Supply of Research Services to establish MSY proxies for data-limited stocks (2017-18) to the Marine Institute, Rinville, Oranmore, Co. Galway. (Ref: ITT17-015)

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SUMMARY

This report summarises the main activities and outcomes of MyDas (MSY proxies for DAta-limited Stocks) with respect to the proposed tasks: i) Stock prioritisation, ii) Data Collation, iii) Framework Development; iv) Performance Appraisal, v) Reference Point Comparison, vi) Liaison and vii) Linkage with other Projects.

The main outcomes were i) R packages with documentation, ii) vignettes with reproducible examples, iii) manuscripts and peer review papers, and iv) evaluations of Management procedures for data poor stocks.

Initially a number of stocks were proposed as potential case studies and then fisheries dependent and independent data and life history characteristics were collated. After discussion with the Marine Institute (MI) seven case study stocks, i.e. sprat, brill, turbot, pollack, ray, razor clams and lobster, were selected, based on ecological and economic importance.

Data-poor stock assessment models in use worldwide were reviewed and simulation tested. The best performing methods were identified and then implemented in a Management Strategy Evaluation framework based on R. Two R packages were developed: **FLife** for simulating stocks based on life history theory and **mydas** for running and testing data poor harvest control rules. The packages include a number of live vignettes with examples (links provided herein). The framework was tested at an MI workshop and results presented at the ICES Workshop On The Development Of Quantitative Assessment Methodologies Based On Life-History Traits, Exploitation Characteristics, And Other Relevant Parameters For Data-Limited Stocks (WKLIFE).

Contents

Still To Do

Hans can add comments using \hans{...}

- Task 7 (section 8) needs work - expand briefly on 2.7
- Additional pieces on a delay-differential framework are less developed but conducted under mydas and could perhaps be included in an additional work section

1. Introduction

The goal of MyDas was to develop and test a range of assessment methods to establish Maximum Sustainable Yield (MSY) or proxy MSY reference points, across the spectrum of data-limited stocks.

Case studies were identified based on their economic and ecological importance and then appropriate datasets on life histories, commercial catches and surveys collated. Candidate data poor assessment methods were identified and their performance evaluated using simulation. A Management Strategy Evaluation (MSE) framework for data poor stocks was developed in R, using FLR, a collection of tools for quantitative fisheries science, developed in the R language [Kell et al., 2007]. This required extending existing FLR packages; for example FLife was extended to include methods to build simulation models based on life history theory. A new package mydas was developed to allow the assessment methods to be run with FLR and to provide tools for simulation of data advice frameworks.

As well as liason with the Marine Institute and connected projects, MyDas supported participation at the ICES Workshop On The Development Of Quantitative Assessment Methodologies Based On Life-History Traits, Exploitation Characteristics, And Other Relevant Parameters For Data-Limited Stocks (WKLIFE).

Outputs from MyDas included

- R packages with assessment models for data-limited stocks implemented in an MSE framework.
- R Vignettes describing the methods and findings.
- Publication in peer-reviewed journals on data poor approaches methods.

Each of these outputs is detailed in the following sections and mapped against the project tasks, which are described next.

2. Tasks

There were seven tasks i.e. i) Stock prioritisation, ii) Data Collation, iii) Framework Development; iv) Performance Appraisal, v) Reference Point Comparison, vi) Liaison with Marine Institute, and vii) Linkage with other Projects. Here we summarise the main activities and outcomes, and provide links to appropriate reports and cloud based resources.

2.1 Stock Prioritisation

- **Objective** A number of potential stocks were identified at the start of the project from which the final choice of case studies were selected based on economic value; importance of the species to the ecosystem (i.e. key-stone species); sensitivity to the impacts of fishing; and availability of data.
- **Outcome** The final case studies chosen were sprat, brill, turbot, thornback ray, pollack, lobster, and razor clams, and reflect a range of valuable stocks, ecological roles and life histories.

2.2 Data collation

- **Objective** Data collation ran in parallel with other tasks, and relied on existing data sets which were either available from the Marine Institute, other European labs/agencies or publicly available.
  - The main datasets were fishery independent surveys, commercial catches, stock assessment inputs and outputs and life history parameters.
- **Outcome** The data were collated into a PostgreSQL database database and summarised, using R code.
  - At the end of the project the data were archived on google drive.

2.3 Assessment Methods

- **Objective** A number of data limited methods already exist, in order to allow them to be simulation tested and their performance compared they were implemented within a common R framework.
- **Outcome** Data limited methods in use worldwide were summarised in a google spreadsheet. Following a review five catch-only and three length-only assessment methods were then compared, and the best performing methods identified.
  - Two peer review papers were produced that evaluated length based methods [Pons et al., 2019] and compared length and catch based methods [Pons et al., submitted].
  - The best performing methods were Length Based Spawning Potential Ratio [LBSPR Hordyk et al., 2014] and Depletion Based Stock Reduction Analysis [DBSRA Dick and MacCall, 2011].
  - These were then implemented as in the mydas package, see the vignettes lbspr andbdsra written to ensure reproducibility.

2.4 Performance Appraisal

- **Objective** Method performance appraisal was based on the development of a set of diagnostics that can be applied across a range of models to assess the stability of the model, sensitivity to assumptions and bias.
- **Outcome** A simulation framework based on R. This was based on FLR, a collection of tools for quantitative fisheries science developed in the R language, that facilitates the construction of simulation models of fisheries systems. Development focussed on two main R packages, FLife which uses life history theory to build simulation models and mydas which provides an interface to the data poor methods for simulation testing. Vignettes document the approach and provide worked examples.
  - Operating Models conditioned on life history theory were developed for each of the case studies.
  - An Observation Error Model was developed to simulate pseudo data under a range of assumptions to allow the bias and sensitivity of stock estimates and reference points to be estimated.
  - Vignettes include examples of conducting MSE and the use of parallel computing, estimation of proxy reference points, OM conditioning, calculation of performance metrics, and simulation testing length and running catch

2.5 Simulation

- **Objective** Once reference points are identified, their performance was evaluated through simple Management Strategy Evaluations.
- **Outcome**
  - Simulation testing was conducted for the ICES control rule using the FLife package for data limited stocks [Fischer et al., submitted].
  - A comparison of length based indicators was conducted and a peer review paper is currently in preparation.
  - An emprical control rule was simulation tested using MSE, and a peer review paper is in preparation.

2.6 Liason

- **Objective** Meetings on a regular basis with the MI.
- **Outcome** Meetings at the Marine Institute ensured that the over-arching goals of the project were achieved.
  - Regular presentations were made at the MI and a Workshop was held where the methods were tested.
  - In addition to ensure good communication between the consortium and the Marine Institute and that the project keeps focus and delivers as well as the scheduled meetings code, data and results were made available on the cloud and in a github repository during the life of the project. This has now been turned into the **mydas** package wiki

2.7 Linkage

- **Objective** Linkage with other projects
- **Outcome**
  - The MyDas framework was developed though case studies in collaboration with the MI.
  - Direct links to Cullen fellowship project *Monkfish management strategy evaluation* (CF/16/03) were established. In particular, Ph.D. candidate Luke Batts is testing stage-based stock assessment methods using monkfish stocks simulated with FLife. This project has also made extensive use of the MSE frameworks established within MyDas and FLR to test key uncertainties in advice for monkfish stocks.
  - Attendance at Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE) and the Working Group for the Celtic Seas Ecoregion (WGCSE), see presentations.
    - WKLIFE VIII
    - WKLIFE IX
  - Attendance at the first Irish Environmetrics Forum where methods for policy-relevant advice were presented and discussed.

3. Case Studies

A number of example stocks were identified in the original call, i.e.

- Sprat in the Celtic Sea and West of Scotland Sprat (Sub-area VI & Divisions VIIa-c and f-k)
- Grey gurnard VI & VII (excl. VIId)
- Ling IIIa, IVa, VI, VII, VIII, IX, XII, and XIV
- Rays, primarily in areas VIIa,f,g
- John dory in ICES Sub-area VII and Divisions VIIIa,b and d (Northeast Atlantic)
- In collaboration with Newport STO:
  - Saithe VII, VIII, IX, X
  - Pollock VII
- Turbot VIIe,f,j,h and sub area VIII and IXa
- Brill VII (or suitably defined)

Available data sources and relevant publications were reviewed (Table 1). Following which the final choice of case studies was then made in liaison with the Marine Institute based on economic value of the stock; importance of the species to the ecosystem (key-stone species); sensitivity to the impacts of fishing and available data.

Species	TAC	Commercial Data	Data	Comments
Sprat	No	Targeted species for small fleet	Poor; mainly landings weights	Key-stone prey fish
Gurnards	No	Nearly 100% discarded & Reasonable discard and survey data. No age data	Key-stone prey – widely distributed and abundant	
Saithe, Pollock Ling	Yes	Mixed fishery	Some port sampling, observer and survey data. Very limited age data	Key-stone predator
Rays, Skates	Yes	Targeted and mixed fishery	Some port sampling, observer and survey data. No age data	Sensitive species – slow reproduction
John Dory	No	Mixed fishery but can be targeted to an extent	Some port sampling, observer and survey data. No age data	Sensitive species – valuable non-TAC species (not protected by fisheries management)
Turbot, Brill	No	Mixed fishery but can be targeted to an extent	Some port sampling, observer and survey data. Very limited age data	Sensitive species – valuable non-TAC species (not protected by fisheries management)

Table 1: Summary of potential study stocks.

The final case studies were sprat, pollack, brill, turbot, thornback ray, lobster and razor clams as these represent a range of life histories, and have a variety of roles in maintaining the structure of pelagic and demersal communities. The data on vertebrate life histories were accessed directly from fishnets.

Figure 1: Life history parameters for case study vertebrate stocks.

4. Data Collation

The project relied on existing datasets rather than collecting new data and collating these data ran in parallel with other tasks. As well as Marine Institute data datasets were also obtained from ICES[1] and the JRC[2]. While life history parameters were obtained from Fishbase[3] and fishnets[4], and stock assessment inputs and outputs from stockassessment.org[5].

A database was designed see the database summary in the Appendix. These data were summarised to help identify the case studies. To select the case studies a key dataset were the life history parameters. Many studies have shown that relationships between life history traits exists for processes such as growth, maturity and natural mortality. For data poor stocks, where information on key processes is lacking, life history theory can therefore be used allowing simulation models to be developed. See the vignette on conditioning Operating Models on life history parameters.

[1] https://www.ices.dk/marine-data/dataset-collections/Pages/default.aspx
[2] https://stecf.jrc.ec.europa.eu/dd/medbs/ram
[3] http://www.fishbase.org/search.php
[4] https://github.com/fishnets/fishnets
[5] https://www.stockassessment.org

The various preliminary analyses based on the datasets compiled during MyDas in addition to life history theory are archived on https://drive.google.com/open?id=1rR917GQhDm_b9bzCCxorwBAWvaTVDbixgoogle drive.

5. Assessment Methods

A number of data-limited methods already exist, in order to compare their performance they need to be run in a common framework. Therefore methods were interfaced to R, using the Fishery Library in R (**FLR**) [Kell et al., 2007] a toolset that is composed of a variety of packages, covering the various steps in the fisheries advice and simulation workflow. Using **FLR** means that advantage can be taken of existing methods, and that dissemination and support is easier and will be maintained after the life of the project.

To identify the appropriate advice given the quality of data rules ICES classifies stock assessments into six categories on the basis of the available data, e.g. total landings, indices of abundance, length frequency and age data.

Category 1: stocks with quantitative assessments Full analytical assessments and forecasts as well as stocks with quantitative assessments based on production models.

Category 2: stocks with analytical assessments that are only treated qualitatively Quantitative assessments and forecasts which for a variety of reasons are considered indicative of trends in fishing mortality, recruitment, and biomass.

Category 3: stocks for which survey based assessments indicate trends Survey or other indices are available that provide reliable indications of trends in stock metrics, such as total mortality, recruitment, and biomass.

Category 4: stocks for which only reliable catch data are available Time series of catch can be used to approximate MSY.

Category 5: landings only Only landings data are available.

Category 6: negligible landings Landings are negligible in comparison to discards and stocks that are primarily caught as bycatch species in other targeted fisheries

For data limited stocks a number of methods already exist, for example the ICES Working Group on Category 3 and 4 stocks (WGMSYCAT34) has been working on rules for survey-based assessments which indicate trends in stock status (Category 3) or for which only catch data are available (Category 4).

Data limited methods in use worldwide were summarised in a google spreadsheet. Following which five catch and three length based methods, were then selected for simulation testing. The choice of methods was based on the availability of code, whether the method had been peer reviewed and the appropriateness of estimated quantities for use as proxy reference points. The methods were then simulation tested [Pons et al., submitted] in order to select the best catch and length-only methods.

Catch Only

Catch-only assessment methods evaluated were Catch-Maximum Sustainable Yield [Catch-MSY Martell and Froese, 2013], Depletion Based Stock Reduction Analysis [DBSRA Dick and MacCall, 2011], Simple Stock Synthesis [SSS Cope, 2013], an extension of Catch-MSY (CMSY), and State Space Catch Only Method [SSCOM Thorson and Cope, 2015]. Length based methods evaluated were Length Based Spawning Potential Ratio [LBSPR Hordyk et al., 2014, 2015], Length-Based Integrated Mixed Effects [LIME Rudd and Thorson, 2017], and Length-Based Bayesian [LBB Froese et al., 2018].

Catch-MSY is based on stock reduction analysis (SRA) that assume a Schaefer biomass dynamic model. Inputs are a time series of removals, priors for the population rate of increase at low population size (r), carrying capacity (K), and a probability distribution of stock depletion in the first, final and (optionally) middle years. CMSY, extends Catch-MSY by using a Monte-Carlo filter to fix systematic biases in the Catch-MSY.

DBSRA further modifies the SRA approach by using Monte Carlo draws from the parameter distributions for M, F_{MSY}/M, B_{MSY}/B_0, depletion, and age at maturity (A_{mat}) to separate total biomass into immature and mature biomass using a delay-difference production model.

SSS is based on Stock Synthesis [Methot Jr and Wetzel, 2013], and fixes all parameters in a Stock Synthesis model except for initial recruitment (lnR_0). An artificial index of abundance that represents the relative stock biomass is used for fitting where the first value of the index is 1, and the value in the final year represents depletion (i.e. the proportion of the population left in the final year). Values of steepness (h) and depletion are randomly drawn from a specified distribution using a Monte Carlo approach and lnR_0 is then estimated.

State Space Catch Only Model (SSCOM) 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]. Similar to the original Catch Only Model [Vasconcellos et al., 2005], a coupled biomass-effort dynamics model is assumed.

Length Only

LBSPR, estimates the proportion of the unfished reproductive potential per recruit (SPR) under a given level of fishing pressure. In an exploited population is calculated as a function of the ratio of fishing mortality to natural mortality (F/M), selectivity, and the two life-history ratios M/k and L_m/L_∞; where k is the von Bertalanffy growth coefficient, L_m is the size of maturity and L_∞ is asymptotic size. The inputs are length at maturity specified in terms of L_{50} and L_{95} (the size at which 50% and 95% of a population matures) and length frequency data. LBSPR is an equilibrium based method and assumes asymptotic selectivity, von Bertalanffy growth, length at-age is normally distributed, rates of natural mortality are constant across adult age classes, recruitment is constant over time, and growth rates remain constant across the cohorts within a stock.

LIME like LBSPR uses biological information and the length composition of the catch to estimate F and SPR. Unlike LBSPR, however, it does not assume equilibrium conditions and uses mixed effects to estimate changes in recruitment and fishing mortality separately over time.

LBB is a simple and fast method for estimating relative stock size that uses a Bayesian Monte Carlo Markov Chain (MCMC) approach. LBB uses pre-specified priors on parameters, and thus, technically does not require any inputs other than length frequency data. It does provides the user the option to specify priors for L_∞, length at first capture (L_c), and relative natural mortality (M/k). F/M is estimated over the age range represented in the length-frequency sample.

Evaluation

The methods were simulation tested for three life history types (short, medium and long-lived), three historical exploitation scenarios, and three depleted levels [Pons et al., submitted]. The results of the simulations are shown in Figure 5.. Of the five catch based methods SSCOM performs poorly in terms of precision and bias, while SSS is the least biased and DBSRA the most precise. The length based methods tend to perform less well than the catch based methods, while LIME is the least biased while LBSPR is the most precise.

Bias and precision are both important factors to consider when assessing fish stocks. Bias reflects how close an estimate is to a known value; precision reflects reproducibility of the estimate. For example, if an assessment is to be re-conducted every year to monitor the impact of a management measure, a precise but biased method would be able to detect a trend better than an unbiased but imprecise method. Like all scientific instruments, this trade-off requires calibration to correct for the bias, and such calibration can be explored using closed-loop simulations (i.e. MSE), where the choice of parameters and reference points in a Management Procedure are tuned (i.e. calibrated) to meet the desired management objectives as represented by the Operating Model. Thus, a biased method (e.g., DBSRA) may be preferable to one that is less biased, but more imprecise (e.g., LIME). Alternatively, imprecision can be addressed through the choice of the percentile (e.g., median being the 50% percentile value) for the derived model output used by management (e.g., catch or SPR); assuming that the true value is contained within the parameter distribution. For example, instead of taking the median value, one could instead use the derived model output associated with the 40th percentile to incorporate risk tolerance as reflected in the calculated imprecision. Such an approach [Ralston et al., 2011] is used in fisheries management systems to directly incorporate scientific uncertainty (both bias and imprecision), and can also be explored and tuned using MSE.

The best performing catch-only methods were SSS and DBSRA, SSS was the least biased method while DBSRA was the most precise. A problem with SSS is that it is based on SS3 and so is a complicated method that requires a lot of assumptions in the form of fixed parameters. DBSRA in contrast is based on a biomass based stock production function and so requires fewer assumptions, it also allows data poor and data rich assessments to be compared, i.e. if an index of abundance could be developed then an ICES Category 3 assessment could be converted into a Category 1 assessment. This allows the value of information to be evaluated. Therefore DBSRA was selected for further evaluation.

Both LBSPR and LIME use the same inputs, the main difference is that LIME is a non-equilibrium method, takes longer to run than LBSPR and often failed to converge, so although LIME estimates are less biased than LBSPR it is likely to perform poorly in closed loop simulations. LBB performed poorly in terms of both bias and precision. Therefore LBSPR was selected for the next stage of simulation evaluation.

6. Framework

The majority of fish stocks worldwide lack sufficient data on which to base quantitative assessments. In some cases Management Strategy Evaluation [MSE Geromont and Butterworth, 2014] has been used to develop harvest control rules (HCRs) based on empirical indicators that follow trends in survey estimates of abundance, catch rates or size composition.

A reason for the use of MSE is because it is recognised that the robustness of advice depends on the combination of data, estimation method, choice of reference points as well as the rules used to set management action, i.e. the Management Procedure (MP). When conducting MSE an Operating Model (OM) is used to represent the dynamics of system being managed, and control actions from an MP are fed back into the OM so that its influence on the stock and hence on future fisheries data is propagated through the stock and fishery dynamics.

Conducting MSE requires six steps; namely i) identification of management objectives; ii) selection of hypotheses for the OM; iii) conditioning the OM based on data and knowledge, and possible weighting and rejection of hypotheses; iv) identifying candidate management strategies; v) running the Management Procedure (MP) as a feedback control in order to simulate the long-term impact of management; and then vi) identifying the MPs that robustly meet management objectives.

The MSE framework was based on the Fishery Library in R [FLR Kell et al., 2007], which comprises a variety of packages that cover the various steps in the fisheries advice and simulation workflow. Using **FLR** means that advantage can be taken of existing methods, and that dissemination and support is easier and will be maintained after the life of the project. Under MyDas development focused on two main packages **FLife** and **mydas**. **FLife** is a package for modelling life history relationships and **mydas** provides a set of tools for simulation and conducting Management Strategy Evaluation (MSE) by providing wrappers for the various assessment methods, implementing Observation Error Models (OEMs) to simulate empirical indicators and other datasets, and to model harvest control rules (HCRs).

FLife was used to condition OMs based on life history relationships and ecological theory, MP were then implemented using **mydas**. The link between the OM and the MP is the OEM, which generates fishery-dependent or independent resource monitoring data. The OEM models the uncertainties due to sampling and limited data and so mimics the types of data currently required for each assessment method. In addition the types of a data that could be made available in the future,

Simulation tests were also performed without feedback where the OEM was used to generate datasets from the OM. This allows the performance of the candidate methods to be compared, since if there is little correlation between the estimates of reference points and status from a candidate method and the OM then there is little point in running that method in the MSE. Tests were performed for a category 1 assessment (a biomass dynamic assessment with catch and an index of abundance that estimates stock status and reference points), a category 3 assessment that used a length based indicator, and a category 4 assessment for which only catch data are available.

Performance measures

Management objectives under the Descriptor 3 of the Marine Stewardship Framework Directive and the Common Fisheries Policy of the European Union mandate that stocks should be exploited sustainably consistent with high long-term yields, have full reproductive capacity in order to maintain stock biomass and that the proportion of older and larger individuals should be maintained (or increased) as they are indicators of a healthy stock. These general objectives can be mapped to performance measures, so that alternative management strategies can be compared from both in and outside the ICES framework.

A range of summary statistics are required to illustrate trade-offs between multiple potentially conflicting objectives. Although there are many potential summary statistics so that decision makers can choose between tangible options on the basis of actual projections rather than abstract concepts. Performance statistics should, however, ideally be few, informative and based on principle metrics such as 'stock status, 'safety', 'stability' and 'yield'. It is also necessary to distinguish between technical summary statistics (i.e. those required to evaluate model fits and performance) and those required to evaluate management objectives. Examples of summary statistics include

Safety Probability of avoiding a limit such as B_{lim} where recruitment is impaired

Status Probability of achieving targets related to MSY, e.g. B_{MSY} and F_{MSY}

Yield Annual or cumulative yields

Variability Inter-annual variation in catches or stock status

7. Simulations

ICES is in the process of developing methods to identify MSY proxy reference points for data-limited stocks at the ICES Workshop On The Development Of Quantitative Assessment Methodologies Based On Life-History Traits, Exploitation Characteristics, And Other Relevant Parameters For Data-Limited Stocks (WKLIFE). **MyDas** contributed to this process by proposing and testing new assessment models and methods of establishing reference points and attended both WKLIFE VIII and IX. There are key differences with the ICES approach, however, since **MyDas** stocks are not currently assessed by ICES and **MyDas** focused on the available data for each stock first and then on methods, while the ICES approach focuses on the methods first and then applies a limited number of methods to a large number of stocks.

The importance of the work of **MyDas** was recognised at WKLIFEVIII where recommendations for future directions were made. Following this several examples based on the work of **MyDas** were made at WKLIFEIX. These included i) the use of life history theory to condition the OM used to evaluate the ICES advice rule proposed for category 3 and 4 stocks; ii) Receiver Operating Characteristic (ROC) curves to explore the setting of appropriate reference levels in the the catch rule; and iii) the use of trends in an index without a reference level. It was also recommended to use the methods of **MyDas** to evaluate the robustness of SPiCT based upon the development of Operating Models developed under MyDas.

For stocks with analytical assessments (i.e. category 1 and 2 stocks), the advice rules applied by ICES are consistent with the objective of achieving MSY. For stocks in categories 3 and 4 ICES uses MSY proxy reference points as part of a Precautionary Approach to provide advice on the status of the stock and exploitation. The F_{MSY} proxy corresponds to the exploitation rate that will provide maximum long-term yield, while the $MSY_{Btrigger}$ proxy corresponds to the stock size that triggers a cautious response; i.e. advises a reduced fishing mortality relative to F_{MSY} proxy in order to allow the stock to rebuild.

Advice Rule

For stocks with MSY proxy reference points not derived from an assessment model, ICES uses a generic rule of the form

$$C_{y+1} = C_{current} rfb \tag{1}$$

where $C_{current}$ is the catch either in the most recent year available (typically $y-1$) or the average over a number of recent years (e.g. $y-n, ..., y-1$), r should account for the trend in stock biomass ($r > 0$; with $r = 1$ if there is no trend), f is a proxy for the ratio F_{MSY}/(current exploitation) and $b =$ min(1,proxy for the ratio (current stock size)/($MSY_{Btrigger}$)). The later is in effect a hockey stick type HCR.

f is derived from length based indicators and a number of potential length based reference point and indicators[6] have been identified by ICES for stocks in categories 3 and 4 (see Table 2)

The **mydas** package includes methods to simulate length frequency data and estimate indicators; Figure 3 shows an OM based on pollack that was used to simulate indicators (Figure 4).

To ensure that advice based on such indicators is precautionary, Management Strategy Evaluation was used to evaluate an empirical rule of the form $C_{y+1} = C_{current} rfb$ that bases catch advice on recent catches, information from a biomass survey index (r), length based indicators (f) and proxy MSY reference point (b) [Fischer et al., submitted]. The OM was conditioned on life histories using the method developed by **MyDas** .The performance of the rule varied substantially between stocks, and the risk

[6] http://ices.dk/sites/pub/PublicationReports/GuidelinesandPolicies/16.04.03.02_Category_3-4_Reference_Points.pdf

Indicator	Calculation	Reference point	Indicator ratio	Expected value	Property
$L_{max5\%}$	Mean length of largest 5%	L_{inf}	$L_{max5\%}$ / L_{inf}	> 0.8	Conservation (large individuals)
$L_{95\%}$	95th percentile		$L_{95\%}$ / L_{inf}		
P_{mega}	Proportion of individuals above L_{opt} + 10%. (L_{opt} is estimated from L_{inf}).	0.3 – 0.4	Pmega	> 0.3	
$L_{25\%}$	25th percentile of length distribution	L_{mat}	$L_{25\%}$ / L_{mat}	> 1	Conservation (immatures)
L_c	Length at 50% of modal abundance*	L_{mat}	L_c/L_{mat}	> 1	
L_{mean}	Mean length of individuals > L_c	L_{opt} = $^2/_3$ L_{inf}	L_{mean}/L_{opt}	≈ 1	Optimal yield
L_{max_y}	Length class with maximum biomass in catch	Lopt = $^2/_3$ L_{inf}	L_{maxy} / L_{opt}	≈ 1	
L_{mean}	Mean length of individuals > L_c	$L_{F=M}$ = (0.75L_c + 0.25L_{inf})	L_{mean} / $L_{F=M}$	≥ 1	MSY

*Note this definition is different from the L_c used for the Mean-length Z estimator.

Table 2: Length based indicators.

of breaching limit reference points was inversely correlated to the von Bertalanffy growth parameter k. Stocks with $k > 0.32$ had a high probability of stock collapse. It was shown that a single generic catch rule cannot be applied across all life-histories, and management should instead be linked to life-history traits, and in particular, the nature of the time series. This supported the premise of **MyDas** that to develop robust management it is important to consider the nature of the stock dynamics, knowledge and data. Counter-intuitively the catch rule performed poorly for the more productive stocks (those with higher k) compared to the less productive stocks (with lower k). The performance of the catch rule, however, is an emergent property of the interaction between the operating model and the catch rule. Therefore this is an important result, which would not have been apparent without the work of our manuscript.

The advised catch was mainly influenced by one component of the rule (the trend in the relative index of abundance) and biomass trends for stocks with higher k) are inherently more variable, which in turn leads to higher fluctuations in catch. Therefore when managed by the ICES catch rule, the stocks with higher k) were more likely to collapse during simulation. This behaviour can be attributed to an initial rapid recovery, which resulted in an increase in catch. Once the stocks started to decline again, however, catch was not reduced quickly enough to avoid stock collapse. This undesirable feature is caused by the design of the catch rule, which bases the newly advised catch on the previous catch and observed data with a time-lag. Since the less productive stocks (those with low k) were also less variable, the catch rule was sufficiently reactive to avoid stock collapse.

Therefore two papers are currently being drafted. The first used Receiver Operating Characteristic (ROC) curves used to explore the setting of appropriate reference levels in the f component of the catch rule for the **MyDas** case studies. In particular to explore how these depend on life-history traits and the nature of the time-series. The second evaluated the use of trends in an index without a reference level for pollack. To do this, a Management Strategy Evaluation (MSE) was conducted to evaluate an empirical harvest control rule (HCR) based on a trend in an index of abundance. The Operating Model (OM) was conditioning on pollack life-history characteristics and the HCR was based on that used by the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). The HCR has several parameters that require tuning [Hillary et al., 2015], i.e. the parameters are found by choosing values that best meet the objectives of asset and stakeholders; i.e. optimises the outcomes modelled as a reward function.
Preliminary work within **MyDas** on the spectral decomposition of recruitment time series (appendix) provides a promising avenue to increase the realism of the simulated recruitment time series over simply increasing the process variability.

8. Liason and Linkage

[Expand briefly on section 2.7]

The service provider meet on a regular basis with Marine Institute staff involved in the project. The proposal is ambitious but achievable. However there needs to be good communication between the consortium and the Marine Institute to ensure the project keeps focused and delivers. Therefore we will arrange monthly face-to-face meetings, make all code, data and results available on the cloud and in a suitable repository (e.g. github) and provide a web based interface for model results.

Wider project 6-monthly progress reports and meetings at the Marine Institute will ensure the over-arching goals of the project are achieved.

Task 7 (section 8) needs work - expand briefly on 2.7 Attendance at wklifeix: 4 Length-based approaches and ICES WKLIFE & Working Group for the Celtic Seas Ecoregion (WGCSE)

Linkage with other projects](https://github.com/laurieKell/mydas/wiki/7-Linkage-with-other-projects) *The service provider is required to link research output to the following projects:*

The MyDas framework was developed though case studies in collaboration with a range of partners, as well as the MI and ICES, these included the tuna Regional Management Fisheries Organisations (tRFMOs), the University of Washington and the JRC. These case studies resulted in a number of peer review manuscripts.

- Monkfish
  This project will develop in close collaboration with the Cullen Fellowship of Mr Luke Batts, co-supervised by Dr Hans Gerritsen (MI) and Dr Cóilín Minto (GMIT). Active collaboration will occur with Tasks 3–5, as these are similarly proposed in the Cullen Fellowship where they are applied specifically to *Lophius budegassa* and *Lophius piscatorius* stocks in ICES areas VII-VIII.

- Pollock
  Active collaboration exists between GMIT and the Newport Research Cluster (e.g., *Unlocking the Archive* project). Further collaboration and linkages will be built around data-poor assessment of pollock (liaising with the dedicated Scientific and Technical Officer working on pollock at the Furnace research facility). Both visits to Newport and group attendance at the monthly meetings will facilitate collaboration and crossover.

- DRuMFISH project
  The project will also link with the DGMARE project: "Study on approaches to management for data-poor stocks in mixed fisheries (DRuMFISH)" to which GMIT is a partner in the consortium. Methodological development from DRuMFISH (e.g., hierarchical methods) will be directly relevant to the present proposal.

- CPV codes 71354500-9 Marine survey services 73112000-0 Marine research services 90712300-4 Marine conservation strategy planning 98360000-4 Marine services 77700000-7 Services incidental to fishing 73000000-2 Research and development services and related consultancy services 73110000-6 Research services 73200000-4 Research and development consultancy services 73210000-7 Research consultancy services.

- There are also other projects worldwide that can be link to e.g. the global group on stock assessment methods and the tRFMO MSE WG.

- **Achievements**
- **Promises & Differences**
- **What & Why**

wklifeix: 4 Length-based approaches

wklifeix: ROC

wklifeix: hake

wklifeix: hake

Evaluate further improvements to the performance of the WKMSYCat34 catch rule 3.2.1. Focus on improving the catch rule for stocks with von Bertalanffy growth parameter $k > 0.32$, investigate more extensively the definition of the catch rule components and their impact on performance, and investigate the possibility of alternative catch rules. Explore the operating model set-up for data-limited simulations, including sensitivity analyses based on the Jacobian; e.g. elasticity analysis, on how the different life-history and fishery parameters affect the simulated stock behaviour under exploitation, an analysis of the nature of time-series and trends of observable stock characteristics (such as fishery-dependent and -independent metrics) and how the knowledge gained can be used to further improve the performance of catch rules

The International Council of the Exploration of the Sea (ICES) is in the process of developing methods to identify MSY proxy reference points for data-limited stocks (WKLIFE). The service provider is required to contribute to this process by proposing and testing new assessment models and methods of establishing reference points and will be expected to attend up to 4 one-week meetings at ICES headquarters in Copenhagen. However there are key differences with the ICES approach. Since this research contract will include stocks not currently assessed by ICES; focusing on the available data for each stock first and on the methods second; the ICES approach focuses on the methods first and then applies a limited number of methods to a large number of stocks.

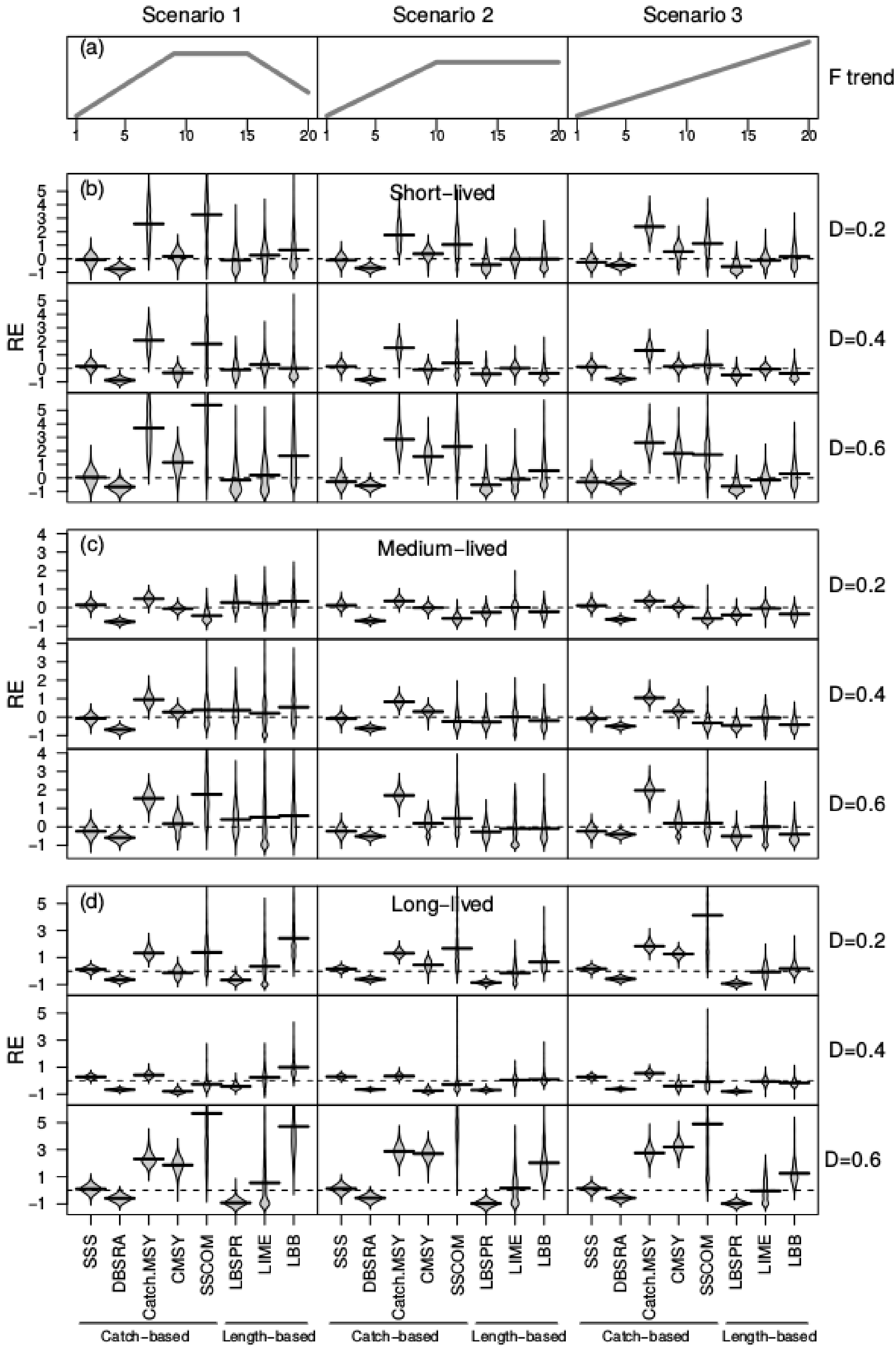

Figure 2: Relative error (RE) in exploitation rate for all the catch-based and length-based models considered under the different harvest scenarios (a) and depletion scenarios for differing life histories, (b) short-lived, (c) medium-lived, and (d) long-lived.

