significant at both the WEA scale and the region scale. Two of these were negative trends, including piscivore consumption and diet diversity. Three of these had positive trends at both scales, including the size-based index of fish condition and the sensitive species indices of black sea bass and the Ctenophore index. When significant trends occurred at both scales, the directionality of the trends concurred in all cases except for gadid biomass. At the WEA scale, gadid biomass showed a significant increasing trend, while at the region scale the significant long-term trend was negative for gadid biomass. There were nine instances where a long-term trend was significant at the region scale but not at the WEA scale (Table 6). This included significant long-term declines in demersal biomass, elasmobranch biomass, flatfish biomass, pelagic biomass, pelagic:demersal ratio, total fish biomass, fish length, benthivore consumption, and planktivore consumption. One indicator, benthivore biomass, showed a significant increasing trend at the WEA scale that was not evident at the region scale. There were nine indicators that showed no long-term trend at either spatial scale, including species diversity, little skate biomass, longfin squid biomass, fish weight, productivity index, forage fish biomass, piscivore biomass, planktivore biomass, and trophic level ratio.

Discussion

Evaluation of candidate indicators

Multiple ecological indices were evaluated that could be used in project level monitoring programs to inform how OWD affects fisheries resources. These candidate indices meet the criteria for useful indicators in the context of OWD in the NES ecosystem; they are scientifically rigorous, measurable, representative of key properties and processes of the system, and sensitive to specific stressors associated with OWD. Establishing a suite of ecological indicators to be measured across projects could provide a powerful approach for assessing the status of fish communities at OWDs. Cross-project comparability would aid in detecting common trends among projects and enable comparisons with regional and ecosystem wide patterns. Ecological indicators could also be informative for stock assessments of species such as black sea bass that are expected to be responsive to OWD through a gain or loss of habitat. Although there are a wide array of potentially informative indicators, this study focused on biotic indicators for which there is peer-reviewed evidence for responsiveness to stressors associated with OWD.

