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Evaluating data and model structure uncertainty for the stock assessment of swordfish (*Xiphias gladius*) in the Indian Ocean

Sheng-Ping Wang[1,4], Mark N. Maunder[2], Tom Nishida[3], Ying-Ru Chen[1]

[1] Department of Environmental Biology and Fisheries Science, National Taiwan Ocean University, Keelung 202, Taiwan

[2] Inter-American Tropical Tuna Commission, La Jolla, California 92037, United States

[3] National Research Institute of Far Seas Fisheries, Fisheries Research Agency, Shimizu, Shizuoka 424-8633, Japan

[4] Center of Excellence for the Oceans, National Taiwan Ocean University, Keelung 202, Taiwan

Abstract

Swordfish in the Indian Ocean (*Xiphias gladius*) have historically been exploited by Japan and Taiwan. Since the early 1990s, the catch of swordfish in the Indian Ocean increased substantially owing to the seasonal targeting of the Taiwanese fishery, the targeting of EU longline fisheries, and exploitation of semi-industrial longline and artisanal fisheries. Although the recent stock assessments suggested that the MSY-based reference points were not exceeded for the Indian Ocean population, these assessment results may be misleading because they lacked the consideration of uncertainty about changes in fishing operations and model structure assumptions. In this study, we conducted a stock assessment using an integrated age-structured model and evaluated estimates of management quantities under alternative assumptions for changes in catchability for CPUE-based indices of abundance and for gear selectivity. The results of this study indicated that assuming time-blocks for catchabilities may be appropriate to reflect the changes in fishing operations of Japanese and Taiwanese longline fleets. This assumption also provided better model performance and more optimistic assessment results because it implied that the decline in indices of abundance may have resulted from changes in catchabilities rather than depletion of biomass. However, assuming time-blocks for selectivities, misspecifying shapes of selectivity curves and changing weights for CPUE data may not be appropriate for this stock assessment because model performance was deteriorated under these assumptions. More generally, substantial changes in catchability (e.g. due to changes in targeting) may not be fully addressed in CPUE standardization and may require modelling catchability within the stock assessment model. Time varying should be applied judiciously because unmodelled changes in catchability may cause distortion

of the selectivity curve to compensate for the changes in selectivity.

Keywords: stock assessment; uncertainty; catchability; selectivity; swordfish; Indian Ocean.

1. Introduction

Swordfish (*Xiphias gladius*) is one of the commercially important species in the Indian Ocean. The catch was historically taken mainly by Japan and Taiwan, but the catch was less than 5,000 t before the late 1980s. Since the early 1990s, the catch of swordfish in the Indian Ocean substantially increased from around 9,000 t in 1991 to a peak of 38,000 t in 1998 (Fig. 1). The main reasons for this significant increase are the change in target species from tunas to swordfish by part of the Taiwanese fleet, the development of longline fisheries in Australia, Reunion island, Seychelles, and Mauritius, and the arrival of longline fleets from the Atlantic Ocean (Portugal, Spain and other fleets operating under various flags) (IOTC, 2013a). The catch declined substantially since 2004 largely due to the continued decline in the number of Taiwanese longline vessels active in the Indian Ocean (IOTC, 2013a). The decline in catch of swordfish in the western tropical Indian Ocean, which comprises most of the catch, is a consequence of a drop in longline fishing effort in the area due to either piracy or decreased fish abundance, or a combination of both (IOTC, 2013a).

The first stock assessment for swordfish in the Indian Ocean was conducted using a nonequilibrium surplus production model (i.e. ASPIC software, Prager (1994)) during the first Working Party on Billfish (WPB) of the Indian Ocean Tuna Commission (IOTC) in 2000, when only catch and effort data were available for use (Yokawa and Shono, 2000). Since size composition data and biological parameters related to reproduction and growth (e.g. Poisson et al., 2009; Wang et al., 2010) were available for swordfish in the Indian Ocean, various age- or length-based integrated assessment approaches began to be applied to evaluate the status for this stock. In 2011, the latest stock status of swordfish in the Indian Ocean was determined based on the performances of ASPIC, production model based on the Bayesian averaging method, age-structured integrated analysis, and Stock Synthesis (Kitakado and Nishida, 2011; Kolody, 2011; Nishida et al., 2011; Wang and Nishida, 2011). All models suggest that the MSY-based reference points were not exceeded for the Indian Ocean population as a whole, but the resource in the southwest Indian Ocean has been overfished during the past decade and biomass remains below the level that would produce MSY (IOTC, 2011).

Nishida and Kitakado (2011) showed a roughly consistent decrease in catch-per-unit-effort (CPUE) series for fleets of Japan, Taiwan, Spain, and La

Reunion in the southwest Indian Ocean during the 1990s in which the Japanese fleets changed their fishing operation from shallow longline to deep longline. Nishida and Kitakado (2011) indicated that Japan had large catch and effort in the same period implying that the sharp drop could be caused by catch and considered to be realistic, but it is difficult to identify which level of decrease in CPUE is real. The Taiwanese longline fleet in the Indian Ocean also changed their targeting species from albacore (*Thunnus alalunga*) to yellowfin tuna (*Thunnus albacares*) and bigeye tuna (*Thunnus obesus*) in the late 1980s (data not shown). The change in fishing operation may have a potential impact on the selectivity and catchability for swordfish in the Indian Ocean since swordfish prefer shallower depths (Nishida, 2008). IOTC (2013b) also indicated that fishing power has increased gradually over the past 30 years in the Indian Ocean and the increases in the average fishing power in the final years may be driven by loss of less efficient vessels from the fleet.

CPUE standardization (Maunder and Punt, 2004) can be used to account for targeting when creating an index of abundance from CPUE data. Unfortunately, targeting information is often not available. Covariates related to targeting (e.g. gear characteristics) can be used as a proxy for targeting in the CPUE standardization. However, Nishida and Kitakado (2011) concluded that the fishing operation did not affect CPUE of the Japanese fleet because the change in targeting could not be accounted for using a GLM with gear characteristics as an explanatory variable. Carvalho et al. (2014) also found that gear characteristics in CPUE standardization did not account for targeting for blue shark. They recommend estimating changes in catchability due to targeting as a time-varying catchability parameter during the fitting of the dynamic model used for the assessment. IOTC (2013b) indicated that the increase in fishing power could be due to technology change, spatial changes, and replacement of older vessels with new, more modern vessels and also commented on the possibility of detecting change in catchability using detailed information such as change in gear, operation, fishing master, etc.

Wang et al. (2014a; 2014b) indicated that misspecified selectivity assumptions can also have a substantial impact on the estimates of both traditional surplus production models and integrated assessment approaches and, consequently, management advice. Wang et al. (2009a) also indicated that incorrect assumptions about the relationship between CPUE and abundance and the form of the selectivity curve can greatly impact the assessment results. Size composition and CPUE data are main inputs for integrated assessment approaches and the influence of different types of data is a major issue in the application of integrated analyses (Francis, 2011). The appropriate weighting of data sets in integrated stock assessment models is an important component of model development (Deriso et al., 2007). However, the influence of changes in the fishing operation and the weighting of data sets were not taken into account in the latest stock assessment framework for swordfish in the Indian Ocean. Therefore, the current assessment results may be misleading because they lack the consideration of uncertainties about changes in fishing operations and alternative assumptions in model structure.

