Title: Temporal patterns and regional comparisons of recruitment rates of United States fish stocks

Running title: Temporal and regional recruitment

Authors:

1. Rachel C. Marshall*
   rcmarshall@uri.edu
   University of Rhode Island
   Graduate School of Oceanography
   South Ferry Rd.
   Narragansett, RI 02882
   USA
2. Jeremy S. Collie
   jcollie@uri.edu
   University of Rhode Island
   Graduate School of Oceanography
   South Ferry Rd.
   Narragansett, RI 02882
   USA
3. Richard J. Bell
   rich.bell@tnc.org
   The Nature Conservancy
   South Ferry Rd.
   Narragansett, RI 02882
   USA
4. Paul D. Spencer
   paul.spencer@noaa.gov
   NOAA Fisheries
   Alaska Fisheries Science Center
   Sand Point Way NE
   Seattle, WA 98115
   USA
5. Cóilín Minto
   coilin.minto@atu.ie
   Marine & Freshwater Research Centre
   Department of Natural Resources and the Environment
   Atlantic Technological University
   Dublin Road
   Galway H91 T8NW
   Ireland

***Corresponding Author**

Abstract

Several previous studies of marine fish stocks have demonstrated time-varying recruitment productivity and indicated that including time-varying parameters can track process variation in recruitment. Few studies have synthesized signal-to-noise ratios and underlying reasons for time-variation across stocks and regions. Using Peterman's Productivity Method (PPM), we provide a broad synthesis of time-varying density-independent productivity in 84 stocks across five regions of the United States. Of all stocks investigated, 50 were found to have time-varying productivity, challenging assumptions on the stationarity of recruitment parameters and dependent reference points. Our results demonstrate the power of PPM for synthesizing the form and pattern of recruitment time-variation among regions, including general summaries of directional change over time. Furthermore, our results show regional differences in time-varying patterns, particularly the signal-to-noise ratio (SNR) of low- to high-frequency variation. The SNR was lower in the California Current region than in two Atlantic regions and two Alaska regions. Generalized linear modeling used to synthesize results suggests that stocks with higher contrast in spawning stock biomass over time, standardized regardless of actual spawning stock size, were more likely to have time-varying productivity than stocks with low contrast. The likelihood of time-variation in productivity of a given stock was also found to be closely related to the autocorrelation of the recruitment time series. Such inter-regional and inter-stock comparisons of variation are vital in understanding the roles of local and global environmental change on fish productivity.

Keywords

Dynamic linear model, Kalman filter, Peterman Productivity Method, Ricker model, Stock-recruit model, Time-varying recruitment

Table of Contents

1. Introduction

Commercial fisheries are an economically important industry globally, in the United States alone supporting 1.7 million jobs and generating over $250 billion USD in sales in 2020 (NMFS, 2022). To support and maintain such a valuable industry, it is important for fisheries scientists and managers to understand the capacity of fish stocks to reproduce and replenish the populations while subject to fishing pressure and other stressors (Hilborn and Walters, 2013). Understanding the temporal behavior of fish stock dynamics and improving the statistical models that inform fisheries management is necessary, especially in the face of local and global environmental change.

Recruitment is the largest source of variability in marine fish stocks (Sissenwine, 1974), and thus understanding recruitment is essential to understanding stock dynamics. Stock-recruitment models explore the relationship between the spawning output of the fish stock and the number of recruits. Age-structured stock assessment models use the numbers-at-age from scientific surveys and fisheries landings in combination with age-specific parameters such as growth, selectivity, and maturity, to estimate the fish population size, spawning output, and recruitment. A stock-recruitment function is then needed to close the life cycle in order to project stock size as a function of fishing pressure. The recruitment model may be simply deviations from the mean, a segmented linear model (Barrowman and Myers, 2000), or one of the classic stock-recruitment models (Beverton and Holt, 1957; Ricker, 1954). Productivity, the capacity of fish stocks to increase their abundance and biomass is one of the parameters in stock-recruitment functions. We focus on the portion of this capacity attributable to reproduction, and define productivity as the density-independent expected number of recruits from an individual spawner or unit spawning biomass. Stock assessment models are frequently run with the assumption that productivity is constant, regardless of varying conditions over time. However, research has increasingly demonstrated that for many stocks, this may not be the case (Peterman et al., 2003; Collie et al., 2012; Minto et al., 2014; Szuwalski et al., 2015; Stock and Miller, 2021). The consequences of incorrectly assuming stationary recruitment productivity may be detrimental to the stock. For example, in cases where productivity has declined over time, assuming an average productivity value overestimates recruitment, resulting in biological reference points and expected yields too high to achieve (Tableau et al., 2019; Collie et al., 2021).

Recognizing time-varying recruitment productivity is important for setting biomass and fishing mortality reference points, catch quotas, rebuilding targets, and other management actions. A dynamic Ricker model fit with a Kalman filter has been used to investigate time-varying productivity for a number of stocks in Canada (Peterman et al., 2003), the United States (Tableau et al., 2019; Bell et al., 2023), other areas of the north Atlantic (Minto et al., 2014; Silvar-Viladomiu et al., 2023) and worldwide (Britten et al., 2016). The Kalman filter is a linear, state-space model that extracts the underlying signal in variable time series data by filtering observations at each time step based on the prediction from the previous time steps, error variances, and the new observation. The Kalman smoother provides smoothed predictions based on both past and future time steps. Using a Kalman filter for stock-recruitment data has been demonstrated to improve predictions of recruitment and calculation of fisheries reference points (Tableau et al., 2019; Collie et al., 2021). In recognition of the seminal contributions of Prof. Randall Peterman and team in developing and applying this method of stock-recruitment analysis, Silvar-Viladomiu et al. (2022) named the time-varying recruitment parameter method "Peterman's Productivity Method" (PPM).

In the present study, we apply the dynamic Ricker model with the Kalman filter to stock assessment time series from stocks with age-structured assessments in five regions on the Atlantic and Pacific coasts of the United States to identify stocks with time-varying productivity. Several stocks in New England, the Mid-Atlantic (Tableau et al., 2019), and the California Current (Bell et al., 2023) have been studied previously. Tableau et al. (2019) and Bell et al. (2023) suggest that the Atlantic stocks are likely to have time-varying productivity, and the California stocks are more often time-invariant, possibly due to oceanographic differences on opposite coasts. We expand on previous research by analyzing all regions together and extending the range of study to include, in addition to the Atlantic and California regions, stocks off of Alaska. Notably, by investigating five regions in a single study, we will be able to (1) explore regional and stock-specific differences in temporal patterns of productivity previously unreported, (2) make regional comparisons on productivity time-variation and the ratio of process error to observation error, and (3) evaluate explanatory factors for time-varying vs. time-invariant productivity. By pinpointing whether productivity changes are occurring pre- or post-recruitment, these analyses will help target management interventions to the appropriate stage of the life cycle.

2. Methods

2.1 Stock assessment time series

Commercial fish stocks with age-structured assessments were candidates for analysis with the dynamic Ricker model. Time series of spawning stock size (in units of kt spawning stock biomass or number of eggs/larvae depending on the stock) and recruitment (numbers at age of recruitment) were compiled directly from publicly available stock assessment reports and supporting material. In a few cases for which time series were not published with the stock assessment reports, the time series were acquired following personal communication with the stock assessment scientists. Effort was made to compile the longest time series possible for each stock for as long as age-structured assessments were conducted. Spawning stock and recruitment information from years before length or age data were available were not included in the present study. Eighty-five time series were compiled in this way, for 84 stocks (Table 1a-e). In cases where multiple models were reported in stock assessments, the author-preferred model was used. Pacific halibut is assessed and managed with an ensemble of multiple assessment models, with no author-preferred model as in other stock assessments with multiple possible models. Time series from two of the Pacific halibut models were included in the present study, Coast-wide Short and Areas-As-Fleet Short (Stewart and Hicks, 2022), to compare results between time series for Pacific halibut and test if both time series accounted for the same underlying qualities of productivity in the Pacific halibut stock (Table 1d). Pacific halibut was grouped with other stocks in the Gulf of Alaska region.

2.2 Dynamic Ricker model

A dynamic Ricker stock-recruitment model estimated with the state-space Kalman filter, was applied to all the compiled stock assessment time series following Peterman's Productivity Method. Early applications of this method by Peterman et al. (2003) and Dorner et al. (2008) used a single-stock approach and compared the Kalman-smoothed single-stock results post-modeling. In the present study, following more recent applications of PPM (e.g. Minto et al., 2014; Tableau et al., 2019; Bell et al., 2023), stocks in each region were fit simultaneously in a multi-stock model format. Within the multi-stock format, the equations in the state-space model for each individual stock include the linearized Ricker model of observations (Eq. 1), where *R* is the recruitment (numbers of recruits), and *S* is the spawning stock size (by kt weight of spawners or numbers of eggs/larvae, depending on the stock); when spawning stock was in units of eggs/larvae, the value was converted to millions to keep the magnitude of productivity on approximately the same scale for all the stocks.

$$log_e\left(\frac{R_{t+r}}{S_t}\right) = a_t - bS_t + v_t \qquad v_t \sim N(0, \sigma_v^2) \qquad \textit{Eq. 1}$$

Both *R* and *S* are time-dependent (subscript *t*), and *r* is the lag between when a fish is spawned and when it reaches age at recruitment. Productivity is defined here as the density-independent coefficient *a* in units of ln(*R*/*S*), and *b* is a constant density-dependent coefficient. Productivity (*a*) is allowed to be time-dependent and modeled with a random walk (Eq. 2).

$$a_{t+1} = a_t + w_t \qquad w_t \sim N(0, \sigma_w^2) \qquad \textit{Eq. 2}$$

Previous studies performing similar analyses have also tested allowing the density-dependent mortality *b* term in Eq. 1 to vary with time instead of and in addition to time-varying *a* (Britten et al., 2016; Szuwalski et al., 2019; Silvar-Viladomiu et al., 2023). Researchers found that it was often difficult to tell whether variability in recruitment was associated with productivity (*a*) or density-dependent mortality (*b*), and the patterns of variation were similar, simply attributed to whichever parameter was allowed to vary in the given model (Szuwalski et al., 2019; Silvar-Viladomiu et al., 2023). Britten et al. (2016) reported results that combined the effects of *a* and *b*, but their supplementary figures (Appendix 1) suggest that variability in recruitment was applied either to *a* or *b* and not a combination of both. Likewise, in other studies, models with time-varying *a* and *b* were rarely statistically better than models with only one time-varying parameter (Szuwalski et al., 2019). Previous studies (Silvar-Viladomiu et al., 2023), and preliminary fits in the present study found more support for models with time-varying *a* than *b*. We therefore chose to focus only on time-varying productivity (*a*) such that variation in density-independent productivity impacts recruitment at all spawning stock sizes, contrary to density-dependent recruit mortality, which has an impact that increases at high recruitment densities expected with higher spawning stock biomass (Peterman et al., 2000).

Equations 1 and 2 are the observation and state equations of the state-space models and each have an error term. In the linearized Ricker stock-recruitment model, "*v*" accounts for observation error (or high-frequency true variability that does not propagate), and in the productivity random walk, "*w*" accounts for the process error, or the signal in the recruitment variability that is accounted for by the variation in the productivity time series. The variances of these error terms are defined as σ_v^2 and σ_w^2. The ratio of the standard deviation of the process errors to the standard deviation of the measurement errors (σ_v/σ_w) is the signal-to-noise ratio (SNR).

Simulation studies conducted as part of previous studies have confirmed the ability to estimate productivity from data simulated with realistic levels of variance (A. Tableau, unpublished data). However, it is challenging to estimate both the process-error (σ_w^2) and observation-error variances (σ_v^2) with the length of time series typically available for fish stocks. To avoid cases in which the Kalman filter resulted in all the variance being assigned to either noise or signal, as opposed to a mixture of the two, we generated more appropriate SNRs by simultaneously modeling all stocks in a given region. Within the multi-stock framework, the individual stock time series were constrained by the regional SNR parameter optimized and estimated in the model, following success of previous research using similar regional assumptions (Tableau et al., 2019; Bell et al., 2023). The SNR may be influenced by other factors besides region, such as stock size, life-history characteristics, or finer-scale environmental factors. However, the assumption that a regional SNR was appropriate for the present study was accepted because of the success of the method in previous studies, and because stocks in a given region are expected to be subject to similar large-scale environmental or anthropogenic conditions that affect variability in productivity, as well as similar fisheries dependent and independent data collection. For example, most of the stocks in each region are demersal, occupying similar habitat, captured within similar fisheries, and surveyed with similar methods. Importantly, by estimating region-specific SNRs we can compare this summary parameter across regions.

In addition to the time-varying productivity model, each stock-recruitment dataset was also modeled with a standard Ricker model with time-invariant productivity. The results of this time-invariant productivity model were compared to those of the time-varying productivity model for each stock, and model selection determined which interpretation of the time series of productivity was more appropriate for each stock. A diagnostic comparison between time-invariant productivity values and mean time-varying productivity values was run by plotting the values against each other on top of a 1:1 line to see whether the time-varying model, constrained by the regional SNR, was producing reasonable estimates relative to the time-invariant model.

Model selection consisted of a likelihood ratio test comparing the time-varying and the time-invariant models. The likelihood ratio has a χ^2 distribution with one degree of freedom to account for the addition of the process-error variance in the time-varying model. A p-value < 0.05 was interpreted as evidence that the time-varying model fit better for the given stock. The time-invariant model was selected in all other cases.

Bell et al. (2023) tested whether the time-varying productivity time series would be different if estimated with a dynamic Ricker model or a dynamic Beverton-Holt model, and the analysis found that while the magnitude of the estimates could be different, the pattern of the time-varying productivity time-series was the same for both stock-recruitment functions. Because the present study is only focused on the patterns in the productivity, only the Ricker model was used. The analyses were performed using R statistical analysis software (v4.2.3, R Core Team, 2023) and the "dlm" package (Petris et al., 2009; Petris, 2010).

2.3 Impact of embedded stock-recruitment model in stock assessment

The stock assessment models used to generate the spawning stock and recruitment time series used in the present study estimate recruitment as deviations from the long-term average or as deviations from a stock-recruitment model. Often the stock-recruitment function provides initial estimates of recruitment that are then adjusted to the length and age data in the catch and survey observational time-series. Provided that the standard deviation of recruits (sometimes termed σ_r) is large enough, the final estimates of recruitment are unconstrained by the stock-recruitment relationship within the stock assessment model.

Small values of σ_r in the stock assessment model constrain the recruitment deviations to be very similar to predicted recruitment values from the stock-recruitment model. As the values of σ_r increase, the recruitment deviations become less and less constrained by the underlying stock-recruitment model. Therefore, σ_r could impact the estimated recruitment, and the time-varying productivity time-series estimates from the dynamic Ricker model used in the present study (described above). To test this potential effect using one data-rich example, the stock assessment model for eastern Bering Sea walleye pollock, for which estimated recruitment is influenced by deviations from a mean level of recruitment as well as deviations from an embedded Ricker stock-recruitment model, was run with several different σ_r values (0.2 to 1.8). Typical σ_r values in the stock assessments investigated in the present study were between 0.4 and 1.0, with a mean value of about 0.6. The output time series of these tests were modeled with the dynamic Ricker stock-recruitment model, and the output productivity estimates were compared to see if changing σ_r in the stock assessment model had a strong impact on the estimates of productivity from the dynamic Ricker model, which would indicate how strongly the variability in estimated recruitment is constrained with assessment assumptions.

2.4 Factors influencing the probability of time-variation

To test which factors might make a stock more or less likely to be time-varying, we compared the stocks that were selected as having time-varying productivity to those that were selected as having time-invariant productivity using a biased-reduced generalized linear model (GLM) with a binomial error distribution implemented in the "brglm2" package in R (Kosmidis, 2023). A biased reduced GLM was used because some combinations of explanatory factors resulted in complete separation of the binary response (Firth, 1993). Possible explanatory variables influencing the probability that productivity was time-varying (Eq. 3) included taxonomic order, total variance calculated from the time-varying model, three summaries of current exploitation status in terms of fishing mortality (F/F_{msy}) and spawning stock size (S/SSB_{msy}) and the proportion of the entire time series that was overfished (PropOF; i.e. SSB was lower than SSB_{msy}, detailed below), an estimate of contrast in the spawning stock time series (detailed below), the length (i.e. number of years of data) of the time series (YOD), and age at maturity. Support for models with all possible combinations of covariates was compared with the Akaike information criterion (AIC) (Akaike, 1974).

$$y_i \sim Bin(n = 1, p_i) \qquad \textit{Eq. 3}$$
$$logit(p_i) = \alpha + Order_i + \beta_1 TotalVar_i + \beta_2 (F/Fmsy)_i + \beta_3 (SSB/SSBmsy)_i + \beta_4 PropOF_i + \beta_5 Contrast_i + \beta_6 YOD_i + \beta_7 MatAge_i$$

Exploitation was summarized in three ways. First, current overfishing status was summarized as the ratio of the estimate of fishing mortality or exploitation rate (depending on the stock) in the terminal year of the stock assessment relative to the reference point (e.g. F_{msy} and proxy values), as reported in the stock assessment to determine overfishing status. Second, current overfished status was summarized as the ratio of the estimate of SSB or spawning output (depending on the stock) in the terminal year of the stock assessment relative to the reference point in comparable units (e.g. SSB_{msy} and proxy values), as reported in the stock assessment to determine overfished status. Measures of terminal year overfished and overfishing status were included to test whether current status could be used as a convenient indicator to fisheries scientists and managers of likely time-variance in a given stock. Third, the proportion of the time-series overfished was summarized as the proportion of the spawning stock time series reported in the stock assessment used (Table 1a-e) that had stock sizes below the reference point in comparable units reported in the same stock assessment to determine overfished status. Ratios, as opposed to the reference points directly, were used in an attempt to standardize the summaries of exploitation across different stock assessment conventions in different regions.

