Integrating multiple surveys to account for changing ocean conditions and spatial distribution shifts of black sea bass

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Abstract:

In US waters of the Atlantic, black sea bass support important commercial and recreational fisheries. The northern stock ranges from the Gulf of Maine to Cape Hatteras, North Carolina. It is well documented that ocean conditions are changing in this region of the Atlantic and it is hypothesized that black sea bass distribution and productivity could be affected by climate change. The current stock assessment does not account for environmental effects and accounts for spatial dynamics by splitting the stock into two regions at Hudson canyon: the north and south. Despite this spatial split, the assessment still has poor retrospective patterns, which could be caused by numerous factors including changing ocean conditions or spatio-temporal dynamics. Here, we fit a series of spatio-temporal models to 10 seasonal trawls surveys in the stock region. Seasonal models were used to produce both aggregated and age-based distribution and abundance estimates. Model selection indicated that for all models, bottom temperature was an important covariate influencing fish density, and survey influenced catchability. Model results suggest that black sea bass center of gravity has shifted northeast in the South and that their range has expanded poleward. Age-based estimates in the spring suggest that all ages have shifted northeast and in both seasons, age-1 fish have increased their range. Results suggest that relative abundance has increased in the North and remained stable in the South. Ultimately, results characterize changes in spatial distribution and provide indices and age-compositions that are robust to spatio-temporal changes for consideration in stock assessment.

Keywords: Spatio-temporal, species distribution, climate change, fisheries independent

Introduction:

In United States waters of the northwest Atlantic, fisheries are an important cultural and economic part of society. Because of this, many governmental agencies, both state and federal, have devoted resources to conducting annual scientific surveys in the region. A primary purpose of these surveys is to monitor fish abundance, distribution, and provide inputs to population assessments. An assumption of using survey estimates in stock assessment is that trends are directly proportional to population abundance. Thus, ideally surveys are designed to have consistent sampling that are representative of populations, in space and time, and can be compared across years.

Even the most well designed surveys are often subject to sampling changes over time (e.g., weather, mechanical issues, changes in survey vessel, Covid -19) that cannot be avoided. Further, many fish have complicated spatio-temporal dynamics that are linked to the environment, while surveys typically have limited temporal sampling windows and for smaller surveys, limited spaital footprints. In the northwest Atlantic, it is well documented that ocean conditions are changing causing spatio-temporal changes in species distribution and abundance (Nye et al., 2009: Pinksy et al. 2013). Failure to account for these changes can lead to inaccurate perception of abundance trends and poor understanding of population dynamics (Wilberg et al. 2010, Link et al 2011).

Spatio-temporal models can estimate changes in population density over time at multiple locations while accounting for environmental variables and unknown processes. These models are being used frequently in climate, habitat and stock assessments (Thorson, 2019). Spatio-temporal frameworks are especially useful for estimating center of gravity because it allows for multiple explanatory covariates to be explored in the same framework (Perretti and Thorson, 2019). These models can then incorporate the potential drivers and spatial changes into indices of abundance and composition data for input into stock assessment (O'Leary et al. 2020). Spatio-temporal models can also be used to integrate multiple surveys into a single index of abundance (O'Leary et al. 2022). A joint index can help reconcile noisy or conflicting indices, account for changes in availability and simplify inputs to stock assessment, allowing for improved assessment performance (Conn, 2010). Additionally, using the results from spatio-temporal models has been demonstrated to yield more precise/accurate indices of abundance (Shelton et al. 2014). Fitting assessments to spatio-temporal standardized indices can also lead to less retrospective bias and outperform assessments with design-based indices (Cao et al. 2017).

Black sea bass are a coastal species that supports important commercial and recreational fisheries. In the western Atlantic, they are assessed as two separate populations: the northern stock and South Atlantic stock. The northern stock is further split into two regions: North and South, with the dividing line being Hudson Canyon. The stock was split into two regions to account for spatial dynamics and improve model diagnostics (NEFSC 2017). Since the last major benchmark in 2017, the stock assessment is fit to 17 indices of abundance, including 14 trawl surveys. Nine of the indices are produced from inshore trawl surveys and have small spatial footprints, while five of the indices are from the Northeast Fisheries Science Center bottom trawl survey, which has a large spatial footprint.

Black sea bass make seasonal migrations, moving inshore in the spring and offshore in the fall (Moser and Shepherd, 2009). Black sea bass distribution has been linked to warming waters on the Northeast US Shelf (Bell et al. 2016) and it is hypothesized that black sea bass are especially susceptible to climate change with likely shifts in distribution and productivity due to warming water temperatures (Hare et al., 2015). Current assessments have major retrospective patterns and account for spatial dynamics by splitting the stock into two assessments. Neither assessment directly accounts for climate effects (NEFSC 2022). Incorporating spatio-temporal dynamics or climate effects could potentially help to improve retrospective patterns (Cao et al. 2017; Mazur et al. 2023). Thus a major research recommendation for this species is to better understand how changes in the environment are affecting life history and spatial dynamics.

Here we fit a series of spatio-temporal models to all available trawl survey data and environmental covariates for the northern stock of black sea bass. Results provide estimates of distribution shifts, area occupied and environmental drives. Further, model output produces a series of joint indices and age composition data that account for these changes and can be directly incorporated into future stock assessments.

Methods:

Ten trawl surveys were available (Table 1; Figure 1). All surveys collected information on: catch (kg & numbers), latitude, longitude, time of tow, bottom temperature and depth of tow. Shelf water volume anomaly was matched to survey data because previous studies suggested this covariate might influence over wintering survival (Miller et al. 2016). There was temporal variability in survey sampling so surveys were grouped into two seasons: Spring (January - June) and fall (July - December). Length information

was available from all surveys; however, ages were not available for all surveys. Ages were available from the Northeast Fisheries Science Center Survey and Massachusetts Division of Marine Fisheries Survey. When ages were not available, lengths were converted to ages using seasonal age-length keys from the available age information. These are the same age-length keys that are used in the stock assessment.

Model:

Vector Autoregressive Spatio-temporal (VAST) is a delta-model that models the probability of an encounter and positive catch rate as two separate generalized linear mixed models. Here we use a binomial distribution for probability of a positive catch and a log-normal distribution for positive catch.

Probability of a black sea bass observation:

$$logit^{-1}(P_{1,i}) = \beta_1(t_i, c_i) + \omega_1(s_i, c_i) + \varepsilon_1(s_{i,}, c_i, t_i) + \sum_{j=1}^{n_j} \lambda_1(j, c_i) x(j, s_i, t_i) Q(i, k_1)$$

Black sea bass catch on positive trips:

$$log(P_{2,i}) = \beta_2(t_i, c_i) + \omega_2(s_i, c_i) + \varepsilon_2(s_{i,}, c_i, t_i) + \sum_{j=1}^{n_j} \lambda_2(j, c_i) x(j, s_i, t_i) Q(i, k_2)$$

Where P_1 is the probability of positive catch, P_2 is the probability of the catch given the catch is positive, $\beta(t_i)$ is the intercept for each year *t* and age-group *c* and is modeled as a random walk, $\omega(s_i)$ is a time-invariant spatial autocorrelated variation for knot *s* and age-group *c*, $\varepsilon(s_{i,}c_{i,}t_i)$ is a time-varying spatial-temporal autocorrelated variation for knot *s* and age-group *c* in year *t*, $\lambda(j, c_i)$ is the effect of covariate *j* on length group *c* , n_j is the number of covariates and $x(j, s_i, t_i)$ is the value of covariate *j* in knot *s* in year *t*, $Q(i, k)$ is the fixed effect estimates for catchability, and the integer subscripts denote the model component (1: presence/absence, 2: non-zero density) for observation *i*.

The spatial processes ($\omega_1(s_i, c_i)$; $\omega_2(s_i, c_i)$) were modeled as Gaussian Markov random fields with correlation over two spatial dimensions.

$$vec(\Omega_p) \sim GRF(0, R_p \otimes V_{wp})$$

Where Ω_p is a matrix composed of $\omega_2(s_i, c_i)$ at every knot *s* and length bin *c*, R_p is correlation between knots, and V_{wp} is correlation between length bins.

$$V_{wp} = L_{wp} L_{wp}^T$$

Where L_{wp} is a matrix representing covariance among age bins. The spatial covariance between knots *s* and s^* was modeled as a Matern process.

$$R_p(s, s^*) = \frac{1}{2^{v-1}T(v)} (K_p H|\, s - s^*|)^v K_v (K_p H|\, s - s^*|)$$

Where *v* is a smoothness parameter that is fixed at 1, K_p controls the distance correlation and reduces to zero, K_v is a Bessel function and ***H*** is a two dimensional anisotropic distance function. The spatio-temporal processes ($\varepsilon_{1,2}(s_{i,}, c_i, t_i)$) were fit independently for each year, and were modeled with Gaussian Markov random fields assuming a Matern covariance.