In this study, we perform a stock assessment using an integrated age-structured model and evaluate the impacts of uncertainties in catchabilities for indices of abundance, alternative assumptions for gear selectivity, and different weights for data sets on the estimates of quantities of management interest. The results of this study provide information that should be considered when conducting future stock assessment and management for swordfish in the Indian Ocean and stock assessments in general.

2. Materials and methods

2.1. Data used

The definitions of fleets used in this study are listed in Table 1. Except for the Australia longline fleet, all fleets were divided further based on four subareas (NW, SE, SW and SE) of the Indian Ocean, which have been used for the CPUE standardization and stock assessment of swordfish in the Indian Ocean since 2008 (IOTC, 2011; Fig. 2).

The same data sets adopted in IOTC (2009), including the catches, length–frequencies and CPUE-based indices of abundance, were used in this study (Table 1). The historical catches in weight and the length-frequencies are available for all fisheries and these data were reported to IOTC by each fleet (Table 1). Generally, the time series of the length-frequency data for these fleets were shorter than the catch data. All of the length-frequency data were aggregated into 3 cm length (lower jaw fork length) intervals for each fleet. The relative indices of abundance were based on the CPUE of Taiwanese (1980-2007) and Japanese (1980-2007) longline fisheries standardized using General Linear Models (GLM) (see Nishida and Wang (2009) and Wang and Nishida (2009) for details).

2.2. Biological information

The parameters of the length-weight relationship and the von Bertalanffy growth function were based on the results of an age and growth study for swordfish in the Indian Ocean (Wang et al., 2010). Poisson et al. (2009) provide the parameters of the logistic maturity curve and also the relationship between sex-ratio and length for swordfish caught by the Reunio-based pelagic longline fishery. The biological parameters used in this study are listed in Table 2. The values for the parameters related to natural mortality (M), the steepness of the stock-recruitment relationship (h), and the extent of variation in recruitment (σ_v) cannot be determined from auxiliary information, nor can they be estimated reliably by fitting the model to the data and must therefore be pre-specified. In this study, values consistent with those used in previous assessment for swordfish in the Indian Ocean (Wang et al., 2009b) were adopted for these parameters: M = 0.2 year^{-1}, h = 0.9 and σ_v = 0.4.

2.3. Assessment model

The age–structured integrated analysis used in this study (named as ASIA by IOTC (2011)) was based on the population dynamics model developed by Wang et al. (2005) and Wang et al. (2007). The model of Wang et al. (2005) and Wang et al. (2007) was modified by eliminating the sex-structured factors from the model because sex-specific length–frequency data were not available for the swordfish in the Indian Ocean. This model considers the lifespan of swordfish from age 0 to 15 (age 15 being treated as a 'plus group'). The model assumes that recruitment is related to spawning stock biomass according to a Beverton–Holt stock-recruitment relationship and that the deviations about this relationship are log-normally distributed. The relationship between sex-ratio and length from Poisson et al. (2009) was used to calculate female abundance for estimating spawning biomass (see eq. (A.10) in Wang et al. (2007)). The recruitment deviations for the years prior to 1980 are all set to zero due to lack of information in the length–frequency about the year-class strength for these years. Years after 1980 are treated as parameters of the assessment model with a penalty based on the distributional assumption.

The parameters of the model can be divided into those for which auxiliary information is available and are estimated outside the assessment model (Table 2) and those which need to be estimated by fitting the stock assessment model to the data (Table 3).

The logistic curve, which assumes that the vulnerability of a fish increases monotonically to an asymptote with increasing length, is commonly used in fisheries stock assessment models to represent selectivity for longline gear. Except for Japanese, Australian and other longline fleets (JPLL, AULL and OTHL), however, few swordfish with length larger than 200 cm were caught (Fig. 3) and the assumption that selectivity follows a logistic curve might be inadequate for other longline fisheries (Wang et al., 2009b). For the "Base-case", therefore, the selectivities were assumed to be logistic for longline JPLL, AULL and OTHLL and a dome-shaped curve (represented by a normal distribution) was used for the other fleets. The catchabilities were assumed to be constant over time for all fleets with CPUE data. Equal weights were assigned to each CPUE series when fitting the model to data.

The objective function was minimized to find the estimates of the estimated parameters of the model. The objective function combines the negative log-likelihoods for the CPUE and length-frequency data, and the penalty for the annual recruitment deviates. The model is implemented using AD Model Builder (Fournier et al., 2012).

2.4. Sensitivity analyses

Several analyses were conducted to investigate the impacts of different assumptions made about catchability, selectivity, and data weighting.

Case 1.The CPUE data of the Japanese and Taiwanese longline fleets in the western subareas revealed significantly different trends around early 1990s (Fig. 4). Therefore, CPUE data of these fleets were separated into two time blocks for examining the influences of changes in catchability on the estimates based on the years when CPUE data substantially declined (1980-1994 and 1995-2007 for JPLL-NW and JPLL-SW; 1980-1989 and 1990-2007 for JPLL-NE and JPLL-SE; 1980-1986 and 1987-2007 for TWLL-NW; 1980-1994 and 1995-2007 for TWLL-SW) (Fig. 4).

Case 2. The time blocks in Case 1 were used to separate selectivities of the Japanese and Taiwanese longline fleets.

Case 3. The time blocks in Case 1 were used to separate both of catchabilities and selectivities of Japanese and Taiwanese longline fleets.

Case 4. To evaluate the impact of selectivity assumptions on the model estimates, the model was conducted based on the assumption that the selectivities were logistic for all longline fleets and dome-shaped for the other fleets.

Case 5. Different weights for each CPUE time series, based on relative coefficient of variation (CV) of each CPUE data, were used to increase the weights for improving model fits to the CPUE data with higher variability (equal weight was used for each CPUE time series in other cases) (Table 4).

For each case, the following five management quantities were estimated.

a) Maximum sustainable yield (MSY).

b) Spawning biomass in 2007 (S_{recent}).

c) Spawning biomass in 2007 as a ratio of the unexploited spawning biomass

(S_{recent}/S_0).

d) Spawning biomass in 2007 as a ratio of that corresponding to MSY (S_{recent}/S_{MSY}).

e) Fleet-aggregated fishing intensity in 2007 (defined as the ratio of total catch to exploitable biomass, see Wang et al. (2005 and 2007) for details) as a ratio of that corresponding to MSY (F_{recent}/F_{MSY}).

The likelihood values were also used to examine the fits of the model to the length-frequency and CPUE data.