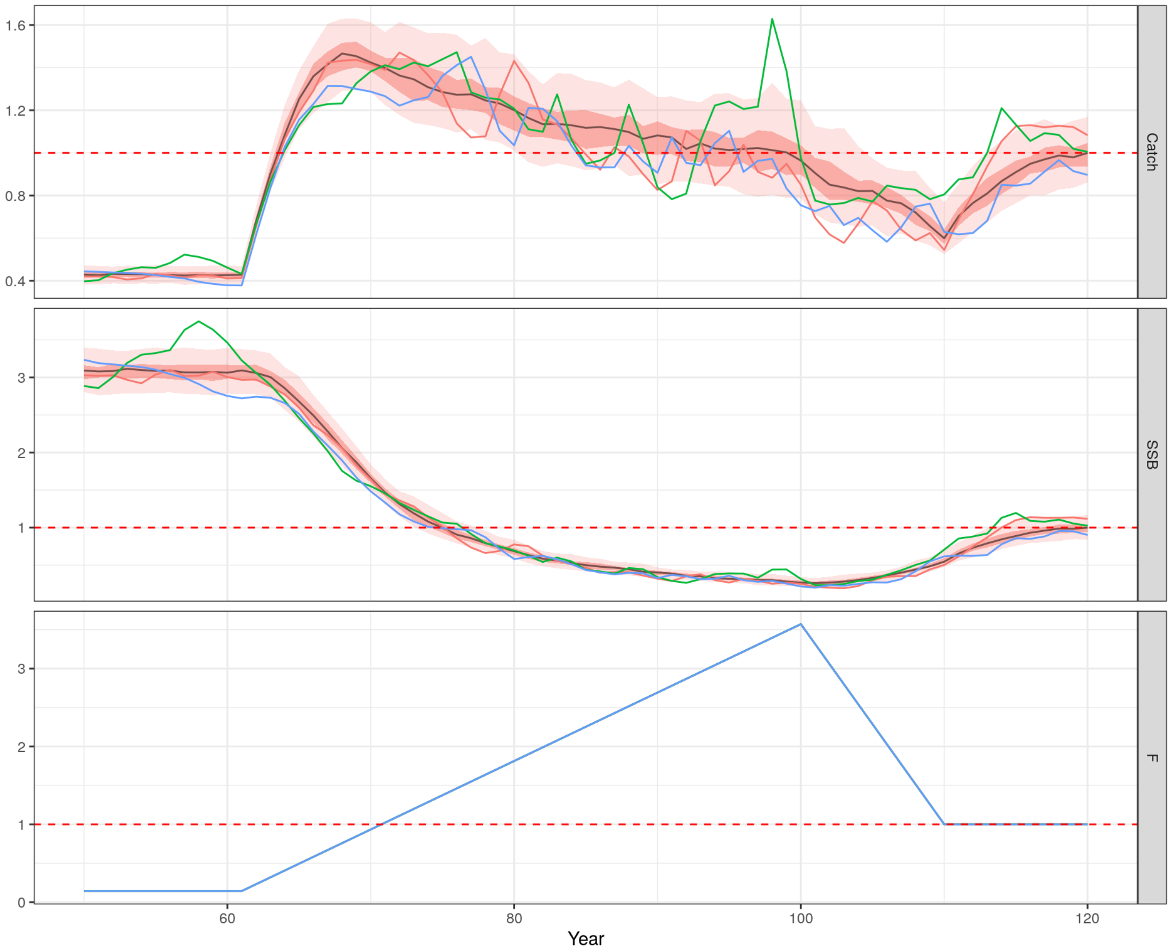

Figure 3: Time series of simulated length based indicators, compared to F/F_{MSY}

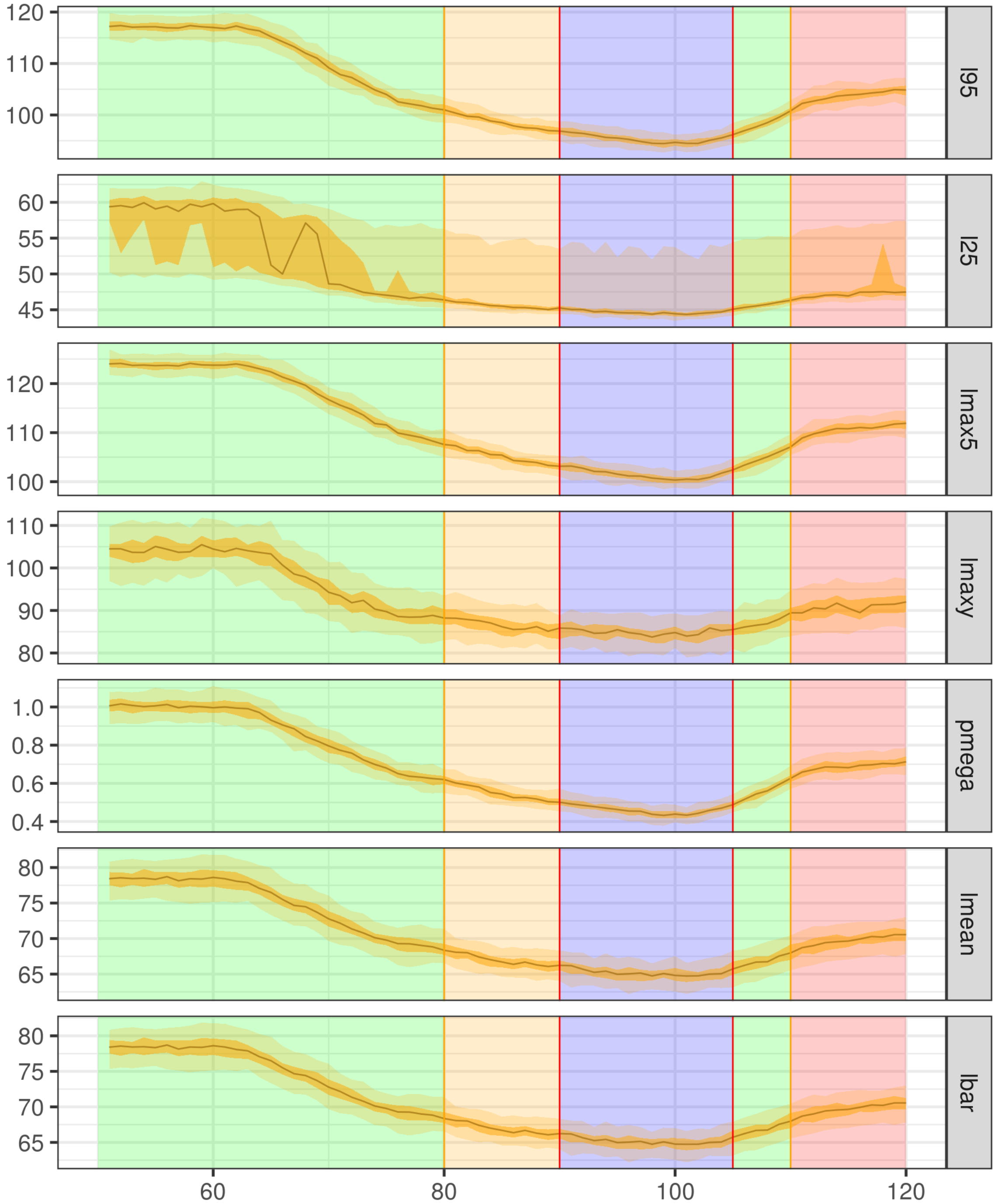

Figure 4: Time series of simulated length based indicators, compared to F/F_{MSY}

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A

A1 Database

PostgeSQL database mydas_dev

data_faocodes (includes price – source Hans Gerritsen Marine Institute)

	Variable name	Type	Description
1	species_fao	Character	e.g. BLL, SPR, LIN, GUG, SKA, POK, POL,TUR, JOD.
2	scientific_name	Character	Latin names e.g. *Sprattus sprattus*.
3	english_name	Character	Sprat.
4	speciesgroup	Character	e.g. ANG, MON, ANF = Monkfish.
5	priceperkg	Double	Irish market prices 2015.

data_icesrects (source ICES web site)

	Variable name	Type	Description
1	longitude	Double	Decimal degrees
2	latitude	Double	Decimal drees
3	ices_rectangle	Character	ICES Rectangle code
4	area_km2	Integer	Area of ICES rectangle.
5	ecoregion	Character	Ecological region

data_icesrects_div (source ICES website)

	Variable name	Type	Description
1	area_27	Character	FAO area code and division notation, i.e. 10.a.1
2	ices_rectangle	Character	ICES Rectangle code
3	ices_division	Character	ICES division.

data_lhistories (life histories of MYDAS species sourced from literature)

	Variable name	Type	Description
1	species	Character	Latin name.
2	speciesgp	Character	e.g. grouping blue ling and common ling into 1 var BLI, LIN = LIN.
3	sex	Character	Code for sex of individual fish i.e. M = Male, F=Female, U=Unsexed
4	t.0	Double	Time at which fish is at 0 length
5	linf	Double	Asymptotic maximum length (cm)
6	k	Double	Growth rate.
7	tm	Double	Age at maturity
8	lmat	Double	Length at maturity (cm)
9	area	Character	Area experiment was performed i.e. North Sea etc.
10	source	Character	Reference from literature source (table on shiny)

data_psa_default (life histories (above) of MYDAS species together with this table produce interactive page for shiny app for year 2015)

	Variable name	Type	Description
1	stock	Character	i.e. Speciesgroup BLL.7 for area 7 catching BLL.
2	gear	Character	Beam, Otter etc..
3	speciesgp	Character	e.g. grouping blue ling and common ling into 1 variable BLI, LIN = LIN.
4	totland	Double	Total landings in tonnes.
5	totfleetarea	Double	Total area gear went km^2
6	stockarea	Double	Total area for the stock
7	olap_percent	Double	Totfleetarea/ stockarea x 100
8	price	Double	Price per kg of the species
9	score_olap	Integer	1 to 3 overlap score 3 is high susceptibility.
10	score_price	Integer	1 to 3 price score 3 is high susceptibility.
11	score_catch	Integer	1 to 3 catachability 3 is high susceptibility.
12	score_postc	Integer	1 to 3 post capture mortality 3 is high susceptibility.
13	tm_score	Integer	1 to 3 ages at maturity 1 is high productivity.
14	fec_score	Integer	1 to 3 fecundity score 1 is high productivity.
15	repro_score	Integer	1 to 3 reproductive score 1 is high productivity.
16	troph_score	Integer	1 to 3 trophic level score 1 is high productivity.
17	lmat_score	Integer	1 to 3 length at maturity score 1 is high productivity.
18	linf_score	Integer	1 to 3 asymptotic maximum length 1 is high productivity.

data_speciescodes (look up table)

	Variable name	Type	Description
1	species_fao	Character	Species FAO codes for MYDAS species
2	scientific_name	Character	Latin names e.g. *Sprattus sprattus*
3	english_name	Character	Sprat.
4	speccode	Integer	WORMS code
5	speciesgp	Character	e.g. grouping blue ling and common ling into 1 var BLI, LIN = LIN.

data_stecf_aer_cpuedays (summary table to calculate cpue for shiny app from STECF annual economic report)

	Variable name	Type	Description
1	year	Integer	Year of fishing activity
2	speciesgp	Character	e.g. grouping blue ling and common ling into 1 var BLI, LIN = LIN.
3	country_code	Character	ESP = Spain etc. See appendix
4	gear_type	Character	Fishing activity etc BEAM = beam trawl see appendix.
5	vessel_length	Character	Length of fishing boat.
6	totval	Double	Total value in Euros (€)
	totctch	Double	Total catch in tonnes (t)
	totdays	Double	Total days fished.

data_stecf_aer_econ (summary table to calculate cpue for shiny app from STECF annual economic report)

	Variable name	Type	Description
1	year	Integer	Year of fishing activity
2	speciesgp	Character	e.g. grouping blue ling and common ling into 1 var BLI, LIN = LIN.
3	country_code	Character	ESP = Spain etc. See appendix
	country_name	Character	Spain
4	fishing_tech	Character	Fishing activity cluster constructed fleet segment. See AER report.
5	variable_name	Character	e.g. vessel tonnage.
6	variable_code	Character	Total vessel tonnage = totgt
	value	Double	Value of variable code

data_stecflandings (just for mydas species/areas) and (data_otherstecflandings – all species)

	Variable name	Type	Description
1	annex	Character	??
2	area	Character	ICES area see appendix below
3	country	Character	ESP = Spain etc. See appendix
4	fishery	Character	??
5	gear	Character	Fishing gear
6	landings	Double	Landings in tonnes
7	mesh	Character	Meshsize range e.g. 100-119
8	quarter	Integer	Given as 1-4
9	ices_rectangle	Character	ICES Rectangle code
10	regulated_area	Character	??
11	regulated_gear	Character	???
12	species	Character	3 letter FAO code
13	specon	Character	???
14	length	Character	Vessel length
15	year	Integer	Year of fishing
16	division	Character	ICES division
17	stock	Character	Mydas stock grouping
18	speciesgp	Character	e.g. grouping blue ling and common ling into 1 var BLI, LIN = LIN.
19	longitude	Double	Midpoint of ices rectangle
20	latitude	Double	Midpoint of ices rectangle
21	area_km2	Integer	Area of ICES rectangle
22	ecoregion	Character	Ecological region

data_stockprior (summary table resulting from PSA and economic weighting – see stock prioritisation code on mydas wiki)

	Variable name	Type	Description
1	year	Character	Year of fishing
2	country	Character	Country i.e ESP
3	gear	Integer	Fishing gear i.e BEAM.

4	rank	Double	Weighted ranked vulnerability
5	value	Double	Total value of catch in €
6	speciesgp	Character	e.g. grouping blue ling and common ling into 1 var BLI, LIN = LIN.

div_area (also geometric table for shiny called ices areas shapefile)

	Variable name	Type	Description
1	subarea	Integer	3, 4, 5 etc..
2	subdiv	Character	d, e, f, g… etc.
3	area_full	Character	Full code for ICES area
4	area_27	Character	Full code for ICES area 27 (North Atlantic)
5	area_km2	Double	Area of sub region in km2
6	division	Character	ICES division.

For tables data_surveybio/data_surveystns (see DATRAS @ ICES)

Appendix 1 Country coding

COUNTRY	CODE
Belgium	BEL
Denmark	DEN
Estonia	EST
Finland	FIN
France	FRA
Germany	GER
Ireland	IRL
Latvia	LAT
Lithuania	LIT
Netherlands	NED
Norway	NOR
Poland	POL
Portugal	POR
Spain	SPN
Sweden	SWE
United Kingdom (Jersey)	GBJ
United Kingdom (Guernsey)	GBG
United Kingdom (Alderny/Sark/Herm)	GBC
United Kingdom (England and Wales)	ENG
United Kingdom (Isle of Man)	IOM
United Kingdom (Northern Ireland)	NIR
United Kingdom (Scotland)	SCO
Other countries	OTH

Appendix 2 Gear coding

<table>
<tr><td colspan="3">TYPES OF FISHING TECHNIQUES</td><td>Gear code</td></tr>
<tr><td rowspan="4">Mobile gears</td><td>Beam trawl</td><td></td><td>BEAM</td></tr>
<tr><td rowspan="2">Demersal trawl & demersal seine</td><td>Bottom trawl</td><td>OTTER</td></tr>
<tr><td>Danish & Scottish seiners</td><td>DEM_SEINE</td></tr>
<tr><td>Pelagic trawl & Seiners</td><td>Pelagic Trawl</td><td>PEL_TRAWL</td></tr>
</table>

		Pelagic seiner & purse seiner	PEL_SEINE
	Dredges		DREDGE
Passive gears	Longlines		LONGLINE
	Drift & fixed Nets except Trammel Nets		GILL
	Trammel Nets		TRAMMEL
	Pots & traps		POTS

Appendix 3 Mesh size coding

Gear type	Mesh size range
Mobile gears	<16
	16-31
	32-54
	55-69
	70-79
	80-89
	90-99
	100-119
	>=120
Passive gears	10-30
	50-59
	60-69
	70-79
	80-89
	90-99
	100-109
	110-119
	120-219
	>=220

A2 Dataset Summary

Dataset for use in data poor methods

Laurence Kell and Alex Tidd

25 December, 2018

MYDAS

Task 5 of the MYDAS project https://github.com/laurieKell/mydas requires a review of data avialble on length composition, mean size, catch and indices of abudance (commercial or survey).

Data are available from the MI or from collective sources such as DATRAS http://www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx for survey data and the STECF https://stecf.jrc.ec.europa.eu/data-dissemination for commercial data.

Work plan

- Condition the operating model using life histories (from table above) from brill, turbot, skate and Pollack as per the Mydas project (see the quick start). Will have to use MI estimates for sprat. Use estimates of length (brill, sprat, skate). Obtain length frequencies for turbot and pollack from MI.

The life histories were reviewed by Hans, using data from the MI databases.

- With further investigation look at predicted abundance estimates for brill, sprat (although on high side) and skate (abundance was for all species of skates and rays, will have to make consistent with commercial species… maybe use thornback only). Pollack and turbot catches are greater than abundance so cannot use these.

If the absolute abundance estimates are wrong relative indices can be used, as normal practice.

- With such good time series of survey length data for brill, sprat and skate it would good to sim test the mean size by using the mlz package https://cran.r-project.org/web/packages/MLZ/vignettes/MLZ.html#introduction. This would give an estimate of Z (assuming constant M) and thus look at changes in F.

MLZ uses mean size, it is unlikely to provide good estimates of Z for sppart due to high M and high recruitment variability, the mean size is therefore determined by recruitment not F.

- It may also be worth pursuing the LBSR for length-based composition for the above (and compare) with life-history parameters M/K ratio and Linf to estimate F/M and F/FMSY. With SPR being the biological reference point. https://cran.r-project.org/web/packages/LBSPR/vignettes/LBSPR.html

LBSPR is better at estimating F.

- For turbot and pollack it maybe beneficially to use and empirical approach (as survey info pretty poor) based on the commercial cpue (biomass index from MI lengths or estimated by weights) such as the ICES 2/3 rule (as per Simon Fischer).

The surveys could be used in the

For the observation model commercial cpues could be used.

Further: Need to discuss with MI what data we can get for Lobsters and Razors in terms of lengths. We have 1 set of priors from Iyves.

Survey data extraction

Extract via sql the case study stocks from Mydas survey database and get numbers at length

For more in depth detail of the data see https://data.marine.gov.scot/sites/default/files//SMFS%200816.pdf

Calculate weighted mean length for case study species

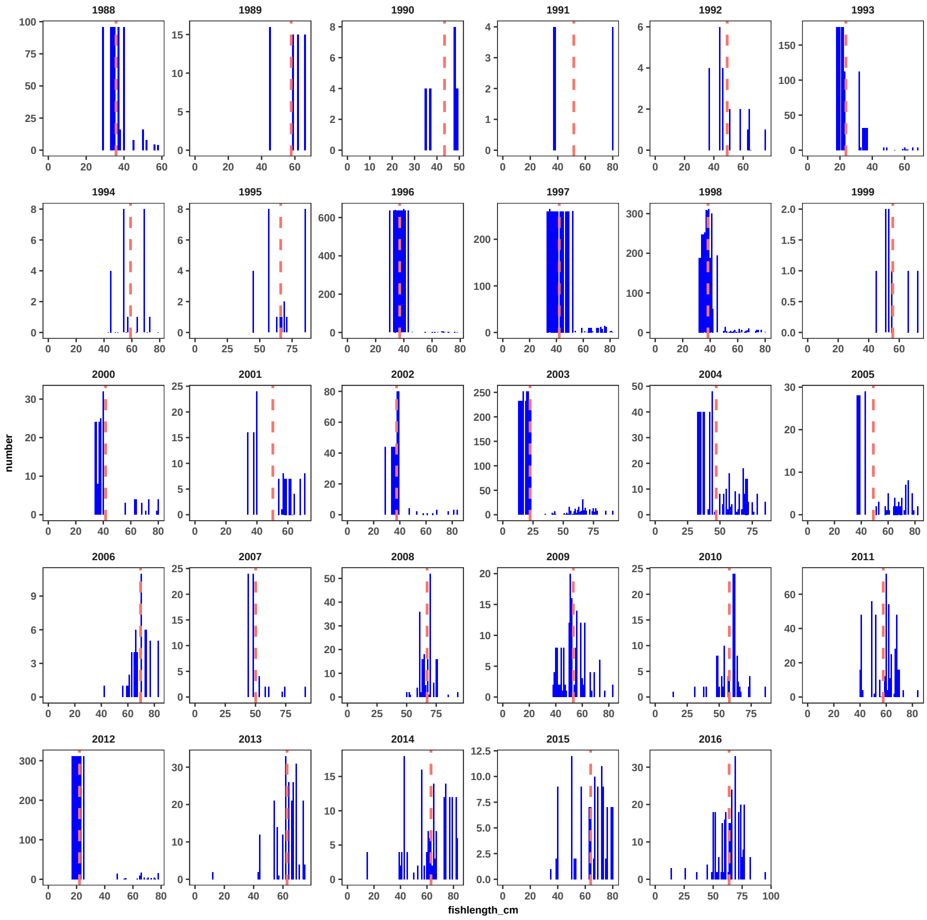


Figure 1 Plot of numbers at length for pollock with weighted mean length represented by dashed red line.

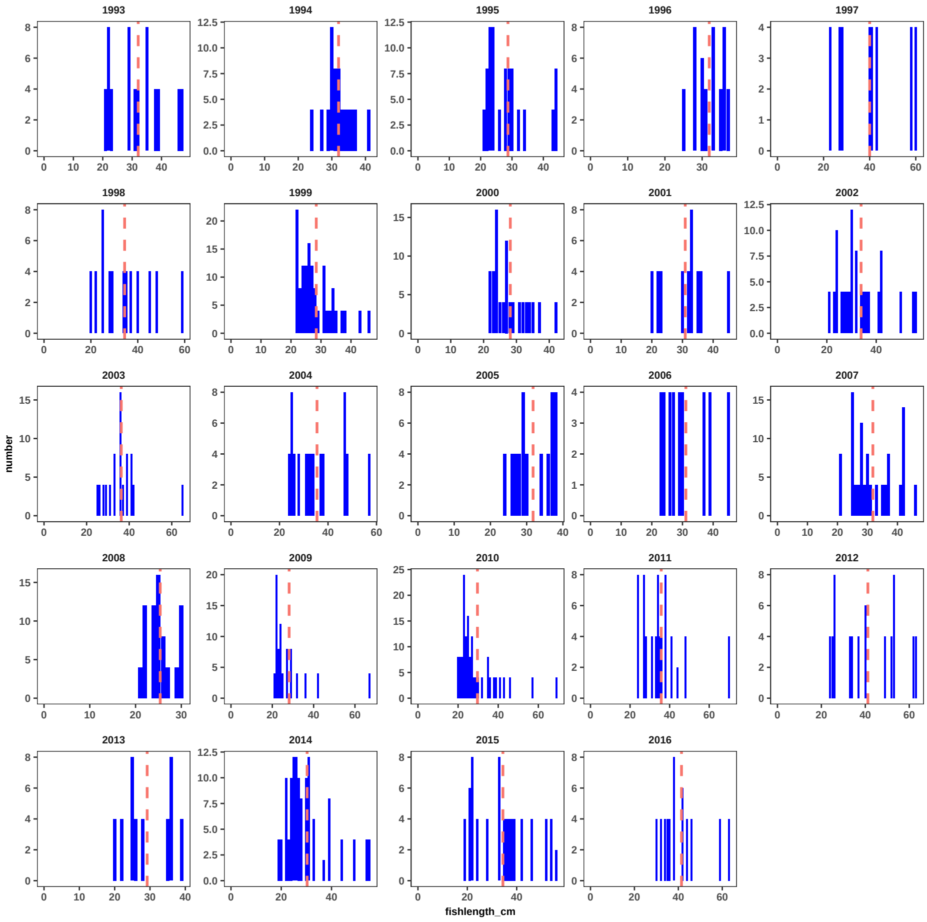


Figure 2 Plot of numbers at length for turbot with weighted mean length represented by dashed red line.

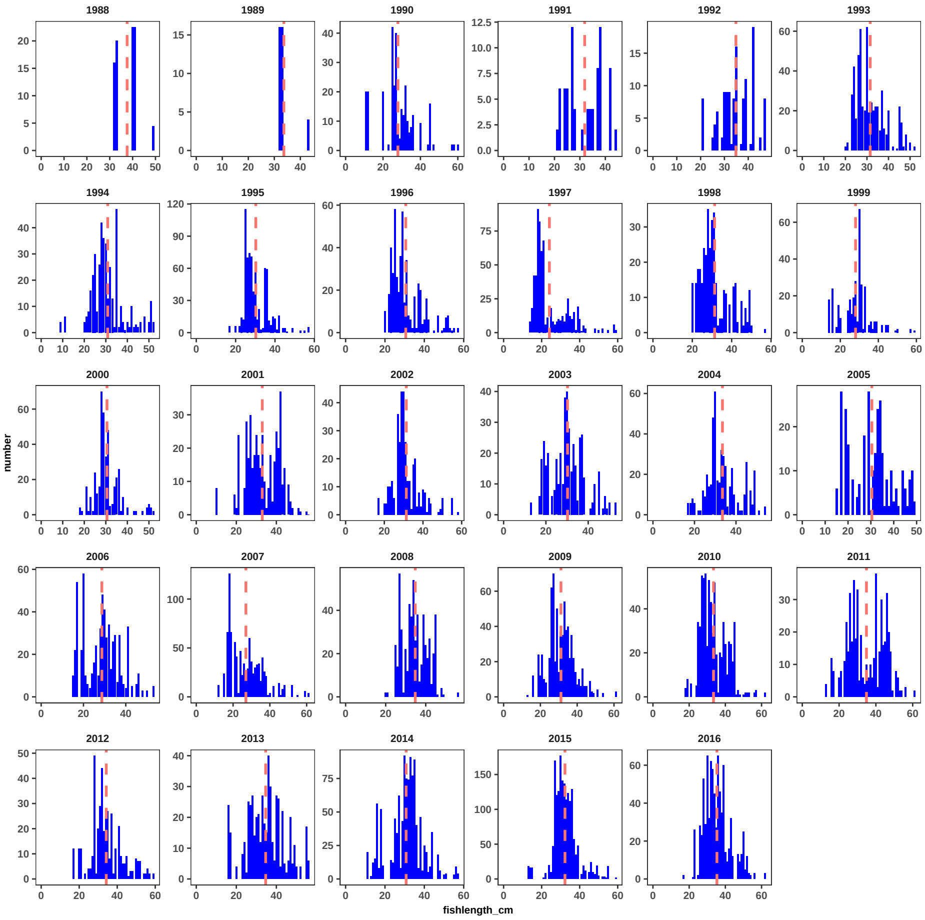


Figure 3 Plot of numbers at length for brill with weighted mean length represented by dashed red line.

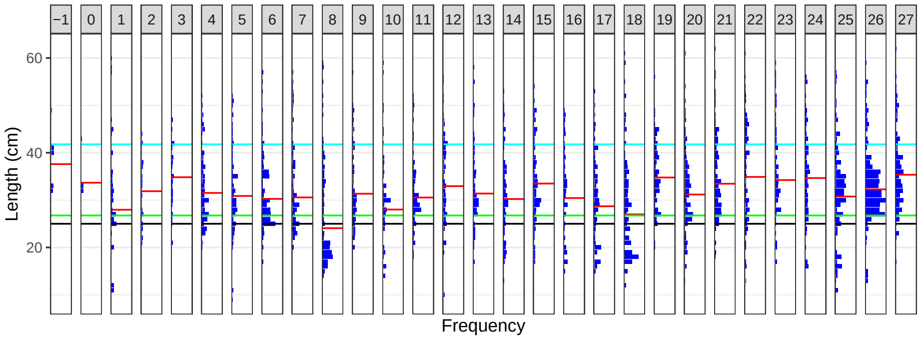


Figure 4 Plot of numbers at length for brill with weighted mean length represented by dashed red line.

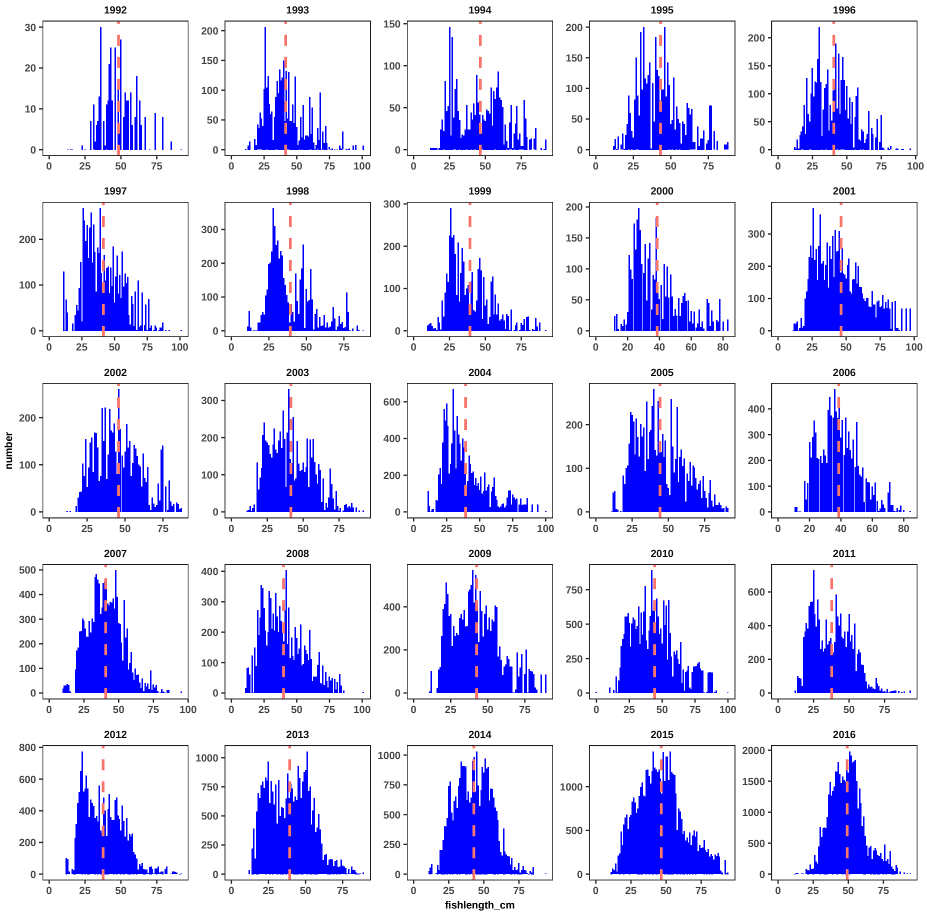


Figure 5 Plot of numbers at length for skate with weighted mean length represented by dashed red line.

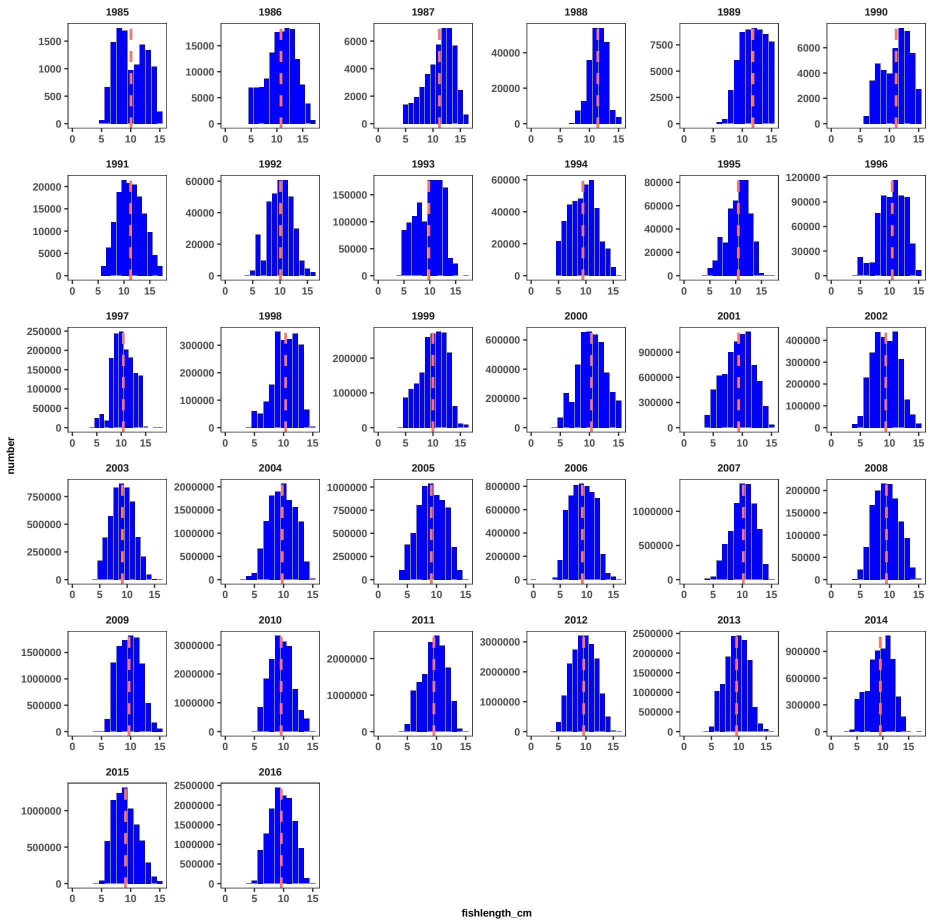


Figure 6 Plot of numbers at length for sprat with weighted mean length represented by dashed red line.

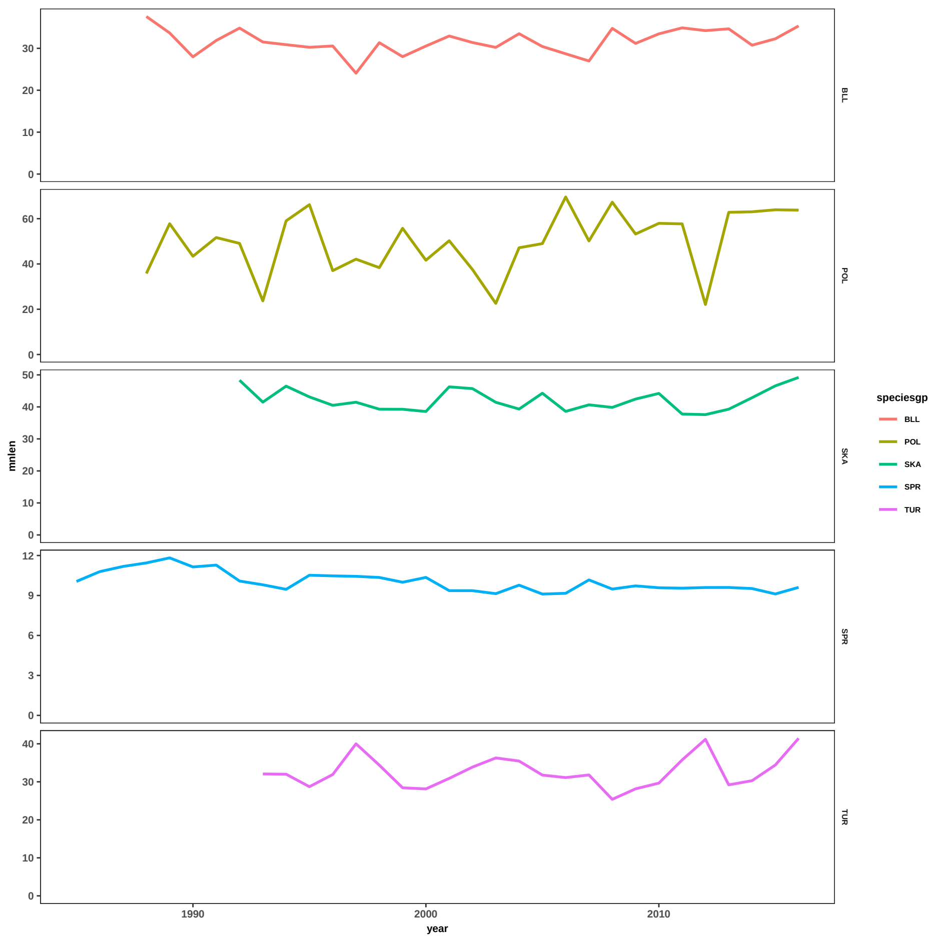


Figure 7 Time series of weighted mean length.

Get all survey data from sql query

Estimate fish weight in kgs

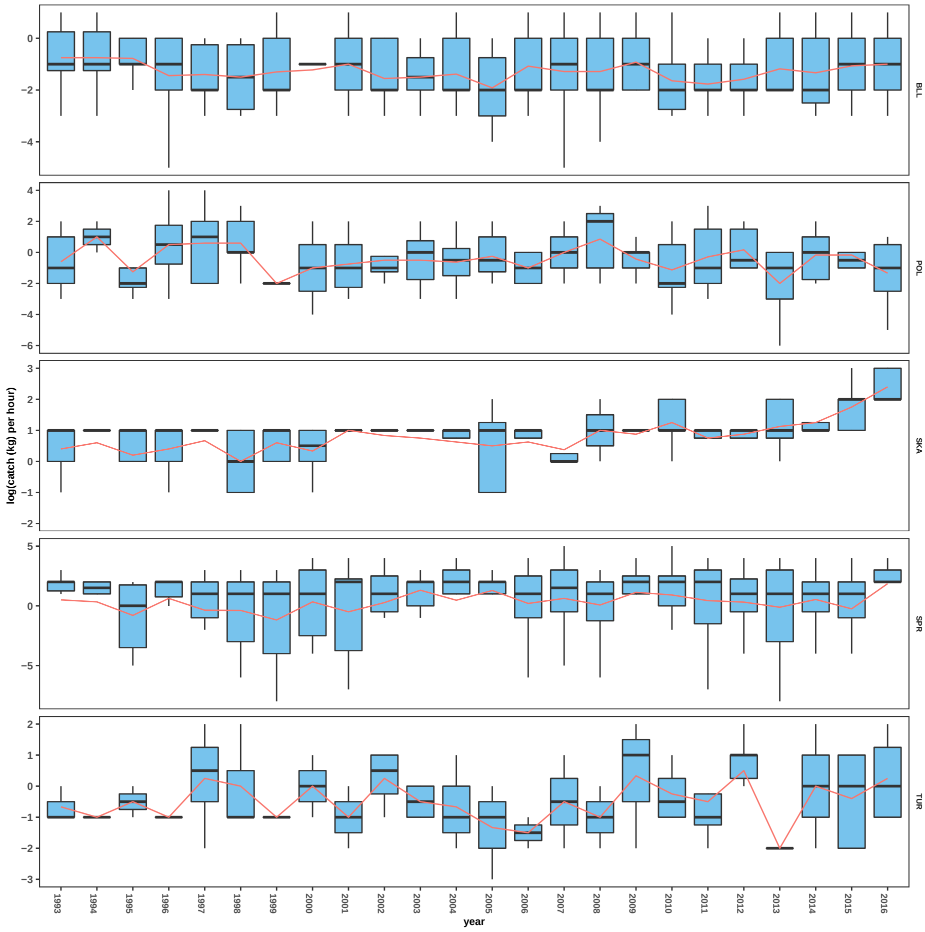


Figure 8 Catch per unit effort in kgs (CPUE) time series with red line depicting mean cpue.

Fish numbers

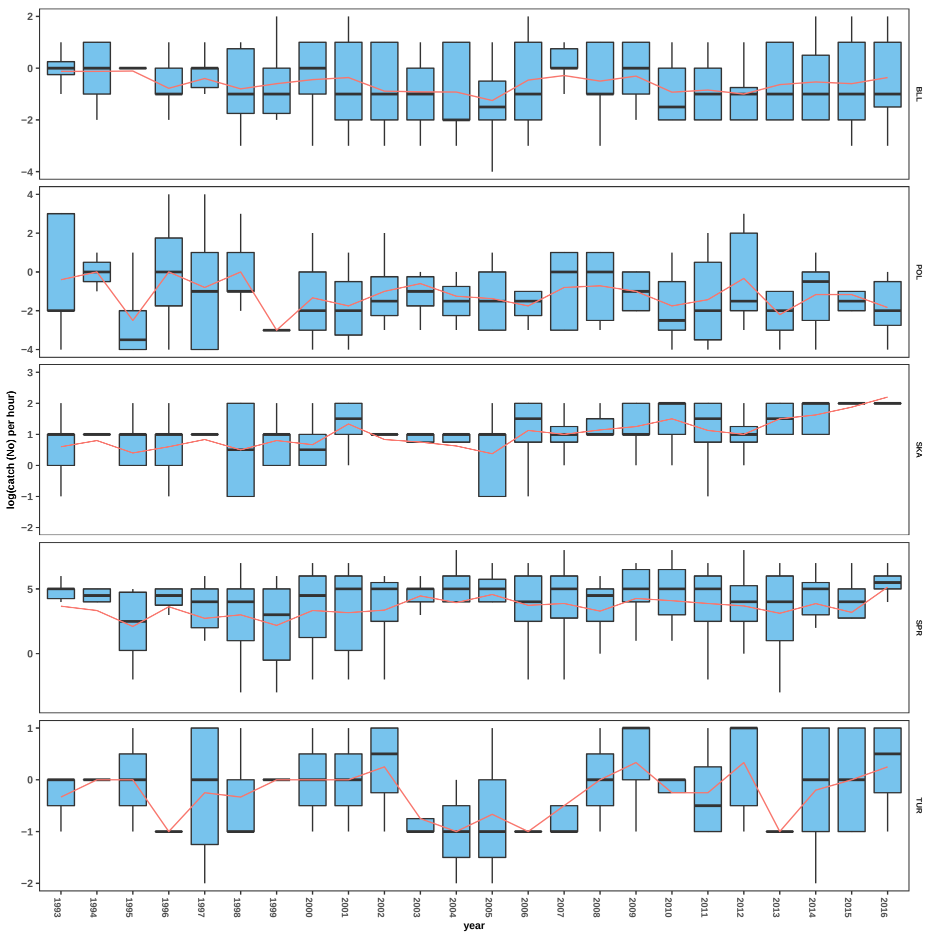


Figure 9 Catch per unit effort in numbers (CPUE) time series with red line depicting mean cpue.

Commercial data

Part of the issues with the main catch data in the stecf database is that the effort does not match up by gear and area with the effort estimations. Here the STECF Annual Economic Report database is used.

Extract the data via sql

Estimate catch in kgs per day

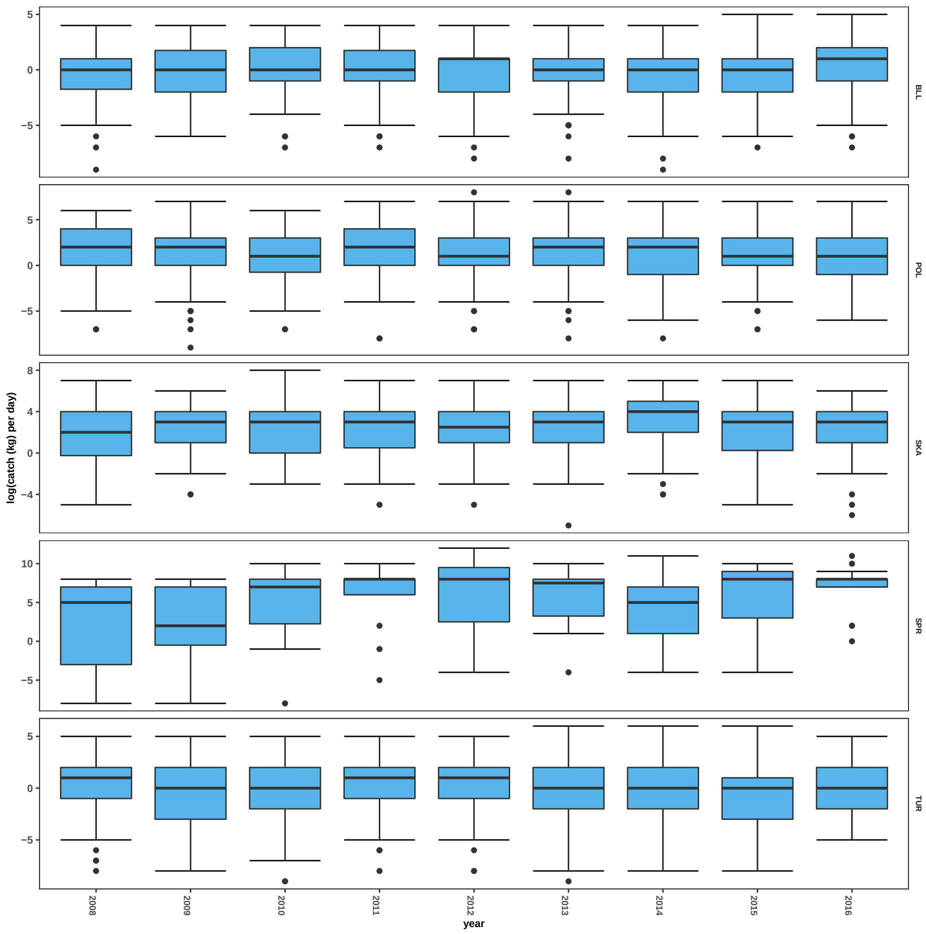


Figure 10 Time series of commercial cpue.

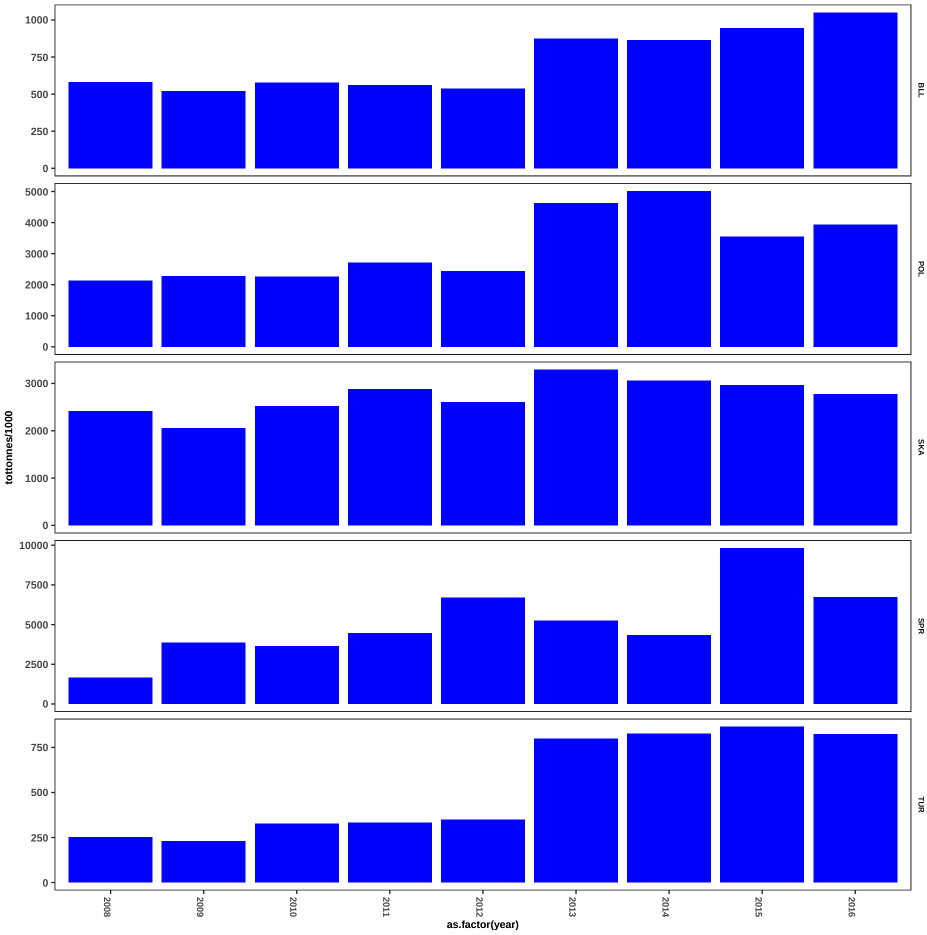


Figure 11 Time series of total catch in tonnes.