In addition to catchability covariate effects, estimated values of the fixed and random effects predicted local density (*d*(*s*, *t*)) for knot *s* and length-group *c* in year *t*.

$$d(s,t) = logit^{-1}\left(\beta_1(t_i, c_i) + \omega_1(s_i, c_i) + \varepsilon_1(s_{i,}, c_i, t_i)\right) \times\ exp\left(\beta_2(t_i, c_i) + \omega_2(s_i, c_i) + \varepsilon_2(s_{i,}, c_i, t_i)\right)$$

The index of abundance (*B*(*t*)) is calculated as the sum of the density of each knot using an area weighted approach:

$$B(t) = \sum_{s=1}^{n_s} (a(s) \times d(s,t))$$

Where *B*(*t*) is the area weighted density for each knot in year *t* throughout the specific domain and *a*(*s*) is the area of knot *s*. A mesh approach (200 knots) which allows for anisotropy was used to fit the model. Parameter estimation used Template Model Builder (Kristensen et al. 2016) and the R program (R Core Team 2020). Model convergence was examined by ensuring the maximum gradient of the likelihood estimation was less than 0.0001 for all parameters and the Hessian matrix was positive definite.

Model configuration:

In total, four different models were built: 1) spring annual index; 2) spring age-composition; 3) fall annual index; 4) fall age-composition. For each model we explored: bottom water temperature, depth and shelf water volume as modulates of density or catchability. Survey was also explored as a modulate of catchability. Collinearity of covariates was examined using generalized variance-inflation factor (GVIF) scores. Any covariate with a score greater than three was removed, and the GVIFs were recalculated (Zuur, et al. 2012). Akaike Information Criterion (AIC) scores were used to determine the best-fitting model. If AIC scores were within two units of one another, the most parsimonious model was selected (Burnham and Anderson, 2004).

Results:

For both the spring and fall, AIC supported including survey as a covariate on catchability and bottom water temperature as a modulate of density (Table 2). The age models also included an interaction of survey/age to account for age-specific catchability between the surveys.

In general, VAST estimates suggest that black sea bass are more abundant inshore in the fall and more abundant offshore in the spring (Figure 3 & 4). For both seasons, the total proportion of black sea bass caught in the northern region has increased over the time series (Figure 5). The stock-wide center of gravity has shifted northeastward (Figure 6).

For both seasons, the center of gravity of black sea bass has generally shifted north in the southern region, while the spatial distribution in the northern region has remained relatively stable (Figure 7 - 8). In contrast, effective area occupied has increased in the northern region in both the fall and spring, while effective area occupied estimates in the south have been variable with no clear trend (Figure 9). Coast-wide age-based estimates suggest that the center of gravity for all ages in the spring has shifted to the northeast (Figure 10). In the fall, coast-wide age estimates show some signs of northeast changes in center of gravity of ages 3-5; however, there is no clear trend (Figure 11). Stock-wide age-based effective area estimates suggest that age-1 fish are using a greater area in both the spring and fall over the course of the time series (Figure 12).

Annual index estimates from VAST suggest that abundance in the north has increased in the spring and fall, while abundance has remained relatively stable in the south (Figure 13). In the spring, stock-wide age-based abundance estimates suggest an increase of age-2 and older fish (Figure 14). In the fall, stock-wide age-based abundance estimates show variability for all ages with no clear trend (Figure 15). In the

spring, age compositions in each region indicate an expansion in the age structure beginning in approximately 2005. Additionally, spring proportions-at-age in the north show the progression of multiple cohorts through the population, including the 2011 and 2015 year classes. In the south, the progression of the 2011 year class is also evident in the spring age compositions, but it is not as pronounced as in the north. In the fall, age compositions in the north show a similar expansion in age structure and progression of the 2011 cohort as in the spring; however, age compositions in the south are dominated by age-2 fish and do not vary notably over the time series (Figure 16).

Discussion:

For the northern black sea bass stock, spatio-temporal models suggest a range expansion to the north, while fish in the south (between Hudson Canyon and Cape Hatteras) are using the same area but with a northeastward shift in their center of gravity. These results support previous studies that have hypothesized and demonstrated poleward shifts in black sea bass distribution (Hare et al. 2015; Bell et al 2016). It is also expected that these poleward shifts could continue into the future due to projected increases in warming and biological demands (Slesinger et al. 2019).

Another previous hypothesis about black sea bass is that their productivity in waters north of Hudson Canyon could be increasing due to increased water temperature and improved overwintering survival (Hare et al. 2015; Miller et al. 2016). Results from this study show that age-1 fish in the spring have shifted northeast and are occupying a greater area. Age-1 abundance has increased in the spring but has remained relatively stable since 2000, while age-1 abundance in the fall has been stable throughout the time series. Thus, the results from the spatio-temporal models suggest that changes in spatial distribution are occurring at a faster rate than changes in productivity. However, it is important to note that the surveys used in this study were not specifically designed to capture age-1 black sea bass. Additionally, productivity is one of the most difficult metrics to measure in fisheries science (Maunder and Thorson, 2019).

Aggregated black sea bass abundance estimates show increases in the northern region and stable trends in the south. Increasing abundance is not surprising given that black sea bass have a preference for warmer water and their range appears to have expanded in the north. Additionally, higher abundance could be the result of increased overwintering survival in the north due to warmer water temperatures (Miller et al 2016). Increasing abundance is also supported by the last black sea bass stock assessment, which estimated large increases in biomass (NEFSC 2022). Black sea bass abundance could continue to

increase in the future. Offshore wind development is rapidly occurring in the northeast US continental shelf with multiple lease areas. These wind farms will increase the amount of structured habitat in the region, which is the preferred habitat for black sea bass (Friedland et al. 2021).

The spatio-temporal models used in this study have several assumptions and limitations. VAST is an area-weighted model, thus, it gives weight to surveys that sample a larger area. In this study, that is the spring and fall NEFSC surveys. Thus, the combined index produced by VAST is pre-weighted (by area) to give more leverage to the offshore surveys. Another assumption of this approach is that the trawl surveys all have similar catchabilities. The model does account for differences between the surveys (using a factor); however, this is a relatively simple adjustment that does not directly account for specific differences (e.g., tow time or net width). Additionally, not all of the surveys have the same temporal coverage but they are grouped into spring and fall (Table 1). The inclusion of water temperature, which is correlated with time of year, should help to account for these differences in the model.

Another limitation of this study was that some environmental covariates that have been shown to affect black sea bass could not be included in the model. For example, black sea bass abundance has been linked to salinity (Miller et al. 2016). We weren't able to explore salinity in the spatio-temporal models because this covariate was not collected by every survey. However, even if other important explanatory covariates were not included, it is likely that they are correlated with the covariates that were explored. Additionally, the random effects of the model can absorb variation that was not attributed to explanatory variables (Perretti and Thorson, 2019). Despite this, further work should consider exploring additional covariates and their effect on black sea bass abundance and distribution.

Despite the limitations, the study also has several advantages. The combined spatial footprints of the different surveys allows for trends representative of the entire stock, while previous studies only focused on offshore waters (Bell et al. 2016; Miller et al. 2016) . The results of the VAST models provide direct inputs for the assessment of the northern stock of black sea bass that can account for changing spatio-temporal dynamics and environmental effects. Another strength is this framework uses a consistent model platform to standardize both the annual index of abundance and composition data. Previous standardizations of inshore surveys only standardized the index of abundance and not the age compositions. Thus, the annual index is corrected for variables influencing catchability, but the age compositions are not. Further, previous standardization models included environmental effects as modulates of catchability. Thus, the annual index is de-trended for these variables. However, if these environmental covariates affect density and not catchability, the standardization could be de-trending

the abundance estimates. The model platform used in this study allowed environmental covariates to influence density estimates and suggests bottom temperature influences black sea bass distribution and abundance.

Another strength of this approach is that this model can be updated for future use. It is clear that ocean conditions are variable and black sea bass distribution and abundance are changing. This framework can be updated with additional data and environmental covariates to quantify and account for these changes in the assessment. Further, with the inclusion of wind farms in the northeast, it is likely that surveys will have to change their sampling protocols and spatial footprints. The VAST models used in this study can be used to make predictions in areas that can no longer be sampled.

The spatio-temporal models presented here integrated 10 different trawl surveys to estimate seasonal changes in the distribution and abundance of the northern black sea bass stock. Results suggest that black sea bass distribution and abundance are driven by bottom water temperature. The distribution of black sea bass is shifting northeast and their range is expanding poleward. Relative abundance has increased in the northern region (north of Hudson Canyon), while remaining relatively stable in the southern region (Hudson Canyon to Cape Hatteras). Age-based estimates suggest shifts in center of gravity and area occupied for all ages in the spring. The indices and age compositions created from the spatio-temporal models account for these shifts and provide time series that can be directly incorporated into the black sea bass stock assessment.

References:

Bell, R. J., Richardson, D. E., Hare, J. A., Lynch, P. D., & Fratantoni, P. S. (2015). Disentangling the effects of climate, abundance, and size on the distribution of marine fish: an example based on four stocks from the Northeast US shelf. *ICES Journal of Marine Science*, *72*(5), 1311-1322.

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: understanding AIC and BIC in model selection. *Sociological methods & research*, *33*(2), 261-304.

Cao, J., Thorson, J. T., Richards, R. A., & Chen, Y. (2017). Spatiotemporal index standardization improves the stock assessment of northern shrimp in the Gulf of Maine. *Canadian Journal of Fisheries and Aquatic Sciences*, *74*(11), 1781-1793.

Conn, P. B. (2010). Hierarchical analysis of multiple noisy abundance indices. *Canadian Journal of Fisheries and Aquatic Sciences*, *67*(1), 108-120.

