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EXPLORATION OF LENGTH-BASED AND CATCH-BASED DATA LIMITED ASSESSMENTS FOR SMALL TUNAS

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SUMMARY

Despite the economic importance of small tunas (SMT) in many small-scale fisheries in the Atlantic, these populations remain unassessed because data are insufficient to perform traditional stock assessments. In such data-limited situations two main quantitative approaches, based on data availability, can be used to assess exploitation status: catch-based models, when only catch data exist, and length-based models, when only information of the length composition of the catch is available. In this study, we explore the applicability of 2 catch-based models (Depletion Based Stock Reduction Analysis–DBSRA– and Simple Stock Synthesis–SSS), 2 length-based models (Length Based Spawning Potential Ratio–LBSPR– and Length-based Integrated Mixed Effects–LIME) and one that combines both data-sets (LIME_Catch) to assess 6 SMT stocks. We found that there is high uncertainty in the estimation of stock status using these models and, since they are highly sensitive to input parameters, more sensitivity analysis should be conducted. With the data available at the moment for SMT, we suggest moving to close loop simulations studies to determine the most feasible management procedures considering current parameters, data and model uncertainties.

RÉSUMÉ

Malgré l'importance économique des thonidés mineurs dans de nombreuses pêcheries artisanales de l'Atlantique, ces populations n'ont pas été évaluées car les données disponibles ne sont pas suffisantes pour évaluer les stocks de manière traditionnelle. Dans de telles situations de données limitées, deux approches quantitatives principales, basées sur la disponibilité des données, peuvent être utilisées pour évaluer l'état d'exploitation : les modèles basés sur la capture, lorsqu'il n'existe que des données de capture, et les modèles basés sur la longueur, lorsque seule l'information sur la composition par taille de la prise est disponible. Dans la présente étude, nous étudions l'applicabilité de deux modèles basés sur la capture (analyse de réduction des stocks basée sur l'épuisement –DBSRA– et Simple Stock Synthesis –SSS), deux modèles fondés sur la taille (ratio du potentiel de reproduction fondé sur la taille (LBSPR) et effets intégrés mixtes fondés sur la taille –LIME) et un modèle qui combine les deux jeux de données (LIME_Catch) pour évaluer six stocks de thonidés mineurs. Nous avons constaté qu'une incertitude élevée entourait l'estimation de l'état du stock au moyen de ces modèles et, comme ils sont très sensibles aux paramètres d'entrée, une analyse de sensibilité plus poussée devrait être menée. Avec les données actuellement disponibles pour les thonidés mineurs, nous suggérons de passer aux études en simulation en boucle fermée afin de déterminer les procédures de gestion les plus réalisables compte tenu des paramètres, données et incertitudes des modèles actuels.

RESUMEN

A pesar de la importancia económica de los pequeños túnidos (SMT) en muchas pesquerías de pequeña escala en el Atlántico, estas especies continúan sin evaluar porque los datos son insuficientes para llevar a cabo evaluaciones de stock tradicionales. En estas situaciones de limitación de datos, dos enfoques cuantitativos principales, basados en la disponibilidad de datos, pueden utilizarse para evaluar la situación de explotación: los modelos basados en la

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captura, cuando solo existen datos de captura, y los modelos basados en la talla, cuando solo se dispone de información sobre la composición por tallas de la captura. En este estudio, se explora la aplicabilidad de 2 modelos basados en la captura (Análisis de reducción del stock basado en la merma–DBSRA– y Stock Synthesis simple–SSS), 2 modelos basados en la talla (Ratio potencial de desove basado en la talla -LLBSPR y Efectos mixtos integrados basados en la talla-LIME) y uno que combina ambos conjuntos de datos, datos basados en la captura y en la talla (LIME_Catch) para evaluar 6 stocks de pequeños túnidos. Hemos hallado que existe una elevada incertidumbre en la estimación del estado del stock utilizando estos modelos y, dado que son muy sensibles a los parámetros de entrada, deberían llevarse a cabo más análisis de sensibilidad. Con los datos disponibles de momento para los pequeños túnidos, sugerimos cambiar a estudios de simulación de círculo cerrado para determinar los procedimientos de ordenación más viables considerando los actuales parámetros, datos e incertidumbres del modelo,

KEYWORDS

catch, length composition, data-limited assessments, stock status, small tunas

1. Introduction

Major commercial tuna species usually have substantial data sets that can be integrated in complex stock assessments models (Methot and Wetzel 2013). These data may include time series of total removals, catch-at-length or -age data, relative abundance indices, fishing effort, tag recoveries, and/or information on life-history parameters. Most of the datasets required for such stock assessments are unavailable for most small-scale fisheries and by-catch species around the world, including many stocks of small tunas, mackerels, Spanish mackerels and bonitos. Fisheries and stocks lacking such multiple data types are commonly known as “data-poor” or “data-limited” fisheries (Costello *et al.*, 2012; Dowling *et al.*, 2015). Recently, many data-limited approaches have been developed to meet an increased demand for science-based fisheries management for unassessed fisheries, stocks and species where resources are limited (Wetzel and Punt 2011; Costello *et al.* 2012; Dowling *et al.* 2015, 2016; Chrysafi and Kuparinen 2016; Rosenberg *et al.* 2017).

There are two big families of data-limited assessment methods that use biological information and fisheries data to estimate proxies of stock status: 1) catch-based models that only use fisheries catch data and some biological information; and 2) length-based models that combine life history information and length composition of the catch.

Assessing stocks using only catch data started many years ago with the development of Stock Reduction Analysis, SRA (Kimura and Tagart, 1982; Kimura *et al.*, 1984). Since then, this method 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 subsequently 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 stock depletion at the start and final of the catch time series (Catch-MSY; Martell and Froese 2013; Froese *et al.* 2017), and age-structured population dynamics (Simple Stock Synthesis; Cope 2013). Despite these differences, this family of catch-based models shares a common dependence upon prior assumptions about final stock depletion. Simulation testing indicates that these methods perform well only when assumptions regarding final relative abundance are met. Also, catch-based methods might be appropriate to predict sustainable catch or biomass at the end of the time series, but not to reconstruct a biomass time series (Wetzel and Punt, 2015). For many small-scale fisheries, obtaining reliable information on historical total catch is difficult, while sampling of length measurements 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 is extended by length-based spawning potential ratio (LBSPR, Hordyk *et al.* 2015) and length-based Integrated Mixed Effects (LIME, Rudd and Thorson 2017) models. These allow the estimation of instantaneous fishing mortality (F) and spawning potential ratio (SPR) when basic biological parameters are known. SPR is the proportion of the unfished reproductive potential per recruit under a given level of fishing pressure (Goodyear, 1993). Both methods have the same data-requirements, but LIME does not assume equilibrium conditions; the mixed-effects aspect of LIME extends length-based methods by estimating changes in recruitment and separating them from fishing mortality over time (Rudd and Thorson, 2018). Also, LIME allows for the inclusion of catch data when available, a method that we will refer to as LIME_Catch from now on.

Some small tunas in the Atlantic Ocean have been assessed before using life history information and length data using LIME and LBSPR (Pons *et al.*, 2019). They found that some stocks are likely to be overfished, such as little tunny (*Euthynnus alletteratus*) in the Southeast Atlantic and wahoo (*Acanthocybium solandri*) in the Northwest Atlantic. These results are based only on length composition of the catch. However, other pieces of information such as landings are available in the ICCAT Task I database, and could be used to compare and complement previous analyses, as recommended by the ICCAT Small Tunas Working group in the 2018 meeting (ICCAT, 2018). This could be done using catch-only-based models or integrated models that use both pieces of information (catch and length). Pons *et al*. (under review), in a simulation study, found that among different catch-based models considered, DBSRA and SSS were less biased and more precise than other catch-based methods such as Catch-MSY and SSCOM (State-space Catch Only Model).

