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Stock Status and Management in Tuna Fisheries: from data-rich to data-poor

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Abstract

Stock Status and Management in Tuna Fisheries: from data-rich to data-poor

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Tunas and billfishes are large migratory species managed by Regional Fisheries Management Organizations (tRFMOs). The current status of these species is well known, and most of the large commercial tuna stocks are managed at sustainable levels. We found that most of the overfished tuna and billfish populations are showing signs of rebuilding as a consequence of the implementation of strong management measures such as fishing quotas. However, management performance among tRFMOs is highly variable among oceans and it is mainly correlated with the overall economic dependence of individual members of the tRFMOs on tuna fisheries. When countries with low governance capacity account for the greatest proportion of total tuna catches, management controls are, on average, harder to implement. On the other hand, some non-commercial valuable tuna stocks, such as mackerels and bonitos, managed under the umbrella of tRFMOs remain unassessed, mainly because of insufficient quantitative data, particularly total

catch. Preliminary assessments for these stocks based only on length composition data from the catch, showed that some of these stocks are experiencing overfishing. These results should encourage the management body in the Atlantic Ocean to take management actions to protect these stocks from overfishing as well as improve data collection programs. When comparing the performance of some length-based and catch-based data limited assessment methods, we found that in many cases, length-based assessments performed as well as other catch-based models. Nevertheless, the performance of different data-limited methods depended not only on the type of data available, but on prior knowledge about the exploitation history of the stock and the biology of each species. We hope that this dissertation helps to improve the current management system for data-rich tuna stocks by highlighting successful management strategies, as well as to improve the estimation of stock status for data-poor tuna fisheries.

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DEDICATION

To Makaira.

Introduction

The oceans have been subjected to intensive fishing pressure over the past century, with fisheries expanding from coastal to pelagic environments (Swartz *et al.* 2010). Today, fishing is one of the most extensive human activities affecting the world's oceans. The oceans provide food, employment and income for billions of people (FAO 2016; Hilborn and Costello 2018). The total capture production in 2014 was 81.5 million tons in the marine environment (FAO 2016) where the total catches of tuna and tuna like species were almost 7.7 million tons. Tuna and tuna like species provide considerable catches and income in both, developed and developing countries, and they vary in status from lightly exploited (e.g. skipjack tunas) to severely depleted (e.g. Pacific bluefin tuna) (Juan-Jordá *et al.* 2011; Pons *et al.* 2017).

Throughout the dissertation, the term tunas and tuna-like species includes several species from (1) the family Scombridae (comprising principal market tunas, small tunas, bonitos, and Spanish mackerels), (2) the family Istiophoridae (including marlins, spearfishes and sailfish) and (3) the family Xiphidae (including swordfish). The principal market tunas are Atlantic bluefin, southern bluefin, Pacific bluefin, bigeye, yellowfin, albacore, and skipjack. These species are caught together in multispecies fisheries in all world oceans.

Tunas and tuna-like species are a diverse group ranging in maximum sizes from 50 cm for bullet tuna to 500 cm for blue marlin. While some of them live up to 5 years (Atlantic bonito) others can live more than 50 (southern bluefin tuna). They are distributed worldwide from coastal to pelagic environments and most of them are highly migratory. Temperate tunas, move latitudinal from temperate feeding areas to tropical spawning areas (Sibert *et al.* 2006). Tropical tunas instead, stay in the tropical region performing longitudinal migrations. Also vertical migrations are very frequent in many tunas and tuna-like species; they can occupy different layers of the water column depending on ontogeny and species. The diversity of physiological and behavioral characteristics, combined with environmental conditions, constrain the vertical and horizontal distribution of tunas and their vulnerability to different fishing gears. For example, tunas that school, like skipjack, yellowfin and young southern bluefin, are mainly caught in purse seine fisheries (ISSF 2012), while adult bigeye tunas have the ability to spend more time below the thermocline (Brill *et al.* 2005) and are mainly caught using longlines.

Because tunas and tuna like species are highly migratory, data collection, scientific monitoring, conservation and management are accomplished by intergovernmental administrations called tuna Regional Fisheries Management Organizations (tRFMOs). There are five tRFMOs: the Commission for the Conservation of Southern Bluefin Tuna (CCSBT), the Inter-American Tropical Tuna Commission (IATTC), the International Commission for the Conservation of Atlantic Tunas (ICCAT), the Indian Ocean Tuna Commission (IOTC) and the Western and Central Pacific Fisheries Commission (WCPFC) (Figure 1).

Tuna RFMOs provide a formal mechanism for fishing countries and states to meet their international obligations to cooperate for the sustainability of shared highly migratory stocks throughout their distributions and to provide compatible measures in areas beyond national jurisdictions. However, due to the diversity of interests among countries involved, this management system is complex. Moreover, management and governance systems differ among and within these organizations adding even more complexity to the system.

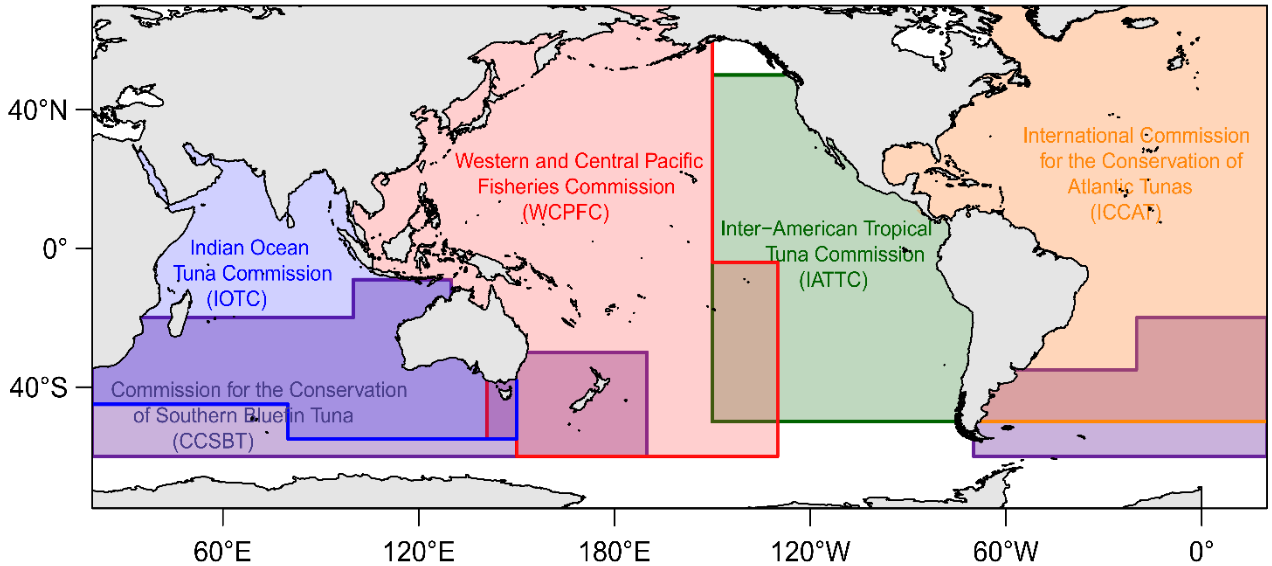

Figure 1. Areas governed by the five tuna Regional Fisheries Management Organizations (tRFMOs).

Fisheries management obliges scientists to determine the status of the stocks relative to limit and target reference points. This involves predicting and evaluating outcomes of management alternatives for reaching the targets while avoiding the limits and requires characterizing uncertainty (de Bruyn *et al.* 2013). Understanding the response of fishing pressure to conservation and management measures and effects on stock status is key to the successful management of these resources.

All tRFMOs have done a good job determining and documenting stock status (biomass and fishing mortality rate) of most of the principal market tunas and swordfish for years (i.e. 22 of 23 stocks of skipjack, yellowfin, albacore, bigeye and bluefin are quantitatively assessed). This is because they are commercially important and a lot of biological and fishery dependent information is available to assess these populations (they are “data-rich” stocks). However, some less important commercial species (e.g. some small tunas, mackerels and billfishes) still remain unassessed (Juan-Jordá *et al.* 2011; Pons *et al.* 2017). In general, this is because data are insufficient to apply conventional stock assessment methods (these are “data-poor” or “data-limited” stocks). In particular, catches are aggregated (spatially and temporally) in groups of different species whose life history parameters are poorly described and likely diverse. For some of them, length information is available and then assessments based in this data might be more reliable.

Assessment and management of tuna fisheries is challenging due to the diversity of life history strategies among species, differences in current stock status, the multispecies and multi-gear context of the fisheries, and the international framework in which they have to be studied, assessed, and managed. In this dissertation we tried to analyze some characteristics that determine stock status and successful management for tunas and tuna like species that have been previously assessed (data-rich stocks) and then we estimate the stock status for some of the tuna like species that have been not previously assessed (data-poor stocks).

The dissertation is structured in 4 chapters: (1) review of the current stock status of tuna and tuna like species worldwide, identifying which are the main factors that determine current stock status and which management measures promote the recovery of overexploited populations; (2) characterization of tRFMO governance systems regarding research, management and enforcement attributes, to explain differences in management among organizations and stocks; (3) estimation of current stock status for some unassessed scombrids in a multi-gear context when only length data are available; and (4) the evaluation of the performance a set of data-poor assessment methods when only one type of information is available (catch or length).

Chapter 1. EFFECTS OF BIOLOGICAL, ECONOMIC AND MANAGEMENT FACTORS ON TUNA AND BILLFISH STOCK STATUS

Abstract

Commercial tunas and billfishes (swordfish, marlins and sailfish) provide considerable catches and income in both developed and developing countries. These stocks vary in status from lightly exploited to rebuilding to severely depleted. Previous studies suggested that this variability could result from differences in life history characteristics and economic incentives, but differences in exploitation histories and management measures also have a strong effect on current stock status. Although the status (biomass and fishing mortality rate) of major tuna and billfish stocks is well documented, the effect of these diverse factors on current stock status and the effect of management measures in rebuilding stocks have not been analyzed at the global level. Here, we show that, particularly for tunas, stocks were more depleted if they had high commercial value, were long-lived species, had small pre-fishing biomass, and were subject to intense fishing pressure for a long time. In addition, implementing and enforcing total allowable catches (TACs) had the strongest positive influence on rebuilding overfished tuna and billfish stocks. Other control rules such as minimum size regulations or seasonal closures were also important in reducing fishing pressure, but stocks under TAC implementations showed the fastest increase of biomass. Lessons learned from this study can be applied in managing large industrial fisheries around the world. In particular, tuna regional fisheries management organizations should consider the relative effectiveness of management measures observed in this study for rebuilding depleted large pelagic stocks.

1.1 Introduction

The oceans have been subjected to intensive fishing pressure over the past 60 years, with fisheries expanding to new geographic areas, shifting from coastal to pelagic environments (Swartz et al. 2010). As a result, an estimated 28-33% of the large well-assessed fisheries of the world are overfished (Branch *et al.* 2011; FAO 2014), while many smaller unassessed fisheries in poorer countries are likely in worse shape (Costello *et al.* 2012). These depleted fisheries have negatively affected food security, fishing-dependent communities, and marine ecosystems globally (Scheffer *et al.* 2005).

Tunas and billfishes are important contributors to food security and income in both developed and developing countries and some of these stocks have experienced high exploitation rates for decades (Collette *et al.* 2011; Juan-Jordá *et al.* 2011; FAO 2014). While tunas and swordfish are the main target species of many fisheries, marlins are a common bycatch, particularly in commercial longline fisheries.

A substantial proportion of these stocks has been categorized as overfished (Restrepo *et al.* 2003; Collette *et al.* 2011; Juan-Jordá *et al.* 2011; Punt *et al.* 2015). In 2003, catch-per-unit-effort data were used to suggest that industrial fishing pressure had reduced the abundance of tunas and billfishes (and other ocean predators) by 90% from preindustrial levels (Myers and Worm 2003). More recent studies based on biomass trends estimated from stock assessment models found that tunas and their relatives had actually declined by an average of 60% from unfished levels (Juan-Jordá *et al.* 2011), for which most stocks were above the biomass level that would produce maximum sustainable yield (MSY), and only a few were fished intensively enough to be classified as experiencing overfishing (Hampton *et al.* 2005; Polacheck 2006; Sibert *et al.* 2006).

Although the status of tunas and billfishes is well documented in the literature, the factors that drive the current status of these stocks are often not jointly analyzed. For example, life history strategies can affect the probability of stock collapse of many fish species (Reynolds *et al.* 2005). Tunas and billfishes range from small tunas and marlins with rapid growth rates and short lifespans to big tunas and swordfish with larger body sizes and longer lifespans (Fromentin and Fonteneau 2001; Juan-Jordá *et al.* 2012). Some tuna studies suggest that attributes such as short life span, wide geographic distribution, and opportunistic behavior make tropical tunas more productive and less susceptible to collapse than temperate tunas (Majkowski 2007; Collette *et al.* 2011; Juan-Jordá *et al.* 2011). Also, Sadovy (2001) suggested that, in long-lived species, the probability of extinction is related to limited geographical range, being part of mixed-species fisheries, or being distributed mainly in areas of intense fishing activity.

Moreover, economic factors may be equally or more important in determining stock status. Fishery profits, and not the trophic levels and associated characteristics of the target species, were found to be the dominant driver of historical fishery development patterns in a study that covered a wide range of stocks (Sethi *et al.* 2010). High market values drive exploitation far below MSY biomass levels and have increased the risk of stock collapse (Collette *et al.* 2011). Notably, while Pacific bluefin tuna and albacore tuna are both temperate species, albacore is used mostly for the cheaper canned tuna market, while Pacific bluefin serves the high-end sashimi market (Majkowski 2007). It may therefore not be surprising that Pacific bluefin is overfished, while some albacore stocks are not.

In addition to life history and economic value, exploitation history and management measures drive the status of tuna and billfish resources. Exploitation history is an important factor affecting the conservation status of many exploited stocks (Melnychuk *et al.* 2013;

Neubauer *et al.* 2013) including tuna species. Atlantic bluefin tuna has been fished in the Mediterranean since the 7th century BC and reconstructed bluefin tuna trap catches date back to the 16th century (Fromentin and Powers 2005). On the other hand, skipjack and yellowfin tuna in the Indian Ocean were not targeted until the development of large-scale commercial purse-seine fisheries in the 1980s (Parks 1991), and these stocks are currently considered to be healthy (Juan-Jordá *et al.* 2011). In general, the development of commercial fisheries started earlier for species that were easily accessible, abundant and valuable and then expanded to less valuable species (Sethi *et al.* 2010).

We also expect that highly regulated stocks are those that have been experiencing overfishing, where strict management measures are placed to rebuild them, while stocks that lack strong regulations are more often not overexploited. As we mentioned before, Tuna and billfish stocks are managed by tRFMOs. International management has clearly failed to keep some bluefin tuna stocks near target reference points despite their high commercial value (Fromentin and Powers 2005; Worm *et al.* 2009), and the ability of tRFMOs to prevent stock depletion and overfishing has been questioned (Cullis-Suzuki and Pauly 2010). The exploitation history and management actions taken vary greatly by tRFMO, and this may have a strong impact on the status of tuna and billfish stocks (Parma *et al.* 2006). Many tRFMOs have implemented a variety of input (or effort) controls, while others have implemented also output (or quota) controls.

Although there has been considerable discussion about what elements are required for successful fisheries management (Hilborn 2007; Beddington *et al.* 2007), the effectiveness of specific management measures for tunas and billfishes has not been analyzed on a global scale. The purpose of this paper is two-fold: 1) to evaluate the effect of different factors (management measures, life-history, economic values or exploitation history) on the current biological status of major tuna and billfish stocks of the world; and 2) to identify which management measures have promoted the recovery of depleted stocks.

1.2 METHODS

In general, among tRFMOs, the stock status is summarized using two biological reference points, B/B_{MSY} (the current biomass, B, in relation to the B that produces MSY) and F/F_{MSY} (the current fishing mortality, F, in relation to the F that produces MSY). Thus, these reference points were considered in this study to define tuna and billfish stock status. Throughout the manuscript, we defined stocks as "overfished" if the biomass was reduced to a level less than what would provide MSY ($B<B_{\mathrm{MSY}}$) and "overfishing" if the stock is subjected to a fishing mortality rate greater than that expected to produce the MSY ($F>F_{\mathrm{MSY}}$). Stocks that had $B>B_{\mathrm{MSY}}$ and $F<F_{\mathrm{MSY}}$ were considered "healthy".

1.2.1 *Data*

Data used to assess the status of tunas and billfishes were obtained from stock assessment outputs compiled in the RAM Legacy Stock Assessment Database (Ricard *et al.* 2012). Most reference points time series available from assessments were current through 2012. We found data for 40 stocks of 13 species, 7 species of major commercial tunas and 6 species of billfishes (Appendix 1.1 and 1.2) from at least 48 stocks defined globally (Table 1.1).

Data for management variables were compiled from information available on the websites and reports of different tRFMOs and through personal communication with their staff. Only regulations that existed during the 5-10 year period leading up to the last stock assessment were considered for each stock, although in some cases new management measures are currently in place. Table 1.1 summarizes all management measures in place by stock and Appendix 1.3 lists the relevant web references.

1.2.2 *Effect of different factors on the current biological status of major tuna and billfish stocks*

To evaluate our first objective in analyzing which factors can predict the biological status of tuna and billfish stocks, we assessed the effect and importance of each predictor (Appendix 1.4) on the geometric mean of the last 10 years of each time series of the two stock performance measures considered (B/B_{MSY} and F/F_{MSY}) using a random forest analysis (Breiman 2001). This approach was used previously to analyze similar data (Melnychuk *et al.* 2013) and has been increasingly used in ecology and fisheries studies (Lennert-Cody and Berk 2007; Gutiérrez *et al.* 2011). The main advantages of this method are that the non-parametric approach does not assume any particular distribution of error, it allows the use of many predictors in relation to the total number of observations, and it allows for visualization of non-linear relationships. It is an ensemble method that aggregates *K* trees (forming the forest), each tree similar to ones constructed with CART (Classification and Regression Trees), and grown using a bootstrapped sample of the original data set. Each tree in the forest uses at each node only a number of variables randomly sampled as candidates from a subset of the explanatory variables (*mtry*), which in our case was equal to a third of the predictor variables (Liaw and Wiener 2002). To stabilize the mean square error, we used 10,000 trees. We used the 'randomForest' package (version 4.6-7) (Liaw and Wiener 2002) in R (version 3.0.1) (R Core Team 2014) for this analysis. We presented variable importance plots for both performance measures as the decrease in mean accuracy resulting from the removal of each variable, and presented partial dependence plots to show the effect of the main continuous predictors on the response variables (Liaw and

Wiener 2002). We showed the results of partial dependence plots for tunas and billfishes independently, to show differences between these taxonomic groups, as well as combined.

The predictors considered (Appendix 1.4) include:

1. Taxa (factor): consisting of two categories, tunas or billfishes.
2. Year of fishery development (continuous): defined as the first year in which the total catch reached 25% of the maximum historical catch for the full time series available since 1950. Those stocks with a maximum catch in 1950 were considered as developed in this year, although we know that some of them developed earlier (Sethi *et al.* 2010). Catch data do not necessarily include discards, unregulated artisanal catches or illegal, unreported and unregulated (IUU) catches.
3. Maximum sustainable yield (MSY, continuous): used on a log scale as a measure of the size of each stock.
4. Generation Time (GT, continuous): we used the values estimated by Collette *et al.* (2011) on a log scale as a biological predictor, because life history parameters such as growth, longevity and age of maturity are considered to be uncertain for most stocks of billfishes, if available (Kopf *et al.* 2009). In the supplemental material of Collette *et al.* (2011) there is a detailed explanation of how GT was calculated for each stock and/or species. The range of this variable is from 1 year for skipjack to 17.2 years for southern bluefin tuna (Appendix 1.5).
5. Market price (continuous): we obtained market price for tunas and billfishes from different sources. For all tunas stocks we used the data available in the FAO economic trade and markets database. However, for billfishes, detailed information by species was not available in this database. Therefore, US market price database for all billfish stocks was considered.

In all cases, we used the average price for the last 10 years, from 2003 to 2012. Prices range from \$0.96 dollars/kg for skipjack tuna to \$14.49 dollars/kg for Southern bluefin tuna (Appendix 1.6).

6. Number of countries fishing each stock (continuous): we considered the smallest number of countries that cumulatively reported more than 75% of the total catch during the past 10 years (2003-2012) as a measure of how the total catch for each stock is allocated among countries (Table 1.1).
7. Total allowable catch (TAC in years, continuous): this was used to take into account the number of years under TAC enforcement. We used a continuous variable ranging from 0 for stocks with no TACs to 31 for western Atlantic bluefin tuna. TACs have been set and enforced for almost all Atlantic tuna stocks and southern bluefin tuna, although for some of them there have been problems with underreporting of catches (Polacheck and Davies 2008; Polacheck 2012). A quota was implemented for white and blue marlins, as well as Pacific bluefin tuna in 2013, but we did not consider these species as having a quota in this study, since it is too early to see the effects of this measure on stock status (Table 1.1).
8. Input management measures were also considered (factor: presence/absence):
   a) seasonal closures, for specific areas and seasons;
   b) minimum size regulations, such as limits in captured length for some species;
   c) fishing capacity limits, for some stocks ICCAT refers to limits in the number of vessels that can be also interpreted as a limit in fishing capacity. The only tRFMO that specifically refers to 'non-increase or reduction in fishing effort' is the WCPFC, but this is measured as number of licenses authorized so, it can be interpreted also as limits in fishing capacity;

d) catch restrictions, caps in relation to some previous catch level, but not as a formal TAC derived from a stock assessment (i.e., catch should not exceed some average historical level).

Some of the stocks, such as the two stocks of Atlantic bluefin tuna, are currently under a formal rebuilding plan that includes at least one of these input measures or a combination of them. In addition, some of the management measures in place can affect several stocks. For example, seasonal closures of purse seine fisheries in the Atlantic Ocean for bigeye tuna also affect the yellowfin tuna stock (Table 1.1), In this case, both stocks were considered as having seasonal closures.

Before conducting random forest analyses, predictors were tested for collinearity using variance inflation factors (VIF) (Appendix 1.7). In addition, we presented in the main text the results from the average of the 10 years leading up to the last assessment for both performance measures (B/B_{MSY} and F/F_{MSY}). However, we also considered the last year assessed and a period of 5 years leading up to the last assessment for sensitivity analyses in the random forest analysis finding that the results were not sensitive to the period selected (Appendix 1.8).

1.2.3 *Effect of management regulations on depleted stocks*

The same type of statistical analysis was used to identify which management measures have the strongest effect on the recovery of previously depleted stocks. We selected those stocks that showed $B<B_{MSY}$ or $F>F_{MSY}$ ten years before the final assessment year. We used as a response variable the geometric mean of the annual rate of change of B and F during this period. We considered biomass levels increasing towards B_{MSY} and fishing mortality rates decreasing towards F_{MSY} as positive signs of stock rebuilding. The same input and output management measures as in the previous analysis were used as predictors.

We conducted two sensitivity analyses, one removing the bluefin tuna stock from the eastern Atlantic, since it is an outlier in the rate-of-change data (Appendix 1.9), and another one removing the western Atlantic bluefin tuna stock, since it has 31 years of TAC implementation and could bias the results. In terms of variable importance, removing these data did not change the main results observed using the complete dataset (Appendix 1.10).

1.3 Results and Discussion

We collected stock assessment information for 22 tunas and 18 billfish stocks covering all oceans (Figure 1.1). There are still some billfishes, such as longbill, Mediterranean, roundscale and shortbill spearfishes, that remain unassessed because they are not commercially important species. These species cannot easily be assessed, since their catch statistics are generally aggregated with other species (Punt *et al.* 2015).

Tuna catches increased steadily from 1950–2000 and then stabilized in the last 10 years (Figure 1.2.a), with greatest catches coming from skipjack, particularly from the Western and Central Pacific Ocean, followed by yellowfin, bigeye, albacore, and bluefin. Billfish catches also increased before declining in recent years (Figure 1.2.b). The most important billfish stock by volume during the 1950-1960s was Pacific blue marlin, while swordfish presently dominate catches in all oceans. However, it should be noted that, because most marlin and sailfish stocks are overexploited, some of these stocks can no longer be retained, and some artisanal catches remain under- or unreported.

In general, tunas have sustainable biomass and fishing mortality rates, with a median B/B_{MSY} of 1.12 and F/F_{MSY} of 0.81 (Figure 1.2.c). Bluefin tuna in the western Atlantic and southern bluefin tuna are not showing signs of overfishing ($F<F_{\mathrm{MSY}}$), but they are still overfished ($B<B_{\mathrm{MSY}}$) due to past overexploitation. Pacific bluefin tuna and bigeye tuna in the West and

Central Pacific Ocean are still experiencing overfishing with mortality rates exceeding 1.5 F_{MSY} (Figure 1.2.c), although substantial management measures have recently been adopted for Pacific Bluefin (ISC 2014b). Overall, 64% of tuna stocks have healthy biomass levels, with B above B_{MSY}.

Billfishes are in slightly worse shape than tunas (Figure 1.2.d), with a median B/B_{MSY} of 0.85 and F/F_{MSY} of 1.01. Sailfish in the eastern and western Atlantic Ocean, and Atlantic blue marlin, are experiencing the highest exploitation rates (with $F>1.5F_{MSY}$), while swordfish in the eastern Pacific and Indian Ocean are above target biomass levels (Figure 1.2.d). For billfishes, only 39% have healthy biomass levels and 22% are still experiencing overfishing.

Overall, most tunas and billfish stocks are in healthy conditions, neither overfished nor subject to excessive fishing pressure. However, 23% of tunas and billfish stocks are still experiencing overfishing and the four stocks of most concern are both heavily depleted ($B<0.5$ B_{MSY}) and have high fishing mortality rates ($F>F_{MSY}$). These stocks are Pacific bluefin tuna, eastern and western Atlantic sailfish, and Atlantic blue marlin.

1.3.1 *Effect of different factors on the current biological status of major tuna and billfish stocks.*

In general, the status of tuna and billfish stocks is the product of diverse exploitation histories, biological characteristics, economic incentives, and management strategies (Figure 1.3). The most important predictor variables affecting both performance measures were MSY and market price. The year of fishery development also affected the F/F_{MSY} ratio and the implementation of quotas the B/B_{MSY} ratio (Figure 1.3). Overall, depletion was greater for less abundant and highly marketable stocks that were subjected to intense fishing pressure for a long time. For both tunas and billfishes, larger stocks had higher values of B/B_{MSY} and lower values of

F/F_{MSY} than smaller stocks. Later-developing fisheries had lower values of F/F_{MSY} than earlier-developing fisheries and although not significant, higher values of B/B_{MSY} (Figure 1.4). The same pattern was observed in the western north American groundfish fisheries (Melnychuk *et al.* 2013).

Tunas and billfishes showed opposite influences of GT and market price. For tunas, higher market price and longer GT were associated with higher rates of overfishing (higher F/F_{MSY}). Regarding the trends in biomass, a lower B/B_{MSY} was observed for highly valuable tunas, however, the trend for GT was not as clear (Figure 1.4). On the contrary, for billfishes, lower market price and shorter GT were associated with higher F/F_{MSY} and lower B/B_{MSY} (Figure 1.4). These differences could be because billfishes, except for swordfish, are typically bycatch species and not primary targets of industrial tuna fisheries, and therefore might not respond in the same way to market price (Gentner 2007). In addition, marlins have shorter GT compared to swordfish and nevertheless they showed higher fishing pressure. This is probably not associated directly to GT but to the fact that marlins have a more restricted distribution, with much smaller population sizes by far smaller than swordfish and can endure lower fishing mortality. Also, unlike on land, Pinsky *et al.* (2011) suggested that long-lived marine fish species have a lower probability of collapse than short-lived species, although there are certainly exceptions to this overall pattern.

1.3.2 *Effect of management regulations on depleted stocks.*

Twelve stocks (30%) had no management measures in place in the last 10 year period (Table 1.1). The other 28 stocks had at least one management measure in place during the past 10 years. Most of these 28 stocks are under input management measures to control fishing mortality, such as seasonal closures, minimum size regulations, input limitations on catch and/or fishing capacity. Only eight stocks have a formal TAC and, except for southern bluefin tuna, all of the stocks are managed by ICCAT (Table 1.1).

Fisheries under different types of management differed in status: TAC-managed fisheries had low biomass and high fishing mortality; input-controlled fisheries had a wide range of biomass and fishing mortality; and those with no management measures generally had high biomass and low mortality rates (Figure 1.5.a-b). Notably, TACs generally have been implemented on less abundant stocks that are already overfished (Figure 1.5.a-b). For example, the eastern and western stocks of Atlantic bluefin tuna have been managed with TACs for 15 and >30 years, respectively. However, the effect of the TAC implementation on these stocks could be more recent because ICCAT did not follow the scientific advice at the beginning and recommended catches that exceeded the scientific recommendations (Fromentin *et al.* 2014). When we take a look at the rate of change over the last 10 years, the biomass of TAC-managed stocks is increasing, and fishing mortality is declining, unlike those managed by input controls or with no controls (Figure 1.5.c-d).

Using a random forest analysis, we identified management measures influencing the recovery of stocks that were below B_{MSY} (17 stocks) or were experiencing fishing mortality above F_{MSY} (19 stocks) 10 years before the last assessment. We found that previously-depleted tuna and billfish stocks that were under some type of management measure showed improvements over the 10-year period leading up to the last stock assessment, with biomass increasing and fishing mortality decreasing over time (Appendix 1.8). Of all management measures considered, the number of years since TAC implementation had the strongest effect on stock rebuilding, especially on increasing biomass, but also to some extent on decreasing fishing mortality (Figure 1.6), as expected from other studies showing the impact of catch limits

(Melnychuk *et al.* 2012; Neubauer *et al.* 2013; Hilborn and Ovando 2014). Although not possible to determine from our analyses, the success of quotas over other management measures may simply be that quotas result from a more serious effort to manage a stock. While TACs were most important in rebuilding biomass, and did decrease fishing mortality, input management measures such as minimum size regulations and seasonal closures were also important in reducing fishing mortality (Figure 1.6), as was suggested particularly for the eastern Atlantic bluefin tuna stock (Fromentin *et al.* 2014). In particular for IOTC stocks, one possible confounding effect regarding the reduction in fishing mortality could be associated with Somali piracy in the Western Indian Ocean starting ~2007 (Dueri *et al.* 2014). This could be considered as a controversial spatial closure that it was not taken into account in this study.

We plotted changes in status for stocks that were below target reference levels ($B<B_{MSY}$ and $F>F_{MSY}$) 10 years before the last assessment, highlighting stocks with and without TACs (Figure 1.7) to show the change in status. Stocks with TACs showed a decrease in fishing mortality (arrows moving from the upper left to the lower left quadrant) and an increase in biomass (arrows moving from the left to the right) (Figure 1.7). This is a clear signal of rebuilding; fishing mortality is reduced and thus biomass increases. Although fishing mortality was reduced for most stocks without TACs, most of these stocks still show a decrease in biomass, consistent with the results from the random forest analysis (Figure 1.6).

Only ICCAT and CCSBT have applied TACs for regionally-managed tuna and billfish stocks. National TACs have been proposed as a possible method to harvest resources in the Eastern Pacific Ocean, but there is a debate among IATTC scientists and managers about how such a quota should be allocated. This tRFMO faces different obstacles to the adoption of allocation systems for tropical tuna fisheries because of the lack of clarity regarding which criteria to apply for assigning fishing rights in light of the considerable heterogeneity of the participants in the fishery (Allen 2010). However, IATTC implemented a TAC of 5,000 t for Pacific bluefin tuna in 2014, although the success of this measure remains to be seen. ICCAT also implemented quotas on yellowfin tuna and blue and white marlin in 2012 (Table 1.1).

Input management measures are relatively easy to implement, but difficult to enforce without an appropriate monitoring and surveillance system (Cochrane and Garcia 2009). Also, effort regulations can be affected by “effort creep” and uncertainty in the relationship between fishing effort and fishing mortality (Punt and Donovan 2007). We know that TACs can also be circumvented by underreporting or illegal fishing, if they are not effectively enforced by authorities. Catches reported to tRFMOs that applied TACs seldom exceed target TACs (Fromentin *et al.* 2014). However, ICCAT has suggested that bluefin catches from the eastern Atlantic and Mediterranean were seriously underreported from 1998 to 2007 and the CCSBT has found evidence that Southern bluefin catches may have been substantially underreported since at least the early 1990s (Polacheck 2012). The latest Atlantic bluefin tuna stock assessments took underreporting into account, and underreporting is thought to have declined in recent years in these fisheries (ICCAT 2015a).

Lessons learned from managing tuna and billfish can be applied to manage other large industrial fisheries. Large targeted stocks that receive direct management attention are generally better managed than small stocks that are caught incidentally, like marlins and sailfish. When fisheries management is weak, high-value species such as bluefin and bigeye tuna are the most likely to be overexploited. Strong management measures such as TACs could prevent the overexploitation of these species, but TACs have not typically been applied until stocks are heavily overfished (Figure 1.5.a). On the other hand, TACs alone are, in some cases, insufficient to ensure sustainable fisheries. For example, overexploitation of bigeye tuna is in part due to the bycatch of small individuals by purse seiners targeting other tuna species, i.e., skipjack and yellowfin. So, other management measures such as seasonal closures or minimum size regulations are also needed to protect this part of the population and avoid overfishing.

Can these lessons about tuna be applied elsewhere? In many regions and fisheries, TACs are not easy to apply, particularly where fleets are small, diverse, and target a range of species. In such fisheries, other management tools may be more appropriate (Worm *et al.* 2009; Gutiérrez *et al.* 2011). Input controls, for instance, may have a higher probability of being accepted by the fishing industry. Nevertheless, where applicable, TACs should be considered as a primary tool for managing depleted stocks as they could lead to faster stock rebuilding. This can be explore using approaches like Management Strategy Evaluation (MSE) to examine both input (effort) and output (catch quota) controls in each fishery (Carruthers *et al.* 2014).

Acknowledgments

This chapter was funded by the Pelagic Fisheries Research Program of the Joint Institute for Marine and Atmospheric Research, and the Walton Family Foundation. I was also supported by a Fulbright Fellowship during the development of this chapter. We thank Carolina Minte-Vera and Alexandre Da-Silva for making some of the IATTC stock assessment data available to update the RAM Legacy database. Also, we thank Tom Nishida, Freddy Arocha, Adam Langley, Dale Kolody, Alec MacCall, Steven Teo and Michael Hinton for their comments during the design of the study, and Wataru Tanoue and Andrés Domingo for their comments on the initial draft of the manuscript.

1.4 TABLES

Table 1.1. Stock status (B/B_{MSY} and F/F_{MSY}) of tuna and billfish stocks assessed up to December 2014

Species	Ocean	tRFMO	Stock common name	Code	B/B_{MSY}	F/F_{MSY}	Reference
TUNAS							
Katsuwonus pelamis	Pacific	WCPFC	Skipjack tuna Central Western Pacific	SKJ-WCPO	1.71	0.62	(Rice *et al.* 2014)
	Atlantic	ICCAT	Skipjack tuna Eastern Atlantic	SKJ-E-AO	1.708	0.27	(ICCAT 2009a)
	Indian	IOTC	Skipjack tuna Indian Ocean	SKJ-IO	1.15	0.62	(Sharma and Herrera 2014b)
	Atlantic	ICCAT	Skipjack tuna Western Atlantic	SKJ-W-AO	1.31	0.83	(ICCAT 2015b)
	Pacific	IATTC	Skipjack tuna Eastern Pacific Ocean	SKJ-EPO	No reference points		(Maunder 2011)
Thunnus alalunga	Indian	IOTC	Albacore tuna Indian Ocean	ALB-IO	1.08	0.69	(Hoyle *et al.* 2014)
	Atlantic	ICCAT	Albacore tuna Mediterranean	ALB-MED	1.91	0.99	(ICCAT 2012b)
	Atlantic	ICCAT	Albacore tuna North Atlantic	ALB-N-AO	0.76	0.75	(ICCAT 2014b)
	Pacific	WCPFC-IATTC	Albacore tuna North Pacific	ALB-N-PO	2.21	0.52	(ISC 2014c)
	Atlantic	ICCAT	Albacore tuna South Atlantic	ALB-S-AO	0.84	1.09	(ICCAT 2014b)
	Pacific	WCPFC	Albacore tuna South Pacific Ocean	ALB-S-PO	2.6	0.21	(Hoyle *et al.* 2012)
Thunnus albacares	Atlantic	ICCAT	Yellowfin tuna Atlantic	YFT-AO	0.67	1.15	(ICCAT 2012c)
	Pacific	WCPFC	Yellowfin tuna Central Western Pacific	YFT-WCPO	1.37	0.72	(Davies *et al.* 2014)
	Pacific	IATTC	Yellowfin tuna Eastern Pacific	YFT-EPO	0.85	0.99	(Minte-Vera *et al.* 2014)
	Indian	IOTC	Yellowfin tuna Indian Ocean	YFT-IO	1.15	0.61	(Lee *et al.* 2013b)
Thunnus maccoyii	Indian	CCSBT	Southern bluefin tuna	SBT	0.23	0.76	(CCSBT 2014)
Thunnus obesus	Atlantic	ICCAT	Bigeye tuna Atlantic	BET-AO	1.01	0.95	(ICCAT 2010b)
	Pacific	IATTC	Bigeye tuna Eastern Pacific	BET-EPO	1.05	0.95	(Aires-da-Silva and Maunder 2014)
	Indian	IOTC	Bigeye tuna Indian Ocean	BET-IO	1.20	0.79	(Langley *et al.* 2013)
	Pacific	WCPFC	Bigeye tuna Western Pacific Ocean	BET-WCPO	0.94	1.57	(Harley *et al.* 2014b)
Thunnus orientalis	Pacific	WCPFC-IATTC	Pacific bluefin tuna Pacific Ocean	PBF	0.42	2.72	(ISC 2014b)
Thunnus thynnus	Atlantic	ICCAT	Bluefin tuna Eastern Atlantic	BFT-E-AO	1.73	0.24	(ICCAT 2015a)
	Atlantic	ICCAT	Bluefin tuna Western Atlantic	BFT-W-AO	0.48	0.85	(ICCAT 2015a)
BILLFISHES							
Xiphias galdius	Pacific	IATTC	Swordfish South Eastern Pacific	SWO-EPO	8.96	0.06	(Hinton and Maunder 2011b)
	Indian	IOTC	Swordfish Indian Ocean	SWO-IO	1.81	0.70	(Sharma and Herrera 2014a)
	Atlantic	ICCAT	Swordfish Mediterranean Sea	SWO-MED	0.96	0.89	(ICCAT 2011b)
	Atlantic	ICCAT	Swordfish North Atlantic	SWO-N-AO	1.14	0.81	(ICCAT 2014a)

	Pacific	WCPFC-IATTC	Swordfish North Pacific	SWO-N-PO	1.2	0.58	(ISC 2014a)
	Atlantic	ICCAT	Swordfish South Atlantic	SWO-S-AO	0.98	0.84	(ICCAT 2014a)
	Pacific	WCPFC	Swordfish South-West Pacific	SWO-SWPO	1.52	0.40	(Davies *et al.* 2013)
Istiophorus albicans	Atlantic	ICCAT	Sailfish Eastern Atlantic	SAI-E-AO	0.26	3.08	(ICCAT 2010a)
	Atlantic	ICCAT	Sailfish Western Atlantic	SAI-W-AO	0.28	2.20	(ICCAT 2010a)
	Indian	IOTC	Indo-Pacific sailfish Indian Ocean	SFA-IO	Not assessed		-----
Istiophorus platypterus	Pacific	IATTC	Indo-Pacific sailfish Pacific Ocean	SFA-PO	No reference points		(Hinton and Maunder 2011a)
Istiompax indica	Indian	IOTC	Black marlin Indian Ocean	BLM-IO	1.17	1.03	(Sharma 2013)
	Pacific	WCPFC	Black marlin Western Pacific	BLM-WCPO	Not assessed		-----
Makaira nigricans	Atlantic	ICCAT	Blue marlin Atlantic	BUM-AO	0.52	2.19	(ICCAT 2012a)
	Indian	IOTC	Blue marlin Indian Ocean	BUM-IO	1.03	1.05	(Sharma 2013)
	Pacific	WCPFC-IATTC	Blue marlin Pacific Ocean	BUM-PO	1.29	0.72	(ISC 2013)
Kajikia albidus	Atlantic	ICCAT	White marlin Atlantic	WHM	0.40	0.84	(ICCAT 2013)
Kajikia audax	Indian	IOTC	Striped marlin Indian Ocean	MLS-IO	0.52	1.12	(Sharma 2013)
	Pacific	IATTC	Striped marlin Northeast Pacific	MLS-EPO	1.52	0.08	(Hinton and Maunder 2010)
	Pacific	WCPFC	Striped marlin Southwest Pacific Ocean	MLS-SWPO	0.83	0.81	(Davies *et al.* 2012)
	Pacific	WCPFC	Striped marlin Western and Central North Pacific	MLS-WCPO	0.35	1.24	(Lee *et al.* 2013a)
Tetrapturus angustirostris	Indo-Pacific	IOTC	Indo-Pacific Shortbill spearfish	SSP	Not assessed		-----
Tetrapturus belone	Atlantic	ICCAT	Mediterranean spearfish	MSP	Not assessed		-----
Tetrapturus georgii	Atlantic	ICCAT	Roundscale spearfish	RSP	Not assessed		-----
Tetrapturus pfluegeri	Atlantic	ICCAT	Longbill spearfish	SPF	Not assessed		-----

Table 1.2. Summary of management measures by stock. The stock codes are listed in Table 1.1.

Code	Year of fishery development	# Countries reporting >75% catches	Year of formal TAC Implementation	Seasonal closures	Catch restrictions, other than TACs	Minimum size regulations	Fishing capacity limits	Description	Reference to Table 1.3 in the Appendix section
SBT	1957	3	2006	No	No	No	No	Although voluntary quotas were put in place in 1985 by the main fishing countries at the time, the first global TACs including all current CCSBT members was agreed in 2007. However, starting in 2006 more effective TAC compliance measures were implemented. In 2011 CCSBT adopted a formal rebuilding plan for SBT.*	1
BET-EPO	1961	19	No quota	Yes	No	No	Yes	IATTC C-02-03, reduction in fishing capacity in purse-seine fisheries; C-02-04,C-03-12,C-04-09, C-10-01, A seasonal closure of the purse seine fishery in an area known as "El Corralito", near Galapagos. C-13-01, annual catch limits. *	2-7
MLS-EPO	1962	16	No quota	No	No	No	No	No management measures in effect.	
SWO-EPO	1987	18	No quota	No	No	No	No	No management measures in effect	
YFT-EPO	1950	19	No quota	Yes	No	No	Yes	IATTC C-02-03, reduction in fishing capacity in purse-seine fisheries; C-02-04,C-03-12,C-04-09, C-10-01, A seasonal closure of the purse seine fishery in an area known as "El Corralito", near Galapagos.	2-6
ALB-MED	1984	11	No quota	No	No	No	No	No management measures in effect.	
ALB-N-AO	1950	30	2001	No	No	No	Yes	ICCAT Rec. 98-08, limits on number of fishing vessels to 1993-1995 average.	8
ALB-S-AO	1960	24	1998	No	No	No	No	No other management measures in effect rather than TAC.	
BET-AO	1965	42	2005	Yes	No	No	Yes	ICCAT Rec. 09-01, Rec. 06-01, limits on numbers of fishing vessels less than average 1991-1992; limits of number of longline and purse seine boats for some countries; ICCAT Rec. 04-01, No purse seine and baitboat fishing during November in the area encompassed by 0º-5ºN and 10ºW-20ºW.	9-11

BUM-AO	1960	32	2013 *	No	Yes	Yes	No	ICCAT Rec. 02-13, stock under a formal rebuilding plan since 2003, which includes minimum size regulation for recreational fisheries and catch limits.	12
BFT-E-AO	1950	23	1999	Yes	No	Yes	Yes	Formal Rebuilding plan since 2007; Rec. 06-05, Rec. 08-05, Rec. 13-08, which includes minimum size regulation, and limits in fishing capacity; Rec. 09-06, calls for a seasonal closure for purse seiners in the eastern Atlantic and Mediterranean between May 15 and June 15.	13-16
BFT-W-AO	1962	9	1982	Yes	No	Yes	Yes	ICCAT Rec. 98-07, Rec. 13-09, formal Rebuilding plan since 1999, with minimum regulation sizes and limits in fishing capacity. ICCAT Rec. 06-06: no directed fishery on bluefin tuna in spawning areas such as the Gulf of Mexico.	17-19
SAI-E-AO	1974	20	No quota	No	No	No	No	No management measures in effect.	
SAI-W-AO	1964	19	No quota	No	No	No	No	No management measures in effect.	
SKJ-E-AO	1970	27	No quota	Yes	No	No	No	ICCAT Rec. 04-01, no purse seine and baitboat fishing during November in the area encompassed by 0º-5ºN and 10ºW-20ºW.	11
SKJ-W-AO	1980	21	No quota	No	No	No	No	No management measures in effect.	
SWO-MED	1972	14	No quota	No	No	Yes	No	ICCAT Rec. 03-04, reduction of juvenile swordfish mortality and driftnet ban.	20
SWO-N-AO	1959	30	1997	No	No	Yes	No	ICCAT Rec. 01-04, Rec. 06-02, Rec. 11-02, Formal Rebuilding Plan since 1999, including minimum size regulations and TAC.	21-23
SWO-S-AO	1970	22	1998	No	No	Yes	No	ICCAT Rec 01-04. Minimum size regulations.	21
WHM	1962	24	2013 *	No	Yes	Yes	No	ICCAT Rec. 02-13, stock under a formal rebuilding plan since 2003, which includes minimum size regulation for recreational fisheries and catch limits.	12
YFT-AO	1959	49	2013 *	Yes	No	No	Yes	ICCAT Rec. 09-01, Rec. 06-01, Limits on numbers of fishing vessels less than average 1991-1992; limits of number of longline and purse seine boats for some countries; ICCAT Rec. 04-01, No purse seine and baitboat fishing during November in the area	9-11

								encompassed by 0º-5ºN and 10ºW-20ºW.	
ALB-IO	1959	30	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
BET-IO	1975	33	No quota	No	Yes	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 05-01. Catch limits. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-26
BUM-IO	1983	25	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
SKJ-IO	1956	33	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
MLS-IO	1985	25	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
SWO-IO	1956	30	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
YFT-IO	1992	39	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
ALB-N-PO	1985	15	No quota	No	No	No	Yes	WCPFC CMM 2005-03 and IATTC C-05-02 called for members not to increase fishing effort directed at North Albacore.	27-28
ALB-S-PO	1950	25	No quota	No	No	No	Yes	WCPFC CMM 2005-02, no increase of number of vessels south of 20S from 2000-2004 levels.	29
BET-WCPO	1960	35	No quota	No	Yes	No	Yes	WCPFC CMM-2005-01, CMM-2008-01, catch limits and reduction of fishing effort. Also, CMM-2013-01, calls for a 3 months (July, August and September) prohibition of setting on FADs for all purse seine vessels. *	30-31
BUM-PO	1957	35	No quota	No	No	No	No	No management measures in effect	

PBF	1953	5	2014 *	No	No	No	No	CMM 2009-07, total fishing effort in the area north of the 20 degrees north shall not be increased from the 2002-2004 level for 2010*; IATTC C-13-02, implementation of TAC. *	32-33
SKJ-WCPO	1952	35	No quota	No	No	No	No	No management measures in effect.	
MLS-SWPO	1978	25	No quota	No	No	No	Yes	CMM-2006-04, shall limit the number of their fishing vessels fishing for striped marlin in the Convention Area south of 150º S, to the number in any one year between the period 2000-2004.	34
MLS-WCPO	1954	35	No quota	No	No	No	No	CMM 2010-01, total catch of North Pacific Striped Marlin will be subject to a phased reduction such that by 1 January 2013 the catch is 80% of the levels caught in 2000 to 2003. *	35
SWO-N-PO	1951	15	No quota	No	No	No	No	No management measures in effect.	
YFT-WCPO	1952	35	No quota	No	Yes	No	Yes	WCPFC CMM-2005-01, CMM-2008-01, catch limits and reduction of fishing effort. Also, CMM-2013-01, calls for a 3 months (July, August and September) prohibition of setting on FADs for all purse seine vessels. *	30-31
BLM-IO	1977	25	No quota	No	No	No	Yes	IOTC CMM. 12-11: limits in fishing capacity. CMM. 12-13, one-month closure for purse seiners and longliners in an area of size 10x20. *	24-25
SWO-SWPO	1988	18	No quota	No	No	No	No	No management measures in effect	

* Management measures in effect in recent years (less than 5 years from the last assessment); it is too early to see the effects.