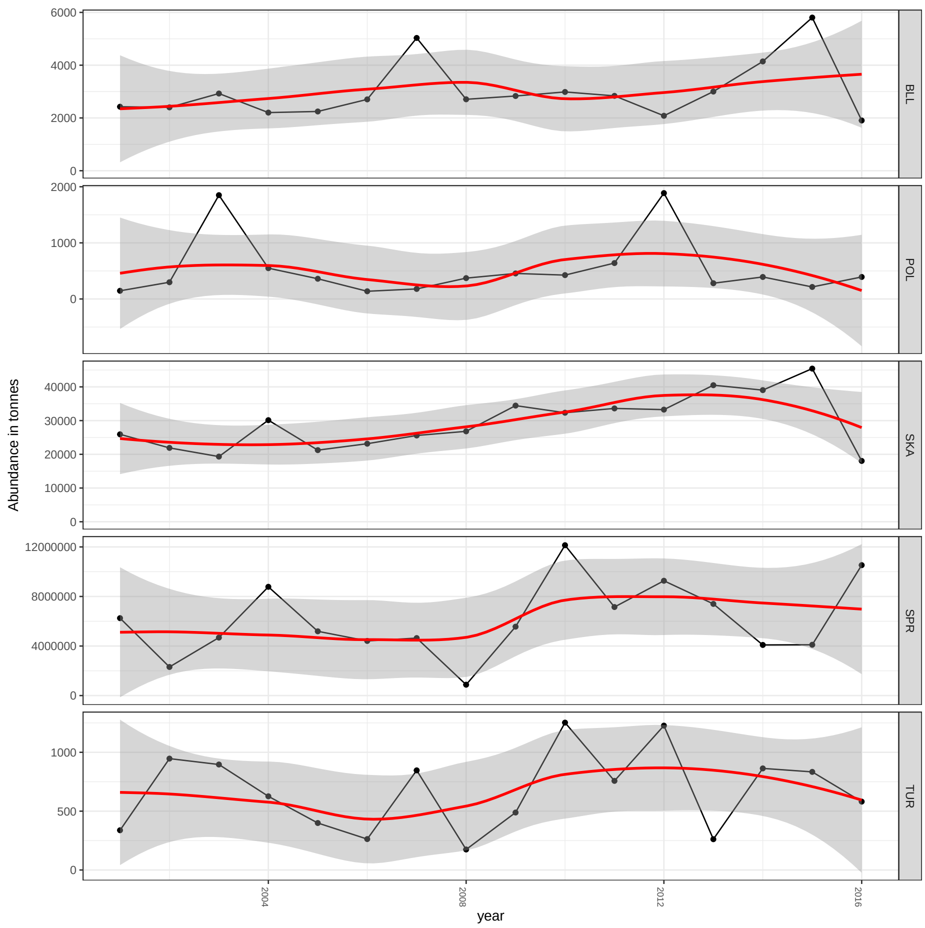
Estimate abundance from survey data

See http://www.fao.org/docrep/w5449e/w5449e0f.htm section 13.7

Get survey stations

Calculate total area/total number of stations the survey covered by division and merge with catch tonnes perkm2

Biomass = totalsurveyarea x 1/total number of stations within the survey area x sum of catch



Life history parameters from the literature

Table 1: life history paramters

id	species	speciesgp	t.0	linf	k	lmat	tm	sex	area	source
1	Amblyraja radiata	SKA		66.00	0.2330	46.0	4.0	U	North Sea	[12]
7	Leucoraja circularis	SKA		98.80	0.1210	51.2	5.3	U	North Sea	[12]
8	Leucoraja fullonica	SKA		98.80	0.1210	51.2	5.3	U	North Sea	[12]
17	Pollachius pollachius	POL		85.60	0.1900	NA	NA	U	North Sea	[18]
18	Pollachius pollachius	POL		85.60	0.1860	44.8	3.7	U	North Sea	[12]
23	Psetta maxima	TUR	-0.05	64.80	0.2600	46.0	NA	F	North Sea	[15]
24	Psetta maxima	TUR	-0.51	49.20	0.3700	NA	NA	M	North Sea	[15]

id	species	speciesgp	t.0	linf	k	lmat	tm	sex	area	source
25	Psetta maxima	TUR		65.20	0.3240	49.0	NA	M	Bay of Biscay	[9], [7]
26	Psetta maxima	TUR		73.60	0.2770	49.0	NA	F	Bay of Biscay	[9], [7]
27	Psetta maxima	TUR	-1.79	69.60	0.2497	49.0	4.5	U	North Sea	[19], [8], [16], [17]
28	Psetta maxima	TUR		57.00	0.3200	46.0	4.5	U	North Sea	[12]
29	Psetta maxima	TUR		52.50	0.3200	NA	NA	M	North Sea	[17]
30	Psetta maxima	TUR	-1.79	70.00	0.1480	NA	NA	F	North Sea	[17]
31	Raja batis	SKA	-1.63	254.00	0.0600	130.0	11.0	U	North Sea	[11]
32	Raja batis	SKA		253.70	0.0570	155.0	15.0	U	North Sea	[12]
33	Raja brachyura	SKA		139.00	0.1200	100.0	9.3	U	North Sea	[12]
34	Raja brachyura	SKA	-0.8	118.00	0.1900	NA	NA	M	Irish Sea	[13]
35	Raja brachyura	SKA	-1.52	139.00	0.1200	NA	NA	F	Irish Sea	[13]
36	Raja clavata	SKA	-1.32	128.00	0.0900	NA	NA	F	Irish Sea	[13]
37	Raja clavata	SKA	-0.6	85.60	0.2100	NA	NA	M	Irish Sea	[13]
38	Raja clavata	SKA		105.00	0.2200	65.0	5.0	U	North Sea	[12]
39	Raja montagui	SKA	-0.37	72.80	0.1800	NA	NA	F	Irish Sea	[13]
40	Raja montagui	SKA	-0.56	68.70	0.1900	NA	NA	M	Irish Sea	[13]
41	Raja montagui	SKA		97.80	0.1480	67.0	6.0	U	North Sea	[12]
42	Raja naevus	SKA	-0.465	92.00	0.1100	59.0	9.0	U	North Sea	[11]
43	Raja naevus	SKA		91.60	0.1090	59.0	9.0	U	North Sea	[12]
44	Raja radiata	SKA		66.00	0.2300	46.0	4.0	U	North Sea	[22]
45	Raja undulata	SKA		112.00	0.1000	57.5	6.3	U	North Sea	[12]
46	Scophthalmus rhombus	BLL		74.88	0.1400	37.0	NA	M	Bay of Biscay	[9], [7]
47	Scophthalmus rhombus	BLL		85.23	0.1470	37.0	NA	F	Bay of Biscay	[9], [7]
48	Scophthalmus rhombus	BLL		50.00	0.2700	37.0	4.5	U	North Sea	[12]
49	Sprattus sprattus	SPR	*	16.00	0.6500	13.0	NA	U	North Sea	[20]

Conclusion from the above analysis for 5 of the 7 case studies

- Pollack and turbot have poor coverage in terms of numbers at length from the survey data and hence potentially poor abundance estimates.

- Brill, sprat and skates have long time series of numbers at length. Brill has adequate numbers from 1993 to 2016 as has skate, while sprat contains a longer time series from 1985-to 2016.

- Observations from the commercial time-series show that for all species there are 9 years of data.

- There are enough life history parameters from the literature to condition an operating model for all case-study species apart from sprat.

Software Versions

- R version 3.5.1 (2018-07-02)
- plyr: 1.8.4
- dplyr: 0.7.8
- ggplot2: 3.1.0
- DBI: 1.0.0
- RPostgreSQL: 0.6.2
- reshape 0.8.8
- **Compiled**: Tue Dec 25 20:37:56 2018

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Session Info

```
R version 3.5.1 (2018-07-02)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 16.04.2 LTS

Matrix products: default
BLAS: /usr/lib/libblas/libblas.so.3.6.0
LAPACK: /usr/lib/lapack/liblapack.so.3.6.0

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=en_GB.UTF-8        LC_COLLATE=en_US.UTF-8
 [5] LC_MONETARY=en_GB.UTF-8    LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_GB.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] splines   stats     graphics  grDevices utils     datasets  methods
[8] base

other attached packages:
 [1] gam_1.16          foreach_1.4.4     bindrcpp_0.2.2
 [4] reshape_0.8.8     RPostgreSQL_0.6-2 DBI_1.0.0
 [7] ggplot2_3.1.0     dplyr_0.7.8       plyr_1.8.4
[10] knitr_1.20

loaded via a namespace (and not attached):
 [1] Rcpp_1.0.0       highr_0.7        pillar_1.3.1     compiler_3.5.1
 [5] bindr_0.1.1      iterators_1.0.10 tools_3.5.1      digest_0.6.18
 [9] evaluate_0.12    tibble_1.4.2     gtable_0.2.0     pkgconfig_2.0.2
[13] rlang_0.3.0.1    rstudioapi_0.8   yaml_2.2.0       withr_2.1.2
[17] stringr_1.3.1    rprojroot_1.3-2  grid_3.5.1       tidyselect_0.2.5
[21] glue_1.3.0       R6_2.3.0         rmarkdown_1.10   reshape2_1.4.3
[25] purrr_0.2.5      magrittr_1.5     backports_1.1.2  scales_1.0.0
[29] codetools_0.2-15 htmltools_0.3.6  assertthat_0.2.0 colorspace_1.3-2
[33] labeling_0.3     stringi_1.2.4    lazyeval_0.2.1   munsell_0.5.0
[37] crayon_1.3.4
```

A3 Recruitment spectral decomposition

Characterising recruitment variability in MYDAS

C. Minto - for discussion

Load the RAM Legacy database[1] version 4.44

```
load("DBdata.RData")
```

Find out which sprat stocks are in RAM, for example

```
## get taxonomic serial number
tsn <- taxonomy$tsn[taxonomy$scientificname == "Sprattus sprattus"]
(tsn <- unique(tsn))

## [1] " 161789"

## link to stock table
idx <- which(stock$tsn == tsn)
stock_df <- stock[idx,]
stock_df[, c("stockid", "stocklong")]

##                   stockid                       stocklong
## 1119           SPRAT22-32 Sprat ICES Baltic Areas 22-32
## 1120            SPRATIIIa   Sprat Kattegat and Skagerrak
## 1121              SPRATNS                 Sprat North Sea
## 1122           SPRATVIIde                     Sprat VIIde
## 1123 SPRATVI-VIIabcfghijk      Sprat VI and VIIabcfghijk
## 1129           SPRBLKGSA29                 Sprat Black Sea
```

Get the stock-recruit data

```
stockids <- stock_df$stockid
## subset to these where recruitment data available
ts_values_df <- subset(timeseries_values_views, stockid %in% stockids & (!is.na(R)))
stockids <- unique(ts_values_df$stockid)

rownames(ts_values_df) <- NULL
head(ts_values_df[, c("stockid", "year", "SSB", "R")])

##      stockid year     SSB        R
## 1 SPRAT22-32 1973      NA 5.04e+10
## 2 SPRAT22-32 1974 1100000 1.89e+10
## 3 SPRAT22-32 1975  867000 1.94e+11
## 4 SPRAT22-32 1976  738000 4.27e+10
## 5 SPRAT22-32 1977 1260000 1.52e+10
## 6 SPRAT22-32 1978  866000 3.05e+10
```

[1] https://www.ramlegacy.org/database/

```r
## these are lagged to the year spawned

## get the units
ts_units_df <- subset(timeseries_units_views, stockid %in% stockids)
rownames(ts_units_df) <- NULL
ts_units_df <- ts_units_df[, c("stockid", "SSB", "R")]

ts_units_df

##        stockid SSB   R
## 1  SPRAT22-32  MT E00
## 2     SPRATNS  MT E00
## 3 SPRBLKGSA29  MT E00

## ssb in metric tonnes and recruitment in numbers
```

Recruitment

Recruitment time series (Figure 1) display

- Similar scale despite no attempt to standardize for area - North Sea is approximately twice the area of either the Black Sea or Baltic - could look into this further to standardise for area and hence do something with more biological information.
- Relatively constrained, in the 10 or 100 billions, notwithstanding the drop for North Sea when also SSB dropped.
- Non-stationary at least in the mean for Baltic and North Sea sprat.
- Local 'spikes' with some evidence of pulses the periodicity of which can be debated.

```r
library(ggplot2); theme_set(theme_bw())
ggplot(ts_values_df, aes(x = year, y = R)) +
    geom_line() +
    facet_wrap(~stockid, ncol = 1) +
    xlab("Year") +
    ylab("Recruitment")
```

Spectral analysis

Loosely a power spectrum tells us the contribution of each frequency to the overall process. This is useful in identifying periodicities and other structures in the time series. To analyse non-stationary random functions, we may proceed in at least two ways: transform the data to stationarity and process with classical spectral analysis or perform some form of time-dependent spectral analysis (see Priestley).
We first detrend the raw series so that they are approximately stationary in the first moment (Figure 2).

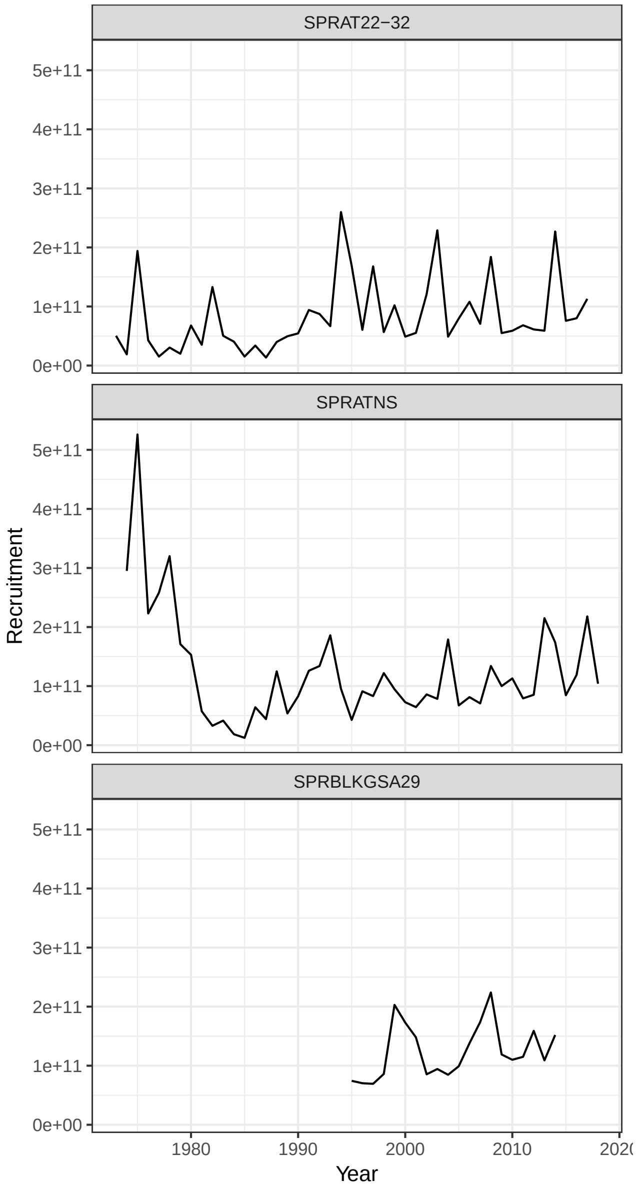


Figure 1: Sprat recruitment time series from the RAM Legacy database. Recruitment is in numbers.

Note that there are various theorems (Grenander and Rosenblatt) proved on the efficiency of spectral estimators with pre-treatment of the data with polynomials and then estimating the spectrum. This likely does not apply to very flexible local polynomials but here we will use relatively inflexible local polynomials that improve on global polynomials with inherent symmetry. We recognise though that by increasing the flexibility of the spline we may remove important periodicity in such short series.

```
library(mgcv)
library(gridExtra)
smoothed_df <- NULL

## fitting on natural log-scale
ts_values_df$logR <- log(ts_values_df$R)

for(i in 1:length(stockids)){
    dat <- subset(ts_values_df, stockid == stockids[i])
    ##fit <- gam(logR ~ s(year, k = 3), data = dat)
    fit <- gam(logR ~ s(year, k = 7), data = dat)
    tmp <- data.frame(stockid = stockids[i],
                      year = dat$year,
                      logR = dat$logR,
                      fit = predict(fit),
                      resid = resid(fit))
    smoothed_df <- rbind(smoothed_df, tmp)
}

raw_plots <- ggplot(smoothed_df, aes(x = year, y = logR)) +
    geom_line(colour = "slategrey") +
    geom_line(aes(y = fit)) +
    facet_wrap(~stockid, ncol = 1)

resid_plots <- ggplot(smoothed_df, aes(x = year, y = resid)) +
    geom_line(colour = "slategrey") +
    facet_wrap(~stockid, ncol = 1)

grid.arrange(raw_plots, resid_plots, ncol = 2)
```

Have a look at the stationarity of the residuals.

```
library(tseries)
for(i in 1:length(stockids)){
    print(stockids[i])
    print(adf.test(smoothed_df$resid[smoothed_df == stockids[i]]))
}

## [1] "SPRAT22-32"
##
##  Augmented Dickey-Fuller Test
##
## data:  smoothed_df$resid[smoothed_df == stockids[i]]
## Dickey-Fuller = -3.9863, Lag order = 3, p-value = 0.01889
## alternative hypothesis: stationary
##
## [1] "SPRATNS"
```

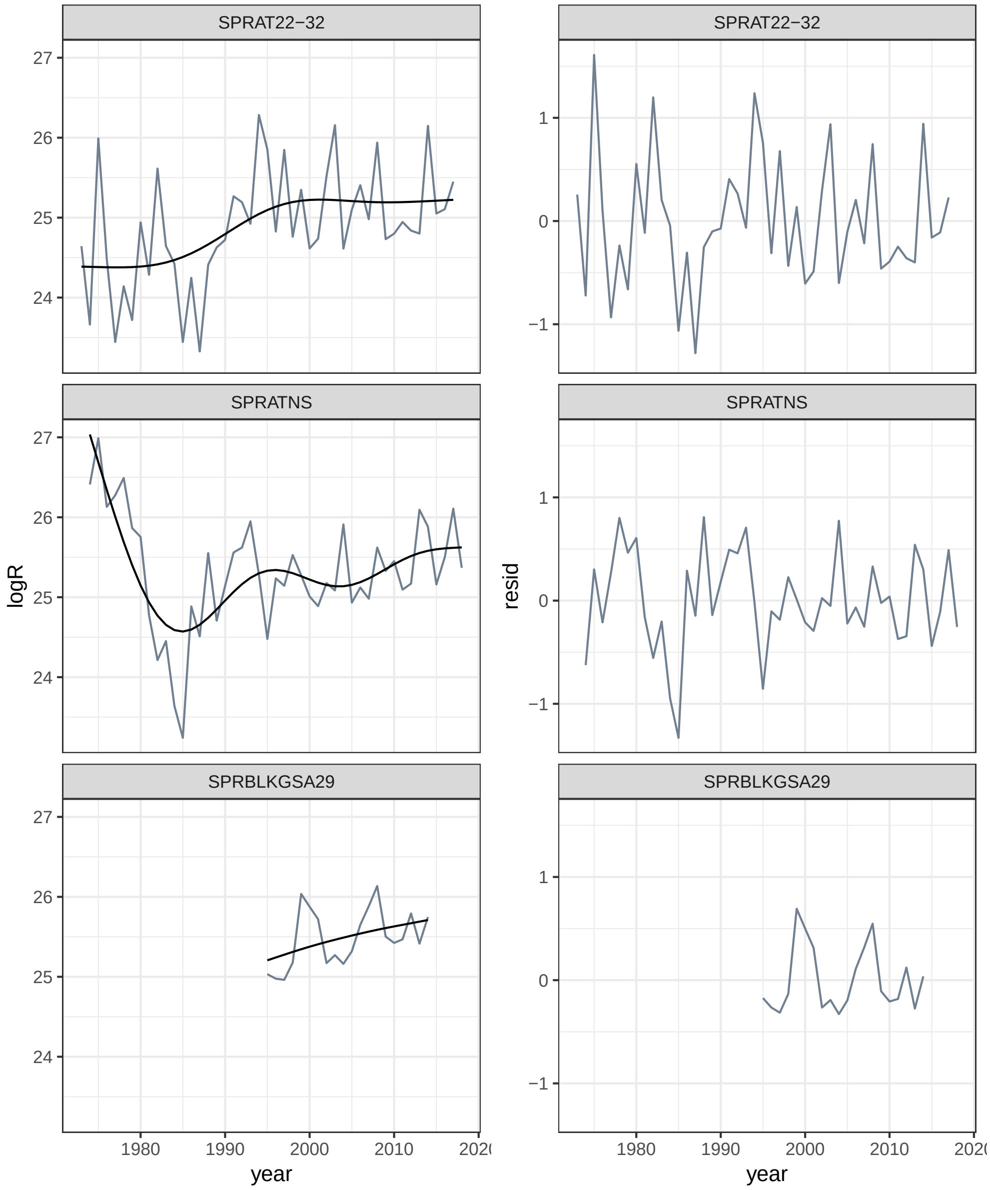


Figure 2: De-trending the natural logarithm of sprat recruitment using a low order basis smoothing spline.

```
##
##  Augmented Dickey-Fuller Test
##
## data:  smoothed_df$resid[smoothed_df == stockids[i]]
## Dickey-Fuller = -3.6101, Lag order = 3, p-value = 0.0431
## alternative hypothesis: stationary
##
## [1] "SPRBLKGSA29"
```

```
## Warning in adf.test(smoothed_df$resid[smoothed_df == stockids[i]]):  p-value smaller
than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  smoothed_df$resid[smoothed_df == stockids[i]]
## Dickey-Fuller = -4.4663, Lag order = 2, p-value = 0.01
## alternative hypothesis: stationary
```

There are various algorithms to conduct an empirical spectral analysis on a time series. As the series are short, here we simply estimate a raw periodogram using FFT with no smoothing or tapering to see what periods dominate the series.

```
spec_df <- data.frame()

for(i in 1:length(stockids)){
    dat <- subset(smoothed_df, stockid == stockids[i])
    ## as the data so short no smoothing of spectrum
    fit  <- spec.pgram(dat$resid, taper = 0, log = "no", plot = FALSE)
    tmp <- data.frame(stockid = stockids[i],
                      freq = fit$freq,
                      period = 1/fit$freq,
                      spec = fit$spec
                      )
    spec_df <- rbind(spec_df, tmp)
}
```

Visualise the raw spectra (Figure 3)

```
ggplot(spec_df, aes(x = period, y = spec)) +
    geom_linerange(aes(ymin = 0, ymax = spec)) +
    facet_wrap(~stockid, ncol = 1) +
    ylab("Spectral density") +
    xlab("Period (years)")
```

High frequency (low period) variability dominates the Baltic and North Sea, superimposed on spectral peaks at approximately an 11 year period.

Next steps:

- Look at smoothing kernels and tapering

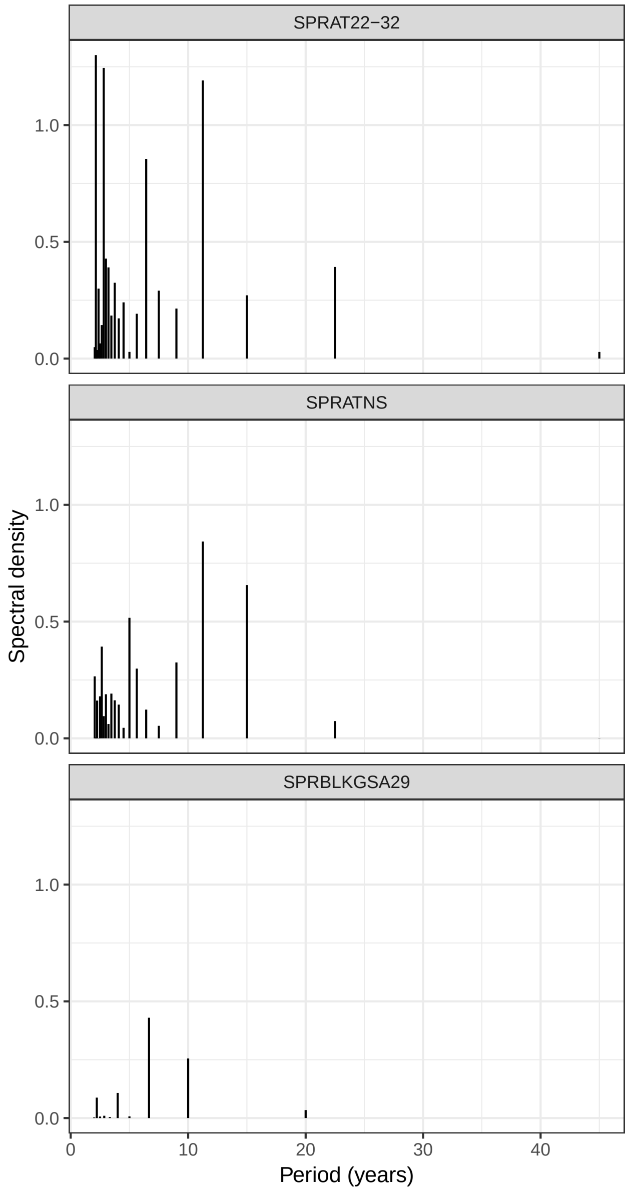


Figure 3: Raw periodograms for the de-trended sprat time series displaying the spectral density at given periods.

- Try a wavelet analysis for kicks, out of the blue and all that - too short here
- Simulate from a process closely matched to these spectra - see relationship of FFT with the coefficients of a harmonic regression.

Simulation

The periodogram value at frequency ω_j can be defined by the coefficients of a harmonic regression

$$I(\omega_j) = \frac{n}{4}(a_j^2 + b_j^2) \tag{1}$$

where a_j and b_j are the cosine and sine coefficients of the harmonic regression

$$y_t = \sum_{j=0}^{n/2} a_j \cos(\omega_j t) + b_j \sin(\omega_j t) \tag{2}$$

```
## fit the periodogram yourself
dat <- subset(smoothed_df, stockid == stockids[1])
fit  <- spec.pgram(dat$resid, taper = 0, log = "no", plot = FALSE, detrend = FALSE)

## set up the basis
n <- nrow(dat)
freq <- seq(1/n, by = 1/n, length.out = floor(n/2))
t <- 0:(n-1)
cos_x <- sapply(freq, function(f){cos(2 * pi * f * t)})
sin_x <- sapply(freq, function(f){sin(2 * pi * f * t)})

y <- dat$resid

fit_lm <- lm(y ~ -1 + cos_x + sin_x)

ab <- coef(fit_lm)

a <- ab[grep("cos_", names(ab))]
b <- ab[grep("sin", names(ab))]

## periodogram ordinate
Iom <- n/4 * (a^2 + b^2)

range(fit$spec - Iom)

## [1] -2.886580e-15  1.804112e-15
```

As the spectral representation is exact, if we predict forward in time we obtain a repeat of the time series (Figure 4)

```
## set up another "cycle"
plot(y, type = "l", xlim = c(0, 2 * n), bty = "l")
```

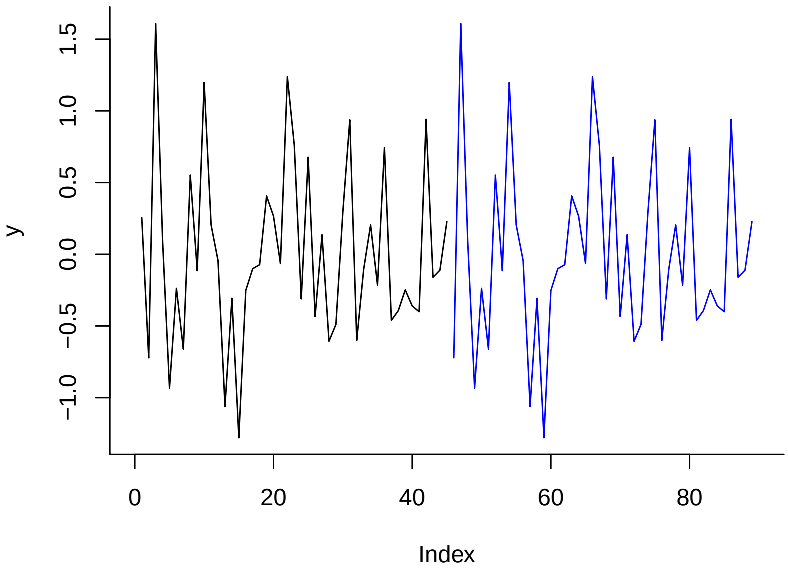


Figure 4: Prediction illustrating that the function repeats exactly under the raw periodogram.

```
t_new <- seq(n+1, 2 * n - 1)

cos_x <- sapply(freq, function(f){cos(2 * pi * f * t_new)})
sin_x <- sapply(freq, function(f){sin(2 * pi * f * t_new)})

y_pred <- c(cos_x %*% a + sin_x %*% b)

lines(t_new, y_pred, col = "blue")
```

We need an approach to introduce randomness. Here we introduce randomness by sampling the periodogram such that the probability a given frequency is chosen is proportional to its periodogram ordinate (Figure 5).

```
## think about this
p_Iom <- Iom / sum(Iom)

## control number of samples
m <- 50
period_sample <- 1 / sample(freq, size = m, prob = p_Iom, replace = TRUE)
```

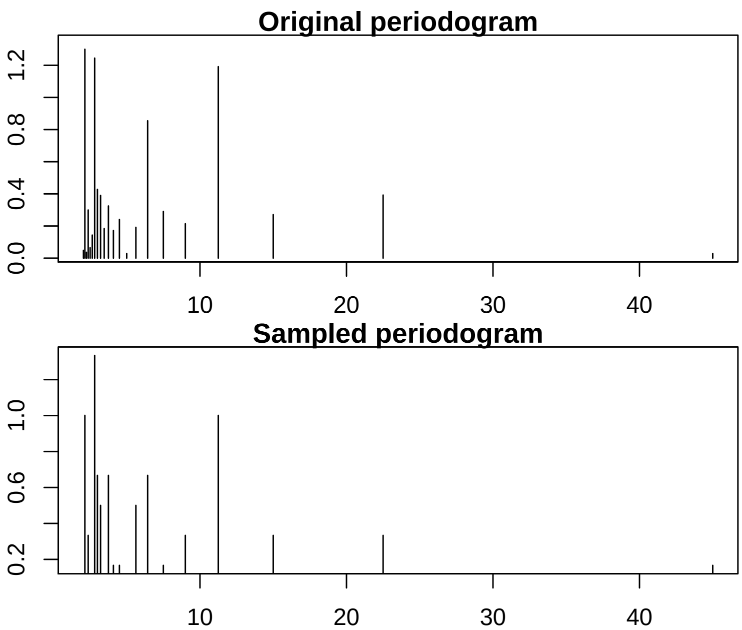


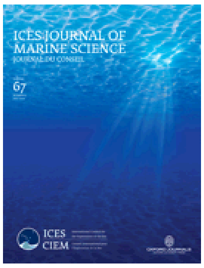
Figure 5: Preliminary sample of periodogram

```
period_sample_tab  <- prop.table(table(period_sample)) * sum(Iom)

par(mfrow = c(2, 1), oma = c(2, 2, 1, 1), mar = c(2, 2, 1, 1))
plot(1/freq, Iom, type = "h", ylim = range(Iom, period_sample_tab),
     main = "Original periodogram")
plot(as.numeric(names(period_sample_tab)),
     as.numeric(period_sample_tab),
     type = "h", main = "Sampled periodogram", xlim = range(1/freq))
```

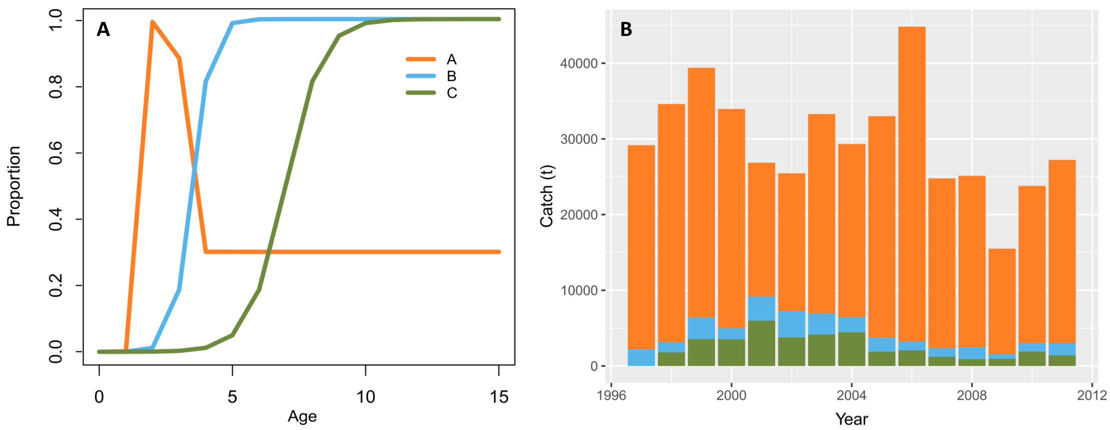
B Peer Review Papers

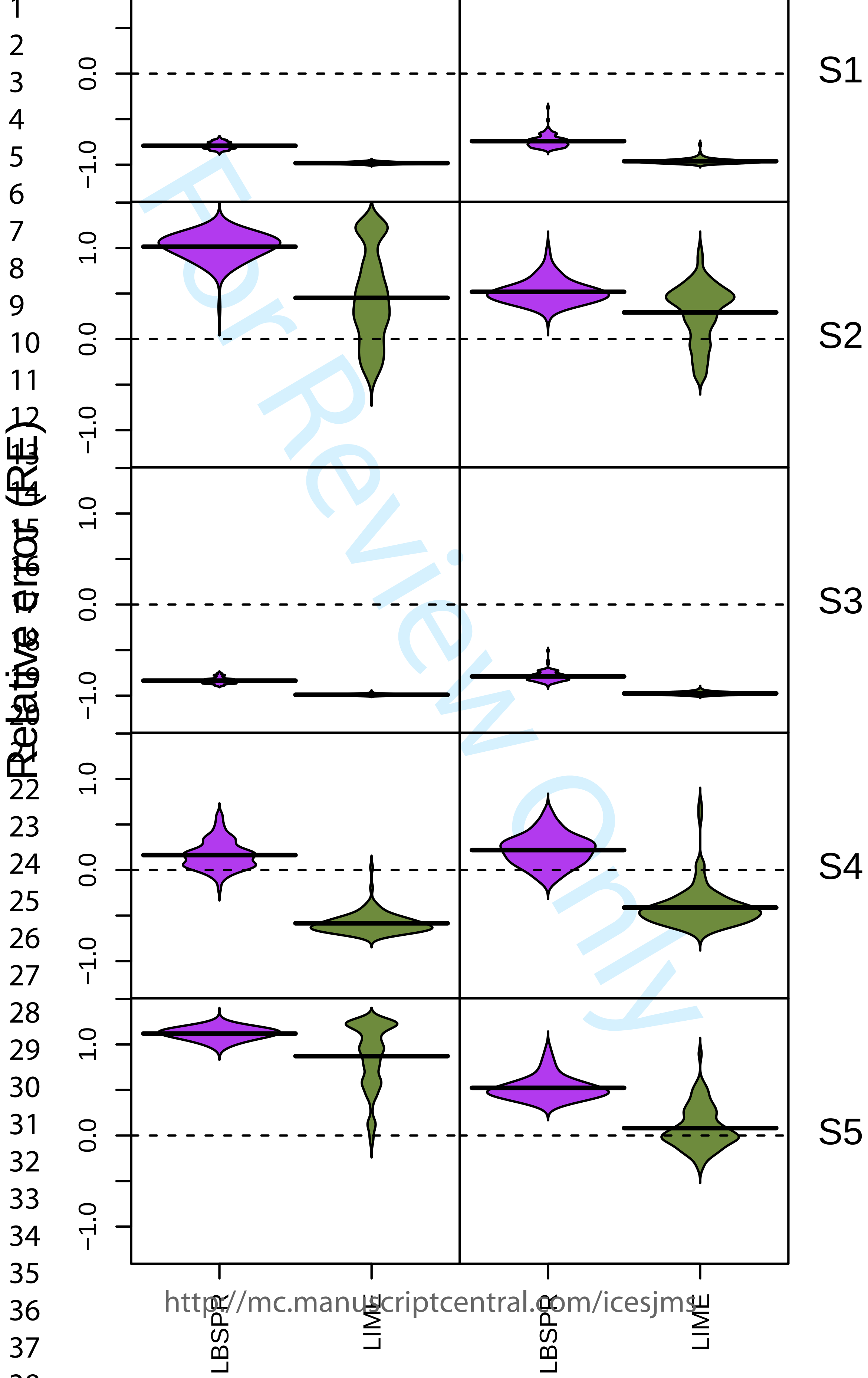
B1 Linking the performance of a data-limited empirical catch rule to life-history traits

