

**Stock assessment of swordfish (*Xiphias gladius*) in the Eastern Pacific Ocean  
through 2012**

Annie Ji-Yih Yau<sup>1</sup>, Yi-Jay Chang<sup>2</sup>, and Jon Brodziak<sup>1</sup>

<sup>1</sup>NOAA Pacific Islands Fisheries Science Center, Honolulu, HI 96822, USA

<sup>2</sup>Joint Institute for Marine and Atmospheric Research, Honolulu, HI 96822, USA

## ABSTRACT

We present an updated stock assessment of swordfish (*Xiphias gladius*) in the Eastern Pacific Ocean through 2012 using a state-space Bayesian surplus production model. Biomass production was modeled using a 3-parameter production model that allowed production to vary from a symmetric Schaefer curve. Input fishery data included nominal landings of swordfish during 1951–2012, which have fluctuated over time but overall increased to almost 10,000 metric tons (mt) in 2012. Potential relative abundance indices for swordfish consisted of standardized CPUE for Japanese and Taiwanese fisheries. Goodness-of-fit diagnostics were used to compare the fits of alternative model configurations, and convergence of each model was tested. The biomass of swordfish in the Eastern Pacific Ocean was estimated to be 59,300 mt in 2012, which is well above the estimated  $B_{MSY}$  of 31,300 mt. The estimated harvest rate for swordfish in 2012 was 0.190, which is slightly higher than the estimated  $H_{MSY}$  of 0.18. Therefore swordfish in the Eastern Pacific Ocean are not overfished ( $B < 0.5 * B_{MSY}$ ), but there is a 56.7% probability that overfishing ( $H > H_{MSY}$ ) was occurring in 2012. We also conducted sensitivity analyses, retrospective analyses, stock projections, and risk analyses under various harvest scenarios. Based on the retrospective analysis, this assessment model overestimates biomass, and any management decisions should consider this fact and the clear retrospective pattern present in the data. If the recently reported high catch levels from 2012 persist, the probability of overfishing will also persist into the future.

## KEY FINDINGS:

- The swordfish stock in the Eastern Pacific Ocean is healthy, and the 2012 estimated biomass is 59,300 mt, well above the  $B_{MSY}$  of 31,300 mt.
- There is a 56.7% probability that overfishing is occurring in the Eastern Pacific stock of swordfish; the 2012 estimated harvest rate is 0.19, slightly higher than the  $H_{MSY}$  of 0.18.
- If the recently reported 2012 catch levels of ~9,000 mt persist, the probability of overfishing will also persist into the future. Catch must be reduced below 9,000 mt in order to reduce the probability of overfishing below 50%.
- This assessment model overestimates biomass and underestimates harvest because there is a clear retrospective pattern in the data, and any management decisions should consider this fact.

## INTRODUCTION

Swordfish (*Xiphias gladius*), also known as broadbill swordfish, inhabit a wide region of the Pacific between the latitudes of 50° N and 50° S (Ward and Elscot 2000). Like other tuna and tuna-like species, swordfish is a highly migratory species with high economic value in both commercial and recreational fisheries. Stock assessments on swordfish in the North Pacific have been conducted primarily using catch, and abundance indices in the form of catch-per-unit effort, or CPUE. In 2004, Kleiber and Yokawa (2004) used MULTIFAN-CL to assess North Pacific swordfish in a four-region model. In two subsequent studies, a similar length-structured modeling approach was applied, which included some sex-specific data (Wang et al. 2005, 2007). These previous studies concluded that there was little contrast in the North Pacific swordfish fishery CPUE data to estimate stock status relative to biological reference points. Updated catch and effort data, however, were expected to improve model fits and to help estimate recent trends in swordfish abundance and harvest rates. In 2009, all swordfish in the North Pacific were assessed as both a single stock north of the Equator and also under a two-stock scenario, with one stock in the Western and Central Pacific Ocean (WCNPO) and another in the Eastern Pacific Ocean (EPO) (ISC 2009), separated by a diagonal boundary extending from Baja, California, to the Equator (Figure 1), based on the analysis by Ichinokawa and Brodziak (2008). The EPO swordfish stock assessment was updated in 2010 using updated catch data (Brodziak 2010). Based on general consensus that a two-stock scenario is likely, we present here an updated assessment of swordfish in the EPO; assessment of the WCNPO swordfish stock is described in a separate working paper from this session by Chang et al. (2014).

The EPO swordfish stock is centered on the Equator in the Eastern Pacific, bounded on the south by 20 °S and extending northeast diagonally from 170 °W towards Baja California (Figure 1) (Ichinokawa and Brodziak 2008). Swordfish are mostly caught by deepwater longline fisheries, some of which target other pelagic species such as tuna. In the EPO, the annual total catch has fluctuated between 4,000 to almost 10,000 metric tons (mt) since 2000. The majority of catch has been taken by longline fishing vessels from Japan, Spain, China, Korea, and Taiwan (Figure 2), which accounted for 91% of the total harvest in the Eastern Pacific in 2012. The remaining catch was taken by Belize, Mexico, Chile, French Polynesia, Peru, Vanuatu, and the United States. There is potential interest in increasing the harvest of swordfish in the Pacific which would require an appropriate stock assessment, management for conservation, and the sustainable development of the fishery.

This stock assessment applies a Bayesian statistical framework to estimate parameters of production models to assess the EPO swordfish stock using updated catch and effort through 2012. The use of a Bayesian approach provides direct estimates of parameter uncertainty that are straightforward to interpret and are appropriate for risk analysis. The production models include both process error for biomass production dynamics and observation errors for fitting the observed CPUE data from multiple fishing fleets. The assessment model estimated biological reference points, biomass, harvest rate, stock status, and associated uncertainties.

We also conducted additional analyses using the assessment model. First, we tested the sensitivity of model fit and outputs to changes in the prior distribution means for each of four key parameters. Next, we conducted a retrospective analysis on the most recent 7 years of data.

We also projected the stock 4 years forward under various harvest and catch scenarios. Finally, we conducted a risk analysis by calculating the probability of becoming overfished and overfishing given various projected future catch levels.

## **METHODS**

### **Data**

#### *Catch*

Fishery catch data for swordfish in the Eastern Pacific Ocean from 1951-2012 were compiled from several sources. Catch data from 1951-2006 were taken from the most recent summary of available fishery-dependent data during the previous assessment (Brodziak 2010). More recent catch data from 2007-2012 were compiled using data provided by the Inter-American Tropical Tuna Commission (IATTC), Western and Central Pacific Fisheries Commission (WCPFC), and individual countries of Japan, Taiwan, Korea, Mexico, and Chile. When a country provided catch data directly, that data were considered more accurate and used in lieu of data provided by the IATTC and WCPFC for those countries. Overall, the catch data will be used to model the effects of fishery removals from the EPO swordfish stock during 1951–2012. A description of each dataset follows.

IATTC data provided a catch dataset for 2007-2012 describing total numbers of swordfish caught by longline by year, country, latitude, and longitude. IATTC also provided a separate smaller dataset on lengths, indicating the total numbers of swordfish caught and their sizes in cm

by year, country, latitude, and longitude. Each dataset was separated into data for the EPO stock and for the WCNPO stock. The lengths dataset was used to convert total numbers caught in the catch dataset into biomass. First, the lengths were converted into biomass using the following conversion factor for swordfish in the Eastern Pacific Ocean (DeMartini et al. 2000, DeMartini et al. 2007):

$$W = 0.0000137 * L^{3.04}, \quad (1)$$

where  $W$  is weight in kg and  $L$  is eye-fork length in cm. Weights were converted from kg into mt. From these weights, the average weight of a swordfish caught in each year was calculated, and this average yearly weight was used to convert the numbers of swordfish caught in the catch dataset into mt of swordfish caught. The catch dataset was then aggregated by country by year to calculate total tons of swordfish caught by each country in each year.

Under the guidance of the IATTC, the entire longline swordfish catch of Peru was considered to likely have taken place in the EPO and the entire catch time series from 1954-2010 was added to the catch data for swordfish in the EPO. Catch data from Peru came from the most recent assessment of swordfish by the IATTC (Hinton and Maunder 2011). This is the first time that swordfish data from Peru was included in the EPO assessment. The annual EPO swordfish catch for 2011-2012 was estimated as the average catch from 2007-2010.

WCPFC provided data for 2007-2012 north of the Equator on swordfish numbers and tons caught by year, country, latitude, and longitude. This data were separated by stock (EPO versus WCNPO) and aggregated by country by year to calculate the total tons of swordfish caught by each country in each year.

Japan provided total swordfish catch in mt from their offshore and distant-water longline fleet for 1951-2012, with data from 2011 and 2012 still preliminary (Kimoto and Yokawa 2014). This data were used for 2007-2012, since it was considered more accurate than the sums of the IATTC and WCPFC data. The updated Japanese catch data for 1951-2006 were considered the best available data to date, so Japanese catch time series used in the previous assessment was replaced with the updated data and the total catch time series was updated.

Taiwan provided total swordfish catch in mt from their offshore and distant water longline fleet from 1964-2012. The updated Taiwanese catch data for 1964-2006 were used in lieu of the Taiwanese time series of catch used in the previous assessment. Taiwan also provided a brand new time series of swordfish catch for their offshore longline and other fisheries. The total catch of swordfish in the EPO was updated using these two catch time series. The Taiwanese catch data for 2007-2012 were used in place of summed Taiwanese data from IATTC and WCPFC.

Korea provided total swordfish catch in mt for 2007-2012 from their tuna longline fisheries, by year, latitude, and longitude. This data was separated by stock area (EPO versus WCNPO), and then aggregated by year to calculate the total tons of swordfish caught in each year from 2007-2012. Again, this country-provided data was used in lieu of catch data for Korea from the IATTC and WCPFC.

Swordfish catch for Mexico's longline fishery for 2007-2010 was taken from the most recent country report by Mexico to the ISC (Dreyfus et al. 2013). The annual EPO swordfish catch for

2011-2012 was estimated as the average catch from 2007-2010. Data were not available by latitude and longitude, but maps indicate that the majority of swordfish are caught in the EPO rather than in the WCNPO. Thus all swordfish caught by Mexico are assumed to be in the EPO stock.

Swordfish catch data from Chile was updated for 2007-2012 using Annual Statistics of Fisheries and Aquaculture reports from the Chilean fisheries agency, Servicio Nacional de Pesca y Acuicultura (SERNAPESCA 2007-2012). At the guidance of the IATCC, it was assumed that swordfish landed in Chile's two northernmost regions (Regions XV and I) which lie north of the southern boundary of the EPO were likely harvested in the EPO. The total landings of swordfish from these two regions were summed up for each year.

### ***CPUE***

Estimates of standardized commercial fishery CPUE were provided by Japan (Kimoto et al. 2014) and Taiwan (Sun et al. 2014) through 2012. The Japanese longline CPUE time series spanned 58 years (1955–2012), but was divided into three separate series: 1955-1974, 1975-1993, and 1994-2012. The Taiwanese distant water longline CPUE time series spanned 13 years (2000–2012). A second Taiwanese distant water longline CPUE time series exists for 1968-1999, but ultimately was not used because the inclusion of this CPUE series resulted in poor model fit and a model that never converged. These standardized CPUE series from Japan and Taiwan served as relative abundance indices for swordfish in the EPO, and were used to model changes in the relative abundance of swordfish through time. We calculated the Pearson's correlation coefficient for the two CPUE series that overlapped in time: Japanese CPUE from 1994-2012,

and Taiwanese CPUE from 2000-2012. The CVs of CPUE were all assumed to be a value of 1, following the same methods as the previous assessment (Brodziak 2010).

### **Production Model**

Swordfish production models followed a similar structure to the previous production model used for Pacific swordfish (Brodziak and Ishimura 2009, Brodziak 2010). Production models were formulated as Bayesian-state space models with explicit observation and process error terms (e.g., Meyer and Millar 1999, Brodziak 2007). The biomass time series comprised the unobserved state variables which were estimated from the observed relative abundance indices (i.e., CPUE) and from catches using observation error likelihood function and prior distributions for model parameters ( $\theta$ ). In this case, the observation error likelihood measured the discrepancy between observed and predicted CPUE, and the prior distributions represented the relative degree of belief about the possible values of model parameters.

The process dynamics represented the fluctuations in exploitable swordfish biomass due to density-dependent processes and fishery harvests. The production dynamics of biomass were based on a power function model with an annual time step. Under this three-parameter model, biomass in year  $T$  ( $B_T$ ) depends on the previous biomass ( $B_{T-1}$ ), catch ( $C_{T-1}$ ), intrinsic growth rate ( $R$ ), carrying capacity ( $K$ ), and a production shape parameter ( $S$ ) for  $T = 2, \dots, N$ :

$$B_T = B_{T-1} + R \cdot B_{T-1} \left( 1 - \left( \frac{B_{T-1}}{K} \right)^S \right) - C_{T-1} \quad (2)$$

The production model shape parameter,  $S$ , determines where surplus production peaks as biomass varies as a fraction of carrying capacity. If the shape parameter is less than unity ( $0 < S$

$< 1$ ), then surplus production peaks when biomass is below  $\frac{1}{2}$  of  $K$  (i.e., a left-skewed production curve) and the stock has relatively high productivity. If the shape parameter is greater than unity ( $S > 1$ ), biomass production is highest when biomass is above  $\frac{1}{2}$  of  $K$  (i.e., a right-skewed production curve), and the stock has relatively low productivity. If the shape parameter is identically unity ( $S = 1$ ), the production model is identical to a discrete-time Schaefer production model where maximum surplus production occurs when biomass is equal to  $\frac{1}{2}$  of  $K$ . Thus, the shape of the biomass production curve can be symmetric, right-, or left-skewed depending on the estimated value of  $S$ .

