Predicting Fish Recruitment in the Northeast Pacific Using Climate Indices

by
Shannon Leah Riley

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Predicting recruitment, which is dependent on parent stock size and climate, is vital for forecasting productivity of fish stocks. The effects of climate can be analyzed via the use of climate indices. Three climate indices, the Pacific Decadal Oscillation, the North Pacific Gyre Oscillation, and the Oceanic Niño Index describe the main climate patterns of the Northeast Pacific Ocean. PDO was expected to be the most influential for the majority of fish stocks in the East Bering Sea region, NPGO for the Gulf of Alaska, and ONI for the West Coast. The data were split between 1988 and 1989 to account for the effects of a regime shift. Models were created with each climate index for each stock, then compared to find the index with the most influence. No region had a single climate index that best predicted the majority of stocks, either before or after the regime shift. The influence of the PDO was expected to decrease after the 1988/89 regime shift, which was confirmed. Understanding the effects of climate on recruitment, and recognizing how those effects change over time, will allow scientists and managers to better predict recruitment and maintain fish stocks at healthy levels.

Key Words: Recruits per spawner ratio, climate indices, Northeast Pacific, regime shift

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I understand that my project will become part of the permanent collection of Oregon State University, Honors College. My signature below authorizes release of my project to any reader upon request.

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Predicting Fish Recruitment in the Northeast Pacific Using Climate Indices

Introduction

The study of recruitment in fisheries began with Johan Hjort in the early twentieth century. Many important discoveries have been made since then and important theories were developed. However, there are still many questions involving recruitment, from the broad “what determines recruitment?” to the more specific “what aspects of the environment have the greatest impact on recruitment?” These questions focus on one of the most unpredictable aspects of a population. It is vital to understand these questions to successfully predict the future state of stocks and allow managers to formulate strategies that keep stocks at healthy, consistent levels.

Keeping stocks at healthy levels depends on all life stages of the species, but some are more important than others. Recruitment in particular is important to the overall population for many reasons. Recruitment is the addition of a new group of individuals to an existing pool of individuals. In a population context, this is often regarded as the addition of young individuals to the pool of adults. It is highly variable (Rothschild 2000). It is the step between the larval and juvenile life stages and adulthood, controlling the size of each age class in a stock. It is strongly affected by both changes in the environment and variations in the size of the reproductive stock (Planque and Frédou 1999). Furthermore, it has been difficult to separate the effects of environment and parental stock size (Planque and Frédou 1999).

Predicting stock-recruitment relationships remains a challenge to successful recruitment forecasting. It is well-known that spawning stock biomass is one of the most important predictors of recruitment (Subbey et al. 2014). However, the importance of other factors is still being realized and implemented into recruitment predicting models.

Traditionally, most fish stock predictions were based only on short-term biological variables, such as a population's age structure, growth rates, and levels of recruitment (Brander 2003). However, this method does not account for climatic variability and cannot give long-term predictions. It also does not include the effects of fishing pressure. Adding important environmental variables such as sea surface temperature, salinity, and rainfall has allowed for the creation of models with much stronger predictive power (Sundby and Nakken 2008). However, adding more variables also makes models more complicated, which decreases their practicality, efficiency, and ease of use. Also, relationships between recruitment variability and environmental variables may change over time (Myers 1998). Clearly, environmental variables, particularly ones with long-term, large-scale variability need to be included in predictions, especially long-term predictions (Brander 2003).

This inclusion is especially important due to changing climate-recruitment correlations. The effects of climate on fish productivity are non-stationary, meaning they change over time, so modelling relationships between them clearly has limitations when working over long time periods (Litzow et al. 2018). Climate-biology relationships can weaken over time, but may not be synchronous over a community scale (Puerta et al. 2019).

Regime shifts are another example of the importance of considering large-scale climate variability in long-term predictions. A regime shift is often defined as an abrupt change in the characteristic behavior of a natural phenomenon from one mean state to another, which persists for a decade or more (Hare and Mantua 2000). They have occurred successively in the Pacific Ocean, although do not appear to have a temporal pattern. The best-known regime shift in the Pacific Ocean is the 1976/77 regime shift. This regime shift has had far-reaching impacts on the ecosystems in the North Pacific Ocean (Hare and Mantua 2000). Another regime shift, the 1988/89 regime shift is not as well-studied, in part because it was less obvious in the climate data (Hare and Mantua 2000). However, it is clearly visible in biological records of fish species (Hare and Mantua 2000).

Regime shifts can lead to a reorganization of the community structure of ecosystems (Anderson and Piatt 1999). Recruitment can be affected and rates of predation can change (Anderson and Piatt 1999). These can cause drastic changes in the size of a population. If these changes are not addressed by managers, overfishing and eventually fishery collapse can occur. Studying regime shifts provides useful information on how fish stocks are affected, which allows the incorporation of regime shifts into the assessment and management of fisheries resources (King et al. 2015).

More recent analyses and predictions of fish stock population have included climatic variation in the form of climate indices. These multivariate indices were developed to represent the complex variability of oceanic environmental patterns (Keyl and Wolff 2008). Many climate indices exist, each of which is based on certain parameters in a specified area, so each describes only certain aspects of the climate (Integrated Climate Data Center 2019). In the Pacific Ocean, some of these indices include: Pacific Decadal Oscillation Index, Pacific North American Index, Oceanic Niño Index, Western Pacific Index, and the Northern Oscillation Index.

Climate indices vary in which environmental variables are used to derive them and where the data are from. This means that each index has a geographic center of influence. As such, some indices are better at describing the climate in a particular area than others are. However, the climatic features described by the climate index may have effects in areas distant from the geographic area where the data from that index have originated. There are several reasons for why this may be the case. For example, species with long migratory strategies may integrate the effect of environmental variability over spatially large scales. Also, the presence of atmospheric teleconnections, which are large-scale patterns of pressure and circulation anomalies that cover great distances, may generate influences from one area (e.g. tropics) to another (e.g. extratropics) (Climate Prediction Center 2008).

Including climate indices in models used for prediction is useful because they are a simple way to integrate over a wide range of information which may not have direct known connections to the fish stock being predicted. Local climate measures, typically average monthly temperature or rainfall, often fail to capture complex associations between weather and ecological processes, which may explain why large-scale climate indices are better than local ones for predicting ecological processes (Hallett et al. 2004). Climate indices allow for longer-term predictions than local environmental variables (Keyl and Wolff 2008). Studies have long been testing the relationship between climate indices and stock productivity. An example is a study relating the North Pacific Gyre Oscillation (NPGO) index, the Pacific Decadal Oscillation (PDO) index, and the Multivariate El Niño-Southern Oscillation Index (MEI) with productivity estimates of the North Pacific albacore tuna (*Thunnus alalunga*) population (Zhang et al. 2014).

Considering more than one species will allow scientists to make conclusions that can be adapted to a variety of life history strategies and may be more useful when making preliminary predictions or predictions for data-poor species. The use of climate indices, since they describe large-scale climate patterns, is useful for this purpose. Climate indices such as the ones described above are calculated from data that comes from a large region of the ocean, but not necessarily the same region the stock of interest is from. Because of this, it is useful to consider the predictive power of a climate index on species from the same geographic region. We hypothesize that climate indices derived from data originating from the same region as the target species are more likely to have a significant effect on recruitment than indices from other geographic regions.

This study seeks to use climate indices to address some of the many questions that still surround the recruitment of fish larvae. Its overarching purpose is to determine how the productivities for a range of fish stocks in the eastern Pacific Ocean are related to climate indices. This information could then be used to predict recruitment in the future with only knowledge of climate indices and spawning stock biomass. Two hypotheses are tested. First, stocks in the same region will be best predicted by the climate index most influential in that region. Previous literature indicates that in the East Bering Sea, that means the PDO (Mantua et al. 1997). In the Gulf of Alaska, it is the NPGO (Di Lorenzo et al. 2008). In the west coast, ENSO becomes more important (Dahlman 2016). Second, there will be a decrease in number of stocks best predicted by the Pacific Decadal Oscillation from before the 1988/89 regime shift to after it.

Methods

The data used in this study consist of fish spawning stock biomass, recruitment, and climate index values. Spawning stock biomass is "The total weight of the fish in a stock that are old enough to spawn" (Froese and Pauly 2019). In this study, recruitment is the amount of fish added to the exploitable stock each year due to the number of fish from a year class reaching a certain age (Wallace and Fletcher 2000). Climate indices are calculated values that can be used to describe the state and the changes in the climate system (Integrated Climate Data Center 2019).

The spawning stock biomass and recruitment data were obtained from the National Oceanographic and Atmospheric Administration (NOAA) Fisheries Service, the federal office responsible for the stewardship of U.S. ocean resources. NOAA Fisheries Service assesses and predicts the status of fish stocks, sets catch limits, and ensures compliance with fisheries regulations. NOAA Fisheries Service collects data from commercial and recreational catch records and surveys (trawl and acoustic). These data are then input into stock assessment models. The output of these models was used in this study. The fish stock data were downloaded from NOAA Fisheries Service online Species Information System Public Portal (https://www.st.nmfs.noaa.gov/sisPortal/sisPortalMain.jsp) between 2016 and August 2018. The stock list provided by the portal shows all federally managed fish stocks by region. Stocks in the Bering Sea, Gulf of Alaska, and Pacific Coast were examined for availability of recruitment and spawning stock biomass data and estimates starting more than eight years before 1988. Stocks meeting both of these criteria were included in the preliminary analysis.

The spawning stock biomass (SSB) and recruitment for each stock were extracted from stock assessment time series. All SSB and recruitment data were log-transformed (log base 10). Recruitment data were also lagged to age zero if necessary to reconcile with the parental stock biomass and climate indices and referred to the year of birth. Recruitment was plotted versus time to determine if the data had anomalous patterns that would raise red flags (Appendix 1). If only a portion of the data showed a trend, that portion was removed from the dataset. This was done to remove any artefacts of the stock assessment model analyses. The removed portion was always the first data point(s) (earliest year(s)) or last data point(s) (most recent year(s)). Because the data is from stock assessment models, results from the oldest and most recent years may be less accurate than data from the middle period. One stock that showed anomalous variation throughout the entire time period was also removed. One stock did not have eight years of data before 1988 after its anomalous portion was removed, so it was removed from the analysis.

In the final analysis, thirty stocks from twenty-four different species were included (Table 1). The stocks are from three regions in the eastern Pacific Ocean: East Bering Sea, Gulf of Alaska, and West Coast (Figure 1). The East Bering Sea (EBS) region has twelve stocks. The Gulf of Alaska (GOA) region has seven stocks. The West Coast (WC) region has eleven stocks.

Because the commercial fisheries for many WC species extend along the entire WC, from British Columbia to California, not all stocks from this region could be attributed to any specific section of the West Coast, such as Southern Pacific Coast or Northern Pacific Coast. However, some species were more likely to be found in certain areas. The chilipepper rockfish (*Sebastes goodei*) is considered a south WC species, common only below 42°N (Field et al. 2016). Boccaccio (*Sebastes paucispinis*) is also considered southern Pacific coast species in its stock assessment (NOAA Fisheries 2017). Splitting the stocks from this region into three sections: Southern Pacific Coast, Northern Pacific Coast, and Pacific Coast, would have resulted in very small sample sizes for each section, so all stocks were retained in a general Pacific Coast section.

