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Incorporating specific change points in catchability in fisheries stock assessment models: An alternative approach applied to the blue shark (*Prionace glauca*) stock in the south Atlantic Ocean

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ABSTRACT

Fishermen frequently switch their target fish species without documenting changes in which species they are targeting and the used fishing practices, generating misleading catchability information about the caught fish. To date, changes in target species have been incorporated in stock assessments at two different levels in analyses. First, these changes are taken into account during the parameterization of generalized linear models used to compute the CPUE index standardization. Second, changes in target species are directly incorporated as a time-varying catchability parameter during the fitting of the dynamic model used for the assessment. Here, we present an alternative method for this incorporation by specifying a single change point in the stationary distribution of the catchability coefficient in a Bayesian state-space production model. Two models were fitted to the time series of the south Atlantic blue shark (*Prionace glauca*) stock. In one of the models, only one catchability coefficient was estimated. In the other model, a changing point was included, and two catchability coefficients were estimated, one before the changing point, and the other after. Despite the latter model introducing an extra parameter, it produced a significantly better fit than the modeling approach before the change point. Although including a single change point in the catchability coefficient had no significant impact on the status of south Atlantic blue shark (which is still above B_{MSY}), it provided a robust way of accounting for changes in catchability as a result of fishermen changing target species.

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1. Introduction

The majority of abundance indices used in stock assessments are derived from estimates of catch-per-unit effort (CPUE), the number or biomass of fish caught as a function of effort (Quinn and Deriso, 1999). The primary assumption behind a CPUE-based abundance index is that changes in the index are assumed to be proportional to changes in the actual stock abundance (Maunder and Punt, 2004). The catchability coefficient, the proportionality constant between an abundance index and population size, can be an influential parameter in many stock assessment models (Arreguín-Sánchez, 1996). In general, the catchability coefficient is

assumed to be constant over time and independent of population size. These assumptions are unrealistic because many biological, management-based, and fishery-dependent factors may influence catchability in fisheries, such as: spatial and temporal aggregation of fish, changes in fishing power, gear selectivity, environmental variability, and dynamics of the population or fishing fleet (Maunder et al., 2006; Carruthers et al., 2010). In addition to these other factors, fishermen often change the species they target without documentation (Hutchings and Myers, 1994; Salthaug and Aanes, 2003), adding ambiguity to the catchability information of the caught species (Carvalho et al., 2010).

A number of alternative methods can be used to account for variation caused by the above-mentioned factors in the catchability coefficient over time, represented here as time-varying catchability. Two methods are commonly used to address this variability: (1) standardization of the CPUE-derived indices via generalized linear models (GLMs) with the aim of correcting the raw dataset for known factors before the stock assessment is conducted, and (2) direct specification of time-varying catchability during the fitting

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of the dynamic model used for the assessment. If the GLM approach is used, one way to compensate for changes in target species in a multi-species fishery over time is to include changes in target species, along with other factors that are known to influence catchability, in the CPUE standardization process. Carvalho et al. (2010), for example, used cluster analysis and GLMs to incorporate changes in target species of the Brazilian longline fishery when estimating abundance indices for the south Atlantic blue shark (*Prionace glauca*) stock. Their results clearly showed a major change in target species occurring in 1996 when most of the fleet started targeting swordfish (*Xiphias gladius*) instead of tunas (*Thunnus* spp.), with a concomitant switch from using multifilament to monofilament longlines with chemically luminescent light-sticks. Swordfish and blue sharks are commonly caught together in the longline fishery (Campana et al., 2011), and thus this change in target species also increased blue shark catches. However, it was still unclear if the standardization process was able to fully account for the effects of changes in target species on blue shark CPUE variability, indicating a need for further study.

In the assessment process, state-space models are an alternative method to model time-varying catchability. They can be formulated to estimate the catchability coefficient, historical abundance, and other parameters simultaneously, and allow them to vary over time without specifying the source of variation (Wilberg et al., 2010). The interest in state-space models as a modeling tool in fisheries management has increased in the last decade (e.g. Rivot et al., 2004; Michielsens et al., 2006). One of the most important advantages of state-space models is that they can separate an observed process into two components: a system process that models the biological process over time and an observation process that accounts for imperfect detection of the system process, such as measurement error (Buckland et al., 2004; Dennis et al., 2006). Another way to accommodate time-varying catchability in stock assessment models is through the estimation of the variance parameter of the likelihood for the CPUE data (Wilberg et al., 2010). This method does not explicitly model catchability, but estimating an additive variance parameter accommodates additional white-noise variation in the catchability coefficient. Other methods that explicitly model time-varying catchability in stock assessment have also been developed (see Wilberg et al., 2010).

The management of blue shark stocks in the Atlantic Ocean is under the jurisdiction of the International Commission for the Conservation of Atlantic Tunas (ICCAT). In 2008, ICCAT conducted a stock assessment for south Atlantic blue shark using a Bayesian surplus production model and multiple CPUE time series from various fishing fleets. All analyses indicated that current fishing mortality rates for blue shark in the south Atlantic are sustainable. However, the general conclusion of the assessment was that the results needed to be interpreted with considerable caution due to data deficiencies and the resulting uncertainty in the assessment (ICCAT, 2008). The ICCAT working group on assessment methods also expressed concern that some CPUE series used in the assessments might be misleading due to target species changing within the fishery.

Time-varying catchability remains a central concern in fisheries science due to its potential to create biases in stock assessments. The present study aimed to improve the understanding of how changes in catchability over time, specifically due to changes in target species, affected the CPUE standardization process. Furthermore, we illustrate how specifying a single change point in the stationary distribution of the catchability coefficient can lead to different estimates of biological reference points and subsequent harvest quota options. For this purpose, a methodology to incorporate specific changing points in the catchability coefficient in a Bayesian state-space production model was developed and applied to the south Atlantic blue shark stock.

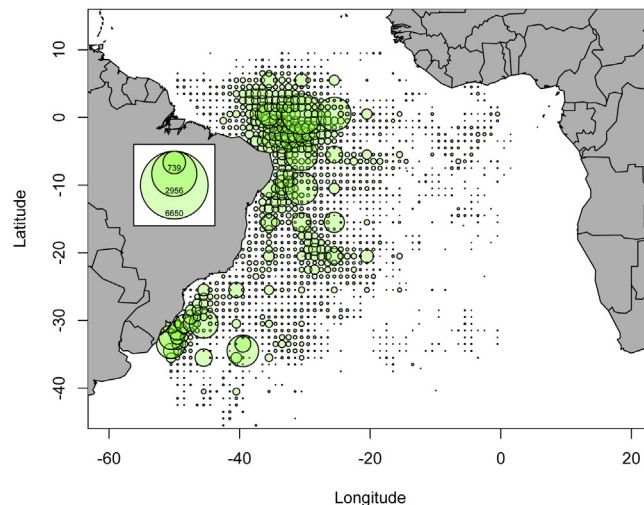


Fig. 1. Distribution of fishing effort in number of hooks by the Brazilian pelagic longline fleet between 1978 and 2012.