3. Results

3.1. Model performance based on alternative assumption

Compared to the Base-case, the negative log-likelihood for the CPUE data decreased substantially when separating CPUE data of JPLL, TWLL-NW and TWLL-SW into two time blocks (Case 1), while the values of the negative log-likelihood for length-frequency data were more similar between two cases (Table 5). The model fits to CPUE data of JPLL, which decreased around the early 1990s, were substantially improved when incorporating the assumption that the catchabilities for these fleets varied in the time blocks, while the model fits to CPUE data of TWLL-NW and TWLL-SW were less influenced since they lacked the sharp declining trends (Fig. 4). Although, within time blocks the fit to the Japanese CPUE was still poor and the model predicted more large fish than was observed for the fisheries with asymptotic selectivities.

The model estimated selectivities of JPLL, TWLL-NW and TWLL-SW revealed distinct patterns for different time periods when separating their selectivities into two time blocks (Case 2) (Fig. 5). Japanese longline fleet tended to select small fish in the early years and changed to select large fish thereafter. For the Taiwanese longline fleet, TWN-NW tended to select small fish in the early years and TWN-SW targeted large fish, while TWN-NW change to select large fish and TWN-SW changed to select small fish thereafter and both fleets tended to target fishes with similar age. Compared to the base-case, an increased value of the negative log-likelihood for the length-frequency data indicated that separating selectivities into two time blocks slightly deteriorated the model fits to the length-frequency data, but improved the model fits to CPUE data (Table 5; Figs. 3 and 4).

The model fits to CPUE data were best among all cases when separating both of catchabilities and selectivities into two time blocks (Case 3) (Table 5; Fig. 4). However, the improvement in the negative log-likelihood was negligible for length-frequency data although the model fits to length-frequency data improved for some fleets (Table 5; Fig. 3). For the changes in selectivity, selectivities for Japanese longline fleet did not obviously change between two-time blocks and revealed similar patterns to the results when selectivities were assumed to be time-invariant (Base-case), while the selectivities for the Taiwanese longline fleet differed between blocks (Fig. 5). The estimates were similar to Case 2 except the early selectivity for TWLL-NW.

When assuming selectivity is logistic for all longline fisheries and dome-shaped for other fisheries (Case 4), the estimated selectivities changed and most longline fleets tended to select more large fish (Fig. 6). However, the negative log-likelihoods indicate that model fits to both length-frequency and CPUE deteriorated (Table 5; Figs. 3 and 4).

Although the value of the negative log-likelihood for the CPUE data obtained from the assumption that the weights for CPUE data differed among fleets (Case 5) may not be comparable with that obtained from other cases (Table 5), increasing the weights for the JPLL CPUE data, which changed over time, did not visually improve the model fits to their CPUE data (Fig. 4). The model fits to the length-frequency data were not influenced when changing the weights for CPUE data (Table 5).

3.2. Comparison of management quantities

Diverse estimates of the management quantities were obtained when different model assumptions were adopted (Table 5). The estimate of S_{recent} was most sensitive to the model assumptions in most cases. The estimates of MSY were also sensitive and varied from 11,384 t to 79,411 t, which may lead to completely different management decisions. For the results of most cases, the estimates of relative quantities of S_{recent}/S_0, S_{recent}/S_{MSY} and F_{recent}/F_{MSY} indicated that F_{recent} was lower than F_{MSY} and S_{recent} remained at a relatively high proportion of S_0 and was also much higher than S_{MSY}. However, assuming selectivities to be logistic for all longline fisheries and dome-shaped for other fisheries (Case 4) resulted in the most pessimistic assessment results, indicating that the estimate of S_{recent} was at low proportion of S_0 and close to S_{MSY}, and F_{recent} exceed F_{MSY}. This may be because a large amount of large fish was selected when selectivities for all longline fisheries were assumed to be logistic (Fig. 6). In contrast, separating CPUE into two time blocks (Case 1 and 3) led to the most optimistic assessment results, which indicated that the stock is only lightly depleted at worst and F_{recent} is at a relatively low level.

The Kobe plot was drawn based on the estimates of S_{recent}/S_{MSY} and F_{recent}/F_{MSY} obtained from the various model assumptions (Fig. 7). Although the model estimates were diverse based on different model assumptions, the results of most cases indicated that swordfish in the Indian Ocean is not experiencing overfishing and not overfished. However, this stock may be experiencing overfishing based on the assumption that selectivities are separated into two time blocks (Case 2) and selectivities for all longline fisheries are logistic (Case 4).

4. Discussion

4.1. Influence of alternative assumptions for catchability and selectivity

Catchability is generally assumed to be constant over time and independent of population size, but this assumption is unrealistic because many biological, management-based, and fishery-dependent factors may influence catchability in fisheries (Maunder et al., 2006; Carruthers et al., 2010). Based on the results of this study, separating the CPUE into two time blocks (Case 1 and 3) provided best model fits to both CPUE and length-frequency data of swordfish in the Indian Ocean (Table 5; Figs. 3 and 4). Carvalho et al. (2014) indicated that incorporating time-varying catchability in stock assessment models by specifying a single change point in the catchability coefficient can result in significant improvements in model fit. If the assumption of time-varied catchability is appropriate to a stock, it implies that substantial decreases in relative indices of abundance are most likely due to changes in catchabilities rather than the depletion of the biomass. Therefore, in this study, the most optimistic assessment results were obtained when separating the CPUE into two time blocks (Table 5). The two catchability time blocks corresponded to known changes in fishing operations for Japanese and Taiwanese longline fleets, especially for the Japanese longline fleet. Wang et al. (2009a) also found that a change in targeting from albacore to bigeye tuna in a longline fleet had a great influence on the CPUE-based index of abundance for bigeye tuna in the eastern Pacific Ocean and led to an increase in CPUE of bigeye tuna unrelated to abundance. The change in catchability may be influenced by many factors, but the most significant one is target species, which can be addressed to some extent by using the characteristic of fishing operation (e.g. number of hooks between floats) in the CPUE standardization procedure (IOTC, 2013b). Nishida and Kitakado (2011) considered that the effect of fishing operation did not affect CPUE of Japanese fleet, because the change in targeting could not be accounted for by using a GLM with gear characteristics as an explanatory. Carvalho et al. (2014) also found that gear characteristics in CPUE standardization did not account for targeting for blue shark. Variable catchability should be incorporated into the model, otherwise changes in CPUE that are due to variable catchability may be incorrectly concluded to be due to changes in abundance (Bishop, 2006; Wang et al., 2009a). In addition, possible factors affecting catchability should be taken into account either in assessment models or CPUE standardizations because the effects and magnitudes of change in catchability can differ over time, i.e.

changes in catchability occur neither in step function nor continuous/consisted ways, but in complex way by various factors.