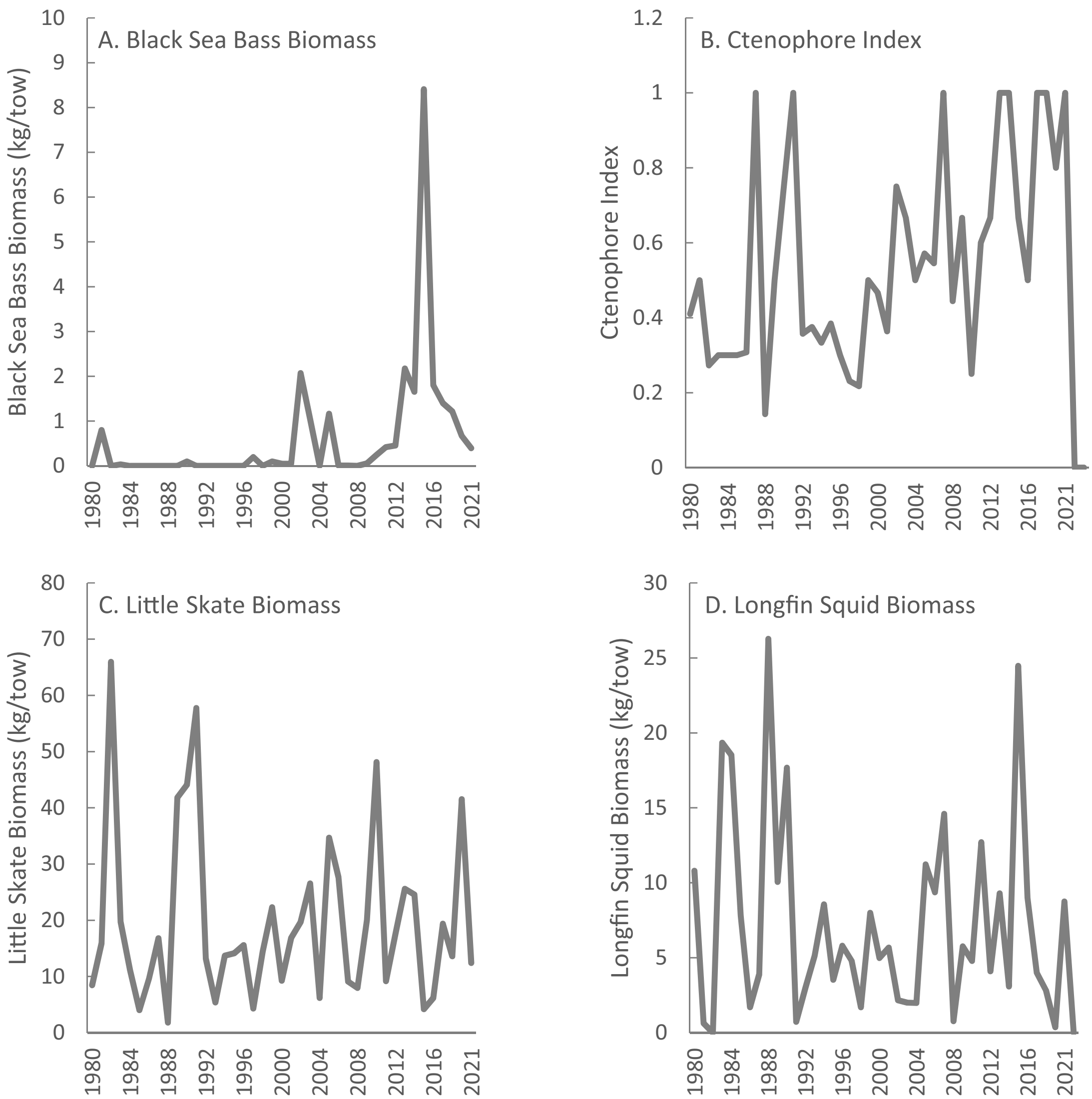

Figure 5. Sensitive species indicator time series at the scale of the Southern New England WEA. (A) Black Sea Bass Biomass (kg/tow); (B) Ctenophore Index; (C) Little Skate Biomass (kg/tow); (D) Longfin Squid Biomass (kg/tow)

Short-term and long-term variability in candidate indicators

The majority of indicators evaluated exhibited substantial year-to-year variation at both the WEA and region scales as demonstrated by the general concurrence among three indices of short-term temporal variability. Significant long-term trends were also observed for many indicators at both the WEA and region scales. The directionality of long-term trends generally concurred between scales (5 instances). This was evident when trends occurred broadly across the region and in the WEA (Heim et al. 2021, Gervelis et al. 2023). Trends observable at the region scale but absent at the WEA scale (9 instances) may be due to spatially heterogeneous trends in the region that do not overlap the WEA. An alternative explanation is that the sample size at the WEA scale was not sufficient to characterize the long-term trends at that scale, highlighting the importance of sufficient sample replication. A trend evident only at the scale of the WEA but absent at the region scale (1 instance) would reflect very localized trends inside the WEA and perhaps elsewhere in the region that are not evident at the scale of the region. The directionality of trends for one indicator, gadid biomass, exhibited non-concurrence between the WEA and region scales, suggesting that some portions of the region such as the WEA may be particularly important for these species.

Challenges of temporal variability for the detection of impacts at OWDs

Existing temporal variability poses a challenge to monitoring OWDs in the ocean using common experimental designs. Chief among these is the ability to understand existing patterns of variability so that treatment effects can be distinguished from background variation. Control-impact and before–after–control–impact (BACI) designs (Green 1979) are currently the most common experimental designs used to monitor OWD effects on marine fish and shellfish (Methratta 2020, 2021). In the USA, OWD monitoring programs typically propose a BACI design that collects 0–2 years of pre-construction data, 0–1 year of data during construction, and 1–3 years of post-construction data at the impact site and at

