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Addressing Spatiotemporal Data Gaps in Fish Abundance Modelling: Insights From Offshore Wind Impacts in the U.S. Mid-Atlantic

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ABSTRACT

Aim: Spatiotemporal data gaps in fishery-independent surveys—arising from offshore wind development, marine protected areas or spatially uneven sampling effort—pose challenges to the consistency and reliability of abundance indices that inform stock assessments. This study evaluates how survey preclusion affects the spatial and temporal behaviour of abundance indices, using offshore wind survey exclusion in key NOAA fisheries surveys in the Mid-Atlantic as a case study to assess impacts on temporal trends, deviations over space and uncertainty for four iconic stocks.

Location: Mid-Atlantic Ocean, US.

Methods: Using four species as case studies, we compared design-based abundance indices derived from a Full dataset (without offshore wind) and a wind energy excluded (WEE) dataset that hypothetically removed all survey tows within wind energy areas (WEAs) across the full time series. Model-based approaches, including statistical models, machine learning methods and vector autoregressive spatial–temporal model (VAST), were then applied to reconstruct tow-level survey data using the WEE dataset and derive spatial and temporal abundance indices. Model-based indices were evaluated in terms of deviations in spatial abundance indices, changes in relative precision, and consistency of temporal trends relative to design-based indices.

Results: Design-based indices retained consistent temporal trends despite emerging errors in absolute abundance estimates and increased variance. Model-based reconstruction partially recovered spatial information within WEAs, but reconstructed spatial abundance indices exhibited greater variability in deviations inside WEAs than outside, whereas changes in relative precision were generally small. Temporal trends in model-based indices were generally consistent with design-based indices, though sensitivity varied by species and time series. Differences among modelling approaches were species-dependent, reflecting contrasts in mobility, spatial aggregation and life history traits.

Main Conclusions: This offshore wind case study demonstrates that survey preclusion primarily affects the spatial representation and magnitude of abundance indices, whereas temporal trend signals can remain robust under moderate data loss. No single modelling approach was consistently robust to survey preclusion across species and index dimensions, reflecting trade-offs between spatial reconstruction behaviour, uncertainty propagation and temporal stability. Species life history traits played a role in model performance: mobile species with stronger spatial autocorrelation were generally less sensitive to spatial preclusion than sessile species with

patchy distribution. These general patterns highlight the need for dimension-specific, life-history-informed modelling approaches when addressing spatiotemporal data gaps arising from marine development and other forms of conflicting marine use.

1 | Introduction

Fishery-independent surveys are an integral component of fisheries management. They provide critical abundance indices and representative biological information for stock assessments, making them essential for fisheries management. Robust survey data are obtained through statistically rigorous design that is strictly followed over time to ensure spatiotemporal abundance is truthfully reflected. However, the consistency in survey design can be compromised by other conflicting marine uses such as offshore wind development or marine protected areas (MPAs).

These marine uses can impact survey data in four ways. First, habitat condition changes due to altered species distributions shaped by closures or man-made facilities; second, navigation difficulties such as having to traverse around the preclusion areas could reduce sampling efficiency; third, sampling gear restrictions often prevent survey operations within the immediate vicinity of the preclusion areas and fourth, the loss of sampling stations due to spatial preclusion reduces statistical power. Although the first two impacts are measured with reliable survey data, the last two impacts essentially disrupt the continuity of existing survey time series. This results in spatially imbalanced survey effort that complicates catch per unit effort standardisation, ultimately diminishing both the survey data quality and quantity. They may also prevent direct comparisons between existing and future survey data due to violations of statistical design, potentially leading to unreliable abundance indices and biased scientific advice for fisheries management actions (Haase et al. 2025; ICES 2023; Anderson et al. 2024).

Among these drivers, offshore wind energy is expanding rapidly worldwide and poses unique and increasing challenges to survey continuity. In the United States, it plays a key role in meeting increasing energy demands and contributes to climate change mitigation (D.O.E. 2023). The Mid-Atlantic region has seen considerable activity and is projected to reach a capacity of 22 Gigawatts in the next decade (Miles et al. 2021). This rapid expansion brings increasing interactions with marine ecosystems and fisheries. Conservation benefits included habitat protection through fisheries exclusion (Gill et al. 2020) and potential increases in local primary production (Floeter et al. 2017). Negative impacts include acoustic disturbance during construction and operation (Mooney et al. 2020) and considerable overlap with long-running fishery-independent survey domains, preventing surveys using extractive gears such as trawls and dredges from operating due to safety zones, infrastructure obstacles and other operational constraints (Lipsky et al. 2025).

These survey preclusion effects and risks to survey integrity are particularly acute in the US Mid-Atlantic, where offshore wind areas overlap substantially with federal survey domains (BOEM 2021). Recognising this issue, the National Oceanic and Atmospheric Administration (NOAA) and the Bureau of Ocean Energy Management (BOEM) have jointly developed a federal mitigation strategy with the common goal of mitigating impacts of offshore wind on fishery surveys (Hare et al. 2022). The strategy identifies federal surveys that are essential to the Mid-Atlantic fisheries stock assessments including the Northeast Fisheries Science Center (NEFSC) Spring and Fall Bottom Trawl Surveys (BTS) and the Atlantic Surfclam and Ocean Quahog Dredge Survey (SCOQ). Although this challenge has raised widespread concern, evaluation and mitigation of survey impacts are still rare globally (Lipsky et al. 2024). Given that the Mid-Atlantic is one of the most productive marine ecosystems in the US and supports commercially and culturally iconic shellfish and finfish fisheries, offshore wind impacts on surveys pose considerable risks for sustainable fisheries management with significant socioeconomic implications.

Spatiotemporal modelling is an instrumental tool supporting fish stock assessments. Spatially, it reveals species distribution patterns and preferred habitats associated with key biotic and abiotic features, which are vital to spatial management and conservation efforts (Grüss and Thorson 2019). Temporally, model-based abundance indices can improve abundance estimates by standardising catch rates with hidden dynamics that cannot be accounted for with the design-based indices (Bryan and Thorson 2023). These model-based indices can demonstrate temporal variations and seasonal patterns in population processes (e.g., phenology), enabling the detection of climate-driven shifts in population dynamics (Thorson, Adams, et al. 2020). Spatiotemporal models are particularly useful in the era of increased marine use. They can quantify spatial overlap between fish distribution and areas of survey preclusion, which are vital to the evaluation of socio-ecological consequences in fisheries management, marine spatial planning and marine conservation (Gill et al. 2020; Stelzenmüller et al. 2021; Püts et al. 2023).

Spatiotemporal modelling approaches offer unique advantages and opportunities to address the gaps created by survey preclusion from WEAs (ICES 2023; Lipsky et al. 2025; Murray et al. 2024). One of the strengths of spatiotemporal models is their capacity to predict abundance in areas with little-to-no survey data such as WEAs (Thorson, Maunder, and Punt 2020). This can be achieved by making predictions through interpolation, extrapolation or forecasting based on selected covariates (Martínez-Minaya et al. 2018). A wide array of spatiotemporal modelling methods provides different options under varying data quality and availability for different species (Guisan and Thuiller 2005). These methods have their own strengths and weaknesses. Traditional statistical models, such as generalised linear models (GLMs) and generalised additive models (GAMs), are among the most widely used tools in fisheries spatiotemporal modelling for their capacities to explain patterns in covariates and make predictions (Elith and Leathwick 2009). Advances in machine learning methods have further expanded spatiotemporal modelling capacities with survey data, offering strong predictive performance, despite the poor explanatory power of covariate effects compared to statistical models (Chu et al. 2016; Lei et al. 2024). Recent developments in spatiotemporal models, such as the

TABLE 1 | Case study species stock assessment and survey information.

Species	Scientific name	Assessment model	NEFSC survey	Survey time series range
Summer flounder	*Paralichthys dentatus*	Age-structured Assessment program	BTS spring and fall	1982–2023
Longfin squid	*Doryteuthis* (*Amerigo*) *pealeii*	Index method	BTS spring and fall	1976–2023
Atlantic surfclam	*Spisula solidissima*	Stock synthesis	SCOQ dredge survey	1982–2022
Ocean quahog	*Arctica islandica*	Stock synthesis	SCOQ dredge survey	1982–2016

Note: The survey time series range used in these stock assessments are defined by benchmark stock assessment models and may differ from the full range of the available survey dataset.

vector autoregressive spatial–temporal (VAST) model, have incorporated spatial–temporal variation and autocorrelation. VAST distinguishes itself from traditional statistical and machine learning models by fitting spatial–temporal variation and autocorrelation as processes, instead of treating them as covariates, which can better reflect the spatiotemporal interaction in distributional dynamics (Thorson and Barnett 2017; Thorson 2019). To date, spatiotemporal models used in offshore wind-related studies have focused mainly on characterising changes in ecosystem structure (Bergström et al. 2013; Gușatu et al. 2021), with limited application in assessing preclusion effects and their implications for abundance modelling and stock assessments. This issue is particularly pressing in the US Mid-Atlantic region, where rapid offshore wind development has introduced challenges for fisheries data collection and management.

In this study, we evaluate spatiotemporal data gaps due to survey preclusion using offshore wind development in the U.S. Mid-Atlantic as a case study. Specifically, we quantify spatial overlap between WEAs and two NOAA Fisheries surveys, assess how hypothetical tow exclusion alters design-based abundance indices for four key stocks, and evaluate a suite of modelling approaches for reconstructing tow-level biomass and resulting spatial abundance indices under preclusion. We further assess whether model-based indices retain temporal trend consistency with design-based indices. Although focused on offshore wind, the framework is transferable to other contexts involving survey closures or spatially imbalanced sampling effort. This study does not model offshore wind–induced redistribution of fish biomass because the historical data do not support realistic projections of behavioural responses or future habitat shifts.

2 | Methods

2.1 | Data Source and Case Study Fisheries

The present study used spatial data of offshore wind areas and fishery-independent surveys. The WEAs geographic information system data in the Mid-Atlantic region were obtained from BOEM as shapefiles (https://www.boem.gov/renewable-energy/mapping-and-data/renewable-energy-gis-data). The NEFSC Spring and Fall BTS and SCOQ survey data were acquired from the NEFSC data port (NEFSC 2024a, 2024b, 2024c). Both surveys follow random-stratified design. Survey data used in this study included survey station spatial location, survey time, tow status and tow-level catch data. Survey statistical design and strata structure information were obtained from NEFSC survey protocols for each survey (Politis et al. 2014; Jacobson and Hennen 2019). Environmental data were also used from the NEFSC data port corresponding to each fish survey tow such as temperature at surface and bottom.