Eight stocks from the East Bering Sea region included both East Bering Sea and Aleutian Islands data.

Three climate indices were used in this analysis: Oceanic Niño Index (ONI), North Pacific Gyre Oscillation (NPGO), and Pacific Decadal Oscillation (PDO). The ONI data came from NOAA Climate Prediction Center (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring /ensostuff/ONI_v5.php), NPGO data from Georgia Institute of Technology (http://www. o3d.org/npgo/), and PDO data from the Joint Institute for the Study of the Atmosphere and Ocean (http://research.jisao.washington.edu/pdo/).

There are multiple indices that describe the El Niño Southern Oscillation (ENSO) climate pattern. ONI is NOAA's primary indicator for measuring ENSO (Dahlman 2016). El Niño conditions exist when the ONI is +0.5 or higher and La Niña conditions exist when it is -0.5 or lower (Dahlman 2016). ONI is measured over the region 120°-170°W. ENSO is driven by the difference in sea level pressure between the eastern and western tropical Pacific.

The North Pacific Gyre Oscillation (NPGO) index is defined as the second principal component (PC) of sea surface height anomalies (SSHa) over the region (180°W–110°W; 25°N–62°N) (Di Lorenzo et al. 2008). It is driven by difference in sea level pressure between two atmospheric features, the North Pacific High and the Aleutian Low.

The Pacific Decadal Oscillation (PDO) index is defined as the first principal component of sea surface temperature anomalies (SSTa) over the region (20°N-70°N) (Mantua et al. 1997). It is driven by the Aleutian Low. The PDO is also forced by atmospheric variability in the tropics. During ENSO events, an atmospheric bridge connects the North Pacific with the equatorial Pacific, causing alterations in the equatorial Pacific to affect the North Pacific (Newman et al. 2016). For example, when El Niño events peak during the northern hemisphere winter, the Aleutian Low deepens, causing changes in the surface ocean that lead to a positive PDO pattern (Newman et al. 2016).

All three indices are calculated either monthly or on a sliding bimonthly (Jan-Feb, Feb-Mar, etc.) scale. In order to compare them with the annual stock data, a single value was calculated by averaging the January through April values. These four months were selected to create an average value for the year because many species spawn during this period, so their larvae are exposed to the climate conditions at this time. The young larvae are strongly affected by environmental conditions during their first few months of growth (Houde 2008).

All three variables were split into two time periods for the analysis, separated between 1988 and 1989, because a regime shift occurred in the winter of 1988/89 and that had strong impacts on the influence of different climate patterns.

A recruits per spawners ratio, which is a common measure of productivity, was calculated by subtracting the log-transformed spawning stock biomass values from the log-transformed recruitment values. Using RStudio (R version 3.4.1, http://www.r-project.org/), four generalized additive models (GAMs) were created for each stock where R is recruitment, SSB is stock spawning biomass, α_0 is the intercept, α_1 is the effect of spawning stock biomass, α_2 the effect of a climate index (NPGO or ONI or PDO) and ε is an error term (Eq. 1).

$$Log(R) - Log(SSB) = \alpha_0 + \alpha_1(SSB) + \alpha_2(climate\ index) + \varepsilon \quad Eq. 1$$

All models included the effect of spawning stock biomass on the recruits per spawner ratio. Each model included the effect of a different climate index and the fourth model did not include the effect of any climate index.

The AIC (Akaike Information Criterion) was used to determine which model was best at predicting each stock. The AIC is a technique that estimates the likelihood a model will predict or estimate the future values, and a good model is one that has minimum AIC among all the other models (Mohammed et al. 2015). The AIC of each of the four models was obtained and the model with the lowest AIC value was considered the best predictor of the stock-recruitment relationship for that particular stock. Each best model was tested for temporal autocorrelation at lag one.

If there was not significant temporal autocorrelation at lag one, the model was considered the final selection for best predictor of the stock-recruitment relationship. If there was significant temporal autocorrelation at lag one, generalized additive mixed models (GAMMs) were created for each climate index. Two models were created per index, one with an autocorrelation structure and one without. The two were compared via AIC. The best model of the two was in turn compared via AIC with the best models with and without autocorrelation comparisons for the other three indices. In summary, this final AIC was a four-way comparison of whichever model (with or without autocorrelation structure) had the lowest AIC score for each of the indices (NPGO, ONI, PDO, and none). The model with the lowest AIC was selected as the best for that stock.

Residuals were examined for normality and homogeneity of variance and any issues were noted (Table 2, Appendix 2). However, violations of either were not fixed because we deemed them to be influential, given the small sample size (i.e. difficult to test for normality and homogeneity of variance with only 10-20 data points available).

The AIC was used to determine the significance of the best model. The effect of the climate index on the ratio of recruits to spawners for the best model for each stock was examined and described (Appendix 3). Effects were described by the following terms: no effect, linear positive, linear negative, nonlinear positive, nonlinear negative.

This procedure was done separately on both sets of times series data, through 1988 and after 1988. After the analysis, the results of the two time periods were compared.

Results

Of the thirty-two stocks in the collection phase, thirty, representing twenty-three species, fit the criteria and were used in the subsequent analysis (Table 1). There was a range in the number of years of data in the period before and after the regime shift (Figure 2).

No stocks were temporally autocorrelated in the 1988 and earlier time period, whereas six stocks were temporally autocorrelated in the 1989 and after time period. Of these, the models with the autocorrelation structure improved the fit for four of the six stocks. For the other two stocks

(EBS turbot, WC widow rockfish), there was a problem with convergence once the autocorrelation structure was included. Therefore, the original best model, which was temporally autocorrelated, was used. This may result in slightly decreased predictive power for these few stocks.

In the period before and including 1988, all indices best predicted roughly the same percentage of the thirty stocks (Figure 3). The highest was PDO, which best predicted 30% (9 stocks) of the stocks, then NPGO and none with 27% of the stocks each (8 stocks), and lastly ONI, with 16% of the stocks (5 stocks).

Considering each of the three regions individually, although there are some similarities between them, each shows a different climatic influence on recruitment (Figure 4a, Figure 4b). In the period before and including 1988, all three had the same number of stocks best predicted by PDO. No region had a considerable majority of stocks predicted by a single index. In the EBS, four stocks were best predicted by ONI, three by each PDO and none of the indices, and two stocks by NPGO. This is a sharp contrast to the GOA, which is spatially close. In that region, three stocks were best predicted by each NPGO and PDO, and one stock by the model with no indices included. No stocks were best predicted by ONI. In the WC, four stocks were best predicted by the model with no indices included, three by each NPGO and PDO and one stock by the model with ONI.

After the regime shift in the winter of 1988/89, most stocks were best predicted by a different climate index (Table 3). A different pattern in the distribution of stocks appears (Figure 5). There was a 10% increase (to 13 stocks) in the number of stocks best predicted by the model with no climate index and a 17% decrease (to 3 stocks) in the number of stocks best predicted by PDO. The number of models best predicted by ONI increased slightly, from 5 to 7, and the number of stocks best predicted by NPGO decreased slightly, from 8 to 7.

In the EBS region, five stocks were best predicted by the model without a climate index, followed by four stocks by ONI, two by NPGO, and one by PDO (Figure 6a). In the GOA region, three stocks were best predicted by the model without a climate index, two by ONI, and one each by NPGO and PDO. In the WC region, the number of stocks best predicted by each model barely changed from the earlier time period. Three stocks were best predicted by each NPGO and the model with no climate index, two stocks by PDO, and one stock by ONI. The regions can easily be contrasted based on the percent of stocks best predicted by each index (Figure 6b).

For each stock, the model plot of the model which best predicted that stock was produced for both time periods (Table 4). These plots represent how recruitment changes with a change in the climate index. Before the regime shift in the EBS, four stocks were best predicted by ONI. Of these, one had a nonlinear negative effect, one had a linear negative effect, and two had nonlinear positive effects. Two stocks were best predicted by NPGO, one of which had a nonlinear negative effect and the other of which had a nonlinear positive effect. Three stocks were best predicted by PDO, two with nonlinear positive effects and one with a linear negative effect. In the GOA before the regime shift, three stocks were best predicted by PDO, one of which had a nonlinear positive effect and the other two of which had linear positive effects. Another three stocks were predicted by NPGO, two with linear positive effects and one with a nonlinear positive effect. Before the regime shift in the WC, three stocks were best predicted by NPGO, with one each nonlinear positive, nonlinear negative, and linear positive. Three more stocks were best predicted by PDO, all three of which were positive linear effects. One stock was best predicted by ONI and had a linear negative effect.

After the regime shift, two stocks in the EBS were best predicted by NPGO, one each with a linear positive and a linear negative effect. Four stocks were best predicted by ONI, three with a nonlinear positive effect and one with a nonlinear negative effect. In the GOA after the regime shift, two stocks were best predicted by ONI, one each with a nonlinear positive and nonlinear negative effect. PDO and NPGO each best predicted one stock, with a nonlinear negative effect for PDO and a linear positive effect for NPGO. After the regime shift in the WC, four stocks were best predicted by NPGO, three with linear positive effects and one with a nonlinear positive effect. Two stocks were best predicted by PDO, both with linear negative effects. One stock was best predicted by ONI and had a linear positive effect.

Discussion

This study seeks to use climate indices to address some of the many questions that still surround the recruitment of fish larvae. Its purpose is to determine how the predictors of the stock-recruitment relationship for a range of stocks in the eastern Pacific Ocean have changed over time, by using the effect climate index. Two hypotheses are tested. First, stocks in the same region will be best predicted by the climate index most relevant to that region. This means, as indicated in previous literature, that PDO should predict the most stocks in the EBS, NPGO in the GOA and northern WC, and ONI in the southern WC (Mantua et al. 1997, Di Lorenzo et al. 2008, Dahlman 2016). Second, there will be a decrease in number of stocks best predicted by the Pacific Decadal Oscillation from before the 1988/89 regime shift to after it. This hypothesis reflects the findings of studies, such as Yeh et al. 2011, that found PDO became less influential after 1988 due to the 1988/89 regime shift.

The second hypothesis is simpler to address, so it will be discussed first. When considering specifically the influence of PDO, it is clear that the number of stocks best predicted by this climate index decreased after the regime shift. The decrease was from nine stocks out of thirty (30%) to only three stocks out of thirty (10%). The decrease in number of stocks best predicted by PDO suggests that its importance in driving recruitment has decreased. This agrees with other research that has found the PDO to be less influential after the regime shift (Yeh et al. 2011, Litzow and Mueter 2014, Litzow et al. 2018).

Before the 1988/89 regime shift, no region had a majority of stocks best predicted by the index expected to be most influential in that region. After the regime shift, different indices predicted the majority of stocks in each region, but again, they were not the expected indices. This mismatch between the climate index that has the most influence in a region and the climate index that best predicted the highest number of stocks suggests that different aspects of climate have more impact on fish than the region as a whole.