2. Materials and methods

Three sequential procedures were used to relate target species changes, catchability, and CPUE time-series to production models: (1) a cluster analysis was used to identify target species in the Brazilian longline fishery in the southwest Atlantic Ocean; (2) standardized CPUE abundance indices for blue shark were constructed with and without the “target species” factor identified through the cluster analysis; and (3) standardized abundance (CPUE) indices were fit to a Bayesian state-space production model under two scenarios. In scenario I, the CPUE series was split into periods pre- and post-1996, the year when there was a marked change (change-point) in the targeted species. The catchability coefficient values were then estimated for each period. In scenario II, the CPUE series used in the model was not split and a single value was estimated for the catchability coefficient. Biological and management reference point estimates from both scenarios were then compared.

2.1. Catch and effort data

Blue shark catch and effort data used in Carvalho et al. (2010) were updated to 2012, increasing the total number of longline sets made by the Brazilian pelagic tuna longline fleet to 72,231, including both national and chartered vessels fishing from 1978 through 2012 (Fig. 1). Logbooks were made available by the Ministry of Fisheries and Aquaculture within the Brazilian government. Longline sets were distributed throughout a wide area of the southwestern Atlantic Ocean, ranging from 10° E and 50° W longitude and between 10° N and 45° S latitude. This total fishing ground was divided into two areas, north and south of 15° S, based on differences in the oceanographic characteristics (Carvalho et al., 2010) (Fig. 1).

The Bayesian state-space production model used the total catch per year for the south Atlantic blue shark between 1978 and 2012. Because the catches reported to ICCAT over time are known to represent only a portion of total removals of the species of concern to ICCAT, working groups have resorted to various methods to estimate a time series of the total catch. Two such methods were used by ICCAT in its last blue shark assessment. The first method, developed by Clarke et al. (2006), estimates shark catches in the Atlantic by all fleets based on a characterization of the global shark fin trade as of 2000, including number and biomass by shark species. In this method, Hong Kong fin trade-based estimates for 2000 were scaled to annual global values for 1980–2006 using the observed

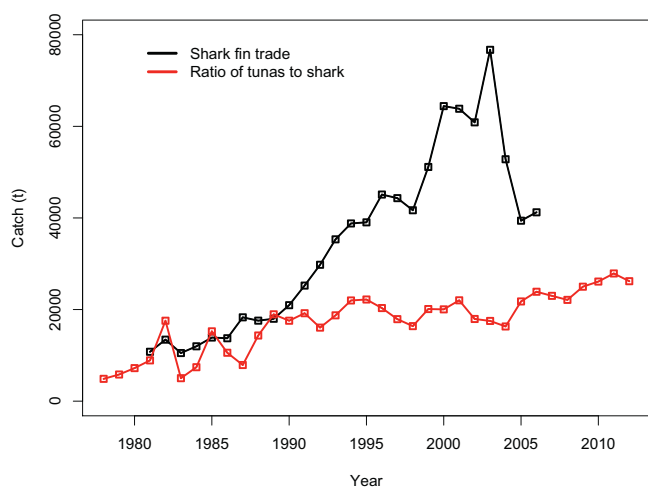


Fig. 2. Annual catches (1978–2012) of blue shark in the south Atlantic Ocean estimated by using data supplied by ICCAT and methods that use either: (1) the ratio of tunas to sharks in the catch; or (2) the total shark fins in the shark-fin trade.

quantity of imports to Hong Kong and an approximation of Hong Kong's share of the global trade in each year. The resulting global fin trade for each year was then scaled to Atlantic-specific values (Clarke, 2008; ICCAT, 2008). The second method was developed by the ICCAT shark working group (ICCAT, 2005). It estimates the percentage of reported shark catch vs. the combined total catch of tunas, swordfish, and billfish. The ratio from this calculation was aggregated by gear and fleet characteristics and applied to strata for which no shark catch information is available in order to estimate possible catch levels of blue shark for non-reporting fleets over the period 1978–2012 in the south Atlantic. As it was in the last ICCAT blue shark assessment, the total catch in each year was set equal to the maximum of the catch estimated from the tuna ratio and the catch estimated from the fin trade data. Except when no fin trade estimates were available during 1978–1980, 1982, 1985, 1989, and 2006–2012, catches were much higher in the fin ratio based estimate than in the tuna ratio based estimate (Fig. 2).

2.2. Cluster analysis

We used cluster analysis to account for changes in target species of the Brazilian longline fishery from 1978 through 2012, as described by Carvalho et al. (2010). Data for the cluster analysis were obtained from the logbooks of the Brazilian longline fishery, which included such information as: vessel identification, fishing locations, starting times of setting and retrieval, number of hooks deployed, and number of fish caught by species. Clusters were developed using SAS 9.3 software (SAS Institute, Cary, NC). First, we fit a non-hierarchical cluster analysis (*K*-means method; Johnson and Wichern, 1988) in order to identify the ideal number of clusters associated with targeting different groups of fish. After the cluster analysis, percentages of the species and species groups were calculated for each cluster. These clusters comprised the “target” species factor in the GLM.

2.3. CPUE standardization

Two standardizations were performed for blue shark catch and effort data using GLMs. In order to assess the impact of the “target” factor in the standardization, this factor was added to one of the models. The number of zero blue shark catches was relatively high in the dataset (56%) and a Tweedie distribution with a log-link

function was therefore used in the GLMs following Carvalho et al. (2010). The models used the following formulas:

$$E[Y](= E[CPUE] = \mu) \\ = \exp((\text{intercept}) + (\text{year}) + (\text{quarter of the year}) + (\text{area})) \\ \text{Var}[Y](= \phi \text{var}[\mu]) = \sigma^2 \mu^p$$

and

$$E[Y](= E[CPUE] = \mu) \\ = \exp((\text{intercept}) + (\text{year}) + (\text{quarter of the year}) + (\text{target}) + (\text{area})) \\ \text{Var}[Y](= \phi \text{var}[\mu]) = \sigma^2 \mu^p$$

where μ is the location parameter; σ^2 is the diffusion parameter; and p is the power parameter (Shono, 2008).

The selection of predictors was evaluated using AIC. The 95% confidence intervals were computed using the bootstrapping method with 1000 resampling data. The GLMs were computed in the R language for statistical analysis (R Development Core Team, 2011).

2.4. Bayesian state-space production model

South Atlantic blue shark population dynamics were modeled within a surplus production model framework using AD Model Builder (ADMB; Fournier et al., 2012). Surplus-production models are the most commonly used stock assessment approach when data are comprised of only harvest and relative abundance time series (Hilborn and Walters, 1992). South Atlantic blue shark stock dynamics were accounted for by fitting a surplus-production model using a logistic difference equation to predict changes in population biomass (B) in year y (Eq. (1)). In this model, population change is governed by two population parameters while the harvest process is linked with changes in population size (Hilborn and Walters, 1992):

$$B_y = B_{y-1} + rB_{y-1} \left(1 - \frac{B_{y-1}}{K}\right) - C_{y-1} \quad (1)$$

where B_y is the biomass at the start of year y , r is the intrinsic growth rate, K is the carrying capacity, and C_y is the total catch during year y .

In order for model predictions to be useful for comparison in a management context, it is important to be able to make probabilistic statements regarding the likelihood of a particular outcome. Parameter estimation is therefore done using either a Bayesian or a Maximum Likelihood approach, with both methods incorporating external information of the parameters of interest. In the case of a Bayesian approach, this information comes in the form of a prior; the lack of parameter identifiability does not impose an inferential problem as long as this lack of information can be compensated using priors based on expert knowledge. Under Maximum Likelihood, extra information about the parameters of interest can be incorporated by writing the Joint Likelihood function of the external data and the focal data of interest. In this latter approach, data, not priors, are elicited to solve the identifiability problem (Ponciano et al., 2012).