The power function model will be re-parameterized using the proportion of carrying capacity ( $P = B/K$ ) to improve the efficiency of the Markov Chain Monte Carlo algorithm used to estimate parameters (i.e., Meyer and Millar 1999). Given this parameterization, the process dynamics for the power function model are:

$$P_T = P_{T-1} + R \cdot P_{T-1} \left(1 - P_{T-1}^S\right) - \frac{C_{T-1}}{K} \quad (3)$$

### **Biological Reference Points**

The values of biomass and annual harvest rate that maximize biomass production are relevant as biological reference points for maximum sustainable yield ( $MSY$ ). For the discrete-time power function model, the biomass that produced  $MSY$  ( $B_{MSY}$ ) is:

$$B_{MSY} = K \cdot (S + 1)^{\frac{-1}{S}} \quad (4)$$

The corresponding annual harvest rate that produced  $MSY$  ( $H_{MSY}$ ) was:

$$H_{MSY} = R \left( 1 - \frac{1}{S+1} \right), \quad (5)$$

and the associated value of maximum sustainable yield (*MSY*) was:

$$MSY = R \left( 1 - \frac{1}{S+1} \right) \cdot K (S+1)^{\frac{-1}{S}}. \quad (6)$$

Note that  $H_{MSY}$  can be converted to its instantaneous equivalent,  $F_{MSY}$  by the following equation:

$$F_{MSY} = -\log(1 - H_{MSY}). \quad (7)$$

Thus, the production model produces direct estimates of biological reference points for swordfish that are commonly used for determining stock status.

### Observation Error Model

The observation error model relates the observed fishery CPUE to the exploitable biomass of the swordfish stock under each scenario. It is assumed that each CPUE index ( $I$ ) is proportional to biomass with catchability coefficient  $Q_I$ :

$$I_T = Q_I B_T = Q_I K P_T. \quad (8)$$

The observed CPUE values are subject to natural sampling variation which is assumed to be lognormally distributed. The observation errors are distributed as  $v_T = e^{V_T}$ , where the  $V_T$  are independent and identically distributed normal random variables with a mean of 0 and variance  $\tau^2_I$ .

Given the lognormal observation errors, the observation equations for each CPUE index ( $I$ ) for each annual period indexed by  $T = 1, \dots, N$  are:

$$I_T = Q_I K P_T \cdot v_T \quad (9)$$

This specifies the general form of the observation error likelihood function  $p(I_T|\theta)$  for each fishing fleet through time.

### Process Error Model

The process error model compares the dynamics of exploitable biomass to natural variability in demographic and environmental processes affecting the swordfish stock. The deterministic process dynamics (Equation 3) are subject to natural variation as a result of fluctuations in life history parameters, trophic interactions, environmental conditions and other factors. In this case, the process error represents the joint effects of a large number of random multiplicative events which combine to form a multiplicative lognormal process under the Central Limit Theorem. As a result, the process error terms are assumed to be independent and lognormally distributed random variables  $\eta_T = e^{U_T}$  where the  $U_T$  are normal random variables with mean 0 and variance  $\sigma^2$ .

Given the process errors, the state equations define the stochastic process dynamics by relating the unobserved biomass states to the observed catches and the estimated population dynamics parameters. Assuming multiplicative lognormal process errors, the state equations for the initial time period ( $T = 1$ ) and subsequent periods ( $T > 1$ ) are:

$$\begin{aligned} P_1 &= \eta_1 \\ P_T &= \left( P_{T-1} + R \cdot P_{T-1} (1 - P_{T-1}^S) - \frac{C_{T-1}}{K} \right) \cdot \eta_T \quad \text{for } T > 1 \end{aligned} \quad (10)$$

These coupled state equations set the conditional prior distribution for the proportion of carrying capacity,  $p(P_T)$ , in each time period  $T$ , conditioned on the proportion in the previous period.

## Prior Distributions

Under the Bayesian paradigm, prior distributions are employed to quantify existing knowledge, or the lack thereof, of the likely value of each model parameter. For the production model, the model parameters consist of the carrying capacity ( $K$ ), the intrinsic growth rate ( $R$ ), the shape parameter ( $S$ ), the catchability coefficients ( $Q_I$ ), the process and observation error variances ( $\sigma^2$  and  $\tau^2$ ), and the annual biomasses as a proportion of carrying capacity ( $P$ ). Auxiliary information was incorporated into the formulation of the prior distributions when it was available. A summary of the assumed prior distributions is available in **Table 1** and detailed below.

### Prior for Carrying Capacity

The prior distribution for the carrying capacity  $p(K)$  is a lognormal distribution with mean ( $\mu_K$ ) and variance ( $\sigma_K^2$ ) parameters:

$$p(K) = \frac{1}{\sqrt{2\pi}K\sigma_K} \exp\left(-\frac{(\log K - \mu_K)^2}{2\sigma_K^2}\right) \quad (11)$$

The variance parameter is set to achieve a coefficient of variation (CV) for  $K$  of 50%, e.g.,

$CV[K] = (\exp(\sigma_K^2) - 1)^{\frac{1}{2}} = 0.5$ . The mean  $K$  for swordfish in the Eastern Pacific Ocean was set at 75,000 mt. This mean value is chosen to reflect the magnitude of exploitable biomass likely needed to support the observed fishery catches.

### Prior for Intrinsic Growth Rate

The prior distribution for intrinsic growth rate  $p(R)$  is a lognormal distribution with mean ( $\mu_R$ ) and variance ( $\sigma_R^2$ ) parameters set to achieve a CV for  $R$  of 50%:

$$p(R) = \frac{1}{\sqrt{2\pi R}\sigma_R} \exp\left(-\frac{(\log R - \mu_R)^2}{2\sigma_R^2}\right) \quad (12)$$

The mean  $R$  parameter is set to be  $\mu_R = 0.5$ . This mean value is slightly higher than the range of prior means of (0.40, 0.43) estimated for North and South Atlantic swordfish, respectively, based on an analysis of life history parameters (McAllister et al. 2000). A similar analysis using life history parameters for North Pacific swordfish and the mean generation time approach (see McAllister et al. 2001) suggested higher mean values of  $R$  of approximately 0.9 to 1.0 were appropriate. This analysis assumed female growth and maturation from DeMartini et al. (2000) and DeMartini et al. (2007) and used five alternative natural mortality rate estimators (Hoenig, Alverson and Carney, Pauly, Beverton-Holt 2<sup>nd</sup> invariant, and Lorenzen Tropical) from Brodziak (2009) to calculate five alternative estimates of  $R$ . The primary difference between the Atlantic and Pacific swordfish life history parameters was the value of natural mortality. McAllister et al. (2000) assumed a constant natural mortality rate of  $M = 0.2$  for Atlantic swordfish, while the Pacific swordfish natural mortality rate was estimated to be  $M \approx 0.35$ , roughly 75% higher than the Atlantic swordfish value. While there is uncertainty about an appropriate prior mean for  $R$ , setting the prior mean to be  $\mu_R = 0.5$  with a CV of 50% allows sufficient flexibility to estimate the probable value of  $R$  given the observed catch and CPUE data.

### **Prior for Production Shape Parameter**

The prior distribution for the production function shape parameter  $p(S)$  is a gamma distribution with rate parameter  $\lambda$  and shape parameter  $k$ :

$$p(S) = \frac{\lambda^k S^{k-1} \exp(-\lambda S)}{\Gamma(k)} \quad (13)$$

The values of the rate and shape parameters are set to  $\lambda = k = 2$ . This choice of parameters sets the mean of  $p(S)$  to be  $\mu_S = 1$ , which corresponds to the value of  $S$  for the Schaefer production model. This choice also implies that the CV of the shape parameter prior is 71%. In effect, the shape parameter prior is centered on the symmetric Schaefer model as the default with sufficient flexibility to estimate a nonsymmetrical production function if needed.

### **Prior for Catchability**

The prior for the catchability coefficient  $p(Q_I)$  for a given fleet  $I$  is chosen to be a diffuse inverse-gamma distribution with scale parameter  $\lambda$  and shape parameter  $k$ :

$$p(Q_I) = \frac{\lambda^k Q_I^{-(k+1)}}{\Gamma(k)} \exp\left(\frac{-\lambda}{Q_I}\right) \quad (14)$$

The scale and shape parameters are set to be  $\lambda = k = 0.001$ . This choice of parameters implies that  $1/Q_I$  has a mean of 1 and a variance of 1000 and produces a relatively uninformative prior. Since  $1/Q_I$  is unbounded at  $Q_I = 0$ , an additional numerical constraint that  $Q_I$  be no smaller than 0.0001 is imposed for the Markov Chain Monte Carlo (MCMC) sampling.

### **Priors for Process and Observation Error Variances**

Priors for the process error variance  $p(\sigma^2)$  and observation error variance  $p(\tau_I^2)$  for each fleet  $I$  are chosen to be inverse-gamma distributions. The choice of an inverse gamma distribution implies that the associated prior for error precision ( $\pi = 1/\sigma^2$ ) was effectively  $p(\pi) \propto \pi^{-1}$  which is the Jeffrey's prior for the precision parameter (Congdon 2001). As a result, inferences based on the

gamma assumption are scale invariant and are not affected by changing the scale of the variance parameter. For the process error variance prior, the scale parameter is set to  $\lambda = 4$  and the shape parameter is  $k = 0.1$ . This choice of parameters produces an expected value of approximately  $E[\sigma^2] = 0.025$  with a CV of 16%. Similarly, for the observation error variance prior, the scale parameter is set to  $\lambda = 2$  and the shape parameter is  $k = 0.45$ . This choice of parameters produced an expected value of approximately  $E[\tau^2_I] = 0.223$  with a CV of 50%. Given these prior assumptions, the initial observation error variance is roughly threefold greater than the process error variance. Of course, the posterior means of the process and observation errors estimated from the MCMC sampling also depend on the model fits to the observed data.

### **Priors for Proportions of Carrying Capacity**

Prior distributions for the time series of the proportion of biomass to carrying capacity,  $p(P_T)$ , are lognormal distributions as specified in the process dynamics. The mean proportion of carrying capacity for the initial year of 1951 ( $P_1$ ) is set to 0.9. This corresponded to an assumption that the Eastern Pacific swordfish population was lightly exploited and had biomass near its carrying capacity following a period of limited directed fishing during World War II.

### **Posterior Distribution**

The joint posterior distribution of the swordfish production model needs to be sampled to make inferences about estimates of the model parameters. Given the catch and the CPUE data  $D$ , the posterior distribution  $p(\theta|D)$  is proportional to the product of the prior distributions and the likelihood of the CPUE data via Bayes' theorem:

$$p(\theta | D) \propto p(K)p(R)p(S)p(Q)p(\sigma^2)p(\tau^2)\prod_{T=1}^N p(P_T)\prod_{T=1}^N p(I_T | \theta) \quad (15)$$

Parameter estimation for this nonlinear multi-parameter model is based on generating a large number of independent samples from the posterior distribution. In this case, the Markov Chain Monte Carlo (MCMC) simulation using Gibbs sampling is applied to numerically generate a sequence of samples from the posterior distribution (Gilks et al. 1996). The WINBUGS software (Spiegelhalter et al. 2003) is used to set the initial conditions, perform the MCMC calculations, and summarize the results.

Markov Chain Monte Carlo simulations are conducted by simulating three chains of 130,000 samples simulated for each model. A burn-in period of 10,000 samples is removed from each chain to remove any dependence of the MCMC samples on the initial conditions. Next, each chain is thinned by 5 to reduce autocorrelation. As a result, 72,000 samples from the posterior are used for summarizing model results. Convergence of the MCMC simulations to the posterior distribution is checked using the Geweke diagnostic (Geweke 1992), Gelman and Rubin diagnostic (Gelman and Rubin 1992), and the Heidelberger and Welch stationarity and half-interval test (Heidelberger and Welch 1983), as implemented in the R Language (R Development Core Team 2013) using the CODA software package (Plummer et al. 2006). These convergence diagnostics are monitored for several key model parameters (intrinsic growth rate, carrying capacity, production function shape parameter, and catchability coefficients) to verify convergence of the MCMC chains to the posterior distribution.

### **Model fits to CPUE**

Goodness-of-fit to CPUE was measured to compare alternative production models using model residuals, root mean-squared error (RMSE), and the correlation between observed and predicted CPUE. Model residuals for the CPUE series are the log-scale observation errors  $\varepsilon_T$ :

$$\varepsilon_T = \ln(I_T) - \ln(QKP_T). \quad (16)$$

A nonrandom pattern in the residuals indicates that the observed CPUE did not conform to one or more model assumptions. The RMSE of the CPUE fit provides another goodness-of-fit diagnostic with lower RMSE indicating a better fit when comparing models with the same number of parameters. Similarly, a higher correlation between observed and predicted CPUE indicates a better model match to observed CPUE trend.