Contrast in the spawning stock data was calculated as another summary of stock history following methods by Rindorf et al. (2022). Contrast summarizes the spread of the spawning stock data, standardized across all stocks. The contrast term encompasses whether or not the stock ever reached particularly low or high spawning stock sizes. High contrast means that the stock has experienced a full range of spawning stock sizes. As a covariate in the GLM, contrast was calculated using 90th percentiles and 10th percentiles of the spawning stock time series data for each stock (Eq. 4).

$$Contrast = \log_e\left(\frac{S90\%}{S10\%}\right) \qquad \textit{Eq. 4}$$

2.5 Quantifying temporal patterns in productivity

We used a weighted linear regression to quantify patterns of directional change in the productivity time series that were selected as time-varying. We conducted weighted linear regressions of the productivity full time series, and then repeated the method on the last ten years and the last five years to indicate recent trends in productivity to compare to the overall time series. Weights were equal to the inverse of the variance on each *a* estimate ($1/\sigma_a^2$). If regression coefficients were significant ($p < 0.05$), the sign of the coefficient was used to indicate whether the productivity had increased or decreased over the given time interval.

Additionally, the mean and standard deviation of the normal distribution of the difference in estimated productivity between the beginning and the end of each stock time series were also used to estimate the change in productivity (Eq. 5).

$$Difference \sim N(\mu, \sigma^2) \qquad \mu = \mu_{end} - \mu_{start} \qquad \sigma = \sqrt{\sigma_{end}^2 + \sigma_{start}^2} \qquad \textit{Eq. 5}$$

If ≥ 80% of the joint distribution was > 0, i.e. the difference was positive between the current (with regard to the stock assessment used in the present study) productivity and the productivity at the start of the time series; this indicated that the productivity is currently higher than at the start of the time series. Conversely, if ≤ 20% of the distribution was > 0, this indicated that the productivity is currently lower. If < 80% but > 20% of the distribution was > 0, it was determined that there was no clear positive or negative change in productivity since the beginning of the time series. We performed the same method on the last five years and the last ten years of the timeseries.

3. Results

The dynamic Ricker stock-recruitment model with the Kalman filter was applied to 85 stock-recruitment time series of US commercial fish stocks with age-structured stock assessments from five regions (Table 1a-e).

3.1 Impact of embedded stock-recruitment model in stock assessment

The temporal pattern of the productivity parameter estimated from assessment estimates of stock and recruitment were similar across various values of σ_r in the assessment for eastern

Bering Sea walleye pollock. At some time points, the scale of the productivity parameter changed slightly at lower values of σ_r, but the time series remained largely unchanged (Figure 1). These results indicated that even at the lower end of σ_r values at which the recruitment deviations are more constrained, information from the length and age data are informing the temporal pattern of estimates of recruitments, and patterns of time-varying productivity could be extracted with a dynamic Ricker stock-recruitment model applied to stock assessment output with a range of σ_r values, ranging both smaller and greater than the 1.0 σ_r value used in the eastern Bering Sea pollock stock assessment.

3.2 Dynamic Ricker model

The time-invariant productivity values and mean time-varying values of productivity were well correlated (Figure 2a), as were the estimates of the density-dependence term (Figure 2b). The time-invariant model is estimating a value of productivity and density dependence comparable to the average productivity and constant density dependence from the time-varying model, such that by constraining the dynamic Ricker model with a regional SNR, we are not introducing unforeseen bias into the model estimates that would affect how productivity was interpreted for further stock assessment and management, e.g. calculating biological reference points.

The multi-stock models yielded unique SNRs for each region (Figure 3), which constrained the single-stock model outputs for each region: 0.799 (New England), 0.762 (Mid-Atlantic), 0.396 (California Current), 0.790 (Gulf of Alaska), and 0.957 (eastern Bering Sea/Aleutian Islands). When compared to the standard Ricker model with time-invariant productivity, the dynamic model with time-varying productivity was selected by the likelihood ratio test for 50 stocks, and the time-invariant model was selected for 34 stocks (35 time series including both Pacific halibut time series). By region, New England had 11 (85%) time-varying and 2 time-invariant stocks, the Mid-Atlantic had 10 (71%) time-varying and 4 time-invariant stocks, the California Current had 15 (48%) time-varying and 16 time-invariant stocks, the Gulf of Alaska had 6 (50%) time-varying and 6 time-invariant stocks (7 time-invariant time series including both Pacific halibut time series), and the eastern Bering Sea/Aleutian Islands had 8 (57%) time-varying and 6 time-invariant stocks (Table 1a-e). Stock-recruitment relationships for all stocks are shown in Supplementary Figures S1a-e.

Recruitment autocorrelation, calculated for each stock time series, indicated that time series that were selected for time-varying productivity more often than not had higher autocorrelation than those that were time-invariant (Figure 4).

3.3 Factors influencing the probability of time-variation

Using only complete cases (i.e. removing two stocks for which there were no estimates of F/F_{msy} or SSB/SSB_{msy}), the full biased-reduced GLM model with all predictors, and all possible combination models were investigated for GLM model selection. Whether a stock's productivity was time-varying or time-invariant was best explained by any of nine possible GLMs (Table 2) with AIC values within two units of the lowest AIC model (Burnham and Anderson, 2002). The only significant covariate was contrast in two of the ten models, such that stocks with higher contrast in the spawning stock time series were significantly more likely ($p < 0.05$) to have time-varying productivity than stocks with lower contrast (Figure 5). Investigating all combinations of covariates, contrast was significant in 5 models, including the two models within two AIC units of the lowest AIC value.

3.4 Temporal patterns in productivity

Time series of productivity estimated by the time-varying and time-invariant models are shown for all stocks in Supplementary Figures S2a-e, and a selection of stocks are highlighted in Figure 6. Patterns of productivity varied widely between stocks, but there were some recurring patterns that were observed, such as positive (e.g. Atlantic mackerel) and negative (e.g. SNE yellowtail flounder, DMV tautog), or cyclical frequency (e.g. decadal GOM haddock) trends with time (Figure 6). For comparison, time series of spawning stock size and recruitment used in the present study from the stock assessments are shown in Supplementary Figures S3a-e.

Weighted regression applied to the productivity time series summarized well the trends in productivity that mirrored the observable temporal patterns in the time series (Figure 6). Some stocks appear to have decreased productivity at the end of the time series relative to the beginning, although a decreasing trend only persisted through recent years for a few stocks, particularly in the Mid-Atlantic and Gulf of Alaska (Figure 7). There were overall fewer cases of increasing trends in productivity across the entire time series, but there were some increases in more recent years across most regions (Figure 7). However, some stocks with time-varying productivity did not show any distinct positive or negative trend in the productivity over the whole time series, or in the most recent years (Figure 7).

Sometimes a stock (e.g. Figure 6, CC dover sole) showed no distinct change in productivity across the time series or in recent years, and the productivity time series appears to have low temporal variation, but the time-varying model was still selected as the best model for the stock. Such cases suggest low-amplitude variability such that allowing productivity to vary with time still improves the model fit, even though the confidence interval is wide.

Comparing the productivity estimates at the end of the time series to the beginning, or to the past five or ten years, using the analytical approach with mean and variance of the joint distribution also suggested some patterns of change in productivity, but the results were not as easily interpretable as those from the weighted linear regression. Results from this analytical comparison are presented in Supplementary Figure S4.

4. Discussion

We analyzed time-variation in recruitment rates of 84 stocks from five regions around the United States. Consistent with previously reported results, our results demonstrate that applying the Kalman filter to the linearized Ricker stock-recruitment model is an effective way to determine time-variation in productivity, a parameter typically modeled as time-invariant. A test case of eastern Bering Sea walleye pollock (*Gadus chalcogrammus*) indicated that time-variation in productivity was insensitive to assumptions made about recruitment in the stock assessment model. This result held true, even with a stock-recruitment model embedded in the assessment model that output the time series, because the estimates of recruitment were largely unconstrained by the internal stock-recruitment relationship. For data-rich stocks such as eastern Bering Sea walleye pollock, this result reflects that recruitment estimates are largely determined from informative age and length composition data rather than the stock-recruitment relationship. It is important to note that while changing the standard deviation of recruitment (σ_r) in the stock assessment model did not change the temporal pattern of productivity, changing σ_r can alter the scale of recruitment and SSB estimates, which would result in different values of MSY-based reference points calculated from parameters in the stock-recruitment model. However, in our test case, the magnitude of productivity was not strongly impacted by changing the underlying Ricker model over a range of σ_r values.

We used a likelihood-ratio test to classify stocks as time-varying or time-invariant. Our results highlight regional differences in the percentage of time-varying stocks in a region, and in the relative extent to which the signal from time-varying productivity is influencing recruitment variability (i.e. the SNRs). A higher percentage of both the New England and Mid-Atlantic stocks had time-varying productivity than the west coast and Alaska stocks, which may be a result of less risk-averse management strategies in the Atlantic relative to the Pacific, or of different Pacific region climate drivers relative to the Atlantic. Similarly, the SNR value for California Current was lower than that of the other four regions, suggesting that the low-frequency productivity signal was less important in the California Current ecosystem. This difference could occur, either because total variability was lower than in other regions, or because the process variability was high frequency, which may suggest differences in the environmental drivers in the northeast Pacific and northwest Atlantic Oceans. The California Current has not experienced the same long-term rate of warming compared to the Atlantic (Lima and Wethey, 2012), which may be associated with less time-variance in productivity. Also, Bell et al. (2023) suggested that the productivity of species in the California Current may be less influenced by large-scale environmental processes such as El Nino because the species have evolved to live under these types of changing conditions.

Additionally, we note that time-varying stocks generally had higher autocorrelation in their recruitment than time-invariant stocks. This simple diagnostic helps to distinguish stocks with high frequency or low frequency dynamics, and suggests that they may be subject to different frequencies of environmental forcing.

The estimation of the dynamic Ricker model and the use of regionally constant SNRs is intended to identify time series behavior apart from high-frequency patterns. In practice, however, the estimates of recruitment and stock size from assessments are not data and have estimation variances that are expected to be larger in the most recent years (Brooks and Deroba, 2015). In theory, the time series of estimated variances of recruits and stock size could be used as a minimal estimate of observation error (v_t), although this is complicated by the response variable being a ratio of two random variables. While we expect estimates of general patterns of productivity over the time series to be generally robust, interpretation of the productivity parameter in the last five to ten years of each time series should recognize higher observation variances in recent years. Thus, we consider our methodology for describing temporal patterns of productivity over various time spans appropriate as a descriptive procedure to summarize general patterns in the time-varying productivity time series.

Of the 85 time series, 50 were selected as having time-varying productivity. Similar to the results reported by Britten et al. (2016), Tableau et al. (2019), and Bell et al. (2023), the Atlantic stocks were more likely to have time-varying productivity than the Pacific stocks. Generalized linear modelling indicated that time-varying productivity was more prevalent among stocks with higher contrast in the spawning stock time series. Stocks that, over the course of the time series, had experienced a full range of stock sizes, both high and low relative to the median, likely allowed better parametrization of the time-varying model because they had data at both the origin and the compensation maximum ends of the Ricker curve. From a stock assessment perspective, stocks with higher contrast are more likely to have estimable time-varying parameters that differ from the time-invariant parameters. Alternatively, stocks with low contrast may not be well fit with a Ricker model, in which case the time-varying model would not improve on the time-invariant model. Low spawning stock sizes may result from a combination of environmental and anthropogenic conditions, including overfishing. Stocks with low contrast in the present study often did not have low spawning stock sizes. Such low-contrast stocks may have been subject to different exploitation history that did not lead to extensive overfishing or stock crashes, which may reflect the management history of regional management councils. Stocks from the Pacific regions also had less contrast than stocks from the Atlantic regions. Because the time-varying vs. time-invariant stocks in the Pacific regions were not defined by a particular taxonomic or community group, this result suggests that a history of management in the Pacific that has kept stocks from dropping to low spawning stock sizes may play a role in the temporal variability of productivity in these stocks (Bell et al., 2023).

Time series length was not a significant covariate in the GLM analysis explaining which stocks were time-varying. Shorter time series, such as the 29-year time series of DE/MD/VA tautog (*Tautoga onitis*) in the Mid-Atlantic (Figure 6), could still be selected as time-varying if the variation in productivity was strong enough. However, time series lengths in the present study ranged from 15 to 90 years (median 43), and sensitivity analysis of those selected as time-varying indicated that when the time series were shortened, either from the beginning or the end, the shorter time series were more likely to be time-invariant than the time series that were longer. While the stock with the longest time series (Georges Bank haddock, *Melanogrammus aeglefinus*) had time-invariant productivity, it is still possible that in the future, as time series get longer, it will become more necessary to account for time-variation, even for stocks that appear time-invariant at present. Additionally, there is certainly room for uncertainty in model selection for stocks that may be borderline, or have wide confidence intervals. An example of this is dover sole (*Microstomus pacificus*), which was selected as having time-varying productivity, although the magnitude of the variation was low (Figure 6).

Of the 50 commercial fish stocks that were selected as having time-varying productivity, the estimated productivity time series displayed a range of stock-specific patterns that may not be accounted for in current model projections and calculation of biological reference points. Consistent with previous studies, stocks from the northwest Atlantic were much more likely to have declined in productivity over time compared to the Pacific stocks, which had much more neutral productivity trends, even for the stocks for which productivity was time-varying (Britten et al., 2016; Tableau et al., 2019; Bell et al., 2023).

For stocks with positive productivity trends, future recruitment may be underestimated under an assumed average productivity model. The time series of productivity for Atlantic mackerel (*Scomber scombrus*) has an observably positive trend in productivity (Figure 6) that is significant according to weighted regression analysis (Figure 7). Despite the apparent increase in productivity with time, i.e. number of recruits per unit spawning biomass, both spawning stock size and recruitment appear to have decreased (NEFSC, 2021), suggesting that recruitment productivity alone is not enough to compensate for other factors involved in the decrease of stock size. Pre-recruit survival may be successful (i.e. increased productivity), while subsequent limits to survival occur post-recruitment, such as limited prey availability. Another notable case of productivity increase is Gulf of Maine haddock (*Melanogrammus aeglefinus*), which appears to follow a decadal trend (Figure 6) that is not clearly reflected in the recruitment time series (NEFSC, 2022a). On the other hand, sablefish (*Anoplopoma fimbria*) productivity did not increase over the entire time series, but did increase in recent years (Figures 6 and 7), which is consistent with recent increases in recruitment (Goethel et al., 2021). Tolimieri and Haltuch (2023) linked sablefish recruitment to sea level, and their model performed well even for recent years with increased recruitment.

A more worrying productivity pattern is one for which productivity is decreasing with time, because in this case, assuming an average productivity would result in overestimates of future recruitment and subsequently reference points and harvest regulations too high to maintain the stock under current, lower productivity conditions (Tableau et al., 2019). Southern New England yellowtail flounder (*Limanda ferruginea*) had a comparatively steep declining trend in productivity for most years except for a sharp increase in recent years (Figure 6). SNE yellowtail flounder recruitment has also been linked to the Cold Pool Index in the region (Stock and Miller, 2021; du Pontavice et al., 2022), and methods are being explored to incorporate this climate variable into the stock assessment (NEFSC, 2022b). Recruitment of other stocks have also been linked to regional climate variables (e.g. winter flounder, Bell et al., 2014, 2018), and incorporating these climate correlates into stock assessment models is one way to account for underlying time-variation in productivity in stock assessments (Stock and Miller, 2021; Tolimieri and Haltuch, 2023). However, further study at the individual stock level is necessary to understand what environmental factors may be influencing the productivity of each stock, and the best method for incorporating these factors into assessment and management.

Stocks for which the time-invariant productivity model was selected often had time series of spawning stock size and recruitment that were also fairly stable with time. For example, the time-invariant model was selected for walleye pollock in the eastern Bering Sea (Figure 6), although research has suggested that recruitment was affected by regime shifts in 1977 and 1989 (Benson and Trites, 2002). Further research linked recruitment to temperature, with warmer springs being favorable for survival of age-0 EBS walleye pollock to summer, but warm temperatures in late summer and fall reducing zooplankton prey, overwinter survival, and subsequent age-1 recruitment (Hunt et al., 2011; Mueter et al., 2011; Spencer et al., 2016). However, while the spawning stock size and recruitment of EBS walleye pollock has been variable, it has not apparently experienced long-term trends over time (Ianelli et al., 2021), which is consistent with the behavior observed in the productivity time series in the present study.

Alternatively, as in the case of Pacific cod (*Gadus macrocephalus*) in the Gulf of Alaska, spawning stock size and recruitment have been decreasing with time (Barbeaux et al., 2021). Pacific cod recruitment was affected by the 2014 to 2016 marine heatwave, which resulted in the loss of thermal spawning habitat (Laurel and Rogers, 2020). Despite the demonstrated effect of temperature on hatching success, productivity was also selected as time-invariant in the present study (Figure 6). In this case, and others like it, where productivity remains approximately constant, declines in stock size must be driven by other factors besides recruitment rate, such as declines in post-recruitment survival. Both EBS walleye pollock and GOA Pacific cod exhibited high-frequency variability in recruitment without clear trends, such that the time-invariant model was selected for these stocks.

As the results of the present study demonstrate, time-varying productivity is more prevalent in commercial fish stocks than may be currently accounted for in stock assessment models that assume productivity to be a constant average over time. Additionally, accounting for known time-variation can improve model estimates, including estimates of recent recruitment and one-year-ahead forecasts, and subsequent calculation of reference points and implementation of fishing regulations (Tableau et al., 2019; Collie et al., 2021; Tolimieri and Haltuch, 2023). It is important to note that time-varying density-dependent mortality was not explored in the present study, and as such, more complex time-variation at higher spawning stock sizes may not be completely captured in our results for certain stocks. However, the results of the present study may serve as justification for incorporating dynamic models into current stock assessment protocols and using dynamic reference points. Stock-specific analyses will need to be conducted to fully understand the recruitment dynamics of different stocks in different regions under different environmental and anthropogenic conditions, but the present study represents a starting point for understanding general trends that may be applicable for further investigation.

