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Improving data limited methods for assessing Indian Ocean neritic tuna species

Shijie Zhou[1*], Dan Fu[2], Paul DeBruyn[2], Sarah Martin[2]

[1]CSIRO Oceans and Atmosphere, 306 Carmody Road, St. Lucia, QLD 4067, Australia

[2]Indian Ocean Tuna Commission, Le Chantier Mall, PO BOX 1011, Victoria, Mahe, Seychelles

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*Corresponding author: Phone: +61 7 3833 5968. Emails: Shijie.Zhou@csiro.au

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Executive summary

The Indian Ocean Tuna Commission (IOTC) manages 16 tuna and tuna-like species in the Indian Ocean, including six neritic tuna that are predominantly harvested along the coastal areas. The six species are: Bullet tuna (BLT), Spanish mackerel (COM), Indo-Pacific King mackerel (GUT), Frigate tuna (FRI), Kawakawa tuna (KAW), and Longtail tuna (LOT). Unlike more valuable species, only limited data, primarily catch, exist for neritic tunas. So far it is difficult to conduct formal stock assessment for neritic tunas, and the data-poor, catch-based methods have been used instead. In recent years, development of data-poor methods is an active research area and new methods frequently appear in journal publications. The Commission recognized a need to review available data-limited methods that are potentially applicable for neritic tunas, and to incorporate new information in the catch-based methods currently used for neritic tunas.

In this report, we conduct a literature review on data-limited methods. We categorize methods into traditional stock assessment, area-based ERA methods, age-based methods, length-based methods, and catch-only (or catch-based) methods. Catch-based methods have been adopted for neritic tuna assessment in the past several years and are deemed the best choice for the available data in IOTC. Besides catch-based methods, it is possible to use area-based methods, particularly the sustainability assessment for fishing effect (SAFE) approach, to assess fishing mortality status for neritic tuna because SAFE is flexible to accommodate varying data types and there appears to have sufficient information for such an analysis for several neritic tunas. Length-based methods require a range of assumptions that are difficult to meet for widely distributed migrating species that are captured by various gear types at different life stages, such as neritic tunas. However, because length data is the second most abundant information held by IOTC Secretariat, it would be interesting to explore length-based methods and see whether they can provide meaningful fishery status information.

The second section of the report aims to improve the estimation of priors needed for catch-based methods: the level of stock depletion and the rate of intrinsic growth. We focus on two promising catch-based methods: the optimized catch-only method (OCOM) and Catch-MSY (CMSY), because the two approaches do not assume a fixed level of stock depletion as other catch-based methods do. The OCOM adopts a depletion prior using recently developed BRT (boosted regression trees) model, whereas CMSY derives depletion prior based on the ratio between last year's catch and the maximum catch in the history of the stock. The two approaches also differ in deriving prior for the intrinsic population growth rate. For the OCOM, population growth rate is based on empirical correlation with other life-history parameters (mainly the natural mortality rate), whereas for CMSY is it based on a "resilience" parameter. Because data quality remains a concern, integrating the two approaches leads to a third method.

The results indicate that Method 1 (OCOM prior) produces a higher r than Method 2 (CMSY prior) for all six species. The high r by OCOM prior causes a low K while a low r by CMSY prior causes a high K. The joint effect results in a similar MSY by either methods. Without independent study to compare the two methods, the integrated method may have an advantage over using either one of them.

In addition to improving prior information, we attempt to enhance the existing neritic tuna assessment in two areas. Limited cpue data exist for two species, Kawakawa and Longtail tuna. In OCOM's objective function, we simultaneously minimize the squared error in depletion and cpue. The method is now not catch-only, but plus (OCOM$^+$). Depending on the trend and contrast in cpue data, results from OCOM$^+$ can differ significantly from OCOM. If cpue data are reliable, this can avoid a need for depletion prior—a new technique.

The final development is a multi-stock assessment for neritic tunas. Since stock structure is unknown for neritic tunas, a single stock has been routinely assumed in the whole Indian Ocean for each species. Due to fishing intensity varies across regions, overfishing in some areas is a real concern if sub-stock exists. We tentatively divide Indian Ocean into four stock regions: northwest, northeast, southwest, and southeast.

The estimated key parameters vary among species and stocks. For example, for Longtail tuna, stock is in the worst status in the southeast region.

We recommend that catch-based assessment continues to be the preferred method for neritic tuna until sufficient data become available for applying data-rich traditional stock assessment. Reliable cpue standardisation can avoid the requirement of depletion prior and improve the parameter estimation. Standardizing cpue for major fisheries, even just for a few recent years, can be very useful for $OCOM^{+}$. Area-based assessment such as SAFE, and length-based analysis, should also be considered in near future research planning.

1 Introduction

The Indian Ocean Tuna Commission (IOTC) manages 16 tuna and tuna-like species in the Indian Ocean with its primary objective the conservation and optimum utilization of the stocks for long-term sustainability. The scientific advice and management recommendations on the status of IOTC fish stocks are based upon the results of fisheries stock assessments and the analyses of the available information. Stock assessment is critical to enhance scientific elements in the conservation and sustainable exploitation of these valuable fishery resources.

The development of quantitative, semi-quantitative, or qualitative assessment approaches depend on appropriate information. The high value species such as bigeye tuna, yellowfin tuna and swordfish caught in large volume by industrial fleets are subject to intense data collection and there is a greater amount of information that enables fully quantitative stock assessments to be undertaken on these species. However, the data collection and reporting mechanisms are limited in the artisanal and semi industrial sectors. As a result, the quality and quantity of data is more variable for many commercial target and bycatch species including neritic tuna, billfish, and shark species, and most of these species and stocks are lacking sufficient biological and/or exploitation information to produce a defensible quantitative stock assessment.

Assessing the status of these data-limited stocks is a highly pertinent issue for the IOTC and has been discussed by many of its subsidiary bodies including the Working Party on Neritic Tunas, the Working Party on Billfish and the Working Party on Ecosystems and Bycatch as well as the Scientific Committee. There is growing need for IOTC CPCs and other fisheries stakeholders to assess these fish stocks with low levels of data. A catch-based stock reduction method was developed in 2013 and was applied to low information stocks of Kawakawa and Longtail tuna (Zhou and Sharma, 2013). Since then catch-based methods have become the primary technique for assessing IOTC neritic tuna species.

In the last several years, a number of progresses have been made in the assessment of data-limit fisheries. Froese et al. (2017) extended the Catch-MSY method (Martell and Froese, 2013) to estimate reference points. Zhou et al. (2017) developed a boosted regression tree (BRT) model for estimating stock depletion level based on catch data alone. The optimised catch-only method (OCOM) used for IOTC neritic tunas has also been improved (Zhou et al., 2017b). In addition, length-based methods have been advanced in recent years (Froese et al., 2018; Hordyk et al., 2016; Rudd and Thorson, 2017) and these methods can potentially be used to complement the catch-only methods to improve the model performance.

In view of the recent methodological development, The IOTC is proposing a project to review and improve available methods that have been or can potentially be applied to data-limited stocks under IOTC mandate. This project aims to expand the assessment options and increase the capacity to conduct assessments for IOTC species, as well as provide the guidance necessary to design possible harvest control rules.

This report includes several sections. We first conduct a brief review of existing data-limited methods, particularly those potentially suitable for the type of data held by the IOTC secretariat. We then devote effort to improve the estimation of priors on the level of stock depletion and the rate of intrinsic growth by incorporating new information including growth parameters, and new techniques for estimating natural mortality and stock depletion. The improvement has been made for all six neritic tuna or tuna-like species: Bullet tuna (*Auxis rochei*), Narrow-barred Spanish mackerel (*Scomberomorus commerson*), Frigate tuna (*Auxis thazard*), Indo-Pacific king mackerel (*Scomberomorus guttatus*), Kawakawa (*Euthynnus affinis*), and Longtail tuna (*Thunnus tonggol*). Consequentially, two most promising catch-based methods are integrated to enhance the model performance, and to explore potential options of developing an amalgamated model that synthesises and combines different assessment approaches. Uncertainty from various sources are considered when making management advice.

Furthermore, the study investigates additional data availability, including limited cpue from certain fleets, and to explore the possibility of incorporating these data into catch-based models for fine-tuning the model.

Finally, the study explores alternative assumptions on the stock structure, i.e., an ocean-wide single stock versus multiple regional stocks, and to investigate their potential impact on stock assessment results.

This study is considered to enhance current data-limited assessment methods for Indian Ocean neritic tuna species as well as species with similar data. Further research and potential methodologies for the types of data available are recommended at the end of the report.

2 Review of data-limited methods

There have be several reviews on data-limited assessment methods in recent years (Cruz *et al.*, 2011; Edwards, 2015; Geromont and Butterworth, 2015; Oliveira *et al.*, 2017). The majority of published methods have been covered in these reviews. Our review focuses on methods that can be potentially useful for the neritic tunas in the Indian Ocean.

2.1 Traditional stock assessment

Traditional stock assessment models include surplus production models (biomass dynamics models), statistical catch-at-age models, delay-difference models, and virtual population analysis models. Traditional stock assessment models require various data, including at least a time series of catch and biomass index (often CPUE) records. The models produce biological and management quantities that quantify biological status, fishing impact, and at the same time produce corresponding reference points (i.e., there is no need to calculate reference points separately using additional models). This cohesive approach avoids possible inconsistency between reference points and biological status because both refer to the same type of fish in terms of their age/size/sex composition.

However, it is difficult to use traditional assessment methods for IOTC neritic tunas at this time because of a lack of basic information such as standardized cpue. Preliminary studies on cpue standardization exist for small regional fisheries, e.g., longtail tuna (Thunnus tonggol) catch rates of drift gillnet fisheries in Sultanate of Oman, and Kawakawa pole and line fishery in Maldives. The scales of these fisheries are very small compared to catch in the whole Indian Ocean, and the time series in these fisheries are short.

2.2 Area-based ERA methods

Until more data become available and their quality improves, alternative data-poor techniques are more appropriate for these neritic tunas. In the last two decades, an area-based ecological risk assessment approach has become increasingly popular. The assessment involves two separate components: (i) estimating fishing impact using available fishery and ecological data; (ii) deriving reference points based on biological and life-history traits.

The sustainability assessment for fishing effect (SAFE) (Zhou and Griffiths, 2008; Zhou *et al.*, 2011) is an area-base ERA method to estimate the annual instantaneous fishing mortality for a species in defined period (i.e. one year):

$$\boldsymbol{F} = \frac{\boldsymbol{C}}{\overline{\boldsymbol{N}}} \approx \frac{\sum_t \boldsymbol{a}_{s|A,t}}{\boldsymbol{A}} \boldsymbol{q}_h \boldsymbol{q}_\lambda (\boldsymbol{1} - \boldsymbol{S}) \qquad \textbf{(Eqn 1)}$$

Where *C* is catch, $\overline{N}$ is average abundance over the period, *A* is the species distribution range, $a_{s|A,t}$ is gear affected area by one unit of fishing effort when fishing site *s* is within *A* at time *t*, catchability is a combination of habitat-dependent encounterability q_h and size- and behaviour-dependent selectivity q_λ, and *S* is the discard survival rate or escapement rate in some gear types (e.g. gear fitted with bycatch reduction device). This equation assumes that fish density is constant within its distribution range, and encounterability and selectivity can be predefined by fish size and behaviour. It implies that fishing mortality is the fraction of overlap between fished area and the species distribution area within the jurisdiction (availability), adjusted by catchability and post-capture mortality. This simple approach has been referred to as base SAFE (or bSAFE, AFMA, 2017).

For the neritic tunas in the Indian Ocean, catch data are available. If fishing effort is also available, it may be possible to enhance the bSAFE by estimating fish density and gear efficiency:

$$F = \frac{C}{\bar{N}} = \frac{C}{\sum_s (d_s A_s)}$$

$$\boldsymbol{d_s} = \frac{\boldsymbol{1}}{\boldsymbol{n}} \sum_{\boldsymbol{t}}^{\boldsymbol{s}} \frac{\boldsymbol{C_{s,t}}}{\boldsymbol{Qa_{s,t}}} \quad \textbf{(Eqn 2)}$$

where d_s is fish density at site *s*, $C_{s,t}$ is catch in event *t* within site *s*, *Q* is catch efficiency, $a_{s,t}$ is gear-affected area (fishing effort) in event *t*, and *n* is the total fishing events in site *s* within specific time. This version has been referred to as enhanced SAFE (or eSAFE, AFMA, 2017). These basic equations have been modified in various ways depending on available data. Modification can be made to each of the input variables in the equations.

To conduct eSAFE, several quantities are needed: species distribution, fishing effort, area affected by major fishing gears, and gear efficiency.

2.2.1 Species distribution

Species distribution can be obtained from survey data (Zhou and Griffiths, 2008; Zhou *et al.*, 2009a; Ministry for Primary Industries, 2016; Grüss *et al.*, 2018), existing distribution maps based on habitat and other information (Zhou *et al.*, 2009b; Ministry for Primary Industries, 2016), and fishery data (Zhou *et al.*, 2009c, 2015; Hoyle *et al.*, 2017; Fu *et al.*, 2018). Relative fish density is an important feature of species distribution. Depending on available information, homogeneous or random distribution may be assumed for data-poor species. If catch at location or presence-absence are available, heterogeneous density can be estimated and predicted through various statistical models as such GLMM, GAM, N-mixture, and geostatistical models (Zhou and Griffiths, 2007, 2008; Zhou *et al.*, 2013; Hoyle *et al.*, 2017; Fu *et al.*, 2018; Grüss *et al.*, 2018). Models that include environmental data can be used to extend predicted distributions into areas with insufficient fishery data (Hoyle et al 2017).

2.2.2 Area affected by fishing

The simplest method is to divide the management area into many small equal-sized cells and count the number of cells with fishing effort greater than a threshold (e.g., 3 boat-days or 1 unit of fishing effort) (Zhou and Griffiths, 2008; Griffiths *et al.*, 2018). It may be preferable to calculate actual gear affected area from gear dimension (i.e., length of longline, gillnet, and seine, or trawl opening width) and soak time (Zhou *et al.*, 2011, 2013; Ministry for Primary Industries, 2016). The total area affected by fishing is a function of the total fishing effort and the gear-affected area per set.

2.2.3 Gear efficiency

This term is sometime called catch efficiency, fishing power, or catchability. Unlike catchability parameter *q* in stock assessment model, *Q* is the probability of catching a particular fish in one gear setting (deployment) when that fish is within the gear affect area. It may be considered as the combined effect of encounterability and selectivity (Zhou *et al.*, 2011, 2016a). For data-poor species, a constant value may be assumed and assigned to encounterability and selectivity for each gear type based on fish size and behaviour (e.g. low 0.33, medium 0.67, high 1.0). If sufficient set-by-set catch data are available, gear efficiency can be estimated by abundance and detectability (referred to as N-mixture) models (Zhou and Griffiths, 2007; Zhou *et al.*, 2013, 2014; Campbell *et al.*, 2017).

Gear efficiency *Q* is directly related to catchability *q* in stock assessment models. When individuals are assumed to be randomly or evenly distributed in stock distribution area *A*, the relationship between these two quantities is $q = Qa/A$, where *a* is the average gear affected area by one unit of fishing effort. Hoyle *et al*. (2017) and Fu *et al*. (2018) took a different approach to derive catchability for Porbeagle shark and Bigeye thresher shark. They used a subset of the observer data within a subsection of the assessment area A_Ω where the data are believed to have good quality. They fitted a Bayesian state-space biomass dynamic model to an index of relative abundance in the selected sub-area. Catchability q_Ω is one of the three parameters (the other two parameters are carrying capacity *K* and intrinsic population growth rate *r*) in the biomass dynamics model. This q_{Ω} is then adjusted by area and used to estimate fishing mortality. This approach may be compared with the N-mixture model for estimating gear efficiency.

Conceptually, area-based method is analogous to formal stock assessment as both indicator (F_{cur}) and reference points (F_{RPs}) are equivalent to those in formal stock assessment. This group of methods can be flexibly modified to suit the existing data. Limited catch-effort data are available for neritic tunas. The dataset IOTC-2018-WPNT08-CECoastal.csv contains some important information: fleet, gear, fishing year, month, fishing location (grid), fishing effort, and catch. It may be possible to estimate species distribution and gear efficiency from this dataset. It should be noted that area-based methods involve a series of assumptions regarding species distribution pattern and range, area affected by fishing gear, and gear efficiency. Accuracy can be improved with more data and better estimators, but uncertainly may still be high.

2.3 Age-based methods—catch curve

Statistical catch-at-age methods are considered the state-of-the-art in modern stock assessment. Catch curves represent the simplest catch-at-age methods. If catch-at-age data are available, catch curve analysis may be carried out to estimate total mortality *Z* and fishing mortality *F* if natural mortality *M* is known. There are alternative methods for estimating Z from catch curve data, including regression-based methods, the Chapman-Robson estimator, and the Heincke estimator. These methods generally require that vulnerability to fishing gear is constant above the age when maximum catch occurs, and that the population has a stable age structure. For example, a dome-shaped selectivity curve may distort the linear relationship between log(catch) and age. Catch curve analysis can be applied to catches taken in the same year so the fish are composed of cohorts born in different years. In this case catch curve analysis has to assume (i) a constant recruitment for these cohorts; (ii) similar survival history for these cohorts (Quinn and Deriso, 1999).

In additional to potential violations of assumptions, non-random sampling, and inaccurate ageing data, stochastic error in the true mortality rate, recruitment, and ageing affect the accurate of the estimated mortality. Comparison between the Chapman-Robson and regression estimators found the Chapman-Robson estimator to be more accurate than regression methods (Dunn *et al.*, 2002). Another comparison study comparing three catch-curve methods (the Chapman–Robson, regression, and Heincke estimators) also showed that the Chapman-Robson estimator generally out-performed the other two methods (Smith *et al.*, 2012) and was recommended, after correction for over-dispersion, for estimating total mortality.

Age-based methods generally require constant recruitment, growth, natural mortality, selectivity, and fishing mortality rate, in addition to the requirement that the age composition in the sample truly represents those of the exploited age/size range of the stock. However, age data are expensive to obtain and the samples often come from selected sub-populations.

Currently, age composition data are very limited for the neritic tuna in the Indian Ocean. Sporadic sampling and aging information in some areas may not represent the ocean-wide fishing impact, even if catch-curve can be developed.

2.4 Length-based methods

The most common length-based model is the Beverton-Holt "per-recruit" estimator (BHE) based on von Bertalanffy growth model with an assumption that total mortality *Z* is constant beyond the age of recruitment (Quinn and Deriso, 1999). Z is calculated as

$$Z = \frac{k(L_{inf} - \bar{L})}{\bar{L} - L_c} \quad \textbf{(Eqn 3)}$$

where κ and L_{inf} are VB growth parameters, $\bar{L}$ is the mean length in the catch, and L_c is the length at recruitment age. The BHE (Eqn 3) assumes steady-state conditions, deterministic vB growth function, a constant mortality rate of all fully recruited fish, and continuous and constant recruitment to the fishery.

As length is a function of age, length frequency data can be converted to age under the assumption of deterministic growth following a vB growth model. Hence, the length converted catch curve (LCCC) method was developed. It has been shown that the standard LCCC overestimates *Z*, but by explicitly considering seasonal growth oscillations LCCC can produce unbiased estimates (Pauly *et al.*, 1995).

Recently, Hordyk *et al.* (2014, 2016) have developed the length-based spawning potential ratio (LB-SPR) mortality estimator. This is an equilibrium age-structured model that converts the predicted age distribution of the catch to a length distribution. Given known M/κ, the LB-SPR estimates the parameters F/M from the standardized length composition of the catch.

Huynh *et al.* (2018) compared these three length-based methods used Monte Carlo simulations across a range of scenarios with varying mortality and life history characteristics. They showed that neither the LCCC nor the BHE was uniformly superior in terms of bias or root mean square error across simulations, but these estimators performed better than LB-SPR, which had the largest bias in most cases. Generally, if the ratio of natural mortality (*M*) to the von Bertalanffy growth rate parameter (κ) is low, then the BHE is preferred, although there is likely to be high bias and low precision. If M/κ is high, then the LCCC and BHE performed better and similarly to each other.