An interesting result of the analysis is that twenty-four of thirty (80%) stocks were predicted by a different climate index before the regime shift than after. This could indicate that climate influences on recruitment are less coherent than predicted.

The mismatch in predicted best model and the observed spread in best models could also be due to differences in life history between different types of fish. For example, groundfish are planktonic for the first part of their life cycle, before they settle to seafloor habitat. Only averaged winter values for the indices were used in the models. It is possible that a differently timed index would have been a better predictor.

Climate in a specific region may be described by a climate index focused on that area, but it is still affected by atmospheric teleconnections with other regions. In particular, the tropics are connected to the North Pacific through atmospheric teleconnections which strengthen during El Niño conditions. The NPGO and PDO are both forced by the Aleutian Low, so they are connected that way. In addition, climate indices, although they are a convenient way to link climate and its effects on biological systems, may not be the ideal way to do so. In many cases, they perform better than local weather conditions because they are larger-scale (Forchhammer and Post 2004). However, climate indices can hide some local weather and environmental patterns that may have been better predictors of biological systems than the indices themselves.

This study did not consider the effects of the 1976/77 regime shift on the stocks, using data both before and after that regime shift in the before 1989 period. This regime shift had less of an obvious impact on biology, but may have still had some effect, which could have affected which climate index was the best predictor of each stock. However, the time series were not long enough to test a community-wide hypothesis in relation to the 1976/77 regime shift. This study also did not consider the effects of recent heatwave anomalies, such as the “Blob,” that negatively affected many marine organisms, including fish (Walsh et al. 2018).

Considering only the West Coast, some of the variability may be due to the size of the region. Many stocks in that region are found along the entire coast, while others exist on one end or the other. It is likely that different climate features are influential in different parts of the region. For example, ONI, may be more influential on the southern species than the northern ones. Other species that have a wider range may be best predicted by the model with none of the climate indices because the influence of different climate features may cancel out when considering the entire stock.

Several studies have performed analyses similar to those in this study, including Litzow and Mueter (2014). Their study combined multiple time series of biological data and summarized the ecological variability with principal component analysis (Litzow and Mueter 2014). It used a range of biological time series, including salmon, groundfish, small pelagic fishes, and macroinvertebrates and found that the abrupt change in amplitude of the PDO pattern after the

1988/89 regime shift was associated with a gradual decline in its connection to biological variability (Litzow and Mueter 2014). Puerta et al. (2019) found similar results when focusing on the Gulf of Alaska, namely a reduced importance of the PDO and a non-stationary relationship between climate forcings and biological responses. Their study also used principal component analysis (Puerta et al. 2019). An interesting future project would be to substitute principal component analysis for the methodology used in this study, which would provide an aggregated population response for each region of the Northeast Pacific Ocean. However, care must be taken with the use of PDO, which assumes stationary relationships among the intervening time series (Puerta et al. 2019).

One important consideration for the reliability of the results of this study is the variation in the amount of data available for the model to be run on. Particularly in the pre-1989 period, some stocks had years more data than others. More data could mean that the model performs better because any small variations are drowned out. However, a long time series could also mean the climate pattern most influencing the stock changed during the period the model was run on.

This study was performed using the output of NOAA Fisheries Service stock assessment models as data. The use of assessment output as data for further analysis is becoming more common as the availability of assessment results increases (Brooks et al. 2015). However, analyses using these results as data often overlook uncertainty, bias, and structural assumptions in the stock assessment model (Brooks et al. 2015). This can lead to a reduced accuracy in analyses using assessment results and less confidence in the results of such analyses (Brooks et al. 2015). Avoiding using assessment results as data is the ideal fix, but if that is not possible the assessment results should be checked for potential problems (Brooks et al. 2015). This can be done by completing sensitivity analyses and cross-validation methods, among other techniques (Brooks et al. 2015). In this study, the assessment results were checked for bias in the form of anomalous patterns of recruitment (Appendix 1, 2).

Understanding how climate affects recruitment is vital to the health of ecosystems and fisheries, as it has such a strong impact on adult biomass. In particular, studying how climate impacts recruitment in separate regions is important to understand how stocks in that specific region will respond to different climate forcings. Furthermore, studying the impacts of climate over different periods of time illustrates how important it is to maintain current data and utilize new data. Regime shifts, in particular, rapidly change climate patterns, which leads to different influences on fish stocks in a region. Further complicating the picture is global warming, which also needs to be studied to understand its impacts. Sustainable fisheries and healthy ecosystems depend on this knowledge. By considering these changing patterns and influences of climate when making management decisions will allow future scientists and managers to set sustainable goals for fisheries.

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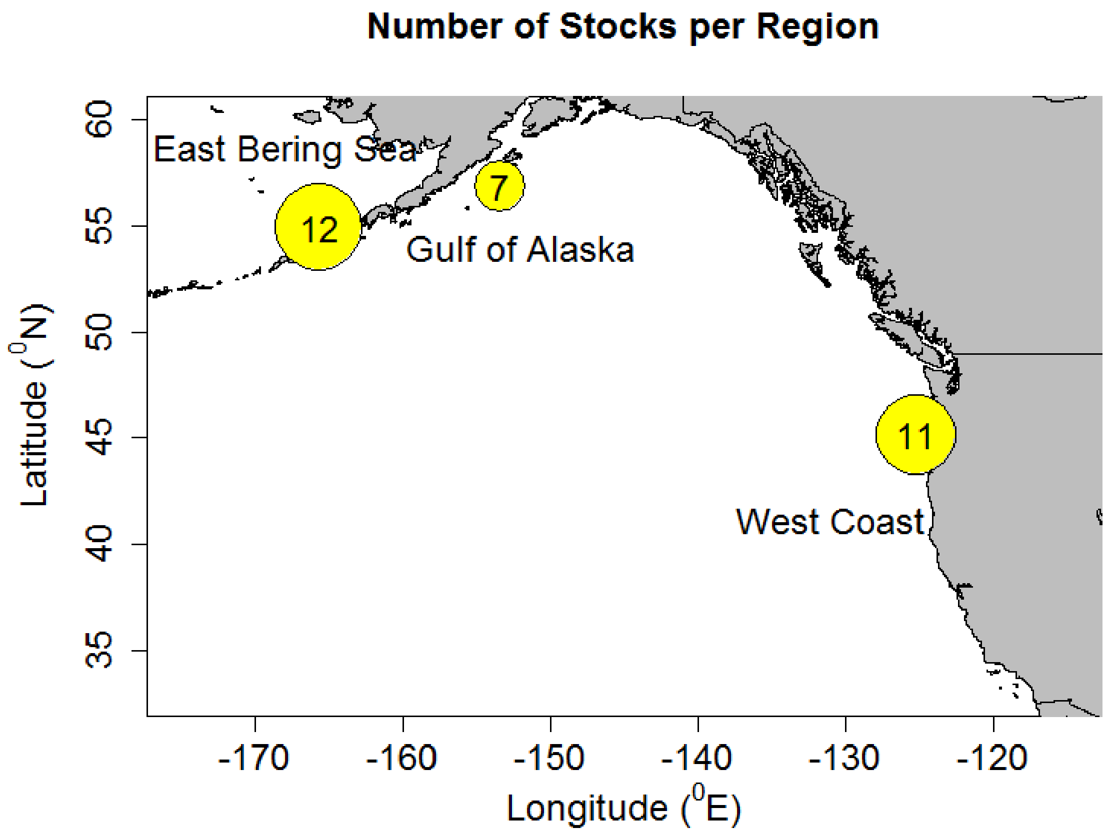


Figure 1. Map of the Northeast Pacific Ocean showing the general location of the three regions and the number of stocks in each region.

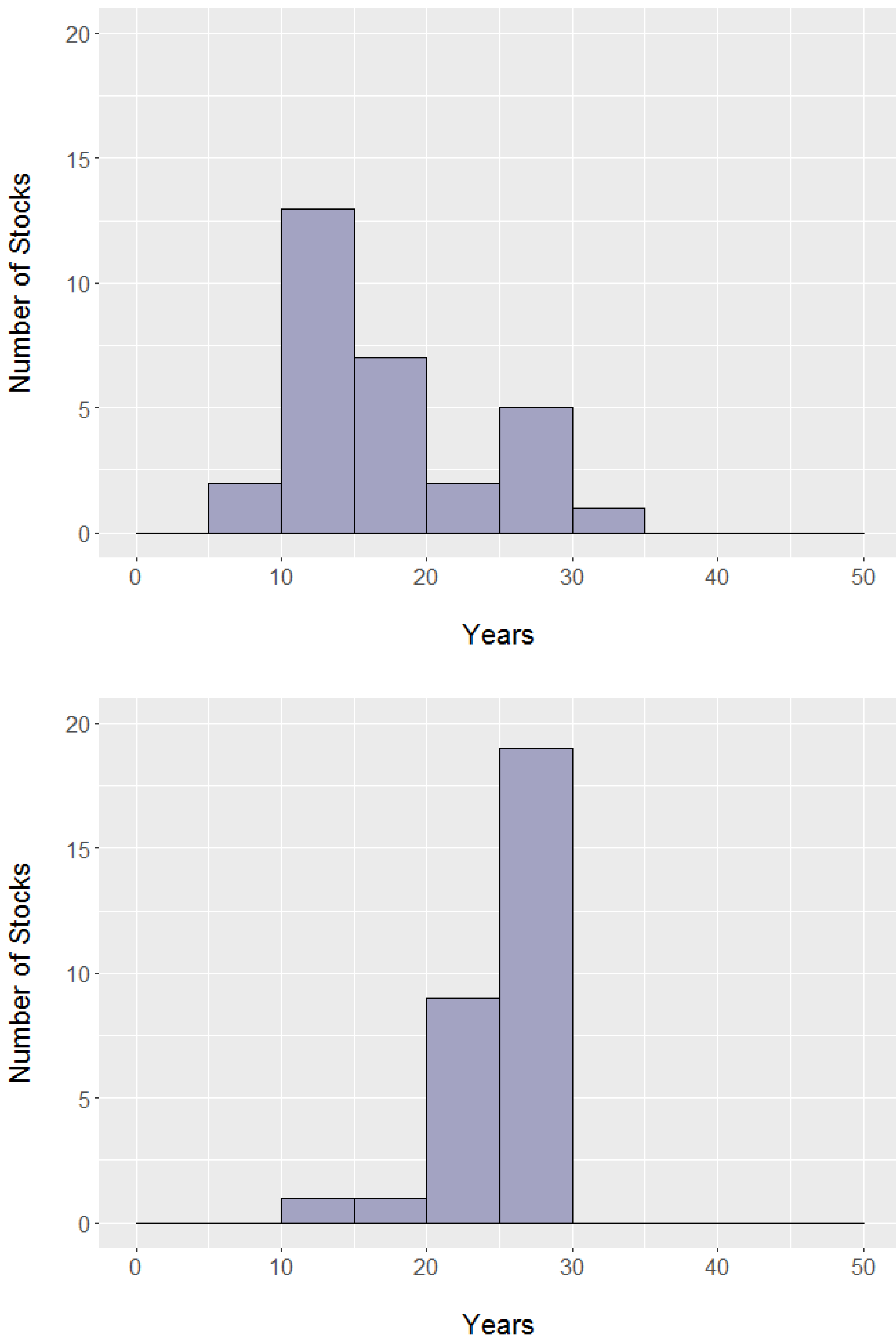


Figure 2. The number of stocks with the number of years of stock assessment data each model was run on.

