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Offshore wind farm-induced spatial redistribution of abundance alters survey indices and stock assessment performance

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Abstract

Fishery-independent surveys provide the primary fish relative abundance information for stock assessments, yet their performance can be compromised when the survey area is restricted and population distributions change spatially. Offshore wind development introduces both challenges by precluding some forms of survey sampling within Wind Energy Areas (WEAs) and by potentially altering fish abundance patterns through attraction- or production-driven processes. However, the combined consequences of these mechanisms for survey indices and stock assessment inference remain poorly quantified. The present study evaluated how spatial abundance redistribution interacts with survey preclusion to influence survey-derived indices and assessment outcomes using a simulation-based approach with historical survey datasets. Three Mid-Atlantic stocks (summer flounder, longfin squid, and Atlantic surfclam) were examined to represent contrasting life histories and assessment frameworks. Two redistribution mechanisms were simulated: attraction-driven redistribution, in which abundance increased inside WEAs through spatial reallocation, and production-driven increases, in which local abundance increased without depletion elsewhere. Redistribution was applied at multiple intensities to recent survey data and propagated through assessments using both complete survey coverage (FULL) and spatially truncated datasets excluding WEAs (Wind Energy Excluded; WEE). This simulation-based exercise represented a full-buildout WEA spatial-exposure scenario over a 10-year operational timeframe. Results showed that increasing redistribution intensity elevated overall and interannual variability in survey indices and increased survey residual dispersion from assessment model results, particularly when abundance change inside WEAs was not accounted for. In contrast, monotonic trends inferred from abundance indices remained largely consistent between FULL and WEE datasets. Estimates of spawning stock biomass showed greater sensitivity to spatial redistribution and survey preclusion than fishing mortality, while retrospective patterns exhibited species- and model-specific responses. Together, these findings demonstrate that survey preclusion and altered spatial abundance patterns can interact to influence stock assessment reliability through reducing the precision and accuracy of survey indices. Differences between findings for different stocks highlight the utility of propagating the effect of survey disruptions through assessment models to inform species-specific mitigation strategies, and the need for this type of quantitative analysis to be standard practice as offshore wind development continues to expand.

Keywords attraction-production, fishery-independent surveys, offshore wind energy, spatial abundance dynamics, stock assessment, survey preclusion

Introduction

Offshore wind development is expanding rapidly across continental shelf ecosystems, increasingly interacting with regions that support productive fisheries and long-standing fishery-independent survey programs. Globally, Wind Energy Areas (WEAs) are often designated, leased, or constructed within intensively fished waters that support regional seafood production and coastal economies, resulting in loss of fishing opportunity and socioeconomic consequences (Bonsu et al. 2024, Campbell et al. 2025). As offshore wind infrastructure proliferates, concerns have grown regarding its potential ecological effects and its implications for fisheries management. Although offshore wind development is known to alter seafloor structure, habitat conditions, and access to fishing grounds, evidence of its overall ecological effects remains mixed, with both positive and negative outcomes

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reported at local scale (Watson et al. 2025). These contrasting findings raise important questions about how offshore wind development may influence fish distribution patterns overall and, consequently, affect fisheries stock assessment and management (Borsetti et al. 2023, Sun et al. under review).

Fishery-independent surveys (referred to as surveys) that employ towed sampling gear are among the activities most directly affected by the preclusion effects of offshore wind development (Lipsky et al. 2024, Haase et al. 2025). Surveys provide critical information on fish abundance, demographic structure, and population trends and are designed to sample spatial domains consistently through time. Their designs allow changes in population status to be interpreted with statistical rigor, largely independent of fishing behavior or management regulations (Mesnil et al. 2009). Any process that alters either the spatial distribution of fish or the areas accessible to survey sampling therefore has the potential to compromise the interpretability of survey indices and, by extension, the assessments that rely on them. In the US Atlantic where a series of WEAs have been designated, studies have shown that survey preclusion can lead to substantial loss of survey effort and introduce bias into spatiotemporal abundance indices derived from historical data generated by major survey programs (Miller 2025, Sun et al. 2026). These estimates generally reflected broad WEA spatial-designation scenarios intended to evaluate potential survey consequences, which might not fully match operational offshore wind footprint.

A key ecological consequence of offshore wind development that has not been fully evaluated using quantitative approaches is its potential to alter fish abundance distributions. Empirical studies and meta-analyses have reported elevated fish abundance within offshore wind farms relative to surrounding areas, often attributed to increased habitat complexity, refuge availability, or enhanced local carrying capacity associated with turbine foundations and scour protection (Methratta and Dardick 2019, Lemasson et al. 2024, Watson et al. 2025). In many respects, these responses resemble artificial reef effects commonly leveraged for marine restoration and conservation (Degraer et al. 2020). However, such effects are often localized to WEAs and their immediate surroundings and vary substantially among taxonomic groups (Friedland et al. 2023, 2025). The resulting spatial heterogeneity in abundance inside and outside WEAs suggests divergent habitat-use behaviors that may influence survey sampling and assessment outcomes.

Despite these observations, wind farm-induced changes in spatial abundance remain mechanistically ambiguous, reflecting the classic "attraction–production" debate associated with artificial reef effects (Pickering and Whitmarsh 1997, Cowan et al. 1999). Specifically, increased abundance within WEAs may reflect redistribution of existing populations through attraction from adjacent areas, or alternatively, localized increases in production that do not diminish abundance elsewhere (Claisse et al. 2014, Roa-Ureta et al. 2019). This unresolved attraction-production distinction has direct implications for fisheries monitoring and assessment. Redistribution without net population change may alter survey indices primarily through spatial sampling effects, whereas true production could modify both survey spatial representativeness and population dynamics. When combined with survey preclusion inside WEAs, these mechanisms may interact in complex ways, potentially obscuring population trends, altering assessment diagnostics, or biasing key management quantities. Despite their relevance, the combined effects of spatial redistribution mechanisms and incomplete survey observation on stock assessment performance under offshore wind development remain poorly understood.

In this study, we evaluated how offshore wind farm-induced spatial redistribution of fish populations may alter survey-derived abundance indices and propagate through stock assessment diagnostics and estimates when surveys are precluded inside WEAs. Using three Mid-Atlantic stocks that differ in life history, survey dependence, and assessment framework, we simulated two plausible abundance redistribution mechanisms representing attraction-driven redistribution and production-driven local increases within WEAs. We further examined how these dynamics interact with survey preclusion by comparing indices and assessment outcomes derived from complete survey coverage and spatially truncated datasets that exclude WEAs. By jointly evaluating changes in index variability, temporal trends, assessment residual patterns, key assessment quantities, and retrospective performance, this work provides a mechanistic assessment of when and how altered spatial abundance patterns and incomplete survey observation may influence stock assessment inference under emerging offshore wind development. The present study should be interpreted as a scenario-based simulation of potential survey and assessment consequences under a broad WEA spatial-exclusion scenario, rather than an evaluation of realized impacts from currently operational offshore wind projects.

Methods

Study area and data source

The present study focused on US Mid-Atlantic stocks as case studies to evaluate impacts of offshore wind development-induced spatial abundance redistribution on survey indices and stock assessment. The Mid-Atlantic region was selected for three primary reasons. First, it represents one of the strongest areas of interaction between offshore wind development and commercial fisheries in the United States. The region contains substantial leased WEAs, covering more than 3 400 km^2 (BOEM 2022, 2023, Fig. 1 and Fig. S1). At the same time, the Mid-Atlantic marine ecosystem supports productive and economically valuable fisheries targeting shellfish, finfish, and cephalopods (Gaichas et al. 2018), providing important food resources and supporting coastal communities and fishing industries (Scheld et al. 2022). Second, WEAs in the Mid-Atlantic region overlap extensively (10% of potential effort, Sun et al. 2026) with the spatial domains of several major fishery-independent surveys, including the Northeast Fisheries Science Center Bottom Trawl Survey (NEFSC BTS) and the NEFSC Atlantic surfclam and ocean quahog dredge survey (hereafter NEFSC dredge survey). This overlap poses substantial challenges to survey design integrity, spatial coverage, and data quality (Hare et al. 2022, Lipsky et al. 2024). Third, previous studies have demonstrated that WEAs in the Mid-Atlantic exert strong survey preclusion effects, leading to reduced available survey area, biased abundance estimates (Sun et al. 2026), and altered stock assessment outcomes (Sun et al. under review). Together, these characteristics highlight the potential for substantial interactions between offshore

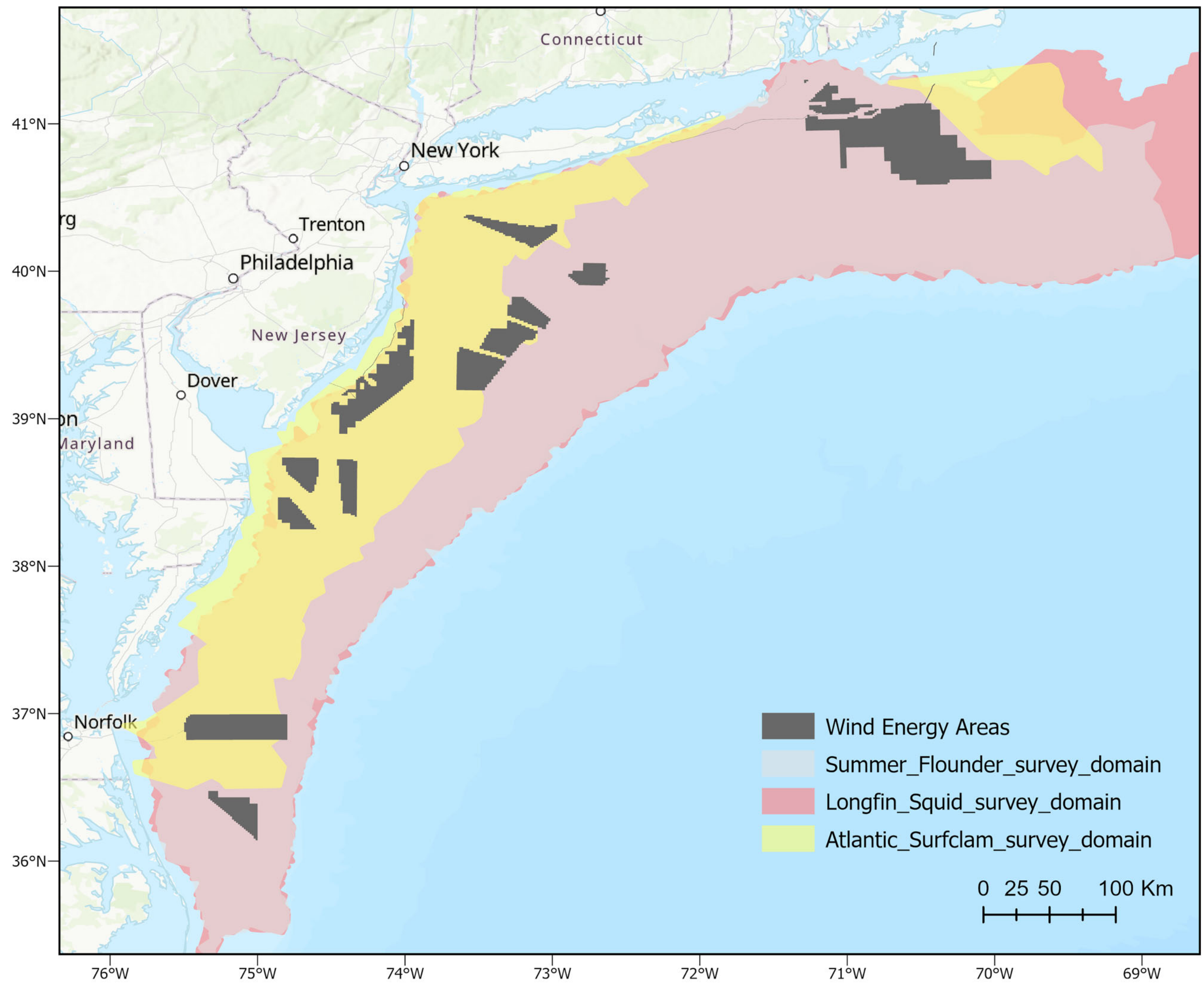

Figure 1 Mapping of the Wind Energy Areas and survey domains for the three species in the Mid-Atlantic region. The survey domains are defined as the concave hull covering survey tows footprint adjusted by a 2-km buffer. Tows outside the Mid-Atlantic Bight region are not reflected in the survey domains.

