Plaice Ecosystem Drivers

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1. Introduction

Fish population dynamics are strongly dependent upon the environment in which the populations exist (Pershing et al. 2021; Nye et al. 2009; Brodziak and O'Brien 2005). Environmental conditions such as bottom water temperature, sea surface temperature (SST), salinity, current direction, and strength, etc. are known to affect fish survival rates, recruitment strength, growth, and distribution, amongst other population dynamics. However, the environmental drivers determined to have a significant or strong effect may vary across species and/or spatial locations because such impacts are specific to each ecosystem and are difficult to generalize (Brodziak and O'Brien 2005).

For American plaice (*Hippoglossoides platessoides*), a cold-water demersal flatfish species native to the North Atlantic and Arctic oceans (NEFMC 1985), water temperature could be a potential environmental driver for recruitment, as the thermal survival and incubation limit for their eggs is 14 °C, and sea surface temperatures in some areas of their range are already exceeding this limit by the end of the spawning season (Howell and Caldwell 1984). Temperature has also been associated with changes in plaice distribution as plaice have been shifting into deeper waters overtime, a change which is often associated with changing ocean conditions (DisMAP 2022; Nye et al. 2009). And finally, temperature has also shown effects on growth and maturity of plaice as warmer temperatures have been associated with accelerated growth rates, reductions in body size, and earlier ages at maturity (Levangie et al. 2021; Zheng et al. 2020). Temperature is one of many potential ecosystem drivers of American plaice stock dynamics, but has surfaced as a prevalent potential driver after conduction of a literature review (Behan et al. 2021, Working Paper 14 Appendix A of American Plaice WG Draft Report).

Although it is uncommon for stock assessments to explicitly incorporate considerations of environmental influences on population dynamics, inclusion of such influences could reduce scientific uncertainty (Sararese et al. 2015) or improve model parameter estimates (Maunder and Watters 2003; Schirripa et al. 2009). When environmental drivers are excluded from stock assessment models, those same influences might instead be expressed as anomalies or biases, thus affecting the accuracy and/or precision of the stock assessment (Sararese et al. 2015).

To help identify ecosystem and climate influences on American plaice stock dynamics, generalized additive models (GAMs) were used to examine associations between potential environmental drivers (identified through a literature review) and American plaice recruitment, distribution, and growth in the Gulf of Maine (GOM) region. Tested environmental effects include (1) bottom water and sea surface temperature anomalies, (2) the Atlantic Multidecadal Oscillation (AMO), (3) the North Atlantic Oscillation (NAO), (4) the Gulf Stream Index (GSI), and (5) density-dependent effects (SSB). If incorporated into future assessments, identified ecosystem and climate influences on recruitment. Distribution, and growth may reduce uncertainty in stock assessments of GOM American plaice.

2. Methods

2.1. Study Area and Data Sources

2.1.1. Dependent Variables

For the recruitment analysis, recruitment data were sourced from the 2019 American plaice stock assessment, which uses the Northeast Fisheries Science Center (NEFSC) bottom trawl survey.

Spring and fall surveys were used and can be accessed from tables 9a and 9b from https://apps-nefsc.fisheries.noaa.gov/saw/sasi/uploads/2019_PLA_UNIT_TAB_OA2017_DATA_RESULTS_TABLES.pdf. These data represent the standardized stratified mean number per tow of American plaice, by age, in offshore strata 13-30 and 36-40 of the Gulf of Maine (GOM) and Georges Bank (GB) areas. There are yearly data available from 1980-2019 for the spring research bottom trawl survey, and 1980-2018 for the fall survey. The spring trawl survey runs from February-April, while the fall survey runs from September-October of each year.

Spawning stock biomass (SSB) data were also used in the calculation of a recruitment survival success metric (Perretti et al. 2017). SSB data were estimated using spring and fall NEFSC bottom trawl survey numbers at age for American plaice. The aggregate biomass for these indices was calculated for each year (1980-2019) and for each season, in Albatross calibrated units (kg/tow). The dependent variable used is a metric of recruitment success (Perretti et al. 2017), denoted as recruit abundance in year *t* per spawning stock biomass in year *t-x* , where *x* =1, (R_t/SSB_{t-x}).

American plaice mean depth and mean latitude (center of gravity) timeseries were sourced from the Distribution Mapping and Analysis Portal (DisMAP), by NOAA Fisheries for the distribution analysis. This portal can be accessed from https://apps-st.fisheries.noaa.gov/dismap/DisMAP.html. These seasonal data are derived from the NMFS Regional Bottom Trawl Survey, and are calculated as biomass-weighted averages of depth and latitude, weighted by the interpolated biomass at each depth or latitude for each year (1974-2019) of the survey, respectively. More information about these data can be found in the DisMAP technical document (DisMAP Technical Report 2022).

The growth analysis utilized both American plaice relative condition index data (weight at length) as well as weight at age data, as a proxy of growth. The condition index data were used in the 2022 State of the Ecosystem (SOE) New England report, and were sourced directly by Laurel Smith at the Northeast Fisheries Science Center. These data represent the ratio of observed weight to predicted weight from the Fall NEFSC trawl survey and span from 1992-2019.

American plaice weight at age (WAA) anomaly data were estimated from weight at age data used by the American Plaice Stock Assessment Research Track Working Group. These seasonal data are from the NEFSC Bottom Trawl survey include year classes 1-11+ and span from 1992-2019. Due to the limited timespan of these data, the full timeseries (1992-2019) were used as the baseperiod for the anomaly estimates. Please refer to the Supplemental Figures section at the end of this document for plotted timeseries of all dependent variable data mentioned above.

2.1.2. Independent Variables

Bottom water temperature and sea surface temperature (SST) data were sourced from the Finite-Volume Community Ocean Model (FVCOM) data. The FVCOM has demonstrated correspondence with bottom temperatures taken by the NEFSC bottom trawl survey (Turner et al. 2017), making it appropriate for use in this exploration. The FVCOM was developed by University of Massachusetts Dartmouth and Woods Hole Oceanographic Institution. More information about the FVCOM can be found in Chen et al. (2006). Monthly averaged FVCOM data were sourced between the years 1978-2019, which is the full time series of all FVCOM data currently available. From these temperature data, temperature anomalies were calculated using 1981-2010 as a reference baseline period for comparison.

North Atlantic Oscillation (NAO) data were sourced from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information and can be accessed from https://www.ncdc.noaa.gov/teleconnections/nao/. These data are monthly anomalies of the surface sea level pressure difference (hPa) calculated from the 1950-2000 climatological daily mean and standard deviation base period. These data span from January 1950 to present and are calculated over 0-90 °N latitude.

Atlantic Multidecadal Oscillation (AMO) index data were sourced from the NOAA Physical Sciences Laboratory and can be accessed from https://psl.noaa.gov/data/timeseries/AMO/. This timeseries spans from 1948-present and is calculated from the Kaplan sea surface temperature dataset, which represent gridded global sea surface temperature anomalies. The AMO index is recorded at a monthly time interval and has options for a 121-month smoothed dataset, although the unsmoothed dataset was used in this study.

The Gulf Stream Index (GSI) dataset was sourced through direct communication with Dr. Zhuomin Chen at Woods Hole Oceanographic Institute where data were derived following the methods of Joyce et al. (2019). These data characterize a 200-m depth 15°C isotherm derived GSI and were recorded at monthly time interval for years 1954-2019. This GSI timeseries are not publicly available, however the source dataset was obtained from NOAA's National Oceanographic Data Center (NODC) and represent 3-month smoothed ocean temperature values at 200m along the north wall from 75°W to 55°W at a resolution of 1° latitude/longitude. These source data can be accessed at https://www.ncei.noaa.gov/access/global-ocean-heat-content/. Temperature variability of the Gulf stream is equivalent to a 50-100 km north-south shift (Joyce et al. 2019) and thus the Gulf Stream Index is recorded in terms of the Gulf Stream Position anomaly (degrees latitude). More information about the analytical methods used to derive this dataset can be found in Joyce et al. (2019).

Seasonal American plaice spawning stock aggregate biomass data were also used as independent variables in the distribution and growth analyses. These data are from the NEFSC Bottom Trawl survey and represent annual calendar year means (January-December), in Albatross calibrated units (kg/tow). This timeseries spans from1980-2019.

2.2 Model Development

2.2.1 Recruitment Analysis Model Development

Timeseries data for all environmental variables (AMO, NAO, GSI, bottom temperature, and SST) were clipped to match the timespan of the NEFSC bottom trawl recruitment data: 1980-2019 for the spring survey and 1980-2018 for the fall survey. Recruitment data were divided into 2 groups based on season (spring & fall).

Explanatory variables tested for associations with recruitment data include averaged bottom temperature anomalies, sea surface temperature anomalies, AMO, NAO, and the Gulf Stream Indices. Each of these explanatory variables were aggregated into separate annual and 6-month means, where the annual and 6-month means represent the 12-month and 6-month period before the start of each seasonal trawl survey, respectively. The NEFSC spring trawl survey runs from February-April, while the fall survey runs from September-October of each year. Thus, the 12-month mean for each environmental variable spans from March$_{(year-1)}$ – February$_{(year)}$ for spring data, and October$_{(year-1)}$ – September$_{(year)}$ for fall data. Likewise, the 6-month mean for each environmental variable spans from September$_{(year-1)}$ – February$_{(year)}$ for spring data, and April$_{(year)}$ – September$_{(year)}$ for fall data. This time period selection method was used in (Fredston-Hermann 2020) and ensures that only environmental data prior to the survey is considered as potentially influential on recruitment. Two environmental variables tested in the recruitment analysis are an exception: a 6-month averaged bottom temperature variable and a 4-month averaged SST anomaly variable. In the recruitment analysis, only one 6-month bottom temperature anomaly average was tested, which represents a mean March-August period each year, to capture the thermal environment in the typical first 6 months of life, starting from the beginning of the typical spawning season (March) in the GOM (Johnson 2004). Similarly, 4-month SST average anomalies spanned from March-June to correspond with the beginning of the spawning season and because post spawning, plaice eggs typically float at or near surface waters for 4 months before descending towards the bottom (Huntsman 1918; Johnson 2004).

