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Abstract

The health of fish stocks greatly depends on the largest individuals within a population due to their high fecundity and genetic value, which contribute to the overall resilience and adaptability of the population. However, large fish are a common oversight in data-limited management decisions. Because of this, size truncation, the removal of large fish from an exploited population, poses significant ecological and management implications. This research presents a comprehensive analysis of size truncation in three rockfish species in Southern California – grass rockfish (*Sebastes rastrelliger*), squarespot rockfish (*S. hopkinsi*), and speckled rockfish (*S. ovalis*). This study applied Convergent Cross Mapping (CCM), which is a powerful statistical methodology often used for detecting causality in complex, non-linear ecosystems. I used CCM to identify the non-linear factors driving the size of both large and small fish, and the relative strengths of each factor, for three commonly caught species in California. Using an extensive dataset spanning 2004-2022 from the California Recreational Fisheries Survey (CRFS), alongside environmental variables including Scripps Pier ocean bottom temperature and Biologically Effective Upwelling Transport Index (BEUTI), this research identifies key patterns and relationships affecting fish size. The results reveal the complexities between fishing pressure and environmental variables, revealing that these factors exert distinct influences across different species. Most notably, [redacted] a stronger driver of big fish size than small fish size, while the opposite [redacted]re. These findings can provide valuable insights into the intricate dynamics contributing to size truncation and fishery recruitment, with implications for sustainable fisheries management.

Introduction

History of the California Groundfish Fishery

Groundfish fishing in California, including rockfish and flatfish, has a history over a century long, initially driven by Native American subsistence fishing, and later by commercial and recreational pursuits (Miller et al., 2014). The Gold Rush in the 1850s caused an upsurge in fishing activities, leading to worries about inshore groundfish stock depletion (Miller et al., 2014). This prompted an expansion into offshore habitats and the implementation of fish harvest tracking systems in the early [redacted]t al., 2014). This was followed during the mid-20th century by significant t[redacted]ements, such as diesel engines and better refrigeration, facilitating the diversification of the fishery (Miller et al., 2014). However, the rapid expansion of both domestic and foreign fisheries from the 1960s to the 1980s led to significant species depletion (Miller et al., 2014).

In response to this overexploitation, the early 2000s saw the declaration of seven rockfish species as overfished (Miller et al., 2014). Consequently, measures were taken to rebuild populations, including restrictions on allowable catches, depth restrictions, gear restrictions, and the establishment of large no-fishing zones, such as the Cowcod Conservation Areas in southern California (Miller et al., 2014). West coast groundfish management is now employing a diverse portfolio of management measures to support long-term fisheries sustainability for many species that are inherently vulnerable to overfishing.

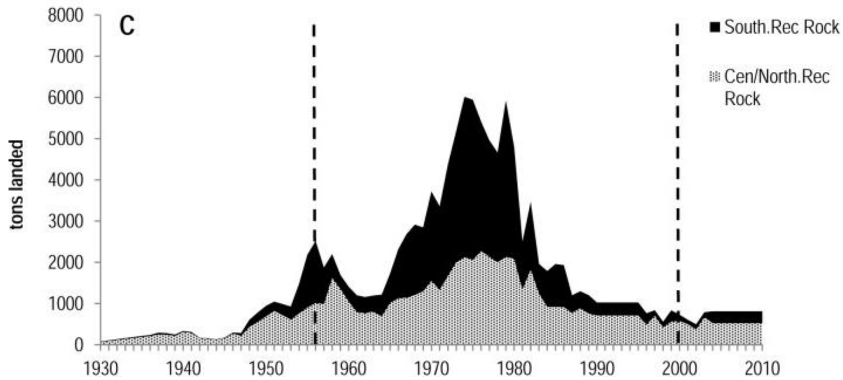


Figure 1 from Miller et al. (2014). Shows Recreational rockfish landings for Northern, Central, and Southern California from 1930 to 2010.