In the present study, we extended the work of Pons *et al*. (2019) to assess a set of small tuna stocks in the Atlantic Ocean using catch-based models (DBSRA and SSS) and the integrated version of LIME (LIME_Catch). From the 10 stocks analyzed in Pons *et al*. (2019), we selected 6 that also have a long time series of catch data. These stocks are: North East bonito (*Sarda sarda,* BON_NE), North East and South East frigate tuna (*Auxis thazard*, FRI_NE and FRI_SE), Mediterranean and South East little tunny (LTA_Med and LTA_SE) and North East wahoo (WAH_NE).

2. Methods

For the catch-based models we used the catch data available in the ICCAT Task I database from 1950 to 2016 by region. All gear types were pooled together to obtain the total catch by regions/stock. We defined the stocks based on the 5 ICCAT regions (North East, South East, North West, south West and Mediterranean), as recommended by the group for the assessment of the small tuna species (ICCAT, 2018). **Figure 1** shows the total catch time series for the most important small tuna (SMT) stocks. As we mentioned before, only 6 stocks are considered here, with long time series of catch (**Figure 1**) and with enough length data information. For the length-based methods, we used the size Task II ICCAT database only for the period 2010-2016 (**Figure 2**). We used only these years of length composition data because they were identified by Pons *et al*. (2019) as a period with enough sampled specimens (>100 by year/gear type). For the length-based models, we only used length data information coming from the gear that catches the broadest range of sizes for each species as proved by Pons *et al*. (2019) as the least biased way to estimate exploitation status using length-based methods.

To apply SSS and DBSRA, not only catch data is needed; these methods also require extensive prior information, such as growth, maturity, F_{MSY}/M and B_{MSY}/B_0 parameters. We took prior values for F_{MSY}/M and B_{MSY}/B_0 from meta-analyses by Zhou *et al.*, (2012) and Thorson *et al.*, (2012), respectively. All life history information was extracted from Pons *et al*. (2019), and these parameters and other model inputs are presented in **Table 1**.

For the catch-based models, the results of stock status are presented in terms of B/B_{MSY} (current biomass over the biomass that produces the Maximum Sustainable Yield), and for the length-based assessment, results are given in terms of SPR. In fisheries, without total catch data or information on relative or absolute abundance, stock assessments typically use SPR as an alternative reference point. A harvest strategy that targets a fishing mortality rate that is expected to result in 40% of the unfished spawning output (SPR40%) is considered a reasonable proxy even for stocks with very low resiliency (Clark, 2002).

The catch-based and length-based methods used here are briefly described below:

2.1. Catch-based data-limited methods

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

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

where B_t is the biomass at the start of the 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 equal to *K*. The package *fishmethods* version 1.10-3 was used to perform this analysis (Nelson, 2017). For DBSRA we used the age at maturity (*Amat*), and 5 priors: F_{MSY}/M, B_{MSY}/B_0, carrying capacity (*K*), final stock depletion and natural mortality (*M*) (distributions in Table 1). Each of these is assigned a distribution from which the Monte Carlo draws are taken. A thousand of iterations were run for ach stock.

Simple Stock Synthesis (SSS). This method is based on the SS package (Methot and Wetzel, 2013). The approach uses the SS framework by fixing all parameters in the model except for initial recruitment ($\ln R_0$), which is the only estimated parameter. It also sets up an artificial index of abundance that represents the relative stock biomass. Thus the first value of the index is always 1, and the final year value represents the percent of the population left in that year. The values of steepness (*h*) and the final year of the abundance survey are all randomly drawn from specified distribution using a Monte Carlo approach (Cope, 2013), and $\ln R_0$ is then estimated. The code for loading the SSS library in R and user instructions can be found at https://github.com/shcaba/SSS. Benefits of this approach are that it retains the same model structure of the data-rich stock assessments, but still allows for flexibility in a variety of parameter and model specifications, if desired. Selectivity was assumed to be equal to maturity, a shared assumption with DBSRA. The input priors used for SSS were: relative stock status, *M*, and *h*. SSS is very time consuming, so only 100 iterations were considered in this study for each species.

2.2. Length-based data-limited methods

Length based spawning potential ratio (LBSPR). In LBSPR, SPR in an exploited population is a function of the ratio of fishing mortality to natural mortality (*F/M*), 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 LBSPR are: *M/k*, L_∞, the variability of length-at-age (CVL_∞), which is normally assumed to be around 10%; and length at maturity specified in terms of L_{50} and L_{95} (the size at which 50% and 95% of a population matures). Given that the assumed values for *M/k* and L_∞ and length composition data are from an exploited stock, 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 the relative fishing mortality (*F/M*), and these are used to calculate SPR (Hordyk *et al.*, 2015). 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.*, 2015). Analyses were conducted using LBSPR package version 0.1.2 in R (Hordyk 2017). We used the Rauch-Tung-Striebel smoother function available in the LBSPR package to smooth out the multi-year estimates of *F* and *SPR*.

Length-based integrated mixed effects (LIME). Length data and biological information are used 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 over time (Rudd and Thorson, 2018). LIME uses automatic differentiation and Laplace approximations as implemented in Template Model Builder (TMB; Kristensen *et al.*, 2015) 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.*, 2015). The inputs to LIME 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**).

3. Results and Discussion

The results from this study are not final, and they are presented with the main purpose of serving as a discussion point in the Stock Assessment Methods working group meeting. Most of the catch-based models showed more optimistic results than the length-based models, estimating that most of the stocks are not overfished or are close to MSY reference points. This could be caused by the observed increasing trends in the catch time series. ICCAT recognized that, despite the important progress made in recent years (i.e. by historical data recovery programs and work of national scientists), the majority of the small tuna populations still have highly incomplete catch time series in the official ICCAT statistics (varying depending on the species). Even for the stocks selected in this study, it is difficult to determine if the increasing trends in catches (**Figure 1**) are due to a real increase in total catch or just an increase in reporting by the different CPCs. The knowledge of the secretary and national scientists is critical to understand these catch trends in order to use this information in assessment models and we suggest that these data should be review by the SMT working group.

Reconstructing catch time series is difficult and sometimes impossible in many small to medium size fisheries. For fisheries where the time series of catch are unavailable, getting length-composition data could give a good approximation of the status of the stock. Pons *et al*. (under review) showed that, in some cases, length-based models can give the same or less biased estimates of exploitation status than catch-based models. In this case, it is important to have length samples representative of the length composition of the exploited population, as well as good priors for selectivity.

The results from the length-based models were already presented in Pons *et al*. (2019), but we included them here for comparison with the catch-based model results. For bonito in the North East Atlantic, LBSPR estimated that SPR is below the reference point of 40% SPR, while LIME estimated that it is above 40% SPR (**Figure 3**). For the same stock, all catch-based models estimated that total biomass (B) was above B_{MSY}. For frigate tuna in the North East and South East Atlantic and little tunny in the Mediterranean, both model approaches are in agreement and showed that these stocks are above reference points. However, for little tunny in the South East only LIME_Catch estimated that the stock is above reference points (**Figure 3**). The majority of the models showed that this stock is overfished. For wahoo in the North West, the length-based assessments and the combined LIME_Catch showed that this stock might be overfished (**Figure 3**).

For those interested, in **Figure 4** and **Figure 5** we presented the distribution of the parameters with the accepted and rejected draws for DBSRA and SSS, respectively. In addition, sensitivity analyses were carried out to test the sensitivity of the catch-based models (SSS and DBSRA) to final depletion assumptions. Both SSS and DBSRA were sensitive to prior assumptions on depletion levels (**Figure 6**). Higher depletion assumptions resulted in lower current values of B/B_{MSY} and lower depletion assumptions in higher current B/B_{MSY}. The advantage of the integrated LIME_Catch is that depletion priors are not needed and both pieces of information (catch and length) are considered in the likelihood equations. However, LIME is sensitive to life history parameters (Rudd and Thorson, 2018) and this has not been tested here.