In addition, a secondary NAO variable was also tested in each model, one that was lagged an additional year. This additional NAO variable was tested because in general, there is a two-year lag between changes in the NAO and changes in the position of the Gulf Stream's northern boundary (Taylor and Stephens 1998). Additionally, one study found that a NAO explanatory variable forward lagged by 2 years had the largest impact on recruits per spawner anomalies amongst 12 New England groundfish stocks (Brodziak and O'Brien 2005). A full list of environmental variables and associated time-lags tested for each model can be found in Table 1.

2.2.2 Distribution Analysis Model Development

Environmental variables considered for the distribution analysis include AMO, NAO, GSI, bottom temperature anomaly, and spawning stock biomass (SSB). Timeseries data were clipped to correspond with the shortest timeseries included in the model: SSB. Therefore, the timeseries used in the distribution analysis spanned from 1980-2019 for both depth and latitude models. Similar to the recruitment analysis, data were divided into 2 groups based on season (spring and fall). However, the depth data available were derived from a fall survey, thus only three models were tested for this analysis: 1 depth model (fall), and 2 latitude models (spring and fall).

With the exception of SSB, all environmental variables were aggregated into 6-month and 12-month means, prior to each seasonal survey. Refer to section 2.2.1 for more information on these aggregation methods. A full list of environmental variables and associated time-lags tested for each model can be found in Table 1.

2.2.3 Growth Analysis Model Development

Two separate analyses were conducted for growth: a weight at length analysis using condition index data, and a weight at age analysis (WAA) using weight at age anomaly data. Similar to the distribution analysis, environmental variables considered for the growth analyses include AMO, NAO, GSI, bottom temperature anomaly, and spawning stock biomass (SSB). Timeseries data were clipped to correspond with the shortest timeseries included in the model: the dependent condition index and WAA data. Therefore, the timeseries used in the growth analyses spanned from 1992-2019 for both depth and latitude models. Similar to the recruitment analysis, data were divided into 2 groups based on season (spring and fall). A total of 24 models were constructed and tested for this analysis, with 2 models run for the condition index analysis (fall and spring), and 22 models run for the WAA anomaly analysis (11 year-classes × 2 seasons).

With the exception of SSB, all environmental variables were aggregated into 6-month and 12-month means, prior to each seasonal survey. Refer to section 2.2.1 for more information on these aggregation methods. A full list of environmental variables and associated time-lags tested for each model can be found in Table 1.

Table 1: Environmental Variables Tested in Each Model. Unless specifically noted otherwise, variables denoted with "(6-month mean)" represent the mean of the 6-months prior to the start of the corresponding seasonal survey used in each model. Likewise, variables denoted with "(annual mean)"

represent the mean of the 12-months prior to the start of the corresponding seasonal survey used in each model, unless specified otherwise. “Bt” denotes bottom temperature.

Recruitment	Distribution	Growth
GSI (6-month mean) GSI (annual mean)	GSI (6-month mean) GSI (annual mean)	GSI (6-month mean) GSI (annual mean)
AMO (6-month mean) AMO (annual mean)	AMO (6-month mean) AMO (annual mean)	AMO (6-month mean) AMO (annual mean)
NAO (6-month mean) NAO (annual mean) NAO (annual mean, lagged additional year)	NAO (6-month mean) NAO (annual mean)	NAO (6-month mean) NAO (annual mean)
Bt Anomaly (6-month mean: March-August) Annual Bt Anomaly SST (4-month mean: March-June)	Bt Anomaly (6-month mean) Annual Bt Anomaly	Bt Anomaly (6-month mean) Annual Bt Anomaly
	SSB (annual mean: Jan-Dec)	SSB (annual mean: Jan-Dec)

2.3 Model Fitting and Validation

Pearson correlation coefficient tests were conducted prior to model construction to test for variable independence. There was a high dependence between GSI and all temperature variables (bottom temperature and SST), as well as between AMO and NAO variables. Subsequently, if both variables were significant in the model, the significant ($p < 0.05$) variable that resulted in the lowest model Akaike Information Criterion (AIC; Akaike 1974) was kept in the model, and the other eliminated. Similarly, duplicate variables (e.g. SST vs. bottom temperature anomalies and 6-month vs. 1 year NAO, AMO, GSI) were filtered from final models such that each potential covariate was tested in each model, but only unique variables were kept in the final model, if significant, to avoid effects of multicollinearity in the final models.

Each of the dependent variables were modeled independently using generalized additive models (GAMs; Hastie and Tibshirani 1986). GAMs are an extension of a generalized linear model (GLM), with a smoothing function added. GAMs estimate relationships between independent and dependent variables by use of spline functions, allowing them flexibility to model relationships beyond the parametric forms common to GLMs (Wood 2017; Yee and Mitchell 1991). Often, nonlinear relationships are observed between species population dynamics and environmental drivers. In this study, GAMs were used to evaluate the relationships between American plaice population dynamics (recruitment, distribution, and growth) and environmental variables. A backward fitting technique based upon covariate significance ($p < 0.05$) and AIC were used in tandem to build and select the best fitting model for each population dynamic × season group. AIC is a method which tests the goodness of fit of a model while also including considerations of model complexity, unlike other similar statistics, like deviance explained. A smaller returned AIC value indicates a better fitting model (Zuur et al. 2009). An example GAM equation for the recruitment analysis, including all potential variables and before eliminating variables due to collinearity, non-significance, duplicates, etc. can be written as:

$$Mean\ number\ of\ age_x\ plaice\ per\ tow\ (y) = s(GSI6) + s(GSI12) + s(AMO6) + s(AMO12) + s(NAO6) + (NAO12) + s(NAO2) + s(Bt) + s(Bt6) + s(SST4)$$

where y is the dependent variable of mean number of plaice per tow at age *x*, *s* is a spline smoother, and *GSI, AMO, NAO, NAO2, Bt, Bt6*, and *SST4* are the independent variables representing the Gulf Stream Index (6- and 12-month), the Atlantic Multidecadal Oscillation (6- and 12-month), the North Atlantic Oscillation (6-month, 12-month, and lagged an additional year), 12-month mean bottom temperature anomalies, 6-month mean bottom temperature anomalies, and 4-month mean SST anomalies, respectively. Similar GAM equations were constructed for the distribution and growth analyses based upon these methods.

3. Results

3.1 Summary of Results:

- **Recruitment:** AMO was significant in both fall and spring models.
- **Distribution:** Bottom temperature anomaly and SSB were significant in both fall depth and spring and fall latitude models.
  - NAO was also significant in fall depth and spring latitude models.
- **Growth:** AMO was the most prevalent significant variable between both the condition index and WWA anomaly analyses.
  - Significant variables in the condition index model also included bottom temperature anomaly and SSB.
  - Significant variables in the WAA anomaly models also included GSI, SSB, and bottom temperature anomaly.

3.2 Recruitment Analysis Results, Model Performance, and Validation

Explanatory variables used in the final models differed between population dynamic × season groups. The AMO variable was found to be significant in both fall and spring models, while GSI was also significant, but only in the fall model, and did not contribute much deviance explained (1.13% when in the model alone). AMO however, was estimated to explain 26-36.6% of variation in the fall and spring models, respectively, when tested as a singular variable in each model. Final models, when GSI and AMO were combined, resulted in 33.1% deviance explained with an AIC of 43.15 for the fall model and 36.6% deviance explained with an AIC of -65.04 in the spring model. See Table 2 for a full list of environmental variables that were included in each finalized model and for more details on model fit diagnostics.

Table 2: Recruitment Model Result Diagnostics and Significant Variables: The abbreviation "DE" denotes deviance explained.

Model	Significant Covariates (% DE when alone in model)	Full Model DE	Full Model AIC	Reduced Model DE	Reduced Model AIC
Fall	AMO – 6-month mean (26.0%) GSI – Annual mean (1.13%)	53.7%	39.46	33.1%	43.16

Spring	AMO – 6-month mean (36.6%)	63.4%	-75.96	36.6%	-65.04

Model residual plots were generated and can be found in Figure 1 below. All model residual plot fits look similar, with slightly better fits generated from the spring model when compared to the fall.

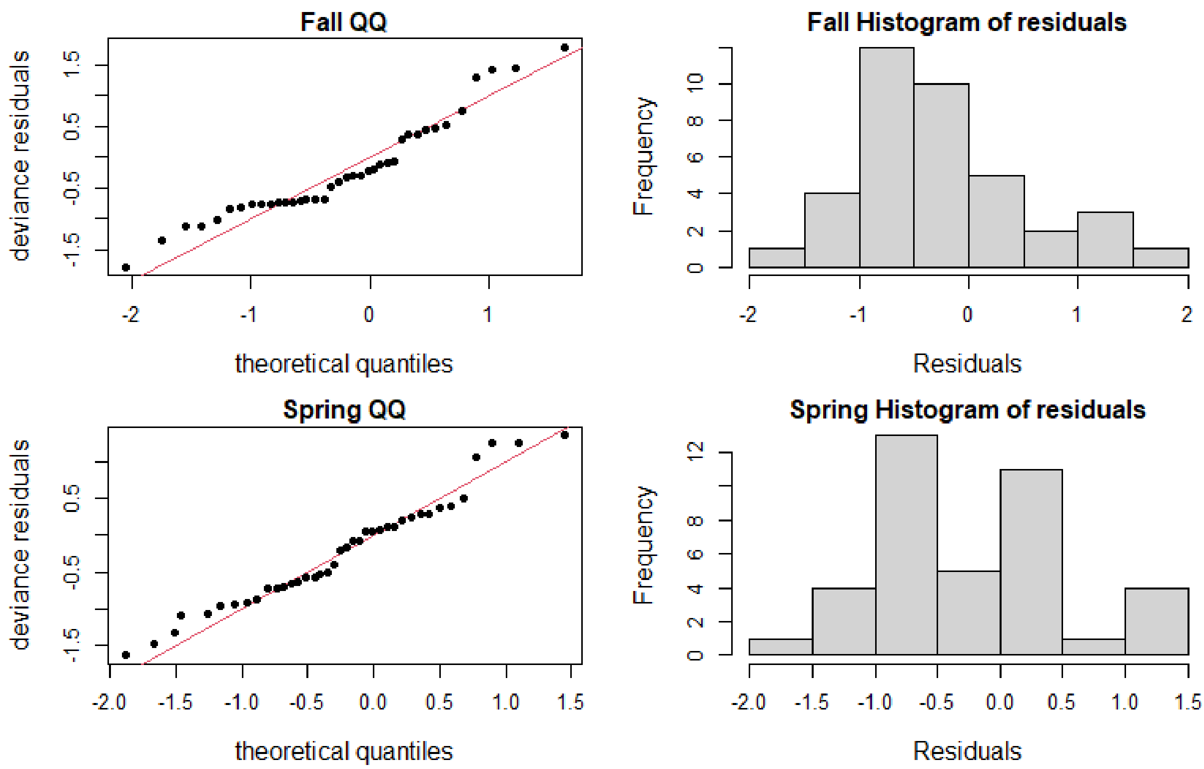


Figure 1: Recruitment Model Residual Diagnostic Plots for both Fall (top row) and Spring (bottom row).