Importance of fish stock size structure

Size structure analysis is an important tool in fisheries management, providing insights into recruitment, growth, and mortality rates (Neumann & Allen, 2007). Length-frequency data can help identify issues such as inconsistent year-class strength, slow growth, or excessive mortality (Neumann & Allen, 2007). Examining size structure can also provide indications of overfishing (Haedrich & Barnes, 1997). For example, when average fish size decreases, this may be an indicator of good recruitment or of overfishing (Haedrich & Barnes, 1997). Also, understanding size structure can be a relatively easy first step in managing data poor fisheries (Prince & Hordyk, 2019). Size distributions can be used to identify both growth overfishing (when small fish become less abundant) and recruitment overfishing (when larger individuals become less abundant) (Kell et al., 2022).

There are numerous negative effects associated with size/age truncation. First, size truncation negatively effects recruitment because the largest fish tend to produce the most and highest quality eggs (Calduch-Verdiell, 2014; Hixon et al., 2014). These larger fish help reduce population instability by “bet-hedging” in environmental conditions that are not ideal for survival (Hsieh et al., 2010). Because fish of different sizes spawn at different times of the year, there are additional bet-hedging characteristics of allowing a wide range of age classes in a fish population (Hixon et al., 2014). It has also been suggested that age truncation is most harmful when successful reproduction is significantly variable (Berkeley et al., 2004). And most rockfish populations fall into this category of significantly variable successful reproduction (Berkeley et al., 2004). Additionally, the fecundity of adult fish shows a nearly linear increase with body mass, while it exhibits a geometric growth pattern with length (Berkely et al., 2004). Secondly, **i**ncreased recruitment variability can have economic and food security consequences via increased population variability. Increased population variability can lead to economic challenges since variable populations lead to smaller sustainable harvest rates and increased risks that populations collapse (Ohlberger et al., 2014). This can also have food security implications. Third, genetic consequences can occur because the largest and oldest fish in a population tend to be genetically predisposed to faster growth and later maturity (Berkeley et al., 2004). This means that the selection pressure caused by fishing might favor early maturing and slower growing fish (Berkeley et al., 2004). Lastly, biodiversity can be impacted by age truncation because it compromises trait diversity (Barnett et al., 2017). Food web dynamics that contribute to the relationship between diversity and stability can be harmed by age truncation (Barnett et al., 2017). The diversity of life history, typically connected to an individual's age or size, tends to increase stability by promoting group asynchrony, enhancing varied responses to fishing activities and environmental shifts (Barnett et al., 2017). Furthermore, age truncation is associated with the standardization of a population's spatial structure, making communities susceptible to environmental variations, thereby increasing fluctuations in community structure and compromising ecological stability (Barnett et al., 2017).

Purpose of This Study

The purpose of this study is to evaluate whether recreational fishing can cause size truncation in California fisheries, and to identify other possible drivers of size truncation in California fisheries. To accomplish this, we used the California Recreational Fisheries Survey (CRFS) dataset, which spans from 2004 to present. Prior research has often focused on age truncation rather than size truncation. As shown by Beverton & Holt (1959), size and age are typically positively related, although the relationship is nonlinear. Because of this, this study refers to age truncation research with the understanding that age and size are closely related, and that size truncation likely also indicates age truncation. Overall, this work contributes to a more comprehensive understanding of the dynamics in California fisheries by identifying and quantifying drivers of size truncation.

Methods

Study Area and Data Sources

This study used a combination of various data sources. The California Recreational Fisheries Survey (CRFS) length, landings, and effort datasets served as the primary data sources for our analyses. These datasets span the west coast of the United States from 2004 to present. Fishing effort from the CRFS dataset was filtered as follows – trip types only included bottom fish trips, fishing modes only included private/rental boats and party/charter boats. Landings in this study refers to total mortality as estimated by the CRFS dataset. Since fish landings can be filtered to the specific species, this was the only filter applied to landings. Landings and effort data were restricted to the Central, Channel, and South regions as described by the CRFS methods document (Figure 2). This paper refers to those regions collectively as Southern California. Environmental variables were also included in the analysis. These included ocean bottom temperature data from the Scripps Institution of Oceanography pier in La Jolla, California, obtained through daily sampling at the Scripps Institution of Oceanography Pier, and the Biologically Effective Upwelling Transport Index (BEUTI) values from the 33° and 35° latitudes. The BEUTI is a measure of nitrate flux near the coast, which is determined by estimating vertical transport and the amount of subsurface nitrate at the time of transport (Jacox et al., 2018). It is used in this study since it may be more important to some biological processes than upwelling itself (Jacox et al., 2018).