Assumptions about selectivity play an influential role in the outcome of fisheries stock assessment, particularly for catch-at-length models (Wang et al., 2009a; Wang et al., 2014a and 2014b). Wang et al. (2009a) indicated that the model miss-fit to the length-frequency data may be due to the selectivity varying over time and the size sampling not being random in space and time. In this study, however, separating only selectivity into two time blocks did not improve the model fits to the length-frequency data (Case 2) (Table 5; Fig. 3). Estimated time-invariant selectivities (Base-case) for Japanese longline fleet tended to be consistent with the estimated selectivities in the first time block (Case 2), while estimated time-invariant selectivities for Taiwanese longline fleet were quite similar to the estimated selectivities in the second time block (Fig. 5). Poor sample size and time-area coverage for length-frequency data of swordfish in the Indian Ocean from the Japanese longline fleet after the early 1990s and substantially increased sample size for length-frequency data of the Taiwanese longline fleet after early 1990s (Herrera and Pierre, 2011) may be the reason that assuming separating selectivities in two time blocks failed to improve the model fits to length-frequency data. In addition, estimated CPUE time series were also substantially influenced by the assumption of time-varied selectivities because the estimated CPUE is proportional to exploitable biomass, which is the product of selectivity and biomass at age (Table 5; Fig. 4) (see Wang et al., 2005 and 2007 for details). Although separating both of catchability and selectivity in two time blocks (Case 3) provided best model fits to CPUE and length-frequency data, the influence of time-varied catchability on model fits may be much more important than that of time-varied selectivity because separating only catchability (Case 2) provided the greatest improvement in model fits (Table 5). In addition, unrealistically high estimates of biomass were obtained when time-varied catchability and selectivity were assumed (Table 5).

An inappropriate assumption for the selectivity curve may lead to problematic assessment results (Wang et al., 2009a; Wang et al., 2014a and 2014b). In this study, we examined the impact of different selectivity curves on the estimates of management quantities for swordfish in the Indian Ocean. In this study, assuming selectivities to be logistic for all longline fleets (Case 4) led to the most pessimistic assessment results, although model fits to CPUE and length-frequency data were not obviously deteriorated (Table 5; Figs. 3 and 4). Assuming an asymptotic selectivity curve includes the assumption that large fish are fully selected and the level of depletion will often be overestimated if a fishery’s selectivity is constrained to be asymptotic when the actually selectivity is dome-shaped (Wang et al., 2009a). In addition, female swordfish are known to mature at a relatively old age (Poisson and Fauvel, 2009) and thus biased estimates of spawning biomass and stock status may be obtained for swordfish in the Indian Ocean if inappropriate selectivity curves are assumed.

The assessment model predicts more old fish than were observed for the fisheries that have asymptotic selectivity (Fig. 3). This over prediction may be due to the asymptotic length being too large, total mortality (either fishing or natural mortality) being too low, or dome-shaped selectivity. The mode see for large fish is due to the models plus group being too low so that the plus group has a substantial number of fish and occurs at an age when growth is still rapid. Doubling the plus group age to 30 removes this mode, but also increases the maximum size in the model so that the model still over-predicts the proportion of large fish (results not shown). The model fit to the length composition data is improved if the growth curve is modified to have a lower maximum length (e.g. if the male growth curve is used; results not shown). The growth curves are based on fish aged 10 years or less (Wang et al., 2010) and therefore the maximum length is an extrapolation and highly uncertain. Research should focus on providing a better estimate of growth to improve the assessment.

4.2. Consideration for data weights

The CPUE data of Japanese and Taiwanese longline fleets were the key indices for representing the pattern of relative abundance. However, the CPUE data for these two fleets have inconsistent trends (Nishida and Wang, 2009; Wang and Nishida, 2009) and several different models were unable to provide satisfied fits to these two CPUE data in previous assessments (Kitakado and Nishida, 2011; Kolody, 2011; Nishida et al., 2011; Wang and Nishida, 2011). This study attempted to increase the weights for the CPUE data of the Japanese longline fleet that declined by the late 1980s and early 1990s (Case 5), but this did not improve the model fits to CPUE data (Table 5; Fig. 4). This suggests that the change in Japanese longline CPUE is inconsistent with the assumed population dynamics and catch supporting the change in catchability hypothesis. The weight assigned to each data set can be determined using statistical approaches, but these are based on the model being correctly specified (Maunder and Starr 2003; Deriso et al., 2007; Maunder, 2011; Francis 2011). Lee et al. (2014) suggested reducing the data weightings to lessen the influence of secondary data components and therefore increase the importance of primary data components, but down-weighting composition data and emphasize abundance index may not be feasible and could potentially lead to substantial uncertainty in the estimates of absolute abundance. Therefore, adopting alternative assumption related to data weights should be carefully applied when performing a stock assessment for a fishery resource.

4.3. Uncertainty not being incorporated

The catches are fairly well known for swordfish in the Indian Ocean; however catches were uncertain for some small scale and artisanal fisheries and also for discards, but this does not lead to significant changes in the total catch estimates (IOTC, 2011). Wang et al. (2005) indicated that the impact of the uncertainty in catch data on the model estimates would be relative small, while the uncertainty about the relationship between catch-rate and abundance has the greatest impact on the performance of the model. Therefore, the improvement in collection of effort data and the procedure of CPUE standardization is the most important issue for the assessment of swordfish in the Indian Ocean.

Swordfish in the Indian Ocean are known to be sexually dimorphic (Poisson and Fauvel, 2009; Wang et al., 2010). Wang et al. (2005) indicated that ignoring sex-structure when conducting population model-based stock assessments can lead to biased assessment results, especially for absolute management quantities (e.g. estimates of spawning stock biomass and MSY). Due to the absence of sex-specific length-frequency data for swordfish in the Indian Ocean, however, a sex-aggregated age-structured assessment model was applied to perform the assessment for this stock. Collecting sex-specific biological and catch data is important for improving the assessment.

Wang et al. (2007) indicated the results of the assessment model for swordfish in the North Pacific Ocean are sensitive to the values for natural mortality and the steepness of the stock-recruitment relationship. In addition, Wang and Nishida (2011) indicated that the assessment results for swordfish in the Indian Ocean were very sensitive to the assumption of the steepness of the stock-recruitment relationship and the stock status could shift from an optimistic condition using a high reproductivity assumption to a pessimistic condition using a low reproductivity assumption. The uncertainty in these biological parameters is also an issue for many others fish stocks.

The IOTC (2011) identified swordfish in the southwest Indian Ocean as a management unit of particular concern, because it seems to be more depleted than other regions in the Indian Ocean, and has been overfished for the past decade. However, the stock structure of swordfish in the Indian Ocean is uncertain. Lu et al. (2006) indicated “samples drawn from the waters off northern Madagascar and the Bay of Bengal were 2 distinct groups compared to the other populations from the Indian Ocean and western Pacific”, while Muths et al. (2012; 2013) indicated “at the scale of the Indian Ocean, results obtained from both markers are consistent with swordfish belonging to a single unique panmictic population or at least several breeding grounds with significant exchange of genetic material” and “suggests as satisfactory to consider swordfish as a single panmictic population in the Indian Ocean”. Although a lack of genetic difference among areas is not necessarily a reason to reject area specific management, separate unit stock assumption may need to be reconsidered when performing stock assessment and providing management advice for swordfish in the Indian Ocean since stock structure of swordfish in the Indian Ocean is still uncertain.