We focused on four case study species in the Mid-Atlantic region including summer flounder (*Paralichthys dentatus*), longfin squid (*Doryteuthis* (*Amerigo*) *pealeii*), Atlantic surfclam (*Spisula solidissima*) and ocean quahog (*Arctica islandica*). These species were selected considering their key socioeconomic status in the Mid-Atlantic region (Gaichas et al. 2018), high reliance on the two NEFSC surveys, and distinctive stock assessments that integrate survey data in different ways (Table 1). Additionally, these case study species represented diverse life history (finfish, cephalopod and shellfish) and movement ability, with the summer flounder and longfin squid being mobile while Atlantic surfclam and ocean quahog are sessile, which might have implications for spatial abundance estimates.

Spatial intersection analysis was used to assess the spatial overlap between survey stations and lease wind energy areas (WEAs). Although the first settled lease areas were not occupied until 2016, we hypothetically applied all the existing settled leased areas to the entire historical survey datasets. This retrospective evaluation allowed us to examine the long-term effects of offshore wind development under the current survey design, reflecting a worst-case scenario where no mitigation was conducted. We did not include planning areas in this analysis due to the high uncertainty surrounding their future status, as these areas have not been formally leased and remain subject to shifting regulatory and political decisions. The collection of tows that were located within the WEAs was then removed from the 'Full dataset', generating a 'wind energy excluded (WEE) dataset' that only contained tows outside WEAs (Figure S1). The WEE dataset essentially covered the spatial areas that have been continuously fished, representing a scenario with compromised yet consistent survey protocol (Ono et al. 2015). A complete analytical framework was developed to address the modelling performance of the two datasets (Figure 1). Technical details of each procedure are presented below.

Preliminary data screening showed that the four selected species were among the most heavily impacted in the two surveys concerned (Appendix S1 and Figures S1–S4). The catch data for

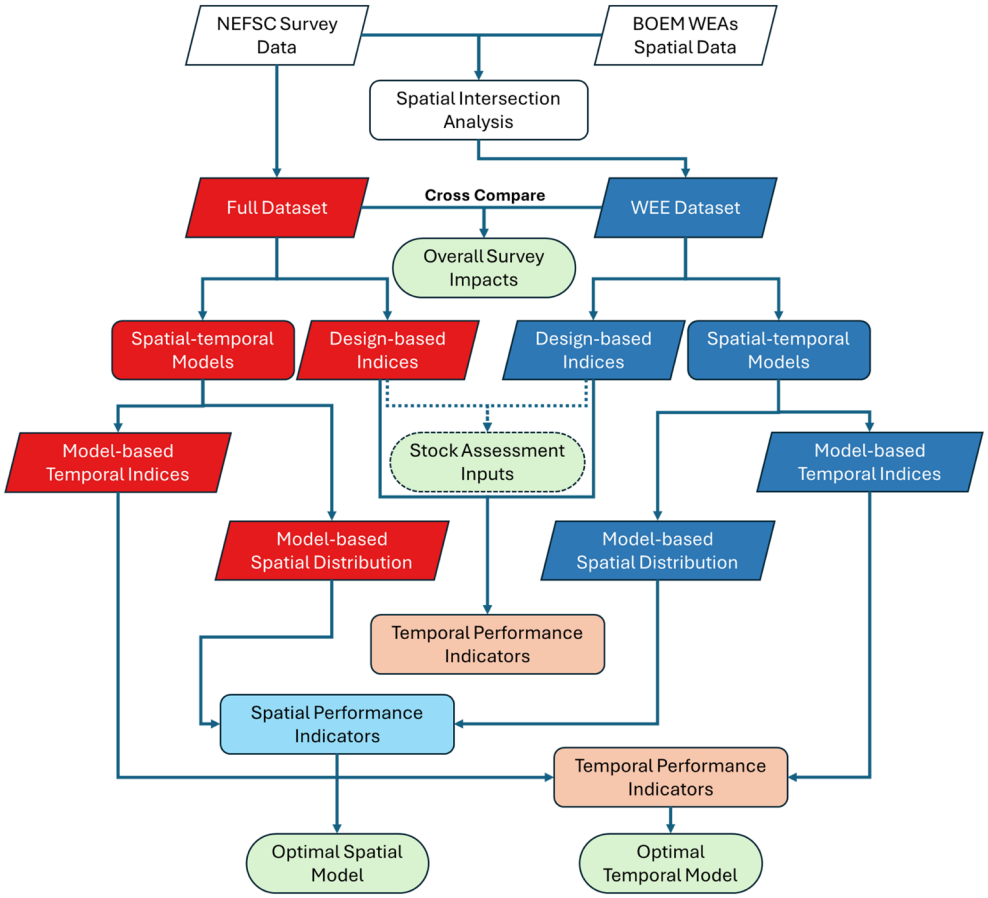

FIGURE 1 | A stepwise workflow of the presented work. Parallelograms represent input or output components at each step. Rectangles represent analyses and indicators. Ovals represent end products, where dashed lines indicate that 'Stock Assessment Input' is not a research subject in this study. The components from the two datasets are coloured in red and blue. WEAs, wind energy areas; WEE, wind energy excluded.

each species were acquired first by extracting the corresponding species information from the NEFSC survey datasets. The resultant dataset then went through a filtering process based on criteria defined for each species' stock assessment purposes, ensuring all the data used in this study were qualified for calculating abundance indices at stock assessment standards. An additional survey data calibration was performed for BTS catch data after 2009 to address bias due to vessel change (Miller et al. 2010).

2.2 | Design-Based Abundance Indices

Design-based abundance indices over time were used in each case study species assessment model. Design-based abundance indices were estimated using the Full and WEE datasets to show their potential discrepancy as a measurement of offshore wind impacts on abundance estimates from the NEFSC surveys. The spring and fall BTS were used to calculate summer flounder and longfin squid abundance indices, whereas the SCOQ were used for Atlantic surfclam and ocean quahog, considering their respective catchability. Design-based indices were calculated as the weighted mean biomass across the entire Mid-Atlantic region based on the random-stratified survey design following the original stratification structure, using raw survey data from the BTS and SCOQ survey database (Cochran 1977; data available at https://www.fisheries.noaa.gov/inport/item/22549). The estimated abundance indices from two datasets were compared for their relative discrepancy and variability by year, as well as overall trend consistency (see Section 2.4 for details).

2.3 | Spatiotemporal Modelling Framework

We developed a spatiotemporal modelling framework consisting of five candidate models with varied statistical design and methods. Spatiotemporal modelling was performed for the four species individually using the WEE dataset to evaluate their ability to reconstruct tow-level catch data inside WEAs and derive abundance indices.

The first model considered was a Generalised Additive Model with Tweedie distribution (Tweedie GAM) via a log link. The Tweedie distribution is a compound Poisson-Gamma distribution featuring a power parameter p, ranging from 1 (Poisson distribution) to 2 (Gamma distribution) in this study (Shono 2008). This assumption has been shown to be effective in handling zero-inflation, which is common in NEFSC trawl and dredging survey data (Leavitt et al. 2018; Roberts et al. 2022). The model structure for Tweedie GAM is as follows:

$$\log(\mu(x)) = X\beta + \sum_j s_j(\mathrm{cov}_j), \quad (1)$$

where $\mu(x)$ denotes the biomass for tow x, $X\beta$ denotes the linear predictor and $s_j(\mathrm{cov}_j)$ denotes the smooth functions of the jth covariate (Supporting Information).

The second model considered was a Delta Generalised Additive Model (Delta-GAM). The Delta-GAM fits two independent models: first the presence probability using a binomial GAM with logit link for all tows, then fitting the level of biomass for tows where present with a Gamma GAM with log link. This two-stage design is favoured in modelling large fisheries survey datasets (Grüss et al. 2014; Kleisner et al. 2017). The Delta-GAM model structure is as follows:

$$\mathrm{logit}(p(x)) = X_1\beta_1 + \sum_j s_j(\mathrm{cov}_j), \tag{2}$$

$$\log(\mu(x)) = X_2\beta_2 + \sum_k s_k(\mathrm{cov}_k), \tag{3}$$

where $p(x)$ denotes the probability of presence for tow x from stage 1, $\mu(x)$ denotes the biomass from stage 2, $X\beta$ denotes the linear predictor and $s(x)$ denotes the smooth functions of the jth and kth covariate for each stage. The overall predicted abundance $\hat{y}(x)$ for tow x is the product of the probability of presence and conditional biomass for each tow:

$$\hat{y}(x) = p(x) \cdot \mu(x). \tag{4}$$

In addition to these traditional statistical models, we further included two machine learning methods that are more data-driven and less model-explicit. The third model, Random Forest (RF), is an ensemble learning method that makes predictions based on numerous decision trees where each tree represents a bootstrapping subsample of data and keeps splitting iteratively by partitioning along individual covariates to minimise the intergroup variance (Biau and Scornet 2016). In this study, RF is applied to model biomass levels as a regression task, rather than classification. A semi-mathematical representation of a regression RF model and single tree is as follows:

$$\hat{y}(x) = \frac{1}{T} \cdot \sum_{t=1}^{T} h_t(x), \tag{5}$$

where $\hat{y}(x)$ denotes the biomass prediction for tow x, T denotes the number of trees in the forest and $h_t(x)$ denotes the prediction results from the tth decision tree. Key parameters in an RF model include T (each has a bootstrap sample) and the optimal number of variables at split (*mtry*). Splits of trees are chosen to maximise the decrease in impurity (variance for regression). The splitting stops when the minimum node size is reached.

The fourth model evaluated was the other tree-based machine learning approach—Bayesian Additive Regression Trees (BART). BART is an ensemble of decision trees model and uses Bayesian inference via MCMC (Carlson 2020) to determine the posterior probability of a model (P(trees|data)) shaped by priors P(trees) and tree parameters (P(data|trees)). BART then models the predictions additively across all trees (sum-of-tree) instead of averaging across them. In this study, we revised BART into a two-stage procedure resembling the Delta-GAM in order to handle the non-positive prediction often generated from BART regression for zero-inflated data. The categorisation modelling (presence/absence) in the first stage was realised by optimising a cutoff threshold that minimised the misclassification error. A semi-mathematical representation of a two-stage BART model is as follows:

$$\hat{y}(x) = \sum_{t=1}^{T} g_t(x), \tag{6}$$

where $\hat{y}(x)$ denotes both the presence probability and biomass prediction, where present, for tow x following the same structure, T denotes the number of trees and $g_t(x)$ denotes the prediction results from the tth tree. Similar to the Delta-GAM, the overall predicted biomass is the product of presence probability and the predicted biomass from the two stages. Prior parameters for tree, node and residual were set following the guidelines by Chipman et al. (2010) and Dorie et al. (2024).