Environmental variables were explored via GAM response curves for each significant predictor variable. The shape of the response curves varied amongst predictor variables but showed consistency within variables (Figures 2 & 3). For example, the shape of the fall model AMO response curve differs from that of the GSI response curve (Figure 2), but response curve shapes for fall AMO and spring AMO demonstrate similarity in shape. Highest partial effect on (R_t/SSB_{t-x}) for AMO occurred at positive changes in SST anomalies between (<1.0 °C and >2.5 °C).

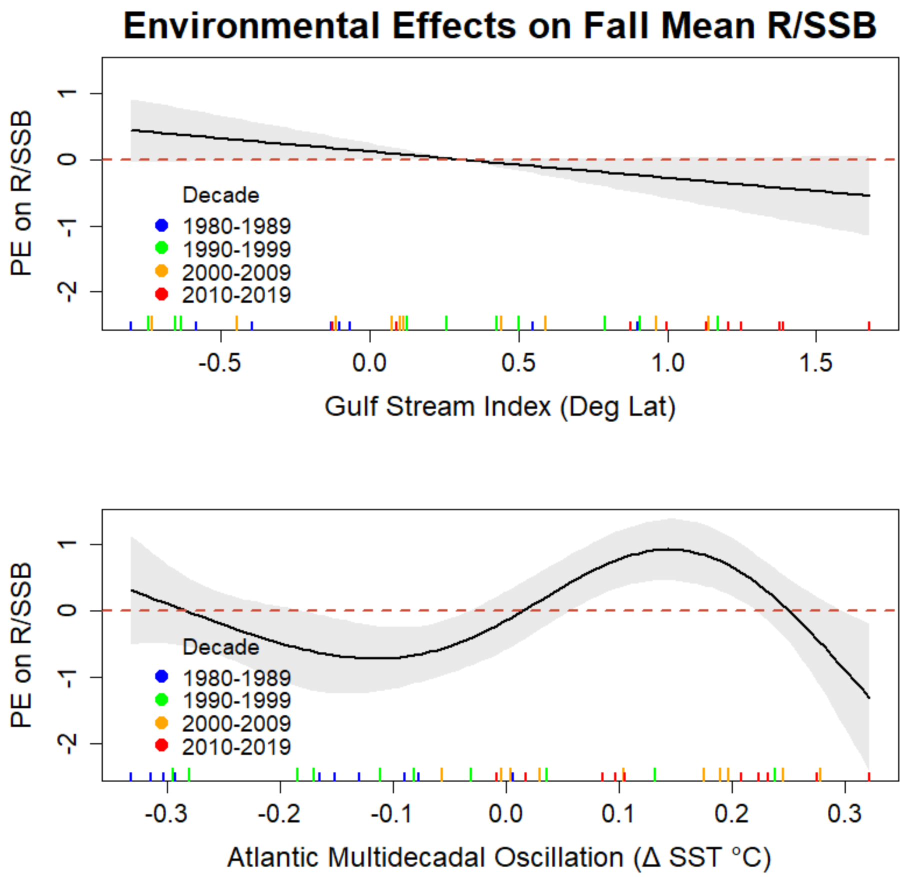


Figure 2: GAM Response Curves of Significant Covariates in Fall Recruitment Model. "PE" denotes the partial effect the independent variable has on the dependent variable, R/SSB. Rug plot lines along the x-axis of each plot indicate distribution of the independent data, colored by decade of occurrence, as shown in the legend. Shaded regions indicate the standard error confidence intervals.

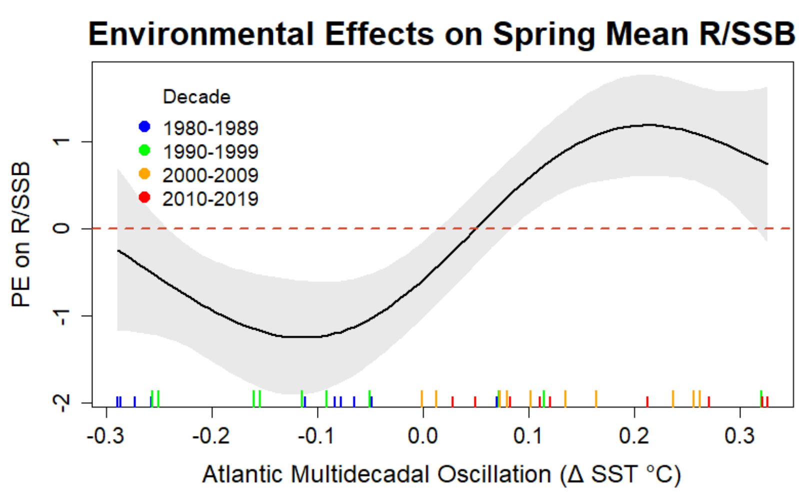


Figure 3: GAM Response Curves of Significant Covariates in Spring Recruitment Model. "PE" denotes the partial effect the independent variable has on the dependent variable, R/SSB. Rug plot lines

along the x-axis of each plot indicate distribution of the AMO data, colored by decade of occurrence, as shown in the legend. Shaded regions indicate the standard error confidence intervals.

3.3 Distribution Analysis Results, Model Performance, and Validation

The distribution analysis is composed of two separate analyses: one that examines the relationship between mean depth of occurrence vs. environmental variables, and another that examines the relationship between mean latitude of occurrence vs. environmental variables. Results from these analyses revealed differences in significant variables associated with each population dynamic × season groups. There were no significant variables in the spring depth model, a result which may be attributed to the lack of change in observed spring depth of occurrence (see Supplementary Figure 2). Bottom temperature anomaly and SSB were found to have significant relationships in the fall depth, fall latitude, and spring latitude models. Additionally, the NAO was found to be significant in the fall depth and spring latitude model, while the fall latitude model revealed a significant relationship with the AMO. Tweedie, gaussian, and gamma family distributions were tested for each model. Although all three family types resulted in similar fit diagnostics, tweedie distributions were chosen due to a combination of best looking residual plots and AIC scores. See Table 3 for a full list of environmental variables that were included in each finalized model and for more details on model fit diagnostics. Additionally, model residual plots were generated and can be found in Figure 4 below.

Table 3: Distribution Model Result Diagnostics and Significant Variables: The abbreviation "DE" denotes deviance explained.

Model	Significant Covariates (% DE when alone in model)	Full Model DE	Full Model AIC	Reduced Model DE	Reduced Model AIC
Fall Depth	NAO – Annual (16.9%) 6-Month Bt Anomaly (7.4%) SSB (5.99%)	55.6%	264.2	53.3%	262.43
Spring Depth	No Variables Returned Significant	N/A	N/A	N/A	N/A
Fall Latitude	AMO – 6-Month Mean (3.74%) Annual Bt Anomaly (24.8%) SSB (14.1%)	70.5%	-77.39	60.6%	-75.87
Spring Latitude	NAO – 6-Month Mean (9.39%) Annual Bt Anomaly (33.9%) SSB (14.1%)	73.9%	-101.22	69.5%	-101.40

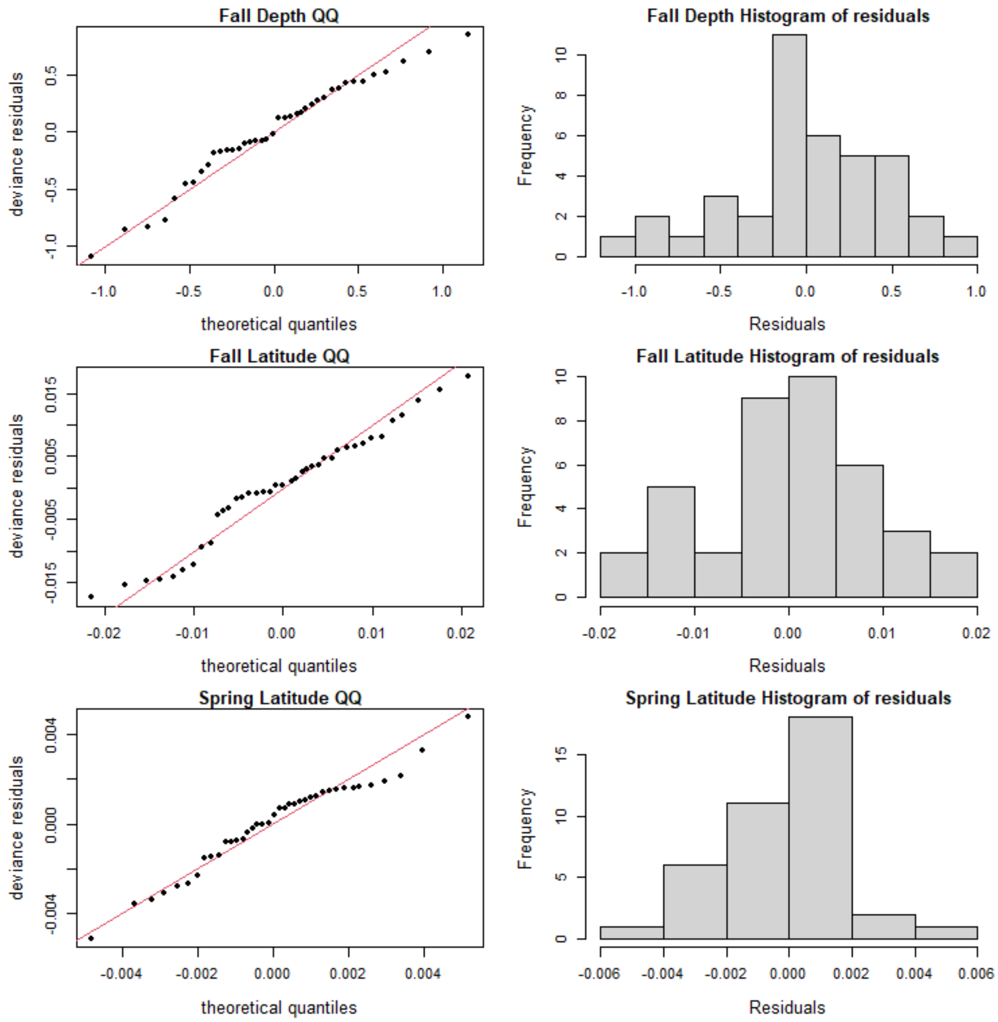


Figure 4: Distribution Model Residual Diagnostic Plots for both fall depth (top row), fall latitude (middle row), and Spring latitude (bottom row).