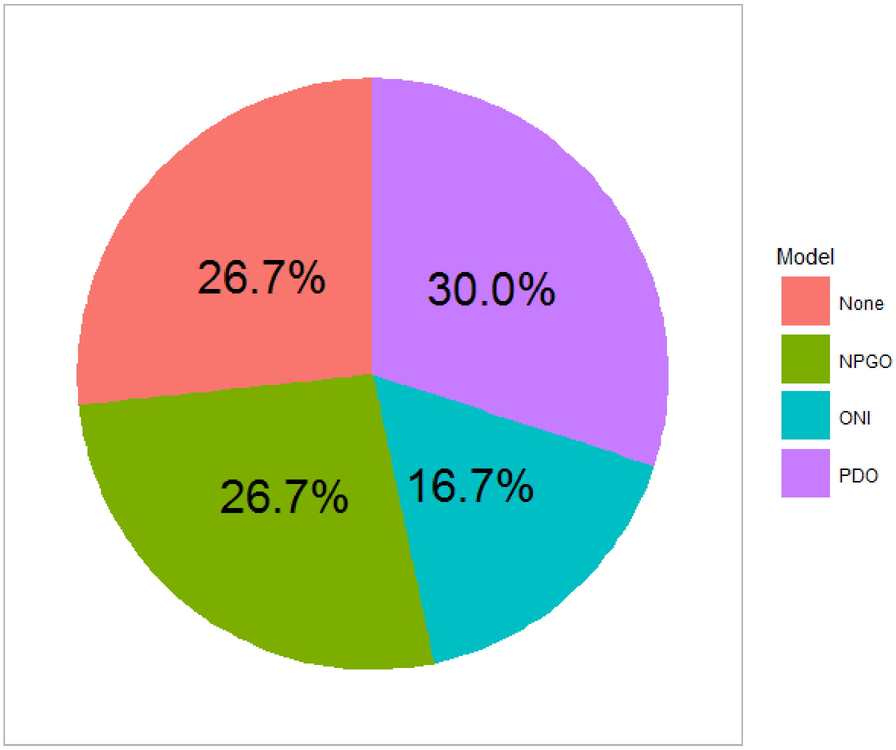


Figure 3. Percentage of total stocks best predicted by each model in the period before and including 1988.

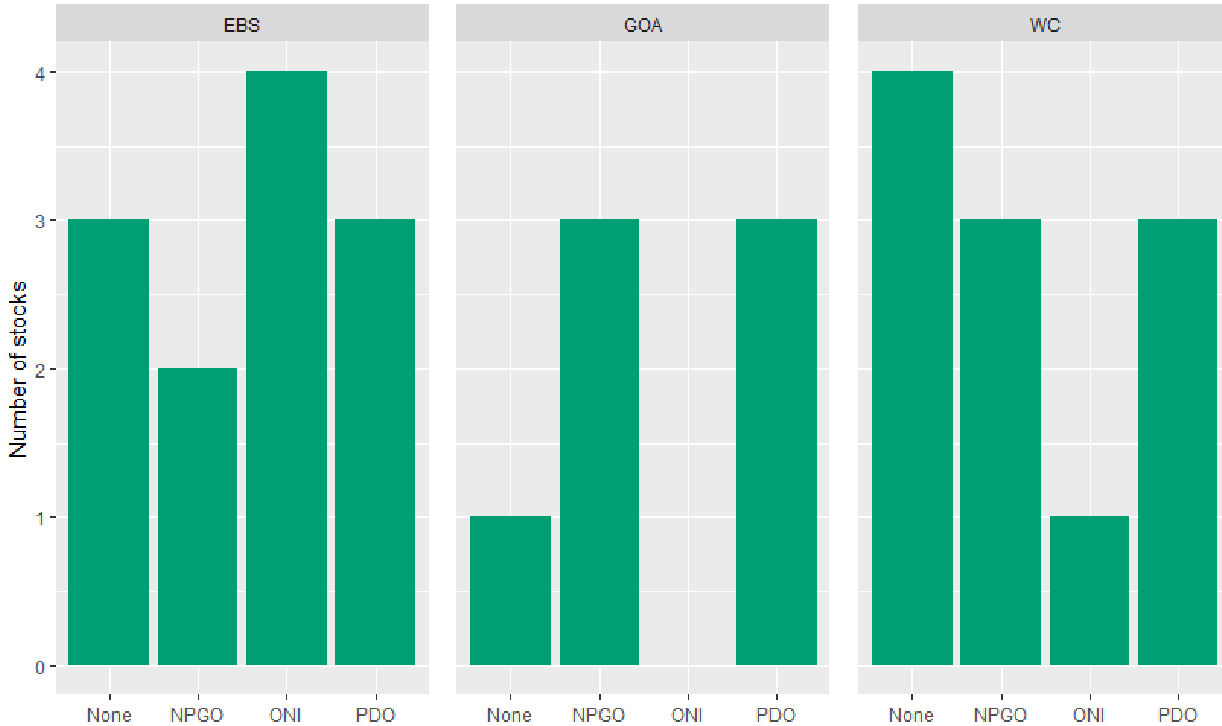


Figure 4a. Number of stocks best predicted by each model in each region through 1988.

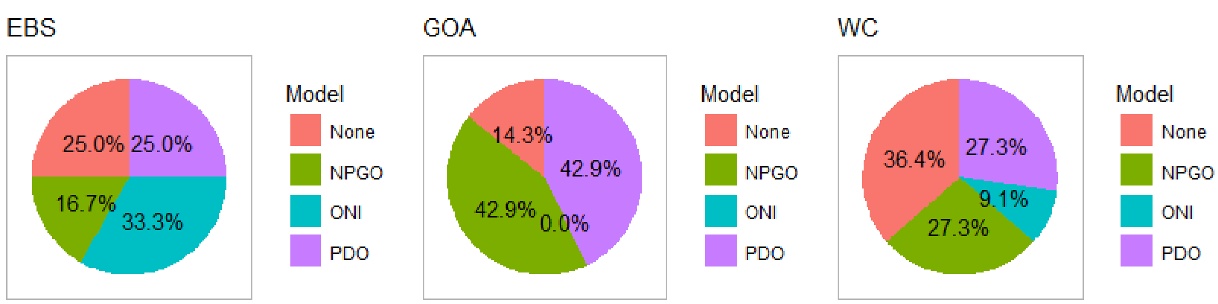


Figure 4b. Percent of stocks in each region best predicted by each climate index in the period through1988.

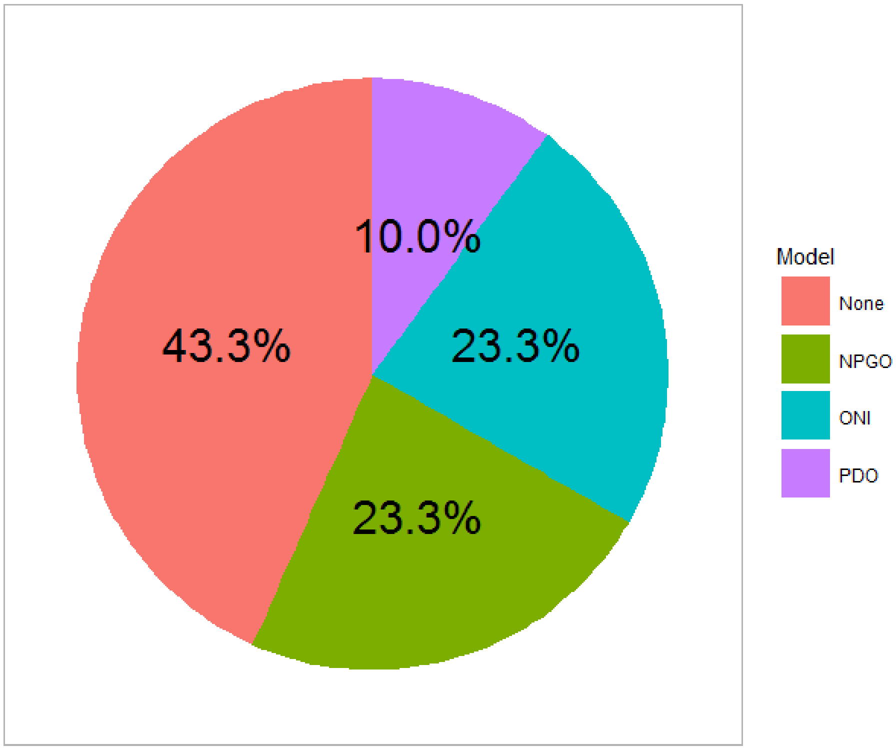


Figure 5. Percentage of total stocks best predicted by each model in the period starting in 1989.

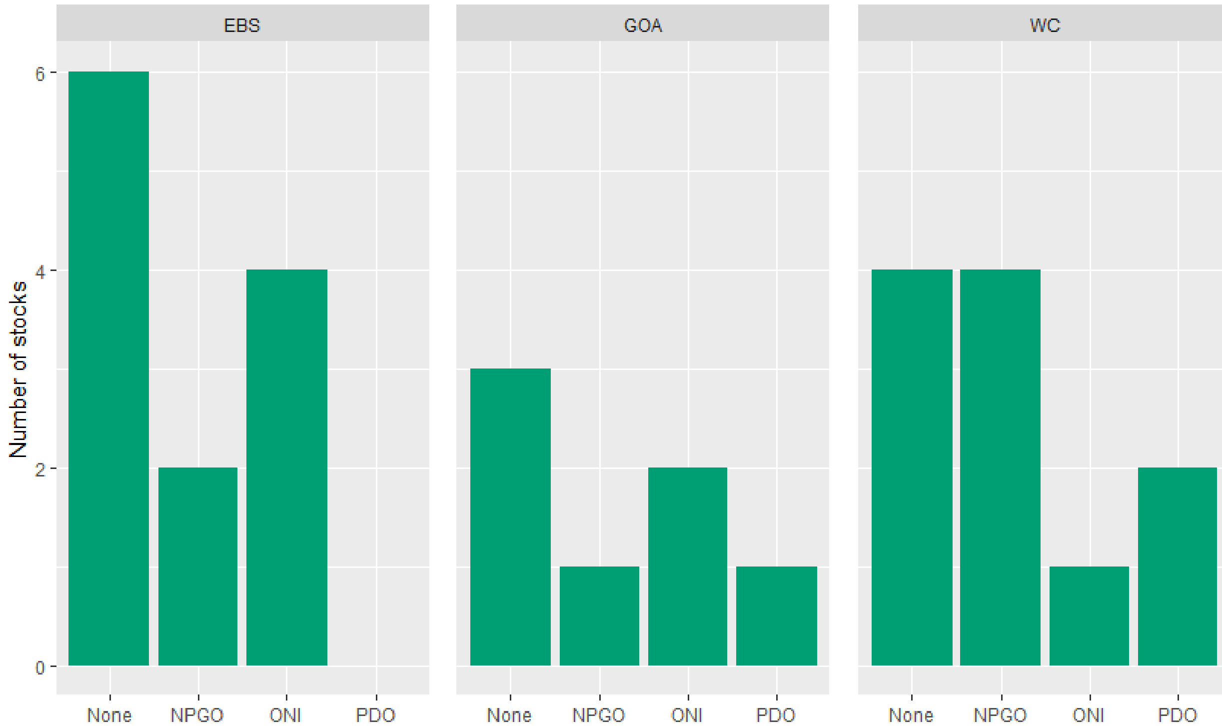


Figure 6a. Number of stocks best predicted by each model in each region after 1988.