The fifth model considered was vector autoregressive spatial–temporal (VAST) model (Thorson and Barnett 2017; Thorson 2019). VAST is essentially a delta-model built on two linear equations that predict encounter probability and positive catch rates separately. This study used a modified version of VAST in the following form (Thorson 2019):

$$p_1(i) = \beta_1(t_i, c_i) + \omega_1(s_i, c_i) + \epsilon_1(s_i, t_i, c_i) + \nu_1(t_i, c_i) \tag{7}$$

where $p_1(i)$ denotes the predictor for observation i, of category c_i at location s_i in time step t_i. The seven terms included in the equation reflect temporal variation (β_1), spatial variation (ω_1), spatiotemporal variation (ϵ_1) and habitat covariates effect (ν_1). The second linear predictor for positive catch rates has the same variables and parameters. The present study worked with calibrated NEFSC data, hence the modified VAST did not include vessel effects, catchability covariates and fishing impacts, which were already accounted for. We developed single-species univariate VAST models without multispecies or size/age/stage factors, hence category (c_i) was not considered a variable. The VAST models were developed following the best practices guidelines (Thorson 2019) with a quantitative optimal model structure selection procedure to choose error distribution and link function from candidate settings based on Akaike Information Criterion (AIC) and residual mean square error (RMSE) with bias correction assuming anisotropy (Cacciapaglia et al. 2024). Details of the final model structures can be found in Tables S1 and S2.

Environmental and spatiotemporal covariates were included in the two statistical models and two machine learning models. The initial candidate covariates were common variables considered in species distribution modelling including year, season/day, latitude, longitude, surface temperature, bottom temperature and depth. These covariates were then filtered with correlation analysis and boosted regression tree analysis to remove the strong collinearity between them (high correlation) and weak effects (low weighting) on biomass (Xue et al. 2017). The ultimate covariates considered in the model

included year (as a categorical variable to avoid a distribution assumption), latitude, bottom temperature and depth. This set of covariates aligned with variables selected from previous spatiotemporal modelling using NEFSC survey data in the US Northeast (Kleisner et al. 2016, 2017), indicating similar environmental and spatiotemporal effects were considered. For VAST, the environmental covariates were incorporated as density covariates after identifying the best VAST model structure for each species with a two-degree b-spline for both stages, following a pattern characterised by an inverted U-shape, with a peak representing the optimal effect along the curve. The inclusion of these environmental covariates was determined by model fitting diagnostics (see Section 2.4 for details).

2.4 | Model Performance Evaluation

We evaluated abundance estimates across space and time to assess how offshore wind–related survey preclusion and modelling approach influence abundance indices used for stock assessment. Rather than focusing on a single performance metric, we implemented three complementary comparisons designed to isolate distinct mechanisms through which survey preclusion and model choice may affect index behaviour:

Comparison 1: temporal trends and errors in design-based indices derived from Full and WEE datasets, demonstrating preclusion effects on nominal design-based indices.

Comparison 2: deviations and precision of abundance indices derived from original survey data and model-reconstructed survey data using the WEE dataset, demonstrating preclusion effects on spatial abundance indices.

Comparison 3: temporal trends and precision of model-based and design-based estimates using the WEE dataset, demonstrating model effects on temporal abundance indices.

2.4.1 | Spatial Abundance Indices Evaluation

Spatial abundance indices were defined as stratified mean biomass aggregated separately for regions inside and outside WEA, summarised by survey event (year × season) and by time series. Evaluation of deviation and precision in spatial abundance indices was conducted in three steps.

First, candidate models were used to reconstruct the tow-level abundance data. The reconstruction was achieved using the WEE dataset, representing a scenario where tows inside WEAs became unviable due to preclusion effect. Candidate models were developed by fitting the WEE dataset and predicting the inside WEA tows. Model predictions were then generated on the full set of survey locations to reconstruct tow-level abundance within and outside WEAs. To characterise model behaviour at the tow level, agreement between predicted and observed catch values was summarised using a suite of indicators, including centered root mean square error (cRMSE) as a bias-independent error metric, Pearson correlation coefficient (r) as a linear association indicator, and standard deviation (SD) as a variability level indicator, with the following equations:

$$\mathrm{cRMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left((Y_i - \overline{Y}) - \left(E_i - \overline{E}\right)\right)^2}{n}}, \tag{8}$$

$$r = \frac{\sum_{i}^{n}\left(E_i - \overline{E}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(E_i - \overline{E}\right)^2 \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}}, \tag{9}$$

$$\mathrm{SD} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}{n}}, \tag{10}$$

where n is the number of tows evaluated, Y_i is the model predicted abundance at tow i, E_i is the observed abundance, $\overline{E}$ is the average of observed abundance and $\overline{Y}$ is the average of predicted abundance. These results were concisely presented with Taylor diagrams, a visualisation technique summarising relative pattern agreement, variability and bias-independent error structure (Taylor 2001; Kell et al. 2016). Because the primary objective of this study was to evaluate historical reconstruction rather than future spatial redistribution of abundance, no assumptions were made regarding behavioural or distributional changes inside WEAs beyond the observed survey domain. Spatial hold-out validation, in which models fitted to outside-WEA tows were evaluated against observed inside-WEA tows, was conducted as a supplementary analysis to illustrate out-of-sample reconstruction skill; normalised RMSE was used as the primary indicator and results are provided in Supporting Information.

Second, spatial abundance indices were calculated as design-based stratified mean biomass estimates using the reconstructed survey dataset, following the procedure described in Section 2.2. Although WEA boundaries may partially intersect original survey strata, original stratification and associated area weights were retained to ensure consistency across scenarios. Indices were computed separately for inside- and outside-WEA regions for each survey event. Reference spatial abundance indices were calculated from the original survey data (Full dataset) using the same stratified mean estimator, representing indices without survey preclusion.

Third, reconstructed spatial abundance indices were compared to reference indices to evaluate relative deviations and changes in precision associated with survey preclusion and reconstruction. Deviations were quantified as standardised differences between reconstructed and reference indices, calculated as the difference between index values divided by the long-term mean reference index for each time series. This standardisation places deviations on a common scale across models and seasons while reducing sensitivity to low-abundance years. Precision of reconstructed spatial indices was quantified using standard errors (SEs) from the stratified mean estimator and compared to SEs from reference indices. To facilitate comparison of relative precision while accounting for differences in absolute abundance magnitude, SEs were normalised by the long-term mean of the corresponding index time series. Differences between normalised SEs from reconstructed and reference indices were then

used to summarise changes in relative precision. Normalised SE (nSE) was used in place of the coefficient of variation (CV) because survey events with zero estimated abundance (e.g., all inside-WEA tows equal to zero) yield undefined CV values, which would otherwise reduce the effective sample size for comparison.

2.4.2 | Temporal Abundance Indices Evaluation

Temporally, we compared the correlation between design-based and model-based temporal abundance indices as well as their relative precisions, both derived from the WEE dataset. This comparison represented a potential mitigation strategy that entailed using modelling approaches to generate alternative abundance indices when the original survey statistical design was violated. The Spearman correlation coefficient (ρ) was used to measure the strength of monotonic relationships and trends between the two time series.

$$\rho = 1 - \frac{6\sum_i^n d_i^2}{n\left(n^2 - 1\right)}, \tag{11}$$

where d_i is the difference between the two ranks of each observation.

Precision was calculated for each year to examine the presence of drastic changes in variability over time. The annual precision was then aggregated to show overall distributions for each species-model combination in the form of relative change in CV compared to design-based abundance estimates.

Temporal evaluation was performed for both Comparisons 1 and 3. We additionally compared the model-based temporal abundance estimates using the Full and WEE datasets to demonstrate the model stability in the face of preclusion effects. These analyses were presented in Supporting Information.

3 | Results

3.1 | Comparison 1: Design-Based Indices

Discrepancies of varied magnitudes were observed between design-based indices using Full and WEE datasets for four species (Figure 2). For the BTS, the relative differences between the two time series did not follow a consistent seasonal pattern for summer flounder and longfin squid. Specifically, summer flounder demonstrated primarily negative relative difference in the fall, with large discrepancies (≤ -0.3) frequently occurring after 2007, whereas the relative differences in the spring were generally positive and negligible. In contrast, longfin squid exhibited predominately large negative relative differences in the spring (≤ -0.3 and occasionally ≤ -0.6), with an almost random pattern observed in the fall. The SCOQ survey, which did not have seasonal abundance indices, showed very small relative differences between the two datasets for both Atlantic surfclam and ocean quahog. Despite the presence of large relative differences in certain cases, the correlations between the two sets of design-based indices were consistently very high for all species (> 0.93). Despite the fluctuations in survey effort and sample size loss over the survey period (Figures S5 and S6), we only observed significant correlation between survey effort loss and magnitude of relative difference in the BTS spring abundance (Figure S7).

CV trends for the design-based indices between the two datasets demonstrated distinct patterns by species (Figure 3). Summer flounder showed larger increases in CV for its fall abundance, along with poor trend correlation between the two datasets, whereas its spring counterparts had negligible changes and high correlation. Longfin squid, on the contrary, exhibited smaller CV when using the WEE dataset, as well as high trend correlation. The CV changes in shellfish were both negligible in relative differences and trends. There was also a lack of correlation between survey effort loss and changes in CV by year, except for summer flounder in spring in spite of a close-to-zero slope (Figure S8).

3.2 | Comparison 2: Spatial Abundance Indices

3.2.1 | Reconstructed Survey Data

Taylor diagrams summarised two-level agreement between original and model-reconstructed survey data and revealed species-specific differences in reconstruction behaviour, with comparatively smaller differences among modelling approaches within species (Figure 4). For inside-WEA tows, reconstruction behaviour was broadly similar across models for summer flounder and longfin squid, with all models exhibiting moderate correlation (approximately 0.4), comparable cRMSE (approximately 1–1.2), and reduced variability relative to observations. For surfclam, reconstruction diagnostics were also broadly consistent across models, with VAST exhibiting slightly lower correlation but variability more closely aligned with observed values. For ocean quahog, reconstructed variability was generally comparable to observations across models, with VAST exhibiting marginally higher correlation. For outside-WEA tows, random forest (RF) often showed slightly higher tow-level agreement with observations outside WEAs according to correlation and centered root mean square error (cRMSE), although differences among models were modest.