Figure 2 from California Department of Fish and Wildlife, Pacific States Marine Fisheries Commission, & NOAA Fisheries (2020). The Central, Channel, and South regions are the regions used in this study.

Data Quality Control

The study faced several challenges, particularly regarding the appropriate manipulation of size data. Because CCM tends to be more effective with longer time series, generating high-resolution time-series from the available data was a key aspect of this study. Although CRFS spans from 2004 to present, COVID-19 caused a substantial gap in data after 2019. Because of this, and because landings data started in 2005, the time period studied in this analysis spans 2005 to 2020. It should be noted that Marine Recreational Fishery Statistical Survey (MRFSS) data, which began much before CRFS, was collected, but since it did not include the lengths of individual fish, it was not suitable for this study.

Creating an optimal time-series representing large fish, minimally influenced by incoming age classes, posed a significant challenge. A solution was developed in which the average sizes of the top ‘n’ number of fish per quarter were examined. This approach was chosen to avoid potential sampling errors associated with the absolute largest fish and to minimize the impact of younger fish on the largest size trend through time. However, there were times of the year when sampling was minimal for all species. Given that it's generally easier to catch smaller fish than larger ones, the largest fish during these periods might not accurately represent the population of the largest fish. To mitigate this effect, the data was aggregated into quarterly figures, followed by a 4-quarter moving average calculation, mitigating the artificial seasonality caused by low sampling during certain periods.

Data Analyses

Simplex Projection

To determine the optimal number of top ‘n’ fish, 50 time series were created for each species. The first of these 50 time series consisted of the size of the largest fish per quarter, the second time series consisted of the average of the top 2 largest fish per quarter, the third time series consisted of the average of the top 3 largest fish per quarter, and so on until the 50^{th} time series was created. For each of these time series, a simplex projection, as described by Sugihara et al. (1990), was conducted to measure the maximum predictability for each time series created from each of the 1 through 50 top ‘n’ number of fish. To clarify further, for each species, 50 separate time series were tested, and the time series exhibiting the most coherent signal was selected. Special consideration was given to quarters where the sample size was less than 150 fish. In these situations, only the top three fish were selected, irrespective of the ‘n’ value. For sample sizes below 75, only a single fish was selected. This was done because, after visually analyzing the relationship between sample size and size of the largest fish, the effect of sample sizes below these numbers seemed to have an even larger effect in skewing the data.

The selection of the optimal time series for each species was based on the one that exhibited the best predictability and thus the most coherent signal (i.e., the time series that displays the least amount of noise). For grass rockfish, which only had sample sizes less than 150, only the special considerations were applied. For squarespot rockfish, the top 20 fish were chosen. And for speckled rockfish, the top 1 largest fish were selected. The same method was applied in reverse to the small fish time series (i.e., for the smallest fish instead of the largest). This method provided a mechanism for creating time series which produced the most coherent signal possible, given the available data and inherent challenges, ensuring the validity of subsequent analyses.

Species Selection and Size Truncation Analysis

The methodology detailed above was applied to fifteen species in Southern California, California halibut, brown rockfish, lingcod, pacific sanddab, grass rockfish, starry rockfish, bocaccio, squarespot rockfish, flag rockfish, rosy rockfish, greenstriped rockfish, speckled rockfish, chilipepper rockfish, widow rockfish, and halfbanded rockfish. Species whose average size of the top ‘n’ largest fish demonstrated a significant negative correlation with time, were flagged as demonstrating size truncation during this period. Using Pearson Correlation, three species were identified as showing significant signs of size truncation: grass rockfish, squarespot rockfish, and speckled rockfish (top ‘n’ numbers for these species are given above). Consequently, these species were selected for further analysis in the study (Figure 3).