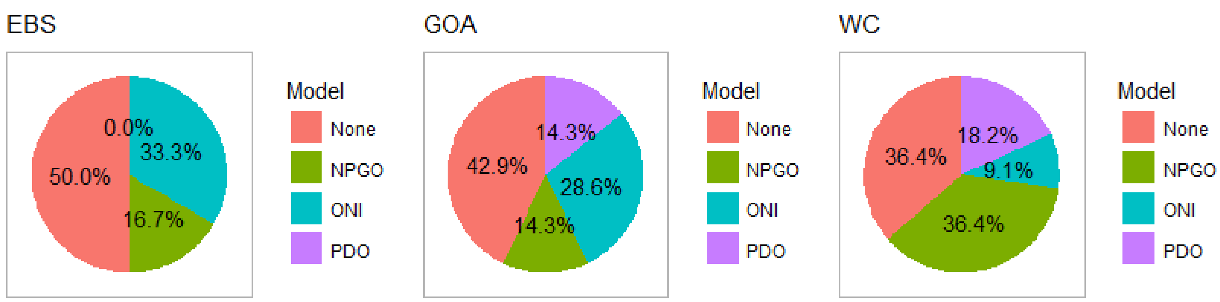


Figure 6b. Percent of stocks in each region best predicted by each climate index in the period after 1988.

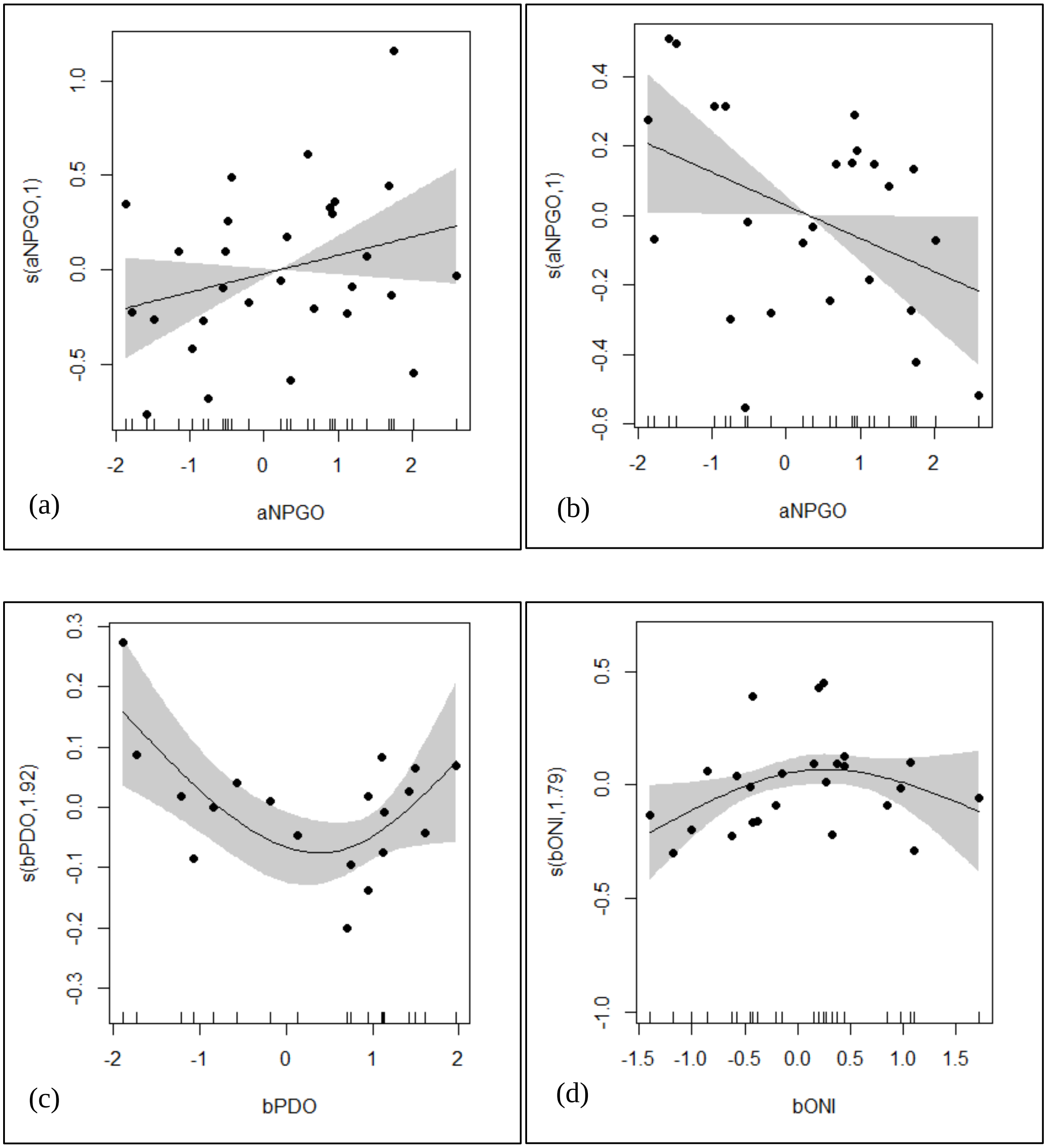


Figure 7. Examples of each type of relation between climate index and recruitment. The types are positive linear, positive nonlinear, negative linear, and negative nonlinear. (a) is positive linear, symbolized by / (WC Chilipepper rockfish, after). (b) is negative linear, symbolized by \ (EBS Northern rockfish, after). (c) is negative nonlinear, symbolized by ⋂ (EBS Pollock, before). (d) is positive nonlinear, symbolized by ⋃ (GOA Arrowtooth flounder, before). The shape of the relationship for the best model of every stock is shown in Table 4.

Table 1. Each stock separated by region with the time period for which data were available.

Region	*Stock*	*Scientific Name*	*Time Period*	*Duration (years)*
East Bering Sea	Pollock	*Gadus chalcogrammus*	1964-2015	51
	Pacific cod	*Gadus macrocephalus*	1977-2016	39
	Yellowfin sole	*Limanda aspera*	1954-2015	61
	Greenland halibut	*Reinhardtius hippoglossoides*	1950-2016	66
	Arrowtooth flounder	*Atheresthes stomias*	1976-2015	39
	Rock sole	*Lepidopsetta spp.*	1975-2008	33
	Flathead sole	*Hippoglossoides elassodon*	1977-2013	36
	Alaska plaice	*Pleuronectes quadrituberculatus*	1975-2015	40
	Atka mackerel	*Pleurogrammus monopterygius*	1977-2015	38
	Pacific ocean perch	*Sebastes alutus*	1960-2013	53
	Northern rockfish	*Sebastes polyspinis*	1977-2013	36
	Blackspotted and Rougheye rockfish complex	*Sebastes aleutianus*	1977-2013	36
Gulf of Alaska	Pacific ocean perch	*Sebastes alutus*	1961-2014	53
	Pollock	*Gadus chalcogrammus*	1970-2015	45
	Pacific cod	*Gadus macrocephalus*	1977-2016	39
	Arrowtooth flounder	*Atheresthes stomia*	1961-2015	54
	Dusky rockfish	*Sebastes ciliatus*	1977-2012	35
	Flathead sole	*Hippoglossoides elassodon*	1978-2015	37
	Northern rockfish	*Sebastes polyspinis*	1961-2014	53
West Coast	Pacific mackerel*	*Scomber japonicus*	1983-2016	33
	Sablefish	*Anoplopoma fimbria*	1950-2015	65
	Dover sole	*Microstomus pacificus*	1950-2011	61
	Widow rockfish	*Sebastes entomelas*	1950-2015	65
	Chilipepper rockfish	*Sebastes goodei*	1950-2017	67
	Bocaccio	*Sebastes paucispinis*	1950-2017	67
	Canary rockfish	*Sebastes pinniger*	1950-2017	67
	Pacific hake	*Merluccius productus*	1966-2017	51
	Arrowtooth flounder	*Atheresthes stomia*	1950-2017	67
	Lingcod	*Ophiodon elongatus*	1950-2009	59
	Longspine thornyhead	*Sebastolobus altivelis*	1962-2013	51
	Petrale sole	*Eopsetta jordani*	1950-2015	65
	Shortspine thornyhead*	*Sebastolobus alascanus*	1950-2013	63

*These stocks were not included in the analysis due to not having enough data and showing an anomalous pattern of recruitment throughout the time series, respectively.

Table 2. Which index each stock was best predicted by before and after the 1988/89 regime shift and which stocks changed the model they were best predicted by.