4.4. Conclusion

Although the stock assessment for swordfish in the Indian Ocean has been conducted using several approaches (Kitakado and Nishida, 2011; Kolody, 2011; Nishida et al., 2011; Wang and Nishida, 2011) and recent status of this stock has also been concluded by IOTC (IOTC, 2011), diverse stock assessment results may be obtained if alternative assumptions are adopted. To consider the influence of the change in fishing operation on the stock assessment, this study investigated the impacts of different assumptions about the CPUE time series and selectivities for Japanese and Taiwanese longline fleets on the model performance and model estimates. The results indicated that the model performance can be substantially improved when separating the catchabilities for indices of abundance into two time blocks. The most optimistic stock status was also obtained based on this assumption because the sharp decline in the CPUE may be due to the changes in catchabilities rather than depletion of biomass. These time-varied catchabilities may also appropriately reflect the changes in fishing operations for these two main fleets, which historically exploited swordfish in the Indian Ocean. However, assuming time-varied selectivities for these two fleets did not improve the model fits to length-frequency data, but improved the model fits to CPUE data. This implied that the selectivities of these two fleets for swordfish in the Indian Ocean might not change while shifting their targeting from bigeye tuna to albacore, but the model performance was influenced by changes in catchabilities. Blindly including time varying selectivity may be dangerous because the time varying selectivity may be estimated to account for model mispecification (e.g. time varying catchabiliy). Selectivities for longline fleets are generally assumed to be logistic, but this assumption may be inappropriate for swordfish in the Indian Ocean because the model performance was substantially deteriorated when conducting the assessment for this stock. In addition, down weighting the length composition data or up weighting the CPUE data too much may be inappropriate because it could allow selectivity to be estimated to explain other model misspecification. Although the uncertainty in biological characteristics was not incorporated in the analysis of this study, previous studies indicated that assumed values of biological parameters and differences between males and females have significant influence on the assessment results and this should be taken into account for future assessments of swordfish in the Indian Ocean.

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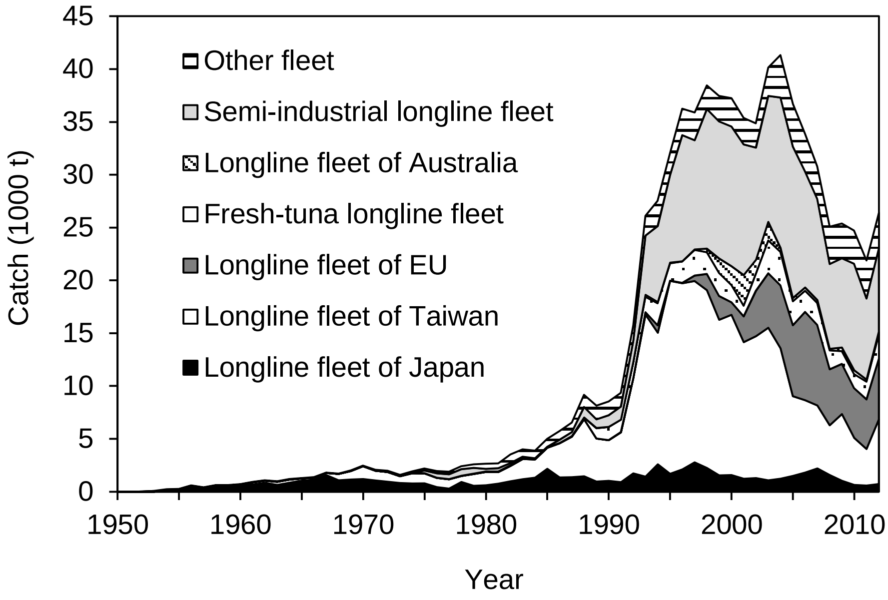

Fig. 1. Annual catches of swordfish by fleets in the Indian Ocean.

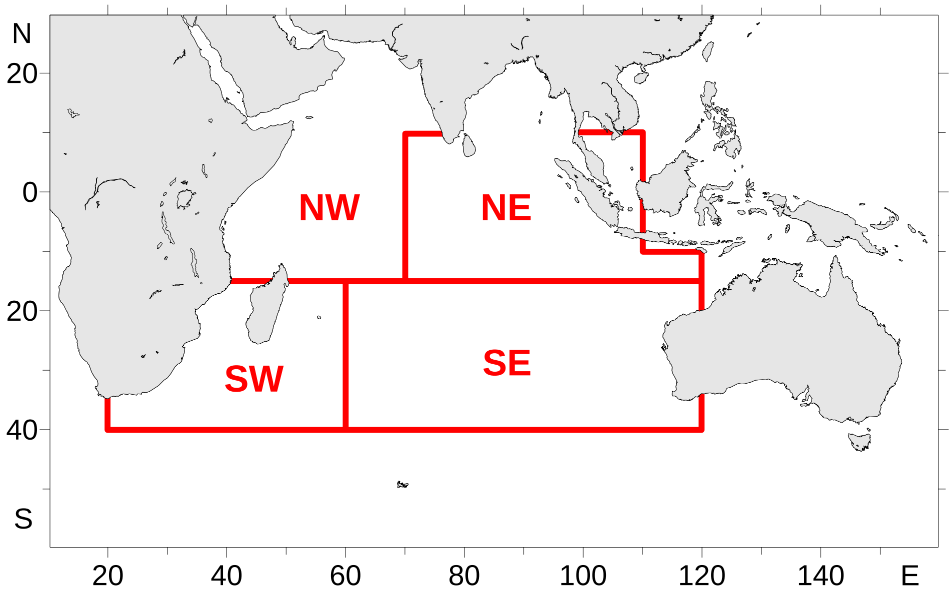

Fig. 2. The definition of subareas used in the stock assessment for swordfish in the Indian Ocean.