The requirement of constant fishing mortality and recruitment over time has been relaxed by a recent developed length-based method. Rudd and Thorson (2017) extended the length-only approaches to account for time-varying recruitment and fishing mortality using a Length-based Integrated Mixed Effects (LIME) method. LIME requires a single year of length data and basic biological information and can fit to multiple years of length data, catch, and an abundance index if available.

The most recent development in this area is length-based Bayesian biomass estimation method (LBB) (Froese *et al.*, 2018). The method estimates asymptotic length, length at first capture, relative natural mortality, and relative fishing mortality using length frequency data. Standard fisheries equations can then be used to approximate current exploited biomass relative to unexploited biomass.

Unfortunately, this powerful method was found to be flawed. Hordyk *et al.* (2019) found that the method to calculate equilibrium numbers-at-length is incomplete and leads to negatively biased estimates of fishing mortality. The method is highly sensitive to several key assumptions, including equilibrium conditions, approximation of population average asymptotic length by the largest observed size (L_{max}), and the ratio of natural mortality (*M*) to the von Bertalanffy growth parameter (κ; M/κ). Furthermore, the method is essentially a per-recruit model, which does not account for the decline in average recruitment that typically occurs when spawning biomass is reduced below unfished levels. Therefore, their estimates of F_{MSY} are equivalent to estimates of F_{max} from a conventional yield-per-recruit model and the ratio of B/B_0 does not represent the true biomass depletion.

Similar to age-based method, length-based methods also require constant recruitment, growth, natural mortality, gear selectivity, fishing mortality, as well as the requirement that length frequency data in the sample truly represent those of the exploited size range of the stock (e.g., samples not just from selected sub-populations).

Length-based methods typically assume that selectivity in fish is size-dependent, which results in differential fishing mortality rates across fish of the same age. But there are scenarios where this assumption is likely to be violated. For example, species that have an ontogenetic migration may be better described by age-based selectivity or a combination of age- plus size-based selectivity (Francis, 2016; Hordyk *et al.*, 2016b).

Length-based methods also assume a fixed selectivity pattern (often knife-edge, but can asymptotic). For migration species that is harvested by multiple gear types at varying life stage, it is unclear whether the combined length frequency data from multiple fleets are sufficient to allow estimating biological parameters and fishing impact.

Finally, length-based methods are based on per-recruit analysis where the final output is the spawning potential ratio (SPR, aka spawning stock biomass per-recruit) (Hordyk *et al.*, 2014, 2016b; Rudd and Thorson, 2017). The utility of SPR has been examined recently for (Zhou *et al.*, 2019). Spawning potential ratio is estimated as (Goodyear, 1993):

$$\boldsymbol{SPR} = \frac{\boldsymbol{SSBR_{fished}}}{\boldsymbol{SSBR_{unfished}}} \qquad \textbf{(Eqn 4)}$$

Fishing mortality rate that corresponds to SPR ($F_{\%SPR}$) can be derived similar to yield per recruit (YPR) analysis. The analysis focuses on a single cohort, so does not consider population dynamics from one generation to the next (e.g., a stock-recruitment relationship). Assuming a constant year class, SPR can be obtained by following a cohort through their entire life from growth, maturation, natural and fishing mortality rates, to the end of their maximum life span.

A critical question is how SPR and $F_{\%SPR}$ link to the absolute stock size and true fishing mortality. It is worth to point out that although SPR refers to spawning biomass, this biomass is not the biomass of the population but a relative value, in terms of “per recruit”. Any arbitrarily number, such as 1 or 1000 fish, can be used as the initial population size to derive SPR. $F_{x\%SPR}$ refers to the fishing mortality that corresponds to the percentage of depletion in spawning biomass from an unfished level on a “per recruit” basis. Therefore, an estimated SPR alone does not clearly indicate stock status, i.e., whether the stock can sustain the impact in long term. It is necessary to define a proxy comparable with sustainability benchmark as such F_{msy}.

Extensive studies have examined the appropriate $F_{x\%SPR}$ proxy for F_{msy}, and a range from $F_{20\%}$ to $F_{70\%}$ have been suggested. Brooks *et al.* (2010) demonstrated that SPRx% is a function of the stock productivity quantified as life time reproduction rate, which is a product of the slope at the origin of a stock-recruitment function and SPR when no fishing. In other words, to maintain stock biomass at certain x% of unfished level or of a reference point (i.e., 20%B_0 or 10%B_{msy}) requires varying SPRx% from species to species. It is inappropriate to use a common x% such as F40% for all stocks unless they have the same productivity.

Real fisheries data may violate many assumptions required by length-based methods. In a review of data-poor methods, Edwards (2015) recommended that pending further testing by proponents of these approaches, length-based methods were not considered suitable for immediate application in New Zealand. A review on length-based indicators and reference points for elasmobranchs (ICES, 2018) found that life-history parameters estimated from length were uncertain. The ICES Working Group suggested that trend-based metrics should be considered until the length-based methods are validated.

Nevertheless, length data is another abundant piece of information for neritic tunas (besides catch data). It may be worth to explore methods that primarily use length data to derive indicators and reference points, as well as potentially estimating fishing mortality.

2.5 Catch-only methods

There has in recent years been an increasing interest in developing catch-only methods. These methods require only time series of catch data and perhaps some life history parameters, so they can be applied to many fisheries where catch records are available. These methods typically require information about stock depletion. Model performance will be affected by the depletion level chosen so methods that assume a common depletion have limited application. Amongst the catch-only methods, Catch-MSY (Martell and Froese, 2013b; Froese *et al.*, 2017) and OCOM (Zhou *et al.*, 2017a) attempt to come up a depletion prior based on catch history. Hence, they are more promising than other catch-only methods. Catch-MSY and OCOM produce time series of biomass, fishing mortality, and both F-based and B-based reference points such as B_{msy} and F_{msy}. The main disadvantage of catch-only methods is their potentially inaccurate results for some stocks, particularly for unproductive, lightly fished, or highly depleted stocks.

Before deciding which category of approaches may be tested for neritic tunas in the Indian Ocean, a few factors should be taken into consideration. It is essential to examine the data inventory, including the types of data available and their quality and quantity. The key assumptions required by each potential method should be examined. As there are several neritic tuna species, applying consistent methodology across multiple species could facilitate both assessment and management.

3 Improving the estimation of priors on the level of stock depletion and the rate of intrinsic growth

Because of data-poor circumstances, catch-only methods use a simple population dynamics model. The biomass dynamics model, aka surplus production model, is perhaps the most simple fishery model that allows estimation of fundamental management quantities. For the two catch-only methods, the optimized catch-only method (OCOM) (Zhou *et al.*, 2018) and Cath-MSY method (CMSY) (Froese *et al.*, 2016), it is essential to construct two leading priors: the level of stock depletion and the rate of intrinsic growth.

3.1 Stock depletion level

Stock depletion level is defined as the fraction of population that has been depleted (removed) from unfished level: $D = 1 – B_t/B_0$, where B_t is biomass at time t and B_0 is virgin biomass often assumed to be the carrying capacity K. The fraction of remaining biomass may be called saturation, $S = B_t/B_0$. Unlike some catch-based methods that assume constant S for all stock (e.g., 0.5 or 0.4), OCOM and Catch-MSY attempt to come up a prior based on catch history. In the previous assessments for IOTC's neritic tunas (IOTC, 2015; IOTC Secretariat, 2015a; Martin and Sharma, 2015), OCOM assumed multiple potential saturation levels: 0.05-0.5, 0.05-0.6, 0.05-0.7, and 0.05-0.8. Catch-MSY had two saturation levels: if $C_{\mathrm{last}}/C_{max} > 0.5$, S = 0.3-0.7; if $C_{\mathrm{last}}/C_{max} \le 0.5$, S = 0.01-0.4.

There have been some new developments in this area in recent years. Based on patterns in catch history of 191 data-rich species, Zhou *et al.* (2017b) developed a boosted regression tree (BRT) model to predict stock saturation. This BRT model provides a basis for OCOM to construct S prior using following distributions:

$$S_{\mathrm{last}} \sim sNorm(\text{mean} = S_{BRT,\mathrm{last}} - 0.072, \text{SD} = 0.189, \text{skewness} = 0.763), \text{ when } S_{BRT,\mathrm{last}} \le 0.5 \quad \text{(Eqn 5)}$$

$$S_{\mathrm{last}} \sim sNorm(\text{mean} = S_{BRT,\mathrm{last}} + 0.179, \text{SD} = 0.223, \text{skewness} = 0.904), \text{ when } S_{BRT,\mathrm{last}} > 0.5,$$

where *sNorm* is a skewed normal distribution, $S_{BRT,\mathrm{last}}$ is the predicted value of S from the BRT model. Equation 6 accounts for bias in the BRT estimates by adjusting the prediction of the mean. The samples from the S prior are constrained within the range of [0, 1].

CMSY extends the original two levels of S to three broad saturation ranges (Table 1) and assumes a uniform distribution between S.low and S.high. The range may not cover the estimate from BRT model (Table 2). Agreements between the two approaches are found in two out of the six species. However, if the original two levels of S in the Catch-MSY method (Martell and Froese, 2013a) are adopted, four out of the six species would fall in the similar S ranges.

For method 1 (OCOM), a large number of random S are generated from skewed normal distributions in Eqn 6. For method 2 (CMSY), a large number of S are generated from uniform distribution between S.low and S.high. The third method is to integrate S from method 1 and method 2 by combining the equal number of samples from the two approaches.

Table 1. CMSY rule for saturation based on the ratio of last year's catch to the maximum catch in the time series.

C_{last}/C_{max}	*S*.low	*S*.high
> 0.7	0.5	0.9
< 0.3	0.01	0.4
>=0.3, <=0.7	0.2	0.6

Table 2. Stock saturation prior from BRT and CMSY for the six neritic tunas. Two BRT models are used: one with 8 predictors (BRT-S8) and the other one with 38 predictors (BRT-S38).

Species	BRT-S8	BRT-S38	Mean S	S.low	S.high
BLT	0.59	0.51	0.55	0.5	0.9
COM	0.48	0.41	0.44	0.5	0.9
FRI	0.28	0.27	0.28	0.5	0.9
GUT	0.63	0.52	0.58	0.5	0.9
KAW	0.43	0.40	0.41	0.5	0.9
LOT	0.36	0.35	0.36	0.5	0.9

3.2 Rate of intrinsic growth

In the previous neritic tuna assessments, the prior for population growth rate r in the surplus production model was derived as $r = 2\ F_{MSY}$ and F_{MSY} in turn was based on an relationship with instantaneous natural mortality rate M (Zhou *et al.*, 2012): $F_{MSY} = 0.87M$ for teleosts. Natural mortality was sourced from literature available at that time (IOTC, 2015; IOTC Secretariat, 2015a; Martin and Sharma, 2015). Two recent studies may help to improve the prior on the rate of intrinsic growth.

Using r estimated from the Schaefer surplus production model for 189 fish and invertebrate stocks worldwide, (Zhou *et al.*, 2016b) developed empirical relationships between r and other life history parameters (LHPs) using Bayesian hierarchical error-in-variables models that incorporate uncertainty in LHPs themselves. Among the various models tested, they found that r was strongly correlated with natural mortality (M), while other LHPs, such as the von Bertalanffy growth rate (κ), asymptotic length (L_{∞}), maximum age (t_{max}), length and age at maturity (L_{mat} and t_{mat}), added minor improvement to the relationship. The best model was $r = 2.02\ M$ for invertebrates (SD = 0.21, n = 28), $r = 0.76\ M$ for elasmobranchs (SD = 0.11, n = 25), and $r = 1.73\ M$ for teleosts (SD = 0.08, n = 136). The result for teleosts was remarkably similar to $r = 2F_{MSY} = 1.74M$ based on $F_{MSY} \sim M$ relationship.

It is difficult to directly estimate natural mortality. The common approach is to derive M from other life-history parameters that are relatively easier to obtain. One of most common M estimator uses von Bertalanffy growth parameters. However, independent studies on the growth of neritic tuna species in various regions across the Indian Ocean resulted in highly variable parameter estimates, possibly due to distinctive subpopulation and differences in sampling or analytical methods. To obtain representative growth parameters in the Indian Ocean at the basin-scale, a meta-analysis was carried out recently to collate the data from various regions and use a consistent analytical method (Zhou *et al.*, 2017c). In that study a Bayesian hierarchical model (BHM) was developed, which enabled estimating growth parameters from very few length modes by analysing all data together. The method was applied to six neritic tuna species: Spanish mackerel, Longtail tuna, Frigate tuna, Kawakawa tuna, Bullet tuna, and Indo-Pacific King mackerel.

Here, we combine the estimated growth parameters from this meta-analysis with existing literature to increase the reliability of *M* estimate. We use the following equation as the primary *M* estimator (Then *et al.*, 2015a):

$$\boldsymbol{M = a\kappa^{b} L_{inf}^{c} = 4.118\ \kappa^{0.73} L_{inf}^{-0.33}} \quad \textbf{(Eqn 6)}$$

Several alternative estimator based on von Bertalanffy growth parameters have be proposed (Pauly, 1980; Gislason *et al.*, 2010; Charnov *et al.*, 2012; Hamel, 2015). Equation 7 results from re-analysing all available data and does not require water temperature and length at maturation as in other estimators.

Limited information on maximum age is available for some neritic tuna species. This enables using t_{max}-based *M* estimator (Hamel, 2015; Then *et al.*, 2015b):

$$\boldsymbol{M = at_{max}^{b} = 4.899\ \ t_{max}^{-0.916}} \quad \textbf{(Eqn 7)}$$

$$\boldsymbol{M = \frac{4.374}{t_{max}}} \quad \textbf{(Eqn 8)}$$

Tables 3-3 to 3-8 provide the estimated *M* based on other life-history parameters, as well as *M* from literature for six neritic tuna (or tuna-like) species: Bullet tuna (BLT), Spanish mackerel (COM), Frigate tuna (FRI), Indo-Pacific King mackerel (GUT), Kawakawa tuna (KAW), and Longtail tuna (LOT).

The summary *M* values are used to derive *r* priors for these species. To avoid potentially negative values being sampled, we use a lognormal distribution: $r \sim$ lognormal(μ_r, σ_r^2), where μ_r = log(2F_{MSY}) and $\sigma_r^2 = \sigma_M^2 + \sigma_e^2$. Measurement error and variability resulted from alternative life-history invariant equations can be large. This uncertainty may lead to unrealistic *r* values. For example, using σ_r^2 = 0.23 can yield *r* >> 1 for some stocks. To avoid this dilemma we exclude unrealistic samples that are greater than 2 (note that *r* can be greater than 1 for highly productive species).

In CMSY, the broad ranges of *r* prior is predefined by "resilience" parameter that can be obtained from fishbase.org for most species (Table 3).

Table 3. CMSY rule for defining *r* range.

Resilience	*r*.low	*r*.high
High	0.6	1.5
Medium	0.2	0.8
Low	0.05	0.5
Very low	0.015	0.1

Similar to saturation prior, for Method 1 (OCOM), a large number of random *r* are generated from $r \sim$ lognormal(μ_r, σ_r^2) distributions. For Method 2 (CMSY), a large number of *r* are generated from uniform distribution between *r*.low and *r*.high in Table 22. The third method is to integrate *r* from method 1 and method 2 by combining the equal number of samples from the two approaches.

4 Catch-based methods and possible improvement

4.1 Material and methods

4.1.1 Available data

The IOTC Secretariat maintains fisheries database (catch, effort, and length-frequency) for all 16 IOTC species, including six neritic tunas: Bullet tuna (BLT), Frigate tuna (FRI), Kawakawa (KAW), Longtail tuna (LOT), Indo-Pacific king mackerel (GUT) and Narrow-barred Spanish mackerel (COM). These data are available online at https://www.iotc.org/data-and-statistics.

There are three catch-effort datasets downloadable in csv format: (i) IOTC-2018-WPNT08-DATA04-CELongline.csv; (ii) IOTC-2018-WPNT08-DATA05-CESurface.csv; and (iii) IOTC-2018-WPNT08-DATA06-CECoastal.csv). The longline dataset does not have any catch of neritic tuna. The surface dataset has only 19 records of neritic tuna caught by purse seine. Among these files, only the coastal dataset is potentially useful. Because the data are composed of multiple fleets, grids, effort types, and span several years, cpue calculated from the catch and effort should be standardized. We may include these variables in the statistical models such as the generalized additive models (GAM). However, because of few records for each year/fleet/grid/effort_unit, the standardized cpue is quite uncertain. To examine the feasibility of including cpue data, we use standardized Maldives pole and line fishery data for Kawakawa (IOTC Secretariat, 2015b) and standardized Oman drift gillnet fishery data for Longline tuna (Al-siyabi *et al.*, 2014).

The length frequency database for neritic tunas includes length samples since 1983 from 10 fleets (i.e., countries and gear combination) using a variety of fishing gears (a total of 15). Length frequency data were recorded by species, fleet, year, gear, month and 5° x 5° latitude/longitude area and the sample size in each stratum ranged from 1 to over 56,000 fish. This database contains valuable information for deriving biological and potentially fisheries parameters for neritic tuna. However, as discussed in the review section, length data do not contain information about stock biomass. Per-recruit using length data cannot provide information about the stock depletion level as claimed by some studies (Froese *et al.*, 2018; Hordyk *et al.*, 2019). As such, no further exploration of using length data for deriving prior for stock status has been conducted.

As its name stands, catch-only method primarily uses catch data. IOTC Secretariat provided data file "IOTC-2018-WPNT08-DATA03-NC.xlsx" that contains catch history from 1950 to 2018 for the six neritic tunas.

4.1.2 Catch-only methods

Two catch-only methods, OCOM and CMSY, are considered in this study. There are some similar features as well as differences between the two methods. Both methods use the Graham-Schaefer surplus production model, as it is very simple and has been widely used:

$$\boldsymbol{B_{y+1} = B_y + rB_y\left(1 - \frac{B_y}{K}\right) - C_y} \qquad \textbf{(Eqn 9)}$$

where B_y is the biomass at the start of time step y, r is the intrinsic growth rate, K is the carrying capacity (equal to the unfished or initial biomass B_0 for a surplus production model), and C_y is the (known) catch during time-step y. This model has two unknown parameters, r and K. CMSY attempts to construct priors for these two parameters. It defines a possible range for r based on stock productivity, called "resilience", and defines a range for K based on maximum catch and constructed r values. Stock saturation $S_{last} = B_{last}/K$ at the end of the catch time series (i.e. 2017) is required to infer depletion. CMSY defines the range for S_{last} based on the ratio C_{last}/C_{max}. With these three pieces of information, a large number of biomass trajectories are produced by Monte Carlo simulation and trajectories that satisfy the predefined conditions set by the three priors are retained for inferring model outputs.

In contrast, OCOM uses two priors on r and S (not K). The prior distribution for population growth rate r is deduced from natural mortality M, which in turn can be estimated from other life-history parameter as described in the previous section. The prior distribution of saturation parameter S_{last} is derived from catch trend over the fishery history. With these two priors, K in equation 10 can be solved by using an optimisation algorithm. Note that the so-called "prior" in this report is essentially the range or distribution of possible values and it differs from prior in Bayesian models.

Both OCOM and CMSY may have some unique advantage so it can be beneficial to integrate certain features from both approaches. A straightforward option is to combine the priors from both methods. Hence, we use both natural mortality M and resilience to derive a prior for r with equal weight, and use catch trend and C_{last}/C_{max} to derive prior for S_{last}. In the results section below, Method 1 refers to using empirical relation to derive r prior and using BRT to derive S prior; Method 2 refers to using resilience to derive r prior and C_{last}/C_{max} to derive S prior; and Method 3 refers to integrating both Methods 1 and 2.

