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Changes in the productivity of US West Coast fish stocks

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Abstract

The California Current ecosystem is highly dynamic at interannual to interdecadal time scales. Variability has been documented in pelagic and other fish species, but climate change may be altering the historical models of variation. This study investigates changes in productivity of 31 fish stocks in the California Current ecosystem. Productivity was measured from recent stock assessments, as the per-capita recruitment rate, estimated with a dynamic stock-recruitment model. Contrary to expectations, the dynamic stock-recruitment model fit better than the corresponding stationary model

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for only seven of the 31 stocks. There was little evidence of linear drift in productivity that might be expected to result from climate change. Climate variables improved forecast accuracy for a few stocks, but there was no common climate signal in productivity. One explanation of these results is that most of the west coast stocks are above their biomass levels for maximum sustainable yield, making them less susceptible to environmental variation. On the other hand, the dynamic recruitment models improved short-term forecasts for all stocks, which may be useful for quota setting. Finally, results for the subset of stocks with dynamic recruitment models could be used to establish dynamic biological reference points.

Keywords

Stock productivity, spawner-recruit models, stock assessment, time-varying parameters, US west coast, groundfish

1 Introduction

Climate variability and change have a large impact on natural marine resources (Hollowed et al., 2013; Hutchings et al., 2012). The main ways in which climate impacts fish stocks is by changes in distribution, changes in phenology, and changes in productivity. Changes in distribution have been demonstrated for fish stocks all over North America and beyond (Cheung et al., 2008; Nye et al., 2009; Perry et al., 2005; Pinsky et al., 2013) while changes in seasonal timing have been recorded for a range of marine and anadromous species (Henderson et al., 2017; Langan et al., 2021; Otero et al., 2014). Productivity refers to a fish stock's population growth and is a function of recruitment, survival, and individual growth (Shelton et al., 2006; Silvar-Viladomiu et al., 2022; Tableau et al., 2019). Productivity is impacted by density-dependent factors such as abundance and age-structure and by density-independent factors such as the environment. The physical medium of water can exert a strong regulatory function on fundamental aspects of fish biology such as metabolism (Manderson, 2016). Through these biological functions, the environment can therefore regulate where an individual can live, how well it will survive and what capacity it has for reproduction thereby determining its productivity in a given year.

On the west coast of the United States, a number of fish stocks show evidence of environmental influence. Pacific sardines and northern anchovies have varied substantially over time, often in the absence of fishing (Lindegren et al., 2013; Schwartzlose et al., 1999). Studies have shown that changes in water temperature and upwelling driven by large scale climate cycles, combined with density-dependent effects are major factors regulating abundance. The environment is considered such an important driver for Pacific sardines that the management of the stock is one of few in the world that specifically includes a temperature time-series (Lindegren and Checkley, 2012; PFMC, 2015). Sablefish have exhibited a relationship with copepod abundance and sea surface height under the hypothesis that changes in atmospheric-ocean circulation impact the available prey items for early life stages and cross shelf transport to nursery areas (McFarlane and Beamish, 1992; Johnson et al., 2016; Tolimieri et al., 2018). The relationship is strong enough that time series of copepod abundance and sea surface height are directly evaluated in the stock assessment model (Johnson et al., 2016; Kapur et al., 2021). Recently, a marine heat wave ("The Blob") had major impacts on the California current ecosystem resulting in distribution shifts, an influx of southern species, Dimoic acid outbreaks, fishery closures and a spike in whale entanglements with fishing gear, showing the impacts changes in the environment can have on marine species (Cavole et al., 2016; Chasco et al., 2022; Jacox et al., 2018; Peterson et al., 2016; Santora et al., 2020). In addition, research recommendations from the groundfish assessments suggest some synchrony among rockfish recruitment at certain spatial and temporal scales (Field et al., 2021; Stachura et al., 2014) and the California Scorpionfish assessment recommended further research into a potential relationship with sea surface temperature (Monk et al., 2017). Understanding how the environment influences natural marine resources can be important for sustainable management.

The California current ecosystem is a large upwelling system spanning most of the west coast of the United States (Harvey et al., 2022). The cold water current flows from north to south resulting in the entire coastline being relatively well connected. Many stocks are managed as single populations along the entire coast, though some because of lack of more detailed data. The ecosystem is heavily influenced by large-scale, atmospheric-ocean cycles such as El Nino and the Pacific Decadal Oscillation that alter temperature, stratification, winds and upwelling. These changes affect nutrient availability, prey density and advection towards or away from nursery areas (Harvey et al., 2022). As the environment often has the largest impact on the early life stages of natural marine resources (Houde, 1987), much of the climate and fisheries work is focused around the recruitment process. Our goal was to evaluate if there have been changes in the productivity of commercial fish stocks along the west coast of the United States by examining the recruitment process.

We tested for changes in productivity with a time-varying Ricker stock-recruitment model (Peterman et al., 2003; Dorner et al., 2008; Silvar-Viladomiu et al., 2022). The inputs for the model are the spawning stock biomass and recruitment outputs from an age-structure stock assessment. While the products are modeled data, they represent the best current sources of spawning stock biomass and recruitment information integrated across the entire population (Silvar-Viladomiu et al., 2022). The environment is rarely included in assessment models (Essington et al., 2016); however, it is possible that the output of an assessment model can contain the signature of the impact of the environment. For stocks with age-structured assessments (relatively small number, but high number by volume of total landings), changes in weight-at-age, fecundity-at-age and the annual age-structure are directly incorporated into the model. Annual changes in these inputs are often the result of changes in the environment. The spawning stock biomass and recruitment estimates from an assessment model can therefore show the impact of an environmental change, without the assessment directly incorporating it, or explaining it. Lack of inclusion of an environmental term in an age-structured assessment does not really change the estimates of biomass (Bell et al., 2018), but lack of an environment driver in the model can change the understanding of the drivers of stock abundance or stock status.

We examined changes in productivity, the reproductive potential of a stock, for a range of species managed by the Pacific Fisheries Management Council with a linear state-space modeling approach. The goals of the study were first to determine if stock productivity varied over time for thirty-one commercially important west coast species and to see if the time-varying productivity of each stock exhibited any directionality or was related to large-scale environmental drivers. Once the time-varying productivity time series were estimated, we investigated whether there were any common patterns among the different species that might indicate large-scale environmental forcing and if stock status may be related to whether a stock exhibited time-varying or time-invariant productivity.

2 Methods

To examine changes in stock productivity and investigate potential drivers and patterns across the different species, the study was broken into four components. 1) To determine if productivity changed over time, we fit a time-varying Ricker model and a time-invariant (standard) Ricker model to all thirty-one commercially important stocks. The best model was determined with a likelihood ratio test, however, as a separate analysis, we also investigated whether the time-varying or time-invariant Ricker model was better able to forecast recruitment one to three years in the future (termed forecast accuracy). 2) As a means to understand potential drivers of changes in productivity, we incorporated a linear trend and a range of climate variables into the time-varying Ricker model and compared the results to the best fit model from component one (climate drivers). 3) Broad scale patterns in productivity across the thirty-one stocks were examined with Dynamic Factor Analysis. And 4) to determine if fishing or depletion was a potential driver, we investigated whether there was a relationship between stock status and variable productivity.