5. Acknowledgements

We would like to thank Cody Szuwalski and Melissa Haltuch for their excellent comments and suggestions on the manuscript. We would also like to thank Ann Henning Jocelyn and Robert Jocelyn, Doonreagan House, Cashel, Connemara, Ireland for their hospitality and hosting of our working group. We would also like to thank all our reviewers, and NOAA for funding this research through the Climate and Fisheries Adaptation Program, award number NA210AR4310384.

6. Data Availability Statement

Every time series used as data in the present study was available from published stock assessment reports or personal communication with stock assessment scientists. The data files and computer code used are available by request from the corresponding author.

7. Conflict of Interest Statement

The authors have no conflicts of interest to declare for the present study.

8. References

Akaike, H., 1974. A new look at the statistical model identification. *IEEE Transactions on Automated Control* 19, 716–723. https://doi.org/10.1109/TAC.1974.1100705

Barbeaux, S.J., Ferriss, B., Laurel, B., Litzow, M., McDermott, S., Nielsen, J.M., Palsson, W., Shotwell, K., Spies, I., Wang, M., 2021. Assessment of the Pacific cod stock in the Gulf of Alaska. *In* Stock assessment and fishery evaluation report for the groundfish resources of the Gulf of Alaska. *North Pacific Fishery Management Council*, Anchorage, AK.

Barrowman, N.J., Myers, R.A., 2000. Still more spawner-recruitment curves: the hockey stick and its generalizations. *Canadian Journal of Fisheries and Aquatic Sciences* 57, 665–676. https://doi.org/10.1139/f99-282

Bell, R.J., Collie, J.S., Branch, T.A., Fogarty, M.J., Minto, C., Ricard, D., 2018. Changes in the size structure of marine fish communities. *ICES Journal of Marine Science* 75, 102–112. https://doi.org/10.1093/icesjms/fsx118

Bell, R.J., Hare, J.A., Manderson, J.P., Richardson, D.E., 2014. Externally driven changes in the abundance of summer and winter flounder. *ICES Journal of Marine Science* 71, 2416–2428. https://doi.org/10.1093/icesjms/fsu069

Bell, R.J., Tableau, A., Collie, J.S., 2023. Changes in the productivity of US West Coast fish stocks. *Fisheries Research* 264, 106712. https://doi.org/10.1016/j.fishres.2023.106712

Beverton, R.J.H., Holt, S.J., 1957. On the Dynamics of Exploited Fish Populations, *Fish and Fisheries Series 11*. Springer Science & Business Media.

Benson, A.J., Trites, A.W., 2002. Ecological effects of regime shifts in the Bering Sea and eastern North Pacific Ocean. *Fish and Fisheries* 3, 95–113. https://doi.org/10.1046/j.1467-2979.2002.00078.x

Britten, G.L., Dowd, M., Worm, B., 2016. Changing recruitment capacity in global fish stocks. *Proceedings of the National Academy of Sciences* 113, 134–139. https://doi.org/10.1073/pnas.1504709112

Brooks, E.N., Deroba, J.J., 2015. When "data" are not data: the pitfalls of post hoc analyses that use stock assessment model output. *Canadian Journal of Fisheries and Aquatic Sciences* 72, 634–641. https://doi.org/10.1139/cjfas-2014-0231

Burnham, K., Anderson, D., 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*, 2nd ed. Springer, New York, New York, USA.

Collie, J.S., Bell, R.J., Collie, S.B., Minto, C., 2021. Harvest strategies for climate-resilient fisheries. *ICES Journal of Marine Science* 78, 2774–2783. https://doi.org/10.1093/icesjms/fsab152

Collie, J.S., Peterman, R.M., Zuehlke, B.M., 2012. A fisheries risk-assessment framework to evaluate trade-offs among management options in the presence of time-varying productivity. *Canadian Journal of Fisheries and Aquatic Sciences* 69, 209–223. https://doi.org/10.1139/f2011-148

Dorner, B., Peterman, R.M., Haeseker, S.L., 2008. Historical trends in productivity of 120 Pacific pink, chum, and sockeye salmon stocks reconstructed by using a Kalman filter. *Canadian Journal of Fisheries and Aquatic Sciences* 65, 1842–1866. https://doi.org/10.1139/F08-094

du Pontavice, H., Miller, T.J., Stock, B.C., Chen, Z., Saba, V.S., 2022. Ocean model-based covariates improve a marine fish stock assessment when observations are limited. *ICES Journal of Marine Science* 79, 1259–1273. https://doi.org/10.1093/icesjms/fsac050

Firth, D., 1993. Bias reduction of maximum likelihood estimates. *Biometrika* 80, 27–38. https://doi.org/10.1093/biomet/80.1.27

Goethel, D.R., Hanselman, D.H., Rodgveller, C.J., Echave, K.B., Williams, B.C., Shotwell, S.K., Sullivan, J.Y., Hulson, P.F., Malecha, P.W., Siwicke, K.A., Lunsford, C.R., 2021. Assessment of the sablefish stock in the Eastern Bering Sea. *In* Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/Aleutian Islands regions. *North Pacific Fishery Management Council*, Anchorage, AK.

Hilborn, R. and Walters, C.J., 2013. *Quantitative fisheries stock assessment: choice, dynamics and uncertainty.* Springer Science & Business Media.

Hunt, G.L., Jr, Coyle, K.O., Eisner, L.B., Farley, E.V., Heintz, R.A., Mueter, F., Napp, J.M., Overland, J.E., Ressler, P.H., Salo, S., Stabeno, P.J., 2011. Climate impacts on eastern Bering Sea foodwebs: a synthesis of new data and an assessment of the Oscillating Control Hypothesis. *ICES Journal of Marine Science* 68, 1230–1243. https://doi.org/10.1093/icesjms/fsr036

Ianelli, J.N., Fissel, B., Stienessen, S., Honkalehto, T., Siddon, E., Allen-Akselrud, C., 2021. Assessment of the walleye pollock stock in the Eastern Bering Sea. *In* Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/Aleutian Islands regions. *North Pacific Fishery Management Council*, Anchorage, AK.

Kosmidis I., 2023. brglm2: Bias Reduction in Generalized Linear Models. *R package version 0.9*, https://CRAN.R-project.org/package=brglm2.

Laurel, B.J., Rogers, L.A., 2020. Loss of spawning habitat and prerecruits of Pacific cod during a Gulf of Alaska heatwave. *Canadian Journal of Fisheries and Aquatic Sciences* 77, 644–650. https://doi.org/10.1139/cjfas-2019-0238

Lima, F.P., Wethey, D.S., 2012. Three decades of high-resolution coastal sea surface temperatures reveal more than warming. *Nature Communications* 3, 704. https://doi.org/10.1038/ncomms1713

Mueter, F.J., Bond, N.A., Ianelli, J.N., Hollowed, A.B., 2011. Expected declines in recruitment of walleye pollock (*Theragra chalcogramma*) in the eastern Bering Sea under future climate change. *ICES Journal of Marine Science* 68, 1284–1296.

Minto, C., Mills Flemming, J., Britten, G.L., Worm, B., 2014. Productivity dynamics of Atlantic cod. *Canadian Journal of Fisheries and Aquatic Sciences* 71, 203–216. https://doi.org/10.1139/cjfas-2013-0161

NEFSC, 2021. Northwest Atlantic mackerel 2021 Management Track Assessment Report. *Northeast Fisheries Science Center*, Woods Hole, MA.

NEFSC, 2022a. Gulf of Maine haddock 2022 Management Track Assessment Report. *Northeast Fisheries Science Center*, Woods Hole, MA.

NEFSC, 2022b. Southern New England-Mid Atlantic yellowtail flounder 2022 Management Track Assessment Report. *Northeast Fisheries Science Center*, Woods Hole, MA.

NMFS, 2022. Fisheries Economics of the United States, 2020. U.S. Dept. of Commerce, *NOAA Technical Memorandum* NMFS-F/SPO-236A, 231 p.

Peterman, R.M., Pyper, B.J., Grout, J.A., 2000. Comparison of parameter estimation methods for detecting climate-induced changes in productivity of Pacific salmon (*Oncorhynchus* spp.). *Canadian Journal of Fisheries and Aquatic Sciences* 57, 181–191. https://doi.org/10.1139/f99-204

Peterman, R.M., Pyper, B.J., MacGregor, B.W., 2003. Use of the Kalman filter to reconstruct historical trends in productivity of Bristol Bay sockeye salmon (*Oncorhynchus nerka*). *Canadian Journal of Fisheries and Aquatic Sciences* 60, 809–824. https://doi.org/10.1139/f03-069

Petris, G., 2010. An R Package for Dynamic Linear Models. *Journal of Statistical Software* 36, 1–16. https://doi.org/10.18637/jss.v036.i12

Petris, G., Petrone, S., Campagnoli, P., 2009. Dynamic Linear Models with R, useR! Springer-Verlag, New York.

Ricker, W.E., 1954. Stock and Recruitment. *Journal of the Fisheries Research Board of Canada* 11, 559–623. https://doi.org/10.1139/f54-039

Rindorf, A., van Deurs, M., Howell, D., Andonegi, E., Berger, A., Bogstad, B., Cadigan, N., Elvarsson, B.Þ., Hintzen, N., Savina Roland, M., Taylor, M., Trijoulet, V., van Kooten, T., Zhang, F., Collie, J., 2022. Strength and consistency of density dependence in marine fish productivity. *Fish and Fisheries*. 23, 812–828. https://doi.org/10.1111/faf.12650

R Core Team, 2023. R: A language and environment for statistical computing. *R Foundation for Statistical Computing*, Vienna, Austria. URL https://www.R-project.org/.

Silvar-Viladomiu, P., Minto, C., Brophy, D., Reid, D.G., 2022. Peterman's productivity method for estimating dynamic reference points in changing ecosystems. *ICES Journal of Marine Science* 79, 1034–1047. https://doi.org/10.1093/icesjms/fsac035

Silvar-Viladomiu, P., Minto, C., Lordan, C., Brophy, D., Bell, R., Collie, J. and Reid, D., 2023. Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion, *ICES Journal of Marine Science*, fsad146, https://doi.org/10.1093/icesjms/fsad146

Sissenwine, M.P., 1974. Variability in recruitment and equilibrium catch of the Southern New England yellowtail flounder fishery. *ICES Journal of Marine Science* 36, 15–26. https://doi.org/10.1093/icesjms/36.1.15

Spencer, P.D., Holsman, K.K., Zador, S., Bond, N.A., Mueter, F.J., Hollowed, A.B., Ianelli, J.N., 2016. Modelling spatially dependent predation mortality of eastern Bering Sea walleye pollock, and its implications for stock dynamics under future climate scenarios. *ICES Journal of Marine Science* 73, 1330–1342. https://doi.org/10.1093/icesjms/fsw040

Stewart, I., Hicks, A., 2022. Assessment of the Pacific halibut (*Hippoglossus stenolepis*) stock at the end of 2022 IPHC-2023-SA-01, 37p.

Stock, B.C., Miller, T.J., 2021. The Woods Hole Assessment Model (WHAM): A general state-space assessment framework that incorporates time- and age-varying processes via random effects and links to environmental covariates. *Fisheries Research* 240, 105967. https://doi.org/10.1016/j.fishres.2021.105967

Szuwalski, C.S., Britten, G.L., Licandeo, R., Amoroso, R.O., Hilborn, R., Walters, C., 2019. Global forage fish recruitment dynamics: A comparison of methods, time-variation, and reverse causality. *Fisheries Research* 214, 56–64. https://doi.org/10.1016/j.fishres.2019.01.007

Szuwalski, C.S., Vert-Pre, K.A., Punt, A.E., Branch, T.A., Hilborn, R., 2015. Examining common assumptions about recruitment: a meta-analysis of recruitment dynamics for worldwide marine fisheries. *Fish and Fisheries* 16, 633–648. https://doi.org/10.1111/faf.12083

Tableau, A., Collie, J.S., Bell, R.J., Minto, C., 2019. Decadal changes in the productivity of New England fish populations. *Canadian Journal of Fisheries and Aquatic Sciences* 76, 1528–1540. https://doi.org/10.1139/cjfas-2018-0255

Tolimieri, N., Haltuch, M.A., 2023. Sea-level index of recruitment variability improves assessment model performance for sablefish *Anoplopoma fimbria*. *Canadian Journal of Fisheries and Aquatic Sciences* 80, 1006–1016. https://doi.org/10.1139/cjfas-2022-0238

9. Tables

Table 1: The "Productivity" column refers to whether a stock was found to have time-varying or time-invariant productivity parameters in the present study.

Table 1a: New England (NE) stocks.

Common Name	Scientific Name	Time Series	Assessment	Productivity
Acadian redfish	*Sebastes fasciatus*	1960-2018	2020	Time-varying
American plaice	*Hippoglossoides platessoides*	1980-2020	2022	Invariant
Atlantic cod (Gulf of Maine)	*Gadus morhua*	1982-2018	2021	Time-varying
Atlantic herring	*Clupea harengus*	1965-2020	2022	Time-varying
Atlantic wolffish	*Anarhichas lupus*	1968-2020	2022	Time-varying
Haddock (Georges Bank)	*Melanogrammus aeglefinus*	1931-2020	2022	Invariant
Haddock (Gulf of Maine)	*Melanogrammus aeglefinus*	1977-2020	2022	Time-varying
Pollock	*Pollachius virens*	1970-2020	2022	Time-varying
White hake	*Urophycis tenuis*	1963-2020	2022	Time-varying
Winter flounder (Georges Bank)	*Pseudopleuronectes americanus*	1982-2019	2020	Time-varying
Winter flounder (S. New England)	*Pseudopleuronectes americanus*	1981-2020	2022	Time-varying
Yellowtail flounder (Gulf of Maine)	*Limanda ferruginea*	1985-2021	2022	Time-varying
Yellowtail flounder (S. New England)	*Limanda ferruginea*	1973-2020	2022	Time-varying

Table 1b: Mid-Atlantic (MDA) stocks

Common Name	Scientific Name	Time Series	Assessment	Productivity
Atlantic mackerel	*Scomber scombrus*	1968-2018	2021	Time-varying
Atlantic menhaden	*Brevoortia tyrannus*	1955-2021	2022	Time-varying
Black sea bass	*Cetropristis striata*	1989-2018	2021	Invariant
Bluefish	*Pomatomus saltatrix*	1985-2019	2021	Invariant
Butterfish	*Peprilus triacanthus*	1989-2019	2020	Time-varying
Golden tilefish	*Lopholatilus chamaeleonticeps*	1971-2019	2021	Time-varying
Scup	*Stenotomus chrysops*	1984-2019	2021	Time-varying
Striped bass	*Morone saxatilis*	1982-2016	2018	Invariant
Summer flounder	*Paralichthys dentatus*	1982-2019	2021	Invariant
Tautog (DE/MD/VA)	*Tautoga onitis*	1990-2019	2021	Time-varying
Tautog (Long Island Sound)	*Tautoga onitis*	1984-2019	2021	Time-varying
Tautog (MA/RI)	*Tautoga onitis*	1982-2019	2021	Time-varying
Tautog (NJ/NY Bight)	*Tautoga onitis*	1989-2019	2021	Time-varying
Weakfish	*Cynoscion regalis*	1982-2016	2019	Time-varying

Table 1c: California Current (CC) stocks

Common Name	Scientific Name	Time Series	Assessment	Productivity
Arrowtooth flounder	*Atheresthes stomas*	1965-2016	2017	Time-varying
Aurora rockfish	*Sebastes aurora*	1978-2012	2013	Invariant
Black rockfish	*Sebastes melanops*	1975-2014	2015	Time-varying
Blackspotted/rougheye rockfish	*S. melanostictus / S. aleutianus*	1980-2012	2013	Invariant
Blue/deacon (CA)	*Sebastes diaconus*	1960-2016	2017	Time-varying
Blue/deacon (OR)	*Sebastes diaconus*	1970-2016	2017	Invariant
Bocaccio	*Sebastes paucispinus*	1954-2016	2017	Time-varying

Cabezon (N. CA)	*Scopaenichthys marmoratus*	1962-2018	2019	Time-varying
Cabezon (OR)	*Scopaenichthys marmoratus*	1980-2018	2019	Invariant
Cabezon (S. CA)	*Scopaenichthys marmoratus*	1970-2018	2019	Invariant
Canary rockfish	*Sebastes pinniger*	1968-2014	2015	Time-varying
Chilipepper rockfish	*Sebastes goodei*	1965-2014	2015	Invariant
Darkblotched rockfish	*Sebastes crameri*	1960-2016	2017	Invariant
Dover sole	*Microstomus pacificus*	1975-2020	2021	Time-varying
Greenstriped rockfish	*Sebastes elongatus*	1970-2008	2009	Invariant
Kelp greenling	*Hexagrammos decagrammus*	1980-2014	2015	Time-varying
Lingcod (N.)	*Opiodon elongatus*	1960-2020	2021	Time-varying
Lingcod (S.)	*Opiodon elongatus*	1972-2020	2021	Invariant
Longspine thornyhead	*Sebastes altivelus*	1997-2012	2013	Invariant
Pacific hake	*Merluccius productus*	1975-2020	2021	Invariant
Pacific ocean perch	*Sebastes alutus*	1975-2016	2017	Time-varying
Petrale sole	*Eopsetta jordani*	1959-2018	2019	Invariant
Quillback rockfish (CA)	*Sebastes maliger*	1991-2020	2021	Time-varying
Quillback rockfish (OR)	*Sebastes maliger*	1980-2020	2021	Invariant
Sablefish	*Anoplopoma fimbria*	1975-2020	2021	Invariant
Sanddab	*Citharichthys sordidus*	1977-2012	2013	Time-varying
Scorpionfish	*Scorpaena guttata*	1965-2016	2017	Time-varying
Splitnose rockfish	*Sebastes diploproa*	1960-2008	2009	Time-varying
Widow rockfish	*Sebastes entomelas*	1970-2018	2019	Invariant
Yelloweye rockfish	*Sebastes ruberrimus*	1980-2016	2017	Time-varying
Yellowtail rockfish (N.)	*Sebastes flavidus*	1970-2016	2017	Invariant

Table 1d: Gulf of Alaska (GOA) stocks, including two time series representing Pacific halibut