Environmental variables were explored via GAM response curves for each significant predictor variable. The shape of the response curves varied amongst predictor variables but showed consistency within most variables (Figures 5-7). For example, the shape of all bottom temperature anomaly and SSB response curves demonstrate a similar positive relationship. However, although both the mean depth and latitude dependent variables are meant to serve as proxies of distribution for American plaice, the resulting relationship curve between fall depth and NAO and spring latitude and NAO demonstrate disagreement in relationship trends, as the NAO fall depth relationship curve displays an overall negative trend (Figure 5), and the NAO spring latitude relationship curve displays an overall positive trend (Figure 7).

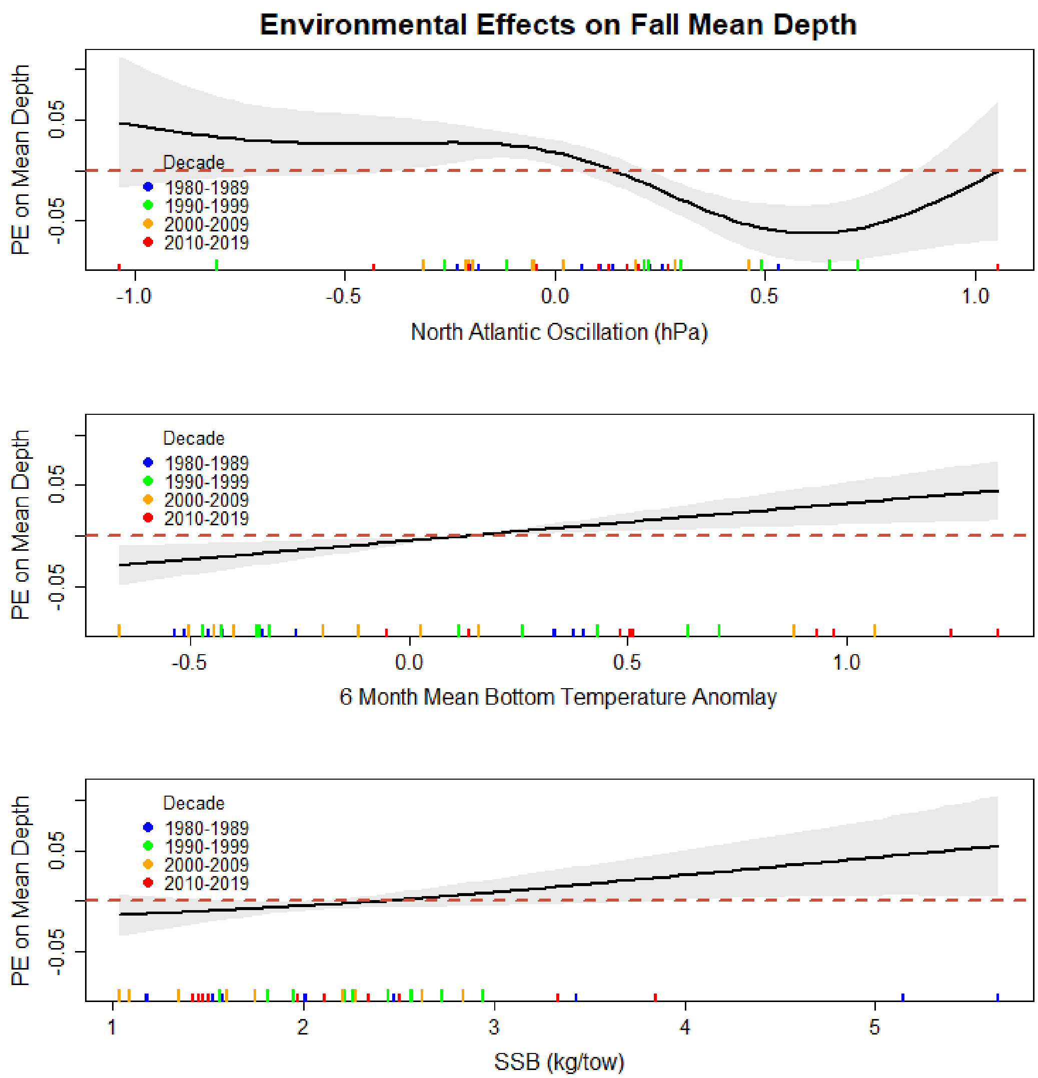


Figure 5: GAM Response Curves of Significant Covariates in Fall Distribution Model (Fall Depth). "PE" denotes the partial effect the independent variable has on the dependent variable, mean depth of occurrence (m). Rug plot lines along the x-axis of each plot indicate distribution of the independent data, colored by decade of occurrence, as shown in the legend. Shaded regions indicate the standard error confidence intervals.

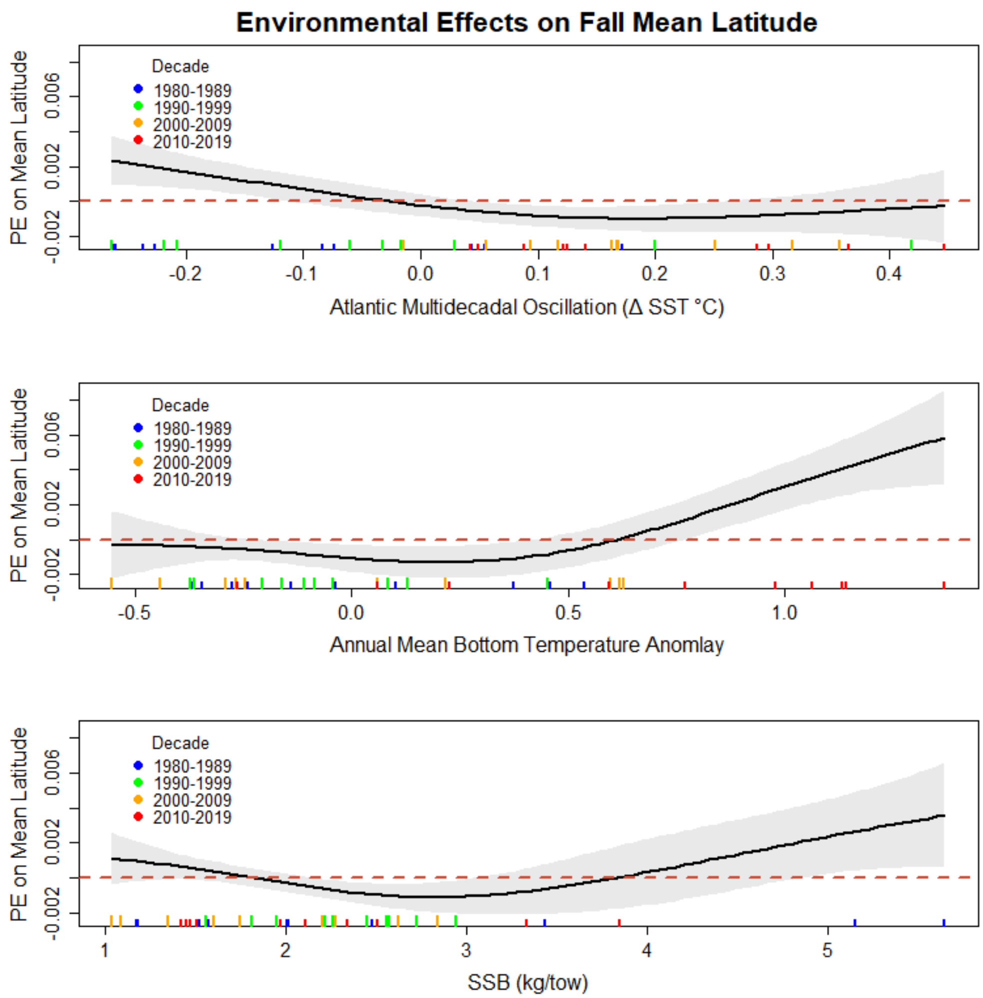


Figure 6: GAM Response Curves of Significant Covariates in Fall Recruitment Model (Fall Latitude). "PE" denotes the partial effect the independent variable has on the dependent variable, mean depth of occurrence (m). Rug plot lines along the x-axis of each plot indicate distribution of the independent data, colored by decade of occurrence, as shown in the legend. Shaded regions indicate the standard error confidence intervals.