Data Visualization and Convergent Cross Mapping (CCM)

As a first step in understanding the relationship between the predictor and response variables, the mean size of the largest ‘n’ fish of each species exhibiting size truncation was plotted against all independent variables. This helped identify broad trends between the dependent and independent variables. Next, CCM was performed with the independent variables as the target (potential driving) variables, with large and small fish sizes as separate library (response) variables. Utilizing the ccm() function from the rEDM v0.7.5 package in R, CCM was implemented allowing a time delay (tp) of -1 through -12 and an embedding dimension ranging from 1 to 10 for each target/library combination (Ye, n.d.). A comprehensive explanation of these input parameters is available in Sugihara Lab (2022). The right aligned, 4-quarter moving average was applied to each time series in this analysis.

The output data from CCM includes several metrics such as predictive skill (rho), mean absolute error, “num_pred” (number of predictions made in the given analyses), and root mean square error. To mitigate potential rho value inflation due to removal of time series segments, num_pred was filtered to only include values above 48. An additional column was then generated to represent the difference between rho and the absolute value of the correlation at the given time delay (tp). This allowed for the identification of the highest rho-correlation difference values for each library-target combination. Using this approach, linear effects could be excluded, thereby revealing the strongest nonlinear influences of the independent variables on the large and small fish for each species.

Additional Variables and Additional Notes

To determine whether big fish size influenced small fish size, and whether small fish size had an effect on big fish size, the time-series for each respective size were included as target variables in the CCM analysis. The variable described as “Landings*Effort” consisted of the landings per quarter multiplied by the effort per quarter. This variable was included to capture how the combination of effort and landings may be important in understanding fish size dynamics. All variables received a right aligned 4-quarter moving average transformation followed by min-max normalization prior to performing CCM. All time-series plots shown here represent the data with this 4-quarter moving average applied, but not normalized.

Results

Correlation

A significant negative correlation over time with respect to the average size of the top ‘n’ largest fish of three species was identified. The three species are: grass rockfish, squarespot rockfish, and speckled rockfish. The data from the first three quarters are not included in the figures, as the right-aligned moving average method used causes the removal of this initial period. The results can be seen in Figure 3, where the data demonstrate a clear downward trend over time. This provides empirical evidence of size truncation for these fish species in Southern California throughout the study period. The following analyses further explore the potential drivers of these negative trends.

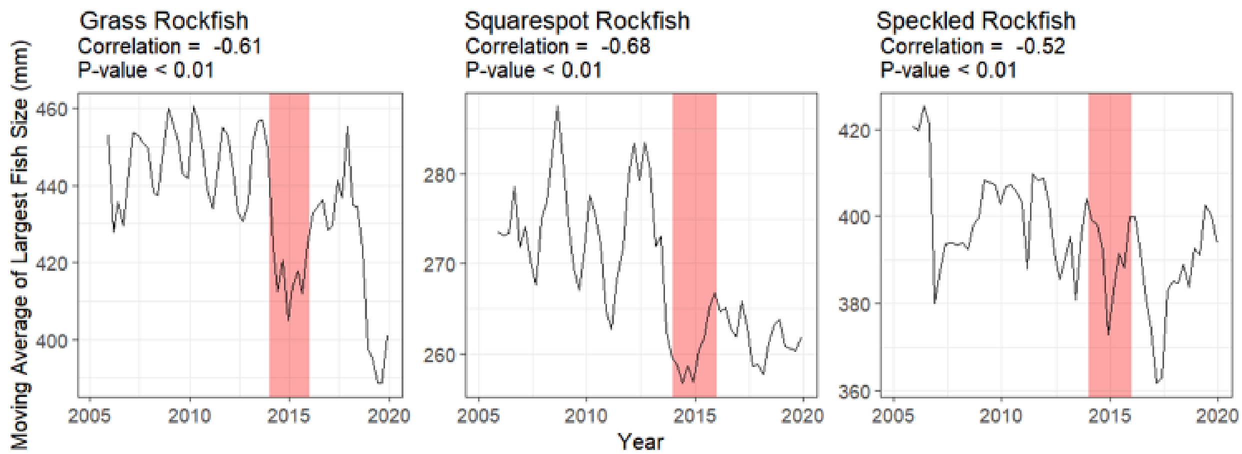


Figure 3 data from Pacific States Marine Fisheries Commission (n.d.). This figure shows the correlation of the yearly moving average of the top 'n' fish for the three species identified as having a negative correlation with time. The red highlights an extreme warm period in 2014 and 2015.