1.5 FIGURES

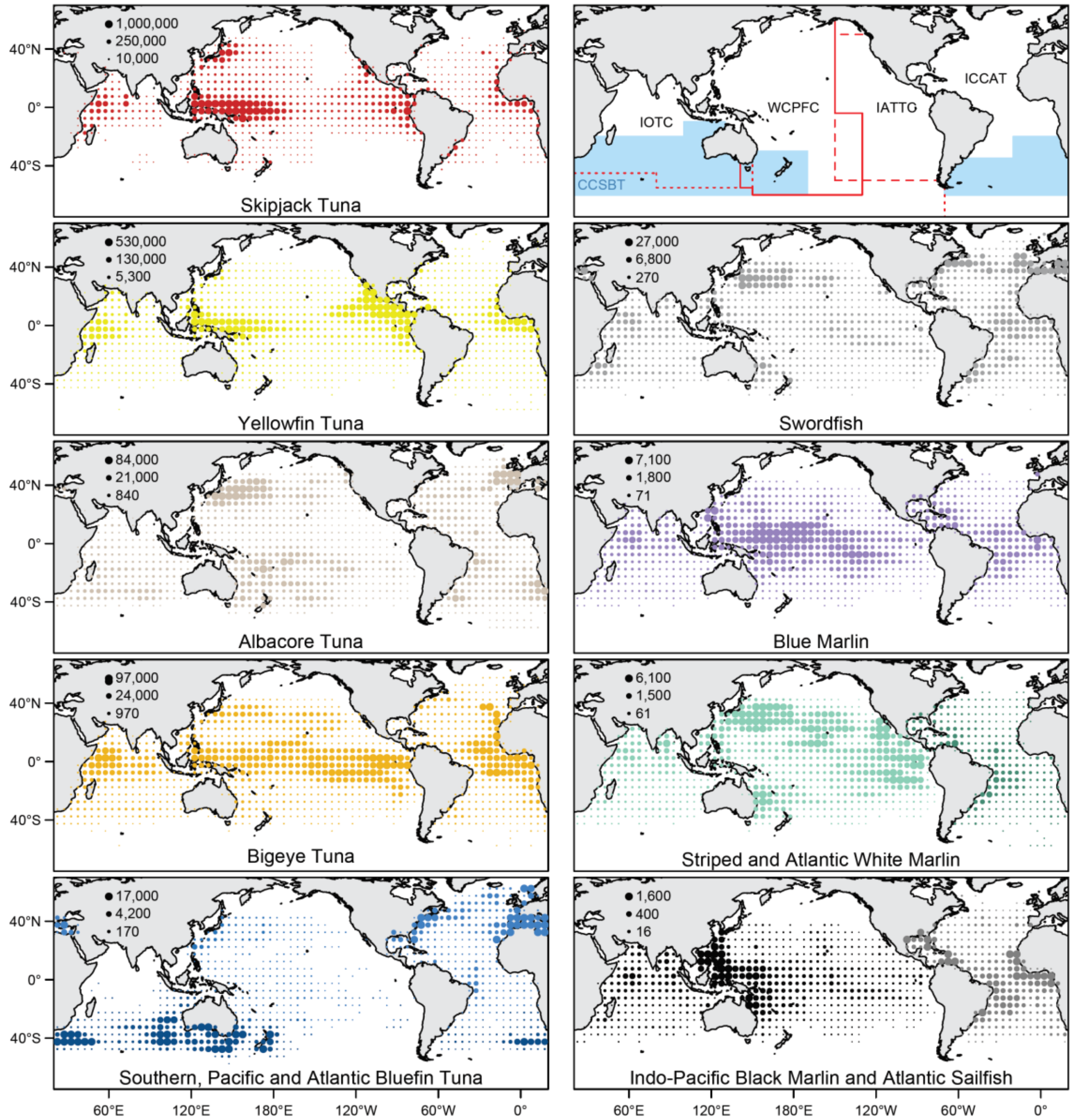

Figure 1.1. Geographical patterns of total cumulative catch (1950-2012) in tones by 5×5° of major tuna and billfish species. Within each panel, different color shading is used to represent individual species. The top right panel shows the areas governed by the five tuna regional fisheries management organizations: ICCAT= International Commission for the Conservation of Atlantic Tunas; IOTC= Indian Ocean Tuna Commission; IATTC= Inter-American Tropical Tuna Commission (dashed red lines); WCPFC= Western and Central Pacific Fisheries Commission (solid red line); and CCSBT= Commission for the Conservation of Southern Bluefin Tuna (blue shading).

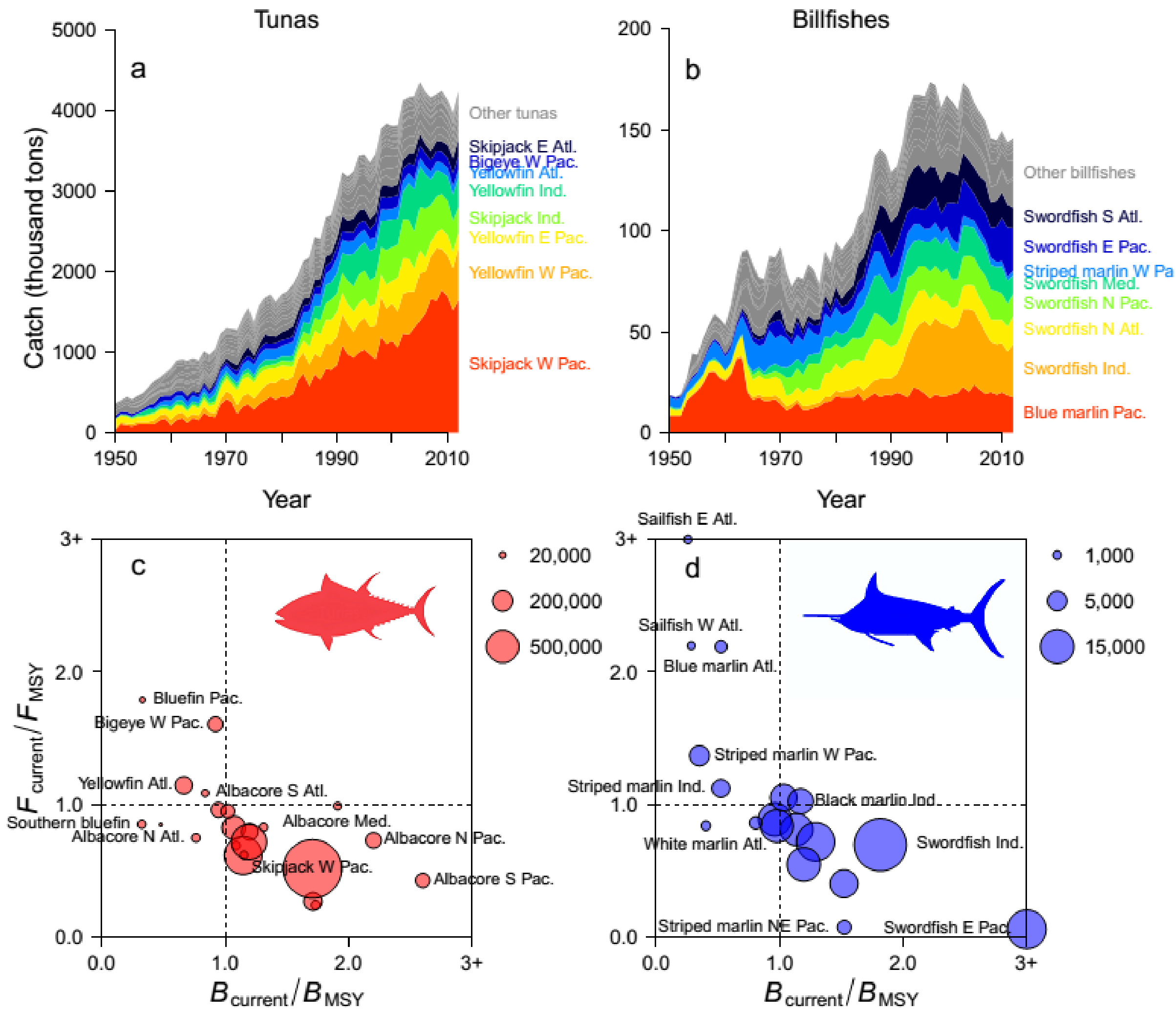

Figure 1.2. Global catches and current status of tuna and billfish stocks. (a) Time trends of tuna catches by stock. The eight with greatest catches are highlighted in color. (b) Time trends in billfish catches by stock. Stock status relative to target reference points (dashed lines) for fishing mortality (FMSY) and biomass (BMSY) for (c) tunas and (d) billfishes. Horizontal and vertical dashed lines show MSY target reference points commonly used among tRFMOs. The area of circles within each plot is proportional to MSY (t).

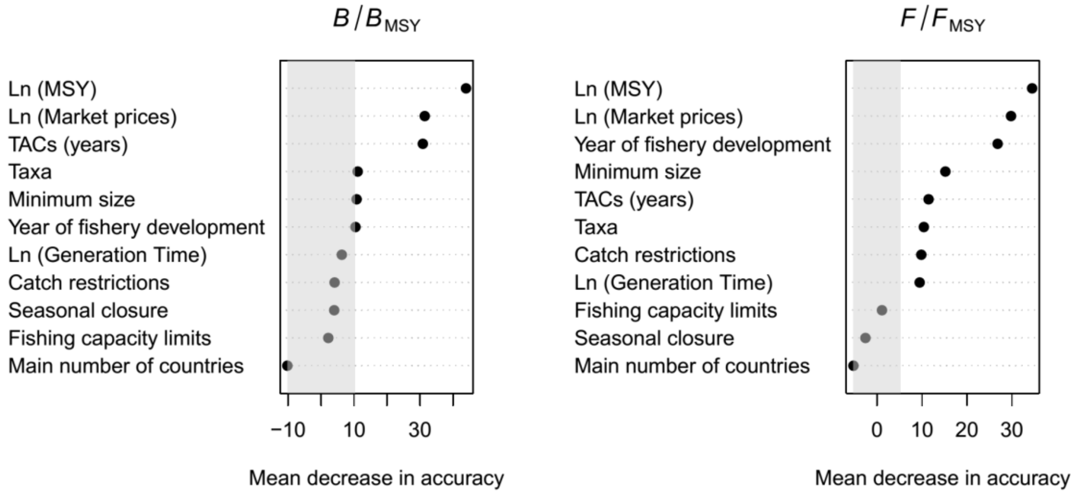

Figure 1.3. Variable importance score of different predictors on the current stock status (B/B_{MSY} and F/F_{MSY}) of tunas and billfishes. The most influential variables are those with the greatest decrease in accuracy. Variables in the grey shaded area are considered as not influential. They are significant if their importance value is above the absolute value of the lowest negative-scoring variable. Log refers to the natural logarithm.

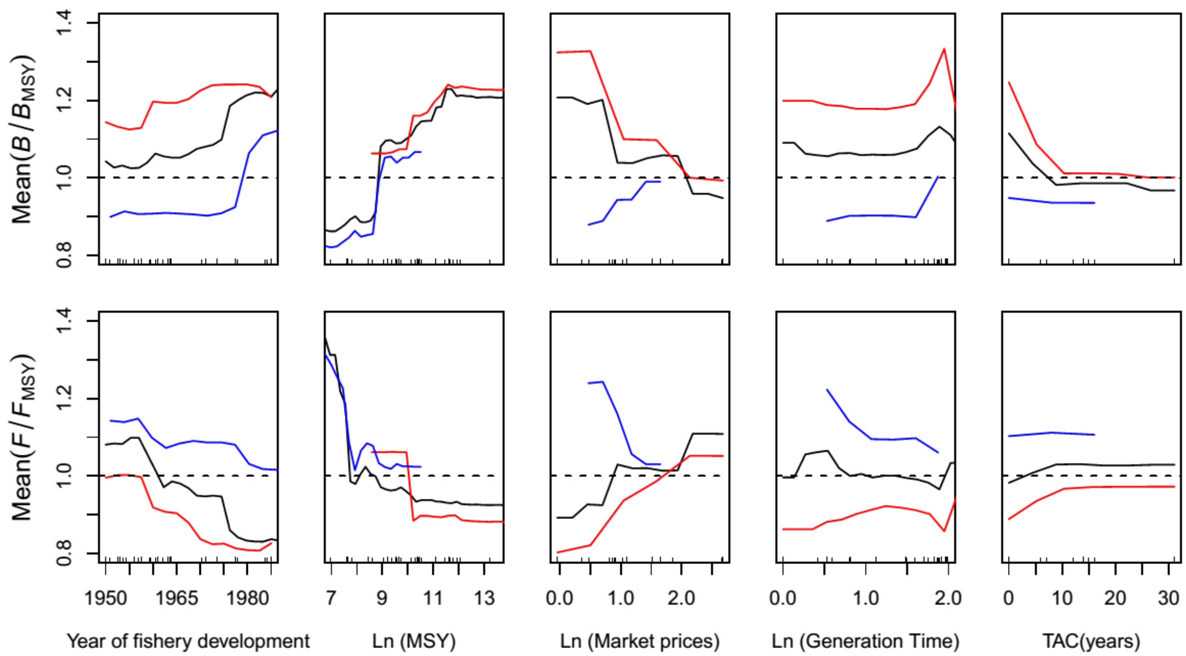

Figure 1.4. Partial dependence plots of the most important continuous predictors of stock status. The geometric mean of B/B_{MSY} and F/F_{MSY} correspond to the 10 years prior to the last assessment for each stock. Red lines represent tunas, blue lines billfishes and black lines both combined. Dashed lines show general management targets. Ln refers to the natural logarithm and the tic marks on the x-axis represent the data available.

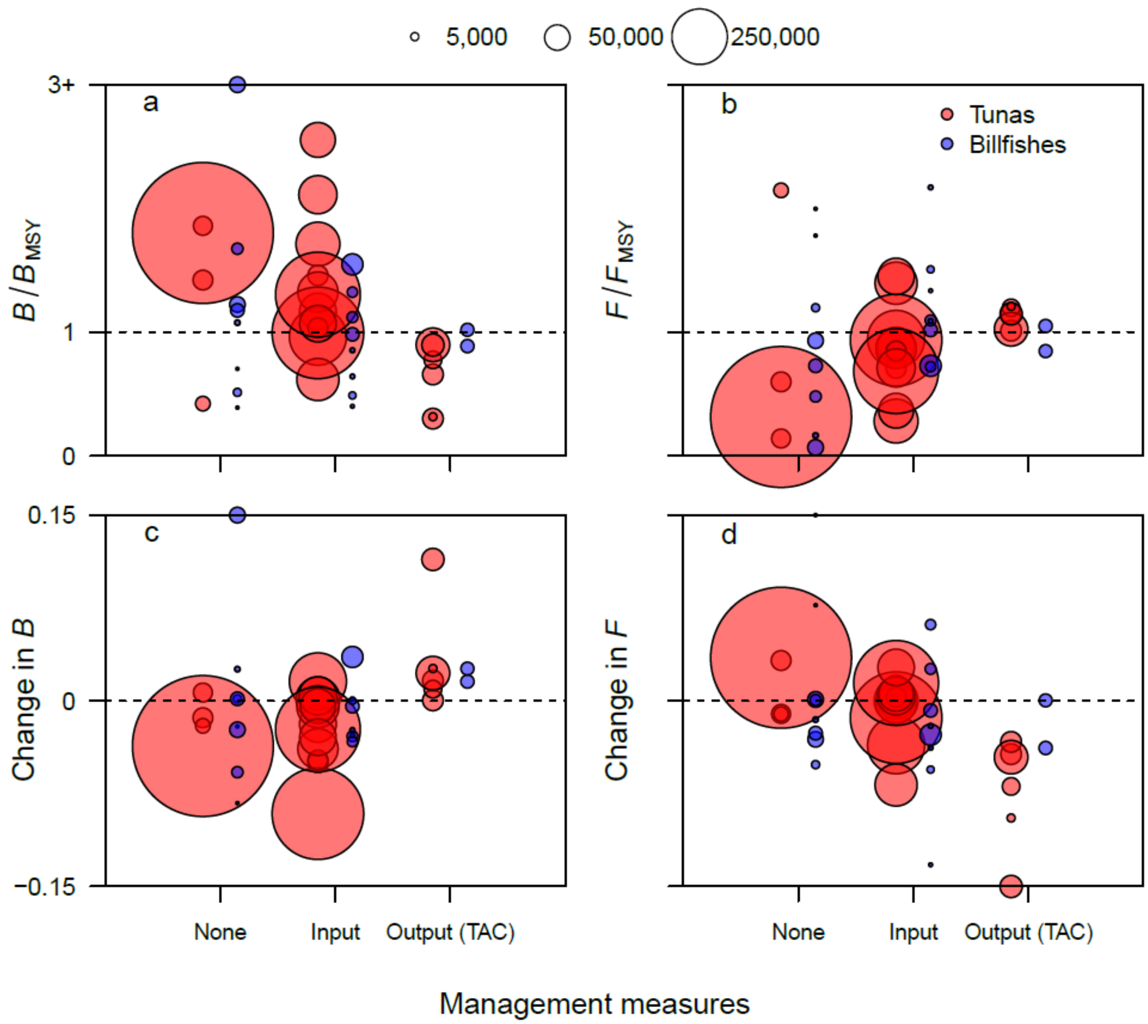

Figure 1.5. Effect of current management measures on tuna and billfish stocks. Geometric means of (a) B/B_{MSY} and (b) F/F_{MSY} over the final 10 years from the latest stock assessment. Dashed lines represent target reference points (B_{MSY} and F_{MSY}). Annual mean rates of change of (c) biomass and (d) fishing mortality. Dashed lines represent no changes in B or F. In all panels, stocks are categorized by whether there are no management measures in effect, some input management measures, or output measures (TACs), and separated by taxa (tunas or billfishes). The area of circles within each plot is proportional to MSY (mt).

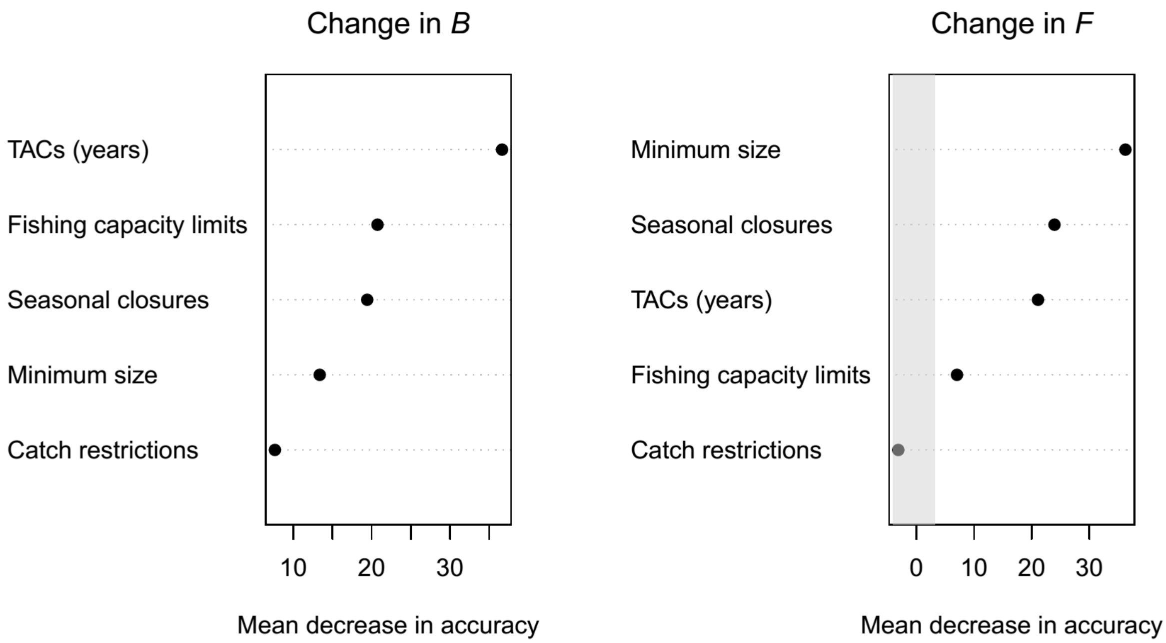

Figure 1.6. Variable importance scores of different management measures on stock rebuilding. The response variables are the geometric mean of the annual rates of change of biomass (*B*) and fishing mortality rates (*F*) for stocks declared overfished or experiencing overfishing 10 years before the last assessment. The most influential variables are those with the greatest decrease in accuracy. Variables in the grey shaded area are considered not influential. They are significant if their importance value is above the absolute value of the lowest negative-scoring variable.

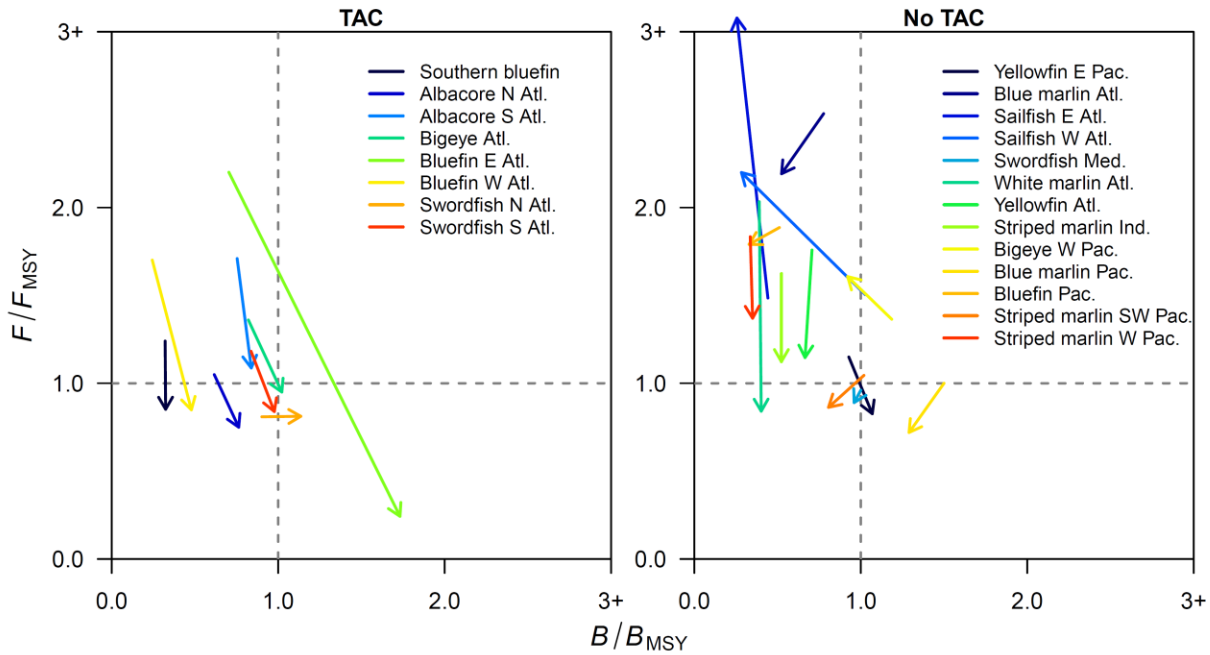

Figure 1.7. Change in status (B/B_{MSY} and F/F_{MSY}) for stocks declared overfished or experiencing overfishing 10 years before the last assessment to the present. Results are shown for stocks with and without TAC regulations. Vertical and horizontal lines represent target reference points (for B_{MSY} and F_{MSY}, respectively).

Chapter 2. MANAGEMENT EFFECTIVENESS OF LARGE PELAGIC FISHERIES IN THE HIGH SEAS

Abstract

Large pelagic fishes are assessed and managed by tuna Regional Fisheries Management Organizations (tRFMOs). These organizations have been criticized for not meeting conservation objectives, which may relate to aspects of governance and management. No previous studies have systematically evaluated why management performance differs among tRFMOs and among stocks within each tRFMO. In this study, we collected data on the nature of research, management, enforcement, and socioeconomics of management systems in the five principal tRFMOs of the world's oceans. We quantified influences of economic and fishery-related factors on these management characteristics, and examined how these factors vary among tRFMOs. We found that tRFMOs with a greater number of member countries, a greater economic dependency on tuna resources, a lower mean per-capita Gross Domestic Product, a greater number of fishing vessels, and smaller vessels, were associated with less intensive research, management and enforcement in these tuna fisheries. We also quantified the influence of specific management attributes and of biological, economic and fishery-related factors on the trends and current status of large pelagic fish stocks in these regions. The most important factors correlated with trends and current stock status were external to the management systems, and included stock size, age at maturity, ex-vessel price, and economic dependency of countries on tuna fisheries. To improve the overall status of large pelagic fish stocks in the global high seas, more intensive data collection, research and management is needed in certain areas, especially in the Indian Ocean, and for certain stocks, especially non-target species.

2.1 INTRODUCTION

Recent years have seen increasing concern over whether fisheries can sustainably provide seafood without overfishing fish populations. Large pelagic fishes, especially tunas but also billfish and sharks, are important contributors to food security and income in many developed and developing countries. Tuna fisheries are worth $42 billion dollars annually to the global economy—more than the gross national product of 108 countries (Galland *et al.* 2016). Because some of the most economically important tuna stocks—i.e. southern bluefin tuna (*Thunnus maccoyii*, Scombridae), Pacific bluefin (*Thunnus orienta*lis, Scombridae), Atlantic bluefin (*Thunnus thynnus*, Scombridae), western Pacific bigeye (*Thunnus obesus*, Scombridae) and Atlantic bigeye—have been categorized as overfished (ICCAT 2011a, 2015a; CCSBT 2014; Harley *et al.* 2014a; ISC 2014b), there have been major concerns about the sustainability of these stocks and the management performance of tuna Regional Fisheries Management Organizations (tRFMOs) (Ceo *et al.* 2012). However, it has recently been shown that the implementation of strong management measures (e.g. catch quotas) by some tRFMOs is promoting the recovery of overfished tuna and billfish stocks (Pons *et al.* 2017).

All tRFMOs face various obstacles in the adoption of allocation systems for tuna fisheries, largely because it is unclear how to best assign fishing rights among diverse participants in each fishery (Allen 2010). Two tRFMOs, the International Commission for the Conservation of Atlantic Tunas (ICCAT) and the Commission for the Conservation of Sothern Bluefin Tuna (CCSBT), have implemented total allowable catches (TACs) for most of the stocks under their authority. Three others, the Indian Ocean Tuna Commission (IOTC), the Inter American Tropical Tuna Commission (IATTC) and the Western and Central Pacific Fisheries Commission (WCPFC), have widely used input controls, such as limits in fishing capacity and seasonal closures. An annual TAC was recently set for Pacific bluefin tuna managed by IATTC and WCPFC, and IATTC recommended quotas for bigeye tuna this year for different fleets (IATTC Res. 2017). Moreover, in 2016, IOTC adopted a harvest strategy for skipjack tuna (*Katsuwonus pelamis,* Scombridae) which prescribes quotas and catch reductions for industrial yellowfin tuna (*Thunnus albacares,* Scombridae) fisheries (IOTC Res. 2016a; 2016b).

Regional Fisheries Management Organizations provide a formal mechanism for fishing countries to meet their international obligations to cooperate for the sustainability of shared highly migratory stocks and to provide compatible measures in areas beyond national jurisdictions (Allen 2010). Within a country's EEZ, fisheries governance and management is complex, including a wide range of policies and regulations to meet conservation and socioeconomic goals (Melnychuk *et al.* 2017a). For tRFMOs, which involve multiple countries, management systems are even more complex due to the diversity of economies, interests and priorities among countries. Moreover, management and governance differ among tRFMOs and among stocks within each organization, adding more complexity to the system.

Previous studies have presented divergent views of how well tRFMOs meet their conservation and management mandates. In Cullis-Suzuki and Pauly (2010), the authors suggested that tRFMOs are not meeting best practice standards and are failing to stop the dramatic declines of fish stocks for which they have management responsibility. However, we demonstrated that some tRFMOs have been successful in rebuilding tuna stocks when strong management measures are applied (Pons *et al.* 2017). Further, Clark *et al.* (2015) found several good practices amongst tRFMOs, with no single tRFMO standing out as having particularly poor transparency practices. No previous studies have systematically evaluated why management performance differs among tRFMOs and among stocks within each tRFMO.

In this study, we collected data on the nature of research, management, enforcement, and socioeconomics of management systems in the five principal tRFMOs. We examined influences of economic and fishery-related factors on these management characteristics and how these factors vary among tRFMOs. Finally, we quantified the impact of management attributes and of biological, economic and fishery factors on the trends and current status of a semi-randomized set of large pelagic fish stocks managed by each tRFMO.

2.2 METHODS

2.2.1 *Expert surveys*

To characterize the management systems for large pelagic fishes in the high seas, we conducted expert surveys for stocks within each tRFMO during 2015 and 2016. We used the Fisheries Management Index (FMI) survey described by Melnychuk *et al.* (2017a), slightly reworded to better pertain to high seas tRFMOs instead of to national jurisdictions (Appendix 2.1). The main purpose of this survey was to determine what measures and approaches are currently in use and effective at limiting fishing pressure within each management system.

The survey consisted of 38 questions (criteria) nested within 12 attributes, which in turn are nested within 4 dimensions (Appendix 2.2): 1) research (programs for collection of landings data and body size/age data, abundance trend estimates, and stock assessments); 2) management (management plans, limits on fishing pressure, and capacity to adjust fishing pressure); 3) enforcement (monitoring and observing programs, penalties, and discarding or bycatch measures); and 4) socioeconomics (control access into the fishery, transparency, involvement, and absence of subsidies). Answers to questions consisted of values of 0, 0.5, or 1, reflecting whether the criterion was not met, partially met, or met, respectively.

Fishery experts familiar with the management systems of specific tRFMOs were invited to participate in the survey. Respondents were instructed to complete a questionnaire for 10 fished stocks in each tRFMO jurisdiction (except for CCSBT, for which only one species was included, southern bluefin tuna). Answers were provided for each question and each of the 10 species independently. A variety of backgrounds were represented by respondents including: 1) government managers, 2) government scientists, 3) university researchers, 4) environmental NGOs, 5) tuna fishing industry, and 6) external (i.e. people from FAO, external reviewers, consultants, etc.). The list of 10 stocks for each survey included the four stocks with greatest landings and the four stocks with greatest landed values within the tRFMO. Overlaps were possible; the remaining 2-6 stocks were randomly sampled in proportion to their standardized landings and standardized landed values (Melnychuk et al. 2017a). This resulted in species lists reflecting the major stocks caught in each tRFMO management jurisdiction, but occasionally including minor bycatch species or groups of species (Appendix 2.1).

Responses to survey questions were aggregated into attributes (12), dimensions (4), or an overall FMI value for each survey (Appendix 2.2). When aggregating, answers were weighted by confidence scores provided for each question, which ranged from A (answers across all 10 stocks are known and accurate) to D (answers may be too high or too low for 5 or more stocks). Numeric weights assigned to these qualitative confidence categories were: A=1; B=0.8; C=0.6; D=0.4. Weighted mean responses of each attribute, each dimension, or each overall FMI score were subsequently aggregated across respondents for comparing tRFMOs and stocks within each tRFMO.

2.2.2 *tRFMO-level predictors*

Governance, fishery, and economic factors were compiled for each tRFMO to analyze associations with FMI values. We consider the year when the *Convention Agreement* entered into force as an indicator of when the assessment and management started in each tRFMO. The *number of countries* in each organization was also considered under the hypothesis that tRFMOs with more member states have greater challenges in implementing and enforcing management measures (Appendix 2.3).

To account for differences in the economies of the countries within each tRFMO, we considered the per-capita *Gross Domestic Product* (GDP) (World-Bank 2015) of each country as well as the per-capita *Seafood Protein Provision* (SPP) (FAOSTAT 2017), which provides an index of a country's dependence on seafood. Each country's per-capita GDP and SPP was weighted by the total reported catches for the main 10 species in each tRFMO during 2005-2014 to provide a weighted total per-capita GDP and SPP value by tRFMO. The level of *economic dependency* on *tuna fisheries* (tunas and tuna-related species) was calculated as the average ratio of landed value of the same 10 species—based on estimated ex-vessel prices from Melnychuk *et al.* (2017b)—to the per-capita GDP of each country (Appendix 2.3).

Three fishery-related predictors were considered. The *year of fisheries development* in each convention area was calculated as the first year when total landings reached 25% of the historical maximum landings (Sethi *et al.* 2010). For example, tuna fisheries in the Indian Ocean developed later than those in the Atlantic Ocean (Pons *et al.* 2017). The *number of registered and authorized vessels* and the *mean vessel length* (m) were calculated for each tRFMO (Appendix 2.3); a lower mean vessel size indicates a higher proportion of artisanal or small-scale fisheries in the region.

2.2.3 *Stock status and stock-level predictors*

We used variables based on maximum sustainable yield (MSY) reference points extracted from stock assessments and compiled in the RAM Legacy database (Ricard *et al.* 2012) as measures of stock status. In particular, we considered the biomass (*B*) related to the *B* that produces MSY (B/B_{MSY}) and the fishing mortality (*F*) related to the *F* that produces MSY (F/F_{MSY}). Of the 40 stocks included in expert surveys, only those with reliable time series estimates of B/B_{MSY} and F/F_{MSY} were included in this analysis (N=27, Table S1). We considered four response variables based on the most recent 10-year period series estimates for each stock: 1) geometric mean of B/B_{MSY}; 2) trend in *B*; 3) geometric mean of F/F_{MSY}; and 4) trend in *F*.

Several covariates were considered to explain variability in the FMI values observed among individual stocks (Appendix 2.4). *Age at 50% maturity* was used as a life-history covariate, *MSY* was used to account for different stock sizes (Juan-Jordá *et al.* 2012), and the *year of fishery development* (Sethi *et al.* 2010) provided historical information about the fishery for each stock. Three economic covariates were included: *ex-vessel price* (Melnychuk *et al.* 2017b), weighted mean per-capita *GDP* of the countries fishing the stock (weighted by catch), and weighted mean *economic dependency* on the stock by countries fishing the stock, weighted by country catch (Appendix 2.4). The 12 management attributes from FMI surveys, representing different aspects of the intensity of management, were also included as covariates to quantify the association with stock status. Unlike the six “external” covariates, these 12 management attributes cannot be considered exogenous, as fisheries management systems respond to the perceived status of fish stocks, but we include these in the analysis to show the relative strength of their association with stock status metrics.

2.2.4 *Analysis*

Neither tRFMO-level nor stock-level response variables consistently followed a particular probability distribution, and the ratio of predictors to observations was relatively high under typical rules-of-thumb for regression models, so we used the non-parametric method of Random Forests which is robust to over-parameterization. Moreover, these models allow for non-linearities without having to explicitly incorporate quadratic or higher-order terms like in a linear regression, and also account for interactions among predictors without having to explicitly incorporate interaction terms. Random Forest analysis (Breiman 2001) is an ensemble method that aggregates *N* numbers of trees which together create the "forest". Each regression tree is grown using a bootstrapped sample of the original dataset (e.g. 2/3). Each tree in the forest uses at each node only a specified number of variables, randomly sampled as candidates from a subset of the explanatory variables, which in our case was equal to 1/3 of the number of predictor variables considered (Liaw *et al.* 2015). To stabilize the mean square error in the model, forests of 10,000 trees were used, which diagnostics showed were adequate. We present partial dependence plots to show the association of the main predictors with the response variables, ordered by the calculated importance score of predictors. For model fitting and plotting, we used the 'randomForest' package (version 4.6-12) (Liaw *et al.* 2015) in R (version 3.2.0). This work represents a synthesis of multiple datasets and not a controlled experiment; in applying these models we are cognizant of our limited ability to claim causation by exogenous predictors. We instead use these methods to describe associations and discuss the implications of this usage.

2.2.5 *Sensitivity analyses*

For sensitivity purposes, we ran the same analysis for the most recent 5-year period and presented the results in the Appendices 2.5 and 2.6. The results were similar to those from the key run presented in the main text. The most important factors explaining the trends and current stock status in biomass and fishing mortality were also external to the management systems, and included stock size, age at maturity, ex-vessel price, and economic dependency of countries on tuna fisheries, although the order of variable importance differed slightly.

We also visually compared FMI scores (overall, and for each dimension separately) assigned to a given species among the different tRFMOs in which that species is managed. This comparison (Appendix 2.7) showed that average scores for each tRFMO were partly the result of species composition effects and partly the result of overall tRFMO effects.

2.3 Results

2.3.1 *tRFMO-level analysis*

Of 142 invitations sent out, 54 surveys were returned, with representation across respondent backgrounds (Appendix 2.8) in each tRFMO. Differences among organizations in the overall FMI and average survey value by dimension were observed. CCSBT scored significantly higher than the others across all dimensions, receiving the highest overall FMI value (Figure 2.1). In general, attributes were positively correlated with each other such that if one tRFMO scored higher than others in one dimension (e.g. *Research*) it tended to score higher in the others as well (Appendix 2.9). IOTC had the lowest overall FMI value (Figure 2.1) but was not significantly different from the other tRFMOs. In all tRFMOs, average scores for *Research* were the highest among the four dimensions, average scores for enforcement were lowest, and *Management* and *Socioeconomics* scores tended to be intermediate.

Among *Research* attributes, all tRFMOs had good performance in collecting landings data, and have assessed most of the stocks considered. The IOTC had the lowest average score for collection of body size/age data, and for estimating relative abundance trends (Figure 2.2). In the *Management* dimension, average values were higher for tRFMOs with management plans like CCSBT and ICCAT, and were lowest for WCPFC and IOTC in terms of the presence of fishing limits and the capacity to adjust fishing pressure. Among *Enforcement* attributes, the lowest score was observed for discarding and bycatch measures in most tRFMOs. For *Socioeconomics*, all tRFMOs scored high in transparency, but with the exception of CCSBT, scored lower in other attributes, particularly fishing access and entry controls for IOTC and "bad" subsidies for WCPFC (Figure 2.2).

Part of the observed differences among tRFMOs in overall FMI scores and in scores for individual dimensions are the result of differences in species composition; the semi-randomized list of species in expert surveys differed among tRFMOs. A sensitivity analysis restricting comparisons across tRFMOs to a same species in common provided evidence for overall differences among tRFMOs as well as differences due to species composition (Appendix 2.7). Bigeye tuna, yellowfin tuna, and swordfish (*Xiphias gladius*, Xiphiidae) had similar patterns across tRFMOs as the patterns shown in Figure 2.1, with greater scores for IATTC and ICCAT than for IOTC and WCPFC. On the other hand, skipjack tuna, which tends to be managed less intensively, had similar scores across tRFMOs. Bluefin tuna had relatively high scores in the three tRFMOs in which it was included in surveys—CCSBT, ICCAT, and IATTC—which contributed to the high overall scores for these tRFMOs (Appendix 2.7).

The relative importance of predictor variables and the forms of the relationships between survey scores and predictors differed among dimensions. Higher scores by dimension were typically associated with lower economic dependency on tuna, fewer vessels, fewer countries, and greater per-capita GDP (Figure 2.3). These patterns were heavily influenced by the CCSBT, which had values of these variables far outside the range of the other tRFMOs (Figure 2.3).

Partial dependence plots from the Random Forest models, ordered by overall importance across dimensions, show that economic dependency on tuna had the greatest overall importance and convention year had the least overall importance among the 8 predictors (Figure 2.3). For *Research* attributes, the most important variable affecting average scores was *per-capita GDP*, suggesting that research intensity is higher in tRFMOs with countries that have stronger economies (CCSBT and ICCAT, Figure 2.3). For *Management* attributes, the three most important predictors were the *number of countries* members and *number of vessels* authorized in each tRFMO and the *economic dependency on tuna fisheries*. More vessels (i.e. IATTC and IOTC) and more countries highly dependent on tuna fisheries (i.e. IOTC and WCPFC) were associated with lower average *Management* values. The year of fisheries development played a significant role in *Enforcement* attributes, with earlier developed fisheries (i.e. CCSBT in 1959) having higher enforcement scores than later developed fisheries (i.e. IOTC in 1982). Also, enforcement appears to be lower for tRFMOs with countries that have greater economic dependence on tuna fisheries. For *Socioeconomic* attributes, average scores were typically lower for tRFMOs with higher economic dependency on tuna fisheries, fisheries with later year of development (i.e. IOTC), and lower per-capita GDP among countries (Figure 2.3).

2.3.2 *Stock-level analysis*

At the level of individual stocks, the greatest differences among stocks were observed for *Research* and *Management* attributes, and the least differences was observed for *Socioeconomics* attributes. Stocks with the highest average *Research* values were those with a stock assessment, generally large commercial tuna species—i.e. southern bluefin tuna, Atlantic bluefin, yellowfin, bigeye and albacore (*Thunnus alalunga*, Scombridae)— and swordfish. Marlins and spearfishes (Istiphoridae), small tunas and mackerels (Scombridae), and sharks had lower values, especially those without an assessment (Figure 2.4). The highest *Management* scores were observed for southern and Atlantic bluefin and other large tunas in the Atlantic Ocean. These two bluefin stocks also had the highest *Enforcement* scores. The lowest *Socioeconomics* scores were typically seen in stocks that have been not assessed (Figure 2.4).

Among the 40 stocks considered in the questionnaires, 27 had estimates of MSY reference points used for management advice (Appendix 2.1). When relating stock-specific covariates to stock status, several covariates had strong association with the four metrics, i.e. current status and trends in F and B. The most important predictors tended to be biological and economic factors outside the management system rather than any *Research*, *Management*, *Enforcement*, or *Socioeconomics* attributes of the FMI survey (Figure 2.5 and 2.6). Larger stocks (principally skipjack tuna) showed the lowest fishing mortality rates but the highest recent increases in F (Figure 2.5). Other important predictors of F/F_{MSY} and trends in F were the three economic factors: stocks targeted by countries with higher per-capita GDP and stocks with higher prices had higher current F/F_{MSY}, although the trend in F is decreasing. Stocks whose countries of capture have greater economic dependency on tuna fisheries showed the greatest recent increases in F (Figure 2.5). The next-most important predictor, with greater variable importance scores than all 12 endogenous, management-related attributes, was the categorical variable tRFMO which showed that average trends in F were declining for CCSBT and ICCAT stocks.