The differences among model estimations for both length and catch-based models are mainly due to differences in model structure and assumptions. We could consider in the future to use an ensemble of methods to estimate stock status, taking into account model misspecifications. In the meantime, due to discrepancies in model estimations and uncertainty around those estimates (**Table 2**), we suggest moving away from trying to estimate stock status with the data available for SMT until better data become available. Instead, more effort should be placed in creating a consistent operating model to include in a Management Strategy Evaluation (MSE) framework to evaluate different management procedures for management advice (see SCRS/2019/041).

Future analysis

- Sensitivity analysis for different priors of parameters such as M, F_{MSY}/M and B_{MSY}/B_0 and other life history information.
- Different time periods for the catch time series analysis to only include the most reliable information.
- Including other length-based methods such as length-converted catch curve (LCCC) (Huynh *et al*. 2018) and length-based Bayesian biomass estimation method (LBB) (Froese *et al*. 2018)
- Include other catch-based methods such as catch-only Monte-Carlo filter method CMSY (Froese *et al*. 2017).

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Table 1. Life history information and priors for the 6 stocks evaluated in the study. Notation: Normal (μ, σ2). For the same species: **A**, information borrowed from the Northwest stock; **B**, information borrowed from the North East stock; **C**, information borrowed from the South East stock, and **D**, information borrowed from the South West stock. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea.

Model inputs	**Symbol**	**BON_NE**	**LTA_SE**	**WAH_NW**	**LTA_Med**	**FRI_SE**	**FRI_NE**
Maximum age	A_{max} *(years)*	5 (Baibat *et al.*, 2016)	8 (Cayré and Diouf, 1980) B	9 (McBride *et al.*, 2008)	10 (Hattour, 2009)	4 (Grudtsev and Korolevich, 1986)	4 (Grudtsev and Korolevich, 1986) C
Age at 50% maturity	A_{mat} *(years)*	1	2	1	2	2	2
Length were 50% of the fish are mature (FL)	L_{50} *(cm)*	42.6 (Baibat *et al.*, 2016)	42.0 (Diouf, 1980) B	92.5 (Jenkins and McBride, 2009)	51.1 (Hajjej *et al.*, 2012)	30 (Cayré *et al.*, 1993)	30 (Cayré *et al.*, 1993) C
Length were 95% of the fish are mature (FL)	L_{95} *(cm)*	52.0 (Baibat et al., 2016)	58.0 (Diouf, 1980) B	110 (Jenkins and McBride, 2009)	60.0 (Hajjej *et al.*, 2012)	40 (Cayré *et al.*, 1993)	40 (Cayré *et al.*, 1993) C
Length-weight scaling parameter	*WL_a (g)*	5.0×10^{-5} (Baibat *et al.*, 2016)	1.4×10^{-5} (Diouf, 1980) B	2.0×10^{-6} (Beerkircher 2005)	1.2×10^{-5} (Saber *et al.*, 2017)	8.9×10^{-6} (Frota *et al.*, 2004) D	8.9×10^{-6} (Frota *et al.*, 2004) D
Length-weight allometric parameter	*WL_b*	2.79 (Baibat *et al.*, 2016)	3.04 (Diouf, 1980) B	3.24 (Beerkircher 2005)	3.06 (Saber *et al.*, 2017)	3.17 (Frota *et al.*, 2004) D	3.17 (Frota *et al.*, 2004) D
Von Bertalanffy Brody growth coefficient	k *(years $^{-1}$)*	0.31 (Baibat *et al.*, 2016)	0.26 (Cabrera *et al.*, 2005) A	0.32 (McBride *et al.*, 2008)	0.19 (Hattour, 2009)	0.32 (Grudtsev and Korolevich, 1986)	0.32 (Grudtsev and Korolevich, 1986) C
Von Bertalanffy asymptotic length	L_{∞} *(cm)*	73 (Baibat *et al*, 2016)	86 (Cabrera *et al.*, 2005) A	180 (McBride *et al.*, 2008)	117 (Hattour, 2009)	52 (Grudtsev and Korolevich, 1986)	52 (Grudtsev and Korolevich, 1986) C
Theoretical age at length=0	*to (years)*	-2.45 (Baibat *et al.*, 2016)	-0.32 (Cabrera *et al.*, 2005) A	- 1.91 (McBride *et al.*, 2008)	- 1.13 (Hattour, 2009)	-0.83 (Grudtsev and Korolevich, 1986)	-0.83 (Grudtsev and Korolevich, 1986) C
Coefficient of variation length at age for all ages	*CVL*	0.1	0.1	0.1	0.1	0.1	0.1
Natural mortality (fixed in length based models)	M *(years $^{-1}$)*	0.78 *	0.53 *	0.49 *	0.43 *	1.01 *	1.01 *
Steepness (fixed in length based models)	*h*	0.7	0.7	0.7	0.7	0.7	0.7
Observation error in catch	σ_C	0.2	0.2	0.2	0.2	0.2	0.2
Recruitment variations	σ_R	0.4	0.4	0.4	0.4	0.4	0.4
Vulnerability (used for DBSRA)	F_{MSY}/M	*Normal* (0.922, 0.1)	*Normal* (0.922, 0.1)	*Normal* (0.922, 0.1)	*Normal* (0.922, 0.1)	*Normal* (0.922, 0.1)	*Normal* (0.922, 0.1)
Compensation (used for DBSRA)	B_{MSY}/B_0	*Normal* (0.353, 0.1)	*Normal* (0.353, 0.1)	*Normal* (0.353, 0.1)	*Normal* (0.353, 0.1)	*Normal* (0.353, 0.1)	*Normal* (0.353, 0.1)
Model inputs parameter distributions							
Depletion (used for DBSRA and SSS)	XB_0	*Normal* (0.5, 0.1)	*Normal* (0.3, 0.1)	*Normal* (0.3, 0.1)	*Normal* (0.6, 0.1)	*Normal* (0.6, 0.1)	*Normal* (0.5, 0.1)
Carrying capacity (used for DBSRA)	*K*	Low=max(catch) Up=max(catch)x100) **	Low=max(catch) Up=max(catch)x100) **	Low=max(catch) Up=max(catch)x100) **	Low=max(catch) Up=max(catch)x100) **	Low=max(catch) Up=max(catch)x100) **	Low=max(catch) Up=max(catch)x100) **
Steepness (used for SSS)	*h*	*Normal* (0.7, 0.1)	*Normal* (0.7, 0.1)	*Normal* (0.7, 0.1)	*Normal* (0.7, 0.1)	*Normal* (0.7, 0.1)	*Normal* (0.7, 0.1)
Natural mortality (used for DBSRA and SSS)	*M* *	*Normal* (0.78, 0.1)	*Normal* (0.53, 0.1)	*Normal* (0.49, 0.1)	*Normal* (0.43, 0.1)	*Normal* (1.01, 0.1)	*Normal* (0.43, 0.1)

*M was calculated using a suite of empirical life history-based methods (Cope, 2017, see http://barefootecologist.com.au/shiny_m).

** Low and Up are the lower and upper bounds of the minimization routine in R using the package "fishmethods". The equation ((B_tK)-(B[refyr]/K))^2 is used as the objective function to find K. refyear is the last year in time series of catch.

Table 2. Estimates of biomass (B), B/B_{MSY} and SPR for the models used in this study. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea.