Independent Variables Versus Dependent Variables

Figure 4 shows moving averages of the largest 'n' fish for each species plotted against the independent variables used in this study.

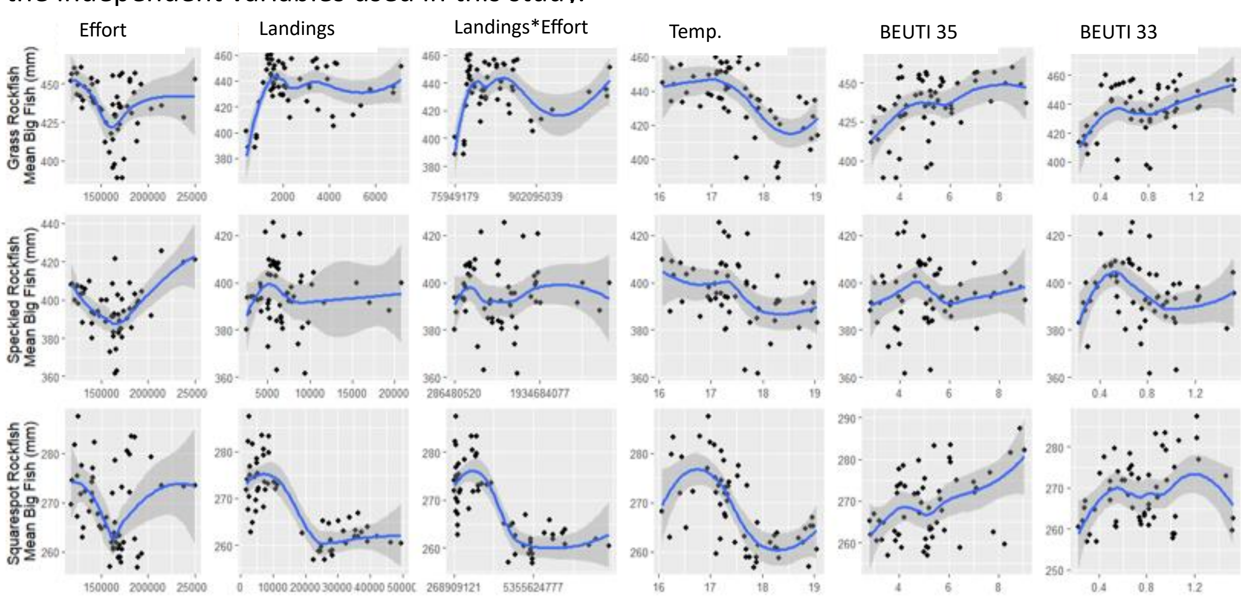


Figure 4. Image shows the moving average of the largest 'n' fish for each species per quarter plotted against the equivalent time series of each independent variable. A LOESS (Locally Estimated Scatterplot Smoothing) line is fit to the data within each plot for visualization purposes.

Together, these plots show the pervasive non-linearity in the dynamics between fish size, fishing, and environmental variables.

CCM

In this section, the term "effect" is exclusively used to refer to non-linear effects. The outcomes from Convergent Cross Mapping (CCM) analysis are presented in Figure 5. Two generalizations can be deduced from these figures:

1. Temperature consistently shows a more pronounced effect on small fish than on large fish across all three species.
2. Effort has a more significant impact on large fish than on small fish for all three species.