2.1 Assessment models

Spawning stock biomass (SSB) and recruitment from age-structured stock assessments were used as the input for the analysis. While the output of an assessment is an estimate, it represents the best estimates of SSB and recruitment available, integrating multiple data sources including fisheries independent and fisheries dependent data to produce time series of SSB and recruitment (Tableau et al., 2019; Silvar-Viladomiu et al., 2022). The most up-to-date stock assessments for commercial groundfish managed by the Pacific Fisheries Management Council were taken from the Council website in the winter of 2022.

https://www.pcouncil.org/stock-assessments-star-reports-stat-reports-rebuilding-analyses-terms-of-reference/groundfish-stock-assessment-documents/

All included assessments were run in Stock Synthesis (Methot and Wetzel, 2013) and included a Beverton-Holt stock recruitment function within the assessment model. Only models that included non-deterministic recruitment were used, however. Non-deterministic recruitment means that the estimates of recruitment could deviate from the stock-recruitment function as recruitment deviations, within certain constraints. The constraints typically defined a distribution for the recruitment deviations with a mean of zero and a specified standard deviation regulating how much the recruitment deviations could deviate from the stock-recruitment function. The recruitment deviations enable the estimates of recruitment to be informed by the survey-at-age and catch-at-age data and are largely unconstrained by the stock-recruitment function. The standard deviation of recruitment deviations was examined to ensure recruitment estimates were able to fully deviate from the Beverton-Holt stock-recruitment curve included in the assessment model when listed in the assessment report. When not reported, a visual inspection of the spawning stock biomass and recruitment was conducted. In many cases the assessments estimated biomass going back to the late 1800s-early 1900s, however length or age data was not collected till the later half of the 1900s. The state-space analysis used only estimates of spawning stock biomass (SSB) and recruitment that were informed by length or age data with starting years varying between 1954 and 1997 depending on the stock. For most stocks in the study, start dates were in the 1960s or 1970s. While most assessments output SSB in weight, some output it in number of eggs. As a simple means of scaling all units to biomass, the numbers of eggs were converted to weight by dividing the total number of eggs each year by one million. The SSB-egg scaling factor simply resulted in the productivity term for all species being within the same range.

2.2 Climate data

Eight climate variables were examined to determine if they had a relationship with changes in stock productivity (Table 1 & Figure 1). All variables were available from the California Current Ecosystem Status Report (Harvey et al., 2022). For all variables, monthly values were averaged to produce an annual mean. Sea surface temperature was obtained for three different latitudes (33°N, 39°N, 44°N) and matched with the location of the stock. If the stock spanned the entire west coast the middle latitude was selected. To ensure independence, all variables were examined for correlation. Variables with a correlation coefficient greater than 0.7 ($r \geq 0.7$) were not included in the time-varying stock-recruitment model.

2.3 Time-varying productivity: component I

Potential changes in productivity were examined with a time-varying Ricker model (Peterman et al., 2000, 2003; Collie et al., 2012; Britten et al., 2016). In the standard Ricker model, the number of recruits at time t (R_t) is equal to the spawning stock biomass at time *t-1* (SSB_{t-1}) times the density-independent, productivity term (α) and modified by the density-dependent term (β) (Quinn and Deriso, 1999). The model assumes that productivity, the slope at the origin, α ($\alpha = e^a$), is stationary and that recruitment varies only with SSB. However, studies have demonstrated that recruitment variation is more than simply a function of SSB and can often be heavily influenced by the environment (Szuwalski et al., 2015).

The time-varying Ricker model was fit within a state-space framework by maximum likelihood using a Kalman filter. State-space models are a means of identifying the true state of a quantity while accounting for the observation error in the quantity (Peterman et al., 2000; Silvar-Viladomiu et al., 2022). All observations are a combination of their true state plus some observation error. The state-space model uses two equations. An observation equation, the linearized Ricker model, accounts for observation error by explicitly modeling the variance.

$$ln\left(\frac{R_t}{S_{t-1}}\right) = a_t - bS_{t-1} + v_t \tag{1}$$

$$a_t = a_{t-1} + w_t^a \tag{2}$$

$$v_t \sim N(0, V) \tag{3}$$

$$w_t^a \sim N(0, W_a) \tag{4}$$

The process equation models the true state of the quantity, in this case, as a random walk. The observation error (v_t) and random walk parameter (w_t) are normally distributed with mean zero. The model estimates two parameters: the variance of v_t (V) and the variance of the random walk (W_a) for the time varying value (a_t) that varies as a random walk capturing potential changes in the productivity of the stock. The changes could be due to changes in the external environment such as upwelling or prey availability or to changes in the biology of the fish themselves (changes in fecundity, spawner success, etc...) that could be influenced by the environment or other stressors. The random walk captures the empirical changes in the parameters directly from the input time series.

To improve the robustness of the analysis, we followed extensions of the state-space method (Peterman et al., 2000; Dorner et al., 2008) made by Tableau et al. (2019). The state-space framework includes both measurement error and process error in an attempt to model the true state of a parameter. One of the challenges when using state-space models is partitioning the total error between measurement error (noise) and process error (signal). Following a similar study on the US Northeast Shelf (Tableau et al., 2019), we pooled the available data to estimate a single signal-to-noise ratio (snr), the ratio of process error to measurement error, across all species to produce robust estimates of productivity. The method estimates separate error terms for all species, but estimates a single snr for all species. Different populations of the same species (Manderson, 2008; Minto et al., 2013) or groups of different species in the same area can exhibit similar ratios of process error to measurement error (Tableau et al., 2019). Parameters of all stocks were estimated together with a single, signal-to-noise ratio (snr), the ratio of process-error variance (W_a) to observation-error variance (V). The same model with the linear Ricker model as the observation equation and the random walk as the process equation was used (Equation 1 & 15), but it was formulated in matrix form.

$$Y_t = F_t X_t + v_t \text{ with } v_t \sim N(0, V) \tag{5}$$

$$X_t = G_t X_{t-1} + w_t \text{ with } w_t \sim N(0, W) \tag{6}$$

Within the matrix form, $Y_t = ln\left(\frac{R_{i,t}}{S_{i,t-1}}\right)$ for each stock i from 1,...,I. The time varying productivity terms for each stock ($a_{i,t}$) and time-invariant density-dependent term for each stock (β_i) are included as X_t. The linearized Ricker model is F which includes the SSB for each stock i. Matrix G is the identity matrix linking the process equation to the observation equation. The total variance in the observations $ln\left(\frac{R_{i,t}}{S_{i,t-1}}\right)$ is partitioned into three sources, the observation error (v_t), the process error (w_t) and the density dependence from SSB for each stock. The error vectors follow the multivariate normal distributions defined by the covariance matrices V (dimension IxI) and W

(dimension 2Ix2I). Matrix W is the variance determining the range of the random walk (w_t).

To examine the potential for model misspecification a time-varying Beverton-Holt stock recruitment function was fit to the spawning stock biomass and recruitment information and compared to the output of the time-varying Ricker model (supplemental material).

2.4 Climate drivers: component II

In addition to the standard, time-invariant Ricker model, and the time-varying Ricker model fit with a common signal-to-noise-ratio within the state-space framework fit to examine changes in productivity in component one, the study fit an additional model variant to examine large-scale drivers. In component two, We fit a time-varying Ricker model that included a drift or climate term to explicitly incorporate either a linear trend or climate signal within the state-space framework. The drift or climate term (c_j) was included in the process equation (eq 7) where $H_{j,t-lag}$ is the environmental time series, j defines which time series and $t - lag$ determines which lag is examined. The drift term was also modeled as c_j and the time series H was a series of ones. All other terms are as defined in eq 15. Not all environmental time series were available for the full length of the SSB and recruitment time series. The models were fit for only the years available for the shortest of the environmental or SSB-R time series.

$$a_t = a_{t-1} + c_j H_{t-lag} + w_t^a \tag{7}$$

$$w_t^a \sim N(0, W_a) \tag{8}$$

All the time-varying models (components I and II) were fit with the package dlm (Dynamic Linear Modeling) in the software package R (Petris et al., 2009).