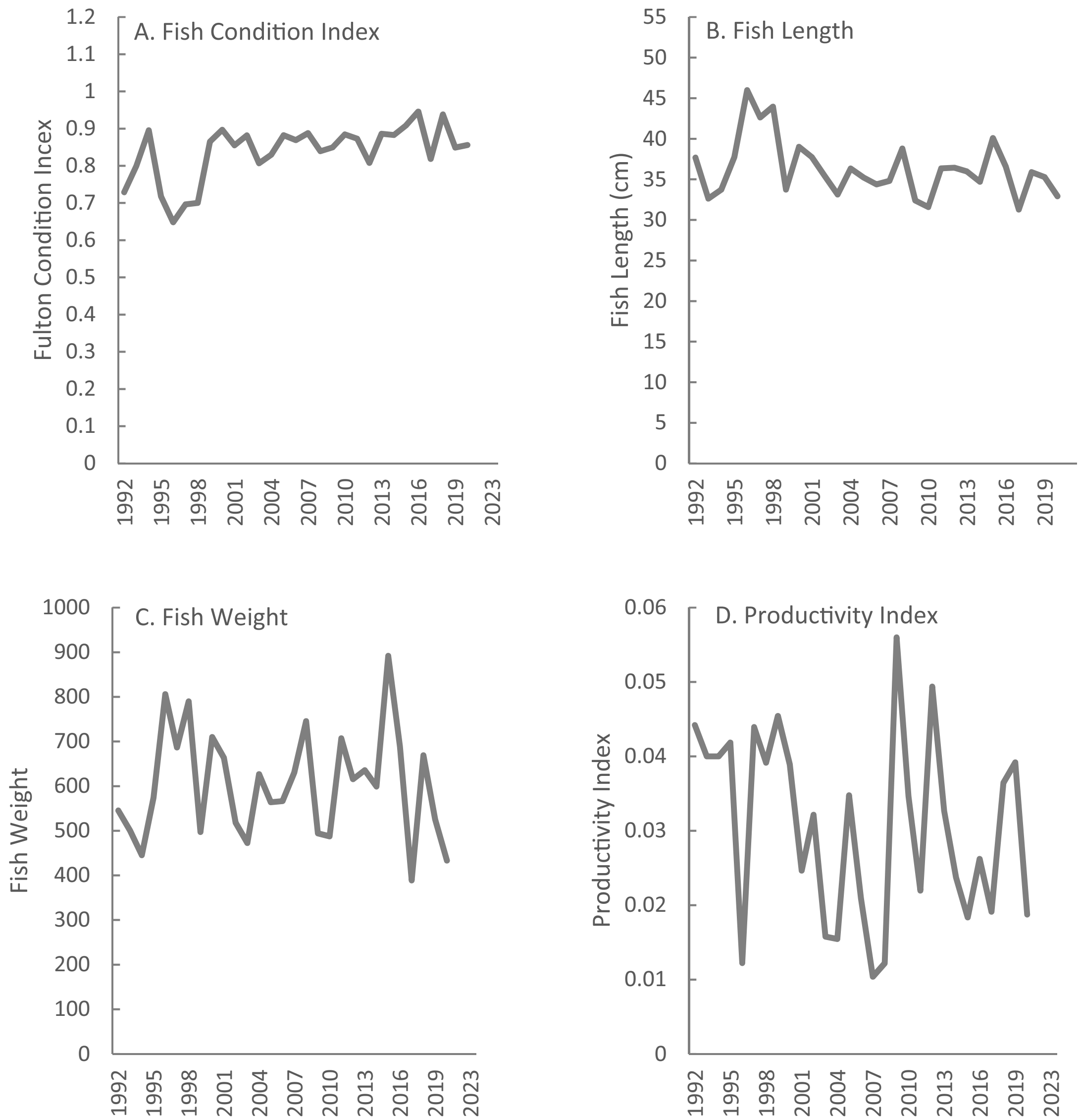

Figure 6. Size-based indicator time series at the scale of the Southern New England WEA. (A) Fish Condition Index; (B) Fish Length (cm); (C) Fish Weight (g); (D) Productivity Index.

one or more control sites (Methratta et al. 2023). Limited pre- and post-construction sampling duration prevents a critical assessment of the existing temporal structure in the ecological responses measured and an understanding how these patterns change with OWD. Without this information, researchers can only discuss temporal patterns anecdotally in the interpretation of results. In the NES ecosystem and elsewhere, a well-established body of knowledge has demonstrated clear and directional changes in the distribution and abundance of marine species over time associated with climate change (Lucey and Nye 2010, Bell et al. 2015, Walsh et al. 2015). Disentangling OWD effects from this and other pressures acting on the system requires an understanding of the temporal structure of the indicators being measured. The analyses presented here underscore the substantial short- and long-term temporal variability in candidate indicators for OWD impacts, highlighting the importance of understanding the temporal structure in these measures and the need for long-term monitoring to do so.