### **Sensitivity Analysis**

The sensitivity of model outputs to priors was tested by varying the initial prior means of four key parameters:  $R$ , intrinsic growth rate;  $K$ , carrying capacity;  $S$ , shape parameter; and  $P_1$ , initial proportion of biomass to carrying capacity. For each of these prior means, we varied the prior mean by 25% higher and 25% lower, and compared resulting model outputs. These were considered to be useful high and low bounds for understanding which parameter was most important for estimating outputs, and more importantly, whether assessment results were robust to a 25% change in an input prior.

### **Retrospective Analysis**

Next, we tested for any possible retrospective pattern (systematic inconsistencies among our model estimates of biomass and harvest rate based on increasing periods of data) by sequentially removing the most recent year of data going back 7 years, re-analyzing the model, and

comparing estimated biomass and harvest rates. We also calculated and compared Mohn's rho statistic for these two outputs (Mohn 1999, Legault 2008).

## **Projections**

We conducted stochastic projections to illustrate the possible changes in exploitable biomass and catch under various harvest scenarios, including scenarios requested by the Western and Central Pacific Fisheries Commission's 9<sup>th</sup> session of the Northern Committee. The following harvest scenarios were projected 4 years forward from 2012, the most recent year included in the assessment: a) status quo harvest rate from the most recent 3 years; b) status quo catch from the most recent 3 years; c) the maximum historically-observed single-year harvest rate; and d)  $F_{MSY}$  multiples of 0.5, 0.75, 1.0, 1.25, and 1.5. The projected harvest was sampled from a normal distribution with a mean corresponding to each scenario harvest value, and the standard deviation of harvest or catch values for the most recent 3 years (scenarios a and b) or a standard deviation assumed to be 5% of the mean value (scenarios c and d). Projections included process error and uncertainty in parameter estimation. The initial conditions for the projections are based on the MCMC samples from the estimated posterior distribution of exploitable swordfish biomass in the most recent year.

## **Risk Analysis**

Finally, we conducted a risk analysis by calculating the probability of becoming overfished ( $B < 0.5 * B_{MSY}$ ) and overfishing ( $H > H_{MSY}$ ) given a range of different projected future total catch levels. We projected 5 years forward from 2012, the most recent year included in the assessment, using catch levels at set intervals from 0 mt to 40 mt, which is approximately four times the most

recent average catch. Projected catch was sampled from a normal distribution centered at the projected catch level with a standard deviation of the most recent 3 years of catch. Similar to the projections, the initial conditions for the projections are based on the MCMC samples from the estimated posterior distribution of exploitable swordfish biomass in the most recent year. The projected harvest scenarios included uncertainty in parameter estimation and process error, which are thus included in estimated probabilities of overfishing or becoming overfished.

## **RESULTS**

### **Data**

#### *Catch*

In recent years (2007-2012), Japan and Spain had the highest swordfish catch in the Eastern Pacific Ocean, each catching over 2,000 mt in 2012 (Table 2, Figure 2). China and Taiwan also caught large amounts of swordfish, over 1,500 mt in 2012. These four countries (Japan, Spain, China, and Taiwan) jointly caught 85% of the total swordfish harvest in the EPO in 2012. Korea, Belize, Mexico, and Chile caught moderate amounts of swordfish. French Polynesia, Peru, the United States, and Vanuatu caught nominal amounts of swordfish.

Input data for the assessment model is provided in Table 3 and Figure 3. Catch is listed in units of 1000 mt from 1951-2012. Catch was low in the early years of the fishery and steadily increased until 1970, after which point catch fluctuated between 1,000 and 7,500 mt. In 2002

catch peaked at 9,940 mt, then declined again to 2,800 mt in 2006. Catch in the most recent 3 years (2010-2012) has been close to the historic peak, hovering around 9,700 mt.

### ***CPUE***

The two early standardized CPUE time series for Japan are each relatively stable, fluctuating around an average value (Table 3, Figure 3). The third and most recent CPUE series for Japan shows a sharp threefold increase in the most recent years, 2006-2012. The single CPUE series for Taiwan for 2000-2010 fluctuated around an average value. The most recent Japanese CPUE (1994-2012) and the Taiwanese CPUE (2000-2012) were moderately positively correlated with a Pearson correlation coefficient of  $\rho = 0.50$ .

### **Production Model**

All key model parameters (intrinsic growth rate, carrying capacity, production function shape parameter, and catchability coefficients) and biological reference points converged according to the Geweke diagnostic (Geweke 1992), Gelman and Rubin diagnostic (Gelman and Rubin 1992), and the Heidelberger and Welch stationarity and half-interval tests. A visual inspection of model parameter posterior distribution density plots indicated that these densities were smooth and unimodal for all parameters as expected for a convergent sequence of MCMC samples. Overall, the convergence diagnostics that were examined indicated that the MCMC samples generated from the production model had numerically converged to the posterior distribution.

### ***Model Fits to CPUE***

The model generally fit well to standardized CPUE series (**Figure 4**). Standardized log residuals for the first and second Japanese CPUE series appeared to fluctuate randomly about the observed CPUE. Standardized log residuals for the third Japanese CPUE series were not random because the model underestimated Japanese CPUE in the most recent years (2006-2012) which exhibited a twofold increase over those few years. Since the model was fitting to the high Japanese CPUE, the residuals for the most recent years of Taiwanese CPUE also did not appear random although the magnitude of the residuals was relatively small. However, the Shapiro-Wilks normality test indicated that standardized log residuals from each CPUE series were normally distributed ( $P>0.05$ ). Standardized log residuals of the first Japanese CPUE, third Japanese CPUE, and Taiwanese CPUE exhibited a time trend ( $P\leq 0.01$ ) according to a regression of standardized log residuals against time. Bartlett's test showed that the variance of standardized log residuals for the first and third Japanese CPUE were not homogeneous ( $P<0.05$ ), but were homogeneous for the Taiwanese CPUE ( $P>0.05$ ). Standardized log residuals for the second Japanese CPUE series showed no time trend ( $P>0.05$ ) and had homogeneous variance ( $P>0.05$ ).

Based on RMSE values, model fits were best for the first two Japanese CPUE series (1952-1974, 1975-1993), followed by the Taiwanese series (2000-2012) (

Table 4). The poorest fit (highest RMSE value) came from the model fit to the third Japanese CPUE series from 1994-2012, which is reflective of the challenges of fitting the model to the high values of CPUE in recent years. The correlation coefficients for all Japanese CPUE series are greater than 0.50 and indicate a generally good model fit to CPUE trend. The correlation coefficient for the Taiwan CPUE series was a moderately good fit to CPUE trend with a value of 0.43. Overall, the model fit well to all CPUE series with some exceptions for the most recent years of high CPUE from the third Japanese series.

### ***Estimated Parameters, Outputs, and Reference Points***

The estimated key model parameters from the Bayesian state-space production model are shown in Table 5. The intrinsic growth rate was estimated at 0.45 and the carrying capacity was ~66,000 mt with a maximum sustainable yield of 5,390 mt. Biomass at maximum sustainable yield was estimated to be about 50% of the carrying capacity at 31,300 mt, and harvest rate at maximum sustainable yield was estimated to be 0.18. The initial proportion of biomass to carrying capacity was 0.88, close to the initially assumed value of 0.90. The production shape parameter was estimated as 0.91, close to a symmetric Schaefer curve, but had a very high standard deviation of 0.71.

The model also estimated exploitable biomass and harvest rate over the entire time period of catch data from 1951-2012 (**Table 6, Figure 5**). Exploitable biomass was initially near carrying capacity and has fluctuated ranging from 30,000 to 60,000 mt, generally remaining above  $B_{MSY}$  over the time period. The estimated 95% confidence intervals are large enough that the lower 95% confidence limit falls below  $B_{MSY}$  over much of the time period. Harvest rate was initially

low and steadily increased, likely exceeding  $H_{MSY}$  in 1998, 2002, 2003, and the most recent year, 2012. The trends for biomass and harvest rate in relation to biological reference points are presented as a Kobe plot in **Figure 6**, illustrating that overfishing may have occurred at a few points in the history of the fishery, and is likely occurring in the most recent years. Swordfish in the EPO are currently experiencing overfishing with a 56.7% probability.

### **Sensitivity Analysis**

The sensitivity analysis using high (+25%) and low (-25%) values of input prior means for the parameters  $R$ ,  $K$ ,  $S$ , and  $P_1$  generally indicated that the model results were robust to changes in the prior assumptions (**Table 7**). Estimates of biomass and harvest rate trend and scale were also robust to the high and low alternative prior means (**Figure 7**). Overall, this suggested that the priors were not unduly influential for the base case EPO swordfish production model results.

### **Retrospective Analysis**

The retrospective analysis reveals a clear and consistent pattern that the base case terminal year assessment (ending in 2012) overestimates exploitable biomass and underestimates harvest compared to model runs that sequentially remove recent years of data (**Figure 8**). This result suggests there is a retrospective pattern in the data, the cause of which is unknown and cannot be determined. Thus our base case assessment exaggerates biomass estimates, resulting in underestimates of historic harvest rates and overestimates of  $MSY$ . Any management decisions based on the results of this assessment should consider the fact that this model overestimates biomass because of a clear retrospective pattern in the data.

## Projections

Stochastic projections revealed that biomass will follow a decreasing trajectory over time under all future harvest scenarios (**Table 8, Figure 9**). Under the most aggressive future harvest scenarios (recent status quo catch, maximum observed harvest rate, and  $1.50 * F_{MSY}$ ), biomass values were estimated to be just above  $B_{MSY}$  after 4 years. These aggressive future harvest scenarios, including  $1.25 * F_{MSY}$ , resulted in harvest rates above  $H_{MSY}$ . The most conservative future harvest scenario of  $0.50 * F_{MSY}$  resulted in the smallest decline of biomass, from 50,800 mt in 2013 to 48,800 mt in 2016. Overall, the projections showed that if recent high catch levels persist, biomass will likely decrease and overfishing will likely continue to occur.

## Risk Analysis

The risk analysis showed that the probabilities of overfishing and becoming overfished increased as future projected catch increased (**Table 9, Figure 10**). Catch levels must be below ~9,000 mt, below the average current catch, for the probability of overfishing to fall below a moderate risk threshold of 50%. At this catch level there is a 0% probability of becoming overfished. A reduced catch level of 5,800 mt resulted in a probability of overfishing of 16%. A moderate, 50% probability of becoming overfished did not occur until catch was ~30,000 mt, at which point there was a 100% probability of overfishing occurring.

## DISCUSSION

Our assessment using a Bayesian state-space production model produced estimates and associated uncertainty of parameters, biological reference points, stock status, and future stock status given different harvest scenarios. Results indicated that overfishing may be occurring in the swordfish longline fishery in the Eastern Pacific Ocean. This result reflects model fittings to the catch and CPUE time series, including the increases in catch and Japanese CPUE in recent years. The high increase exhibited by Japanese CPUE was not mirrored by the Taiwanese CPUE. Our results were robust to the values of assumed prior means. There is a 56.7% probability that overfishing was occurring in 2012, while there is a 0% chance that the stock was overfished in 2012. If the 2012 high catch levels persist, the risk of overfishing will also persist. Therefore the EPO swordfish stock is at a healthy level, but the most recent catch levels may be high if the long-term sustainability of the fishery is a management goal.

During the model selection process and prior to settling on the base case model presented here, model runs that included the early Taiwanese CPUE series (1968-1999) (Sun et al. 2014) failed to converge, so the early Taiwanese CPUE series was omitted from the final base case model. Future assessments should explore the inclusion of this CPUE series using updated catch and CPUE data, and perhaps a different model.

Applying a Bayesian estimation framework allowed us to make clear statements about the degree of confidence in estimated quantities (Ellison 2004), including biological reference points and the effect of various future harvest scenarios on the stock. By providing probabilities of overfishing and becoming overfished for future harvest scenarios, we empower managers to implement a precautionary approach to swordfish fishery management in which managers can

choose acceptable risk levels for undesirable outcomes and apply decision tables to judge the efficacy of alternative management options (Hilborn and Peterman 1996, McAllister and Kirkwood 1998). A notable result from using the Bayesian estimation framework is the large 95% confidence intervals for biomass estimates indicating moderately high uncertainty over the time series of the fishery (1951-2012) and also in the projections and risk analysis. We also apply the Bayesian framework in our risk analysis, providing probabilities of status outcomes (overfished and overfishing) across a range of assumed future catch levels.

We caution that our analysis revealed a clear retrospective pattern in the data, resulting in our assessment model overestimating exploitable biomass and underestimating historic harvest rates. Any management decisions should take into account this tendency of our model to overestimate biomass and  $B_{MSY}$ . We recommend that further assessment work on North Pacific swordfish should be conducted to determine whether the retrospective pattern can be accounted for, and should also move towards using more detailed biological data with age- or length-structured models.

## **ACKNOWLEDGMENTS**

We sincerely thank the ISC Billfish Working Group for their help in preparing and providing information for this assessment update.