Common Name	Scientific Name	Time Series	Assessment	Productivity
Arrowtooth flounder	*Atheresthes stomas*	1977-2020	2021	Time-varying
Blackspotted/rougheye rockfish	*S. melanostictus / S. aleutianus*	1977-2018	2021	Invariant
Dusky rockfish	*Sebastes* sp. cf. *ciliatus*	1977-2017	2020	Invariant
Flathead sole	*Hippoglossoides elassodon*	1978-2012	2017	Invariant
Northern rockfish	*Sebastes polyspinus*	1977-2018	2020	Time-varying
Pacific cod	*Gadus macrocephalus*	1977-2020	2021	Invariant
Pacific halibut (AAF Short model)	*Hippoglossus stenolepis*	1992-2017	2022	Invariant
Pacific halibut (Coast-wide short model)	*Hippoglossus stenolepis*	1992-2017	2023	Invariant
Pacific ocean perch	*Sebastes alutus*	1961-2019	2021	Time-varying
Rex sole	*Glyptocephalus zachirus*	1982-2020	2021	Time-varying
Rock sole (N.)	*Lepidopsetta bilineata*	1977-2020	2021	Invariant
Rock sole (S.)	*Lepidopsetta bilineata*	1977-2020	2021	Time-varying
Walleye pollock	*Gadus chalcogrammus*	1970-2020	2021	Time-varying

Table 1e: Eastern Bering Sea/Aleutian Islands (BSAI) stocks

Common Name	Scientific Name	Time Series	Assessment	Productivity
Alaska plaice	*Pleuronectes quadrituberculatus*	1975-2014	2021	Time-varying
Arrowtooth flounder	*Atheresthes stomas*	1976-2019	2020	Time-varying
Atka mackerel	*Pleurogrammus monopterygius*	1977-2020	2021	Invariant
Blackspotted/rougheye rockfish	*S. melanostictus / S. aleutianus*	1977-2014	2020	Time-varying
Flathead sole	*Hippoglossoides elassodon*	1964-2016	2020	Time-varying
Greenland turbot	*Reinhardtius hippoglossoides*	1945-2019	2020	Time-varying
Kamchatka flounder	*Atheresthes evernanni*	1991-2018	2020	Time-varying

Northern rockfish	*Sebastes polyspinus*	1977-2015	2021	Invariant
Pacific cod (Aleutian Islands)	*Gadus macrocephalus*	1991-2020	2021	Invariant
Pacific cod (Bering Sea)	*Gadus macrocephalus*	1977-2020	2021	Invariant
Pacific ocean perch	*Sebastes alutus*	1960-2014	2020	Time-varying
Sablefish	*Anoplopoma fimbria*	1960-2018	2021	Time-varying
Walleye pollock (Aleutian Islands)	*Gadus chalcogrammus*	1978-2017	2020	Invariant
Walleye pollock (Bering Sea)	*Gadus chalcogrammus*	1964-2020	2021	Invariant

Table 2: Biased reduced GLMs in the present study were compared with the AIC values. Reported here is the full model including all fixed effects, and models within 2 units of the lowest AIC model, assumed to be functionally equivalent in best explaining the variability in the response variable (Burnham and Anderson, 2002). Significant covariates in each model are indicated in bold italics. The sign of the parameter estimates for each covariate are indicated with the sign (plus/minus) preceding the covariate.

	Fixed Effects	AIC	r^2	Delta AIC
Full Model	± Order − TotalVar + F/F_{msy} + SSB/SSB_{msy} + PropOF + Contrast + YOD + MatAge	122.67	0.154	12.54
Null Model	*Intercept Only*	112.53	0.000	2.40
Lowest AIC Models within 2 units	+ Contrast − TotalVar	110.13	0.071	0.00
	+ Contrast − TotalVar + YOD	110.53	0.089	0.40
	+ ***Contrast*** + SSB/SSB_{msy} − TotalVar	111.12	0.082	0.99
	+ Contrast	111.39	0.034	1.26
	+ ***Contrast*** − F/F_{msy} − TotalVar	111.58	0.077	1.45
	+ Contrast + SSB/SSB_{msy} − TotalVar + YOD	111.62	0.098	1.49
	+ Contrast + Order	112.11	0.137	1.98
	+ Contrast − PropOF − TotalVar	112.13	0.071	2.00
	+ Contrast + MatAge − TotalVar	112.13	0.071	2.00

10. Figures

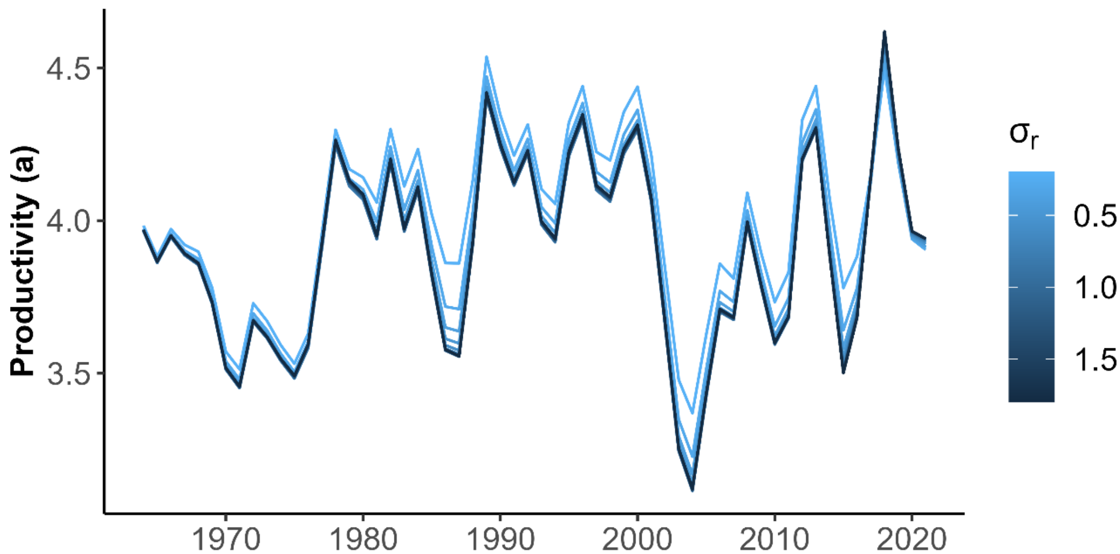


Figure 1: Productivity (*a*) time series estimated by the dynamic Ricker model with the Kalman filter applied to stock assessment model outputs of eastern Bering Sea walleye pollock stock-recruitment time series calculated with different values of σ_r influencing the recruitment deviations from a mean recruitment level and fit with an internal Ricker stock-recruitment relationship.

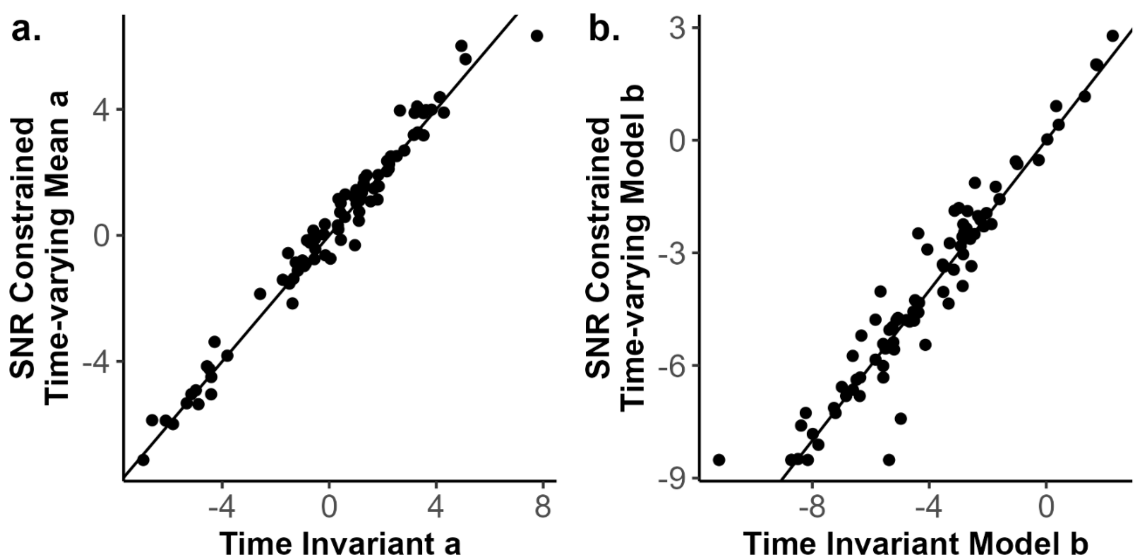


Figure 2: Diagnostic plot of coefficients on a log scale estimated by the time-invariant *a* model relative to the mean values from the time-varying model *a* constrained by a regional SNR, plotted on top of the 1:1 line. Each point corresponds to one stock.

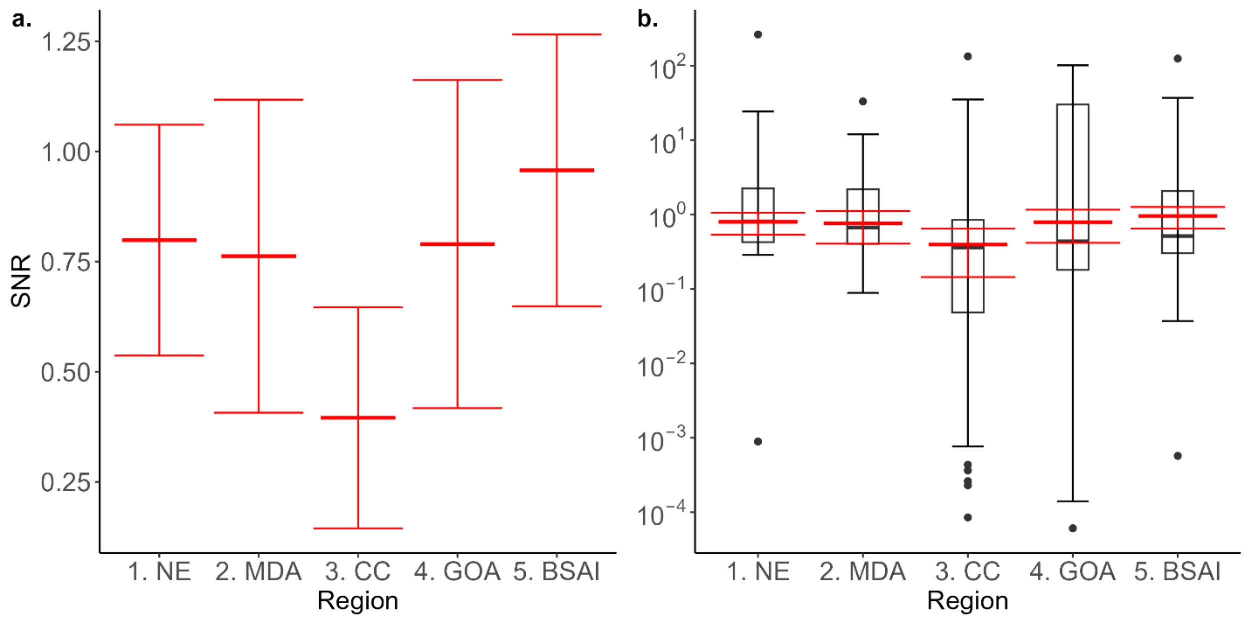


Figure 3: Regional SNRs and confidence intervals estimated by the multi-stock model plotted relative to each other (a.) and in relation to the SNRs estimated by the single-stock models for each region initially, unconstrained by a prescribed SNR (b.), plotted on a log scale because of some extreme unrealistic SNR values estimated for the single-stock models unconstrained by regional SNRs.

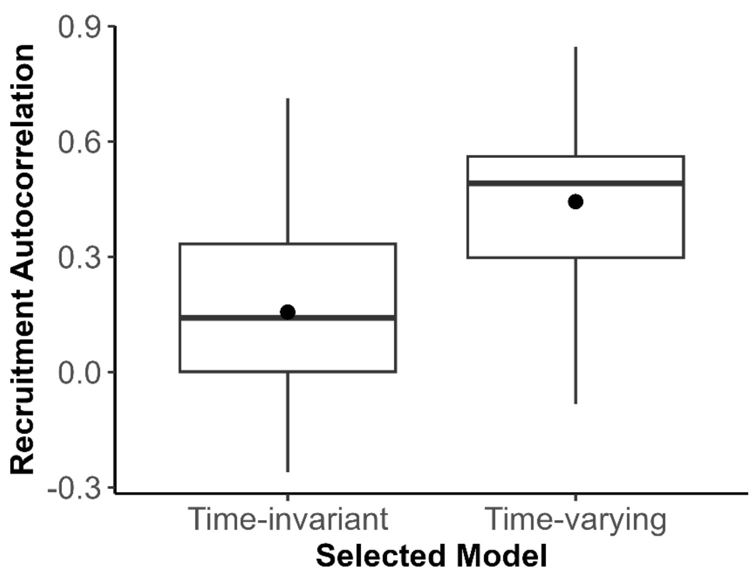


Figure 4: Autocorrelation in the recruitment time series for each time-invariant and time-varying productivity stock. Box plots indicate the medians, first and third quartiles, and whiskers extending to the last values ≤1.5 times the interquartile range. Mean values are indicated by single points.

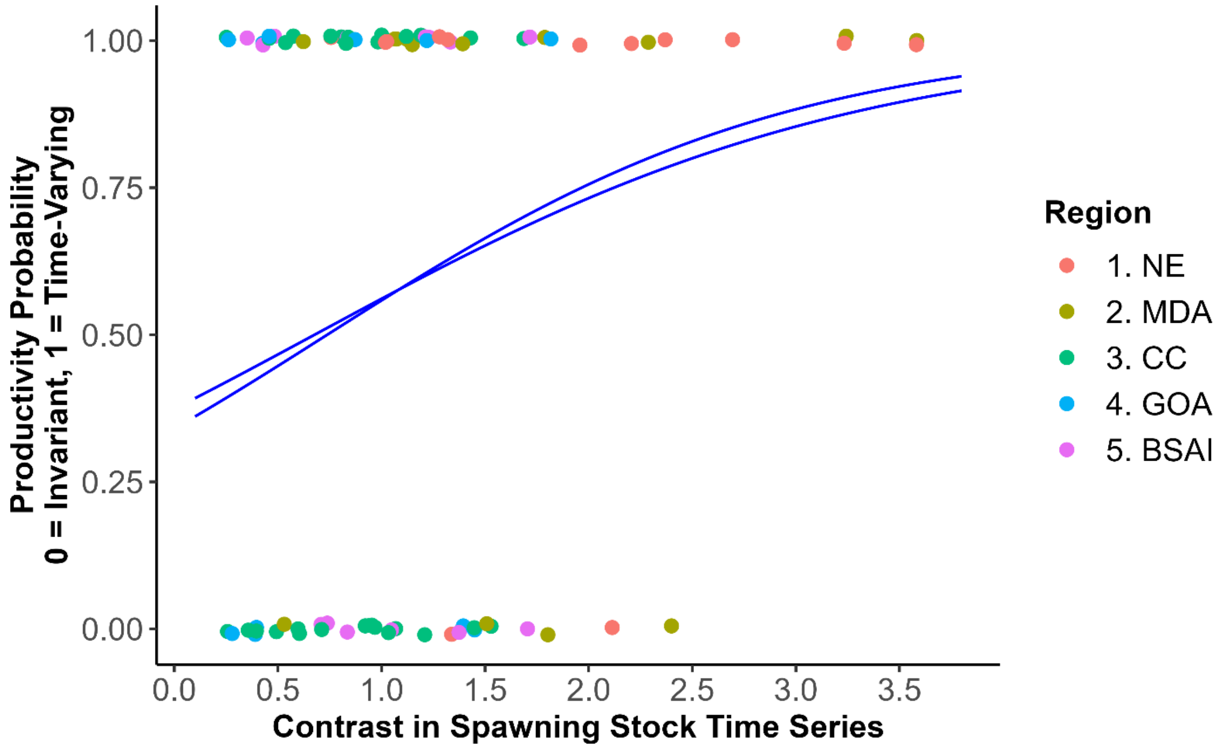


Figure 5: Partial effect of contrast on whether a stock was selected as having time-varying or time-invariant productivity. Results are shown for the two lowest AIC models (within 2 units) for which contrast was a significant predictor. Points indicate the contrast in the spawning stock time series for each stock, and colors indicate region.