4.1.3 Incorporating cpue data into catch-based methods

If two or more years of cpue are available, it is possible to include them in the OCOM. Since $cpue_y = qB_y$, assuming catchability coefficient q is constant over year y, the mean squared error between the scaled cpue and scaled biomass B is:

$$\boldsymbol{MSE_{cpue} = \frac{1}{n}\left(\frac{cpue_y}{\overline{cpue}} - \frac{B_y}{\bar{B}}\right)^2} \qquad \textbf{(Eqn 10)}$$

where n is the number of years with cpue data, $\overline{cpue}$ is the mean cpue over those available years, and $\bar{B}$ is the mean biomass over the same period. This $MSEcpue$ can be minimized together with $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ to find corresponding K for each random r and S. Depending on the quality of quantity of cpue data, there are multiple options for its weight w:

(i) No cpue (w = 0): objective function = $\left(\frac{B_{last}}{K} - S_{last}\right)^2$

(ii) Equal weight (w = 1): objective function = $\left(\frac{B_{last}}{K} - S_{last}\right)^2 + \frac{1}{n}\left(\frac{cpue_y}{\overline{cpue}} - \frac{B_y}{\bar{B}}\right)^2$

(iii) w times of weight (w = w): objective function = $\left(\frac{B_{last}}{K} - S_{last}\right)^2 + \frac{w}{n}\left(\frac{cpue_y}{\overline{cpue}} - \frac{B_y}{\bar{B}}\right)^2$

(iv) cpue only: objective function = $\frac{1}{n}\left(\frac{cpue_y}{\overline{cpue}} - \frac{B_y}{\bar{B}}\right)^2$

4.1.4 Assumption of multi-stock structure

Stock structure for the neritic tunas in the Indian Ocean is unknown. Currently, it is assumed that for each species there is only one stock in the whole ocean. As fishing intensity varies across the ocean, if multiple stocks exist, the status of some stocks may be worse than the others. To explore this concern, we tentatively assume four stock regions in the Indian Ocean: 1 = northwest, 2 = northeast, 3 = southwest, and 4 = southeast (Figure 10). Catches are assigned to one of the four sub-stock regions by a combination of Fleet and Area codes (Table 23).

4.2 Results

4.2.1 Alternative priors and methods

We run the catch-only model for three scenarios using alternative priors and methods. The summary output of the key parameters are listed in Table 24 to Table 26. We further present the result from Method 3 in Figure 1 to Figure 6. Figure 7 compares the difference in six key parameters between the three methods for each of the six species.

The results indicate that Method 1 (OCOM prior) produces a higher *r* than Method 2 (CMSY prior) for all six species. In Method 1, *r* is based on empirical correlation with natural mortality rate. It is likely that *M* from the literature may have been overestimated in many studies as it is not uncommon to see the estimated *M* > 0.8 in Table 4 to Table 21. *M* = 0.8 is equivalent an annual survival rate of 45%. On the other hand, *r* based on resilience parameter may underestimate neritic tuna's productivity.

The high *r* by OCOM prior leads to a low *K* while a low *r* by CMSY prior leads to a high *K*. The joint effect results in a similar MSY by either methods. This outcome confirms the earlier finding that MSY is more reliable than *r* or *K*, and should be preferred as a management quantity.

Other model outputs and indirectly derive parameters, including S_{last}, F_t, B_t, B_t/B_{msy}, and F_t/F_{msy}, can vary between the two methods, but the difference is typically less than *r* and *K* but greater than MSY (Figure 7). The general pattern shows a poorer stock status (i.e., lower Blast/B_{msy} and higher Flast/F_{msy}) by OCOM than by CMSY. Without further evidence and independent study, the results from the integrated method should be preferred at this stage.

Because of a similarly increase catch trend over time for the six species, their biomass trajectories also show a similarly declining trend whereas the fishing mortality trajectories exhibit an increasing pattern. The major difference between species is the extent of decline in B (or increase in F) and their relative status in regards to reference points B_{msy} and F_{msy}. Amongst the six species, BLT and GUT appear to be in best situation, with median B_{2017}/B_{msy} > 1.4 and F_{2017}/F_{msy} < 0.7. For the other four species, median B_{2017}/B_{msy} and median F_{2017}/F_{msy} are close to 1.

4.2.2 Effect of cpue

Including cpue has a noticeable impact on the estimated parameters. However, the impact differs between the two species that have very limited cpue data. For Kawakawa, including cpue and as the weight of cupe increases from 1 to 2 (i.e., equal weight as S and twice as large as S), the estimated *K*, *r*, MSY, S_{last}, B_{msy}, B_{last}, $B_{\mathrm{last}}/B_{msy}$—all increases (Table 27). As a result, F_{last} and $F_{\mathrm{last}}/F_{msy}$ decrease. This indicates that the status of the stock tends to be better when cpue is taken into consideration, as the trend of cpue is not very clear or slightly increasing over time (Figure 8, Biomass panel). Because of a lack of contrast and clear pattern in the available cpue time series, option (iv), i.e., the objective function based on cpue alone, cannot be performed for Kawakawa.

The situation is opposite for the Longtail tuna: all biomass based parameters decrease and fishing mortality F-based parameters increase (Table 28). The sharp decline of cpue over time has a substantial impact on estimated parameters (Figure 9). Using cpue alone in the objective function (Option iv) results in dire stock status with a median B2017/B_{msy} = 0.4 and median F2017/F_{msy} = 3.54.

4.2.3 Variation among assumed sub-stocks

We carried out analysis for six species in four stock-region using three methods, resulting in a total of 72 stock-method assemblages. To reduce the length of the report, we present the results from integrated Method 3 only in Table 29 to Table 34 for each species. The estimated key parameters vary among species and stocks. For example, for Longtail tuna, stock is in the worst status in the southeast region (median S_{2017} = 0.36 and median F_{2017}/F_{msy} = 1.66). Current fishing mortality is above F_{msy} in all regions except NE, thanks to a large decline in catch in this region in recent years (Figure 11 to Figure 14). Southwest region has the lowest K and MSY, reflecting the lowest catch over the entire history (Figure 15).

5 Discussion and recommendations

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Table 4. Natural mortality based on von Bertalanffy growth parameters for Bullet tuna.

Region	L_{inf}	κ	*M* (Then)
Turkey	45.1	0.34	0.533
India	42.3	0.61	0.834
India (south Kerala)	34	1.1	1.379
Mediterranean (west)	44	0.7	0.910
Atlantic (east)	41.5	0.32	0.524
India	59.9	0.91	0.996
Sri Lanka	103.5	0.18	0.255
India (media)	56.2	0.36	0.517
Sri Lanka (median)	64.6	0.18	0.298

Table 5. Natural mortality from literature and based on maximum age for Bullet tuna.

Region	*M*	t_{max}	*M* (Then)	*M* (Hamel)
Turkey	0.6	8.4	0.70	0.52
India	1.2			
India (south Kerala)	1.9			

Table 6. Overall natural mortality from Table 4 and Table 5 for Bullet tuna.

Statistics	*M*
Mean	0.797
SD	0.453
Median	0.649
N	14

Table 7. Natural mortality based on von Bertalanffy growth parameters for Spanish mackerel.

Region	L_{inf}	κ	*M* (Then)
Saudi Arabia	138	0.38	0.400
Oman	119	0.6	0.586
Australia (Male)	127.5	0.25	0.302
Australia (Female)	155	0.17	0.214
Persian Gulf and Oman Sea	140	0.42	0.428
Persian Gulf and Oman Sea	175.26	0.45	0.418
Oman	226	0.28	0.272
Oman	193.6	0.292	0.295
Oman	138.3	0.362	0.386
Oman	131.2	0.614	0.577
Oman	140	0.309	0.342
Oman	118.8	0.595	0.583
Oman	164	0.34	0.348
Southern India	187	0.18	0.210
Southwest India	131	0.78	0.687
Southeast India	178	0.38	0.368
Djibouti, Ford Watford	136	0.21	0.261
Gulf of Aden, Yemen	230	0.12	0.146
Saudi Arabian Gulf	165	0.26	0.286
Sri Lanka	146	0.37	0.385
Persian Gulf and Oman Sea	189	0.24	0.258
North Persain Gulf and Oman	151	0.46	0.446
Southern Arabian Gulf (all fish)	139	0.21	0.259
Southern Arabian Gulf (Female)	136	0.24	0.287
Southern Arabian Gulf (Male)	126	0.22	0.276
Persian Gulf and Oman Sea	156	0.24	0.274
Dar es Salaam	110	0.3	0.363
Oman	146	0.216	0.260
Gulf of Oman (Male)	131	0.33	0.367
Gulf of Oman (Female)	154	0.17	0.214
Arabian Sea (Male)	119	0.65	0.621
Arabian Sea (Female)	133	0.41	0.428
Iran	140.1	0.57	0.535
Sri Lanka	141.4	0.41	0.419
Oman	140.4	0.55	0.521
Pakistan	139.6	0.42	0.428
Thailand	140.3	0.51	0.493

Table 8. Natural mortality from literature for Spanish mackerel.

Region	*M*
Iran	0.49
Persian Gulf and Sea of Oman	0.5
Oman	0.49
Oman	0.38
North Persian Gulf and Oman Sea	0.54
Persian Gulf and Oman Sea	0.35
Persian	0.5
Southern Arabian Gulf	0.26
Persian Gulf and Oman Sea	0.43
Dar es Salaam, Tanzania	0.74
Pangani, Tanzania	0.43
Southwest India	0.78
Saudi Arabian Gulf	0.36
Sri Lanka	0.605
Oman	0.376
Oman	0.49
Gulf of Oman	0.44
Oman	0.526

Table 9. Overall natural mortality from Table 7 and Table 8 for Spanish mackerel.

Statistics	*M*
Mean	0.411
SD	0.138
Median	0.400
n	55

Table 10. Natural mortality based on von Bertalanffy growth parameters for Frigate tuna.

Region	L_{inf}	κ	*M* (Then)
Philippines	36.6	1.21	1.443
Taiwan	48.2	0.52	0.711
India (Veraval)	46.6	0.93	1.099
India	57.9	1.2	1.233
Indai (East coast)	53.8	1.04	1.138
India (Tuticorin) Male	49	1.3	1.381
India (Tuticorin) female	51.2	1.3	1.361
India	63	0.49	0.623
Indnesia	47.5	0.7	0.888
Sri Lanka	58	0.54	0.688
Thailand (Gulf of)	52	1.4	1.429
Thailand (West coast)	47.2	0.8	0.981
Philippines	47	0.73	0.919
European Union	110.1	0.21	0.279
India	90.5	0.24	0.329
Sri Lanka	152.1	0.11	0.157
Maldives	92.6	0.2	0.285
Malaysia	70.9	0.61	0.703
Thailand	43.8	0.63	0.844

Table 11. Natural mortality from literature and based on maximum age for Frigate tuna.

Region	*M*
Philippines	1.95
Taiwan	0.91
India (Veraval)	1.48

Table 12. Overall natural mortality from Table 10 and Table 11 for Frigate tuna.

Statistics	*M*
Mean	0.947
SD	0.461
Median	0.914
n	22

Table 13. Natural mortality based on von Bertalanffy growth parameters for King mackerel.

Region	L_{inf}	κ	*M* (Then)
India	78.5	0.34	0.444
India (Veraval)	61.3	1.4	1.354
India (West coast)	66.3	1.04	1.062
India (East coast)	76.3	1.49	1.318
India (West coast)	69	1	1.018
India (Chennai)	73	0.72	0.786
India (Mandapam Camp)	109.2	0.85	0.777
India (Mangalore)	68	0.84	0.901
India (Veraval)	69	0.8	0.865
India (South)	127.8	0.18	0.238
India (South)	116.3	0.18	0.245
Bangladesh	73.5	0.6	0.687
Bangladesh	65.1	0.6	0.715

Table 14. Natural mortality from literature and based on maximum age for King mackerel.

Region	*M*	t_{max}	*M* (Then)	*M* (Hamel)
India		8.5	0.69	0.51
India (Veraval)	1.79			
Bangladesh	1			
India (West coast)	1.41			

Table 15. Overall natural mortality from Table 13 and Table 14 for King mackerel.

Statistics	*M*
Mean	0.879
SD	0.410
Median	0.826
n	18

Table 16. Natural mortality based on von Bertalanffy growth parameters for Kawakawa tuna.

Region	L_{inf}	K	M (Then)
Seychelles	90	0.45	0.521
South Africa	82	0.51	0.588
Northwest Sumatra	64.58	1	1.041
Persian Gulf & Sea of Oman	95.06	0.67	0.684
Tanzania	80	0.78	0.809
Persian Gulf & Sea of Oman	87.66	0.51	0.576
India	81.7	0.79	0.811
Iran	78	0.52	0.607
Indonesia	63.53	0.63	0.747
Pakistan	81.92	0.56	0.630
Gulf of Thailand	79	0.96	0.945
Java Sea, Indonesia	59.63	0.91	0.997
Sri Lanka	63	0.61	0.731
India	81	0.366	0.464
India	75	0.42	0.526
Veraval, India	72.5	0.56	0.656
India	55.2	0.71	0.854
Iran	76.4	0.66	0.727
Sri Lanka	70.8	0.41	0.527
Maldive	89.4	0.21	0.299
Malaysia	55.3	0.81	0.939
Oman	71.3	0.83	0.879
Pakistan	79.4	0.73	0.773
Thailand	62	0.45	0.589

Table 17. Natural mortality from literature for Kawakawa tuna.

Region	M
South Africa	0.68
Seychelles	1.44
Persian Gulf and Sea of Oman	0.76
Tanzania	1.09
Persian Gulf and Sea of Oman	0.65
India	0.928
Iran	0.655
Indonesia	1.07
India	0.93
Java Sea, Indonesia	1.13
India	0.76
Veraval, India	0.94

Table 18. Overall natural mortality from Table 16 and Table 17 for Kawakawa tuna.

Statistics	*M*
Mean	0.776
SD	0.224
Median	0.753
n	36

Table 19. Natural mortality based on von Bertalanffy growth parameters for Longtail tuna.

Region	L_{inf}	κ	*M* (Then)
Australia	110	0.32	0.380
Australia	135.4	0.23	0.279
Persian Gulf and Sea of Oman	133.72	0.35	0.380
India	123.5	0.51	0.514
Papua New Guinea	122.9	0.41	0.439
Papua New Guinea	131.8	0.4	0.421
India	93	0.45	0.515
Oman	133.6	0.23	0.280
Gulf of Thailand	108	0.55	0.568
North Persian Gulf and Oman Sea	133.8	0.35	0.380
Inda	85	0.48	0.556
Veraval, India	107.4	0.18	0.252
Japan	55	1.7	1.617
Iran	105.7	0.54	0.564
Malaysia	93.6	0.24	0.325
Oman	103.2	0.6	0.614
Pakistan	103.8	0.49	0.529
Thailand	94.4	0.23	0.314

Table 20. Natural mortality from literature for Longtail tuna.

Region	*M*	t_{max}	*M* (Then)	*M* (Hamel)
Fishbase	0.54	9	0.65	0.49
India	0.77			
Persian Gulf and Sea of Oman	0.44			
India	0.8			
Oman	0.43			
Persian Gulf and Sea of Oman	0.44			
Veraval, India	0.4			

Table 21. Overall natural mortality from Table 19 and Table 20 for Longtail tuna.

Statistics	*M*
Mean	0.514
SD	0.260
Median	0.440
n	27

Table 22. Prior range for intrinsic population growth rate based on resilience parameter.

Species	Resilience	*r*.low	*r*.high	Mean
BLT	medium	0.2	0.8	0.5
COM	medium	0.2	0.8	0.5
FRI	medium	0.2	0.8	0.5
GUT	medium	0.2	0.8	0.5
KAW	medium	0.2	0.8	0.5
LOT	low	0.05	0.5	0.275

Table 23. Define substock by fleet and area codes.

Flt_Area	Substock	Flt_Area	Substock	Flt_Area	Substock
ARE_F51	NW	GIN_F57	SE	MYS_F51	SW
AUS_F57	SE	IDN_ IO	SE	MYS_F57	NE
BGD_F57	NE	IDN_F57	SE	NEI_ IO	NE
BHR_F51	NW	IND_F51	NW	NEI_F51	NW
BLZ_F51	SW	IND_F57	NE	NEI_F57	NE
BLZ_F57	SE	IRN_ IO	NE	OMN_F51	NW
CHN_F51	SW	IRN_F51	NW	PAK_F51	NW
CHN_F57	SE	IRN_F57	NE	PHL_F51	NW
COM_ IO	SW	ISR_F51	NW	PHL_F57	NE
COM_F51	SW	JOR_F51	NW	QAT_F51	NW
DJI_F51	SW	JPN_F51	NW	SAU_F51	NW
EGY_F51	NW	JPN_F57	NE	SDN_F51	NW
ERI_F51	NW	KEN_F51	SW	SEN_F51	SW
EUB_F51	SW	KEN_F57	SE	SEN_F57	SE
EUD_F51	SW	KOR_F51	NW	SUN_F51	NW
EUE_F51	SW	KOR_F57	NE	SUN_F57	NE
EUE_F57	SW	KWT_F51	NW	SYC_F51	SW
EUF_F51	SW	LKA_ IO	NE	SYC_F57	SE
EUF_F57	SE	LKA_F51	NW	THA_F51	NW
EUG_F51	SW	LKA_F57	NW	THA_F57	NE
EUG_F57	SE	MDG_F51	SW	TMP_F57	SE
EUI_F51	SW	MDG_F57	SW	TWN_F51	NW
EUM_F51	SW	MDV_F51	NW	TWN_F57	NE
EUM_F57	SE	MDV_F57	NE	TZA_ IO	SW
EUP_F51	SW	MMR_F57	NE	TZA_F51	SW
EUP_F57	SW	MOZ_F51	SW	TZA_F57	SE
EUR_F51	SW	MOZ_F57	SE	VUT_F57	SE
GBR_ IO	NW	MUS_F51	SW	YEM_F51	NW
GBR_F51	NW	MUS_F57	SE	ZAF_ IO	SW
GIN_F51	SW	MYS_ IO	NE	ZAF_F51	SW

Table 24. Key output from catch-only assessment Method 1 where prior *r* is based on empirical relationship with natural mortality and prior *S* is based on BRT model of catch history.