wind development, fishery surveys, and stock assessments, making the US Mid-Atlantic fisheries a compelling system for evaluating assessment responses to spatially redistributed survey information.

Spatial data delineating WEAs were obtained as shapefiles from the Bureau of Ocean Energy Management (BOEM) data portal (https://www.boem.gov/renewable-energy/mapping-and-data/renewable-energy-gis-data, version 7/30/2025). These WEA boundaries were used as the spatial exposure layer for simulation because they represent the most up-to-date official spatial data available from BOEM. We did not stratify simulations by project-development status because lease and operational status are not consistently available as spatially explicit layers across all areas considered (Supplementary Materials Table S12). In addition, project-status information from different sources is not always temporally synchronized or directly linked to WEA polygons. Therefore, we treated all BOEM-designated WEA boundaries as a broad full-buildout exposure scenario for evaluating potential survey preclusion and ecological redistribution effects.

Focal study fisheries and assessment setting

We selected three ecologically and socio-economically important stocks in the Mid-Atlantic region as case studies: summer flounder (*Paralichthys dentatus*), longfin squid (*Doryteuthis* (*Amerigo*) *pealeii*), and Atlantic surfclam (*Spisula solidissima*) (Table 1). These stocks represent distinct taxonomic groups (finfish, cephalopod, and bivalve), differ in life-history characteristics, are assessed using varied stock assessment approaches and survey data utilization which rely heavily on surveys affected by spatial exclusion (Sun et al. 2026).

Summer flounder is the largest flatfish stock in the US Atlantic, with annual landings of ~10 000 metric tons (NEFSC 2023a). Its most recent Management Track Assessment (MTA) was conducted using the Age-Structured Assessment Program (ASAP; NEFSC 2022), which integrates age-specific catch and survey data to estimate fishing mortality (F) and stock abundance (Legault and Restrepo 1998). The assessment incorporated 26 survey abundance index time series, including the heavily impacted NEFSC

Table 1. Summary of case study fisheries stock assessment and survey abundance indices modified with spatial abundance dynamics.

Species	Assessment model	Impacted abundance indices	Modified time-range	Indices type
Summer Flounder *Paralichthys dentatus*	Age-Structured Assessment Program	BTS BIG spring	2013–2022 (DP = 10)	Swept Area Numbers (constant CV)
		BTS BIG fall	2013–2022 (DP = 9∗)	Swept Area Numbers (constant CV)
Longfin Squid *Doryteuthis (Amerigo) pealeii*	Index-base Method	BTS (ALB + BIG) spring	2013–2022 (DP = 10)	calibrated stratified mean biomass (no CV)
		BTS (ALB + BIG) fall	2013–2022 (DP = 9∗)	calibrated stratified mean biomass (no CV)
Atlantic Surfclam *Spisula solidissima*	Stock Synthesis 3	Dredging MCDS	2013–2022 (DP = 3∗∗)	stratified mean abundance from Modified Commercial Dredge (year-specific CV)

∗2020 Fall indices not included in the assessment model due to missing surveys during COVID-19.
∗∗MCDS dredge survey cruise were conducted for 2015, 2018, and 2022.
"Time-range" represent the time period of the entire abundance indices, and only the most recent 10 years were adjusted for simulated spatial abundance. The altered abundance indices values can be found in Supplementary Materials (Figs S4–S8). DP: Data points modified; BTS: NEFSC Bottom Trawl Survey; BIG: Henry B. Bigelow vessel; MCDS: Modified Commercial Dredge; S: Southern Strata.

BTS conducted in both spring and fall since 1982 (Sun et al. under review). Two of these indices were derived from BTS data collected by the vessel *Henry B. Bigelow* (2009 and onward) during spring and fall. Abundance indices were calculated as stratified mean abundance following the BTS random stratified survey design (Cochran 1977), Politis et al. 2014) and subsequently scaled to swept-area estimates (NEFSC 2019).

Longfin squid exhibits a broadly distributed but highly variable population in the Northwest Atlantic, characterized by strong interannual and seasonal fluctuations driven by environmental sensitivity, short lifespan, and semelparous reproduction (Arkhipkin et al. 2015, Hendrickson 2017). Owing to these challenges, the most recent MTA adopted a data-limited, index-based approach that relied on survey-derived biomass estimates and catch data to construct exploitation indices as proxies for fishing intensity (NEFSC 2023b). Biomass estimates were derived from NEFSC BTS spring and fall surveys, supplemented by the Northeast Area Monitoring and Assessment Program (NEAMAP; Bonzek et al. 2012). NEAMAP data were not considered in the present study when evaluating potential interactions with offshore wind development due to limited evidence of spatial overlap. As with summer flounder, stratified mean biomass (a proxy for abundance) was calculated and scaled to the full population domain using swept-area methods (NEFSC 2011).

Atlantic surfclam is one of the largest and most stable bivalve fisheries in the US Atlantic, with annual landings of ˜10 000 metric tons (NEFSC 2024a). Its MTA was conducted using Stock Synthesis 3 (SS3; Methot and Wetzel 2013), which integrates catch-at-age, survey indices, and fishery-dependent data within a two-area (North and South) modeling framework to estimate F and stock abundance for individual and combined areas. The assessment relied exclusively on NEFSC dredge survey data to derive three abundance time series, each calculated as stratified means and adjusted for differences in gear configuration and dredge efficiency (Hennen et al. 2016, Jacobson and Hennen 2019). Because offshore wind development in the Mid-Atlantic primarily overlaps with the southern dredge survey strata, only the southern time series was considered in this study.

NEFSC BTS and dredge survey data, including tow-level catch information and survey stratification design, were obtained from the NEFSC survey data portal (NEFSC 2024b, 2024c, 2024d). Tows used to derive survey abundance indices were filtered following the criteria specified in each corresponding stock assessment with species-specific calibration procedures. The original stock assessment model specifications and versions can be accessed at NEFSC Stock Assessment Support Information (SASINF; https://apps-nefsc.fisheries.noaa.gov/saw/sasi.php).

Simulation scenario design

Spatial abundance dynamics

To evaluate the mechanisms underlying abundance redistribution associated with offshore wind infrastructure, we simulated spatially explicit changes in survey-observed abundance under two contrasting scenarios representing the attraction-production debate (Bohnsack and Sutherland 1985, Methratta and Dardick 2019) (Fig. 2).

The first scenario represented an "attraction" mechanism (Scenario 1; S1), in which survey-observed abundance was assumed to increase inside WEAs during the relevant survey season through redistribution from non-WEA areas. This scenario was not intended to imply permanent residency within WEAs, but rather a seasonal or survey-window-specific spatial concentration of abundance. Under this scenario, survey abundance for all tows located inside WEAs was increased by a specified proportional factor (Δ). To conserve total abundance, this increase was offset by applying a uniform proportional reduction to all non-WEA tows, such that the total abundance across all survey tows remained unchanged.

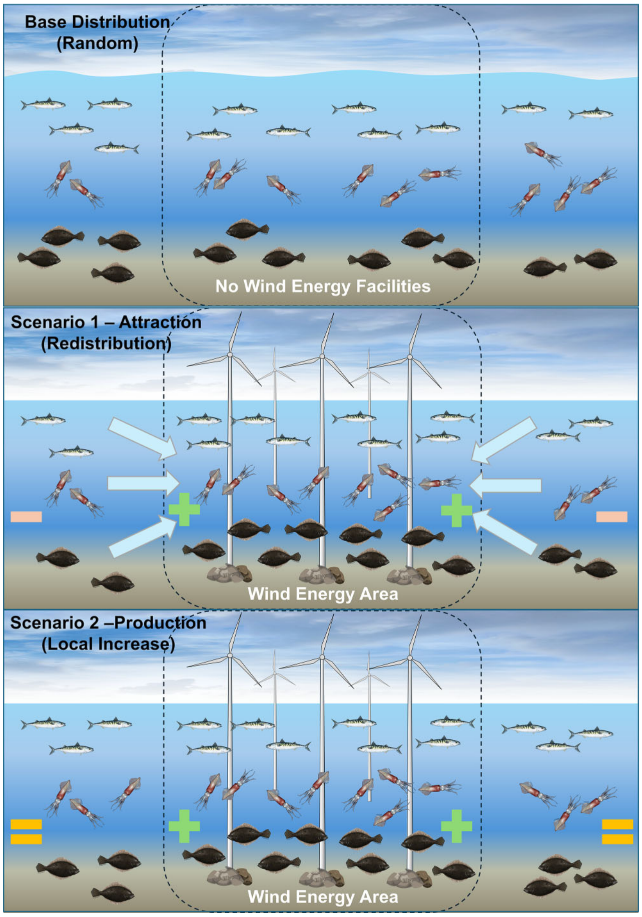

Figure 2 Conceptual illustration of spatial abundance dynamics under offshore wind development. Base scenario (top) represents a random spatial distribution without wind energy facilities. Scenario 1 (middle) represents attraction-driven redistribution, where abundance increases inside the Wind Energy Area (WEA) through redistribution from surrounding areas without net population change. Scenario 2 (bottom) represents production-driven local increase, where abundance increases inside the WEA without redistribution from outside, resulting in a net population increase. Dashed outlines denote the WEA.