In the present assessment, an existing Bayesian estimation framework developed by Meyer and Millar (1999) was used. This framework explicitly considers both observation error and process error to estimate south Atlantic blue shark population parameters while also providing probability distributions associated with population predictions. This model assumes there is a single closed stock, and that the dynamics of the stock (e.g. density-dependent growth, mortality, and recruitment processes) are well described by the Schaefer model (Schaefer, 1954).

Variability is an important feature of natural populations and ignoring it often leads to an incomplete representation of the state of a population and an incorrect prediction of its future. The process error model relates the dynamics of a population to natural variability resulting from demographic and environmental processes. Here, the process model uses a state-space representation of the Schaefer surplus production model. With this parameterization, the deterministic equation (Eq. (1)) is rewritten into a stochastic population model with population state values expressed as a proportion of the carrying capacity ($P_t = B_t/K$) (Eq. (2)). The biomass in the first year of the time series was scaled using the model parameter φ , which is defined as the ratio of the biomass in the first year of the CPUE time series to K .

$$P_1 = \varphi$$

$$P_t | P_{t-1}, K, r, \tau^2 = \left(P_{t-1} + rP_{t-1}(1 - P_{t-1}) - \frac{C_{t-1}}{K} \right) e^{u_t - (\tau^2/2)} \quad (2)$$

$$u_t \sim N(0, \tau^2)$$

where P_1, \dots, P_N are the unknown states and u_t the process error for year t .

The observation error model connects the state process (Eq. (2)) to CPUE (I_t), assuming CPUE is proportional to biomass (Eq. (3)). An “additional variance” approach, where the variance of measurement errors is the sum of variance estimates from index standardization and additional variance, was also implemented.

$$I_t = q_t K P_t e^{v_t}$$

$$v_t \sim N(0, \phi_t + \sigma^2) \quad (3)$$

where q is the catchability coefficient, in year t , and v_t is the observation error for year t . Observation error variance, process error variance, and index standardization variance, are defined by the parameters σ^2 , τ^2 , and ϕ , respectively. When evaluating the joint-posterior distributions of the observed and unobservable processes (Eq. (4)), we used a reciprocal prior on the catchability coefficient (uniform on log-scale), which is the Jeffrey’s prior (i.e. invariant under re-parameterization, see Millar, 2002). Separate catchability coefficient (q) values were estimated for each period (pre- and post-1996) in scenario I, while a single value was estimated in scenario II.

Using Bayes’ theorem, a posterior distribution for the fully conditional joint probability distribution of parameters was specified based on the observed information. The posterior distribution given assumed known catch removals and CPUE data is proportional to the product of the priors and the likelihood of the observable and unobservable processes (Eq. (4)):

$$p(r, K, \varphi, q, \sigma^2, \tau^2, P_1, \dots, P_N, I_1, \dots, I_N)$$

$$= p(r)p(K)p(\varphi)p(\sigma^2)p(\tau^2)p(P_1 | \tau^2, K, C_1) \prod_{t=2}^N p(P_t | P_{t-1}, K, r, \tau^2)$$

$$\prod_{t=1}^N p(I_t | P_t, q, \sigma^2) \quad (4)$$

2.5. Prior distributions

In the present study we assumed non-informative prior distributions for all model parameters except r and φ . For K , σ^2 and τ^2 we assigned an inverse-gamma prior distribution with the scaling

parameters λ and k set to 0.001 (Brodziak and Ishimura, 2012) (Eq. (5)).

$$p(x) = \frac{\lambda^k x^{k-1} e^{-\lambda x}}{\Gamma(k)} \quad (5)$$

The prior for φ was based on the analysis of historical catch and effort data of the Brazilian pelagic longline fishery, which can be divided in three distinct periods: I (1958–1962); II (1968–1970); and III (1978–present). The average blue shark CPUE during period II (unpublished data) was 86% of that during period I (Carvalho et al., 2008). Based on this value, φ was fixed at 0.86. In order to take into account the high uncertainty around this value we set a coefficient of variation (CV) of 45% (e.g. Hampton et al., 2004). There are no records on longline fishing activity by the Brazilian fleet in between these three periods. Additionally, the target species (yellowfin tuna) and gear (Japanese-type longline) were the same for periods I and II, meeting the assumptions required for calculating the depletion between these two periods.

An informative prior distribution was developed for the population intrinsic rate of increase r following the demographic method outlined in McAllister et al. (2001). In this analysis, prior distributions for age-specific fecundity, maturity, and natural mortality are converted into prior distributions for r . This conversion is done using the Leslie matrix projection approach. The Leslie matrix model used is based on two equations: (1) the survival equation $N_{i+1,t+1} = N_{i,t} \times S_i$, where $N_{i,t}$ is the number of age i individuals at time t , and S_i the survival rate from age i to age $i + 1$; and (2) the reproduction equation $N_{0,t+1} = \sum_{i=0}^A N_{i,t} \times m_i$, where m_i is the expected number of female pups per female. The number of age 0 individuals depends on m_i , the average number of age zero individuals produced by an individual of age i . In matrix form, the model is written $[N_i]_{t+1} = L \times [N_i]_t$, where $[N_i]_t$ is the vector of the numbers of individuals in age group i at time t and $L =$ Leslie matrix of the form:

$$\begin{bmatrix} m_0 & m_i & m_A & 0 \\ S_0 & 0 & \dots & 0 \\ 0 & S_i & \dots & 0 \\ 0 & 0 & S_A & 0 \end{bmatrix}$$

When the matrix coefficients are all positive, the rate of population growth is $r = \ln(\eta)$, where η is the dominant eigen value of matrix L . A distribution of population intrinsic rate of increase was computed and a probability density function was fitted for values of r generated from 20,000 Leslie population matrices.

The life history information and parameters used to construct the prior distributions for r were sourced from previous studies on blue shark life-history and are summarized in Table 1. To account for uncertainty we used a simulation approach as in Cortés (2002), where statistical distribution functions were defined for each life-history parameter, based on published records. A total of 20,000 independent vectors were randomly drawn to calculate the different components of the Leslie population matrices, i.e. annual survivorship at age i (S_i) (age 1–16; the maximum age in the calculations was based on Aires-da-Silva and Gallucci, 2008), survival of age 0 (young-of the year) (S_0), and expected number of female pups per female (m_i), respectively. The expected number of female pups produced per female is given by $m_x = sr \times f_x \times O_x$, where m_x is the mean number of age 0 female pups produced per age x female, sr is the sex ratio (1:1 embryonic sex ratio was assumed based on Hazin et al., 2000), f_x is the fecundity at age x , and O_x is the proportion of mature female at age x . Age-specific fecundities for blue

Table 1

Growth parameters values used in the Demographic analysis for South Atlantic blue shark. L_{∞} : asymptotic length; $K(y^{-1})$: growth Coefficient; x_0 : age at zero length; x_{m50} : age at 50% mature; and x_{max} : maximum age.