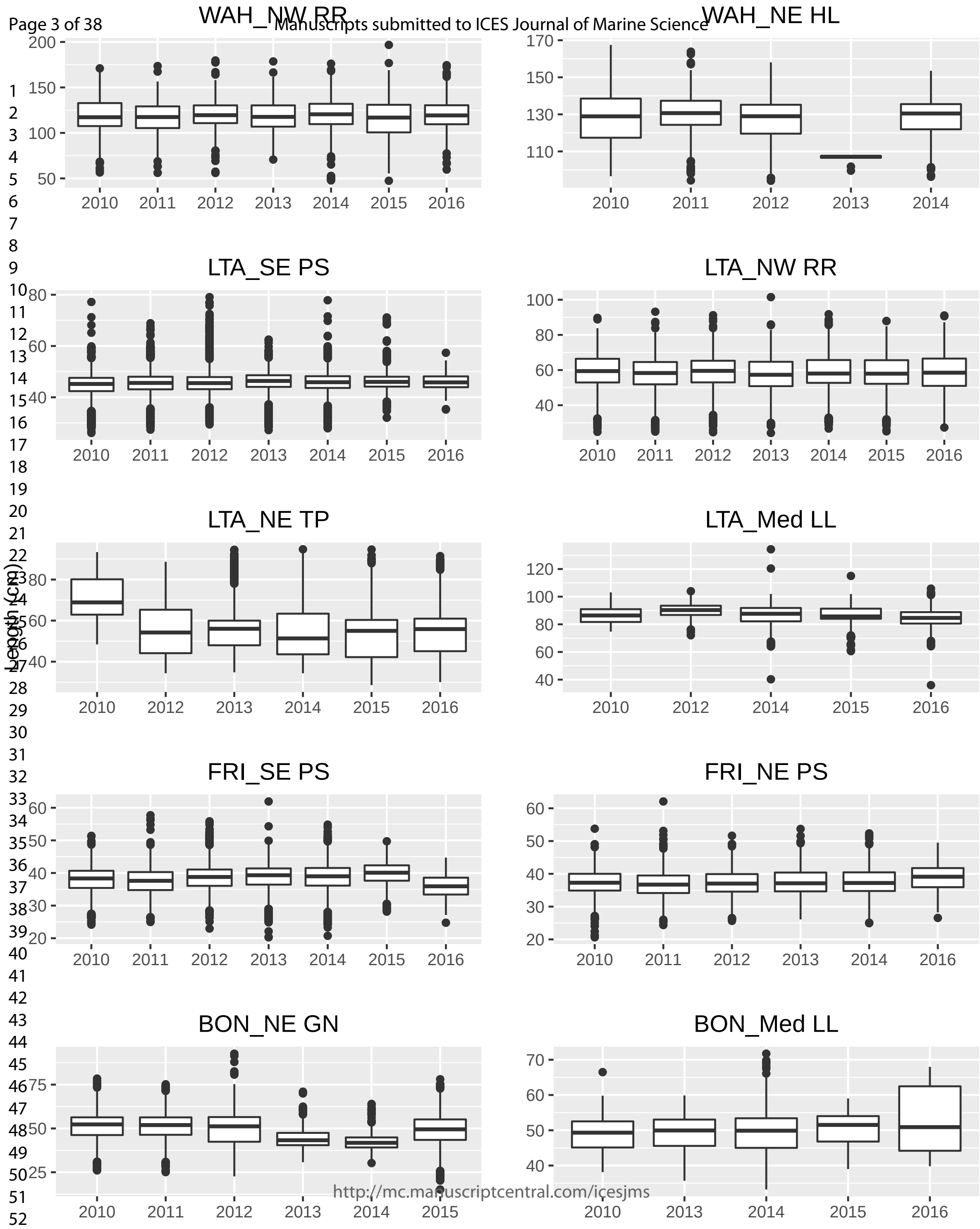


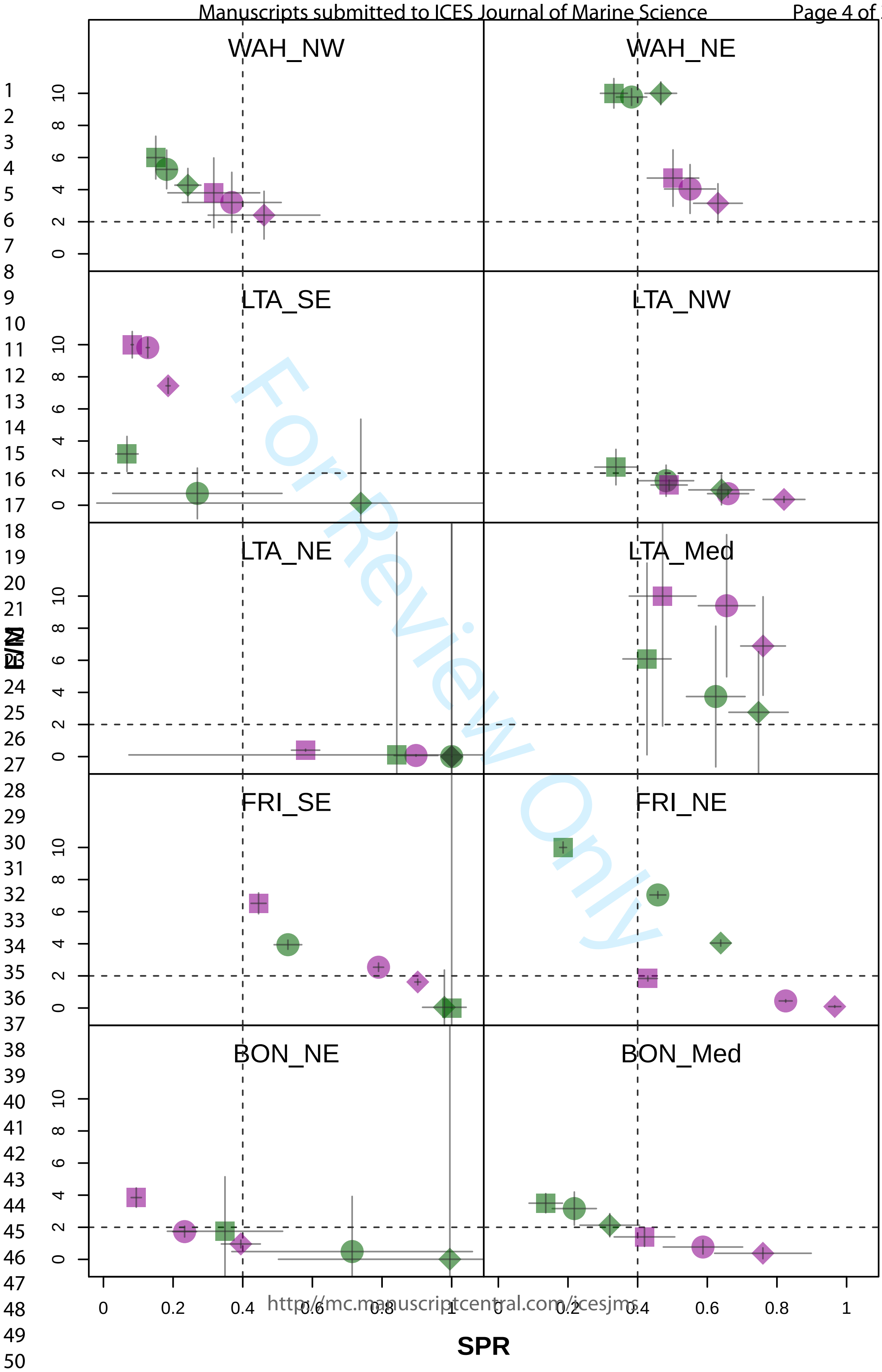
Performance of length-based data-limited methods in a multi-fleet context: application to small tunas, mackerels and bonitos in the Atlantic Ocean

Journal:	*ICES Journal of Marine Science*
Manuscript ID	ICESJMS-2018-485.R1
Manuscript Types:	Original Article
Date Submitted by the Author:	20-Dec-2018
Complete List of Authors:	Pons, Maite; University of Washington, School of Aquatic and Fishery Sciences Kell, Laurence; Imperial College London, Centre for Environmental Policy Rudd, Merrill; University of Washington, School of Aquatic and Fishery Sciences; National Marine Fisheries Service, Northwest Fisheries Science Center Cope, Jason; Northwest Fisheries Science Center, National Oceanic and Atmospheric Administration Fisheries Lucena Frédou , Flávia; Universidade Federal Rural de Pernambuco, Departamento de Pesca e Aquicultura
Keyword:	length based assessments, spawning potential ratio, Scombrids, management


A
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
Age
A
B
C
B
Catch (t)
0
10000
20000
30000
40000
1996
2000
2004
2008
2012
Year


Relative error (RE)
1.0
0.0
−1.0
S1
S2
S3
S4
S5
LBSPR
LIME
LBSPR
LIME


WAH_NW RR
WAH_NE HL
LTA_SE PS
LTA_NW RR
LTA_NE TP
LTA_Med LL
FRI_SE PS
FRI_NE PS
BON_NE GN
BON_Med LL
Length (cm)
2010
2011
2012
2013
2014
2015
2016


WAH_NW
WAH_NE
LTA_SE
LTA_NW
LTA_NE
LTA_Med
FRI_SE
FRI_NE
BON_NE
BON_Med
F/M
SPR
0
0.2
0.4
0.6
0.8
1
0
2
4
6
8
10

Supplementary information: ICES Journal of Marine Science, 76

Performance of length-based data-limited methods in a multi-fleet context: application to small tunas, mackerels, and bonitos in the Atlantic Ocean

Maite Pons, Laurence Kell, Merrill B. Rudd, Jason M. Cope, and Flávia Lucena Frédou

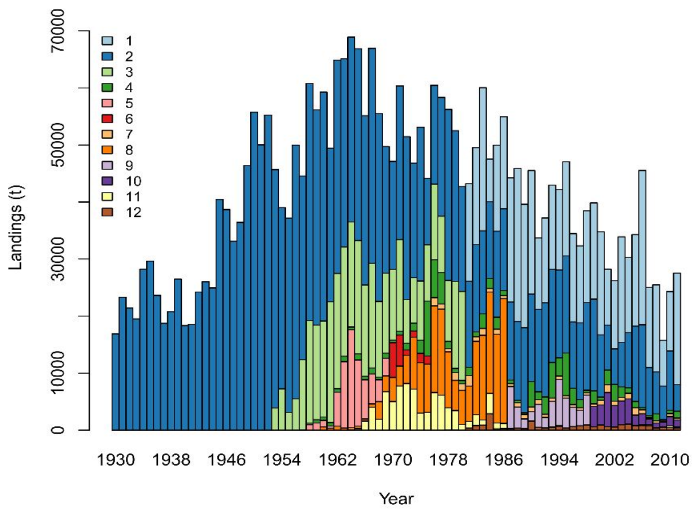


Figure S1. Catch of North Atlantic albacore by fleet from 1930 to 2011. Fleets 1–12 were defined in the 2013 stock assessment performed by ICCAT (see the ICCAT, 2014 report for more details).

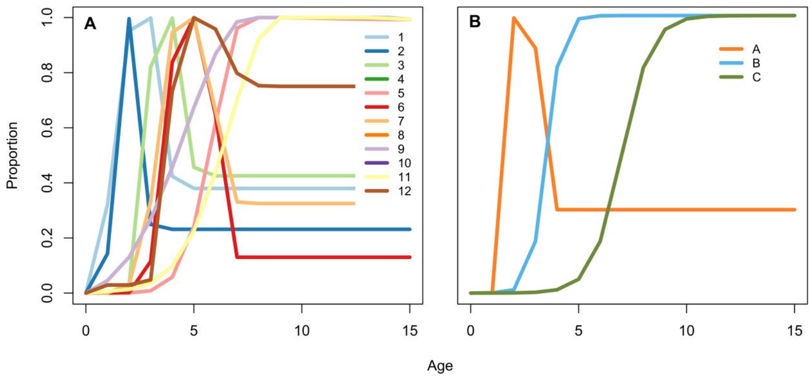


Figure S2. Selectivity curves. (a) The 12 selectivity curves used in the 2013 North Atlantic albacore assessment (fleets 10 and 11, 8 and 9, and 4 and 12 have the same selectivity pattern). (b) Combined selectivity curves to test under the different scenarios for the fleets that operated in the last 15 years (fleets A–C). Label the two curves as (a) and (b), not A and B.

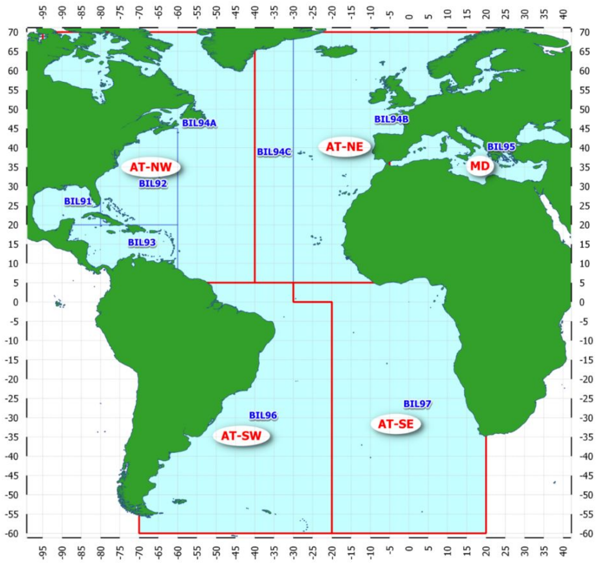


Figure S3. ICCAT geographical definitions (Version: 2016.02) for small scombrids. Taken from: http://iccat.es/Data/ICCAT_maps.pdf.

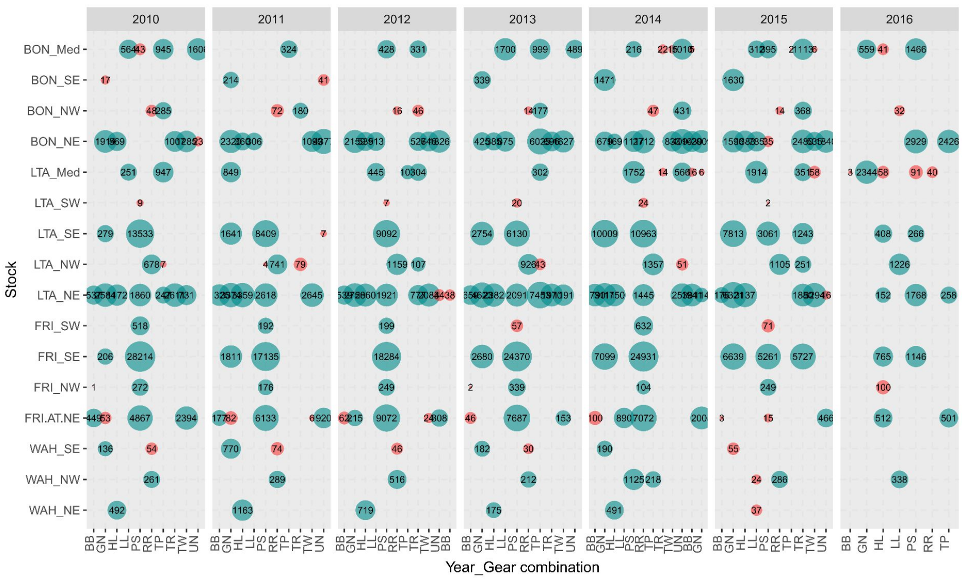


Figure S4. Number of fish measured by stock, year, and gear during 2010–2016. The size of the bubbles is proportional to the logarithm of the number of fish measured, and the number is inside the bubble. Bubbles where the number of fish measured is less than 100 are in red. Gears: gillnet (GN); handline (HL); longline (LL); purse-seine (PS); trap (TP); trolling (TR); trawl (TW); sport (SP); baitboat (BB); rod and reel (RR); haulseine (HS); trammelnet (TN); unclassified (UN).

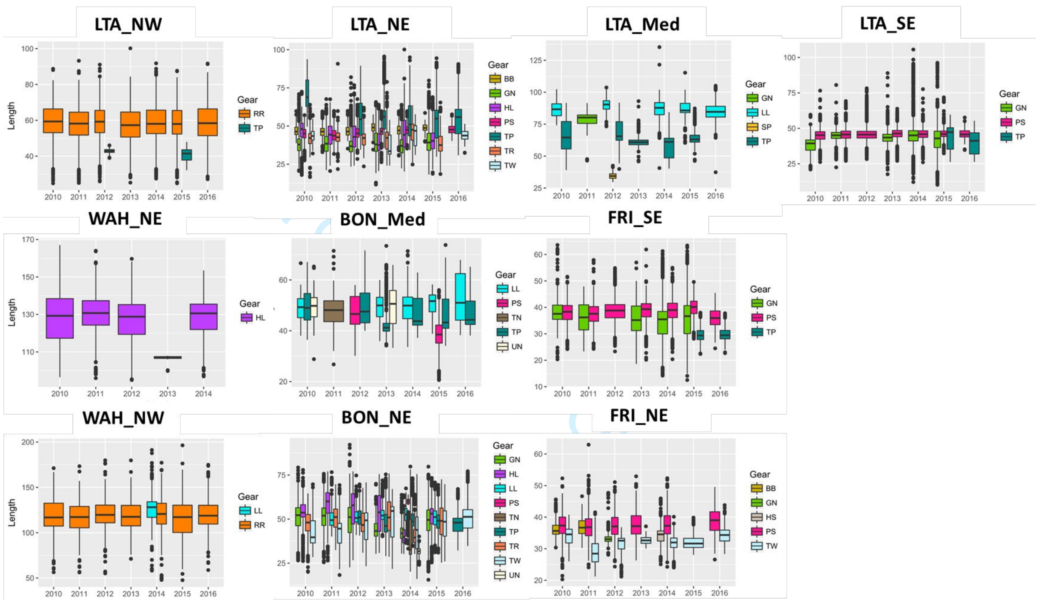


Figure S5. Length composition data for the main stocks of small scombrids by gear in the Atlantic Ocean available in Task2sz database of ICCAT. LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. BB, bait boat; GN, gillnet; HL, handline; HS, haulseine; LL, longline; PS, purse-seine; RR, rod and reel; SP, sport; TN, trammerlnet; TP, trap; TR, trolling; TW, trawl; UN, unknown. NE, Northeast; SE, Southeast; NW, Northwest, and Med, Mediterranean Sea.

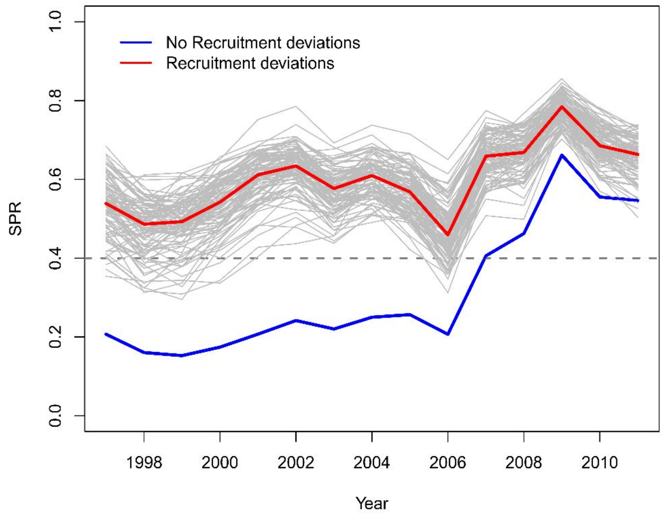


Figure S6. Time-series of the true SPR for the two OM (with and without recruitment deviations). Grey lines are the SPR time-series for each of the 100 runs with random recruitment deviations.

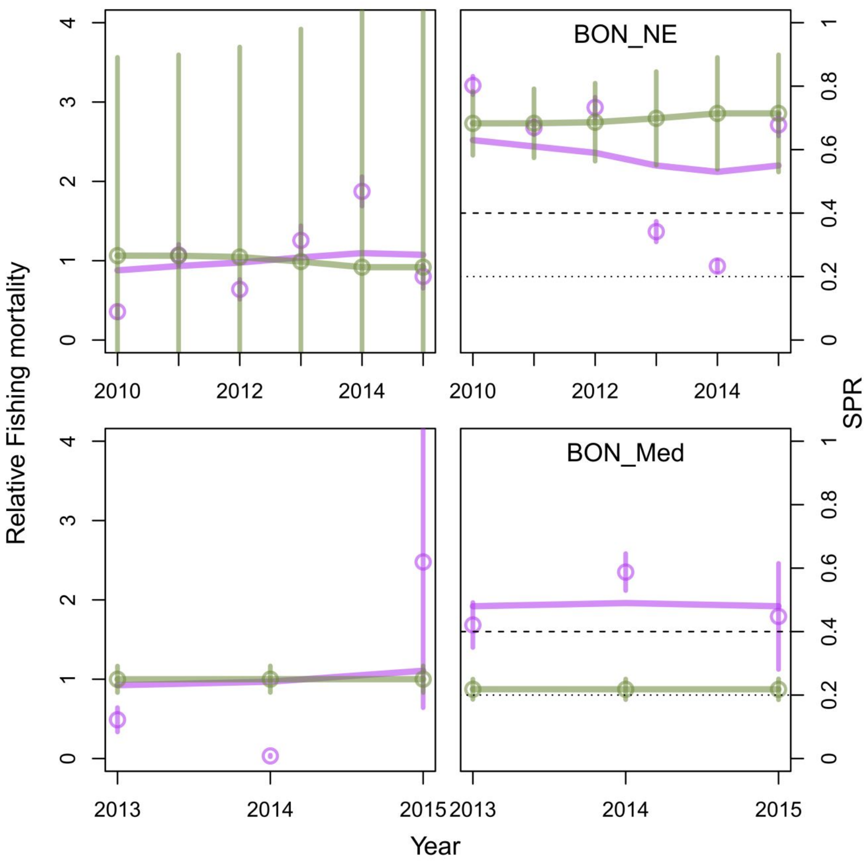


Figure S7. Bonito (BON) estimates of fishing mortality and SPR in the Northeast (NE) Atlantic and in the Mediterranean Sea (Med). Estimates from LIME are in green, and estimates from LBSPR are in purple. Bars represent standard deviation of the estimates.

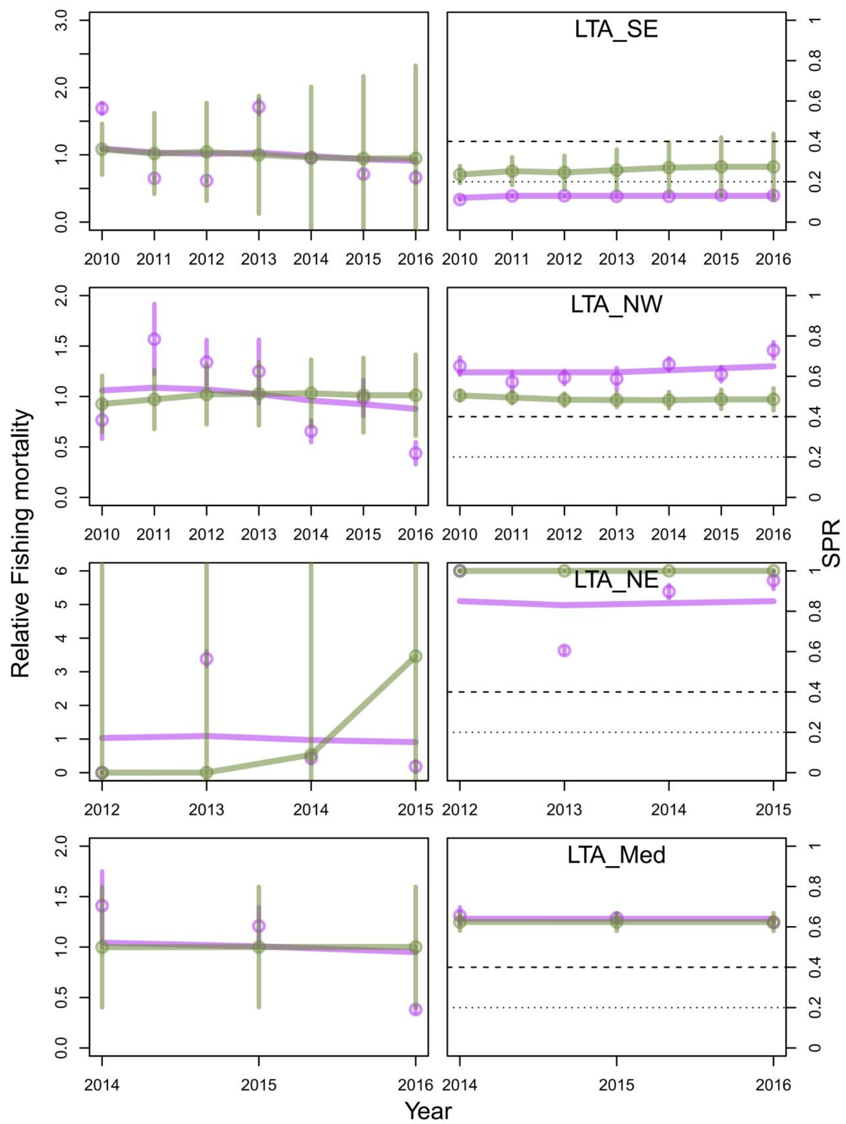


Figure S8. Little tunny (LTA) estimates of fishing mortality and SPR in the Southeast (SE), Northwest (NW), and Northeast (NE) Atlantic Ocean and in the Mediterranean Sea (Med). Estimates from LIME are in green, and estimates from LBSPR are in purple. Bars represent standard deviation of the estimates.

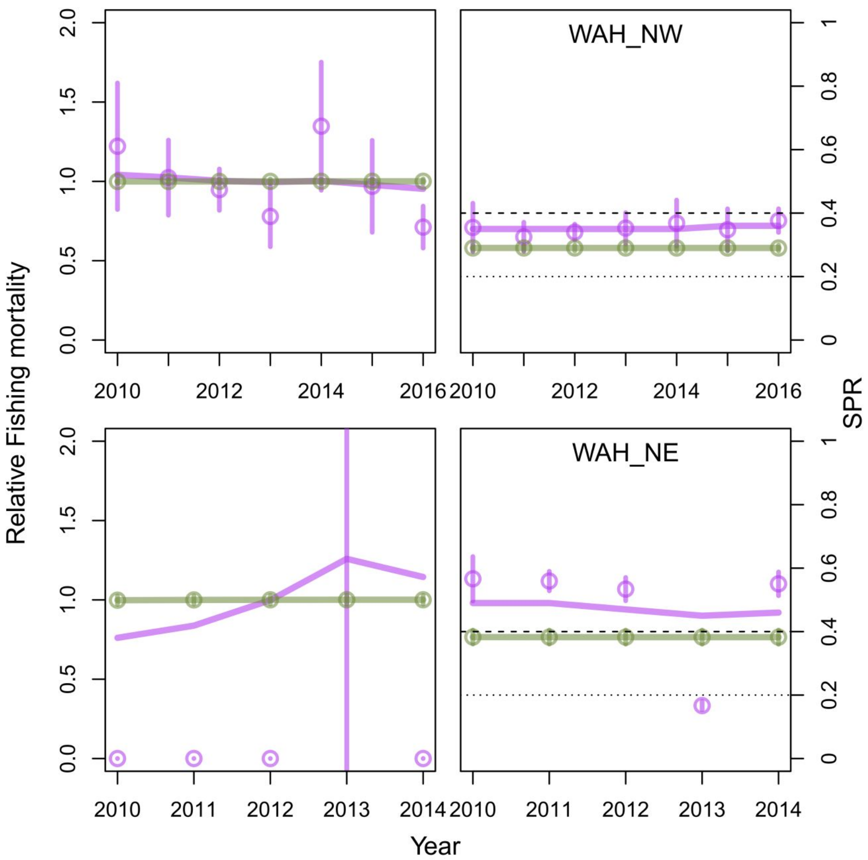


Figure S9. Wahoo (WAH) estimates of fishing mortality and SPR in the Northwest (NW) and Northeast (NE) Atlantic Ocean and in the Mediterranean Sea (Med). Estimates from LIME are in green, and estimates from LBSPR are in purple. Bars represent standard deviation of the estimates.

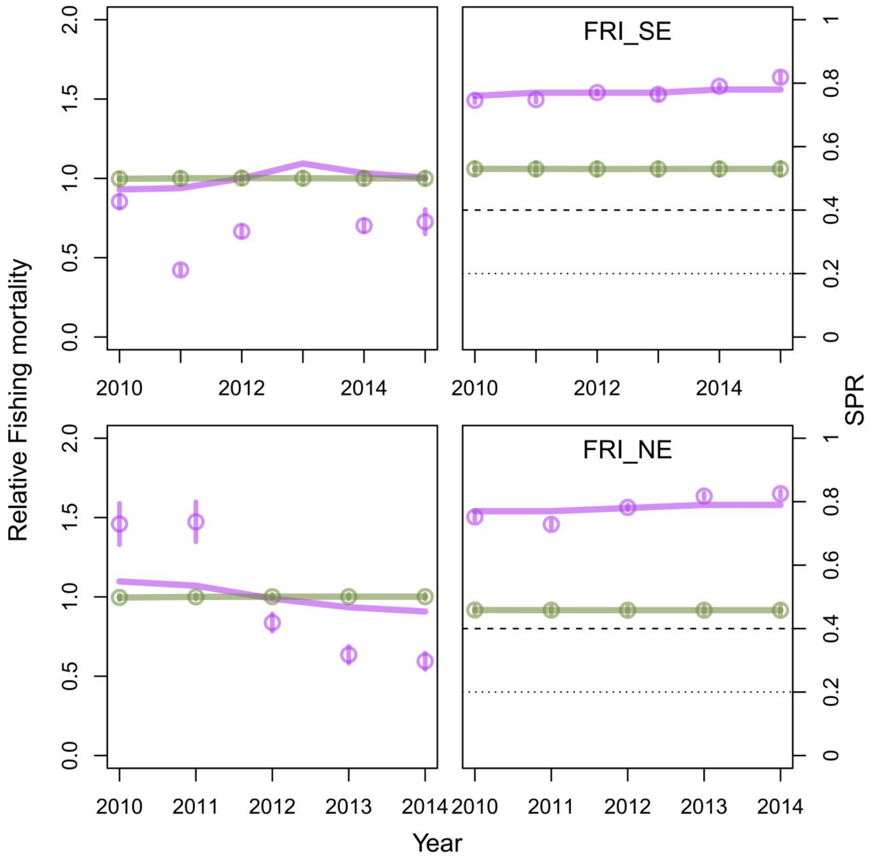


Figure S10. Frigate tuna (FRI) estimates of fishing mortality and SPR in the Southeast (SE) and Northeast (NE) Atlantic Ocean. Estimates from LIME are in green, and estimates from LBSPR are in purple. Bars represent standard deviation of the estimates.

Table S1. 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

Table S2. 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

Table S3. We run the OMs under perfect equilibrium conditions and three different scenarios using one fleet: (i) fish selected before maturing; (ii) fish selected at the length at maturity; and (iii) fish selected after maturing. A large sample size of 12 000 individuals was used. It seems that a persistent bias exists for both assessment methods compared with the OM, particularly for LIME in all cases and LBSPR except when fish are selected before maturing. LIME underestimates SPR for this species (albacore tuna), particularly when individuals are selected by the fishery before maturing. LIME also overestimates selectivity. LBSPR, however, is unbiased when fish are selected by the fishing gear before maturing and positively biased when fish are caught after maturing. For LBSPR, selectivity values are very close to the real values. These results under perfect equilibrium conditions help to understand biases in performance by both methods when different OMs are used.

Scenario	Year	SPR_OM	SPR_LBSPR	SPR_LIME	S_{50}_OM	S_{95}_OM	S_{50}_LBSPR	S_{95}_LBSPR	S_{50}_LIME	S_{95}_LIME
i	Last year	0.42	0.41	0.09	78	86	77	91	81	89
ii	Last year	0.42	0.56	0.16	90	96	89	103	95	99
iii	Last year	0.42	0.68	0.21	101	108	96	112	113	125

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Performance of length-based data-limited methods in a multi-fleet context: application to small tunas, mackerels, and bonitos in the Atlantic Ocean

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Large scombrids, commercial tuna species, are regularly assessed and managed. However, most of the small scombrids, many mackerels and bonitos, lack accurate catch data to implement traditional stock assessments despite their economic importance in many small-scale fisheries. In this study, we analyzed different approaches using length composition data from multiple fleets with different gear selectivity to assess small scombrids in the Atlantic Ocean. Using simulated populations, we compared two length-based methods [length-based spawning potential ratio (LBSPR) and length-based integrated mixed effects (LIME)], under different length data grouping scenarios. We found that using length data from the fleet targeting the broadest range of sizes resulted in the lowest bias in spawning potential ratio of all options tested. Based on these results, we used biological and length data to estimate a quantitative proxy of current stock status for ten small scombrid stocks in the Atlantic Ocean. We found that some small scombrid stocks are likely to be overfished, such as little tunny (*Euthynnus alletteratus*) in the Southeast Atlantic and wahoo (*Acanthocybium solandri*) in the Northwest Atlantic. This is a starting point in the estimation of stock status for these species, but should not be thought of as a replacement for other more data-intensive assessment techniques. Instead, the framework developed should be used to help identify the data and knowledge needed to improve the sustainable utilization of these species.

Introduction

For the "principal market tunas", like Southern (*Thunnus maccoyii*), Pacific (*T. orientalis*), and Atlantic bluefin (*T. thynnus*), bigeye (*T. obesus*), yellowfin (*T. albacares*), albacore (*T. alalunga*), and skipjack (*Katsuwonus pelamis*), 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, Spanish mackerels and bonitos" (from now on "small scombrids"), that account for a notable proportion of the total tuna and tuna-like species catch and 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 that of the principal market tunas (Collette *et al.*, 2011), they sustain important regional commercial fisheries in many coastal communities throughout their distributions (Majkowski, 2007). Juan-Jordá *et al.* (2011) showed that within the Scombridae family, the fastest declines in biomass are exhibited not only for the largest, longest-lived, most valuable tunas, but also for a few smaller, short-lived mackerels. Also, some small Scombridae stocks in the Atlantic Ocean were assigned as "moderate to high risk" of being overfished or subject to overfishing in a recent qualitative risk assessment, even if they have not been formally assessed in recent years (Lucena-Frédou *et al.*, 2017a).

Total catch is one of the main data sources required for most classical stock assessment methods, particularly when estimating 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. Available catch data usually consist of incomplete catch time-series from tuna regional fisheries management organizations (tRFMO) statistics and from 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 to infer the exploitation status of the stocks (Chrysafi and Kuparinen, 2016; Dowling *et al.*, 2016). In 2017, Lucena-Frédou *et al.* (2017b) 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 the highly targeted *Sarda sarda* (bonito) and *Auxis thazard* (frigate tuna). This 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. In addition, qualitative risk assessment methods have been questioned recently since their performance is poor under a wide range of conditions (Hordyk and Carruthers, 2018).

The International Commission for the Conservation of Atlantic Tunas (ICCAT) suggested that length composition of the catch available in the ICCAT database should be used to quantitatively assess the status of these species and inform management advice (ICCAT, 2017). In fisheries without total catch data or information on relative or absolute abundance, stock assessments typically use the spawning potential ratio (SPR) as an alternative reference point to the biomass at maximum sustainable yield (B_{MSY}). SPR can be expressed in terms of spawning stock biomass per recruit (SSBR), which is often defined as the expected lifetime reproductive potential of an average recruit. SPR then is the ratio of the fished SSBR to the unfished SSBR under equilibrium conditions (Goodyear, 1993). SPR has been recommended for data-limited assessment because it can be estimated using only biological information and length data (Brooks *et al.*, 2010).

There are several methods that use life history information and length composition from the catch to estimate fishing intensity and derive values of SPR that can be used as a proxy for stock status. One of them is length-based spawning potential ratio (LBSPR, Hordyk *et al.,* 2015). This method uses the Beverton–Holt life history ratios in an equilibrium-based population model applying the shape of the length composition data compared with the expected unfished length structure to estimate the ratio of fishing mortality and natural mortality (*F/M*) and derive SPR. Another new method is the length-based integrated mixed effects model (LIME, Rudd and Thorson, 2018), that also requires biological information and length composition data to derive SPR, but relaxes the equilibrium conditions by treating recruitment as a random effect over time and estimating annual *F* as fixed effects (Rudd and Thorson, 2018). Both methods can be implemented in *R* (Hordyk, 2017; R Core Team, 2017; Rudd, 2018).

Data-limited, length-based stock assessment methods typically assume selectivity is asymptotic by default (Hordyk *et al.*, 2015; Rudd and Thorson, 2018). If large fish are absent from the catch, logistic selectivity models assume that they do not exist in the population (as opposed to being present in the population, but evading the fishing gear). The logistic selectivity assumption is usually violated in highly size-selective fisheries (i.e. gillnets), and it could be problematic in multifleet 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 pole and line fisheries which have dome-shaped selectivity, catching mainly juvenile albacores. 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, 2014). These different selectivity patterns, catches, and indices of abundance are included in complex assessment models that allow for multiple fleet interactions in the formal assessment performed regularly by ICCAT. When fitting only to the length composition of a proportion of the catch, assumptions regarding fishery dynamics, particularly the shape of the selectivity curve, need to be carefully analyzed.

The main objective of this study is to determine the current stock status of small scombrids in the Atlantic Ocean. However, the only data available to evaluate these populations are limited biological information and length composition of the catch coming from different fleets with different selectivity patterns. Therefore, before applying any length-based assessment, we need to determine how to combine these length data to obtain an unbiased estimate of fishing intensity. Developing best practices for combining length data across multiple fleets for length-based assessments of small scombrids in the Atlantic Ocean thus becomes a critical challenge to face in order to estimate stock status. To address this challenge and meet the main objective, we used simulation testing to evaluate the performance of LBSPR and LIME by combining length composition data of the catch from multiple fleets with different selectivity patterns. Using conclusions from the simulation, we applied both length-based approaches to estimate a proxy of stock status for the priority small scombrid species determined by ICCAT (ICCAT, 2018).

Methods

First, we compared the performance of two length-based methods using a simulation study based on North Atlantic albacore. Then, based on the insight about the robustness of the methods, we estimated stock status for the small tuna stocks.

Simulation study

We chose the North Atlantic albacore stock on which to develop an operating model (OM) to simulate resource dynamics in order to evaluate the performance of the different assessment methods. ICCAT, in the 2017 report of the small tunas species group intersessional meeting

(ICCAT, 2017), suggested the North Atlantic albacore stock as a good example of a multifleet fishery to use for simulation purposes, where the selectivity patterns are considered well estimated for 12 different fleets (ICCAT, 2014). This stock is targeted by pole and line, troll, longline, and other surface gears in the Atlantic Ocean.

In the next sections, we describe the data and specifications used in the OM, the estimation models (EM), namely LBSPR and LIME, and how we measured their performance under different scenarios.

Operating models

Input data

We extracted the catch time-series (Figure S1 in the Supplementary material), selectivity patterns from 12 different fleets (Figure S2 in the Supplementary material), and the biological parameters (Table 1) from the formal assessment performed by ICCAT in 2013 for North Atlantic albacore (ICCAT, 2014) to use for the OM. For simplicity and based on similarity of selectivity patterns (Figure S2 in the Supplementary material), we combined some fleets using an average age-specific selectivity: (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 S2 in the Supplementary material). During the last 15 years only, the three fleet combinations mentioned earlier were still operating plus fleet 7, which is a longline fleet that captures less than 1% of the total catch. Eighty-seven percent of the total catch corresponds to the fleets' bait boat and troll fisheries (A), 6% longline (C) and 7% other surface gears with same selectivity (B) (Figure 1).

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). The depletion value was arbitrarily selected to mimic the current depletion of the North Atlantic albacore population. All parameters were fixed, except the average recruitment in the unfished state (R_0). We assumed a Beverton–Holt spawner-recruit function (Beverton and Holt, 1957; Methot and Wetzel, 2013). We simulated two populations, one with and one without recruitment deviations in order to verify if the outputs were different between the estimations models since LIME specifically estimates recruitment.

Fishing intensity in SS was 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). Single estimates of fishing mortality rates (F) were calculated for all gears combined in stock synthesis. LBSPR and LIME (see the estimation models section) assume a single gear, so the F estimates represent the F as covered by the stock sampled. SS calculates the SPR 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 SS to generate the OM, 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 transition matrix output from SS to assign a distribution of length at each age (Table S1 in the Supplementary material). Summing across each length bin by gear gave us the length distribution of the catch. We used a 2-cm length bin, which corresponds to the bin structure applied in the formal ICCAT assessment (ICCAT, 2014). In order to analyze different length sampling scenarios, we sampled 100 individuals from the catch by year and fleet 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. We chose to sample only 100 individuals because no big differences in the results were found when using a larger sample size (i.e. 1000 and 10 000 individuals), just a small reduction in variance (see Pons, 2018).

Scenarios

A common question that arises with length data from multifleet fisheries with different selectivity patterns is which fleets to use and how to combine data 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". The single fleet could actually be one selected fleet or multiple fleets combined in some way. In all scenarios, the selectivity for this one fleet was estimated and starting values were the same for each model run. We explored five possible scenarios:

- Scenario 1: Length composition sampled proportional to the catch of each fleet (Figure 1). 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 has a dome-shaped selectivity (Figure 1a) where the true S_{50} is 57 cm (~ age 1.5) and S_{95} is 61 cm (~ age 2). It was modeled in SS with a double normal distribution with 6 parameters. This fishery catches mainly juveniles and it is the main fishery for North Atlantic albacore in terms of catch (Figure 1b).
- Scenario 4: Only use length data from the fleet that targets a broad range of lengths (fleet B). Fleet B has an asymptotic selectivity 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 1a). In terms of catch, this fleet resents a small proportion of the total (Figure 1b).
- 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 (Figure 1b), but is a longline fishery that targets mainly adults with a true S_{50} of 100 cm (~ age 7) and a S_{95} of 108 cm (~ age 9) (Figure 1a).

Estimation models

In LBSPR, SPR in an exploited population is a function of the ratio of fishing mortality to natural mortality (*F/M*), selectivity 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.*, 2015). 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 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.*, 2015). LBSPR estimates a selectivity curve for each length sample. Estimates of SPR are primarily determined by the length of the fish in a sample, relative to the maturity and L_∞. For example, if a reasonable proportion of fish in a sample attain lengths approaching $L_{\infty,}$ estimates of *F/M* will be relatively low leading to a high estimate of SPR. However, the proportion of length samples near L_∞ will vary with the life history parameters such as fecundity-at-age/length and selectivity. 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) constant recruitment (Hordyk *et al.*, 2015). In this study, we used LBSPR package version 0.1.2 in R (Hordyk, 2017). The LBSPR package uses the Rauch–Tung–Striebel smoother function to smooth out the multiyear estimates of SPR (Hordyk, 2017), and these smoothed values were used for comparisons with the OM.

LIME is an integrated, age-structured model which requires, as input, biological information such as growth, natural mortality, and maturity, and, at minimum, one year of length composition data. LIME estimates, as fixed effects, annual fishing mortality rates *F*, S_{50}, and S_{95}, the recruitment standard deviation, and a Dirichlet-multinomial parameter governing the relationship between the nominal and effective sample size of length measurements. LIME has most of the same assumptions as LBSPR, but LIME does not assume equilibrium conditions when recruitments can be estimated (i.e. more than one year of length data). LIME extends length-based methods by deriving time-varying recruitment deviations (Rudd and Thorson, 2018) using automatic differentiation and Laplace approximations (TMB) (Kristensen *et al.*, 2015) to calculate the marginal likelihood for the random effect on recruitment. Using the assumed biological information, recruitment deviates, estimated *F*, and estimated selectivity, LIME calculates the predicted abundance-at-age over time. To predict length composition of the catch, LIME calculates the predicted probability of being captured at age over time, the probability of being in a length bin given age, and then the probability of being captured in each length bin. LIME fits the predicted length composition to the observed length composition using the Dirichlet-multinomial likelihood function. In addition to the length composition marginal likelihood, the joint negative log likelihood also includes a penalty on the fishing mortality rate to avoid varying unrealistically between years and the likelihood of the random effect of annual recruitment deviations. 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).

Performance measures

The performance of the EMs under different scenarios was compared with the simulated "truth" from the OM 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.

Assessment of small scombrids in the Atlantic Ocean

Little tunny, bonito, wahoo, king mackerel, and frigate tuna have been identified as priority to be evaluated by ICCAT in 2017 (ICCAT, 2017). In the present study, the only species that we did not evaluate was king mackerel. In the Southwest Atlantic, there is no good information on length data to evaluate this stock; in the Northwest Atlantic, it 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, 2014b). According to these reports, neither stock of king mackerel in the Northwest Atlantic is currently overfished nor undergoing overfishing.

None of the other four species of small scombrids have studies defining stocks boundaries in the Atlantic Ocean. 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 (Figure S3 in the Supplementary material). Hence, we decided to use these areas as proxies for stock boundaries to assess these putative "stocks".