2.5 Model comparison

Model comparison was done with two techniques: a likelihood ratio test and an evaluation of forecast accuracy (Tableau et al., 2019). The two techniques are complementary, but provide different information. The likelihood ratio test compares the full time-series of the estimated $ln\frac{R}{S}$ from the different models (e.g. time-invariant to time-varying) with a $\tilde{\chi}^2$ distribution to determine the overall best fit model. The forecast accuracy test was designed to determine whether the time-invariant or time-varying model could better forecast $ln\frac{recruits}{spawner}$ one to d years into the future. It does not test for a significant difference. The test uses only the data up to time step t to predict $ln\frac{recruits}{spawner}$ d time steps into the future. The test compares forecast from the time invariant model to the known value of $ln\frac{recruits}{spawner}$ and the forecast from the time-varying model to the known value.

$$Acc_d = \frac{\sum_{t=T-15}^{T-d}(F_{t+d|t,null} - Y_{t+d,obs})^2 - \sum_{t=T-15}^{T-d}(F_{t+d|t,alt} - Y_{t+d,obs})^2}{\sum_{t=T-15}^{T-d}(F_{t+d|t,null} - Y_{t+d,obs})^2} \tag{9}$$

Forecast accuracy (Acc) is equal to the forecast (F) from the time invariant (null) model minus the observed value (Y) subtracted from the forecast from the time varying (alt) model minus the observed value divided by the forecast from the time invariant model minus the observed value.

The difference between the known and predicted value (residuals) for each model averaged over the last fifteen years was examined to determine the best model. The last fifteen years were selected because the early part of the time-series can have extremely large confidence intervals making comparisons challenging. The likelihood ratio test examines which model provides the best fit to the data over the entire course of the time-series. The forecast accuracy test examines how well the model can predict d time steps into the future. It is possible that the model which provides the best fit over the entire time-series may not provide the best forecast one, two, or three years in the future.

2.6 Dynamic Factor Analysis: component III

A number of the west coast stock assessments recommended examining if different stocks exhibited similar patterns over time. Dynamic Factor Analysis (DFA) was used to examine if there were common trends across the productivity time-series of the stocks (Zuur et al., 2003a,b). DFA distills multiple time series into common underlying state processes or trends within a state-space model. The method is particularly useful for examining non-stationary, short time-series. A state process, represented as a random walk was fit to the productivity time series. The productivity time series were standardized by subtracting the mean and dividing by the standard deviation. We fit from one to four trends and used AICc to determine the most appropriate number of trends. The process error equation within the DFA state-space model was a random walk.

$$x_{t+1} = x_t + w_t \text{ with } w_t \sim MVN(0, I) \tag{10}$$

The x's are the common trends (from one to four) among the different time series with multivariate normal (MVN) process error. The I matrix is the identity matrix with the same dimensions as the number of trends. The time-varying productivity time-series for each stock (a_t) are linear combinations of the user defined number of state processes (x) (the number of trends) times the Z matrix with measurement error v.

$$a_{t+1} = Zx_t + v_t \text{ with } v_t \sim MVN(0, R) \tag{11}$$

The Z matrix represents the contribution of each common trend to the original observed time series for each species and is termed the factor loadings. If a stock has a large, positive loading in the Z matrix, its productivity time-series is very similar to the common trend while a large, negative loading indicates the productivity time-series is opposite the common trend. Stocks with small loadings are generally not well explained by the common trend. To maximize convergence, the variance-covariance structure was constrained to estimate different variances along the diagonal, but to not have any off-diagonal terms. The DFA was fit in the R package MARSS (Holmes et al., 2013, 2014).

2.7 Productivity and Stock Status: components IV

We tested if the nature of stock productivity (time-varying or constant) was related to stock status with a logistic regression. Stock status, defined as $\frac{B}{B_{msy}}$, was regressed against productivity defined as a binary term: time-varying or constant. Stock status was taken directly from the appropriate stock assessment or taken from the National Marine Fisheries Service Status of the Stock report in the appropriate year for each stock (NMFS, 2021). The stocks and productivity time series from this study were combined with the stocks and productivity time series from a study investigating stock productivity on the US Northeast Shelf with very similar methods (Tableau et al., 2019).

3 Results

In total, time-varying productivity was estimated for thirty-one stocks managed by the Pacific Fisheries Management Council (Table 2). The model with a single, signal-to-noise ratio converged and produced good results (snr = 0.40) (Figure S2). In general, the estimated productivity varied over time, but none of the stocks showed clear increasing or decreasing trends, except for a possible decrease in CA Blue-Deacon rockfish and CA Quillback rockfish. Across the stocks, the productivity term exhibited a range from 0.25 on the low end and up to 3.0 at the high end. This number is the range in the number of recruits that a metric ton of spawning stock biomass on a logarithmic scale could produce over the time-series after accounting for SSB. For many of the stocks, the variability in productivity was not particularly large and/or the confidence intervals were quite wide indicating that the more parsimonious time-invariant model fit the data better. Only seven of the thirty-one stocks were better fit with the time-varying model based on the likelihood ratio test (Figure 2).

The time-varying Ricker and time-varying Beverton-Holt models estimated very similar patterns in productivity, the slope at the origin of the stock recruit curve (Figure S1). The scale of the estimates differed depending on the species, but the overall pattern between the two models was generally the same. The current study is explicitly examining the time-varying patterns in productivity and not the absolute value so the difference in scale for some species does not alter the overall results.

We fit a DFA to discern if there were common patterns across all stocks. The model with four common trends provided the best fit to the productivity time series based on AICc. Overall the trends explain a limited amount of the variability in the majority of the productivity time series. The factor loadings were relatively low for most stocks with only a handful accounting for more than 20% of the variability. Trend one had the most support. It was lowest in the early part of the time series and then generally increased to the early 1990s (Figure 3). It then declined and was low in the early 2000s before increasing to some degree in the 2010s. The productivity time series of species loaded positively and negatively, but generally the magnitude of the loadings was low for the majority of species. Trend two began with an increasing trend up to the early 1980s, then declined till the early 2000s before increasing to the present (Figure S3). All the factor loadings were low except for Longspine Thornyhead. Trend three was highest in the late 1960s - early 1970s before declining till the mid 1980s (Figure S4). It then increased through the 1990s before slowly declining. Longspine Thornyhead again had a very strong loading while the majority of the other species were low. Trend four was highest in the early part of the time series and generally declined till the late 1990s before largely increasing to the end of the time series (Figure S5). The factor loadings were again relatively low. The DFA identified four common trends, but the majority of species loaded relatively weakly on the trends indicating that there were not strong patterns across all the species.

The gain in forecast accuracy examined the ability of the time-varying and time-invariant model to predict the $ln\frac{recruits}{spawner}$ one to three years forward using only the information available up to the current time step. We examined this only over the last fifteen years of the time-series. A negative value indicates that the forecast from the time-invariant model performed better than the time-varying model. Across all stocks, the time-varying model provided a better forecast than the time-invariant model one year ahead and for most stocks, two years ahead as well (Figure 4). At the two year ahead mark, two of thirty-one stocks were slightly negative (Cabezon OR, -1% & Widow rockfish, -5%) while all others were positive. The gain in forecast accuracy with the time-varying model declined with the three year forecast. The forecasts for the seven stocks in which the time-varying model was significantly better than the time-invariant model based on the likelihood ratio test, had better forecasts one, two and three years ahead.

The inclusion of the drift or climate variable within the state-space model was also tested with both the likelihood ratio test and the gain in forecast accuracy test. The best fitting model (base model) for each stock from above (time-varying or time-invariant) was tested against a time-varying model that included a drift or climate term (Figure 5). The likelihood ratio test determines if the base model or the time-varying model with the climate variable provided the best fit to the full time series of $ln\frac{recruits}{spawner}$. The forecast accuracy test examined if the base model or the time-varying model with the climate variable provided the better one year ahead forecast of $ln\frac{recruits}{spawner}$ given only the SSB and recruits up to time t and the climate variable up to time $t+1$. While the future value of the climate variables can not be known, we assumed the future climate variable was known perfectly in order to understand the full potential of each climate variable to accurately forecast changes in $ln\frac{recruits}{spawner}$. The North Pacific High and the Northern Oscillation Index were highly correlated with the PDO ($r \geq 0.7$) and not included in further analyses. All other variables had correlations less than 0.7. The North Pacific Gyre Oscillation metric was significant for black rockfish CA and CA scorpionfish and is not displayed.