The second scenario represented a "production" mechanism (Scenario 2; S2), in which abundance increased locally within WEAs without a compensatory reduction outside. Under this scenario, survey abundance for inside-WEA tows was increased by the same proportional factor (Δ) used in S1, but abundance outside WEAs was left unchanged. Consequently, total population abundance increased at the domain scale.

Both scenarios generated modified tow-level abundance datasets, which were subsequently used to derive updated survey abundance indices (see next paragraph for procedures). These revised indices were then propagated through the respective assessment models for both estimated index values and associated uncertainty [e.g. coefficient of variation (CV)] to explore the effects of the simulated redistribution.

To examine sensitivity to the magnitude of redistribution, we implemented a range of proportional increases inside WEAs (20%–100%), spanning effect sizes consistent with empirical syntheses reporting positive local abundance responses around offshore wind infrastructure (Methratta and Dardick 2019, Lemasson et al. 2024). In both scenarios, abundance at each tow located inside WEAs was increased proportionally by a scaling parameter Δ, such that abundance was multiplied by $1 + \Delta$ (e.g. $\Delta = 0.2$ represents a 20% increase). This redistribution was interpreted as the spatial abundance pattern observable during the spring or fall survey window, rather than a year-round distributional state.

In the attraction scenario (S1), the total increase in abundance within WEAs was calculated as the sum of tow-level increases and was offset by applying a uniform proportional reduction to all non-WEA tows, such that total survey abundance across all tows remained unchanged. The magnitude of this reduction depended on the relative contribution of WEA and non-WEA tows to total sampled abundance and was therefore not a fixed percentage (Supplementary Materials Figs S14 and S15).

In contrast, under the production scenario (S2), no compensatory reduction was applied, and the increase in total survey abundance arose directly from the cumulative tow-level increases within WEAs. Consequently, the magnitude of total abundance change varied among years depending on both the number of tows located within WEAs and the observed abundance at those tows.

Redistribution effects were applied to the most recent 10 years of survey data (Table 1), reflecting short- to mid-term impacts of wind farm-induced abundance change. This time window was selected because simulation studies suggest that a 10-year period is sufficient to capture altered population signals, with limited additional changes beyond that (Campbell et al. 2025).

We did not modify age- or size-composition data in the surveys, owing to a lack of empirical evidence to support realistic parameterization of such changes. Catch data were also held constant across scenarios. This decision was motivated by several considerations. First, empirical studies suggest that spillover effects associated with spatial exclusion are generally localized and result in minimal changes to total catch (Halouani et al. 2020). Second, fleet behavioral responses to WEAs are complex and not consistently attributable to offshore wind development alone (Gray et al. 2016, Borsetti et al. 2026). Third, both evidence- and simulation-based studies indicate that fisheries responses to spatial exclusions tend to be modest over short time periods (Van Hoey et al. 2021, Campbell et al. 2025), limiting the feasibility of constructing defensible catch-adjustment scenarios.

Survey preclusion effect

To evaluate whether altered abundance distributions could be reliably observed by existing survey programs, we further examined the interaction between abundance redistribution and survey preclusion associated with offshore wind development.

Survey preclusion was implemented using a spatial intersection approach following established procedures (Sun et al. 2026). Specifically, the complete set of survey tows (hereafter referred to as the FULL dataset) was spatially intersected with WEA boundaries using ArcGIS. All tows located within WEAs were removed, generating a spatially truncated dataset consisting only of tows outside WEAs, referred to as the Wind Energy Excluded (WEE) dataset. WEE dataset represents an unmitigated survey-preclusion scenario under the existing survey design, in which inaccessible WEA stations result in reduced survey effort rather than replacement sampling elsewhere. This approach was used to isolate the effect of spatially structured loss of survey access before considering potential mitigation or survey-redesign strategies. Both datasets retained full tow-level spatial, temporal, and catch information.

This approach reflected survey inaccessibility within WEAs while preserving the original statistical survey design, and has been widely applied to evaluate the effects of spatial closures and Marine Protected Areas on fishery-independent surveys (Ono et al. 2015, Anderson et al. 2024). By comparing assessment performance derived from the FULL and WEE datasets under identical redistribution scenarios, we isolated the extent to which survey preclusion interacts with abundance redistribution to bias survey indices and downstream stock assessment outputs.

Abundance indices evaluation

Prior to fitting stock assessment models, we evaluated the statistical properties of recalculated abundance indices under each spatial abundance dynamic scenario. Index variability and temporal structure were quantified using a suite of diagnostics, including the CV, consecutive disparity (CD), and relative trend consistency between datasets. Together, these metrics characterize changes in overall index noise, short-term temporal instability, and long-term trend detectability that are most relevant to stock assessment performance.

Overall variability

Overall index variability was quantified using CV, a dimensionless measure of relative dispersion in an abundance index time series:

$$\mathrm{CV} = \frac{SD}{\bar{I}}, \tag{1}$$

$$\mathrm{SD} = \sqrt{\frac{\sum_{t=1}^{n}\left(I_t - \bar{I}\right)^2}{n}}, \tag{2}$$

where I_t denotes the abundance index in year t, $\bar{I}$ denotes the mean predicted index, n denotes the total number of index values, and SD denotes the standard deviation. CV summarizes the magnitude of index fluctuations relative to the mean level and is independent of scale, reflecting the level of uncertainty and fitting flexibility for input data used in stock assessment. In this study, CV was used to evaluate whether altered spatial abundance dynamics associated with WEAs changed the overall variability level of recalculated indices. Higher CV values indicate noisier indices, whereas lower CV values indicate more stable estimates with less variability.

Interannual variability

While CV summarizes overall dispersion, it does not account for the temporal ordering of observations or changes in year-to-year variability. Interannual variability in abundance indices is important in stock assessment because abrupt year-to-year changes can create temporal conflicts with population dynamics assumptions, catch histories, and other data sources. Spatial redistribution and survey preclusion may increase short-term instability in survey signals that may be difficult for assessment models to reconcile, even when overall index dispersion summarized by CV remains similar. We therefore quantified interannual variability using CD, which measures the average magnitude of proportional changes between consecutive years:

$$\mathrm{CD} = \frac{1}{n-1}\sum_{t=2}^{n}\left|\ln\left(I_t\right) - \ln\left(I_{t-1}\right)\right|, \tag{3}$$

where I_t and $I_{t\text{-}1}$ denote index values in consecutive years t and $t-1$, respectively. The logarithmic transformation ensures that changes are evaluated on a relative scale, allowing comparisons across indices with different magnitudes. Higher CD values indicate greater interannual volatility and reduced temporal coherence, whereas lower values indicate smoother indices dominated by gradual changes rather than short-term fluctuations. Note that CD does not apply to zero index values, which did not occur for the species evaluated.

Relative trend consistency

To assess whether exclusion of survey observations within WEAs alters the long-term trends (full time series) inferred from survey abundance indices under different spatial abundance dynamics (10-year range), we compared temporal trends between indices derived from the FULL and WEE datasets. For each species, survey, and scenario, paired index time series from the FULL ($I_{FULL,t}$) and WEE ($I_{WEE,t}$) datasets were aligned by year and converted to a relative log-ratio series (R_t), retaining only years with non-missing values in both series (missing values for BTS 2020 fall and 2017 longfin squid). This formulation evaluates relative changes on a proportional scale and requires index values to be strictly positive.

A nonparametric Mann–Kendall (MK) trend test was then applied to the log-ratio series R_t to detect monotonic temporal changes in the relative trends between the two datasets. The MK test detects monotonic trends by comparing the ranks of all pairwise observations in a time series, allowing robust inference of directional change without assumptions of linearity or normality (Hardison et al. 2019). Kendall's tau statistics describe the direction and strength of the monotonic relationship. A statistically significant positive tau indicates that the WEE-derived index increases relative to the FULL-derived index over time, whereas a significant negative tau indicates that the WEE-derived index decreases relative to the FULL-derived index. Non-significant results indicate no detectable monotonic difference in trends between the FULL and WEE indices. Statistical significance was evaluated at alpha = 0.05. Because effective sample size differed among indices, trend-consistency results should be interpreted cautiously for short time series. In particular, MK results for indices with very few paired observations were used only as descriptive diagnostics and rather than strong evidence for long-term trend consistency.

Assessment performance evaluation

Key quantity estimates

We first examined estimated population quantities and their associated uncertainty across scenarios, seasons, and values of Δ with spatial redistribution of abundance. For model-based assessments, we focused on spawning stock biomass (SSB) and fishing mortality (F), together with their uncertainty summarized using confidence intervals (CI) derived from asymptotic standard errors (SE). For longfin squid, which was assessed using an index-based approach without a fitted population model, we evaluated survey-derived biomass and exploitation indices as proxies for SSB and F, respectively.

For summer flounder (ASAP) and surfclam (SS3) estimates of SSB and F were obtained directly from the fitted assessment models under each scenario. In the ASAP model, survey CVs were specified as constant across years, therefore were held unchanged across scenarios to maintain consistency with the original model configuration. In contrast, the SS3 model incorporates year-specific CVs for survey indices; accordingly, CVs were updated by year to reflect scenario-specific changes in index values and their associated uncertainty. SSB was defined as the total mature biomass at the beginning of the year, and F for surfclam was defined as a stock size-weighted F from the two sub stocks (NEFSC 2024a). Uncertainty in these quantities was summarized using model-reported 95% CI, which reflect the combined effects of observation error and model structure under each assessment framework.

Longfin squid was assessed using an index-based approach without an explicit population dynamics model or likelihood. Therefore, we evaluated survey-derived biomass and exploitation indices as proxies for SSB and F, respectively, following the MTA procedure (NEFSC 2023b). Specifically, annualized biomass was used as a proxy for SSB and was defined as the average of spring and fall survey biomass estimates. To reduce short-term interannual variability and emphasize broader temporal patterns, a 2-year moving average was then applied (years with unavailable biomass estimates were dropped from the analysis). The resulting smoothed annualized biomass was used as a proxy for SSB. An exploitation index was then calculated as the ratio of total catch to the 2-year moving average of annualized biomass. This exploitation index was treated as a proxy for F. Although exploitation index does not represent an instantaneous fishing mortality rate, it provides a consistent, dimensionless measure of exploitation intensity derived from the same survey information used to construct the biomass proxy. Because these squid quantities are derived directly from survey indices and catch data without an associated statistical model, SEs were not calculated for squid quantities.

Survey residuals

To evaluate how offshore wind-driven spatial redistribution and dataset truncation altered survey information used in stock assessments, we examined survey residuals across scenarios, seasons, and values of Δ. Survey residuals were treated as diagnostic quantities describing the agreement between observed and predicted survey indices (Karp et al. 2022), and were summarized across years to assess systematic shifts in residual structure under alternative spatial configurations.

For model-based assessments (ASAP and SS3), survey residuals were defined on the log scale as deviations between observed survey indices and values expected under the fitted assessment model. For year t, the log-scale deviation was defined as

$$\mathrm{Dev}_t = \log\left(I_t^{\mathrm{obs}}\right) - \log\left(I_t^{\mathrm{exp}}\right), \tag{4}$$

where I_t^{obs} denotes the observed survey index provided as input to the assessment, and I_t^{exp} denotes the model-expected index value for the same year.