		Stock					
Model	Value (average 2014-2016)	BON_NE	FRI_NE	FRI_SE	LTA_Med	LTA_SE	WAH_NW
	Catch	3,091	4,794	5,655	6,656	1,446	1,348
DBSRA	Biomass	7,712	16,993	26,924	35,041	10,148	2,831
	Biomass sd.	15,582	34,027	13,505	23,755	5,348	1,021
	B/Bmsy	1.63	1.64	1.79	1.88	**0.69**	1.02
	B/Bmsy sd.	0.26	0.27	0.26	0.25	0.27	0.24
SSS	Biomass	5,221	11,642	21,685	35,311	11,180	3,503
	Biomass sd.	2,544	4,629	86,875	149,690	20,991	5,589
	B/Bmsy	1.98	2.50	2.65	2.33	**0.94**	1.34
	B/Bmsy sd.	0.50	0.61	0.96	1.02	0.67	0.80
LIME_Catch	Biomass	45,730	153,778	61,801	28,662	15,033	2,306
	B/Bmsy	2.02	1.29	1.10	1.08	1.83	0.86
LBSPR	SPR	**0.23**	0.83	0.79	0.66	**0.13**	**0.37**
LIME	SPR	0.71	0.46	0.53	0.62	**0.27**	**0.29**
SSS	SPR	0.50	0.49	0.61	0.51	0.64	**0.32**
LIME_Catch	SPR	0.84	0.94	0.83	0.56	0.65	**0.24**

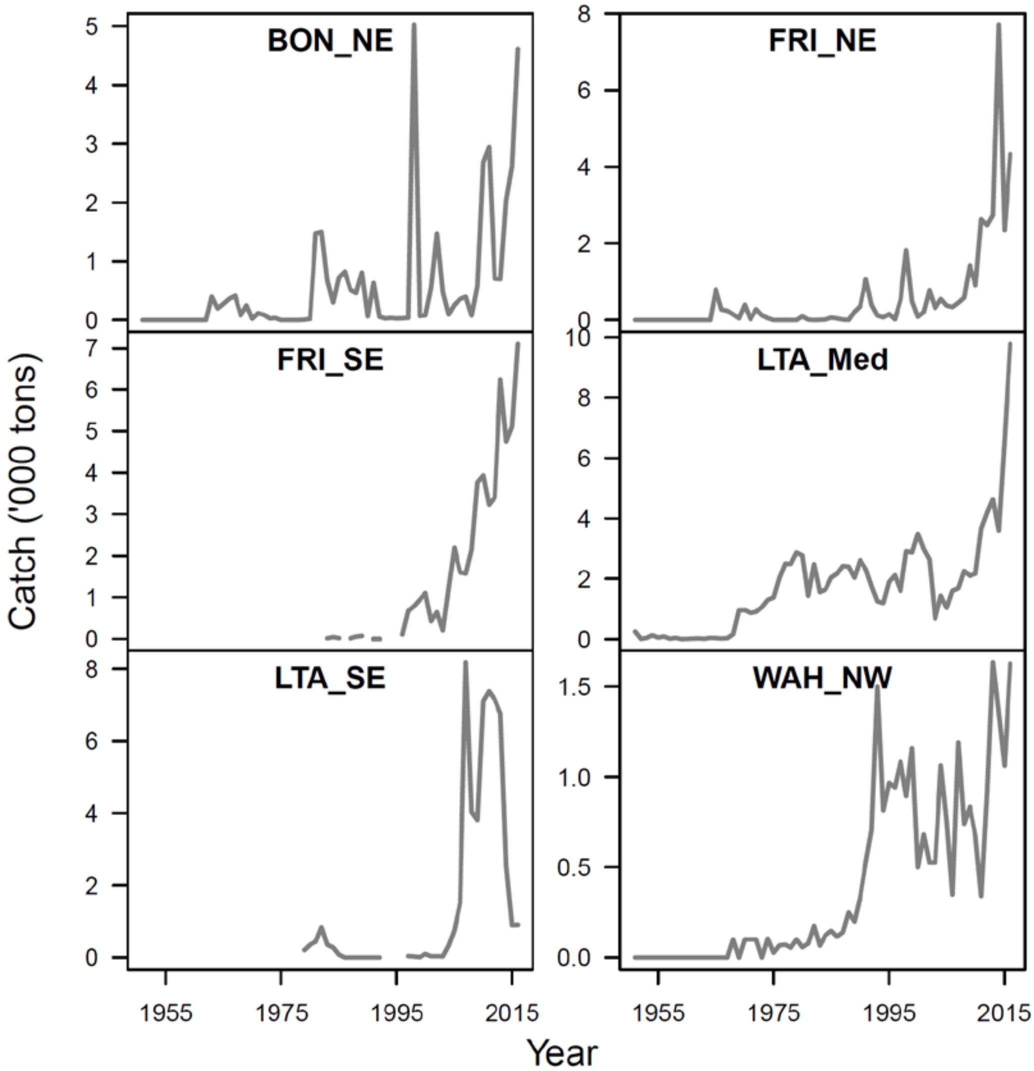


Figure 1. Catch time series for the 6 stocks evaluated in this study. Data from ICCAT Task I database up to 2016. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea.

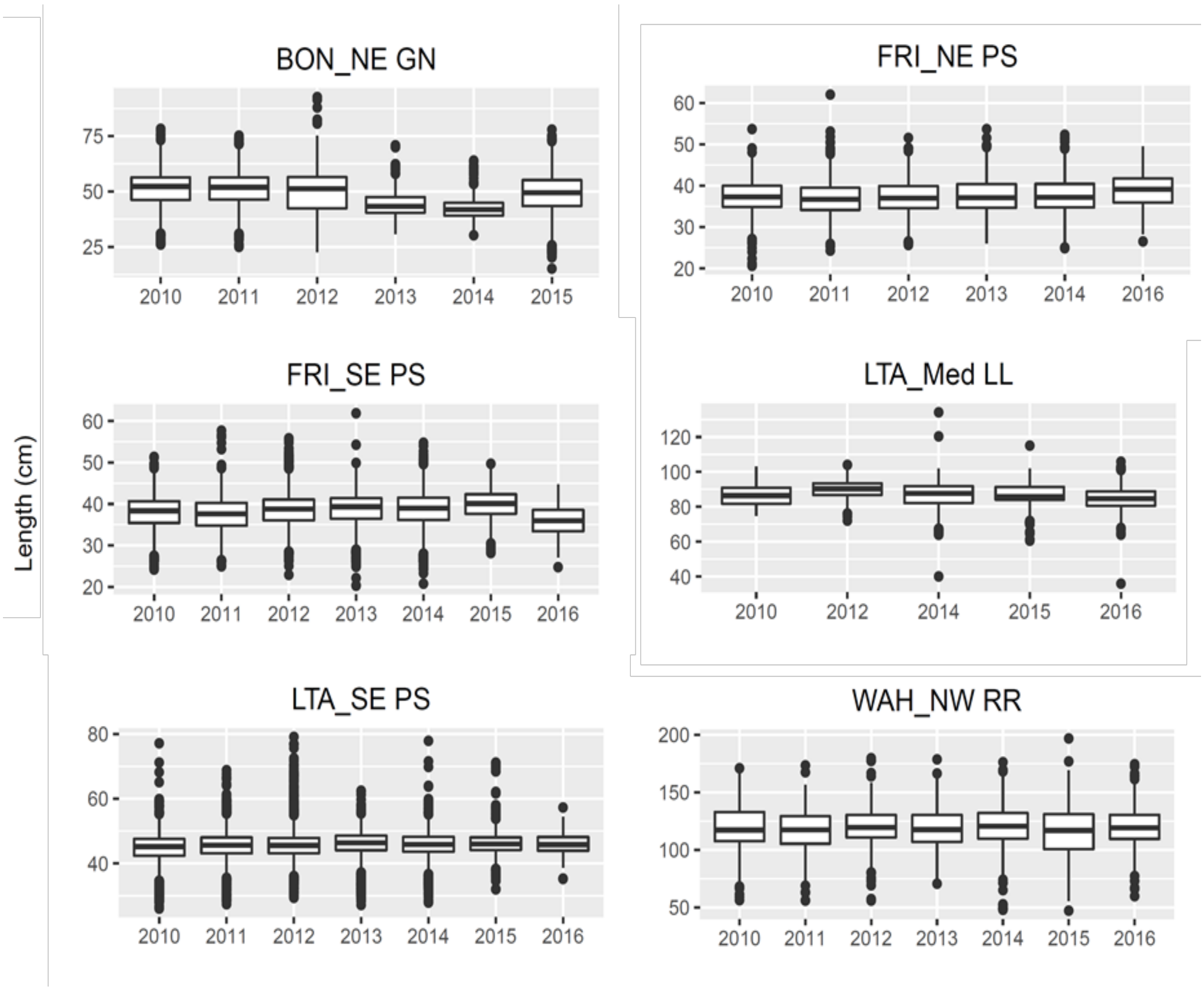


Figure 2. Length distribution for the 6 stocks evaluated in this study. Data from ICCAT Task II database up to 2016. The selection of the gear used in this study comes from Pons *et al*. (2019). Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea. Gears code: RR, rod and reel; PS, purse-seine; LL, longline; GN, gillnet.