The year of fisheries development as well as biology and life-history traits were highly correlated with metrics of abundance. As age at maturity initially increased, B/B_{MSY} declined, but B/B_{MSY} increased sharply for species maturing after age 5 (i.e. swordfish or southern bluefin tuna) (Figure 2.6). Trends in abundance were positively correlated with age at maturity but had negative values throughout the range. Larger stocks had higher values of B/B_{MSY} but negative trends in abundance. Economic predictors were also important: stocks with higher ex-vessel prices had lower values of B/B_{MSY}, although biomass has recently increased. Stocks whose countries of capture were more economically dependent on tuna fisheries had greater B/B_{MSY}, but with a negative trend in recent years. As was observed with F/F_{MSY} and trends in F, stocks whose countries of capture had greater per-capita GDP tended to have low B/B_{MSY} but the greatest recent increases in B (Figure 2.6). The tRFMO ranked 6th as a predictor, with greater declines in recent abundance observed for IOTC and WCPFC stocks relative to those from other tRFMOs. The 12 fishery management attributes considered had only weak associations with metrics of biomass (Figure 2.6).

2.4 DISCUSSION

There are many factors associated with the intensity of management among tRFMOs across multiple dimensions. These consist not only of differences in the history of exploitation among oceans, but even more in fleet diversity, economic diversity of member countries, and economic dependency on tuna and tuna-related fisheries. These factors affect the ability of these organizations to apply and enforce management measures and consequently have an impact on the status of the stocks under their jurisdictions. Although these results show that current stock status is highly correlated with biological and economic factors, with management attributes playing a secondary role, management attributes such as the establishment and enforcement of quotas are still important for rebuilding overexploited populations (Pons *et al.* 2017).

One possible explanation for CCSBT scoring significantly higher than other tRFMOs is that they only manage one stock, southern bluefin tuna. However, when comparing the FMI values for bluefin tuna alone in different basins, CCSBT still scored higher than the other tRFMOs (Figure S6). Although this population has been overexploited for decades, recent improvements in management and enforcement have resulted in it no longer experiencing overfishing and now showing sign of rebuilding (CCSBT 2014; Hillary *et al.* 2015; Pons *et al.* 2017). On the other hand, IOTC was the tRFMO with the lowest score, characterized by the latest developed fisheries, countries with the lowest average per-capita GDP, high economic dependency on tuna fisheries, smallest vessels, and most vessels (Figure 2.3). These factors negatively influence the performance of tRFMOs in separate dimensions and in the overall FMI score.

All tRFMOs scored consistently high in *Research*, consistent with observations by Cullis-Suzuki and Pauly (2010). The highest values were observed in tRFMOs with countries with stronger economies, probably because they can allocate more resources for data collection and research in general (Melnychuk *et al.* 2017a). Some developing countries lack appropriate scientific expertise and, even where such expertise is available, budgetary constraints limit their participation in Commission meetings, especially those of the Scientific Committees (Ceo *et al.* 2012). IOTC scored particularly low in the attribute regarding body-size and/or age data collection (Figure 2.2), likely because the developing countries associated with this tRFMO have limited capacity to fulfill these requirements. According to Ceo *et al.* (2012), many developing countries are experiencing serious capacity and infrastructure constraints which impede their ability to comply with their obligations, especially in terms of data collection, reporting and processing. IOTC is not the only tRFMO facing such issues. ICCAT has developed multiple research programs and training workshops to improve data collection and analysis in developing countries (Anon 2010; ICCAT 2016a). This aims to improve and coordinate data collection and sharing programs among counties, and could facilitate monitoring, control and surveillance systems as well (Lodge *et al.* 2007). The low *Research* scores associated with a higher proportion of smaller vessels in the fishery is because overall data collection is less coordinated and more complicated in artisanal fisheries. Onboard observers are also less commonly used in small-vessel fisheries, potentially also impacting management and enforcement outcomes.

Among tRFMOs, there has been increasing recognition of the need to improve governance, conservation and management of fishery resources by expanding their mandates from target species to more broadened expectations (de Bruyn *et al.* 2013; Gilman *et al.* 2014). Scores were relatively low for fisheries enforcement in general, and in particular for discarding and bycatch measures in all tRFMOs, likely because there are no severe consequences for exceeding bycatch limits in any tRFMOs (Gilman *et al.* 2014). This is also reflected in the low scores of stocks that are not targeted in tuna fisheries, such as marlins and sharks, which scored lower in all dimensions and particularly in *Management* and *Enforcement* (Figure 2.4).

We found similar results to Clark *et al.* (2015) in relation to transparency practices among tRFMOs, with no single tRFMO standing out as having particularly poor transparency practices compared to others. In general, tRFMOs publicly disclose their management decisions and the reasons for these decisions, and in most of them there are opportunities for stakeholders to provide input into the management decision process (Clark *et al.* 2015). However, socioeconomic issues are limited to transparency; the lowest scores in this dimension were observed for fishing access and fishing controls, particularly in the IOTC, and for absence of ‘bad’ or ‘capacity-enhancing’ subsidies in the WCPFC as well (Figure 2.2). Both of these criteria could generate overcapacity, the first by unlimited increases in the number of vessels and fishing effort, and the second by an excess of subsidies which artificially increase profits and stimulate effort and resource overexploitation (Sumaila *et al.* 2010). Socioeconomic measures appear to be particularly poor when there is high economic dependency on tuna fisheries (Figure 2.3).

Economic dependency on tuna fisheries was the most important covariate in explaining differences in FMI values among tRFMOs. When countries with low governance capacity account for the greatest proportion of total catches, management controls are, on average, harder to enforce. Indonesia, India, Philippines, and some Parties of the Nauru Agreement (PNA) like Papua New Guinea, Kiribati, Marshall Islands and Solomon Islands were the nations identified in this study as the most dependent on tuna fisheries in WCPFC and IOTC areas. However, we recognize the limitations of the estimation of tuna dependency as we used it in this study since it does not include other revenues, e.g. processing jobs or vessel-days trades (Yeeting *et al.* 2016). For some PNA countries this dependency could be even higher.

The negative correlation between management scores and number of countries in each tRFMO suggests that increased state membership hinders decision processes when consensus is necessary; the more voting members, the greater the difficulty in achieving agreements (ICCAT 2009b). Cooperation is unlikely as the number of interested parties increases unless a strong institutional and jurisdictional framework is established. This incentivizes individual governments to conduct their business as usual, which may be less compatible with conservation and sustainability goals (Hannesson 1995; Gjerde *et al.* 2008).

Member countries within ICCAT and CCSBT typically have stronger economies, more industrialized fisheries, lower economic dependency on tuna fisheries, and, in turn, higher FMI values. However, due to the history of exploitation, those tRFMOs also have the lowest B/B_{MSY} values on average across stocks (Figure 5 and 6). Pons *et al.* (2017) showed that it is not until tuna and billfish stocks are heavily depleted that tRFMO tend to implement strong management measures such as quotas controls. Stocks show the greatest intensity of management as reflected by FMI values are therefore typically target species that are currently overfished or were overfished in the recent past (i.e. southern and eastern Atlantic bluefin tunas). Other stocks like marlins and sharks (bycatch in tuna fisheries) or small tunas (less commercially-important) had much lower FMI scores despite also being highly depleted. Management may be less intense for these stocks because the economic importance of the main target species makes mitigation measures difficult to implement without impacting the catch of those main target species (Hilborn *et al.* 2012).

The most important factors determining current stock status and trends were related to biological and economic variables external to the management system (Pons *et al.* 2017). Not surprisingly, economic variables were important drivers of fishing mortality (Sethi *et al.* 2010) and life-history attributes were important drivers of biomass (Collette *et al.* 2011; Juan-Jordá *et al.* 2012). Stocks fished by countries with higher per-capita GDP had higher F/F_{MSY} values, but also had greater recent decreases in F, suggesting that these countries have greater capacity to adjust fishing pressure. Of particular concern is the observation that stocks targeted by countries with higher dependency on tuna fisheries are also those with greater recent increases in F and deceases in B (Figure 2.5 and 2.6). Controlling fishing pressure in developing countries in which fisheries play an important role in their economies is challenging for both national and international governance bodies (McClanahan *et al.* 2015). In addition, the importance scores were lower for the tRFMO covariates in relation to economic and biological predictors, meaning that even though there are strong differences among tRFMOs in current levels and trends in stock status, when you control for external/economic differences among those regions, the residual effects of tRFMOs are not as important.

Finally, among the 12 management attributes considered, fisheries enforcement was the most important associated with trends in biomass. These findings agree with Pons *et al.* (2017), who showed that when strong management controls like quotas are enforced, this could lead to a faster rebuilding of tuna and billfish stocks. However, we acknowledge that fisheries management interventions are not exogenous to stock status, limiting our ability to establish causal relationships.

To improve the overall status of large pelagic fish stocks in the global high seas, more intensive data collection and research is needed, in certain areas, especially in the Indian Ocean, and for certain stocks, especially non-target species. Additional resources and capacity building for developing nations will probably be required for some tRFMOs to achieve these objectives (Anon 2010; ICCAT 2016a). This will be very important when trying to implement and enforce management strategies to ensure that these measures will be effective in guarding against current and future overfishing.

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2.5 FIGURES

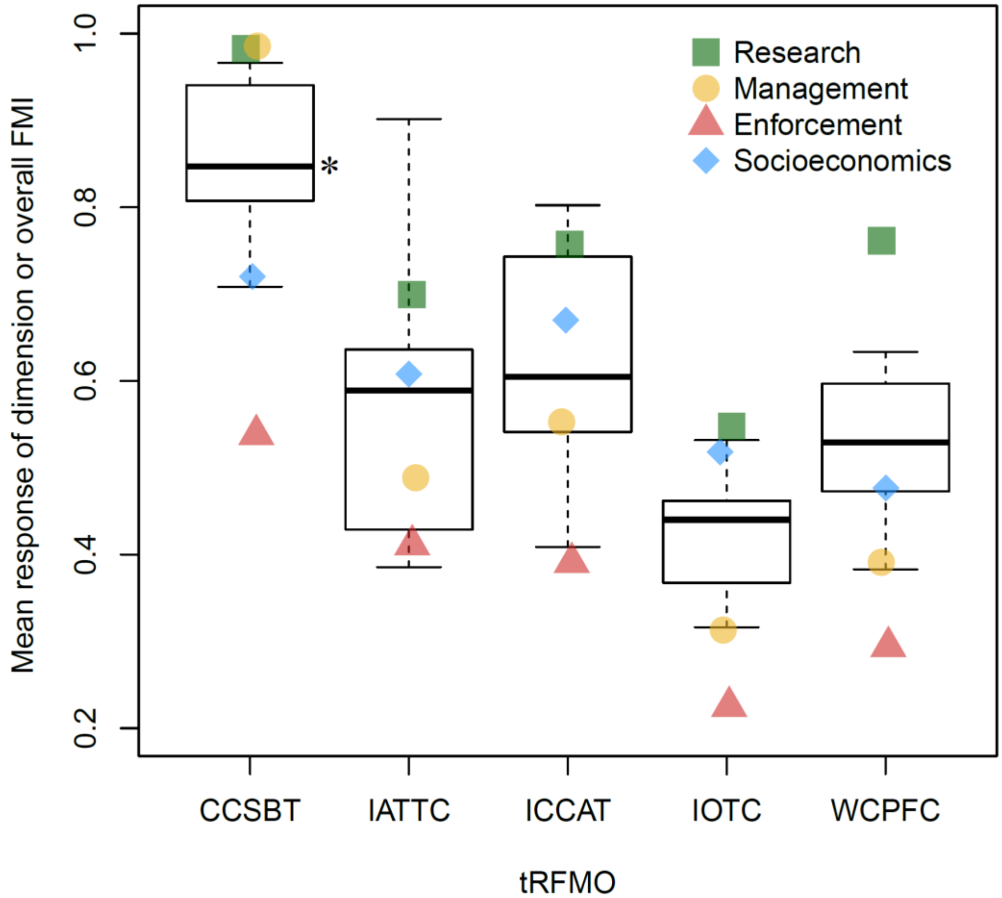

Figure 2.1. Summarized survey answers by tRFMO and FMI dimension (*Research, Management*, *Enforcement* and *Socioeconomics*). Responses are weighted by the confidence in individual answers provided. Overlaid boxplots show the 25th, 50th and 75th percentiles (bottom, band and top of the box respectively) of overall FMI scores, which are aggregates of the four dimensions. * Dunn's test of multiple pairwise comparisons with Bonferroni correction give adjusted p-values of: CCSBT & IATTC, 0.022; CCSBT & ICCAT, 0.113; IATTC & ICCAT, 0.999; CCSBT & IOTC, <0.001; IATTC & IOTC, 0.339; ICCAT & IOTC, 0.087; CCSBT & WCPFC, <0.001; IATTC & WCPFC, 0.999; ICCAT & WCPFC, 0.999; and IOTC & WCPFC, 0.737.

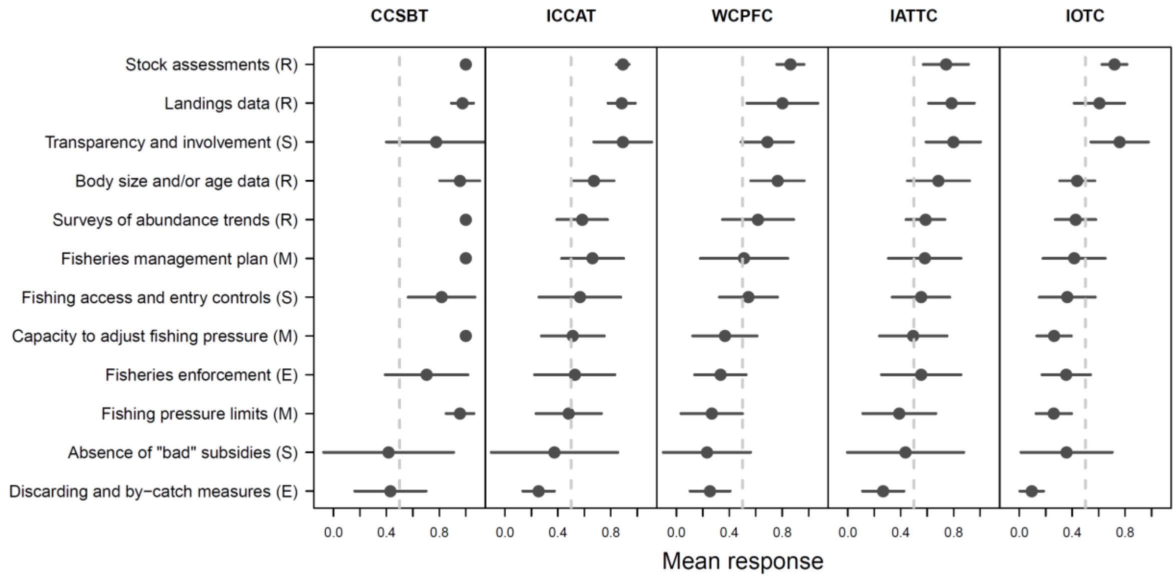

Figure 2.2. Summarized survey answers by tRFMO and FMI attribute. Responses are weighted by the confidence in individual answers provided. Dashed lines show values of 0.5 for reference. Error bars show one standard deviation from the mean. Attributes are ordered by global FMI values for each tRFMO.

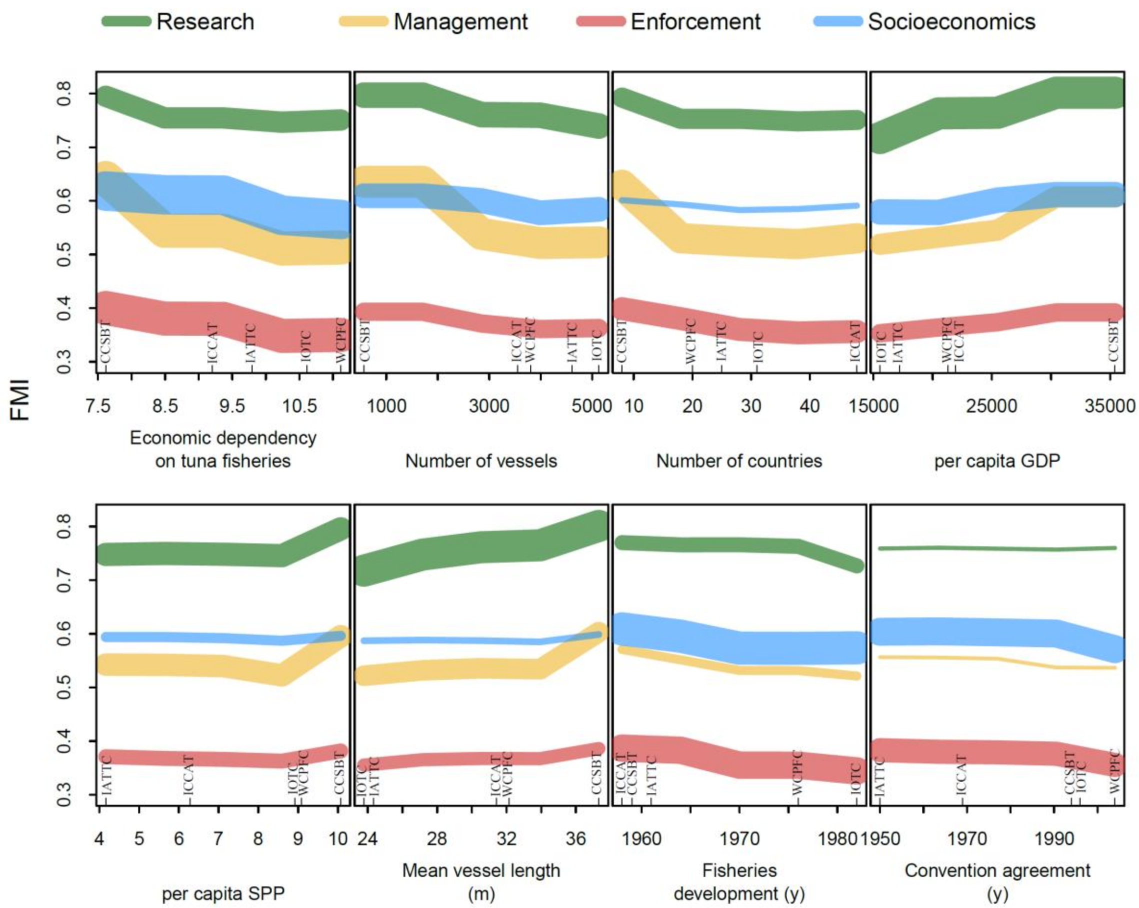

Figure 2.3. Partial dependence plots showing the effect of tRFMO-level predictors on weighted mean responses of FMI dimensions. Line thicknesses are proportional to predictor variable importance scores from random forest analyses, separately for each response variable. Panels are sorted left to right by the sum of variable importance scores across all four response variables. Predictor variable values for each tRFMO are indicated adjacent to axes.

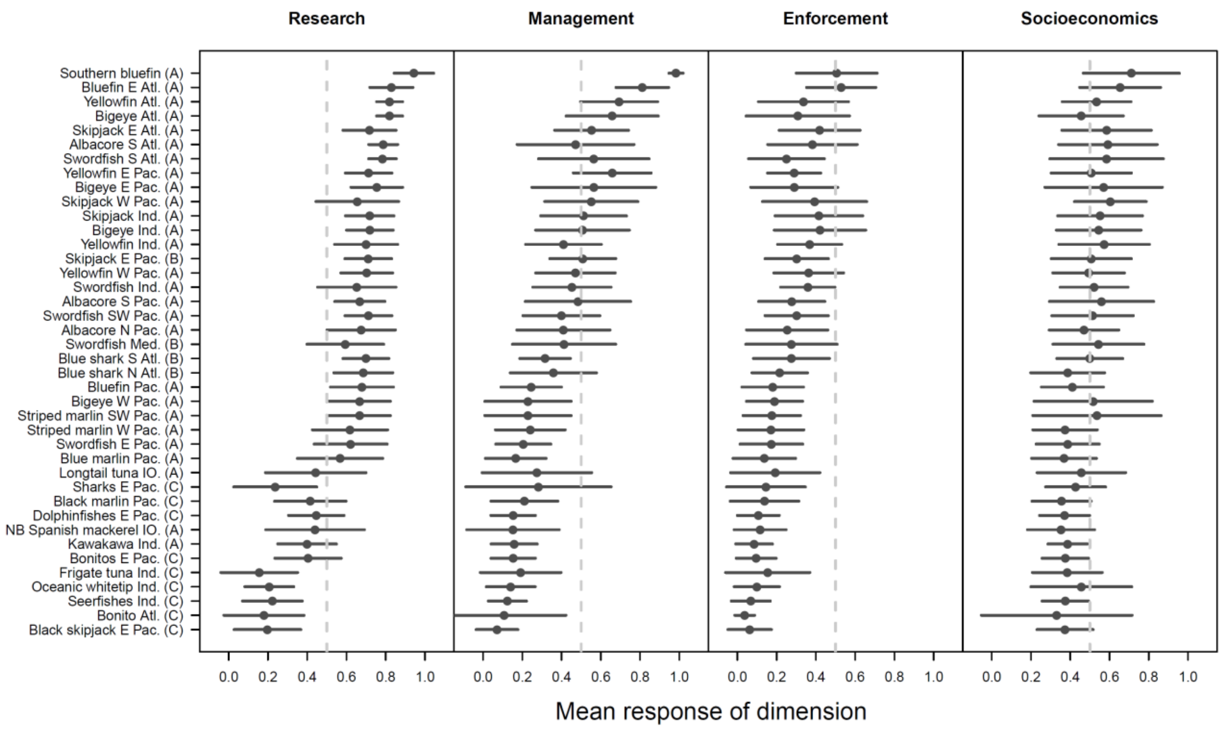

Figure 2.4. Summarized survey answers by stock and FMI dimension. Responses are weighted by the confidence in individual answers provided. Letters in parentheses next to stock names indicate: A=assessment with reliable reference points; B=assessment with no estimation or non-reliable reference points; and C= no assessment. Dashed lines show values of 0.5 for reference and error bars show one standard deviation from the mean. Attributes are ordered by global FMI values for each stock. Species or group of species not mentioned in the main text: blue shark (*Prionace glauca*, Carcharhinidae), striped marlin (*Kajikia audax*, Istiophoridae), blue marlin (*Makaira nigricans*, Istiphoridae), longtail tuna (*Thunnus tonggol*, Scombridae), black marlin (*Istiompax indica*, Istiphoridae), dolphinfishes (*Coryphaena* spp., Coryphaenidae), narrow-barred (NB) Spanish mackerel (*Scomberomorus commerson*, Scombridae), kawakawa (*Euthynnus affinis*, Scombridae), frigate tuna (*Auxis thazard*, Scombridae), oceanic whitetip shark (*Carcharhinus longimanus*, Carcharhinidae), Atlantic bonito (*Sarda sarda*, Scombridae), black skipjack (*Euthynnus lineatus*, Scombridae), and bonitos and seerfishes (Scombridae).

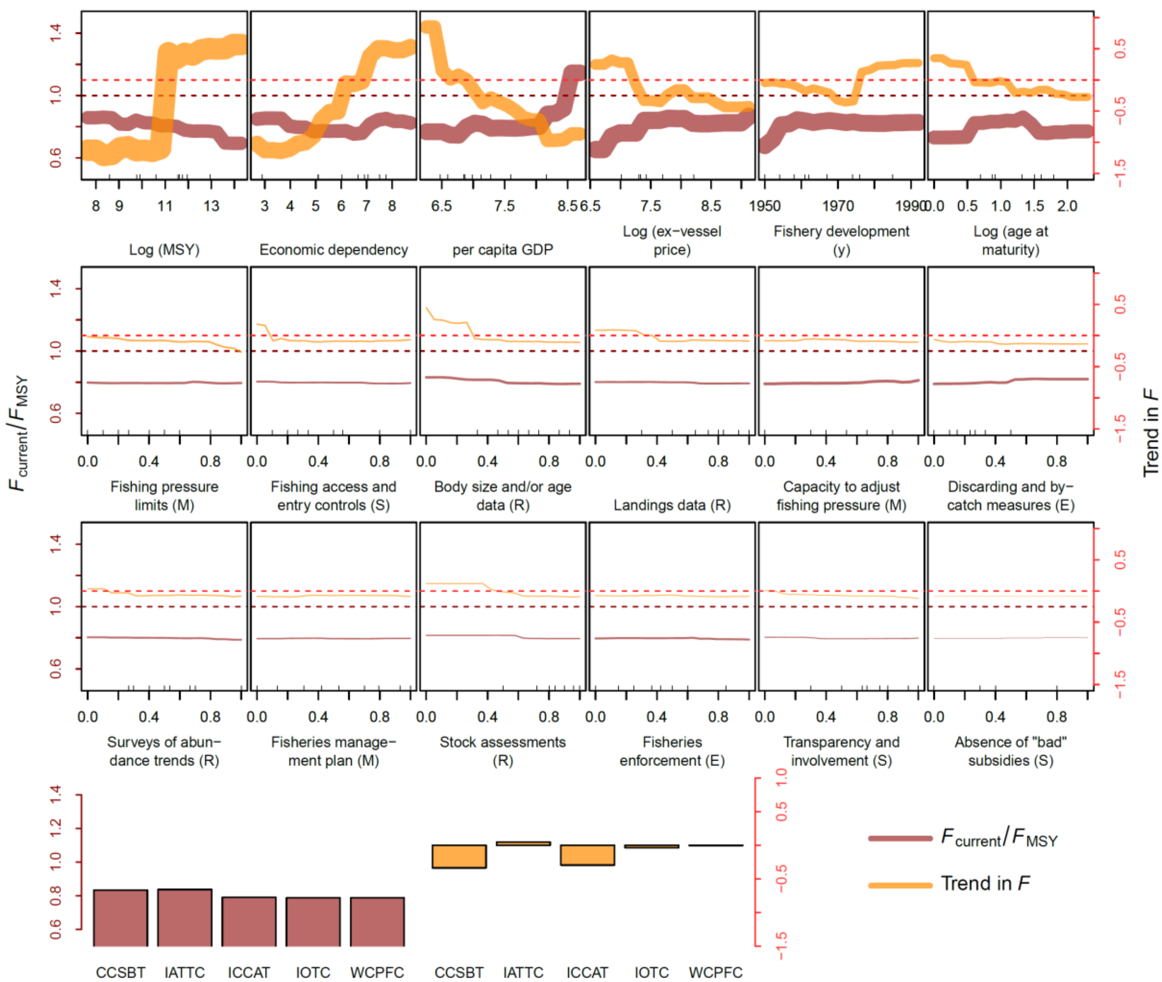

Figure 2.5. Effects of stock-level biological, economic, and fishery factors as well as FMI attributes on current F/F_{MSY} and recent trends in F (mean annual percent of change). Line thicknesses are proportional to predictor variable importance scores from random forest analyses, separately for each response variable. Panels are sorted left to right by the sum of variable importance scores across the two response variables. Barplots represent categorical variables, in this case tRFMOs, which ranked 7th as a predictor. Dashed lines show reference cases of F/F_{MSY} = 1 and annual trend in F = 0%.

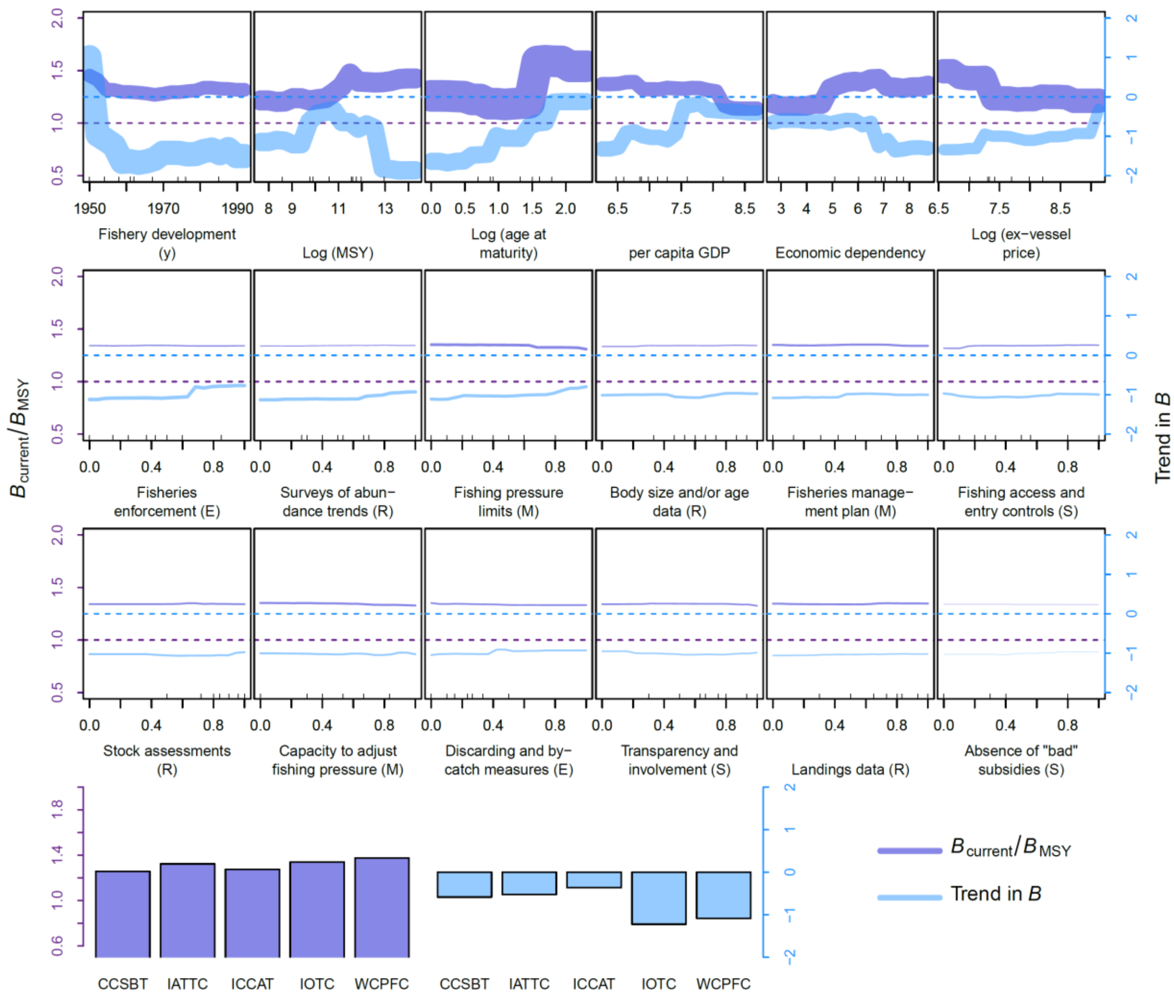

Figure 2.6. Effects of stock-level biological, economic, and fishery factors as well as FMI attributes on current B/B_{MSY} and recent trends in B (mean annual percent of change). Line thicknesses are proportional to predictor variable importance scores from random forest analyses, separately for each response variable. Panels are sorted left to right by the sum of variable importance scores across the two response variables. Barplots represent categorical variables, in this case tRFMOs, which ranked 6th as a predictor. Dashed lines show reference cases of B/B_{MSY} = 1 and annual trend in B = 0%.

Chapter 3. PERFORMANCE OF LENGTH-BASED DATA-LIMITED METHODS IN A MULTI-FLEET CONTEXT: APPLICATION TO SMALL TUNAS, MACKERELS AND BONITOS IN THE ATLANTIC OCEAN.

Abstract

Generally, large scombrids (data-rich commercial tuna species) are regularly assessed and managed. However, most of the small scombrids (data-poor mackerels and bonitos) lack accurate catch data to implement traditional stock assessments. In this study we analyzed different approaches to using length composition data from multiple fleets with different selectivity patterns to assess small scombrids in the Atlantic Ocean, comparing two length-based methods: length-based spawning potential ratio (LBSPR) and length-based integrated mixed effects (LIME). Using length data from the fleet targeting the broadest range of sizes resulted in the lowest bias of all options tested. We estimated for the first time a proxy of current stock status for 10 small scombrid stocks in the Atlantic Ocean. We found that some small scombrid stocks have high chances of undergoing overfishing, such as little tunny in the southeast Atlantic and wahoo in the Northwest. Other stocks have high probability of experiencing overfishing, including little tunny in the Mediterranean and wahoo in the Northeast. Stocks likely experiencing overfishing have no trend by region. This is a starting point in the estimation of stock status for these species, but should not replace other more data-intensive assessment techniques as new data become available due to high uncertainty associated with data-limited

assessments. Improved life history information would be an important step towards decreasing uncertainty for most of the small scombrids stocks in the Atlantic Ocean.

3.1 INTRODUCTION

For the "principal market tunas", like bluefin, bigeye, yellowfin, albacore and skipjack, stock assessments are performed regularly and a variety of management procedures are in place to protect these stocks from overfishing (Pons *et al.* 2017). However, there are also other scombrid species, commonly referred to as small tunas, mackerels and bonitos (from now on small scombrids), that account for a notable proportion of the total tuna and tuna-like species catch, that are mostly unassessed and unmanaged (Juan-Jordá *et al.* 2015; Pons *et al.* 2018). Small scombrids are generally coastal and associated with continental shelves and islands (Collette and Nauen 1983). Although their economic value is lower than the principal market tunas (Collette *et al.* 2011), they sustain important regional commercial fisheries in many coastal communities throughout their distributions (Majkowski 2007). Juan-Jorda *et al.* (2011) showed that within all of the Scombridae, the steepest declines in biomass are exhibited not only for the largest, longest lived, highest value tunas, but also for a few smaller, short-lived mackerels.

Total catch is one of the main data sources required for most of the classical stock assessment methods, particularly when deriving absolute estimates of spawning or total biomass. Stock assessment methods used for principal market tunas use catch data, but obtaining accurate landings and discards for small scombrids is generally challenging (Pitcher *et al.* 2002). Small scombrids are targeted by multiple fleets, particularly medium- and small-scale fisheries, and caught as bycatch in many industrial fisheries targeting commercial tuna species. The catch data available usually consist of incomplete catch time series from tuna Regional Fisheries Management Organizations (tRFMO) statistics, and catch time series that might be highly aggregated by species from the Food and Agriculture Organization (FAO) database (FAO 2016). While quantifying total catch is difficult, there is a wide-ranging toolbox of qualitative and quantitative assessment approaches for data-limited fisheries that use life history characteristics and length data to infer the exploitation status of the stocks (Chrysafi and Kuparinen 2016; Dowling *et al.* 2016). In 2017, Frédou et al. (2017) performed a qualitative risk assessment for small scombrids in the Atlantic Ocean. They identified five of 13 species as priority for evaluation and implementation of future management actions: the low productivity and susceptible *Euthynnus alletteratus* (little tunny), *Acanthocybium solandri* (wahoo) and *Scomberomorus cavalla* (king mackerel); and highly targeted *Sarda sarda* (bonito) and *Auxis thazard* (frigate tuna) (ICCAT 2017a). This 2017 study served to identify priority species, but does not estimate population processes, productivity, or stock status that would be required for more specific management advice.

The International Commission for the Conservation of Atlantic Tunas (ICCAT) suggested that length composition of the catch could be used to quantitatively assess these species' status and inform management advice. In fisheries without total catch data or information on absolute abundance, stock assessments typically use the spawning potential ratio (SPR) as an alternative reference point to maximum sustainable yield (MSY). SPR is defined as the proportion of the unfished reproductive potential per individual under a given level of fishing pressure (Goodyear 1993) and it has been recommended for data-limited assessment because it requires only biological information and an estimate of fishing mortality (Brooks *et al.* 2010). An

SPR of 40% is often used as a conservative proxy for the MSY reference point, even for stocks with relatively low resiliency (Clark 2002).

This study explores two methods for length-based, data-limited stock assessment that require length composition data and life history information, both of which are available for small scombrids. Length-based spawning potential ratio (LBSPR, Hordyk *et al.* 2015a) uses the Beverton-Holt life history invariants in an equilibrium-based population model using the shape of the length composition data compared with the expected unfished length structure to estimate *F/M* and derive SPR. The length-based integrated mixed effects model (LIME, Rudd and Thorson 2017) requires assumptions about *M*, growth, and maturity parameters in an age-structured model fit to length composition data, relaxing equilibrium conditions of previous methods by treating recruitment as a random effect over time and estimating annual *F* as fixed effects (Rudd and Thorson 2018).

Data-limited, length-based stock assessment methods assume selectivity is asymptotic by default (Hordyk *et al.* 2015a; Rudd and Thorson 2018). If large fish are absent from the catch it is assumed they do not exist in the population (as opposed to being less vulnerable to the fishing gear). This assumption is usually violated in highly size-selective fisheries (i.e. gillnets) and it could be problematic in multi-fleet fisheries where stocks are caught in different proportions by multiple gears with different selectivity patterns. As an example, the majority of the catch of the North Atlantic Albacore stock comes from bait boat and trawl fisheries which have a dome-shaped selectivity, catching mainly juvenile albacore. In addition, a smaller proportion of the catch comes from longline fisheries targeting larger individuals, but with different selectivity patterns depending on the fishery (ICCAT 2014b). These different selectivity patterns, catch, and indices of abundance are included in complex assessment models that allow for multiple fleet interactions in the formal assessment performed regularly by ICCAT. Fitting only to length composition, data-limited methods must make more assumptions regarding fishery dynamics, often including the shape of the selectivity curve.

The overarching objective of this study was to develop best practices for combining length data across multiple fleets for length-based assessments of small scombrids in the Atlantic Ocean. To address this objective, we used simulation testing to evaluate the performance of LBSPR and LIME combining length composition data of the catch from multiple fleets with different selectivity scenarios. Using conclusions from the simulation, we applied both length-based approaches to estimate stock status for the priority small scombrid species determined by ICCAT.

3.2 METHODS

We chose the North Atlantic albacore stock on which to develop an operating model for the simulation study. ICCAT, in the 2017 Report of the small tunas species group intersessional meeting (ICCAT 2017b), suggested the North Atlantic albacore stock as a good example of a multi-fleet fishery to use for simulation purposes, where the selectivity patterns are known for 12 different fleets (ICCAT 2014a). This stock is targeted by baitboat, troll, longline and other surface gears in the Atlantic Ocean. In the next sections, we describe the data and specifications used in the operating model (OM), the estimation models (EM), namely LBSPR and LIME, and how we measured their performance under different scenarios.

3.2.1 *Operating models*

Input data – We extracted the catch time series (Figure 1), selectivity patterns from 12 different fleets (Figure 2.A), and the biological parameters (Table 1) from the formal assessment performed by ICCAT in 2013 for North Atlantic Albacore (ICCAT 2014a) to use for the OM. Catches started increasing in 1930 as the fishery was developing, grew rapidly until they reached the maximum development in 1965 and then declined after 1965 (Figure 1). In 2001, ICCAT implemented a quota of 34,500 tons to rebuild this stock because it was overfished. Today the stock is rebuilt. The European Union has the majority of the quota (~75%), harvesting the majority of the catch from bait boat and troll fisheries (ICCAT 2017b). We only included the last 15 years of the time series of length data (1997-2011).

We included 9 fisheries in the operating model with their corresponding catch and selectivity patterns. This included all fleets individually but for simplicity and based on similarity of selectivity patterns (Figure 3.2.A), we combined (*a*) fleets 1 and 2 (bait boat and troll fisheries) which target small individuals and have a dome-shaped selectivity curve; (*b*) fleets 4 and 12 which are other surface gears targeting a broader range of sizes; and (*c*) fleets 10 and 11 which are longline fisheries targeting mainly adults with an asymptotic selectivity curve (Figure 3.2.B). During the last 15 years only 4 of the fisheries were still operating (the three fleet combinations mentioned earlier plus fleet 7 which is a longline fleet that capture Albacore only as bycatch).

Model specifications - We simulated an age structured population using Stock Synthesis (SS) Version 3.30.10 (Methot and Wetzel 2013; Methot *et al.* 2018). We specified a final depletion fitting to an artificial abundance survey index equal to 1 at the beginning of the time series (1930) and 0.4 B_0 in the last year (2011). All parameters were fixed, except the average recruitment in the unfished state (R_0). We simulated 2 populations, one with and one without recruitment deviations. We used the Beverton-Holt spawner-recruit function:

$$R_y = \frac{4hR_0SB_y}{SB_0(1-h)+SB_y(5h-1)}e^{-0.5b_y\sigma_R^2+\tilde{R}_y} \qquad \tilde{R}_y \sim N(0;\sigma_R^2)$$

where R_0 is the unfished equilibrium recruitment, SB_0 is the unfished equilibrium spawning biomass, SB_y is the spawning biomass at the start of the spawning season during year *y*, *h* is the steepness parameter (Table 3.1), b_y is a bias adjustment fraction applied during year *y*, σ_R (fixed to 0.4) is the standard deviation among recruitment deviations in log space, and $\tilde{R}_y$ is the lognormal recruitment deviation for year *y*.

Fishing intensity in SS is directly estimated to match the observed North Atlantic Albacore catch. SS assumes that the absolute level of catch is known, using the catch time series to calculate the level of fishing intensity needed to obtain that level of catch conditioned on the model's current estimate of age-specific population abundance and age-specific selectivity (Methot and Wetzel, 2013). SS calculates the true SPR values as the equilibrium level of spawning biomass-per-recruit that would occur with the current year's level of fishing intensity relative to the unfished level of spawning biomass-per-recruit (Goodyear 1993).

After running the OM in SS, we extracted the expected catch at age by year and fleet from the SS report. We converted this catch at age in biomass into catch at age in numbers using the mean weight at age. We used the age-length key output from SS to assign a distribution of length at each age (Appendix 3.2). Summing across each length bin by gear gave us the length distribution of the catch. We used a 2 cm length bin as in the formal ICCAT assessment (ICCAT 2014). In order to analyze different length sampling scenarios, we sampled from the catch by year and fleet using different sample sizes annually (N= 100, N=1000 and N=10,000) with a multinomial distribution using the probability of being harvested at each length bin for each year.

We repeated this process of simulating a population and generating data for 100 replicates for each scenario.

Scenarios – A common question that arises with length data from multi-fleet fisheries with different selectivity patterns is which fleets to use and how to combine data from them when applying length-based data-limited methods that only estimate selectivity and fishing mortality for one fishing gear. We explored the performance of each estimation method under different approaches combining length data into one common "fleet" (combined length frequencies coming from all of the fleets when more than one fleet was used). In all scenarios the selectivity for this one fleet was estimated and starting values were the same for each model run. We explore 6 possible scenarios:

Scenario 1 – Length composition sampled proportional to the catch of each fleet (Appendix 3.4). This means that fish measured from the fleet with the highest catch would be more represented in the length composition data than other fleets.

Scenario 2 – Length composition sampled with equal weight from each fleet. This means that the same number of individuals were measured from each fleet and combined in one length-sample. All fleets are equally represented in the length composition data.

Scenario 3 – Only use length data from the fleet that targets small individuals (Fleet A). Fleet A (Figure 3.4.A) has a dome-shape selectivity where the true S_{50} is 57 cm (~ age 1.5) and S_{95} is 61 cm (~ age 2, Figure 3.2.B). This fishery catches mainly juveniles and it is the main fishery for North Atlantic Albacore in terms of catch (~ 88%, Appendix 3.4).

Scenario 4 – Only use length data from the fleet that targets a broad range of lengths (Fleet B). Fleet B, which is only 5% of the total albacore catch (Appendix 3.4), has an asymptotic selectivity (Figure 3.2.B) harvesting both juveniles and adults, with a true S_{50} of 78 cm (~ age 3.5) and S_{95} of 90 cm (~ age 5, Figure 3.4.B).

Scenario 5 – Only use length data from the fleets that target adults (Fleet C). Fleet C also catches a small fraction of the total catch (~5 %, Appendix 3.4) but it is a longline fishery that targets mainly adults (Figure 3.4.C) with a true S_{50} of 100 cm (~ age 7) and a S_{95} of 108 cm (~ age 9, Figure 3.2.B).

Scenario 6 – Length composition sampled proportional to the catch from the 2 fleets with logistic selectivity (longline and other surface gears, Figure 3.2.B).

3.2.2 *Estimation models*

In LBSPR, SPR in an exploited population is a function of the ratio of fishing mortality to natural mortality (F/M), and the two life history ratios M/k and L_m/L_∞; k is the von Bertalanffy growth coefficient, L_m is the size of maturity and L_∞ is asymptotic size (Hordyk *et al.* 2015a). The inputs to the LBSPR are: M/k, L_∞, the variability of length-at-age (CVL_∞), which was set as 10% in the OMs; and size of maturity specified in terms of L_{50} and L_{95}, the size at which 50% and 95% of a population matures (Table 3.1). Given the assumed values for the M/k and L_∞ parameters, and length composition data from an exploited stock, the LBSPR model uses maximum likelihood methods to estimate the selectivity ogive, which is assumed to be a logistic curve defined by the selectivity-at-length parameters S_{50} and S_{95}, and the relative fishing mortality (F/M), which are then used to calculate the SPR (Hordyk *et al.* 2015a). LBSPR estimates a selectivity curve for each time step. Estimates of SPR are primarily determined by the length of the fish in a sample, relative to the maturity and L_∞. If a reasonable proportion of fish in a sample attain lengths approaching L_∞, estimates of F/M will be relatively low leading to a high estimate of SPR. LBSPR is an equilibrium-based method with some underlying assumptions including: (i) asymptotic selectivity, (ii) growth adequately described by the von Bertalanffy equation, (iii) a single growth curve can be used to describe both sexes which have equal catchability, (iv) length at-age is normally distributed, (v) rates of natural mortality are constant across adult age classes, (vi) growth rates remain constant across the cohorts within a stock, and (vii) and constant recruitment (Hordyk *et al.* 2015a). In this study we used LBSPR package version 0.1.2 in R (Hordyk 2017).