The ICCAT database (http://iccat.es/en/accesingdb.htm) has length data from 1975 to 2016 for the four priority species assessed in this study. The length composition data available for each stock come from different regions and different gear types. 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 S4 in the Supplementary material). We used the length data reported in 1- and 2-cm bins and 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 (Figure S4 in the Supplementary material). We presented the stock status for the year 2014 where there are more length data and are consistent among species and representative of different gears.

For some stocks, the length data available were limited, so we removed samples numbering fewer than 100 fish per year and gear combination (Figure S4 in the Supplementary material). Some stocks, such as wahoo in the Southwest Atlantic, 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 Southeast, 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 (Figure S5 in the Supplementary material, Table 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.*, 2015; Rudd and Thorson, 2018). In 2018, the ICCAT small tunas working group met, and a set of life history parameters were agreed among scientists from each region in the Atlantic Ocean for each stock to run data-limited methods (ICCAT, 2018, Table S2 in the Supplementary material). There are many gaps in the life history information available for these species. In cases where there was missing information, we borrowed information from the nearest stock of that species (i.e. when missing information existed for the Southeast Atlantic, we borrowed the information from the Northeast Atlantic) to run the length-based models.

Table 2 shows the final parameters used for each stock to run LBSPR and LIME. Natural mortality (*M*) was calculated using a suite of empirical life history-based methods (Cope, 2017, see http://barefootecologist.com.au/shiny_m). We used nine empirical methods that used growth parameters ($L\infty$, k, t_0, and maximum age). Four of these methods are described in Then *et al*. (2015), two in Jensen (1996), and the other three in Alverson and Carney (1975), Chen and Watanabe (1989), and Jensen (1997), respectively. Table 2 shows the median and first and third 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 these parameter estimations.

Reference points for small scombrids

We used SPR as a biological reference point. In general, it is used as a proxy for B_{MSY} when information on the scale population size is not available. A harvest strategy that targets a fishing mortality rate that is expected to result 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% SPR is sometimes considered a threshold beyond which overfishing would be occurring (Clark, 2002; Nadon *et al.*, 2015; Rudd and Thorson, 2018). In addition, we presented the estimated ratio *F/M* for each stock.

Results

Simulation testing: length data in multifleet 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; for the OM that includes random recruitment deviations, the median was 0.66, with a range 0.50–0.74 (Figure S6 in the Supplementary material). LBSPR was least biased when using length data from the fleet with asymptotic selectivity catching a broad range of lengths from juveniles to adults (Scenario 4; Figure 2). LIME was least biased with length data from the fleet that targets only adults when considering recruitment variability (Scenario 5; Figure 2). In the Supplementary information, we presented potential biases in the estimation models compared with our OMs under perfect equilibrium conditions. It seems that a persistent bias exists for both assessment methods compared with the OM, except for LBSPR when fish are selected before reaching the length at maturity. In general, LIME underestimates SPR for this species (North Atlantic albacore), particularly when individuals are selected by the fishery before maturing. LIME also overestimates selectivity most of the time, but is less biased when adults are present in the samples. LBSPR is slightly positively biased only when the sampled individuals are above the size at maturity (Table S3 in the Supplementary material).

In Scenario 1, length composition data was weighted by the fleet's proportional catch, meaning that more weight was given to the fleet with dome-shaped selectivity. In this scenario, both LBSPR and LIME underestimated SPR on average in both recruitment scenarios (Figure 2). 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 SPR lower than the truth. LIME estimated SPR to be almost zero. 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.

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 biased, although LIME was less biased, but less precise. Under these scenarios, the proportion of large individuals in the catch was overrepresented, 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 due to the proportions of large individuals in the catch. However, as was shown under perfect equilibrium conditions (Table S3 in the Supplementary material), LIME tends to be less biased when large individuals are in the samples.

LBSPR was less biased in Scenario 4 when considering only the fleet with an asymptotic selectivity that captures a broad range of sizes (from juveniles to adults), 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 2). We observed that, in many cases, even under equilibrium conditions (Table S3 in the Supplementary material), LIME estimated higher selectivity parameter values, S_{50} and S_{95}, and lower SPR values than LBSPR. This is probably the reason why LIME performs better when using fleets that target large fish and why LIME SPR estimates are lower than LBSPR SPR estimates when using the same data.

Assessments of small scombrids in the Atlantic Ocean

Based on simulation testing, none of the scenarios produced the best performance for both estimation models (LIME and LBSPR) simultaneously. 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, where mainly adults were represented in the catch. So, 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, but not restricted to the adult portion of the catch. The gears used then varied among small tuna stocks (Figure 3).

The length composition data for each stock by gear, filtered by year–gear combinations with at least 100 length measurements, varies among areas. These differences likely stem from variable fleets operations in each region. Length composition data for little tunny are available for two gears in the Northwest Atlantic, but rod and reel has more representative sampling by year and length range compared with traps (Figure S5 in the Supplementary material). In this case, we used length data only from rod and reel to assess this stock (Figure 3). 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; for the Southeast Atlantic, we used data from gillnets (Figure S5 in the Supplementary material, Figure 3). For wahoo in the Northeast, we used the length composition from handlines since it was the only information available; we used rod and reel data for the Northwest. For bonito in the Mediterranean, we used length data coming from longlines, such as for little tunny in the same area. Finally, for frigate tuna in the Northeast and Southeast, we selected the length data coming from purse-seine fisheries (Figure S5 in the Supplementary material, Figure 3).

For some small scombrid stocks, the SPR estimates were below the target of 40%, but the results varied between assumptions about M and the estimation method considered (Figure 4). LBSPR and LIME predicted different values of SPR; the estimated values were sometimes 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 higher *F* and lower SPR than LBSPR (Figure S7 in the Supplementary material). In contrast, for bonito in the Northeast, LIME estimated a higher selectivity ogive, lower *F*, and higher SPR than LBSPR. For 2014, LIME estimated high recruitment; 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* (Figure S7 in the Supplementary material). As expected, when *M* was assumed to be lower than in the base case scenario (median *M*), the SPR estimations were lower (Figure 4).

SPR for little tunny in the Southeast was below 0.40 in all cases, except when LIME assumed a high *M*, which resulted in a SPR estimate of 0.70 (Figure 4). Assuming the median value of *M*, LBSPR predicted a very high *F* and SPR values below 0.20 for the entire time-series. LIME also predicted low SPR values, around 0.30, and a much lower S_{50} than LBSPR (Figure S8 in the Supplementary material). The results of LBSPR and LIME were more similar for little tunny in the Northwest, Mediterranean, and Northeast Atlantic (Figure S8 in the Supplementary material). SPR for these stocks were above the 40% target reference point. For little tunny in the Mediterranean, the ratio 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 (Figure S9 in the Supplementary material). None of the frigate tuna stock assessments estimated SPR below 40%, except with LIME in the low *M* scenario where SPR was estimated at ca. 20% for the Northeast and Southeast stocks (Figure 4, Figure S10 in the Supplementary material). Table 3 summarizes the status of the ten small Scombrids stocks assessed under the base-case scenario, considering the median of the *M* distribution.

Discussion

Length data in multifleet fisheries

We showed how stock assessment results could be highly biased when using only one gear that is 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 dome-shaped 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 actual value. Even if the asymptotic selectivity assumption is met (i.e. albacore length data coming from longline fleets targeting adults), SPR was overestimated. Hordyk *et al.* (2015) 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 positively biased when fish are caught after reaching the size at maturity L_{50} (Table S3 in the Supplementary material). In all the scenarios analyzed by Hordyk *et al.* (2015), the S_{50} was lower than the L_{50}, but in our scenarios 5 and 6, the S_{50} was higher than L_{50}, 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 L_{50} and L_{∞}. In our Scenario 4, where the S_{50} was lower than the L_{50}, LBSPR was less biased, as we also showed assuming perfect equilibrium conditions (Table S3 in the Supplementary material).

Rudd and Thorson (2018) tested the performance of LIME under LBSPR's own OM (Hordyk *et al.,* 2015), with relative ages based on the *M/k* ratio. They found that LBSPR performs well across all life history types, but LIME underestimated SPR for the medium- and longer-lived life history types and overestimated 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 albacore tuna. Also, we showed how, even under equilibrium conditions, that different OMs structures can show biases in the performance of the estimation models (Table S3 in the Supplementary material).

Based on our results, we recommend that, when there are multiple fleets with different selectivity patterns targeting one stock, and the length-based estimator assumes asymptotic selectivity, 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. In particular, it is important to include juveniles because SPR estimates improve when the catch length sample is representative of the length composition of the entire exploited population.

Small scombrids stock status

LBSPR estimates of SPR, selectivity parameters, and the ratio of fishing mortality to natural mortality (*F/M*) are independently determined each year. However, LIME includes length composition data available for multiple years in the same model to estimate a single selectivity curve for all years, but fishing mortality and recruitment can vary among years. Therefore, assumptions and model structure are different between LIME and LBSPR, leading, unsurprisingly, to different results on the proxy of the stock status for small scombrids.

We did not find a specific pattern in exploitation status among regions (Figure 4) as regions in the Atlantic Ocean showed comparable stock status. 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 two stocks out of ten are overfished: the 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 and both assessment methods indicated that these stocks are above stock status targets (SPR>0.4). On the other hand, for little tunny in the Southeast, most of the fish caught were below the length at maturity and, in most of the scenarios, this stock was estimated to be overfished. These results agree 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 population was found at moderate risk (Lucena-Frédou *et al.,* 2017b). This species has an estimated maximum age between 8 and 10 years (Cayre and Diouf, 1980) and an estimate of L_{∞} between 86 and 117 cm. Adults of this species (>60 cm) in the Southeast are scarce in the length composition leading to low estimates of SPR. Along with bonito and frigate tuna, this species is one of the most captured among all small scombrids in the Atlantic Ocean (ICCAT, 2018).

Bonito

In the base-case scenario, bonito in the Northeast was estimated to have a SPR below target reference points (SPR<0.4) 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. 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 5 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 based on length samples and catch-curve analysis using lengths converted to age and cohort slicing (Ahmed *et al.*, 2015). Assuming $M = 0.2$, they found that fishing mortality is twice this value and suggested that this stock might be fully exploited. The M values used in the present study were >0.2 in all cases, so using such a low value for M could give similar results as in Ahmed *et al.* (2015). However, for this short-lived species, we assume natural mortality should be >0.2 (as is typical for other short-lived species).

This species is the most captured among all small scombrids (ICCAT, 2018), but the biological information as well as the length composition data available are highly fragmented and variable. Our results should be analyzed with caution; as better data becomes available, these stocks should be re-evaluated. This should be a high priority item for ICCAT.

Frigate tuna

In almost all scenarios, the stocks were estimated to be >40% SPR. However, assessments for the Northeast stock always estimated lower SPR values than for 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 (Lucena-Frédou *et al.,* 2017b). 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. In particular, for LIME, this could indicate an unconverged model (Figure S8 in the Supplementary material). 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 a fishery is occurring. L_∞ might be too low, 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 in order to consider different life history values for this stock.

Wahoo

Both LIME and LBSPR estimated low SPR values for the Northwest stock, suggesting that this stock is overfished. In the Northeast, only LIME in the base case and low M scenarios estimated that this stock is overfished, but not LBSPR. In the South Atlantic, wahoo has been categorized as high risk, and no assessments are available for this stock. This species, along with bonito, should be considered as a priority to assess by ICCAT.

Future directions

We estimated for the first time a proxy of current stock status for ten stocks of the small scombrid group of species in the Atlantic Ocean. This is a very important 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 still needs to support the collection of improved life history information, length data from all fishing gears, and total removals for these stocks and associated fishing data. While collecting such information in small coastal fisheries is challenging, particularly for catch and effort data, it is important to develop indices of abundance. A full assessment might return estimates with higher precision, although it does not mean that it would be more accurate than the estimates provided here. Data collection should focus on filling gaps and improving existing biological information, particularly for stocks such as little tunny in the Southeast Atlantic, where data were borrowed from the Northwest Atlantic stock. Also, ICCAT should emphasize the importance of obtaining length data across the different gears, particularly those that cover a broad range of sizes. For example, wahoo in the Southwest Atlantic were excluded from the analysis because they are targeted by multiple fleets, but length data are available only for one gear (gillnets) and using only this data could bias the results.

LBSPR and LIME, like all age- or length-based methods, are sensitive to misspecifications of the inputs of life information (Hordyk *et al.*, 2015; Kokkalis *et al.*, 2017; 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 small scombrid 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 specifying prior distributions for life history parameters (Prince *et al.*, 2015) for this group of species.

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 the exception of some regions in the Northwest Atlantic, such as in the US. Determining stock status is the first step to protect these stocks from being overfished and to apply management measures to rebuild overfished stocks. Since stock status for these species is highly uncertain, simulation testing is needed to evaluate different management procedures accounting for data and model uncertainty in a management strategy framework. Management strategy evaluation (MSE) could be used to develop robust management frameworks for such stocks, e.g. using the data-limited-methods toolkit (DLMtool, Carruthers and Hordyk, 2018).

Conclusions

The present study analyzed different approaches using length-based, data-limited assessments when length composition data come from fisheries with multiple gears with different selectivity patterns. An aim of this study was to evaluate how to use length composition data from multifleet fisheries to estimate stock status for small scombrids. We recommend that length-based models should be applied to the length data coming from the fleet that targets the broadest range of sizes, including juveniles and adults when the data are available. Even though the results observed here can be applied to other multifleet fisheries, the results show biases under different selectivity assumptions for the simulated albacore population, so further simulation testing for data-poor, multifleet fisheries with variable life history, selectivity, and exploitation patterns should be explored.

Small tunas are an important social and economic resource for many coastal communities; however, most of these stocks have not been assessed, and their status is unknown. This work is, therefore, an important first step in developing management plans, particularly as the evaluation of uncertainty recognizes where data are needed to identify stock status and reduce risks of overfishing. Little tunny in the Southeast and wahoo in the Northwest are undergoing overfishing, despite the method and *M* used, which confirms the previous perception of ICCAT. These species have already been assigned priority, given their social-economic importance and also considering that they were two of the top three stocks at risk in the Atlantic Ocean, hence deserving most of the managers' attention (SCRS, 2018). For the Southeast little tunny, life history parameters for the given "stock" are not available, and data used within this study were borrowed from other areas, which may hamper our analysis. This species should be certainly considered as a priority for data collection within the small tuna group within ICCAT. For the Northwest wahoo, although life history parameters are available, length composition is only available for rod and reel, which may not include the majority of size classes. For both species, ICCAT has already developed a research programme to address knowledge gaps regarding size data and biological parameters (both from biological sampling and tagging programmes).

Supplementary information

The Supplementary material available at the *ICESJMS* online version of this paper includes Figures S1–S10 and Tables S1–S3.

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Table 1. 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 (cm)	L_{50}	90
Length where 95% of the fish are mature (cm)	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 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 first quantile, median, and third quantile are presented. For the same species: [A]information borrowed from the Northwest stock, [B]information borrowed from the Northeast stock, [C]information borrowed from the Southeast stock, and [D]information borrowed from the Southwest stock. Please provide this table in an editable format, i.e. not as a figure.

Species	Parameter	Northeast	Southeast	Mediterranean	Northwest	Southwest
Sarda sarda (BON)	L_∞ (cm)	73 (Baibat *et al*, 2016)	Insufficient length data	70 (Kahraman *et al.*, 2014)	Insufficient length data	Insufficient length data
	k (years^{-1})	0.31 (Baibat *et al.*, 2016)		0.44 (Kahraman *et al.*, 2014)		
	to (years)	- 2.45 (Baibat *et al.*, 2016)		- 1.33 (Kahraman *et al.*, 2014)		
	Tmax (years)	5 (Baibat *et al.*, 2016)		5 (Cayré *et al.*, 1993)		
	L_{50} (cm)	42.6 (Baibat *et al.*, 2016)		39.9 (Saber *et al.*, 2017)		
	M * (years^{-1})	0.43; 0.78; 1.11		0.60; 0.83; 1.09		
	WL_a (g)	5.0×10^{-5} (Baibat *et al.*, 2016)		6.3×10^{-6} (Saber *et al.*, 2017)		
	WL_b	2.79 (Baibat *et al.*, 2016)		3.21 (Saber *et al.*, 2017)		
Euthynnus alletteratus (LTA)	L_∞ (cm)	86 (Cabrera *et al.*, 2005) [A]	86 (Cabrera *et al.*, 2005) [A]	117 (Hattour, 2009)	86 (Cabrera *et al.*, 2005)	Insufficient length data
	k (years^{-1})	0.26 (Cabrera *et al.*, 2005) [A]	0.26 (Cabrera *et al.*, 2005) [A]	0.19 (Hattour, 2009)	0.26 (Cabrera *et al.*, 2005)	
	to (years)	- 0.32 (Cabrera *et al.*, 2005) [A]	- 0.32 (Cabrera *et al.*, 2005) [A]	- 1.13 (Hattour, 2009)	- 0.32 (Cabrera *et al.*, 2005)	
	Tmax (years)	8 (Cayré and Diouf, 1980)	8 (Cayré and Diouf, 1980) [B]	10 (Hattour, 2009)	8 (Cayré and Diouf, 1980) [B]	
	L_{50} (cm)	42.0 (Diouf, 1980)	42.0 (Diouf, 1980) [B]	51.1 (Hajjej *et al.*, 2012)	39.7 (Ramirez-Arredondo, 1993)	
	M * (years^{-1})	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 (g)	1.4×10^{-5} (Diouf, 1980)	1.4×10^{-5} (Diouf, 1980) [B]	1.2×10^{-5} (Saber *et al.*, 2017)	2.1×10^{-5} (Ramirez-Arredondo, 1996)	
	WL_b	3.04 (Diouf, 1980)	3.04 (Diouf, 1980) [B]	3.06 (Saber *et al.*, 2017)	2.96 (Ramirez-Arredondo, 1996)	
Acanthocybium solandri (WAH)	L_∞ (cm)	179.7 (Viana *et al.*, 2013) [A]	Insufficient length data	Stock not defined	179.7 (Viana *et al.*, 2013)	Insufficient length data
	k (years^{-1})	0.32 (McBride *et al.*, 2008) [A]			0.32 (McBride *et al.*, 2008)	
	to (years)	- 1.91 (McBride *et al.*, 2008) [A]			- 1.91 (McBride *et al.*, 2008)	
	Tmax (years)	9 (McBride *et al.*, 2008) [A]			9 (McBride *et al.*, 2008)	
	L_{50} (cm)	92.5 (Jenkins and McBride, 2009) [A]			92.5 (Jenkins and McBride, 2009)	
	M * (years^{-1})	0.43; 0.49; 0.60			0.43; 0.49; 0.60	
	WL_a (g)	2.8×10^{-4} (Santana *et al.*, 1993)			2.0×10^{-6} (Beerkircher 2005)	
	WL_b	2.72 (Santana *et al.*, 1993)			3.24 (Beerkircher 2005)	
Auxis thazard (FRI)	L_∞ (cm)	52 (Grudtsev and Korolevich, 1986) [C]	52 (Grudtsev and Korolevich, 1986)	Insufficient length data	Insufficient length data	Insufficient length data
	k (years^{-1})	0.32 (Grudtsev and Korolevich, 1986) [C]	0.32 (Grudtsev and Korolevich, 1986)			
	to (years)	-0.83 (Grudtsev and Korolevich, 1986) [C]	-0.83 (Grudtsev and Korolevich, 1986)			
	Tmax (years)	4 (Grudtsev and Korolevich, 1986) [C]	4 (Grudtsev and Korolevich, 1986)			
	L_{50} (cm)	30 (Cayré *et al.*, 1993) [C]	30 (Cayré *et al.*, 1993)			
	M * (years^{-1})	0.48; 1.01; 1.37	0.48; 1.01; 1.37			
	WL_a (g)	8.9×10^{-6} (Frota *et al.*, 2004) [D]	8.9×10^{-6} (Frota *et al.*, 2004) [D]			
	WL_b	3.17 (Frota *et al.*, 2004) [D]	3.17 (Frota *et al.*, 2004) [D]			

Table 3. Summary of stock status for small scombrids in the Atlantic Ocean. SPR is shown for both models, LBSPR and LIME, with the lower (CI_low) and upper (CI_up) confidence interval for the base model (median *M*).

		LBSPR			LIME		
Species	**Stock**	**SPR**	**CI_low**	**CI_up**	**SPR**	**CI_low**	**CI_upp**
Little tunny	Southeast	0.13	0.12	0.13	0.27	0.03	0.51
Bonito	Northeast	0.23	0.20	0.27	0.71	0.37	1.06
Wahoo	Northwest	0.37	0.23	0.51	0.29	0.27	0.31
Wahoo	Northeast	0.55	0.48	0.62	0.38	0.34	0.43
Bonito	Mediterranean	0.59	0.47	0.70	0.22	0.15	0.28
Little tunny	Mediterranean	0.66	0.57	0.74	0.62	0.54	0.71
Little tunny	Northwest	0.66	0.60	0.72	0.48	0.40	0.56
Frigate tuna	Southeast	0.79	0.78	0.80	0.53	0.49	0.57
Frigate tuna	Northeast	0.83	0.81	0.84	0.46	0.44	0.48
Little tunny	Northeast	0.90	0.83	0.96	1.00	1.00	1.00

Figure captions

Figure 1. (a) Selectivity patterns include in the operating model (OM) for each fleet. (b) Catch time-series included in the OM by fleet in the last 15 years (1997–2011) taken from the North Atlantic albacore assessment (ICCAT, 2013). Fleets A, B, and C are combination of fleets described in the main text. Label to two graphs as (a) and (b) instead of as A and B. On graph (a), rotate the y-axis numbers 90° clockwise. On graph (b), change the y-axis numbers to 10, 20, 30, and 40 and change the caption to "Catch ('000 t)".

Figure 2. Relative error (RE) for the five scenarios tested (S1–S5) for LIME (green) and LBSPR (purple) compared with the OMs with (right column) and without (left column) recruitment deviations. On the y-axis, rotate all the numbers 90° clockwise and use the en dash (–) instead of the hyphen (-) to designate a minus sign.

Figure 3. Length distribution (in cm) included in LBSPR and LIME models by stock. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; and FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest, and Med, Mediterranean Sea. Gears code: RR, rod and reel; HL, handline; PS, purse-seine; TP, trap; LL, longline; and GN, gillnet.

Figure 4. Proxy of stock status for priority small scombrid species. Vertical dashed line represents where SPR = 40% and horizontal line represents $F/M = 2$. Results from LIME are in green, and results from LBSPR are in purple for the three values of M considered. Circles are median M, squares are M at the first quartile, and diamonds M at the third quartile. Grey lines are the confidence intervals of the estimated SPR and F/M. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; and FRI, frigate tuna. Stock areas code: NE, Northeast; SE, Southeast; NW, Northwest, and Med, Mediterranean Sea. On the y-axis, rotate all the numbers 90° clockwise

B2 Performance of length-based data-limited methods in a multi-fleet context

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Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries

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Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries

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Abstract

The quantity of data from many small-scale fisheries is insufficient to allow for the application of conventional assessment methods. Even though in many countries they are moving to close-loop simulations to assess the performance of different management procedures in data limited situations, managers in most developing countries are still demanding information on stock status. In this study we use the common metric of harvest rate to evaluate and compare the performance of the following catch-only and length-only assessment models: Catch-Maximum Sustainable Yield (Catch-MSY), Depletion Based Stock Reduction Analysis (DBSRA), Simple Stock Synthesis (SSS), an extension of Catch-MSY (CMSY), Length Based Spawning Potential Ratio (LBSPR), Length-Based Integrated Mixed Effects (LIME), and Length-Based Bayesian (LBB). In general, results were more biased for slightly depleted than for highly depleted stocks, and for long-lived than for short-lived species. Length-based models, such as LIME, performed as well as catch-based methods in many scenarios and, among the catch-base models the one with the best performance was SSS.

Keywords: data-limited assessment methods, depletion, life-history, harvest rates

INTRODUCTION

Major commercial fish species usually have substantial sets of data that can be integrated by complex stock assessment models (e.g., Methot and Wetzel 2013); these data may include time series of total removals, catch-at-length or -age, relative or absolute abundance indices, fishing effort, and information on life-history parameters. Such datasets are typically unavailable for most of the small-scale fisheries and by-catch species around the world. Fisheries and stocks lacking comprehensive datasets 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 increasing demand for science-based fisheries management of unassessed fisheries where data and 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 only catch and life-history data started many years ago with the development of Stock Reduction Analysis (SRA; Kimura and Tagart 1982; Kimura et al. 1984). Since then, SRA has been extended to estimate productivity and reconstruct historical abundance trends by making assumptions about final biomass relative to unfished or initial biomass (i.e., stock depletion; Thorson and Cope 2015). SRA has been further extended 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-Maximum Sustainable Yield, Catch-MSY; Martell and Froese 2013), bayesian approches (CMSY, Froese et al. 2017), and age-structured population dynamics (Simple Stock Synthesis, SSS; Cope 2013). Despite these differences, this family of catch-only models share a common dependence on prior assumptions about final stock depletion. Simulation testing has previously indicated that these methods perform well only when assumptions regarding final relative abundance are met (Wetzel and Punt 2015). Unsurprisingly, because final stock depletion is a prior assumption, the methods perform differently under different stock depletion levels (i.e., highly depleted or slightly depleted stocks, Walters et al. 2006) or under different harvest history or catch trends.

For many small-scale fisheries, obtaining reliable time series on historical total catch is difficult, whereas sampling lengths from the catch is easier. Mean-length mortality estimators (Beverton and Holt 1957) assume that fishing mortality directly influences the mean length of the catch under equilibrium conditions. This basic method has been extended by length-based spawning potential ratio (LBSPR, Hordyk et al. 2015a), length-based Integrated Mixed Effects (LIME, Rudd and Thorson 2017) and Length-Based Bayesian approach (LBB, Froese et al. 2018) models, among others. These allow for the estimation of instantaneous fishing mortality (F) and spawning potential ratio (SPR) when basic biological parameters are known. In contrast to LBSPR and LBB, LIME does not assume equilibrium conditions. The mixed-effects aspect of LIME extends length-based methods by estimating changes in recruitment and separating them from fishing mortality over time (Rudd and Thorson 2018).

It is good practice to simulation test the performance of assessment methods before applying them in practice (Cope 2008). This can be done using a variety of approaches, though it is most often accomplished using an Operating Model (OM) to generating pseudo-data with error to fit an assessment model (Punt et al. 2016). Simulation can either be an open loop or a closed loop with feedback. Carruthers (2016), using closed loop simulations, 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 (Carruthers et al. 2014). In many data poor fisheries, measuring total removals is difficult, as is enforcing catch limits. Recently, 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. They found that the LBSPR assessment model with an iterative effort-based harvest control rule can be used to rebuild an overfished stock to sustainable levels or fish down a stock to the target SPR. So far, these two approaches, output-based limits versus input/effort-based limits, have not been directly tested.

In addition, there are some studies comparing the performance in determining stock status of catch-based (Wetzel and Punt, 2015; Rosenberg et al. 2017) and length-based assessment models (Chong et al. 2019). However, a comparison of the performance of both length-based and catch-based methods to estimate stock status is needed. Unfortunately, finding a common metric between catch-based and length-based stock status metrics is difficult; the former measures overfishing via fishing rates and the latter biomass-based catch limits.

Even though many countries are moving to close-loop simulations or Management Strategy Evaluation (MSE) to assess the performance of different management procedures (i.e., the combination of analytical method and control rule) for data-limited fisheries (Harford and Carruthers, 2017), it remains a need to understand how the individual analytical methods perform. Therefore, this study used a simulation approach to better estimate relative bias and precision of a range of data-limited methods so researchers can choose which one could be more appropriate to use for the fishery they need to assess, with the results providing general information needed to construct an appropriate control rule for a given method’s performance.

We used OMs (here considered just as a simulated population model) to represent the main sources of uncertainty and to generate data for use in data-limited stock assessment methods and to evaluate how well the methods perform when the data and knowledge requirements are met. A common metric is then used for comparison across model types, namely exploitation or harvest rates, to evaluate the performance of both catch-based and length-based models in a simulation context. We evaluate performance considering three fish populations with contrasting life-history strategies, under three different harvest trends, and three different levels of final stock depletion.

METHODS

Simulation studies commonly make different operating model assumptions from those of the methods being tested to allow the evaluation of robustness; in some cases, however, the same population model is used for both simulation and estimation, i.e. self-testing (Deroba et al., 2015). Using the same model structure for simulation and estimation can result in more optimistic results that might not be true under many scenarios (Francis, 2012) since it is not possible to explore the impact of model assumptions when the model used for simulation and estimation is the same. If a method performs poorly, however, when the assumptions in the OM are the same as the assessment model, it is unlikely to perform well in practice. To evaluate robustness to model structure our approach evaluated multiple data-limited assessment methods with a range of assumptions about population and fishery dynamics using an OM decoupled from the tested methods.

Twenty-seven different OMs were created using a factorial design comprising 3 harvest rates, 3 life-history types, and 3 depletion scenarios. The different harvest rates scenarios, each considered a 20-year time series of fishing, correspond to fishing mortality histories commonly seen in many fisheries. In harvest rate scenario 1, fishing mortality increases until it reaches a maximum and starts declining afterwards. This is commonly seen once management measures are implemented to reduce fishing pressure. Harvest rate scenario 2 assumes that fishing mortality increases and remains constant after reaching a maximum. This harvest rate profile could result from the implementation of catch or effort management limits. Harvest rate scenario 3 has constantly increasing fishing mortality, which would occur for fisheries that are still developing (Figure 1a).

Three life history types of varying longevity and somatic growth rate were simulated, namely (i) a short-lived fast-growing species, Pacific chub mackerel (*Scomber japonicus*), (ii) a medium-lived medium-growing fish, albacore tuna (*Thunnus alalunga*), and (iii) a longer-lived slow-growing species, canary rockfish (*Sebastes pinniger*) (Table 1). Finally, the following three final depletion levels (D) were considered: (i) heavily fished (D = 0.2; *i.e.* stock biomass in the last year is 20% of virgin biomass), (ii) moderately fished (D = 0.4) and (iii) lightly fished (D = 0.6).

Operating model specifications

The OM was developed to simulate resource dynamics under the different fishing scenarios, life histories and final depletion levels. The OMs consist of an age-structured population with numbers at age over time modelled as follows:

$$N_{a,t} = \begin{cases} R_t, & a = 0 \text{ and } t = 0 \\ N_{a-1,t}\, e^{(-M - F_t S_{a-1})}, & 0 < a < A \text{ and } t = 1 \\ \dfrac{N_{a-1,t}\, e^{(-M - F_t S_{a-1})}}{1 - e^{(-M - F_t S_{a-1})}}, & a = A \text{ and } t = 1 \\ N_{a-1,t-1}\, e^{(-M - F_t S_{a-1})}, & 0 < a < A \text{ and } t > 1 \\ (N_{a-1,t-1} + N_{a,t-1})\, e^{(-M - F_{t-1} S_{a-1})}, & a = A \text{ and } t > 1 \end{cases}$$

R_t is the number of age-0 animals at the start of year t, $N_{a,t}$ is the number of fish of age a at the start of the year t, S_a is the selectivity at age, F_t is the instantaneous fishing mortality rate during year t, M is the instantaneous rate of natural mortality, and A is the age of the plus group. Fishing mortality deviations were included as $F_t \sim lognormal\ (F_{t-1},\sigma_F^2)$. A Beverton–Holt spawner–recruitment function (Beverton and Holt 1957) and annual normally distributed recruitment deviations $N(0,\sigma_R)$ were assumed (Table 1).

The biomass in each year t was calculated as $B_t = \sum_{a=1}^{A} N_{a,t} w_a$ where $w_a = \alpha L_a^{\beta}$ (parameters in Table 1). In addition, the predicted total catch by year (C_t) was calculated as $C_t = \sum_{a=0}^{A} C_{a,t}$ with:

$$C_{a,t} = \frac{F_t S_a}{M + F_t S_a} N_{a,t}\left(1 - e^{(-M - F_t S_a)}\right)$$

For each OM (N=27), 100 time series of fishing mortality were simulated, and the harvest rate per year (U_t) as C_t/B_t calculated (Figures S1 to S3). Each simulated population began at the unfished biomass level and all fishing trend scenarios terminate at the specified depletion level (Appendix Figures A1 to A27).

To condition the OM, published life-history parameter values (Table 1) reported in formal stock assessments were used (Crone and Hill 2015 for the short-lived Pacific chub mackerel; Anon 2014 for the medium-lived albacore tuna; and Thorson and Wetzel 2015 for long-lived canary rockfish). Each population was assumed to be targeted in a single area, by one fleet with a selectivity pattern (Table 1) that was logistic and constant through time.

Length bins were defined as they were in their respective assessments; every 2 cm (Crone and Hill 2015; Anon 2014; Thorson and Wetzel 2015). To obtain the catch length frequency, the probability (p) of being in a length bin (j) given age (a) was calculated as:

$$p_{j,a} = \begin{cases} \emptyset\left(\dfrac{j - L_a}{L_a CV_L}\right), & j = 1 \\ \emptyset\left(\dfrac{j - L_a}{L_a CV_L}\right) - \emptyset\left(\dfrac{j - 1 - L_a}{L_a CV_L}\right), & 1 < j < J \\ 1 - \emptyset\left(\dfrac{j - 1 - L_a}{L_a CV_L}\right), & j = J \end{cases}$$

With the predicted probability of harvest by length bin being:

$$\pi_j = p_{j,a} \frac{\sum_{a=0}^{A} N_{a,t} S_a}{N_t}$$

One thousand fish per year were drawn using a multinomial distribution with a π_j probability (Rudd and Thorson 2018).

Comparing methods outputs

One of the challenges when comparing catch-based and length-based methods is that they produce different model outputs. Catch-only models calculate total and/or spawning stock biomass and MSY, whereas length-based models estimate exploitation and transient SPR, which can be used to infer stock status. These are fundamentally different measures of the population status. As a result, our performance metric is defined as the error relative (RE) to the OM, where RE = (U_{Method} - U_{OM}) / U_{OM}. This allows for a measure of uncertainty, in both bias and precision, for all 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 OM. Imprecision is related to the variability (variance) around the central tendency.

We used U as a common measure for comparisons between each data limited method and the OM. For catch-only approaches it is defined as the ratio catch/biomass; while for the length-based models, the estimated F was transformed to an exploitation rate via $U = 1 - exp$

(- F). In addition, we present the average RE across the last five years of the time series, not along the entire time series of data, because we are interested in the estimation of the current exploitation rates. Also, multiple studies have shown that catch-based methods might be appropriate to predict sustainable catch at the end of the time series, but not to reconstruct a biomass time series (Carruthers et al. 2012; Wetzel and Punt 2015).

Estimation models

All simulations, and data-limited model calculations, were conducted using the open-source statistical software R (R Core Team 2018). Each catch-based and length-based method evaluated here are summarized below.

Catch-based data-limited methods

Catch-MSY (Martell and Froese 2013) is a SRA approach that assume a Schaefer biomass dynamic model. Inputs are a time series of removals, priors for the population rate of increase at low population size (r), carrying capacity (K), and a range of stock depletion in the final year (Table 1). Values of r and K are randomly sampled using a Monte Carlo approach to detect 'viable' r-K pairs. A parameter pair is considered 'viable' if the corresponding biomass trajectories calculated from a production model are compatible with the observed catches, so that the population abundance never falls below 0, and is compatible with the prior assumption of relative biomass (i.e., stock depletion; Martell and Froese 2013). 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. Catch-MSY uses catch and productivity to estimate MSY. Here we use the modified version of Catch-MSY (Rosenberg et al. 2017) to extract biomass trends from all viable r-K pairs using the R package *datalimited* version 0.1.0 (Anderson et al. 2016). The biomass trajectory is calculated as the median of all viable biomass trajectories generated under the Monte Carlo process. We decided to include Catch-

MSY in this performance comparison analysis since it is a method that has become very popular in developing countries because of its easy implementation through R libraries.

CMSY (Froese et al. 2017) extends Catch-MSY by using a Monte-Carlo filter (instead of the SIR algorithm) that fixes systematic biases in the Catch-MSY method. It also, explicitly incorporates process error and estimates target reference points (MSY, F_{MSY}, B_{MSY}) as well as relative stock size (B/B_{MSY}) and exploitation (F/F_{MSY}) from catch data and priors for *r* and depletion at the beginning and the end of the time series. CMSY has an inbuilt piecewise "hockey-stick" to prevent over-estimating of rebuilding potential at very low abundance $B<0.25B_0$. The CMSY package implements a Bayesian state-space implementation of the Schaefer surplus production model (Winker 2019). CMSY was included in this paper because it has been described as an unbiased version of Catch-MSY and it has been already implemented in different parts of Europe (Froese et al. 2018) and explored by Regional Fisheries Management Organizations such as the International Commission for the Conservation of Atlantic Tunas, ICCAT (Winker et al. 2017, ICCAT 2017). We included a prior for depletion in this method (see Table 1).

DBSRA (Dick and MacCall 2011) modifies the SRA approach by using Monte Carlo draws from four parameter distributions (M, F_{MSY}/M, B_{MSY}/B_0, and depletion) and age at maturity (A_{mat}) to separate the total 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:

$$B_{t+1} = B_t + P(B_{t-Amat}) - C_t$$

where B_t is the biomass at the start of year t, $P(B_{t-Amat})$ is the latent annual production based on a function of adult biomass in year *t-Amat* and C_t is the catch in year t. Biomass in the first year (B_0) is assumed to be equal to K. The package *fishmethods* version 1.10-3 was used to perform this analysis (Nelson 2017). For DBSRA we used the *Amat* and *M* as fixed inputs and three priors: final stock depletion, F_{MSY}/M, and B_{MSY}/B_0 (distributions in Table 1). Each of these is assigned a distribution from which the Monte Carlo draws are taken. We chose DBSRA to be included in our analysis because it is currently used for providing fisheries management advice on the US West Coast.

SSS is based on the Stock Synthesis age-structured stock assessment model (Methot and Wetzel 2013). SSS fix all parameters in the Stock Synthesis model except for initial recruitment ($\ln R_0$). It also sets up an artificial index of abundance that represents the relative stock biomass. The first value of the index is always 1, and the value in the final year represents the percent of the population left in that year (final depletion). The values of steepness (*h*) and the final year of the abundance survey are all randomly drawn from a specified distribution using a Monte Carlo approach (Cope 2013) and $\ln R_0$ is then estimated. Benefits of this approach are that it retains the same modelling framework as the data-rich stock assessments, but still allows for flexibility in a variety of parameter and model specifications, if desired. The input priors used for SSS were relative stock status and steepness and selectivity was matched to the OM (Cope 2019). We chose SSS to be included in our analysis because it is gaining use as a flexible platform to incorporate more data as it is collected, as well as providing an age-based alternative to the other catch-only models.

Length-based data-limited methods

SPR is the proportion of the unfished reproductive potential per recruit under a given level of fishing pressure (Goodyear 1993). In **LBSPR,** SPR in an exploited population is calculated as a function of the ratio of fishing mortality to natural mortality (F/M), selectivity, 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 of LBSPR are M/k, L_∞, the variability of length-at-age (CVL_∞), which is normally assumed to be around

10%, and the 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 M/k and L_∞ and that length composition data come from an exploited stock, the LBSPR model uses maximum likelihood methods to estimate the selectivity ogive, which is assumed to be of a logistic form defined by the selectivity-at-length parameters S_{50} and S_{95} (the size at which 50% and 95% of a population is retained by the fishing gear), and F/M. The selectivity ogive and relative fishing mortality are then used to calculate SPR (Hordyk et al. 2015a, 2015b). Estimates of SPR are primarily determined by the length of fish relative to L_{50} and L_∞, but it also depends on life history parameters such as fecundity-at-age/length and selectivity. 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 the LBSPR package, version 0.1.3 in R (Hordyk 2018). We used the Rauch-Tung-Striebel smoother function available in the LBSPR package to smooth out the multi-year estimates of F. We decided to include LBSPR in the analysis as its easy implementation through R libraries and online apps have made it a popular, widespread choice.

LIME uses length composition of the catch and biological information to estimate F and SPR. LIME has the same data requirements as LBSPR, but does not assume equilibrium conditions. The mixed effects aspect of LIME extends length-based methods by estimating changes in recruitment and fishing mortality separately 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). The inputs to LIME (Rudd 2019) are: M, k, L_∞, t_0, CVL_∞, L_{50}, L_{95}, h, and the parameters of the length-weight relationship a and b (Table 1). We decided to include LIME in our analysis because is the only length-based method that allows for recruitment deviations and it has not been widely tested.

LBB is a simple and fast method for estimating relative stock size that uses a Bayesian Monte Carlo Markov Chain (MCMC) approach (Froese et al. 2018). In contrast to other length-based methods, LBB uses pre-specified priors on parameters, and thus, technically does not require further inputs in addition to length frequency data, if the user is willing to accept the life history defaults. However, it provides the user the option to specify priors for the inputs L_∞, length at first capture (Lc), and relative natural mortality (M/k). We specified the true M/k value and we let the model calculate Lc (length where 50% of the individuals are retained by the gear) and L_∞, which is approximated by the maximum observed length L_{max}. In addition, F/M is estimated as means over the age range represented in the length-frequency sample. We decided to include LBB because it has not been widely tested and compared with other length-based assessments methods. As well as CMSY, LBB is gaining consideration as a plausible method in some international commissions such as ICCAT (Anon, 2019).

During our simulation testing, we assumed that length models had the correct values for the von Bertalanffy length-at-age relationship, L_∞, k and t_0, length-weight parameters α and β, M, and the parameters L_{50} and L_{95} from a logistic maturity-at-length curve. We did not evaluated misspecifications in life history parameters inputs. The objective is only to compare the performance of different data-limited methods under different scenarios, not to evaluate each of them under different parameters misspecifications, which has already been done in the original publications of each method.