Spatial hold-out validation, in which models fitted to outside-WEA tows were evaluated against observed inside-WEA tows, indicated more pronounced model differences for summer flounder and longfin squid in spring, with RF exhibiting lower prediction error and VAST exhibiting higher error (Figure S9). Across species and models, residual summaries indicated a general tendency toward underestimation of tow-level biomass (Table 2). However, spatial residual maps showed no consistent large-scale spatial structure across the Mid-Atlantic region (Figures S10 and S11).

3.2.2 | Spatial Indices Deviations

Deviations in spatial abundance indices derived from model-reconstructed survey data were generally small relative to reference indices for the same survey events (year × season),

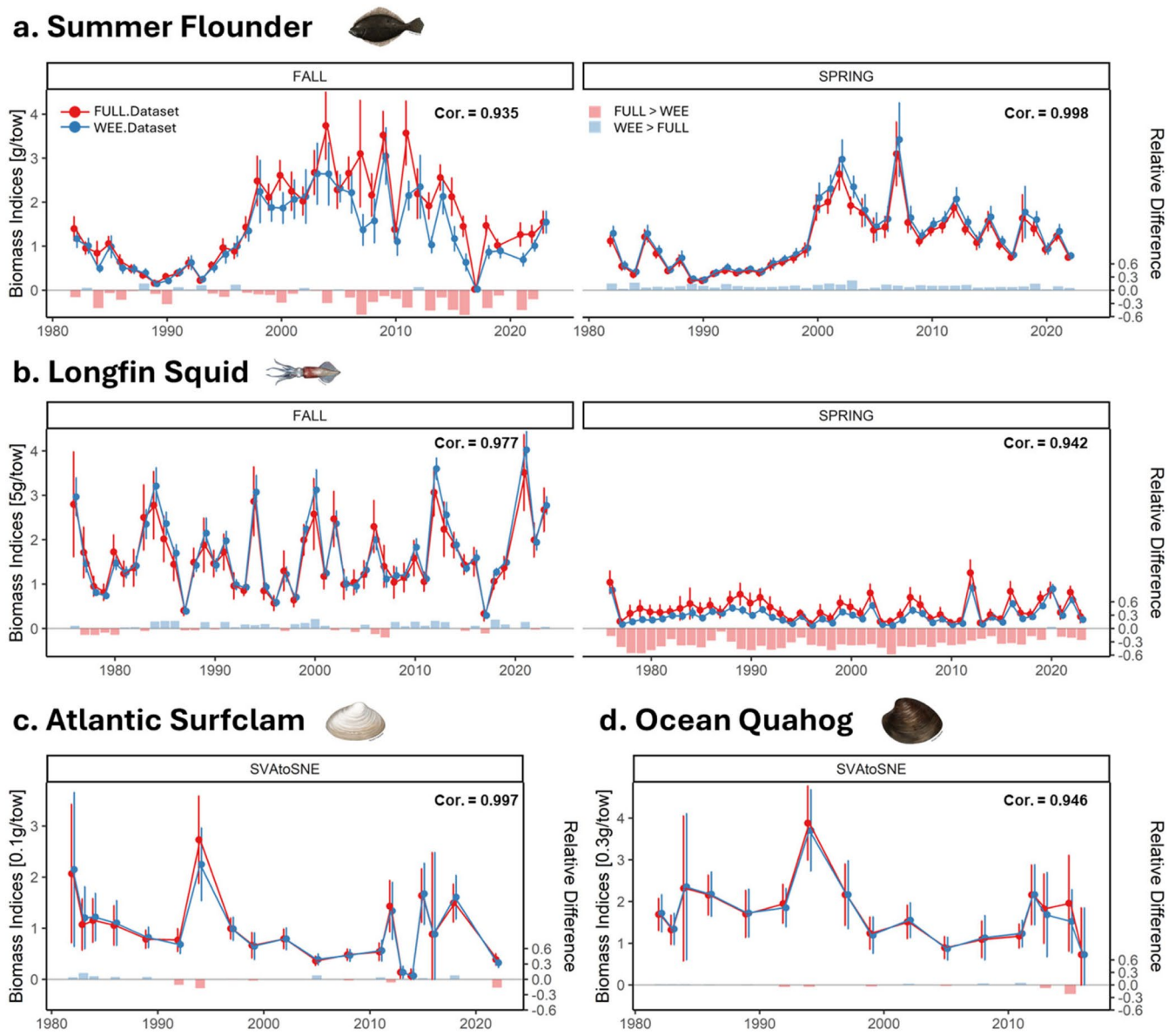

FIGURE 2 | Design-based abundance indices calculated using the Full dataset and WEE dataset for (a) Summer Flounder, (b) Longfin Squid, (c) Atlantic Surfclam, and (d) Ocean Quahog. Note that the time period here corresponds to the survey indices used in the respective stock assessments for each species. Line and dots show the random-stratified indices trend over time with error bars representing 95% confidence interval of estimates. Relative differences between the two time series are shown with bar plots for each year. Spearman correlation values between the indices generated from two datasets are shown on the top-right of each panel.

as indicated by median standardised differences close to zero across species and models (Figure 5). However, the spread of deviations was consistently larger for indices inside WEAs than for those outside WEAs, indicating greater variability in reconstruction outcomes under spatial survey preclusion.

For summer flounder, spatial abundance indices inside WEAs tended to be lower than reference indices during fall, with larger negative deviations occurring in years with relatively high reference abundance (Figure S12). For longfin squid, spring spatial indices inside WEAs tended to show positive deviations, reflecting overestimation relative to reference indices. Surfclam and quahog exhibited more stable deviations over space, with median standardised differences close to zero and comparatively smaller variability across models and survey events. Model-specific patterns in deviations in spatial abundance were species dependent. Across species, Tweedie-GAM, Delta-GAM and Random Forest generally exhibited median deviations closer to zero, whereas VAST more frequently showed median deviations further from zero, indicating larger deviation from reference spatial indices under reconstruction.

3.2.3 | Spatial Indices Precision

Changes in precision of spatial abundance indices derived from model-assisted reconstructed survey data were generally small relative to reference indices for the same survey events (year×season), as indicated by median differences in normalised standard errors (nSE) close to zero across species and

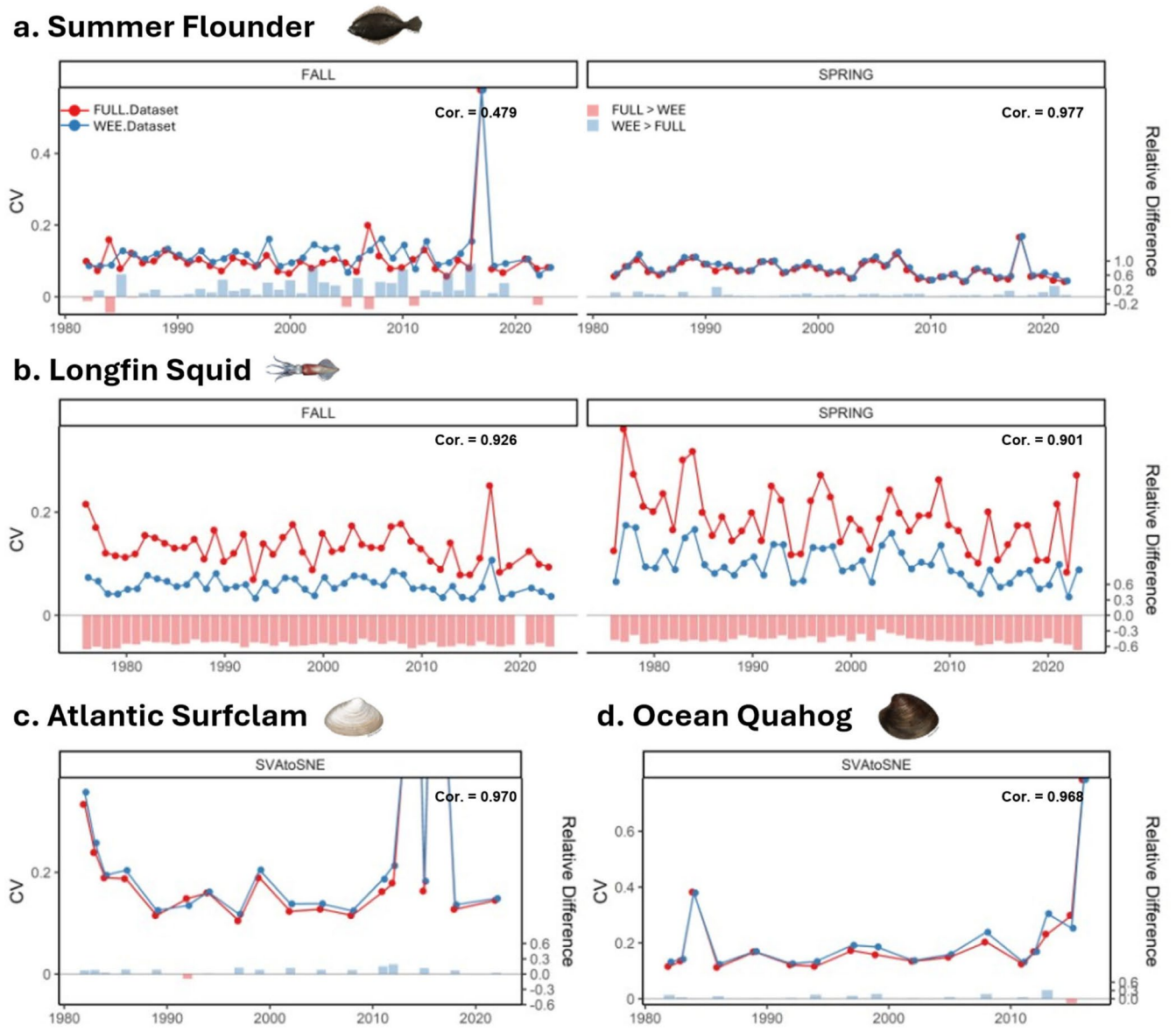

FIGURE 3 | CV of design-based abundance indices shown in Figure 2 for (a) Summer Flounder, (b) Longfin Squid, (c) Atlantic Surfclam, and (d) Ocean Quahog. Line and dots show the annual CV trend over time. Relative differences between the CVs from the two time series are shown with bar plotsfor each year.

models (Figure 6). This pattern was particularly evident for indices inside WEAs, for which median differences were near zero in most cases. An exception occurred for summer flounder in fall, where larger departures from zero were observed, although the magnitude of change in nSE remained modest (generally <0.5).