Before and 1988

	East Bering Sea												Gulf of Alaska							West Coast											
Indices	POLL	COD	YFS	TRBT	ATF	RSOLE	FSOLE	ATKA	AKPLA	POP	NROCK	BROCK	POP	POLL	COD	ATF	DUSK	FSOLE	NROCK	MACK	SAB	DSOLE	WIDOW	CHILI	BOCACC	CANARY	HAKE	ATF	LING	LSTH	PSOLE
ONI	X		X						X		X									X	X										
NPGO				X				X						X				X	X			X			X				X		
PDO		X				X				X			X			X	X						X	X			X				
None					X		X					X			X											X		X		X	X

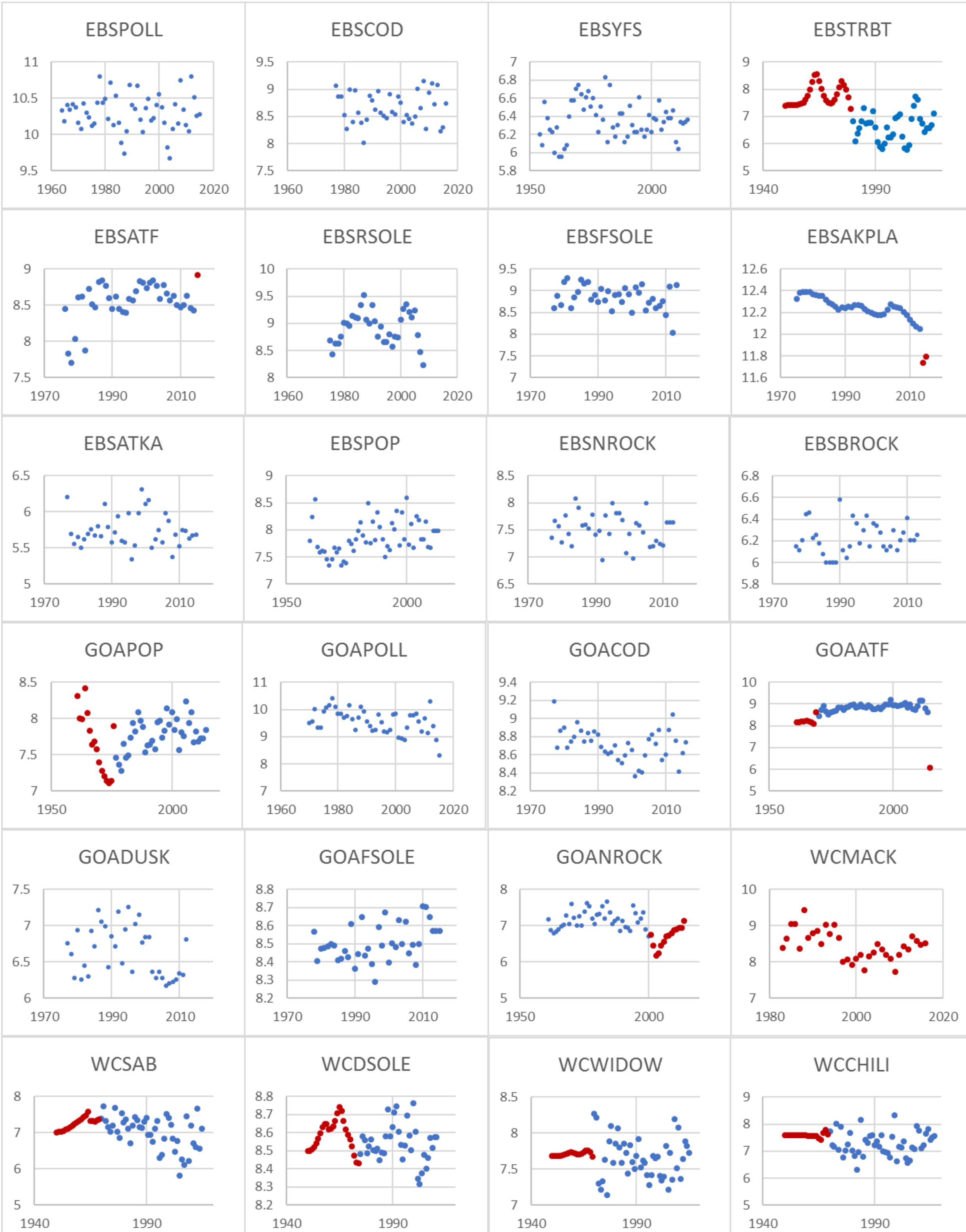
1989 – present (After 1988)

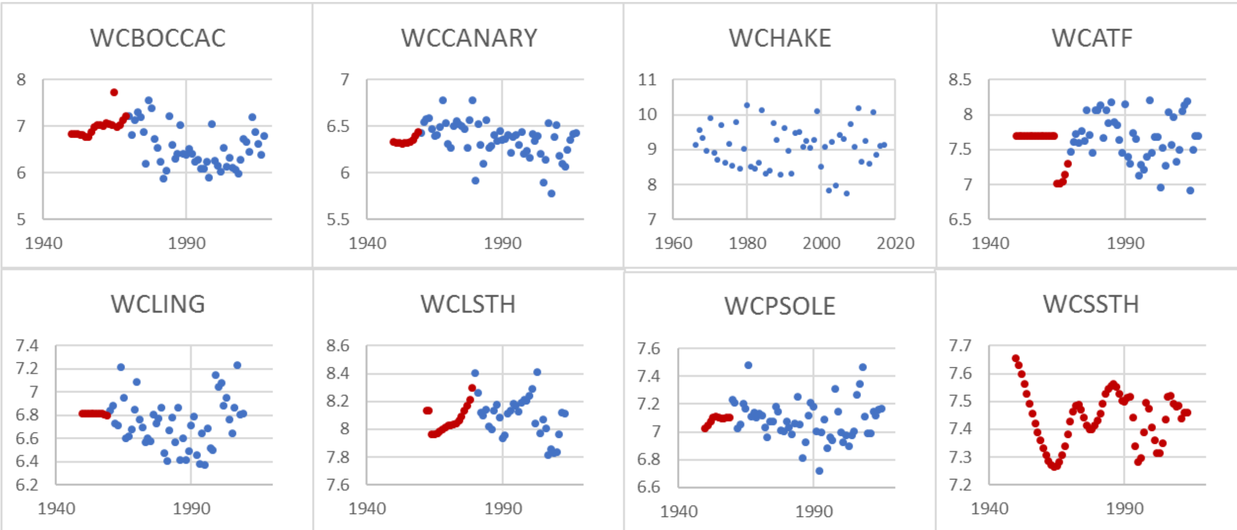
	East Bering Sea												Gulf of Alaska							West Coast											
Indices	POLL	COD	YFS	TRBT	ATF	RSOLE	FSOLE	AKPLA	ATKA	POP	NROCK	BROCK	POP	POLL	COD	ATF	DUSK	FSOLE	NROCK	MACK	SAB	DSOLE	WIDOW	CHILI	BOCACC	CANARY	HAKE	ATF	LING	LSTH	PSOLE
ONI	X	X		X		X											X		X							X					
NPGO					X						X					X				X	X			X					X	X	
PDO								X						X								X						X			
None			X				X		X	X		X	X		X			X					X		X		X				X
Best model changed		X	X	X	X	X		X	X	X	X		X	X		X	X	X	X	X	X	X	X	X	X	X	X	X		X	

Table 3. Effect of climate index on recruitment. The symbols in the table represent the shape of the relationship. Examples of the four general shapes are shown in Figure 7.

Region	Stocks	Before		After	
		Best Model	Effect	Best Model	Effect
East Bering Sea	Pollock	ONI	∩	ONI	∪
	Pacific cod	PDO	\	ONI	∪
	Yellowfin sole	ONI	∪	None	\
	Greenland halibut	NPGO	∩	ONI	∪
	Arrowtooth flounder	None	-	NPGO	/
	Rock sole	PDO	∪	ONI	∩
	Flathead sole	None	-	None	-
	Alaska plaice	ONI	∪	None	-
	Atka mackerel	NPGO	∪	None	-
	Pacific ocean perch	PDO	∪	None	-
	Northern rockfish	ONI	\	NPGO	\
	Blackspotted and Rougheye rockfish	None	-	None	-
Gulf of Alaska	Pacific ocean perch	PDO	/	None	-
	Pollock	NPGO	/	PDO	∩
	Pacific cod	None	-	None	-
	Arrowtooth flounder	PDO	∪	NPGO	/
	Dusky rockfish	PDO	/	ONI	∪
	Flathead sole	NGPO	∪	None	-
	Northern rockfish	NPGO	/	ONI	∩
West Coast	Sablefish	ONI	\	NPGO	/
	Dover sole	NPGO	∪	PDO	\
	Widow rockfish	PDO	/	None	-
	Chilipepper rockfish	PDO	/	NPGO	/
	Bocaccio	NPGO	/	None	-
	Canary rockfish	None	-	ONI	/
	Pacific hake	PDO	/	None	-
	Arrowtooth flounder	None	-	PDO	\
	Lingcod	NPGO	∩	NPGO	/
	Longspine thornyhead	None	-	NPGO	∪
	Petrale sole	None	-	None	-

Appendix 1. Plots of recruitment versus time for each stock, used to determine if any anomalous patterns exist. Red points were not included in the analysis, blue points were included.