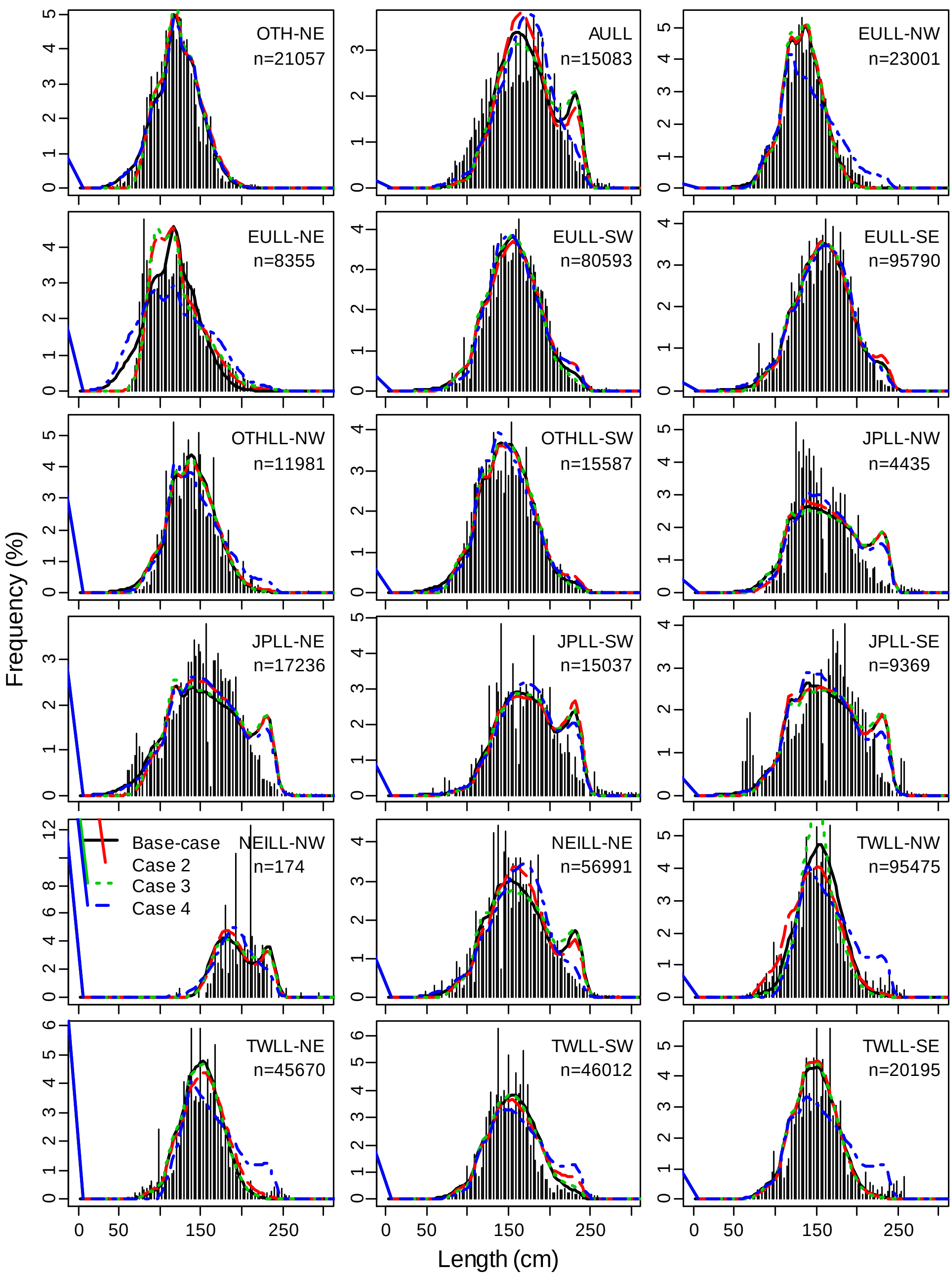

Fig. 3. Observed (histograms) and model-estimated (lines) length-frequencies of swordfish in the Indian Ocean based on the Base-case, separating selectivities of Japanese and Taiwanese longline fleets into two time-blocks (Case 2), separating catchabilities and selectivities of Japanese and Taiwanese longline fleets into two time-blocks (Case 2), and assuming logistic curves selectivities for all longline fleets and dome-shaped selectivities for the other fleets (Case 4).

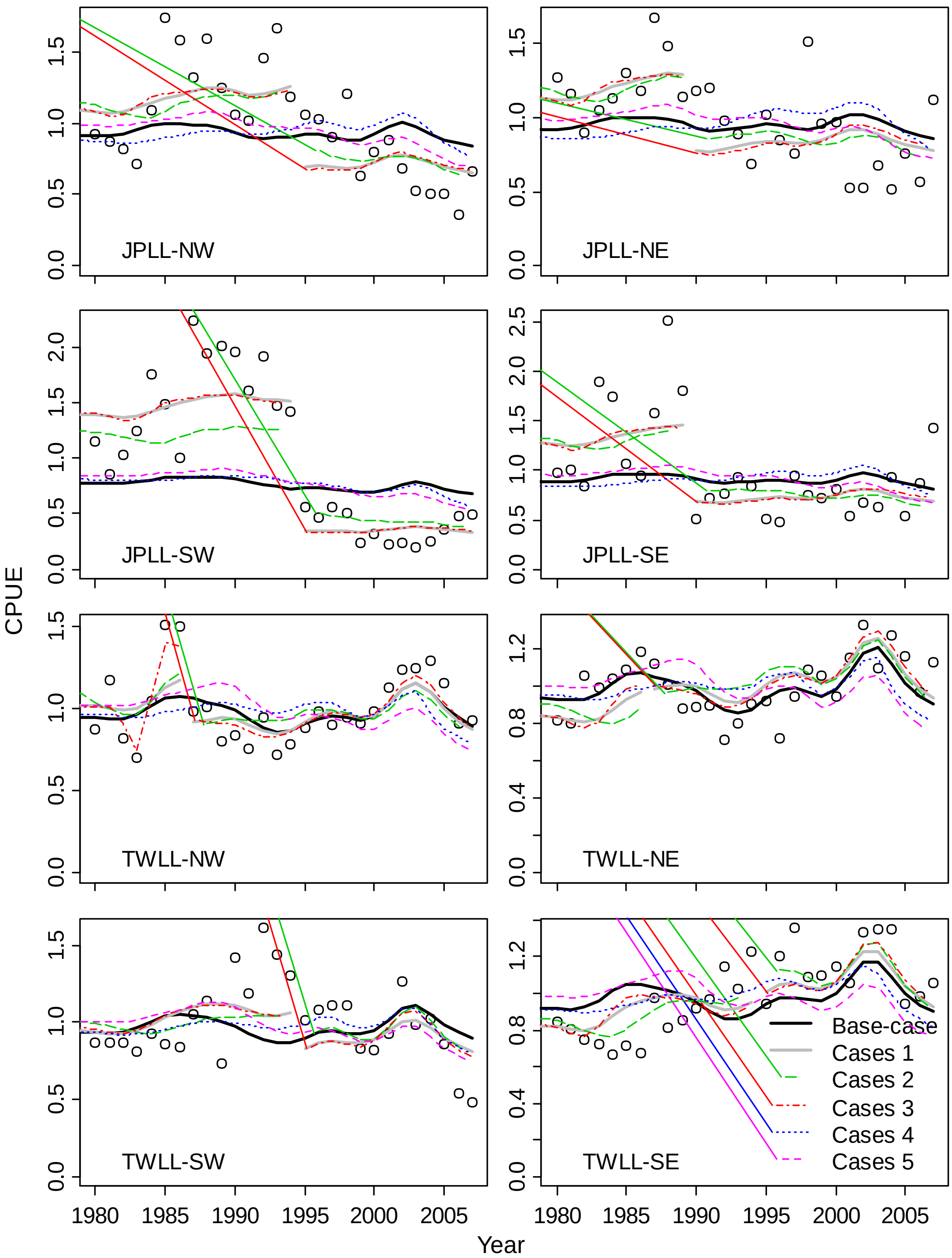

Fig. 4. Observed (dots) and model-estimated (lines) CPUE of swordfish in the Indian Ocean based on various model assumptions conducted in this study.