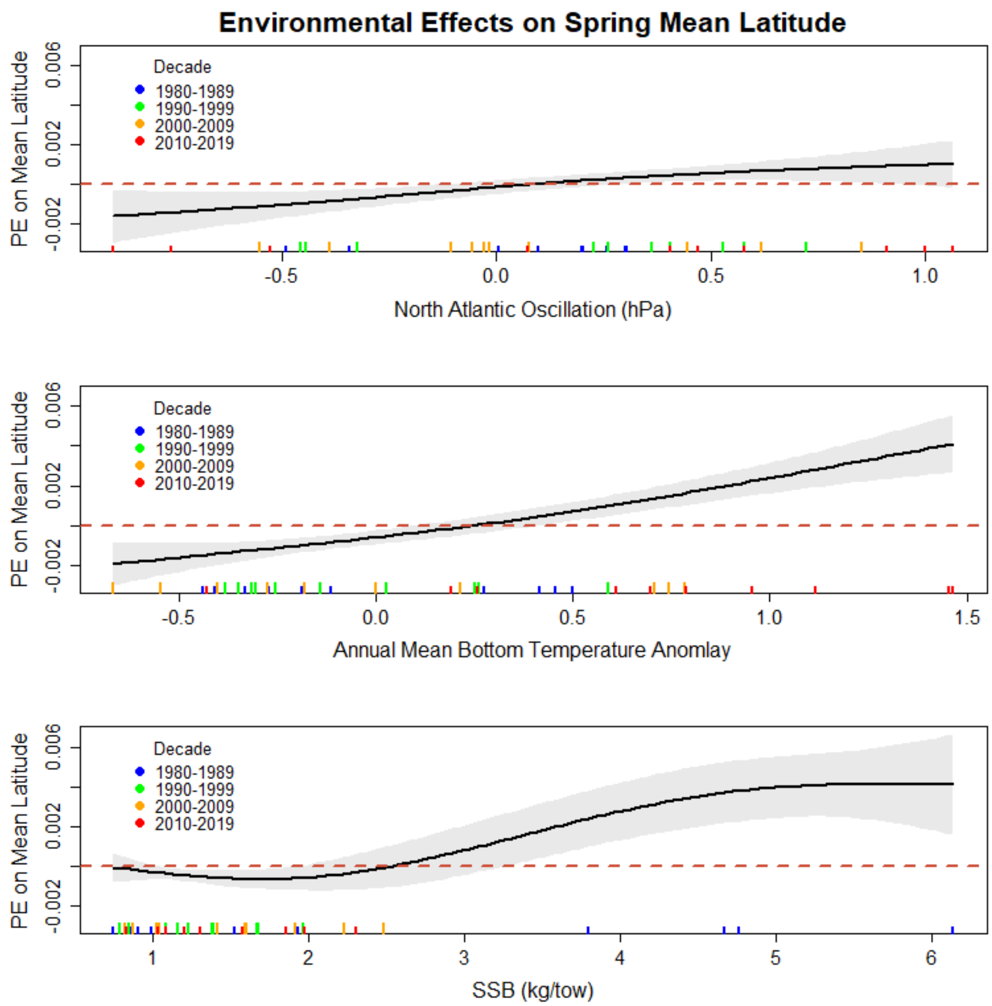


Figure 7: GAM Response Curves of Significant Covariates in Recruitment Model (Spring Latitude). "PE" denotes the partial effect the independent variable has on the dependent variable, mean depth of occurrence (m). Rug plot lines along the x-axis of each plot indicate distribution of the independent data, colored by decade of occurrence, as shown in the legend. Shaded regions indicate the standard error confidence intervals.

3.4 Growth Analysis Results, Model Performance, and Validation

The growth analysis is also composed of two separate analyses: one that examines the relationship between mean fish condition (index of weight at length) vs. environmental variables, and another that examines the relationship between mean weight at age vs. environmental variables. These data represent the ratio of observed weight to predicted weight from the Fall NEFSC trawl survey, and as a result, only a fall model was run using these data. Results from this analysis showed SSB to have the most significant relationship with mean condition, followed by annual bottom temperature anomaly, and a 6-month mean AMO variable. This model explained 57.5% of variation, and the model fit diagnostics and residual plots can be found in Table 4 and Figure 8, respectively.

Table 4: Model Result Diagnostics and Significant Variables for Growth Analyses (Fall Condition Index): The abbreviation "DE" denotes deviance explained.

Model	Significant Covariates (% DE when alone in model)	Full Model DE	Full Model AIC	Reduced Model DE	Reduced Model AIC
Fall Condition Index	AMO – 6-month mean (10.2%) Annual Bt Anomaly (12.1%) SSB (25.5%)	58.3%	107.28	57.5%	-111.255

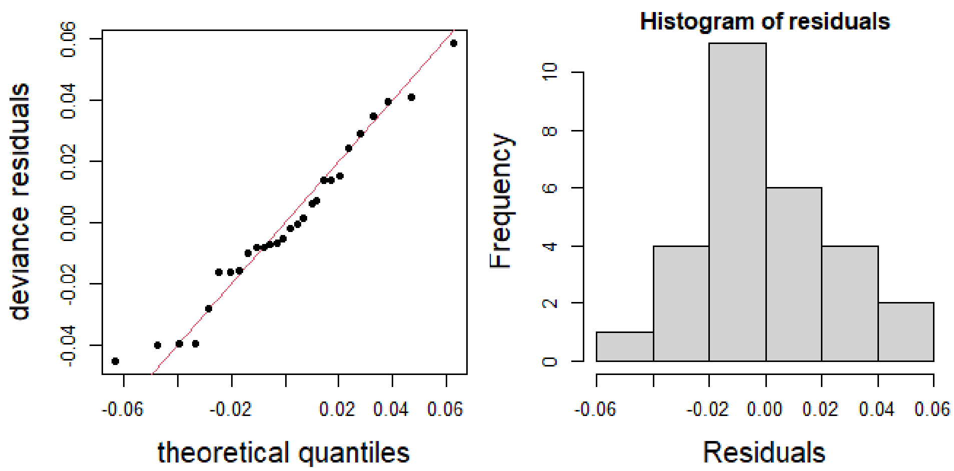


Figure 8: Growth Model (Fall Condition Index) Residual Diagnostic Plots.

For the weight at age anomaly analysis, a unique model was run for each year class (1-11+) and each season, for a total of 22 model runs. AMO was the most prominent significant variable amongst the year classes, demonstrating a significant relationship in 9/11 fall year classes and 10/11 spring year classes. In addition, GSI and SSB showed relationships in some year classes, ranging between age 2–6-year classes. Finally, the bottom temperature anomaly variable also displayed some significance, but only in the younger & older year classes; namely, ages 1 and 9 in the fall models and ages 10 and 11+ in the spring. See Figure 9 for a visualization of significant variables by year class. Diagnostic results of the 22 weight-at-age model runs can be found in tables 5 and 6.

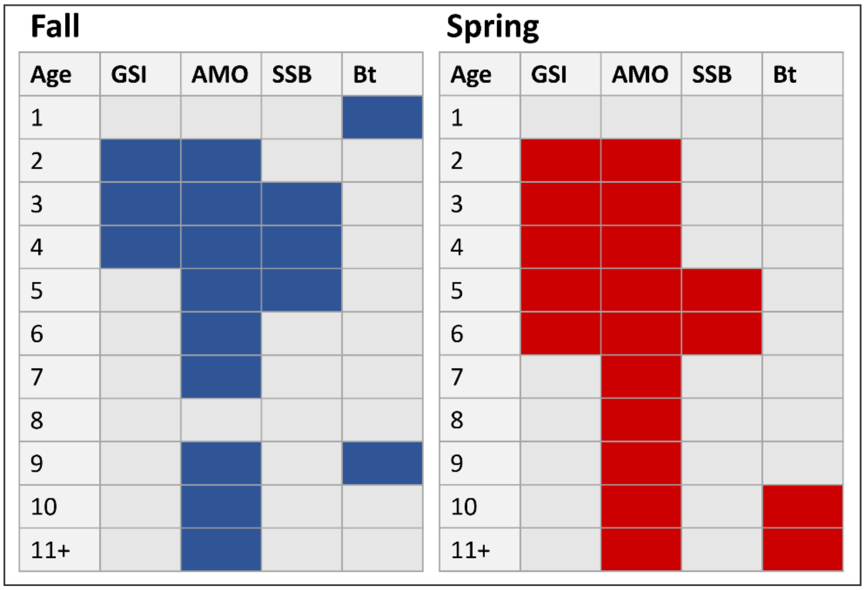


Figure 9: Visualizing Significant WAA Anomaly Variables by Year Class. "Bt" denotes the bottom temperature anomaly variable. Each shaded cell signifies the corresponding environmental variable (column) and year class (row) displayed significance in the model.

Table 5: Model Result Diagnostics and Significant Variables for Growth Analyses (Fall Weight at Age): The abbreviation "DE" denotes deviance explained.

Age	Significant Covariates (% DE when alone in model)	Full Model DE	Full Model AIC	Reduced Model DE	Reduced Model AIC
1	Annual Bt Anomaly (35.6%)	46.9%	-310.40	35.6%	-311.30
2	GSI – Annual (25.5%) AMO – Annual (1.76%)	73%	-260.85	34.5%	-239.58
3	GSI – Annual (25.7%) AMO – Annual (2.59%) SSB (36%)	73.1	-192.99	55.6%	-181.29
4	GSI – Annual (20.3%) AMO – Annual (2.77%) SSB (28.4%)	64.3%	-141.56	45.4%	-135.01
5	AMO – Annual (14.2%) SSB (21.7%)	36.4%	-91.18	32.4%	-94.02
6	AMO – Annual (24.6%)	45.8%	-65.17	24.6%	-62.69
7	AMO – Annual (21.1%)	46.9%	-18.50	21.1%	-15.23
8	Nothing Significant	N/A	N/A	N/A	N/A
9	AMO – 6 Month Mean (18.4%) 6 Month Mean Bt (14.9%)	42.6%	22.96	33.7%	20.31
10	AMO – Annual (21.1%)	57.0%	18.49	21.1%	25.88
11+	AMO – Annual (7.05%)	18.0%	51.51	7.05%	48.54

Table 6: Model Result Diagnostics and Significant Variables for Growth Analyses (Spring Weight at Age): The abbreviation "DE" denotes deviance explained.