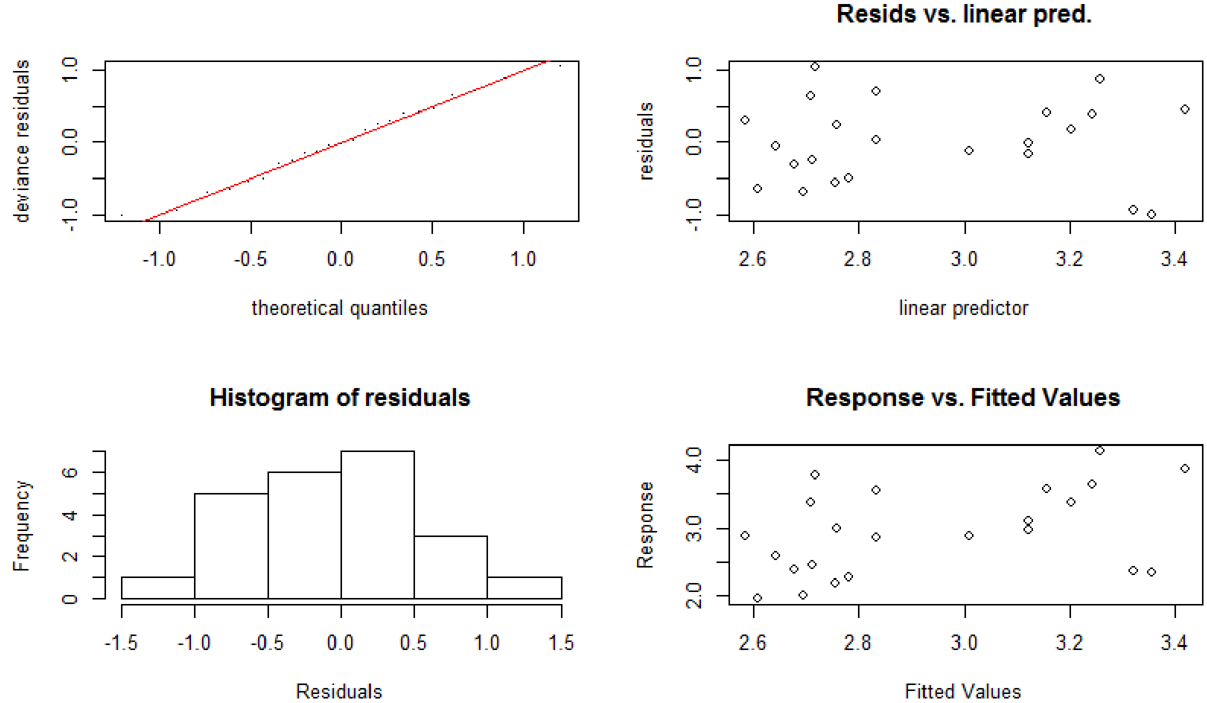



WCBOCCAC
WCCANARY
WCHAKE
WCATF
WCLING
WCLSTH
WCPSOLE
WCSSTH

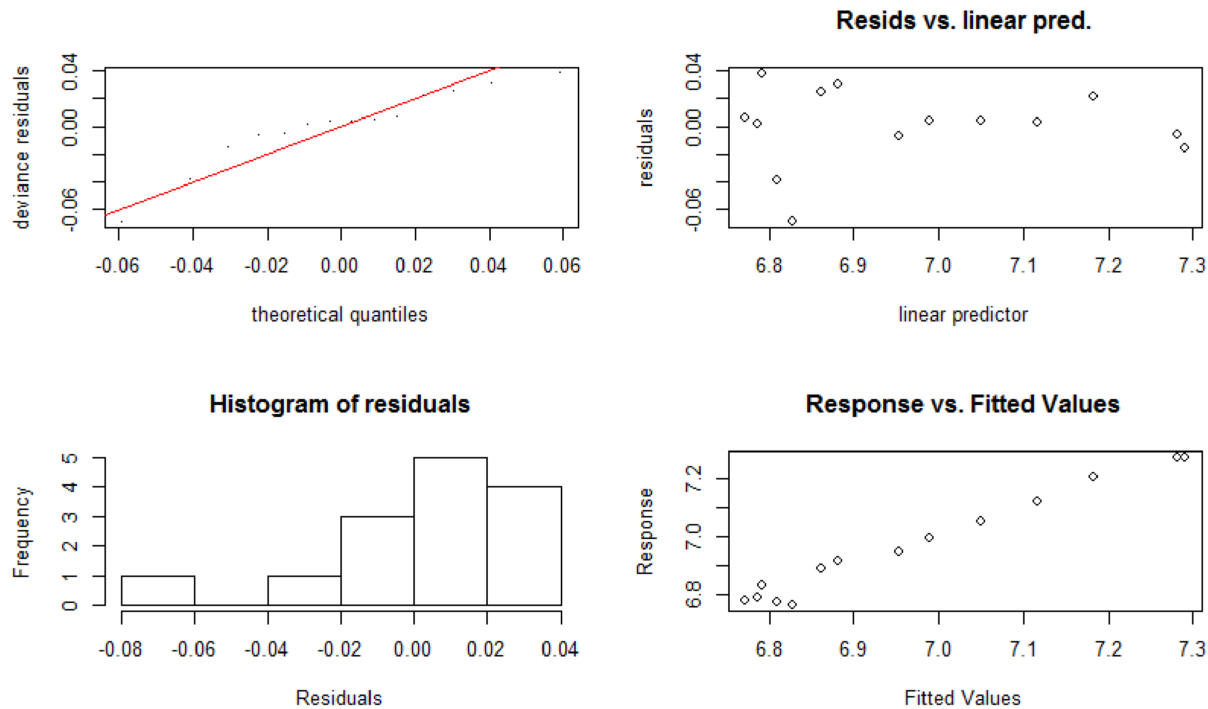
Appendix 2. Check of assumptions. Independence refers to temporal autocorrelation where "yes" means there is no temporal autocorrelation. Examples of "good" and "bad" normality and homogeneity of variance are shown below the table, as well as an example of temporal autocorrelation.

		Before			After		
Region	Stocks	Normality	Homogeneity of Variance	Independence	Normality	Homogeneity of Variance	Independence
EBS	POLL	N	N	Y	N	N	Y
	COD	Y	N	Y	N	Y	Y
	YFS	Y	N	Y	Y	N	Y
	TRBT	N	N	Y	N	Y	N
	ATF	N	N	Y	N	Y	Y
	RSOLE	N	N	Y	N	N	Y
	FSOLE	N	N	Y	N	Y	N
	AKPLA	N	N	Y	N	N	N
	ATKA	N	N	Y	N	N	Y
	POP	N	Y	Y	N	N	N
	NROCK	N	N	Y	N	Y	Y
	BROCK	N	Y	Y	N	N	Y
GOA	POP	N	N	Y	N	Y	Y
	POLL	N	Y	Y	N	N	Y
	COD	N	N	Y	N	N	N
	ATF	N	N	Y	Y	N	Y
	DUSK	N	N	Y	N	N	Y
	FSOLE	N	N	Y	N	N	Y
	NROCK	N	Y	Y	N	N	Y
WC	SAB	N	N	Y	N	Y	Y
	DSOLE	N	N	Y	N	Y	Y
	WIDOW	Y	N	Y	N	N	N
	CHILI	N	N	Y	N	Y	Y
	BOCACC	N	N	Y	N	N	Y
	CANARY	N	N	Y	N	N	Y
	HAKE	Y	N	Y	Y	Y	Y
	ATF	N	N	Y	N	Y	Y
	LING	N	Y	Y	N	N	Y
	LSTH	Y	N	Y	N	N	Y
	PSOLE	Y	N	Y	N	N	Y

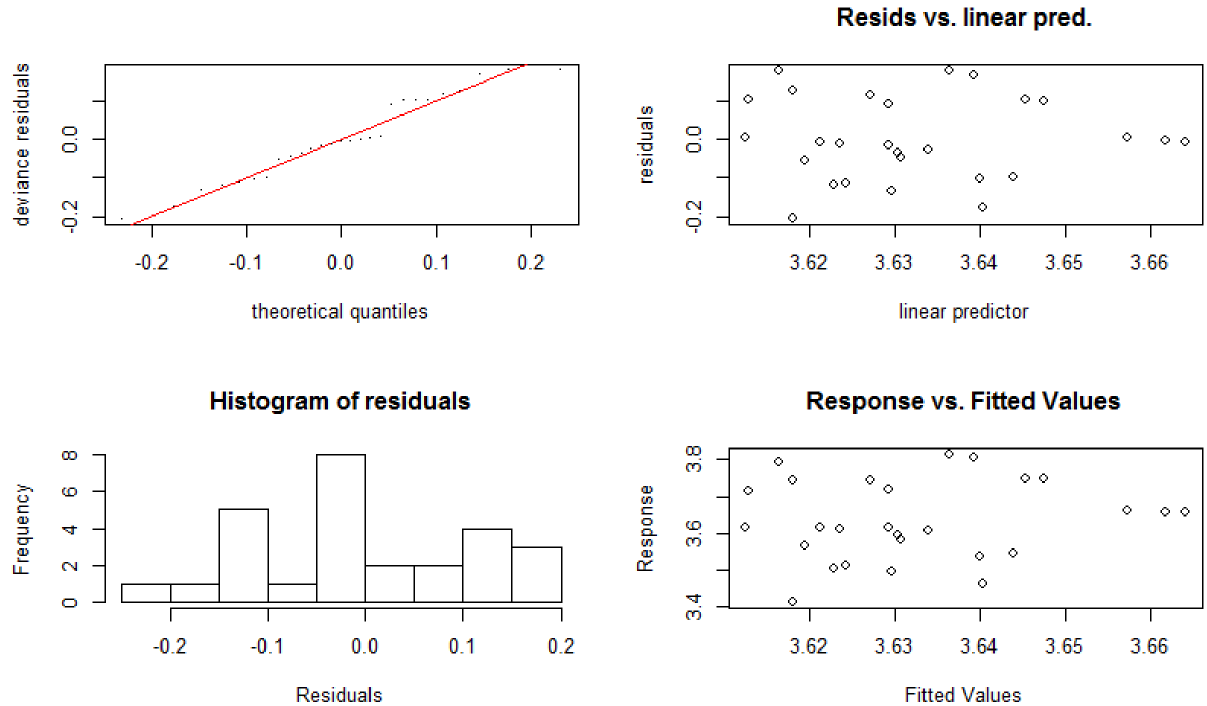
WC Hake – before: good example of normality



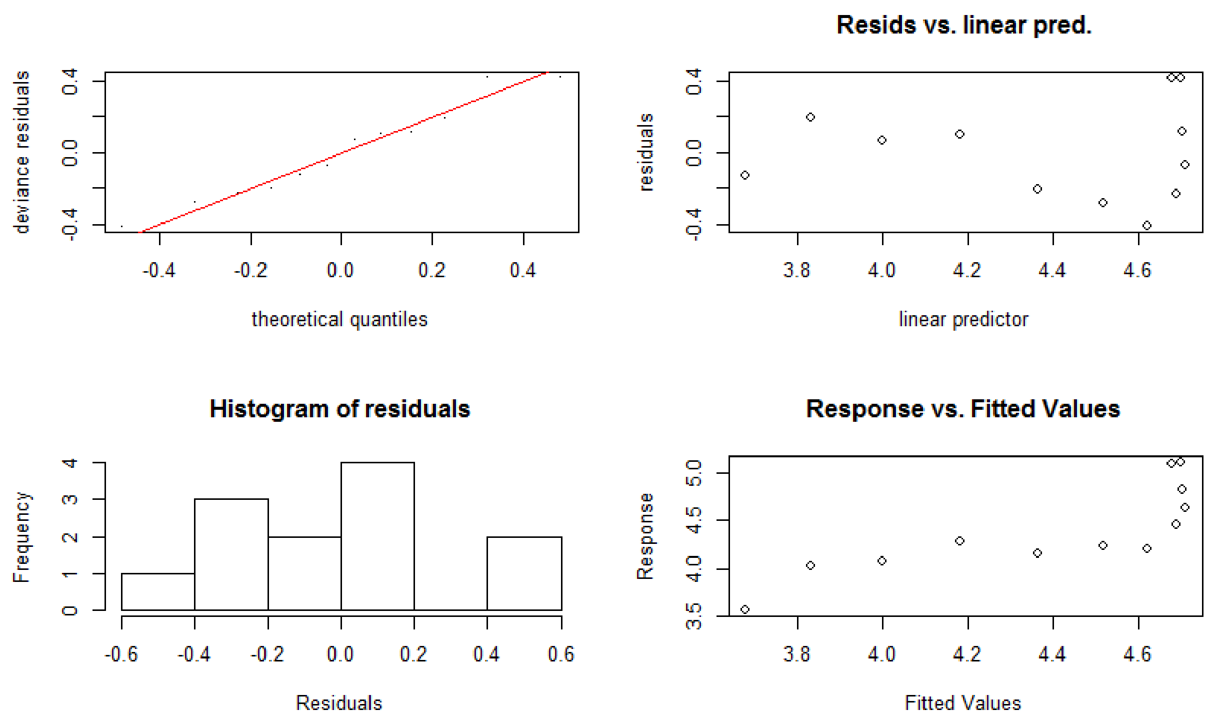
EBS Alaska Plaice – before: bad example of normality