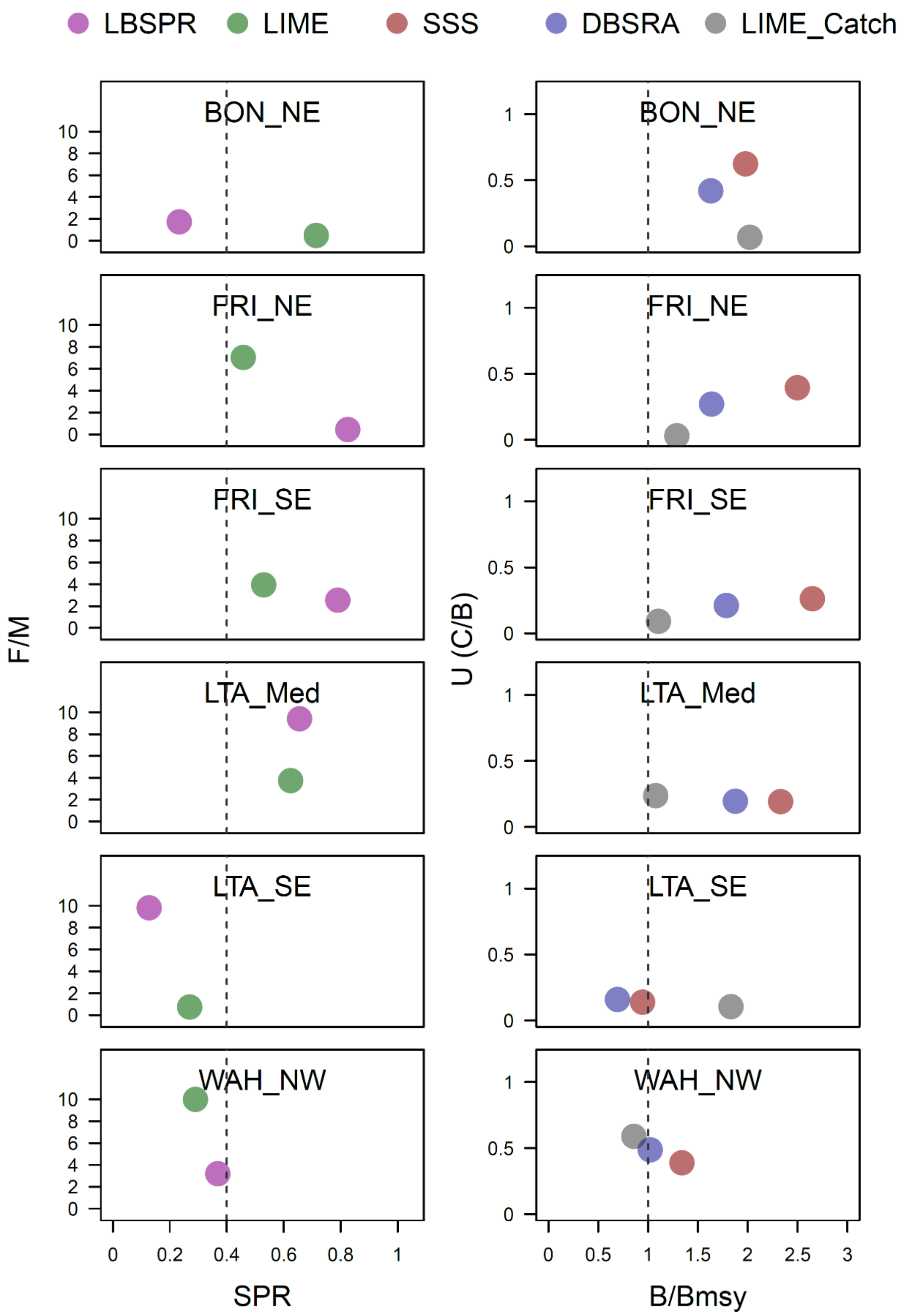
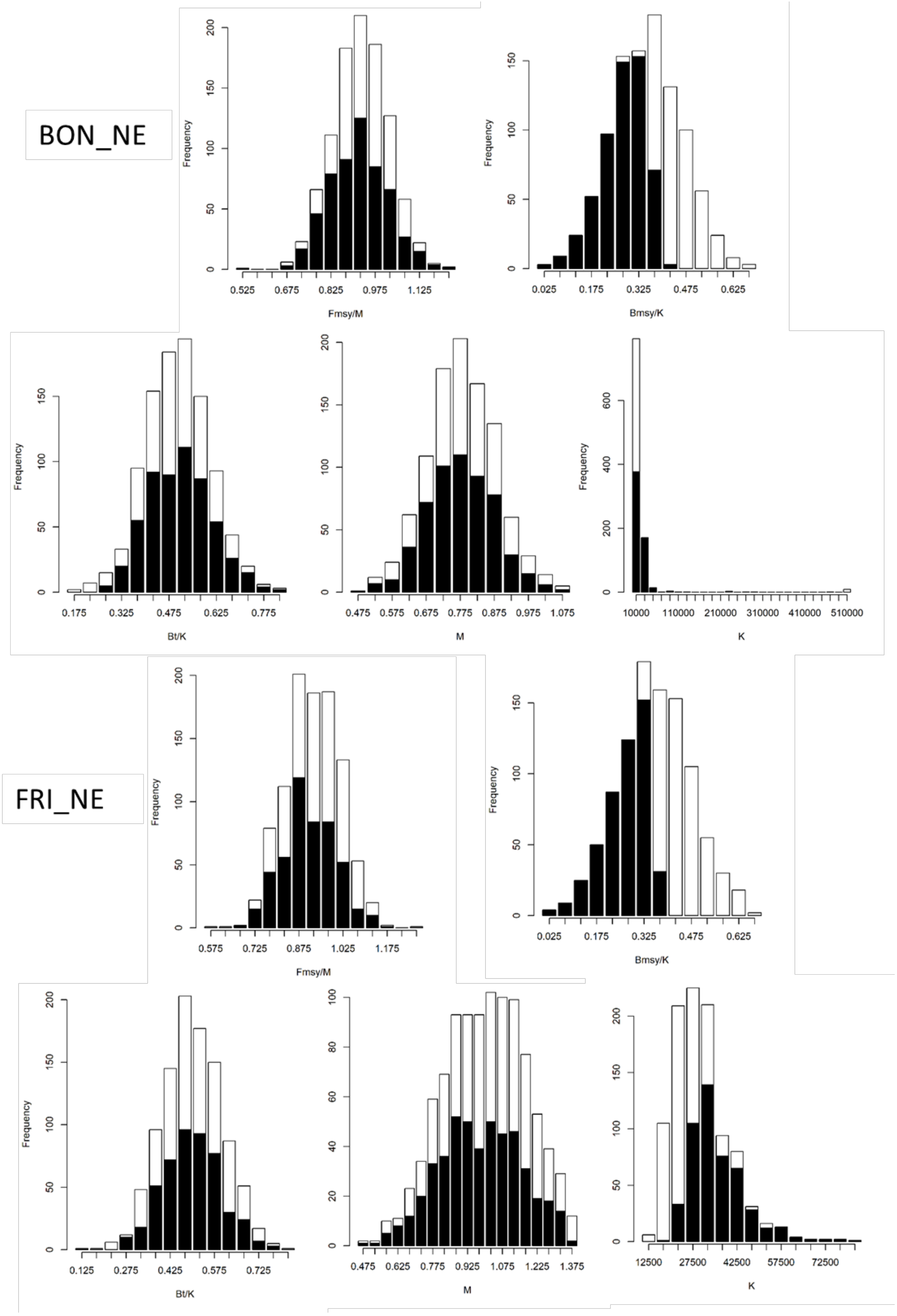


Figure 3. Proxy of stock status for each stock. Length based (LIME and LBSPR) on the left and catch based on the right (DBSRA, SSS and LIME_Catch). Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea.