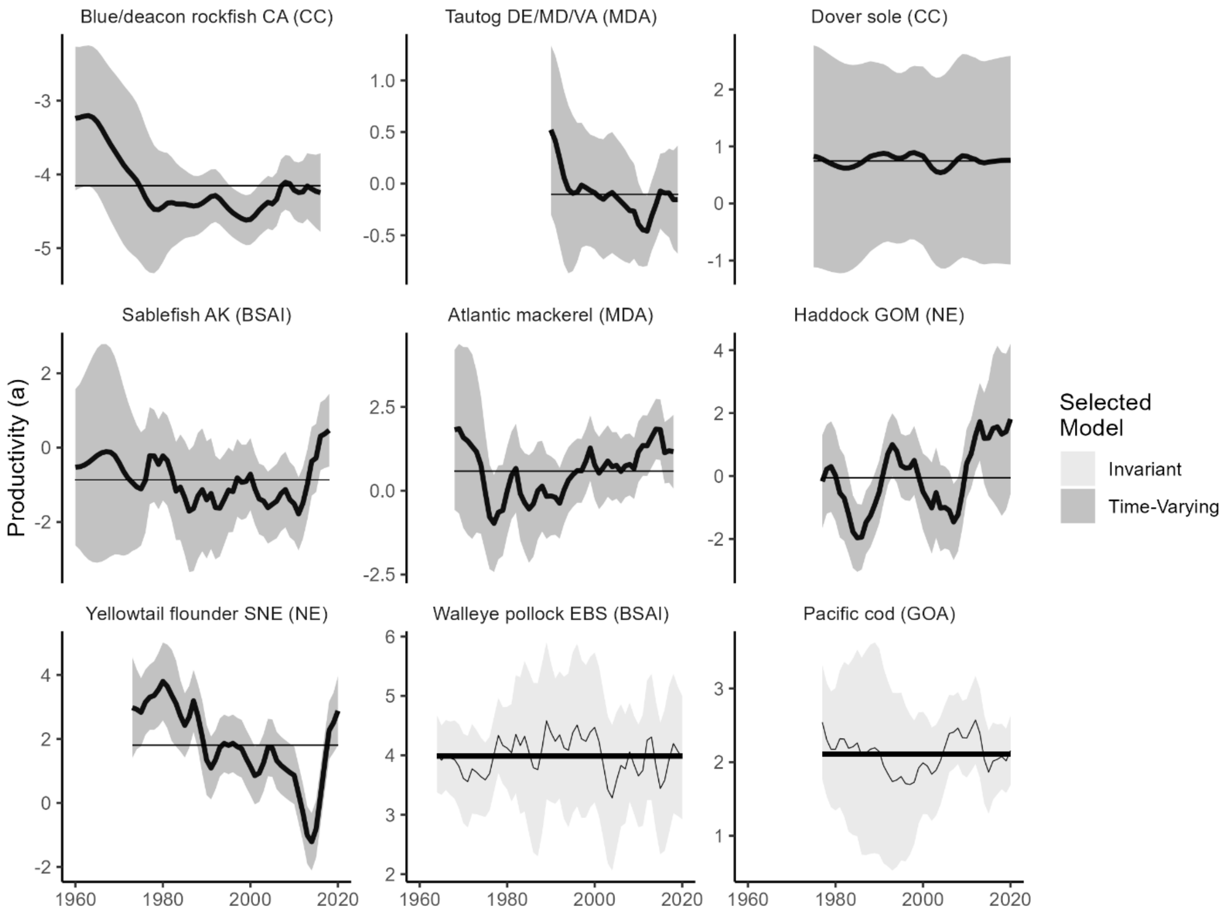


Figure 6: Time series of estimated productivity (*a*) in units of log(R/S), for nine highlight cases from the total stock list. The selected model output is shown in bold line (time-varying for all except GOA Pacific Cod and Bering Sea Walleye Pollock).

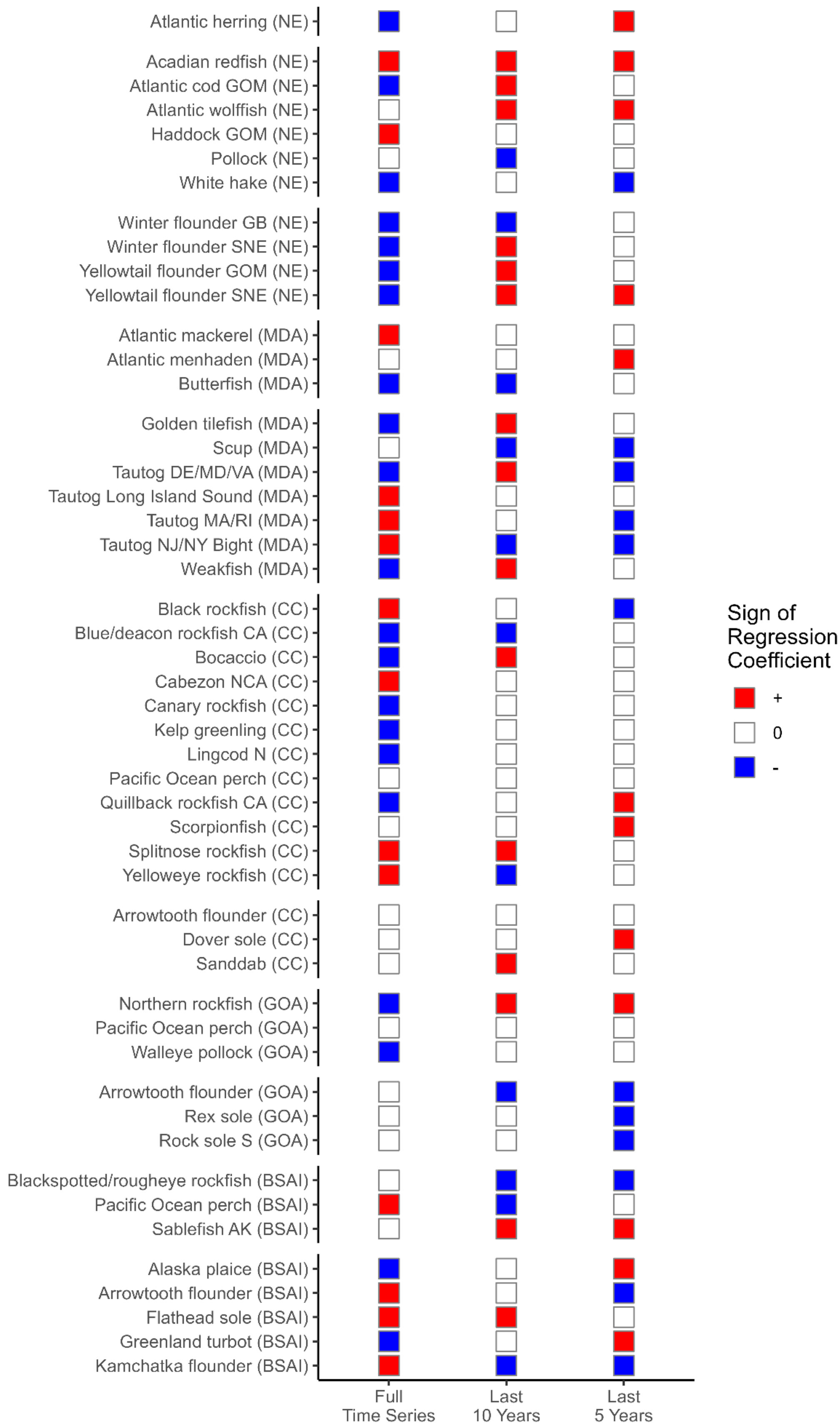

Atlantic herring (NE)
Acadian redfish (NE)
Atlantic cod GOM (NE)
Atlantic wolffish (NE)
Haddock GOM (NE)
Pollock (NE)
White hake (NE)
Winter flounder GB (NE)
Winter flounder SNE (NE)
Yellowtail flounder GOM (NE)
Yellowtail flounder SNE (NE)
Atlantic mackerel (MDA)
Atlantic menhaden (MDA)
Butterfish (MDA)
Golden tilefish (MDA)
Scup (MDA)
Tautog DE/MD/VA (MDA)
Tautog Long Island Sound (MDA)
Tautog MA/RI (MDA)
Tautog NJ/NY Bight (MDA)
Weakfish (MDA)
Black rockfish (CC)
Blue/deacon rockfish CA (CC)
Bocaccio (CC)
Cabezon NCA (CC)
Canary rockfish (CC)
Kelp greenling (CC)
Lingcod N (CC)
Pacific Ocean perch (CC)
Quillback rockfish CA (CC)
Scorpionfish (CC)
Splitnose rockfish (CC)
Yelloweye rockfish (CC)
Arrowtooth flounder (CC)
Dover sole (CC)
Sanddab (CC)
Northern rockfish (GOA)
Pacific Ocean perch (GOA)
Walleye pollock (GOA)
Arrowtooth flounder (GOA)
Rex sole (GOA)
Rock sole S (GOA)
Blackspotted/rougheye rockfish (BSAI)
Pacific Ocean perch (BSAI)
Sablefish AK (BSAI)
Alaska plaice (BSAI)
Arrowtooth flounder (BSAI)
Flathead sole (BSAI)
Greenland turbot (BSAI)
Kamchatka flounder (BSAI)
Full Time Series
Last 10 Years
Last 5 Years
Sign of Regression Coefficient
+
0
-

Figure 7: Summary of productivity trends estimated with weighted regression across the full time series (col. 1), ten years prior to current (col. 2), and five years prior to current (col. 3). Red squares indicate that productivity has increased, and blue squares indicate that productivity has decreased. White squares indicate that the regression coefficient was insignificant, i.e. productivity has not followed a detectable trend in the given time interval.

Supplementary Figure S1a-e

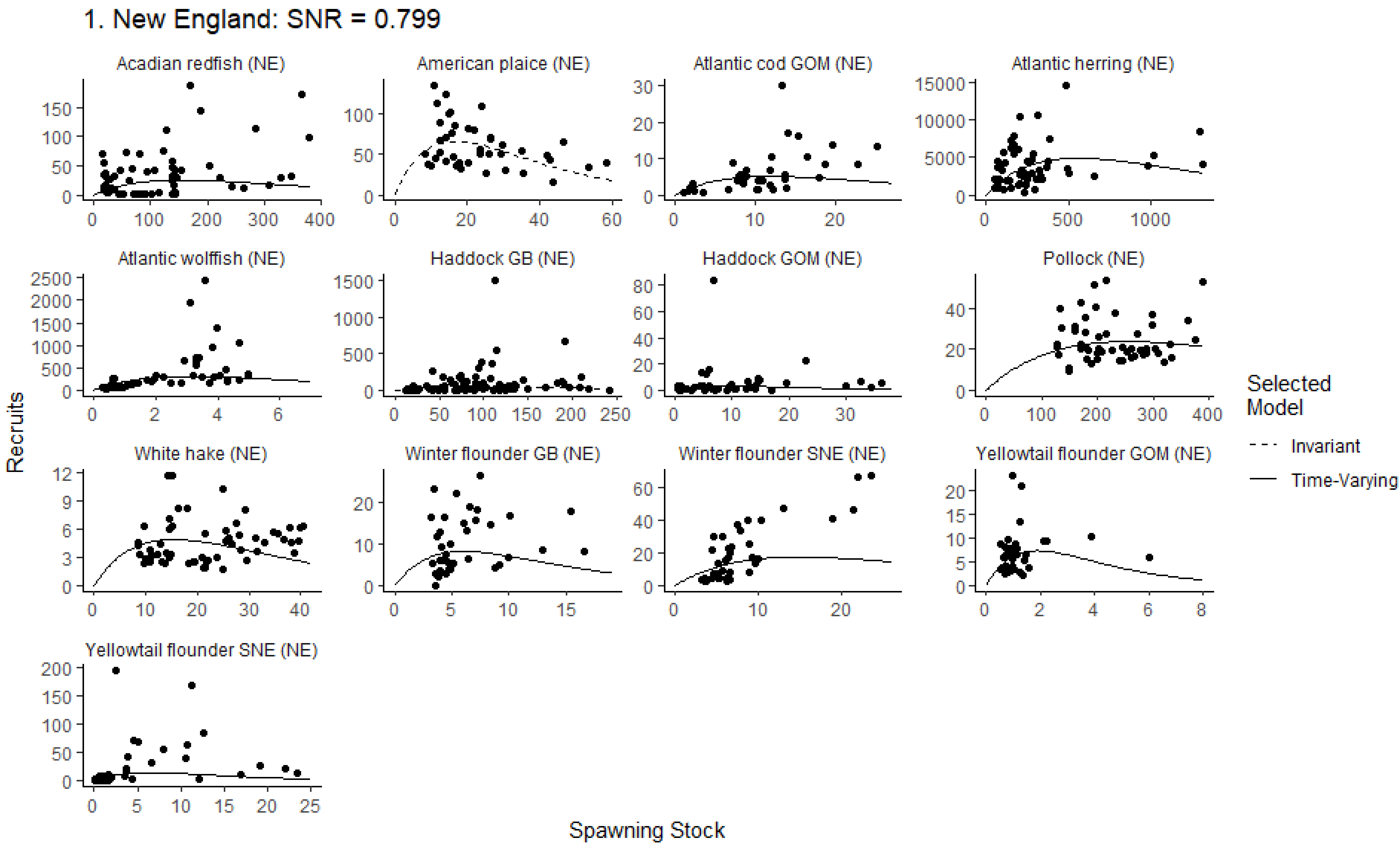


Figure S1a: Stock-recruitment values from stock assessment reports (points), and the estimated Ricker curves based on the average productivity estimated by the dynamic Ricker model with the Kalman filter. Solid lines indicate that the productivity was selected as time-varying, and thus the average is not the best fit of the data, and dashed lines indicate that the productivity was selected as time-invariant. Units are SSB (kt) and recruits (millions).

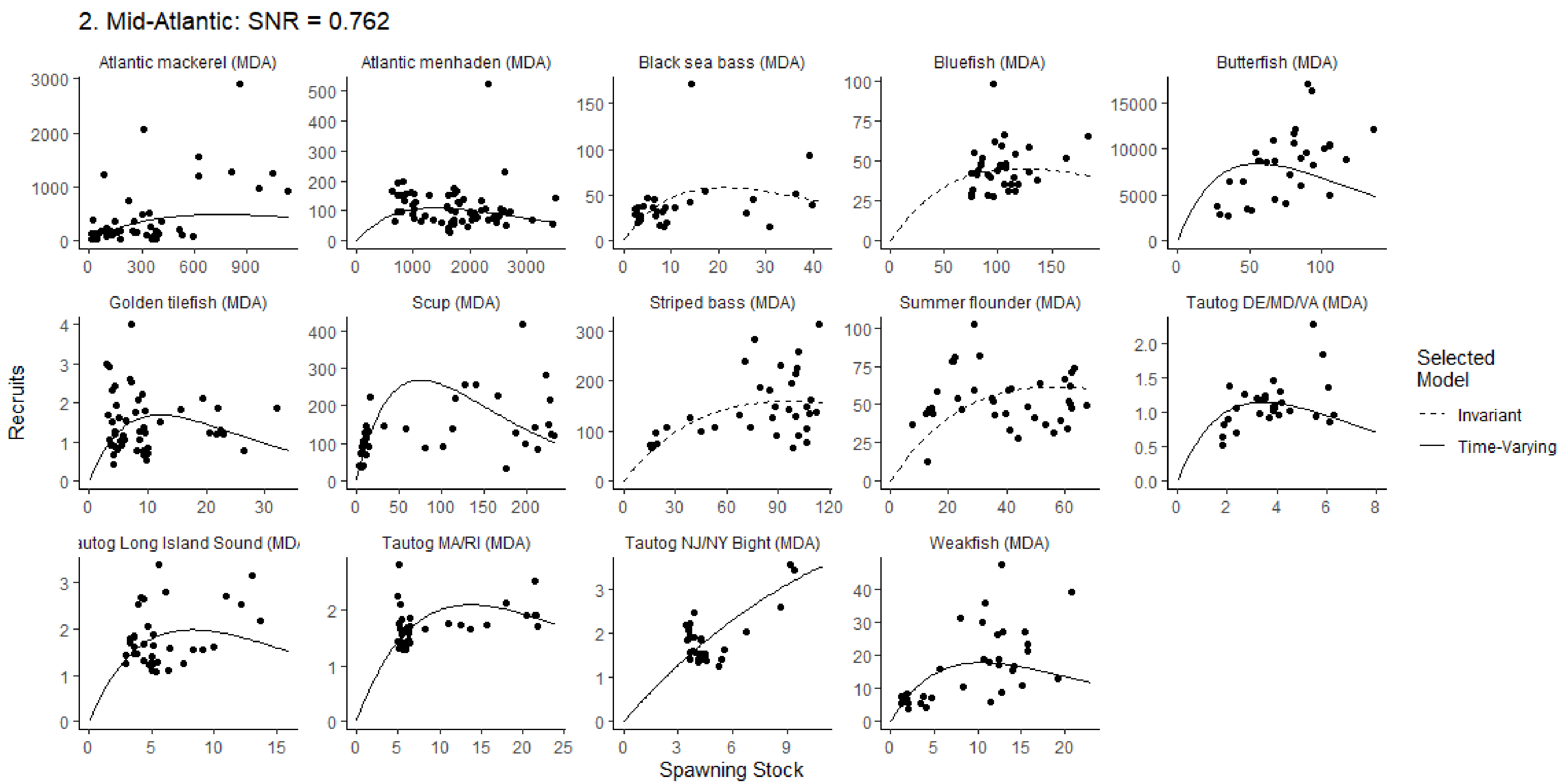


Figure S1b: Stock-recruitment values from stock assessment reports (points), and the estimated Ricker curves based on the average productivity estimated by the dynamic Ricker model with the Kalman filter. Solid lines indicate that the productivity was selected as time-varying, and thus the average is not the best fit of the data, and dashed lines indicate that the productivity was selected as time-invariant. Units are SSB (kt) and recruits (millions), except for Atlantic menhaden, which has units of spawning output (trillion eggs) and recruits (billions).