Hare JA, Morrison WE, Nelson MW, Stachura MM, Teeters EJ, Griffis RB, Alexander MA, Scott JD, Alade L, Bell RJ, et al. 2016. A Vulnerability Assessment of Fish and Invertebrates to Climate Change on the Northeast U.S. Continental Shelf. PLOS ONE. 11(2):e0146756.

Link, J.S., Nye, J.A., Hare, J.A. 2011. Guidelines for incorporating fish distribution shifts into a fisheries management context. Fish Fish. 12:461-469.

Maunder, M. N., & Thorson, J. T. (2019). Modeling temporal variation in recruitment in fisheries stock assessment: a review of theory and practice. *Fisheries Research*, *217*, 71-86.

Mazur, Mackenzie D., Jerelle Jesse, Steven X. Cadrin, Samuel B. Truesdell, and Lisa Kerr. "Consequences of ignoring climate impacts on New England groundfish stock assessment and management." *Fisheries Research* 262 (2023): 106652.

Moser, J., & Shepherd, G. R. (2008). Seasonal Distribution and Movement of Black Sea Bass (Centropristis striata) in the Northwest Atlantic as Determined from a Mark-Recapture Experiment. *Journal of Northwest Atlantic Fishery Science*, *40*.

Northeast Fisheries Science Center (NEFSC). 2017. 62nd Northeast Regional Stock Assessment Workshop (62nd SAW) Assessment Report. US Dept Commer, Northeast Fish Sci Cent Ref Doc. 17-03; 822 p. Available from: National Marine Fisheries Service, 166 Water Street, Woods Hole, MA 02543-1026, or online at http://www.nefsc.noaa.gov/publications/

Northeast Fisheries Science Center (NEFSC). 2022. Management Track Assessment: June 2021. US Dept Commer, Northeast Fish Sci Cent Ref Doc. 22-10; 79 p. https://doi.org/10.25923/4m8f-2g46

Nye, J. A., Link, J. S., Hare, J. A., & Overholtz, W. J. (2009). Changing spatial distribution of fish stocks in relation to climate and population size on the Northeast United States continental shelf. *Marine Ecology Progress Series*, *393*, 111-129.

O'Leary, C. A., Thorson, J. T., Ianelli, J. N., & Kotwicki, S. (2020). Adapting to climate-driven distribution shifts using model-based indices and age composition from multiple surveys in the walleye pollock (Gadus chalcogrammus) stock assessment. *Fisheries Oceanography*, *29*(6), 541-557.

O'Leary, C. A., DeFilippo, L. B., Thorson, J. T., Kotwicki, S., Hoff, G. R., Kulik, V. V., ... & Punt, A. E. (2022). Understanding transboundary stocks' availability by combining multiple fisheries-independent surveys and oceanographic conditions in spatiotemporal models. *ICES Journal of Marine Science*, *79*(4), 1063-1074.

Perretti, C. T., & Thorson, J. T. (2019). Spatio-temporal dynamics of summer flounder (Paralichthys dentatus) on the Northeast US shelf. *Fisheries Research*, *215*, 62-68.

Pinsky, M. L., Worm, B., Fogarty, M. J., Sarmiento, J. L., & Levin, S. A. (2013). Marine taxa track local climate velocities. *Science*, *341*(6151), 1239-1242.

Shelton, A. O., Thorson, J. T., Ward, E. J., & Feist, B. E. (2014). Spatial semiparametric models improve estimates of species abundance and distribution. *Canadian Journal of Fisheries and Aquatic Sciences*, *71*(11), 1655-1666.

Thorson, J. T. (2019). Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments. *Fisheries Research*, *210*, 143-161.

Wilberg, M.J., Thorson, J.T., Linton, B.C., Berkson, J. 2010. Incorporating time-varying catchability into population dynamic stock assessment models. Rev. Fish. Sci. 18: 7-24.

Zuur, A.F., Saveliev, A.A., Ieno, E.N., 2012. Zero Inflated Models and Generalized Linear Mixed Models with R. Highland Statistics Ltd, Newburgh

Table 1: Summary of trawl surveys that catch black seabass in the mid-Atlantic.

Survey	Years	Months	region	Ages
Northeast Fisheries Science Center (NEFSC)	1989 – 2022	1-12	North and South	Yes
Northeast Assessment and Monitoring survey (NEAMAP)	2007 – 2022	4-6; 9_12	North and South	
Massachusetts Division of Marine Fisheries (MADMF)	1989 – 2022	4-6; 9,10	North	Yes
Rhode Island Division of Environmental Management (RIDEM)	1989 – 2022	4-6; 9-11	North	
Connecticut Department of Energy and Environmental Protection	1989 – 2022	4-6; 9-10	North	
New York Department of Environmental Conservation	1989 – 2022	4-11	North	
New Jersey Department of Environmental Protection	1989 – 2022	1-12	South	
Delaware Department of Fish and Wildlife	1989 – 2022	1-12	South	
Maryland department of Natural Resources	1989 – 2022	4-10	South	
Virginia Institute of Marine Science	1989 – 2022	1-12	South	

Table 2: AIC scores for VAST models.

Model	Season	Covariate	Type	AIC
Annual index	Spring	-	-	67201
		Survey	Catchability	52846
		Bottom temperature	Density	52013
		Depth	Density	52048
		Shelf water volume anomaly	Density	54031
Annual index	Fall	-	-	64801
		Survey	Catchability	54202
		Bottom temperature	Density	53308
		Depth	Density	53446
		Shelf water volume anomaly	Density	54482

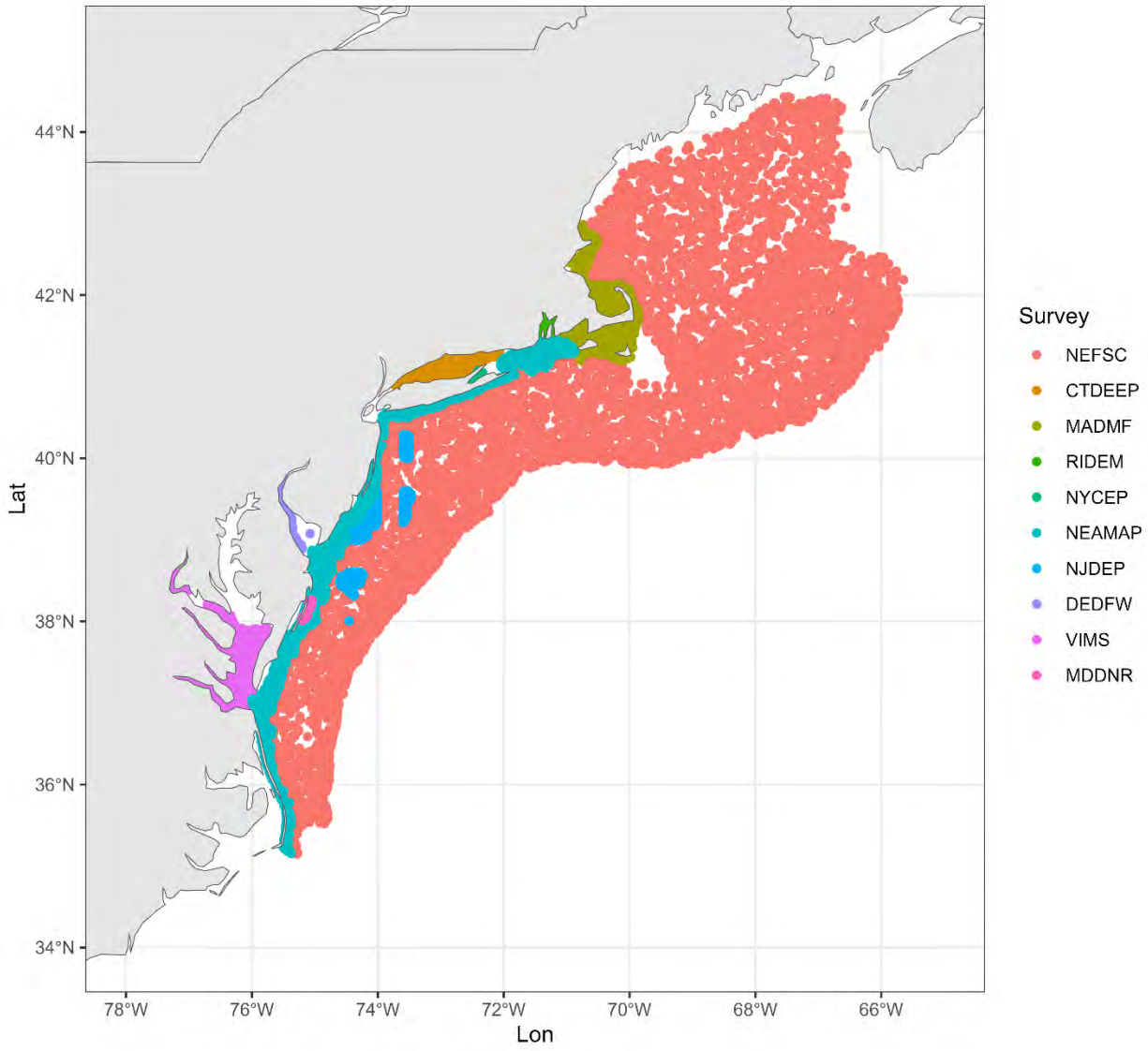

Figure 1: Different trawl surveys fit by VAST.