LIME uses length data and biological information to estimate annual F, the selectivity-at-length parameters S_{50} and S_{95}, recruitment standard deviation, and the Dirichlet-multinomial parameter related to effective sample size of the length data. These parameters are used in an underlying age-structured model to derive population parameters such as SPR and relative spawning biomass. LIME has the same assumptions as LBSPR, but LIME does not assume equilibrium conditions; LIME extends length-based methods by deriving time-varying recruitment deviations (Rudd and Thorson 2018). LIME uses automatic differentiation and Laplace approximations (TMB) (Kristensen *et al.* 2018) to calculate the marginal likelihood for the random effect on recruitment. All other data requirements are the same as LBSPR but LIME estimates one selectivity curve for the entire time series of length data, while LBSPR estimates one selectivity for each year since LBSPR treats multiple years of length data independently (Hordyk *et al.* 2015a). LIME can also accommodate catch and/or abundance data if available (Rudd and Thorson 2018), although this feature was not used in this study. We used the LIME package version 1.0.5 (Rudd 2018).

3.2.3 *Performance measures*

The performance of the EMs under different scenarios were compared with the simulated "truth" using relative error (RE) calculated as (*estimated-true)*/*true,* where *estimated* comes from the EM and *true* from the OM. This is a measure of uncertainty, in both bias and precision, of the EM under each scenario, and it is commonly used as a standardized metric of model performance. We used SPR as the performance measure for all scenarios estimated by both LIME and LBSPR. We presented the relative error of the last year of the time series of SPR in all cases for the 100 simulation replicates for each scenario.

3.2.4 *Small scombrids in the Atlantic Ocean.*

Five species were identified as priority to be evaluated by ICCAT in 2017: little tunny, bonito, wahoo, king mackerel and frigate tuna (ICCAT 2017b). In the present study we did not evaluate king mackerel because it is distributed only in the western Atlantic and is regularly assessed by the US as two independent stocks: one in the Gulf of Mexico and the other off the Southeast coast of the US (SEDAR 2014a,b). Neither stock of king mackerel are currently overfished nor undergoing overfishing.

None of the other four species of small scombrids have studies defining stocks boundaries in the Atlantic Ocean are lacking. So, for management purposes, ICCAT uses five sampling or statistical areas for small scombrids: Northwest Atlantic, Southwest Atlantic, Northeast Atlantic, Southeast Atlantic and Mediterranean Sea (Appendix 3.2). Since there are no genetic stock differentiations for these species in the Atlantic Ocean, we decided to use these areas as a proxy of stock boundaries to assess these putative "stocks".

The ICCAT Task2sz database (http://iccat.es/en/accesingdb.htm) has length data composition from 1975 to 2016 for the four priority species assessed in this study. The length composition data available for each stock comes from different regions and different gear types. Since our main goal is to estimate current stock status, we used only data from 2010 to the present where there is a better representation of the length composition of the catch by year and gear (Figure 3.3) were omitted. We used the length data reported in 1 and 2 cm bins and we pooled them into 2 cm length bins for the analysis. The number of fish measured by year for the priority species varies between 17,429 individuals measured in 2016 to 98,173 in 2014, all species combined. Although we ran the models from 2010 to 2016 when data were available, we presented the stock status for the year 2014 where there are more length data and they are consistent among species and representative of different gears (Figure 3.3).

For some stocks the length data available was limited, so samples numbering fewer than 100 fish per year and gear combination from 2010 to 2016 (Figure 3.3). Some stocks, such as wahoo in the South West, were excluded from the analysis because they are targeted by multiple fleets, but length data are available only for one gear (gillnets) and would bias the results. This filtering process reduced the number of stocks with enough information to run the length-based models. We did not run these models for bonito in the South East, Northwest and Southwest, little tunny in the Southwest, wahoo in the Mediterranean, Southeast and Southwest (stock not present in the Mediterranean), and frigate tuna in the Mediterranean, Southwest and Southeast resulting in 10 stocks with representative information of length composition data of catch by gear (Table 3.2).

Both LBSPR and LIME require life history information on growth, maturity and length-weight relationships as input parameters. These methods are very sensitive to these parameters (Hordyk *et al.* 2015a; Rudd and Thorson 2018). In 2018, the ICCAT small tunas working group met and a set of life history parameters were agreed among scientist from each region in the Atlantic Ocean for each stock to run data-limited methods (ICCAT 2018, Appendix 3.3). There are a lot of gaps in the life history information available for these species. In cases where there were missing information for the life history parameters, we borrowed information from the nearest stock of that species (i.e. when missing information existed for the South East Atlantic, we borrowed the information from the Northeast Atlantic) to run the length-based models.

Table 3.2 shows the final parameters used for each stock to run LBSPR and LIME. Natural mortality (*M*) was calculated using different empirical life-history based methods (Cope 2017, see http://barefootecologist.com.au/shiny_m). We used 9 methods which use growth life history parameters ($L\infty$, k, t_0 and maximum age) (Alverson and Carney 1975; Chen and Watanabe 1989; Jensen 1996, 1997; Then *et al.* 2015). Table 3.2 shows the median and 1st and 3rd quantile of the distribution of *M* estimated for each stock. LBSPR and LIME were run with these three *M* values to test their sensitivity to this parameter estimation.

Reference points for small scombrids – We used SPR as a biological reference point. In general, it is used as a proxy of MSY when information on the scale population size is not available. A harvest strategy that targets a fishing mortality rate that is expected to results in 40% of the unfished spawning output ($SPR_{40\%}$), is considered a reasonable proxy even for stocks with very low resiliency (Clark 2002). Moreover, 30% of SPR is sometimes considered a threshold beyond which overfishing would be ocurring (Clark 2002; Nadon *et al.* 2015; Rudd and Thorson 2018). In addition, we presented the estimated ratio *F/M* for each stock.

3.3 RESULTS

3.3.1 *Simulation testing: length data in multi-fleet fisheries*

Based on the observed catch data for North Atlantic Albacore used in the OM, the true SPR value in the terminal year was 0.55 for the OM without recruitment deviations, and for the OM that includes random recruitment deviations the median was 0.66 with a range between 0.50

and 0.74 (Figure 3.5). LBSPR was least biased in when using length data from the fleet with asymptotic selectivity catching a broad range of lengths from juveniles to adults (Scenario 4; Figure 6). LIME was least biased with length data from the combined fleets that target a broad range of lengths under both OMs (Scenario 6) and the fleet that targets only adults when considering recruitment variability (Scenario 5; Figure 3.6). Both models estimated SPR higher than the truth when using the length composition data weighted by catch (Scenario 1) and length data from the fleet with dome-shape selectivity (Scenario 3). SPR was highly overestimated when considering the same weight for each fleet (Scenario 2). LBSPR was biased when using length composition from the fleets targeting only adults (Scenario 5 and 6; Figure 3.6).

In general, the results of LIME and LBSPR in the equilibrium model became more similar with more individuals measured. There was not much variability in results between scenarios that assumed recruitment variability across different sample sizes. LBSPR was not sensitive to sample size, although precision increased as more fish were measured (Figure 3.6).

In Scenario 1 length composition data was weighted by the catch, so in this case more weight was given to the fleet with dome-shape selectivity. In this scenario both LBSPR and LIME underestimated SPR on average in both recruitment scenarios (Figure 3.6). Under an asymptotic selectivity assumption, if large individuals are absent from the catch, both assessment methods estimate *F* to be higher than the truth and then SPR lower than the truth. LIME estimated SPR to be almost zero for the runs with no recruitment deviates, with RE similar to LBSPR when sampling 10,000 fish. Results from Scenario 3 were similar to Scenario 1 since both scenarios put higher weight on length compositions consisting of mainly juveniles or smaller individuals than the full span of vulnerable fish (Appendix 4).

Under Scenario 2 sampling the same number of individuals by gear type, LBSPR and LIME estimated SPR higher than the truth, particularly when the OM did not consider recruitment variability. When considering recruitment variability, LBSPR was positively bias although LIME was less biased but less precise. Under these scenarios the proportion of large individuals in the catch was overrepresented (Appendix 3.5), leading to the EMs estimating higher SPR values than expected. The same overestimation of SPR occurred in Scenario 5 using the fleet that targets adults when no recruitment variability was included in the OM and Scenario 6 when only considering the length composition data coming from the two fleets with asymptotic selectivity due to the proportions of large individuals in the catch in both cases (Figure 3.6).

LBSPR was less biased in Scenario 4 when considering only the fleet with an asymptotic selectivity that captures a broad range of sizes, while LIME was less biased under the scenarios with recruitment variability when considering the fleets with gears that selected mainly adults in Scenario 5 (Figure 3.6). We observed that in many cases LIME estimates higher selectivity parameter values, S_{50} and S_{95}, than LBSPR, meaning that the model expects larger individuals in the length composition of the catch than was observed and then estimates low SPR values. This is probably the reason why LIME performs better when using fleets that target large fish and why LIME SPR estimate are lower than LBSPR when using the same data.

3.3.2 *Assessments of small scombrids in the Atlantic Ocean.*

Based on simulation testing, LBSPR performed best in Scenario 4 which used the length data coming from the fleet with an asymptotic selectivity targeting a broad range of lengths. LIME however, performed better in Scenarios 5 and 6, where mainly adults were represented in the catch. Based on these results, we decided to apply both LIME and LBSPR using the length composition data from small scombrids from the fleet that has a broader range of sizes including adults, available in the ICCAT database. The gears used varied among stocks.

The length composition data for each stock by gear, filtered by year-gear combinations with at least 100 length measurements, varies among areas likely based on differences between fleets operating in each region (Figure 3.7). Length composition data for little tunny is available for two gears in the Northwest Atlantic, but rod and reel has better representation by year and length range compared with traps. In this case we used length data from rod and reel only to assess this stock. For little tunny in the Northeast Atlantic we selected the length data coming from traps since they cover a broader range of ages including adults, despite the fact that there are no data in 2011. For little tunny in the Mediterranean we used length data from longlines and for the Southeast Atlantic we used data from gillnets (Figure 3.7). For wahoo in the Northeast we used the length composition from hand lines since is the only information available, and rod and reel for the Northwest. For bonito in the Mediterranean, we used length data coming from longlines just as we did for little tunny in the same area. Finally, for frigate tuna in the Northeast and in the Southeast we selected the length data coming from purse seine fisheries (Figure 3.7).

For some small scombrids stocks, the SPR estimates were below the target of 40%, but the results varied between assumptions about *M* and the estimation method considered (Figure 3.8). LBSPR and LIME predicted different values of SPR, and sometimes the estimated values were far apart, such as for bonito in the Mediterranean and in the Northeast (e.g. 0.2 with LIME and 0.6 with LBSPR). LIME estimated a lower selectivity than LBSPR and then a higher *F* and lower SPR (Appendix 3.6.A). On the contrary, for bonito in the Northeast, LIME estimated a higher selectivity ogive and a lower *F* and higher SPR than LBSPR. LIME estimated that during 2014 there was a high recruitment and then the small individuals in the catch were attributed to the recruitment spike, as opposed to LBSPR which interpreted the small individuals as a high *F* (Appendix 3.6.B). As expected, when *M* was assumed to be lower than in the base case scenario (median *M*), the SPR estimations were lower (Figure 3.8).

Little tunny in the Southeast was below 40% in all cases except when LIME assumed a high *M*, leading to an SPR estimate of 0.7 (Figure 3.8). Assuming the median value of *M*, LBSPR predicted a very high *F* and SPR values below 20% for the entire time series. LIME also predicted low SPR values, around 30%, and a much lower S_{50} than LBSPR (Appendix 3.7.A). The results of LBSPR and LIME were more similar for little tunny in the Northwest (Appendix 3.7.B), Mediterranean (Appendix 3.7.C) and Northeast Atlantic (Appendix 3.7.D), estimating that SPR for these stocks were above the 40% target reference point. For little tunny in the Mediterranean the ration between *F/M* is high (above 2) even though SPR is above 40%.

SPR estimates for both LBSPR and LIME for wahoo in the Northwest were below 40% (except in the high *M* scenario with LIME). LIME predicted very high *F/M* and SPR below 40% except when assuming a higher *M* for wahoo in the Northeast. In both the Northwest and Northeast, LIME predicted a higher S_{50} and a lower SPR than LBSPR (Appendix 3.8.A and B). None of the frigate tuna stocks assessments estimated SPR below 40% except with LIME in the low *M* scenario where SPR was estimated at approximately 20% for the Northeast and Southeast stocks (Figure 3.8).

3.4 Discussion

The present study analyzed different approaches to use length-based data-limited assessments when length composition data come from fisheries with multiple gears with different selectivity patterns exist. The idea was first developed to explore how to use the length composition data from multi-fleet fisheries to estimate stock status for small scombrids. The results show enough variation in results, so we recommend further simulation testing for multi-fleet fisheries with variable life history and exploitation patterns.

3.4.1 *Length data in multi-fleet fisheries*

We showed how stock assessment results could be highly biased when using only one gear, not representative of the length of the exploited population, particularly when the assumptions of asymptotic selectivity are violated (e.g. albacore length data coming from bait boat and troll fisheries targeting juveniles with a dome-shape selectivity). In this case, high catches of smaller individuals resulted in an underrepresentation of the proportion of adults in the population, estimating a lower SPR value than the truth. Even if the asymptotic selectivity assumption is met (i.e. albacore length data coming from longline fleets targeting adults), LBSPR and LIME overestimated SPR. Hordyk *et al.* (2015a) suggested that when there are multiple fleets targeting the same stock, the LBSPR model should be applied to the data from the fleet that targets the adult portion of the stock. However, we found that SPR estimates were biased for small scombrids in this case. In all the scenarios analyzed by Hordyk *et al.* (2015a) the S_{50} was lower than the L_{50}, but in our scenarios 5 and 6, the S_{50} was higher than the L_{50}, potentially explaining why they did not find this bias in their results. SPR estimates are primarily determined by the size of the fish in a sample relative to both size at maturity and L_{∞}. In our Scenario 4, where the S_{50} was lower than the L_{50}, LBSPR was less biased.

Based on our results, we recommend that when there are multiple fleets with different selectivity patterns targeting one stock, length-based models should be applied to the length data coming from the fleet that targets the broadest range of sizes including adults, but not restricted only to the adult portion of the catch. SPR estimates improve when the catch length sample is representative of the length composition of the exploited population. In addition, we found that the precision in the SPR estimates was greatly improved when increasing the sample size for both LBSPR and LIME consistently with Hordyk *et al.* (2015a) and Rudd and Thorson (2017). To improve estimates, more from the fishery with the broadest size distribution is preferred.

Rudd and Thorson (2017) tested the performance of LIME under LBSPR's own OM (Hordyk *et al.* 2015a), with relative ages based on the *M/k* ratio. They found that LBSPR performs well across all life history types, but LIME under-estimated SPR for the medium- and longer-lived life history types, and over-estimated SPR for the short-lived life history type. However, in most of the non-equilibrium scenarios LIME performed better than LBSPR. We also found in most of the scenarios considered that LIME estimated a lower SPR than LBSPR for this medium lived tuna species. This suggests that LIME provides status determinations that are more conservative.

3.4.2 *Small scombrids stock status*

LIME has been used in data-limited stock assessments for small-scale fisheries in Costa Rica and Kenya (Rudd 2017) and LBSPR in Palau (Prince *et al.* 2015). LBSPR is run independently each year, resulting in separate annual estimates of SPR, selectivity parameters, and the ratio of fishing mortality to natural mortality (*F/M*). However, LIME includes length composition data available for multiple years in the same model to estimate a single selectivity curve for all years and fishing mortality and recruitment that can vary among years. Therefore, assumptions and model structure are different between LIME and LBSPR, so it is unsurprising that results differed.

We did not find a specific pattern in exploitation status among regions, meaning that any particular region showed more small scombrids stocks under overfishing than others regions

(Figure 3.8). Although some combinations of stock assessment model and natural mortality rate resulted in differing estimates of stock status, the approaches agreed under the base scenario with median *M* that 2 stocks out of 10 are undergoing overfishing: little tunny in the Southeast and wahoo in the Northwest.

Little tunny: the length composition data for little tunny in the Northeast and Northwest Atlantic from purse seiners were very similar (Figure 3.7), where the median length by year was just below 50 cm, but above the length at maturity (Table 3.2). Both assessment methods estimated SPR values above 40% indicating that these stocks are not undergoing overfishing. However, assessments for little tunny in the Southeast estimated SPR values below the target reference point of 40% in almost all scenarios considered, except when using LIME under a high *M* assumption. Most of the fish caught were below the length at maturity and this stock was estimated to be undergoing overfishing (Figure 3.8). These results are in agreement with a preliminary qualitative risk assessment analysis performed for small scombrids in the Atlantic Ocean considering two populations, North and South. The southern stock was found at high risk, while the northern populations were found at moderate risk (Frédou *et al.* 2017). This species has an estimated maximum age between eight and ten years (Cayre and Diouf 1980) and an estimate of L_∞ between 86 and 117 cm. Adults of this species above 60 cm in the Southeast are scarce in the length composition sample of the catch leading to low estimates of SPR.

Bonito: In the base case scenario bonito in the Northeast was estimated to have a SPR below target reference points with LBSPR, but not with LIME. The opposite was observed in the Mediterranean, where LIME estimated a lower SPR than LBSPR. Rudd and Thorson (2018) found that LIME generally estimated a higher SPR than the truth for short-lived fish in a yearly time step (see Chapter 4). A monthly time step could be considered in the future for this species to test for sensitivity to this assumption since the life span for this species is five years (Baibbat *et al.* 2016).

Previous data-limited assessment methods were applied for bonito in the Northeast using Morocco landings data between 2012 and 2014. A Powell-Wetherall plot approach was used to explore changes in total mortality (Z) based on length samples and catch curve analysis using lengths converted to age and cohort slicing (Ahmed *et al.* 2015). Assuming an M of 0.2 they found that fishing mortality is twice this value and they suggested that this stock might be fully exploited. The M values used in the present study were higher than 0.2 in all cases, so using such a low value for M could give similar results as in Ahmed *et al.* (2015). Frédou *et al.* (2017) found that bonito for the North Atlantic was not vulnerable but they also noted that the quality of the data used to evaluate this stocks was low.

Frigate tuna: In almost all scenarios, the stocks were estimated to be above 40%. However, assessments for the Northeast stock always estimated lower SPR values than the one in the Southeast. Again, these results matched the preliminary risk assessment for small scombrids in the Atlantic Ocean, where stocks in the South are at lower risk than the ones in the North (Frédou *et al.* 2017). However, both F and SPR estimates in the Southeast should be considered with caution since some of the results are in the low right quadrant at F close to 0 and SPR close to 1 with very high uncertainty. If F was estimated to be close to 0 it is likely that the life history information is inaccurate because we know the F is not 0 since the fishery is occurring. L_∞ might be too high, so both models would estimate no fishing if the observed lengths are very close to the asymptotic length. The growth parameters should be discussed again at the next small tuna group meeting to consider different values for life history for this stock.

Wahoo: This species in the North Atlantic was identified previously as low risk using a qualitative ecological risk assessment (Frédou *et al.* 2017). However, both LIME and LBSPR estimated low SPR values for the Northwest stock, suggesting that this stock is undergoing overfishing. In the Northeast, only LIME in the base case and low *M* scenarios estimated that this stock is experiencing overfishing, but not LBSPR.

3.4.3 *Future directions*

Here, we estimate for the first time a proxy of the current stock status for 10 stocks of the small scombrids group of species in the Atlantic Ocean. This is a starting point in the estimation of stock status for these species, but the wide uncertainty in estimates combined with differences in results between LBSPR and LIME demonstrate that data-poor methods are not substitutes for more data-intensive assessment techniques. ICCAT should keep supporting the collection of improved life history information, length data from all gears, catch data, and and fisheries for these 10 stocks and for all Small scombrids, as well as motivating for data that measure trends in abundance directly, in addition to improving biological information and catch data to perform a full assessment.

LBSPR and LIME, like all the age or length-based methods, are sensitive to misspecifications of the inputs of life information (Hordyk *et al.* 2015a; Rudd and Thorson 2018). Sensitivity tests in these studies demonstrated the impact of the misspecification of biological parameters. Quantification of uncertainty is one of the next steps in the evaluation of these stocks, not only for *M*, but for other growth and maturity parameters, to provide support for local biological studies of these species. To account for the uncertainty in the biological parameters with the current information available in the Scombridae database (Juan-Jordá *et al.*

2016), a Monte Carlo algorithm could be applied in future studies specifying prior distributions for life history parameters (Prince *et al.* 2015).

3.4.4 *Conclusions*

Small scombrid fisheries in the Atlantic Ocean are medium to small-scale, data-limited and generally unassessed, with a lack of management and enforcement, with exception of some regions in the Northwest Atlantic such in the US. Determining stock status is the first step to protect these stocks from overfishing and apply management measures to rebuild stocks that are currently undergoing overfishing. Since stock status for these species is highly uncertain, a management strategy evaluation is needed to evaluate different harvest control rules accounting for data and model uncertainty. There are still many gaps in the biological information available for these stocks, so basic biological information such as growth, reproduction and natural mortality estimates are essential to improve our understanding of fishing impacts on these populations.

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3.5 Tables

Table 3.3. OM biological inputs parameters for North Atlantic Albacore (ICCAT 2014).

Biological information	**Symbol**	**Value**
Maximum age (years)	T_{max}	15
Length where 50% of the fish are mature	L_{50}	90
Length where 95% of the fish are mature	L_{95}	100
Length-weight scaling parameter (g)	a	1.34×10^{-5}
Length-weight allometric parameter (g)	b	3.107
Von Bertalanffy Brody growth coefficient	k	0.209
Von Bertalanffy asymptotic length (cm)	L_{∞}	122
Theoretical age at length=0	t_0	-1.3
Variability of length at age	CVL_{∞}	0.1
Recruitment deviations	σ_R	0.4
Steepness	h	0.9

Table 3.2. Life history parameters used as inputs to assess stock status of small scombrids in the Atlantic Ocean using length-based data limited methods. * M was estimated empirically through different methods. The 1st quantile, median, and 3rd quantile are presented.

Species	Parameter	Northeast	Southeast	Mediterranean	Northwest	Southwest
Sarda sarda (BON)	*Lmax*	91.40	Insufficient length data	91.40	Insufficient length data	Insufficient length data
	Linf	73.01		69.57		
	k	0.31		0.44		
	to	-2.45		-1.33		
	Tmax	5		5		
	Lm50	42.60		39.93		
	*M **	0.43; 0.78; 1.11		0.60; 0.83; 1.09		
	WL_a	5.00×10^{-5}		6.32×10^{-6}		
	WL_b	2.79		3.21		
Euthynnus alletteratus (LTA)	*Lmax*	82.60	82.60	122.00	106.68	Insufficient length data
	Linf	86.00	86.00	117.00	86.00	
	k	0.26	0.26	0.19	0.26	
	to	-0.32	-0.32	-1.13	-0.32	
	Tmax	8	8	10	8	
	Lm50	42.00	42.00	51.13	39.70	
	*M **	0.4; 0.53; 0.68	0.4; 0.53; 0.68	0.29; 0.43; 0.54	0.4; 0.53; 0.68	
	WL_a	1.38×10^{-5}	1.38×10^{-5}	1.24×10^{-5}	2.05×10^{-5}	
	WL_b	3.04	3.04	3.06	2.96	
Acanthocybium solandri (WAH)	*Lmax*	200.00	Insufficient length data	Stock not defined	200.00	Insufficient length data
	Linf	179.70			179.70	
	k	0.32			0.32	
	to	-1.91			-1.91	
	Tmax	9			9	
	Lm50	92.50			92.50	
	*M **	0.43; 0.49; 0.60			0.43; 0.49; 0.60	
	WL_a	2.75×10^{-4}			2.04×10^{-6}	
	WL_b	2.72			3.24	
Auxis thazard (FRI)	*Lmax*	65.00	65.00	Insufficient length data	Insufficient length data	Insufficient length data
	Linf	51.47	51.47			
	k	0.32	0.32			
	to	-0.83	-0.83			
	Tmax	4	4			
	Lm50	30.00	30.00			
	*M **	0.48; 1.01; 1.37	0.48; 1.01; 1.37			
	WL_a	8.90×10^{-6}	8.90×10^{-6}			
	WL_b	3.17	3.17			

3.6 FIGURES

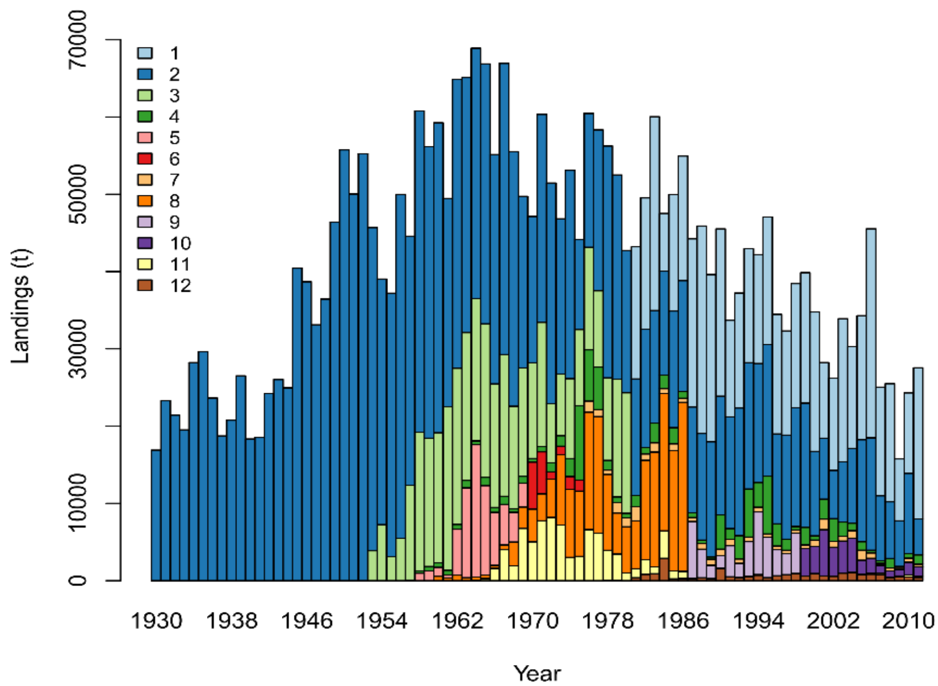

Figure 3.1. Catch of North Atlantic Albacore by fleet from 1930 to 2011 (ICCAT 2014).

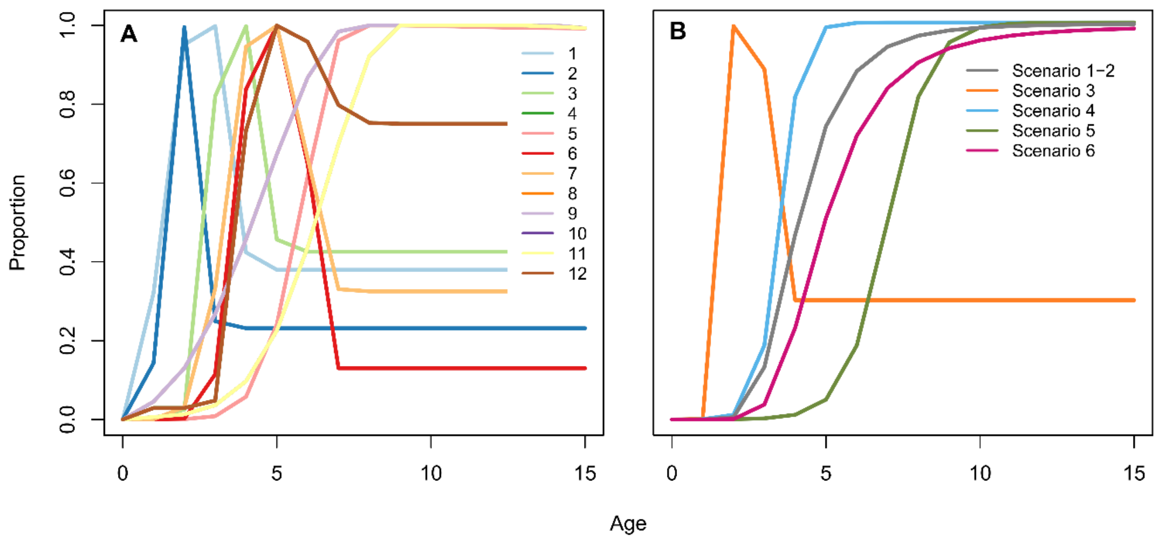

Figure 3.2. Selectivity curves. A: the 12 selectivity curves used in the 2013 North Atlantic Albacore assessment (Fleets 10 and 11, 8 and 9, and 4 and 12 have the same selectivity pattern). B: Combined selectivity curves to test under the different scenarios for the fleets that operated in the las 15 years. Scenario 1 and 2 use a combined selectivity from all the fleets. Scenario 3 uses information only coming from fleets targeting small individuals (bait boat and troll fisheries, fleets 1 and 2) with a dome shape selectivity. Scenario 4 uses information from other surface gears with a broader and asymptotic selectivity (includes fleets 4 and 12). Scenario 5 used information from longline fleets (fleet 10 and 11) with an asymptotic selectivity targeting mainly adults. Scenario 6 uses a combined selectivity from Scenario 4 and 5.

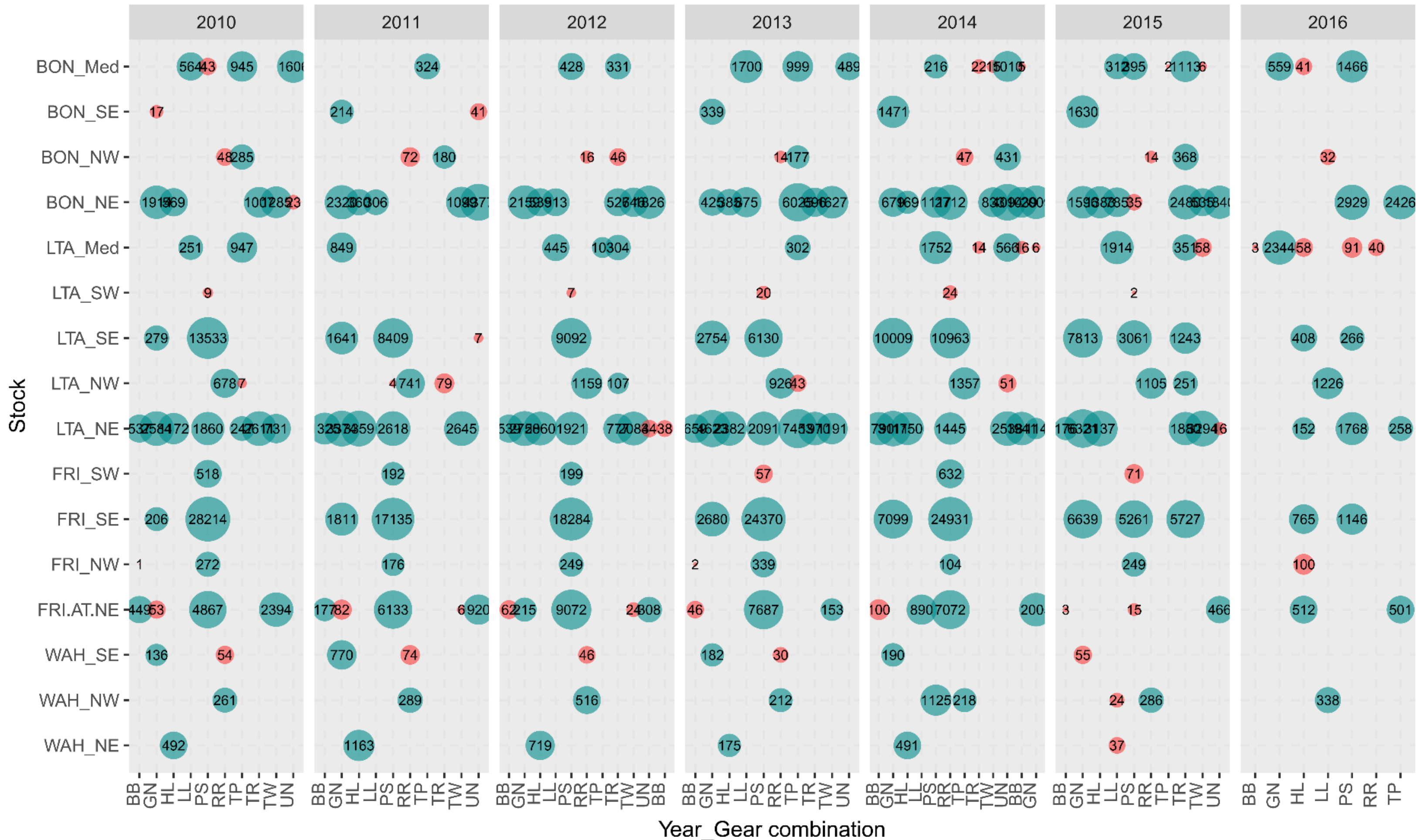

Figure 3.3. Number of fish measured by stock, year and gear from 2010 to 2016. The size of the bubbles is proportional to the logarithm of the number of fish measured and the number is inside the bubble. In red are those where the number of fish measured is less than 100. Gears: gillnets (GN); handline (HL); longline (LL); purse seine (PS); trap (TP); trolling (TR); trawl (TW); sport (SP); baitboat (BB); rod and reel (RR); haul seine (HS); trammel net (TN); unclassified (UN).

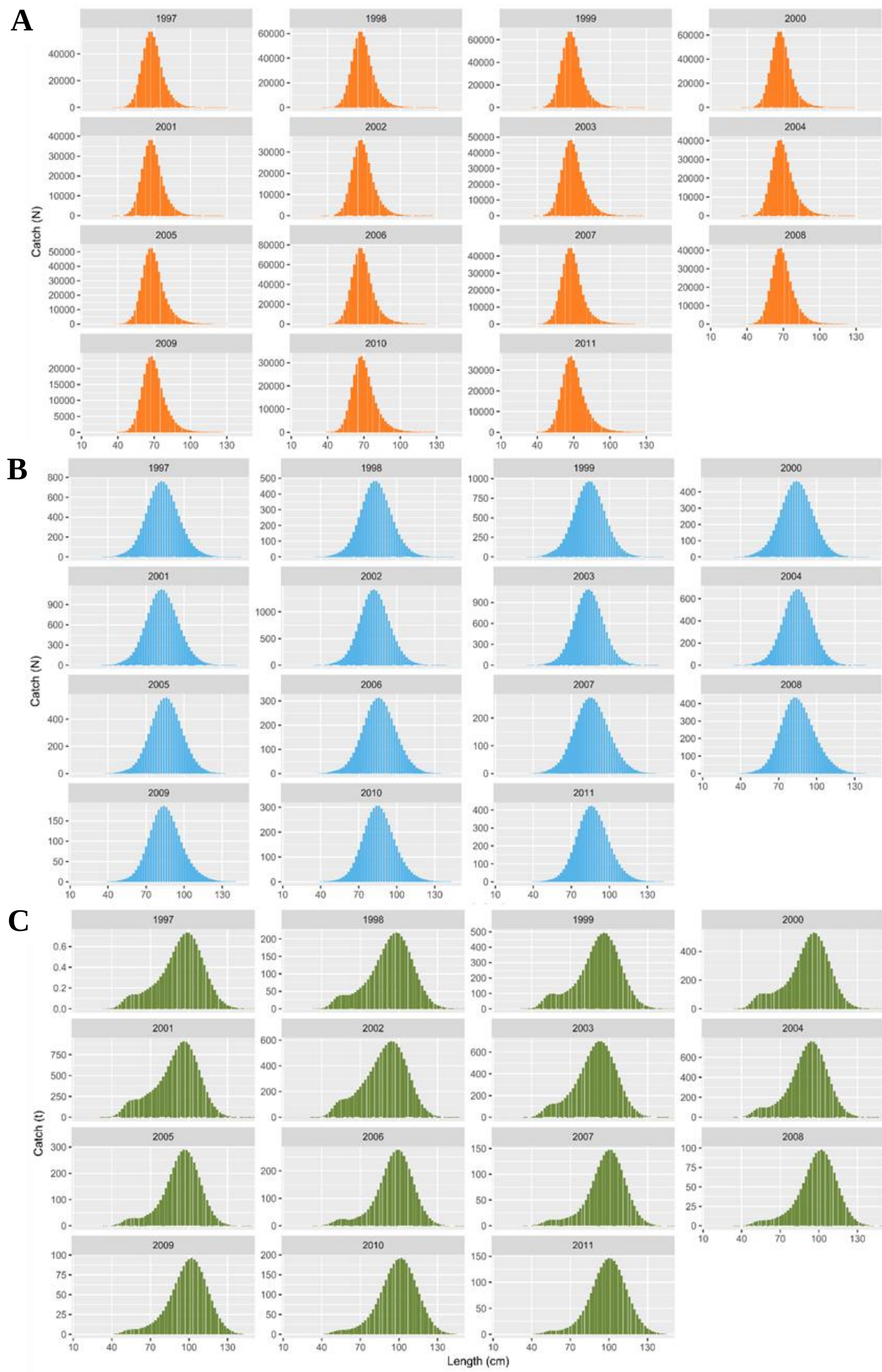

Figure 3.4. Length distribution of the total catch (no sampling) for the last 15 years for the main fleets using in the length-data weighting scenarios. A: fleet A, targeting small albacore. B: fleet B targeting a broader range of sizes. C: fleet C, targeting adult albacore tunas.

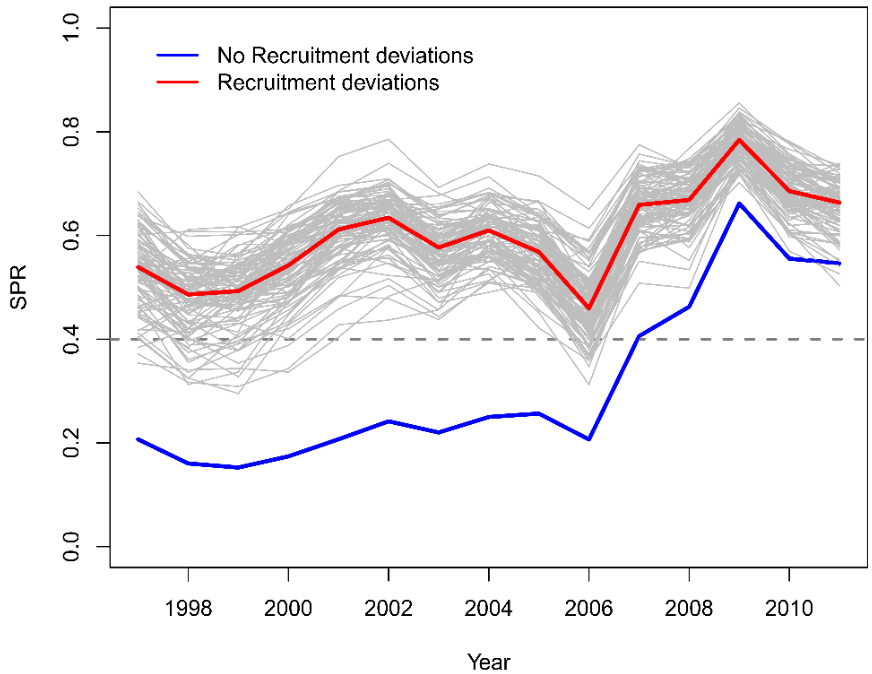

Figure 3.5. Time series of the true SPR for the 2 OM (with and without recruitment deviations). The grey lines are the SPR time series for each of the 100 runs with random recruitment deviations.

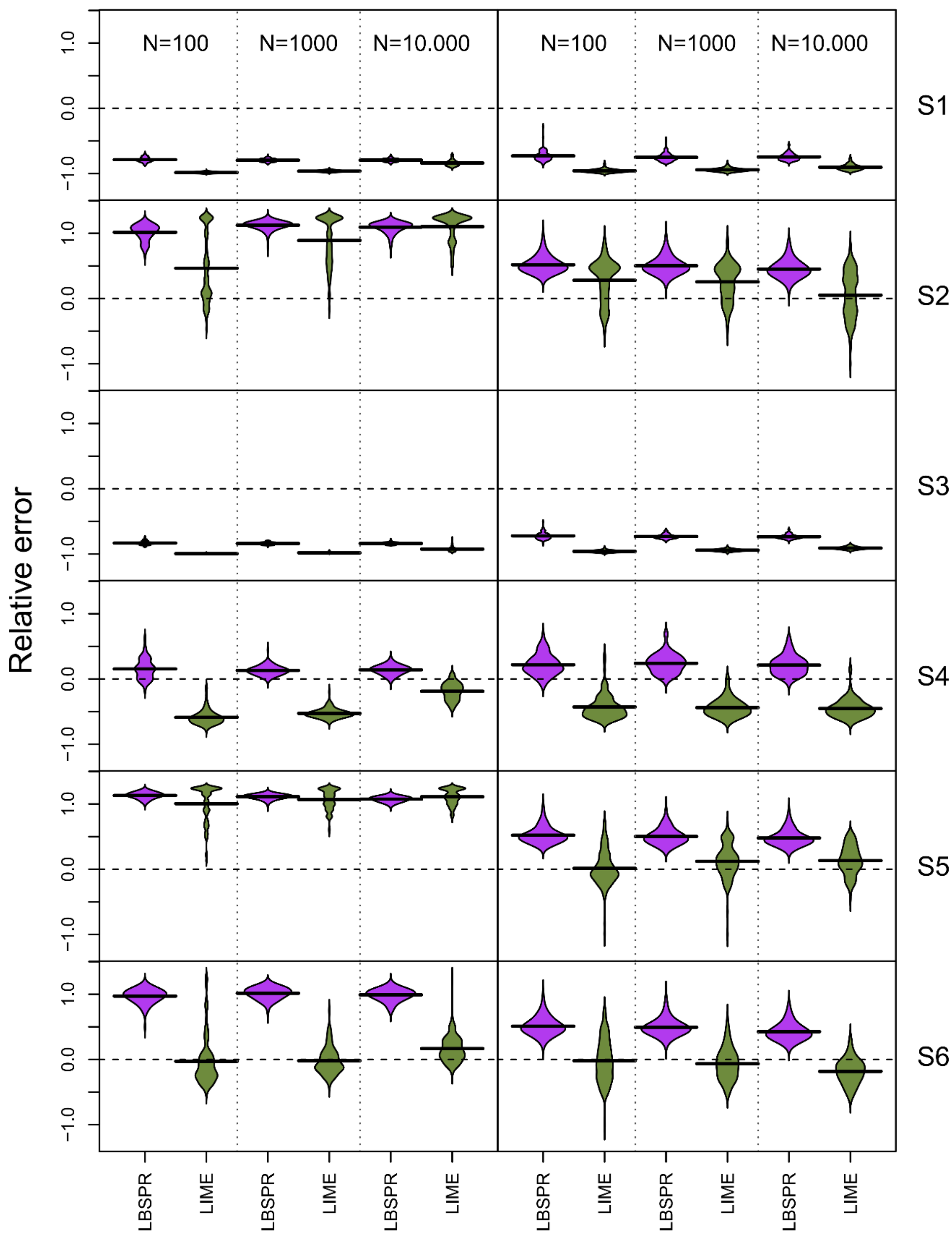

Figure 3.6. Relative error for the 6 Scenarios tested (S1 to S6) for LIME (green) and LBSPR (purple) compared with the OMs with (right column) and without (left column) recruitment deviations.