## **REFERENCES**

- Brodziak, J. 2007. An investigation of alternative production models to assess the Hawaiian bottomfish complex. Administrative Report H-07-01, Pacific Islands Fisheries Science Center, National Marine Fisheries Service, NOAA, Honolulu, HI, 96822.
- Brodziak, J. 2009. Potential natural mortality rates of North Pacific swordfish. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/09/BILLWG-1/13.
- Brodziak, J. 2010. Update of the production model assessment of the Eastern Pacific swordfish stock (*Xiphias gladius*) in 2010. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/10/BILLWG-1/02.
- Brodziak, J. and G. Ishimura. 2009. Development of Bayesian surplus production models for assessing the North Pacific swordfish population. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/09/BILLWG-2/02.
- Chang, Y.-J., A. Yau, and J. Brodziak. 2014. Stock assessment of Western and Central North Pacific Ocean swordfish (*Xiphias gladius*) through 2012. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/14/BILLWG-1/02.
- Congdon, P. 2001. Bayesian statistical modeling. Wiley, New York.
- DeMartini, E. E., J. H. Uchiyama, R. L. Humphreys Jr, J. D. Sampaga, and H. A. Williams. 2007. Age and growth of swordfish (*Xiphias gladius*) caught by the Hawaii-based pelagic longline fishery. Fishery Bulletin **105**:356-367.

- DeMartini, E. E., J. H. Uchiyama, and H. A. Williams. 2000. Sexual maturity, sex ratio, and size composition of swordfish, *Xiphias gladius*, caught by the Hawaii-based pelagic longline fishery. *Fishery Bulletin* **98**:489-506.
- Dreyfus, M., L. A. Fleischer, J. L. Castillo-Géniz, L. V. González-Ania, A. Liedo-Galindo, J. Tovar-Ávila, P. A. U. Ramírez, and J. G. D. Uribe. 2013. National report of Mexico. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific. ISC/13/PLENARY/08.
- Ellison, A. M. 2004. Bayesian inference in ecology. *Ecology letters* **7**:509-520.
- Gelman, A. and D. B. Rubin. 1992. Inference from iterative simulation using multiple sequences. *Statistical science* **7**:457-472.
- Geweke, J. 1992. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. Pages 169-193 *Bayesian Statistics 4*. Oxford University Press, Oxford, U.K. .
- Gilks, W. R., S. Richardson, and D. J. Spiegelhalter. 1996. Markov chain Monte Carlo in practice. CRC press, London.
- Heidelberger, P. and P. D. Welch. 1983. Simulation run length control in the presence of an initial transient. *Operations Research* **31**:1109-1144.
- Hilborn, R. and R. Peterman. 1996. The development of scientific advice with incomplete information in the context of the precautionary approach. Pages 77-97 *FAO Fisheries Technical Paper*. FAO, Lysekil, Sweden.
- Hinton, M. G. and M. N. Maunder. 2011. Status of Swordfish in the Eastern Pacific Ocean in 2010 and Outlook for the Future. Inter-American Tropical Tuna Commission, Scientific Advisory Committee. SAC-02-09.

- Ichinokawa, G. and J. Brodziak. 2008. Stock boundary between possible swordfish stocks in the northwest and southwest Pacific judged from fisheries data of Japanese longliners. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/08/BILLWG-SS/04.
- ISC. 2009. ISC Plenary, Annex 7. Report of the Billfish Working Group Workshop 19-26 May, 2009, Busan, Korea., International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group.
- Kimoto, A., M. Kanaiwa, and K. Yokawa. 2014. Update of the catch per unit effort (CPUE) distribution of swordfish (*Xiphias gladius*) by the Japanese offshore and distantwater longline fishery in the Pacific. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/14/BILLWG-1/07.
- Kimoto, A. and K. Yokawa. 2014. Updated catch amount of swordfish (*Xiphias gladius*) by the Japanese coastal, offshore, and distant-water longline fishery in the Pacific. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/14/BILLWG-1/04.
- Kleiber, P. and K. Yokawa. 2004. MULTIFAN-CL assessment of swordfish in the North Pacific. International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Swordfish Working Group. ISC/04/SWO-WG/07.
- Legault, C. M. C. 2008. Report of the retrospective working group, January 14-16, 2008, Woods Hole, Massachusetts. Page 30. Working Paper 4.1. Groundfish Assessment Review Meeting (GARM III) Part 2. Assessment Methodology 2008. February 25-29, US Dept of Commerce, Northeast Fisheries Science Center.

- McAllister, M., E. Babcock, E. K. Pikitch, and M. H. Prager. 2000. Application of a non-equilibrium generalized production model to South and North Atlantic swordfish: Combining Bayesian and demographic methods for parameter estimation. Col. Vol. Sci. Pap. ICCAT **51**:1523-1550.
- McAllister, M. and G. Kirkwood. 1998. Bayesian stock assessment: a review and example application using the logistic model. ICES Journal of Marine Science **55**:1031-1060.
- McAllister, M., E. K. Pikitch, and E. Babcock. 2001. Using demographic methods to construct Bayesian priors for the intrinsic rate of increase in the Schaefer model and implications for stock rebuilding. Canadian Journal of Fisheries and Aquatic Sciences **58**:1871-1890.
- Meyer, R. and R. B. Millar. 1999. BUGS in Bayesian stock assessments. Canadian Journal of Fisheries and Aquatic Sciences **56**:1078-1087.
- Mohn, R. 1999. The retrospective problem in sequential population analysis: An investigation using cod fishery and simulated data. ICES Journal of Marine Science: Journal du Conseil **56**:473-488.
- Plummer, M., N. Best, K. Cowles, and K. Vines. 2006. CODA: Convergence diagnosis and output analysis for MCMC. R news **6**:7-11.
- R Development Core Team. 2013. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- SERNAPESCA. 2007-2012. Anuario Estadístico de Pesca y Acuicultura. Servicio Nacional de Pesca y Acuicultura, Valparaiso, Chile.
- Spiegelhalter, D., A. Thomas, N. Best, and D. Lunn. 2003. WinBUGS user manual.
- Sun, C. L., N. J. Su, and S. Z. Yeh. 2014. Standardized CPUE of swordfish (*Xiphias gladius*) for the Taiwanese distant-water tuna longline fishery, based on a two stock scenario in the

- North Pacific. . International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific, Billfish Working Group. ISC/14/BILLWG-1/07.
- Wang, S.-P., C.-L. Sun, A. E. Punt, and S.-Z. Yeh. 2005. Evaluation of a sex-specific age-structured assessment method for the swordfish, *Xiphias gladius*, in the North Pacific Ocean. Fisheries Research **73**:79-97.
- Wang, S.-P., C.-L. Sun, A. E. Punt, and S.-Z. Yeh. 2007. Application of the sex-specific age-structured assessment method for swordfish, *Xiphias gladius*, in the North Pacific Ocean. Fisheries Research **84**:282-300.
- Ward, P. and S. Elscot. 2000. Broadbill swordfish: Status of world fisheries. Bureau of Rural Sciences, Commonwealth Department of Agriculture, Fisheries and Forestry, Canberra, Australia.

Table 1. Parameters and assumed prior distributions for a Bayesian state-space surplus production model of swordfish in the Eastern Pacific Ocean.

Parameter	Description	Assumed Distribution	Assumed Mean	Assumed CV
$R$	Intrinsic growth rate ( $\text{yr}^{-1}$ )	$R \sim \log N(\log(0.5) - \frac{\sigma_R^2}{2}, \sigma_R^2)$	0.5	50%
$K$	Carrying capacity (1000 mt)	$K \sim \log N(\log(75) - \frac{\sigma_K^2}{2}, \sigma_K^2)$	75,000 mt	50%
$S$	Production shape parameter	$S \sim \text{Gamma}(2,2)$	1.0	71%
$Q_I$	Catchability coefficient for fleet $I$	$1/Q_I \sim \text{Gamma}(0.01,0.01)$	$1/Q_I = 1.0$	Variance = 1000
$P_I$	Initial proportion of biomass to carrying capacity	$P_I \sim \log N(\log(0.9) - \frac{\sigma_{P_I}^2}{2}, \sigma_{P_I}^2)$	0.90	10%
$\tau_I^2$	Observation error variance for fleet $I$	$1/\tau_I^2 \sim \text{Gamma}(2,0.45)$	0.223	50%
$\sigma^2$	Process error variance	$1/\sigma^2 \sim \text{Gamma}(4,0.1)$	0.025	16%

$$CV_\theta = (\exp(\sigma_\theta^2) - 1)^{1/2}$$

Table 2. Swordfish (*Xiphias gladius*) catch in the Eastern Pacific Ocean from 2007-2012, by country and data source. A ‘-’ indicates no effort or data is not available, and “0” indicates catch of less than 1 metric ton. Japanese catch in 2011 and 2012 is provisional.

<b>Country Data Source Fishery</b>	<b>Belize IATTC Longline</b>	<b>Chile Chile</b>	<b>China IATTC Longline</b>	<b>French Polynesia IATTC Longline</b>	<b>Japan Japan Offshore + Distant Water Longline</b>	<b>Korea Korea Longline</b>	<b>Mexico Mexico Longline</b>	<b>Peru IATTC Longline</b>	<b>Spain IATTC Longline</b>	<b>Taiwan Taiwan Offshore + Distant Water Longline</b>	<b>United States WCPFC Longline</b>	<b>Vanuatu WCPFC Longline</b>	<b>Grand Total Catch (mt)</b>
<b>Year</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>	<b>Catch (mt)</b>
2007	-	246	50	28	1386	284	172	46	661	819	2	9	3701
2008	-	312	660	35	1634	424	242	124	390	439	-	2	4262
2009	-	391	573	37	2079	687	394	25	2546	739	1	0	7473
2010	110	472	858	31	2653	398	222	5	3780	1101	1	-	9631
2011	230	182	1571	40	3094	715	257	50	2364	1076	-	8	9586
2012	288	221	1552	55	2986	601	257	50	2377	1509	5	9	9910

Table 3. Input data used for assessment of swordfish (*Xiphias gladius*) in the Eastern Pacific Ocean. Catch is in units of 1000 metric tons. A '-' indicates no effort or data available.

Year	Catch (1000 mt)	Japan CPUE 1	Japan CPUE 2	Japan CPUE 3	Taiwan CPUE
1951	0.00	-	-	-	-
1952	0.00	-	-	-	-
1953	0.00	-	-	-	-
1954	0.72	-	-	-	-
1955	0.41	0.069	-	-	-
1956	0.61	0.049	-	-	-
1957	0.72	0.201	-	-	-
1958	0.48	0.118	-	-	-
1959	0.48	0.066	-	-	-
1960	0.52	0.091	-	-	-
1961	0.83	0.157	-	-	-
1962	1.36	0.180	-	-	-
1963	1.79	0.232	-	-	-
1964	3.97	0.196	-	-	-
1965	2.02	0.171	-	-	-
1966	2.23	0.189	-	-	-
1967	2.84	0.200	-	-	-
1968	3.16	0.204	-	-	-
1969	7.15	0.241	-	-	-
1970	6.41	0.280	-	-	-
1971	2.32	0.218	-	-	-
1972	3.23	0.180	-	-	-
1973	5.46	0.246	-	-	-
1974	2.37	0.260	-	-	-
1975	2.19	-	0.351	-	-
1976	3.27	-	0.359	-	-
1977	3.13	-	0.388	-	-
1978	2.63	-	0.347	-	-
1979	1.88	-	0.290	-	-
1980	2.76	-	0.311	-	-
1981	3.62	-	0.384	-	-
1982	3.36	-	0.321	-	-
1983	2.12	-	0.317	-	-
1984	1.46	-	0.258	-	-
1985	1.13	-	0.236	-	-
1986	2.51	-	0.279	-	-
1987	3.48	-	0.302	-	-
1988	3.46	-	0.255	-	-
1989	3.01	-	0.257	-	-
1990	5.57	-	0.304	-	-
1991	4.07	-	0.258	-	-
1992	5.03	-	0.244	-	-
1993	3.73	-	0.273	-	-
1994	3.50	-	-	0.261	-
1995	2.83	-	-	0.266	-
1996	3.94	-	-	0.301	-
1997	5.50	-	-	0.349	-
1998	7.14	-	-	0.405	-
1999	3.18	-	-	0.387	-
2000	5.08	-	-	0.480	0.440

2001	6.94	-	-	0.552	0.571
2002	9.94	-	-	0.437	0.531
2003	7.24	-	-	0.410	0.500
2004	5.87	-	-	0.346	0.509
2005	3.27	-	-	0.353	0.425
2006	2.80	-	-	0.444	0.447
2007	3.70	-	-	0.519	0.478
2008	4.26	-	-	0.676	0.492
2009	7.47	-	-	0.853	0.571
2010	9.63	-	-	1.009	0.502
2011	9.59	-	-	0.999	0.510
2012	9.91	-	-	1.023	0.571

Table 4. Summary of model diagnostics for a Bayesian state-space model of swordfish in the Eastern Pacific Ocean. DIC is the deviance information criterion (a model fit statistic used to compare models that use the same datasets), RMSE is root mean-squared error from fitted versus observed CPUE, and  $\rho$  is the correlation coefficient between observed and predicted CPUE.