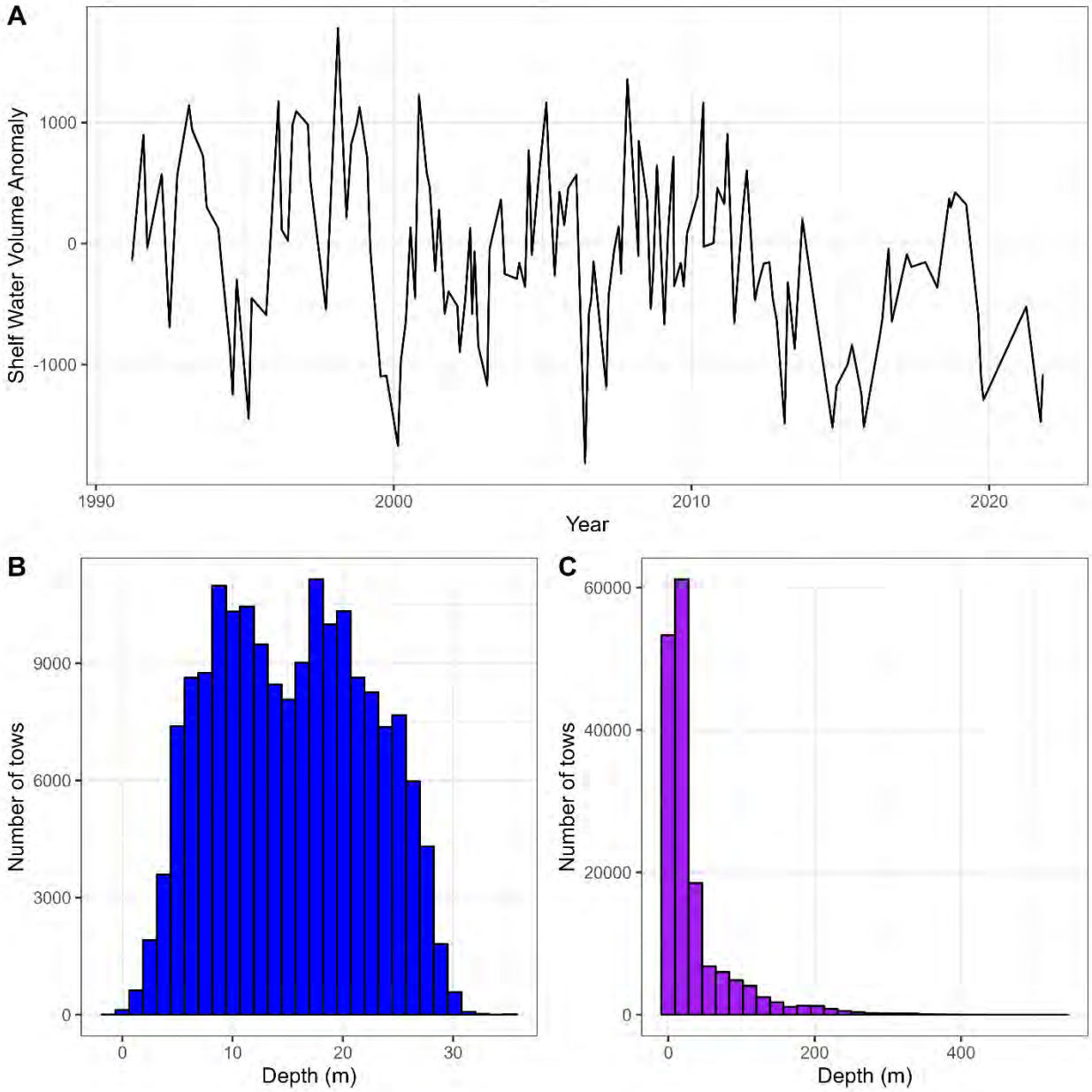

Figure 2: Covariates explored as influencing density in VAST model runs.

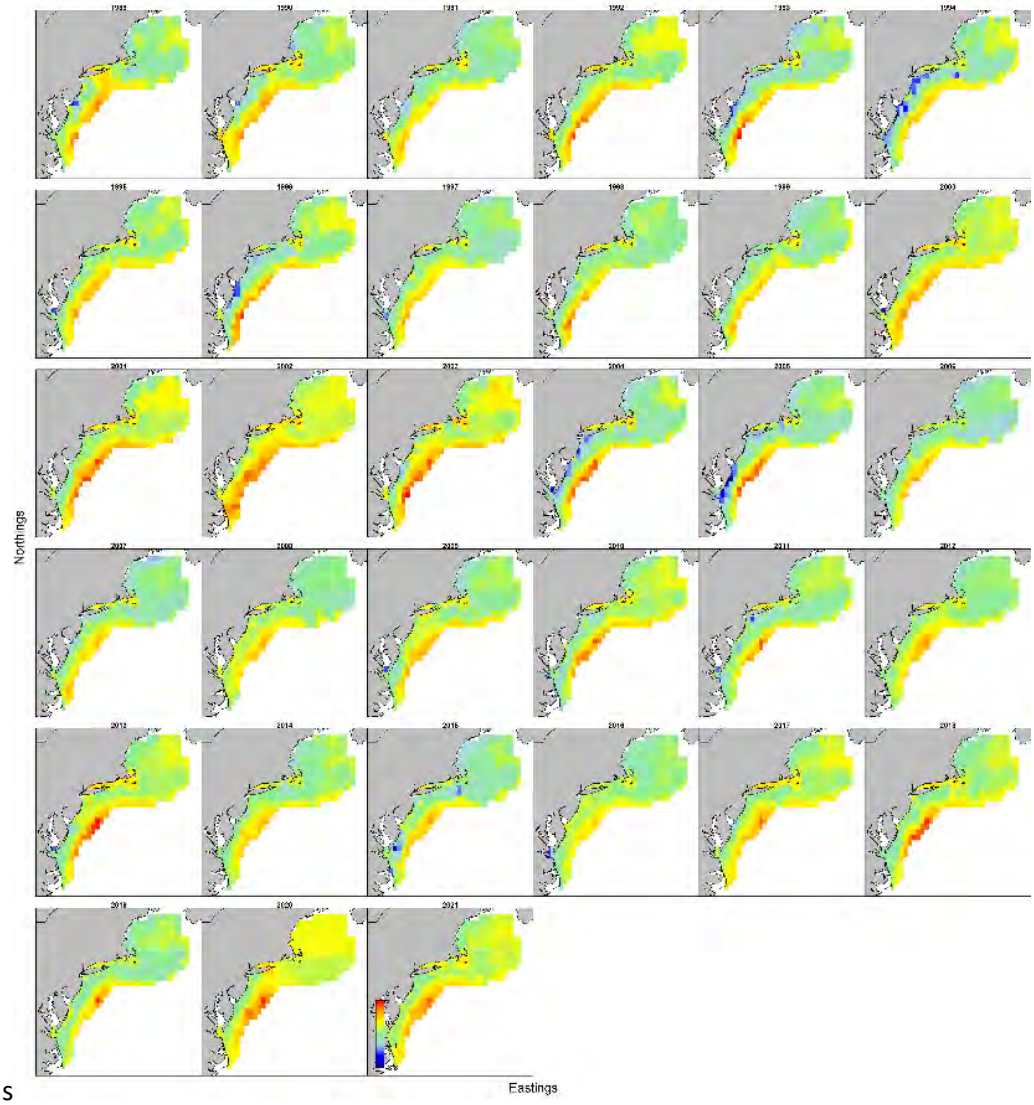

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Figure 3: Abundance estimates produced from VAST for black sea bass in the Spring.