To account for differences in assumed observation uncertainty across surveys and scenarios, deviations were standardized using the index uncertainty specified within each assessment framework. In Stock Synthesis, the standard error (SE) associated with each survey index is reported directly on the log scale and corresponds to the observation error assumed by the catch per unit effort (CPUE) likelihood. Standardized survey residuals were therefore computed as

$$r_t = \frac{\mathrm{Dev}_t}{\mathrm{SE}_t}, \tag{5}$$

where SE_t is the log-scale standard error reported for the survey index in year t.

In ASAP, survey indices are likewise assumed to follow a lognormal error structure and remain constant over time, but uncertainty is specified through a CV on the arithmetic scale. For consistency with Stock Synthesis, deviations were computed on the log scale and standardized using the implied log-scale standard error derived from the input CV:

$$\mathrm{SE}_t = \sqrt{\log\left(1+\mathrm{CV}_t^2\right)}, \tag{6}$$

$$r_t = \frac{\log\left(I_t^{\mathrm{obs}}\right) - \log\left(I_t^{\mathrm{exp}}\right)}{\mathrm{SE}_t}. \tag{7}$$

Under both assessment frameworks, the resulting residuals represent unitless, standardized measures of survey fit, with values centered near zero indicating close agreement between observed and expected indices. Systematic shifts in the distribution of standardized residuals away from zero or increases in residual dispersion were interpreted as evidence of altered survey–model agreement associated with offshore wind-driven spatial redistribution.

For longfin squid, which was assessed using an index-based approach without an explicitly fitted population model, we constructed a nominal residual to quantify differences in derived survey indices attributable to dataset truncation under identical spatial redistribution settings.

For each year t, scenario, season, and value of q, the residual-like index deviation was defined as the nominal log-scale difference between indices estimated from the WEE and FULL datasets:

$$r_t = \log\left(I_t^{\mathrm{WEE}}\right) - \log\left(I_t^{\mathrm{FULL}}\right). \tag{8}$$

This quantity captures the magnitude and direction of divergence in the derived index associated with excluding survey observations from WEAs. Because no statistical model is fitted and no observation-error likelihood is specified for the squid assessment, these residual-like diagnostics were not standardized by uncertainty and are interpreted as nominal log-scale deviations rather than standardized residuals. Departures of values from zero indicate systematic differences between indices derived from the WEE and FULL datasets.

Retrospective error

We evaluated retrospective behavior across assessment scenarios using Mohn's rho for SSB and F. Retrospective analysis is commonly used to diagnose the temporal stability of assessment estimates by examining how terminal-year estimates change as recent observations are sequentially removed from the data set. Persistent retrospective patterns may indicate structural model misspecification, changing data informativeness, or sensitivity of estimates to recent observations, and are therefore widely interpreted as indicators of assessment reliability.

Following standard practice, retrospective error was quantified using 5-year Mohn's rho, which measures the average proportional difference in estimates derived from progressively "peeled" time series relative to the corresponding estimates from the full data set (Mohn 1999):

$$\rho = \frac{1}{P}\sum_{p=1}^{P} \frac{\hat{X}_{Y-p,\,Y-p} - \hat{X}_{Y-p,\,Y}}{\hat{X}_{Y-p,\,Y}}, \tag{9}$$

where P is the number of retrospective peels, Y is the terminal year of the full assessment, $\hat{X}_{(Y-p,Y-p)}$ is the estimate of quantity X in year $Y-p$ obtained using data only through year $Y-p$, and $\hat{X}_{(Y-p,Y)}$ is the estimate of the same quantity in year $Y-p$ obtained from the assessment fit to the full data set. Values of ρ near zero indicate low retrospective bias and greater temporal stability, whereas consistently positive or negative values indicate systematic over- or under-estimation in terminal years.

For the index-based longfin squid assessment, retrospective analysis in the traditional sense is not applicable because no fitted population model is available and estimates are derived directly from survey-based indices. Instead, we evaluated temporal stability using a signal-to-noise ratio (SNR) analysis, which has been widely applied to assess the interpretability of fisheries time series (Payne et al. 2009). Although SNR does not quantify retrospective bias per se, it serves a conceptually similar diagnostic role by evaluating the extent to which long-term trends are distinguishable from short-term variability.

To estimate the underlying signal, we applied a LOESS smoother with a span of 0.5 to the annual exploitation index to capture the overall temporal trend. Signal was defined as smoothed annualized biomass estimates, whereas noise was defined as the year-to-year deviations from this smoothed trajectory. The signal-to-noise ratio was then calculated as:

$$SNR = \frac{Var\,(signal)}{Var\,(noise)}, \tag{10}$$

where higher values indicate stronger, more coherent temporal signals, and lower values indicate time series dominated by short-term variability.

Results

Abundance indices evaluation

Overall variability

Overall variability in abundance indices, quantified by CV (Fig. 3), did not differ greatly across spatial abundance scenarios (S1 and S2), the magnitude of redistribution (Δ), and whether abundance changes inside WEAs were observable (FULL vs. WEE datasets). Increasing values of Δ led to larger departures in index variability from the baseline scenario for summer flounder fall index under the attraction scenario (S1). In comparison, Atlantic surfclam demonstrated slightly decreased variability under S1 with FULL dataset. Under the production scenario (S2), the decreased in Atlantic surfclam index variability was slightly more pronounced. All WEE index CV values under S2 remained constant as the abundance outside WEAs were unchanged.

The sensitivity of CV to redistribution magnitude varied among species, with summer flounder and Atlantic surfclam showing stronger responses than longfin squid. When spatial abundance changes inside WEAs were observable (FULL dataset), deviations in CV from the baseline scenario were generally smaller than when inside-WEA information was excluded (WEE dataset). In contrast, loss of abundance information within WEAs often amplified changes in index variability and, in some cases, resulted in opposite directions of CV change relative to the FULL dataset, particularly for summer flounder and Atlantic surfclam.

Interannual variability

Interannual variability in abundance indices, quantified using CD (Fig. 4), exhibited patterns broadly consistent with those observed for CV, indicating similar behaviors between year-to-year instability and overall variability in survey indices as spatial abundance dynamics intensified. Responses differed between scenarios, with CD increasing more strongly with Δ under S1 (attraction) than under S2 (production), suggesting that local increases in abundance within WEAs generated less pronounced interannual instability than redistribution alone.

Differences between the FULL and WEE datasets were also evident. When abundance changes inside WEAs were observed (FULL dataset), CD values generally remained closer to baseline levels. In contrast, exclusion of inside-WEA observations (WEE dataset) resulted in consistently higher CD for surfclam and summer flounder in fall, indicating reduced temporal coherence in indices derived from spatially truncated surveys. This effect was most pronounced for summer flounder and Atlantic surfclam, whereas longfin squid exhibited relatively modest changes in CD across scenarios and datasets.

Relative trend consistency

Differences in monotonic trends between abundance indices derived from the FULL and WEE datasets, evaluated using the Mann–Kendall test (Table 2), were characterized by consistently high p-values across species, scenarios, and values of Δ. This indicates an overall absence of detectable monotonic divergence in long-term trends between indices derived from the FULL and WEE datasets, suggesting that exclusion of survey observations within WEAs did not substantially alter the inferred direction of abundance trends. For Atlantic surfclam this divergence might be poorly detected due to the extremely sparse data points. Detectable divergences in monotonic trends ($P < 0.05$) were limited and observed only for summer flounder at higher levels of redistribution ($\Delta \geq 0.8$), particularly in the spring survey. In contrast, longfin squid and Atlantic surfclam exhibited no evidence of trend divergence regardless of redistribution scenarios or magnitudes.

Assessment performance

Key quantity estimates

Across species, increasing redistribution magnitude (Δ) led to progressively larger divergence between SSB estimates derived from the FULL and WEE datasets (Fig. 5), with differences becoming most pronounced at higher values of Δ ($\Delta \geq 0.8$). The direction and magnitude of these changes varied among species. For summer flounder, median SSB estimates remained close to baseline levels across Δ, with substantial overlap of 95% CIs between FULL and WEE datasets. SSB derived from FULL dataset showed minimal deviations from the baseline under S1 and modest increase under S2, whereas WEE-derived SSB exhibited small decrease under S1 and remained unchanged under S2. Longfin squid showed a directional response under Scenario 1, with negative deviations from the baseline becoming larger as Δ increased. Atlantic surfclam showed the strongest response to increasing Δ under S1. Specifically, FULL-derived SSB increased monotonically under both scenarios, whereas WEE-derived SSB declined steadily with increasing Δ only for S1 and remained unchanged for S2.

In contrast to SSB, estimated F exhibited comparatively negligible responses to increasing (Δ), with most F estimates remaining close to baseline levels across scenarios (Fig. 6). Divergence between FULL- and WEE-derived F estimates was generally smaller