For indices outside WEAs, differences in nSE were typically slightly negative across models, indicating marginally lower relative uncertainty in reconstructed indices compared to reference indices. Model-specific differences in precision change were generally weak. Across species and seasons, Random Forest tended to exhibit differences in normalised SE closest to zero, suggesting greater preservation of relative precision under reconstruction; however, differences among models were small relative to variability across survey events.

3.3 | Comparison 3: Temporal Abundance Indices

3.3.1 | Temporal Trend Correlation

With the WEE dataset, the temporal trend correlation between the design-based indices and the model-based indices showed medium (rank correlation coefficients between 0.5 and 0.75) to strong (correlation coefficients >0.75) consistency across most models and species (Figure 7), indicating the model-based approaches could reproduce the temporal trends from design-based indices. For summer flounder and longfin squid, VAST produced the highest correlation for both seasons, followed by RF. These species also exhibited contrasting seasonal patterns, with higher correlations observed in spring for summer flounder and fall for longfin squid. Tweedie- and Delta-GAM consistently generated better trend analogues for summer flounder than

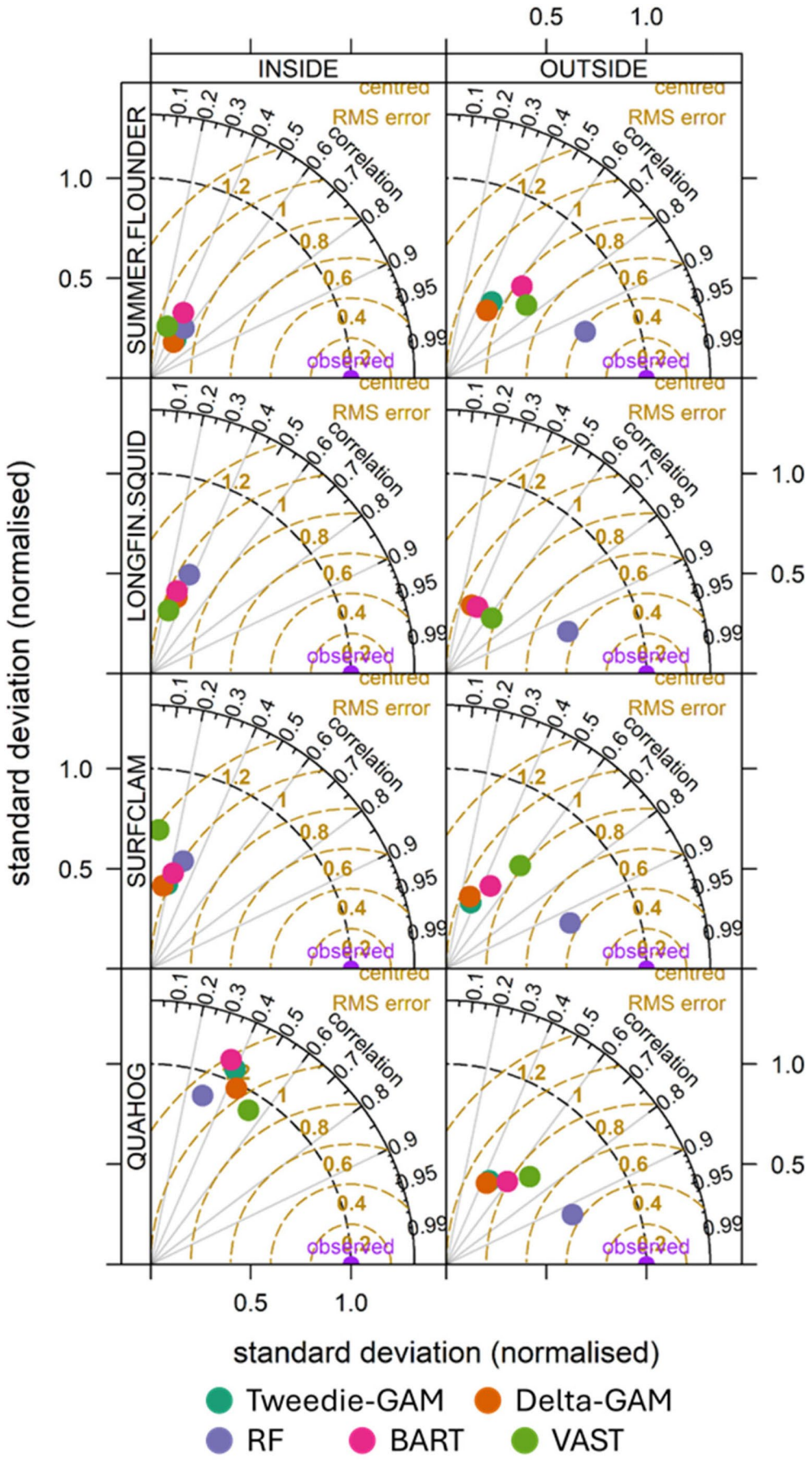

FIGURE 4 | Legend on next page.

FIGURE 4 | Taylor diagram summarising tow-level agreement between observed and model-reconstructed biomass inside and outside WEAs. Purple points labelled 'observed' denote the reference observations. Radial distance represents normalised standard deviation of reconstructed biomass relative to observations, angular position indicates Pearson correlation, and dashed arcs denote centered root mean square error (cRMSE).

TABLE 2 | Normalised prediction error (NPE) of model-based spatial abundance estimates using WEE dataset.

Species	Region	Model				
		Tweedie-GAM	Delta-GAM	RF	BART	VAST
Summer Flounder	WEA					
	Outside					
Longfin Squid	WEA					
	Outside					
Atlantic Surfclam	WEA					
	Outside					
Ocean Quahog	WEA					
	Outside					

Note: Red and blue indicate the proportions of tows with positive NPE (overestimated biomass) and negative NPE (underestimated biomass), respectively.

longfin squid. In contrast, for the two shellfish species, the statistical models produced higher correlations than RF, whereas VAST performed extremely poorly (correlation coefficient <0.3).

The partial year effect was extracted from model results to represent the temporal trend in abundance as model-based indices (Figures S13–S16). Overall, the model-based indices derived from the Full and WEE datasets had highly consistent trend correlations (>0.95) in most cases and small relative disparities between them (mean relative error close to 0) (Table S3).

3.3.2 | Temporal Indices Relative Precision

The relative precision of model-based temporal indices compared with design-based indices revealed substantial variation in relative changes in CV across species and models (Figure 8). Overall, model-based indices using the WEE dataset tended to increase the CV in most scenarios (positive relative change) compared to design-based indices, reflecting a general reduction in temporal trend precision when using model-based approaches with the truncated dataset. Seasonal discrepancies were observed for summer flounder, with the greatest ranges and highest median values of relative changes in CV among all species occurring in spring, except for VAST. Longfin squid demonstrated smaller seasonal discrepancies yet moderate variations between models, with BART demonstrating negligible changes in CV. The two shellfish species (Atlantic surfclam and ocean quahog) showed similar patterns in model performance, with VAST and Delta-GAM producing the largest relative changes in CV, whereas BART exhibited the smallest changes. However, BART exhibited the most frequent presence of extreme outliers for summer flounder, Atlantic surfclam and ocean quahog.

The model-based indices derived from the Full and WEE datasets mostly showed negligible changes in relative precisions (mean relative changes in CV close to 0), except for occasional high changes in Tweedie-GAM (Table S3).

4 | Discussion

Excluding tows inside WEAs through the WEE dataset altered survey coverage and influenced both the spatial representation of the survey and the behaviour of abundance indices. Across species and models, we observed: (1) ~10% loss of survey effort and slightly $<10\%$ loss of samples with interannual variability; (2) minimal trend changes for design-based indices (correlation >0.9) despite moderate differences in index magnitude (relative difference <0.6); (3) greater variability in spatial deviations for reconstructed indices inside WEAs than outside, with generally small changes in relative precision and (4) moderate–strong temporal trend consistency between design- and model-based indices (correlation >0.5) alongside shifts in relative precision. Together, these results suggest that survey preclusion primarily affects the spatial representativeness of survey information and can propagate to index magnitude and spatial stability, whereas temporal trends are comparatively robust under modest coverage loss.

These patterns highlight the complementary roles of design- and model-based approaches under survey preclusion. Design-based indices showed limited trend impacts, whereas spatiotemporal model reconstruction enabled partial recovery of spatial information within WEAs by filling tow-level data gaps. Consistent with previous studies, our results indicate that modest losses in survey coverage do not necessarily result in substantial changes in temporal trends of design-based indices when unaffected areas remain informative. However, we found that the effects of survey preclusion are more pronounced in space than in time: reconstructed tow-level biomass and spatial abundance indices exhibited greater deviation from reference indices than outside WEAs, whereas changes in relative precision and temporal trend consistency were generally small. These findings highlight that model sensitivity to survey preclusion depends on the dimension being evaluated (spatial vs. temporal) and emphasise the need to assess model behaviour across both dimensions when selecting approaches for survey preclusion mitigation. Below we summarise how modelling approaches differ in sensitivity to preclusion across both spatial reconstruction and temporal