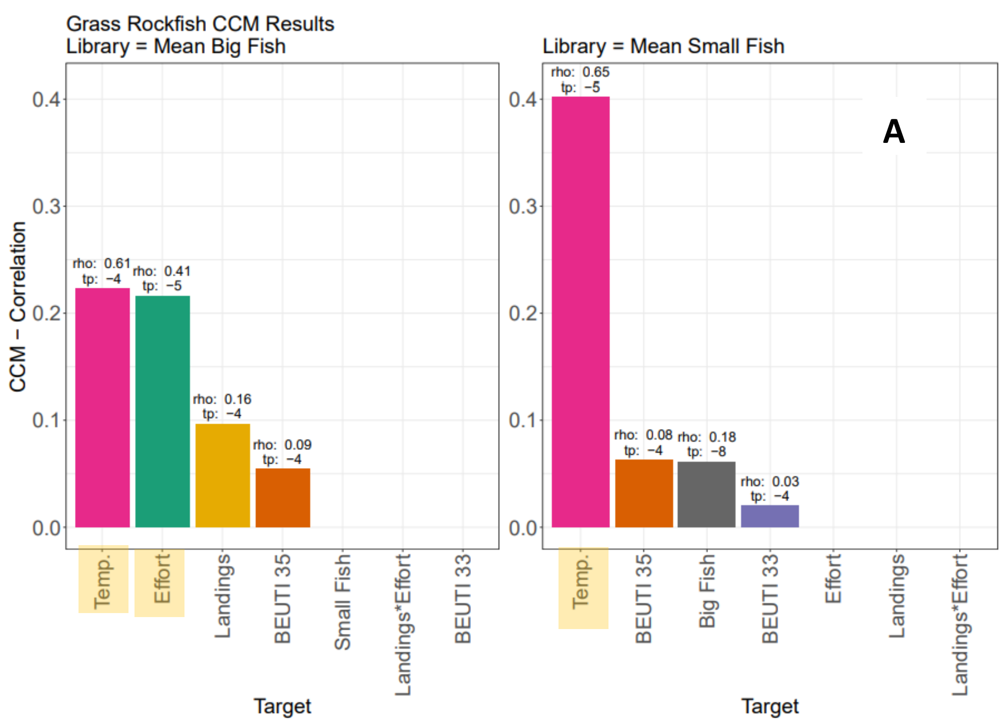
Further exploration of the predominant driver of big fish size for each species is discussed below.

Grass Rockfish

For this species, temperature appears as the most significant factor affecting both the small and large fish of this species. While it is possible that the influence of temperature on large fish is a transitive effect of the influence of temperature on small fish, this is unlikely given the insignificant effect of small fish on large fish. Furthermore, the time delay (tp) for the effect of temperature on large fish is -4, equating to a lag of one year. According to the Von Bertalanffy growth curve from Love & Johnson (1999), most of the grass rockfish in the large fish time-series used in this analysis are over ten years old, while the smaller ones are less than five years old. At the 4-quarter time delay, these two variables demonstrate a negative correlation of -0.38 (p-value < 0.01). The evidence that temperature produces the strongest effect on large fish size aligns with the results shown in Figure 3. In this figure, you can see that size is relatively stable until approximately 2014 when a large drop in size occurs.

Squarespot Rockfish

The top three driving variables for large squarespot rockfish are all fishing variables, with landings showing the strongest non-linear effect and a correlation of -0.65 (p-value < 0.01). The relationship between these two variables can be seen in Figure 6.



Speckled Rockfish

In the case of speckled rockfish, effort emerges as the primary driver of large fish size, with a tp of -8, corresponding to a lag of two years. Calculating age using the Von Bertalanffy growth function and growth parameters from FishBase (n.d.), it is estimated that the age of big speckled rockfish in this time series is generally greater than six years. The correlation between effort, lagged by eight quarters, and the size of large Speckled Rockfish is -0.2 (p-value~ 0.08).