Method	Species	Param	q0.05	q0.25	q0.5	q0.75	q0.95
1	BLT	K	24,642	36,121	**55,176**	91,607	300,455
1	BLT	r	0.37	0.67	**0.97**	1.33	1.82
1	BLT	MSY	7,797	9,643	**12,030**	18,398	58,453
1	BLT	S_{last}	0.31	0.56	**0.70**	0.83	0.95
1	BLT	B_{msy}	12,321	18,060	**27,588**	45,803	150,228
1	BLT	F_{msy}	0.19	0.33	**0.49**	0.67	0.91
1	BLT	B_{last}	8,987	20,928	**36,948**	70,515	284,221
1	BLT	F_{last}	0.04	0.16	**0.30**	0.53	1.23
1	BLT	B_{last}/B_{msy}	0.61	1.12	**1.40**	1.65	1.90
1	BLT	F_{last}/F_{msy}	0.10	0.37	**0.66**	1.07	2.23
1	COM	K	552,258	686,224	**798,885**	927,847	1,261,671
1	COM	r	0.45	0.58	**0.68**	0.81	1.04
1	COM	MSY	117,956	126,303	**134,705**	146,476	176,375
1	COM	S_{last}	0.11	0.30	**0.41**	0.53	0.68
1	COM	B_{msy}	276,129	343,112	**399,442**	463,923	630,836
1	COM	F_{msy}	0.22	0.29	**0.34**	0.40	0.52
1	COM	B_{last}	75,957	202,721	**319,759**	460,666	777,423
1	COM	F_{last}	0.20	0.35	**0.50**	0.79	2.10
1	COM	B_{last}/B_{msy}	0.23	0.59	**0.83**	1.06	1.36
1	COM	F_{last}/F_{msy}	0.67	1.02	**1.44**	2.15	5.91
1	FRI	K	194,831	213,236	**234,429**	265,896	330,860
1	FRI	r	1.00	1.30	**1.50**	1.70	1.92
1	FRI	MSY	82,489	85,790	**88,276**	90,823	93,734
1	FRI	S_{last}	0.04	0.16	**0.26**	0.37	0.51
1	FRI	B_{msy}	97,415	106,618	**117,214**	132,948	165,430
1	FRI	F_{msy}	0.50	0.65	**0.75**	0.85	0.96
1	FRI	B_{last}	8,998	38,278	**60,867**	85,424	137,908
1	FRI	F_{last}	0.54	0.87	**1.23**	1.95	8.30
1	FRI	B_{last}/B_{msy}	0.08	0.32	**0.51**	0.73	1.02
1	FRI	F_{last}/F_{msy}	0.81	1.16	**1.66**	2.67	11.28

Table 4-1 continues

Method	Species	*Param*	q0.05	q0.25	**q0.5**	q0.75	q0.95
1	GUT	K	102,277	131,554	**167,364**	250,497	734,185
1	GUT	r	0.96	1.21	**1.43**	1.65	1.90
1	GUT	MSY	43,602	46,706	**56,108**	86,811	235,922
1	GUT	S_{last}	0.37	0.59	**0.72**	0.85	0.95
1	GUT	B_{msy}	51,138	65,777	**83,682**	125,249	367,093
1	GUT	F_{msy}	0.48	0.61	**0.71**	0.83	0.95
1	GUT	B_{last}	42,529	75,808	**115,836**	208,010	694,249
1	GUT	F_{last}	0.07	0.24	**0.43**	0.66	1.17
1	GUT	$B_{\mathrm{last}}/B_{msy}$	0.74	1.17	**1.44**	1.70	1.90
1	GUT	$F_{\mathrm{last}}/F_{msy}$	0.11	0.34	**0.62**	0.91	1.55
1	KAW	K	336,926	398,848	**457,552**	532,571	659,783
1	KAW	r	0.86	1.09	**1.28**	1.49	1.82
1	KAW	MSY	134,448	141,476	**146,330**	151,030	164,664
1	KAW	S_{last}	0.08	0.25	**0.38**	0.48	0.63
1	KAW	B_{msy}	168,463	199,424	**228,776**	266,285	329,891
1	KAW	F_{msy}	0.43	0.55	**0.64**	0.74	0.91
1	KAW	B_{last}	34,785	111,029	**163,266**	229,857	352,059
1	KAW	F_{last}	0.45	0.70	**0.98**	1.44	4.59
1	KAW	$B_{\mathrm{last}}/B_{msy}$	0.16	0.50	**0.75**	0.96	1.26
1	KAW	$F_{\mathrm{last}}/F_{msy}$	0.77	1.13	**1.48**	2.26	6.85
1	LOT	K	370,432	544,892	**707,030**	931,939	1,331,952
1	LOT	r	0.30	0.50	**0.69**	0.98	1.55
1	LOT	MSY	95,079	113,105	**123,974**	134,850	148,340
1	LOT	S_{last}	0.06	0.20	**0.32**	0.42	0.56
1	LOT	B_{msy}	185,216	272,446	**353,515**	465,970	665,976
1	LOT	F_{msy}	0.15	0.25	**0.35**	0.49	0.77
1	LOT	B_{last}	43,542	120,266	**201,712**	317,223	576,670
1	LOT	F_{last}	0.23	0.43	**0.67**	1.12	3.10
1	LOT	$B_{\mathrm{last}}/B_{msy}$	0.12	0.40	**0.64**	0.84	1.12
1	LOT	$F_{\mathrm{last}}/F_{msy}$	0.86	1.27	**1.75**	2.95	9.32

Table 25. Key output from catch-only assessment Method 2 where prior *r* is based on resilience parameter and prior *S* is based on C_{last}/C_{max}.

Method	Species	*Param*	q0.05	q0.25	**q0.5**	q0.75	q0.95
2	BLT	K	55,805	81,940	**111,715**	153,415	247,175
2	BLT	r	0.21	0.28	**0.40**	0.56	0.74
2	BLT	*MSY*	7,102	8,595	**10,449**	13,926	22,781
2	BLT	S_{last}	0.52	0.60	**0.69**	0.79	0.88
2	BLT	B_{msy}	27,902	40,970	**55,858**	76,708	123,588
2	BLT	F_{msy}	0.11	0.14	**0.20**	0.28	0.37
2	BLT	B_{last}	30,800	50,364	**74,136**	120,189	211,339
2	BLT	F_{last}	0.05	0.09	**0.15**	0.22	0.36
2	BLT	B_{last}/B_{msy}	1.04	1.20	**1.38**	1.58	1.76
2	BLT	F_{last}/F_{msy}	0.28	0.51	**0.77**	1.10	1.45
2	COM	K	925,848	1,390,775	**1,933,726**	2,687,893	4,664,566
2	COM	r	0.21	0.27	**0.38**	0.56	0.74
2	COM	*MSY*	127,633	147,722	**174,814**	244,667	369,093
2	COM	S_{last}	0.52	0.61	**0.70**	0.80	0.88
2	COM	B_{msy}	462,924	695,387	**966,863**	1,343,946	2,332,283
2	COM	F_{msy}	0.11	0.14	**0.19**	0.28	0.37
2	COM	B_{last}	547,152	875,092	**1,309,389**	2,066,358	3,989,107
2	COM	F_{last}	0.04	0.08	**0.12**	0.18	0.29
2	COM	B_{last}/B_{msy}	1.04	1.21	**1.40**	1.61	1.76
2	COM	F_{last}/F_{msy}	0.24	0.40	**0.65**	0.89	1.18
2	FRI	K	521,603	749,039	**1,050,242**	1,509,154	2,577,358
2	FRI	r	0.21	0.28	**0.40**	0.57	0.74
2	FRI	*MSY*	75,688	86,656	**99,418**	132,229	208,229
2	FRI	S_{last}	0.52	0.59	**0.69**	0.80	0.88
2	FRI	B_{msy}	260,801	374,519	**525,121**	754,577	1,288,679
2	FRI	F_{msy}	0.11	0.14	**0.20**	0.29	0.37
2	FRI	B_{last}	301,407	481,358	**711,367**	1,158,406	2,174,093
2	FRI	F_{last}	0.03	0.06	**0.10**	0.16	0.25
2	FRI	B_{last}/B_{msy}	1.03	1.18	**1.38**	1.59	1.77
2	FRI	F_{last}/F_{msy}	0.20	0.35	**0.55**	0.74	0.92

Table 4-2 continues

Method	Species	*Param*	q0.05	q0.25	**q0.5**	q0.75	q0.95
2	GUT	K	263,534	386,208	**562,219**	768,103	1,334,892
2	GUT	r	0.21	0.28	**0.40**	0.58	0.76
2	GUT	MSY	38,759	44,141	**51,660**	66,795	104,866
2	GUT	S_{last}	0.52	0.60	**0.70**	0.79	0.88
2	GUT	B_{msy}	131,767	193,104	**281,109**	384,051	667,446
2	GUT	F_{msy}	0.11	0.14	**0.20**	0.29	0.38
2	GUT	B_{last}	151,440	242,157	**372,049**	583,145	1,114,677
2	GUT	F_{last}	0.04	0.09	**0.13**	0.21	0.33
2	GUT	$B_{\mathrm{last}}/B_{msy}$	1.04	1.20	**1.40**	1.58	1.76
2	GUT	$F_{\mathrm{last}}/F_{msy}$	0.27	0.47	**0.69**	0.95	1.21
2	KAW	K	896,632	1,328,863	**1,813,303**	2,487,156	4,390,233
2	KAW	r	0.22	0.28	**0.40**	0.57	0.74
2	KAW	MSY	124,784	145,140	**173,809**	231,648	358,388
2	KAW	S_{last}	0.52	0.59	**0.70**	0.80	0.88
2	KAW	B_{msy}	448,316	664,431	**906,651**	1,243,578	2,195,117
2	KAW	F_{msy}	0.11	0.14	**0.20**	0.28	0.37
2	KAW	B_{last}	508,189	843,090	**1,207,490**	1,889,298	3,699,131
2	KAW	F_{last}	0.04	0.08	**0.13**	0.19	0.31
2	KAW	$B_{\mathrm{last}}/B_{msy}$	1.04	1.19	**1.40**	1.60	1.77
2	KAW	$F_{\mathrm{last}}/F_{msy}$	0.25	0.43	**0.66**	0.94	1.20
2	LOT	K	1,384,198	2,243,178	**3,525,621**	5,233,064	9,803,603
2	LOT	r	0.06	0.08	**0.16**	0.28	0.43
2	LOT	MSY	70,941	102,291	**133,293**	180,205	290,118
2	LOT	S_{last}	0.52	0.60	**0.70**	0.80	0.88
2	LOT	B_{msy}	692,099	1,121,589	**1,762,811**	2,616,532	4,901,802
2	LOT	F_{msy}	0.03	0.04	**0.08**	0.14	0.21
2	LOT	B_{last}	812,437	1,492,813	**2,327,214**	3,997,419	8,205,852
2	LOT	F_{last}	0.02	0.03	**0.06**	0.09	0.17
2	LOT	$B_{\mathrm{last}}/B_{msy}$	1.05	1.20	**1.39**	1.60	1.76
2	LOT	$F_{\mathrm{last}}/F_{msy}$	0.27	0.47	**0.76**	1.10	1.66

Table 26. Key output from catch-only assessment Method 3 where prior *r* and *S* are combined from Methods 1 and 2.

Method	Species	*Param*	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	BLT	K	28,688	52,364	**83,505**	127,503	279,066
3	BLT	r	0.23	0.39	**0.61**	0.99	1.73
3	BLT	MSY	7,146	9,148	**11,502**	16,426	34,650
3	BLT	S_{last}	0.44	0.58	**0.71**	0.81	0.92
3	BLT	B_{msy}	14,344	26,182	**41,752**	63,751	139,533
3	BLT	F_{msy}	0.11	0.20	**0.31**	0.49	0.86
3	BLT	B_{last}	14,462	32,150	**55,015**	96,132	245,903
3	BLT	F_{last}	0.05	0.12	**0.20**	0.35	0.77
3	BLT	B_{last}/B_{msy}	0.88	1.17	**1.41**	1.63	1.84
3	BLT	F_{last}/F_{msy}	0.17	0.42	**0.69**	1.07	1.71
3	COM	K	640,338	837,121	**1,118,942**	1,695,954	3,067,276
3	COM	r	0.23	0.40	**0.58**	0.72	0.93
3	COM	MSY	109,838	128,664	**148,619**	189,531	344,121
3	COM	S_{last}	0.15	0.39	**0.58**	0.72	0.87
3	COM	B_{msy}	320,169	418,560	**559,471**	847,977	1,533,638
3	COM	F_{msy}	0.11	0.20	**0.29**	0.36	0.47
3	COM	B_{last}	123,430	337,316	**614,346**	1,134,486	2,412,601
3	COM	F_{last}	0.07	0.14	**0.26**	0.47	1.29
3	COM	B_{last}/B_{msy}	0.30	0.78	**1.15**	1.43	1.73
3	COM	F_{last}/F_{msy}	0.27	0.59	**0.94**	1.60	4.63
3	FRI	K	203,863	259,274	**453,365**	818,649	1,522,669
3	FRI	r	0.23	0.39	**0.79**	1.48	1.87
3	FRI	MSY	59,797	77,823	**89,576**	99,950	166,984
3	FRI	S_{last}	0.07	0.26	**0.51**	0.69	0.85
3	FRI	B_{msy}	101,932	129,637	**226,683**	409,325	761,334
3	FRI	F_{msy}	0.11	0.20	**0.40**	0.74	0.94
3	FRI	B_{last}	22,385	94,880	**183,736**	377,213	1,175,171
3	FRI	F_{last}	0.06	0.20	**0.41**	0.79	3.34
3	FRI	B_{last}/B_{msy}	0.15	0.52	**1.03**	1.38	1.71
3	FRI	F_{last}/F_{msy}	0.26	0.54	**0.87**	1.85	6.67

Table 4-3 continues

Method	Species	*Param*	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	GUT	K	111,380	163,261	**328,950**	611,612	1,309,213
3	GUT	r	0.23	0.39	**0.76**	1.45	1.86
3	GUT	MSY	39,491	45,727	**53,542**	73,130	160,293
3	GUT	S_{last}	0.46	0.59	**0.71**	0.81	0.92
3	GUT	B_{msy}	55,690	81,630	**164,475**	305,806	654,606
3	GUT	F_{msy}	0.11	0.20	**0.38**	0.72	0.93
3	GUT	B_{last}	60,514	111,478	**216,942**	429,637	1,156,636
3	GUT	F_{last}	0.04	0.12	**0.23**	0.45	0.82
3	GUT	$B_{\mathrm{last}}/B_{msy}$	0.91	1.18	**1.42**	1.63	1.85
3	GUT	$F_{\mathrm{last}}/F_{msy}$	0.17	0.42	**0.66**	0.95	1.30
3	KAW	K	364,417	503,817	**818,296**	1,382,200	2,983,155
3	KAW	r	0.24	0.41	**0.78**	1.28	1.74
3	KAW	MSY	106,704	134,757	**151,239**	177,905	305,668
3	KAW	S_{last}	0.13	0.35	**0.55**	0.70	0.86
3	KAW	B_{msy}	182,209	251,909	**409,148**	691,100	1,491,578
3	KAW	F_{msy}	0.12	0.21	**0.39**	0.64	0.87
3	KAW	B_{last}	75,465	211,734	**392,795**	812,876	2,387,065
3	KAW	F_{last}	0.07	0.20	**0.41**	0.75	2.12
3	KAW	$B_{\mathrm{last}}/B_{msy}$	0.27	0.71	**1.11**	1.40	1.71
3	KAW	$F_{\mathrm{last}}/F_{msy}$	0.31	0.65	**0.99**	1.73	4.83
3	LOT	K	436,314	773,309	**1,342,040**	2,500,095	6,279,964
3	LOT	r	0.07	0.17	**0.39**	0.74	1.41
3	LOT	MSY	58,282	98,488	**128,252**	156,895	264,060
3	LOT	S_{last}	0.10	0.32	**0.54**	0.71	0.86
3	LOT	B_{msy}	218,157	386,655	**671,020**	1,250,048	3,139,982
3	LOT	F_{msy}	0.03	0.08	**0.19**	0.37	0.71
3	LOT	B_{last}	76,669	276,287	**618,968**	1,436,759	4,950,361
3	LOT	F_{last}	0.03	0.09	**0.22**	0.49	1.76
3	LOT	$B_{\mathrm{last}}/B_{msy}$	0.20	0.64	**1.09**	1.42	1.72
3	LOT	$F_{\mathrm{last}}/F_{msy}$	0.30	0.61	**1.08**	2.23	9.08

Table 27. Effect of including cpue on catch-only method for kawakawa tuna. Weight: 0 = minimizing *S* only; 1 = equal weight between *S* and cpue; 2 = cpue has twice weight.

Method	Species	Weight	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	KAW	0	K	373,570	508,032	**825,950**	1,384,251	2,832,359
3	KAW	0	r	0.23	0.42	**0.78**	1.27	1.68
3	KAW	0	MSY	104,800	136,035	**149,976**	177,542	322,364
3	KAW	0	S_{last}	0.26	0.42	**0.55**	0.69	0.87
3	KAW	0	B_{msy}	186,785	254,016	**412,975**	692,126	1,416,180
3	KAW	0	F_{msy}	0.12	0.21	**0.39**	0.64	0.84
3	KAW	0	B_{last}	175,675	235,580	**405,444**	831,118	2,257,139
3	KAW	0	F_{last}	0.07	0.19	**0.39**	0.68	0.91
3	KAW	0	B_{last}/B_{msy}	0.53	0.85	**1.11**	1.39	1.73
3	KAW	0	F_{last}/F_{msy}	0.29	0.65	**0.99**	1.37	2.75
3	KAW	1	K	377,632	517,516	**863,126**	1,549,531	3,213,539
3	KAW	1	r	0.24	0.40	**0.80**	1.29	1.69
3	KAW	1	MSY	105,675	136,926	**153,173**	195,908	368,926
3	KAW	1	S_{last}	0.28	0.44	**0.59**	0.74	0.89
3	KAW	1	B_{msy}	188,816	258,758	**431,563**	774,766	1,606,769
3	KAW	1	F_{msy}	0.12	0.20	**0.40**	0.64	0.85
3	KAW	1	B_{last}	175,952	249,597	**460,334**	972,197	2,679,646
3	KAW	1	F_{last}	0.06	0.16	**0.35**	0.64	0.91
3	KAW	1	B_{last}/B_{msy}	0.55	0.88	**1.18**	1.48	1.77
3	KAW	1	F_{last}/F_{msy}	0.25	0.55	**0.91**	1.32	2.61
3	KAW	2	K	386,571	555,494	**932,211**	1,615,605	3,242,200
3	KAW	2	r	0.23	0.40	**0.78**	1.28	1.71
3	KAW	2	MSY	104,669	137,276	**155,337**	205,061	403,444
3	KAW	2	S_{last}	0.28	0.46	**0.61**	0.76	0.90
3	KAW	2	B_{msy}	193,286	277,747	**466,106**	807,803	1,621,100
3	KAW	2	F_{msy}	0.11	0.20	**0.39**	0.64	0.85
3	KAW	2	B_{last}	176,346	276,121	**514,072**	1,015,604	2,540,988
3	KAW	2	F_{last}	0.06	0.16	**0.31**	0.58	0.91
3	KAW	2	B_{last}/B_{msy}	0.55	0.91	**1.22**	1.51	1.79
3	KAW	2	F_{last}/F_{msy}	0.22	0.52	**0.85**	1.26	2.63

Table 28. Effect of including cpue on catch-only method for Longtail tuna. Weight: 0 = minimizing *S* only; 1 = equal weight between *S* and cpue; 2 = cpue has twice weight; 99 = minimizing cpue only.

Method	Species	Weight	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	LOT	0	K	443,091	783,772	**1,413,188**	2,505,042	5,454,827
3	LOT	0	r	0.06	0.16	**0.39**	0.74	1.38
3	LOT	0	MSY	52,485	96,928	**128,680**	159,326	267,808
3	LOT	0	S_{last}	0.19	0.35	**0.55**	0.71	0.86
3	LOT	0	B_{msy}	221,546	391,886	**706,594**	1,252,521	2,727,413
3	LOT	0	F_{msy}	0.03	0.08	**0.20**	0.37	0.69
3	LOT	0	B_{last}	169,316	284,446	**627,805**	1,438,432	4,280,832
3	LOT	0	F_{last}	0.03	0.09	**0.22**	0.47	0.80
3	LOT	0	B_{last}/B_{msy}	0.37	0.69	**1.09**	1.43	1.72
3	LOT	0	F_{last}/F_{msy}	0.29	0.60	**1.06**	1.97	5.84
3	LOT	1	K	424,629	715,600	**1,241,571**	2,287,100	4,484,043
3	LOT	1	r	0.07	0.16	**0.39**	0.77	1.42
3	LOT	1	MSY	52,232	92,307	**122,767**	146,632	204,006
3	LOT	1	S_{last}	0.17	0.32	**0.50**	0.65	0.80
3	LOT	1	B_{msy}	212,315	357,800	**620,785**	1,143,550	2,242,021
3	LOT	1	F_{msy}	0.03	0.08	**0.19**	0.38	0.71
3	LOT	1	B_{last}	164,373	253,586	**495,950**	1,087,028	3,212,163
3	LOT	1	F_{last}	0.04	0.12	**0.27**	0.53	0.82
3	LOT	1	B_{last}/B_{msy}	0.33	0.63	**0.99**	1.29	1.60
3	LOT	1	F_{last}/F_{msy}	0.42	0.74	**1.25**	2.16	6.26
3	LOT	2	K	397,005	698,661	**1,235,102**	2,140,451	4,015,504
3	LOT	2	r	0.06	0.16	**0.38**	0.78	1.48
3	LOT	2	MSY	47,132	87,148	**120,163**	141,313	172,574
3	LOT	2	S_{last}	0.14	0.30	**0.46**	0.60	0.74
3	LOT	2	B_{msy}	198,502	349,331	**617,551**	1,070,226	2,007,752
3	LOT	2	F_{msy}	0.03	0.08	**0.19**	0.39	0.74
3	LOT	2	B_{last}	162,813	243,524	**448,721**	952,600	2,562,343
3	LOT	2	F_{last}	0.05	0.14	**0.30**	0.55	0.83
3	LOT	2	B_{last}/B_{msy}	0.29	0.60	**0.93**	1.21	1.48
3	LOT	2	F_{last}/F_{msy}	0.54	0.83	**1.35**	2.30	8.63

Table 28 continues.