Source	Parameter						
	Sex	L_{∞}	$K(y^{-1})$	x_0	x_{m50}	x_{max}	Length measurement
Pacific Ocean							
Cailliet et al. (1983)	Male	295.3	0.175	-1.113	4	9	TL
	Female	241.9	0.251	-0.795	5	9	
Nakano (1994) ^b	Male	382.9	0.129	-0.756	5	10	PCL
	Female	321.4	0.144	-0.849	6	10	
Manning and Francis (2005) ^b	Male	410.8	0.088	-1.257	6	22	FL
	Female	320.1	0.126	-1.047	7	19	
Atlantic Ocean							
Stevens (1975)	Combined	423.0	0.110	-1.035	^a	6	TL
Aires-da-Silva (1996)	Combined	340.0	0.138	-1.075	^a	5	TL
Henderson et al. (2001)	Combined	376.5	0.120	-1.330	^a	6	TL
Skomal and Natanson (2003) ^b	Male	282.3	0.180	-1.350	5	16	FL
	Female	310.8	0.130	-1.770	5	15	
Lessa et al. (2004)	Combined	352.1	0.157	-1.010	5	12	TL
Jolly et al. (2013)	Male	294.6	0.140	-1.300	5	14	
	Female	334.7	0.110	-2.190	6	16	
Distribution		Normal	Normal	Normal	Uniform	Uniform	

^a No information available.

^b Given as fork length (FL) or pre-caudal length (PCL) and converted to total length (TL) using equation: $FL = 0.8313(TL) + 1.39$ and $PCL = 0.9075(TL) - 0.3956$ (Kohler et al., 1995).

shark were calculated according the equation proposed by Mejuto and García-Cortés (2005):

$$No. \text{ embryos} = -61.605 + 0.470403 \times (FL \text{ female}) \quad (6)$$

The logistic function that described the proportion of mature female at age x is:

$$O_x = \frac{1}{1 + e^{-\beta(x-x_{m50})}} \quad (7)$$

where β is the slope of the positive linear relationship between litter size and fork length of the pregnant females from Mejuto and García-Cortés (2005) and x_{m50} is the age where 50% of the individuals are mature, which is 5 years according Lessa et al. (2004).

To estimate natural mortality (hence survivorship, $S = e^{-M}$) we applied five methods, including Pauly (1980), Hoening (1983), Chen and Watanabe (1989) and Jensen's (1996) age-at-maturity method; and, Jensen's (1996) K growth coefficient method. All these methods rely on parameter estimates derived from the von Bertalanffy growth function (Cortés, 2002). As suggested by Aires-da-Silva and Gallucci (2008), we used the mean and coefficient of variation (CV) obtained for M across methods as parameter estimates to define a lognormal distribution, which ensures that the transformed estimates and resulting pdf of annual survivorship vary between 0 and 1. This demographic analysis resulted in a prior estimate of 0.297 (SD=0.08) for r .

From Bayes' theorem, the posterior distribution represents the uncertainty about the true parameter values and is used to make probability (or credibility) statements regarding parameter values. In the Bayesian framework, samples are generated from the posterior distribution of parameters, which can be implemented using Markov Chain Monte Carlo (MCMC) techniques (MacKay, 2003). The MCMC samples were calculated using the default algorithm in ADMB (Fournier et al., 2012). MCMC simulations were conducted in an identical manner for each model scenario. Each simulation included five chains with 2 million cycles, discarding the first 200,000 iterations as burn-in phase and then thinning the chain by saving every 200th iteration to reduce autocorrelation. MCMC simulation convergence was tested using the CODA package (Convergence Diagnosis and Output Analysis; Plummer et al., 2006) in R statistics. A minimal thresholds of $p = 0.05$ was adopted for Geweke's diagnostic (Geweke, 1992) and the two-stage Heidelberg-Welch stationary test (Heidelberg and Welch, 1983).

We also used the Gelman and Rubin (1992) approach to evaluate the mixing and convergence of our MCMC sampler Tests results showed no evidence of failure to converge for all model parameters.

The 2.5th and 97.5th percentiles of the posterior distributions are used to represent 95% Bayesian credibility intervals for all parameters, projections, and management quantities. The estimated 95% credibility intervals (CIs) are analogous to 95% confidence intervals and are also conditional on the model. CIs can be interpreted in the sense that there is a 95% probability that the lower and upper credibility intervals include the true value given the prior information and the data.

Model fit was evaluated using a graphical assessment of the 95% prediction credibility intervals. To compare alternative models, the deviance information criterion (DIC) was used. The deviance information criterion is defined as: $DIC = \bar{P}(\theta) + p_D$, where $\bar{P}(\theta) = E[P(\theta)|y]$ is the posterior mean of the deviance, where y are the data, θ are the unknown parameters of the model, and $p_D = \bar{P}(\theta) = E[P(\theta)|y] - P[E(\theta)|y]$ is the difference in the posterior mean of the deviance and the deviance evaluated at the posterior mean of the parameters. As a rule of thumb, if two models differ in DIC by more than three, the one with the smaller DIC is considered the best fitting (Spiegelhalter et al., 2002).

2.6. Biological reference points

For each scenario, harvest management measures can be derived from Eq. (1), including Maximum Sustainable Yield (MSY). The production model provides direct estimates of biological reference points for blue shark used for determining stock status: B_{2012} , the stock biomass at the end of the last year of the assessment period; B_{MSY} , the stock biomass at which MSY is achieved; F_{MSY} , the fishing intensity corresponding to MSY; F_{2012} , the fishing intensity during the last year of the assessment period; B_{2012}/B_{MSY} , the ratio of the spawning stock biomass at the end of the last year of the assessment period to that at which MSY is achieved; and F_{2012}/F_{MSY} , the ratio of the fishing intensity during the last year of the assessment period to that corresponding to MSY. The time series of the exploitable biomass was plotted using the mean values from model parameter joint-posterior distributions. Total Allowable Catch (TAC) was estimated as the product of F_{MSY} and the 2012 biomass.

Table 2
Percentage of each species or group of species per cluster.

	Species	Cluster					
		1	2	3	4	5	6
Yellowfin tuna	<i>Thunnus albacares</i>	5.4	45.1 ^a	9.1	8	2.5	4.3
Bigeye tuna	<i>Thunnus alalunga</i>	70.5 ^a	10.4	6.8	5.5	4.8	2.1
Albacore	<i>Thunnus obesus</i>	5.3	12.3	5.2	9.9	1.5	71 ^a
Swordfish	<i>Xiphias gladius</i>	3.1	7.5	10.4	58.9 ^a	8.3	9
Sailfish	<i>Istiophorus albicans</i>	1.3	2.4	2.1	1.9	0.8	1
White marlin	<i>Tetrapturus albidus</i>	0.7	2.2	1.7	0.9	0.6	0.6
Blue marlin	<i>Makaira nigricans</i>	0.5	1.3	0.7	1.3	0.4	0.9
Other billfishes		0.1	0.1	2.4	0.7	0.3	0
Wahoo	<i>Acanthocybium solandri</i>	0.7	2.9	2.2	0.4	0.3	0.3
Dolphin fish	<i>Coryphaena hippurus</i>	0.4	0.7	6.7	1.5	3.4	0.4
Blue shark	<i>Prionace glauca</i>	4.9	2.3	6.1	6.7	68.2 ^a	4.9
Hammerhead shark	<i>Sphyrna sp.</i>	0	0.5	3.1	0.4	1.6	0
Bigeye thresher	<i>Alopias superciliosus</i>	0	0.1	0.1	0.1	0.3	0
Mako shark	<i>Isurus sp.</i>	0.3	1.6	1.3	0.8	2.8	0.1
Silky shark	<i>Carcharhinus falciformis</i>	0	0.1	5.8	0.1	0.2	0.1
Oceanic whitetip	<i>Carcharhinus longimanus</i>	0	0	0.1	0	0	0
Other sharks		2	1.5	11.6	1	2.4	2.4
Other teleosts		3.9	7.1	24.6 ^a	1.9	1.6	2

^a The target species in each cluster.