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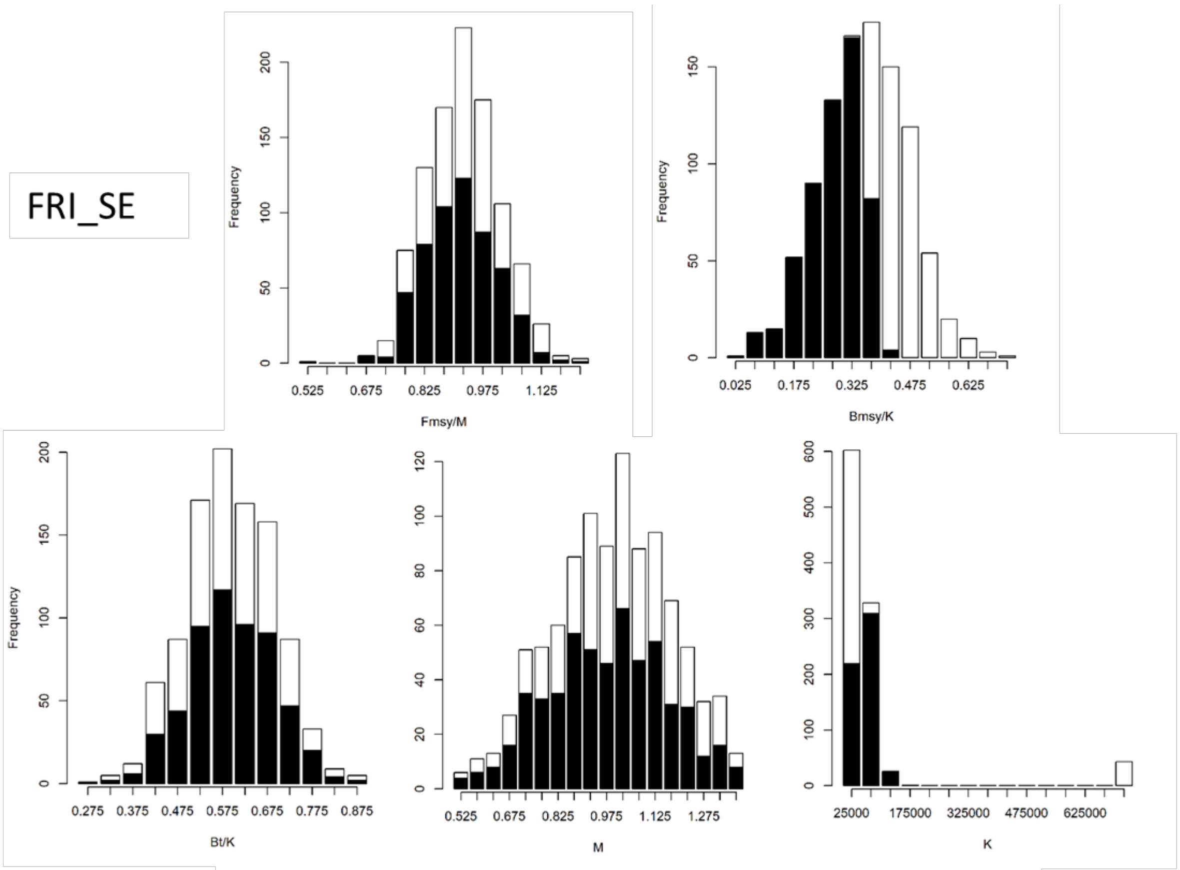
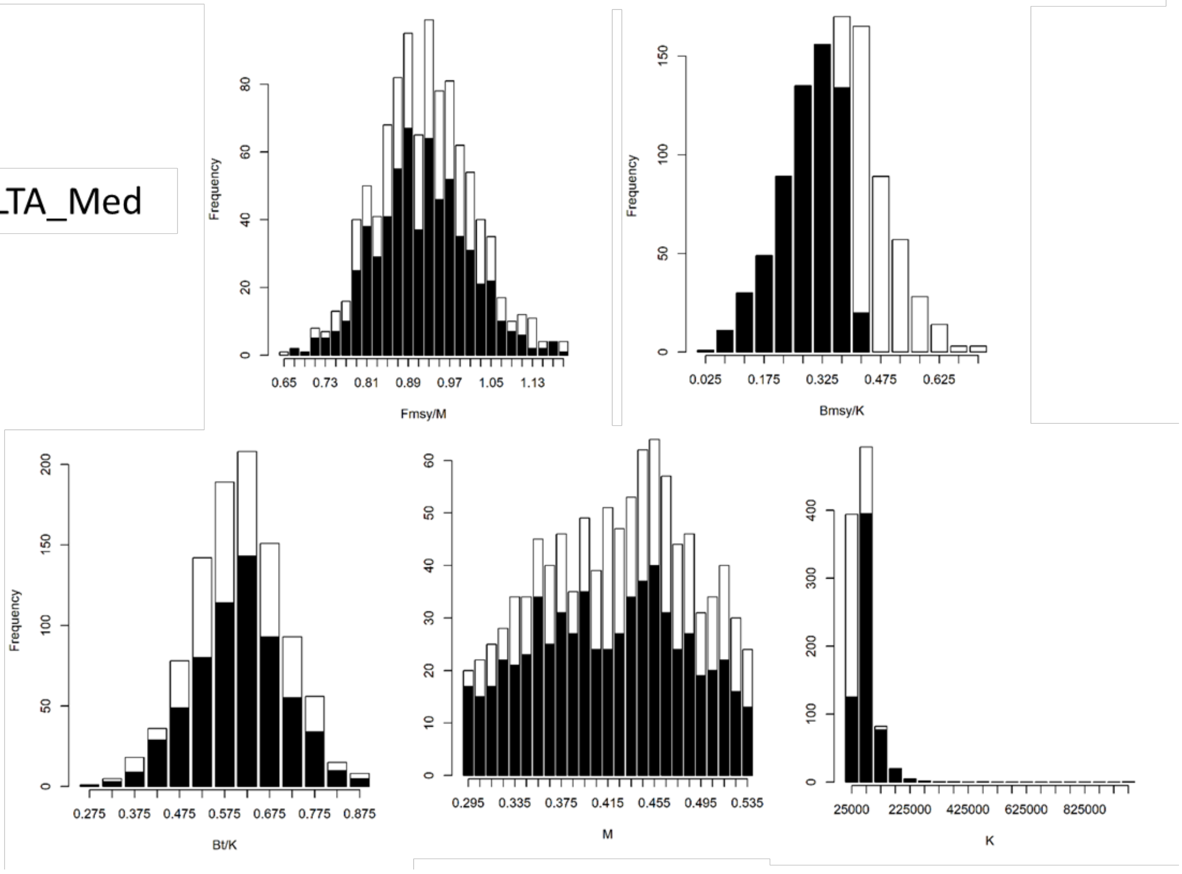
FRI_SE