Method	Species	Weight	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	LOT	99	K	391,373	665,176	**1,048,441**	1,748,143	2,420,696
3	LOT	99	r	0.06	0.14	**0.37**	0.72	1.44
3	LOT	99	MSY	37,210	63,313	**95,705**	119,899	140,426
3	LOT	99	S_{last}	0.11	0.14	**0.20**	0.27	0.36
3	LOT	99	B_{msy}	195,687	332,588	**524,221**	874,072	1,210,348
3	LOT	99	F_{msy}	0.03	0.07	**0.18**	0.36	0.72
3	LOT	99	B_{last}	148283.57	178713.94	**208928.50**	240016.07	255939.69
3	LOT	99	F_{last}	0.53	0.56	**0.65**	0.76	0.91
3	LOT	99	$B_{\mathrm{last}}/B_{msy}$	0.21	0.27	**0.40**	0.53	0.72
3	LOT	99	$F_{\mathrm{last}}/F_{msy}$	1.34	2.12	**3.54**	7.77	17.16

Table 29. Estimated key parameters for BLT in four assumed sub-stock regions.

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	BLT_NE	K	10,713	17,898	**25,603**	37,608	72,998
3	BLT_NE	r	0.23	0.39	**0.60**	0.97	1.65
3	BLT_NE	MSY	2,325	3,214	**3,969**	4,827	8,529
3	BLT_NE	S_{last}	0.24	0.37	**0.55**	0.71	0.86
3	BLT_NE	B_{msy}	5,356	8,949	**12,801**	18,804	36,499
3	BLT_NE	F_{msy}	0.11	0.19	**0.30**	0.48	0.82
3	BLT_NE	B_{last}	4,458	6,567	**12,573**	23,775	59,010
3	BLT_NE	F_{last}	0.07	0.16	**0.31**	0.59	0.87
3	BLT_NE	B_{last}/B_{msy}	0.48	0.75	**1.10**	1.43	1.73
3	BLT_NE	F_{last}/F_{msy}	0.26	0.57	**0.95**	1.53	3.23
3	BLT_NW	K	11,172	15,635	**21,755**	31,462	59,700
3	BLT_NW	r	0.23	0.36	**0.58**	0.99	1.72
3	BLT_NW	MSY	1,888	2,466	**3,223**	4,496	7,887
3	BLT_NW	S_{last}	0.34	0.47	**0.55**	0.69	0.85
3	BLT_NW	B_{msy}	5,586	7,818	**10,877**	15,731	29,850
3	BLT_NW	F_{msy}	0.12	0.18	**0.29**	0.49	0.86
3	BLT_NW	B_{last}	6,182	7,780	**9,297**	20,083	50,345
3	BLT_NW	F_{last}	0.10	0.26	**0.56**	0.67	0.84
3	BLT_NW	B_{last}/B_{msy}	0.67	0.93	**1.10**	1.39	1.71
3	BLT_NW	F_{last}/F_{msy}	0.38	0.90	**1.40**	2.23	4.09
3	BLT_SE	K	5,289	8,092	**12,926**	18,430	26,575
3	BLT_SE	r	0.23	0.37	**0.59**	1.04	1.69
3	BLT_SE	MSY	1,409	1,737	**1,956**	2,134	2,314
3	BLT_SE	S_{last}	0.21	0.31	**0.42**	0.52	0.63
3	BLT_SE	B_{msy}	2,644	4,046	**6,463**	9,215	13,288
3	BLT_SE	F_{msy}	0.11	0.19	**0.29**	0.52	0.84
3	BLT_SE	B_{last}	2,130	2,944	**4,634**	7,672	14,330
3	BLT_SE	F_{last}	0.13	0.24	**0.39**	0.62	0.86
3	BLT_SE	B_{last}/B_{msy}	0.43	0.61	**0.84**	1.04	1.26
3	BLT_SE	F_{last}/F_{msy}	0.63	0.87	**1.16**	1.66	2.72
3	BLT_SW	K	517	1,003	**1,607**	2,616	6,582
3	BLT_SW	r	0.24	0.38	**0.61**	1.02	1.68
3	BLT_SW	MSY	151	189	**224**	311	724
3	BLT_SW	S_{last}	0.45	0.59	**0.71**	0.82	0.93
3	BLT_SW	B_{msy}	258	502	**803**	1,308	3,291
3	BLT_SW	F_{msy}	0.12	0.19	**0.30**	0.51	0.84
3	BLT_SW	B_{last}	291	617	**1,074**	2,003	6,029
3	BLT_SW	F_{last}	0.03	0.09	**0.18**	0.31	0.65
3	BLT_SW	B_{last}/B_{msy}	0.91	1.18	**1.42**	1.64	1.86
3	BLT_SW	F_{last}/F_{msy}	0.14	0.37	**0.59**	0.86	1.31

Table 30. Estimated key parameters for COM in four assumed sub-stock regions.

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	COM_NE	K	120,057	153,163	**205,624**	302,399	576,931
3	COM_NE	r	0.23	0.39	**0.58**	0.72	0.91
3	COM_NE	MSY	19,249	23,566	**25,867**	34,060	63,656
3	COM_NE	S_{last}	0.20	0.28	**0.39**	0.69	0.86
3	COM_NE	B_{msy}	60,028	76,582	**102,812**	151,200	288,466
3	COM_NE	F_{msy}	0.11	0.20	**0.29**	0.36	0.46
3	COM_NE	B_{last}	39,216	43,545	**79,159**	186,519	460,855
3	COM_NE	F_{last}	0.07	0.17	**0.39**	0.71	0.79
3	COM_NE	$B_{\mathrm{last}}/B_{msy}$	0.39	0.56	**0.77**	1.38	1.73
3	COM_NE	$F_{\mathrm{last}}/F_{msy}$	0.28	0.65	**1.54**	2.34	3.95
3	COM_NW	K	293,594	393,978	**527,096**	805,787	1,413,904
3	COM_NW	r	0.23	0.41	**0.57**	0.73	0.99
3	COM_NW	MSY	50,757	59,787	**68,102**	89,364	162,899
3	COM_NW	S_{last}	0.23	0.33	**0.52**	0.69	0.86
3	COM_NW	B_{msy}	146,797	196,989	**263,548**	402,893	706,952
3	COM_NW	F_{msy}	0.11	0.20	**0.29**	0.36	0.50
3	COM_NW	B_{last}	109,208	124,295	**238,746**	497,554	1,157,723
3	COM_NW	F_{last}	0.07	0.17	**0.35**	0.68	0.78
3	COM_NW	$B_{\mathrm{last}}/B_{msy}$	0.45	0.66	**1.04**	1.38	1.71
3	COM_NW	$F_{\mathrm{last}}/F_{msy}$	0.30	0.68	**1.21**	2.14	3.63
3	COM_SE	K	178,033	228,634	**309,262**	477,998	1,264,922
3	COM_SE	r	0.24	0.39	**0.57**	0.73	0.94
3	COM_SE	MSY	27,904	34,230	**38,671**	55,502	141,371
3	COM_SE	S_{last}	0.24	0.38	**0.54**	0.77	0.93
3	COM_SE	B_{msy}	89,017	114,317	**154,631**	238,999	632,461
3	COM_SE	F_{msy}	0.12	0.19	**0.28**	0.36	0.47
3	COM_SE	B_{last}	50,373	91,488	**154,724**	325,526	1,161,763
3	COM_SE	F_{last}	0.03	0.10	**0.22**	0.37	0.67
3	COM_SE	$B_{\mathrm{last}}/B_{msy}$	0.48	0.76	**1.08**	1.55	1.86
3	COM_SE	$F_{\mathrm{last}}/F_{msy}$	0.13	0.40	**0.85**	1.34	2.29
3	COM_SW	K	34,175	44,077	**55,993**	81,210	140,385
3	COM_SW	r	0.24	0.42	**0.59**	0.74	0.94
3	COM_SW	MSY	5,496	6,725	**7,614**	9,452	17,307
3	COM_SW	S_{last}	0.30	0.41	**0.55**	0.69	0.86
3	COM_SW	B_{msy}	17,088	22,039	**27,996**	40,605	70,193
3	COM_SW	F_{msy}	0.12	0.21	**0.29**	0.37	0.47
3	COM_SW	B_{last}	13,389	17,711	**29,598**	52,278	114,111
3	COM_SW	F_{last}	0.09	0.19	**0.34**	0.57	0.75
3	COM_SW	$B_{\mathrm{last}}/B_{msy}$	0.59	0.82	**1.10**	1.38	1.71
3	COM_SW	$F_{\mathrm{last}}/F_{msy}$	0.34	0.77	**1.21**	1.79	2.99

Table 31. Estimated key parameters for FRI in four assumed sub-stock regions.

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	FRI_NE	K	31,892	39,432	**77,567**	145,447	266,464
3	FRI_NE	r	0.23	0.39	**0.76**	1.49	1.85
3	FRI_NE	MSY	11,266	12,926	**14,019**	14,564	32,087
3	FRI_NE	S_{last}	0.25	0.45	**0.60**	0.79	0.91
3	FRI_NE	B_{msy}	15,946	19,716	**38,783**	72,724	133,232
3	FRI_NE	F_{msy}	0.11	0.20	**0.38**	0.75	0.92
3	FRI_NE	B_{last}	20,359	25,637	**33,592**	70,667	216,429
3	FRI_NE	F_{last}	0.03	0.09	**0.18**	0.24	0.30
3	FRI_NE	B_{last}/B_{msy}	0.51	0.90	**1.20**	1.58	1.82
3	FRI_NE	F_{last}/F_{msy}	0.10	0.26	**0.37**	0.53	1.00
3	FRI_NW	K	42,499	56,015	**103,791**	183,458	330,969
3	FRI_NW	r	0.23	0.40	**0.80**	1.48	1.85
3	FRI_NW	MSY	13,909	17,197	**18,932**	22,176	40,546
3	FRI_NW	S_{last}	0.23	0.41	**0.54**	0.69	0.86
3	FRI_NW	B_{msy}	21,249	28,008	**51,895**	91,729	165,484
3	FRI_NW	F_{msy}	0.12	0.20	**0.40**	0.74	0.92
3	FRI_NW	B_{last}	20,355	26,858	**47,855**	97,905	259,551
3	FRI_NW	F_{last}	0.08	0.20	**0.41**	0.73	0.96
3	FRI_NW	B_{last}/B_{msy}	0.47	0.83	**1.09**	1.39	1.73
3	FRI_NW	F_{last}/F_{msy}	0.28	0.63	**0.97**	1.32	2.79
3	FRI_SE	K	129,931	163,050	**309,509**	564,709	1,646,096
3	FRI_SE	r	0.23	0.40	**0.87**	1.50	1.87
3	FRI_SE	MSY	39,468	51,485	**57,701**	68,354	200,594
3	FRI_SE	S_{last}	0.27	0.42	**0.56**	0.74	0.94
3	FRI_SE	B_{msy}	64,965	81,525	**154,754**	282,355	823,048
3	FRI_SE	F_{msy}	0.12	0.20	**0.44**	0.75	0.94
3	FRI_SE	B_{last}	56,085	80,228	**144,200**	326,416	1,515,506
3	FRI_SE	F_{last}	0.03	0.15	**0.33**	0.59	0.84
3	FRI_SE	B_{last}/B_{msy}	0.54	0.84	**1.11**	1.49	1.88
3	FRI_SE	F_{last}/F_{msy}	0.13	0.46	**0.76**	1.14	2.10
3	FRI_SW	K	4,428	4,736	**6,785**	10,240	15,692
3	FRI_SW	r	0.24	0.43	**0.87**	1.46	1.84
3	FRI_SW	MSY	880	1,088	**1,484**	1,787	2,082
3	FRI_SW	S_{last}	0.29	0.39	**0.45**	0.54	0.63
3	FRI_SW	B_{msy}	2,214	2,368	**3,393**	5,120	7,846
3	FRI_SW	F_{msy}	0.12	0.22	**0.44**	0.73	0.92
3	FRI_SW	B_{last}	1,921	2,332	**2,782**	4,218	8,013
3	FRI_SW	F_{last}	0.22	0.41	**0.63**	0.75	0.91
3	FRI_SW	B_{last}/B_{msy}	0.57	0.78	**0.91**	1.08	1.26
3	FRI_SW	F_{last}/F_{msy}	0.68	0.96	**1.32**	1.98	3.39

Table 32. Estimated key parameters for GUT in four assumed sub-stock regions.

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	GUT_NE	K	29,834	42,472	**83,915**	160,525	376,576
3	GUT_NE	r	0.23	0.42	**0.80**	1.46	1.82
3	GUT_NE	MSY	11,069	12,894	**14,461**	20,104	39,426
3	GUT_NE	S_{last}	0.44	0.59	**0.69**	0.81	0.92
3	GUT_NE	B_{msy}	14,917	21,236	**41,957**	80,263	188,288
3	GUT_NE	F_{msy}	0.11	0.21	**0.40**	0.73	0.91
3	GUT_NE	B_{last}	16,298	27,844	**54,938**	111,996	319,447
3	GUT_NE	F_{last}	0.04	0.11	**0.23**	0.45	0.76
3	GUT_NE	$B_{\mathrm{last}}/B_{msy}$	0.89	1.17	**1.39**	1.62	1.83
3	GUT_NE	$F_{\mathrm{last}}/F_{msy}$	0.17	0.38	**0.62**	0.85	1.22
3	GUT_NW	K	51,494	60,658	**111,962**	204,212	356,698
3	GUT_NW	r	0.22	0.38	**0.79**	1.49	1.82
3	GUT_NW	MSY	15,260	18,231	**21,150**	23,983	42,218
3	GUT_NW	S_{last}	0.26	0.51	**0.60**	0.69	0.86
3	GUT_NW	B_{msy}	25,747	30,329	**55,981**	102,106	178,349
3	GUT_NW	F_{msy}	0.11	0.19	**0.40**	0.74	0.91
3	GUT_NW	B_{last}	32,609	34,067	**49,051**	107,092	277,425
3	GUT_NW	F_{last}	0.10	0.25	**0.55**	0.79	0.82
3	GUT_NW	$B_{\mathrm{last}}/B_{msy}$	0.53	1.02	**1.20**	1.38	1.71
3	GUT_NW	$F_{\mathrm{last}}/F_{msy}$	0.37	0.82	**1.06**	1.45	3.25
3	GUT_SE	K	29,049	37,333	**67,298**	124,487	293,264
3	GUT_SE	r	0.23	0.39	**0.77**	1.45	1.80
3	GUT_SE	MSY	8,325	10,957	**12,453**	14,248	34,763
3	GUT_SE	S_{last}	0.27	0.40	**0.54**	0.71	0.91
3	GUT_SE	B_{msy}	14,524	18,667	**33,649**	62,243	146,632
3	GUT_SE	F_{msy}	0.11	0.20	**0.38**	0.72	0.90
3	GUT_SE	B_{last}	12,202	17,532	**31,836**	63,093	263,923
3	GUT_SE	F_{last}	0.04	0.17	**0.33**	0.59	0.85
3	GUT_SE	$B_{\mathrm{last}}/B_{msy}$	0.53	0.81	**1.07**	1.42	1.82
3	GUT_SE	$F_{\mathrm{last}}/F_{msy}$	0.16	0.52	**0.81**	1.20	2.12
3	GUT_SW	K	756	803	**1,318**	2,155	7,842
3	GUT_SW	r	0.24	0.38	**0.79**	1.46	1.84
3	GUT_SW	MSY	142	191	**267**	338	996
3	GUT_SW	S_{last}	0.26	0.50	**0.79**	0.84	0.95
3	GUT_SW	B_{msy}	378	401	**659**	1,077	3,921
3	GUT_SW	F_{msy}	0.12	0.19	**0.39**	0.73	0.92
3	GUT_SW	B_{last}	373	627	**637**	1,267	7,278
3	GUT_SW	F_{last}	0.03	0.16	**0.31**	0.32	0.53
3	GUT_SW	$B_{\mathrm{last}}/B_{msy}$	0.53	0.99	**1.58**	1.68	1.91
3	GUT_SW	$F_{\mathrm{last}}/F_{msy}$	0.10	0.35	**0.47**	1.08	2.27

Table 33. Estimated key parameters for KAW in four assumed sub-stock regions.

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	KAW_NE	*K*	69,985	98,952	**165,024**	306,950	605,554
3	KAW_NE	*r*	0.24	0.41	**0.79**	1.27	1.78
3	KAW_NE	*MSY*	23,652	28,103	**30,111**	35,317	59,155
3	KAW_NE	S_{last}	0.30	0.45	**0.58**	0.71	0.86
3	KAW_NE	B_{msy}	34,993	49,476	**82,512**	153,475	302,777
3	KAW_NE	F_{msy}	0.12	0.20	**0.39**	0.64	0.89
3	KAW_NE	B_{last}	33,328	50,638	**86,390**	172,596	477,500
3	KAW_NE	F_{last}	0.06	0.18	**0.35**	0.60	0.92
3	KAW_NE	B_{last}/B_{msy}	0.60	0.91	**1.15**	1.41	1.71
3	KAW_NE	F_{last}/F_{msy}	0.30	0.62	**0.89**	1.21	2.14
3	KAW_NW	*K*	203,846	270,199	**435,677**	702,878	1,425,880
3	KAW_NW	*r*	0.23	0.41	**0.79**	1.29	1.70
3	KAW_NW	*MSY*	48,102	66,258	**78,894**	96,600	175,811
3	KAW_NW	S_{last}	0.23	0.38	**0.53**	0.70	0.86
3	KAW_NW	B_{msy}	101,923	135,100	**217,839**	351,439	712,940
3	KAW_NW	F_{msy}	0.11	0.21	**0.40**	0.65	0.85
3	KAW_NW	B_{last}	107,152	124,354	**162,143**	370,633	1,110,055
3	KAW_NW	F_{last}	0.08	0.25	**0.58**	0.75	0.88
3	KAW_NW	B_{last}/B_{msy}	0.46	0.77	**1.06**	1.40	1.72
3	KAW_NW	F_{last}/F_{msy}	0.31	0.70	**1.14**	1.83	4.21
3	KAW_SE	*K*	99,548	133,297	**226,926**	391,463	833,576
3	KAW_SE	*r*	0.24	0.41	**0.75**	1.27	1.67
3	KAW_SE	*MSY*	27,722	34,731	**39,404**	44,525	98,889
3	KAW_SE	S_{last}	0.26	0.39	**0.52**	0.69	0.90
3	KAW_SE	B_{msy}	49,774	66,649	**113,463**	195,732	416,788
3	KAW_SE	F_{msy}	0.12	0.21	**0.38**	0.64	0.84
3	KAW_SE	B_{last}	38,541	61,984	**106,397**	209,019	691,869
3	KAW_SE	F_{last}	0.05	0.16	**0.31**	0.54	0.86
3	KAW_SE	B_{last}/B_{msy}	0.52	0.78	**1.05**	1.38	1.80
3	KAW_SE	F_{last}/F_{msy}	0.19	0.54	**0.84**	1.23	2.10
3	KAW_SW	*K*	5,869	7,803	**13,038**	23,538	44,949
3	KAW_SW	*r*	0.23	0.40	**0.77**	1.29	1.70
3	KAW_SW	*MSY*	1,827	2,151	**2,340**	2,799	4,454
3	KAW_SW	S_{last}	0.26	0.44	**0.59**	0.72	0.85
3	KAW_SW	B_{msy}	2,935	3,901	**6,519**	11,769	22,475
3	KAW_SW	F_{msy}	0.12	0.20	**0.39**	0.64	0.85
3	KAW_SW	B_{last}	2,455	3,915	**6,829**	13,499	35,071
3	KAW_SW	F_{last}	0.06	0.16	**0.32**	0.56	0.90
3	KAW_SW	B_{last}/B_{msy}	0.51	0.89	**1.18**	1.44	1.70
3	KAW_SW	F_{last}/F_{msy}	0.29	0.55	**0.81**	1.17	2.30

Table 34. Estimated key parameters for LOT in four assumed sub-stock regions.