2.7. Sensitivity analysis

The assessment of south Atlantic blue shark stock was subject to sensitivity analysis in order to evaluate model performance under alternative priors for r and ϕ . The best model selected between scenarios I and II was used as the base case for the sensitivity analyses. For the alternative prior for r a less informative standard deviation of 0.3 was assigned. The parameter ϕ was given an uninformative (uniform) prior between 0.2 and 1.1 (ICCAT, 2008). Also, as taking the maximum catch in each year might inflate MSY, a catch sensitivity analysis using the tuna ratio catch series instead of the maximum of the tuna ratio and fin trade catch estimates was performed.

3. Results

3.1. Cluster analysis identifying the “Target” factor

The cluster analyses resulted in the separation of the catch into six different clusters representing fishing or target strategies, the % composition of species or species group in each cluster are as follow: Cluster 1 = bigeye tuna (*Thunnus alalunga*, 70.5%); Cluster 2 = yellowfin tuna (*Thunnus albacares*, 45.1%); Cluster 3 = other teleosts (24.6%), together with other sharks (11.6%) and swordfish (*X. gladius*, 10.4%); Cluster 4 = swordfish (58.9%); Cluster 5 = blue shark (68.2%); and Cluster 6 = albacore (*Thunnus obesus*, 71%) (Table 2). These clusters were the same ones identified in the analysis by Carvalho et al. (2010) using data from 1978 to 2006, with only small differences in the % composition of the main species observable with the data updated to 2012.

3.2. CPUE standardization

The final model for the blue shark CPUE standardization that did not include the Target variable consisted of three variables and explained 55% of the total deviance. The relative contribution from each variable in the total explained deviance for the model showed that Year (62%) was the most important factor, followed by Area (31%), and Quarter (7%) (Table 3). The CPUE model that included Target consisted of four variables and explained 61% of the total deviance. Target (51%) and Year (29%) were the most important factors, followed by Area (14%), and Quarter (6%). The estimations of the regression coefficients for the main effects in both models

Table 3

Deviance analysis of explanatory variables in the Tweedie models for blue shark caught by Brazilian pelagic tuna longline fleet, from 1978 to 2012.

	Df	Deviance	Resid. Df	Resid. Dev.	Dev. Exp. (%)	AIC
Model without “Target”						
NULL			37,881	109672.5		4515
Year	34	42308.3	28,413	105041.8	62	3871
Area	1	33566.1	27,109	102637.7	31	3317
Quarter	3	14653.7	26,538	99431.1	7	3291
Model with “Target”						
NULL			39,840	58013.7		9221
Target	5	21745.3	35,611	52085.8	51	7044
Year	34	18451.2	31,714	46728.1	29	6653
Area	1	17617.8	28,045	45115.6	14	5868
Quarter	3	17044.1	27,825	45093.0	6	5776

are shown in Table 4. For both models it can be noted that the estimated catch rates in area 2 were higher than catch rates for area 1 (reference area). Also, catch rates in quarter 4 (October to December) were similar to catch rates gathered in quarter 1 (reference quarter), while catch rates in third and second quarter were lower than quarter 1. As expected, the model that included Target showed higher catch rates in cluster 5 (cluster with the highest % of blue shark catches (Table 2) than in cluster 1 (reference cluster). The standardized CPUE time series showed a stable trend from 1978

Table 4

Estimations of regression coefficients and related statistics for the main effects of the variables included in the GLMs for blue shark caught by Brazilian pelagic tuna longline fleet, from 1978 to 2012.

	Estimate	Std. error	t value	Df	P(> t)
Model without “Target”					
Area 2	0.2164	0.0867	2.14		0.0174
Quarter 2	−0.2513	0.1241	−2.49		0.0087
Quarter 3	−0.2053	0.0921	−3.58		0.0019
Quarter 4	0.0401	0.1142	0.21		0.8315
Model with “Target”					
Area 2	0.2712	0.0973	2.9227		0.0037
Quarter 2	−0.4655	0.2813	−3.7418		0.0042
Quarter 3	−0.3918	0.2902	−2.1933		0.0411
Quarter 4	0.0947	0.0795	1.2867		0.2017
Target 2	−0.5517	0.2844	−2.0272		0.9773
Target 3	0.0114	0.2451	0.4507		0.8022
Target 4	0.0159	0.3317	0.5941		0.5803
Target 5	1.4175	0.1304	9.2506		<0.001
Target 6	0.0749	2.8150	0.0113		0.7548

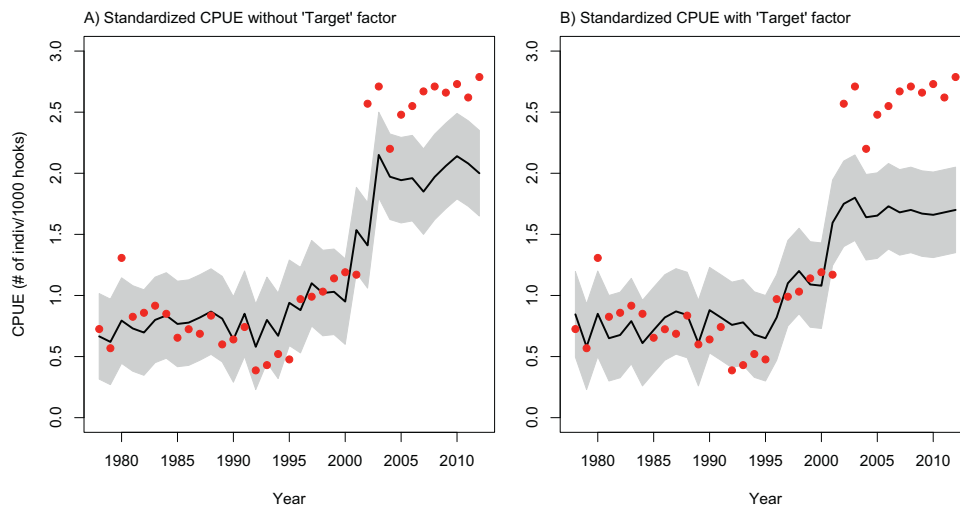


Fig. 3. Nominal (black circle) and standardized (black line) CPUE of blue shark caught by the Brazilian pelagic tuna longline fleet from 1978 to 2012 without and with the “Target” factor. Shaded region represents the 95% credibility interval for predicted CPUE values.

through 1995, increasing from 1996 onwards, and reached a peak in 2003 in both models (Fig. 3). However, from 2002 onwards the model that did not include the Target factor showed higher CPUE values (Fig. 3A) than the CPUE model standardized with it (Fig. 3B).