Age	Significant Covariates (% DE when alone in model)	Full Model DE	Full Model AIC	Reduced Model DE	Reduced Model AIC
1	Nothing Significant	N/A	N/A	N/A	N/A
2	GSI – 6 Month mean (33.1%) AMO – 6 Month mean (2.98%)	56.3%	-302.62	49.8%	-304.67
3	GSI – Annual (14.8%) AMO – Annual (11.4%)	57.1%	-210.11	33.7%	-205.16
4	GSI – 6 Month Mean (47.8%) AMO – Annual (7.39%)	67.1%	-182.03	62.8%	-138.25
5	GSI – Annual (18.3%) AMO – 6 Month Mean (7.79%) SSB (19.8%)	78.4%	-158.62	48.9%	-136.02
6	GSI – Annual (3.7%) AMO – 6 Month Mean (19.4%) SSB (8.87%)	56.3%	-97.07	45.7%	-93.43
7	AMO – Annual (28.0%)	56.8%	-52.78	28.0%	-47.13
8	AMO – 6 Month Mean (16.0%)	27.5%	-6.46	16.0%	-9.14
9	AMO – 6 Month Mean (15.8%)	36.7%	18.85	15.8%	20.63
10	AMO – 6 Month Mean (17.5%) Annual Mean Bt Anomaly (9.04%)	34.6%	20.40	22.5%	18.85
11+	AMO – Annual (17.4%) Annual Mean Bt Anomaly (14.6%)	29.2%	31.67	26.8%	27.01

Model residual plots were generated for each of the weight at age anomaly models that had significant environmental variables. Available WAA anomaly data spanned from 1992-2019, making this time series the shortest used for this analysis, and likely contributing to the variation seen in model residual plot fits. See figures 10 and 11 below:

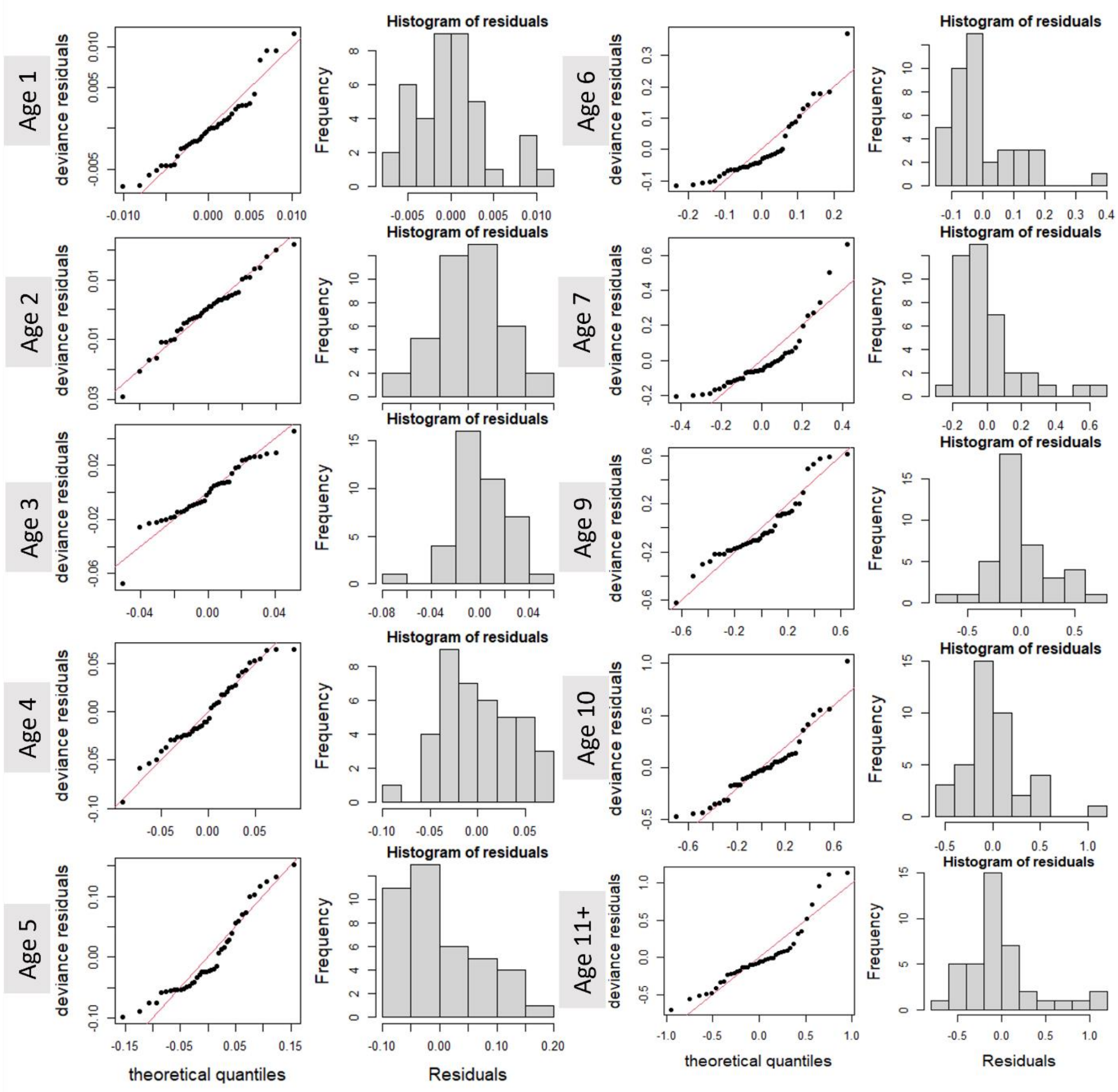


Figure 10: Growth Model (Fall WAA Anomaly) Residual Diagnostic Plots.

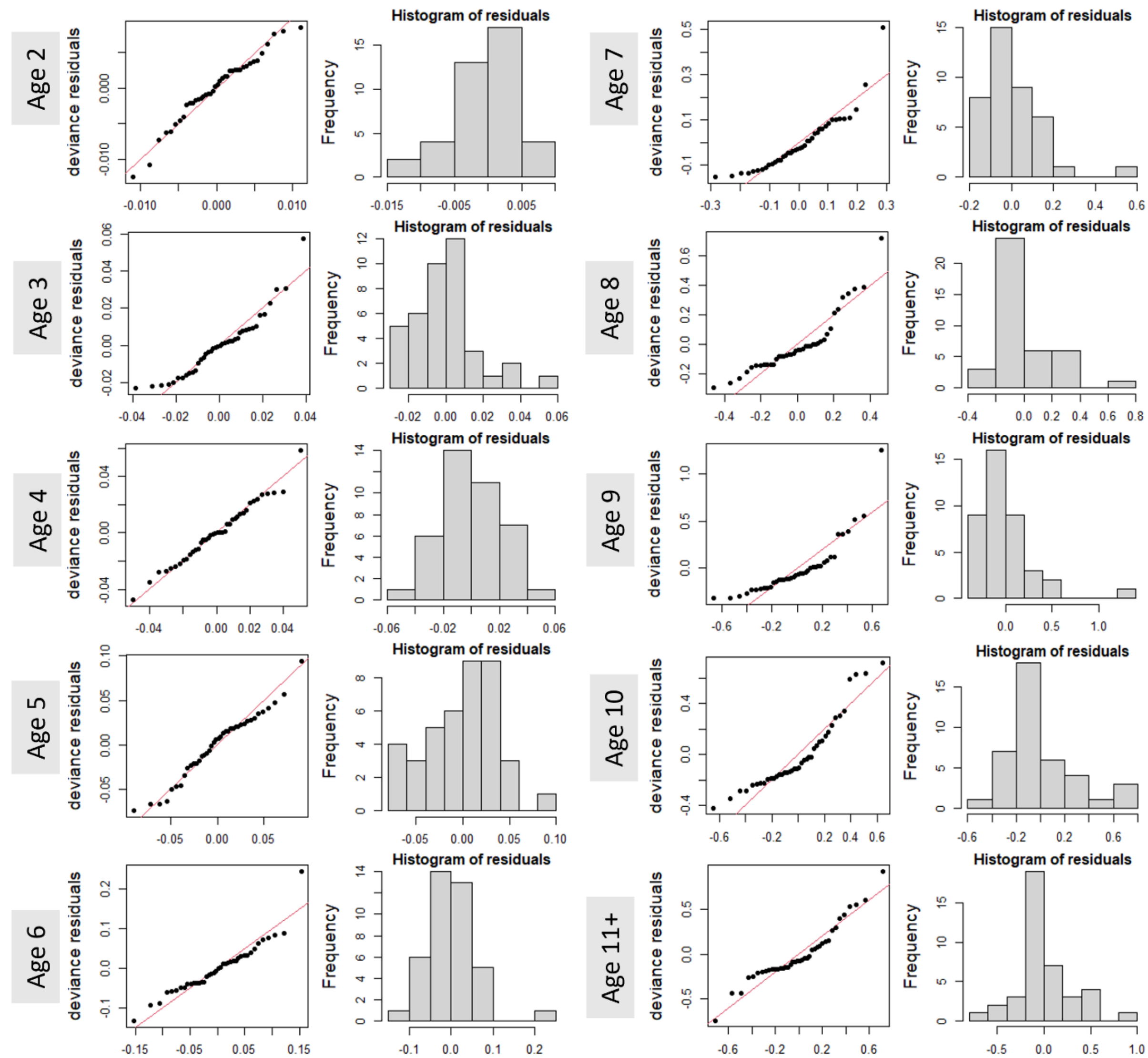


Figure 11: Growth Model (Spring WAA Anomaly) Residual Diagnostic Plots.

Environmental variables were explored via GAM response curves for each significant predictor variable. Similar to the GAM response curve results for the other analyses, the shape of the response curves varied amongst predictor variables but showed consistency within most variables (Figures 12-13). Overall, bottom temperature anomaly curves displayed a negative relationship with WAA anomaly, SSB displayed an overall positive trend then plateaued/declined at greater SSB values. Year-classes which had a significant AMO variable revealed overall negative trending relationships, and GSI displayed an overall positive relationship. The following GAM response curve plots for the growth WAA anomaly analysis are shown below and these plots are grouped by season and by year classes which shared similar significant variables. Some response curve plots contain overlays of multiple year classes. Although some plots with multiple year class overlays can be difficult to distinguish specific year-classes included within the plot, the purpose of these plots is to demonstrate consistency in relationship curve shapes amongst year-classes. Fall mean condition response curves displayed overall agreement in trends with the WAA anomaly response curves, with the exception of the bottom temperature anomaly variable, which displayed a positive trend with fall mean condition rather than negative (Figure 14).