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	LOT_NE	K	53,786	94,022	**170,574**	334,558	894,260
3	LOT_NE	r	0.06	0.16	**0.40**	0.76	1.39
3	LOT_NE	MSY	6,585	11,944	**15,693**	18,535	46,655
3	LOT_NE	S_{last}	0.08	0.23	**0.49**	0.75	0.93
3	LOT_NE	B_{msy}	26,893	47,011	**85,287**	167,279	447,130
3	LOT_NE	F_{msy}	0.03	0.08	**0.20**	0.38	0.69
3	LOT_NE	B_{last}	10,016	30,112	**58,393**	155,062	764,960
3	LOT_NE	F_{last}	0.01	0.04	**0.11**	0.21	0.63
3	LOT_NE	B_{last}/B_{msy}	0.15	0.46	**0.97**	1.50	1.86
3	LOT_NE	F_{last}/F_{msy}	0.07	0.23	**0.49**	1.25	3.85
3	LOT_NW	K	315,096	572,722	**1,011,592**	1,836,756	3,645,319
3	LOT_NW	r	0.06	0.15	**0.38**	0.73	1.39
3	LOT_NW	MSY	38,122	66,353	**92,105**	113,302	193,049
3	LOT_NW	S_{last}	0.21	0.35	**0.54**	0.70	0.86
3	LOT_NW	B_{msy}	157,548	286,361	**505,796**	918,378	1,822,660
3	LOT_NW	F_{msy}	0.03	0.08	**0.19**	0.36	0.70
3	LOT_NW	B_{last}	130,453	201,428	**478,956**	1,037,326	2,905,839
3	LOT_NW	F_{last}	0.04	0.10	**0.23**	0.54	0.83
3	LOT_NW	B_{last}/B_{msy}	0.43	0.70	**1.08**	1.40	1.72
3	LOT_NW	F_{last}/F_{msy}	0.33	0.70	**1.20**	2.18	6.07
3	LOT_SE	K	66,025	112,669	**177,276**	337,658	524,252
3	LOT_SE	r	0.06	0.15	**0.41**	0.74	1.38
3	LOT_SE	MSY	8,034	13,454	**18,312**	21,378	23,616
3	LOT_SE	S_{last}	0.17	0.26	**0.36**	0.45	0.57
3	LOT_SE	B_{msy}	33,012	56,335	**88,638**	168,829	262,126
3	LOT_SE	F_{msy}	0.03	0.08	**0.20**	0.37	0.69
3	LOT_SE	B_{last}	23,078	33,391	**58,106**	112,357	243,643
3	LOT_SE	F_{last}	0.08	0.17	**0.34**	0.59	0.85
3	LOT_SE	B_{last}/B_{msy}	0.34	0.53	**0.71**	0.91	1.14
3	LOT_SE	F_{last}/F_{msy}	0.76	1.14	**1.66**	2.54	5.35
3	LOT_SW	K	2,360	4,597	**8,892**	19,532	54,293
3	LOT_SW	r	0.06	0.18	**0.42**	0.80	1.50
3	LOT_SW	MSY	495	683	**762**	1,023	2,626
3	LOT_SW	S_{last}	0.25	0.40	**0.54**	0.74	0.91
3	LOT_SW	B_{msy}	1,180	2,299	**4,446**	9,766	27,146
3	LOT_SW	F_{msy}	0.03	0.09	**0.21**	0.40	0.75
3	LOT_SW	B_{last}	1,120	2,073	**4,311**	10,310	45,028
3	LOT_SW	F_{last}	0.02	0.08	**0.20**	0.41	0.77
3	LOT_SW	B_{last}/B_{msy}	0.51	0.80	**1.08**	1.48	1.83
3	LOT_SW	F_{last}/F_{msy}	0.18	0.56	**1.10**	1.63	2.92

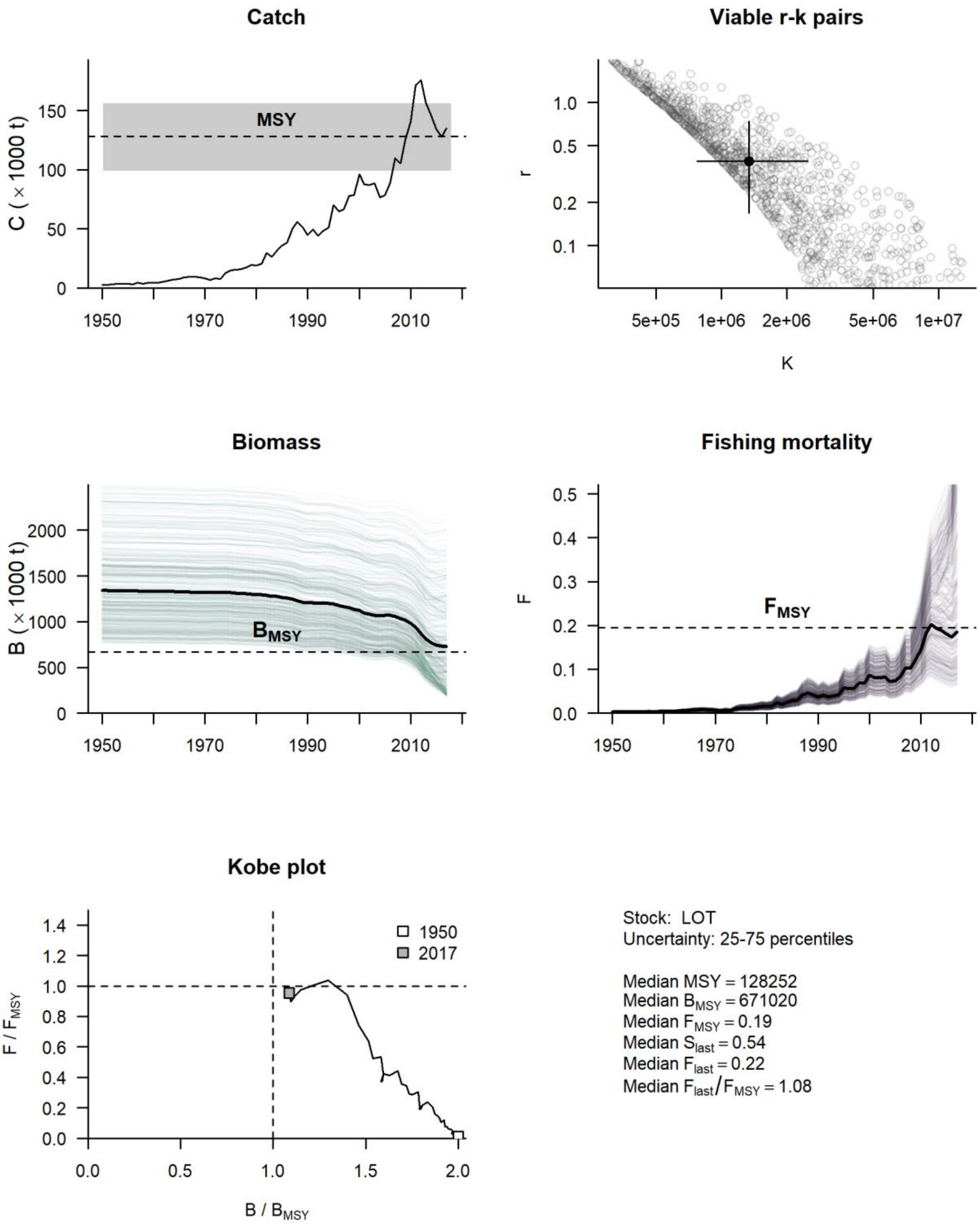

Figure 1. Result from the integrated catch-only method for LOT.

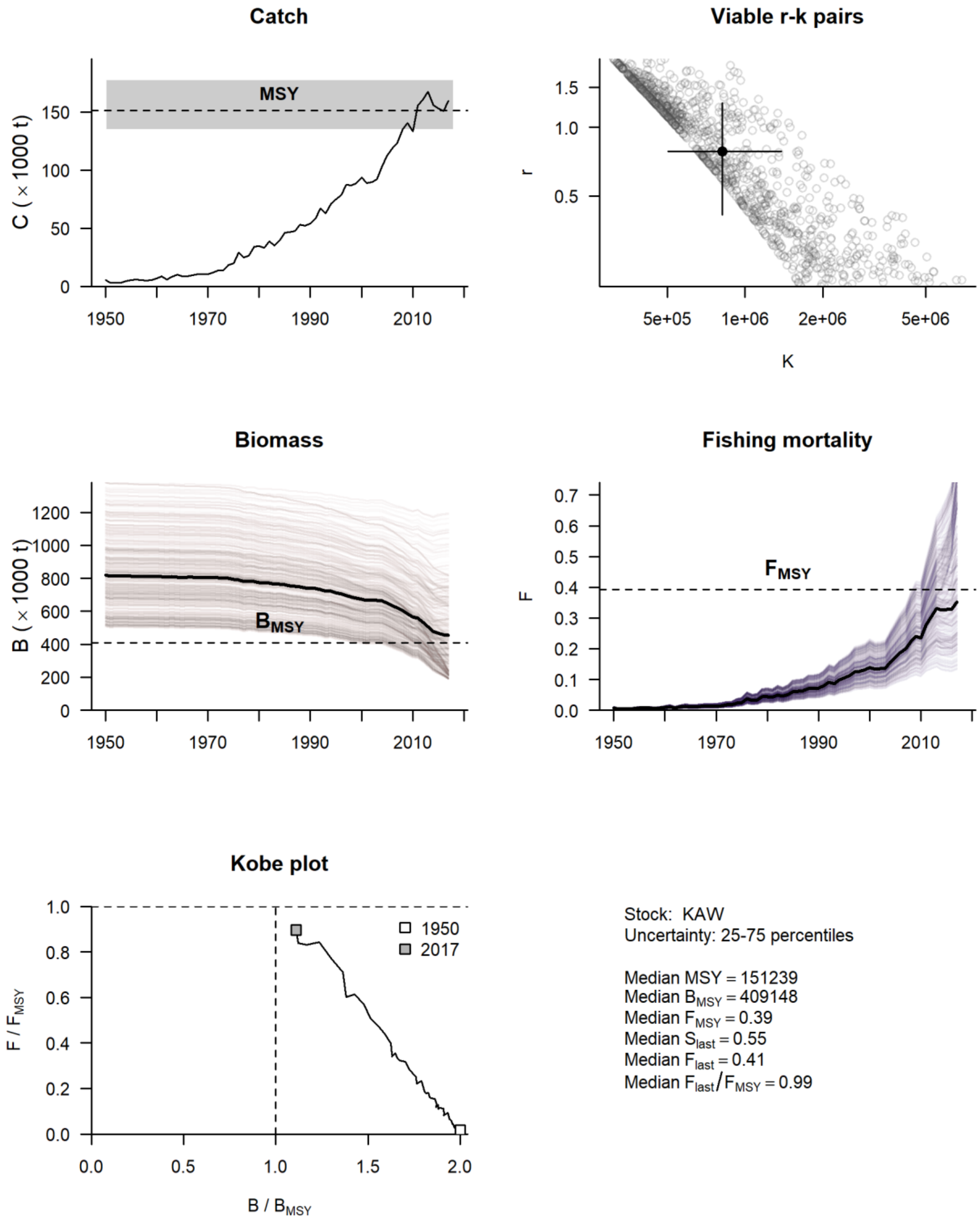

Figure 2. Result from the integrated catch-only method for KAW.

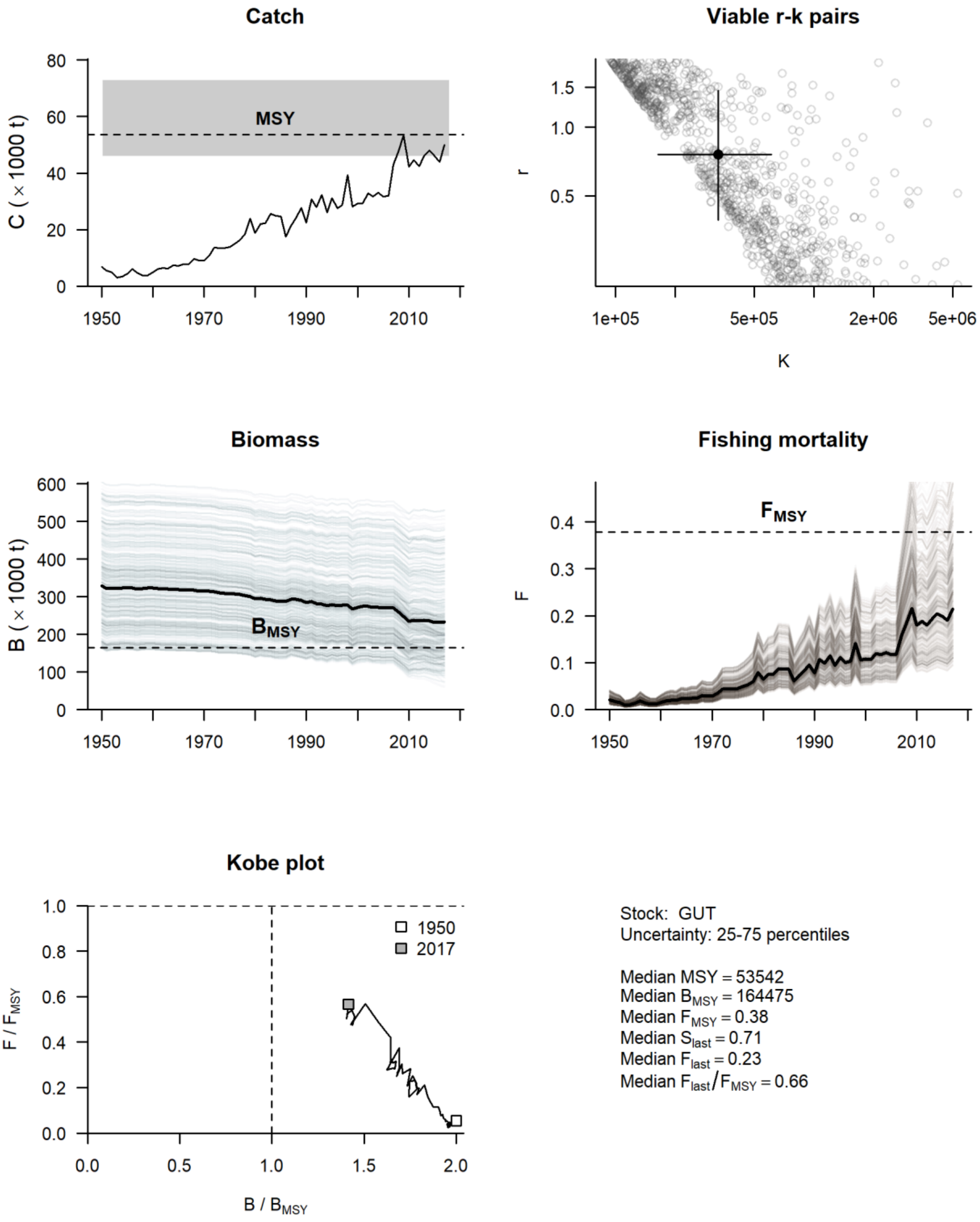

Figure 3. Result from the integrated catch-only method for GUT.

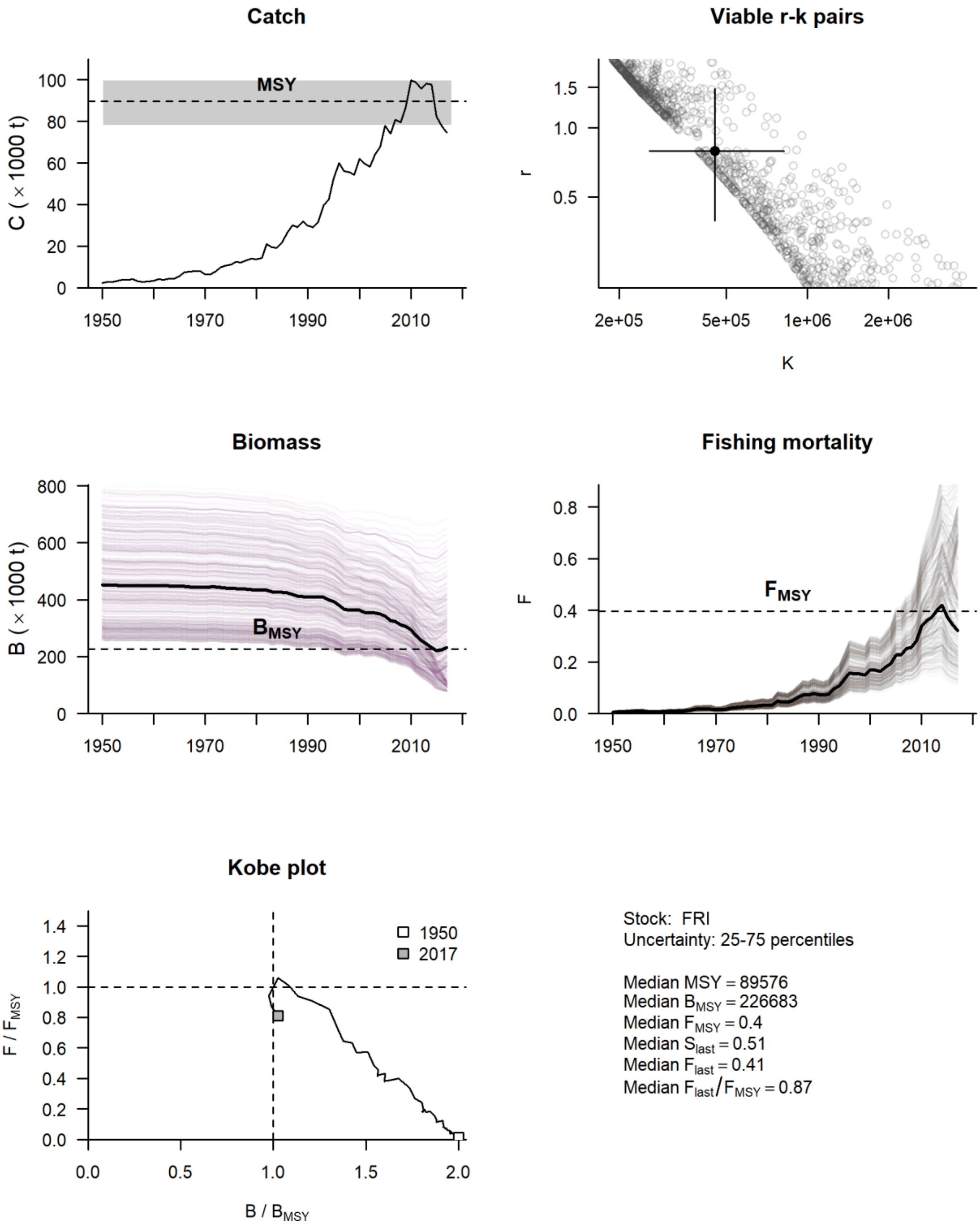

Figure 4. Result from the integrated catch-only method for FRI.