LTA_Med



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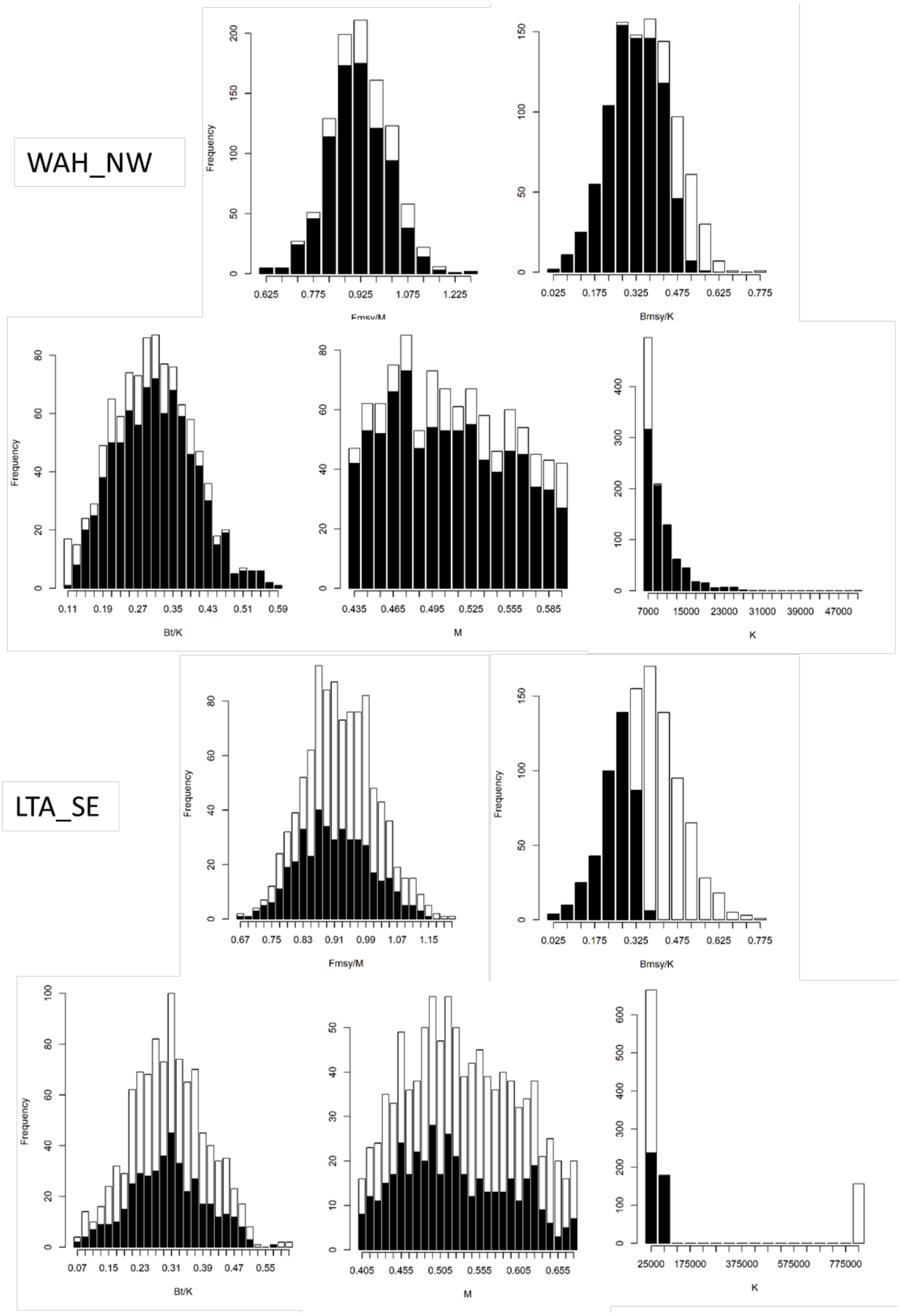
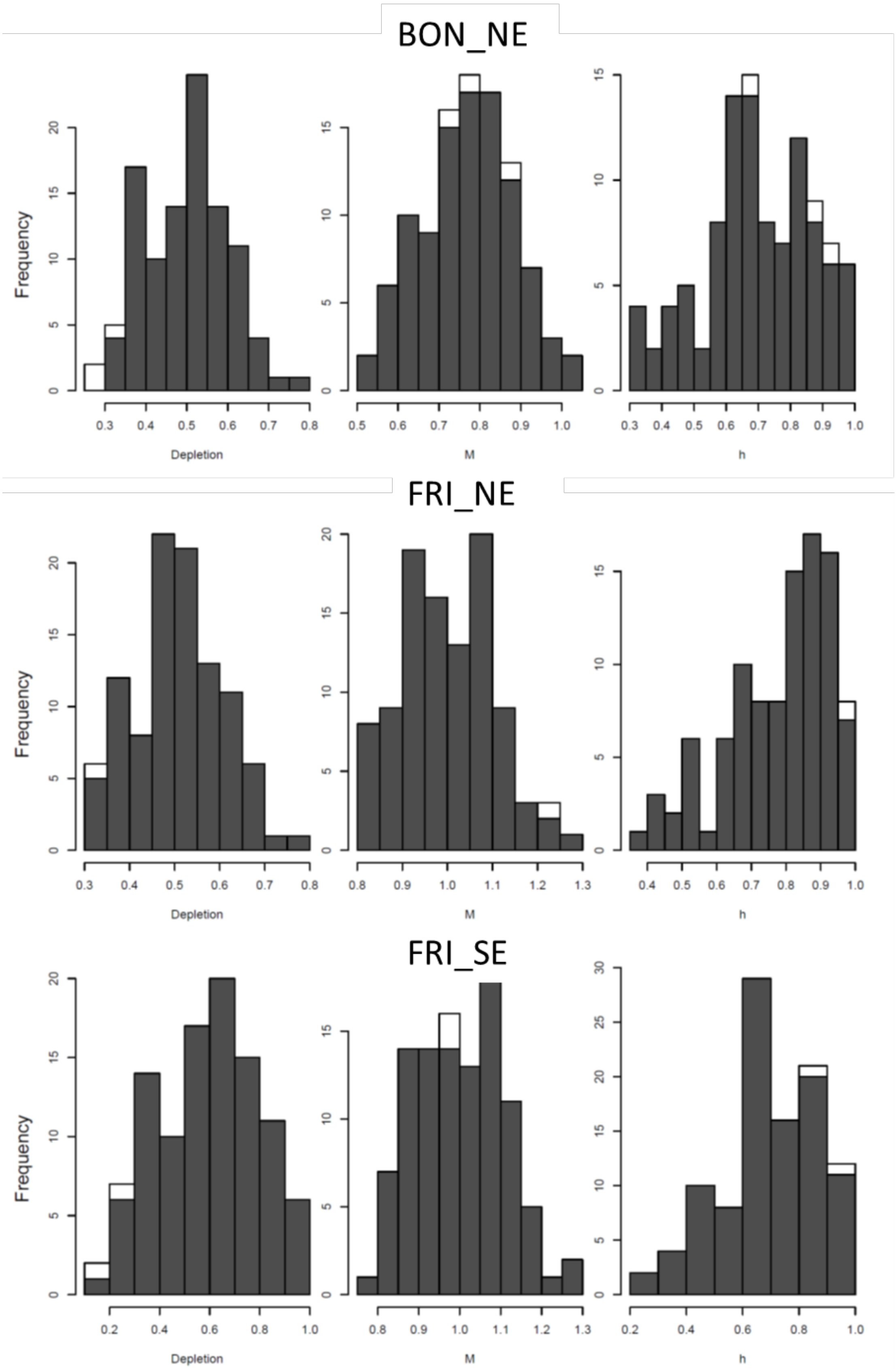


Figure 4. DBSRA parameters distributions. Black: accepted draws. White: rejected draws. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea.