3.3. Biomass dynamic model

We fit the two biomass dynamic models to the blue shark standardized CPUE time series that included Target. The DIC analysis indicated better model fitting under scenario I, as it was 94 deviance points smaller than for the model under scenario II. Under scenario I, predicted CPUE appeared to randomly fluctuate throughout the observed CPUE time series with an increase in both predicted and observed CPUE after 1995, followed by relative stability from 2002 until 2012 (Fig. 4A). Under scenario II (Fig. 4B), the predicted CPUE time series showed similar behavior as scenario I, with a stable trend until 1995 and an increase in CPUE afterward. However, predicted and observed CPUEs from the model under scenario II exhibited similar values until 2001, after which the predicted CPUEs displayed markedly higher values than the observed CPUEs. When comparing the predicted time series between the two models, there was a noticeable discrepancy in the predicted CPUE values. After 2000, scenario II appears to overestimate predicted CPUE values, and the overestimation also seems to occur for scenario I, but to a lesser extent. In 2012, for example, predicted CPUE under scenario I showed a 7.0% of increase from the observed CPUE, while in Scenario II the increase was 19.4%.

The posterior median estimates of parameters r and ϕ , using the baseline priors, showed narrow marginal posterior distributions for both scenarios, and the observed parameter value for r within the predicted range obtained by the demographic analysis. The posterior median values of r and ϕ are greater for scenario II ($r=0.319$, $SD=0.081$; $\phi=0.869$, $SD=0.024$) than scenario I ($r=0.280$, $SD=0.069$; $\phi=0.861$, $SD=0.018$) (Table 5). For carrying capacity (K , the posterior median based on scenario I was 847,311 t ($SD=118,615$) while the median based on scenario II was 971,050 t (126,445). Time series of observation and process errors for both models clearly show a positive trend over time, with no negative values occurring after 1995 (Fig. 5A and B). The posterior median estimates for observation error variance were 0.056 ($SD=0.0094$) for scenario I and 0.139 ($SD=0.0285$) for scenario II. For process error variance, the posterior median estimates were 0.0011 ($SD=0.0002$) for scenario I, and 0.0031 ($SD=0.0005$) for scenario II (Table 5). The amount of change in the catchability

coefficient over time also showed an increase after 1995 for both models (Fig. 5C). Under scenario I median estimates for $q_{pre-1996}$ and $q_{post-1996}$ were 0.0000011 ($SD=0.0000001$) and 0.0000020 ($SD=0.0000001$), respectively, while for scenario II was 0.0000031 ($SD=0.0000009$) (Table 6).

The estimates of the biological reference points were very uncertain and varied between the two scenarios (Table 7). The posterior median estimate of B_{MSY} for scenario I was 14% below the estimate for scenario II. The posterior median estimate of MSY for scenario I was approximately 27% below the estimate for scenario II. All models provided different estimates for the current biomass (B_{2012}). The highest posterior median estimated value was obtained by scenario II (Table 7). The estimate of TAC and the uncertainty around its estimate also varied between scenarios. The posterior median estimates of TAC were 89,106 mt per year based on scenario I, and 116,214 mt per year based on scenario II (Table 7).

There was no practical difference in the estimates of stock status in 2012 between the two scenarios. In particular, the posterior median estimates of B_{2012} were greater than B_{MSY} for both models (i.e. $B_{2012}/B_{MSY} > 1$) and the associated probabilities of B_{2012} being below B_{MSY} were close to zero as well. For scenario I, exploitable biomass fluctuated above B_{MSY} during the entire model timeframe, with biomass fluctuating around 600,000 mt until 1995 when values started increasing, reaching their highest value in 2001, followed by a decrease and subsequent stabilization (Fig. 6A). Biomass estimates for scenario II were similar to scenario I until 1996, after which the model under scenario II presented slightly higher values (Fig. 6B). The trajectories of the posterior median estimates of the ratio of fishing mortality to F_{MSY} for both biomass dynamics models are summarized using a stock-status plot (Fig. 7). The stock biomass displayed similar trends throughout the years for both models, although scenario I produced a higher estimate of F/F_{MSY} in 2012 (0.28) than scenario II (0.26). The ratio of B_{2012} to B_{MSY} showed a lower value (1.49) under scenario I than scenario II (1.56). Both indicated that the stock is currently not overfished ($B > B_{MSY}$) and that overfishing is not taking place ($F < F_{MSY}$) (Fig. 7). All of the sensitivity analyses (Table 7) were consistent in finding that the population abundance is probably above B_{MSY} and fishing mortality is probably below F_{MSY} . Although the sensitivity analyses showed similar population status, the posterior distributions of r and ϕ were more uncertain when less informative priors were used for these parameters. The sensitivity analysis using only the tuna ratio catch series resulted in much lower estimates for k and current biomass (Tables 5 and 7).

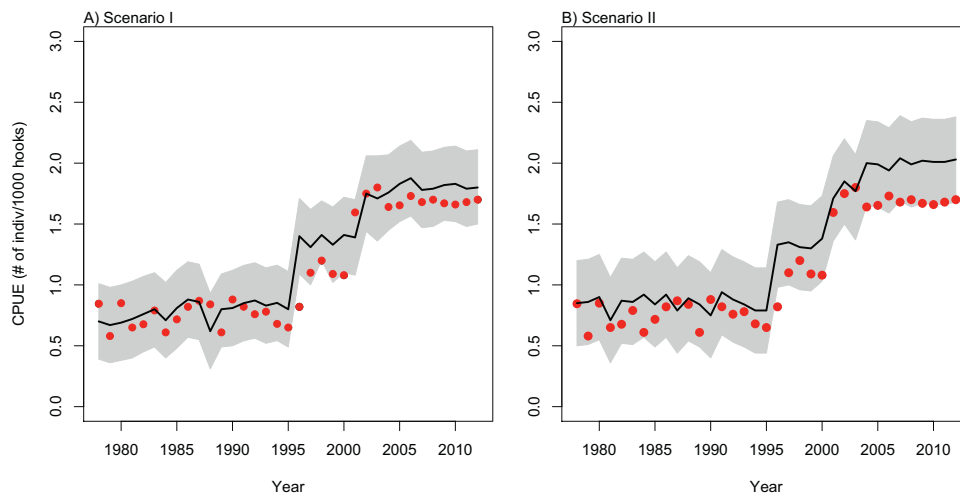


Fig. 4. Time series of observed (black circle) and predicted (black line) CPUE from the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability). Shaded region represents the 95% credibility interval for predicted CPUE values.

Table 5
Estimated parameters from the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability). r : population intrinsic rate of increase; φ : ratio of the biomass in the first year to K ; K : carrying capacity; σ^2 : observation error variance; and τ^2 : process error variance.

	r Median (SD)	φ Median (SD)	K Median (SD)	σ^2 Median (SD)	τ^2 Median (SD)
Scenario I (base case)	0.280 (0.069)	0.861 (0.018)	847,311 (118,615)	0.056 (0.0094)	0.0011 (0.0002)
Scenario II	0.319 (0.081)	0.869 (0.024)	971,050 (126,445)	0.139 (0.0285)	0.0031 (0.0005)
Sensitivity analysis					
Scenario I (less informative r)	0.320 (0.168)	0.859 (0.036)	935,263 (169,011)	0.054 (0.0095)	0.0011 (0.0001)
Scenario I (uninformative prior for φ)	0.313 (0.098)	0.813 (0.154)	927,228 (192,387)	0.062 (0.0093)	0.0022 (0.0003)
Scenario I (tuna ratio catch series only)	0.311 (0.094)	0.848 (0.021)	654,006 (91,473)	0.057 (0.0088)	0.0020 (0.0002)