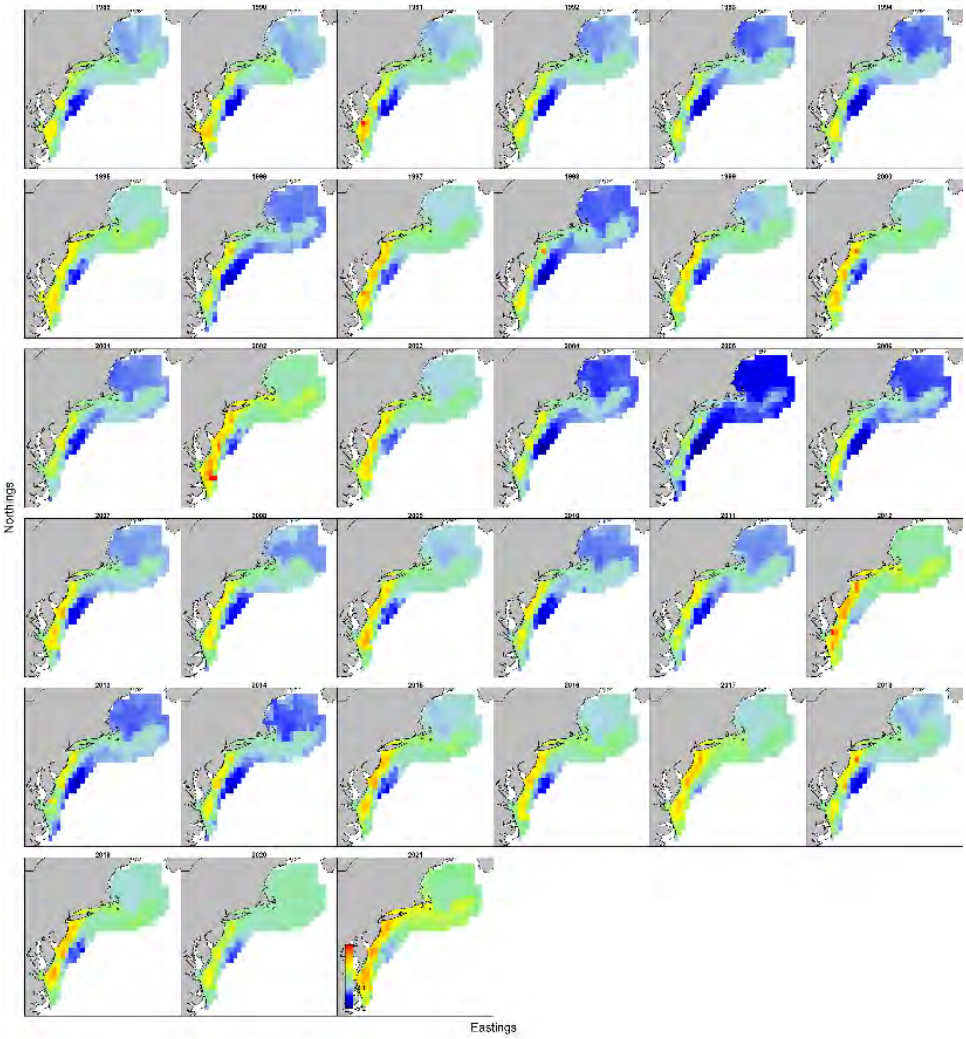

Figure 4: Abundance estimates produced from VAST for black sea bass in the fall.

Figure 5: Proportion of black sea bass caught between the two regions for the spring (A) and fall (B).

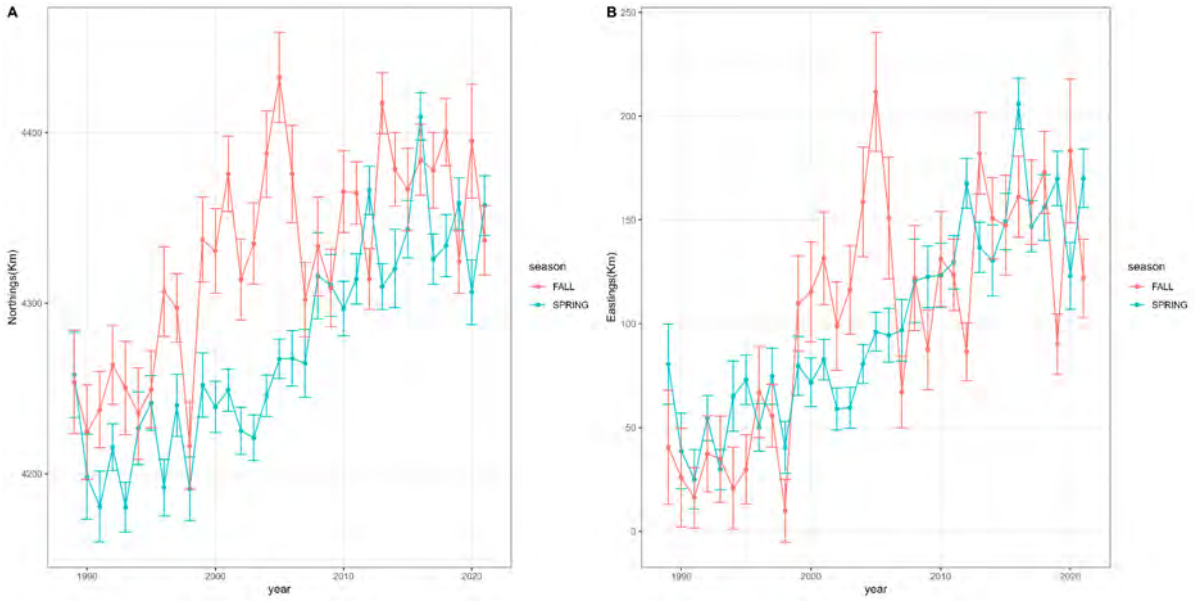

Figure 6: Black sea bass center of gravity estimates from VAST models for the spring and fall.

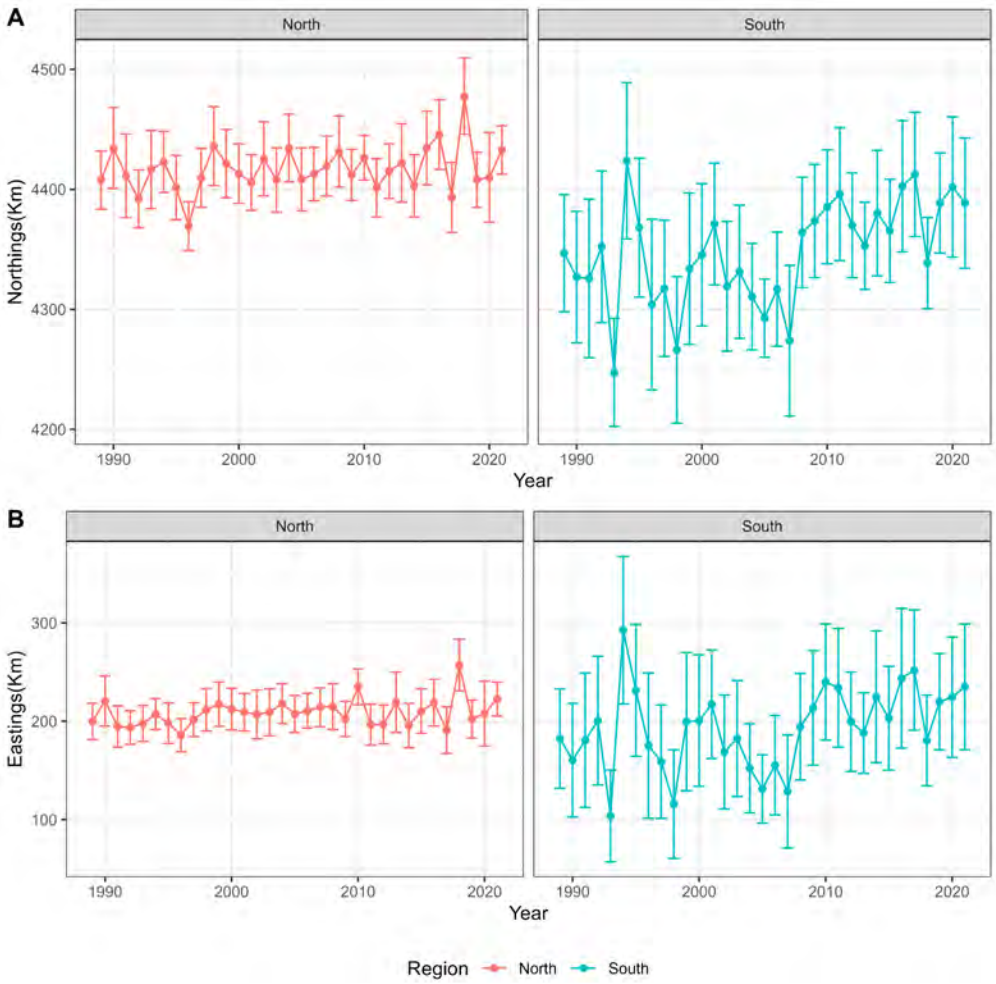

Figure 7: Spring center of gravity estimates from VAST for black sea bass in the north and south regions.

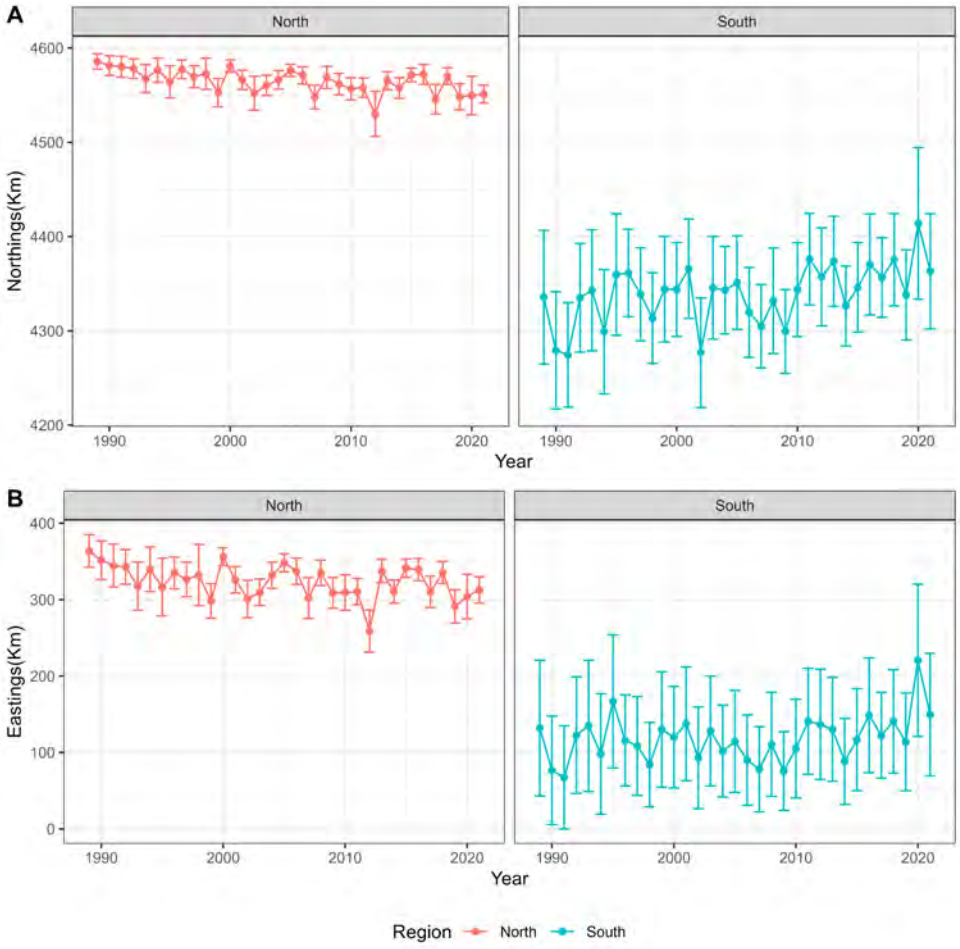

Figure 8: Fall center of gravity estimates from VAST for black sea bass in the north and south regions.