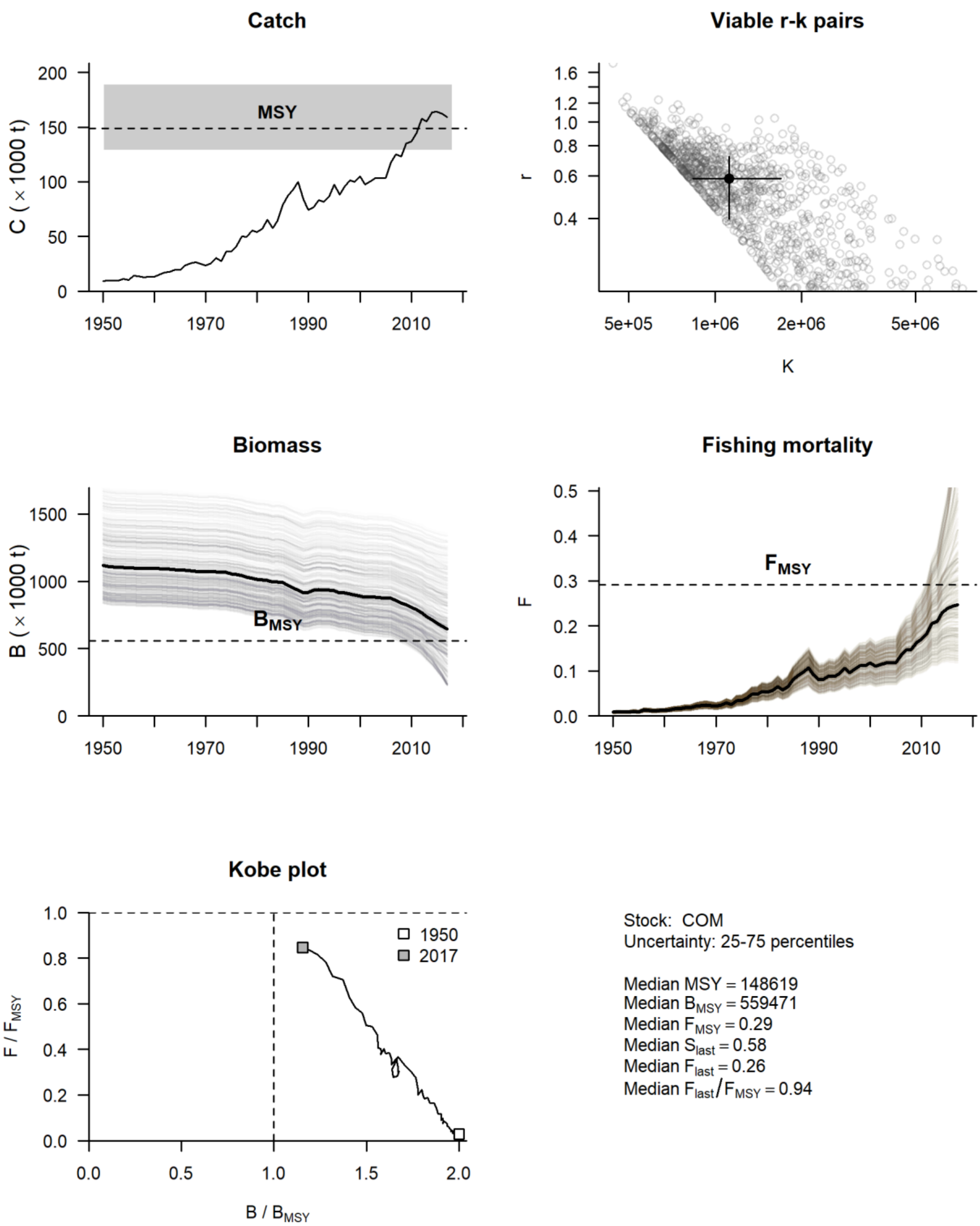

Figure 5. Result from the integrated catch-only method for COM.

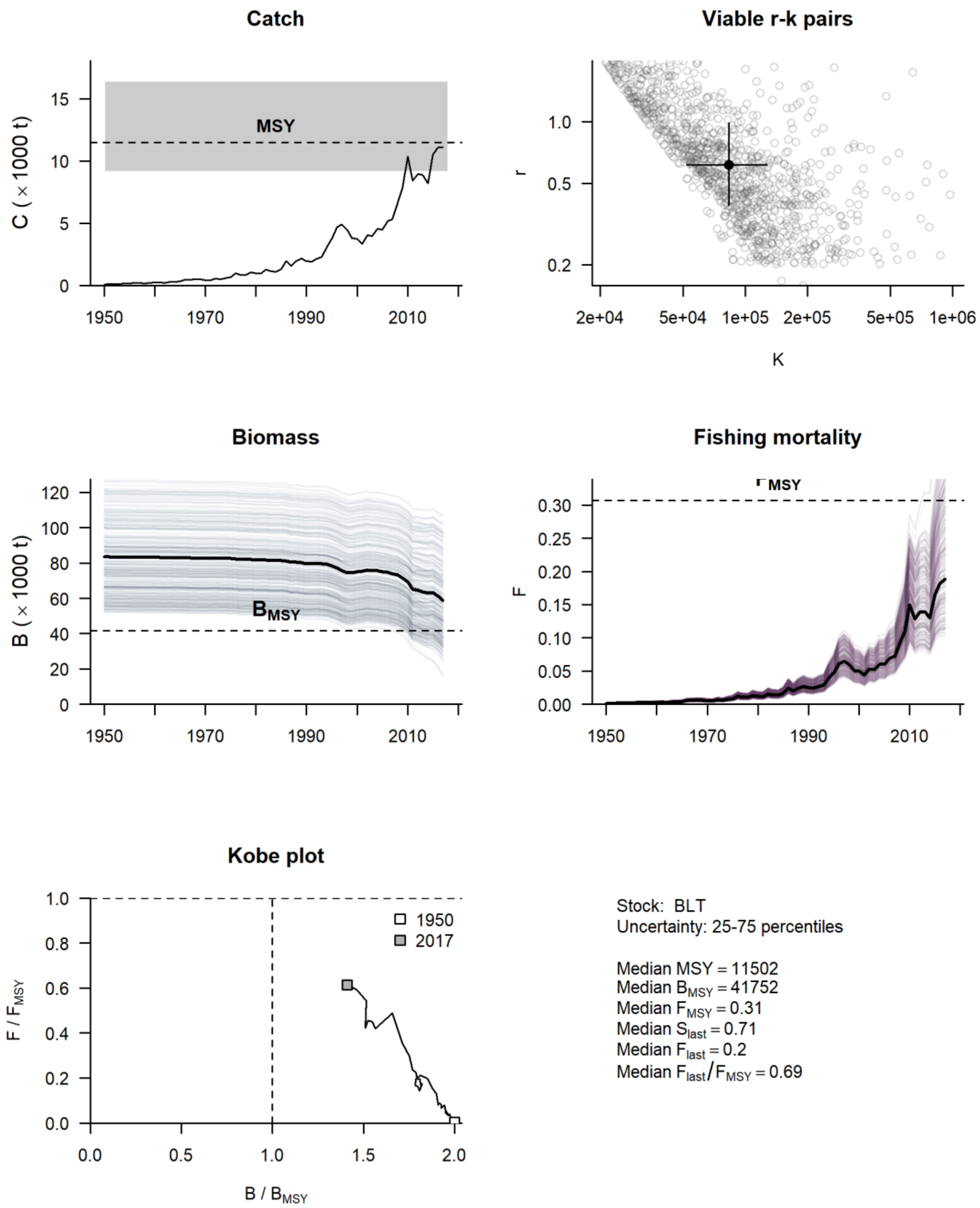

Figure 6. Result from the integrated catch-only method for BLT.

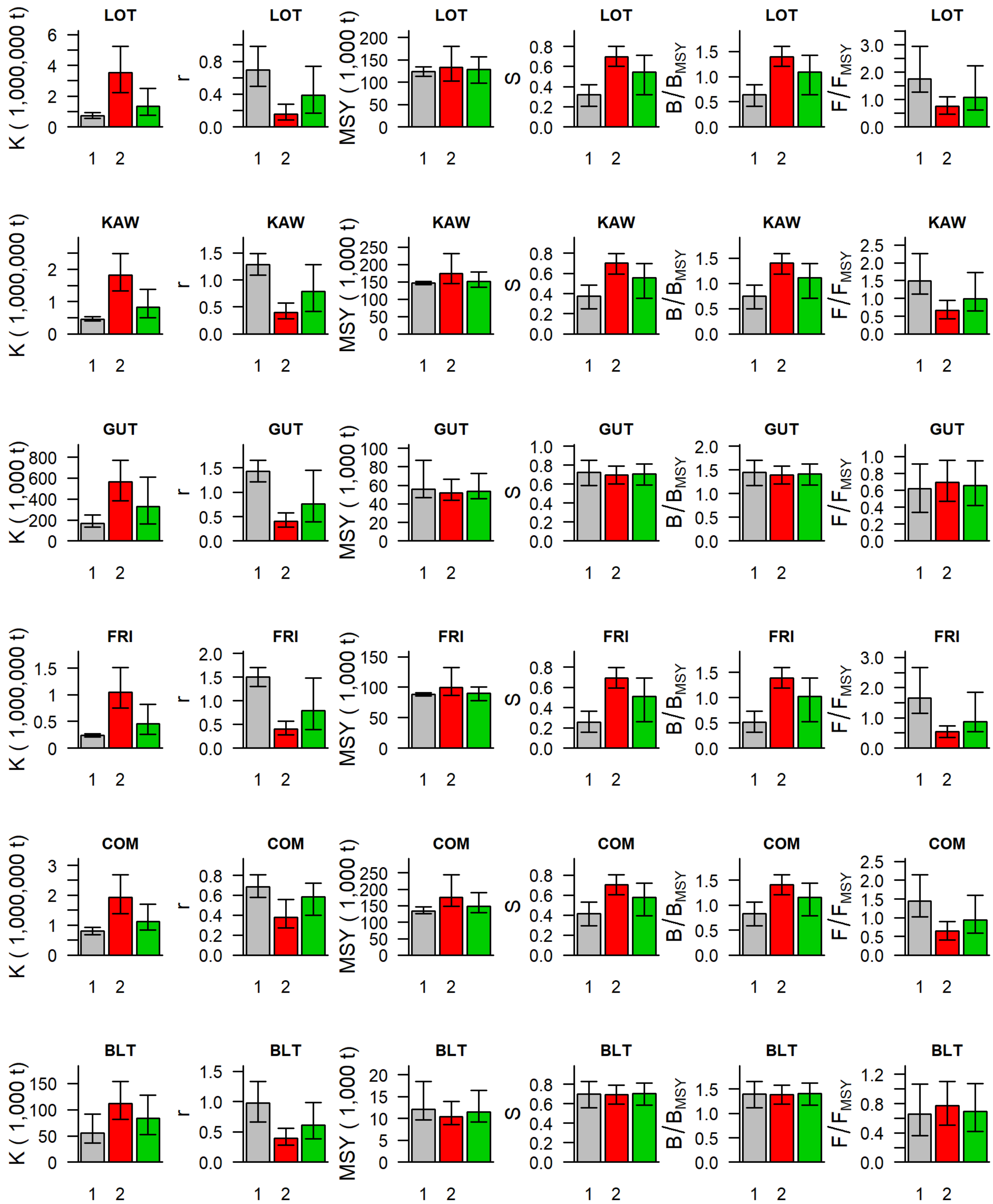

Figure 7. Comparison of two catch-based methods for six neritic tunas. Prior r and S in Method 1 is based on OCOM and in Method 2 is based on CMSY rules. The green bars are integrated from Methods 1 and 2. Error bars are 25 to 75 percentiles.

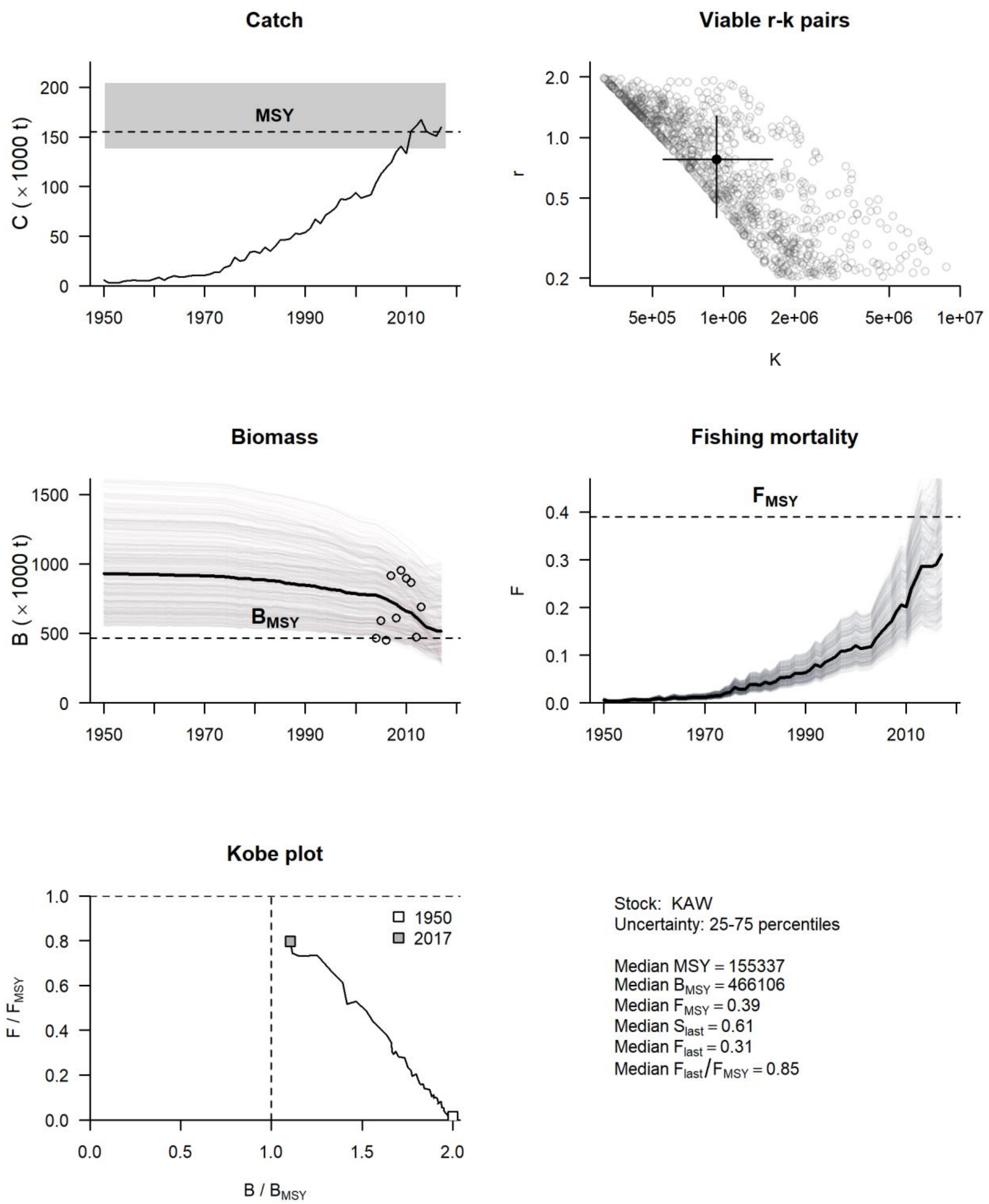

Figure 8. Objective function minimizes both S and cpue with weight of cpue twice of S using Method 3 for Kawakawa tuna.

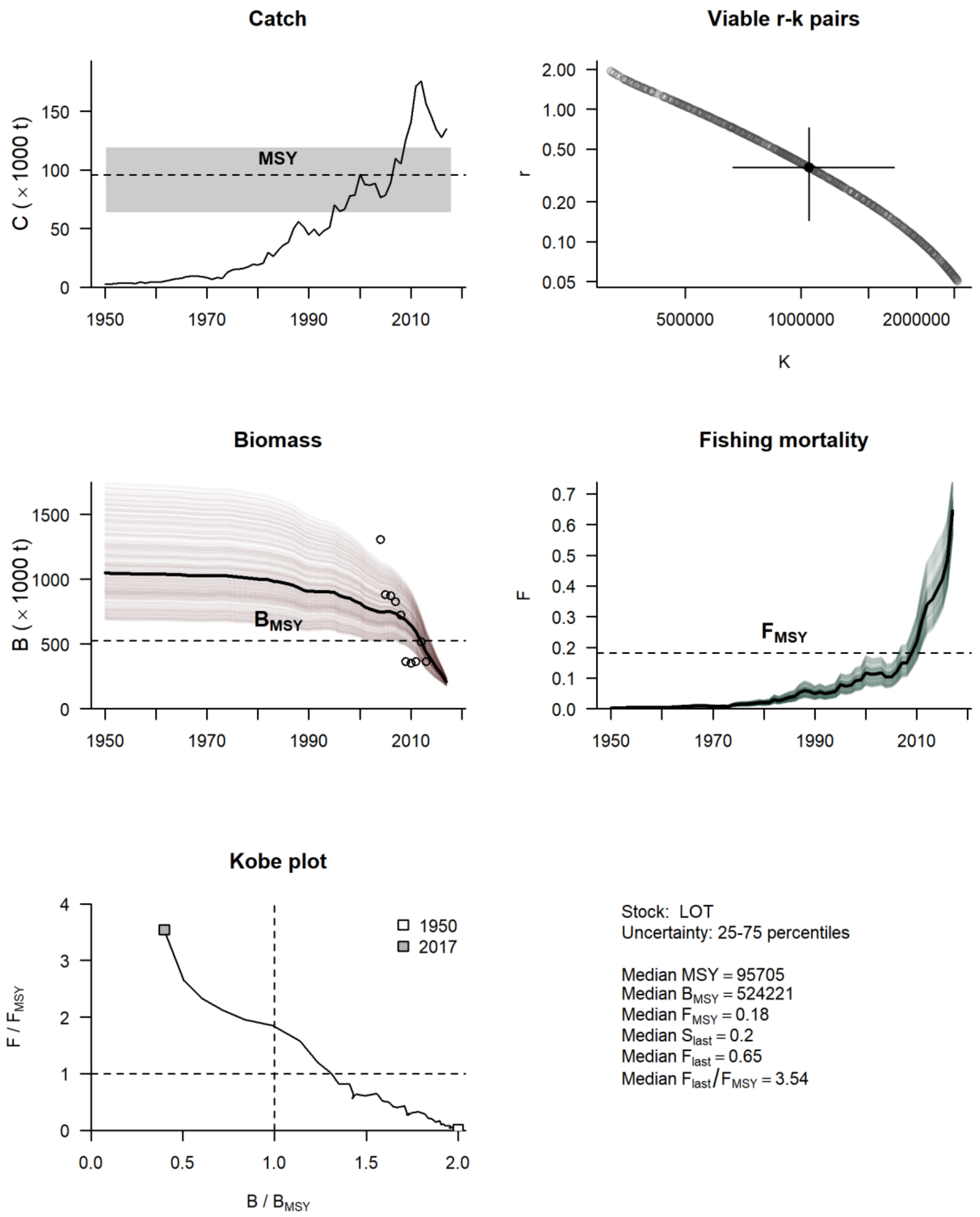

Figure 9. Objective function minimizes cpue only using Method 3 for Longtail tuna.

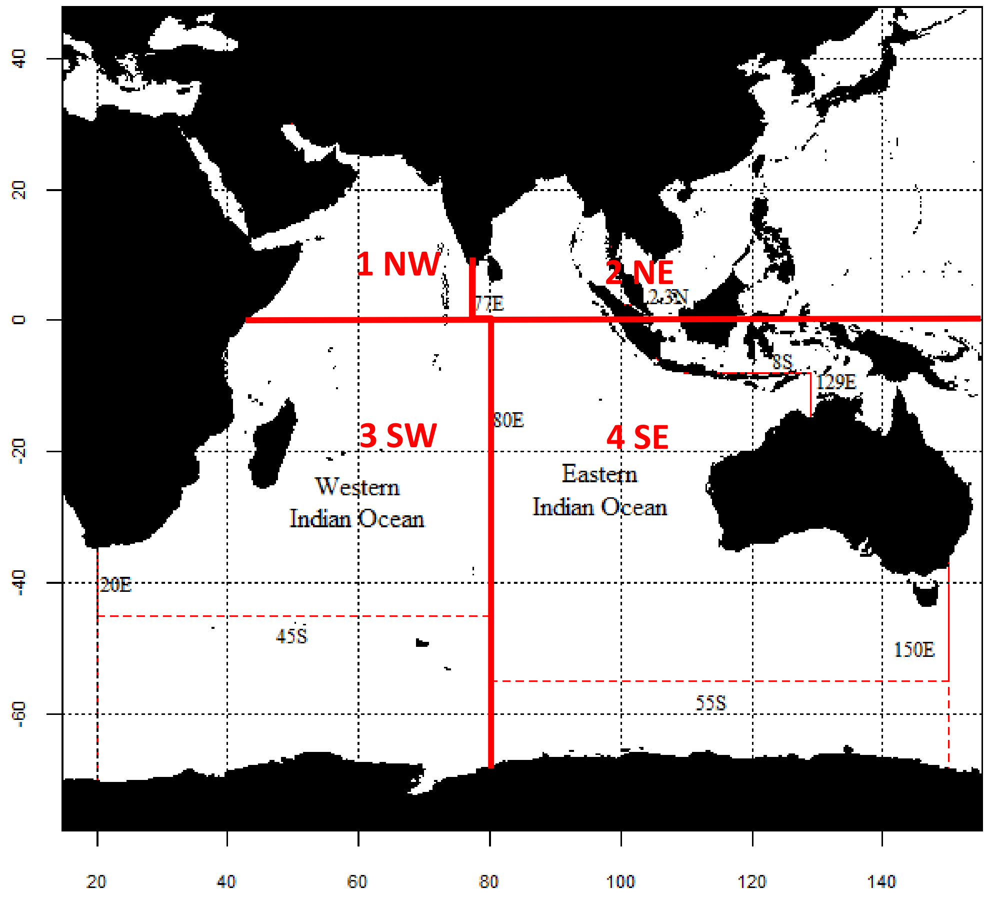

Figure 10. Hypothetical sub-stock regions in the Indian Ocean for the six neritic tuna species.