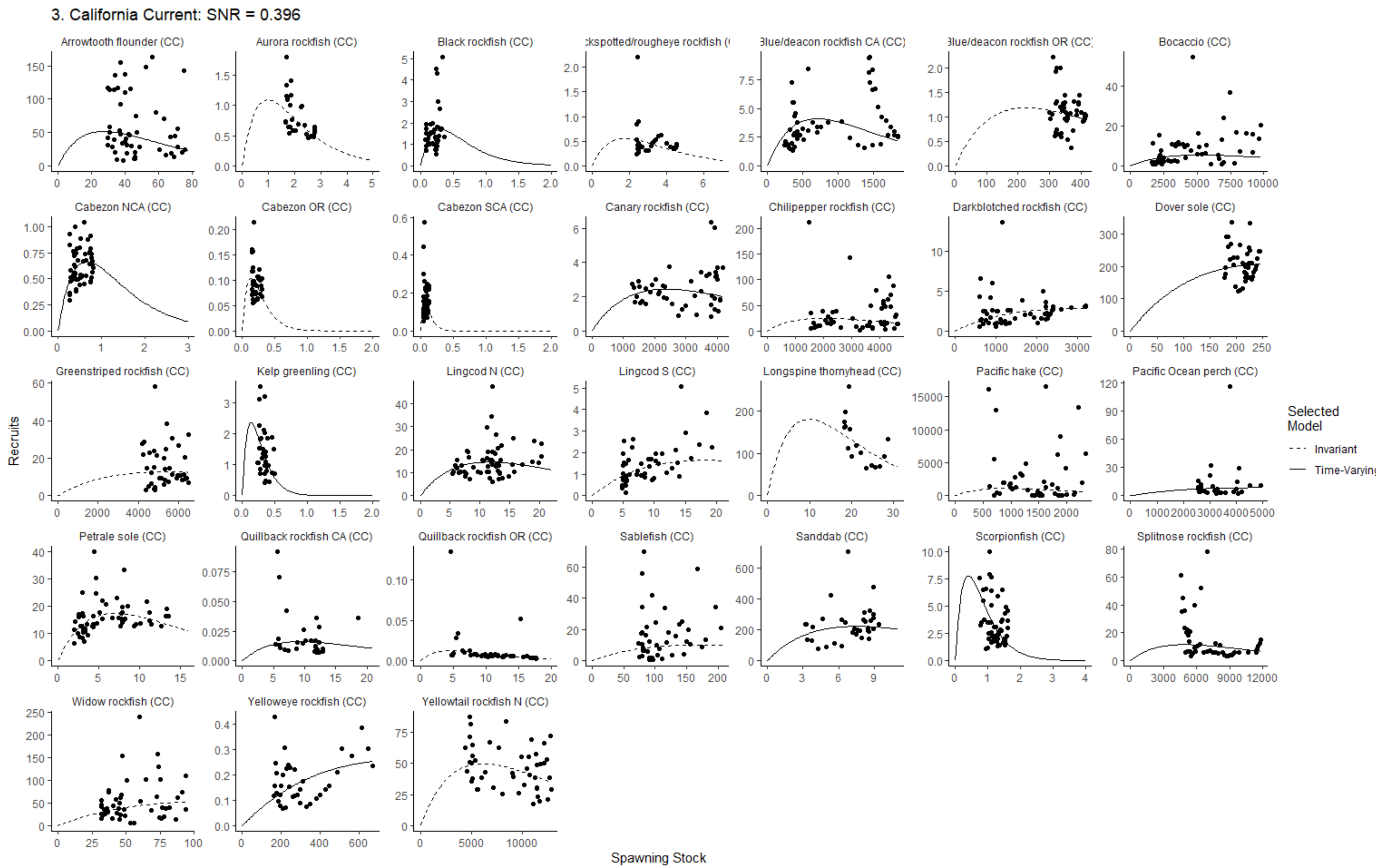


Figure S1c: Stock-recruitment values from stock assessment reports (points), and the estimated Ricker curves based on the average productivity estimated by the dynamic Ricker model with the Kalman filter. Solid lines indicate that the productivity was selected as time-varying, and thus the average is not the best fit of the data, and dashed lines indicate that the productivity was selected as time-invariant. Units are SSB (kt) and recruits (millions), except for 13 rockfish species with units of spawning output (millions/billions of eggs/larvae; see Figure S3c).

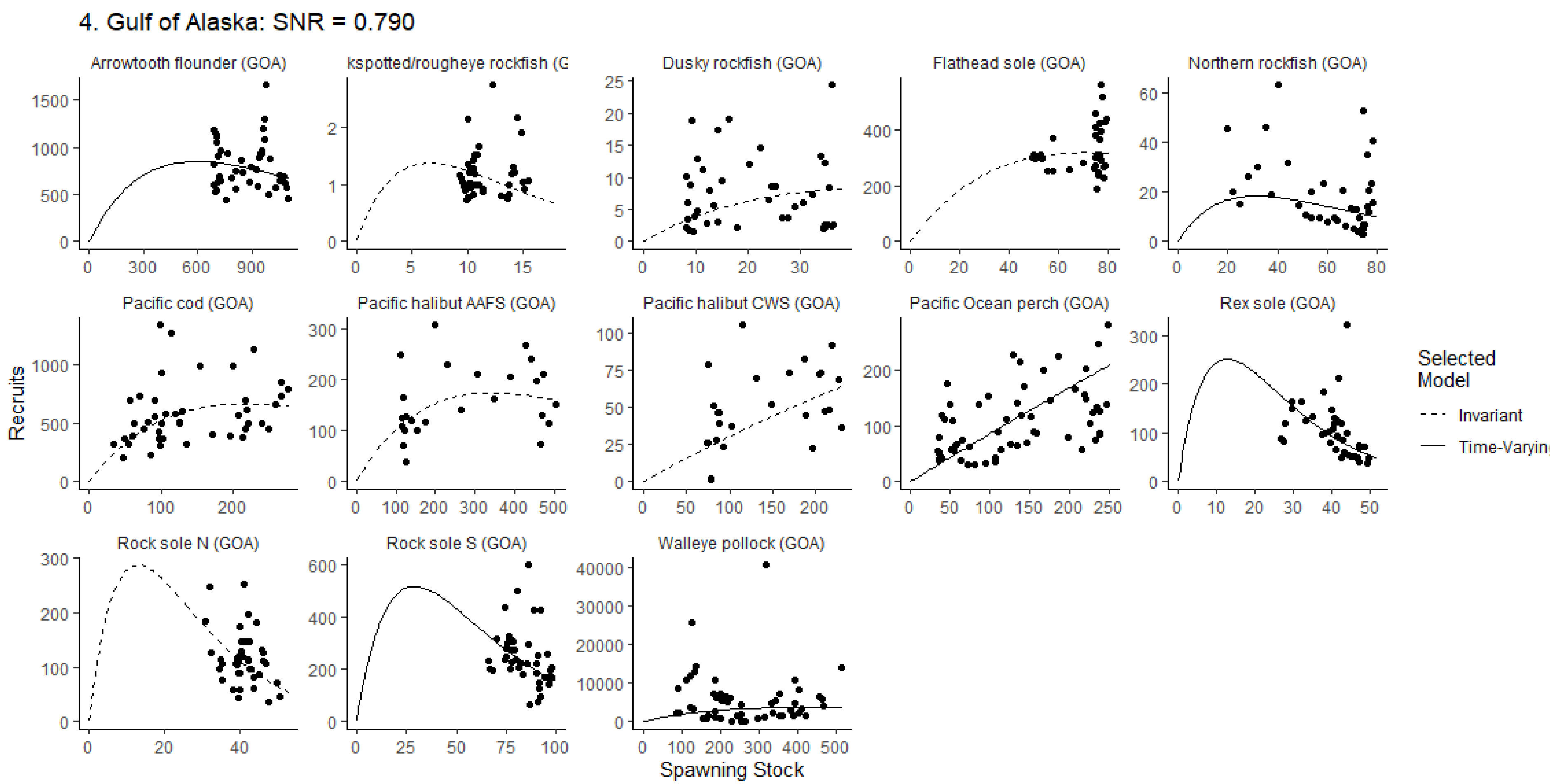


Figure S1d: Stock-recruitment values from stock assessment reports (points), and the estimated Ricker curves based on the average productivity estimated by the dynamic Ricker model with the Kalman filter. Solid lines indicate that the productivity was selected as time-varying, and thus the average is not the best fit of the data, and dashed lines indicate that the productivity was selected as time-invariant. Units are SSB (kt) and recruits (millions).

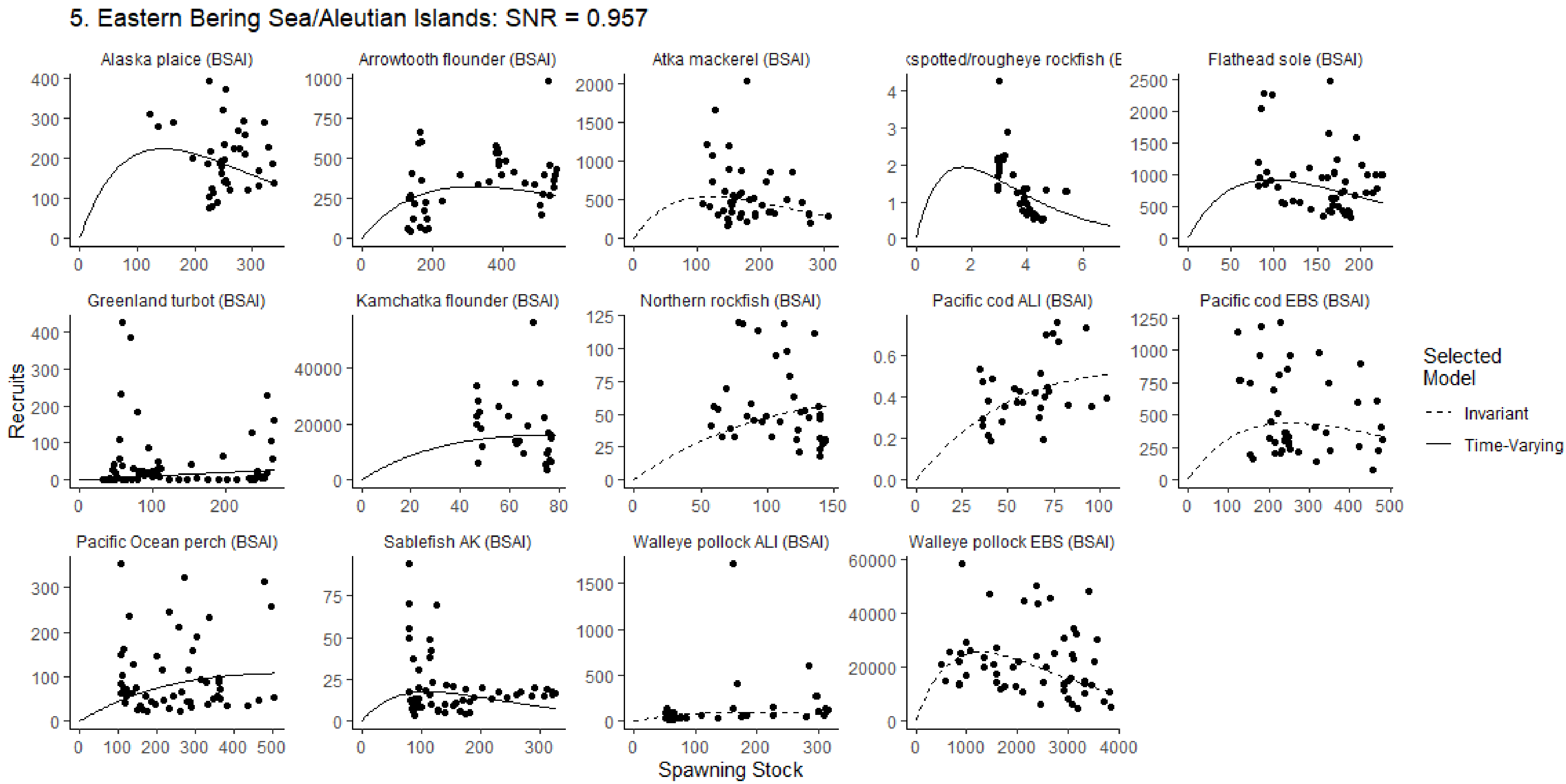


Figure S1e: Stock-recruitment values from stock assessment reports (points), and the estimated Ricker curves based on the average productivity estimated by the dynamic Ricker model with the Kalman filter. Solid lines indicate that the productivity was selected as time-varying, and thus the average is not the best fit of the data, and dashed lines indicate that the productivity was selected as time-invariant. Units are SSB (kt) and recruits (millions).

Supplementary Figure S2a-e

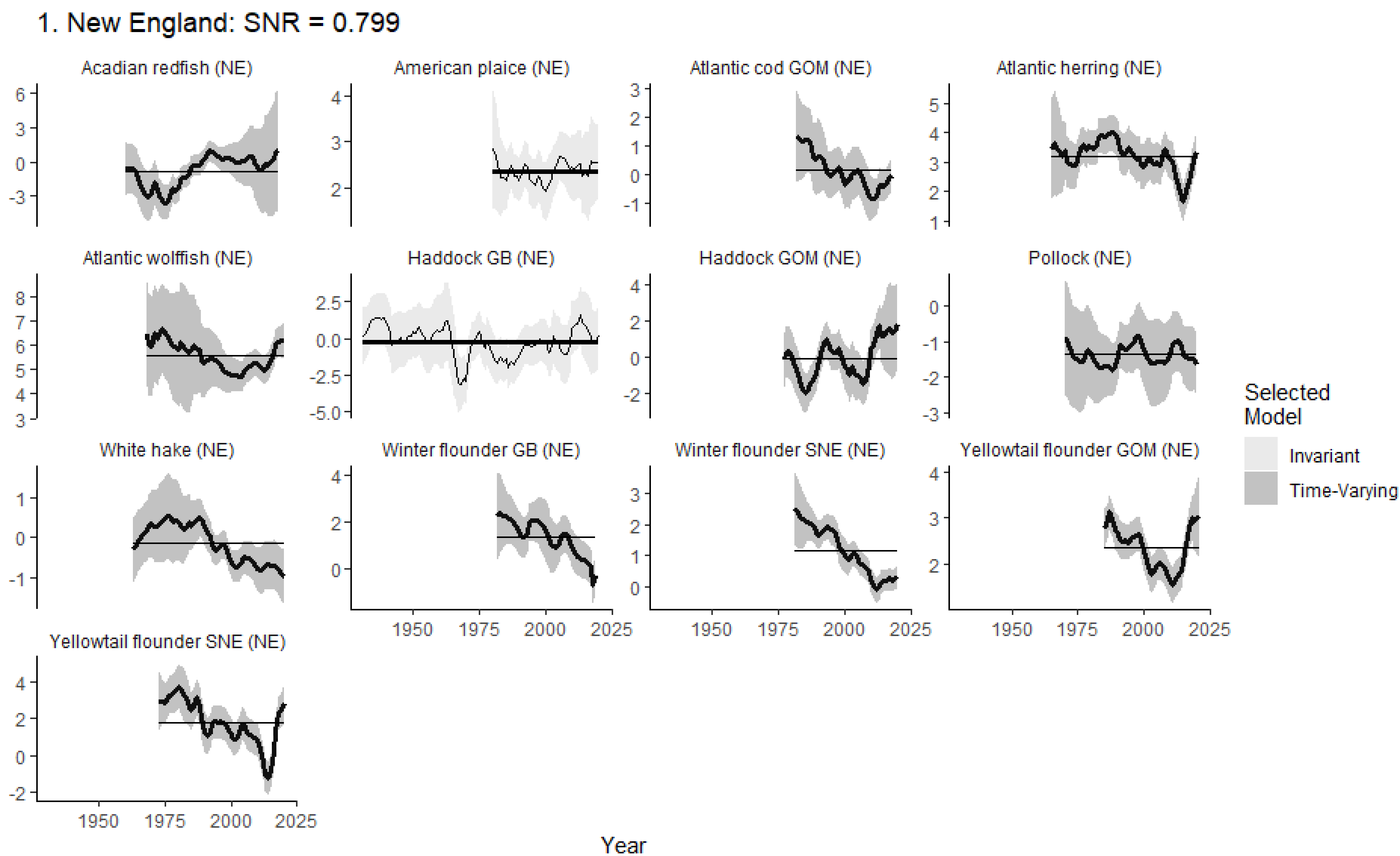


Figure S2a: Time series of productivity (a) in units of log(recruits/spawner) estimated by the dynamic Ricker model with the Kalman filter. Stocks selected as having time-varying productivity are shown with bold productivity time series, and stocks selected as having time-invariant productivity are shown with bold horizontal line indicating average productivity across the estimated time series.

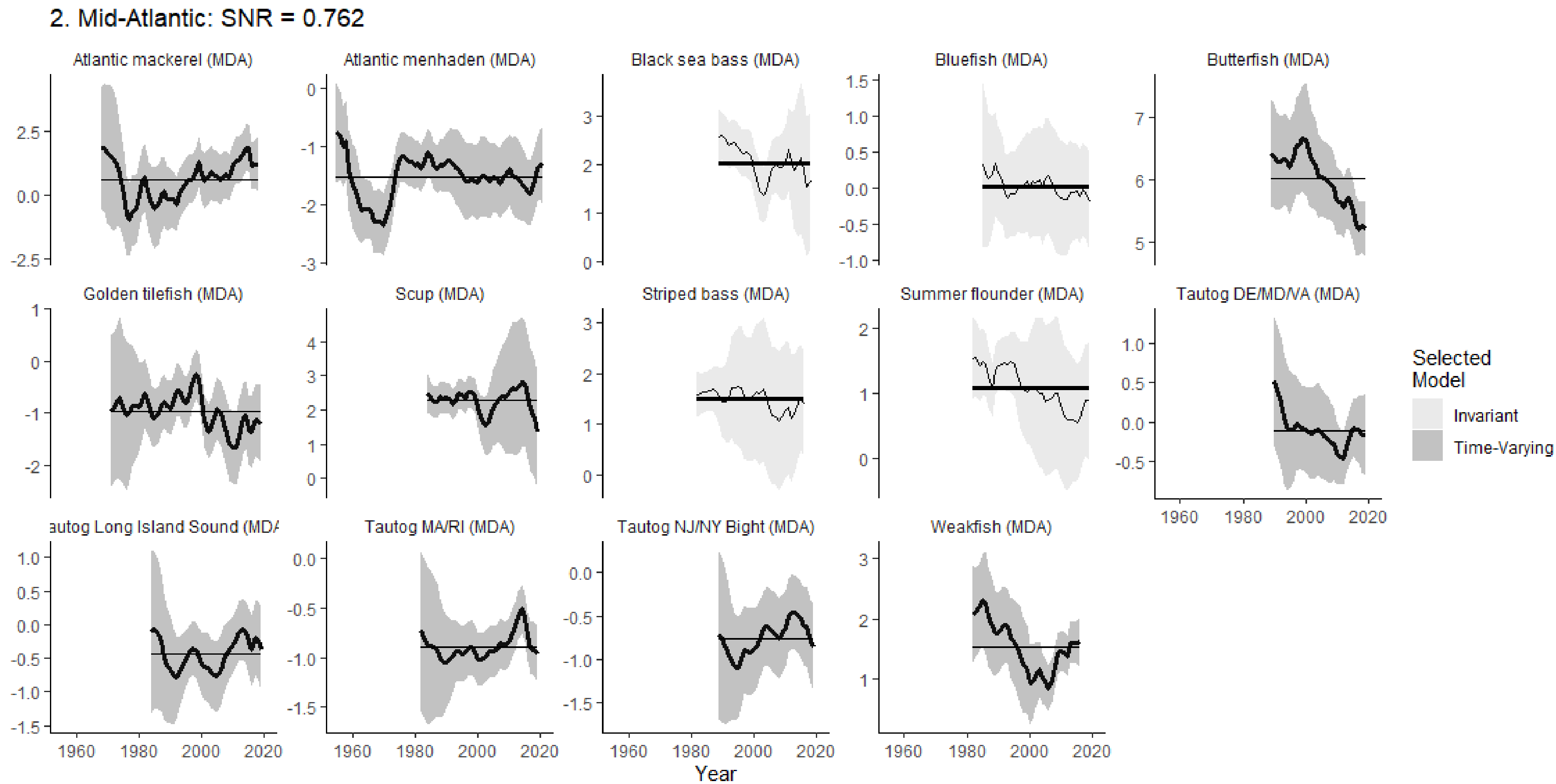


Figure S2b: Time series of productivity (a) in units of log(recruits/spawner) estimated by the dynamic Ricker model with the Kalman filter. Stocks selected as having time-varying productivity are shown with bold productivity time series, and stocks selected as having time-invariant productivity are shown with bold horizontal line indicating average productivity across the estimated time series.