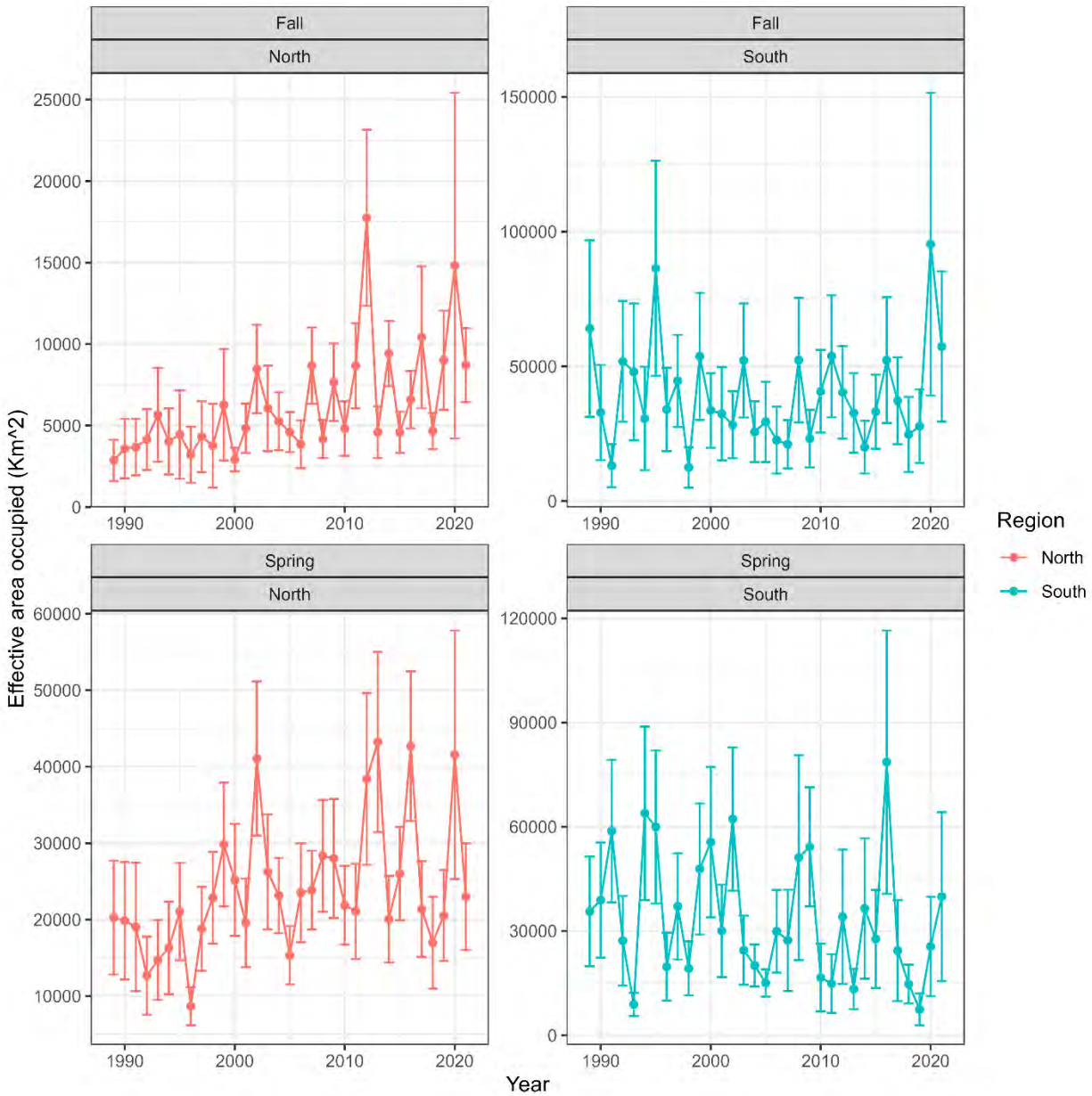

Figure 9: Effective area occupied estimates from VAST models for black sea bass for each season and region

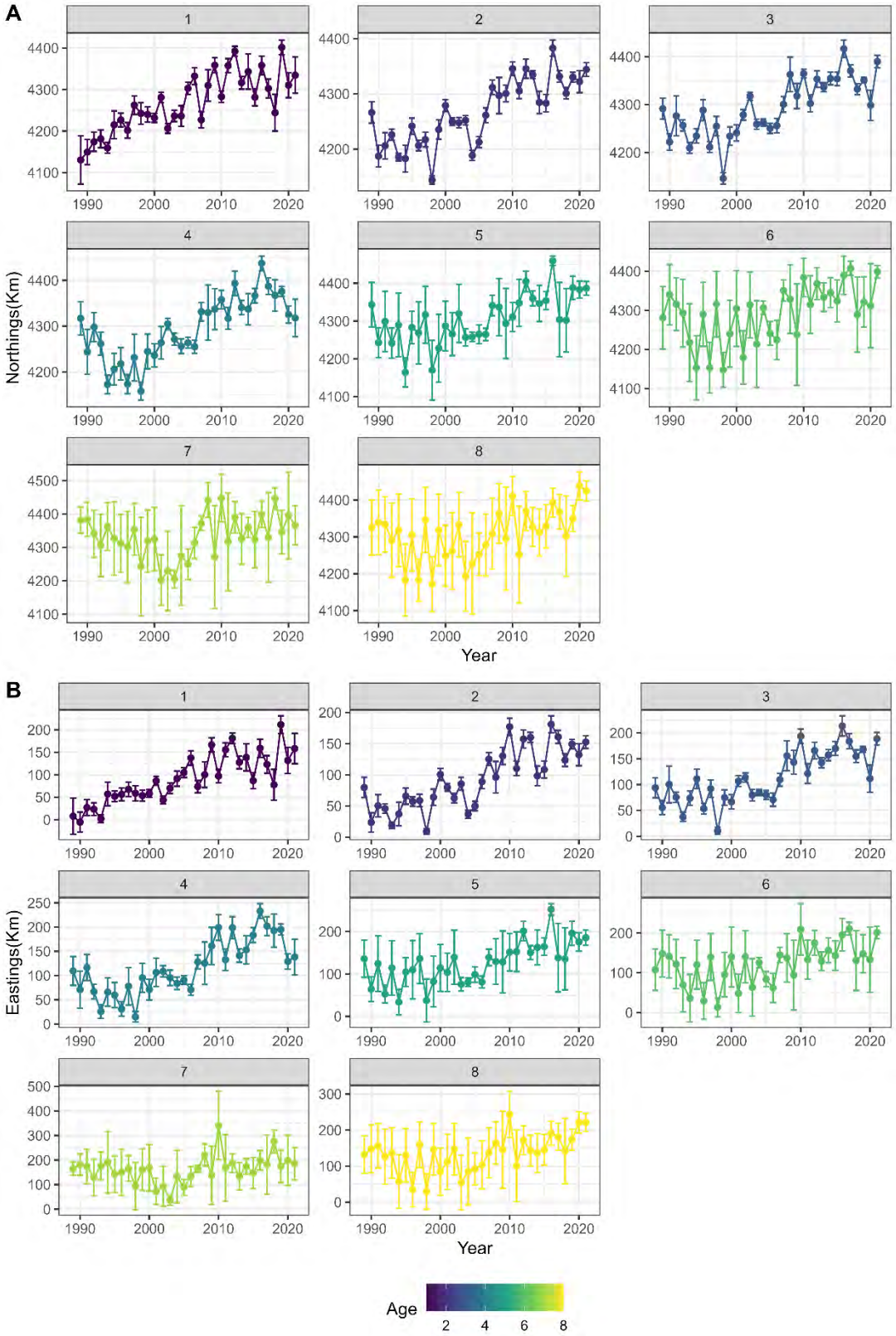

Figure 10: Age specific changes in center of gravity of black sea bass in the spring.