Six stocks had better forecasts when including the drift term based on the gain in forecast accuracy test. The majority of stocks were negative indicating that the drift term made the forecast worse. Based on the likelihood ratio test examining the full time series as indicated above, the inclusion of the drift term in the time-varying model for Canary rockfish provided a significantly better fit than the time-invariant base model. The Oceanic Nino Index improved the forecast for ten stocks and the likelihood ratio test found that the models of five stocks were significantly better when including ONI over the base model. The Pacific Decadal Oscillation made improvements in forecasts for fourteen stocks and significantly improved the full time series fit based on the likelihood ratio test for eight stocks. The time-varying model that included the PDO fit the $ln\frac{recruits}{spawner}$ better than the time-invariant base model for some stocks such as Northern Lingcod based on the likelihood ratio test (full time series), but the time-invariant base model provided better forecasts one time step ahead. Sea Surface Temperature similarly, made modest improvements in forecasts for eleven stocks, and four stocks were significantly better fit with the time-varying climate model. Models with the Habitat Compression Index were significantly better based on the likelihood ratio test for four stocks and provided better forecasts for fifteen stocks. The Mean Heat Wave variable improved forecasts for sixteen stocks and was significantly better based on the likelihood ratio test for three stocks. In general, the inclusion of the climate variables improved the one year ahead forecasts for some stocks, but the results varied considerably from stock to stock. A few stocks exhibited considerably better forecasts across a range of climate drivers such as Sand dab and Southern Lingcod while the inclusion of climate drivers in the forecast for other stocks such as Blue-deacon OR and CA Quillback made the forecasts much worse.

3.1 Productivity and Stock Status

The logistic regression fit the data well and was significant (Table 3). Stocks with biomass above their reference points (not overfished) tended to exhibit time-invariant productivity while stocks that were below their reference point tended to have time-varying productivity. The transition between time-varying and time-invariant productivity occurred around $\frac{B}{B_{msy}} \approx 1$ (Figure 6). Gulf of Maine Haddock in the Northeast had time-varying productivity (Tableau et al., 2019), but its status $\frac{B}{B_{msy}}$ was over seven. Haddock was a highly influential outlier and was removed from the analysis. Haddock were heavily exploited for much of their time series and only recently surged well above their biomass reference point (NEFSC, 2019). It is possible that they were best fit with time-varying productivity because of the long period of time at low biomass.

4 Discussion

As climate change continues to impact the ecosystem, it is important to understand how it will affect natural marine resources. While it is clear that species are shifting their distributions in response to changes in the environment (Cheung et al., 2008; Nye et al., 2009; Pinsky et al., 2013; Perry et al., 2005), measuring and accounting for changes in productivity is more challenging. Work to understand the drivers of recruitment go back over a century (Hjort, 1914), however, environment-recruitment relationships rarely hold up over time (Myers, 1998) and few population models explicitly incorporate environmental drivers (Skern-Mauritzen et al., 2016). In recognition of the resulting changes in productivity due to climate-driven regime shifts, a handful of stock assessments utilize different time series of data that reflect the current productivity regime (tanner crab (Stockhausen et al., 2013), groundfish (NPFMC, 2012)). Other assessment models have simply split certain time-series of data, effectively inserting a shift in productivity. For other stocks there is recognition that environmental drivers are important, but they have been included in the management decisions process instead of explicitly included in the population model (ASMFC , Eckert et al.(2017).

In this study, we examined stock productivity, the reproductive potential, to determine how it had changed over time and if specific climate factors may be driving the changes. Of the thirty-one stocks examined on the west coast of the United States, less than a quarter were found to have time-varying productivity. The time-series of productivity were quite varied and we found relatively weak common patterns across them. Only one stock exhibited a monotonically increasing or decreasing trend suggesting that while productivity was changing, the environment was not consistently driving stocks to low abundance or high abundance. This is in contrast to some stocks on the US Northeast Shelf, such as many flatfish, that show a consistent decline in productivity (Tableau et al., 2019). All the estimated time-varying productivity time-series exhibited periods of declines and increases. Three-quarters of the stocks were better fit with a time-invariant productivity term, likely due to this oscillation about a central tendency, general low levels of variability and/or large confidence intervals.

Many of the fish on west coast are long lived species ($>$ 100 yrs) with much of the biomass in the older year classes (Kolora et al., 2021). While there is certainly recruitment variability, the variability might be less pronounced then that of stocks that have a truncated age-structure and a large amount of the SSB is less-fecund, first-time spawners as can be the case for some East Coast stocks (NEFSC, 2019). The logistic regression indicated that the more heavily a stock is exploited, the more likely it is to have time-varying productivity. As has been found in previous studies, exploitation tends to increase variability (Brander, 2005; Anderson et al., 2008; Hsieh et al., 2006). In this study, we found that the reproductive potential of stocks is more variable and less connected to spawning stock biomass when the biomass was low. This makes exploited stocks more likely to track with environmental drivers or exhibit unstable population dynamics due to the changing life history rates of an age truncated population (Anderson et al., 2008). The stocks tended to transition from time-varying to time-invariant productivity roughly when biomass was at the reference point, providing strong support for maintaining stocks at or above the biomass reference point.

Differences between the coasts might also be related to different oceanographic drivers. On the East Coast, there have been some extreme warm events such as occurred in 2012 (Mills et al., 2013), but in general the water temperature is simply rapidly warming (Friedland and Hare, 2007; NEFSC, 2021), and climate drivers such as the Atlantic Multidecadal Oscillation continue to increase (Nye et al., 2014). The west coast recently experienced an extreme marine heat wave ("The Blob") (Jacox et al., 2018), but there is a somewhat less pronounced warming trend, and strong climate drivers such as El Nino and the PDO. These large-scale climate drivers still exhibit shifts, though possibly different than the past. The fact that some of the major west coast climate drivers still move between the positive and negative phases may help explain why the stock productivity time-series generally varied without trend and many stocks were better fit with a time-invariant term.

Though the majority of stocks were better fit with a time-invariant model (base model), the inclusion of the climate drivers did show some significant relationships. Blue rockfish exhibited a significant relationship with ONI and the marine heat wave index. A CALCOFI report indicated that blue rockfish is a macrozooplankton feeder and had reduced condition factor and gonadal indices during warm water events suggesting a possible mechanism with high SST, deeper thermocline and reduced upwelling as might occur during an El Nino event or a marine heat wave (VenTresca et al., 1995). The more northerly stock of blue rockfish assessed with deacon rockfish, however, did not exhibit a relationship with any of the climate drives (the climate drivers made the forecasts worse). The lack of relationships suggest that the decreased prey fields due to the decline in upwelling hypothesis may not be applicable in the northern part of the range. The biomass of the northern population was also above the biomass reference point, which could make it less likely to track with climate drivers. Arrowtooth flounder was an exception in that the biomass was well above its reference point, but still exhibited time-varying productivity and the model was improved when including climate drivers. A number of studies have found strong influence of climate drivers on Arrowtooth flounder in the North Pacific (Hare and Mantua, 2000; Hunsicker et al., 2013; Wilderbuer et al., 2010), with changes in water temperature and availability of the cold pool habitat showing a relationship with recruitment. The inclusion of SST and the habitat compression index improved the model fits in this study suggesting that similar mechanisms could operate on the west coast. The inclusion of climate drivers in the California Scorpionfish model showed improved forecasts across a range of environmental covariates as well as an overall improvement in the stock-recruitment model. While there have been limited studies on the drivers of Scorpionfish recruitment variability, this study, combined with an environmental relationship noted in the most recent stock assessment (Monk et al., 2017) indicates that more investigation may be warranted. Additionally, previous work found correlations between Splitnose rockfish growth and several drivers including the PDO and upwelling (Black et al., 2005) suggesting that warm, low primary productivity periods reduce growth and may reduce stock productivity given the relationship found with the climate variables PDO and HCI.