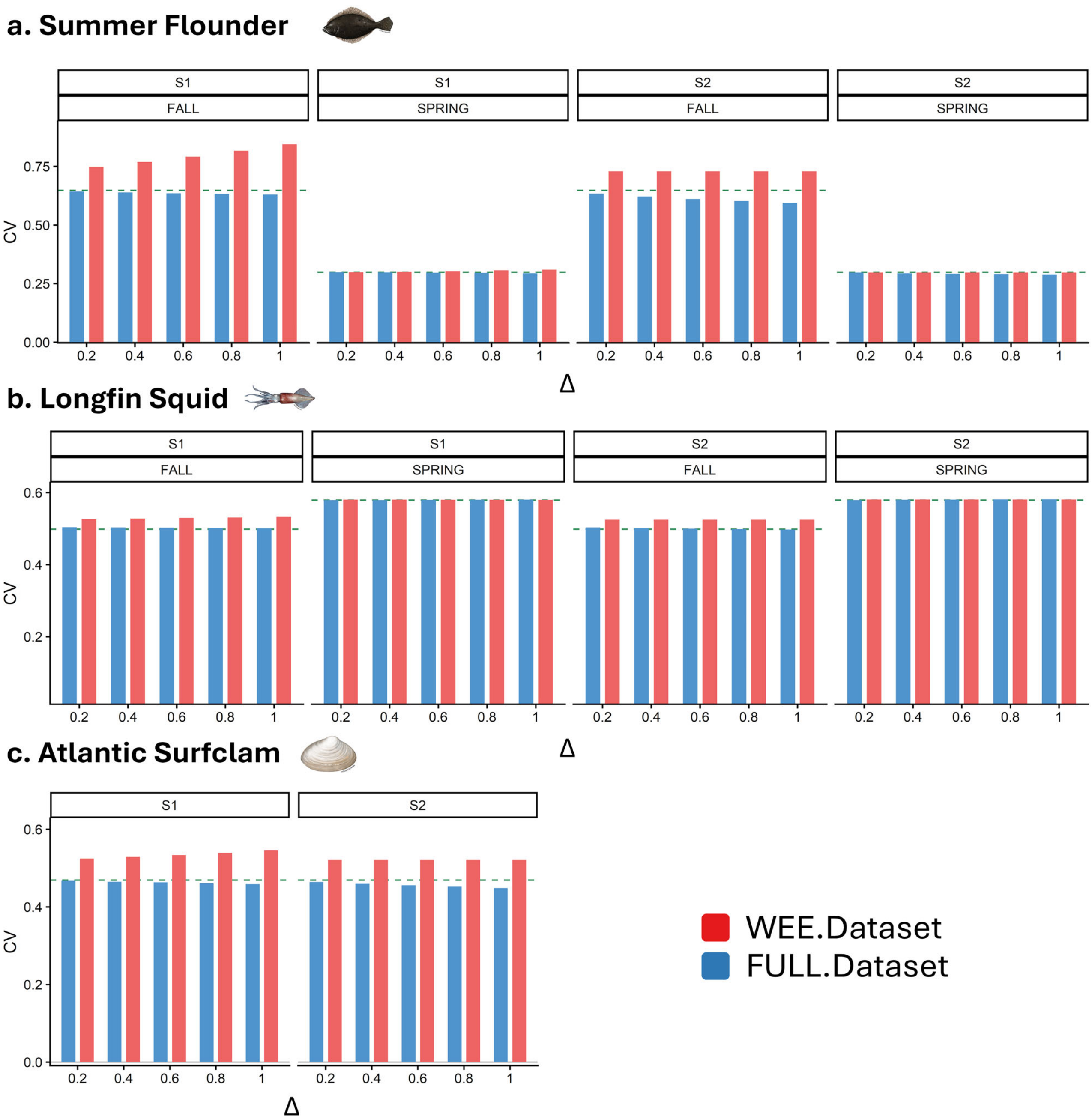

Figure 3 Coefficient of variation (CV) of survey abundance indices estimated using complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets under two spatial redistribution scenarios (attraction, S1; production, S2) and five values of proportional increase factor (Δ), for (a) Summer Flounder and (b) Longfin Squid in spring and fall, and (c) Atlantic Surfclam. Dashed lines indicate baseline CVs without spatial redistribution.

than that observed for SSB, indicating greater robustness of F estimates to spatial redistribution and survey preclusion. For summer flounder, median F estimates remained stable across all values of Δ under both scenarios, with substantial overlap of 95% CIs between FULL and WEE datasets and no consistent directional change relative to the baseline. Longfin squid showed clearer directional responses in F with increasing Δ. Under S1, FULL-derived F declined gradually with increasing Δ, whereas WEE-derived F increased relative to the baseline. Under S2, FULL-derived F decreased more strongly with increasing Δ, while WEE-derived F remained unchanged. Atlantic surfclam exhibited reduced F estimates with increasing redistribution magnitude for both scenarios, with WEE-derived F fluctuated closely around baseline.

Survey residuals

Across species, deviations of residual distributions from baseline levels were generally comparable between the two redistribution scenarios, demonstrated by stable median values close to 0 across Δ (Fig. 7), indicating minimal changes in survey indices residual.

For summer flounder, residuals remained centered near zero under both scenarios for all levels of Δ, with distributions largely overlapping the baseline interquartile range at 50%. With higher

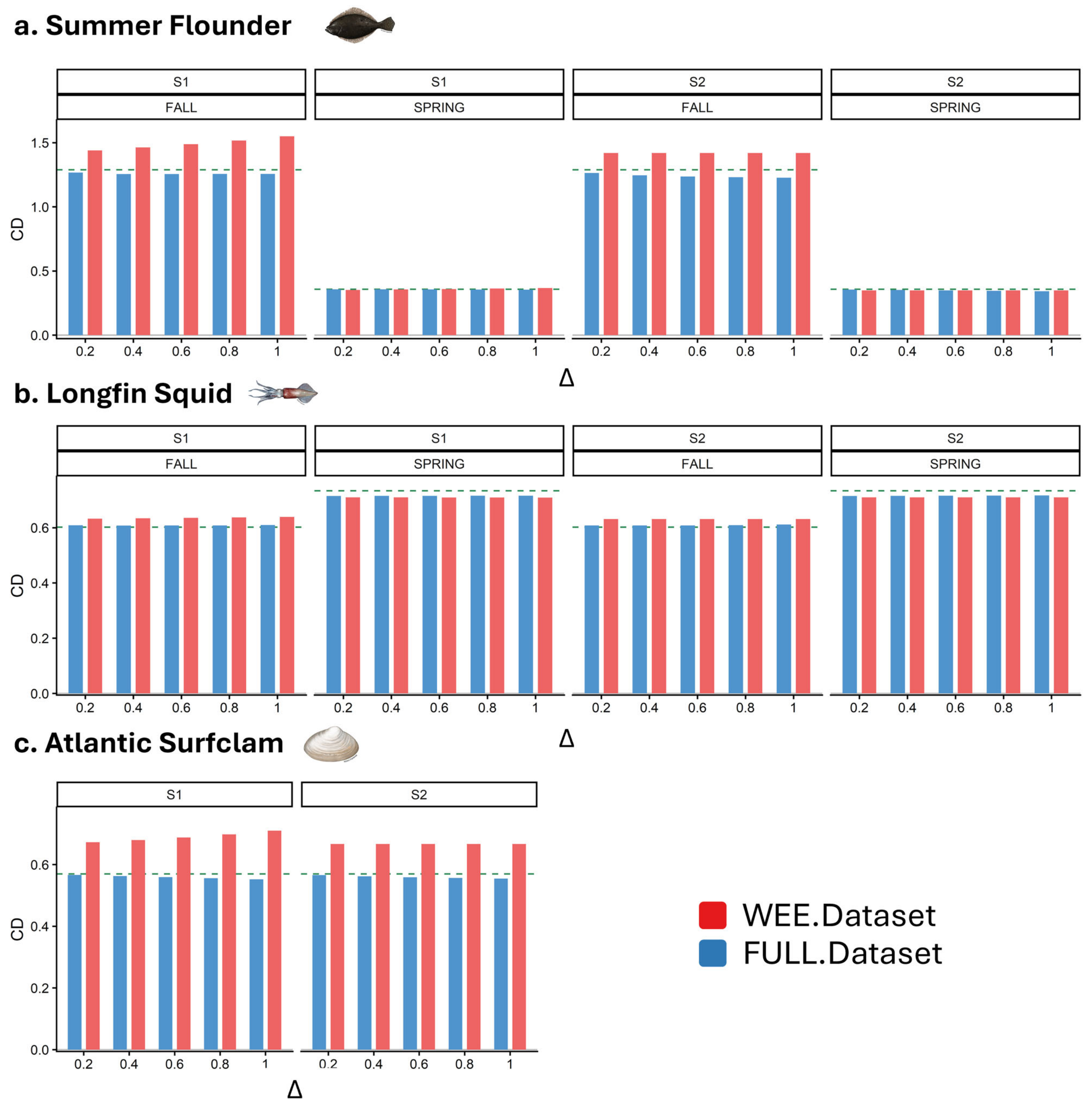

Figure 4 Consecutive disparity (CD) of survey abundance indices estimated using complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets under two spatial redistribution scenarios (attraction, S1; production, S2) and five values of proportional increase factor (Δ), for (a) Summer Flounder and (b) Longfin Squid in spring and fall, and (c) Atlantic Surfclam. Dashed lines indicate baseline CD values without spatial redistribution.

Δ, residual distributions broadened and median residuals shifted away from baseline levels only in fall for S1, while changes in spring were less visible. These patterns were consistent across seasons and scenarios, although variability was more pronounced under the attraction scenario (S1). The disparity in survey residuals between FULL and WEE assessments was not significantly associated with index bias (Supplementary Materials Fig. S2).

Longfin squid showed clear and directional residual patterns. Under both scenarios, residuals became increasingly negative with increasing Δ in fall. In contrast, residuals in spring were centered closer to zero with smaller dispersion, suggesting weaker deviations between datasets for that season. Fall indices from the WEE dataset were smaller than those from the FULL dataset for all values of Δ except 0.2 while spring indices from the WEE dataset were larger than those from the FULL dataset for all values of Δ.

For Atlantic surfclam, residual distribution remained largely intact under WEE data for S1 and constant for S2. But median residuals for the Full dataset shifted progressively away from baseline levels, particularly, which were evident under both S1 and S2, with particularly smaller dispersion observed at higher Δ. The disparity in survey residuals between FULL and WEE assessments was not significantly associated with index bias (Supplementary Materials Fig. S3), suggesting weak connections between indices bias and fitting residuals.

Table 2. Summary of differences in monotonic trends between abundance indices derived from the complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets, evaluated using Mann–Kendall tests applied to the log-ratio time series.

Species	Scenario	Time-series	Δ =0.2	Δ =0.4	Δ =0.6	Δ =0.8	Δ =1
Summer Flounder	S1	Fall [13]	0.951	0.300	0.200	0.077	0.044
		Spring [14]	0.584	0.274	0.063	0.037	0.029
	S2	Fall [13]	0.951	0.760	0.502	0.246	0.127
		Spring [14]	0.584	0.381	0.125	0.063	0.029
Atlantic Surfclam	S1	Annual [4]	1.000	1.000	1.000	0.734	0.734
	S2	Annual [4]	1.000	1.000	1.000	1.000	0.734
Longfin Squid	S1	Fall [46]	0.471	0.835	0.864	0.609	0.449
		Spring [47]	0.340	0.340	0.359	0.389	0.389
	S2	Fall [46]	0.515	0.819	1.000	0.680	0.539
		Spring [47]	0.576	0.576	0.600	0.638	0.638

Each cell reports the Mann–Kendall *P*-value, where values close to 1 indicate no evidence of systematic divergence in relative trends over time. *P*-values below 0.05 indicate detectable divergence in monotonic trends between FULL and WEE indices and are highlighted in red. Mann–Kendall effective sample size is reported following each time series in bracket.

Retrospective error

Across species, retrospective error measured by 5-year Mohn's rho showed varied patterns (Fig. 8). For summer flounder, Mohn's rho values for both F and SSB remained close to the base reference values across all values of Δ under both scenarios, indicating minimal retrospective bias and little sensitivity to spatial redistribution or survey preclusion.

In contrast, longfin squid exhibited substantial increase in Mohn's rho values compared to base model for F under both scenarios, with larger values for the FULL dataset than for the WEE dataset, whereas the increase for SSB were much smaller. This was due to our design of "F proxy" for its index-based assessment.

Atlantic surfclam had the largest disparities between Full and WE-derived results. Specifically, for both F and SSB, retrospective errors were greatly reduced under Full dataset across scenarios, whereas their counterparts under WEE datasets increased beyond the base model level. Moreover, the decrease in Mohn's rho values were larger with increased Δ, indicating alleviated retrospective errors. Mohn's rho values for WEE dataset were less sensitive to Δ and remained constant for S2 according to our simulation design.