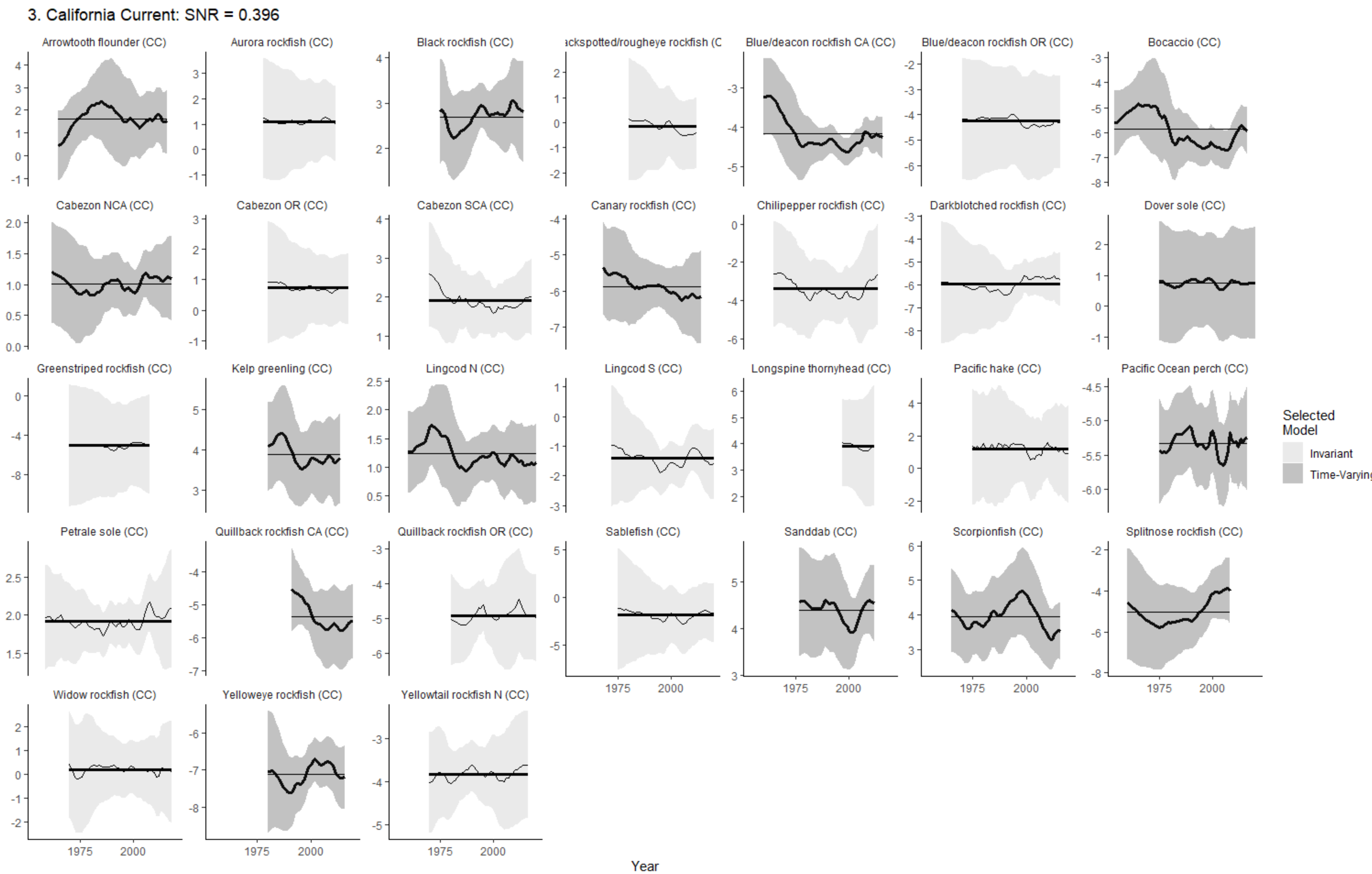


Figure S2c: Time series of productivity (a) in units of log(recruits/spawner) estimated by the dynamic Ricker model with the Kalman filter. Stocks selected as having time-varying productivity are shown with bold productivity time series, and stocks selected as having time-invariant productivity are shown with bold horizontal line indicating average productivity across the estimated time series.

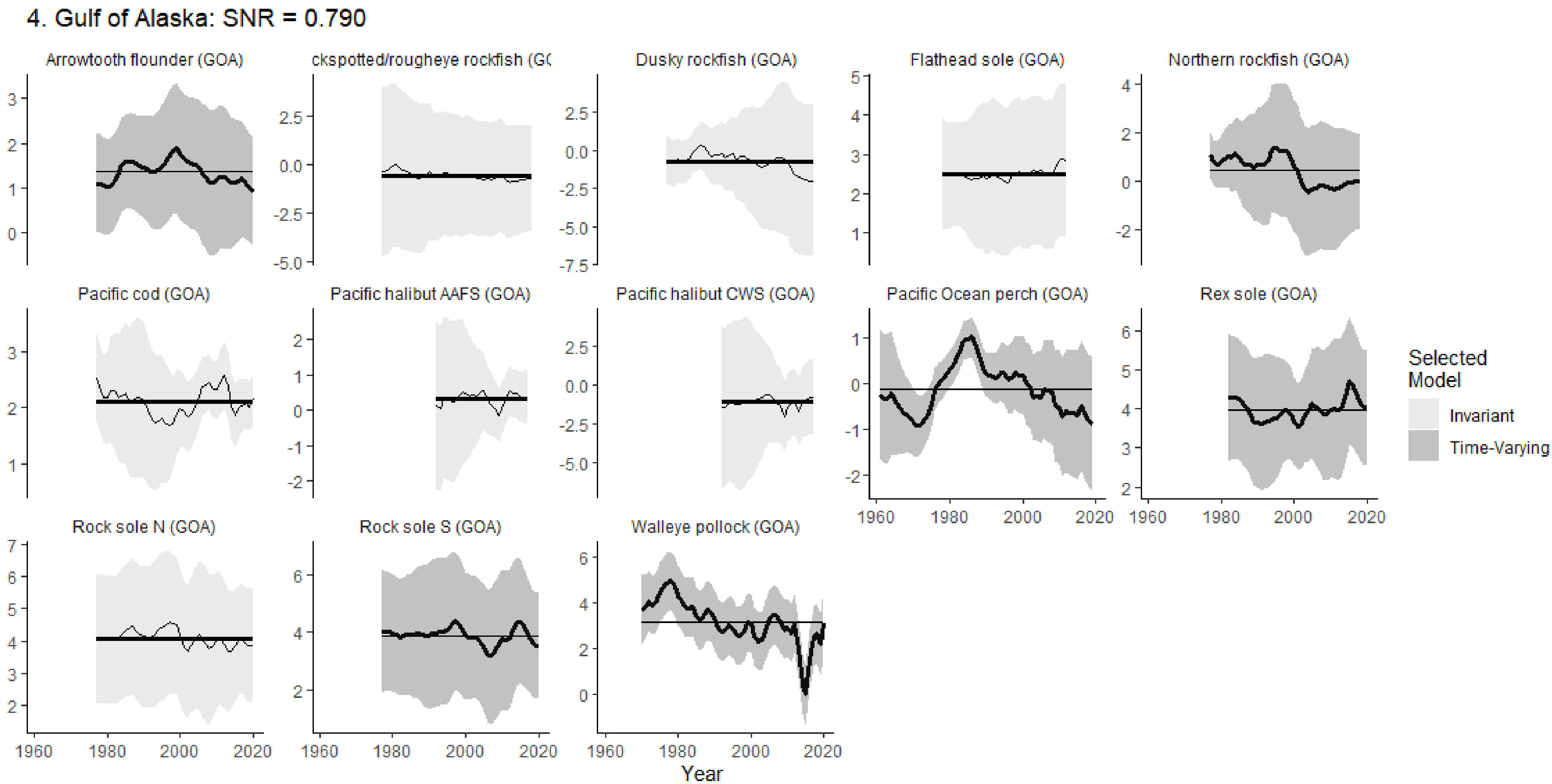


Figure S2d: Time series of productivity (a) in units of log(recruits/spawner) estimated by the dynamic Ricker model with the Kalman filter. Stocks selected as having time-varying productivity are shown with bold productivity time series, and stocks selected as having time-invariant productivity are shown with bold horizontal line indicating average productivity across the estimated time series.

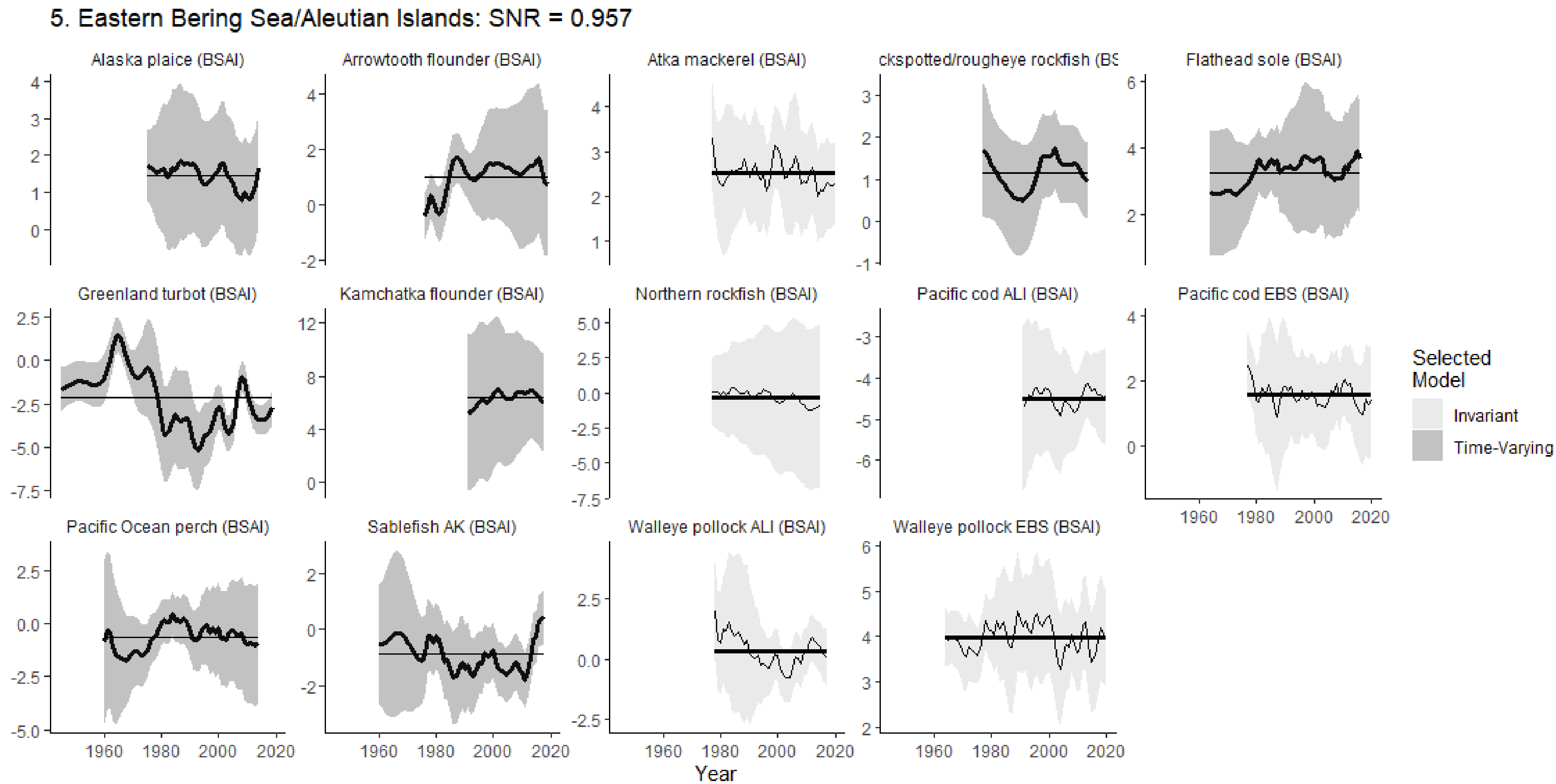


Figure S2e: Time series of productivity (a) in units of log(recruits/spawner) estimated by the dynamic Ricker model with the Kalman filter. Stocks selected as having time-varying productivity are shown with bold productivity time series, and stocks selected as having time-invariant productivity are shown with bold horizontal line indicating average productivity across the estimated time series.

Supplementary Figure S3a-e

1. New England

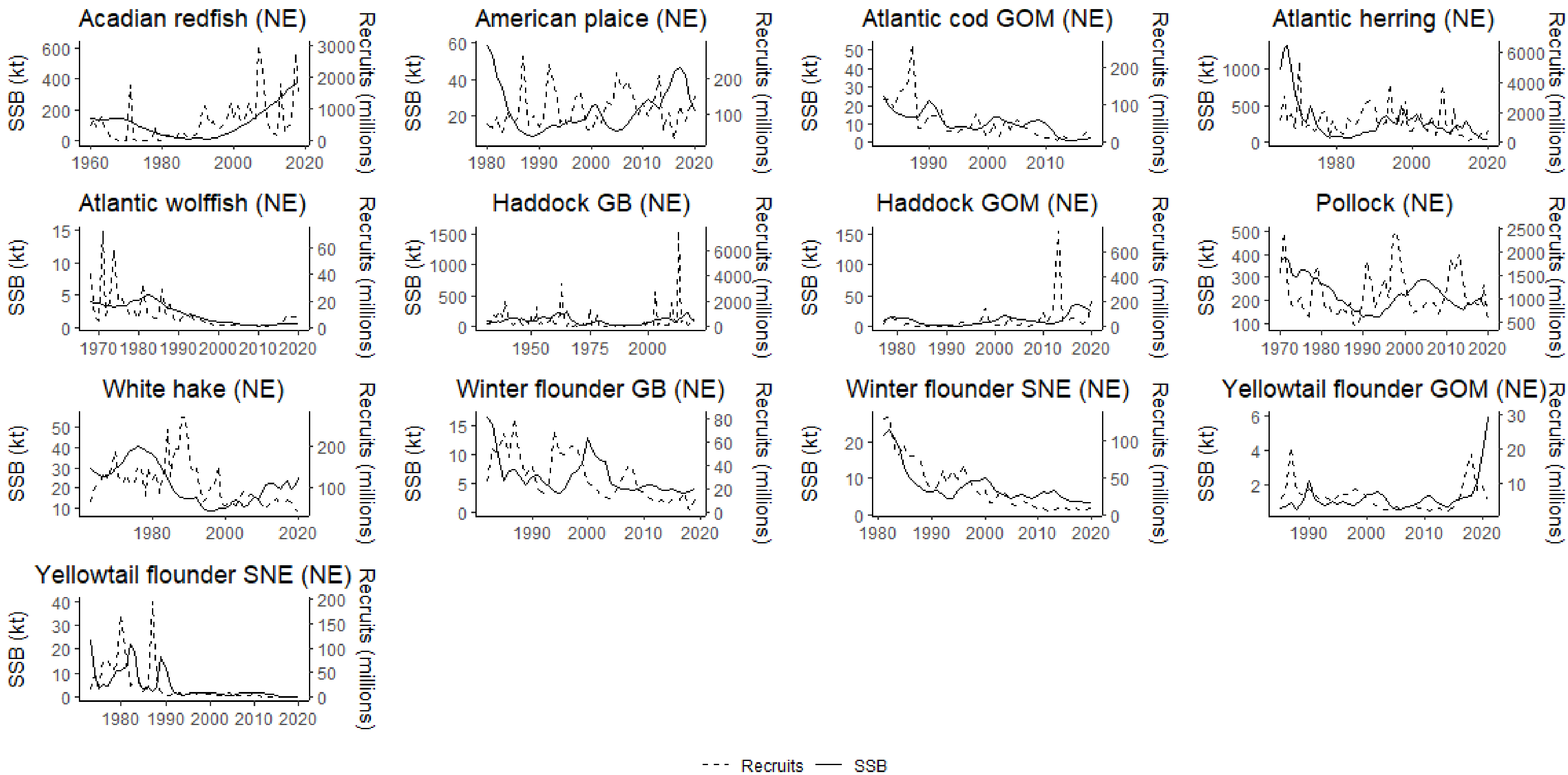


Figure S3a: Time series of spawning stock biomass (solid line) and recruitment (dashed line) from stock assessment reports.