While the inclusion of the climate drivers explained some of variability in productivity, they did not capture it all. As this was a broad meta analysis, we may not have included the correct driver for all stocks, or may not have included drivers in the correct manner. For example, sablefish has exhibited relationships with sea surface height and copepod abundance likely related to upwelling, nutrient abundance and stratification (McFarlane and Beamish, 1992; Johnson et al., 2016; Tolimieri et al., 2018). This study found a relationship with the PDO and SST that can be connected with sea surface height and copepod abundance, but at a relatively coarse scale. A focused study on sablefish (Tolimieri et al., 2018) involving multiple steps, at multiple life stages has attempted to elucidate the stage-specific mechanisms associated with recruitment, which is simply not possible in this type of broad study. Our study provides a rapid synthesis of a large number of stocks without having to know the specific mechanisms, which can be used to focus research attention on those stocks that may be most promising, or may have been over looked (e.g. CA Scorpionfish).

The habitat compression index and the marine heat wave index were included to account for impacts from the extreme marine heat wave ("The Blob") that occurred on the west coast from 2014 - 2016 (Jacox et al., 2018). While the Blob had major impacts on the California current ecosystem (Cavole et al., 2016), we found limited connections with the estimated time-varying productivity of the stocks. The stock assessments for many of the stocks end around this time period so the input information into the analyses likely contain only limited impacts from the heat wave if any. Reconducting the analyses after the majority of the stocks have updated assessments may provide a better picture of the impacts. Additionally, the California current experiences substantial changes from environmental drivers such as El Nino and the PDO. Many of the species are likely adapted to dealing with extreme events and the marine heat wave may simply add variability that is similar to other drivers.

A clear caveat of the results from this study, however, is that SSB and recruitment from a stock assessment are the input into the time-varying stock-recruitment model. The results are therefore contingent on the assumptions and decisions within the stock assessment process. The model could be misspecified and biases could be present, particularly if there are significant amounts of unreported catch or time-varying natural mortality that exhibit strong trends. The stock assessment model, however, integrates a range of information and provides the best current estimates of SSB and recruitment. All the stocks in the study were assessed in Stock Synthesis and include fisheries-dependent and fisheries-independent data, length and age data from both the catch and surveys as well as life history data and largely cover the full range of the stock (Methot and Wetzel, 2013). Large numbers of sensitivity runs are conducted on each assessment to understand the influence of different assumptions and decisions as well as detect potential biases and all the models are peer reviewed.

The state-space method also used a time-varying Ricker model while a Beverton-Holt curve is used within the assessment models. Both the Ricker and Beverton-Hold curves have a similar productivity parameter defining the slope at the origin of the stock-recruitment curve and it is the estimation of the slope at the origin that is the focus of this study. The two models differ in the way they handle density-dependence (Quinn and Deriso, 1999). The recruitment estimates from the assessment model are largely unconstrained by the stock recruitment model within the assessment model, however, because the assessment model specifically includes recruitment deviations. The recruitment deviations enable the estimates of recruitment to largely be informed by the length and age data from both the catch and survey information. For all stocks included in the study, length and age data were available and the standard deviation of the recruitment deviations was large enough that the estimated output had little to no connection with the Beverton-Holt model within the assessment. The variability of the slope at the origin over time followed the same general pattern regardless of whether the Ricker or Beverton-Holt curve was included within the state-space model. While using model output as input into another model can be problematic (Brooks and Deroba, 2015), each assessment was reviewed to ensure they met the conditions above including sufficient length/age data and largely unconstrained recruitment deviations before being included in the study.

The intent of studies such as this is to examine a range of stocks to evaluate which may be exhibiting changes in productivity and to evaluate larger ecological patterns. It provides perspective on the current level of productivity (high or low) that can be useful in a risk assessment framework when providing management advice (Collie et al., 2012) and potentially for biomass projections. It also can help drive future research by showing which species have had the most dramatic changes in productivity and where research should be focused (e.g. forecast accuracy of Sanddab and Southern Lingcod). While working toward understanding specific mechanistic links is extremely important, these studies are challenging, time consuming and often produce relationships that do not hold up over time. The state-space method used here, to some extent is a medium-term solution, as a rapid assessment that quickly provides information to scientists and managers to make decisions even without knowing the full mechanism driving each life stage of each stock. Time-varying recruitment models provide a bridge between stationary stock assessment models and fully coupled climate-fisheries models. The results can be used to calculate dynamic reference points, optimal harvest control rules (Collie et al., 2021), and may be useful for short-term recruitment forecasts.

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Tables and Figures

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ONI	Oceanic Nino Index
NPGO	North Pacific Gyre Oscillation
PDO	Pacific Decadal Oscillation
SST	Sea Surface Temperature
HCI	Habitat Compression Index
NOI	Northern Oscillation Index
NPH	North Pacific High
MHW	Marine Heat Wave

Table 1: The eight climate variables tested for their predictive ability.

Species	Stock	Community	Spawners	Date min	Date max
Arrowtooth Flounder		flatfish	weight	1965	2017
Aurora Rockfish		Sebastidae	weight	1978	2013
Black Rockfish	CA	Sebastidae	weight	1975	2015
Blue and Deacon Rock	CA	Sebastidae	weight	1960	2017
Blue and Deacon Rock	OR	Sebastidae	weight	1970	2017
Bocaccio Rockfish		Sebastidae	eggs	1954	2017
California Scorpionf		Scorpaenidae	weight	1965	2016
Cabezon	NCS	Cottidae	weight	1962	2018
Cabezon	OR	Cottidae	weight	1980	2018
Cabezon	SCS	Cottidae	weight	1970	2018
Canary Rockfish		Sebastidae	eggs	1968	2015
Chilipepper Rockfish		Sebastidae	weight	1965	2014
Darkblotched Rockfis		Sebastidae	eggs	1960	2017
Dover Sole		flatfish	weight	1975	2020
Greenstriped Rockfis		Sebastidae	eggs	1970	2009
Kelp Greenling	OR	Hexagrammidae	weight	1980	2015
Lingcod	north	Hexagrammidae	weight	1960	2020
Lingcod	south	Hexagrammidae	weight	1972	2020
Longspine Thornyhead		Sebastidae	weight	1997	2012
Pacific Ocean Perch		Sebastidae	eggs	1975	2017
Pacific Whiting (Hak		Merlucciinae	weight	1975	2020
Petrale Sole		flatfish	weight	1959	2018
Quillback Rockfish	CA	Sebastidae	eggs	1991	2020
Quillback Rockfish	OR	Sebastidae	eggs	1980	2020
Blackspotted Rockfis		Sebastidae	weight	1980	2013
Sablefish		Anoplopomatidae	weight	1975	2020
Pacific Sanddab		flatfish	weight	1977	2012
Splitnose Rockfish		Sebastidae	eggs	1960	2006
Widow Rockfish		Sebastidae	weight	1970	2018
Yelloweye Rockfish		Sebastidae	eggs	1980	2016
Yellowtail Rockfish	north	Sebastidae	eggs	1970	2016