RESULTS

Large variability is seen in model performance across harvest scenarios, life-history types, and depletion levels (Figure 1b-d, Figure 2). Figures 1 and 2 can be used to search for the best model, i.e. to identify the least biased and least imprecise method based on the life history of the species, harvest trends, and knowledge of final depletion. The imprecision of each method is shown in the variability around those estimations in Figure 1 and the specific values in Figure 2. A robust method would show low bias and high precision for all life history and harvest scenarios; for example, among all catch-based methods, SSS appears to be the most robust method (Figure 2).

In general, catch-based methods tended to be more biased at relatively higher stock sizes (D=0.6) and for long-lived species (Figures 1 and 2). Catch-MSY tended to perform poorly across a range of scenarios. Among the length-based models, all were less biased and more precise for the medium-lived species (Figure 2) without a clear different performance among harvest scenarios. The most biased length-based method was LBSPR although more precise than LIME and LBB (Figure 2). Overall, LIME and SSS were the most robust methods.

Catch-only methods

It was to be expected that the various catch-based models considered in this study would perform differently among them because they have different model structure and assumptions. SSS performed best in most cases estimating unbiased exploitation rates across different scenarios of harvest trends, final stock depletion and life histories (Table 2). However, it tended to underestimate harvest rates by 30% for medium and short-lived species at relatively high stock sizes (D=0.6). For long-lived species the estimations were slightly overestimated for moderately fished stock sizes (D=0.4), but SSS was always the model that was least biased. DBSRA was the most precise but it underestimated harvest rates in general, and in contrast to the other catch-based methods, it was less biased for stocks at relatively high stock sizes (D=0.6, Figure 2). Catch-MSY was the most biased of the catch-based models tested, overestimating harvest rates in particular for stocks lightly fished (D=0.6). It was less biased to itself for medium-lived species and produced non-biased estimates of MSY for highly depleted (D=0.2) medium-lived or short-lived species at moderate stock sizes (D=0.4) (Table A1). CMSY was less biased in the relatively medium to high stock sizes (D=0.4 and D=0.6) and for medium-lived species (Table 2). In general, catch-based models were less biased and more precise when stocks were at relatively low stock sizes (i.e. using a prior centered around 0.2, Figure 1). In general, estimation models in harvest scenario 1 (ramp shaped) produced the most variable estimations in harvest rates (Figure 1, Table 2). The catch-based methods performed the best for the medium-lived species.

Length-based methods

In many cases, length-based models gave a less biased estimation of *U* than catch-based models (Figure 1). LIME was the least biased length-based method (Table 3). However, in general, LIME did not converge around 10% of the time. The three length-based methods used here (LIME, LBSPR and LBB) produced more variable estimations in harvest scenario 1, where the fishing intensity decreased at the end of the time series (Figure 1) but no clear pattern was observed in terms of harvest scenarios in bias (Figure 2). LBSPR in general underestimated harvest rates. Compared to itself, LBB performed better in scenarios where the stocks have relatively low to medium stock sizes (D=0.2 and D=0.4) and for medium-lived species (Figure 2). Both, LBB and LIME were highly variable for long-lived species and harvest scenario 1 (Figure 1). Multiple modes for harvest scenario 1 may suggest poor convergence. Overall, length-based models were less biased for the medium-lived species.

Short-lived species

For the short-lived life-history strategy, SSS was the least biased and most precise among the catch-based methods. The second most precise method was CMSY, but this method was positively biased for lightly fished or relatively high stock sizes (D=0.6). Among the three length-based models, LIME had better overall performance than LBSPR and LBB. However, LBSPR was less biased in harvest scenario 1. LBB was the one model that presented the most variability in harvest-rate estimations for the short-lived species.

Medium-lived species

Both catch-based and length-based models gained more precision as the stocks were more depleted. Among the catch-based methods, CMSY was the less biased followed by SSS, although SSS was more precise. DBSRA was highly negatively biased particularly for relatively low stock sizes (D=0.2). Catch-MSY was highly positively biased but less so for highly depleted stocks (Figure 1c). Between the length-based models, LIME showed very good performance with regards to bias for harvest scenarios 2 and 3 under the three depletion levels, although it was slightly biased for harvest scenario 1. LBSPR and LBB showed similar performance but LBSPR was more precise (Figure 1c).

Long-lived species

Both catch-based and length-based methods were less precise (more variability in RE) as the long-lived stocks had relatively higher stock sizes (D=0.6), as they did for the other life-history strategies. Among the catch-based methods, SSS was the most precise and least biased method except in harvest scenario 1 and D=0.2 where CMSY was the least biased. SSS underestimated harvest rates in scenarios 2 and 3, where the catch history is constant or increases at the end of the time series. Among assessment methods, a less biased and more precise estimation was observed for medium depleted stocks (D=0.4) than for other depletion levels. LBSPR and DBSRA was negatively biased in all cases (Figure 1d). LIME was highly imprecise in harvest scenario 1, but the least biased among the other length-based methods (Figure 1c, Figure 2).

Discussion

It is to be expected that the various methods would perform differently. Rosenberg et al. (2017) used four catch-based data-limited models and found that models frequently disagreed about population status estimations, with no model showing overall good performance, i.e. high precision and low bias across all case studies. When scenarios represent specific resource dynamics or particular stocks or fisheries, it may be difficult to draw any overall conclusions. Therefore, we chose scenarios that represented different fishing intensity trends, depletion levels, and life histories. We found that model performance is highly dependent on all these factors. More imprecision occurred where fishing pressure decreases at the end of the time series (harvest scenario 1), in comparison with harvest scenarios where *F* was either stable or increasing (harvest scenarios 2 and 3) that performed similarly in terms of bias and imprecision. In addition, most bias was found when relative stock abundance is high and/or for the slow-grow long-lived life history.

In particular, catch-based models performed better (i.e. were less biased and more precise) for stocks that were medium to highly depleted than for lightly depleted stocks. Walters et al. (2006) suggested that for SRA, stocks that have experienced extensive historical depletion gain precision due to a high rate of rejected parameter draws. The SSS approach, which tracks age-structure population dynamics, performed better than the models that are based on lumped biomass production functions such as Catch-MSY, CMSY, and DBSRA, even when priors for depletion were centered on the true values for all methods. Although SSS seems to be the least biased catch-based model, unlike other catch-based models, more detailed life-history information (e.g., age and growth estimates) are required by SSS to define age structure and remove catch according to age-/size-based selectivity patterns (Cope, 2013). So, when this information is highly uncertain, sensitivity analysis to parameter misspecifications is strongly recommended.

Catch-MSY performed poorly in all scenarios, overestimating harvest rates even when given a prior for depletion close to the true value. A key point of Catch-MSY 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 100 times the maximum catch as the upper bound for *K* based on Martell and Froese (2013). Other priors for *K* could be explored to see if this improves the outcome, but it remains a difficult parameter to specify under most conditions.

CMSY on the other hand performed particularly well with respect to bias and precision for medium-lived species, even better than SSS for medium to low depleted stocks (Figure 2). Also, CMSY was more accurate than the original Catch-MSY method (Martell and Froese, 2013). The difference is that Catch-MSY was designed to select the most probable *r*-*K* pair as the geometric mean of this distribution, but CMSY searches not in the center of the distribution but rather near the right tip of viable pairs. According to Froese et al. (2017) since *r* is defined as the maximum net productivity, the right tip of the distribution of *r*-*K* pairs is where these parameters should be found. So, between Catch-MSY and CMSY, CMSY is preferred, though its overall poor performance is noted.

Hordyk et al. (2015a) explained how LBSPR relies on detecting the signal of fishing mortality in the right-hand side of the length composition. Consequently, fishing is not likely to have a visible impact on the length composition until fishing mortality is very high and stocks are highly depleted. This is why LBSPR was less biased for more depleted populations and in fishing scenario 1.

Our study found that LIME was highly imprecise for long-lived species. Rudd and Thorson (2017) also showed that LIME is more imprecise for long lived species. The model is trying to track cohorts through the length data to estimate recruitment deviations and this is likely difficult for long-lived species when time series of length data are short or much of the population is found near the asymptotic size (Rudd and Thorson 2017).

Hordyk et al. (2019) suggested that LBB has not been sufficiently simulated tested and it can produce biased estimates of fishing mortality. We found that LBB was the most biased and imprecise length-based method, although for the less depleted stocks it generally performed better than LBSPR. One of criticisms of LBB by Hordyk et al. (2019) is that it *a priori* assumes that M/k = 1.5, however here, we specified the true M/k value. So, the main bias was associated with the estimations of L_∞ due to the approximation using maximum observed length L_{max}. There are many reasons why the maximum length may be a biased measure of L_∞. In addition to L_∞, L_c was always overestimated by the LBB assessment model (see Table A2), likely due to the bias in the L_∞ estimates.

In general, all catch-based and length-based methods seem to perform worse for long-lived life-history types, where there is likely to be less contrast in the dynamics over time (few years relative to their life span), than for medium and short-lived. The length of the time series for the long-lived canary rockfish is therefore probably too short in comparison to the age they reach the maximum length (64 years), to capture the true dynamics of the population and the response to different harvest rates.

The present study did not look at parameter misspecification but correctly specified (i.e., unbiased values) the life-history parameters. As we mentioned before, parameters misspecification testing was performed in the original publications for each method. With accurate prior information, length-based models showed better performance in many cases than some catch-based models, as the latter were more sensitive to the catch history scenarios and depletion levels.

We note that bias is not symmetrically interpretable, as it could, depending on management objectives, be better or worse to be biased high or low. In data-limited management, maximum sustainable yield is often hard to pinpoint, thus a more precautionary pretty good yield (Hilborn 2010) is likely a better target. When measuring exploitation rates, this would translate to being biased high as a preferable way of being wrong rather than underestimating the exploitation rate and possible increasing the fishing rate above the true target. The consideration of asymmetric management significance when measuring bias is an important consideration when using the results presented here to develop control rules.

Bias and precision are both important factors to consider when assessing fish stocks. Bias reflects how close an estimate is to a known value; precision reflects reproducibility of the estimate. For example, if an assessment is to be re-conducted every year to monitor the impact of a management measure, a precise but biased method would be able to detect a trend better than an unbiased but imprecise method. Like a scientific instrument, this trade-off require calibration to correct for the bias, and such calibration can be explored using closed-loop simulations such as management strategy evaluation, where the choice of parameters and reference points in a management procedure are tuned (i.e. calibrated) to meet the desired management objectives as represented by the operating model. Thus, a biased method (e.g., DBSRA) may be preferable to one that is less biased, but more imprecise (e.g., LIME). Alternatively, imprecision can be addressed through the choice of the percentile (e.g., median being the 50% percentile value) for the derived model output used by management (e.g., catch or SPR); assuming that the true value is contained within the parameter distribution. For example, instead of taking the median value, one could instead use the derived model output associated with the 40th percentile to incorporate risk tolerance as reflected in the calculated imprecision. Such an approach (Ralston et al. 2011) is used in fisheries management systems to directly incorporate scientific uncertainty (both bias and imprecision), and can also be explored and tuned using MSE.

Recommendations

To provide estimates of stock status for unassessed fisheries where data are limited, but reconstructing time series of catch is possible, SSS is recommended. The performance of SSS hinges on the correct specification of the input parameters such as stock depletion, productivity, maturity, and growth parameters. Knowledge about some of these parameters, especially stock depletion, is likely to be poor for data-limited stocks, resulting in misspecification of these parameters. Meta-analyses may offer some starting values for life history parameters (e.g., Myers 2001, Thorson *et al.* 2012, and Zhou *et al.* 2012, 2017), however other inputs remain difficult to specify (Chrysafi and Cope *in press*).

For fisheries where the time series of catch are unavailable or catches are not consistently monitored and managed, using length-composition data can provide good approximations of the status of the stock, in particular for medium-lived species. It has been shown here that in some cases, length-based models such as LIME can provide the same or less biased estimates of exploitation status than catch-based models. However, growth parameters are even more important for length-based than for any catch-based method, so it is important to have good estimates of those parameters before using any length-based assessment.

Making recommendations on which models should be applied to estimate exploitation intensity in different fisheries is challenging because model choice is dependent on data availability, trends in fishing intensity, and the biology of the species. If possible, simulation studies testing different data-limited methods with OMs based on the focus species and the dynamics of the fishery can greatly inform which method is most appropriate. Likewise, decision support tools such as FishPath (Dowling et al. 2015) can also help one weigh the input requirements and assumptions to identify the most appropriate methods given data and life history. Based on the OMs used in this study, we conclude that when only catch data is available, SSS should be considered. When only length data is available, LIME may be less biased that LBSPR and LBB if recruitment variability is an important consideration. However, Pons et al. (2019) found that neither LBSPR or LIME are good in all situations, and thus, both should be considered and compared for inconsistent results. LIME sometimes undergoes convergence issues and has difficulties separating changes in recruitment from changes in fishing mortality (Pons 2018; Pons et al. 2019).

For long-lived species it is necessary to have longer time series of data to draw more conclusions. However, Pons (2018) recommended SSS and LBSPR when long time series (i.e. 80 years) of data are available for a species that lives more than 60 years to evaluate changes in fishing intensity.

If both catch and length data are available, models that integrate both data types should be considered. LIME, although primarily length based, allows for the inclusion of catch data as well as an index of abundance if one is available. Moreover, integrated assessment models (that use catch as well as length information) like Stock Synthesis could also be considered (Methot and Wetzel 2013). Length information can therefore be added to the SSS data file, with the possibility of freeing up the stock status assumption input, and running the model more like a traditional statistical-catch-at-age model (Cope 2013; Thorson and Cope 2015).

For the scenarios analyzed here, including the specific life-histories considered, we do not recommend Catch-MSY for estimating exploitation rates, even with a good estimate of stock depletion. This method will however, as it was originally created to do, produce unbiased estimates of MSY, in particular for short and medium-lived and highly depleted species (Table A1).

Future directions

Dowling et al. (2019) in a review of data limited methods, noted the dangers in the indiscriminate use of generic methods (i.e., methods that are either imported as solutions or considered just because no others are understood, but are not rigorously considered for appropriateness given data and assumptions) and recommended obtaining better data, using care in acknowledging and interpreting uncertainties, developing harvest strategies (including control rules) that are robust to these higher levels of uncertainty and tailoring them to the species and fisheries specific data and context. Management actions to regulate fishing can be based on changes in harvest rates, mainly when catch limits are not an option. The steps, for each fishery, would include i) developing reference points, ii) identifying monitoring and assessments options, and iii) a qualitative and possibly quantitative (e.g., closed-loop simulation) evaluation of how to adjust harvest strategies and paired control rules to meet management objectives (Dowling et al. 2008). Control rules linked to methods explored in this work can be tailored and tested based on the bias and imprecision found in this study.

In addition, these data-limited methods could be tested using a fully-specified MSE with stakeholder input to specify the management objectives in order to determine management procedures to help ensure robust and sustainable fisheries management. This evaluation includes the benefits of adaptive improvement of the harvest strategy and management of the fishery.

This study provides steps to the above closed-loop simulation by way of conditioning OMs and generating pseudo data for use by the management procedure. Having a common metric (exploitation rate) to compare methods that are often decoupled in performance testing allows for a comparison of the components of uncertainty, bias and imprecision. Understanding the comparative degree each of these methods express component uncertainty under control simulation testing benefits the next steps of closed-loop performance testing if management procedures. The importance of considering assessment methods as part of a management procedure is that a method that provides biased, yet precise results could, if calibrated correctly, provide useful advice, whereas unbiased estimates with high imprecision would need specific consideration on how to manage the risk inherent in imprecision.

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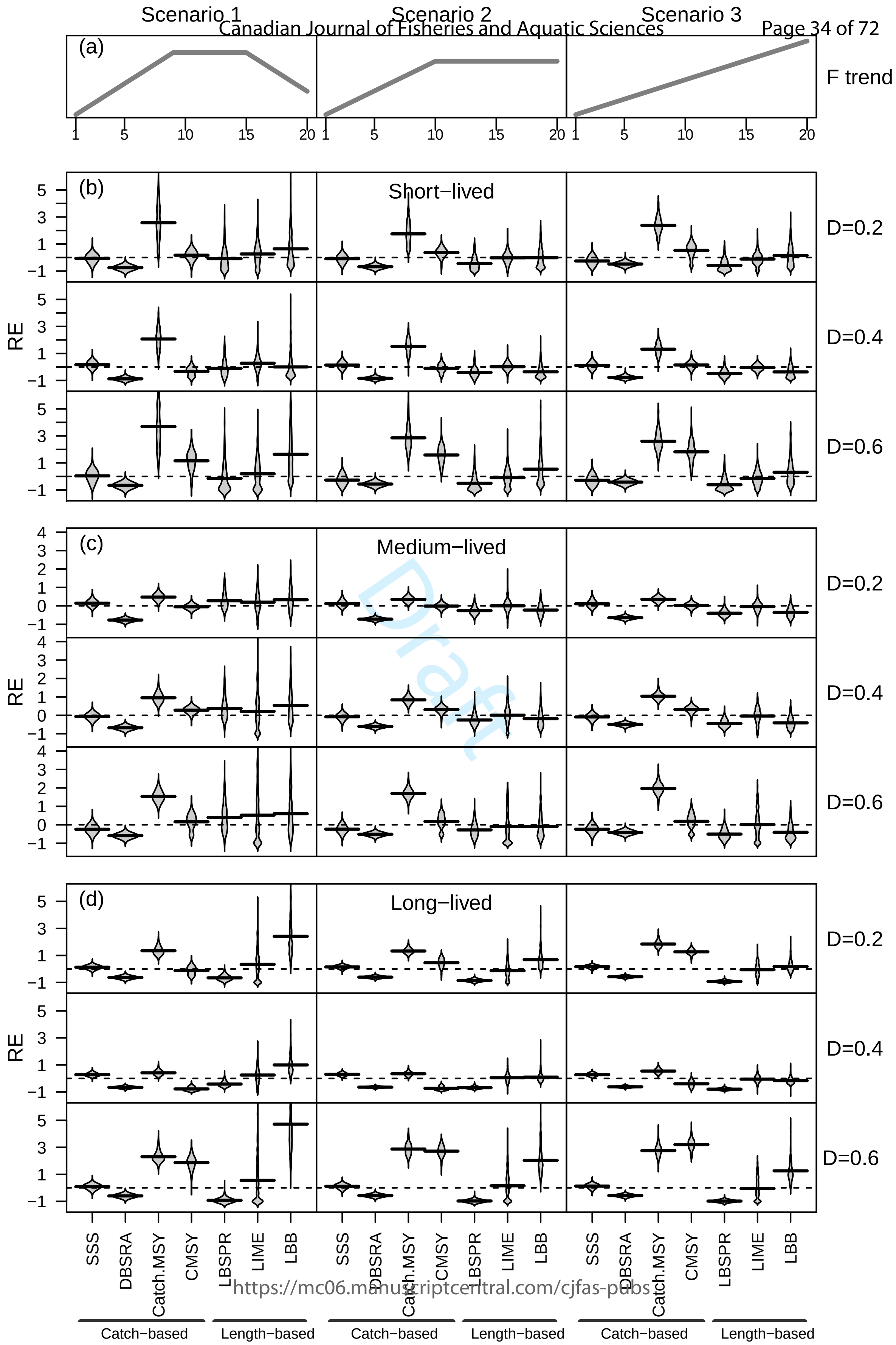
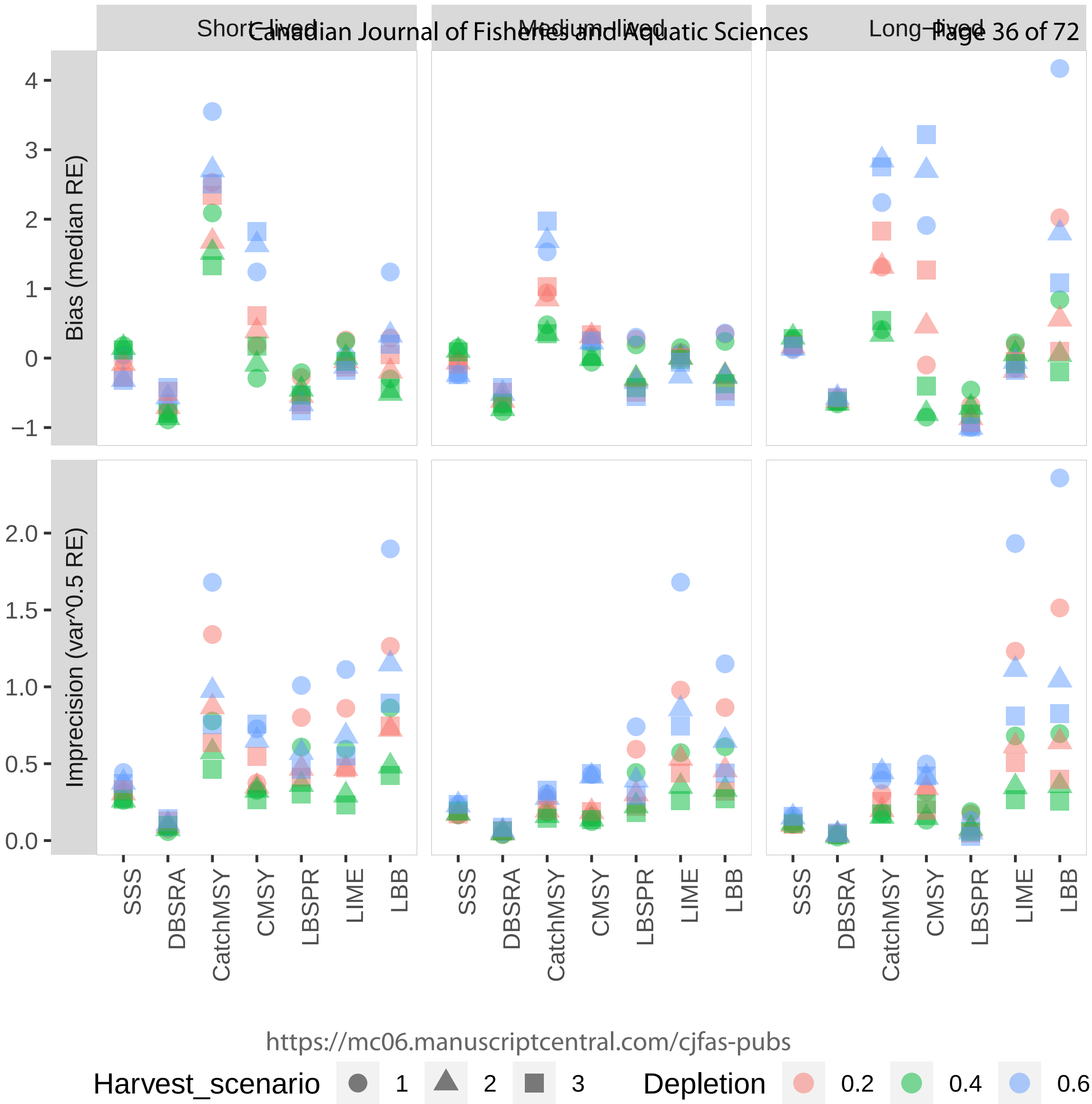


Scenario 1
Scenario 2
Scenario 3
(a)
F trend
1 5 10 15 20
(b)
Short−lived
D=0.2
D=0.4
D=0.6
RE
(c)
Medium−lived
(d)
Long−lived
SSS
DBSRA
Catch.MSY
CMSY
LBSPR
LIME
LBB
Catch−based
Length−based

Table 1. Life-history information and priors for the three species used in the study. Notation is as follows: *Lognormal* (μ, σ^2); Uniform *U* (a, b). Priors for *K* were Uniform between the maximum catch in the time series and 100 times the maximum catch. For the Catch-MSY method, the depletion priors were Uniform centered on the true value with a minimum of *true - 0.1* and a maximum of *true + 0.1*.

Operating model inputs	**Symbol**	**Short-lived**	**Medium-lived**	**Long-lived**
Maximum age	Age_{max}	10	15	64
Age at 50% maturity (years)	A_{mat}	3	5	16
Length where 50% of the fish are mature (FL cm)	L_{50}	29	90	55
Length where 95% of the fish are mature (FL cm)	L_{95}	34	100	57
Length-weight scaling parameter	α	2.73×10^{-6}	1.34×10^{-5}	1.80×10^{-5}
Length-weight allometric parameter	β	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 of length at age for all ages	CVL	0.1	0.1	0.1
Natural mortality (1/years)	M	0.60	0.30	0.05
Steepness	h	0.5	0.9	0.8
Selectivity at 50% (cm)	S_{50}	25	60	45
Selectivity at 95% (cm)	S_{95}	30	75	50
Recruitment deviations	σ_R	0.3	0.4	0.5
Fishing mortality deviations	σ_F	0.2	0.2	0.2
Estimation models prior distributions				
Depletion (used for all catch-based models)	XB_0	*Lognormal* (true, 0.1)	*Lognormal* (true, 0.1)	*Lognormal* (true, 0.1)
Carrying capacity (used for Catch-MSY, CMSY and SSCOM)	K	*U* (max(catch), max(catch)x100)	*U* (max(catch), max(catch)x100)	*U* (max(catch), max(catch)x100)
Population rate of increase (used for Catch-MSY, CMSY and SSCOM)	r	*U* (0.8, 1.2)	*U* (0.2, 0.6)	*U* (0.05, 0.4)
Steepness (used for SSS)	h	*Normal* (0.5,0.1)	*Normal* (0.9,0.1)	*Normal* (0.8,0.1)
Vulnerability (used for DBSRA)	F_{MSY}/M	*U* (0, 2)	*U* (0, 2)	*U* (0, 2)
Compensation (used for DBSRA)	B_{MSY}/B_0	*U* (0, 1)	*U* (0, 1)	*U* (0, 1)



Short-lived
Medium-lived
Long-lived
Bias (median RE)
Imprecision (var^0.5 RE)
4
3
2
1
0
−1
2.0
1.5
1.0
0.5
0.0
SSS
DBSRA
CatchMSY
CMSY
LBSPR
LIME
LBB
Harvest_scenario
1
2
3
Depletion
0.2
0.4
0.6

Table 2 Bias in performance for the catch-based models. The values in between brackets are the

Scenarios	Life-history	Harvest trend	Final depletion	SSS (RE = 0.17)	DBSRA (RE = 0.63)
1	Short-lived (RE = 1.15)	Scenario 1 (RE = 1.53)	0.2	**-0.06**	-0.75
2			0.4	**0.17**	-0.88
3			0.6	**0.04**	-0.66
4		Scenario 2 (RE = 0.97)	0.2	**-0.09**	-0.68
5			0.4	0.14	-0.84
6			0.6	**-0.27**	-0.57
7		Scenario 3 (RE = 0.95)	0.2	**-0.25**	-0.48
8			0.4	**0.11**	-0.77
9			0.6	**-0.29**	-0.42
10	Medium-lived (RE = 0.50)	Scenario 1 (RE = 0.57)	0.2	**-0.06**	-0.67
11			0.4	0.15	-0.77
12			0.6	-0.24	-0.59
13		Scenario 2 (RE = 0.46)	0.2	**-0.08**	-0.60
14			0.4	0.13	-0.72
15			0.6	-0.24	-0.51
16		Scenario 3 (RE = 0.47)	0.2	**-0.09**	-0.49
17			0.4	0.11	-0.65
18			0.6	-0.24	-0.41
19	Long-lived (RE = 1.33)	Scenario 1 (RE = 1.10)	0.2	**0.13**	-0.63
20			0.4	0.28	-0.66
21			0.6	**0.09**	-0.60
22		Scenario 2 (RE = 1.44)	0.2	**0.15**	-0.60
23			0.4	0.30	-0.65
24			0.6	**0.11**	-0.57
25		Scenario 3 (RE = 1.43)	0.2	**0.17**	-0.58
26			0.4	0.28	-0.62
27			0.6	**0.13**	-0.57

mean absolute relative error per factor: harvest rates scenarios, species and final de

Catch-MSY (RE = 1.62)	CMSY (RE = 0.71)	Absolute mean RE
2.57	0.17	1.36
2.07	-0.33	1.05
3.69	1.15	2.19
1.75	0.36	0.79
1.52	**-0.10**	0.60
2.85	1.59	1.52
2.37	0.53	0.95
1.32	0.15	0.52
2.61	1.82	1.37
0.95	0.28	0.47
0.48	**-0.05**	0.38
1.54	**0.16**	0.86
0.84	0.31	0.41
0.35	**-0.01**	0.36
1.70	**0.18**	0.62
1.04	0.32	0.45
0.36	**0.03**	0.35
1.97	**0.19**	0.60
1.34	-0.12	0.72
0.41	-0.78	0.48
2.31	1.87	2.11
1.33	0.46	0.85
0.34	-0.74	0.46
2.87	2.72	3.03
1.84	1.27	1.60
0.55	-0.40	0.38
2.76	3.20	2.31

Table 2 Bias in performance for the length-based methods. The values in between brackets are t

Scenarios	Life-history	Harvest trend	Final depletion	LBSPR (RE = 0.51)	LIME (RE = 0.15)
1	Short-lived (RE = 0.80)	Scenario 1 (RE = 0.39)	0.2	-0.42	**0.25**
2			0.4	-0.69	**0.05**
3			0.6	-0.80	**-0.06**
4		Scenario 2 (RE = 0.69)	0.2	-0.66	**0.34**
5			0.4	-0.85	**-0.13**
6			0.6	-0.92	**-0.06**
7		Scenario 3 (RE = 1.29)	0.2	-0.92	**0.55**
8			0.4	-0.97	**0.15**
9			0.6	-0.98	**-0.05**
10	Medium-lived (RE = 0.31)	Scenario 1 (RE = 0.23)	0.2	-0.10	0.28
11			0.4	-0.40	**0.02**
12			0.6	-0.48	**-0.05**
13		Scenario 2 (RE = 0.26)	0.2	**-0.09**	0.26
14			0.4	-0.44	-0.02
15			0.6	-0.57	**-0.11**
16		Scenario 3 (RE = 0.46)	0.2	**-0.14**	0.20
17			0.4	-0.50	**-0.09**
18			0.6	-0.62	**-0.14**
19	Long-lived (RE = 0.28)	Scenario 1 (RE = 0.23)	0.2	0.27	**0.20**
20			0.4	-0.26	**0.01**
21			0.6	-0.40	**-0.04**
22		Scenario 2 (RE = 0.27)	0.2	0.38	**0.22**
23			0.4	-0.25	**0.01**
24			0.6	-0.45	**-0.04**
25		Scenario 3 (RE = 0.32)	0.2	0.39	0.52
26			0.4	-0.28	**-0.01**
27			0.6	-0.51	**0.01**

:he mean absolute relativ

LBB (RE = 0.73)	Absolute mean RE
1.00	0.56
0.10	0.28
-0.16	0.34
2.41	1.14
0.68	0.56
0.18	0.39
4.71	2.06
2.04	1.05
1.26	0.76
0.01	0.13
-0.36	0.26
-0.37	0.30
0.64	0.33
-0.01	0.16
0.16	0.28
1.64	0.66
0.54	0.38
0.31	0.36
0.33	0.27
-0.23	0.17
-0.35	0.26
0.54	0.38
-0.19	0.15
-0.41	0.30
0.60	0.50
-0.10	0.13
-0.41	0.31

Appendix

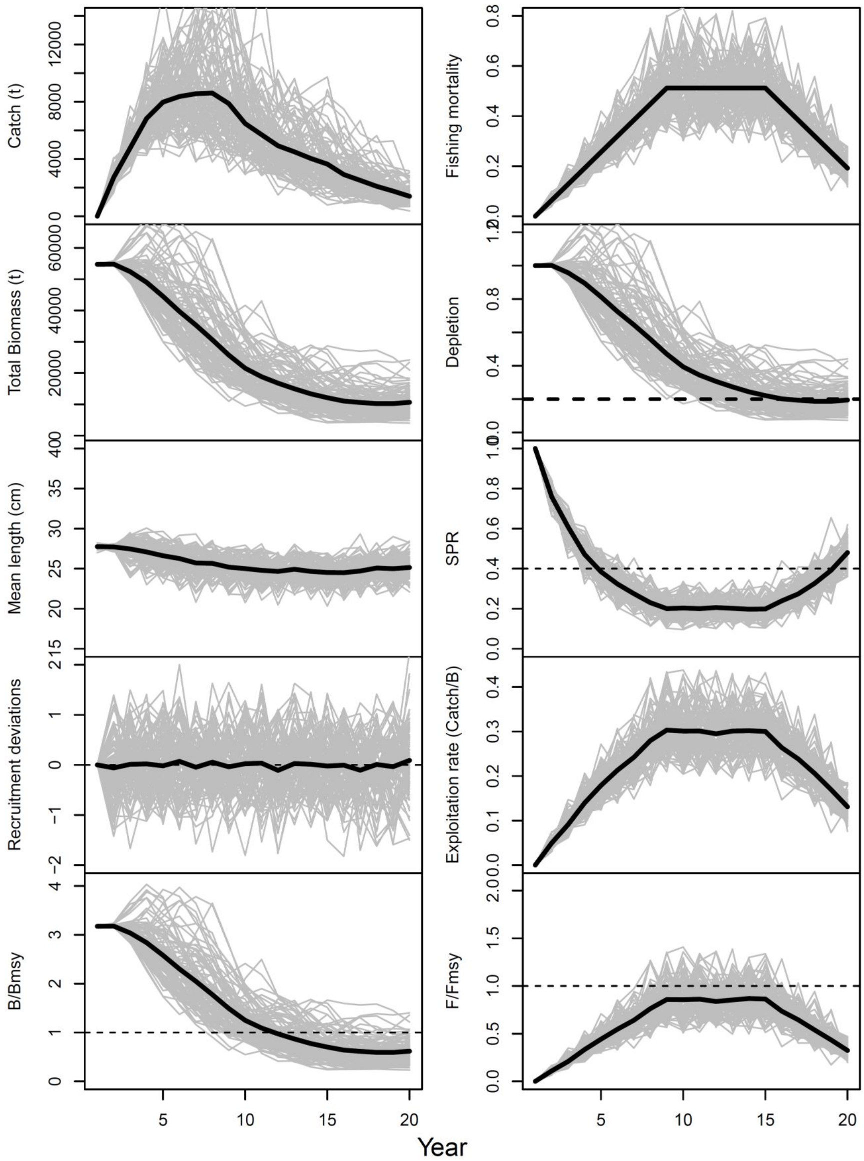


Figure A1. Time series for each simulated fast-grow chub mackerel population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

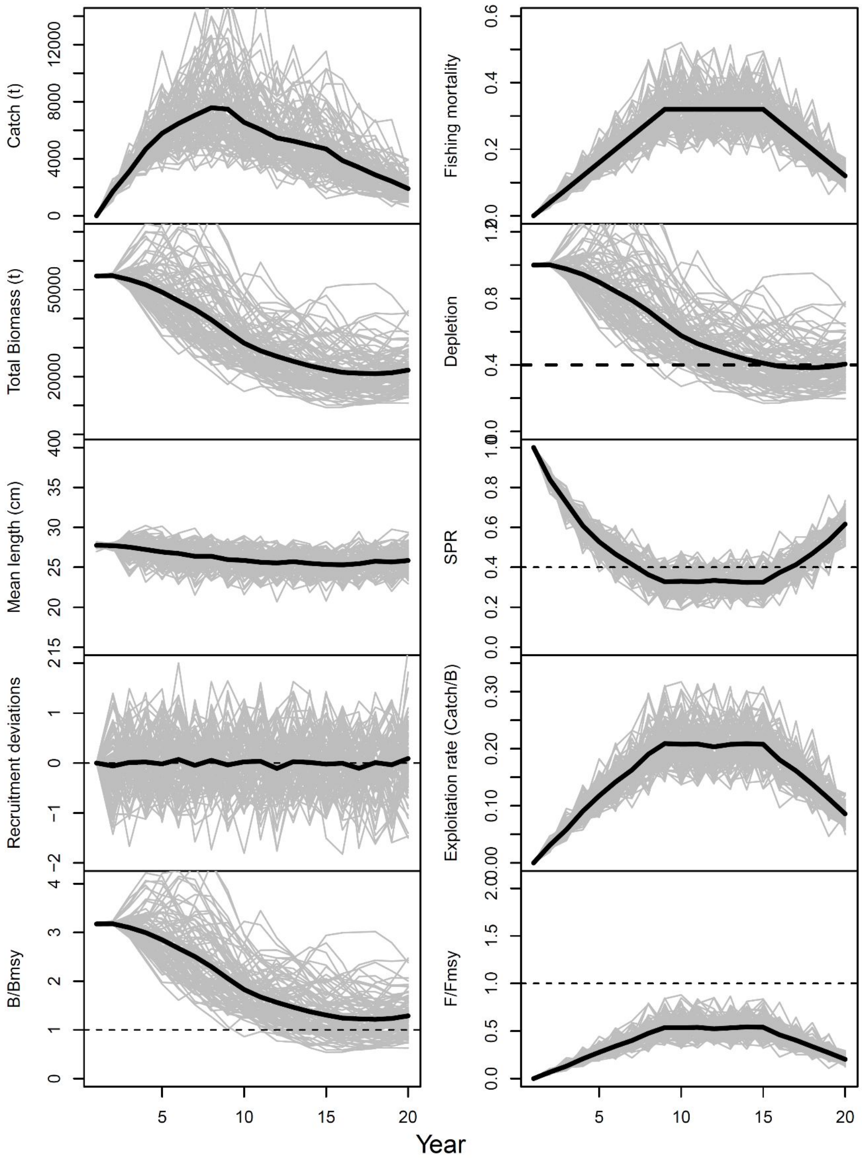


Figure A2. Time series for each simulated fast-grow chub mackerel population for harvest scenario 1 and depletion = 0.4. The black solid lines represent the mean value for all runs.

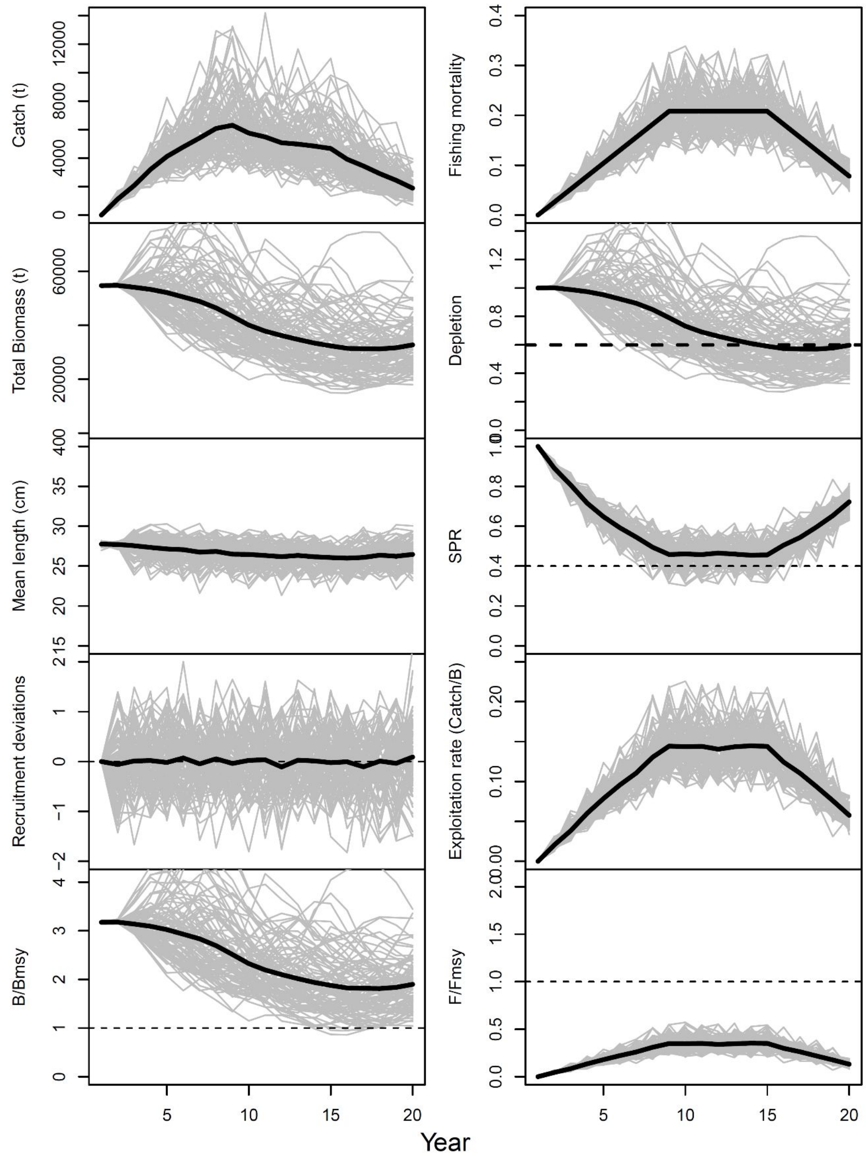


Figure A3. Time series for each simulated fast-grow chub mackerel population for harvest scenario 1 and depletion = 0.6. The black solid lines represent the mean value for all runs.