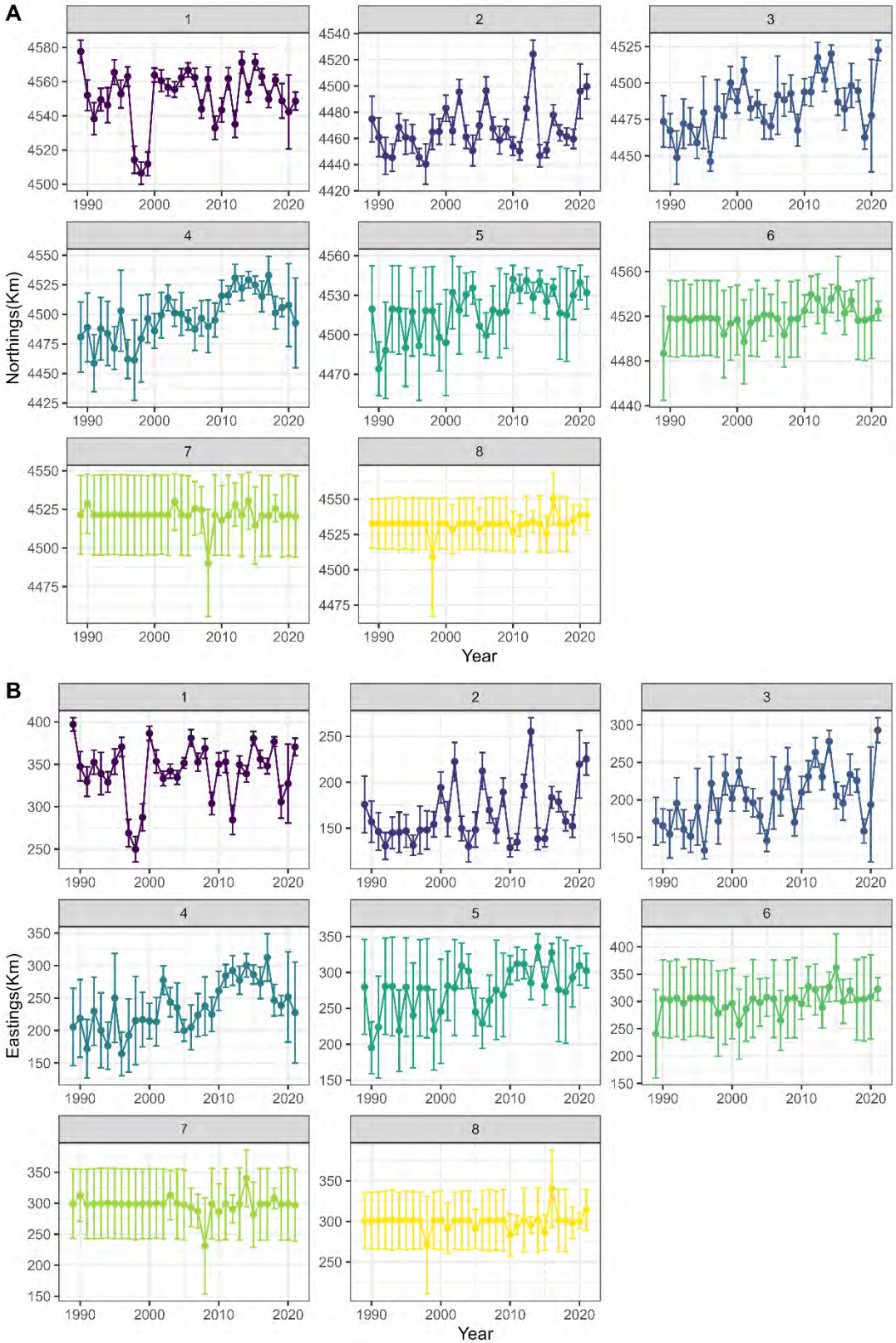

Figure 11: Age specific changes in center of gravity of black seas bass in the fall.

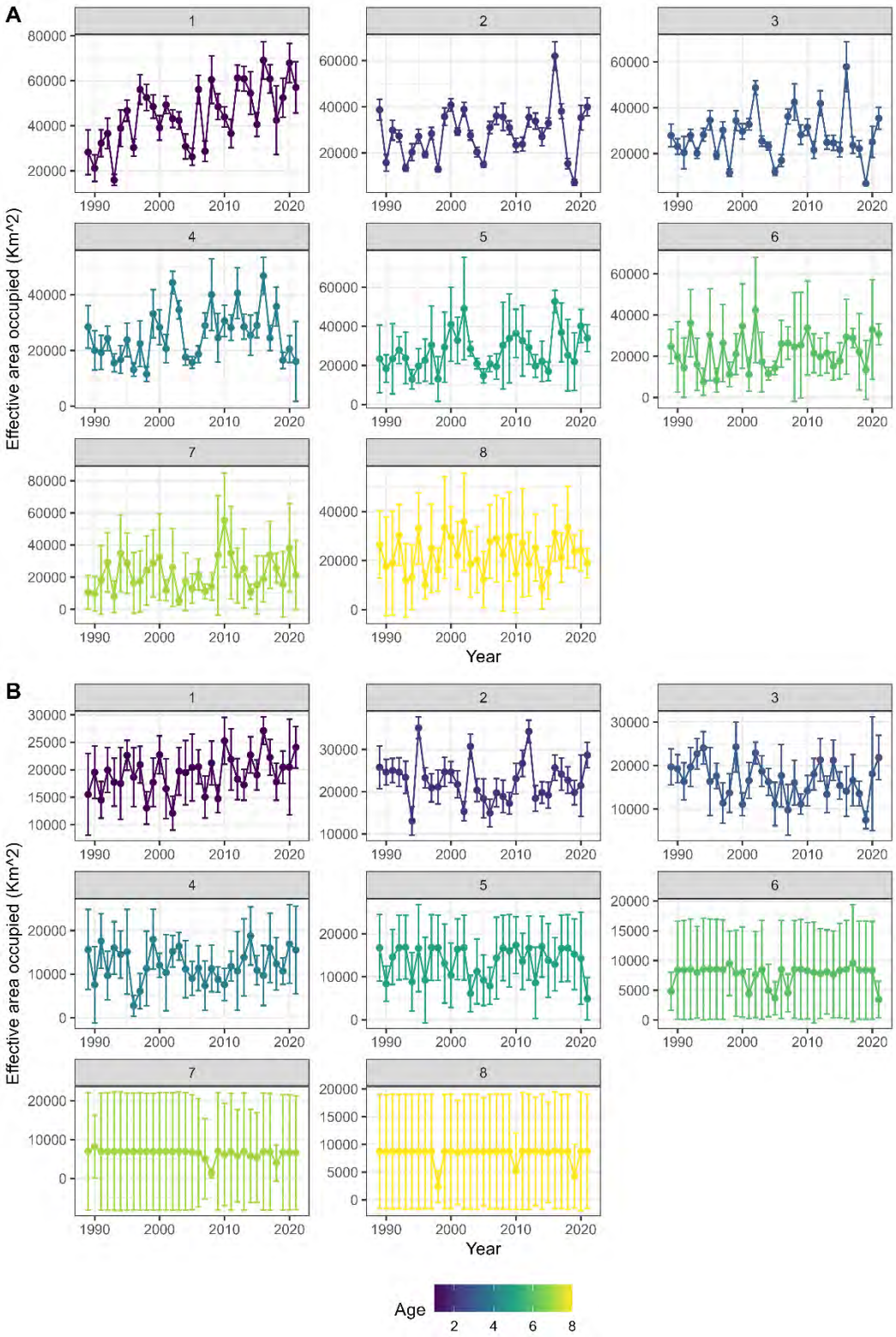

Figure 12: Age specific changes in effective area occupied of black sea bass in the spring (A) and fall (B).