Discussion

This study demonstrates that offshore wind farm-induced spatial abundance redistribution, combined with survey preclusion inside WEAs, can substantially alter survey-derived abundance indices and propagate through stock assessment diagnostics under the full build-out WEAs scenario at 10-year operational time scale, even when long-term trends remain broadly consistent. Across species and assessment methods, increasing redistribution intensity (Δ) could affect index interannual variability, led to altered SSB estimates, increased survey residual dispersion, and varied changes in retrospective errors, with effects generally more pronounced when survey observations within WEAs were excluded. In contrast, monotonic trends inferred from abundance indices were largely robust, and F estimates showed limited sensitivity. Together, these results indicate that altered spatial abundance patterns primarily affect the accuracy and precision of annual abundance indices as well as certain derived assessment quantities, rather than inferred long-term trends. The magnitude of effects differed between stocks depending on life history, assessment method, and number of data sources in the assessment, which are discussed in the following sections along with some caveats due to simulation design. This suggests that the degree of survey mitigation required to maintain assessment quality is likely to be highly variable across different stocks and assessment approaches.

Survey preclusion and abundance redistribution effects on stock assessment

The effects associated with survey preclusion are consistent with previous simulation and empirical studies showing that spatial truncation of fishery-independent surveys can increase index variability and inflate uncertainty in survey indices (Ono et al. 2015, Ducharme-Barth et al. 2022, Anderson et al. 2024). While the trend bias observed in the present study remained negligible under low redistribution intensity, incomplete survey coverage relative to population spatial range has been shown to introduce time-varying catchability (Wilberg et al. 2009). Recent offshore wind-focused studies have likewise emphasized that survey preclusion alone can degrade assessment diagnostics even in the absence of underlying population change (Borsetti et al. 2023, Sun et al. under review).

Redistributed spatial abundance within WEAs began to exert strong influence on assessment performance only at higher redistribution intensities ($\Delta \geq 0.8$). At the level of individual years, changes in abundance indices were generally small, including modest deviations in absolute index values (Supplementary Figs S4–S8) and negligible changes in year-specific CVs, which largely remained within commonly accepted reliability thresholds ($CV < 0.3$; Supplementary Figs S9–S13; Hurtado-Ferro et al. 2015). These isolated changes alone were insufficient to explain the observed degradation in assessment performance; instead, their cumulative effects manifested through increases in overall variability metrics (CV and CD) and altered temporal structure, which subsequently propagated into assessment models.

The magnitude of this propagation depended on two key factors. First, the relative weight of impacted survey indices within

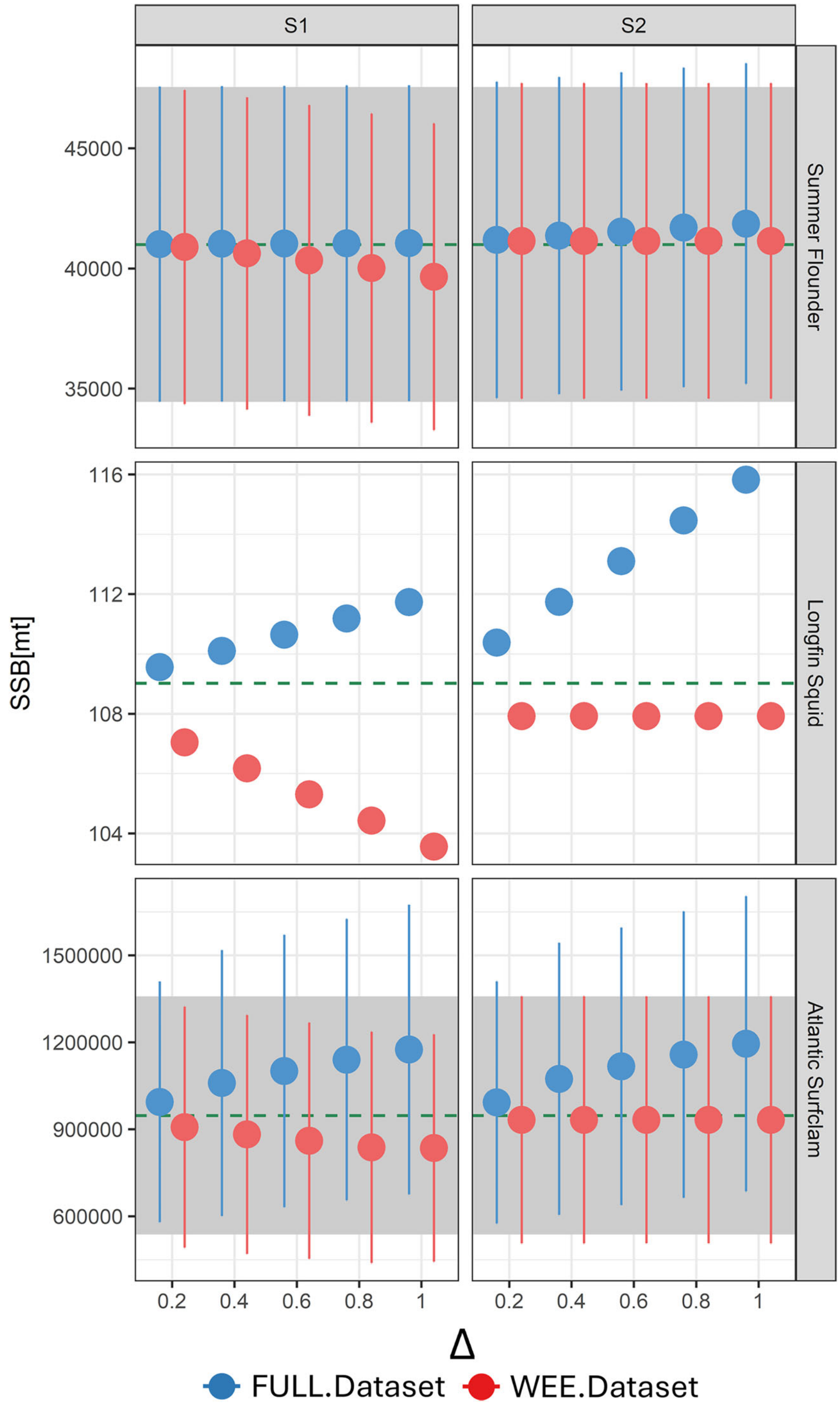

Figure 5 Estimated spawning stock biomass (SSB) using complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets under two spatial redistribution scenarios (attraction, S1; production, S2) across five values of proportional increase factor (Δ), for Summer Flounder, Longfin Squid, and Atlantic Surfclam. Points and vertical lines represent estimated median SSB values and their associated 95% confidence intervals. Shaded areas and green dashed lines represent the 95% confidence interval and median SSB, respectively, from the baseline scenario without spatial redistribution. Longfin squid did not have confidence intervals because the quantities are estimated from index-based method.

an assessment influenced sensitivity, as reflected by weaker responses in summer flounder—where only 2 out of 26 indices (equal weight) were affected—compared to Atlantic surfclam, for which impacted indices comprised the entire fisheries independent data set for recent years. Second, model structure played an important role: the index-based assessment for longfin squid, which lacks an explicit fitting process, exhibited greater sensitivity to redistributed abundance than model-based assessments. Finally, survey design also modulated response to sampling loss. Both the NEFSC bottom trawl survey and dredge survey employ random stratified designs, which have been shown to exhibit intermediate levels of error under reduced sampling effort relative to alternative designs (Conner et al. 2025).

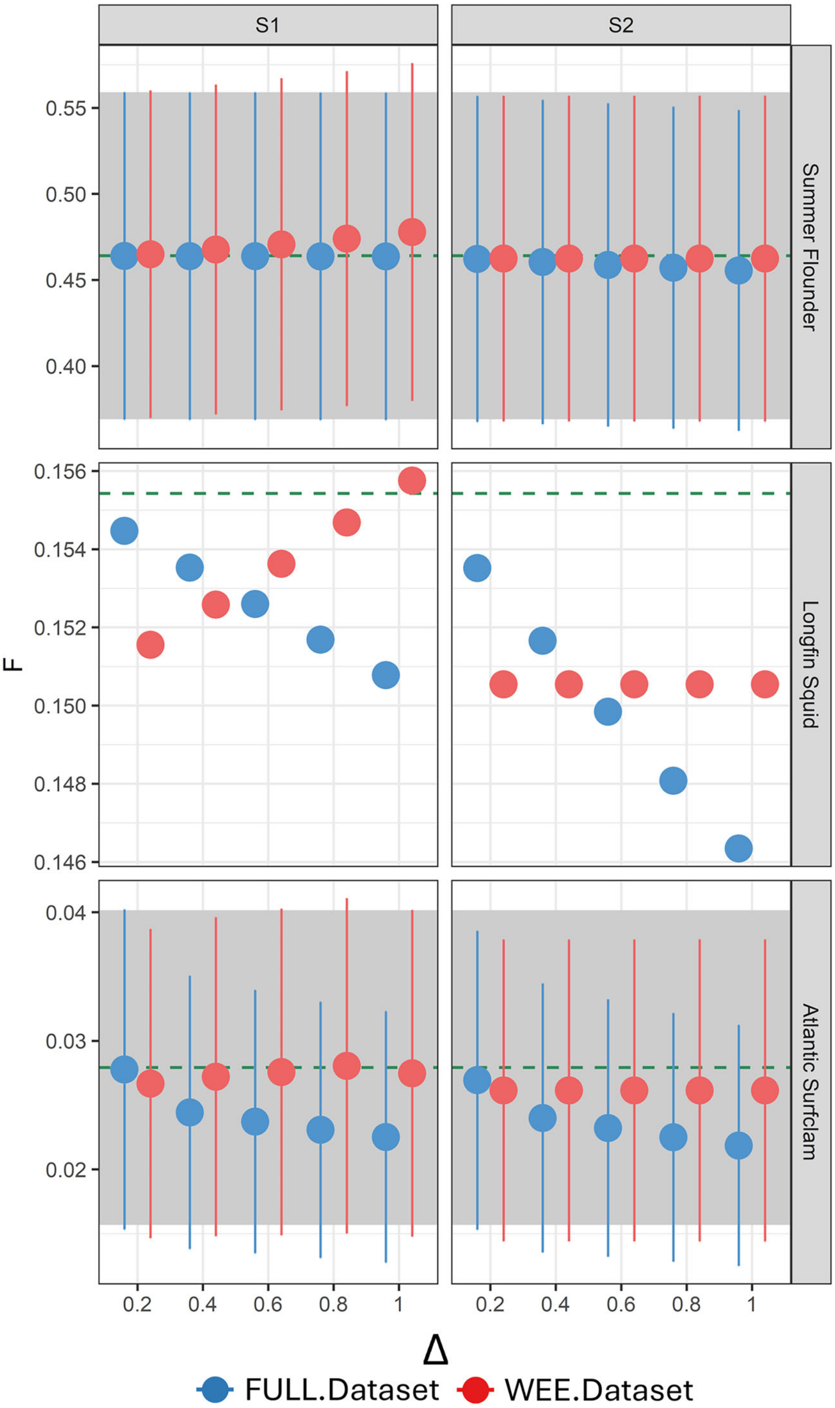

Figure 6 Estimated fishing mortality (F) using complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets under two spatial redistribution scenarios (attraction, S1; production, S2) across five values of proportional increase factor (Δ), for Summer Flounder, Longfin Squid, and Atlantic Surfclam. Points and vertical lines represent estimated median F values and their associated 95% confidence intervals. Shaded areas and green dashed lines indicate the 95% confidence interval and median F, respectively, from the baseline scenario without spatial redistribution. Longfin squid did not have confidence interval because the quantities are estimated from index-based method.