<b>Diagnostic</b>	<b>Mean</b>
DIC	-112.96
RMSE Japan CPUE 1 (1952-1974)	0.053
RMSE Japan CPUE 2 (1975-1993)	0.052
RMSE Japan CPUE 3 (1994-2012)	0.168
RMSE Taiwan CPUE (2000-2012)	0.107
$\rho$ Japan CPUE 1 (1952-1974)	0.61
$\rho$ Japan CPUE 2 (1975-1993)	0.58
$\rho$ Japan CPUE 3 (1994-2012)	0.79
$\rho$ Taiwan CPUE (2000-2012)	0.43

Table 5. Estimated mean and standard deviation model parameter values for a Bayesian state-space production model for swordfish in the Eastern Pacific Ocean.

<b>Parameter</b>	<b>Description</b>	<b>Mean</b>	<b>SD</b>
$R$	Intrinsic growth rate	0.45	0.19
$K$	Carrying capacity (1000 mt)	65.77	15.82
$S$	Production shape parameter	0.91	0.71
$P_1$	Initial proportion of biomass to carrying capacity	0.88	0.09
$MSY$	Maximum sustainable yield (1000 mt)	5.39	1.65
$B_{MSY}$	Biomass at maximum sustainable yield (1000 mt)	31.33	6.90
$H_{MSY}$	Harvest rate at maximum sustainable yield	0.18	0.06
$Q_1$	Catchability coefficient for Japan CPUE 1 (1952-1974)	$3.42 \times 10^{-3}$	$1.11 \times 10^{-3}$
$Q_2$	Catchability coefficient for Japan CPUE 2 (1975-1993)	$7.10 \times 10^{-3}$	$2.06 \times 10^{-3}$
$Q_3$	Catchability coefficient for Japan CPUE 3 (1994-2012)	0.012	$3.67 \times 10^{-3}$
$Q_4$	Catchability coefficient for Taiwan CPUE (2000-2012)	0.011	$3.55 \times 10^{-3}$
$\tau_1^2$	Observation error variance for Japan CPUE 1 (1952-1974)	0.173	0.076
$\tau_2^2$	Observation error variance for Japan CPUE 2 (1975-1993)	0.069	0.026
$\tau_3^2$	Observation error variance for Japan CPUE 3 (1994-2012)	0.114	0.053
$\tau_4^2$	Observation error variance for Taiwan CPUE (2000-2012)	0.097	0.045
$\sigma^2$	Process error variance	0.030	0.011

Table 6. Estimated mean values of exploitable biomass and harvest rate for swordfish in the Eastern Pacific Ocean.

Year	Exploitable biomass (1000 mt)			Harvest rate		
	Mean	Lower 95% C.I.	Upper 95% C.I.	Mean	Lower 95% C.I.	Upper 95% C.I.
1951	57.63	34.18	90.93	0.000	0.000	0.000
1952	55.35	30.71	92.13	0.000	0.000	0.000
1953	50.85	23.53	89.36	0.000	0.000	0.000
1954	45.55	13.29	82.92	0.019	0.009	0.054
1955	38.36	11.49	69.87	0.013	0.006	0.036
1956	37.01	13.19	67.79	0.019	0.009	0.046
1957	41.67	16.77	73.76	0.020	0.010	0.043
1958	40.86	17.24	72.78	0.013	0.007	0.028
1959	39.66	16.98	71.09	0.014	0.007	0.028
1960	42.97	19.33	75.99	0.014	0.007	0.027
1961	49.51	23.60	85.91	0.019	0.010	0.035
1962	55.17	27.24	95.16	0.027	0.014	0.050
1963	59.70	29.98	103.1	0.033	0.017	0.060
1964	60.42	30.17	104.8	0.073	0.038	0.132
1965	58.65	28.37	103.6	0.038	0.019	0.071
1966	60.73	29.91	106.6	0.041	0.021	0.075
1967	62.90	30.99	110.8	0.050	0.026	0.092
1968	64.81	31.86	114.2	0.054	0.028	0.099
1969	67.74	33.36	119.5	0.117	0.060	0.214
1970	65.46	30.99	117.5	0.110	0.055	0.207
1971	61.51	28.81	111.2	0.042	0.021	0.080
1972	61.87	30.35	109.4	0.058	0.029	0.106
1973	63.39	31.87	111.0	0.095	0.049	0.171
1974	60.07	30.13	105.3	0.044	0.022	0.079
1975	56.70	29.63	97.83	0.042	0.022	0.074
1976	56.08	29.39	96.66	0.064	0.034	0.111
1977	55.05	28.50	94.96	0.062	0.033	0.110
1978	52.28	26.83	90.37	0.055	0.029	0.098
1979	49.55	25.29	85.78	0.042	0.022	0.074
1980	50.51	25.98	87.08	0.060	0.032	0.106
1981	52.01	26.77	90.01	0.077	0.040	0.135
1982	48.90	24.88	85.17	0.076	0.039	0.135
1983	46.25	23.28	80.86	0.051	0.026	0.091
1984	43.17	21.63	75.84	0.038	0.019	0.068
1985	42.22	21.24	73.75	0.030	0.015	0.053
1986	44.15	22.50	76.42	0.063	0.033	0.112
1987	44.64	22.87	77.24	0.086	0.045	0.152
1988	42.53	21.83	73.86	0.090	0.047	0.159
1989	42.13	21.50	73.12	0.079	0.041	0.140
1990	43.32	22.66	74.60	0.141	0.075	0.246
1991	39.89	20.43	69.58	0.113	0.059	0.199
1992	38.23	19.86	66.39	0.145	0.076	0.254
1993	35.98	18.33	63.31	0.115	0.059	0.204
1994	32.23	16.06	57.77	0.121	0.061	0.218
1995	31.63	15.51	57.55	0.100	0.049	0.182
1996	33.69	16.88	60.35	0.130	0.065	0.233

1997	36.25	18.49	64.40	0.168	0.085	0.297
1998	38.15	19.49	68.04	0.207	0.105	0.367
1999	38.26	18.81	70.00	0.093	0.045	0.169
2000	43.66	22.62	77.14	0.128	0.066	0.224
2001	47.68	25.24	83.97	0.160	0.083	0.275
2002	46.18	24.45	81.38	0.237	0.122	0.407
2003	41.93	21.05	75.78	0.192	0.096	0.344
2004	39.97	19.72	72.49	0.164	0.081	0.298
2005	39.25	19.23	71.29	0.093	0.046	0.170
2006	43.14	21.57	77.34	0.072	0.036	0.130
2007	48.43	24.72	86.32	0.085	0.043	0.150
2008	54.37	27.86	97.24	0.087	0.044	0.153
2009	61.18	31.52	109.4	0.135	0.068	0.237
2010	62.76	31.64	114.1	0.171	0.084	0.304
2011	61.52	30.03	114.0	0.175	0.084	0.319
2012	59.28	27.67	112.1	0.190	0.088	0.358

Table 7. Effects of high (+25%) and low (-25%) changes in prior means on model parameters including maximum sustainable yield ( $MSY$ ), exploitable biomass to produce  $MSY$  ( $B_{MSY}$ ), and harvest rate to produce  $MSY$  ( $H_{MSY}$ ).

<i>Parameter</i>	<b>Base case</b>		<b>1.25*R</b>		<b>0.75*R</b>		<b>1.25*K</b>		<b>0.75*K</b>		<b>1.25*P<sub>1</sub></b>		<b>0.75*P<sub>1</sub></b>		<b>1.25*S</b>		<b>0.75*S</b>	
	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>
<i>R</i>	0.452	0.194	0.536	0.236	0.370	0.153	0.436	0.194	0.462	0.197	0.451	0.195	0.434	0.188	0.414	0.186	0.482	0.207
<i>K</i>	65.77	15.82	64.81	15.58	67.65	15.57	70.78	18.46	61.19	14.56	62.65	15.15	70.27	16.46	65.38	17.05	68.19	15.78
<i>S</i>	0.913	0.712	0.773	0.589	1.027	0.707	0.993	0.953	0.996	0.769	1.107	0.861	0.759	0.493	1.281	1.181	0.697	0.413
<i>P<sub>1</sub></i>	0.878	0.089	0.879	0.089	0.877	0.090	0.880	0.089	0.881	0.089	1.108	0.116	0.652	0.066	0.883	0.089	0.875	0.089
<i>B<sub>MSY</sub></i>	31.33	6.90	30.09	6.71	33.08	7.27	34.14	10.46	29.54	6.43	30.79	7.01	32.72	7.23	32.76	9.40	31.41	6.88
<i>B<sub>1951</sub></i>	57.63	14.55	56.82	14.42	59.20	14.46	62.17	17.21	53.79	13.47	69.26	17.68	45.76	11.37	57.61	15.89	59.54	14.59
<i>B<sub>1951</sub>/B<sub>MSY</sub></i>	1.84	0.26	1.89	0.26	1.80	0.25	1.84	0.27	1.83	0.26	2.26	0.34	1.40	0.19	1.78	0.28	1.90	0.24
<i>B<sub>2012</sub></i>	59.28	21.83	58.19	21.23	61.56	22.40	63.24	23.35	54.90	20.61	55.92	20.48	63.56	23.28	57.85	21.43	62.24	22.68
<i>B<sub>2012</sub>/B<sub>MSY</sub></i>	1.89	0.55	1.93	0.55	1.86	0.54	1.89	0.58	1.85	0.54	1.82	0.52	1.94	0.56	1.79	0.54	1.98	0.57
<i>H<sub>MSY</sub></i>	0.179	0.063	0.193	0.070	0.160	0.055	0.170	0.060	0.191	0.068	0.193	0.066	0.158	0.055	0.181	0.061	0.171	0.062
<i>H<sub>1951</sub></i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
<i>H<sub>1951</sub>/H<sub>MSY</sub></i>	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
<i>H<sub>2012</sub></i>	0.190	0.069	0.193	0.071	0.182	0.066	0.178	0.066	0.206	0.077	0.201	0.073	0.177	0.064	0.195	0.072	0.180	0.065
<i>H<sub>2012</sub>/H<sub>MSY</sub></i>	1.13	0.44	1.07	0.43	1.21	0.46	1.12	0.43	1.14	0.44	1.10	0.40	1.19	0.46	1.14	0.43	1.13	0.46
<i>MSY</i>	5.39	1.65	5.58	1.75	5.12	1.57	5.62	2.17	5.43	1.64	5.74	1.71	4.99	1.47	5.70	1.88	5.18	1.60

Table 8. Biomass (1000 mt) and harvest rate from eight different harvest scenarios projected forward 4 years.

Year	RECENT HARVEST RATE				RECENT CATCH				MAX OBS. HARVEST RATE				$F_{MSY}$			
	Biomass		Harvest rate		Biomass		Harvest rate		Biomass		Harvest rate		Biomass		Harvest rate	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
2012	59.28	21.83	0.19	0.07	59.28	21.83	0.19	0.07	59.28	21.83	0.19	0.07	59.28	21.83	0.19	0.07
2013	50.79	20.05	0.18	0.06	50.87	19.97	0.22	0.09	50.84	20.01	0.25	0.07	50.73	19.92	0.18	0.06
2014	46.19	19.11	0.18	0.06	44.74	19.85	0.26	0.13	42.62	18.00	0.25	0.07	45.82	18.00	0.18	0.06
2015	42.91	18.34	0.18	0.06	39.33	19.93	0.37	1.66	37.57	16.76	0.25	0.07	42.63	16.88	0.18	0.06
2016	40.61	17.83	0.18	0.06	34.24	20.18	2.49	19.57	34.05	15.97	0.25	0.07	40.35	16.06	0.18	0.06

Year	$0.50 * F_{MSY}$				$0.75 * F_{MSY}$				$1.25 * F_{MSY}$				$1.50 * F_{MSY}$			
	Biomass		Harvest rate													
	Mean	SE	Mean	SE												
2012	59.28	21.83	0.19	0.07	59.28	21.83	0.19	0.07	59.28	21.83	0.19	0.07	59.28	21.83	0.19	0.07
2013	50.81	19.95	0.09	0.03	50.78	19.93	0.14	0.04	50.74	19.95	0.21	0.07	50.79	20.01	0.25	0.08
2014	49.95	19.30	0.09	0.03	47.86	18.65	0.14	0.04	43.80	17.46	0.21	0.07	42.20	17.17	0.25	0.08
2015	49.30	18.81	0.09	0.03	45.86	17.81	0.14	0.04	39.63	16.14	0.21	0.07	37.17	15.55	0.25	0.08
2016	48.85	18.52	0.09	0.03	44.40	17.27	0.14	0.04	36.74	15.14	0.21	0.07	33.65	14.34	0.25	0.08

Table 9. Results from the final projected year of the risk analysis, 2017. Projected catch levels, probability of becoming overfished, and probability of overfishing are presented.