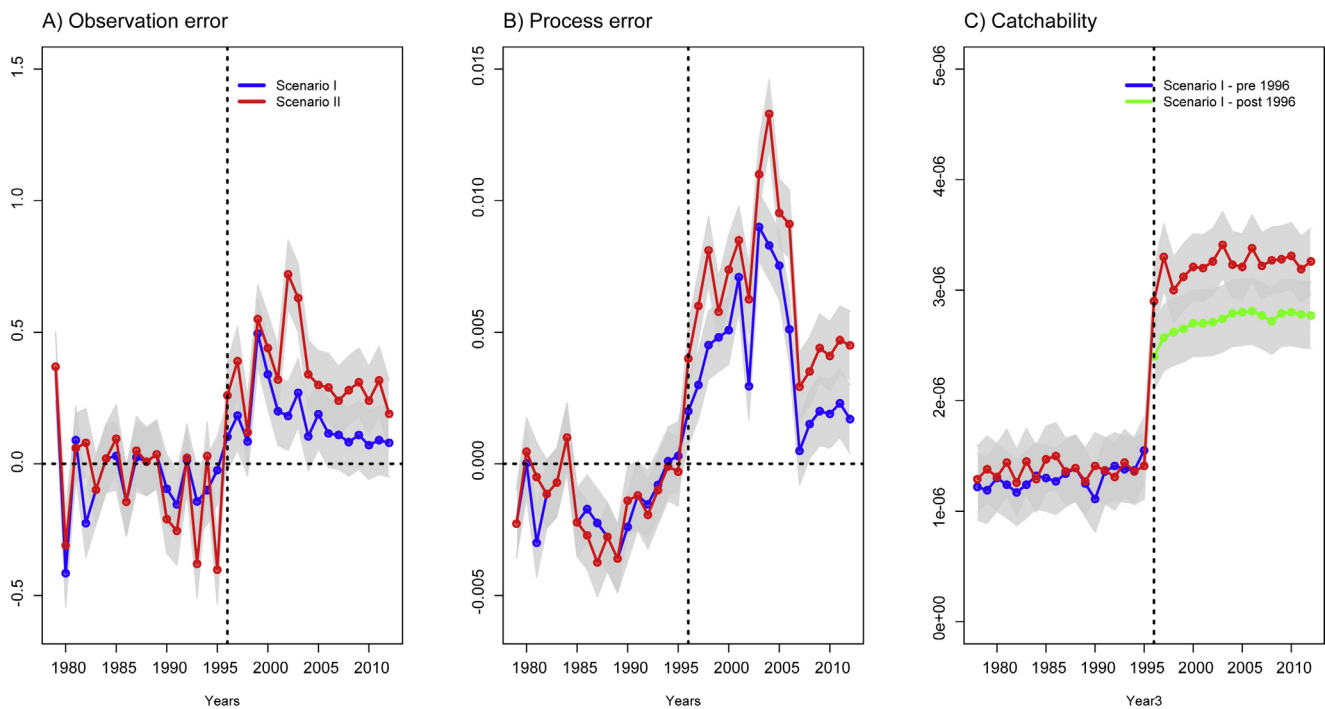


Fig. 5. Time series of observation error, process error, and catchability estimated by the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability). Horizontal dashed lines indicates zero and the vertical dashed line indicates the year 1996. Shaded region represents the 95% credibility interval.

Table 6
Estimated catchability parameters (q) from the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability).

	$q_{pre-1996}$ Median (SD)	$q_{post-1996}$ Median (SD)	q Median (SD)
Scenario I (base case)	0.0000011 (0.0000001)	0.0000020 (0.0000001)	–
Scenario II	–	–	0.0000031 (0.0000009)
Sensitivity analysis			
Scenario I (less informative r)	0.0000012 (0.00000007)	0.0000024 (0.00000010)	
Scenario I (uninformative prior for φ)	0.0000013 (0.00000014)	0.0000019 (0.00000017)	
Scenario I (tuna ratio catch series only)	0.0000010 (0.00000013)	0.0000025 (0.00000011)	

Table 7
Estimated reference points from the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability).

	B_{MSY} Median (SD)	B_{2012} Median (SD)	MSY Median (SD)	TAC Median (SD)
Scenario I (base case)	423,474 (60,018)	632,735 (82,918)	59,324 (8513)	89,106 (11,701)
Scenario II	485,719 (67,833)	757,961 (91,157)	77,469 (9002)	116,214 (19,935)
Sensitivity analysis				
Scenario I (less informative r)	466,485 (85,308)	716,481 (125,009)	72,109 (11,872)	94,377 (13,210)
Scenario I (uninformative prior for φ)	467,127 (85,090)	718,925 (112,016)	70,268 (14,012)	92,273 (16,141)
Scenario I (tuna ratio catch series only)	327,290 (40,011)	437,013 (70,851)	48,102 (6137)	72,014 (9294)

4. Discussion

The tuna longline fishery is complex due to the large variety of boats and fleets and frequent switching of gear type and target species. Since the start of the fishery in 1956, approximately 237 boats, consisting of 20 fleets, have operated in the southwestern Atlantic Ocean. In fisheries where fishery-independent data are not available, such as in the southwestern Atlantic tuna longline fishery, it is necessary to develop models that standardize for the biological, technical, and economic factors that affect catch rates. However, under circumstances of abrupt change, standardization models assuming constant catchability may not be sufficient to minimize the effects of these factors. In the present study, for example, the substantial increase in blue shark nominal CPUE after 1996, due to changes in target species, persists in both standardized CPUE series. Additionally, the variability found in the blue shark stock assessment models for both scenarios indicates that not correcting for time-varying catchability directly in the assessment model can lead to incorrect estimates of stock status and poorly informed management decisions.

Besides CPUE standardization, several more sophisticated modeling procedures have been developed that incorporate time-varying catchability directly in stock assessment models; however, there is little consensus regarding which practice is ideal (e.g. Fox, 1974; Fournier and Archibald, 1982; Freon, 1988; Prager, 1994; Schnute, 1994; Fournier et al., 1998; Shepherd and Pope, 2002; Walters and Martell, 2004). State-space techniques and modeling the catchability coefficient as a function of time do not ascribe causation for changes in catchability (Meyer and Millar, 1999; Punt, 2003), while the use of functions of density or external variables assumes that the variables used are the dominant factors affecting the change.

4.1. Assessment model

In the 1960s and 70s, most shark stock assessments were conducted using some form of the logistic Schaefer model, mainly because of a lack of data and computing power. This model often proved inappropriate to model shark population dynamics since it considered the relationship between surplus production and

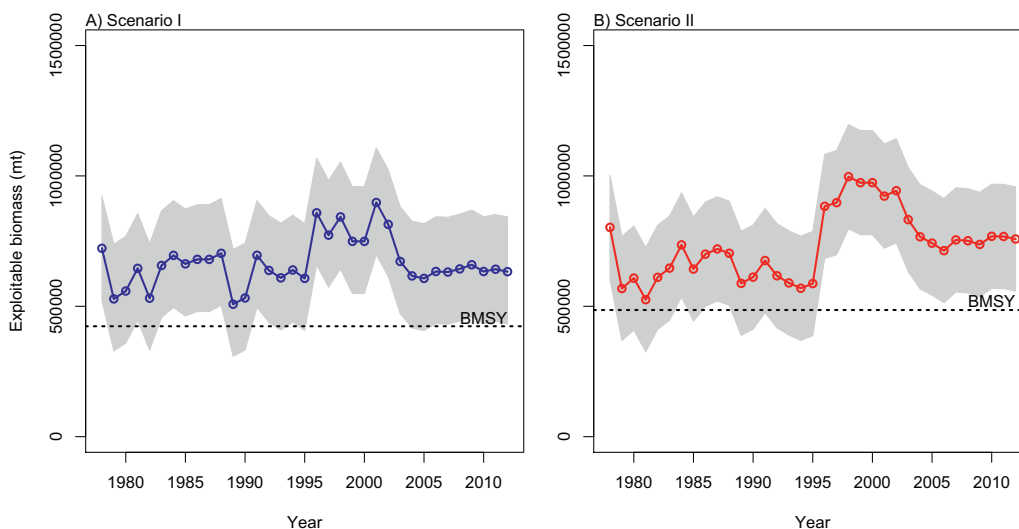


Fig. 6. Time series of exploitable biomass (mt) estimated by the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability). Shaded region represents the 95% credibility interval for predicted biomass values.