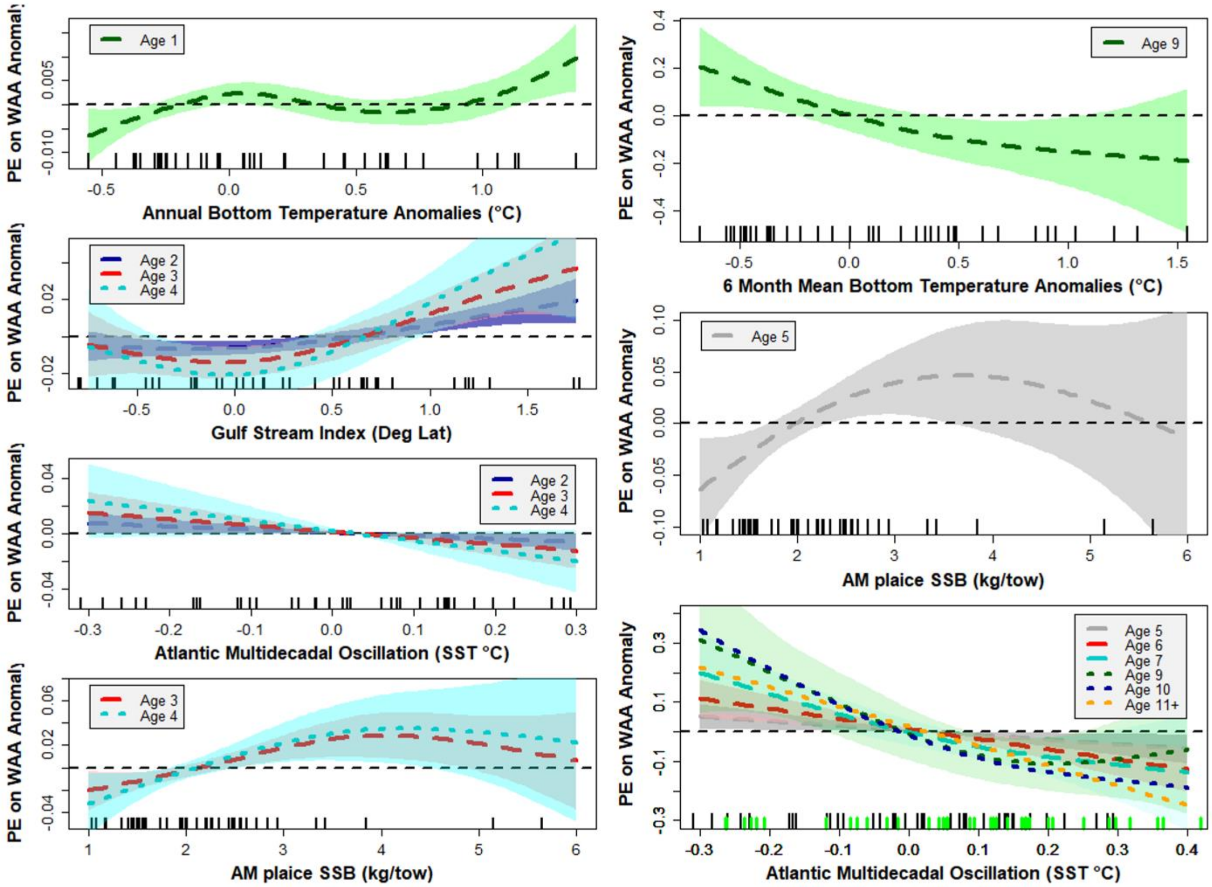


Figure 12: GAM Response Curves of Significant Covariates in Growth Model (Fall WAA Anomaly). Fall year-classes 1-4 are on the left and year classes 5-11+ are on the right. "PE" denotes the partial effect the independent variable has on the dependent variable, mean WAA anomaly. Rug plot lines along the x-axis of each plot indicate distribution of the independent data, colored by year-class, where black represents all year classes and any other color shown corresponds with the year-class of the same color listed in the legend. A maximum of two colors could be displayed in the rug plots to distinguish between 6-month mean and annual mean rug plot lines. Shaded regions indicate the standard error confidence intervals.

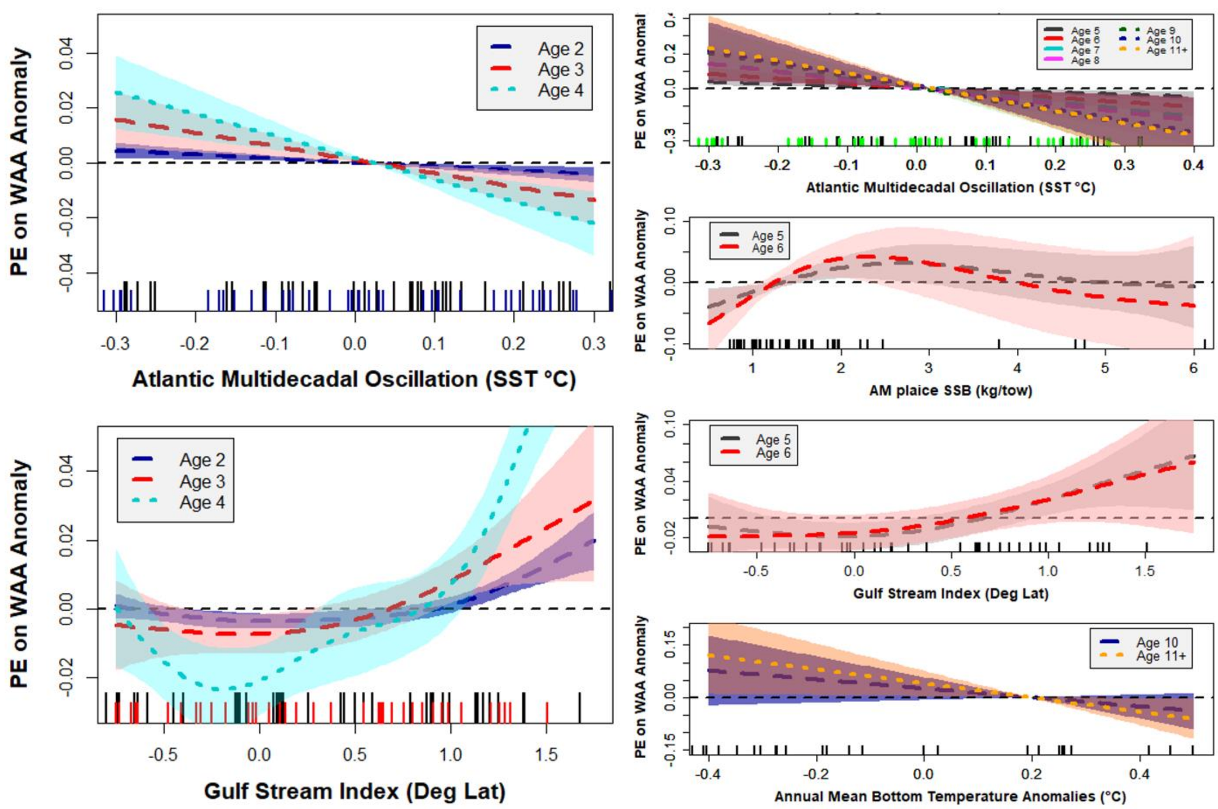


Figure 13: GAM Response Curves of Significant Covariates in Growth Model (Spring WAA Anomaly). Spring year-classes 2-4 are on the left and year classes 5-11+ are on the right. See Figure 12 for figure details.