Toward tackling the challenges of temporal variability in the detection of OWD impacts

Tackling the challenges brought about by temporal variability for the detection of ecological responses to OWD requires at least two elements. The first element is the collection of longer time series of project-level data than are typically proposed in the USA. A minimum of three to five of pre-construction baseline data would be needed to assess existing inter-annual variability. This is because one or two years of data are insufficient to understand the baseline temporal structure of these indicators as evidenced by the results presented here. For example, with one or two years of data, it is not possible to know whether the sampled years are outliers, or perhaps close to the mean of the time series, or if they are possibly part of a pre-existing directional trend. Even three to five years is arguably insufficient to answer these questions, but this would at least enable an initial pattern to be established. Further, there is no reason to expect that impacts will cease within 1–3 years of construction, thus our understanding of the role of

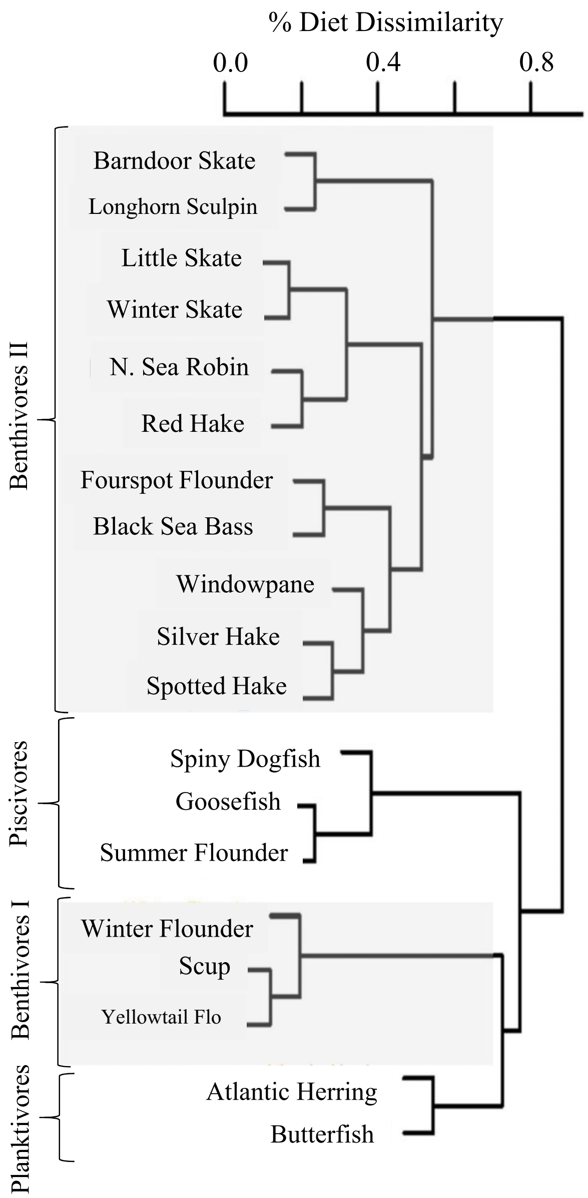

Figure 7. Results of the agglomerative cluster analysis showing the trophic guild clusters. Benthivores I: consumers of decapods and amphipods; Benthivores II: consumers of annelids and amphipods.

OWD at local and broad spatial scales in the NES ecosystem and elsewhere would benefit from post-construction monitoring throughout the entire lifetime (30 + years) of the wind project. The need for long-term monitoring is supported by reports from the longest-running OWD monitoring programs in Europe which show new and ecologically meaningful changes >10 years after construction (Degraer et al. 2021, Buyse et al. 2023). Such long-term monitoring is not unheard of in the context of energy projects. For example, monitoring upstream and downstream passage of anadromous fish at hydroelectric dams to inform mitigation efforts occurs at least 80 hydropower projects across the USA (FERC 2004), with some monitoring spanning >30 years (Normandeau Associates 2021). The utility of long-term monitoring at the OWD project level may become even greater as these studies hold the potential to also fill anticipated gaps in long-term fisheries independent surveys caused by OWD and provide much needed information for stock assessments (Hare et al. 2022, Methratta et al. 2023).