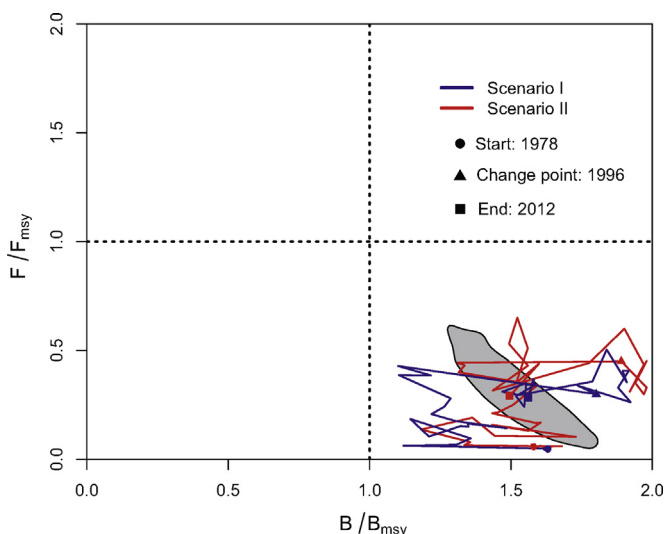


Fig. 7. Estimated trajectories for the posterior median of B/B_{MSY} and F/F_{MSY} from the southern Atlantic blue shark stock assessment using a Bayesian state-space production model under scenarios I (split-catchability) and II (continuous catchability). Shaded region represents the joint 95% credibility interval for B_{2012}/B_{MSY} and F_{2012}/F_{MSY} .

resource biomass to be symmetrical with a maximum at halfway between a resource biomass of zero and the carrying capacity (Maunder, 2003). Pella and Tomlinson (1969) proposed the addition of a supplementary shape parameter to allow the production relationship to be skewed to the left or to the right. However, in order to improve the logistic model approach in the Pella and Tomlinson model, an additional parameter, the shape parameter, must be estimated to fit the model to the data. Despite its flexibility and suitability, this model may perform worse than the Schaefer due to an inverse relationship between the number of parameters to be estimated and model performance (e.g. precision) (Prager, 2002). According to Cortés (2008), the blue shark is a very productive species with high fecundity and an inflection point near 50% of K (i.e. not skewed). For precautionary management, 50% is a reasonable estimate of the critical value. Then, the use of the logistic Schaefer model would be appropriate for blue shark.

The Bayesian estimation approach presented here provided better scientific advice than models that do not incorporate time-varying catchability. The estimated biological reference points from the two scenarios indicated that varying catchability had no qualitative impact on the status of the south Atlantic blue shark population with respect to MSY-based reference points based on current stock size, with both scenarios indicating that the stock is not currently overfished nor undergoing overfishing. Analyses also showed that it was very likely that the south Atlantic blue shark population biomass was above B_{MSY} in 2012, since all scenarios showed $B/B_{MSY} > 1.0$. Regardless of the scenario and the sensitivity analysis used, it is unlikely that the south Atlantic blue shark population was being fished in excess of its optimal equilibrium harvest rate in 2012, similar to the conclusion reached by the south Atlantic blue shark stock assessment in 2008 (ICCAT, 2008). However, it is important to highlight that an evaluation of the stock status for south Atlantic blue shark is strongly compromised by limited fishery statistics, as is an evaluation for any other bycatch shark species. Under- or non-reporting of bycatch, unknown discard levels, unknown status (dead or alive) of discards, and poor knowledge on the extent of finning practices are among the major reasons for the lack of data. In fact, the blue shark catch information provided by ICCAT and catch estimates based on the shark fin trade from Clarke (2008), represent, to date, the only sources

of information on blue shark total removals in the south Atlantic Ocean.

Sharks are usually characterized by slow growth rates, long life spans, late maturity, and production of limited offspring after long gestation periods (Bonfil, 1994). This low reproductive output is responsible for the vulnerability of sharks to harvest, as shown by many cases of overexploitation when data are informative (Cortés, 2004). However, the magnitude of the decline of the south Atlantic blue shark population is less than in other pelagic shark species in the Atlantic, such as the porbeagle (*Lamna nasus*) (ICES/ICCAT, 2009). This seems reasonable in light of their life history characteristics (Aires-da-Silva and Gallucci, 2008). According to Cortés (2002), blue shark have one of the highest fecundities documented among sharks (mean litter size of 37 pups, Mejuto and García-Cortés, 2005; reaching up to 82 pups, Pratt, 1979) and surprisingly fast early growth rates that result in near doubling of pup size over the first year (Skomal and Natanson, 2003).

Despite the benefits of the Bayesian estimation approach, it is important to note that the choice of prior distributions can alter posterior estimates of stock status, especially when data is uninformative. As a result, it is preferable to select prior probability distributions that are consistent with data from other populations. In the present analysis, the prior distribution of south Atlantic blue shark intrinsic rate of increase r , obtained using demographic analyses, encompassed the range of posterior predictions of r from Cortés (2002) and Aires-da-Silva and Gallucci (2008). Graphical analyses of the posterior distributions for r and ϕ from both models were similar to the prior, which indicates the data are uninformative (McAllister and Kirkwood, 1998). The sensitivity analyses also confirmed the current assessment results were sensitive to the prior and catch series choice. For example, the estimate of current biomass for the sensitivity analysis using the tuna ratio catch series is 36% smaller than the base case.

Time-varying catchability is a common feature of many fisheries. Unidentifiable trends in catchability can lead to biased results from stock assessment models and erroneous management recommendations (Pope and Shepherd, 1985; Patterson and Kirkwood, 1995; Wilberg and Bence, 2006; Thorson and Berkson, 2010; Thorson, 2011). As suggested by Wilberg et al. (2010), to best account for the many known causes of time-varying catchability, CPUE should be standardized for factors known to affect catchability while recognizing that it will be difficult to correct for all potential causes. This study implemented an alternative method to incorporate time-varying catchability in stock assessment models by specifying a single change point in the catchability coefficient, which resulted in significant improvements in model fit. Furthermore, a more stable trend and lower values of q , especially after 1995 for scenario I, indicates that the alternative model also better captures changes in catchability over time. We recommend that the alternative method that includes time-varying catchability presented here be tested on other fish stocks, along with other recommendations given by Wilberg et al. (2010). We suggest that the proposed method would be most appropriately applied to assessments where the catch data can clearly be separated into time periods with different fisheries dynamics.

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