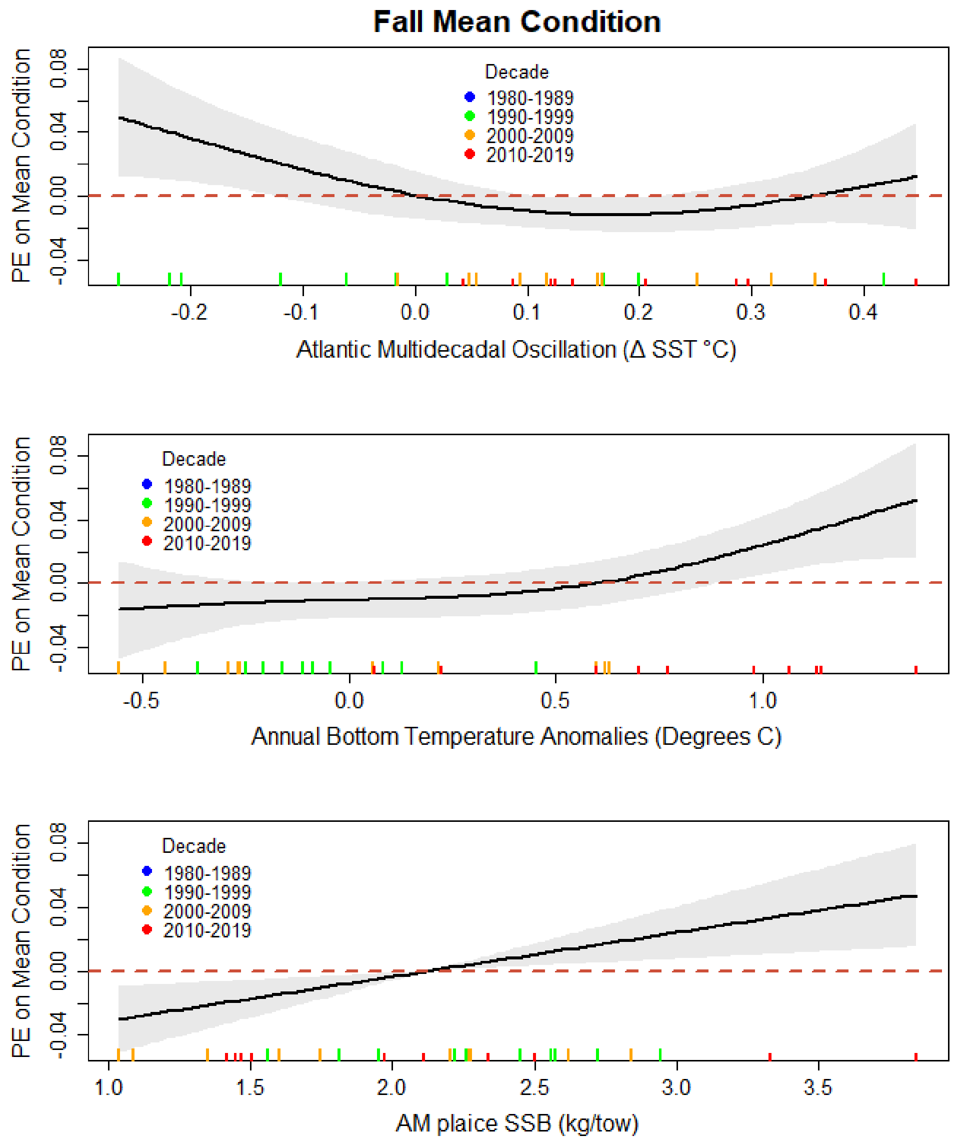
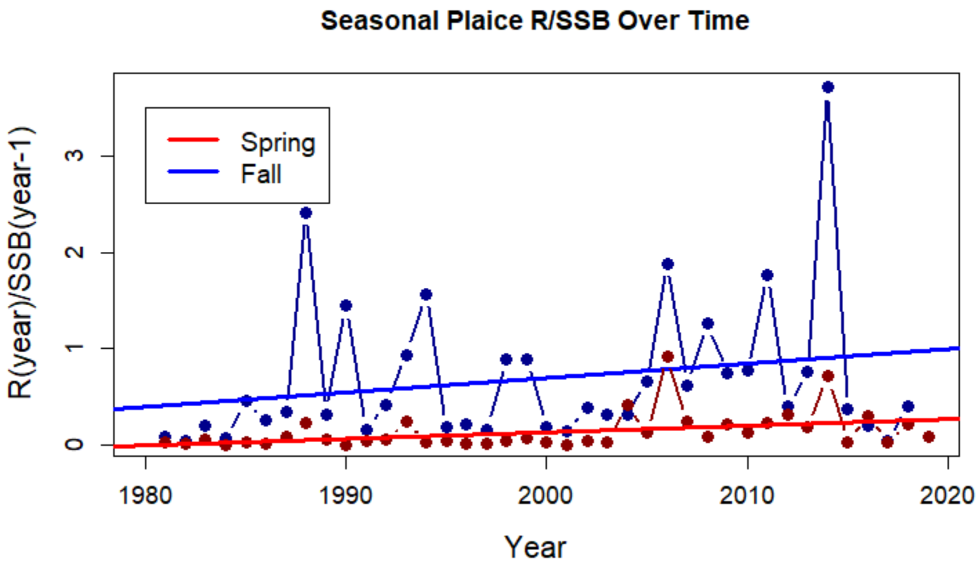
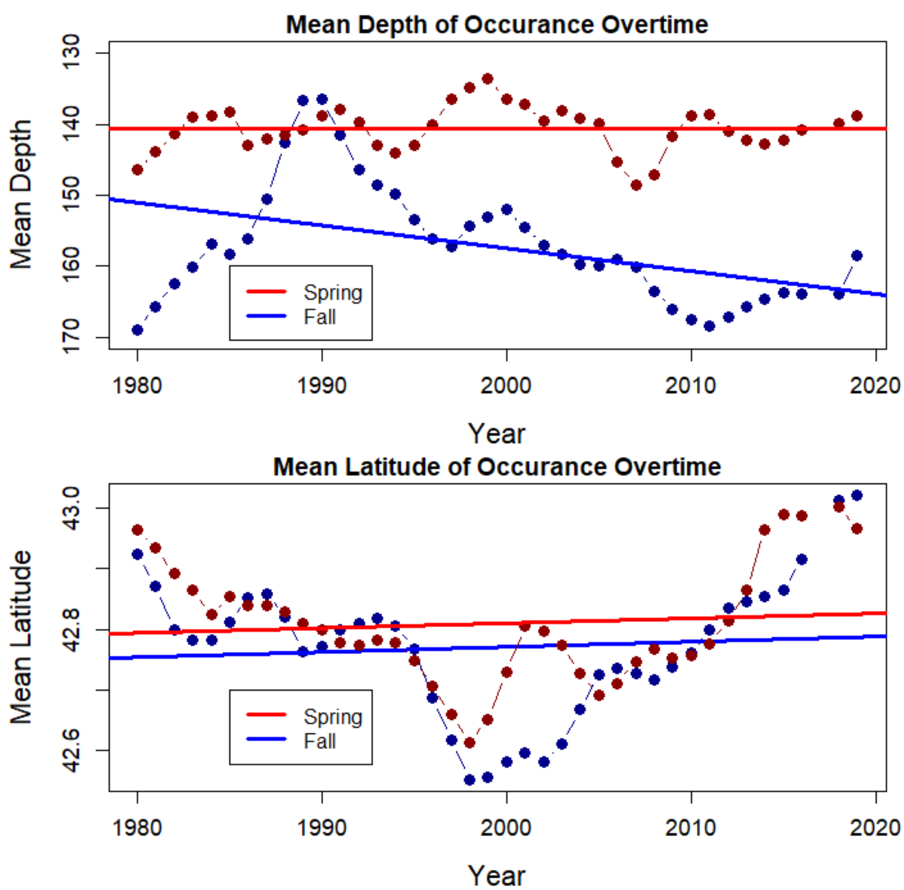


Figure 14: GAM Response Curves of Significant Covariates in Fall Growth Model (Condition Index). "PE" denotes the partial effect the independent variable has on the dependent variable, mean relative condition. Rug plot lines along the x-axis of each plot indicate distribution of the independent data, colored by decade of occurrence, as shown in the legend. Shaded regions indicate the standard error confidence intervals.

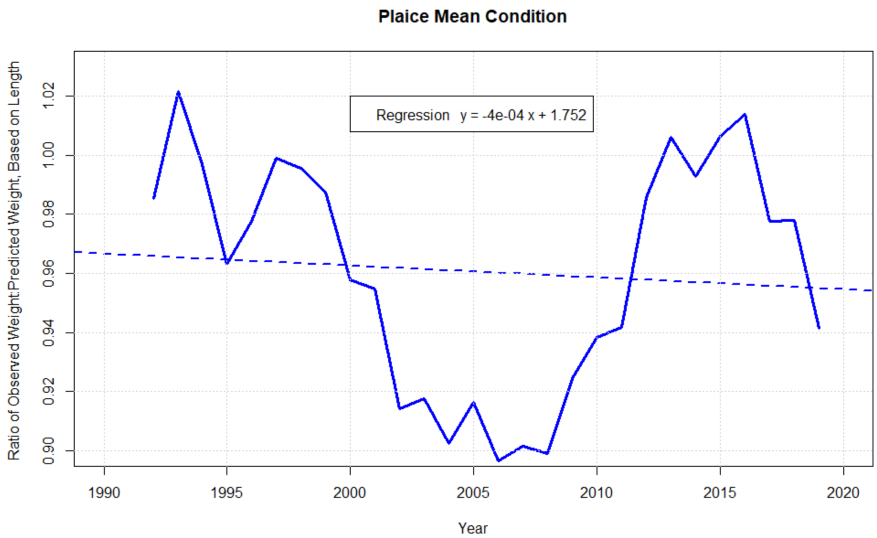
4. **Supplemental Figures**



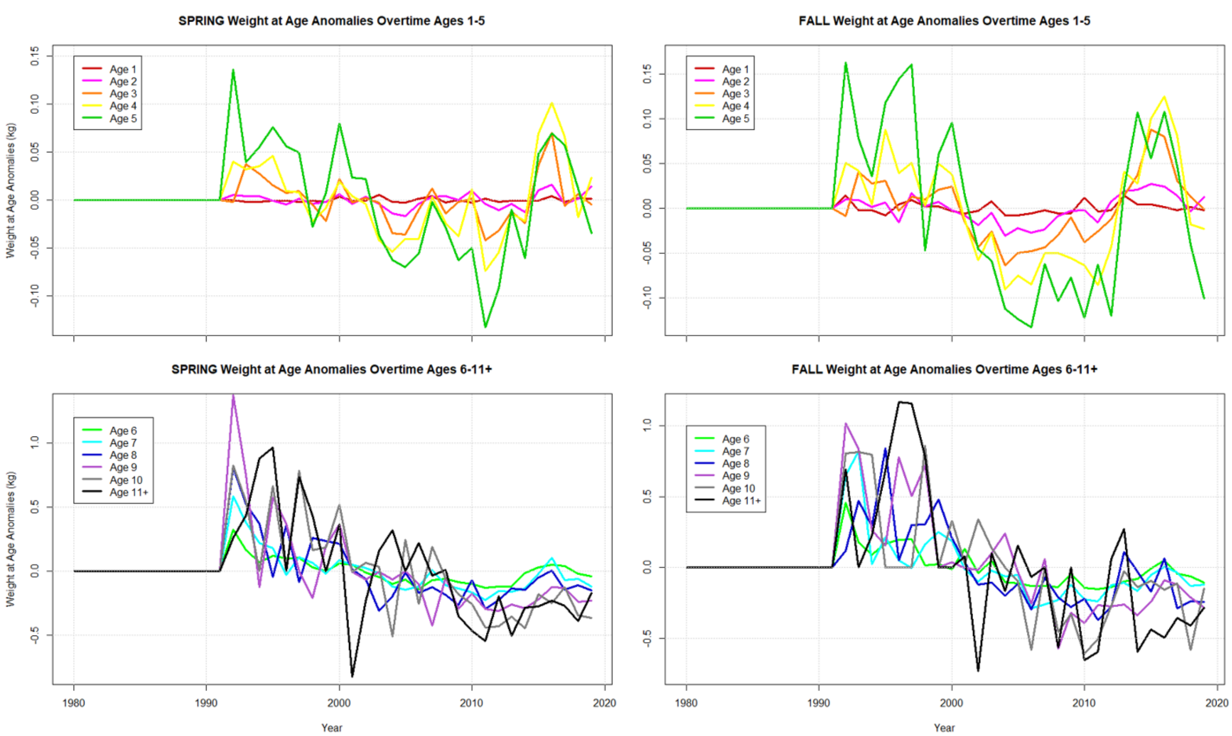
Supplemental Figure 1: Survey Indices of Recruitment Rate (R/SSB).



Supplemental Figure 2: Mean Depth and Latitude of catches from NEFSC spring and fall bottom trawl surveys.



Supplemental Figure 3: Mean Condition Factor from the Fall NEFSC Bottom Trawl Survey.



Supplemental Figure 4: Weight at Age Anomalies from Spring and Fall Surveys.

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