Table 2: The stocks used in the analysis. Only years in which length or age-structured data were available were used in the analysis despite many of the spawner and recruitment time-series going back further in time. Spawners were the unit of spawning stock biomass in the assessment.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-1.1708	0.6428	-1.82	0.0685
β_1	1.2915	0.4867	2.65	0.0080

Table 3: The parameter estimates from the logistic regression of constant or time-varying productivity on $\frac{B}{B_{msy}}$. Gulf of Maine Haddock is not included.

stock	comm
arrowtooth	(Sampson et al., 2017)
aurora	(Hamel et al., 2013)
black_rockfish_CA	(Cope et al., 2016)
blue_deacon_CA	(Dick et al., 2017)
blue_deacon_OR	(Dick et al., 2017)
bocaccio	(He and Field, 2017)
CA_scorpionfish	(Monk et al., 2017)
cabezon_NCS	(Cope et al., 2019)
cabezon_OR	(Cope et al., 2019)
cabezon_SCS	(Cope et al., 2019)
canary	(Thorson et al., 2016)
chillipepper	(Field et al., 2016)
darkblotched	(Wallace and Gertseva, 2017)
dover_sole	(Hicks and Wetzel, 2011)
greenstriped	(Hicks et al., 2009)
kelp_greenling	(Berger et al., 2015)
lingcod_N	(Taylor et al., 2021)
lingcod_S	(Johnson et al., 2021b)
longspine_thornyhead	(Stephens and Taylor, 2014)
ocean_perch	(Wetzel et al., 2017)
pacific_hake	(Johnson et al., 2021a)
petrale_sole	(Wetzel, 2019)
quillback_CA	(Langseth et al., 2021a)
quillback_OR	(Langseth et al., 2021b)
rougheye_blackspotted	(Hicks et al., 2014)
sablefish	(Kapur et al., 2021)
sanddab	(He et al., 2013)
splitnose	(Gertseva et al., 2009)
widow	(Adams et al., 2019)
yelloweye	(Gertseva and Cope, 2017)
yellowtail_N	(Stephens and Taylor, 2018)

Table 4: Stock assessment citations

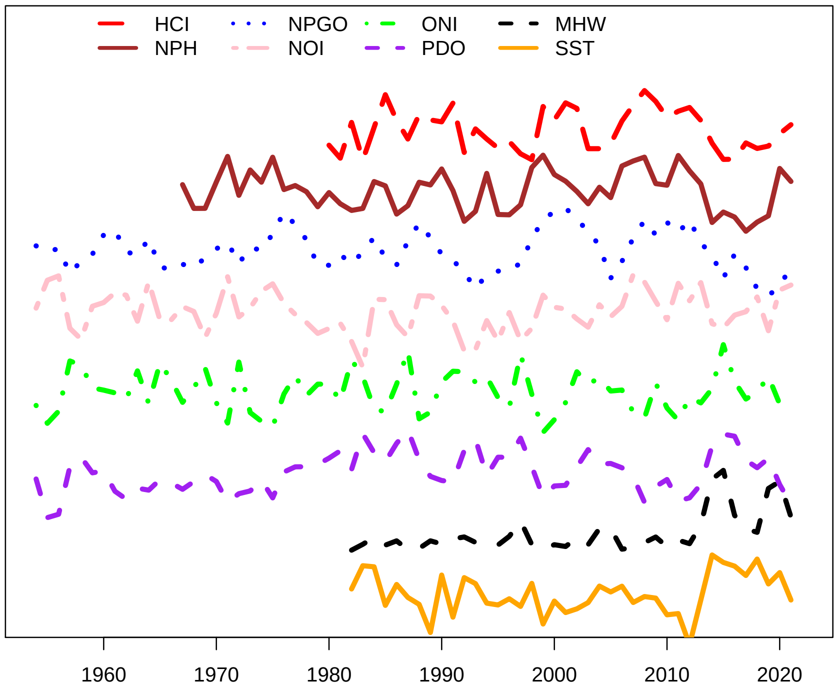

Figure 1: The time-series of climate variables tested in the time-varying productivity model. HCI = Habitat Compression Index, NPH = North Pacific High, NPGO = N. Pacfic Gyre Oscillation, NOI = Northern Oscillation Index, ONI = Oceanic Nino Index, PDO = Pacific Decadal Oscillation, MHW = Marine Heat Wave, SST = Sea Surface Temperature.

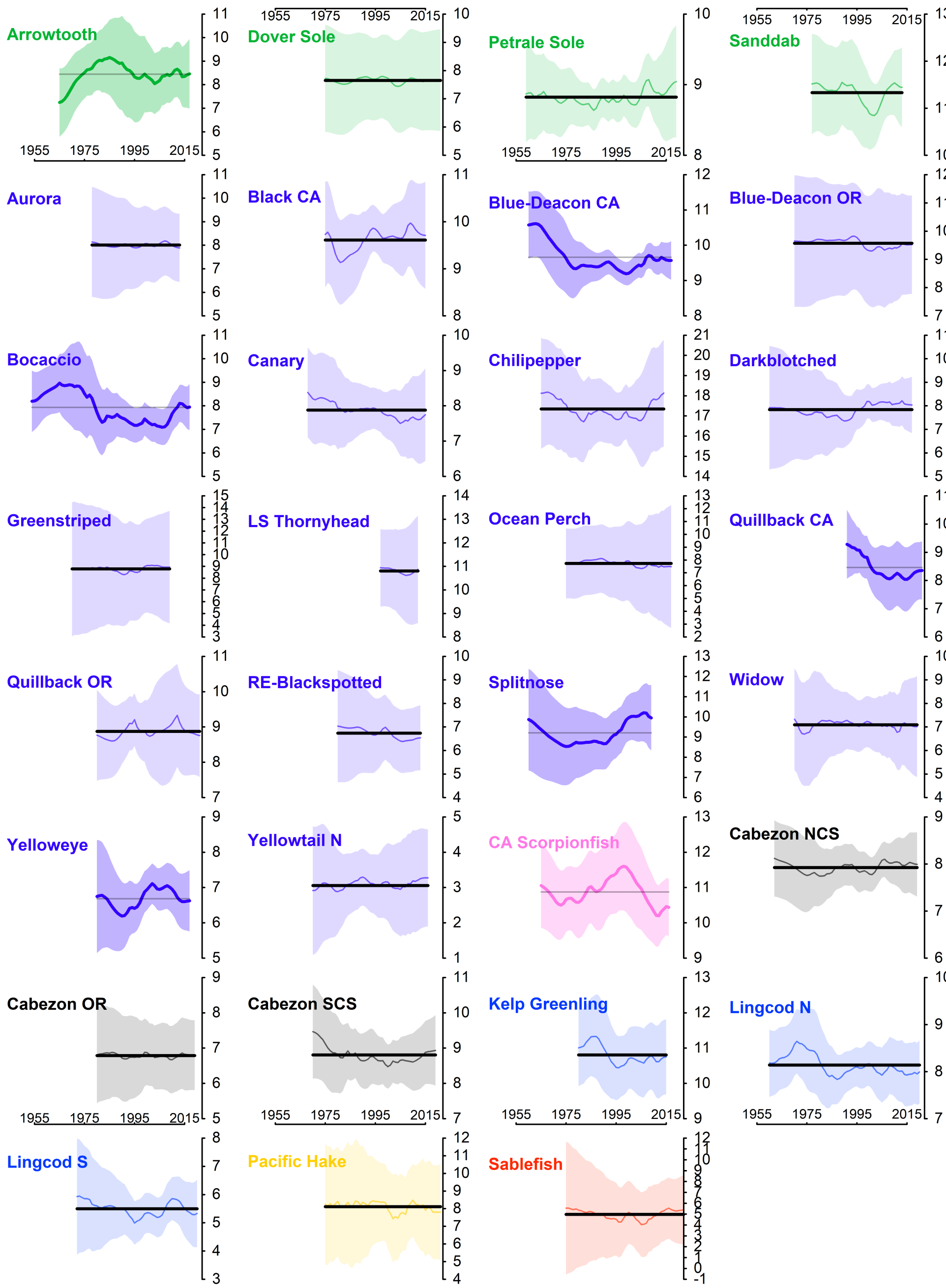

Figure 2: The time-varying and time-invariant productivity term (a) for each stock with 95% confidence intervals. The model that provided the best fit is in bold for each stock (e.g. The time-invariant model provided the best fit for Dover Sole and the static a term has the bold line in the figure).