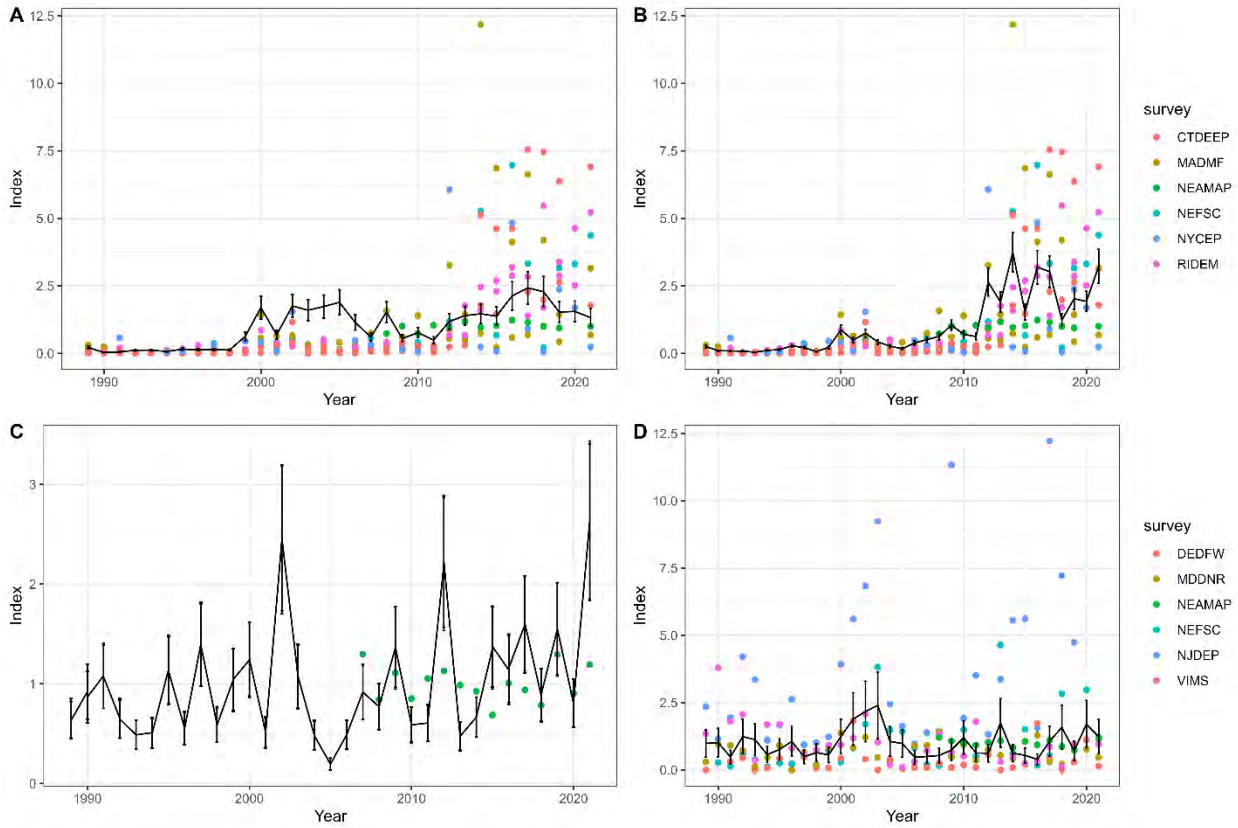

Figure 13: Annual abundance indices produced by VAST (black line) and their associated CVs for the North fall and spring (A & B) as well as the South fall and spring (C & D). Colored points represent the designed based annual abundance estimates from each survey included in VAST.

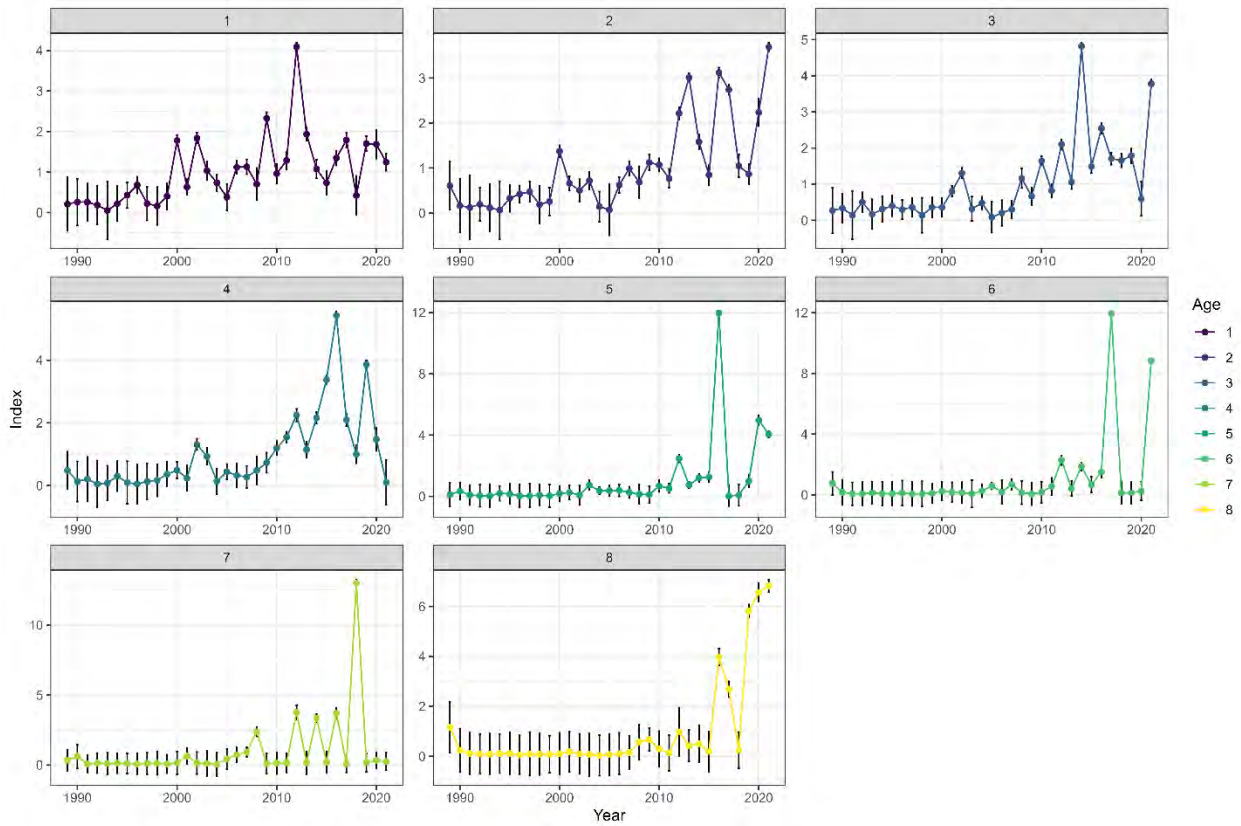

Figure 14: Age based abundance estimate produced VAST for the spring.

Figure 15: Age based abundance estimate produced VAST for the fall.

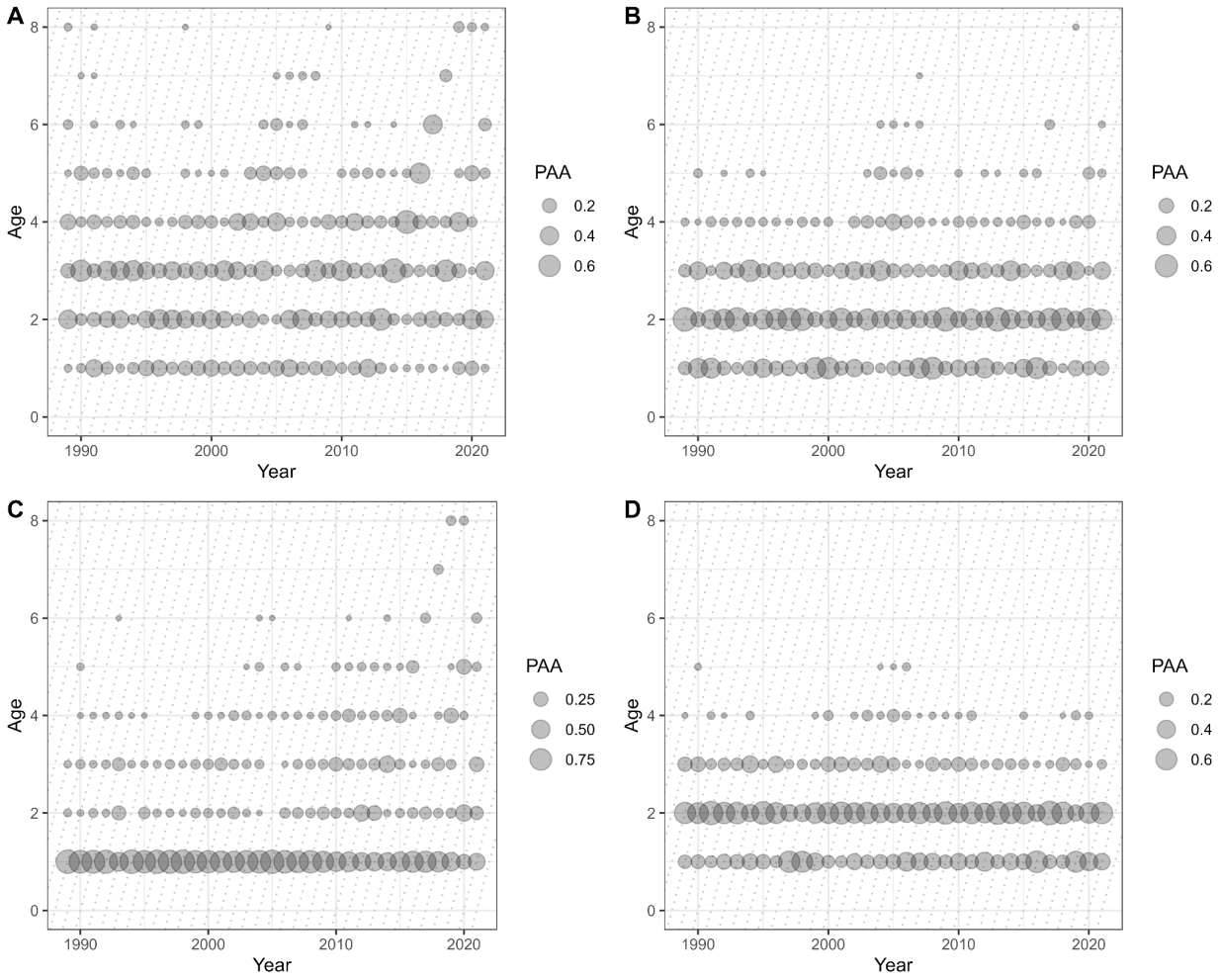

Figure 16: VAST age composition estimates for the northern region (A) and southern region (B) in the spring. VAST age composition estimates for the northern (C) and southern region in the fall (D).