<b>Catch (1000 mt)</b>		<b>Prob(<math>B &lt; 0.5 * B_{MSY}</math>)</b>		<b>Prob(<math>H &gt; H_{MSY}</math>)</b>	
<b>Mean</b>	<b>SE</b>	<b>Mean</b>	<b>SE</b>	<b>Mean</b>	<b>SE</b>
1.94	0.17	0.00	0.00	0.02	0.13
3.88	0.17	0.00	0.01	0.06	0.24
5.83	0.17	0.00	0.02	0.16	0.37
7.77	0.17	0.00	0.03	0.33	0.47
9.71	0.17	0.00	0.06	0.54	0.50
11.65	0.17	0.01	0.10	0.72	0.45
13.59	0.17	0.02	0.14	0.84	0.37
15.53	0.17	0.04	0.21	0.91	0.28
17.48	0.17	0.09	0.28	0.96	0.21
19.42	0.17	0.14	0.34	0.98	0.15
21.36	0.17	0.19	0.39	0.99	0.11
23.30	0.17	0.26	0.44	0.99	0.09
25.24	0.17	0.32	0.47	1.00	0.07
27.18	0.17	0.40	0.49	1.00	0.05
29.13	0.17	0.49	0.50	1.00	0.04
31.07	0.17	0.56	0.50	1.00	0.02
33.01	0.17	0.62	0.49	1.00	0.02
34.95	0.17	0.71	0.45	1.00	0.01
36.89	0.17	0.78	0.42	1.00	0.00
38.84	0.17	0.79	0.41	1.00	0.00

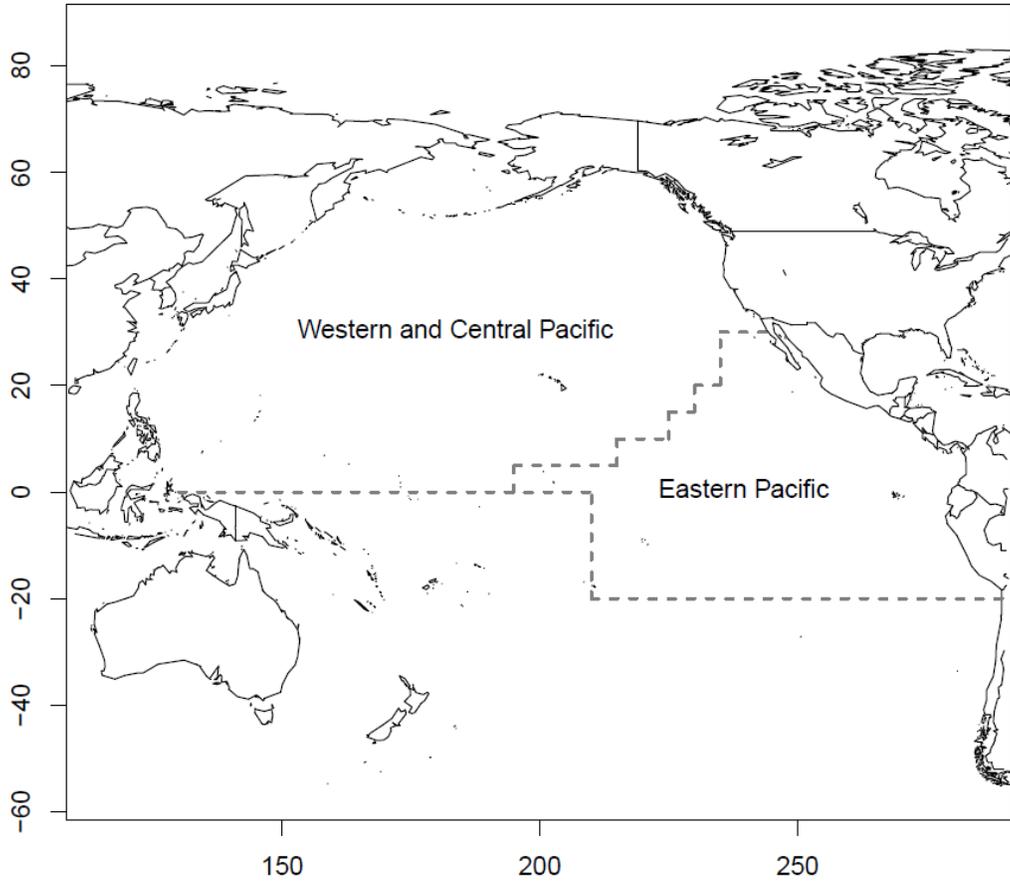


Figure 1. Two-stock structure for swordfish (*Xiphias gladius*) in the North Pacific Ocean, indicating separate stocks in the Western and Central Pacific Ocean and in the Eastern Pacific Ocean. This paper assesses swordfish in the Eastern Pacific Ocean.

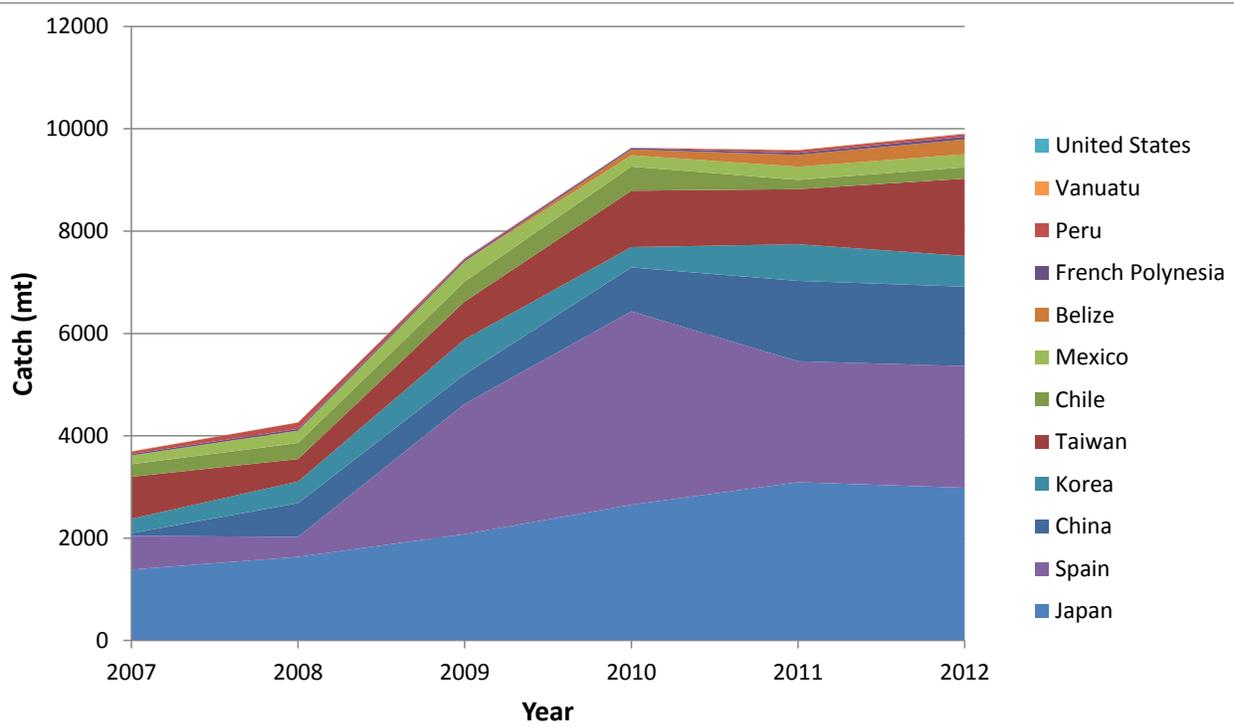


Figure 2. Swordfish (*Xiphias gladius*) catch in the Eastern Pacific Ocean from 2007-2012, compiled using data from IATTC, WCPFC, Japan, Taiwan, Korea, Mexico, and Chile.

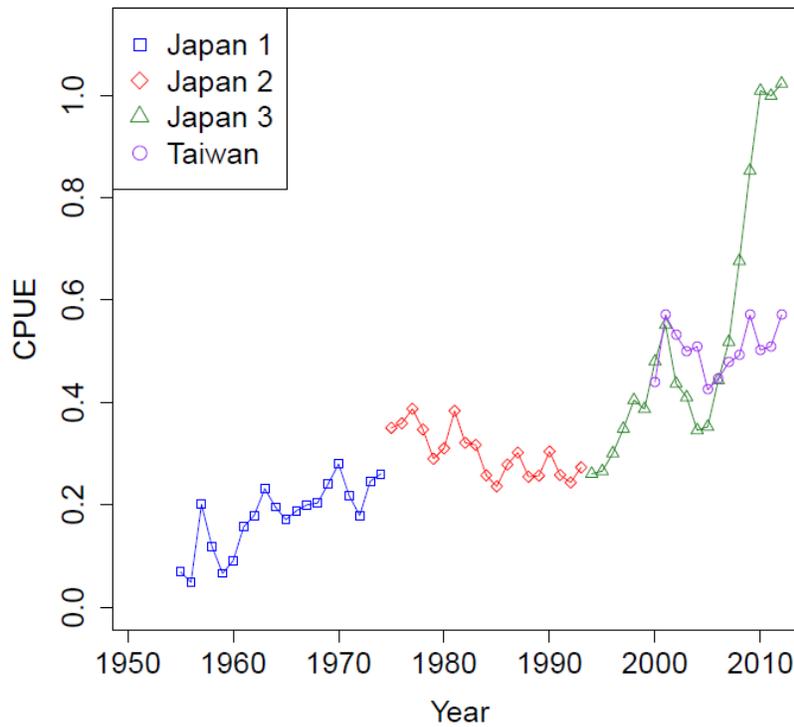
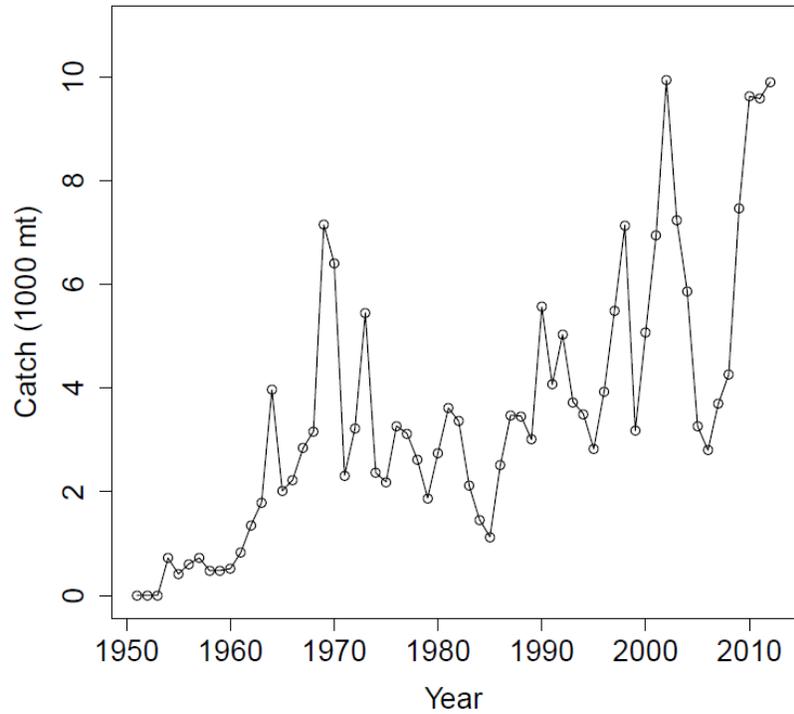


Figure 3. Input data for assessment of swordfish, *Xiphias gladius*, in the Eastern Pacific Ocean. (Top) Total catch data from 1951-2012. (Bottom) Three CPUE time series for Japan and one for Taiwan.