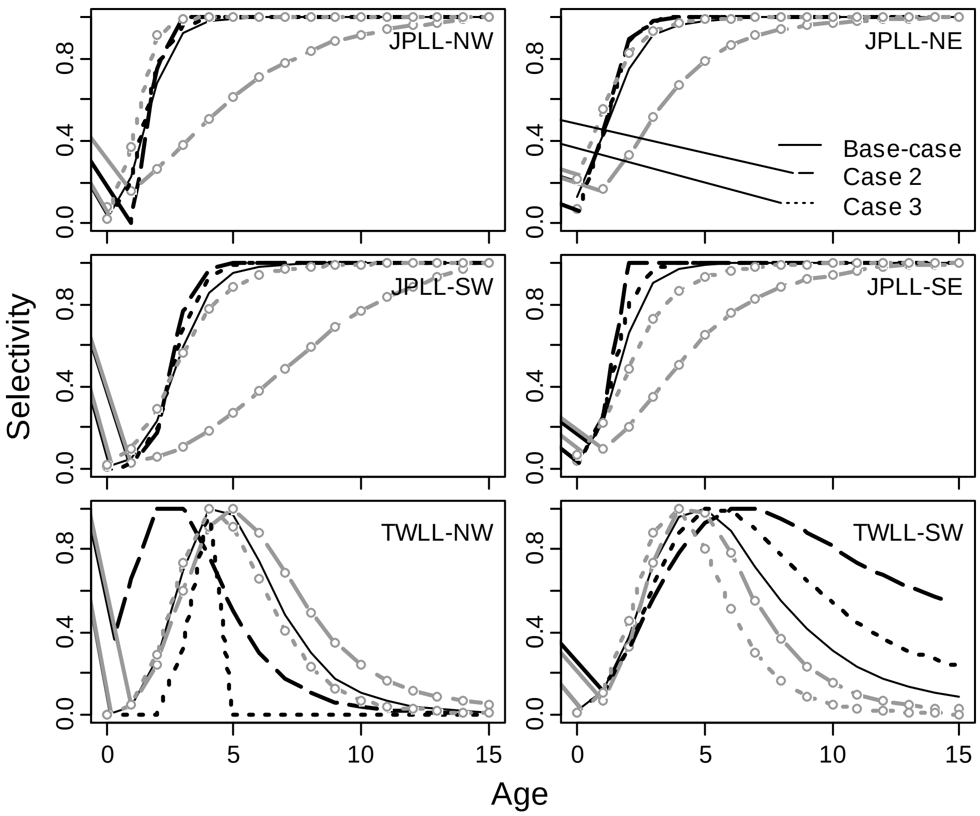

Fig. 5. Model-estimated selectivity curves Japanese and Taiwanese longline fleets in the Indian Ocean based on the Base-case, different time-blocks when separating selectivities into two time-blocks (Case 2), and different time-blocks when separating both catchabilities and selectivities into two time-blocks (Case 4). Black lines for Case 2 and 4 are the selectivities in the first time-block and gray lines with points are the selectivities in the second time-block.

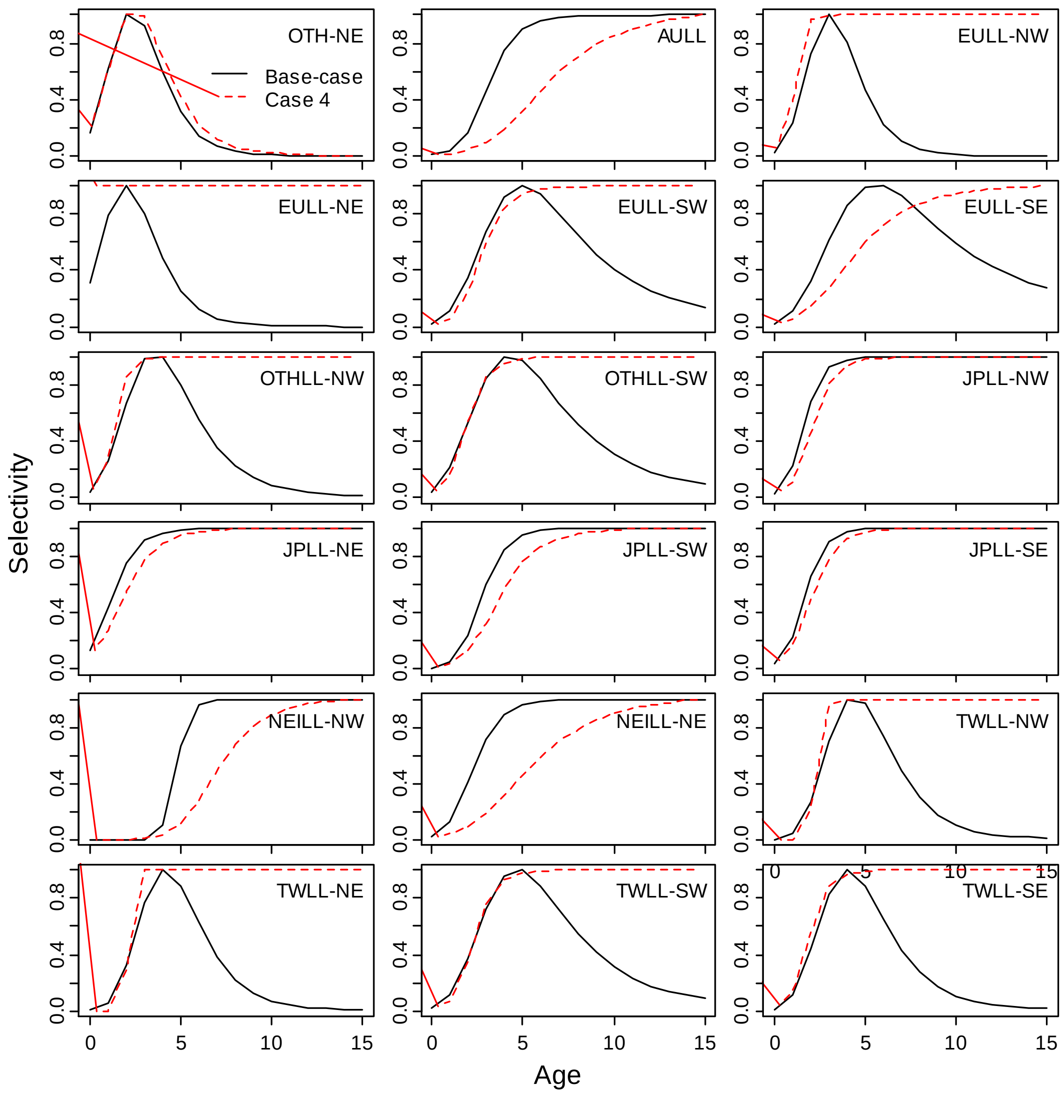

Fig. 6. Model-estimated selectivity curves for swordfish in the Indian Ocean based on the Base-case analysis, and assuming logistic curves selectivities for all longline fleets and dome-shaped selectivities for the other fleets (Case 4).