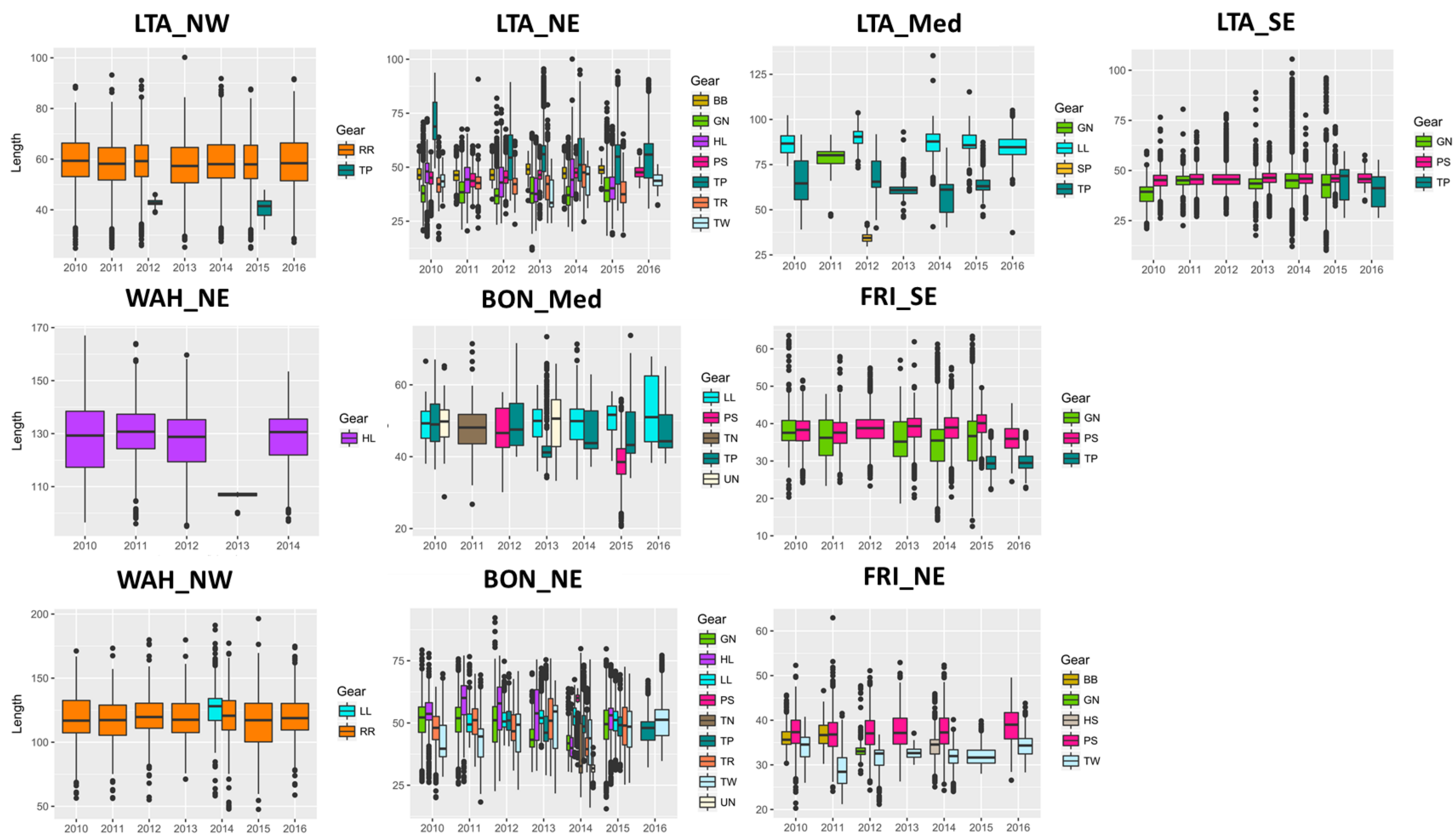

Figure 3.7. Length compostion data for the main stocks of small scombrids by gear in the Atlantic Ocean available in Task2sz databse of ICCAT. LTA: little tunny; WAH: wahoo; BON: bonito; FRI: frigate tuna. BB: bait boats; GN: gillnets; HL: hand lines; HS: haul seine; LL: longline; PS: purse seine; RR: rod and reel; SP: sport; TN: trammerl net; TP: traps; TR: trolling; TW: trawl; UN: unknown. NE: Northeast; SE: Southeast; NW: Northwest and Med: Mediterranean Sea.

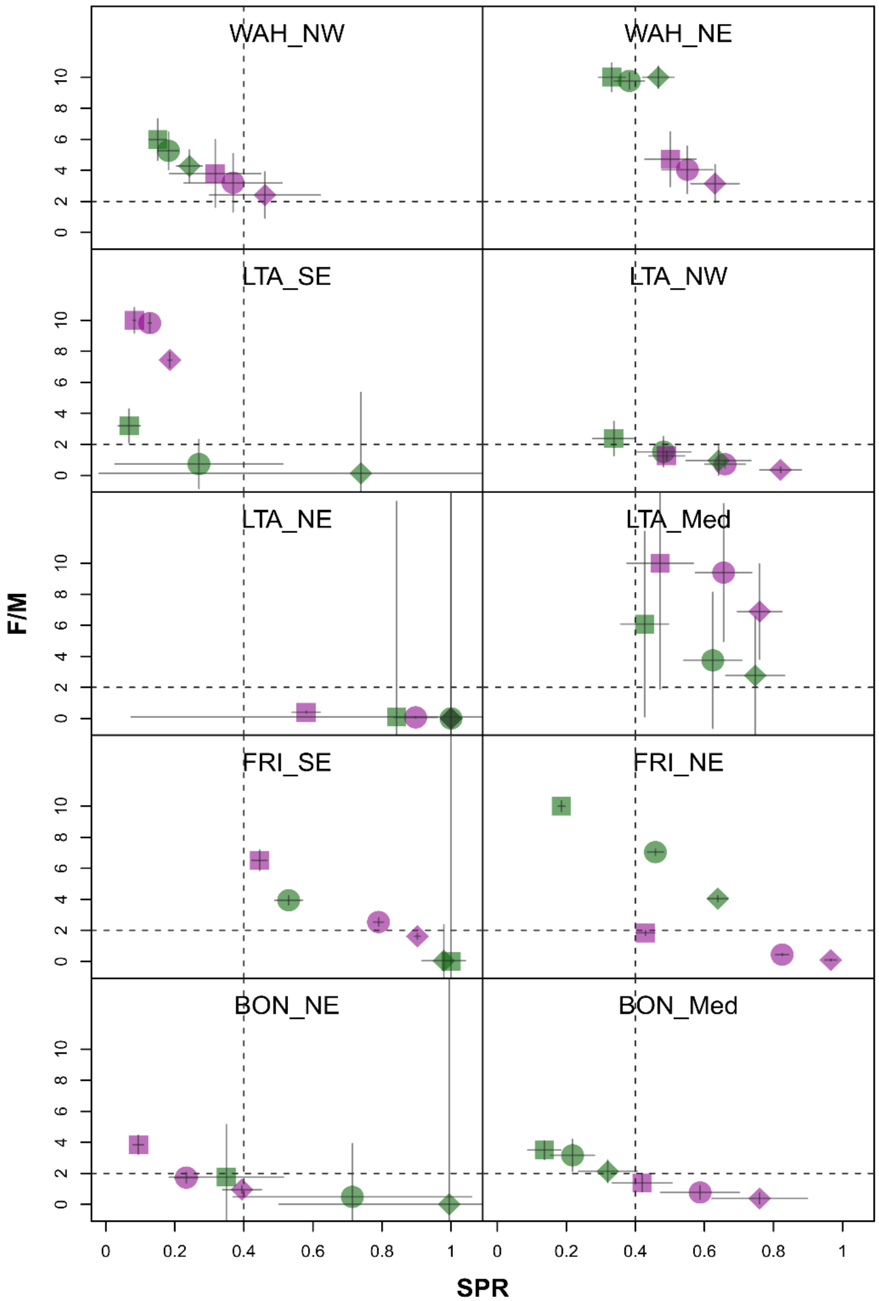

Figure 3.8. Proxy of stock status for priority small scombrid species. The vertical dashed line represents where SPR=40% and the horizontal one represents *F/M*=2. In green are the results from LIME and in purple for LBSPR for the three values of *M* considered. Circles are median *M*, squares are *M* at the 1st quartile and diamonds *M* at the 3rd quartile. The grey lines are the confidence intervals of the estimated SPR and *F/M*. LTA: little tunny; WAH: wahoo; BON: bonito; FRI: frigate tuna.

Chapter 4. PERFORMANCE OF CATCH-BASED AND LENGTH-BASED METHODS IN DATA-LIMITED FISHERIES

Abstract

Most of the data needed to assess exploited populations using conventional stock assessments are unavailable for many small scale fisheries around the world. Many methods have been developed recently to assess fisheries even when data are limited. Catch-based models can be used when only total catch data are available and length-based models when samples of the length composition of the catch are taken. Here, we evaluated the performance of both catch-based and length-based models, using simulation testing to estimate the exploitation status of species with contrasting life histories under different harvest scenarios. For unassessed fisheries where reconstructing time series of catch is possible, catch-based methods such as Depletion Based Stock Reduction Analysis (DBSRA) and Simple Stock Synthesis (SSS) seemed to be a good approach to assess stocks. However, these methods are “data-moderate” and more prior information is needed to apply them. For fisheries that are still developing, where the time series of catch are not available, getting length-composition data could give a good approximation of the exploitation status of the stocks. In many scenario, length-based models such as Length Based Spawning Potential Ratio (LBSPR) and Length Integrate Mixed Effect model (LIME) performed as well as other catch-based models.

4.1 INTRODUCTION

Stock assessment models are commonly used as a starting point for developing management strategies and modelling the response of populations to exploitation and management. Major commercial species usually have substantial data to inform complex stock assessments models (e.g. Methot and Wetzel 2013); this includes long time series of total removals, catch-at-age data, relative abundance indices, fishing effort, size and/or age composition, and information on life-history parameters. Most of the datasets required for these "classical" stock assessments are unavailable for most small-scale fisheries around the world. Fisheries and stocks lacking these multiple data types are commonly known as "data-poor" or "data-limited" fisheries (Costello *et al.* 2012; Dowling *et al.* 2015). Recently, many data-limited approaches have been developed to meet an increase demand for science-based fisheries management for unassessed fisheries where resources are limited (Wetzel and Punt 2011; Costello *et al.* 2012; Dowling *et al.* 2015, 2016; Chrysafi and Kuparinen 2016; Rosenberg *et al.* 2017).

Assessing stocks using primarily catch data started many years ago with the introduction of Stock Reduction Analysis, SRA (Kimura and Tagart 1982; Kimura *et al.* 1984). Since then, many methods have been developed to estimate population productivity and reconstruct historical abundance trends combining time series of catch data with assumptions about final biomass relative to unfished or initial biomass (i.e., stock depletion; Thorson and Cope 2015). SRA has been expanded to incorporate stochastic variability in population dynamics (Stochastic-SRA; Walters *et al.* 2006), a flexible shape for the production function (Depletion-Based SRA; Dick and MacCall 2011), prior information regarding resilience and population abundance at the start of the catch time series (Catch-MSY; Martell and Froese 2013; Froese *et al.* 2017), and age-structured population dynamics (Simple Stock Synthesis; Cope 2013). Despite these differences, this family of catch-only models shares a common dependence upon prior assumptions about final stock depletion. Simulation testing indicates that these methods perform well only when assumptions regarding final abundance are met and might be appropriate to predict sustainable catch or biomass, but not to reconstruct abundance time series (Carruthers *et al.* 2012; Wetzel and Punt 2015).

For many small-scale fisheries, obtaining reliable information on historical total catch is difficult, while collecting length measurements from a portion of the catch. Mean-length mortality estimators (Beverton and Holt 1957) assume that fishing mortality directly influences the mean length of the catch under equilibrium conditions. Length-based spawning potential ratio (LBSPR, Hordyk *et al.* 2015a) and length-based Integrated Mixed Effects (LIME, Rudd and Thorson 2017) models, have recently been developed allowing the estimation of instantaneous fishing mortality (F) and spawning potential ratio (SPR) when basic biological parameters are known (see Chapter 3). SPR is the proportion of the unfished reproductive potential per individual under a given level of fishing pressure (Goodyear 1993). Both methods have the same data-requirements, but LIME does not assume equilibrium conditions; the mixed-effects aspect of LIME extends length-based methods by estimating changes in recruitment and fishing mortality over time (Rudd and Thorson 2018).

There is increasing interest in developing new methodologies to quantitatively assess data-limited fisheries to manage them and prevent overfishing. Usually, these assessment method performances are tested using simulation experimentation (Cope 2008). Carruthers *et al.* (2016) used a closed-loop simulation approach to compare a range of management procedures for setting catch limits in data-limited fisheries. They found that data-limited methods using observations of stock depletion offer the best overall performance across life history types, data quality and autocorrelation in recruitment strength. However, these management procedures are based on setting catch limits and were designed for use in data-limited fisheries for which annual catch data are available, sometimes together with a relative abundance index (delay-difference stock assessment, Carruthers *et al.* 2014). In many data poor fisheries, measuring total removals is difficult, as is enforcing catch limits. Hordyk *et al.* (2015b) tested some harvest strategies using a simulation approach to assess the utility of LBSPR as a tool for management in data-limited fisheries using an effort-based harvest control rule. However, no studies have compared the performance of both, length-based and catch-based methods as estimation models using the same simulated populations because finding a common metric between catch-based and stock status metrics is difficult.

One of the advantages of catch-based methods is that stock size can be estimated. There have been many efforts worldwide to work in catch reconstructions to get this type of information in order to estimate stock status. However, how much different is the estimation in the exploitation status when using catch-based or length-based models? Which methodology should be use depends not only in the type of data available (e.g. catch or length data), but it could vary for different history of exploitation and biological characteristics of the population. Here we evaluated the performance of both catch-based and length-based models using simulation testing to estimate exploitation status for different fish stocks under different harvest scenarios.

4.2 METHODS

4.2.1 *Operating model specifications*

For the operating models (OMs) we use Stock Synthesis (SS) Version 3.30.10 (Methot and Wetzel 2013; Methot *et al.* 2018) to simulate age structured populations. SS was designed around an approach that relies on the absolute level of catch being known well enough to allow the model to calculate the level of fishing intensity needed to obtain that level of catch conditioned on the model's current estimate of age-specific population abundance and age-specific selectivity (Methot and Wetzel 2013). Fishing intensity in SS is estimated to match the observed catch; the harvest rate is therefore the total annual catch divided by the total abundance of the exploited biomass. Different catch histories thus lead to different exploitation histories, and they different scenarios could affect the performance of a data-limited methods.

We specified three different catch scenarios commonly observed in many fisheries to simulate different fishing mortality histories. In the first, catch increases until it reaches a maximum and start declining afterwards; this is a classic example where catch declines because the abundance of the stock decreases or because management measures were implemented to reduce fishing pressure (Figure 4.1.A). The second scenario assumes that catch increases and remains constant after reaching a maximum; this could be due to implementation of catch limits for example (Figure 4.1.B). The third scenario has constantly increasing catch, which would occur for fisheries that are still developing (Figure 4.1.C).

Three population life history types of varying longevity and somatic growth rate were simulated: (i) a short-lived fast-growth species, pacific chub mackerel, *Scomber japonicus*, (ii) a medium-lived medium-growth fish, albacore tuna, *Thunnus alalunga*, and (ii) a longer-lived slow-growth species, canary rockfish, *Sebastes pinniger* (Table 4.1). We input in the OMs their published life history parameter values used in their formal assessments (ICCAT 2014b; Crone and Hill 2015; Thorson and Wetzel 2015). We assumed that these populations were targeted in a single area, by only one fleet with one selectivity pattern that was logistic and constant through time. No indices of abundance were included, but we defined a final stock depletion implemented through the use of a survey index equal to 1 at the beginning of the time series and 0.4 in the last year, so biomass in the last year is 0.4 B_0 (Cope 2013). Each simulated population began at an unfished biomass and all catch scenarios terminate at the same stock depletion level (Appendix 4.1 to Appendix 4.3). In each OM, all parameters were fixed, except R_0, and annual lognormal recruitment deviations (Table 4.1). The Beverton–Holt spawner–recruit function was used (Methot and Wetzel (2013)).

To simulate catch length frequencies, we extracted the expected catch-at-age composition from the SS report file. We used the age-length conversion matrix output from SS to assign a distribution of length to each age. Summing across each length bin gave us the length distribution of the catch. Length bins were defined at every 2 cm from 30 to 150 cm for Albacore, from 12 to 76 cm for Pacific Chub Mackerel and from 8 to 60 cm for Canary Rockfish. To get a sample of the length composition of the catch to use in the length-based assessment models, 1000 fish/year were drawn using a multinomial distribution from the catch at length, using the probability of being caught at each length bin in each year.

In summary, we constructed operating models using a factorial design encompassing 9 sets of assumptions. The factors were (*i*) three scenarios for catches (Figure 4.1) and (*ii*) life history with three levels (Table 4.1). For each OM we simulated 100 data sets of harvest rate (U), total biomass (TB) and SPR (Appendices 4.1 to 4.3).

4.2.2 *Estimation models*

There are different families of data-limited assessment methods based on data requirements: life history-based, catch-based and length-based. The most common data-limited methods are summarized in Appendix 4.4 including data inputs, outputs and links to packages or software required for each method. In this study we applied a subset of these methods, as described below.

4.2.2.1 Catch-based data-limited methods

Catch-MSY (CMSY; Martell and Froese 2013). It is a SRA approach with a Schaefer biomass dynamic model. As input data, it requires a time series of removals, prior ranges of the population rate of increase (*r*) and carrying capacity (*K*), and possible ranges of relative stock sizes in the final year of the time series. Probable ranges for *r* and *K* are filtered with a Monte Carlo approach to detect 'viable' *r-K* pairs. A parameter pair is considered 'viable' if the corresponding biomass trajectories calculated with a production model are compatible with the observed catches, so that the population abundance never falls below 0, and is compatible with prior estimates of relative biomass (i.e., stock depletion; Martell and Froese 2013). The *r-K* pairs are drawn from uniform prior distributions and the Bernoulli distribution is used as the likelihood function for accepting each *r-K* pair. CMSY uses catch and productivity to estimate MSY. However, here we used the modified version of CMSY by Rosenberg *et al.* (2017) to extract biomass trends from all viable *r-K* pairs. Then the biomass trajectory is calculated as the median of all viable biomass trajectories generated during the Monte Carlo process. We used the R package *datalimited* version 0.1.0 (Anderson *et al.* 2016) available at https://github.com/datalimited/datalimited.

Modified Catch-MSY (CMSY2). Froese *et al.* (2017) improved the CMSY method by addressing (*i*) the biased estimation of unexploited stock size and productivity, and (*ii*) adding estimation of biomass and exploitation rate. It addresses a general shortcoming of production models, namely the overestimation of productivity at very low stock sizes. The CMSY algorithm (Martell and Froese 2013) was designed to select the most probable *r-K* pair as the geometric mean of this distribution. CMSY2 differs from the CMSY by searching for the most probable *r* not in the center, but rather in the tip region of the *r-K* pair distribution. This is based on the underlying principle that defines *r* as the maximum rate of increase for the examined population, which should be found among the highest viable *r*-values. In other words, a given time series of catches could be explained by a wide range of large stock sizes and low productivity, or by a narrow range of small stock sizes and high productivity, such as in the extremes of the *r-K* pair distribution (Froese *et al.* 2017). The code to run this method is available in the package *datalimited2* R package version 0.1.0. by Free (2018) at https://github.com/cfree14/datalimited2.

State-space catch-only model (SSCOM). This is a hierarchical model based on a coupled harvest-dynamics model. The model is a Bayesian state-space model that integrates across three stochastic functional forms: variation in effort, population dynamics and fishing efficiency (Thorson *et al.* 2013). SSCOM can reconstruct biomass time series from catch data whenever fishing mortality follows semi-predictable dynamics over time. The different types of population and effort dynamics can be extracted from the same catch stream using nonlinear models for population-dynamics as a function of biomass and linear models for effort dynamics as a function of log-scaled biomass for example. We used the package *datalimited* version 0.1.0 (Anderson *et al.* 2016) to run this model. We modified the code to extract biomass trajectories and to use a lognormal distribution for depletion (Table 4.1). However, the effort dynamic priors were set as in Anderson *et al.* (2017).

Depletion based stock reduction analysis (DBSRA). DBSRA (Dick and MacCall 2011) modifies the SRA approach as it uses Monte Carlo draws from four parameter distributions (M, F_{MSY}/M, B_{MSY}/B_0 and *depletion*) while using age at maturity (A_{mat}) to separate the biomass into immature and mature biomass (fishery selectivity is also assumed to have an identical pattern to the age-at-maturity ogive). It uses a delay-difference production model with a time lag for recruitment and mortality as:

$$B_t = B_{t-1} + P_t(B_{t-Amat}) + (1 - e^{-M})(B_{t-Amat} - B_{t-1}) - C_{t-1}$$

where B_t is the biomass at the start of the year t, M is the instantaneous rate of natural mortality, and $P_t(B_{t-Amat})$ is the latent annual production based on a function of adult biomass in year t-$Amat$. Biomass in the first year (B_0) is assumed equal to k. The package *fishmethods* version 1.10-3 was used to perform this analysis (Nelson 2017).

Simple Stock Synthesis (SSS). This method is based on the Stock Synthesis package (Methot and Wetzel 2013). Like DBSRA, SSS uses Monte Carlo draws of M, steepness (h), and initial recruitment (R_0) while fitting to an artificial abundance survey representing stock depletion (Cope 2013). All fixed values are drawn from prior distributions to represent uncertainty in model-derived outputs. The code for running SSS can be found at https://github.com/shcaba/SSS.

4.2.2.2 Length-based data-limited methods

Length based spawning potential ratio (LBSPR). In LBSPR, SPR in an exploited population is a function of the ratio of fishing mortality to natural mortality (F/M), and the two life history ratios *M/K* and L_m/L_∞; *k* is the von Bertalanffy growth coefficient, L_m is the size of maturity and L_∞ is asymptotic size (Hordyk *et al.* 2015a). The inputs to LBSPR are: *M/k*, L_∞, the variability of length-at-age (CVL_∞), which is normally assumed to be around 10%; and length at maturity specified in terms of L_{50} and L_{95} (the size at which 50% and 95% of a population matures). Given the assumed values for the *M/K* and L_∞ parameters and length composition data from an exploited stock, the LBSPR model uses maximum likelihood methods to estimate the selectivity ogive, which is assumed to be a logistic curve defined by the selectivity-at-length parameters S_{50} and S_{95}, and the relative fishing mortality (*F/M*), and these are used to calculate SPR (Hordyk *et al.*, 2015 a,b). Estimates of SPR are primarily determined by the length of fish relative to L_{50} and L_∞. If a reasonable proportion of fish in a sample attain sizes approaching L_∞ a high estimate of SPR will be derived. LBSPR is an equilibrium based method with the following assumptions: (i) asymptotic selectivity, (ii) growth is adequately described by the von Bertalanffy equation, (iii) a single growth curve can be used to describe both sexes which have equal catchability, (iv) length at-age is normally distributed, (v) rates of natural mortality are constant across adult age classes, (vi) recruitment is constant over time, and (vii) growth rates remain constant across the cohorts within a stock (Hordyk *et al.* 2015a). Analyses were conducted using LBSPR package version 0.1.2 in R (Hordyk 2017).

Length-based integrated mixed effects (LIME). This model uses length data and biological information to estimate *F* and SPR. LIME has the same data-requirements as LBSPR, but LIME does not assume equilibrium conditions; the mixed effects aspect of LIME extends length-based methods by estimating changes in recruitment and fishing mortality over time (Rudd and Thorson 2018). LIME uses automatic differentiation and Laplace approximations as implemented in Template Model Builder (TMB; Kristensen *et al*. 2016) to calculate the marginal likelihood for the mixed-effects. All other assumptions are the same as LBSPR but LIME estimates one selectivity curve for the entire time series of length data while LBSPR estimates one selectivity curve for each year since each time step estimation in LBSPR is independent (Hordyk *et al.* 2015a).

4.2.3 *Comparing methods outputs*

One of the challenges of comparing catch-based and length-based methods is they produce different model outputs. Catch-only models estimate total biomass and/or spawning stock biomass and sustainable catches, whereas length-based models estimate transient SPR, which is similar to relative stock status (an input in the catch-only models). These are fundamentally different measures of the population. Given the challenge of having different metrics, the performance of a method can be compared to the OM and described as the Relative Error (RE), where RE = (*estimated-true*)/*true*. This allows the measure of uncertainty, in both bias and precision, in the methods under each scenario, and is used as a standardized metric of model performance. Bias in this study is how far, on average, the performance measure from each estimation model is from the true value. Imprecision is related to the variability around that estimated average value. We used as a performance measure the fishing intensity, calculated as the catch/biomass for the catch-based models, and as 1-SPR for the length-based models. Both measures range between 0 and 1.

We found that in some cases LIME did not converge, and in others it not only did not converge, but it also did not produce results (during the minimization process the objective function could not find a minimum). We kept the runs where LIME did not converge, but we ran the estimation models until all produced viable runs.

4.3 RESULTS

4.3.1 *Differences among harvest rate scenarios*

In general, catch-based models were more biased and less precise when there was no contrast in the time series of catch data (Scenario 2 and 3). For example, for the fast-growth mackerel, the median RE for CMSY2 was 1.7 in Scenario 1 (range: 1.14 - 2.4) and to 3.2 in Scenario 3 (range: 1.3 – 7.7). However, length-based models (LBSPR and LIME) showed low variability in harvest rate trends in both bias and precision across scenarios (Figure 4.2).

4.3.2 *Catch-based models*

We expected the models considered in this study to perform differently since they have different model structure and assumptions. SSS and DBSRA were, in general, less biased and more precise than other catch-based models, in particular when comparing with both catch-MSY models. Catch-MSY models showed the worst performance among all catch-based models tested in this study. CMSY and CMSY2 presented the highest RE for mackerel in Scenario 3 (median RE=3.1 and RE=3.2, respectively) and the lowest RE for Albacore in Scenario 1 (median RE=0.52 for both models). Even in this case, harvest rates were estimated to be 50% higher than the truth. CMSY and CMSY2 performed very similarly in all cases in terms of bias and precision. Both models were less biased when the catch time series had an increasing followed by a decreasing trend (Scenario1) and highly biased when there was no contrast in the time series of catch (Scenario 2 and 3) for the three species (Figure 4.2).

SSCOM in general was less biased than both catch-MSY models and in some cases less biased than DBSRA or SSS (i.e. for mackerel in Scenario 1; median RE=0.02). However, SSCOM was less precise than any other catch-based model, showing a broader range of RE in most of the cases (Figure 4.2).

SSS estimated unbiased harvest rates across different scenarios of fishing mortality trends and life histories, except for the case of the fast-growth mackerel. It was positively biased in those cases; the harvest rates were estimated to be 60% higher than the true values (median RE=0.6) in Scenario 1 and around 30% in Scenario 2 (median RE=0.34) and Scenario 3 (median RE=0.29). For this species, DBSRA was less biased in the three scenarios (median RE<0.2). SSS was the less biased estimation method for Albacore and Rockfish for the three scenarios. The median RE range between -0.02 in Scenario 3 to 0.15 in Scenario 1 for Albacore, and between -0.09 in Scenario 3 and 0.15 in Scenario 1 for Rockfish. DBSRA seemed to be more sensitive to the different trends in fishing mortality, in particular for the medium-growth Albacore (Figure 4.2).

In summary, among catch-based models, CMSY and CMSY2 were the least precise and positively biased, particularly in Scenario 2 and 3 for the three species. SSCOM was also less precise but less biased than the catch-MSY methods and DBSRA was more precise than these three but positively biased for the fast-growth species. The one that performed better in terms of bias and precision was SSS in general (Figure 4.3). The age-structured aspect of SSS has also been shown elsewhere to be better suited for slower life histories (Wetzel and Punt 2015).

4.3.3 *Length-based models*

In some cases, length models gave a less biased estimation than catch-based models. LBSPR was generally less biased for slow-growth species like rockfish and highly positively biased for fast-growth species like mackerel. LIME was negatively biased for the fast-growth species, positively biased for the medium-growth species and it showed a bimodality for the slow-growth species estimating sometimes a lower harvest rates and sometimes a higher harvest rate than the true values (Figure 4.2).

LBSPR was always more precise than LIME, which means that the range of RE values were narrower. The mean RE were almost the same between LBSPR and LIME models for Rockfish, but LBSPR was less biased for other life-history scenarios (median RE = 0.25 in Scenario 1 and -0.02 in Scenario 3). LBSPR was more biased for Mackerel in Scenario 1 where the median RE was 0.82 (Figure 4.2).

LIME was less biased than LBSPR in most of the scenarios but less precise. LIME did not converge in many cases, between 32% of the times in Scenario 1 and 9% in Scenario 3 for Albacore, between 27% in Scenario 1 and 4% in Scenario 2 for Mackerel, and between 61% in Scenario 1 and 67% in Scenario 3 for Rockfish. For fast-growth species LIME had more difficulties to converge causing probably the bimodality in the results for this stock (Figure 4.2). In all cases, runs that did not converge were kept.

In summary, between the 2 length-based models, LBSPR was more precise than LIME in general. Both showed similar performance for slow-growth and medium-growth species and very different and opposite performance for fast-growth species. In most of the scenarios, length-based methods performed better than CMSY and CMSY2. But, in general, all data-limited models tested here performed worse for the fast-growth species (Figure 4.2).

4.4 DISCUSSION

Simulation studies commonly use different model specifications needed to test the assumptions of the methods to be evaluated; often the same population model is used for simulation and estimation, i.e. self-testing. Using the same model for simulation and estimation could give overly optimistic results (Francis 2012). Our approach evaluated multiple data-limited assessment methods that assume different population dynamics, uncertainty and fishing effort dynamics. We expected, due to these differences, that all of them would perform differently. Rosenberg *et al.* (2017) used four catch-based data limited models and they found that frequently models disagreed about population status estimates with no model performing best across all fish stocks; some models performed better than others depending on the scenarios. Determining which model is better is highly dependent on the life history of the species of concern, the dynamic of the population and the fishing intensity. This is why we included different harvest or fishing mortality scenarios and species with contrasting life histories.

In general, catch-based models were less biased and less precise when there was contrast (e.g., an increase in the catch and then a decrease) in the time series of catch data. Walters *et al.* (2006) suggested that for SRA, stocks that have experienced extensive historical depletion gains precision from a high rate of rejected parameter draws. In Scenario 3, where catch is still increasing, it is very difficult to have a good estimate of the carrying capacity K. So, SSS and DBSRA, which use priors in F_{MSY}/M and B_{MSY}/B_0 performed better than the models that only relied in r and K, even with priors for depletion centered in the true values. Length-based models, on the other hand, were not dependent on the harvest rate trends. This is not surprising for LBSPR since in equilibrium conditions, the estimations are independent in each time step. For LIME, which is not an equilibrium model, Rudd and Thorson (2017) also did not find strong differences for different scenarios of fishing mortality.

The choice of best model might depend on the biological information that is available. SSS seems to be the least biased catch-based model. However, unlike other catch-based models, age and growth estimates are needed in SSS to define age structure and remove catch according to age-/size-based selectivity patterns (Cope 2013). SSS has the same structure as SS and this might be the reason why is the model that performed the best in most cases since the simulation and estimation models have the same structure (Francis 2012).

We found that SSCOM and DBSRA performed similarly in terms of bias. In the SSCOM model, a prior in depletion is not needed, but it can be included as we did in this study. Thorson *et al.* (2013) explored the effect of specifying a prior on final depletion and compared the results with DBSRA. They suggested that using a strong prior on final depletion in SSCOM would result in similar performance to DBSRA. Both, DBSRA and SSCOM approximate biomass dynamics using a production function expressed as exploitable biomass (which is equivalent to spawning biomass given selectivity and maturity curves are assumed identical), and both assume that biomass starts at average unfished biomass. However, DBSRA uses deterministic biomass dynamics and uses an asymmetric production function (Dick and MacCall 2011), while SSCOM has stochastic biomass dynamics and uses a Schaefer production function (Thorson *et al.* 2013), so it unsurprising they did not performed exactly the same. SSCOM was less biased in some cases, but less precise than DBSRA in all cases. Specifying other priors in SSCOM in future studies, for example for effort-dynamics, could increase this precision.

DBSRA and SSS performed very similar in some cases (Albacore Scenario 1, Mackerel Scenario 2 and 3). In structure, both models are very similar, however there are a few notable differences between the population dynamics models used in DBSRA and SSS that could explain the different results found here (Wetzel and Punt 2015).

Both Catch-MSY methods performed very poorly in all scenarios overestimating harvest rate, even when given a prior for depletion close to the true value. A key point of the Catch-MSY approaches is the ability to define a reasonable prior range for the parameters of the Schaefer model in particular k. In our case, we have arbitrarily chosen 50 times the maximum catch as the upper bound for *k*. However, in the Scenario 3, in a developing fishery, or a fishery that has a continuous increase in catch, it will be more difficult to define the upper bound of *K* because the maximum potential has yet to be reached (Martell and Froese 2013), thus limiting the performance of these methods under this scenario. However, they also performed poorly in Scenario 1 and 2, in particular for long-lived and short-lived species. Other *K* values could be explored in future studies to see if this improves the outcomes, but it remains a very difficult parameter to specify. For example, Martell and Froese (2013) used maximum catch multiplied by 100. Rosenberg et al. (2017) and Free et al. (2017) found that CMSY was the one that performed second best and better than SSCOM in their scenarios. One of the differences with our study is that they considered a uniform prior for depletion in SSCOM and we considered a Lognormal prior centered around the true value, but it is apparent that method performance is sensitive to a variety of scenarios.

Length-based models showed in some cases better performance than some catch-based models relative to the output type specific to the method. One of the main advantages of these methods is that only one year of length data are required to assess a stock. However, life history information is also required and these methods have proven to be very sensitive to misspecification of these parameters (Hordyk *et al.* 2015a; Rudd and Thorson 2017). In this study, we assumed that the biological information was known or centered around the correct value, constraining potential bias.

For long-lived species, recruitment variability does not affect the length composition of the catch as much as for short lived species. This is why LBSPR performed pretty well for long-lived species and it was highly biased for short-lived species. LIME however, performed better for short-lived species than LBSPR being able to capture changes in the length composition due to recruitment variability. These results could help to understand some of the differences in results found in stock status for small scombrids species in Chapter 3 where recruitment variability might have more influence in the length composition of those populations. In general, all catch-based and length-based methods seems to perform worse for the faster life history types.

4.4.1 *Conclusions*

For unassessed fisheries where data are limited, but reconstructing time series of catch is possible, catch-based methods SSS or DBSRA provided the most reliable outputs to for management. However, to apply SSS and DBSRA, not only is catch data needed, these methods also require extensive prior information (Appendix 4.4), such as growth, maturity, F_{MSY}/M and B_{MSY}/B_0 parameters. When this prior information is not available, SSCOM could be use with a good prior for depletion. Catch-MSY methods could also be considered, but with caution, because it has been proved here that they can be highly biased and influenced by catch trends and uncertainty in K.

For fisheries that are still developing, where the time series of catch are unavailable, getting length-composition data could give a good approximation of the status of the stock, in particular for medium to long-lived species. It has been shown here that, in some cases, that length-based models can give the same or less biased estimates of exploitation status than catch-based models.

4.4.2 *Future directions*

There has been an emerging field of catch methods and assemble of catch-based methods to estimate global stock status (Costello *et al.* 2012; Anderson *et al.* 2017; Rosenberg *et al.*

2017). The super-ensemble method published by Anderson *et al.* (2017) allows for weighting individual models based on their accuracy. In their study, some models had different assumptions about uncertainty and the dynamics of fishing effort, but all assumed the same population dynamics. A new super-ensemble method that includes models that also assume different population dynamics could be developed in the future based on our results. Combining estimates from different methods in a consistent reproducible manner may provide more stability in the advice for managers. Moreover, these data-limited methods can be used later in a harvest strategy evaluation context to specify harvest control rules that can help ensure sustainable fisheries management (Carruthers *et al.* 2014, 2016) considering, in addition to other uncertainty, model uncertainty.

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4.5 TABLES

Table 4.4. Life history information and priors for the three species used in the study. Notation: *Lognormal* (μ, σ^2); Uniform *U* (*a*, *b*). Priors for k were Uniform between the maximum catch in the time series and 50 times the maximum catch. * For CMSY and CMSY2 the depletion priors were Uniform centered in the true value *U* (0.3, 0.5).

Operating model inputs	**Symbol**	**Pacific Chub Mackerel**	**Albacore tuna**	**Canary Rockfish**
Maximum age	Age_{max}	12	15	64
Length were 50% of the fish are mature (FL cm)	L_{50}	29	90	55
Length were 95% of the fish are mature (FL cm)	L_{95}	34	100	57
Length-weight scaling parameter	a	2.73×10^{-6}	1.34×10^{-5}	1.80×10^{-5}
Length-weight allometric parameter	b	3.444	3.107	3.094
Von Bertalanffy Brody growth coefficient (1/years)	k	0.40	0.21	0.14
Von Bertalanffy asymptotic length (cm)	L_∞	38.2	122.2	60.0
Theoretical age at length=0	t_0	-0.6	-1.3	-1.9
Coefficient of variation length at age for all ages	CVL	0.1	0.1	0.1
Natural mortality (1/years)	M	0.60	0.30	0.05
Relationship between *M* and *K*	M/K	1.50	1.40	0.35
Steepness	h	0.5	0.9	0.8
Selectivity at 50% (cm)	S_{50}	18	78	42
Selectivity at 95% (cm)	S_{95}	25	90	47
Depletion	XB_0	0.4	0.4	0.4
Survey or depletion standard error	σ_S	0.01	0.01	0.01
Observation error in catch	σ_C	0.1	0.1	0.1
Recruitment variations	σ_R	0.3	0.4	0.5
Estimation models prior distributions				
Depletion	XB_0	*Lognormal* (0.4, 0.1) *	*Lognormal* (0.4, 0.1) *	*Lognormal* (0.4, 0.1) *
Carrying capacity	K	*U* (max(catch), max(catch)x50)	*U* (max(catch), max(catch)x50)	*U* (max(catch), max(catch)x50)
Population rate of increase	r	*U* (0.8, 1.2)	*U* (0.2, 0.6)	*U* (0.05, 0.4)
Vulnerability	F_{MSY}/M	*U* (0, 2)	*U* (0, 2)	*U* (0, 2)
Compensation	B_{MSY}/B_0	*U* (0, 1)	*U* (0, 1)	*U* (0, 1)

4.6 FIGURES

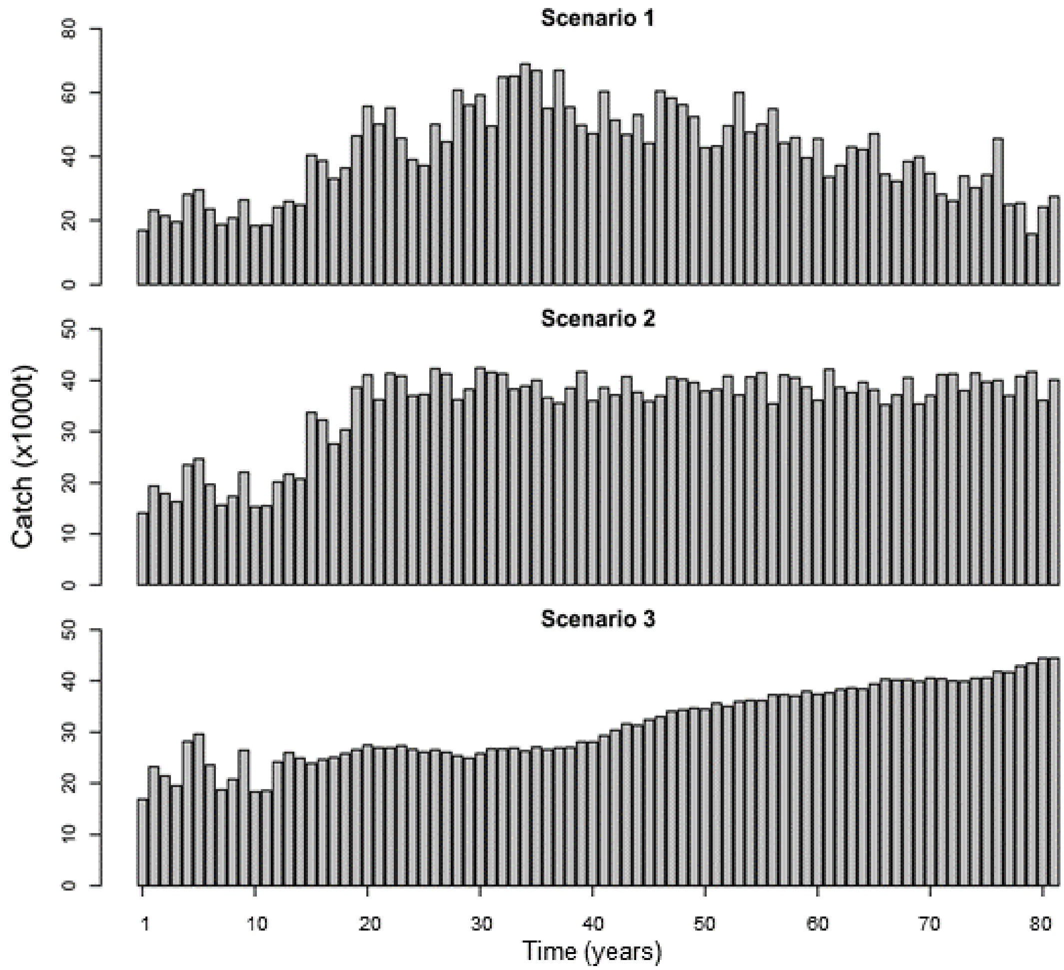

Figure 4.1. Annual harvest scenarios used in the Operating models. A: ramp scenario. B: Constant catch scenario. C: Increasing catch scenario.

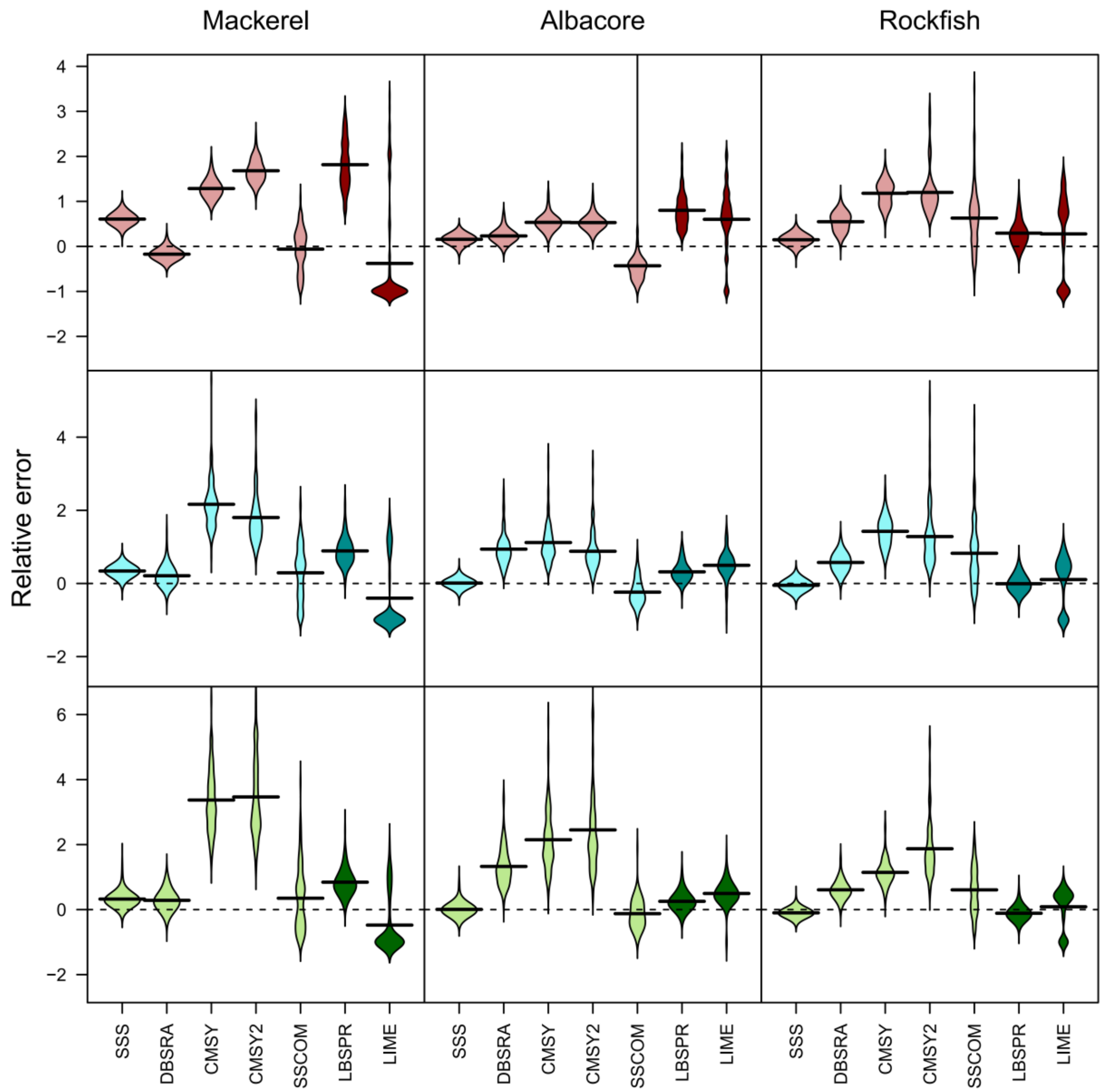

Figure 4.2. Relative error for all the catch-based (light colors) and length-based (dark colors) models considered under the three harvest scenarios for the three species. First row: Scenario 1 – ramp shape harvest rate. Second row: Scenario 2 – constant harvest rate. Third row: Scenario 3 – increasing harvest rate.