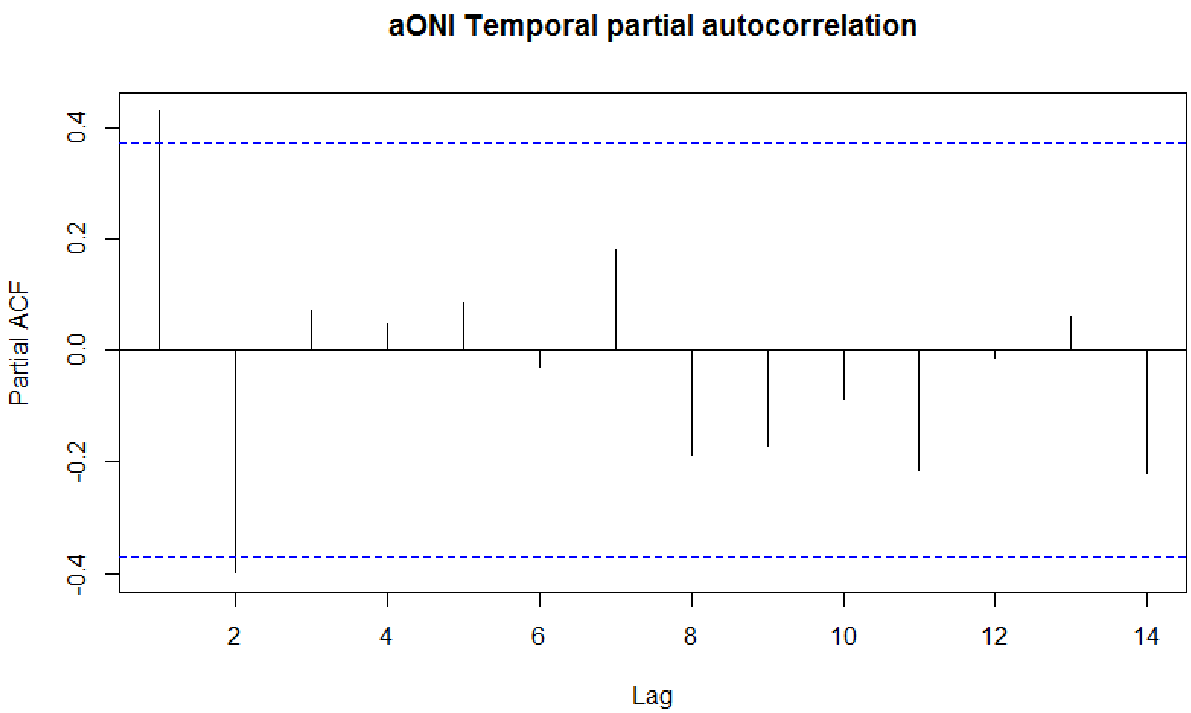
GOA Flathead Sole – after: good example of homogeneity of variance



EBS Flathead Sole – before: bad example of homogeneity of variance



GOA Cod – after: temporal autocorrelation



Appendix 3: R code used for analysis

```
#Shannon Riley Honors Thesis
#Predicting Fish Recruitment in the Northeast Pacific Using Climate Indices
#Code updated 4/21/2019

#INSTRUCTIONS
#run on all stocks, make sure all four models for each stock have same number of data
points
#record AIC results, significance of best, number of observations model is run on
(years of data), autocorrelation at lag 1
#if temporal autocorrelation, run gamm with autocorrelation correction

#Libraries
library(mgcv)



#Data set up
allyears=read.csv("C:/Users/Shannon Leah Riley/Documents/College
Courses/Thesis/Datasets/Final_Clean_Data.csv")
beforeand1988 <- subset(allyears, Year <= 1988)
after1988 = subset(allyears, Year >=1989)


#Set dataframe
#Set stock
beforeand1988$bstrec=beforeand1988$WCWIDOWr          #log base 10 of recruitment up to
and including 1988
beforeand1988$bstssblo=beforeand1988$WCWIDOWssb      #log base 10 of stock spawning
biomass up to and including 1988
beforeand1988$bstssbli=10^(beforeand1988$WCWIDOWssb) #linear stock spawning biomass up
to and including 1988
after1988$astrec=after1988$WCWIDOWr                  #log base 10 of recruitment from
1989 on
after1988$astssblo=after1988$WCWIDOWssb              #log base 10 of stock spawning
biomass from 1989 on
after1988$astssbli=10^(after1988$WCWIDOWssb)         #linear stock spawning biomass
from 1989 on
#Set indices
beforeand1988$bPDO=beforeand1988$PDO.Index.Winter..JAN.APR..Average
beforeand1988$bONI=beforeand1988$ONI.Average..DJF.MAM.
beforeand1988$bNPGO=beforeand1988$NPGO.Index.Winter..1.4..Average
after1988$aPDO=after1988$PDO.Index.Winter..JAN.APR..Average
after1988$aONI=after1988$ONI.Average..DJF.MAM.
after1988$aNPGO=after1988$NPGO.Index.Winter..1.4..Average


#Subset Before and 1988
subset_b=na.exclude(beforeand1988[,c(1,65:70)])

#Before and 1988 gams, pick best via AIC
gam_b_NPGO=gam(I(bstrec-bstssblo)~s(bstssbli, bs="cr", k=3)+s(bNPGO, bs="cr", k=3),
data=subset_b)
gam_b_ONI=gam(I(bstrec-bstssblo)~s(bstssbli, bs="cr", k=3)+s(bONI, bs="cr", k=3),
data=subset_b)
gam_b_PDO=gam(I(bstrec-bstssblo)~s(bstssbli, bs="cr", k=3)+s(bPDO, bs="cr", k=3),
data=subset_b)
gam_b_none=gam(I(bstrec-bstssblo)~s(bstssbli, bs="cr", k=3), data=subset_b)
AIC(gam_b_NPGO,gam_b_ONI,gam_b_PDO,gam_b_none)
```

```
#gam summary
#only need to check model with lowest AIC score
summary(gam_b_NPGO)
summary(gam_b_ONI)
summary(gam_b_PDO)
summary(gam_b_none)

#check Assumptions - GAM, Independence
#only need to check model with lowest AIC score
pacf(residuals(gam_b_NPGO),main='bNGPO Temporal partial autocorrelation')
pacf(residuals(gam_b_ONI),main='bONI Temporal partial autocorrelation')
pacf(residuals(gam_b_PDO),main='bPDO Temporal partial autocorrelation')
pacf(residuals(gam_b_none),main='bNone Temporal partial autocorrelation')

#Validation on residuals
#only need to check model with lowest AIC score
par(mfrow=c(2,2))
gam.check(gam_b_NPGO)
gam.check(gam_b_ONI)
gam.check(gam_b_PDO)
gam.check(gam_b_none)
#Visualize: additive effects
#only need to check model with lowest AIC score
plot(gam_b_NPGO,pages=1,res=T,pch=16,shade=T)
plot(gam_b_ONI,pages=1,res=T,pch=16,shade=T)
plot(gam_b_PDO,pages=1,res=T,pch=16,shade=T)
plot(gam_b_none,pages=1,res=T,pch=16,shade=T)



#Subset After 1988
subset_a=na.exclude(after1988[,c(1,65:70)])

#After 1988 gams, pick best via AIC, is it different than before and 1988 best?
gam_a_NPGO=gam(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aNPGO, bs="cr", k=3),
data=subset_a)
gam_a_ONI=gam(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aONI, bs="cr", k=3),
data=subset_a)
gam_a_PDO=gam(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aPDO, bs="cr", k=3),
data=subset_a)
gam_a_none=gam(I(astrec-astssblo)~s(astssbli, bs="cr", k=3), data=subset_a)
AIC(gam_a_NPGO,gam_a_ONI,gam_a_PDO,gam_a_none)

#gam summary
#only need to check model with lowest AIC score
summary(gam_a_NPGO)
summary(gam_a_ONI)
summary(gam_a_PDO)
summary(gam_a_none)

#check Assumptions - GAM, Independence
#only need to check model with lowest AIC score
pacf(residuals(gam_a_NPGO),main='aNGPO Temporal partial autocorrelation')
pacf(residuals(gam_a_ONI),main='aONI Temporal partial autocorrelation')
pacf(residuals(gam_a_PDO),main='aPDO Temporal partial autocorrelation')
pacf(residuals(gam_a_none),main='aNone Temporal partial autocorrelation')

#Validation on residuals
#only need to check model with lowest AIC score
```

```
par(mfrow=c(2,2))
gam.check(gam_a_NPGO)
gam.check(gam_a_ONI)
gam.check(gam_a_PDO)
gam.check(gam_a_none)
#Visualize: additive effects
#only need to check model with lowest AIC score
plot(gam_a_NPGO,pages=1,res=T,pch=16,shade=T)
plot(gam_a_ONI,pages=1,res=T,pch=16,shade=T)
plot(gam_a_PDO,pages=1,res=T,pch=16,shade=T)
plot(gam_a_none,pages=1,res=T,pch=16,shade=T)




#Temporal Autocorrelation Correction Models

#After 1988 gamms, pick best via AIC
#NPGO
gamm_a_NPGO=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aNPGO, bs="cr", k=3),
data=after1988,method='REML')
gammAR1_a_NPGO=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aNPGO, bs="cr",
k=3),
                    correlation = corAR1(form =~1),data=after1988,method='REML')
AIC(gamm_a_NPGO$lme,gammAR1_a_NPGO$lme) #compare with and without autocorrelation
structure
#ONI
gamm_a_ONI=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aONI, bs="cr", k=3),
data=after1988,method='REML')
gammAR1_a_ONI=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aONI, bs="cr", k=3),
                   correlation = corAR1(form =~1),data=after1988,method='REML')
AIC(gamm_a_ONI$lme,gammAR1_a_ONI$lme) #compare with and without autocorrelation
structure
#PDO
gamm_a_PDO=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aPDO, bs="cr", k=3),
data=after1988,method='REML')
gammAR1_a_PDO=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3)+s(aPDO, bs="cr", k=3),
                   correlation = corAR1(form =~1),data=after1988,method='REML')
AIC(gamm_a_PDO$lme,gammAR1_a_PDO$lme) #compare with and without autocorrelation
structure
#None
gamm_a_none=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3),
data=after1988,method='REML')
gammAR1_a_none=gamm(I(astrec-astssblo)~s(astssbli, bs="cr", k=3),
                    correlation = corAR1(form =~1),data=after1988,method='REML')
AIC(gamm_a_none$lme,gammAR1_a_none$lme) #compare with and without autocorrelation
structure
#Find best model
AIC(gammAR1_a_NPGO$lme,gammAR1_a_ONI$lme,gammAR1_a_PDO$lme,gammAR1_a_none$lme)  #AIC
w/ all autocorrelation structure models

#gamm summary
#only need to check model with lowest AIC score
summary(gammAR1_a_NPGO$gam)
summary(gammAR1_a_NPGO$lme)
summary(gammAR1_a_ONI$gam)
summary(gammAR1_a_ONI$lme)
summary(gammAR1_a_PDO$gam)
summary(gammAR1_a_PDO$lme)
summary(gammAR1_a_none$gam)
summary(gammAR1_a_none$lme)
```

```
#Validation on residuals
#only need to check model with lowest AIC score
par(mfrow=c(2,2))
gam.check(gammAR1_a_NPGO$gam)
gam.check(gammAR1_a_ONI$gam)
gam.check(gammAR1_a_PDO$gam)
gam.check(gammAR1_a_none$gam)
#Visualize: additive effects
#only need to check model with lowest AIC score
plot(gammAR1_a_NPGO$gam,pages=1,res=T,pch=16,shade=T)
plot(gammAR1_a_ONI$gam,pages=1,res=T,pch=16,shade=T)
plot(gammAR1_a_PDO$gam,pages=1,res=T,pch=16,shade=T)
plot(gammAR1_a_none$gam,pages=1,res=T,pch=16,shade=T)
```