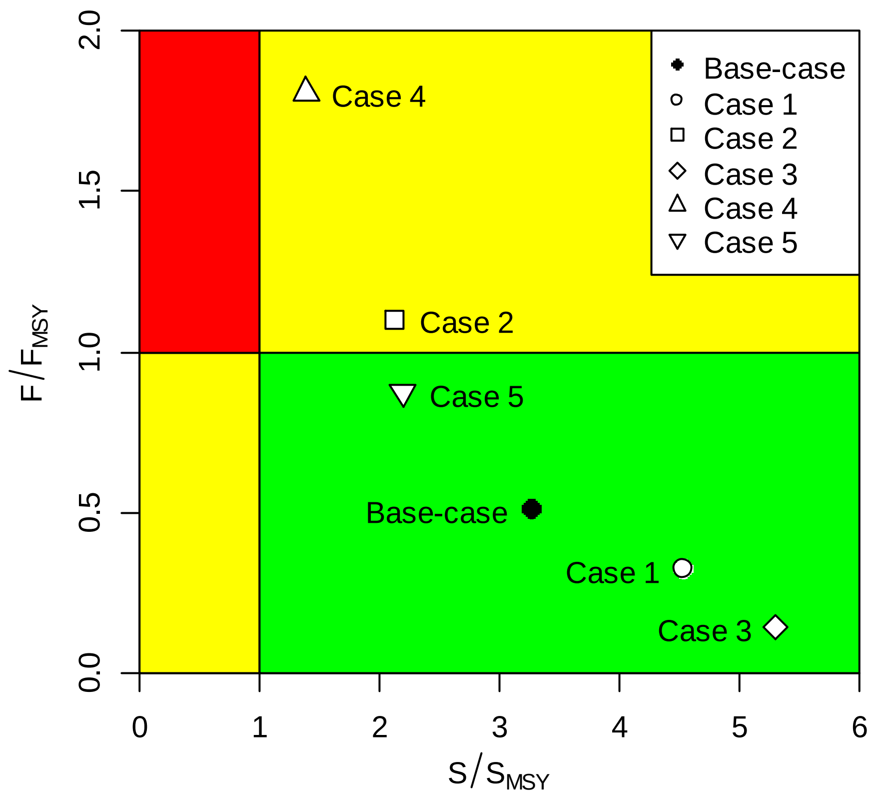

Fig. 7. Kobe plot for swordfish in the Indian Ocean based on various assumptions conducted in this study.

Table 1. Definition of the fleets operating in the Indian Ocean and the data available for each fleet.

Fleet	Fleet Code	Area	Catch data	Length-frequency	CPUE
Gillnet, trolling and other minor artisanal fleets	OTH	NW	1957-2007	-	-
		NE	1951-2007	1988-2006	-
		SW	1988-2006	-	-
		SE	1986-1992	-	-
Longline fleet of Australia	AULL	SE	1989-2005	2001-2005	-
Longline fleets of EU (Spain, Portugal and other fleets)	EULL	NW	1980-2007	1993-2006	-
		NE	1980-2007	1999-2006	-
		SW	1980-2007	1994-2007	-
		SE	1980-2007	1999-2007	-
Semi-industrial longline fleets (France-Reunion, France-Mayotte, Madagascar, Mauritius and the Seychelles)	OTHLL	NW	1995-2007	1995-2007	-
		SW	1991-2007	1997-2007	-
		SE	1995-2007	-	-
Longline fleet of Japan	JPLL	NW	1952-2007	1970-2007	1980-2007
		NE	1952-2007	1970-2007	1980-2007
		SW	1952-2007	1970-2007	1980-2007
		SE	1952-2007	1970-2007	1980-2007
Fresh-tuna longline fleets of Taiwan and Indonesia, sport and hand line fleets	NEIL	NW	1997-2007	2000-2003	-
		NE	1974-2007	1998-2006	-
		SW	1984-2007	-	-
		SE	2001-2007	-	-
Longline fleet of Taiwan	TWLL	NW	1954-2007	1980-2007	1980-2007
		NE	1954-2007	1980-2007	1980-2007
		SW	1954-2007	1980-2007	1980-2007
		SE	1954-2007	1980-2007	1980-2007

Table 2. The biological parameters for length-weight relationships, von Bertalanffy growth curve, and maturity and age for swordfish in the Indian Ocean.

Parameter	Females	Males
Asymptotic size, L_∞ (cm)	274.86	234.00
Growth parameter, K (year^{-1})	0.1377	0.1694
Age-at-zero-length, t_0 (year)	-1.9975	-2.1809
Length-weight parameter, A	9.133×10^{-6}	9.133×10^{-6}
Length-weight parameter, B	3.012	3.012
Maturity slope, r_m	0.0953	-
Length-at-50%-maturity, L_m (cm)	170.4	-
Maximum age, λ (year)	15	15

Table 3. The parameters of the population dynamics model not known from auxiliary information for Base-case.

Parameter	No. of parameters
Estimated	
Unfished recruitment, R_0	1
Process errors, v_t	1 per year from 1980 to 2007
Selectivity	
Dome-shaped	
Length-at-mean-selectivity, L_{mu}^f	1 per fleet, expect for the AULL, JPLL and NEILL
Standard deviation of selectivity, L_{sd}^f	1 per fleet, expect for the AULL, JPLL and NEILL
Logistic curve	
Length-at-50%-selectivity, L_{50}^f	1 per fleet for the AULL, JPLL and NEILL
Length-at-95%-selectivity, L_{95}^f	1 per fleet for the AULL, JPLL and NEILL
Pre-specified	
Natural mortality, M	1
Steepness, h	1
Variation in recruitment, σ_v	1

Table 4. The vaules of coefficient of variation (CV) for CPUE data of Japanese and Taiwanese longline fleets and weights for fitting CPUE data to the assessment model when using different weights for each CPUE time series (Case 5).

Fleet	Area	CV	Weight
JPLL	NW	0.38	1.12
JPLL	NE	0.31	0.91
JPLL	SW	0.67	2.00
JPLL	SE	0.50	1.47
TWLL	NW	0.21	0.63
TWLL	NE	0.16	0.47
TWLL	SW	0.26	0.76
TWLL	SE	0.21	0.63

Table 5. The model estimates of the management quantities, and the values of the negative log-likelihood for CPUE, length-frequency data and total amount including constraint for the deviations about the stock–recruitment relationship based on various assumptions conducted in this study.

						Negative log-likelihood for		
Case	MSY	S_{recent}	S_{recent}/S_0	S_{recent}/S_{MSY}	F_{recent}/F_{MSY}	CPUE	Length-frequency	Total
Base-case	29,327	300,517	0.70	3.26	0.51	-170.65	500.54	338.10
Case 1	37,764	552,208	0.98	4.53	0.33	-223.98	497.57	286.04
Case 2	14,906	42,841	0.44	2.13	1.10	-224.26	508.77	306.79
Case 3	79,411	1,388,340	1.16	5.30	0.14	-235.91	499.06	273.81
Case 4	11,384	44,346	0.29	1.39	1.81	-156.91	543.06	418.20
Case 5	23,434	157,278	0.47	2.20	0.87	-119.94	500.89	387.33