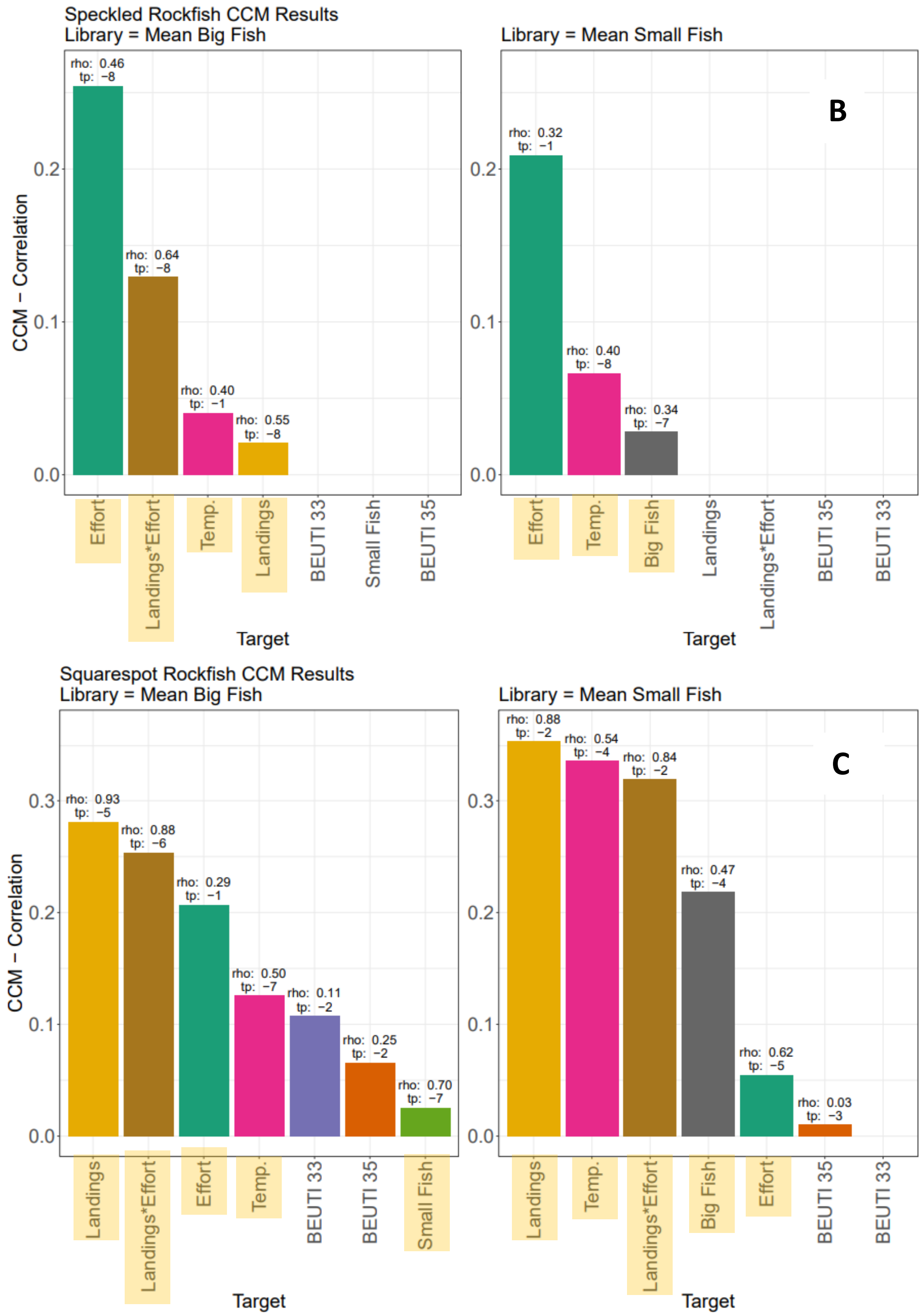


Figure 5. Image shows the results from the CCM analyses for (A) grass rockfish, (B) speckled rockfish and (C) squarespot rockfish. Plots on the left are the results when the library consists of the big fish time series. Plots on the right are the results when the library consist of the small fish time series. For each species/library combination, results are ranked from left to right in order of decreasing non-linear effects. Likely significant (rho > 0.20, degrees of freedom >47) results are highlighted in yellow.

Discussion

The history of groundfish in California has an important implication to this study. Since fishing was so heavy throughout the second half of the 20th century, and since fishing does not only remove biomass but also truncates the size structure of populations, it is likely that many groundfish (which make up most of the 15 species analyzed) populations have already experienced significant size truncation at the beginning of the CRFS dataset time period (Berkeley et al., 2004).