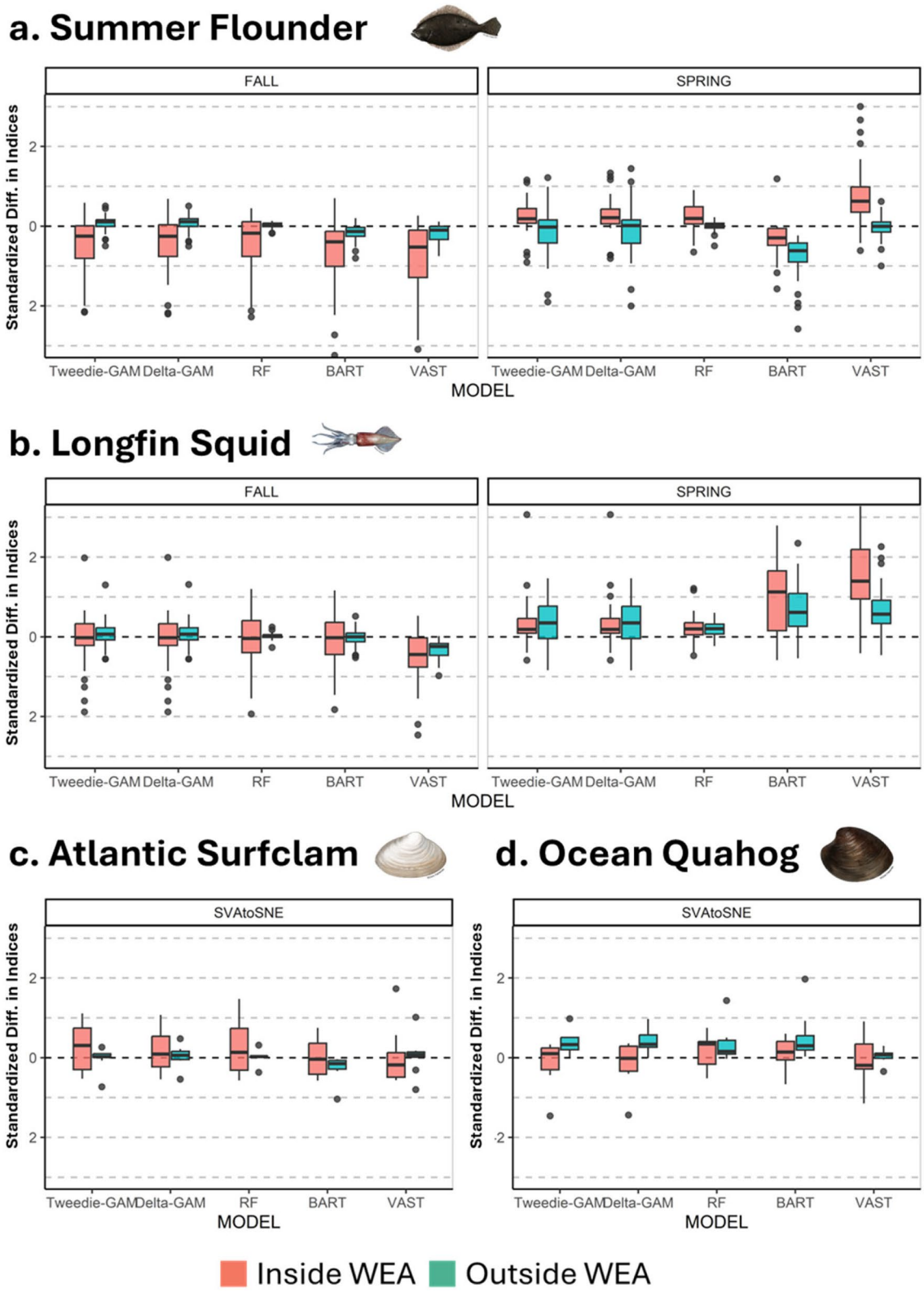

FIGURE 5 | Deviations in spatial abundance indices, summarised as standardised differences between reference indices derived from original survey data and indices derived from model-reconstructed survey data. Boxplots represent survey events (year × season); values near zero indicate minimal deviation, with positive (negative) values indicating higher (lower) reconstructed indices. Ranges of standardised difference are truncated to −3 to 3. Full-scale figure can be fou Deviations in spatial abundance indices for (a) Summer Flounder, (b) Longfin Squid, (c) Atlantic Surfclam, and (d) Ocean Quahog, summarised as standardised differences between reference indices derived from original survey data and indices derived from model-reconstructed survey data. Boxplots represent survey events (year × season); values near zero indicate minimal deviation, with positive (negative) values indicating higher (lower) reconstructed indices. Ranges of standardised difference are truncated to −3 to 3. Full-scale figure can be found in supplementary Materials Figure S12.

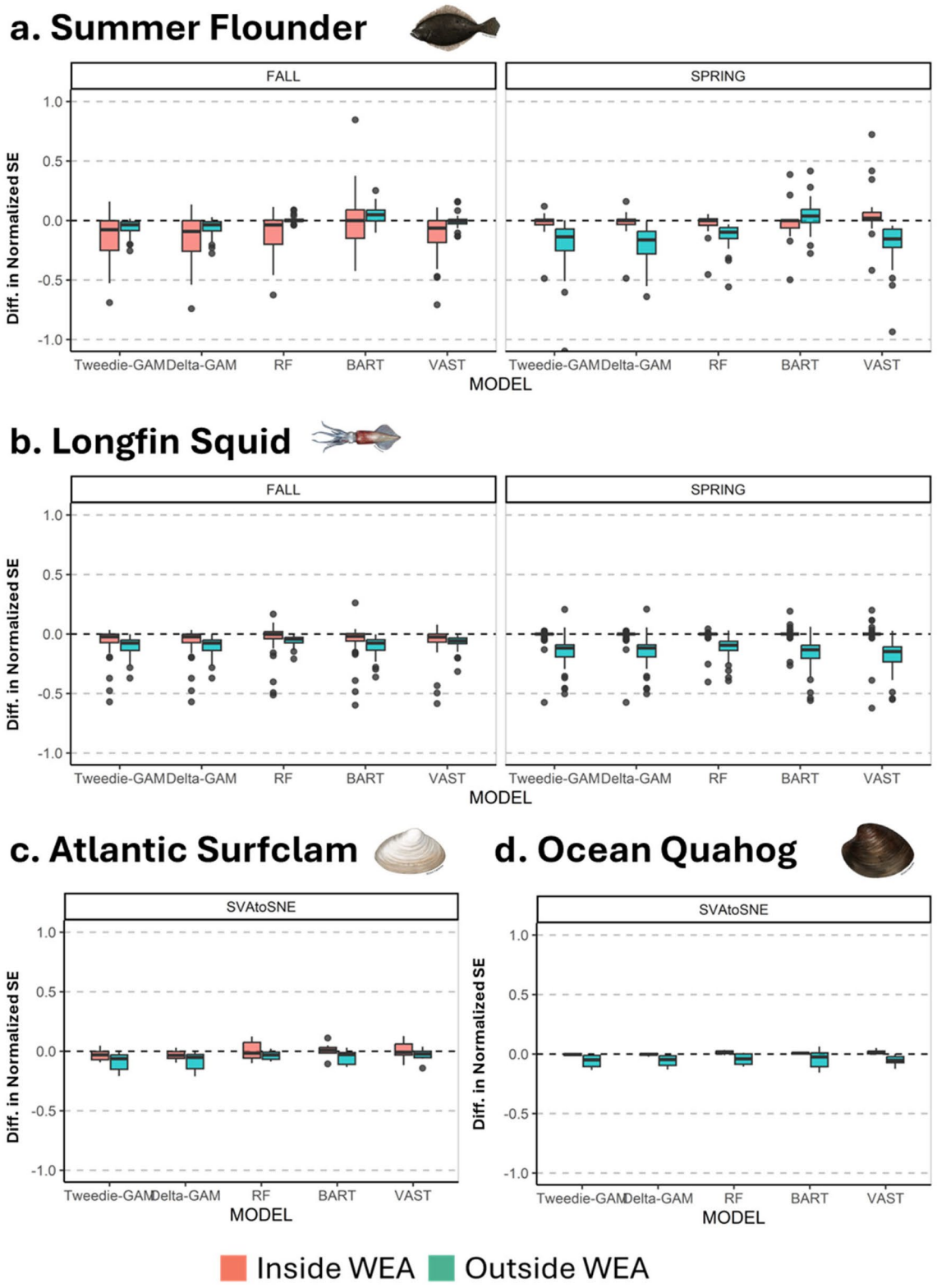

FIGURE 6 | Precision changes in spatial abundance indices for (a) Summer Flounder, (b) Longfin Squid, (c) Atlantic Surfclam, and (d) Ocean Quahog, summarized as differences in normalized Standard Errors between reference indices derived from original survey data and indices derived from model-assisted reconstructed survey data. Values near zero indicate similar relative precision, with positive (negative) values indicating higher (lower) relative uncertainty in reconstructed indices.

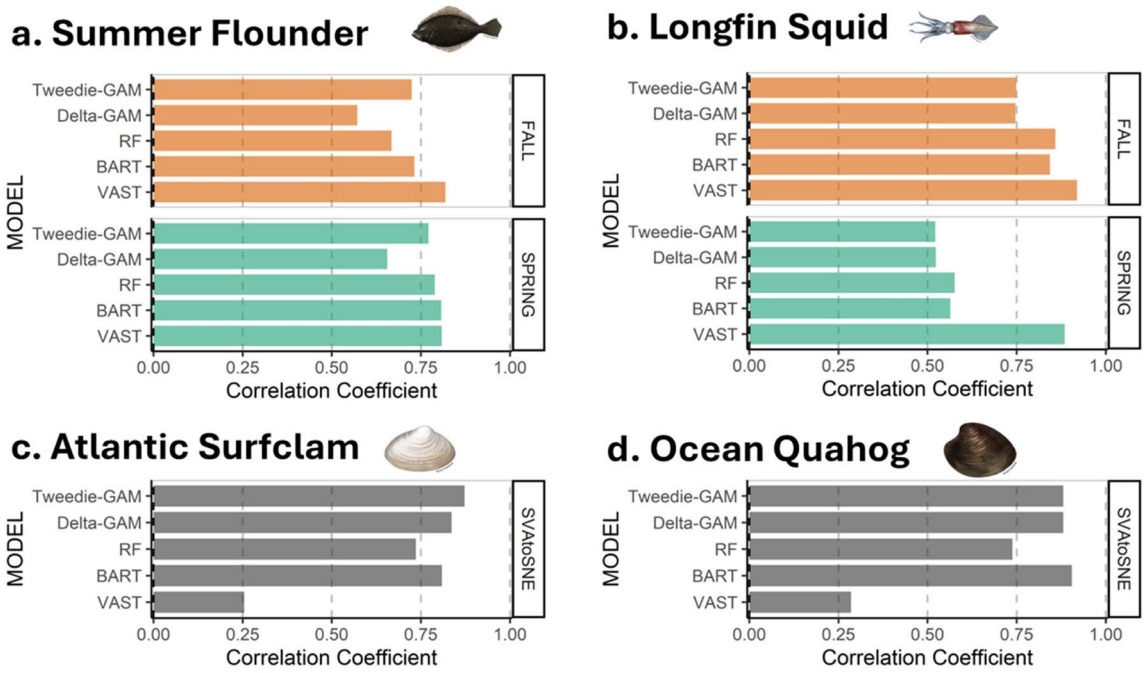

FIGURE 7 | Temporal trend correlation between the design-based indices and the model-based indices (both using WEE dataset) measured with Spearman correlation coefficient for the four species (a–d).