Interpreting attraction-production mechanisms in stock assessment contexts

Failure to account for abundance changes inside WEAs, whether driven by attraction or production mechanisms, increased index variability and degraded assessment performance when survey observations within WEAs were excluded. In contrast, when abundance changes were fully represented in survey data, differences in indices and assessment outcomes between the two mechanisms were comparatively small. These results suggest that stock-wide abundance indices derived from fishery-independent surveys, even when spatially complete, may be insufficient on their

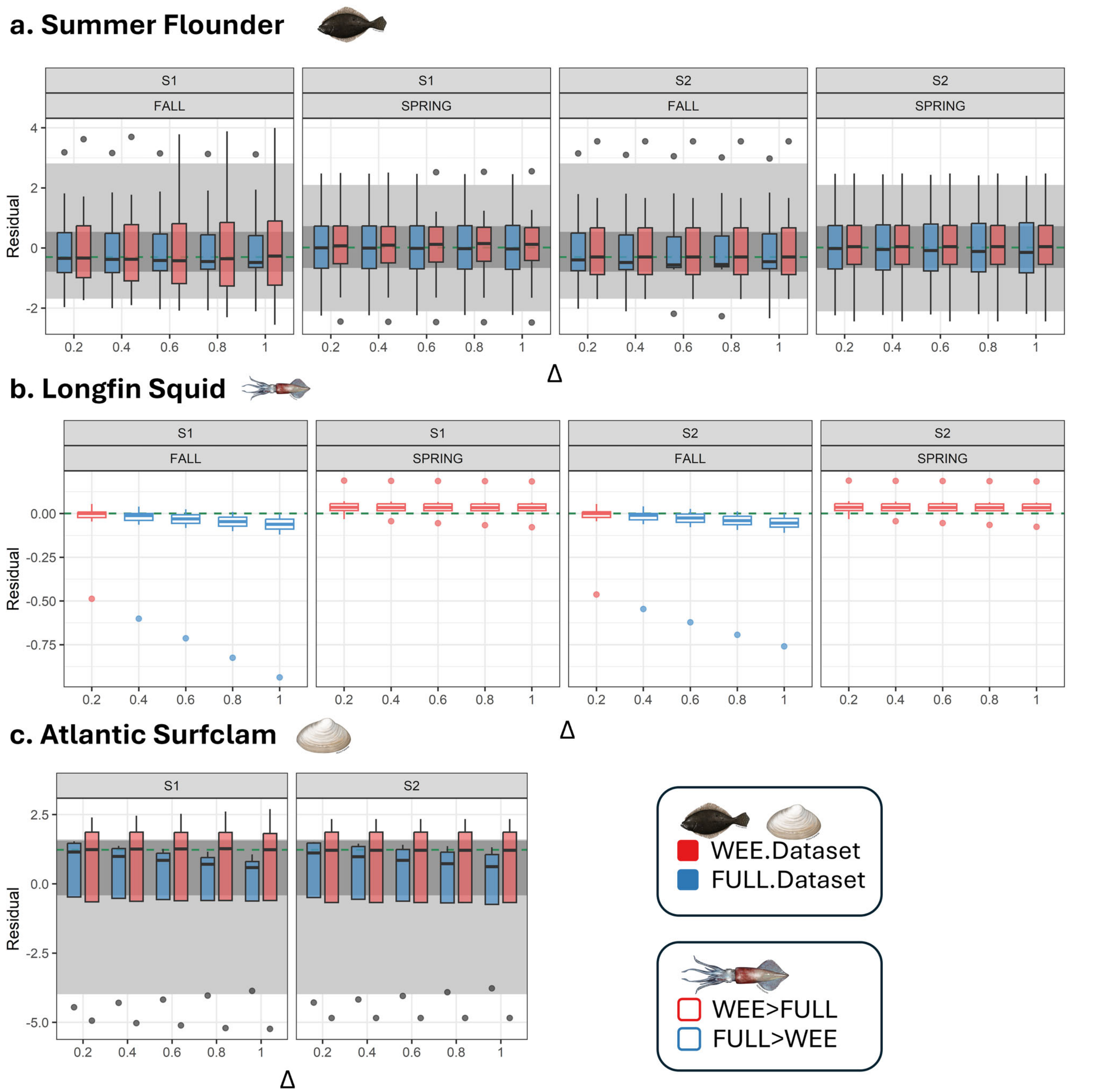

Figure 7 Survey residuals using complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets under two spatial redistribution scenarios (attraction, S1; production S2) across five values of proportional increase factor (Δ), for (a) Summer Flounder and (b) Longfin Squid in spring and fall, and (c) Atlantic Surfclam. Boxplots summarize the distribution of residuals across years, showing medians, interquartile ranges (50%), and whiskers (95%). Shaded areas and green dashed lines indicate the interquartile range (darker for 50% and lighter for 95%) and median residual, respectively, from the baseline scenario without spatial redistribution. For longfin squid, residuals are defined as nominal log-scale deviations between indices estimated from the WEE and FULL datasets and are colored according to the sign of the median deviation.

own to distinguish the underlying ecological processes operating within WEAs.

Although identifying the dominant ecological mechanism was not the primary objective of this study, misinterpretation of attraction and production processes has direct relevance for fisheries management. Overestimating production effects could lead to incorrect expectations of habitat enhancement and increased allowable catches, potentially elevating the risk of overexploitation (Cowan et al. 1999). Attraction effects, by contrast, may concentrate biomass spatially without increasing total population productivity and may vary substantially among species depending on mobility and habitat fidelity (Smith et al. 2015). Recent site-specific studies suggest that offshore wind farms can generate attraction and production effects simultaneously, with demersal species often responding more strongly to production-related habitat changes, whereas pelagic species exhibit clearer attraction responses (Mavraki et al. 2021). While these patterns have important implications for ecosystem-based fisheries management,

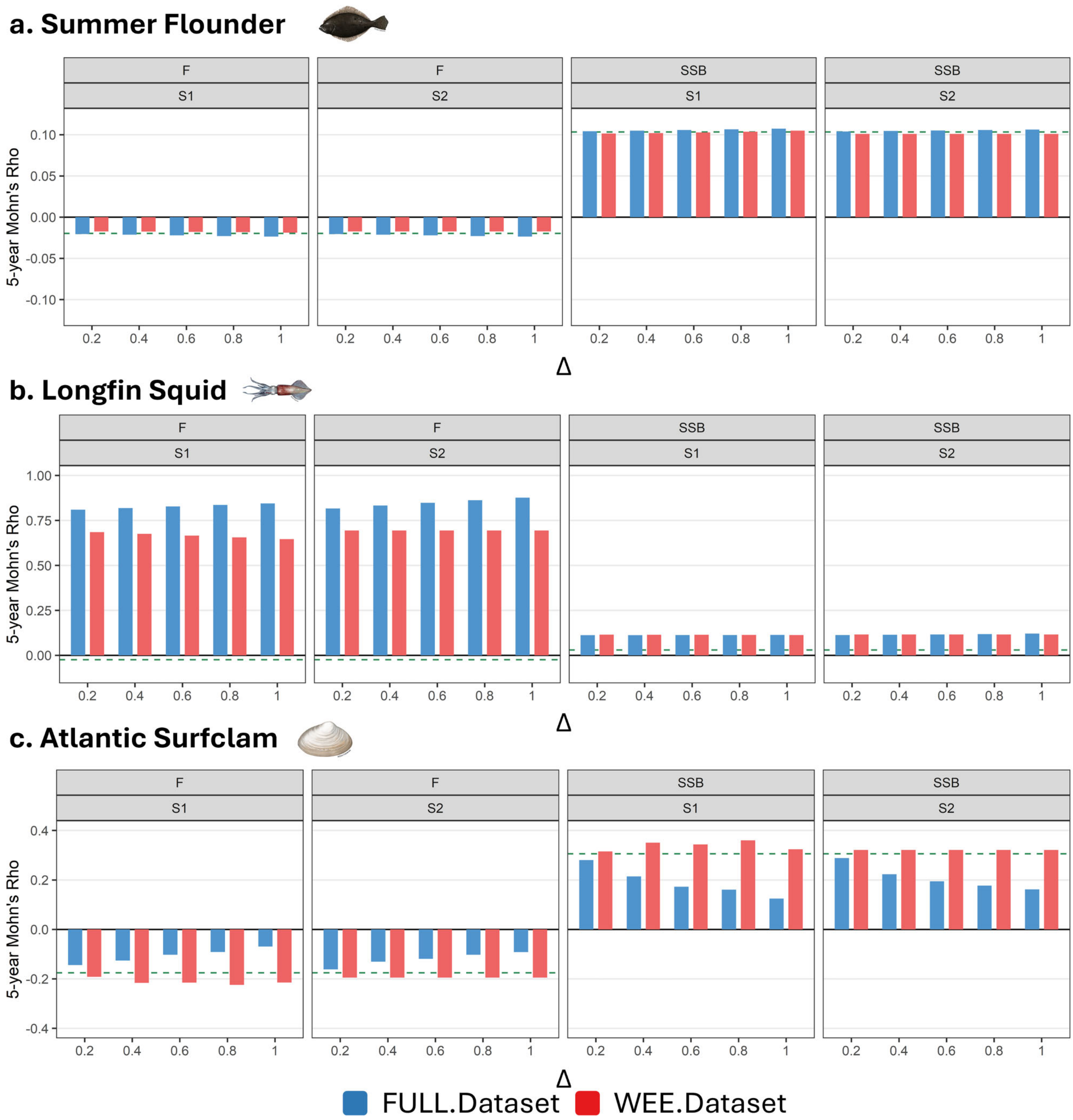

Figure 8 Retrospective error measured by 5-year Mohn's rho for fishing mortality (F) and spawning stock biomass (SSB) estimated using complete survey coverage (FULL) and Wind Energy Excluded (WEE) datasets under two spatial abundance redistribution scenarios (attraction, S1; production, S2) across five values of proportional increase factor (Δ), for (a) Summer Flounder, (b) Longfin Squid, and (c) Atlantic Surfclam. Bars show Mohn's rho calculated from sequential 5-year peel analyses, with values closer to zero indicating lower retrospective bias. Dashed lines denote retrospective error from base scenario without spatial redistribution.

the present study emphasizes that stock assessments are typically conducted at the single-species level, underscoring the need for species-specific interpretation of redistribution processes.