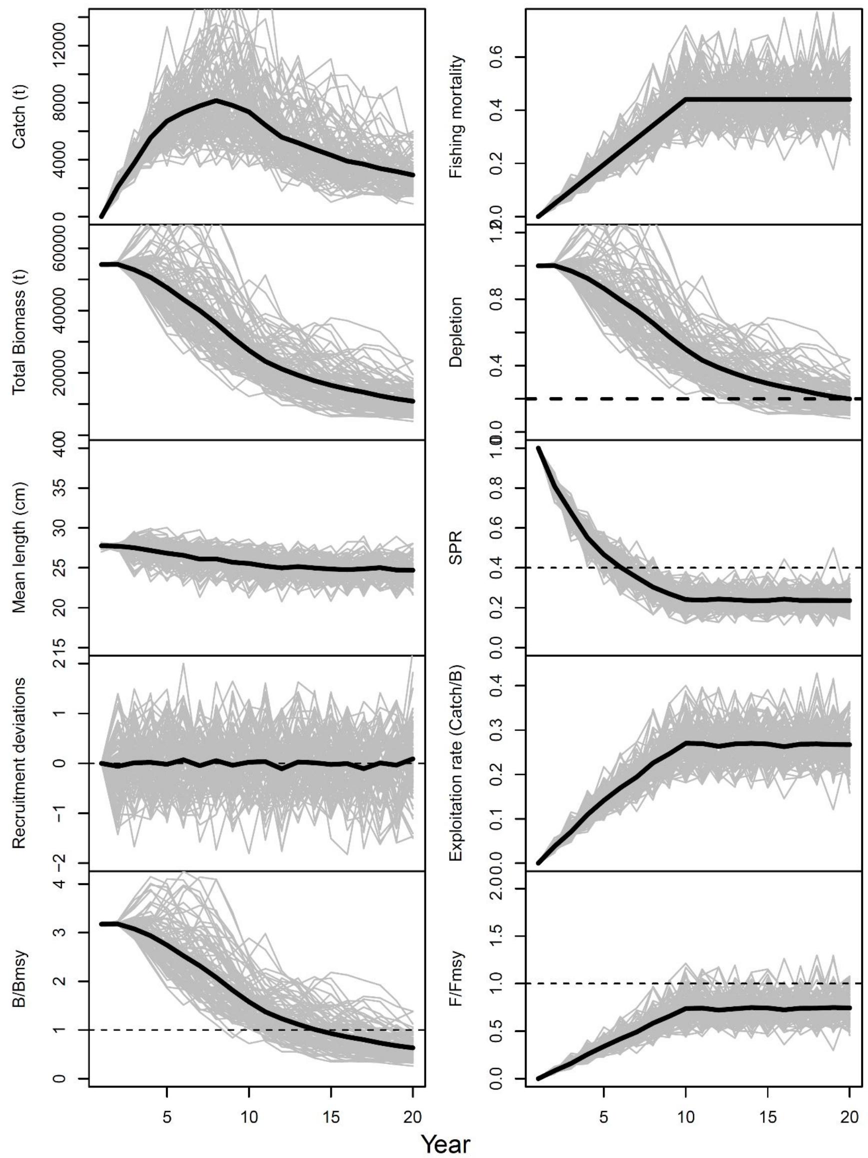


Figure A4. Time series for each simulated fast-grow chub mackerel population for harvest scenario 2 and depletion = 0.2. The black solid lines represent the mean value for all runs.

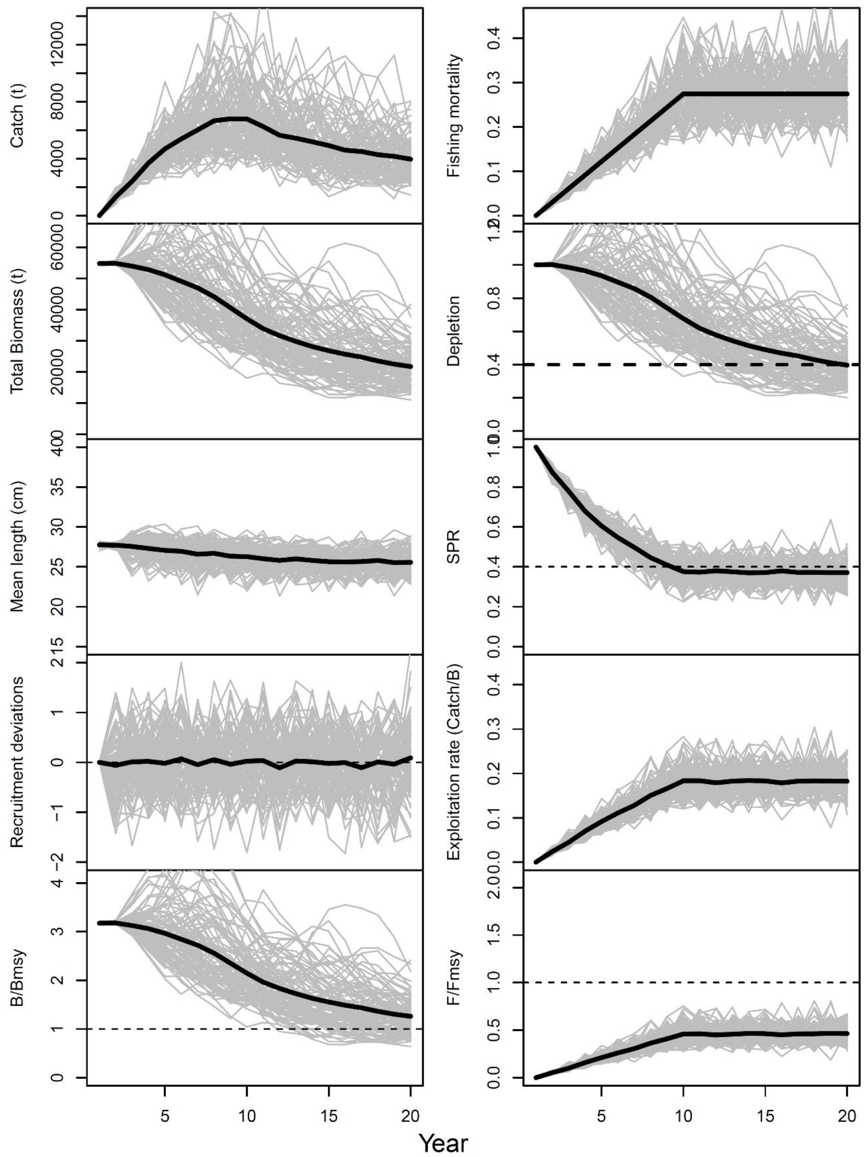


Figure A5. Time series for each simulated fast-grow chub mackerel population for harvest scenario 2 and depletion = 0.4. The black solid lines represent the mean value for all runs.

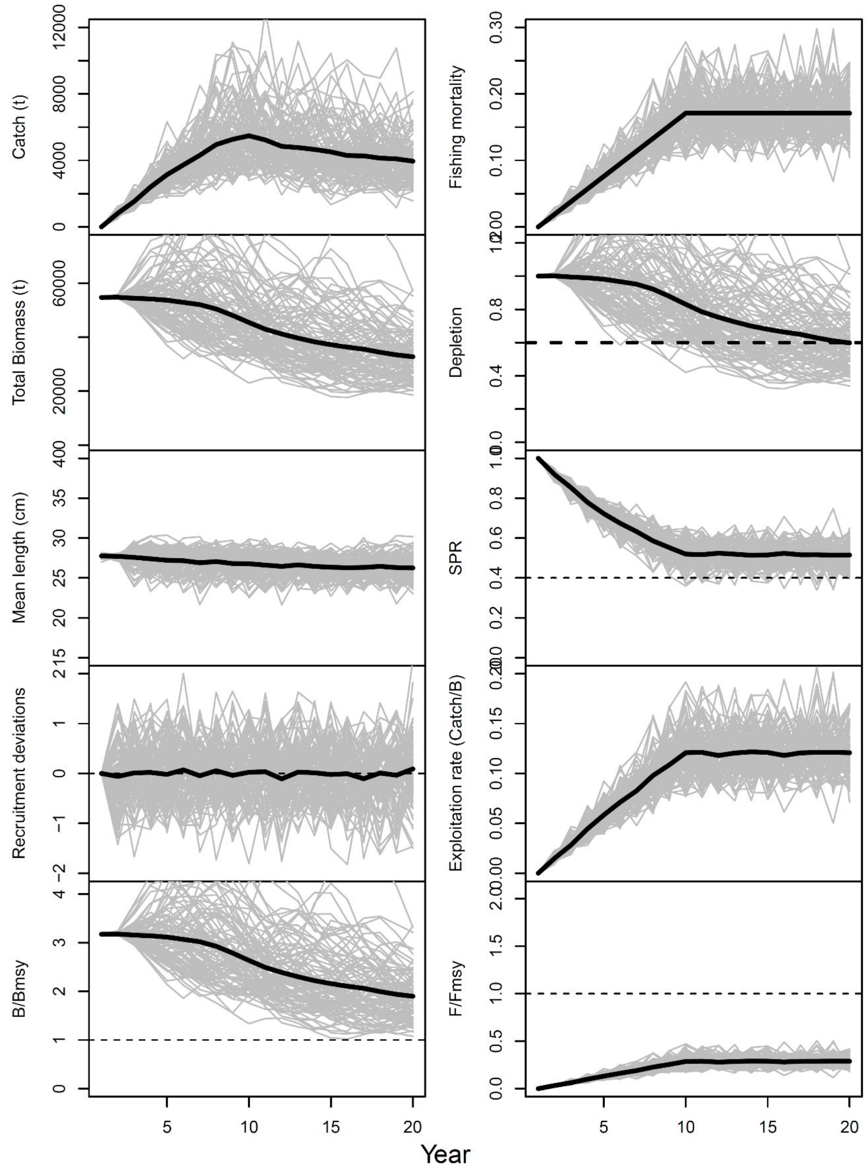


Figure A6. Time series for each simulated fast-grow chub mackerel population for harvest scenario 2 and depletion = 0.6. The black solid lines represent the mean value for all runs.

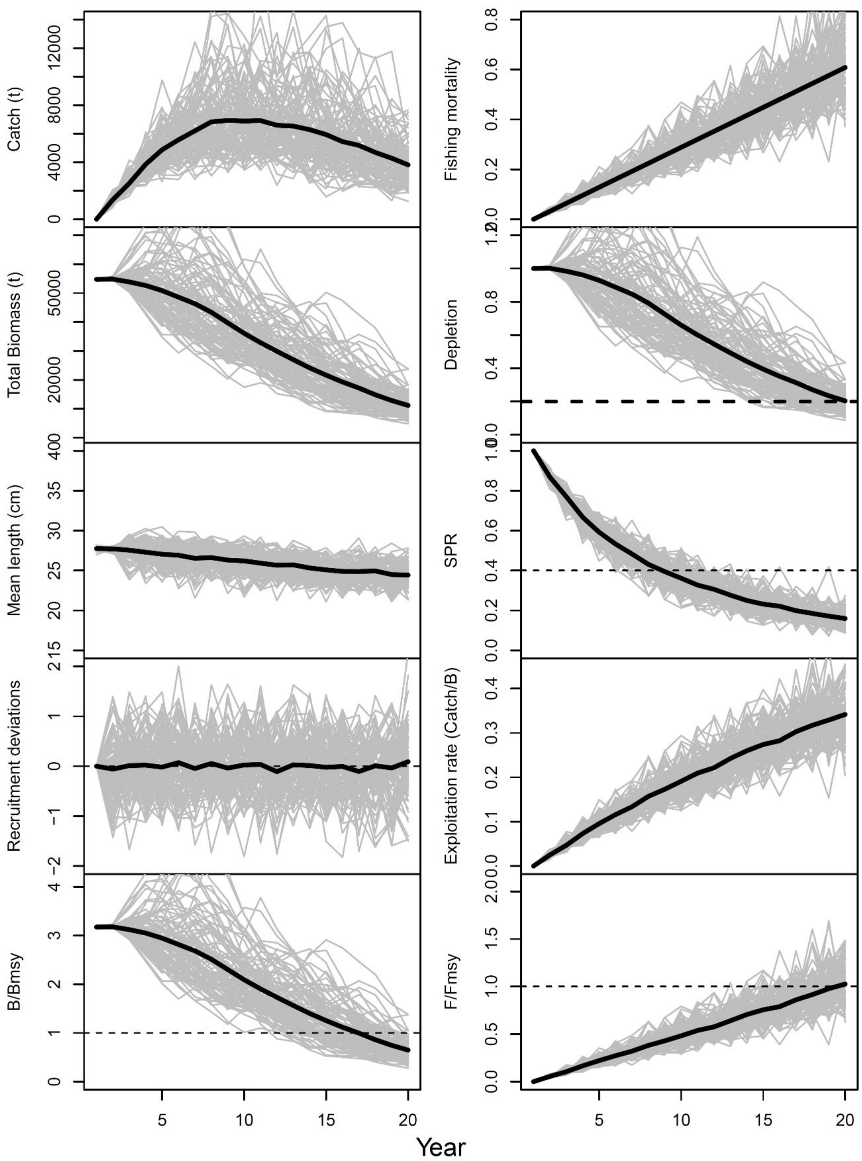


Figure A7. Time series for each simulated fast-grow chub mackerel population for harvest scenario 3 and depletion = 0.2. The black solid lines represent the mean value for all runs.

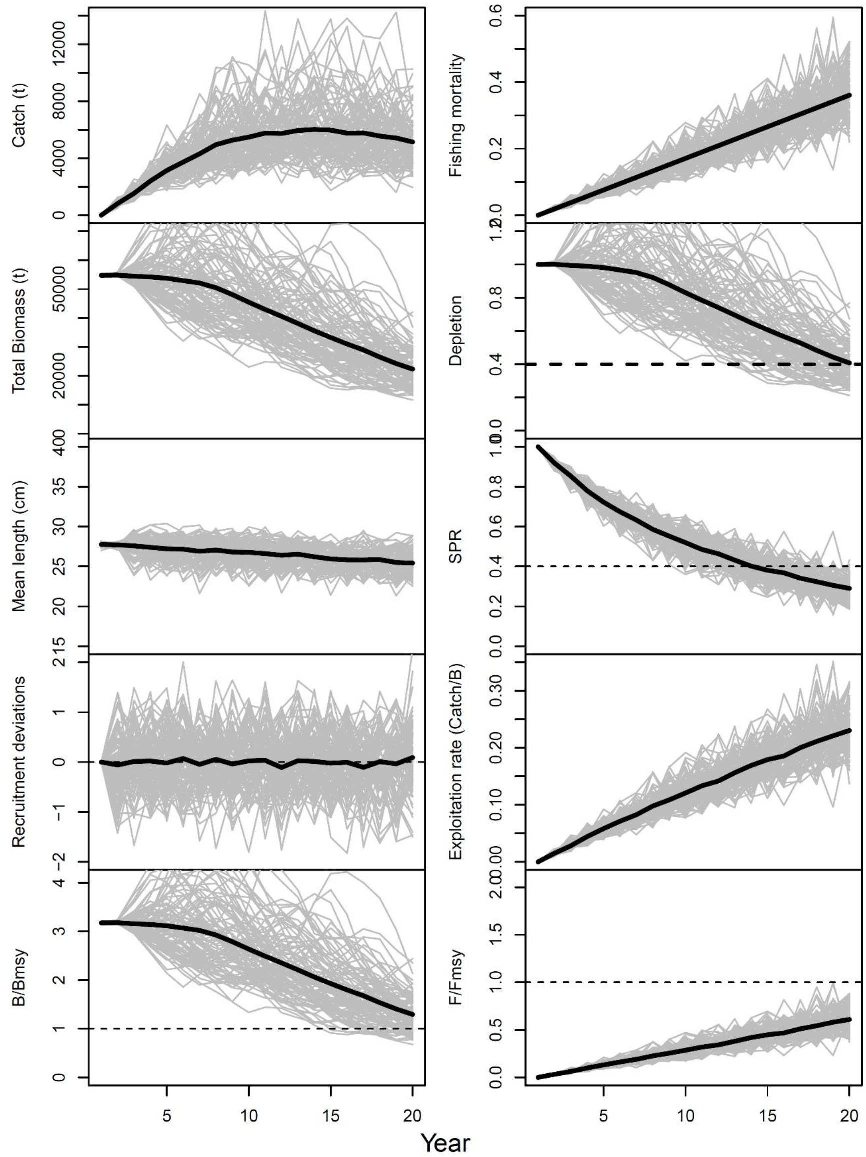


Figure A8. Time series for each simulated fast-grow chub mackerel population for harvest scenario 3 and depletion = 0.4. The black solid lines represent the mean value for all runs.

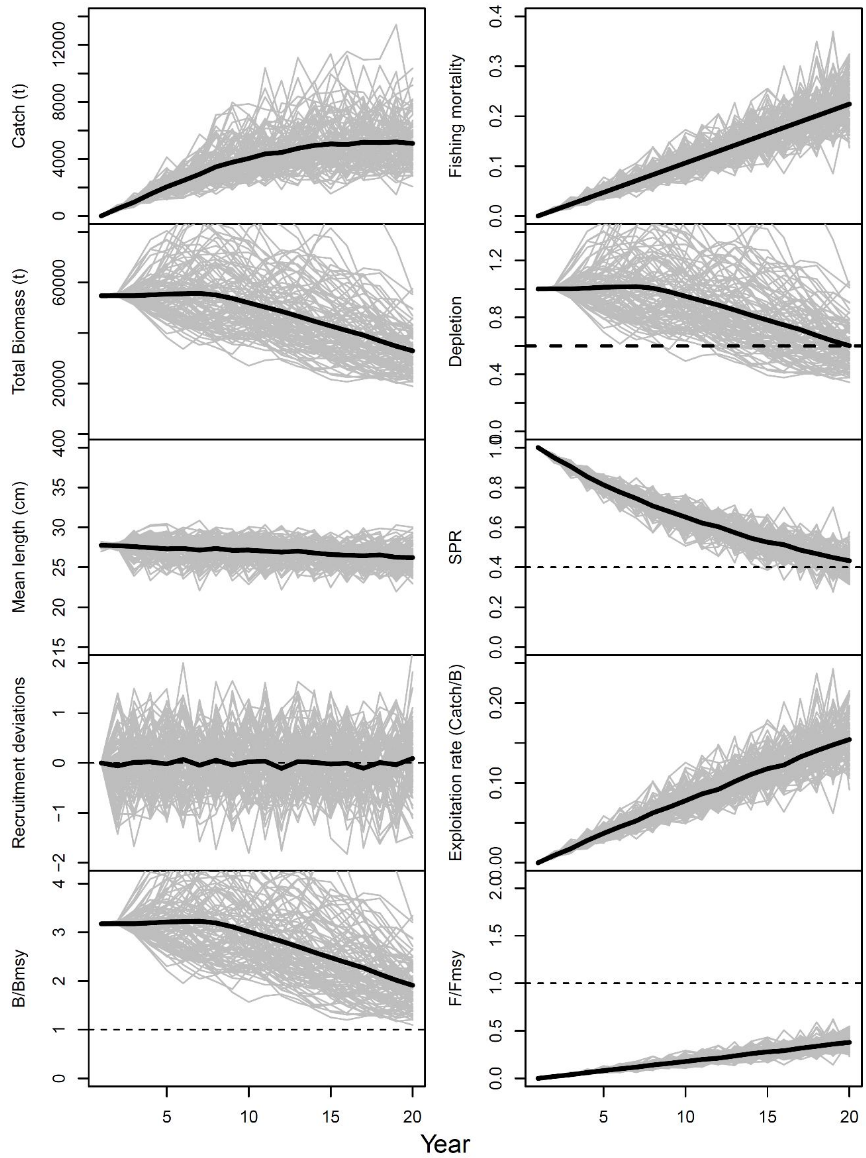


Figure A9. Time series for each simulated fast-grow chub mackerel population for harvest scenario 3 and depletion = 0.6. The black solid lines represent the mean value for all runs.

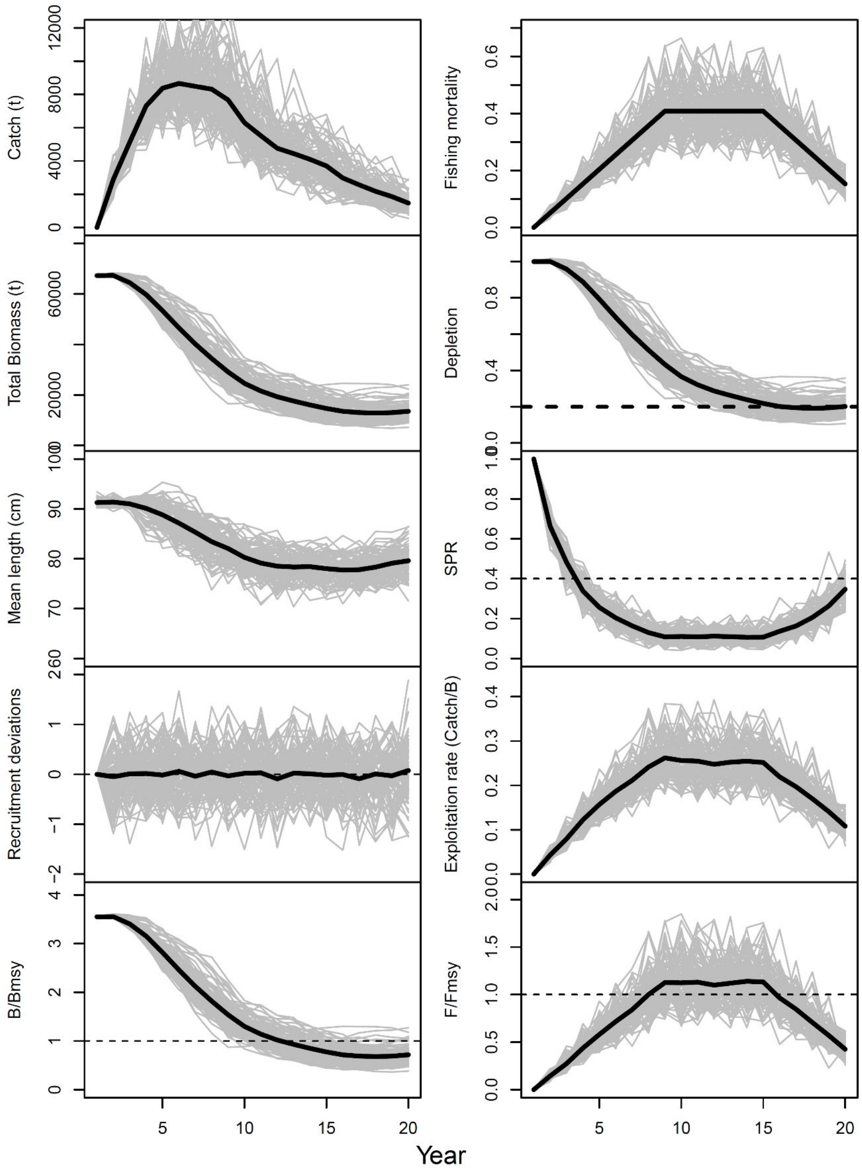


Figure A10. Time series for each simulated medium-grow albacore tuna population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

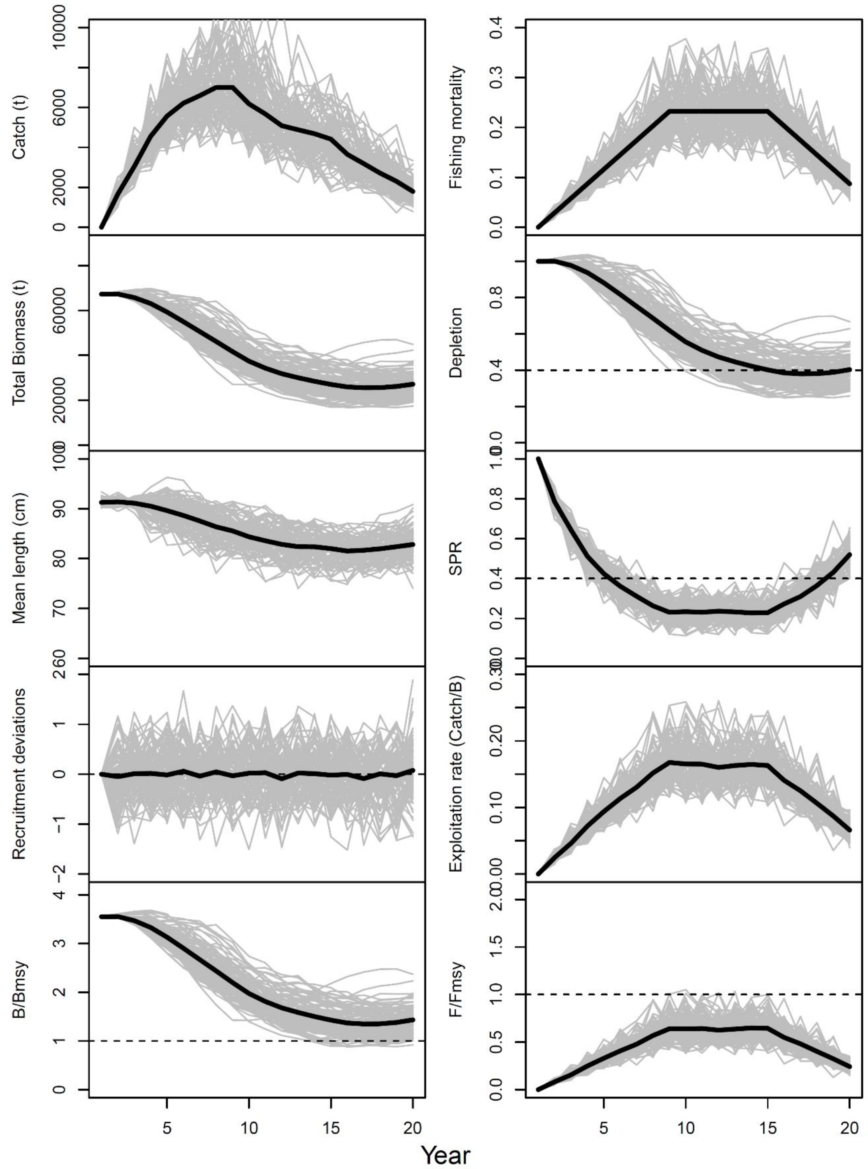


Figure A11. Time series for each simulated medium-grow albacore tuna population for harvest scenario 1 and depletion = 0.4. The black solid lines represent the mean value for all runs.

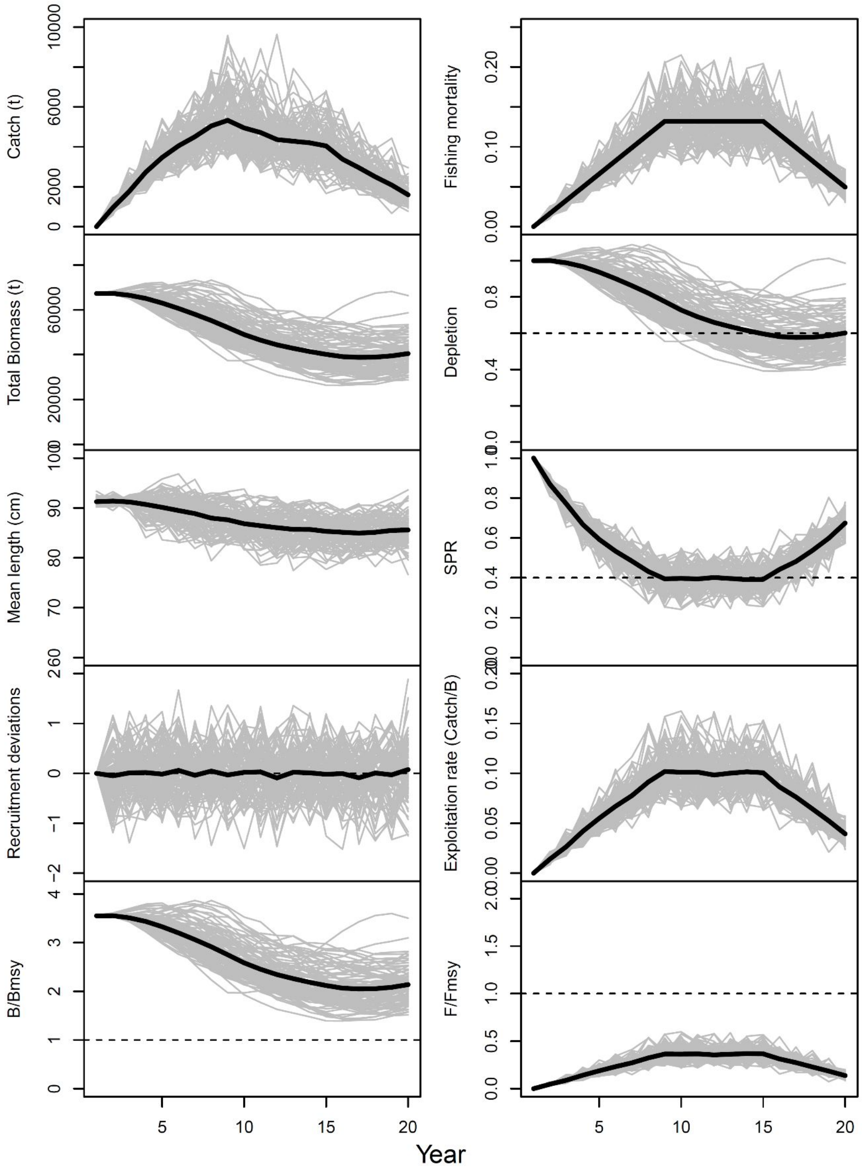


Figure A12. Time series for each simulated medium-grow albacore tuna population for harvest scenario 1 and depletion = 0.6. The black solid lines represent the mean value for all runs.

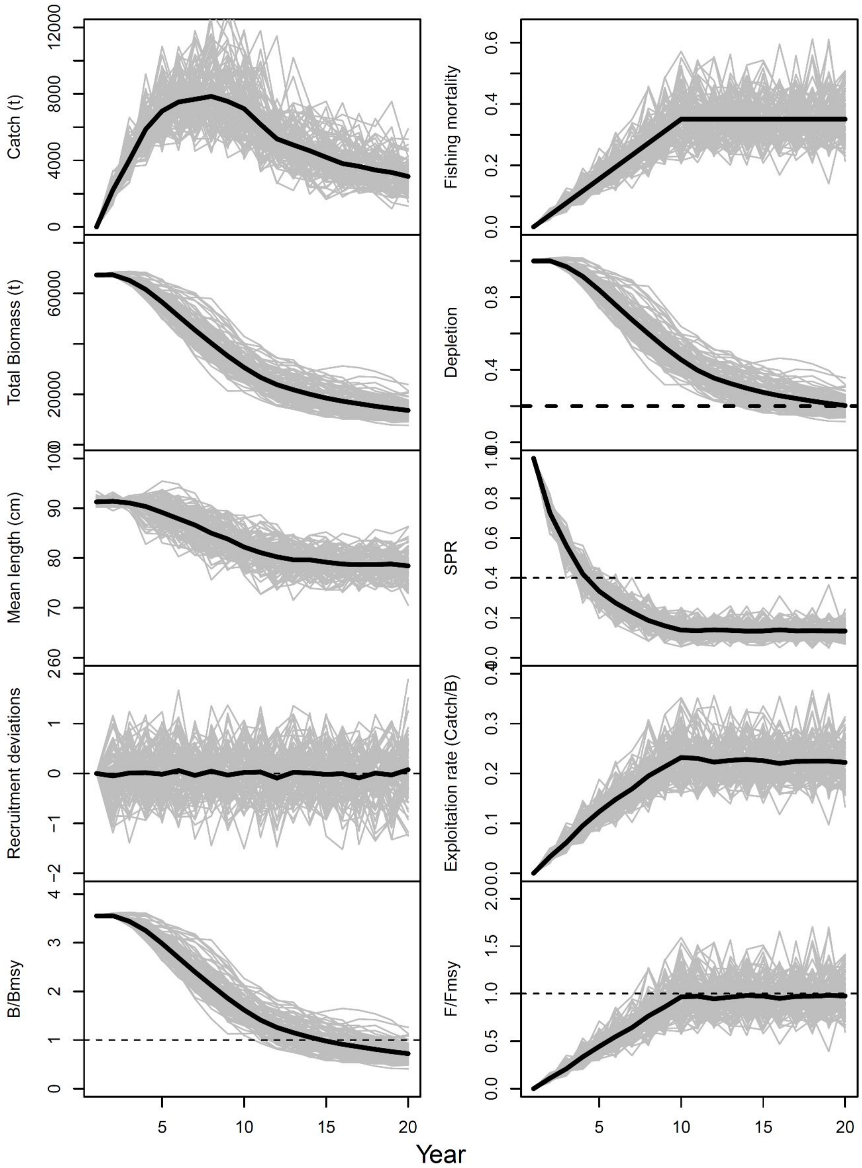


Figure A13. Time series for each simulated medium-grow albacore tuna population for harvest scenario 2 and depletion = 0.2. The black solid lines represent the mean value for all runs.

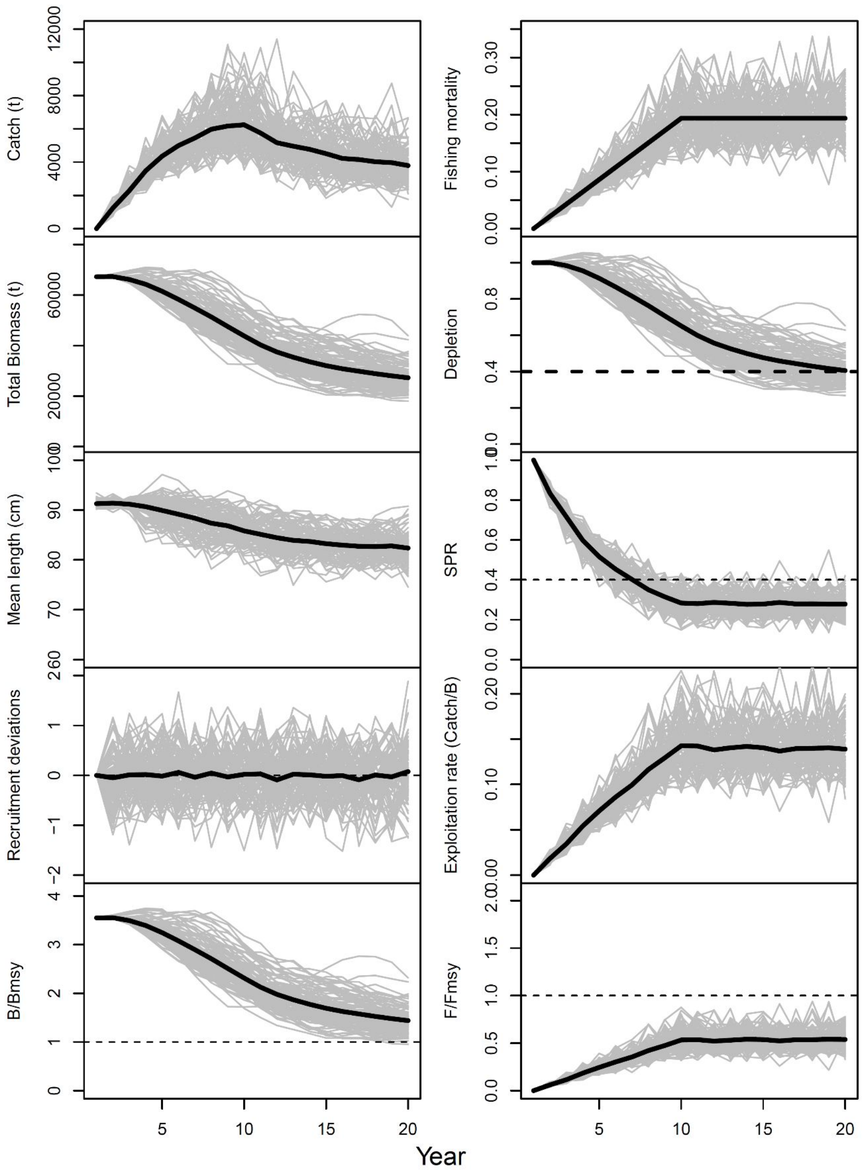


Figure A14. Time series for each simulated medium-grow albacore tuna population for harvest scenario 2 and depletion = 0.4. The black solid lines represent the mean value for all runs.

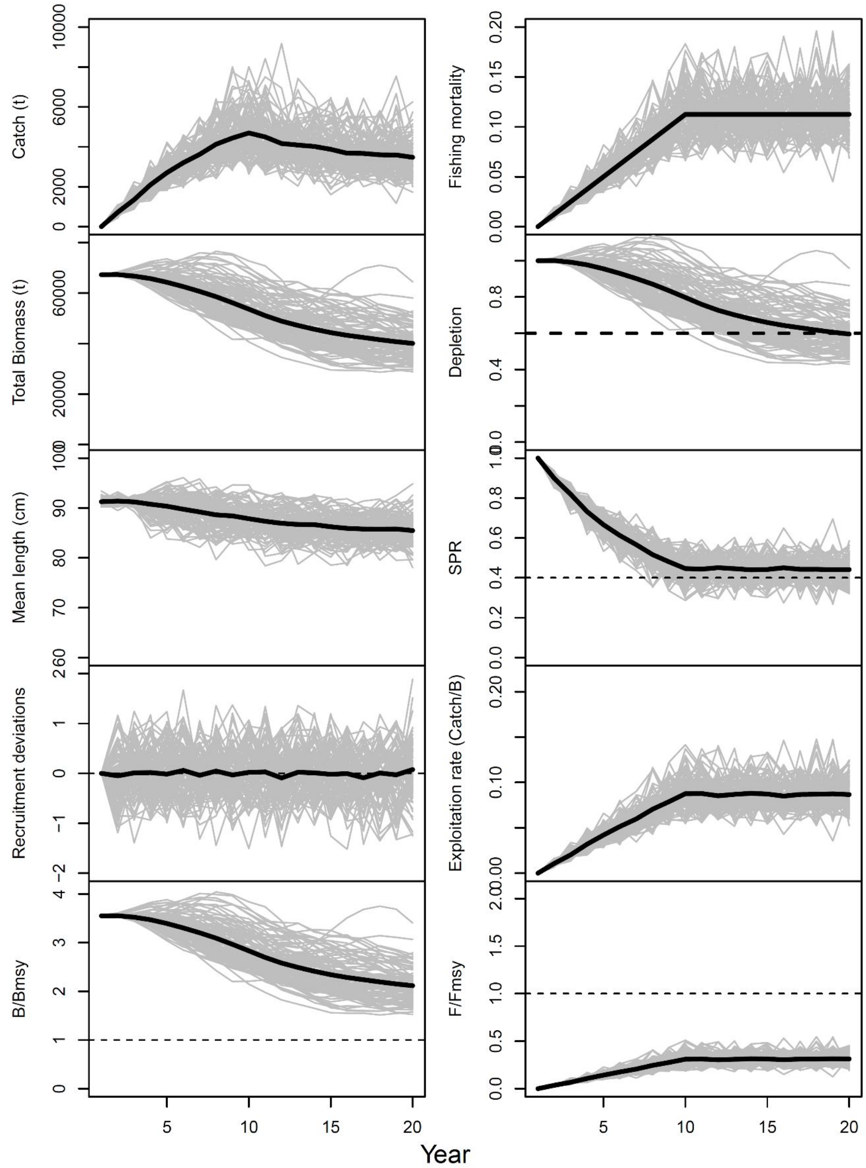


Figure A15. Time series for each simulated medium-grow albacore tuna population for harvest scenario 2 and depletion = 0.6. The black solid lines represent the mean value for all runs.

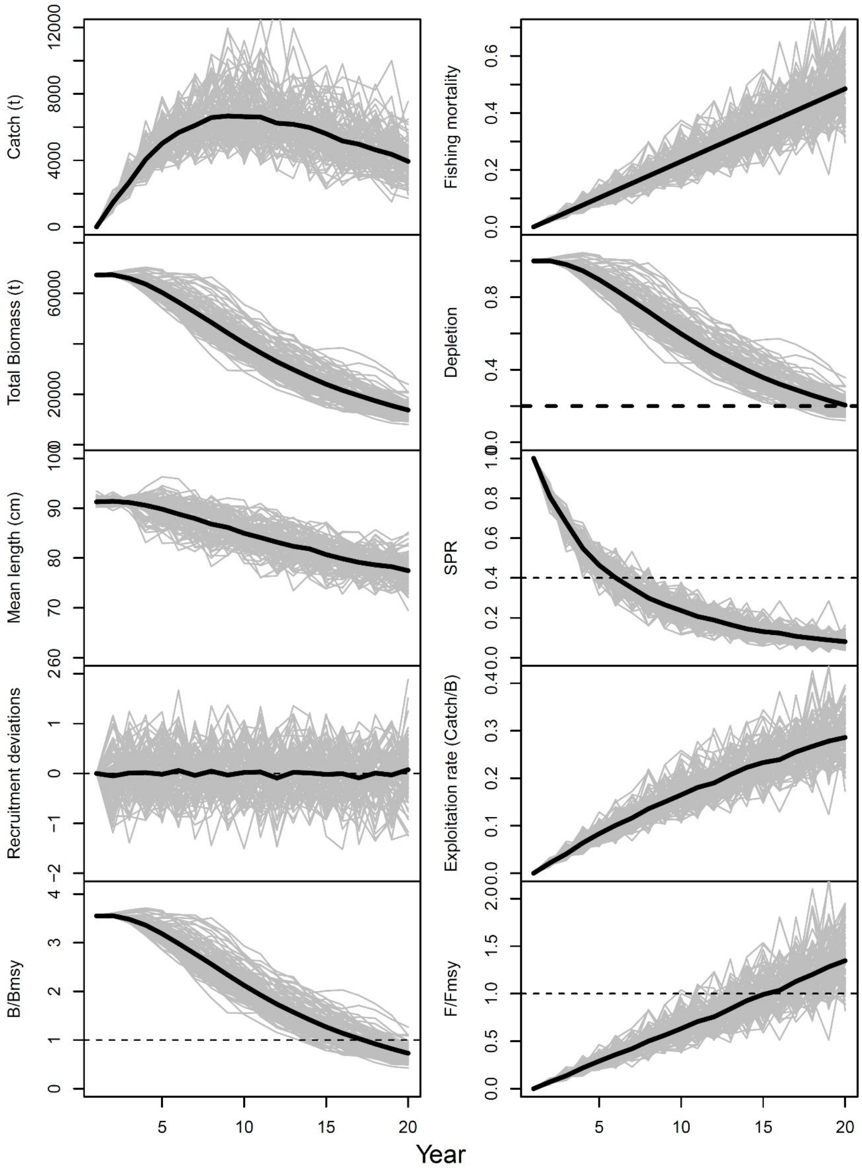


Figure A16. Time series for each simulated medium-grow albacore tuna population for harvest scenario 3 and depletion = 0.2. The black solid lines represent the mean value for all runs.