2. Mid-Atlantic

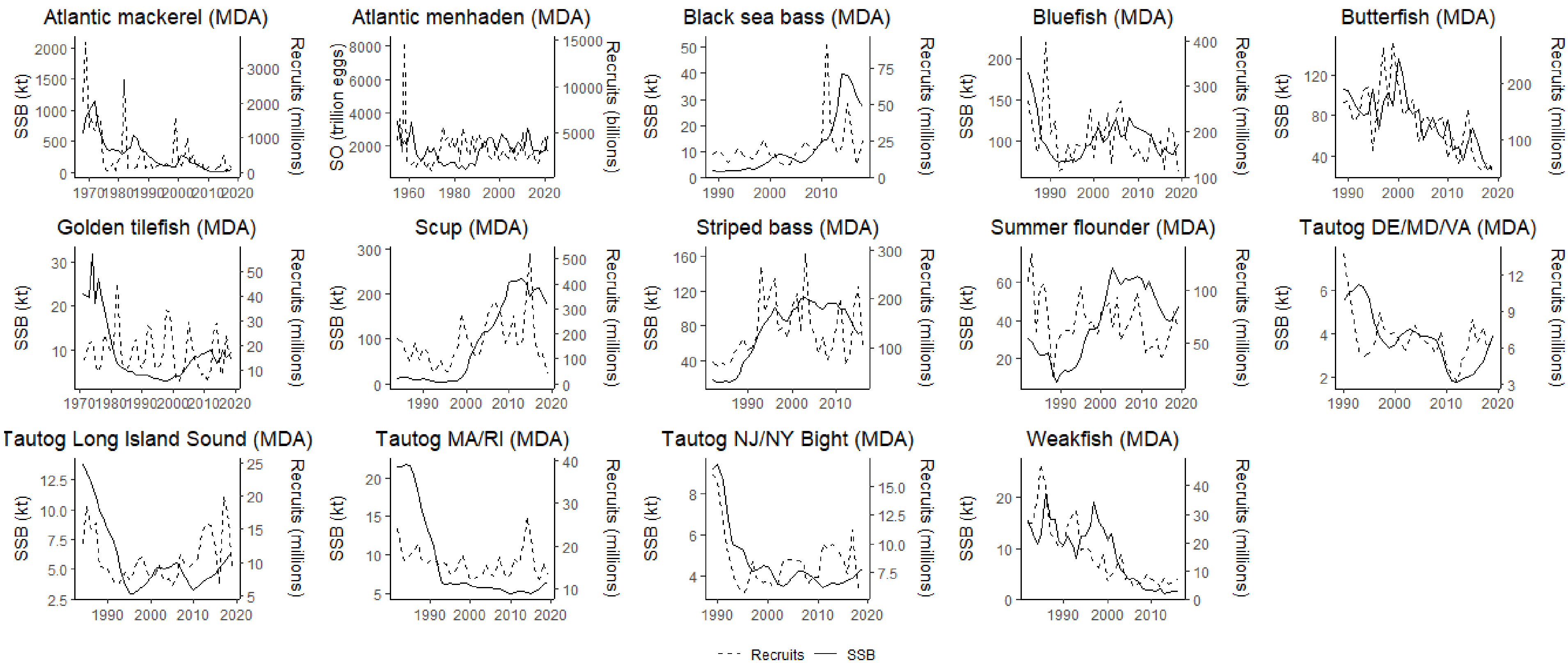


Figure S3b: Time series of spawning stock biomass or spawning output (solid line) and recruitment (dashed line) from stock assessment reports.

3. California Current

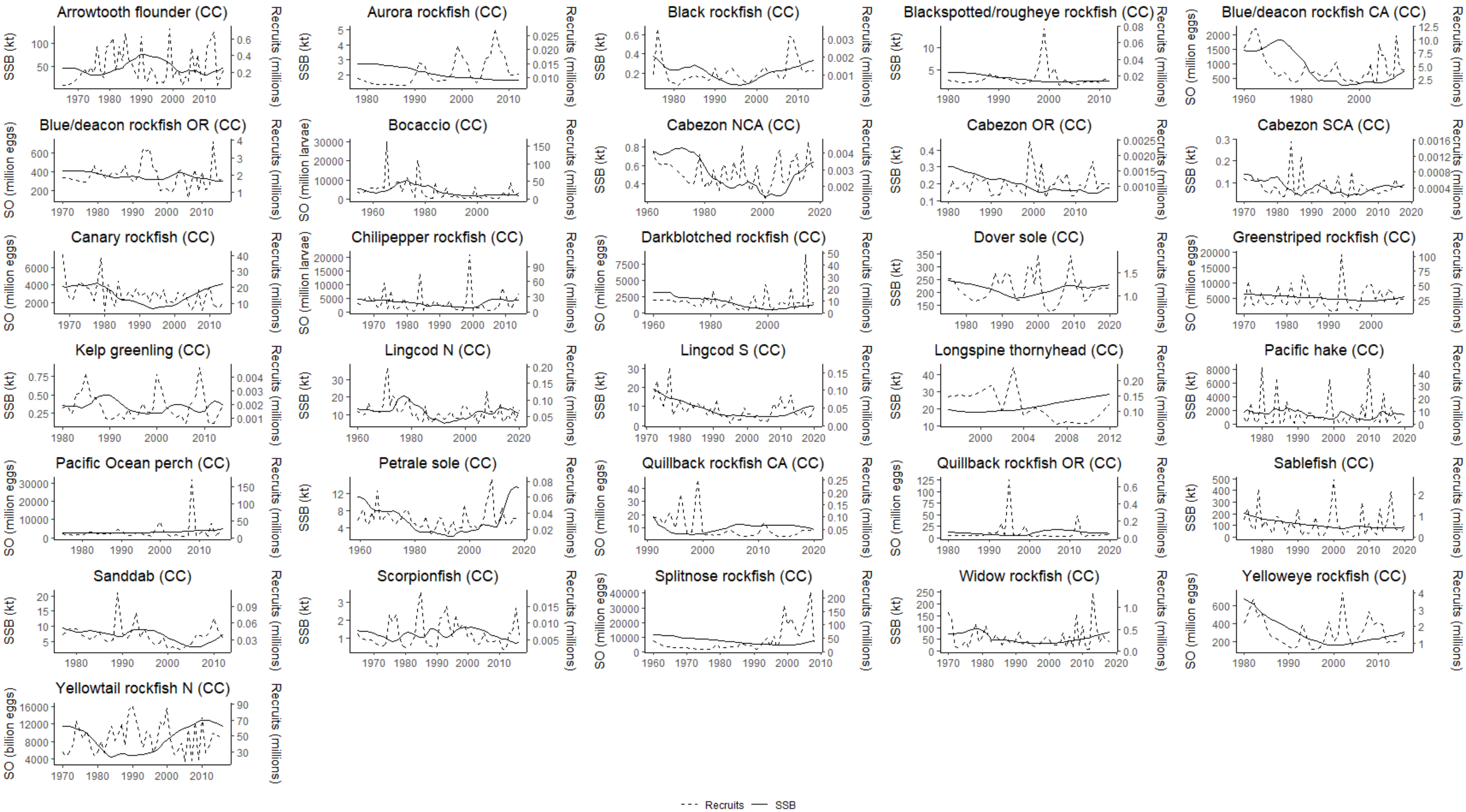


Figure S3c: Time series of spawning stock biomass or spawning output (solid line) and recruitment (dashed line) from stock assessment reports.

4. Gulf of Alaska

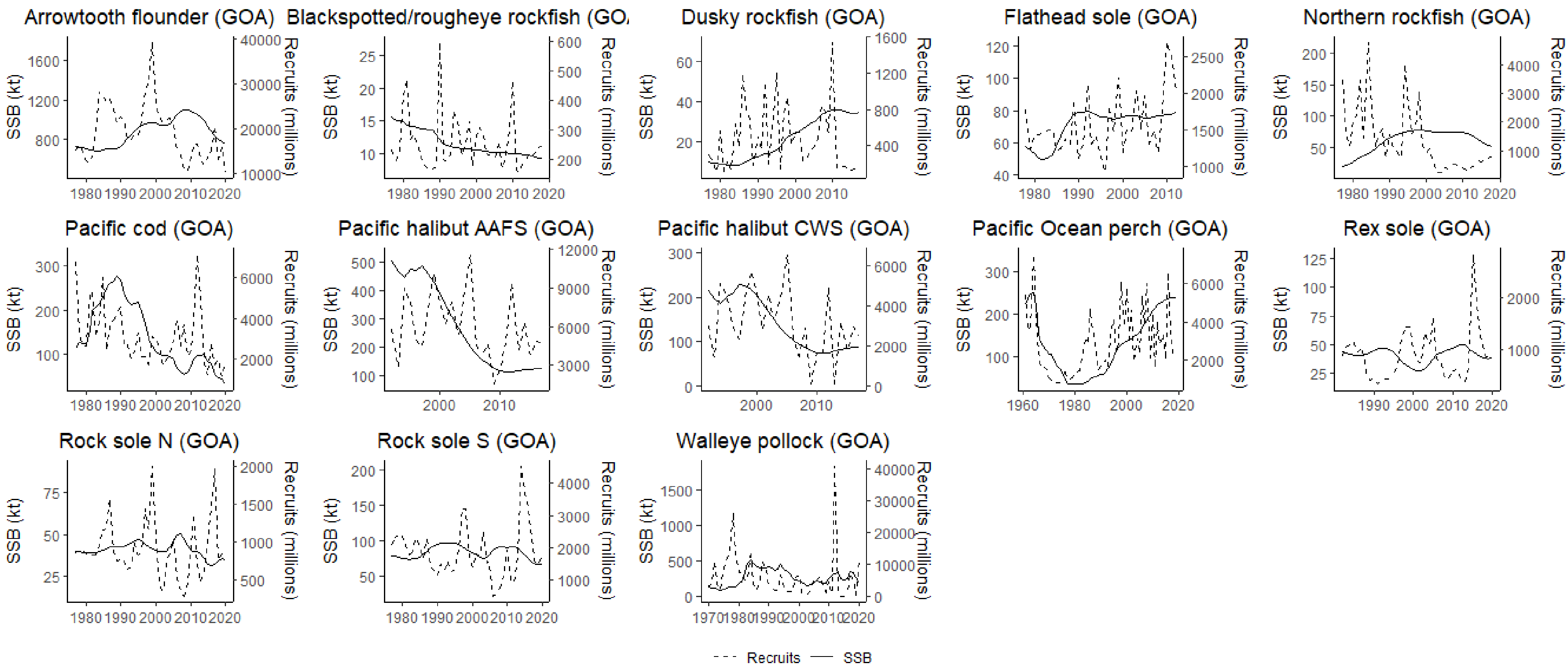


Figure S3d: Time series of spawning stock biomass (solid line) and recruitment (dashed line) from stock assessment reports.

5. Eastern Bering Sea/Aleutian Islands

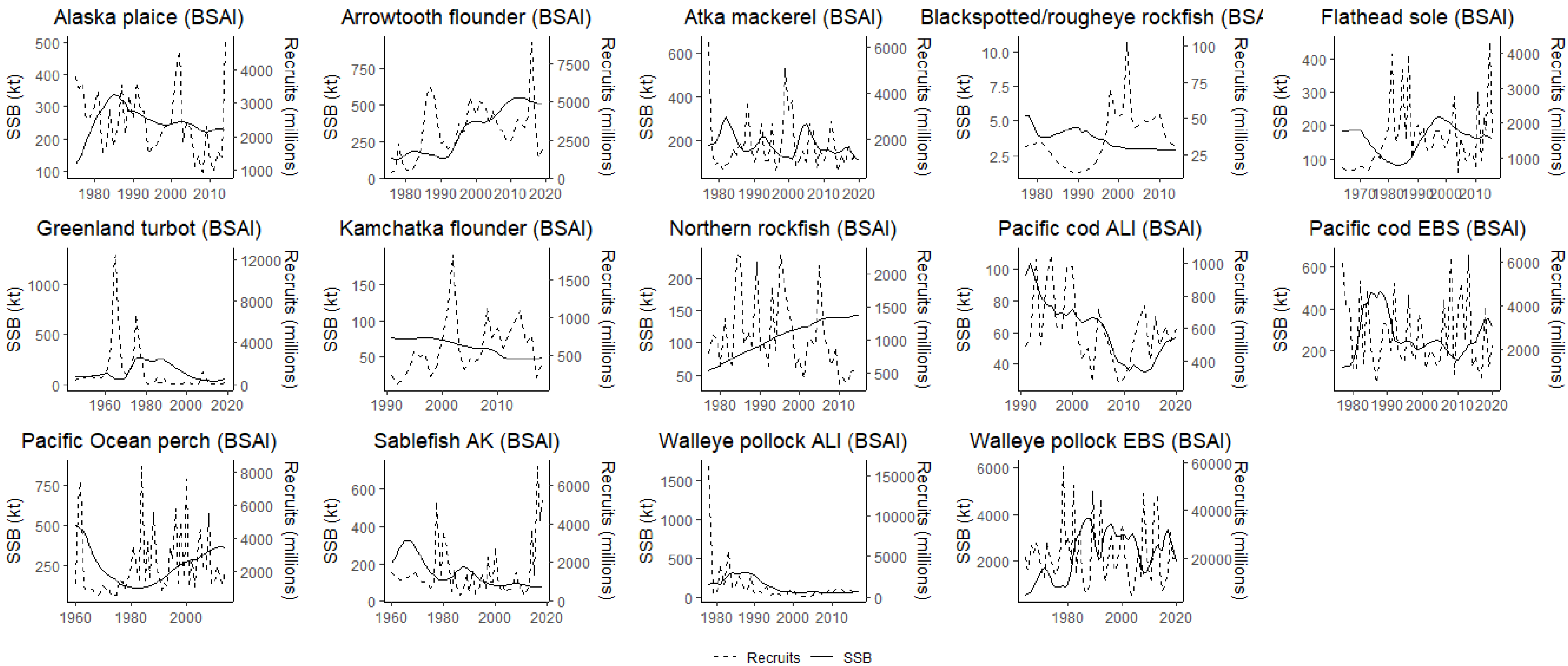
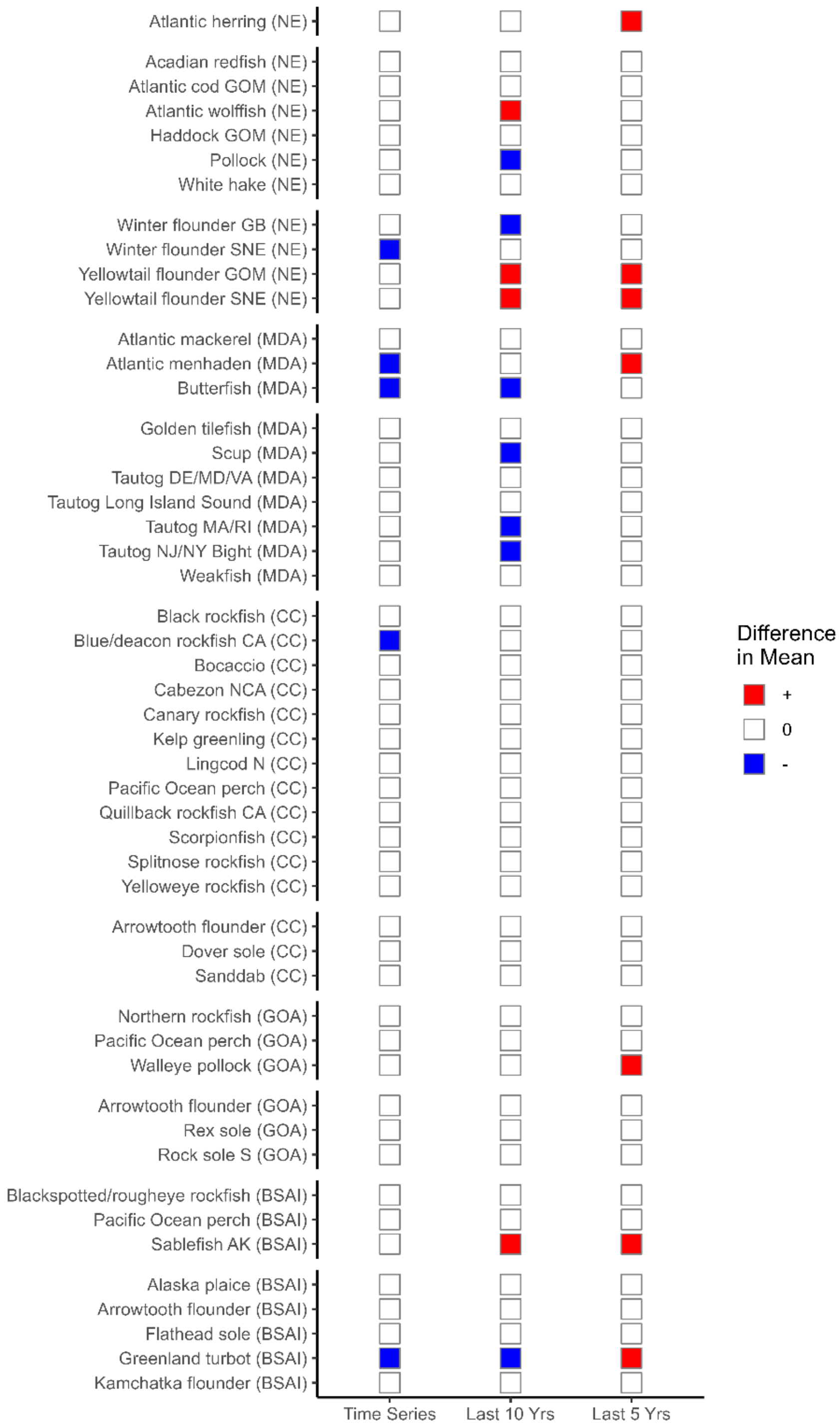


Figure S3e: Time series of spawning stock biomass (solid line) and recruitment (dashed line) from stock assessment reports.



Supplementary Figure S4

Figure S4: Summary of the difference in current mean stock productivity relative to the mean estimated at the beginning of the time series (col. 1), ten years prior to current (col. 2), and five years prior to current (col. 3). Red squares indicate that productivity is currently higher than it was at the beginning of the given time period (i.e. increased), and blue squares indicate that productivity is currently lower (i.e. decreased). White squares indicate that the productivity has not changed notably since the beginning of the given time period, relative to the standard error of the productivity estimate.