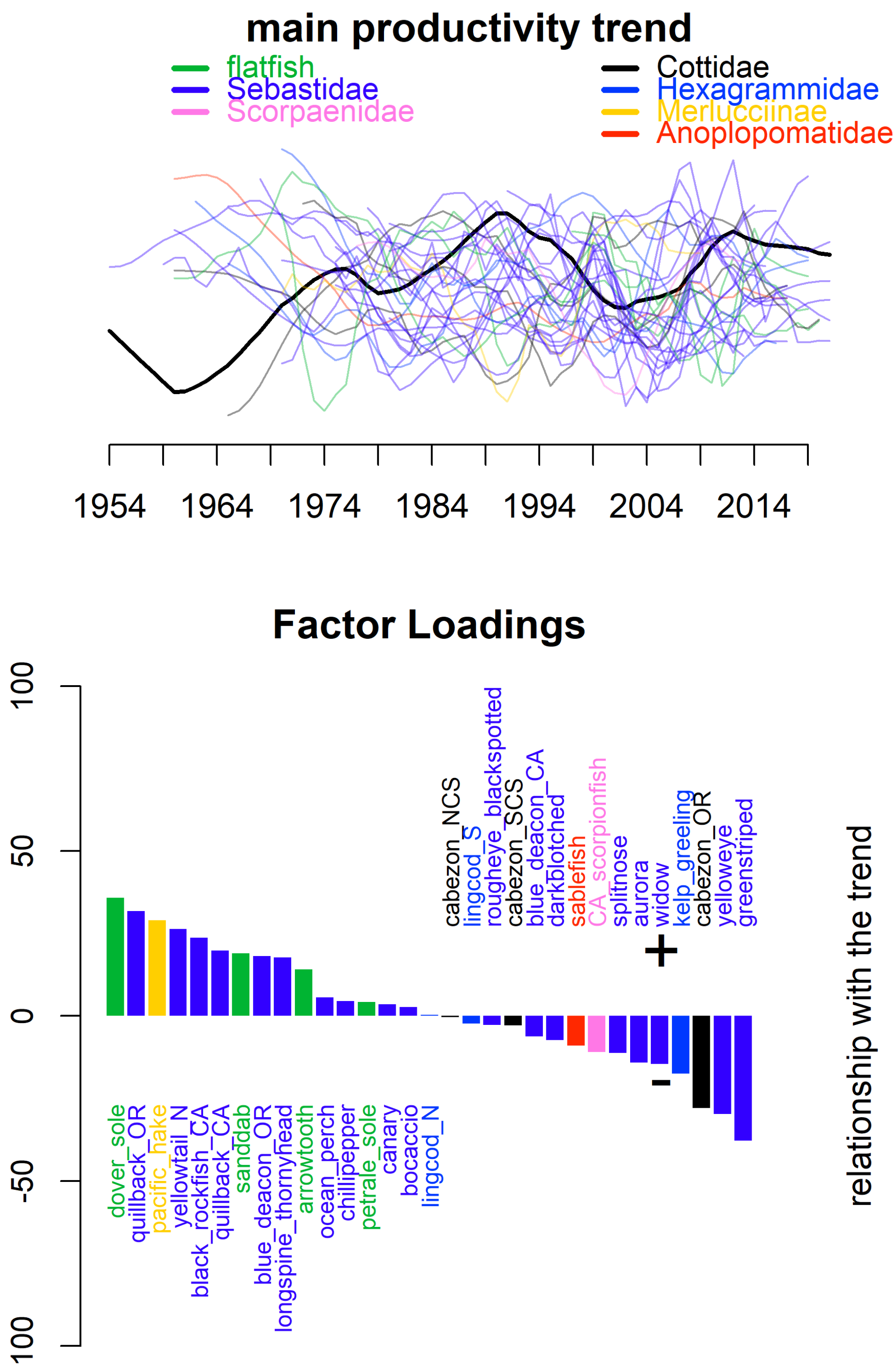

Figure 3: Common trend one (thick black line) of the time-varying productivity terms across all stocks (thin colored lines) from the Dynamic Factor Analysis. The bottom figure represents the percentage of variability the common trend explains for each stock based on the factor loadings (Z matrix).

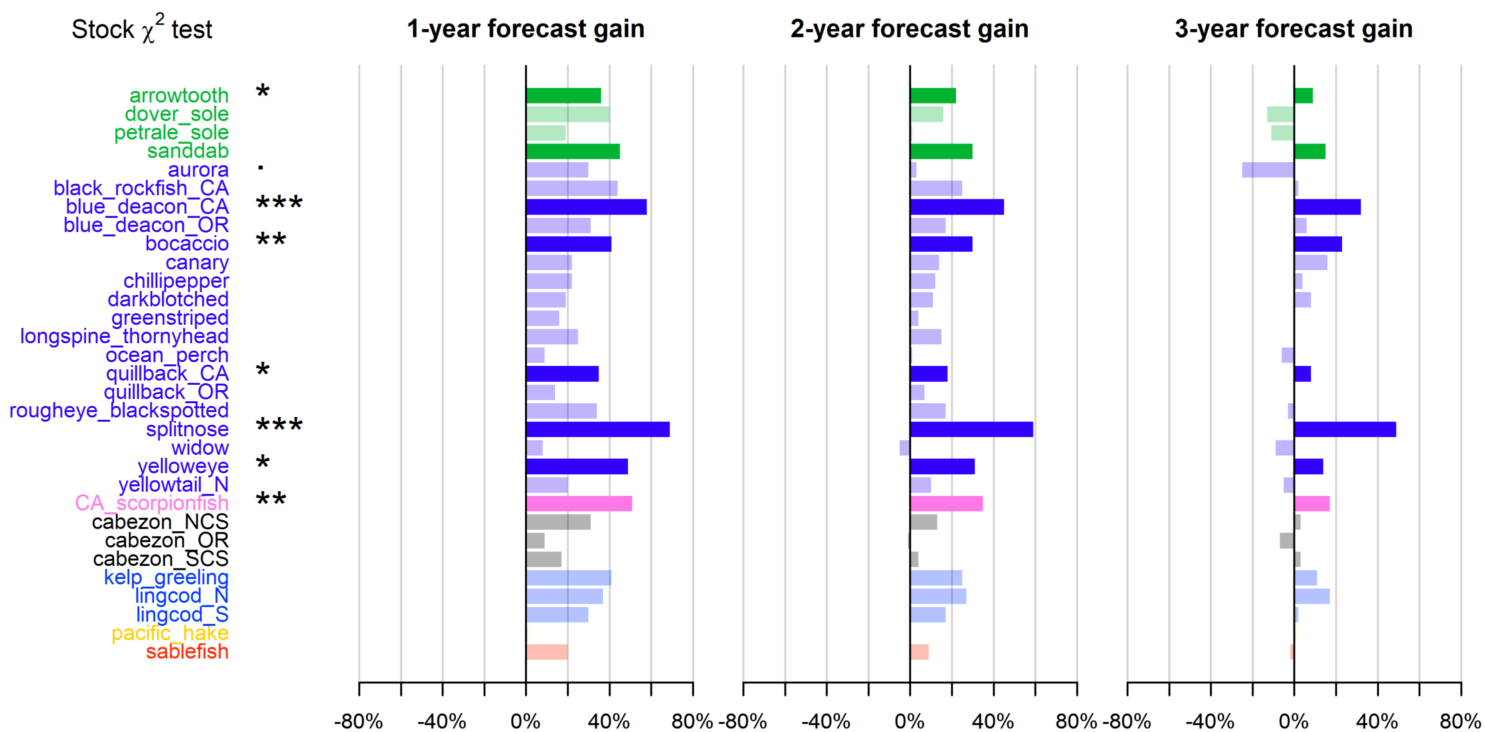

Figure 4: The gain in forecast accuracy predicting the $ln\frac{recruits}{spawner}$ one to three years ahead with the time-varying model compared to the time-invariant model. Bold colors indicate significant forecast gains compared with the time-invariant model. Significance levels are indicated by: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $\cdot p < 0.1$.