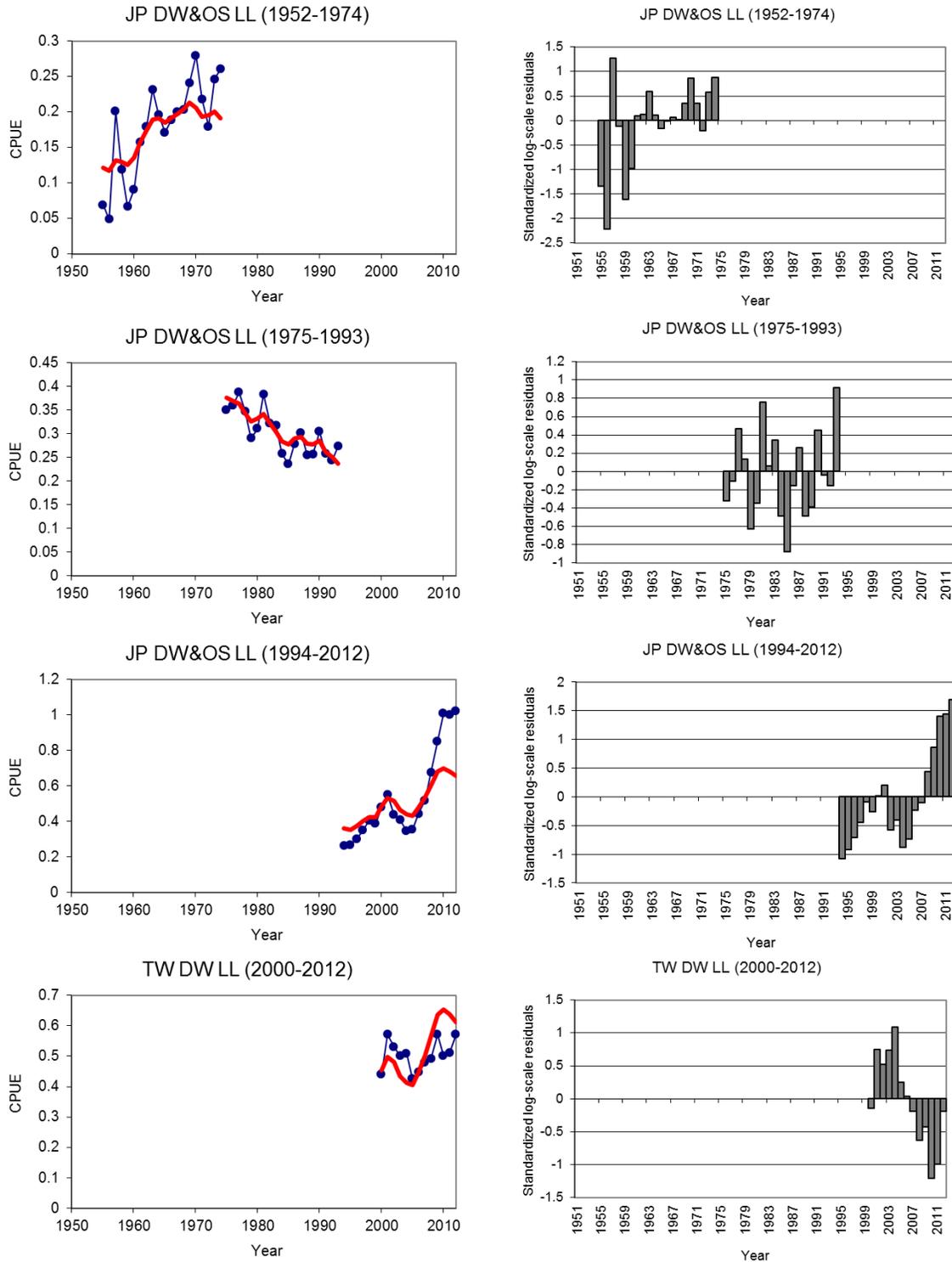


Figure 4. (Left) Bayesian surplus production model fits (solid red line) to standardized CPUE (blue dots and line) for swordfish in the Eastern Pacific Ocean. “JP DW&OS LL” represents the Japanese distant water and offshore longline fleet, and “TW DW LL” represents the Taiwanese distant water longline fleet. (Right) Standardized log residuals from Bayesian surplus production model fits to standardized CPUE.

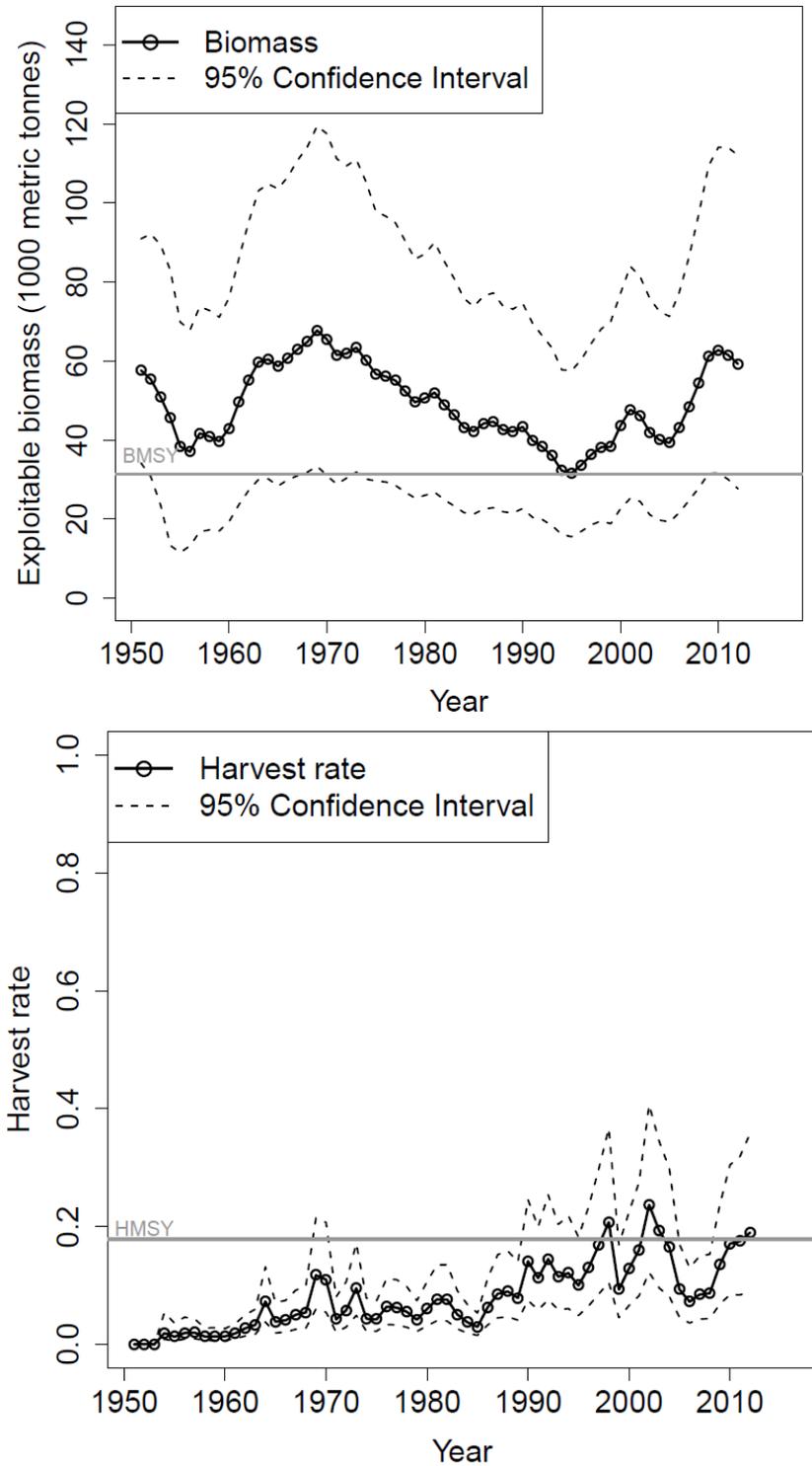


Figure 5. The estimated exploitable biomass (Top) and harvest rate (Bottom) for swordfish in the Eastern Pacific Ocean. Estimated mean values (black dots and solid line), 95% confidence intervals (black dotted line), and estimated biological reference points ( $B_{MSY}$  and  $H_{MSY}$ , gray solid line) are presented.

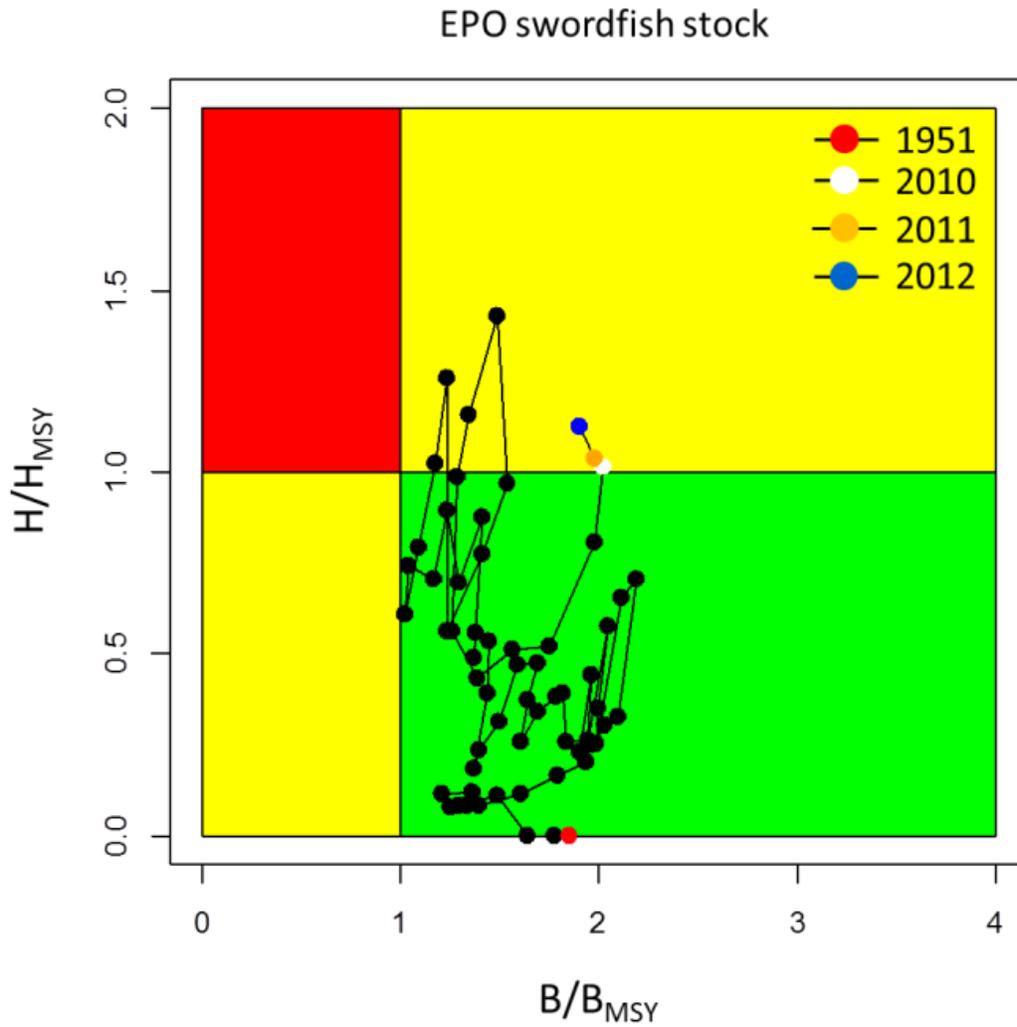


Figure 6. The Kobe plot indicating the status of swordfish in Eastern Pacific Ocean. Green quadrant indicates biomass is above  $B_{MSY}$  and harvest rate is below  $H_{MSY}$ : stock is not overfished, and overfishing is not occurring. Red quadrant indicates stock is overfished and overfishing is occurring.

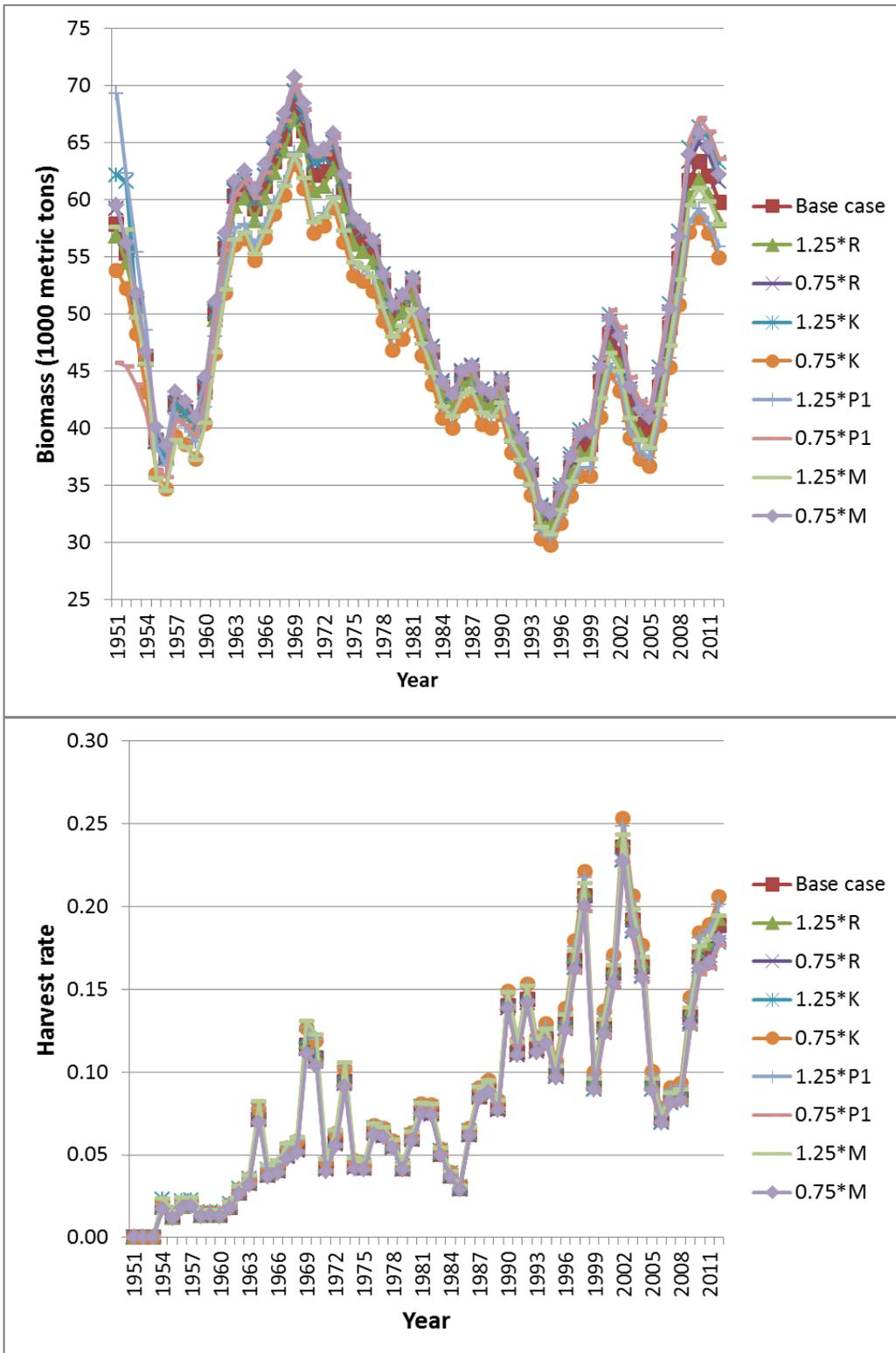


Figure 7. (Top) Exploitable biomass and (Bottom) harvest rate for various sensitivity analysis runs examining the effect of changing a prior mean value on model outputs for swordfish in the Eastern Pacific Ocean.