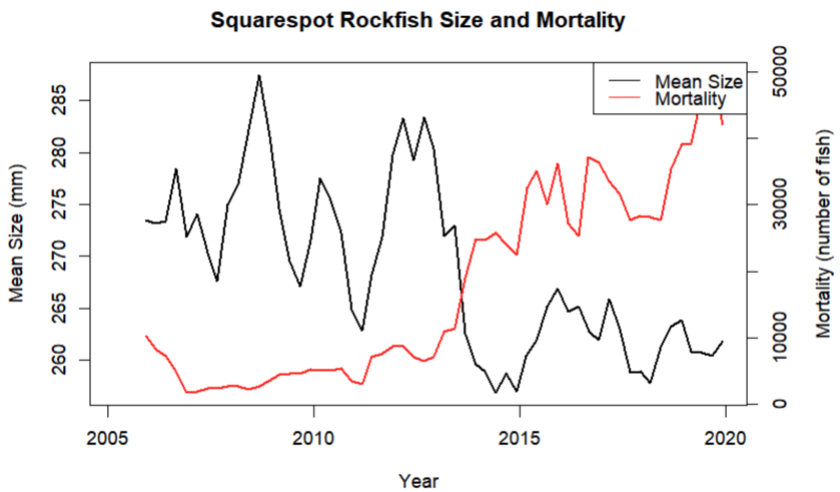


Figure 6. Image shows mortality and mean size of the big fish for squarespot rockfish plotted together.

The first generalization that can be made from the CCM results, which is that temperature displays a greater effect on small fish size than on large fish size, aligns with known biological information. This generalization is consistent with the idea that the recruitment of different species is greatly influenced by the environment (Hjort, 1914, 1926; Houde 1987; Sogard, 1997). The exact mechanism by which temperature is affecting the size of the largest fish during this time period is not apparent from this analysis. Some potential hypotheses include:

- Temperature has an effect on the catchability of large fish. Since all of these measurements come from fishery dependent surveys. The fish must have been caught in order to be measured. This means temperature could have simply reduced catchability. This could happen because fish move to regions where the temperature is more favorable, or because the eating habits of the fish change with temperature, making them more difficult to catch with recreational fishing methods.
- Growth rates of the different species are affected by temperature.
- Certain temperature ranges increase mortality of fish at different ages/sizes resulting in the removal of larger fish.

In addition to the hypotheses above, one more hypothesis can be added as to how temperature may affect small fish. As discussed in the introduction, a decrease in fish size may indicate recruitment. If the effect of temperature on small fish is being seen due to temperatures effect on biological processes prior to recruitment (i.e., survival or growth and not movement patterns), this indicates that temperature is important to recruitment. The second generalization made from the CCM results, that effort has a more significant impact on large fish than on small fish for all three species, makes sense because it is generally more difficult to catch large fish than small fish. Therefore, the more effort put into trying to catch fish, the more of a chance that large fish are going to be removed.

Implications, Limitations, and Future Research

Understanding size truncation in fisheries can help improve fishery management in various ways. This method of analyzing the effects of size on fish could help fishery managers by providing information on the factors that have the greatest impact on fish size (i.e., fishing effort, fishing mortality, or the combination of each). With proper time series, this method could be altered to determine which time periods of fishing have the greatest effect on fish size – which could help fishery managers to set time-based management measures.

The lack of understanding surrounding the mechanism underlying the relationship between temperature and fish size discussed above necessitates further study to better understand this dynamic. Size truncation in fisheries is typically thought to be caused by fishing. If a changing climate is leading to decreases in size of fish, this could be valuable information for fishery managers.

CCM does not directly inform the sign of effect of the target variable. And, in non-linear systems, effects can change based on the system state (Deyle et al., 2013). For this reason, direction of influence can be inferred through general understanding of ecological systems (i.e., it is unlikely that fishing effort is causing fish to grow larger), and through further evidence - for example in Figure 3. Any study is limited by the available data. This means that even though some of the independent variables used in this study were seen to show an effect on big and small fish sizes, there may be additional factors not considered. One example would be the effect of predation.

As discussed, using CCM to analyze the effects of environmental variables on small fish could be a way to identify drivers of fishery recruitment, because the size structure of the small fish in a population should greatly be influenced by recruitment. Because of this, with longer and more temporally resolved datasets, this method could be used to identify even more possible drivers of fishery recruitment.

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