The relative importance of attraction and production mechanisms likely depends on species life-history traits, mobility, and habitat associations. For mobile finfish, turbine foundations and scour protection can create structured habitats that provide shelter, nursery, feeding, and reproductive opportunities, making attraction-driven responses more plausible (Glarou et al. 2020). For benthic invertebrates, offshore wind structures and associated habitat changes may influence local abundance through altered substrate, food availability, benthic conditions, reduced fishing pressure, or post-larval settlement processes (Wilhelmsson and Malm 2008); Chen et al. 2024). For soft-sediment bivalves such as Atlantic surfclam, these responses may operate more indirectly through changes in habitat conditions or food supply rather than active movement toward turbine structures (Moya et al. 2026). Biophysical changes such as enhanced vertical mixing may also increase local nutrient supply and primary production near WEAs (Floeter et al. 2017), potentially strengthening local food availability for Atlantic surfclam.

Robust identification of attraction and production mechanisms associated with offshore wind development therefore requires complementary approaches beyond survey-based abundance indices, in addition to the examination of spatial structure in abundance indices. Modeling approaches applied to long-term monitoring data have been used to infer changes in environmental carrying capacity, where increases in carrying capacity are more consistent with production-driven mechanisms (Roa-Ureta et al. 2019). Trophic analyses, including stomach content and stable isotope studies, can reveal shifts in feeding grounds indicative of attraction toward WEAs (Mavraki et al. 2021). Evidence of increased juvenile recruitment near marine infrastructure may also support production-based interpretations (Claisse et al. 2014), particularly when evaluated using ecosystem energy-flow models. More direct observations of fish spatial behavior can be obtained through acoustic telemetry, which provides insight into aggregation, residency, and seasonal or diel movement patterns around offshore wind farms (Reubens et al. 2013).

However, conclusions drawn from these approaches are strongly influenced by spatial scale and sampling intensity. Small-scale studies may reveal detailed behavioral responses, whereas broader spatial coverage and larger sample sizes are necessary to characterize population-level responses relevant to stock assessment. Integrating these complementary data streams with survey-based indices and assessment models represents a key challenge for interpreting ecological responses to offshore wind development while maintaining reliable stock assessment inference.

Implication for survey mitigation

Both the present study and previous work indicate that offshore wind farm-induced survey preclusion alters the precision and accuracy of survey-derived abundance indices in the US Mid-Atlantic under the full build-out WEAs scenario (Sun et al. 2026). Such alterations can inflate index uncertainty and, in some cases, introduce bias into stock assessment outputs, suggesting necessity of mitigation (Sun et al. under review). However, results from this study demonstrate that increased uncertainty in individual index time series does not necessarily translate into large residuals or degraded assessment performance. Instead, the result depends on the full suite of data that are used and how the model is configured. This suggests that the presence of higher-uncertainty survey indices alone does not automatically warrant exclusion or aggressive mitigation, particularly when those indices remain broadly consistent with other data sources. Moreover, the strength of some diagnostics depended on the number of available index observations. Metrics based on sparse time series, particularly long-term trend tests for Atlantic surfclam, should be interpreted as descriptive indicators rather than strong statistical evidence. Data sparsity can also increase assessment sensitivity to changes in individual survey observations, because each observation may have greater influence on the abundance time series when fewer temporal replicates are available to buffer incidental variability.

In practice, decisions regarding the inclusion or weighting of survey indices in assessment models are not based solely on precision or accuracy metrics. Instead, assessments typically consider whether an index contributes complementary population information and whether its temporal patterns are consistent with other indices, catch data, or fishery-dependent CPUE trends. Indices with relatively low uncertainty but strong disagreement with other data sources may still be down-weighted or excluded, whereas noisier indices that provide unique spatial or demographic information may be retained (Francis 2011), Maunder and Piner 2015). These considerations underscore that effective mitigation should be evaluated in terms of overall assessment performance rather than index-level uncertainty alone.

From this perspective, survey mitigation strategies should aim to preserve or restore robust stock assessment inference relative to baseline conditions where complete survey coverage is available. Offshore wind-related survey preclusion represents a distinct and realistic form of data loss that differs fundamentally from random reductions in survey effort, as it often occurs in spatially contiguous areas and can systematically truncate the survey domain (Conner et al. 2025, Miller 2025). The abundance redistribution effects demonstrated in this study further highlight that survey mitigation strategies may be useful in ensuring survey data quality, yet they could be insufficient in addressing assessment robustness, as changes in fishing behaviors and population demographics shaped by offshore wind may introduce complexities.

One potential mitigation approach is the development of complementary survey programs within WEAs, using alternative gears or non-invasive methods such as cameras, autonomous platforms, or remotely operated vehicles. Indices derived from such surveys could help fill spatial data gaps and improve representation of abundance within excluded areas. However, effective integration of these data into stock assessments will require either careful calibration to account for differences in catchability (Methratta et al. 2023) or a sufficient time series for a stand-alone supplementary index. Ideally, calibration is accomplished through large-scale parallel operation over time, which is resource-intensive and logistically challenging. Even in the best of situations, robust calibration can be exceedingly difficult when observation methods are fundamentally different (e.g. cameras and bottom trawls, longlines and acoustics).

Another potential mitigation approach is to re-stratify the survey. When WEA comprise a proportion of one or more strata, attraction or production driven changes in abundance inside WEA violate the assumption of homogeneity within strata (Cochran 1977). Re-stratifying the survey so that WEAs are a separate stratum could reduce uncertainty in abundance estimation. Similar approaches have been used to stratify surveys for sea scallops (*Placoplecten magellanicus*) based on rotational management areas (Hart and Rago 2006) or habitat and fishery utilization (Smith et al. 2009).

Caveats and prospects

This study simulated survey-derived abundance changes deterministically while holding age and size composition constant within WEAs. This simplification was necessary because limited empirical evidence is available to parameterize realistic age- or size-specific redistribution, and we sought to avoid speculative assumptions in assessment models. However, habitat-mediated redistribution may differ across life-history stages. For example, age-2 red snapper can aggregate disproportionately around oil and gas platforms, producing habitat-specific differences in size and age structure (Gallaway et al. 2009). If similar age- or size-selective responses occur within WEAs, assessment outcomes could be more strongly affected than suggested by abundance-only redistribution, particularly in age-structured models. In addition, while S1 applied compensatory abundance reductions across the full survey domain, real redistribution may occur more locally around marine infrastructure and would require finer knowledge of fish movement to parameterize (Friedland et al. 2025).

We also did not modify catch data or explicitly simulate fleet behavioral responses. This reflected limited empirical guidance on how fleets redistribute effort around WEAs and the difficulty of separating wind-related responses from broader economic and regulatory drivers, which often requires detailed fleet dynamics modeling (Scheld et al. 2022, Campbell et al. 2025). Redistribution was further applied over a fixed recent time window with uniform proportional changes inside WEAs, although real responses are likely to be species-specific, seasonally variable, and influenced by interspecific interactions and development stage (Methratta et al. 2023). For migratory species, WEA-associated redistribution may not persist outside the survey period, so simulated effects should be interpreted relative to the timing of each fishery-independent survey.

Additionally, this study used the full set of WEA boundaries as a broad spatial-exposure scenario. Therefore, the results should be interpreted as potential impacts under a full-buildout or upper-bound preclusion scenario, rather than estimates of impacts from the current operational offshore wind footprint. Evaluating phased development scenarios would require consistent spatially explicit information on project status and future construction timelines.

Future work could extend the present framework by incorporating age- or size-structured redistribution, dynamic fleet responses, and alternative survey designs, as well as by evaluating additional assessment models and ecosystems. Integrating observations—such as telemetry and targeted surveys within WEAs—with simulation-based evaluation will be essential for refining stock assessment strategies under expanding offshore wind development. Incorporation of observation error in survey data and full-loop Management Strategy Evaluation may also allow evaluation of changs in catch advice. Such efforts will be particularly important for identifying species and assessment frameworks most sensitive to spatial redistribution processes and for designing mitigation strategies that remain robust under changing ecological and observational conditions.

Conclusion

This study shows that potential offshore wind farm-induced abundance redistribution can alter survey-derived indices and propagate into stock assessment outputs when redistribution occurs inside areas excluded from fishery-independent surveys. Under the simulated full-buildout WEA scenario, redistribution effects were most evident in increased overall and interannual index variability, altered survey residuals, changes in SSB estimates, and species-specific retrospective patterns. In contrast, monotonic abundance trends and F estimates were generally less sensitive, suggesting that redistribution may affect the precision, representativeness, and diagnostic behavior of survey information more strongly than broad trend direction. The assessment consequences depended on both the redistribution mechanism and whether abundance changes inside WEAs were observable. Attraction-driven redistribution altered spatial abundance without increasing total abundance, whereas production-driven responses represented local abundance gains. However, when WEA observations were excluded, both mechanisms could lead to incomplete or misleading survey signals, and spatially aggregated indices alone may be insufficient to distinguish attraction from production. These findings emphasize that offshore wind-related survey impacts should be evaluated through assessment models, not only through index-level diagnostics. For management, the key challenge is to determine whether abundance changes near offshore wind infrastructure are observable, biologically interpretable, and adequately incorporated into assessment and survey-mitigation strategies.

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Ming Sun (Conceptualization [lead], Data curation [equal], Formal Analysis [lead], Funding acquisition [lead], Investigation [lead], Methodology [lead], Project administration [lead], Resources [equal], Software [lead], Supervision [lead], Validation [lead], Visualization [lead], Writing – original draft [lead], Writing – review & editing [equal]), Derek Bolser (Methodology [equal], Validation [equal], Writing – original draft [equal], Writing – review & editing [equal]), Jessica Blaylock (Data curation [equal], Methodology [equal], Resources [equal], Validation [equal], Writing – review & editing [equal]), Yong Chen (Project administration [equal], Resources [equal], Writing – review & editing [equal]), Daniel Reneau Hennen (Data curation [equal], Methodology [equal], Resources [equal], Validation [equal], Writing – review & editing [equal]), Samuel Truesdell (Data curation [equal], Methodology [equal], Resources [equal], Validation [equal], Writing – review & editing [equal]).

Supplementary material

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

Conflicts of interest

The authors have no conflicts of interest to declare.

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Data availability

The data used in the present study are available online from the NEFSC survey data and stock assessment data portal. The code scripts and scenario-specific configurations used in this study can be accessed at GitHub (https://github.com/mingsun/Stock-assessment-under-spatial-abundance-change.git).

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