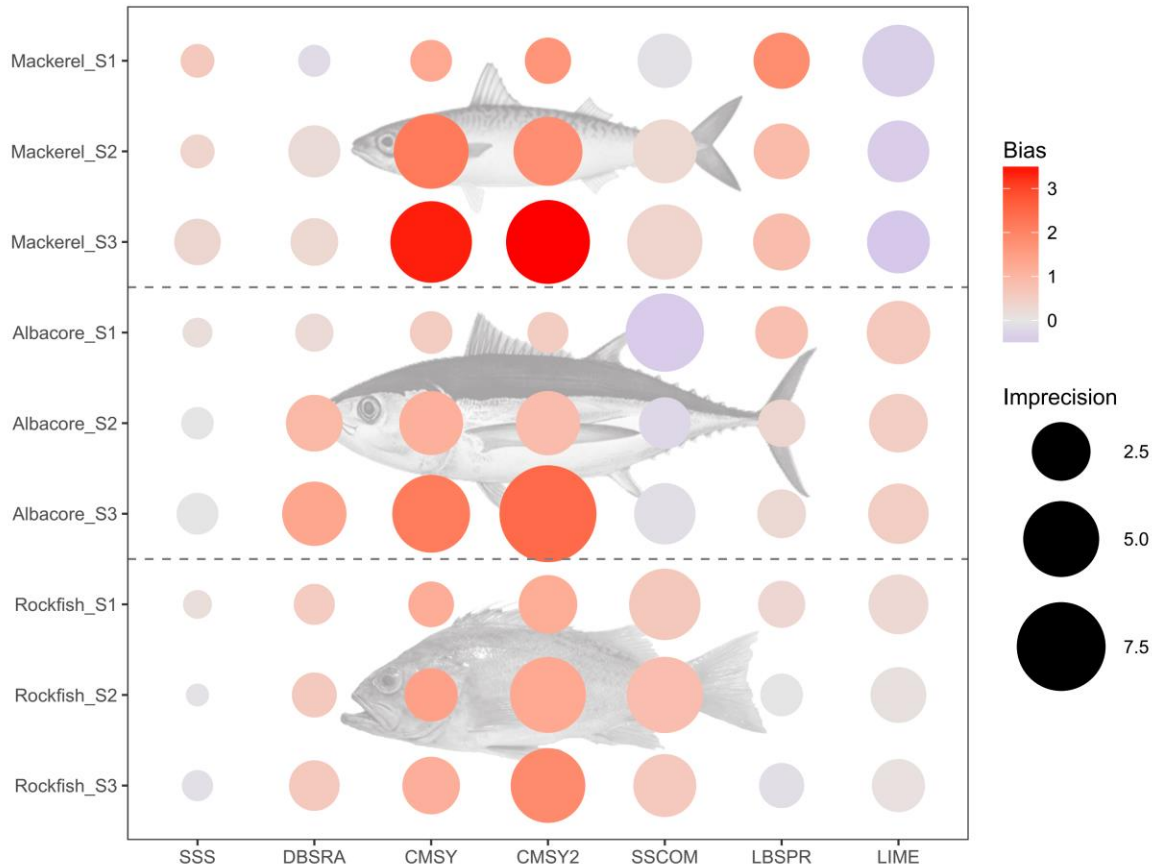

Figure 4.3. Summary performance (bias and precision) of the length-based and catch-based models tested in this study.

GENERAL CONCLUSIONS

In this dissertation we moved from a worldwide approach identifying which are the most important factors explaining the current stock status and management effectiveness of "data-rich" tuna stocks that have been previously assessed (Chapter 1 and 2), to evaluating a candidate of possible data-limited approaches to evaluate "data-poor" tuna stocks that have not been previously assessed (Chapter 3 and 4).

In Chapter 1 we summarized the current stock status for commercial tunas and billfish species at a global scale. Although these species varied in status from lightly exploited to rebuilding to severely depleted, most of them were managed at sustainable levels. We showed that, particularly for tuna species, stocks were more depleted if they have high commercial value, are long-lived, are small populations, and have been subject to intense fishing pressure for a long time. In addition, we demonstrated that implementing and enforcing fishing quotas led to rebuilding overfished tuna populations. We hope that tRFMOs consider the relative effectiveness of the management measures observed in this study to manage depleted large pelagic stocks under their jurisdictions.

In Chapter 2 we systematically evaluated why management and governance performance differs among tRFMOs. We quantified influences of economic and fishery-related factors on different management characteristics, and examined how these factors varied among organizations. We found that tRFMOs with a greater number of member countries, a greater economic dependency on tuna resources, a lower mean per-capita Gross Domestic Product, a greater number of fishing vessels, and smaller vessels were associated with less intensive management. Identifying which are the factors that make governance and management vary among tRFMOs helped us to understand why some organizations have had more success in rebuilding tuna populations than others, and why some management procedures measures are more difficult to enforce in different regions of the world oceans. For example, economic dependency on tuna fisheries was the most important covariate in explaining differences in management among tRFMOs; tRFMOs with more countries highly dependent on tuna fisheries showed lower management performance. When countries with low governance capacity account for the greatest proportion of total catches, management controls are, on average, harder to enforce.

In Chapter 3, we estimate for the first time the current stock status of 10 different small scombrids stocks in the Atlantic Ocean using only life history information and length data. We highlighted stocks in need of management actions since they show signs of being overexploited and/or experiencing overfishing. We also identified gaps in biological and fisheries information needed to better understand the status of these populations. In addition, since most of these species are caught by multiple fishing gears, we suggested a way to weigh the length composition data in multi-fleet situations to best apply length-based assessments.

Finally, in Chapter 4 we evaluate a set of data limited assessments in which only one type of information is available (catch or length data), and we evaluate their performance under different scenarios of exploitation and for species with contrasting life histories. We found that, due to differences in model structures and assumptions, all methods performed differently in each scenario. Which model should be used to assess data-limited fisheries depends not only in the type of data available (catch or length), but in the prior knowledge about the exploitation history of the stocks and the biology of each species.

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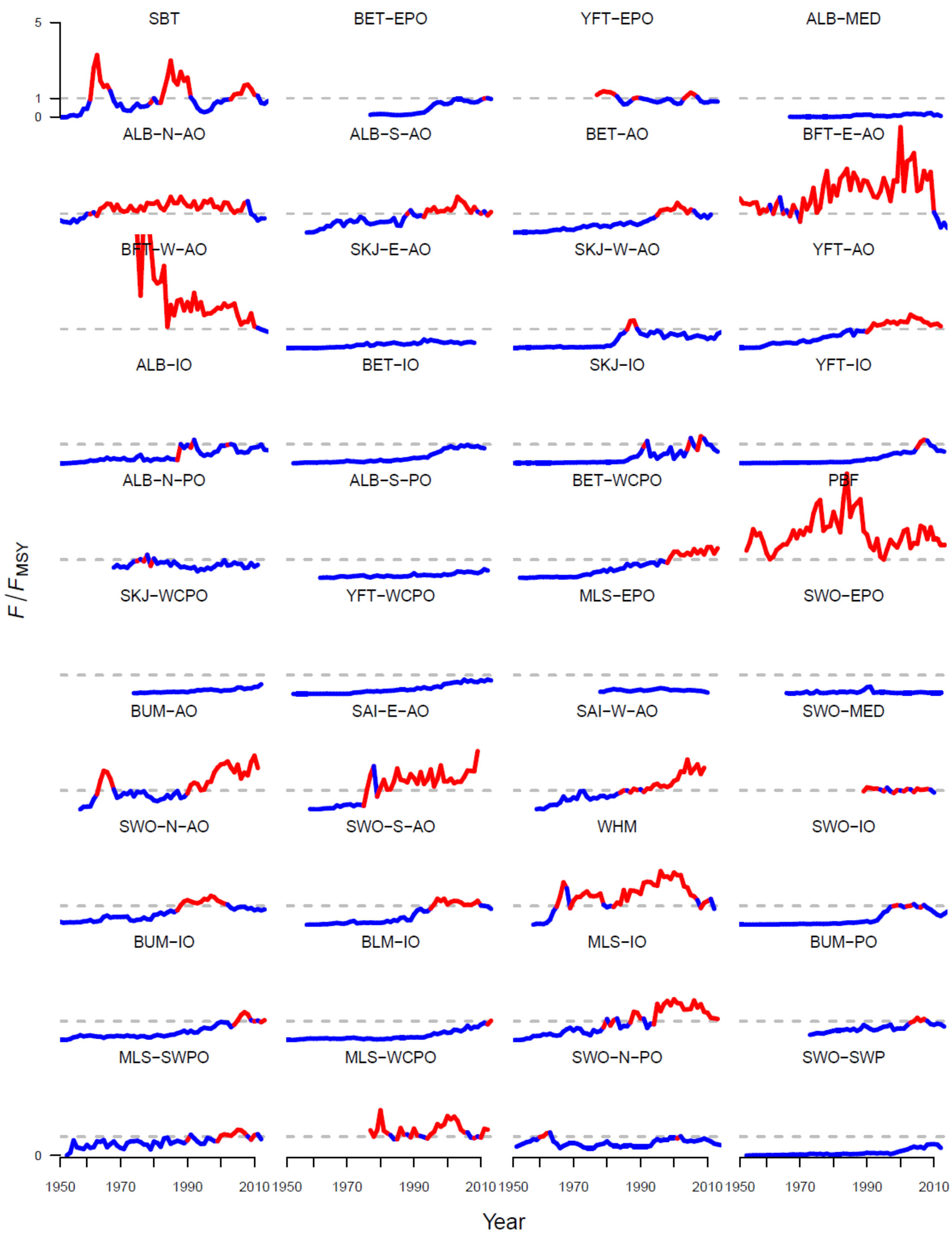
APPENDIX 1

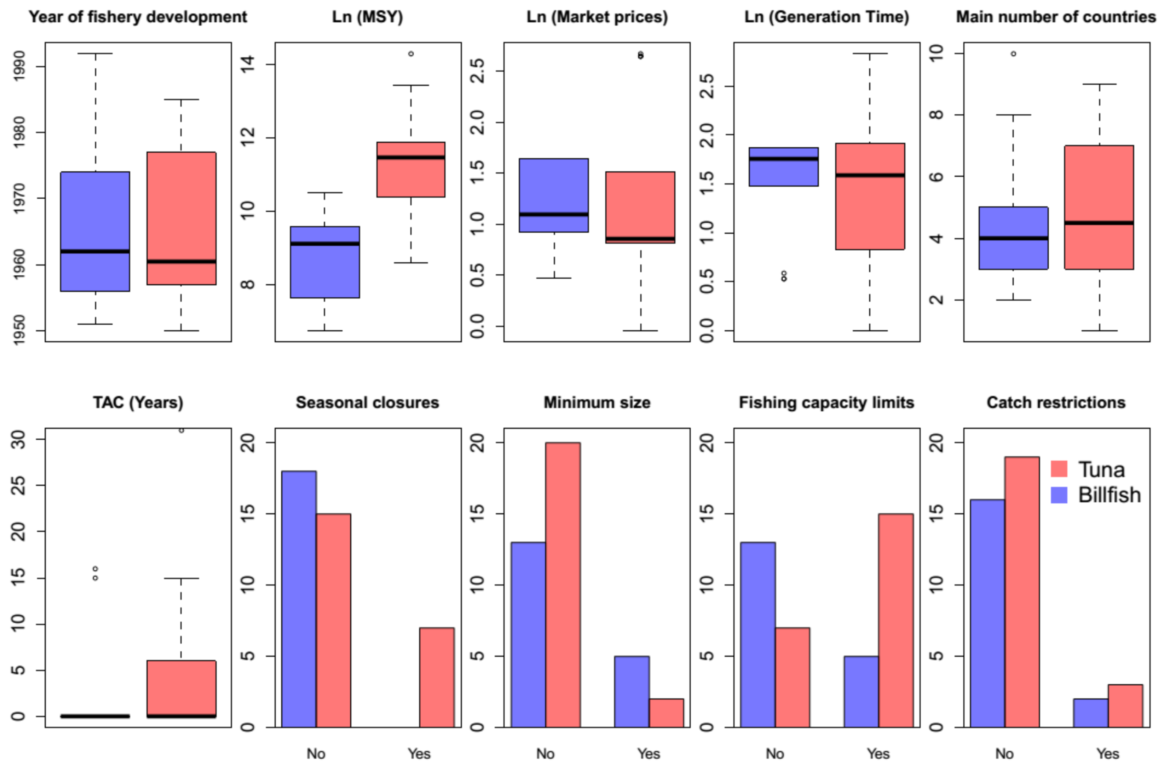


Appendix 1.1. Yearly trends in F/F_{MSY} by stock. Values for $F>F_{MSY}$ are in red. The stock codes are listed in Table S1.

Appendix 1.2. Yearly trends in B/B_{MSY} by stock. Values for $B<B_{\mathrm{MSY}}$ are in red. The stock codes are listed in Table S1.

Appendix 1.3. List of references from Table 1.2. Some of the regulations are not currently active but were active during the last 10 years.

Ref.	Source
1	http://www.ccsbt.org/userfiles/file/docs_english/operational_resolutions/CCSBT_Strategic_Plan.pdf
2	http://www.iattc.org/PDFFiles/C-02-03%20Capacity%20resolution%20Jun%202002%20REV.pdf
3	http://www.iattc.org/PDFFiles/C-02-04%20BET%20YFT%20resolution%20Jun%202002.pdf
4	http://www.iattc.org/PDFFiles2/Resolutions/C-03-12%20Tuna%20conservation.pdf
5	http://www.iattc.org/PDFFiles2/Resolutions/C-04-09_Tuna_conservation_2004-2006.pdf
6	http://www.iattc.org/PDFFiles2/Resolutions/IATTC-81-REC-C-10-01-Conservation-recommendation.pdf
7	https://www.iattc.org/PDFFiles2/Resolutions/C-13-01-Tuna-conservation-in-the-EPO-2014-2016.pdf
8	http://www.iccat.int/Documents/Recs/compendiopdf-e/1998-08-e.pdf
9	http://www.iccat.int/Documents/Recs/compendiopdf-e/2009-01-e.pdf
10	http://www.iccat.int/Documents/Recs/compendiopdf-e/2006-01-e.pdf
11	http://www.iccat.int/Documents/Recs/compendiopdf-e/2004-01-e.pdf
12	http://www.iccat.int/Documents/Recs/compendiopdf-e/2002-13-e.pdf
13	http://www.iccat.int/Documents/Recs/compendiopdf-e/2006-05-e.pdf
14	http://www.iccat.int/Documents/Recs/compendiopdf-e/2008-05-e.pdf
15	http://www.iccat.int/Documents/Recs/compendiopdf-e/2009-06-e.pdf
16	http://www.iccat.int/Documents/Recs/compendiopdf-e/2013-08-e.pdf
17	http://www.iccat.int/Documents/Recs/compendiopdf-e/1998-07-e.pdf
18	http://www.iccat.int/Documents/Recs/compendiopdf-e/2013-09-e.pdf
19	http://www.iccat.int/Documents/Recs/compendiopdf-e/2006-06-e.pdf
20	http://www.iccat.int/Documents/Recs/compendiopdf-e/2003-04-e.pdf
21	http://www.iccat.int/Documents/Recs/compendiopdf-e/2001-04-e.pdf
22	http://www.iccat.int/Documents/Recs/compendiopdf-e/2006-02-e.pdf
23	http://www.iccat.int/Documents/Recs/compendiopdf-e/2011-02-e.pdf
24	http://www.iotc.org/cmm/resolution-1211-implementation-limitation-fishing-capacity-contracting-parties-and-cooperating
25	http://www.iotc.org/cmm/resolution-1213-conservation-and-management-tropical-tunas-stocks-iotc-area-competence
26	http://www.iotc.org/cmm/resolution-0501-conservation-and-management-measures-bigeye-tuna
27	https://www.wcpfc.int/system/files/WCPFC2_Records_F.pdf
28	http://www.iattc.org/PDFFiles2/Resolutions/C-05-02-Northern-albacore-tuna.pdf
29	https://www.wcpfc.int/system/files/WCPFC2_Records_E.pdf
30	http://www.wcpfc.int/system/files/CMM%202005-01.pdf
31	http://www.wcpfc.int/system/files/CMM%202008-01%20%5BBigeye%20and%20yellowfin%5D.pdf
32	http://www.wcpfc.int/doc/cmm-2009-07/conservation-and-management-measure-pacific-bluefun-tuna-replaced-cmm-2010-04
33	http://www.iattc.org/PDFFiles2/Resolutions/C-13-02-Pacific-bluefin-tuna.pdf
34	https://www.wcpfc.int/system/files/Conservation%20and%20Management%20Measure-2006-04%20%5BStriped%20Marlin%5D.pdf
35	https://www.wcpfc.int/system/files/CMM%202010-01%20%5BNorth%20Pacific%20Striped%20Marlin%5D.pdf



Appendix 1.4. Variables considered for the random *forest* analysis of the prediction of the current status of tuna and billfish stocks. Continuous variables are shown with boxplots and categorical variables with barplots for tunas and billfishes separately. In the barplots the y-axis represents frequency in numbers and in the continuos plots the variable itself. Log refers to the natural logarithm.

Appendix 1.5. Generation Time (GT, from Collette et al. 2011). The stock codes are listed in Table 1.1.

Species	Code	GT (years)	Comments
TUNAS			
Katsuwonus pelamis	SKJ-WCPO	1	Collette et al. (2011)
	SKJ-E-AO	1	Collette et al. (2011)
	SKJ-IO	1	Collette et al. (2011)
	SKJ-W-AO	1	Collette et al. (2011)
Thunnus alalunga	ALB-IO	6.7	Collette et al. (2011)
	ALB-MED	6.8	Assumed equal to ALB-N-AO
	ALB-N-AO	6.8	Collette et al. (2011)
	ALB-N-PO	6.3	Collette et al. (2011)
	ALB-S-AO	6.6	Collette et al. (2011)
	ALB-S-PO	7.2	Collette et al. (2011)
Thunnus albacares	YFT-AO	3.5	Collette et al. (2011)
	YFT-WCPO	2.2	Collette et al. (2011)
	YFT-EPO	2.3	Collette et al. (2011)
	YFT-IO	2.9	Collette et al. (2011)
Thunnus maccoyii	SBT	17.2	Collette et al. (2011)
Thunnus obesus	BET-AO	4.8	Collette et al. (2011)
	BET-EPO	4.4	Collette et al. (2011)
	BET-IO	5	Collette et al. (2011)
	BET-WCPO	4.5	Collette et al. (2011)
Thunnus orientalis	PBF	7.3	Collette et al. (2011)
Thunnus thynnus	BFT-E-AO	7.3	Collette et al. (2011)
	BFT-W-AO	9.6	Collette et al. (2011)
BILLFISHES			
Xiphias galdius	SWO-EPO	6.5	The value presented in Collette et al. (2011) is unique for this species
	SWO-IO	6.5	The value presented in Collette et al. (2011) is unique for this species
	SWO-MED	6.5	The value presented in Collette et al. (2011) is unique for this species
	SWO-N-AO	6.5	The value presented in Collette et al. (2011) is unique for this species
	SWO-N-PO	6.5	The value presented in Collette et al. (2011) is unique for this species
	SWO-S-AO	6.5	The value presented in Collette et al. (2011) is unique for this species
	SWO-SWPO	6.5	The value presented in Collette et al. (2011) is unique for this species
Istiophorus albicans	SAI-E-AO	1.7	Assumed equal to *Istiophorus platypterus* presented in Collette et al. (2011)
	SAI-W-AO	1.7	Assumed equal to *Istiophorus platypterus* presented in Collette et al. (2011)
Istiompax indica	BLM-IO	1.8	The value presented in Collette et al. (2011) is unique for this species
Makaira nigricans	BUM-AO	1.8	The value presented in Collette et al. (2011) is unique for this species
	BUM-IO	1.8	The value presented in Collette et al. (2011) is unique for this species
	BUM-PO	1.8	The value presented in Collette et al. (2011) is unique for this species
Kajikia albidus	WHM	5.5	Collette et al. (2011)
Kajikia audax	MLS-IO	4.4	The value presented in Collette et al. (2011) is unique for this species
	MLS-EPO	4.4	The value presented in Collette et al. (2011) is unique for this species
	MLS-SWPO	4.4	The value presented in Collette et al. (2011) is unique for this species
	MLS-WCPO	4.4	The value presented in Collette et al. (2011) is unique for this species

Appendix 1.6. Market price used for the analysis (average price from 2003-2012). The price is species specific not by stock.

Species	Average Price in dollars/kg	Market source
Skipjack tuna	$0.96	FAO*
Albacore tuna	$2.26	FAO*
Yellowfin tuna	$2.35	FAO*
Bigeye tuna	$4.57	FAO*
Atlantic and Pacific bluefin tunas	$14.13	FAO*
Southern bluefin tuna	$14.49	FAO*
White marlin	$1.60	US**
Sailfish	$2.44	US**
Blue marlin	$2.51	US**
Black marlin	$2.82	US**
Striped marlin	$3.00	US**
Swordfish	$5.19	US**

Taken from: * http://www.fao.org/economic/est/statistical-data/en/ (latest access December 2014)

** http://www.st.nmfs.noaa.gov/commercial-fisheries/commercial-landings/annual-landings/index (latest access December 2014)

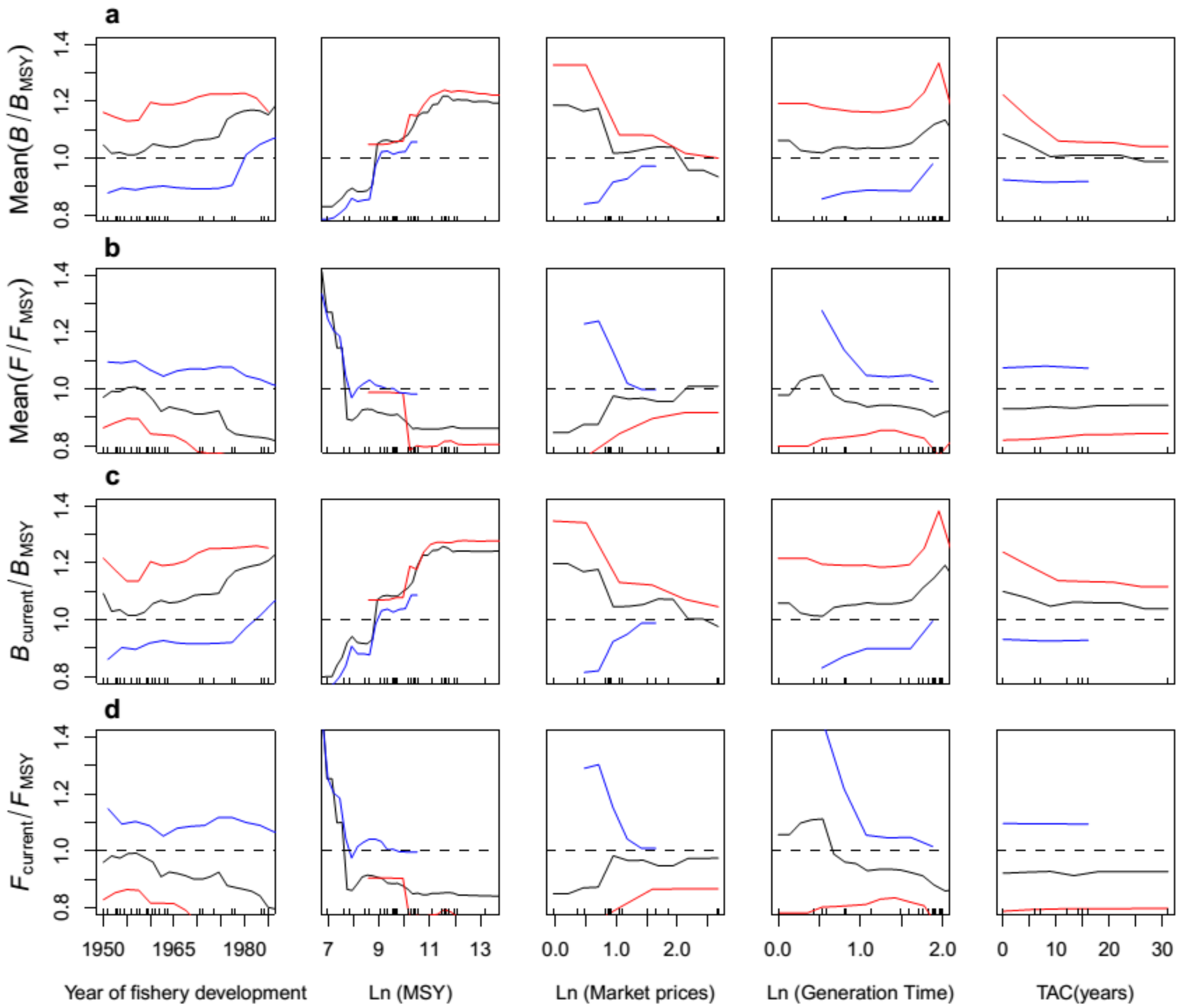
Appendix 1.7. *Correlation Analysis*. Before doing the random forest analyses, predictors were tested for collinearity using Variance Inflation Factors (VIF) to determine if some variables should be dropped before starting the analysis. A cut-off value of 5 can be used to remove collinear variables (Zuur *et al.* 2009). Some predictors that were considered in the analysis but were excluded because they increased VIF values above 5 were:

1. Ocean: We excluded this predictor because it is related to management measures taken by different tRFMOs (i.e. most of the stocks with TACs occur in the Atlantic Ocean, because ICCAT has a large history of using quotas as output management measures).
2. Region (tropical vs. temperate species): We did not consider this predictor because it is correlated with life history characteristics (tropical tunas are highly productive compared to temperate tunas (Juan-Jordá *et al.* 2011)).
3. Maximum length and size/age at maturity: We decided not to include these measures in the analysis even though they have been previously shown to affect current biomass, because there are no reliable estimates of age and growth for most billfish species. Instead we used Generation Time (GT) (Collette *et al.* 2011), which is highly correlated with these life history characteristics.
4. RFMO: We did not consider each RFMO, because this predictor is correlated with some management measures. For example, only ICCAT and CCSBT have applied quotas for managed tuna and billfish stocks.

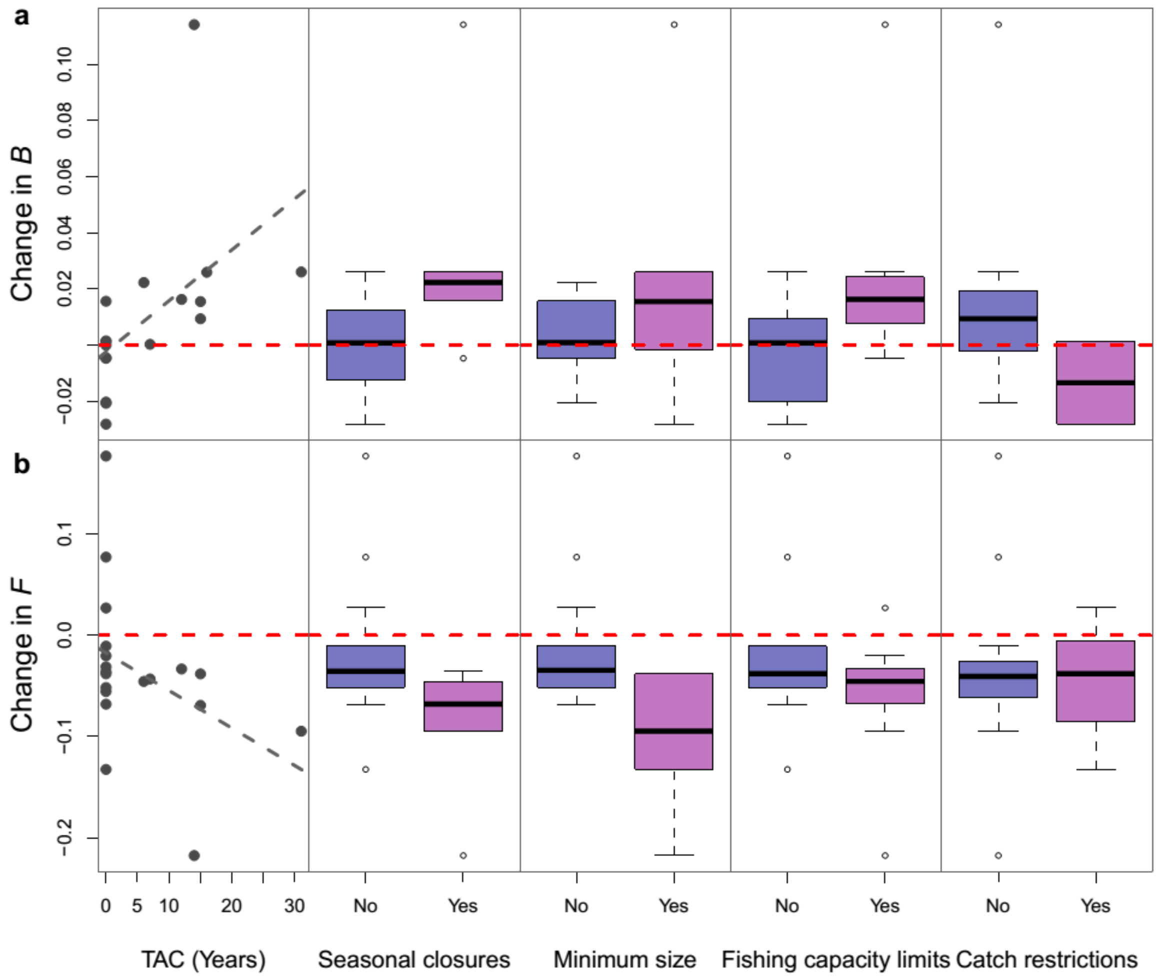
The final variables considered in the random forest analysis are listed in the next table. As all VIF values were less than 3.22, suggesting a low probability of confounding effects among the predictors.

Variance inflation factors (VIF) for continuous predictors used in the random forest analysis. Ln refers to the natural logarithm.

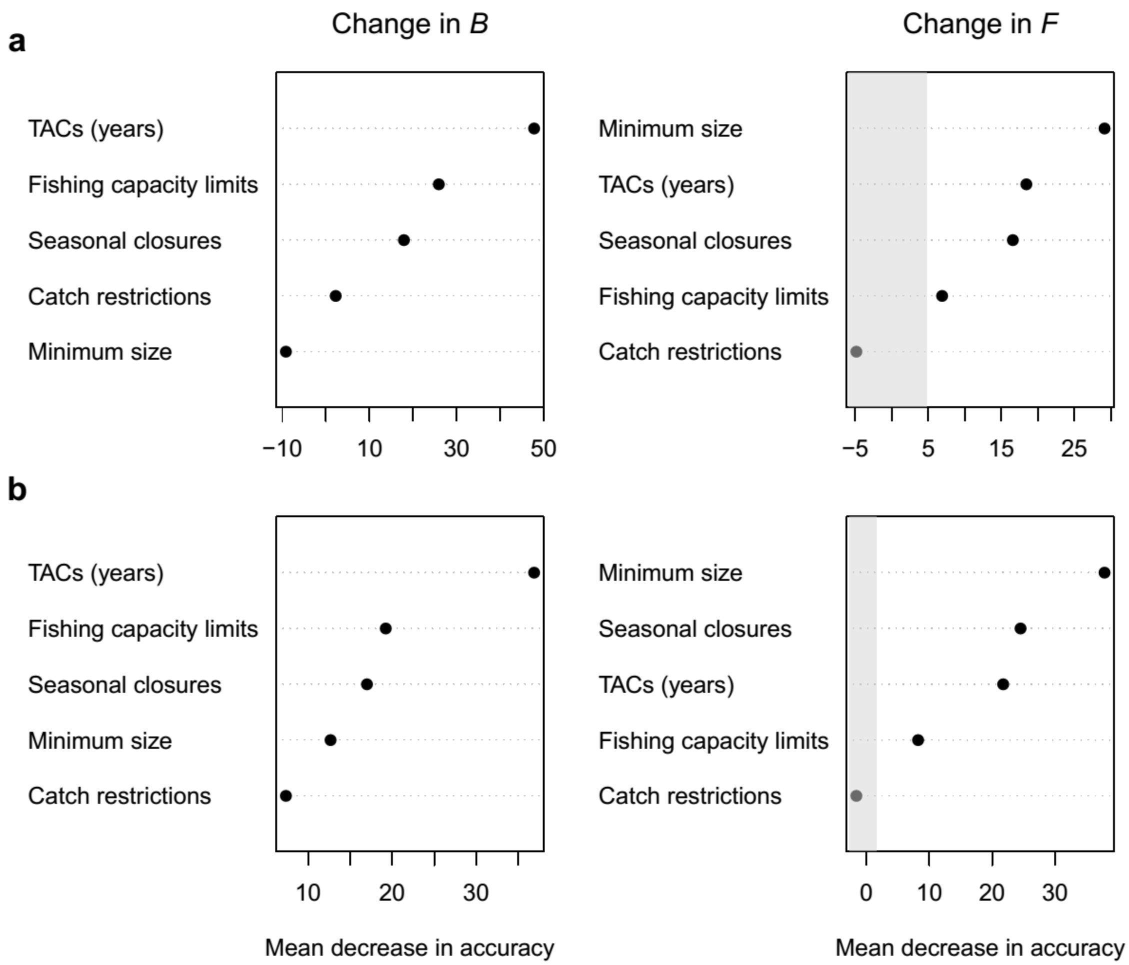
Predictor	**VIF**
Taxa	3.22
Ln (MSY)	2.79
Ln (Generation Time)	2.78
Minimum size	2.61
TACs (years)	2.52
Ln (Market price)	2.41
Seasonal closures	2.18
Catch restrictions	1.86
Main number of countries	1.82
Year of fishery development	1.6
Fishing capacity limits	1.5



Appendix 1.8. Sensitivity analysis *on* the partial dependence plots of the most important continuous predictors of stock status. Partial dependence plots are similar to those in Figure 1.4, with the exception that in (a) and (b), the geometric means of B/B_{MSY} and F/F_{MSY} were calculated for the 5 years prior to the last assessment instead of 10 years, and in (c) and (d), only the final year stock status of B/B_{MSY} and F/F_{MSY} was considered (no averaging). Red lines represent tunas, blue lines billfishes, black lines both combined and dashed lines general management targets. Log refers to the natural logarithm.



Appendix 1.9. Effect of management measures on rebuilding previously depleted tuna and billfish stocks. (a) Annual change in biomass, *B*, and (b) annual change in fishing mortality, *F*, versus management measures. The rate of change was calculated as the geometric mean of the differences in B/B_{MSY} or F/F_{MSY} from one year to the next over the 10-year period leading up to the year of the latest stock assessment. Red dashed lines represent levels of no change. Grey dashed lines are linear trend lines between the rate of change in *B* and *F* against years under TACs.



Appendix 1.10. Sensitivity analysis on variable importance scores of management measures after removing outlying stocks. Variable importance plots are similar to those in Figure 1.3, with the exception that in (a) the Eastern Atlantic bluefin tuna stock is removed, and in (b) the Western Atlantic bluefin tuna stock is removed.

APPENDIX 2

Appendix 2.1. Stocks considered in the questionnaires for each tRFMO and the source where the information of the reference points where extracted. In some cases the reason of why the information was not used in the Random Forest analysis is explained. * http://ramlegacy.org/

Stock	tRFMO	Source for time series and reference points
Southern bluefin	CCSBT	RAM Legacy database *
Swordfish Eastern Pacific	IATTC	RAM Legacy database *
Albacore North Pacific	WCPFC and IATTC	RAM Legacy database *
Bigeye Eastern Pacific	IATTC	RAM Legacy database *
Bluefin Pacific	WCPFC and IATTC	RAM Legacy database *
Skipjack Eastern Pacific	IATTC	Assessed but not used, no estimation of RP (Maunder 2016)
Yellowfin Eastern Pacific	IATTC	RAM Legacy database *
Black skipjack Eastern Pacific	IATTC	No Assessment
Bonitos Eastern Pacific	IATTC	No Assessment
Dolphinfishes Eastern Pacific	IATTC	No Assessment
Sharks Eastern Pacific	IATTC	No Assessment
Albacore South Atlantic	ICCAT	RAM Legacy database *
Bigeye Atlantic	ICCAT	RAM Legacy database *
Bluefin Eastern Atlantic	ICCAT	RAM Legacy database *
Skipjack Eastern Atlantic	ICCAT	RAM Legacy database *
Swordfish Mediterranean	ICCAT	Assessed but not used, non-reliable estimation of RP (ICCAT 2016b)
Swordfish South Atlantic	ICCAT	RAM Legacy database *
Yellowfin Atlantic	ICCAT	RAM Legacy database *
Bonito Atlantic	ICCAT	No Assessment
Blue shark North Atlantic	ICCAT	Assessed but not used, non-reliable estimation of RP (ICCAT 2015c)
Blue shark South Atlantic	ICCAT	Assessed but not used, non-reliable estimation of RP (ICCAT 2015c)
Skipjack Indian	IOTC	RAM Legacy database *
Yellowfin Indian	IOTC	RAM Legacy database *
Bigeye Indian	IOTC	RAM Legacy database *
Kawakawa Indian	IOTC	RAM Legacy database *
Longtail tuna Indian	IOTC	RAM Legacy database *
NB Spanish mackerel Indian	IOTC	RAM Legacy database *
Swordfish Indian	IOTC	RAM Legacy database *
Frigate tuna Indian	IOTC	No Assessment
Oceanic whitetip Indian	IOTC	No Assessment
Seerfishes Indian	IOTC	No Assessment
Albacore South Pacific	WCPFC	RAM Legacy database *
Bigeye Western Pacific	WCPFC	RAM Legacy database *
Blue marlin Pacific	WCPFC	RAM Legacy database *
Skipjack Western Pacific	WCPFC	RAM Legacy database *
Striped marlin South Western Pacific	WCPFC	RAM Legacy database *
Striped marlin Western Pacific	WCPFC	RAM Legacy database *
Swordfish South Western Pacific	WCPFC	RAM Legacy database *
Yellowfin Western Pacific	WCPFC	RAM Legacy database *
Black marlin Pacific	WCPFC	No Assessment

Dimensions (4)	Attributes (12)	Criteria (38 questions)
Research, monitoring, and assessment (R)	• Landings data • Body size or age data • Abundance trends estimation • Stock assessments	Collected annually and consistently across years Collected at the species or stock level, rather than by aggregate groups of several species Recorded landings are thought to capture at least 75% of actual total landings
		Body size data collected using consistent protocols across years, and frequently enough that they are likely to reflect changes in mean body size Age data collected using consistent protocols across years, and frequently enough that they are likely to reflect changes in age structure Size or age data collected at the species or stock level, rather than by aggregate groups of several species
		Fishery-independent surveys are conducted using consistent protocols across years, and frequently enough that they are likely to reflect current trends Fishery-dependent relative abundance estimates (e.g. CPUE, kg/tow) are collected using consistent protocols across years, and frequently enough that they are likely to reflect current trends Fishery-independent or fishery-dependent data are collected at the species or stock level, rather than by aggregate groups of several species
		Some form of assessment of abundance and/or fishing mortality rate exists (including relative abundance trends) Assessments are performed frequently enough that they are likely to reflect current stock status In assessments, population models are fit to catch data to estimate historical time series of biomass and/or fishing mortality rate In assessments, biological reference points are estimated (e.g. Fmsy, B40%, Blim, Fmax, F0.1) For stocks with assessments, assessment results are used to provide advice for fishery management
Management response to stock status (M)	• Fishery management plan • Effective limits on fishing pressure • Capacity to adjust fishing pressure	Management objectives are explicitly stated or well understood Fishery management plan exists and strategies or tactics designed to meet objectives are specified Management plans are specific to stocks, groups of stocks, or fleets
		A target, limit, or range of acceptable levels of abundance and/or fishing mortality rate are specified Regulations to limit fishing pressure are sufficient for actually achieving acceptable levels of abundance and/or fishing mortality rate if they were to be adequately enforced Target fishing pressure is reduced when stock status is more uncertain
		Regulations to limit fishing pressure have been adjusted in the past Decisions to adjust the regulations that limit fishing pressure are based on estimated stock size, stock status, or trends in fishing pressure Management process uses some form of a harvest control rule: a pre-specified rule that recommends changes to fishing pressure in response to changes in estimated stock size or status
Enforcement of management measures (E)	• Fisheries enforcement • Discarding and by-catch measures	Dockside monitoring and enforcement measures of member countries are sufficient for the collective fishery management system to effectively regulate fishing pressure At-sea observer programs and enforcement measures of member countries are sufficient for the collective fishery management system to effectively regulate fishing pressure Penalties or disincentives are thought to be sufficient to ensure compliance with national and international regulations On average, illegal or unreported catch volume is thought to be low enough that the collective fishery management system can still effectively regulate fishing pressure
		Management measures are in place and effective at reducing the catch (or subsequent discard mortality) of juveniles of the target species Management measures are in place and effective at reducing by-catch of non-target species Discard mortality and/or by-catch limits exist, with consequences for exceeding those limits (e.g. penalties; individual quota reductions; fishery shutdown)
Social and economic attributes (S)	• Controls on access and entry into fishery • Transparency and community involvement • Subsidies	Annual records are kept of the number of boats, licenses, or individual quota holders in commercial sectors Limited entry on the number of boats, licenses, or individual quota units in commercial sectors Licenses or individual quota units confer some degree of transferable property rights
		There are opportunities for user groups or stakeholders to provide input into the management decision process Cooperatives, community associations or harvester's associations induce collective action in the management process Management decisions and the reasons for these decisions are transparent (publicly disclosed)
		There are no significant government subsidies provided to the fishing industry for fuel or vessel construction/renovation There are no significant government subsidies provided to the fishing industry in the form of tax exemptions, fishing access agreement payments, or marketing support

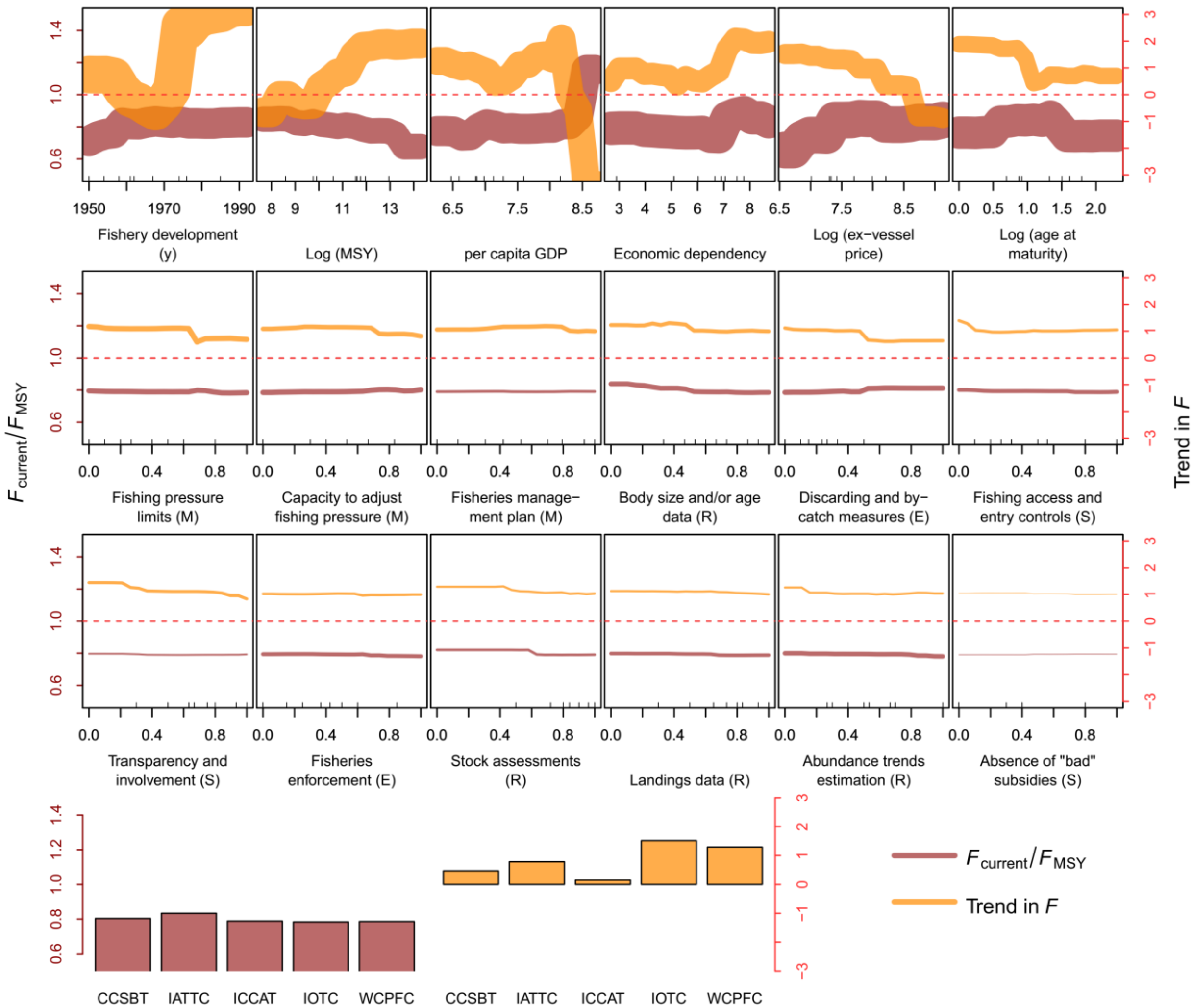
Appendix 2.2. Fishery management survey questionnaire slightly reworded from Melnychuk et al. (2017) to better pertain to high seas tRFMOs instead of to national jurisdictions.

Appendix 2.3. Predictors considered for the random forest analysis. All values are specific to tuna Regional Fisheries Management Organizations, averaged over stocks and member countries as required.