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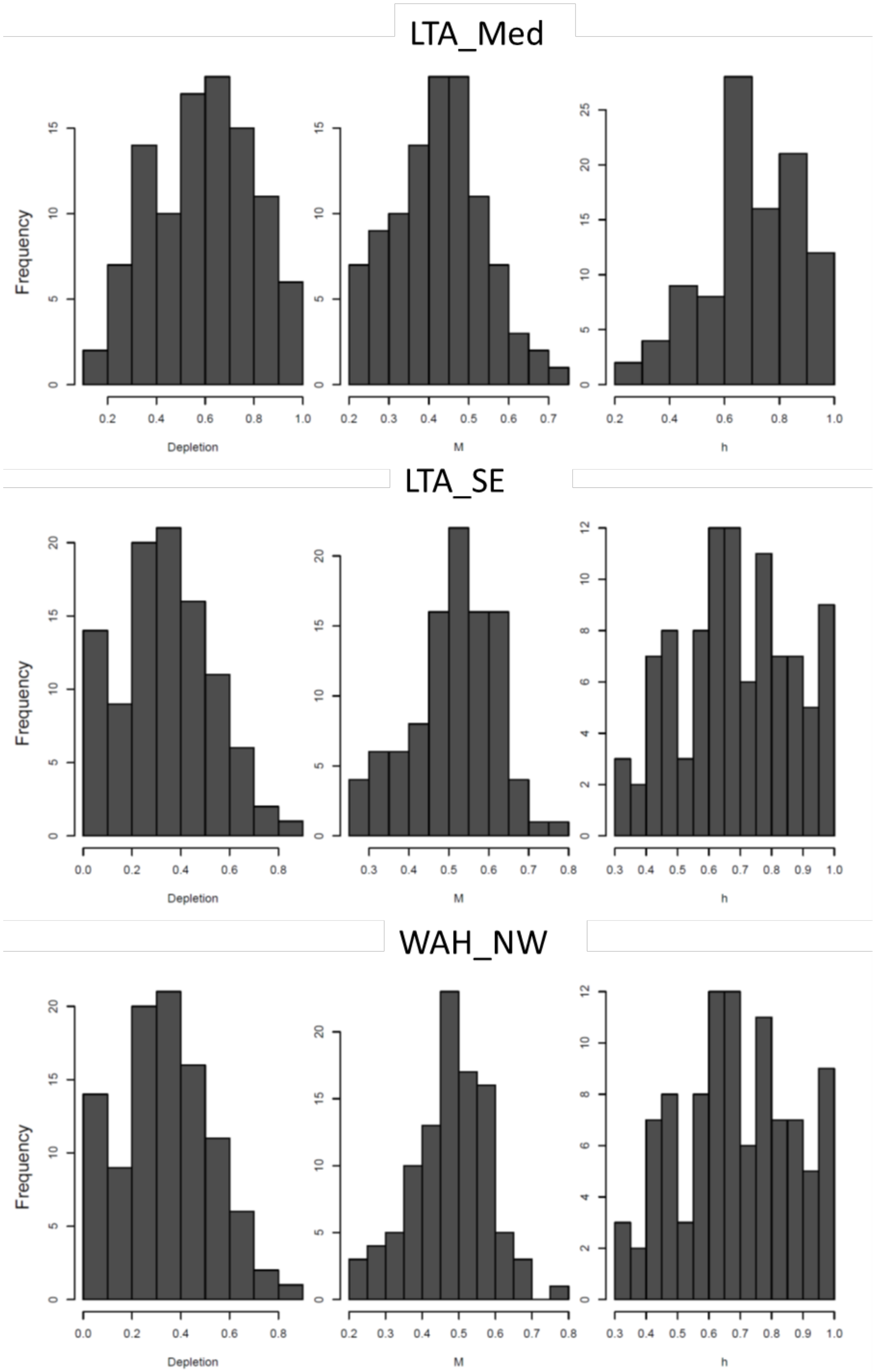

Figure 5. SSS parameters distributions. Dark grey: accepted draws. White: rejected draws. Species codes: LTA, little tunny; WAH, wahoo; BON, bonito; FRI, frigate tuna. Stock area codes: NE, Northeast; SE, Southeast; NW, Northwest; Med, Mediterranean Sea.

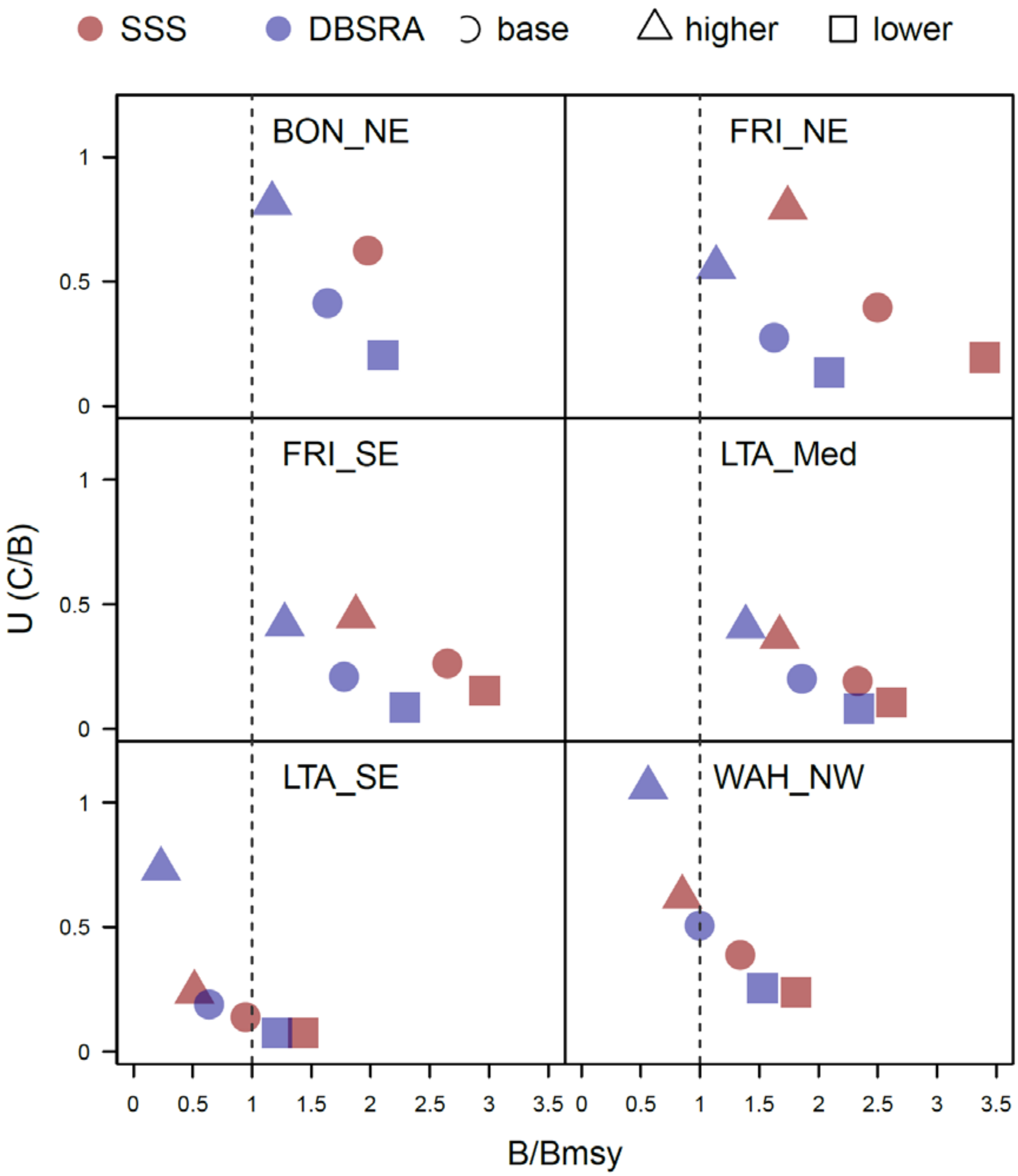

Figure 6. Sensitivity analysis for depletion for SSS and DBSRA. Base is the base model with depletion priors describe in Table 1. Base ± 0.2.