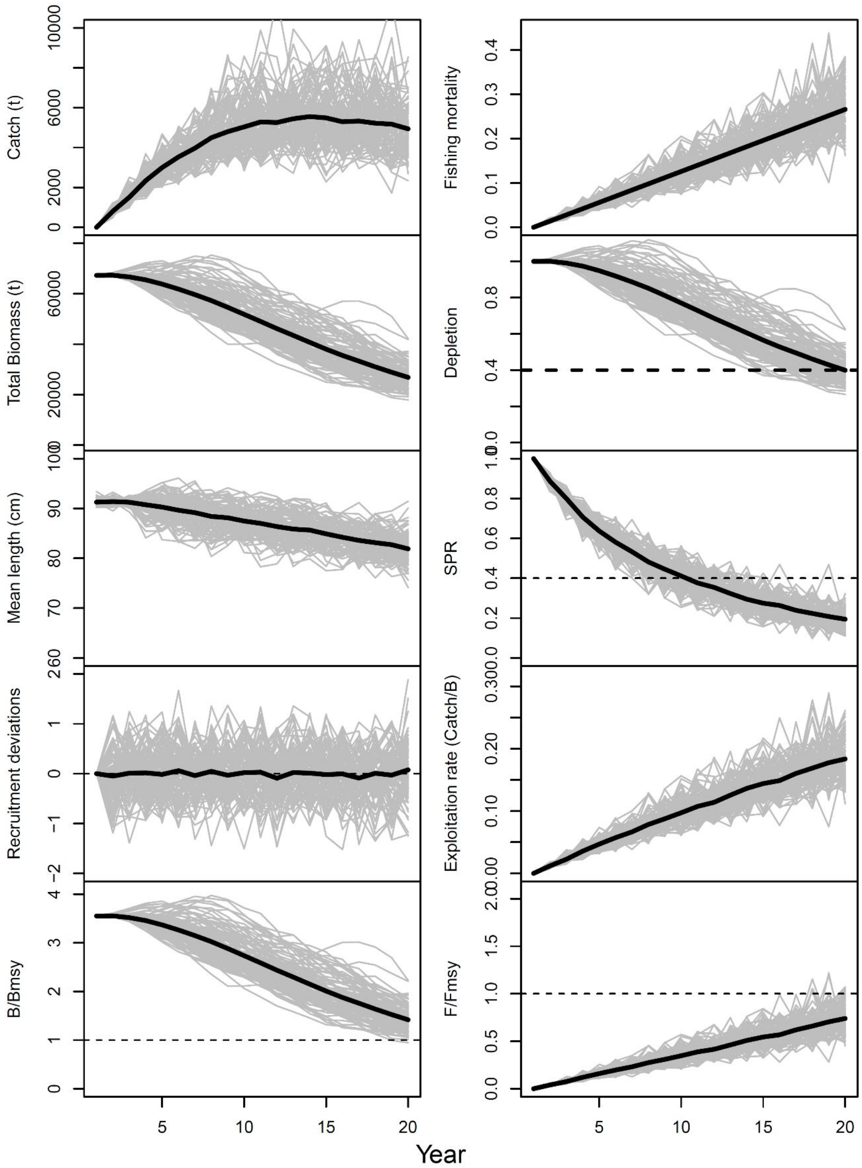


Figure A17. Time series for each simulated medium-grow albacore tuna population for harvest scenario 3 and depletion = 0.4. The black solid lines represent the mean value for all runs.

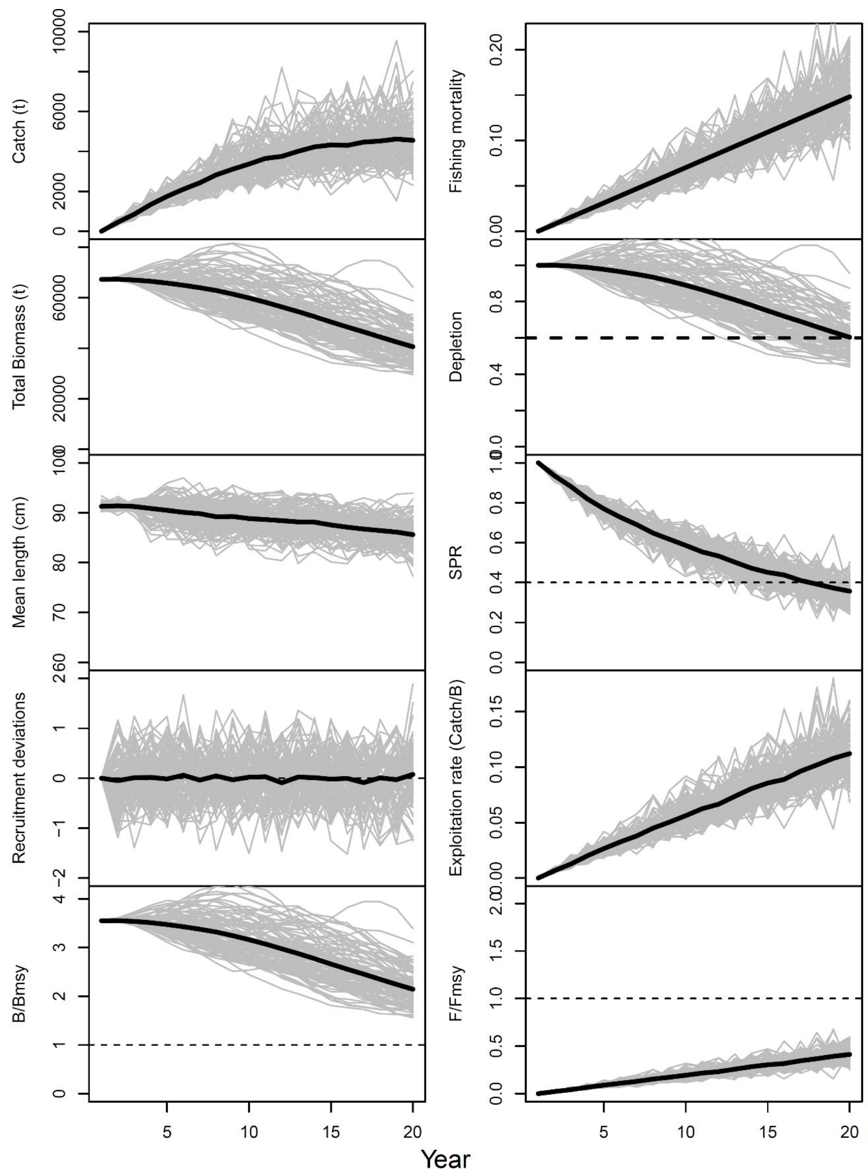


Figure A18. Time series for each simulated medium-grow albacore tuna population for harvest scenario 3 and depletion = 0.6. The black solid lines represent the mean value for all runs.

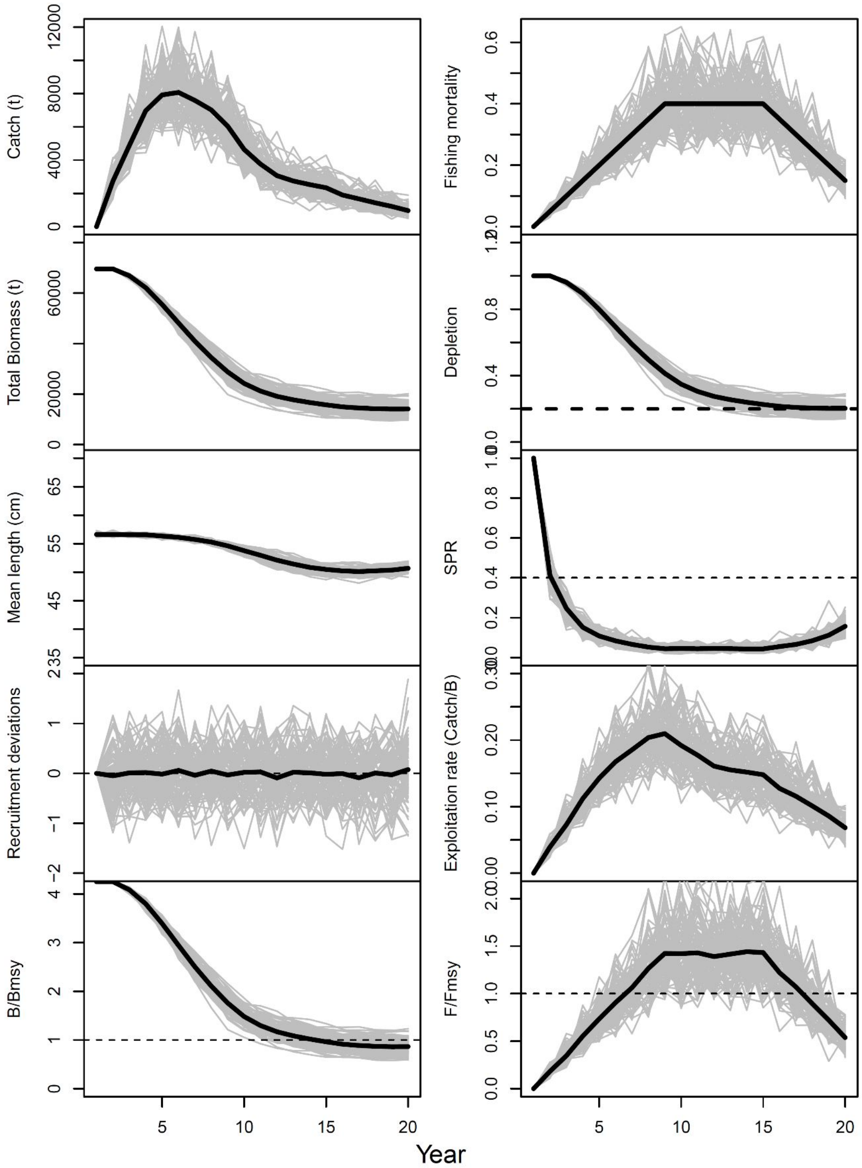


Figure A19. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

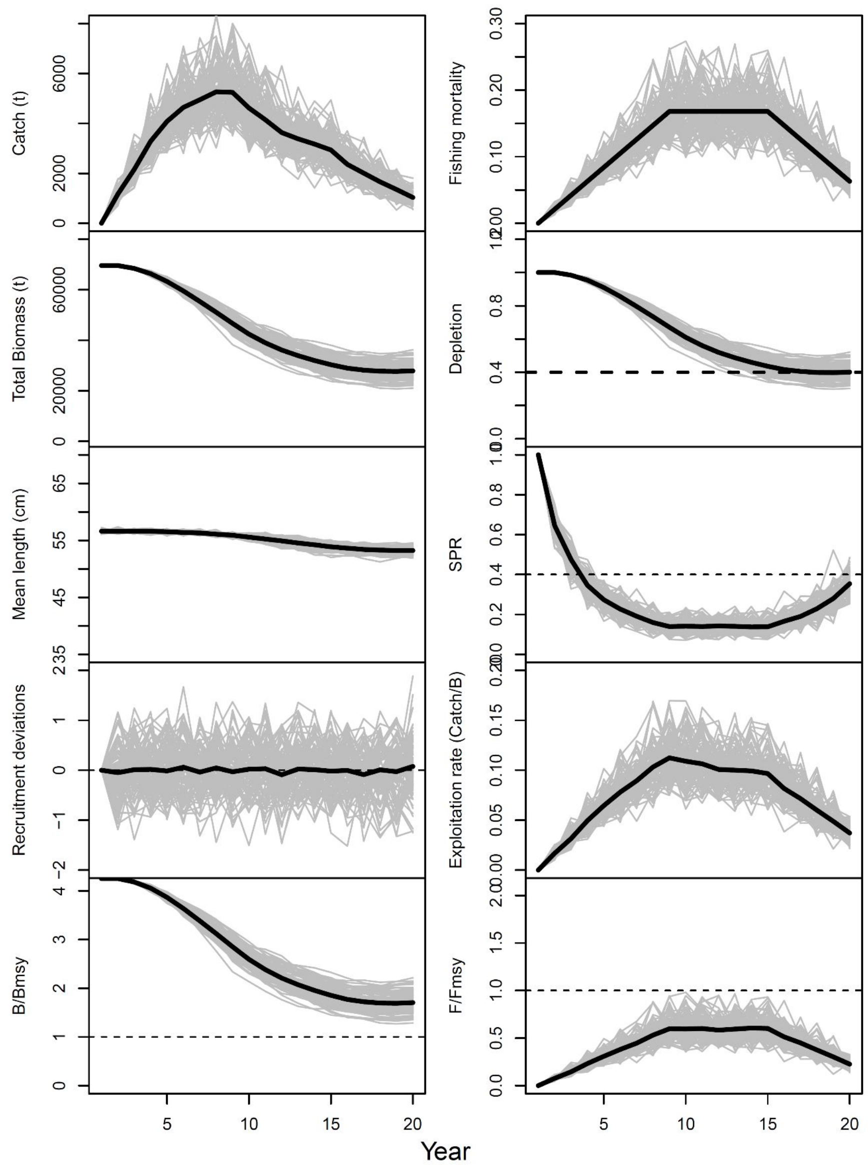


Figure A20. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.4. The black solid lines represent the mean value for all runs.

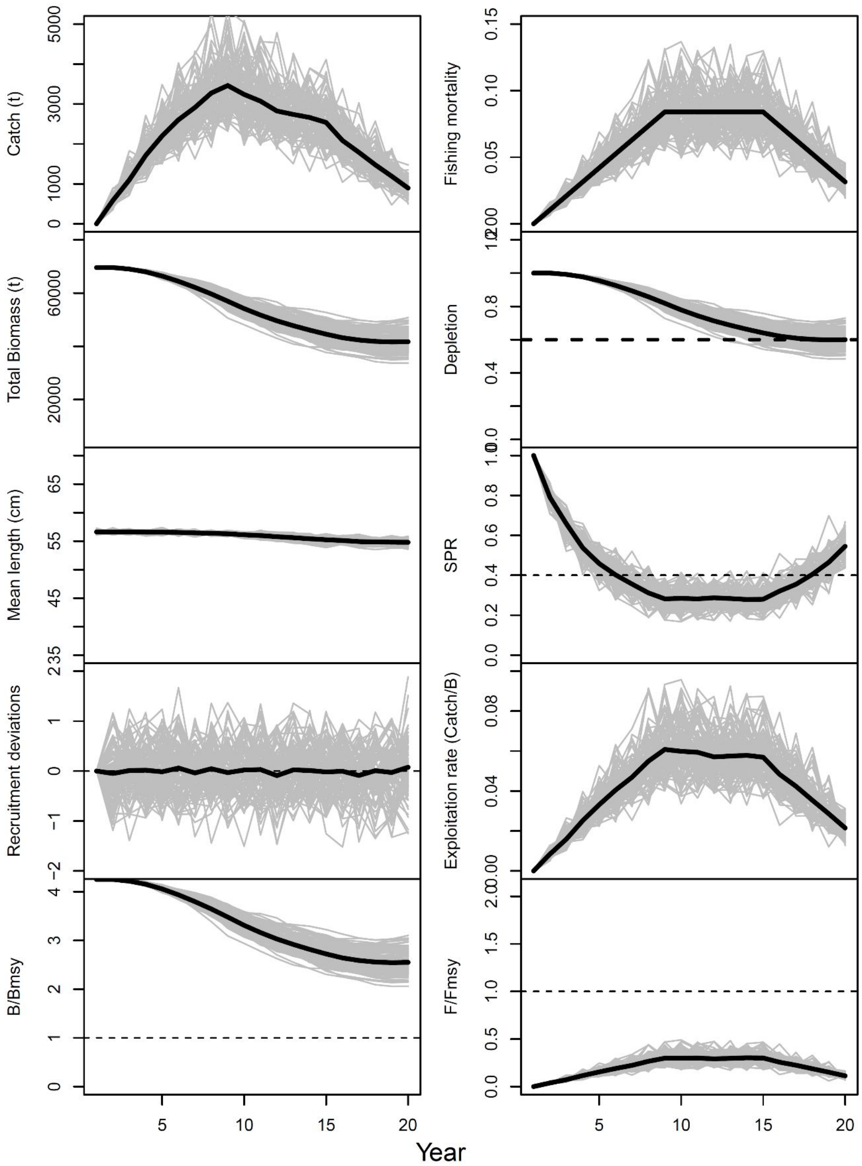


Figure A21. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.6. The black solid lines represent the mean value for all runs.

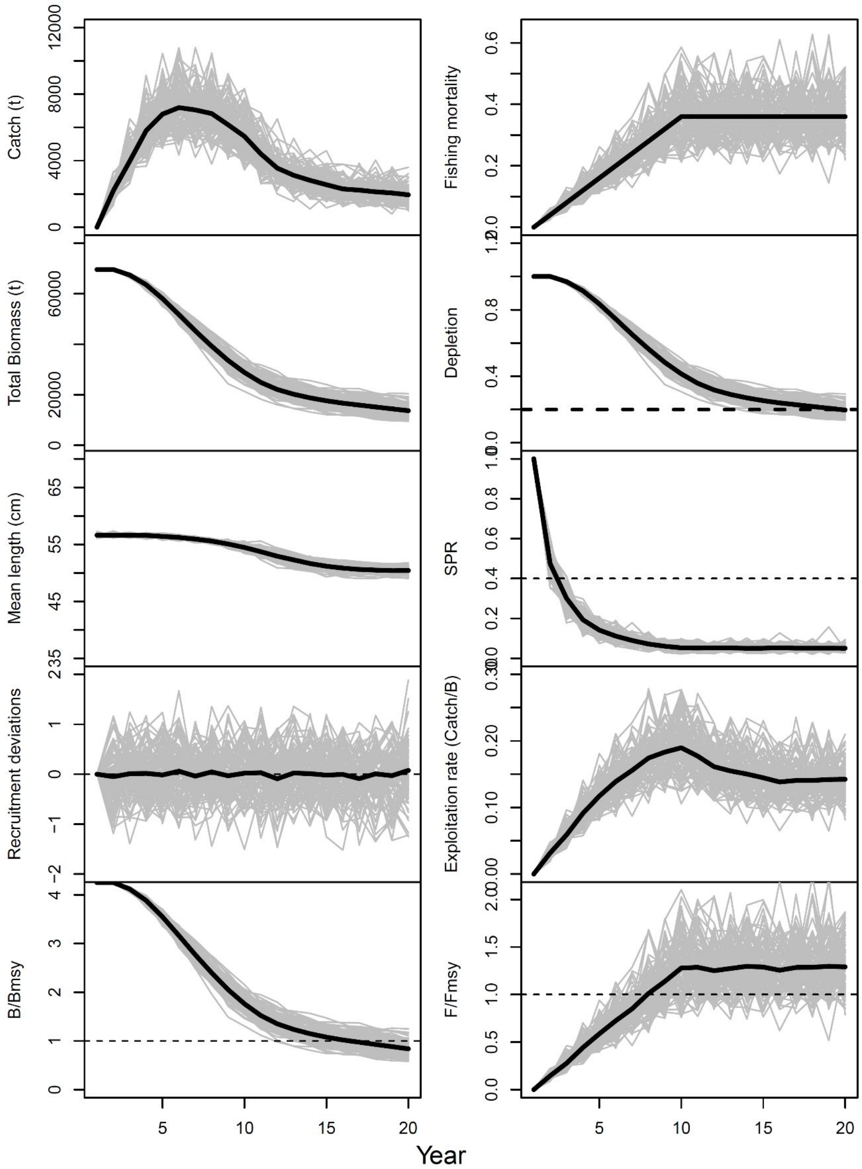


Figure A22. Time series for each simulated slow-grow canary rockfish population for harvest scenario 2 and depletion = 0.2. The black solid lines represent the mean value for all runs.

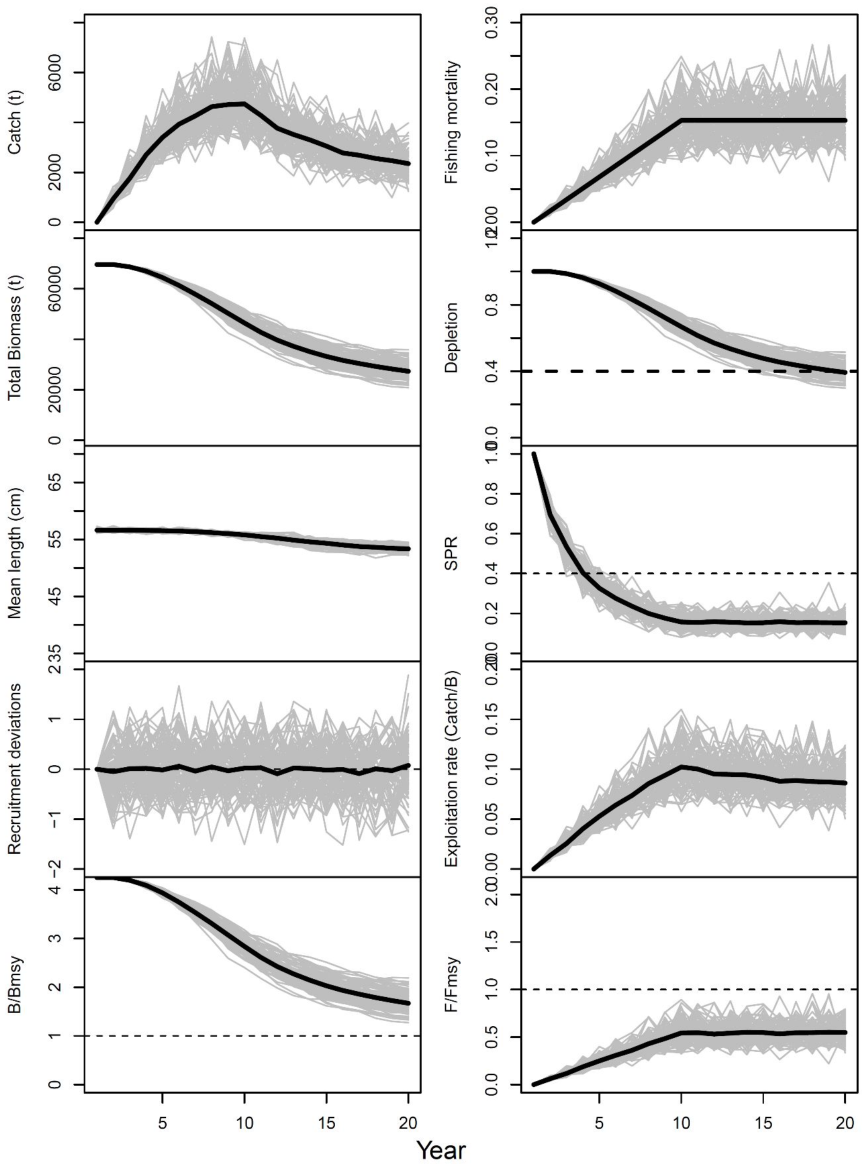


Figure A23. Time series for each simulated slow-grow canary rockfish population for harvest scenario 2 and depletion = 0.4. The black solid lines represent the mean value for all runs.

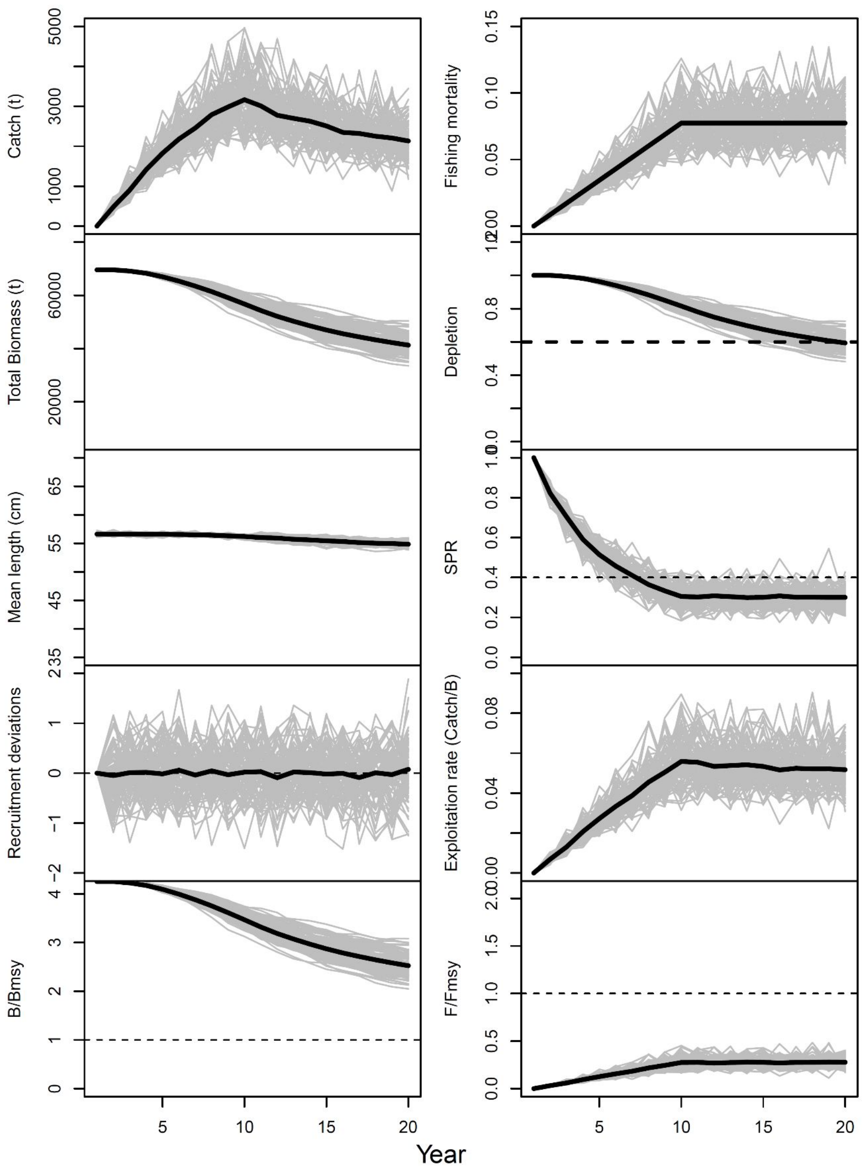


Figure A24. Time series for each simulated slow-grow canary rockfish population for harvest scenario 2 and depletion = 0.6. The black solid lines represent the mean value for all runs.

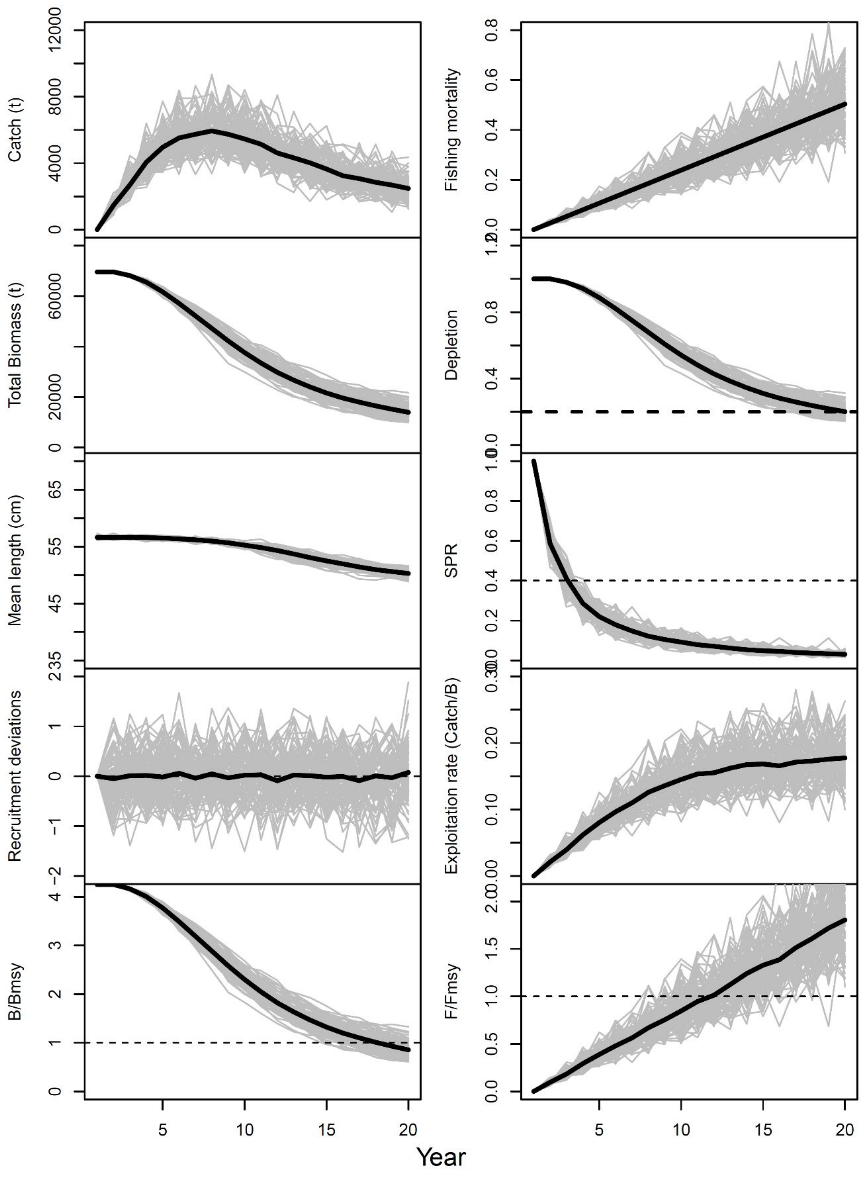


Figure A25. Time series for each simulated slow-grow canary rockfish population for harvest scenario 1 and depletion = 0.2. The black solid lines represent the mean value for all runs.

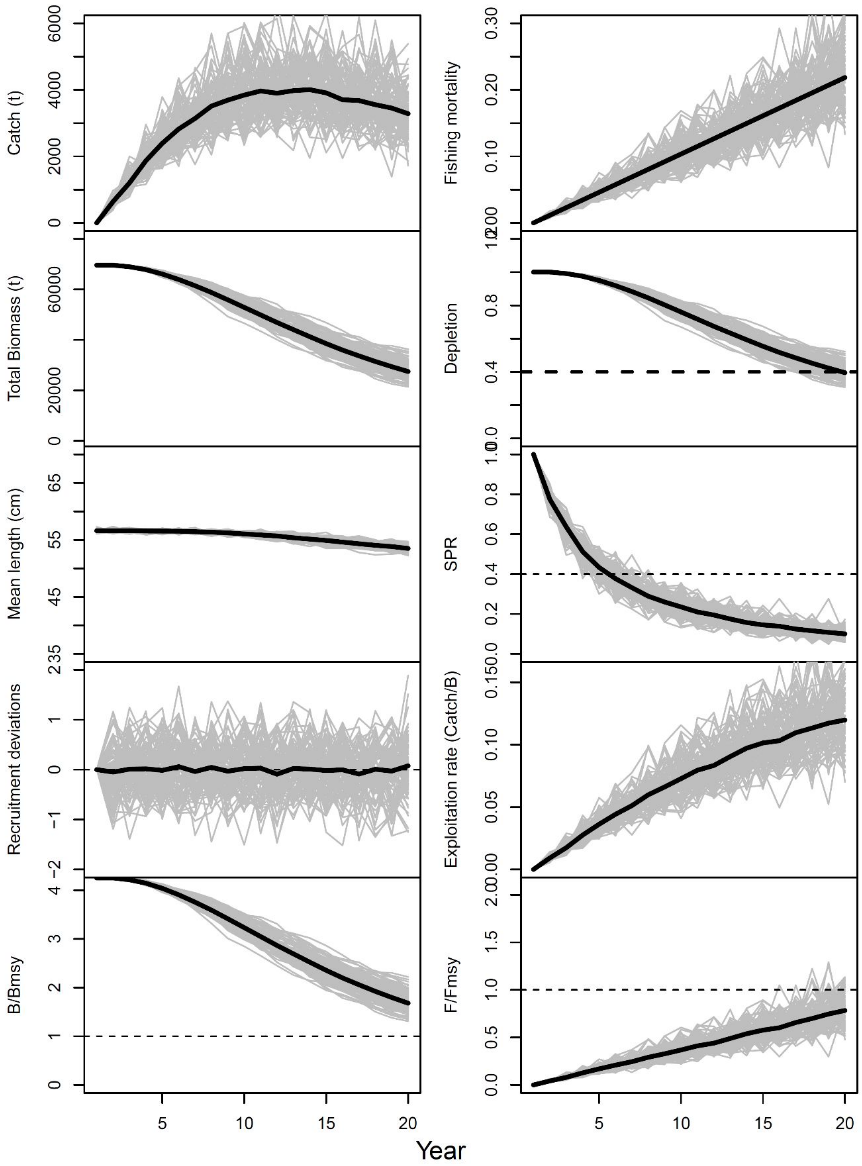


Figure A26. Time series for each simulated slow-grow canary rockfish population for harvest scenario 3 and depletion = 0.4. The black solid lines represent the mean value for all runs.

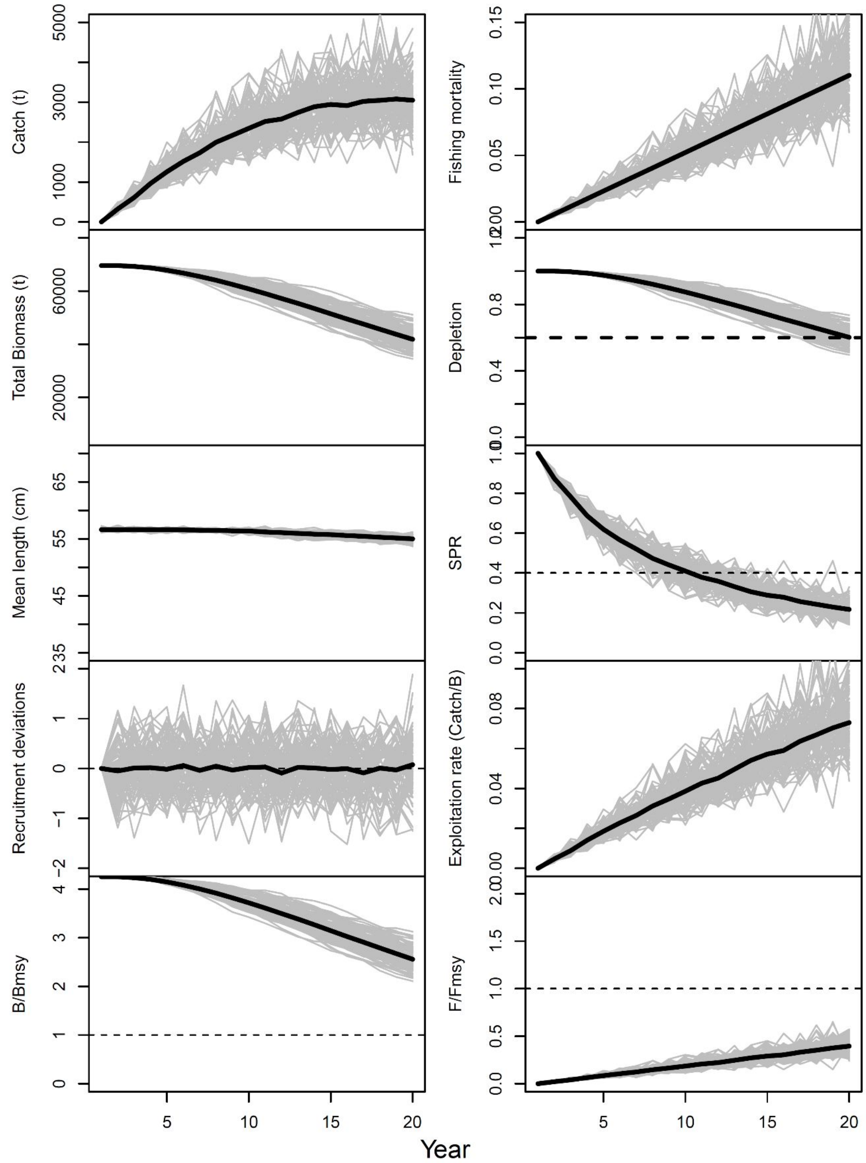


Figure A27. Time series for each simulated slow-grow canary rockfish population for harvest scenario 3 and depletion = 0.6. The black solid lines represent the mean value for all runs.

Table A1. Mean and standard deviation of relative error (RE) between the maximum sustainable yield (MSY) estimated by the operating model (OM) and the MSY estimated by the CMSY method. Values are proportions. Positive values mean that the MSY was overestimated and negative values that it was underestimated.

Species	Harvest Scenario	Mean ± Standard deviation		
		Depletion level		
		0.2	0.4	0.6
Mackerel	Scenario 1	0.37 ± 0.08	0.18 ± 0.09	-0.13 ± 0.15
	Scenario 2	0.28 ± 0.08	0.03 ± 0.09	-0.22 ± 0.13
	Scenario 3	0.33 ± 0.11	0.05 ± 0.11	-0.26 ± 0.14
Albacore	Scenario 1	-0.07 ± 0.02	-0.18 ± 0.03	-0.46 ± 0.02
	Scenario 2	-0.25 ± 0.02	-0.42 ± 0.02	-0.42 ± 0.02
	Scenario 3	-0.12 ± 0.02	-0.24 ± 0.02	-0.43 ± 0.02
Rockfish	Scenario 1	1.61 ± 0.27	1.13 ± 0.31	0.80 ± 0.32
	Scenario 2	1.67 ± 0.26	1.27 ± 0.33	0.86 ± 0.34
	Scenario 3	1.77 ± 0.33	1.29 ± 0.45	0.94 ± 0.45

Table A2. True OM and LBB estimated values for L_∞ and S_{50} (~Lc). LCL is the lower confidence limit and UCL the upper confidence limit for the estimated values.

Scenarios	Life-history	Harvest trend	Final depletion	True L_∞	True S_{50}	Estimated L_∞	Estimated LCL L_∞	Estimated UCL L_∞	Estimated Lc	Estimated LCL Lc	Estimated UCL Lc
1	Short-lived	Scenario 1	0.2	38.2	25	44.5	44.0	45.1	16.9	16.5	17.4
2			0.4	38.2	29	43.6	43.3	44.0	15.6	15.5	15.8
3			0.6	38.2	29	45.1	44.6	45.6	20.1	19.5	20.7
4		Scenario 2	0.2	38.2	29	44.7	44.2	45.2	18.0	17.4	18.6
5			0.4	38.2	29	43.7	43.4	44.1	15.7	15.5	15.8
6			0.6	38.2	29	45.3	45.0	45.8	20.3	19.7	20.9
7		Scenario 3	0.2	38.2	29	45.5	45.2	46.0	20.3	19.8	21.0
8			0.4	38.2	29	44.5	44.0	45.1	15.9	15.7	16.1
9			0.6	38.2	29	45.7	45.4	46.2	20.7	20.1	21.3
10	Medium-lived	Scenario 1	0.2	122.2	60	142.5	141.4	143.6	62.4	61.7	63.2
11			0.4	122.2	60	141.4	140.1	142.5	60.4	59.7	61.0
12			0.6	122.2	60	143.2	142.7	143.9	64.1	63.2	64.9
13		Scenario 2	0.2	122.2	60	143.0	141.8	143.9	62.8	62.0	63.6
14			0.4	122.2	60	141.9	141.1	143.3	60.7	60.0	61.4
15			0.6	122.2	60	143.3	143.0	144.0	64.6	63.8	65.4
16		Scenario 3	0.2	122.2	60	143.3	143.0	144.0	63.3	62.5	64.1
17			0.4	122.2	60	142.5	141.4	143.7	61.1	60.4	61.8
18			0.6	122.2	60	143.5	143.1	144.3	65.4	64.5	66.3
19	Long-lived	Scenario 1	0.2	60.0	60	76.7	76.0	77.6	50.4	49.9	51.0
20			0.4	60.0	45	75.3	74.5	76.3	47.0	46.5	47.4
21			0.6	60.0	45	76.9	76.2	77.8	51.2	50.7	51.8
22		Scenario 2	0.2	60.0	45	76.5	75.8	77.4	50.5	50.0	51.1
23			0.4	60.0	45	75.4	74.6	76.4	47.8	47.2	48.3
24			0.6	60.0	45	77.0	76.3	78.0	51.4	50.8	52.0
25		Scenario 3	0.2	60.0	45	76.8	76.1	77.7	51.0	50.4	51.6
26			0.4	60.0	45	76.0	75.3	76.9	49.5	49.0	50.1
27			0.6	60.0	45	77.1	76.3	78.0	51.7	51.1	52.2

B21 ROC

A peer review paper is being prepared, the results can be found in a vignette and the analysis is on google drive.

B22 Pareto

A peer review paper is being prepared, the results can be found in a vignette and the analysis is on google drive.

B23 Delay Difference

Additional pieces on a delay-differential framework are less developed but conducted under mydas and could perhaps be included in an additional work section