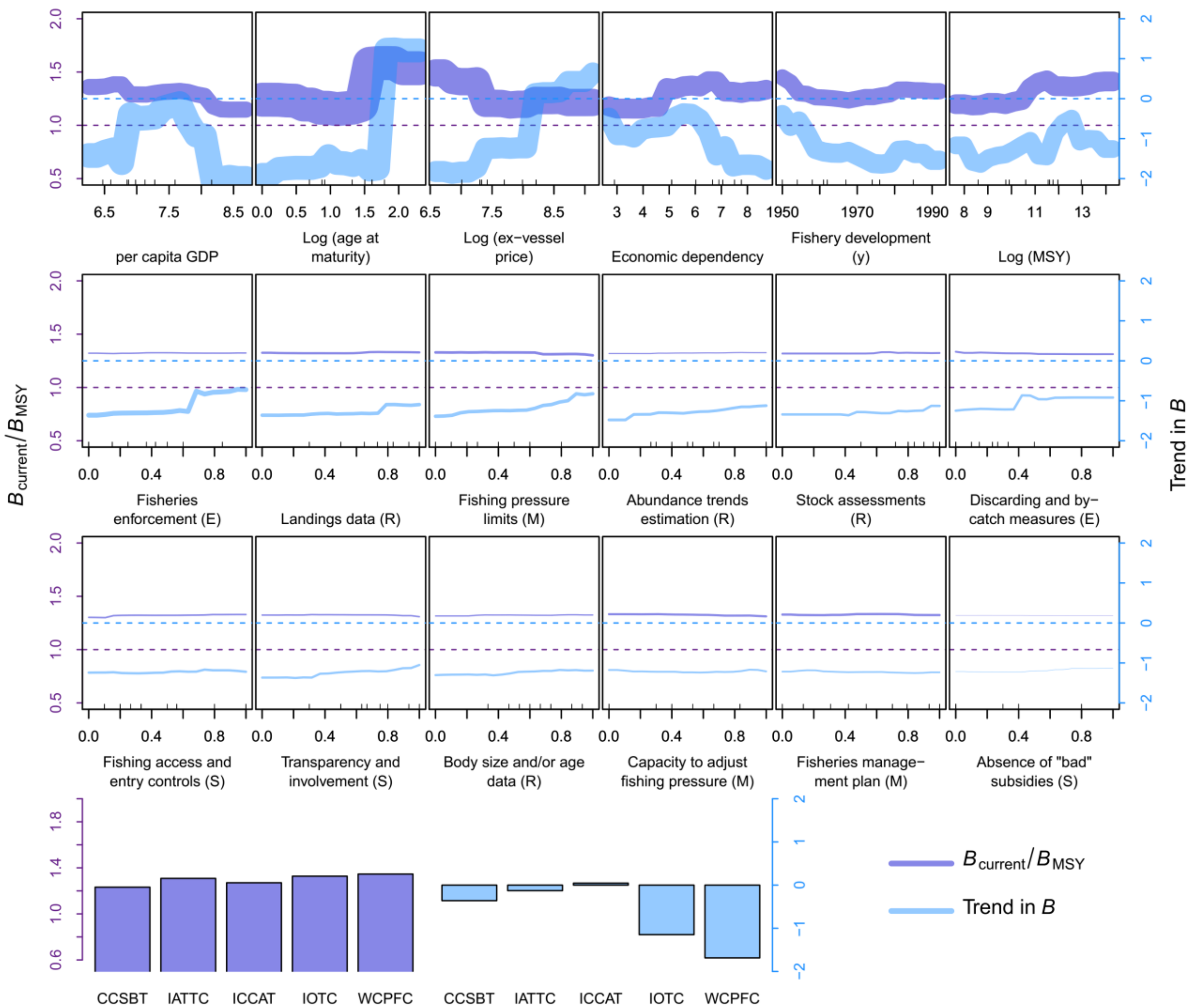
Predictor	Description	Source
Governance predictors		
Convention agreement (year)	Year when the Convention agreement entered into force.	Sydnes (2001)
Number of countries	Number of countries or contracting parties in 2016.	ICCAT: https://www.iccat.int/en/contracting.htm. IATTC: https://www.iattc.org/HomeENG.htm. IOTC: http://www.iotc.org/about-iotc/structure-commission. WCPFC: https://www.wcpfc.int/about-wcpfc. CCSBT: https://www.ccsbt.org/en/content/origins-convention
Economic predictors		
per-capita Gross Domestic Product (GDP)	Sum of per-capita gross domestic product ($USD values for 2013) reported by the World Bank across countries. Country's GDP values were weighted by their total landings.	World-Bank (2015)
per-capita Seafood Protein Provision (SPP)	Sum of SPP country values (g·capita–1·day–1 for 2011) reported by the Food and Agriculture Organization (FAO) of the United Nations across countries. Country's SPP values were weighted by their total landings.	FAOSTAT (2017)
Economic dependency on tuna fisheries	Weighed mean economic dependency on tuna and tuna-related fisheries, calculated as the mean (catch by species * price by species / Country's GDP). Catch and prices for the 10 species with highest catches were included for the calculation.	Catch from each tRFMO webpage; GDP from World-Bank (2015); prices from Melnychuk *et al.* (2017)
Fishery predictors		
Year of fisheries development	First year that total catch across all species managed under the tRFMO reached 25% of the maximum annual catch during 1950 to 2014.	
Number of vessels	Number of registered and authorized vessels in 2016.	http://clav.iotc.org/browser/search/#.WCEpXy0rLct
Mean vessel length (m)	Median vessel overall length (LOA)	http://clav.iotc.org/browser/search/#.WCEpXy0rLct

Appendix 2.4. Predictors considered for the random forest analysis. All values are specific for each stock.

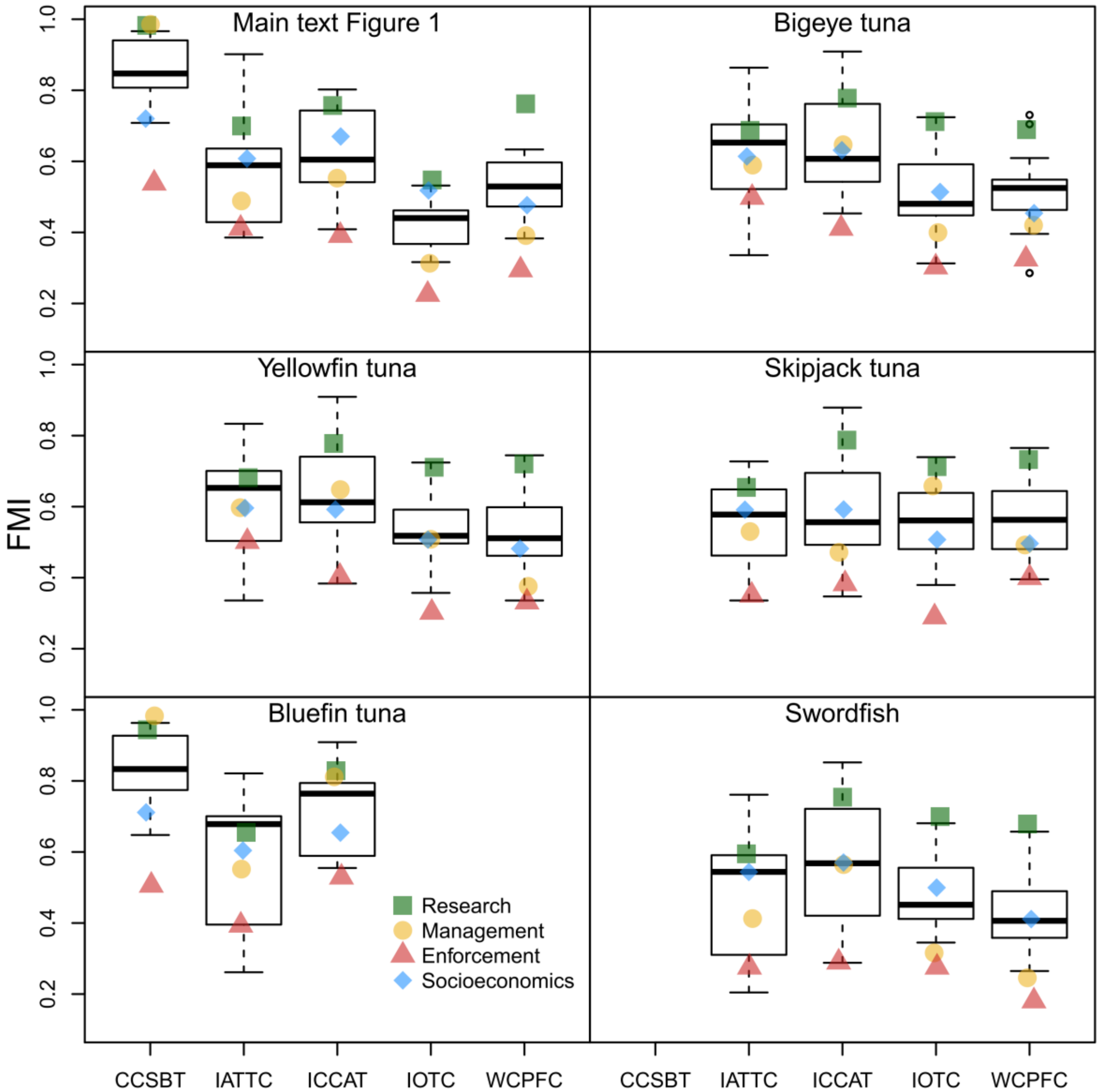
Predictor	Description	Source
tRFMO	Categorical: 5 tRFMOs	
Biology		
MSY	Maximum sustainable yield, extracted from stock assessments outputs, provides a measure of stock size for scale	RAM Legacy database
Age at maturity	Age at which 50% of the female population has reached maturity	Juan-Jordá *et al.* (2016) and http://www.fishbase.org/
Economics		
Ex-vessel price	Average for last 10 years, in $USD per ton	Melnychuk *et al.* (2017)
Average per-capita GDP	Weighted mean gross domestic product across countries, weighted by country catch	Catch from each tRFMO webpage; GDP from World-Bank (2015)
Economic dependency	Weighted mean (catch * price / GDP) across countries, weighted by country catch	Catch from each tRFMO webpage; GDP from World-Bank (2015); prices from Melnychuk *et al.* (2017)
Fishery		
Year of fishery development	First year that total catch reached 25% of the maximum annual catch during 1950 to 2014	Catch from each tRFMO webpage
FMI attributes		
Landings data	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Body size or age data	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Abundance trends estimation	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Stock assessments	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Fishery management plan	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Effective limits on fishing pressure	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Capacity to adjust fishing pressure	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Fisheries enforcement	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Discarding and bycatch measures	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Controls on access and entry into fishery	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Transparency and community involvement	Average score for each stock	FMI survey for tRFMOs (Figure S1)
Lack of subsidies	Average score for each stock	FMI survey for tRFMOs (Figure S1)



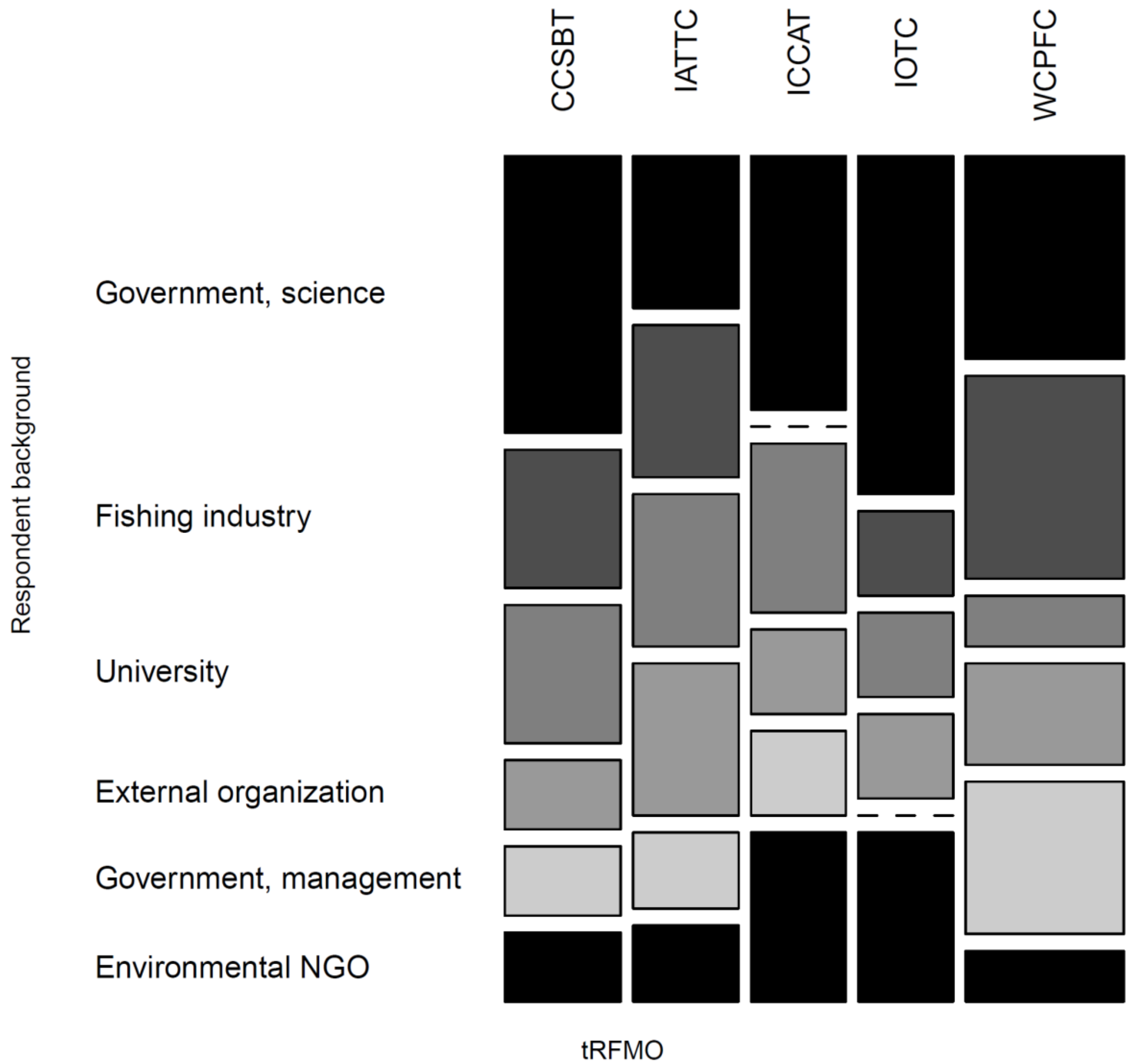
Appendix 2.5. Sensitivity analysis of the effects of stock-level biological, economic, and fishery factors as well as FMI attributes on current F/F_{MSY} and recent trends in F (mean annual percent of change) for the most recent 5-year period. Line thicknesses are proportional to predictor variable importance scores from random forest analyses, separately for each response variable. Panels are sorted left to right by the sum of variable importance scores across the two response variables. Barplots represent categorical variables. Dashed lines show reference cases of F/F_{MSY} = 1 and annual trend in F = 0%.



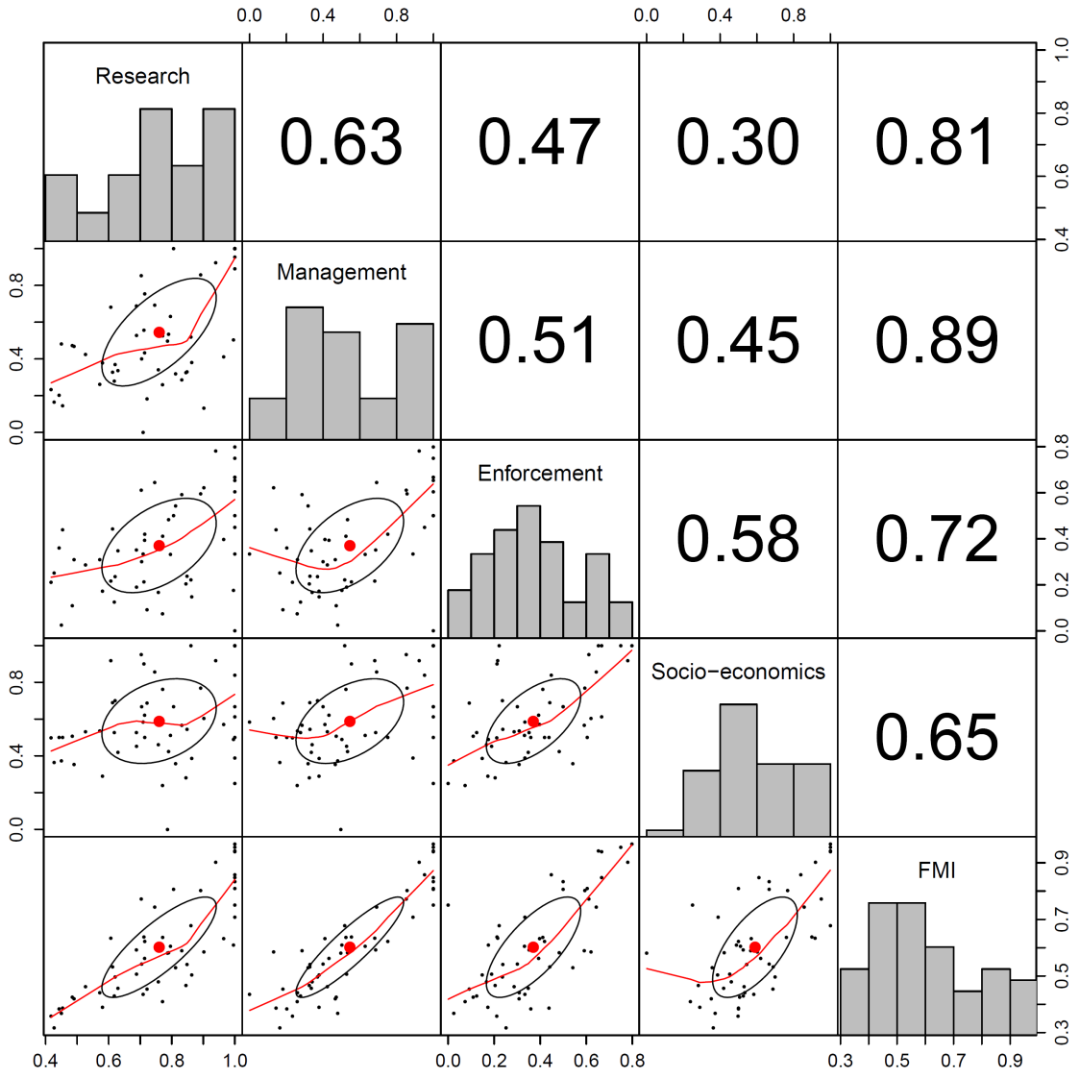
Appendix 2.6. Sensitivity analysis of the effects of stock-level biological, economic, and fishery factors as well as FMI attributes on current B/B_{MSY} and recent trends in B (mean annual percent of change) for the most recent 5-year period. Line thicknesses are proportional to predictor variable importance scores from random forest analyses, separately for each response variable. Panels are sorted left to right by the sum of variable importance scores across the two response variables. Barplots represent categorical variables. Dashed lines show reference cases of B/B_{MSY} = 1 and annual trend in B = 0%.



Appendix 2.7. Sensitivity analysis for considering species composition effects on overall tRFMO scores. Summarized survey answers are shown by tRFMO and FMI dimension (Research, Management, Enforcement and Socioeconomics) for the same species occurring across multiple tRFMOs (bigeye, yellowfin, skipjack and bluefin tunas as well as swordfish. Overlaid boxplots show the 25th, 50th and 75th percentiles (bottom, band and top of the box respectively) of overall FMI scores, which are aggregates of the four dimensions.



Appendix 2.8. Mosaic plot of respondent background category by tRFMO. Bar widths are proportional to the number of respondents in each background category (total n = 54 surveys completed).



Appendix 2.9. Summary statistics of survey answers by dimension. Responses for individual questions within dimensions are weighted by confidence score in the answers provided for individual questions. The FMI is a composite of research, management, enforcement, and socioeconomics dimensions with equal weighting. Diagonals show histograms of survey responses (n = 54) across all tRFMOs and respondents. Lower panels show scatterplots between pairs of dimensions, with correlation ellipses (black lines), loess smoothers (red lines), and bivariate medians (red circles) overlaid. Upper panels show Pearson correlation coefficients between pairs of dimensions.

APPENDIX 3

Appendix 3.1. Life history information and references available for small scombrids in the Atlantic Ocean (ICCAT 2018).

Species	Parameter	Northeast	Source	Southeast	Source	Mediterranean	Source	Northwest	Source	Southwest	Source
Sarda sarda (BON)	Lmax	91.4	Collette and Nauen, 1983			91.4	Collette and Nauen, 1983				
	Linf	73.01	Baibbat et al., 2016			69.565	Kahraman et al., 2014				
	k	0.3075	Baibbat et al., 2016			0.439	Kahraman et al., 2014				
	to	-2.4469	Baibbat et al., 2016			-1.327	Kahraman et al., 2014				
	Tmax	5	Baibbat et al., 2016			5	Cayré et al., 1993				
	Lm50	42.6	Baibbat et al., 2016			36.6-39.93	Hattour, 2000; Saber et al., 2017				
	Tm50					0.71	Kahraman et al., 2014				
	WL_a	5.00E-05	Baibbat et al., 2016			0.006321-0.0082	Saber et al., 2017; Sinovcic et al., 2004			0.0135	Hansen, 1987
	WL_b	2.7852	Baibbat et al., 2016			3.21-3.13	Saber et al., 2017; Sinovcic et al., 2004			2.952	Hansen, 1987
Euthynnus alletteratus (LTA)	Lmax	82.6	Cayré and Diouf, 1980 (spines)			122	Claro, 1994	106.68	IGFA,2011		
	Linf					117-130,8	Hattour, 2009; Hajjej et al., 2012	86	Cabrera et al., 2005		
	k					0.19-0.131	Hattour, 2009; Hajjej et al., 2012	0.26	Cabrera et al., 2005		
	to					-1.13 - -2.22	Hattour, 2009; Hajjej et al., 2012	-0.32	Cabrera et al., 2005		
	Tmax	8	Cayré and Diouf, 1980 (spines)			10-7	Hattour, 2009; Hajjej et al., 2012				
	Lm50	42	Diouf, 1980			44.8-51.13	Hattour, 2009; Hajjej et al., 2012	39.7	Ramirez-Arredondo, 1993		
	Tm50					1.89	Hattour, 2009				
	WL_a	0.0138	Diouf, 1980			0.0329-0.01242	Hajjej et al., 2011; Saber et al., 2017	0.0000205	Ramirez-Arredondo et al., 1996, W in g and FL in mm		
	WL_b	3.035	Diouf, 1980			2.8101-3.058	Hajjej et al., 2011; Saber et al., 2017	2.96	Ramirez-Arredondo et al., 1996, W in g and FL in mm		
Acanthocybium solandri (WAH)	Lmax					Stock not defined		200	Hogarth, 1976	197	Viana et al., 2013
	Linf							179.7	McBride et al., 2008		
	k							0.317	McBride et al., 2008		
	to							-1.911	McBride et al., 2008		
	Tmax							9	McBride et al., 2008		
	Lm50							92.5	Jenkins and McBride, 2009	110	Viana et al., 2013
	Tm50							0.64	Jenkins and McBride, 2009		
	WL_a	0.02749	Santana et al., 1993 (Size distribution)					0.00000204	Beerkircher2005	0.0016	Frota et al., 2004
	WL_b	2.72252	Santana et al., 1993 (Size distribution)					3.242	Beerkircher2005	3.275	Frota et al., 2004
Auxis thazard (FRI)	Lmax										
	Linf			51.47	Grudtsev and Korolevich, 1986						
	k			0.32	Grudtsev and Korolevich, 1986						
	to			-0.83	Grudtsev and Korolevich, 1986						
	Tmax			4	Grudtsev and Korolevich, 1986						
	Lm50			30	Cayré et al., 1993						
	Tm50										
	WL_a									0.0089	Frota et al., 2004
	WL_b									3.17	Frota et al., 2004

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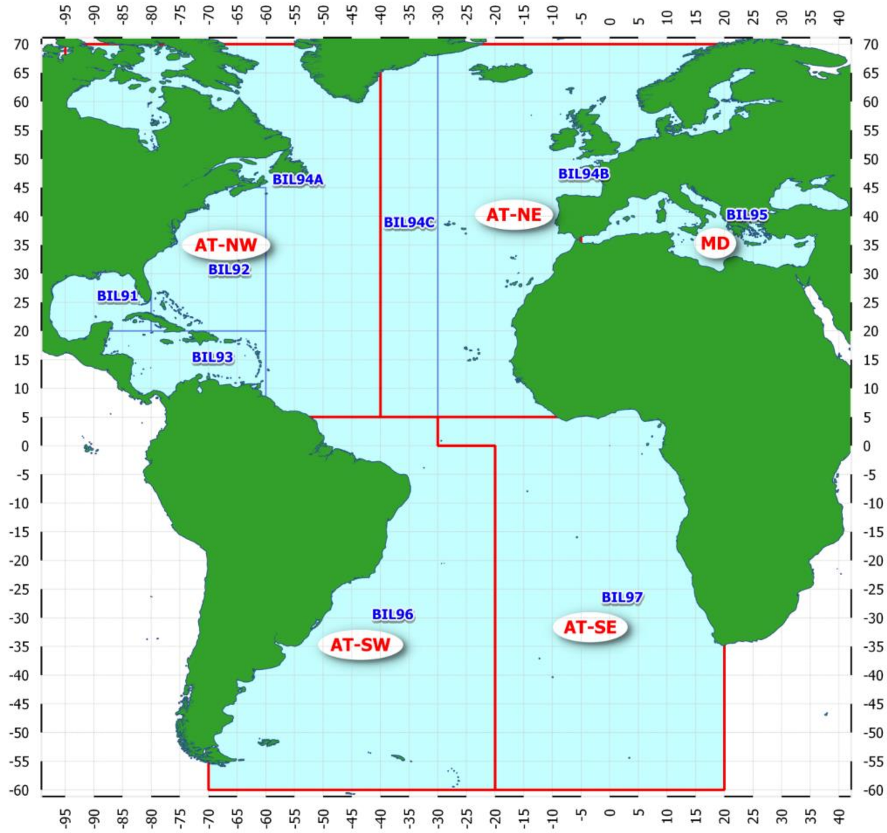
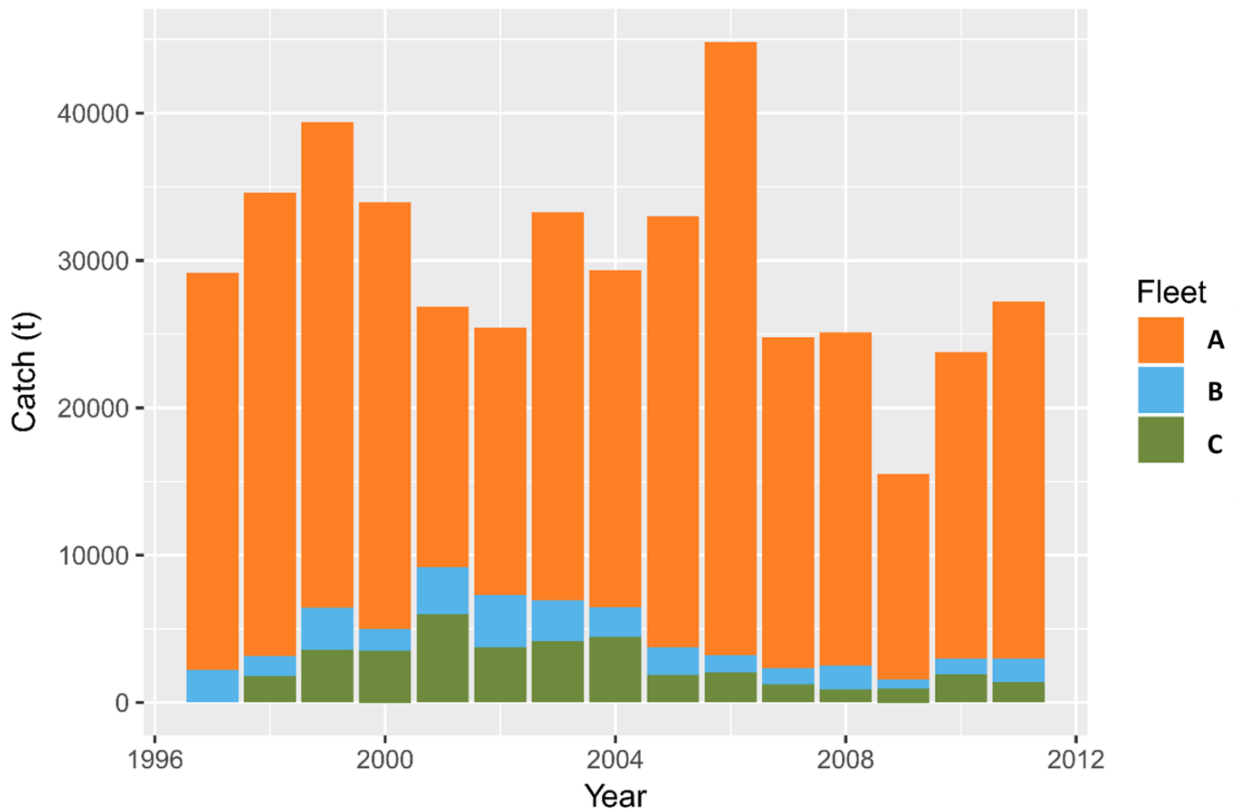
Appendix 3.2. North Atlantic Albacore age-length conversion matrix extracted from SS. Columns are the ages and rows are length bins.

Length/Age	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
150	0.00E+00	0.00E+00	0.00E+00	0.00E+00	6.05E-14	4.10E-10	8.20E-08	2.40E-06	2.29E-05	1.09E-04	3.32E-04	7.47E-04	1.37E-03	2.16E-03	3.07E-03	5.36E-03
148	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.79E-13	1.14E-09	1.59E-07	3.56E-06	2.75E-05	1.11E-04	2.97E-04	6.02E-04	1.01E-03	1.50E-03	2.01E-03	3.19E-03
146	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.47E-12	4.07E-09	4.42E-07	8.32E-06	5.70E-05	2.11E-04	5.28E-04	1.02E-03	1.65E-03	2.37E-03	3.11E-03	4.75E-03
144	0.00E+00	0.00E+00	0.00E+00	0.00E+00	7.33E-12	1.39E-08	1.17E-06	1.87E-05	1.14E-04	3.87E-04	9.08E-04	1.67E-03	2.61E-03	3.63E-03	4.67E-03	6.89E-03
142	0.00E+00	0.00E+00	0.00E+00	1.11E-16	3.46E-11	4.50E-08	3.00E-06	4.05E-05	2.20E-04	6.87E-04	1.51E-03	2.66E-03	4.00E-03	5.42E-03	6.81E-03	9.70E-03
140	0.00E+00	0.00E+00	0.00E+00	4.44E-16	1.55E-10	1.40E-07	7.34E-06	8.45E-05	4.10E-04	1.18E-03	2.45E-03	4.10E-03	5.96E-03	7.85E-03	9.65E-03	1.33E-02
138	0.00E+00	0.00E+00	0.00E+00	4.00E-15	6.59E-10	4.13E-07	1.72E-05	1.70E-04	7.37E-04	1.96E-03	3.83E-03	6.13E-03	8.61E-03	1.10E-02	1.33E-02	1.77E-02
136	0.00E+00	0.00E+00	0.00E+00	2.90E-14	2.65E-09	1.17E-06	3.89E-05	3.29E-04	1.28E-03	3.14E-03	5.80E-03	8.89E-03	1.21E-02	1.51E-02	1.78E-02	2.29E-02
134	0.00E+00	0.00E+00	0.00E+00	1.97E-13	1.01E-08	3.16E-06	8.41E-05	6.12E-04	2.15E-03	4.88E-03	8.51E-03	1.25E-02	1.64E-02	2.00E-02	2.32E-02	2.88E-02
132	0.00E+00	0.00E+00	0.00E+00	1.26E-12	3.65E-08	8.14E-06	1.75E-04	1.10E-03	3.48E-03	7.34E-03	1.21E-02	1.71E-02	2.17E-02	2.58E-02	2.93E-02	3.53E-02
130	0.00E+00	0.00E+00	0.00E+00	7.49E-12	1.25E-07	2.01E-05	3.48E-04	1.90E-03	5.43E-03	1.07E-02	1.67E-02	2.26E-02	2.78E-02	3.23E-02	3.59E-02	4.20E-02
128	0.00E+00	0.00E+00	0.00E+00	4.18E-11	4.06E-07	4.72E-05	6.67E-04	3.16E-03	8.20E-03	1.50E-02	2.22E-02	2.89E-02	3.46E-02	3.92E-02	4.29E-02	4.87E-02
126	0.00E+00	0.00E+00	0.00E+00	2.19E-10	1.25E-06	1.06E-04	1.22E-03	5.07E-03	1.19E-02	2.04E-02	2.87E-02	3.60E-02	4.18E-02	4.63E-02	4.97E-02	5.48E-02
124	0.00E+00	0.00E+00	0.00E+00	1.07E-09	3.64E-06	2.27E-04	2.16E-03	7.82E-03	1.68E-02	2.68E-02	3.60E-02	4.34E-02	4.90E-02	5.31E-02	5.60E-02	6.00E-02
122	0.00E+00	0.00E+00	3.33E-16	4.90E-09	1.01E-05	4.65E-04	3.65E-03	1.16E-02	2.28E-02	3.41E-02	4.36E-02	5.07E-02	5.57E-02	5.90E-02	6.13E-02	6.39E-02
120	0.00E+00	0.00E+00	2.78E-15	2.10E-08	2.64E-05	9.10E-04	5.92E-03	1.66E-02	2.99E-02	4.20E-02	5.12E-02	5.75E-02	6.14E-02	6.38E-02	6.51E-02	6.62E-02
118	0.00E+00	0.00E+00	2.76E-14	8.45E-08	6.55E-05	1.70E-03	9.22E-03	2.30E-02	3.79E-02	5.00E-02	5.83E-02	6.32E-02	6.58E-02	6.70E-02	6.73E-02	6.66E-02
116	0.00E+00	0.00E+00	2.52E-13	3.18E-07	1.54E-04	3.03E-03	1.38E-02	3.05E-02	4.63E-02	5.76E-02	6.42E-02	6.74E-02	6.84E-02	6.83E-02	6.76E-02	6.52E-02
114	0.00E+00	0.00E+00	2.11E-12	1.12E-06	3.43E-04	5.16E-03	1.98E-02	3.90E-02	5.47E-02	6.42E-02	6.85E-02	6.96E-02	6.90E-02	6.76E-02	6.59E-02	6.21E-02
112	0.00E+00	0.00E+00	1.62E-11	3.69E-06	7.26E-04	8.39E-03	2.72E-02	4.80E-02	6.23E-02	6.92E-02	7.09E-02	6.98E-02	6.75E-02	6.49E-02	6.24E-02	5.75E-02
110	0.00E+00	0.00E+00	1.13E-10	1.14E-05	1.45E-03	1.30E-02	3.60E-02	5.70E-02	6.86E-02	7.21E-02	7.10E-02	6.78E-02	6.42E-02	6.06E-02	5.75E-02	5.18E-02
108	0.00E+00	0.00E+00	7.30E-10	3.30E-05	2.76E-03	1.93E-02	4.56E-02	6.51E-02	7.28E-02	7.27E-02	6.89E-02	6.39E-02	5.92E-02	5.50E-02	5.14E-02	4.54E-02
106	0.00E+00	0.00E+00	4.30E-09	8.92E-05	4.96E-03	2.73E-02	5.56E-02	7.16E-02	7.47E-02	7.09E-02	6.47E-02	5.84E-02	5.29E-02	4.84E-02	4.47E-02	3.86E-02
104	0.00E+00	0.00E+00	2.32E-08	2.26E-04	8.46E-03	3.70E-02	6.49E-02	7.58E-02	7.40E-02	6.69E-02	5.89E-02	5.18E-02	4.60E-02	4.14E-02	3.78E-02	3.20E-02
102	0.00E+00	0.00E+00	1.15E-07	5.37E-04	1.37E-02	4.77E-02	7.27E-02	7.74E-02	7.07E-02	6.10E-02	5.19E-02	4.45E-02	3.87E-02	3.43E-02	3.10E-02	2.58E-02
100	0.00E+00	1.11E-16	5.21E-07	1.19E-03	2.09E-02	5.89E-02	7.82E-02	7.61E-02	6.53E-02	5.38E-02	4.43E-02	3.71E-02	3.17E-02	2.77E-02	2.47E-02	2.02E-02
98	0.00E+00	9.99E-16	2.16E-06	2.48E-03	3.04E-02	6.93E-02	8.08E-02	7.20E-02	5.82E-02	4.60E-02	3.67E-02	3.00E-02	2.52E-02	2.17E-02	1.91E-02	1.54E-02
96	0.00E+00	1.92E-14	8.24E-06	4.84E-03	4.18E-02	7.79E-02	8.00E-02	6.56E-02	5.00E-02	3.80E-02	2.94E-02	2.35E-02	1.94E-02	1.65E-02	1.44E-02	1.14E-02
94	0.00E+00	2.95E-13	2.88E-05	8.82E-03	5.45E-02	8.36E-02	7.61E-02	5.76E-02	4.16E-02	3.03E-02	2.28E-02	1.78E-02	1.45E-02	1.22E-02	1.05E-02	8.19E-03
92	0.00E+00	4.00E-12	9.19E-05	1.51E-02	6.73E-02	8.57E-02	6.95E-02	4.87E-02	3.33E-02	2.34E-02	1.72E-02	1.31E-02	1.05E-02	8.73E-03	7.49E-03	5.73E-03
90	0.00E+00	4.73E-11	2.69E-04	2.41E-02	7.88E-02	8.39E-02	6.08E-02	3.96E-02	2.58E-02	1.75E-02	1.25E-02	9.39E-03	7.40E-03	6.08E-03	5.17E-03	3.90E-03
88	0.00E+00	4.91E-10	7.23E-04	3.61E-02	8.74E-02	7.84E-02	5.11E-02	3.11E-02	1.93E-02	1.27E-02	8.82E-03	6.51E-03	5.06E-03	4.11E-03	3.47E-03	2.59E-03
86	0.00E+00	4.46E-09	1.78E-03	5.05E-02	9.20E-02	7.00E-02	4.12E-02	2.35E-02	1.39E-02	8.85E-03	6.02E-03	4.37E-03	3.36E-03	2.70E-03	2.26E-03	1.66E-03
84	0.00E+00	3.55E-08	4.01E-03	6.63E-02	9.17E-02	5.96E-02	3.19E-02	1.71E-02	9.71E-03	5.98E-03	3.99E-03	2.85E-03	2.16E-03	1.72E-03	1.43E-03	1.04E-03
82	0.00E+00	2.47E-07	8.28E-03	8.15E-02	8.66E-02	4.85E-02	2.37E-02	1.19E-02	6.53E-03	3.92E-03	2.56E-03	1.80E-03	1.35E-03	1.07E-03	8.81E-04	6.35E-04
80	0.00E+00	1.51E-06	1.57E-02	9.38E-02	7.75E-02	3.77E-02	1.69E-02	8.06E-03	4.24E-03	2.48E-03	1.59E-03	1.10E-03	8.18E-04	6.42E-04	5.27E-04	3.76E-04
78	0.00E+00	8.08E-06	2.72E-02	1.01E-01	6.58E-02	2.80E-02	1.16E-02	5.23E-03	2.66E-03	1.52E-03	9.55E-04	6.55E-04	4.81E-04	3.75E-04	3.06E-04	2.16E-04
76	0.00E+00	3.79E-05	4.31E-02	1.02E-01	5.29E-02	1.98E-02	7.60E-03	3.27E-03	1.61E-03	8.98E-04	5.57E-04	3.77E-04	2.75E-04	2.13E-04	1.73E-04	1.21E-04
74	0.00E+00	1.55E-04	6.28E-02	9.62E-02	4.03E-02	1.34E-02	4.79E-03	1.97E-03	9.43E-04	5.14E-04	3.14E-04	2.11E-04	1.52E-04	1.17E-04	9.47E-05	6.60E-05
72	0.00E+00	5.59E-04	8.38E-02	8.51E-02	2.91E-02	8.67E-03	2.90E-03	1.14E-03	5.32E-04	2.85E-04	1.72E-04	1.14E-04	8.19E-05	6.27E-05	5.05E-05	3.50E-05
70	0.00E+00	1.76E-03	1.02E-01	7.04E-02	1.99E-02	5.35E-03	1.68E-03	6.40E-04	2.90E-04	1.53E-04	9.10E-05	5.99E-05	4.27E-05	3.26E-05	2.61E-05	1.80E-05
68	0.00E+00	4.85E-03	1.15E-01	5.46E-02	1.29E-02	3.15E-03	9.37E-04	3.44E-04	1.53E-04	7.92E-05	4.67E-05	3.05E-05	2.17E-05	1.64E-05	1.31E-05	9.02E-06
66	0.00E+00	1.17E-02	1.18E-01	3.96E-02	7.94E-03	1.77E-03	5.01E-04	1.78E-04	7.75E-05	3.97E-05	2.32E-05	1.51E-05	1.06E-05	8.05E-06	6.43E-06	4.39E-06
64	0.00E+00	2.48E-02	1.11E-01	2.69E-02	4.63E-03	9.53E-04	2.57E-04	8.90E-05	3.80E-05	1.93E-05	1.12E-05	7.21E-06	5.08E-06	3.83E-06	3.05E-06	2.08E-06
62	0.00E+00	4.60E-02	9.54E-02	1.71E-02	2.55E-03	4.89E-04	1.27E-04	4.28E-05	1.80E-05	9.03E-06	5.21E-06	3.35E-06	2.35E-06	1.77E-06	1.41E-06	9.58E-07
60	0.00E+00	7.48E-02	7.53E-02	1.02E-02	1.34E-03	2.40E-04	5.98E-05	1.98E-05	8.24E-06	4.10E-06	2.35E-06	1.51E-06	1.06E-06	7.95E-07	6.32E-07	4.29E-07
58	0.00E+00	1.06E-01	5.45E-02	5.69E-03	6.63E-04	1.12E-04	2.71E-05	8.83E-06	3.64E-06	1.80E-06	1.03E-06	6.59E-07	4.61E-07	3.46E-07	2.75E-07	1.87E-07
56	0.00E+00	1.33E-01	3.61E-02	2.97E-03	3.12E-04	5.01E-05	1.18E-05	3.79E-06	1.55E-06	7.64E-07	4.36E-07	2.79E-07	1.95E-07	1.47E-07	1.16E-07	7.91E-08
54	0.00E+00	1.45E-01	2.20E-02	1.45E-03	1.39E-04	2.14E-05	4.93E-06	1.57E-06	6.38E-07	3.14E-07	1.79E-07	1.15E-07	8.02E-08	6.03E-08	4.79E-08	3.26E-08
52	1.11E-16	1.39E-01	1.22E-02	6.65E-04	5.86E-05	8.70E-06	1.98E-06	6.25E-07	2.54E-07	1.25E-07	7.12E-08	4.56E-08	3.20E-08	2.41E-08	1.91E-08	1.31E-08
50	3.93E-14	1.16E-01	6.23E-03	2.85E-04	2.35E-05	3.39E-06	7.61E-07	2.40E-07	9.73E-08	4.80E-08	2.74E-08	1.76E-08	1.24E-08	9.33E-09	7.44E-09	5.08E-09
48	6.24E-12	8.53E-02	2.91E-03	1.14E-04	8.90E-06	1.26E-06	2.81E-07	8.85E-08	3.60E-08	1.78E-08	1.02E-08	6.59E-09	4.64E-09	3.51E-09	2.81E-09	1.93E-09
46	6.14E-10	5.49E-02	1.25E-03	4.30E-05	3.20E-06	4.46E-07	9.97E-08	3.15E-08	1.29E-08	6.41E-09	3.70E-09	2.39E-09	1.69E-09	1.28E-09	1.03E-09	7.09E-10
44	3.74E-08	3.09E-02	4.90E-04	1.51E-05	1.09E-06	1.51E-07	3.39E-08	1.08E-08	4.45E-09	2.23E-09	1.30E-09	8.43E-10	5.99E-10	4.56E-10	3.66E-10	2.54E-10
42	1.41E-06	1.53E-02	1.76E-04	4.99E-06	3.52E-07	4.89E-08	1.11E-08	3.56E-09	1.48E-09	7.51E-10	4.39E-10	2.88E-10	2.06E-10	1.57E-10	1.27E-10	8.85E-11
40	3.32E-05	6.60E-03	5.80E-05	1.54E-06	1.08E-07	1.51E-08	3.47E-09	1.13E-09	4.78E-10	2.44E-10	1.44E-10	9.53E-11	6.85E-11	5.27E-11	4.27E-11	3.00E-11
38	4.85E-04	2.50E-03	1.75E-05	4.44E-07	3.12E-08	4.46E-09	1.04E-09	3.47E-10	1.49E-10	7.69E-11	4.59E-11	3.06E-11	2.21E-11	1.71E-11	1.39E-11	9.88E-12
36	4.41E-03	8.29E-04	4.85E-06	1.20E-07	8.58E-09	1.26E-09	3.01E-10	1.02E-10	4.46E-11	2.34E-11	1.42E-11	9.52E-12	6.95E-12	5.41E-12	4.43E-12	3.17E-12
34	2.50E-02	2.41E-04	1.23E-06	3.04E-08	2.23E-09	3.38E-10	8.34E-11	2.90E-11	1.29E-11	6.90E-12	4.23E-12	2.87E-12	2.12E-12	1.66E-12	1.37E-12	9.86E-13
32	8.85E-02	6.13E-05	2.85E-07	7.21E-09	5.52E-10	8.68E-11	2.22E-11	7.93E-12	3.61E-12	1.97E-12	1.22E-12	8.42E-13	6.26E-13	4.94E-13	4.09E-13	2.99E-13
30	1.96E-01	1.37E-05	6.08E-08	1.60E-09	1.29E-10	2.13E-11	5.65E-12	2.09E-12	9.76E-13	5.42E-13	3.43E-13	2.39E-13	1.79E-13	1.43E-13	1.19E-13	8.80E-14
28	2.71E-01	2.67E-06	1.19E-08	3.33E-10	2.86E-11	4.99E-12	1.38E-12	5.30E-13	2.55E-13	1.45E-13	9.30E-14	6.58E-14	5.00E-14	4.02E-14	3.37E-14	2.52E-14
26	2.35E-01	4.57E-07	2.12E-09	6.48E-11	6.02E-12	1.12E-12	3.25E-13	1.29E-13	6.41E-14	3.73E-14	2.45E-14	1.76E-14	1.35E-14	1.10E-14	9.28E-15	7.03E-15
24	1.27E-01	6.85E-08	3.47E-10	1.18E-11	1.20E-12	2.38E-13	7.34E-14	3.04E-14	1.56E-14	9.31E-15	6.23E-15	4.54E-15	3.54E-15	2.90E-15	2.48E-15	1.90E-15
22	4.30E-02	9.00E-09	5.21E-11	2.01E-12	2.26E-13	4.86E-14	1.59E-14	6.89E-15	3.66E-15	2.25E-15	1.54E-15	1.14E-15	9.01E-16	7.47E-16	6.44E-16	5.02E-16
20	9.09E-03	1.03E-09	7.16E-12	3.22E-13	4.05E-14	9.47E-15	3.30E-15	1.50E-15	8.29E-16	5.25E-16	3.67E-16	2.78E-16	2.23E-16	1.87E-16	1.62E-16	1.29E-16

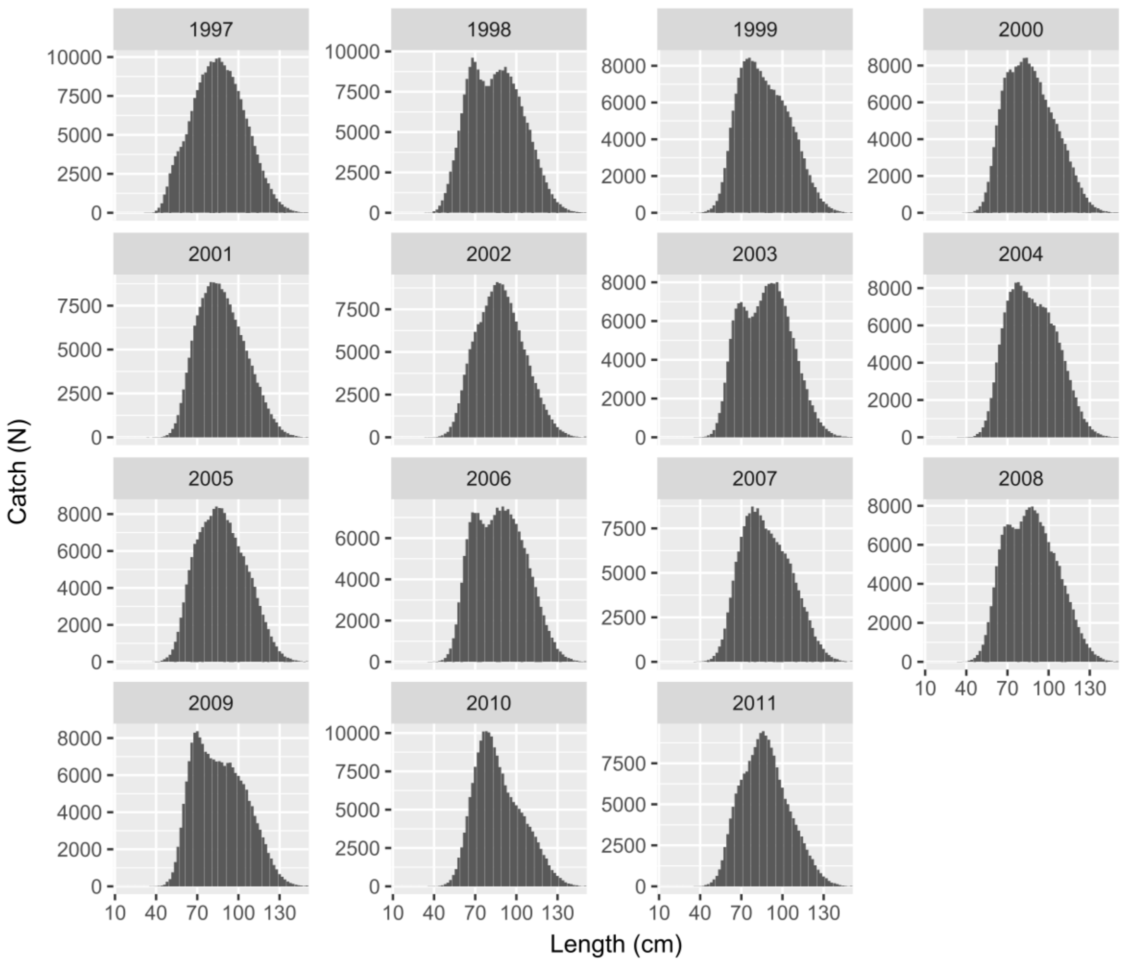
Appendix 3.3. ICCAT geographical definitions (Version: 2016.02) for small scombrids. Taken from: http://iccat.es/Data/ICCAT_maps.pdf.