The second element is the application of analytical tools to OWD monitoring data that can address the question, "how does the temporal trend in meaningful ecological indicators and the causal inferences we make about those trends compare before vs. during vs. after development?" Modern time series analysis techniques are equipped to answer these questions and could be valuable tools for offshore wind researchers. For example, time series analytical methods could be used to compare multiple time series and identify common trends, allowing inferences to be made about potential causal relationships with OWD stressors and other environmental covariates (Zuur et al. 2003a,b, Zimmerman et al. 2018, Navarra et al. 2022). Advancing such methodologies could enable practitioners to consider temporal variance in their study design and statistical analyses, evaluate temporal trends in and around the impact area before and after construction, use quantitative methodologies to make causal inferences about the drivers of temporal trends, and distinguish OWD impacts from other sources of variability. For a robust understanding of the interconnection between stressors derived from OWD and ecological responses, long-term monitoring should be conducted in tandem with targeted research, including both controlled laboratory-based research studies utilizing treatment levels on par with those experienced in the field, and project-level field-based experiments (e.g. Lindeboom et al. 2015, Cresci et al. 2022, Sole et al. 2022).

Selecting ecological indicators for OWD

This study examined biotic indicators for which there is peer-reviewed evidence for responsiveness to stressors associated with OWD. How should a final subset of indicators be selected for monitoring? Evaluating multiple, minimally duplicative indicators across projects would provide a more comprehensive status evaluation than any one indicator because each provides insight into unique aspects of the ecosystem (Trenkel and Rochet 2003, Rombouts et al. 2013). Final selection of which fisheries resource indicators to measure at OWDs should be based on open and transparent discussions with offshore wind stakeholders and be guided by such factors as priority research question and hypotheses to be addressed; fisheries resource species specific to the project area that are vulnerable to OWD; management objectives or needs; the ability to set decision criteria, thresholds, and control rules; and what types of project-level mitigation might be triggered following threshold exceedance (Link 2005, Smit et al. 2021). Indicators selected for studying the response of fisheries resources to project-level impacts could also inform stock assessment models as well as the indicator selection process for ecosystem assessment in the context of the IEA process, a framework for supporting EBM efforts (NOAA 2022a).

Conclusions and recommendations

OWD monitoring programs both in the USA and elsewhere urgently need information-rich monitoring approaches. To that end, the following are recommended: (i) Identify clear monitoring objectives and hypotheses; (ii) Select a set of meaningful ecological indicators that can be sampled across projects within a region that link to stated objectives. The current study offers several potential candidate indicators; (iii) Col-