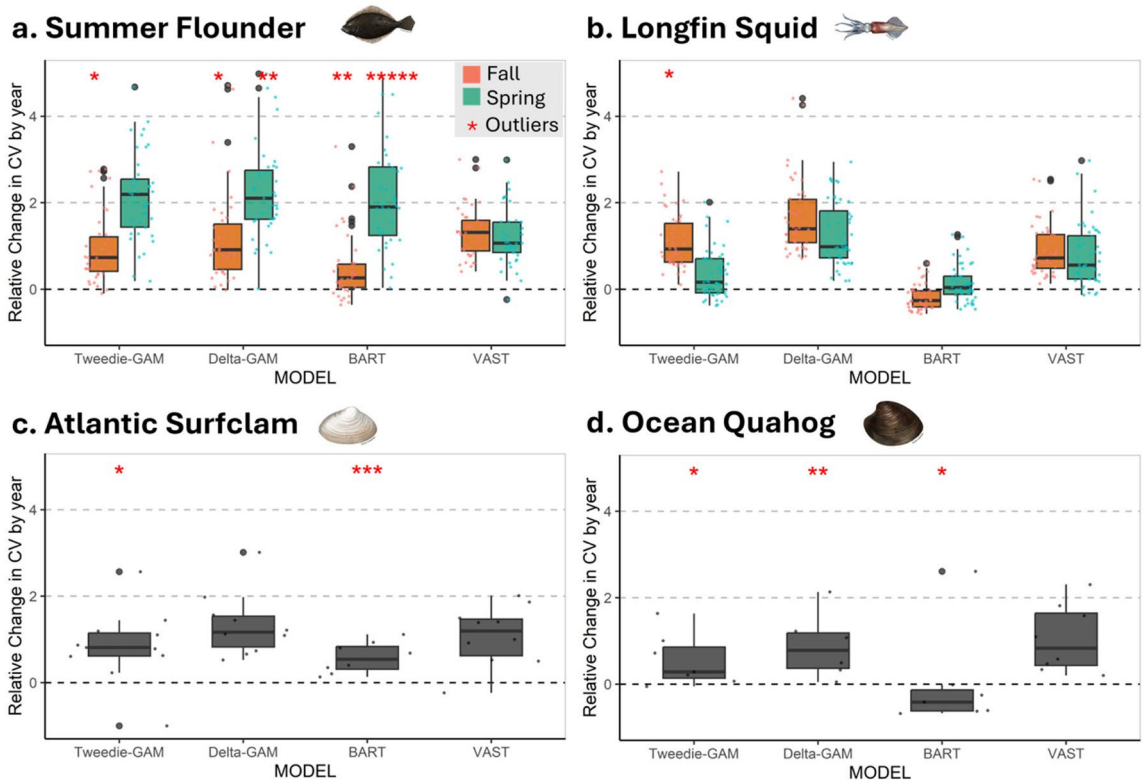

FIGURE 8 | Relative precision of temporal indices modelling performance, comparing the design-based indices with model-based indices (both using WEE dataset) for the four species (a–d). Performance is measured by the relative change in coefficient of variation (CV), calculated as (model-based CV − design-based CV)/design-based CV. Boxplots represent the distribution of relative changes in CV for each year. The number of outliers excluded from calculations is indicated by red asterisks above each model. RF does not produce a comparable precision indicator using CV, thus not shown here. The trend in relative change in CV by year can be found in Figures S17–S20.

index behaviour, discuss potential species-level drivers, and consider implications for stock assessment diagnostics and mitigation strategies.

4.1 | Modelling Survey Impacts: Model Performance and Sensitivity

Survey preclusion is not unique to offshore wind. Similar disruptions arise when surveys are excluded from marine protected areas or when catch per unit effort indices are distorted by spatially imbalanced fishing effort. Across these contexts, restricted access reduces survey coverage, weakens statistical power, and can bias abundance indices. Offshore wind development represents one prominent and growing case, where turbine arrays create preclusion zones that interfere with bottom trawl and dredge surveys (Lipsky et al. 2025). These challenges motivate the application of model-based and model-assisted approaches to evaluate how survey preclusion propagates into abundance indices. For example, VAST and two-stage delta models have been employed to assess MPA impacts on abundance indices, concluding that spatial closure effects reduce the precision of survey abundance indices and introduce trend bias (Ono et al. 2015; Anderson et al. 2024). Studies have found that using data from consistently unaffected survey areas minimises bias from low survey effort loss (Ono et al. 2015), echoing our findings with the WEE dataset, which had less than 10% loss in survey effort and sample size. Additionally, statistical models (GLMs and GAMs), machine learning techniques (RF and neural networks) and VAST have shown the utility of habitat-based approaches combined with spatial autocorrelation and spatiotemporal processes for commercial catch per unit effort standardisation (Li et al. 2015; Xu et al. 2024; Thorson, Maunder, and Punt 2020). Across all models examined, no single method consistently minimised both deviations and changes in relative precision for spatial abundance indices while also preserving temporal trend consistency under survey preclusion. Instead, model sensitivity varied by species, season and index dimension. In the sections below, we discuss how different modelling approaches perform under these constraints and the broader lessons they provide.

4.1.1 | Generalised Additive Models (GAMs)

Tweedie-GAM and Delta-GAM exhibited stable behaviour under survey preclusion, particularly in maintaining temporal consistency of abundance trends and moderate stability in spatial abundance indices. This behaviour reflects the structured formulation of GAMs, which explicitly model smooth relationships between abundance and environmental covariates and provide transparent inference suitable for stock assessment applications (Boenish and Chen 2018; Chang et al. 2023). The Delta-GAM occasionally exhibited slightly reduced dispersion in deviations over space relative to the Tweedie-GAM, particularly in low-abundance seasons, although differences were modest and species dependent. The separation of encounter probability and positive biomass processes may contribute to this behaviour, but presence-absence performance was not evaluated independently in this study. Overall, GAM-based approaches offered a balance between spatial reconstruction stability and temporal trend consistency under moderate survey preclusion, making them suitable for various offshore wind applications (Stenberg et al. 2015; Wilber et al. 2022), provided that appropriate model selection procedures are followed.

4.1.2 | Random Forest (RF)

RF demonstrated relatively stable behaviour under survey preclusion, particularly in preserving the relative precision of spatial abundance indices and maintaining temporal consistency in abundance trends. In the spatial reconstruction diagnostics, RF produced tow-level agreement with observations that was comparable outside WEAs and more variable inside WEAs, and spatial hold-out validation indicated relatively consistent out-of-sample reconstruction performance for some time series. This behaviour is consistent with RF's flexible structure, ability to capture nonlinear interactions in population dynamics and among covariates, and simplicity in parameterization (Li et al. 2015; Stock et al. 2020). However, RF also showed species-specific sensitivity in spatial abundance indices deviations, and its reconstruction behaviour varied more across space than over time. The absence of an explicit likelihood-based framework limits mechanistic interpretation of reconstructed patterns, and uncertainty estimates are indirect relative to parametric approaches. As a result, while RF provides a flexible and practical tool for spatial gaps filling under moderate survey preclusion, its outputs should be interpreted as data-driven reconstructions and applied cautiously when extending inference beyond the surveyed spatial or temporal domain.

4.1.3 | Bayesian Additive Regression Trees (BART)

BART is well suited for modelling binary outcomes such as species presence-absence (Carlson 2020). For zero-inflated biomass survey data, BART can yield unrealistic negative predictions when applied directly, necessitating the two-stage implementation adopted in this study. This framework avoids implausible estimates and enables reconstruction of tow-level biomass under survey preclusion, although deviations in reconstructed spatial abundance indices were more variable across species and seasons, particularly inside WEAs. In addition, BART's fully Bayesian formulation provides posterior uncertainty estimates that can support risk-aware interpretation of reconstructed indices (Thompson et al. 2023). However, the added complexity of the two-stage structure and sensitivity to data sparsity may contribute to increased variability in spatial reconstruction outcomes. Consequently, while BART can be informative for uncertainty characterisation under survey preclusion, careful consideration of data quality and model configuration is required to ensure stable spatial index reconstruction.

4.1.4 | Vector Autoregressive Spatial–Temporal (VAST)

VAST incorporates explicit spatial and spatiotemporal random effects and is widely used to standardise abundance indices under incomplete survey coverage (Ducharme-Barth

et al. 2022; Xu et al. 2024). In this study, VAST exhibited pronounced species-dependent sensitivity to survey preclusion: spatial abundance indices reconstructed with VAST showed standardised deviations that were near zero for some species but further from zero for others, and temporal abundance indices exhibited a wider range of trend correlation with design-based indices relative to other modelling approaches. These patterns suggest that VAST can effectively capture broad spatiotemporal structure but may be sensitive to spatial aggregation and temporal correlation underlying the data examined. Habitat covariates were excluded from the final VAST configurations because dominant spatial and temporal patterns were adequately represented by random effects and covariates did not improve reconstruction diagnostics (Perretti and Thorson 2019). Overall, while VAST has proven a powerful approach in developing abundance indices across a range of species (Cao et al. 2017; Guan et al. 2017; Hodgdon et al. 2020; Hansell and Curti 2023), its performance can be sensitive to species ecology and survey spatial design.

4.2 | Species Life History Effects on Model Outcomes

Life history traits strongly influenced modelling outcomes under survey preclusion for both spatial and temporal indices. Sessile species showed greater annual and trend bias in VAST because patchy distributions and weak spatial autocorrelation conflict with its random-field assumptions. Due to low mobility, sessile species' local abundance is shaped by recruitment and mortality occurring within a limited area (Hennen et al. 2018). Therefore, at the scale of sampling considered here, mobile species exhibit stronger spatial autocorrelation in abundance, whereas shellfish distribution tends to be patchier (Friedland et al. 2023), which can be difficult to represent with stationary spatial autocorrelation assumptions. Furthermore, differences in mobility across life stages add complexity. Although juvenile and adult shellfish exhibit limited mobility post-settlement, they possess greater dispersal capacity during the planktonic stage (Thouzeau et al. 1991; Cadrin 2024). Spatiotemporal modelling might benefit from tailored life-stage-specific model structures (Guisan and Thuiller 2005), which still remain rare. Additionally, survey catchability differences present challenges in identifying shellfish distributions; for example, autocorrelation estimates based on BTS data (Friedland et al. 2023) appear to underrepresent shellfish compared to dredge surveys, which are also common for finfish abundance estimation (Anderson et al. 2024). Future studies are needed to disentangle how species life history and survey design jointly influence deviations in spatial abundance indices and uncertainty propagation in abundance indices under partial survey coverage.