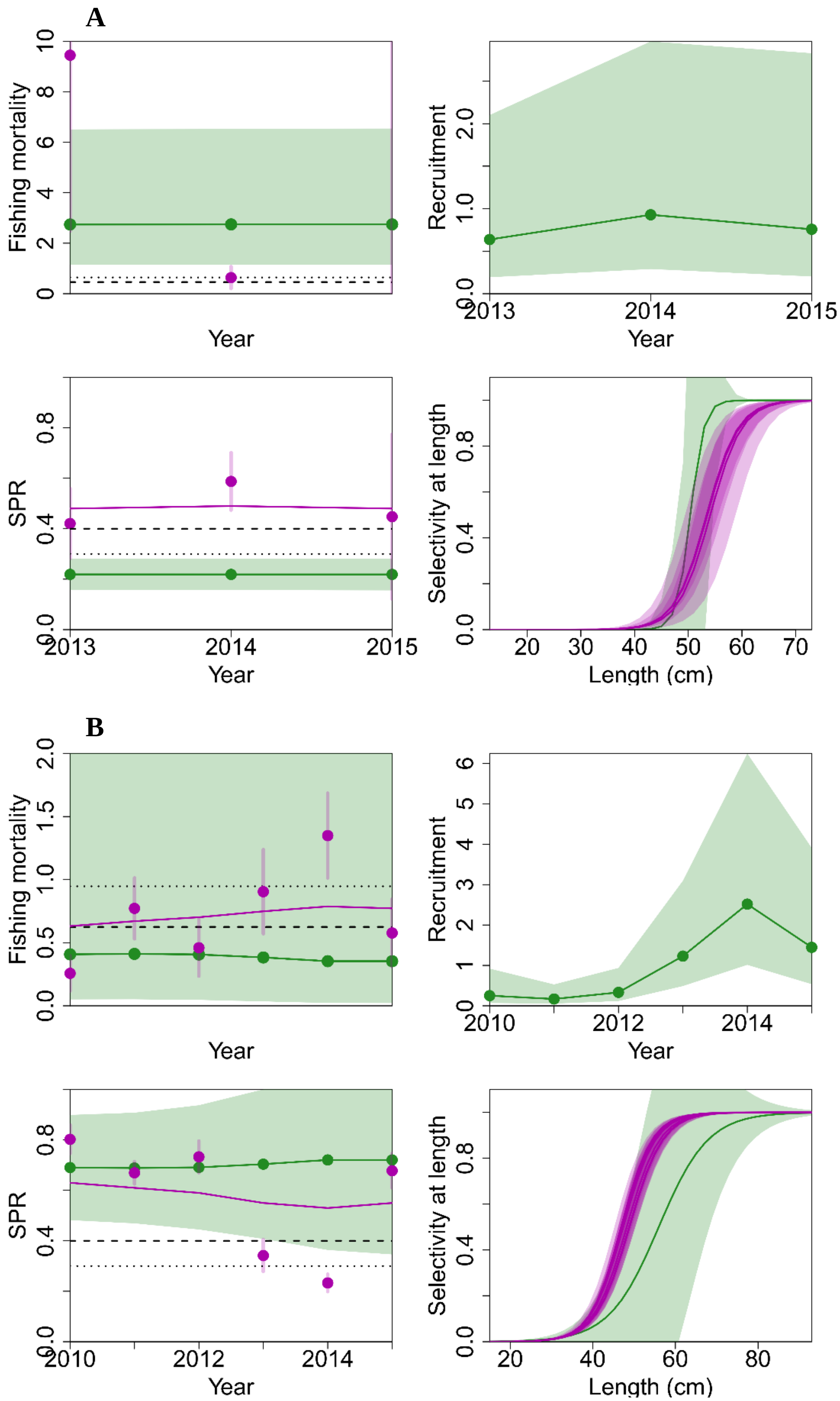
Appendix 3.4. Catch by fleet in the last 15 years (1997-2011). Fleet A is the one used in Scenario 3, Fleet B is the one used in Scenario 4, and Fleet C is the one used in Scenario 5.



Appendix 3.5. Length samples distribution used in Scenario 2.

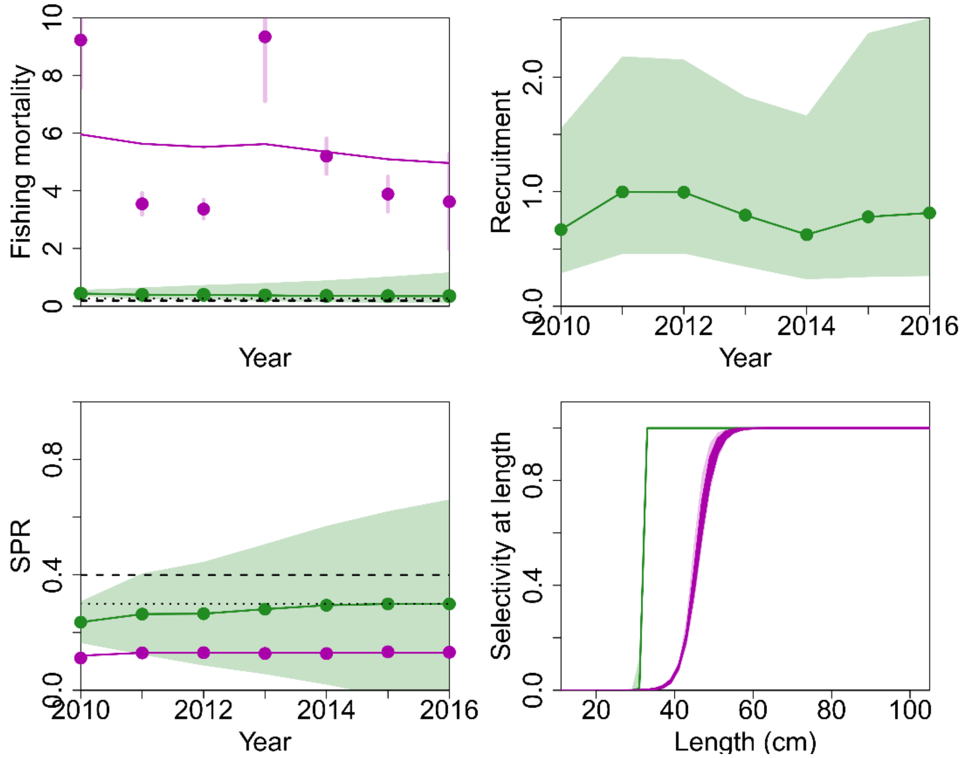


Appendix 3.6. BON in the Mediterranean (A) and in the SE (B) Atlantic. In green estimates from LIME and in purple estimates from LBSPR.

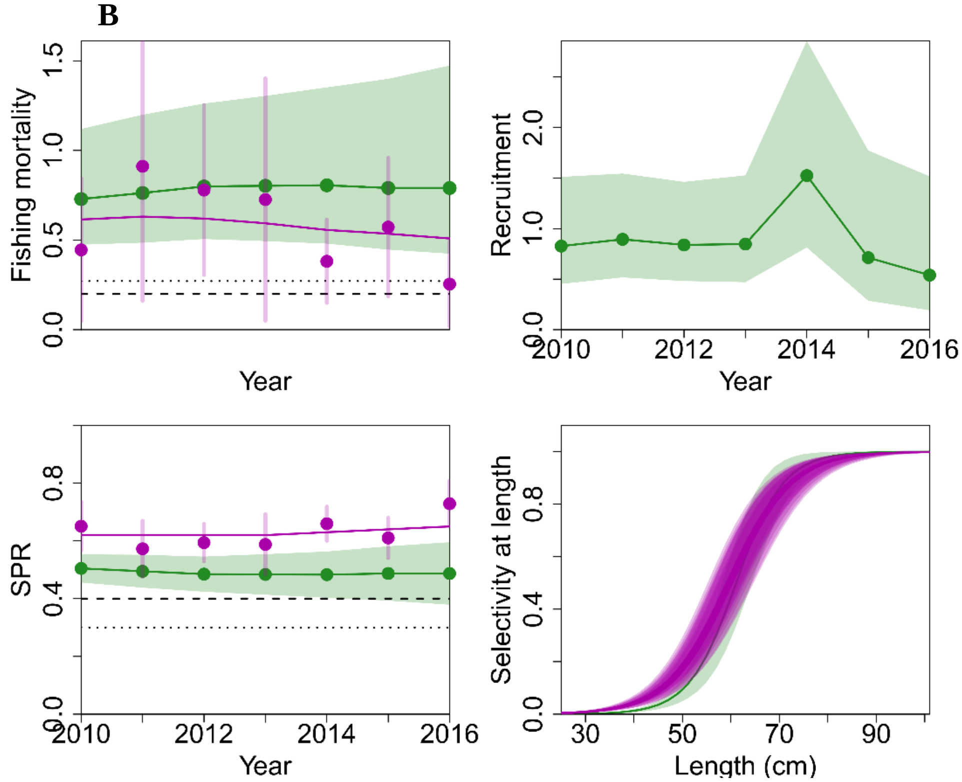


Appendix 3.7. LTA in the in the SE (A) and in the NW (B), Mediterranean (C) and NE (D) Atlantic. In green estimates from LIME and in purple estimates from LBSPR.

A

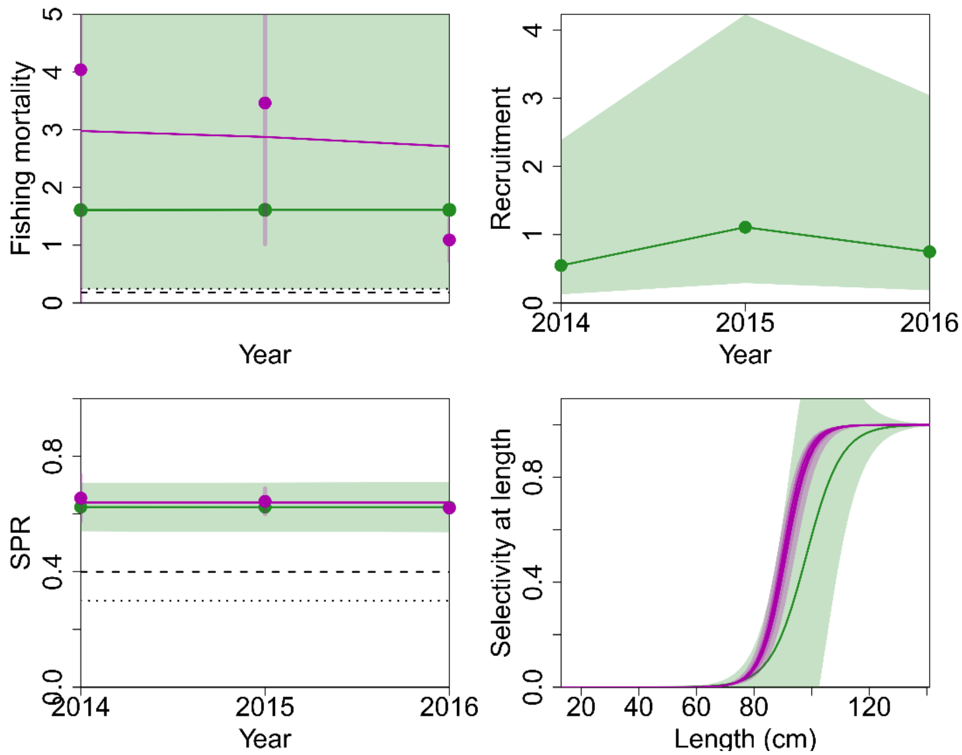


B

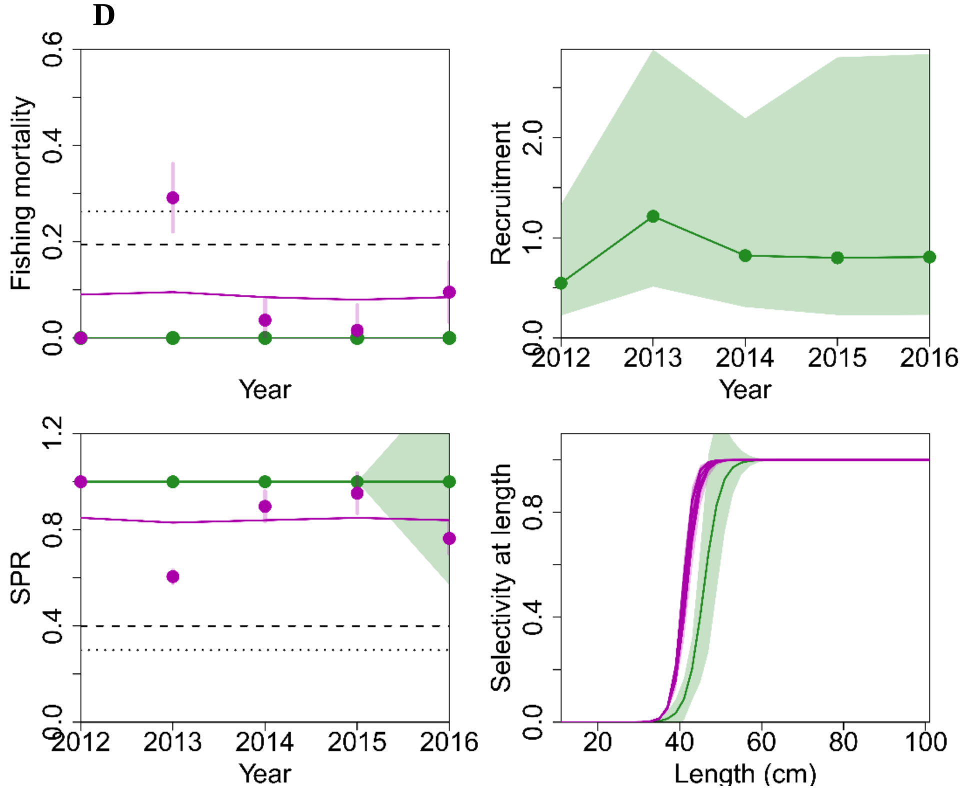


Cont…

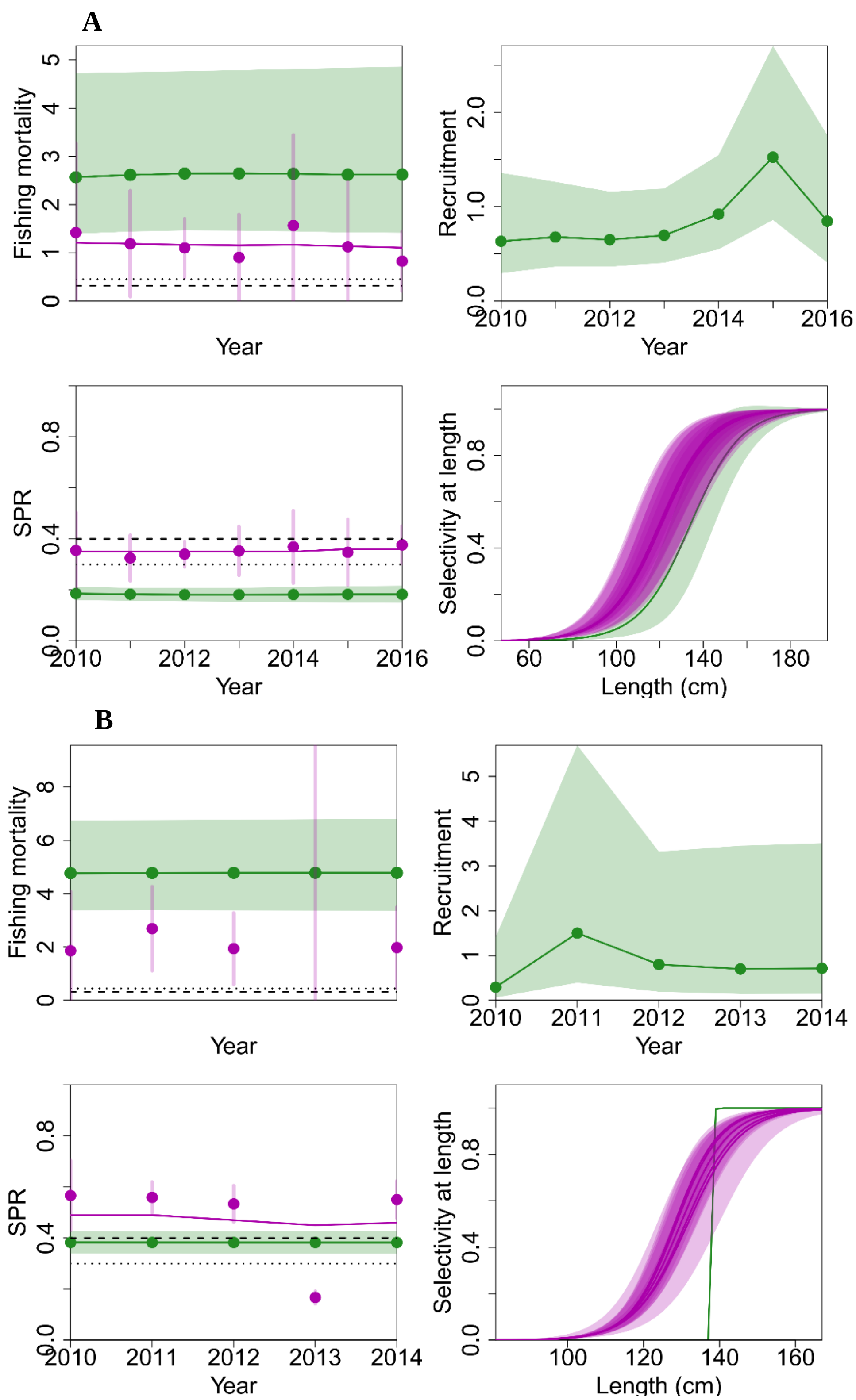
C


Fishing mortality
Year
Recruitment
Year
SPR
Year
Selectivity at length
Length (cm)

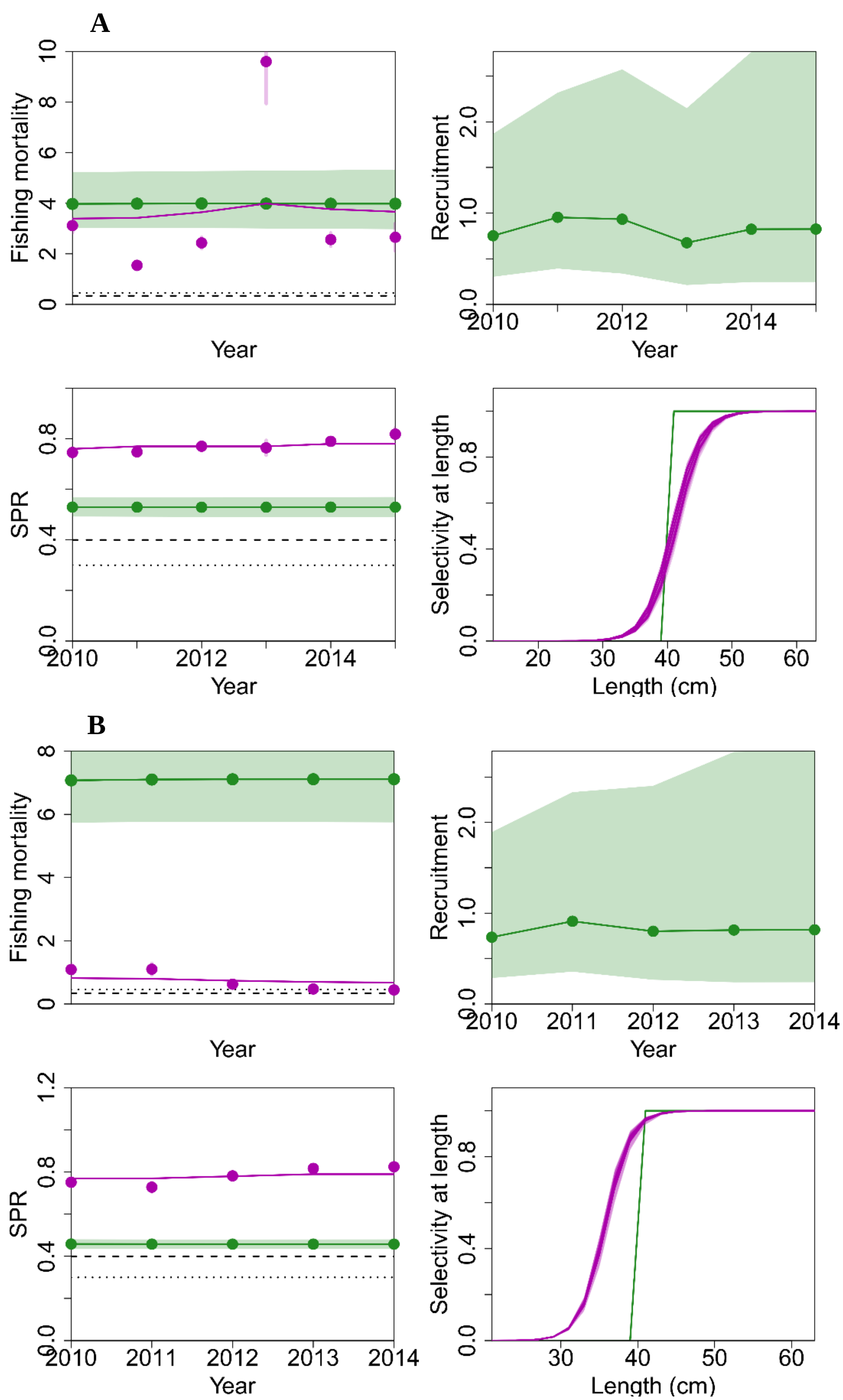
D


Fishing mortality
Year
Recruitment
Year
SPR
Year
Selectivity at length
Length (cm)

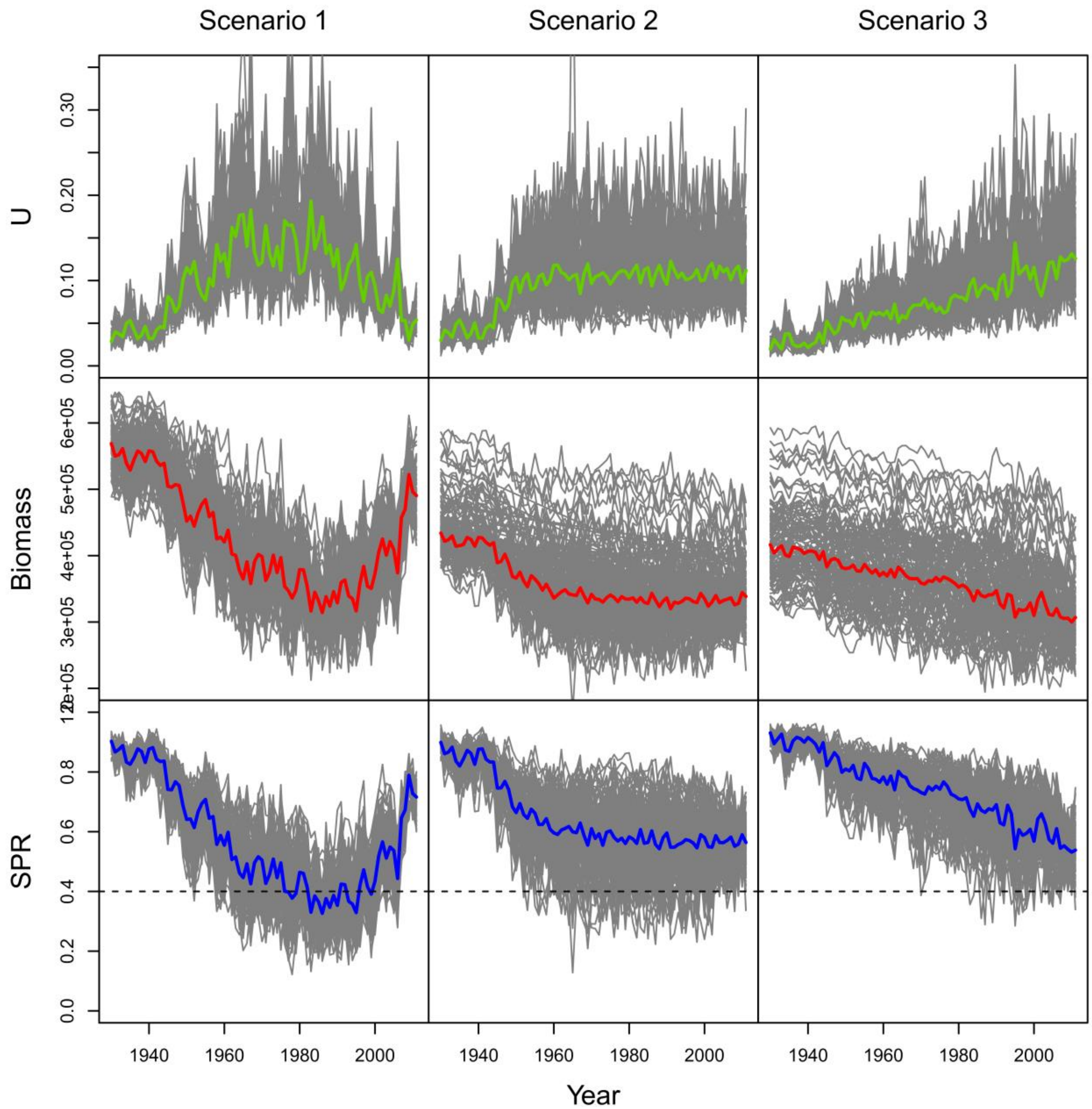
Appendix 3.8. WAH in the in the NW (A) and in the NE (B) Atlantic. In green estimates from LIME and in purple estimates from LBSPR.



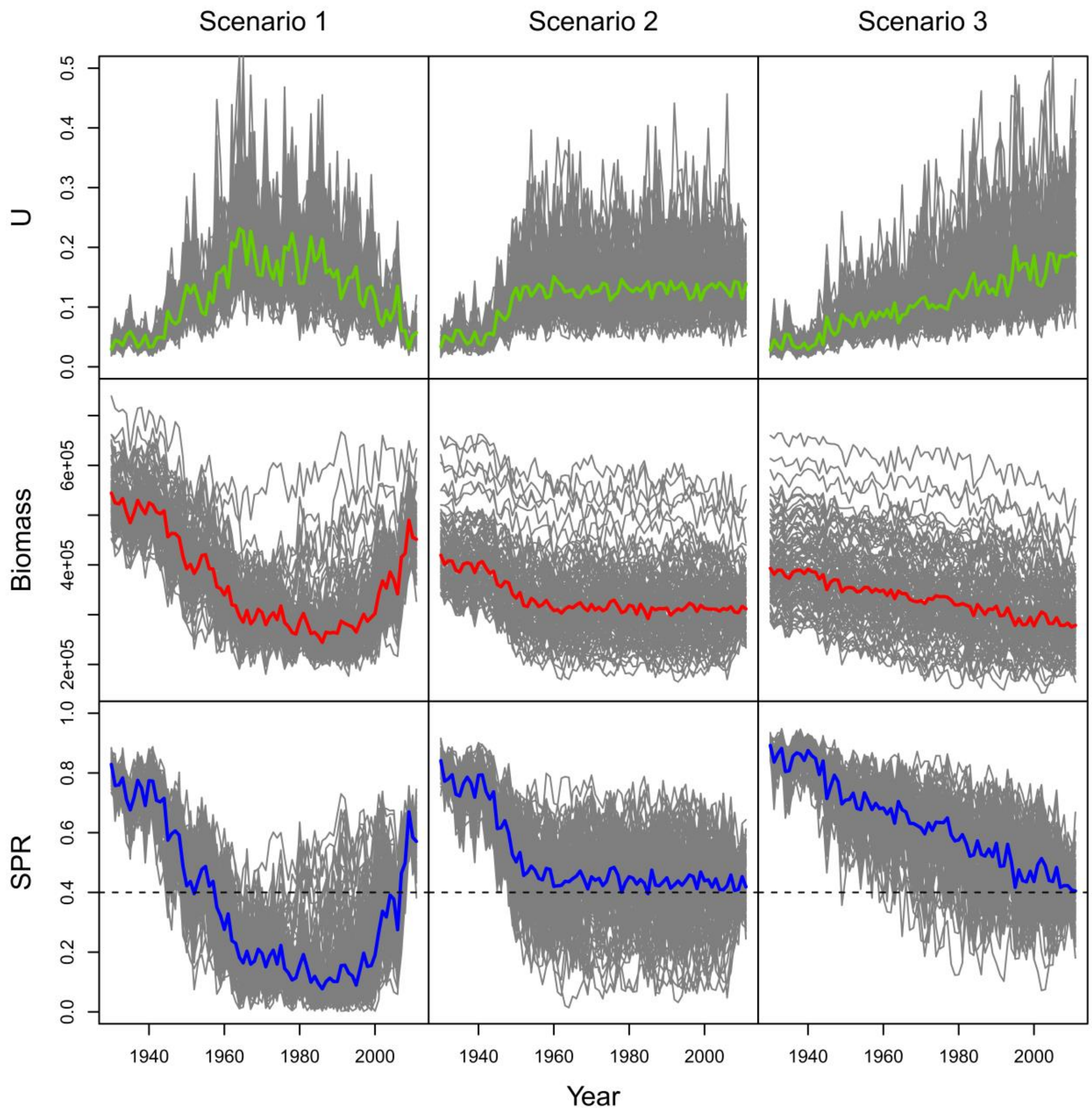
Appendix 3.9. FRI in the in the SE (A) and in the NE (B) Atlantic. In green estimates from LIME and in purple estimates from LBSPR.



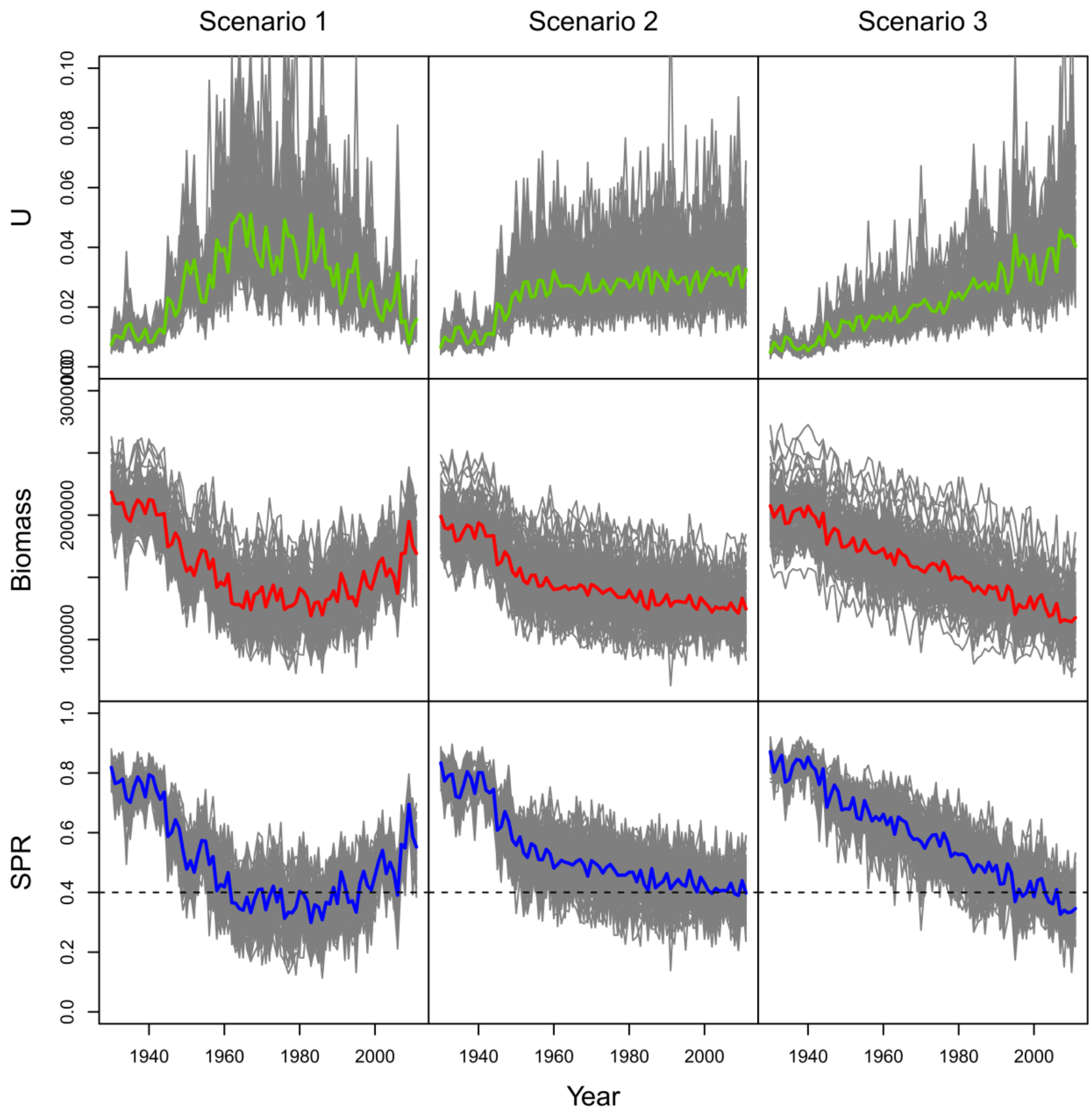
APPENDIX 4



Appendix 4.1. Time series of harvest rate U (fishing mortality), biomass B and spawning potential ratio (SPR) for each simulated Pacific Chub Mackerel population for the three harvest rate Scenarios tested. The color lines represent the median value for all runs.



Appendix 4.2. Time series of harvest rate U (fishing mortality), biomass B and spawning potential ratio (SPR) for each simulated North Atlantic Albacore population for the three harvest rate Scenarios tested. The color lines represent the median value for all runs.



Appendix 4.3. Time series of harvest rate U (fishing mortality), biomass B and spawning potential ratio (SPR) for each simulated Canary rockfish population for the three harvest rate Scenarios tested. The color lines represent the median value for all runs.

Appendix 4.4. Data-limited assessments based in data requirements: life history-based, catch-based and length-based. We summarized data inputs, outputs and, when available, links to webpages with packages or software available to apply each method.

Category based in data requirements	Assessment method	Fishery data			Life history data, priors																			Output	Package and/or Code	Assumptions
		Catch	Length	Abundance Index	Lmax	Amax	S50; S95	K or B0	r	Lc	Lopt	k	Linf	to	Lm50	A50	M	h	M/K	Fmsy/M	Bt/B0	Fecundity and/or	Length-weight relation			
Life history only	YPR (Beverton and Holt, 1957)						X					X	X				X					X	X	F0.1, Fmax, YPR	ypr {fishmethods} YPR {DLMtool}	Stock in equilibruim. Growth curve follow a von Bertalanffy function. Kife-edge selectivity.
Life history only	Utilizing B-H invariants (Beddington and Kirkwood 2005)									X		X	X					X						Fmax, MSY	Equations and Figures in the paper	All fishes with lengths greater than Lc are equally vulnerable to capture.
Life history only	Life-history based (Le Quesne and Jennings 2012)				X		X																	F0.1, F40, Fmax	Relationship of F40, F0.1 and Fmax with Lmax on paper (Figure 1)	Constant recruitment, natural mortality, growth and maturity
Length-based	Mean length at equilibruim (Beverton and Holt 1975)		X							X		X	X											Z (total mortality)	bheq {fishmethods}	Asymptotic growth. M-at-age constant for all fish older than age at first capture
Length-based	LBSPR (Hordyk et al. 2014)		X				X						X		X				X					F/M, selectivity-at length, SPR	https://github.com/AdriannHordyk/LBSPR/tree/master/R	Equilibruim, not recruitment variations
Length-based	B-H invariants and catches as a function of size (Kokkalis et al. 2015)	optional	X									X	X					X	X					F, F/Fmsy	https://github.com/alko989/s6model	B-H assumptions
Length-based	LIME (Rudd and Thorson, in press)	optional	X	optional								X	X	X	X		X						X	F, selectivity-at-length, SPR and rec. devs	https://github.com/merrillrudd/LIME	
Length-based	Indicator based: Length proportions in catch (Froese 2004)		X		X						X				X									Indirect notion of stock status or proxy fishing mortality: Pmat, Popt, Pmega		Catch-at-length data is representative of the entire catch of the fishery. No assumptions about recruitment.
Length-based	Indicator based: FLEP (O'Farrell and Botsford 2005)		X									X	X		X		X						X	Time series of fractional lifetime egg production: FLEP (~SPR or stock status)		Asymptotic selectivity and constant recruitment. Equilibrium
Length-based	Indicator based: LBRP (Cope and Punt 2009)		X									X	X	X	X		X							Decision tree for management based on Pobj = Pmat + Popt + Pmega, and determination of SSB status (below or above RP)	https://github.com/shcaba/LBRP	Catch-at-length data is representative of the entire catch of the fishery
Catch-based	Stock reduction analysis (SRA) (Kimura et al. 1984)	X						X	X												X			Annual fishing mortality rates F1 through Fn		
Catch-based	Stochastic SRA (Walters et al. 2006)	X										X	X		X		X	X						U/Umsy, B/B0		Constant M. Steepness and B-H relationship
Catch-based	DB-SRA (Dick and MacCall 2011)	X														X	X			X	X			K or B0, Bmsy, Fmsy, MSY, and CFmsy	dbsra {fishmethods}	
Catch-based	Indicator based: ORCS (Restrepo et al. 1998)	X					X														X			Assign stock to exploitation category, OFL		Equilibruim or stable abundance
Catch-based	Indicator based: C/Cmax ratio (Froese and Kesner-Reyes 2002)	X																						Defines a fishery as: underdeveloped, developing, fully exploited, overexploited, collapsed		
Catch-based	Indicator based: DCAC (MacCall 2009)	X															X			X	X			Current Catch at Fmsy	http://nft.nefsc.noaa.gov/DCAC.html	It is very dependent of the inputs, Depletion and Fmsy/M
Catch-based	Indicator based: smoothed C/Cmax ratio (Anderson et al. 2012)	X																						Defines a fishery as: underdeveloped, developing, fully exploited, overexploited, collapsed		
Catch-based	Indicator based: Stock status plots (Kleisner and Pauly 2011)	X																						Stock status plot		
Catch-based	Feasible stock trajectories (Bentley and Langley 2012)	X										X	X		X		X	X			X		X	Biomass trajectories		
Catch-based	SSS: "Traditional" catch-at-age (Cope 2013)	X	optional	optional		X						X	X		X		X	X	X	X	X		X	depletion and OFL	https://github.com/shcaba/SSS	
Catch-based	CMSY: Catch and resiliance Monte-Carlo filter (Froese et al. 2016)	X		optional					X																https://github.com/cfree14/datalimited2	
Catch-based	CMSY (Martel and Froese 2013)	X		optional					X			X									X			MSY, Bmsy, Fmsy, OFL, Umsy and Biomass (Modified by Rosenberg et al. 2014)	https://github.com/smartell/CatchMSY; catchmsy {fishmethods}	
Catch-based	COM-SIR (Vasconcellos and Cochrane 2005)	X						X	X															Biomass, B/Bmsy exploitation rate	https://rdrr.io/github/datalimited/datalimited/	Constant catchability. Unregulated fisheries
Catch-based	Modified panel regression (Costello et al. 2012)	X							X			X												B/Bmsy	https://rdrr.io/github/datalimited/datalimited/	
Catch-based	SS-COM (Thorson et al. 2013)	X						X	X												X			Biomass, effort, MSY,B/Bmsy	https://github.com/datalimited/global-status-estimates/blob/master/R	the population was at K at the start of the assessment period. Catch=total catch.
Catch and Ages	CC-SRA: Catch curve stock-reduction analysis (Thorson and Cope 2015)	X	Ages							X		X	X	X		X	X	X					X	F; Selectivity and recruitment parameters. Annual fishing mortality rates F1 through Fn	https://github.com/James-Thorson/CCSRA	Constant M and asymptotic selectivity
Age-based	Catch curves (Chapman and Robson, 1960)		Ages									X	X	X			X					X		F		Catch-at-length data is representative of the entire catch of the fishery
Index of abundance	Life-history and abundance indices based (Brooks et al. 2010)			X												X	X					X		SPRmer, ~FMSY and SMER/S0 (Depletion)		Constant recruitment, M, growth, maturity. All age classes after recruitment are fully selected

VITA

Maite Pons was born and raised in Montevideo, Uruguay. She obtained her B.Sc. in Biology – Ecology at Universidad de la República Oriental del Uruguay in 2006. Before finishing her B.Sc. studies, she started working as a consultant in different research projects at DINARA (Dirección Nacional de Recursos Acuáticos), where she had the opportunity to participate in multiple tuna stock assessment meetings and workshops as part of the Uruguayan delegation. She pursued her Master's degree also in Uruguay, co-advised by researchers from the Rosenstiel School of Marine and Atmospheric Sciences, University of Miami and the Instituto Oceanográfico, Universidad de Oriente, Cumaná, Venezuela. She then moved to Seattle to pursue her doctoral studies at the University of Washington's School of Aquatic and Fishery Sciences (SAFS) under the supervision of the Professor Ray Hilborn. In fall of 2018, Maite will start a postdoctoral fellowship in SAFS working in data-limited assessments for Latin American fisheries.