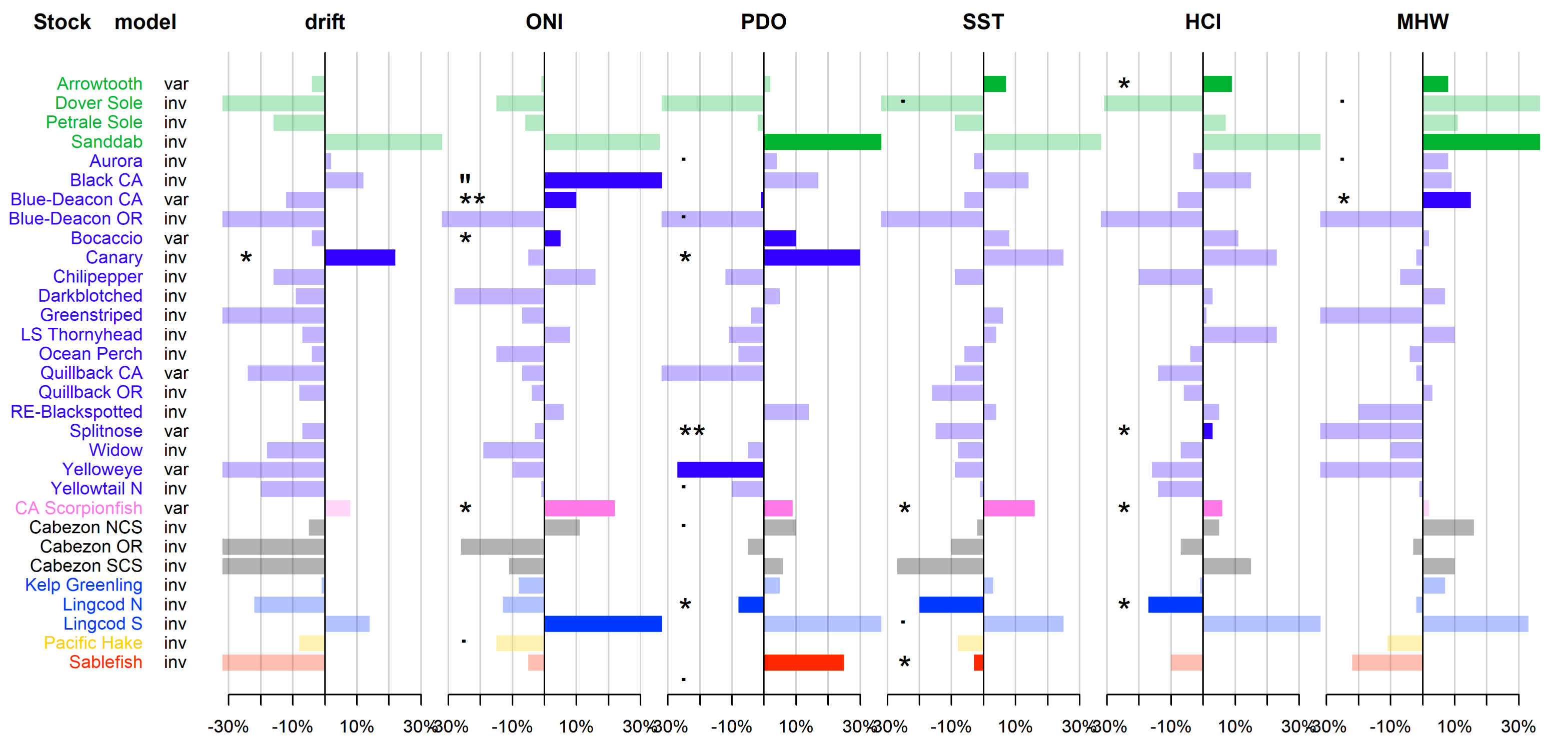

Figure 5: The bars represent the gain in forecast accuracy predicting the $ln\frac{recruits}{spawner}$ one year ahead with the time-varying model that included a climate index compared to the base model for each stock. Significance levels are the output of the likelihood ratio test comparing the climate and base models over the entire time series: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $\cdot p < 0.1$.

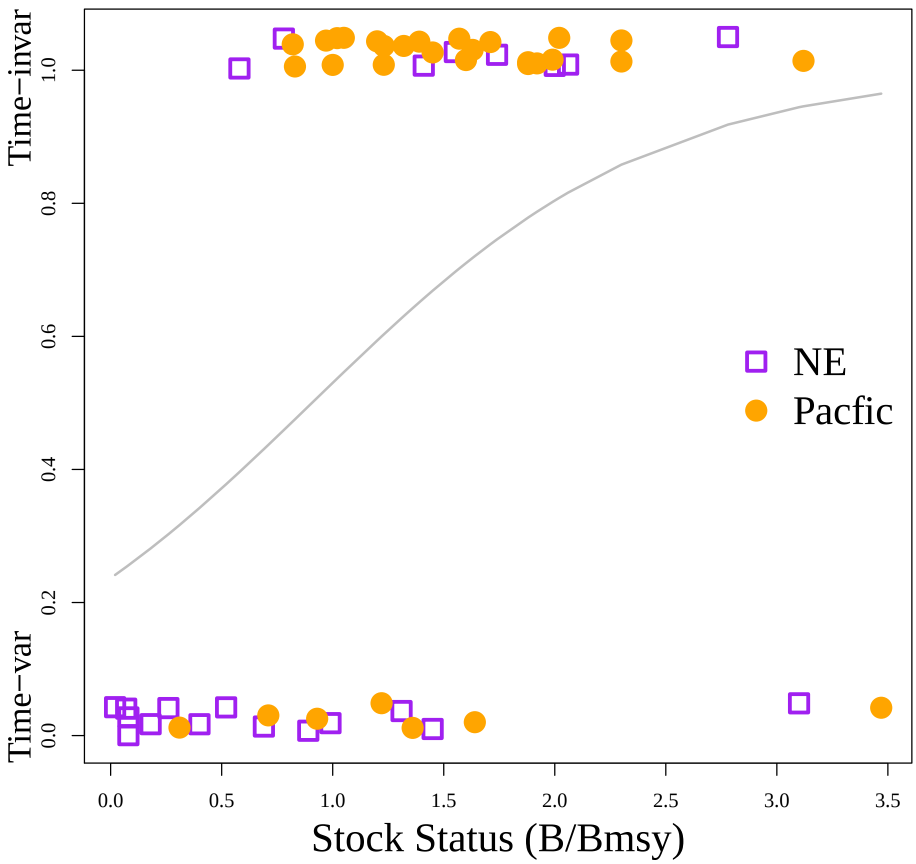

Figure 6: The logistic regression of constant or time-varying productivity on $\frac{B}{B_{msy}}$ for stocks on the northeast US shelf (NE) and the west coast (Pacific). Gulf of Maine Haddock is not included. (Points have been jittered slightly for display purposes.)