The unique life history of longfin squid, including a short lifespan, semelparous reproduction and highly variable growth, has historically complicated stock assessment and population modelling (Arkhipkin et al. 2021). Our study underscores this challenge, reflected by larger variability in spatial abundance index deviations and stronger seasonal differences in abundance indices compared to the other mobile species (summer flounder). Deviations in spatial abundance indices and temporal variability were particularly pronounced for squid in spring, when offshore distribution reduces BTS availability and abundance levels are low, consistent with known seasonal migration patterns (Hatfield and Cadrin 2002). Squid tend to be located further offshore in the spring and are less available to the BTS; while in the fall, they spread more evenly across the continental shelf and become more prevalent in the BTS catches (Figure S2). Meanwhile, summer flounders move inshore during the spring and back offshore in the fall, resulting in seasonal abundance patterns reflected in BTS data (Figure S2). Since cephalopod distribution is largely driven by environmental factors and exhibits catch seasonality by depth, traditional statistical models, such as GAMs, performed well in tracking abundance trends when appropriate environmental (temperature, depth) and spatiotemporal (latitude) covariates were incorporated (Denis et al. 2002; Suca et al. 2022). In our study, models incorporating environmental and spatiotemporal covariates produced reconstructed indices for longfin squid that remained seasonally sensitive under survey preclusion, particularly in spring. Overall, mobile species showed greater seasonal variability in reconstructed indices, whereas temporal trend consistency across approaches was generally maintained, suggesting that life history traits influence not only model performance but also model sensitivity to input data. Given that squids are particularly vulnerable to multiple offshore wind impacts (Methratta 2025), future work should develop more robust modelling approaches to detect changes in squid habitat quality under these stressors.

4.3 | Implications to Stock Assessment and Mitigation Options

Design-based indices are often used to tune stock assessment models as they are assumed to be true representations of stock trends (Thorson et al. 2023). For the four Mid-Atlantic fisheries, design-based indices were minimally affected by the offshore wind preclusion effect in terms of their overall trend. However, the magnitude of abundance estimates and changes in variance (CV) exhibit disparities and variability in comparison with their counterparts using the Full dataset; although, except for longfin squid, these changes appear to be at low to moderate levels. We also found that the magnitude of changes in abundance estimates and CVs was not always significantly linked to the loss of survey effort for each individual year. This finding suggests that there were no systematic patterns in offshore wind survey preclusion effects for design-based indices, and that design-based indices have relatively high temporal stability over time. Nevertheless, the nuanced difference between the examined species and surveys highlights the necessity of more thorough and ad-hoc evaluation for different species and stock assessments. Although our evaluation emphasised CV given its importance in stock assessment methodologies, we recognise that bias is equally critical, since unbiased abundance indices remain valuable even when associated with higher variance.

The introduction of WEAs truncated some existing survey strata, which might require the adjustment of stratification structure to ensure unbiased survey design (Haase et al. 2025). The present work followed the original strata structure and focused on evaluating survey data quality in the current design. Future work is needed to evaluate whether the truncated strata should be treated differently to mitigate the biased estimates. To

fully understand these impacts, it would be beneficial to conduct model-based stock assessments using the WEE dataset and evaluate statistical diagnostics. In some cases, the minimal changes observed in design-based indices could potentially be mitigated by adjusting survey parameterization within the assessment model, rather than altering the survey design itself. For longfin squid, a species traditionally managed using index-based catch limits, seasonal biases could pose challenges in defining an escapement threshold, especially given the potential for strong bias in the spring biomass estimate. Future development of a model-based stock assessment might address these seasonal biases (Arkhipkin et al. 2021).

In comparison, model-based indices cannot precisely replicate the abundance estimates and uncertainty levels from design-based indices (Figures S21–S24). Nevertheless, this disparity does not necessarily imply model-based indices will lead to unreliable stock assessment output. It only meant the model outcomes were not comparable with the design-based indices. On the contrary, the high correlation of the model-based indices proved they could be trusted to capture abundance trends and have the potential to improve stock assessments by incorporating environmental covariates, as seen with tuna and black sea bass stock assessments (NEFSC 2024; Xu et al. 2024). Making these changes, however, may require adjustment to the population dynamics assumptions in assessment models (Maunder and Watters 2003; Hodgdon et al. 2020). Model-based indices should also be interpreted with caution when their estimates show vastly different mean and CV compared to the previously used abundance time series.

One caveat in spatial abundance indices arises from spatial heterogeneity in deviations and relative precision between indices inside and outside WEAs. Although offshore wind impacts were minimal outside WEAs, spatial abundance indices reconstructed inside WEAs exhibited greater variability in deviations, whereas changes in relative precision were generally small. These observations have two implications. First, stock assessment outputs using these indices may reflect spatially heterogeneous deviations and uncertainty patterns within WEAs, complicating interpretation and motivating spatially explicit models treating populations inside and outside the WEAs as separate subpopulations (Punt et al. 2016). Second, variability in deviations without commensurate changes in relative precision for spatial abundance indices highlights the need to carefully evaluate how spatial reconstruction influences assessment inputs. Addressing these topics will require nuanced consideration of species life history differences and the model assumptions underlying the abundance indices. These effects are likely to vary across different offshore wind sites, particularly under shifting climate, pointing to potential challenges in spatial and temporal transferability of species distribution and migration models—a topic currently poorly understood (Methratta, Silva, et al. 2023).

4.4 | Broader Applications Beyond Offshore Wind

Although this study was motivated by offshore wind development in the U.S. Mid-Atlantic, the survey preclusion effects evaluated are not unique to this context. Our findings suggest a transferable diagnostic expectation: under moderate survey preclusion, spatial abundance indices are more sensitive to data loss than temporal trend signals when unaffected survey areas remain informative. This distinction provides a practical lens for evaluating survey impacts beyond offshore wind settings.

Across modelling approaches, no single method was uniformly robust to survey preclusion across spatial and temporal dimensions. Instead, trade-offs emerged among deviations over space, relative precision and temporal trend consistency, indicating that mitigation strategies should be tailored to the specific management objective (e.g., trend monitoring vs. spatial inference). Species life-history traits further shaped sensitivity to survey preclusion, with patchily distributed or sessile species exhibiting greater variability in spatial abundance indices under partial survey exclusion. These patterns emphasise the importance of aligning modelling strategies with species ecology rather than applying uniform solutions, since closures can produce divergent abundance patterns linked to density dependence or habitat shifts (Rose et al. 2001; Zhang et al. 2023). The type of closure also matters: seasonal closures may still allow limited 'snapshot' surveys, survey-only restrictions may require redesigned sampling strategies, and full or permanent closures will create severe data gaps unless new survey programs or technologies are implemented. Effective mitigation should therefore be tailored to the modelling purpose, data demands and management context.

Offshore wind introduces additional, site-specific considerations. Suitable modelling approaches must be paired with realistic ecological assumptions, as the ecological consequences of offshore wind farms remain largely in situ, shaped by physical oceanographic conditions, ecosystem status and gear-specific restrictions (Hooper et al. 2017). Simulation-based studies that integrate data from other offshore wind sites could provide valuable opportunities to refine survey design and anticipate localised impacts.

4.5 | Prospective Modelling Approaches in Supporting Offshore Wind Biological Monitoring

The proposed spatiotemporal modelling and evaluation framework represents a general approach for addressing unavoidable survey preclusion, whether due to offshore wind development, MPA restrictions, or spatially uneven fishing effort. Although our case study is offshore wind-focused, the same principles apply whenever survey effort is reduced or constrained, and they highlight the importance of combining modelling with adaptive survey strategies (ICES 2023). However, model-based approaches alone cannot fully compensate for the loss of abundance observation within the WEAs. Challenges persist with understanding habitat quality alterations resulting from wind energy facilities, as the structure added to WEAs may attract some species of fish while the electrical fields or mechanical noise generated by turbines might repel others. These effects are likely to differ by species and sites, making it impossible to apply model-based approaches without in situ abundance observation. New technologies (e.g., drop cameras, ROVs, video) provide alternatives, but data from these platforms must be reconciled with historical surveys to account for different designs and catchability (Methratta, Lipsky, and Boucher 2023; Benoît

et al. 2020). Combining modelling with innovative monitoring can address these challenges in several ways.

4.5.1 | Calibration

Model-based approaches can calibrate baseline and new survey data, allowing pre–post construction comparisons on a common scale (NOAA Fisheries 2025). Model-based calibration is expected to play a central role in biological monitoring programs within the WEAs, where most impacts occur for existing surveys. Such calibration is critical for assessing offshore wind impacts but often requires side-by-side survey experiments before construction (Pelletier 1998; Pennington and Vølstad 1994; Miller et al. 2010).

4.5.2 | Survey Design

Models can help optimise regional survey designs that integrate multiple WEAs, balancing accuracy and precision in abundance estimates (mean–variance minimization) (Smith 1990). Stratification would likely incorporate traditional factors (e.g., depth) and WEAs designation, necessitating careful area weighting and hierarchical structures (Cao et al. 2014; Shelton et al. 2012). It should be noted that a unified, large-scale survey would still rely on survey platforms capable of operating within WEAs.

4.5.3 | Broader Applications

Beyond survey evaluation, models can support compatibility among offshore wind energy and other ocean uses including commercial fishing, marine spatial planning, shipping and conservation (Methratta, Silva, et al. 2023). These analyses will focus on quantifying trade-offs, guiding adaptive management and communicating uncertainty and risk (ICES 2023). Effective translation of model output will require strong engagement platforms with stakeholders and agencies.

Author Contributions

Ming Sun: conceptualization, data curation, formal analysis, funding acquisition, methodology, project administration, visualization, writing – original draft preparation. **Krystina Braid:** formal analysis, writing – review and editing. **Jessica Blaylock:** data curation, methodology, writing – review and editing. **Daniel Hennen:** data curation, methodology, writing – review and editing. **Samuel Truesdell:** data curation, methodology, writing – review and editing. **Yong Chen:** funding acquisition, project administration, resources, supervision, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in the NEFSC Metadata Library at https://www.fisheries.noaa.gov/inport/item/22549.

Peer Review

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1:** ddi70156-sup-0001-AppendixS1.docx.