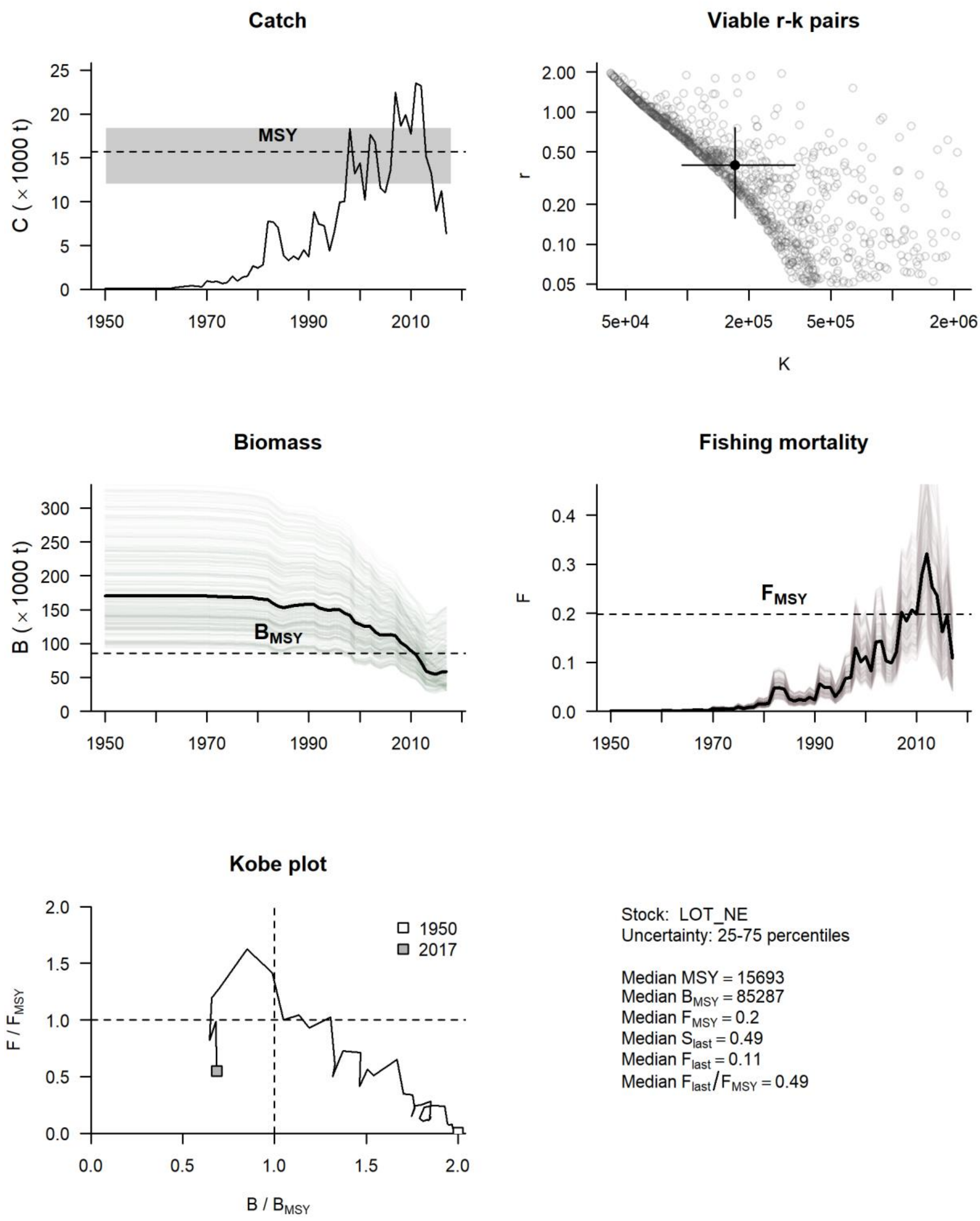

Figure 11. Result from the integrated catch-only method for LOT in the NE region.

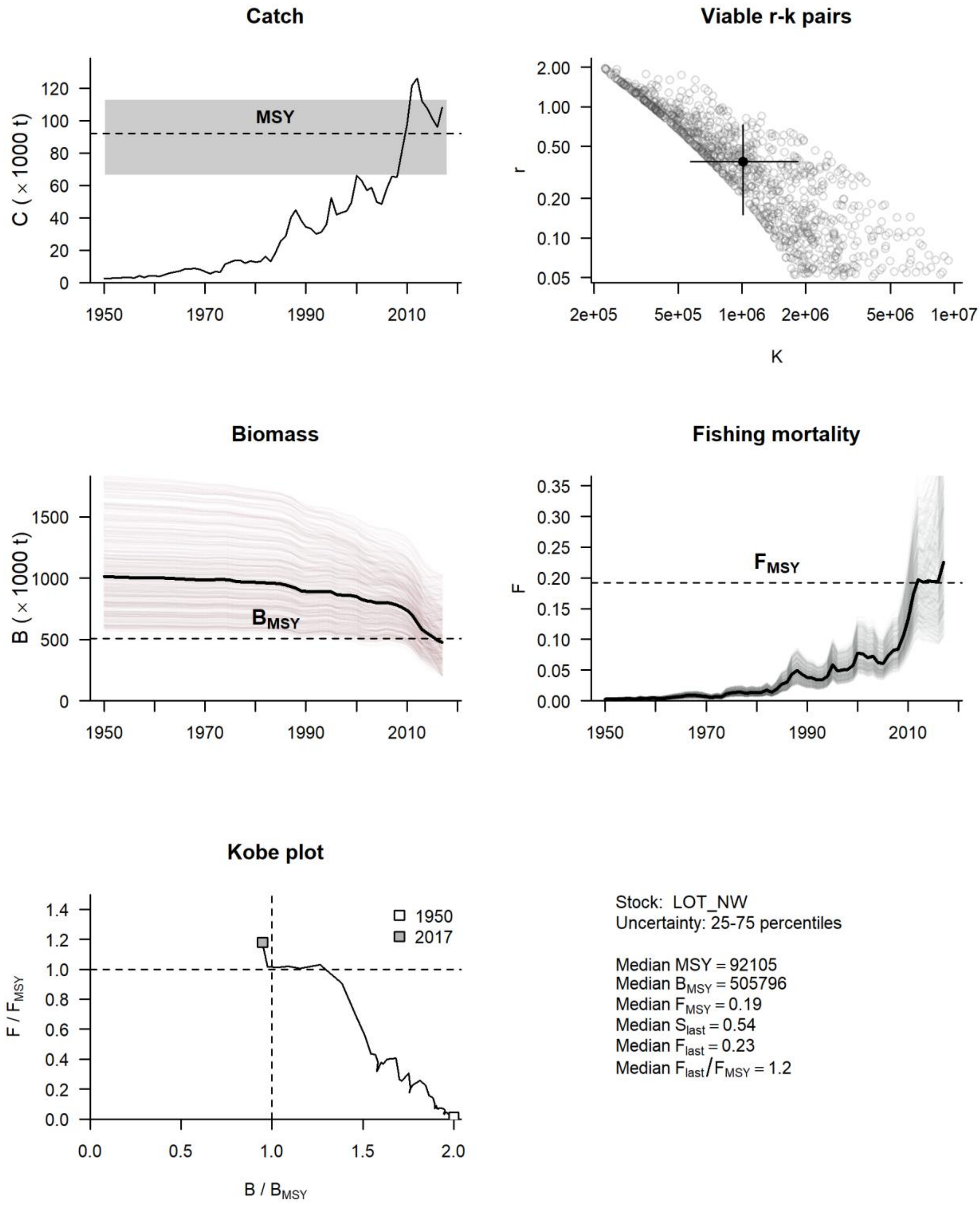

Figure 12. Result from the integrated catch-only method for LOT in the NW region.

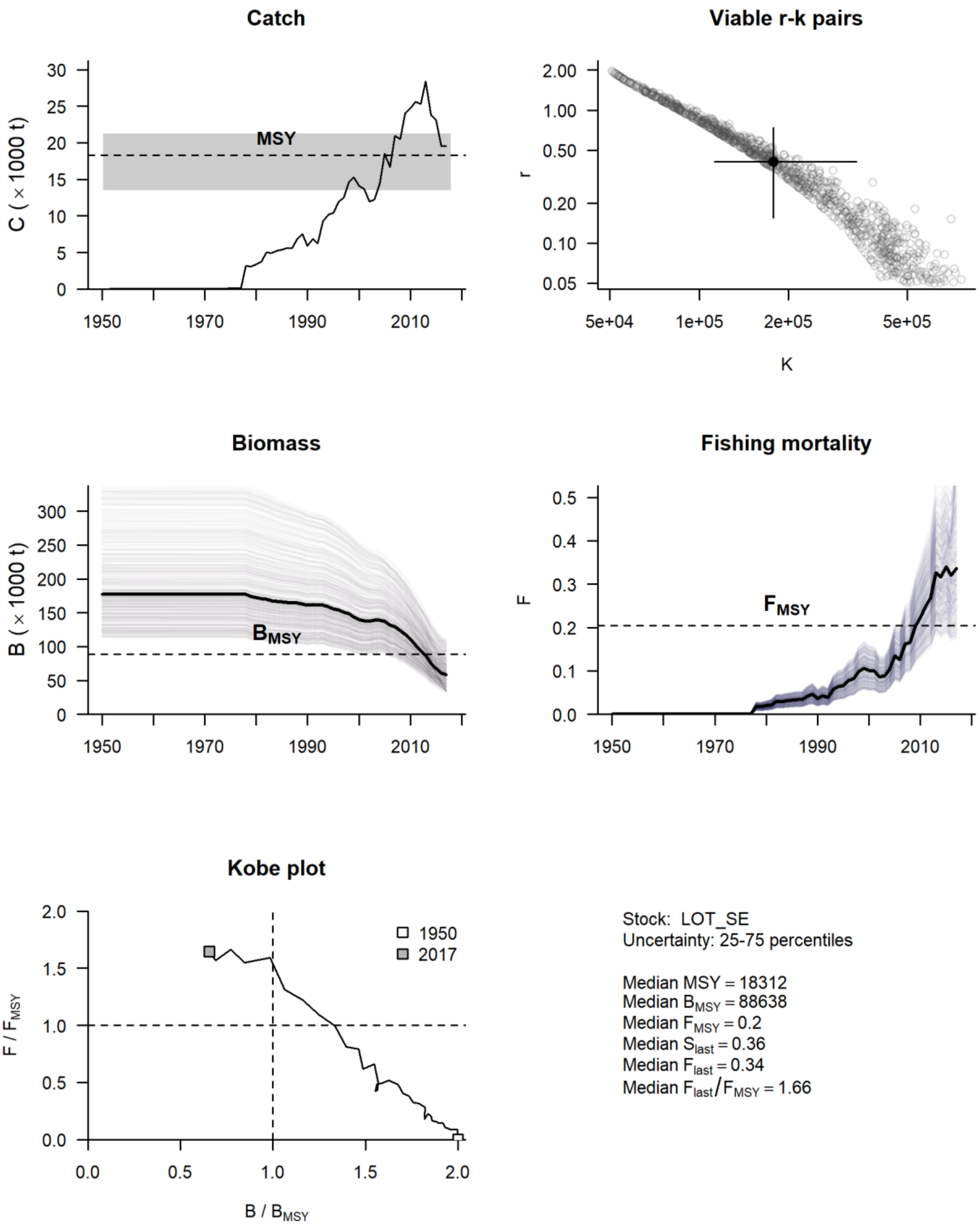

Figure 13. Result from the integrated catch-only method for LOT in the SE region.

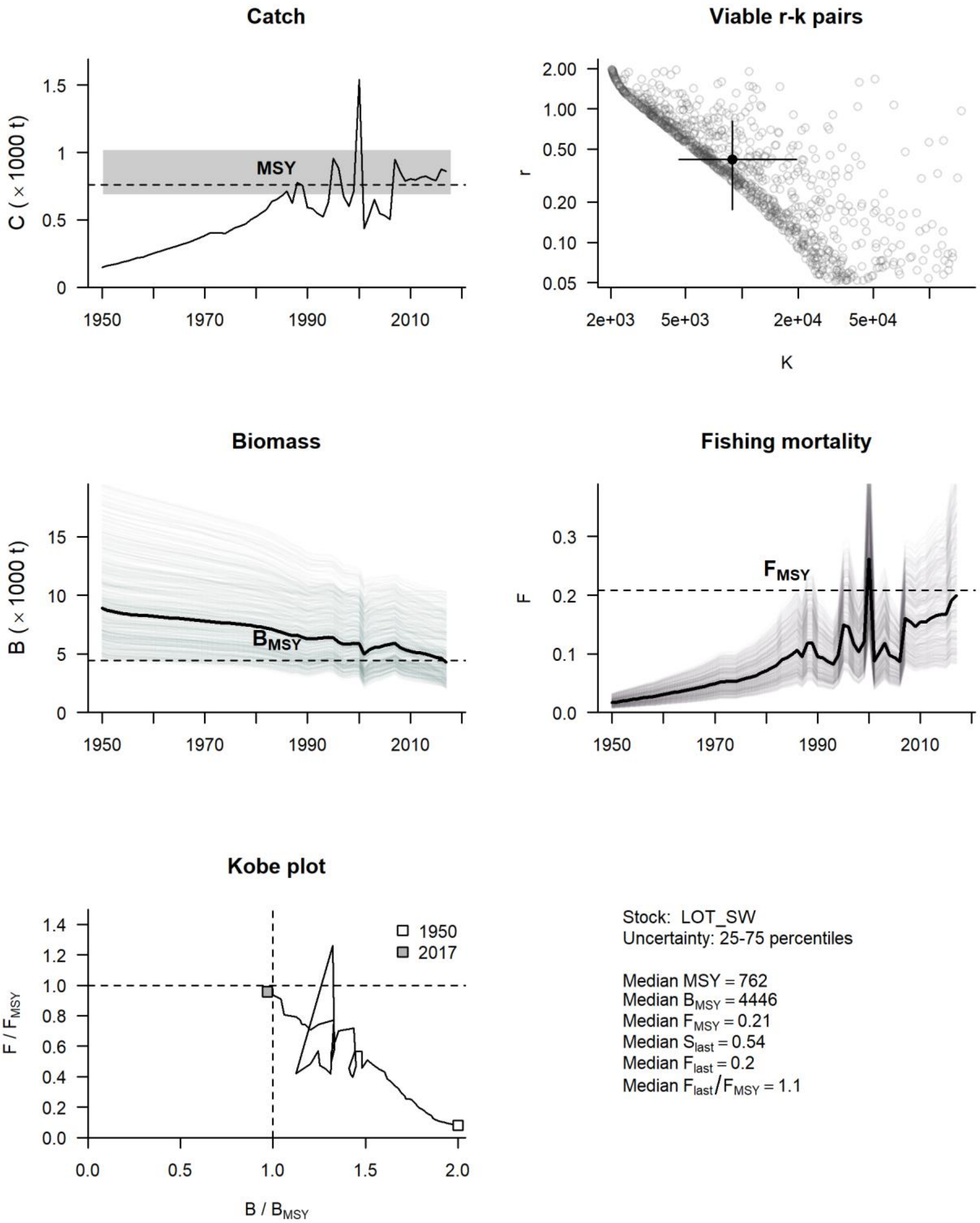

Figure 14. Result from the integrated catch-only method for LOT in the SW region.

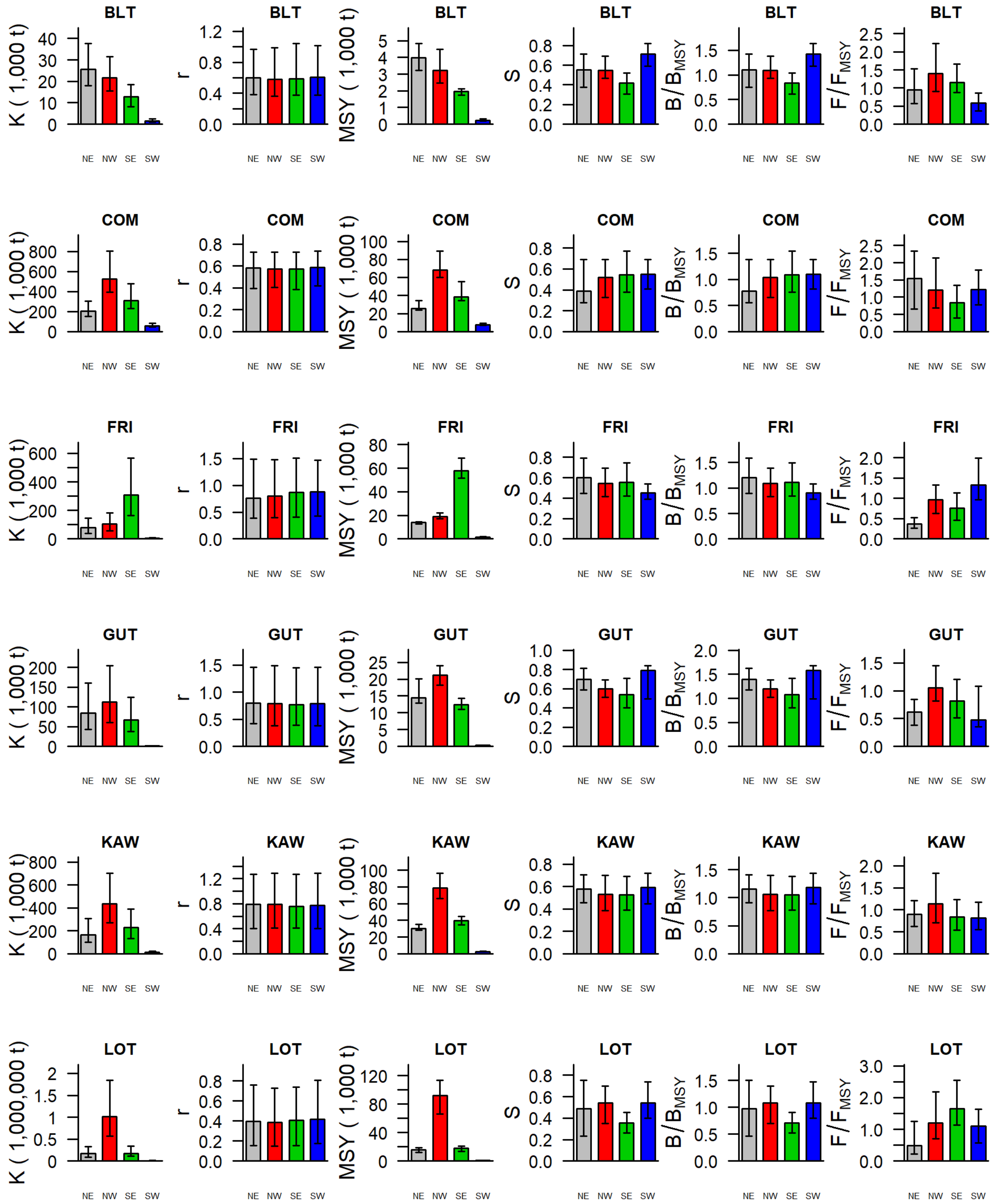

Figure 15. Comparison of sub-stocks for six neritic tunas using Method 3. Error bars are 25 to 75 percentiles.

CONTACT US

t 1300 363 400
+61 3 9545 2176
e csiroenquiries@csiro.au
w www.csiro.au

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Ocean and Atmosphere
Dr. Shijie Zhou
t +61 7 3833 5968
e Shijie.zhou@csiro.au