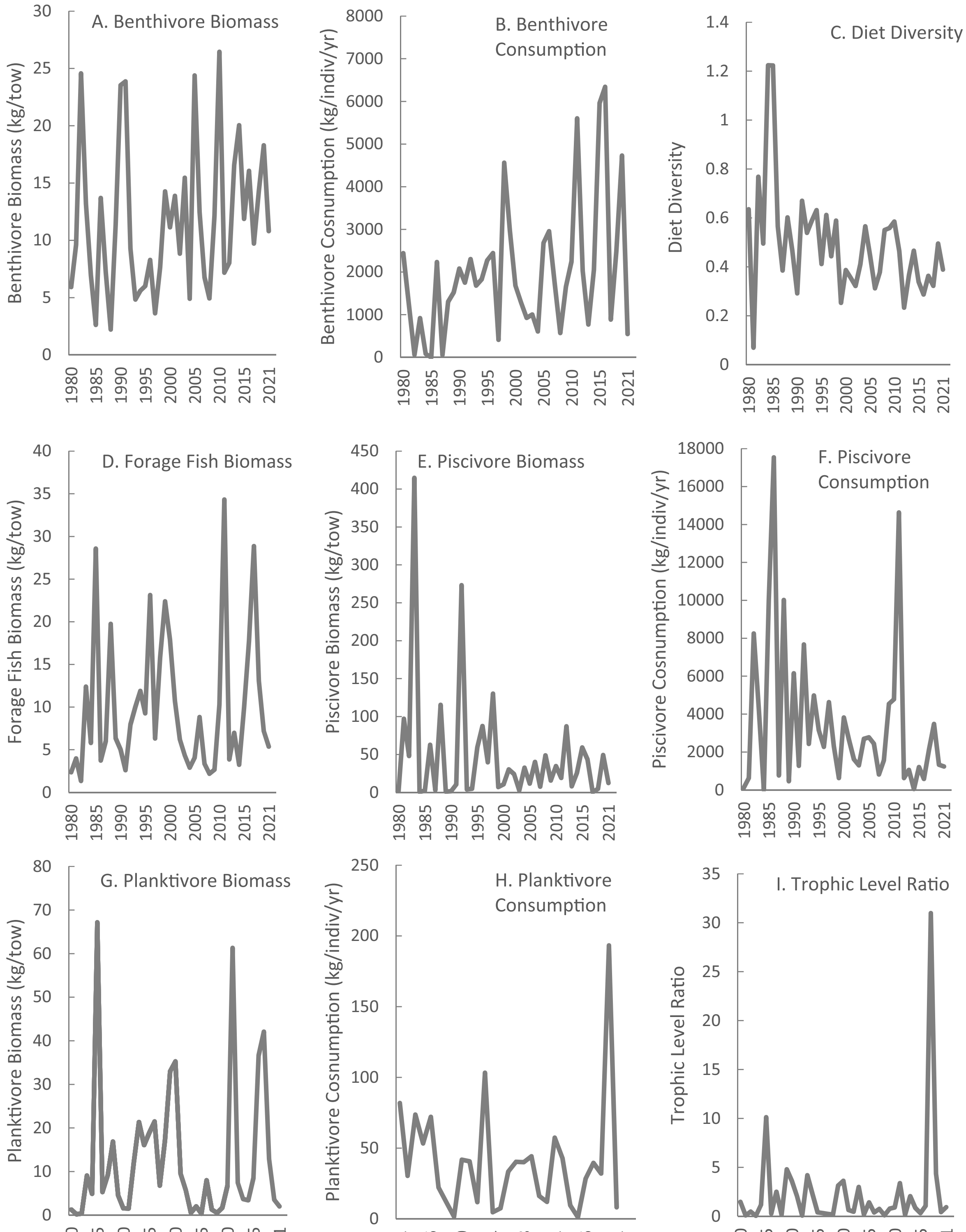

Figure 8. Trophic indicator time series at the scale of the Southern New England WEA. (A) Benthivore Biomass (kg/tow); (B) Benthivore Consumption (kg/individual/yr); (C) Diet Diversity; (D) Forage Fish Biomass (kg/tow); (E) Piscivore Biomass (kg/tow); (F) Piscivore Consumption (kg/individual/yr); (G) Planktivore Biomass (kg/tow); (H) Planktivore Consumption (kg/individual/yr); (I) Trophic Level Ratio.

lect indicator data using standardized methods across projects that are comparable to those used by long-term regional and ecosystem-wide surveys; (iv) Use methodologies that enable cross-scale comparisons (project, region, ecosystem scales) of temporal trends and allow the detection of divergence of project-level trends from broad-scale trends; (v) Collect at least three to five years of project-level baseline indicator data in order to assess inter-annual variability and account for temporal structure in the data analysis phase; (vi) Conduct post-construction project-level monitoring for the lifetime of the project; (vii) Apply quantitative methods that allow for the analysis of trends in time series data, the ability to make inferences about the drivers of those trends, and the ability to determine if those drivers differ before vs. after construction; (viii) Identify, vet with stakeholders, and select meaningful decision criteria, including thresholds at which action should be taken to avoid, minimize, or mitigate adverse impacts; (ix) Incorporate ecological indicators into an IEA framework, enabling evaluation of cross-sector trade-offs (Samhouri et al. 2014, NOAA 2022a, RODA 2023); (x) Provide open and transparent access to data and information to stakeholders.

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Supplementary material

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

Author contributions

The author conceptualized the paper, conducted the analyses, wrote the manuscript, and made the figures and tables.

Conflict of interest: The author has no conflicts of interest or competing interests to declare.

Data availability

Information on how to access the data used for the analyses in this paper is available at the NOAA Fisheries InPort website (https://www.fisheries.noaa.gov/inport/stats/NEFSC/data-sets).

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