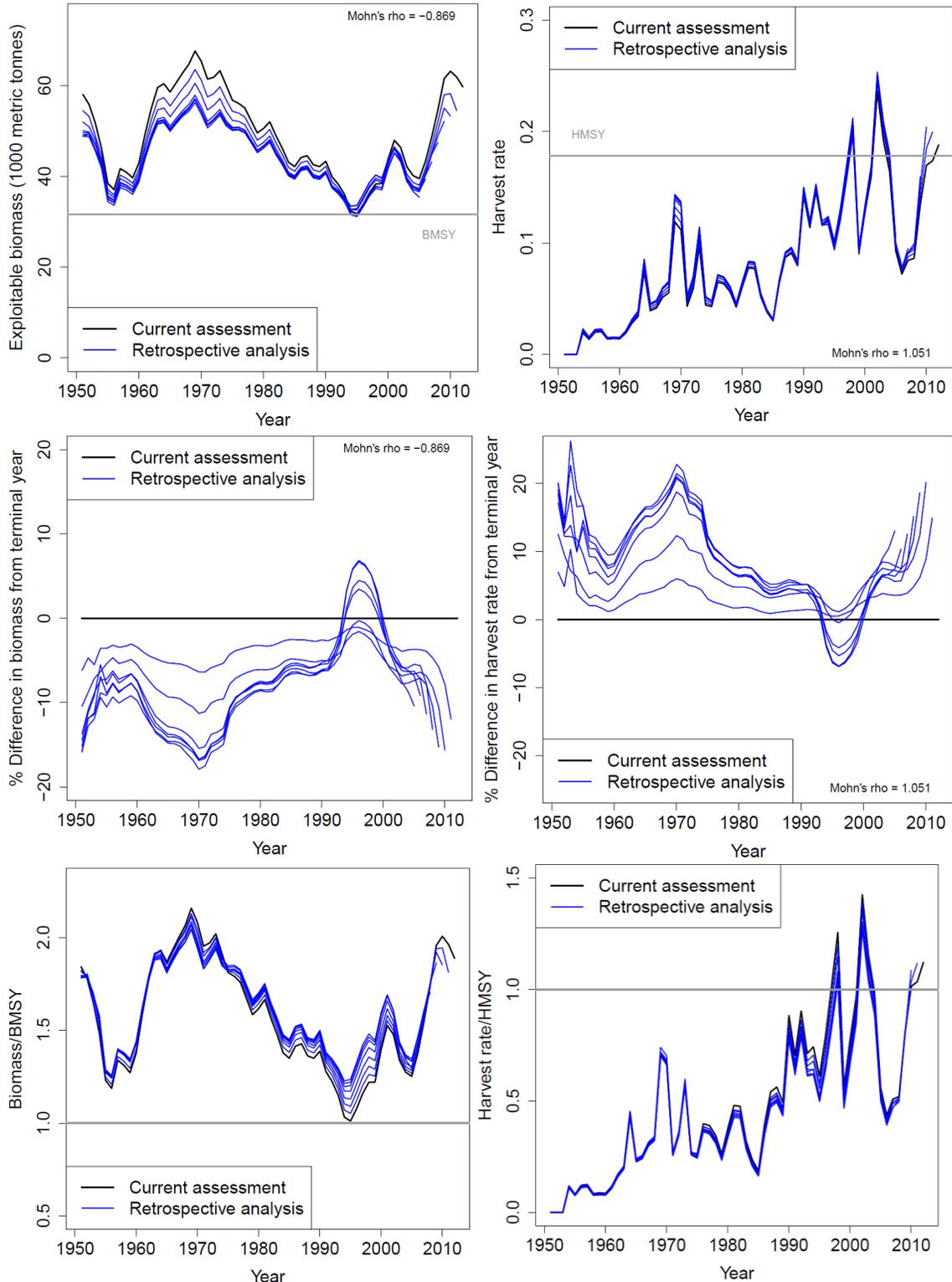


Figure 8. Results for (Left) biomass and (Right) harvest rates estimated from the retrospective analysis for the most recent 7 years. (Top) Estimated biomass and harvest rate trends, (Middle) the percent difference between estimated biomass and biomass using data through the terminal year of 2012, and (Bottom) the status of biomass and harvest rate relative to their estimated reference points from the terminal year assessment ( $B_{MSY}$  and  $H_{MSY}$ , respectively).

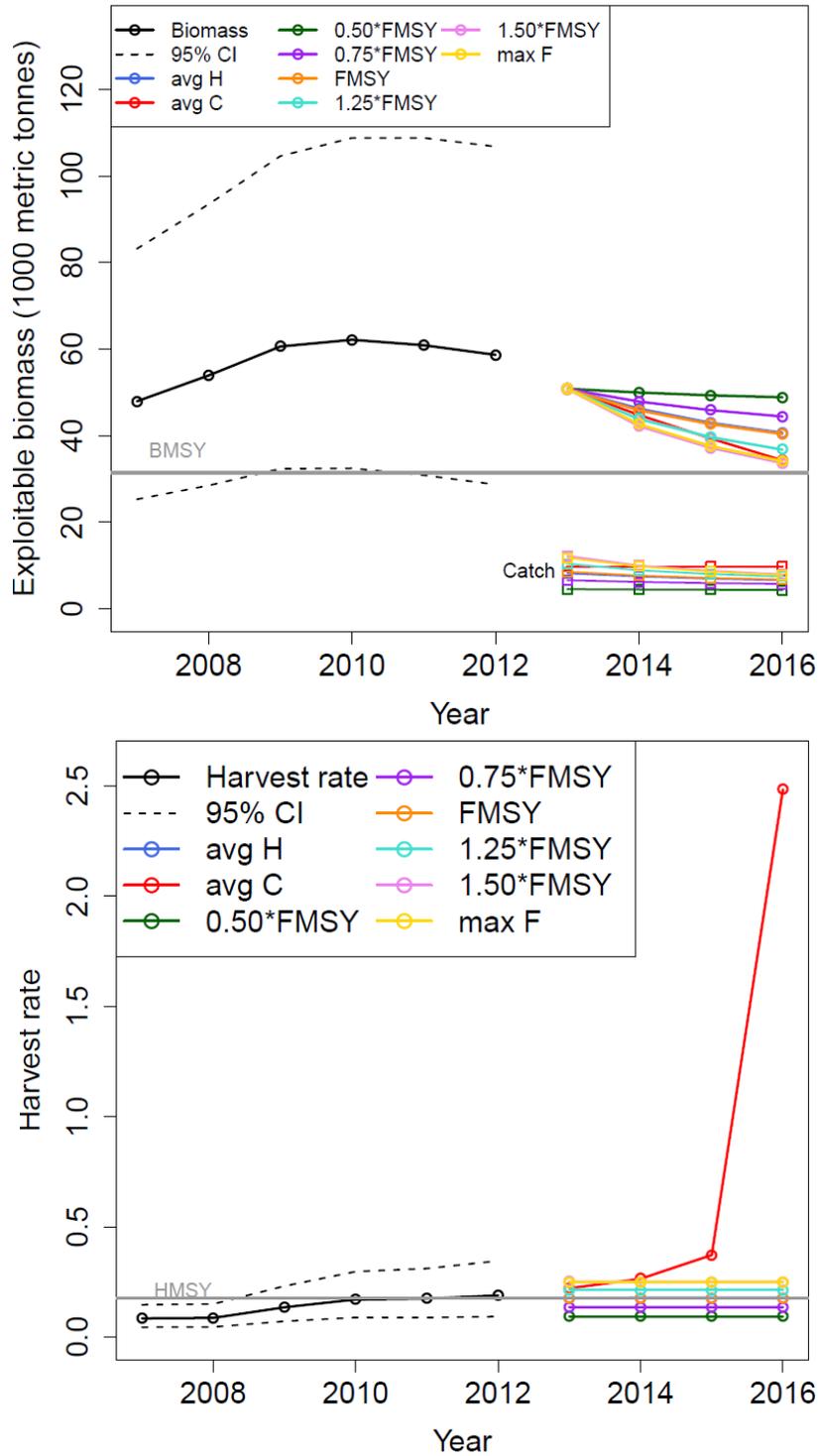


Figure 9. (Top) Biomass and (Bottom) harvest rate results of a projection analysis for swordfish in the Eastern Pacific Ocean. Results from the most recent 6 years of the base case assessment are plotted in black, with estimated reference points plotted as solid gray lines. Abbreviation “avg H” represents the status quo harvest rate from the most recent 3 years, “avg C” represents the status quo catch from the most recent 3 years, and “max F” represents the maximum historically-observed single-year harvest rate.

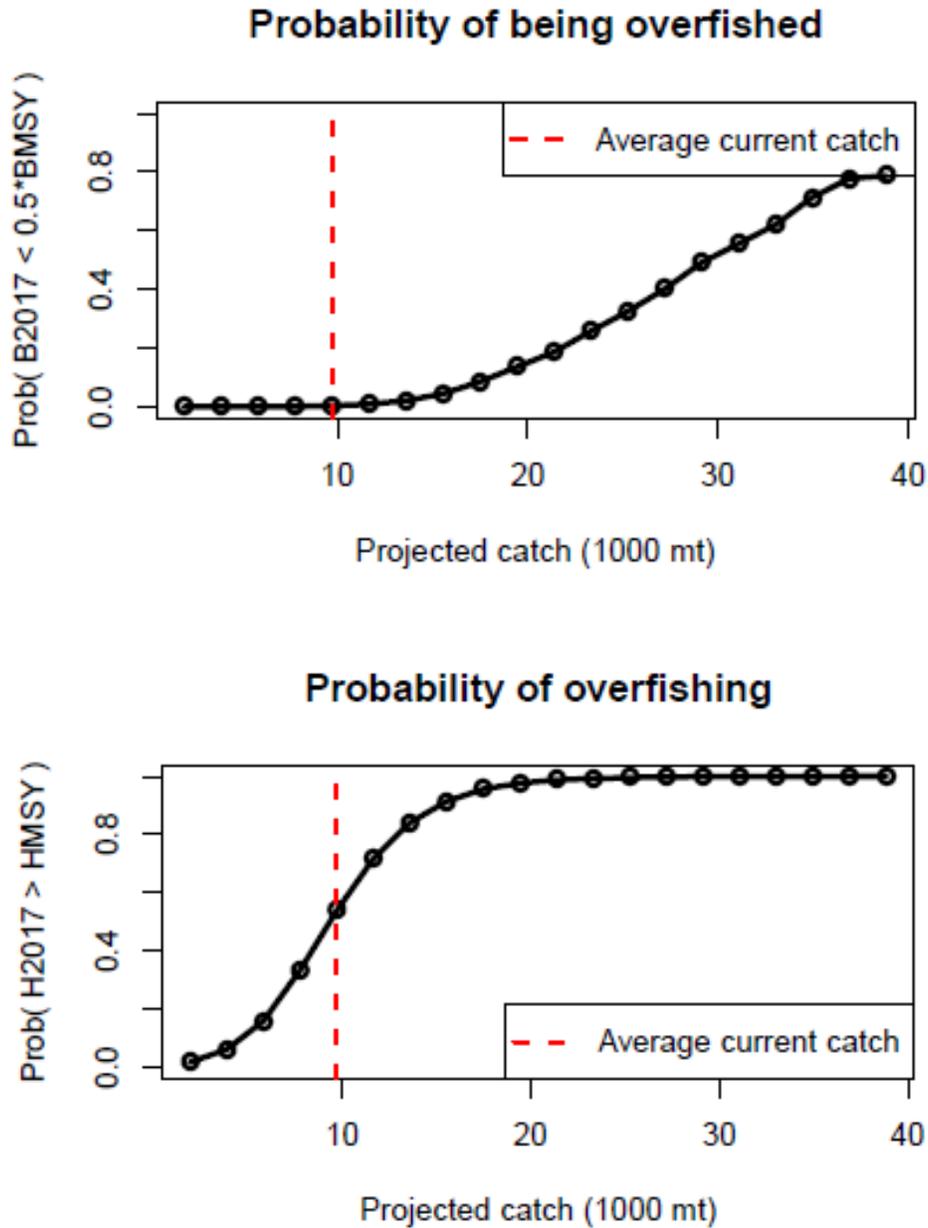


Figure 10. Results from final year of risk analysis (2017) projecting various catch levels for swordfish in the Eastern Pacific Ocean 5 years into the future. The average current catch from the most recent 3 years is indicated by the dotted red line. (Top) Probability of being overfished at the end of 5 years, defined as  $B < 0.5 * B_{MSY}$ . (Bottom) Probability of overfishing at the end of 5 years, defined as  $H < H_{MSY}$ .