ESTIMATES OF INTRINSIC RATE OF POPULATION CHANGE AND STEEPNESS FOR BLUE SHARK (*Prionace glauca*) IN THE INDIAN OCEAN

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SUMMARY

Maximum population growth rates and steepness values were computed for the Indian Ocean blue shark (Prionace glauca) based on biological information available for that Ocean. Uncertainty in the estimates of life history parameters was incorporated through Monte Carlo simulation by assigning statistical distributions to the biological parameters in a Leslie matrix approach. Estimated productivity was high, specifically with $\lambda=1.37\text{-}1.42\ yr^{-1}$ *and* $r_{max}=0.32\text{-}0.35\ yr^{-1}$*, depending on the biological parameters and scenario considered. This is in line with what has been previously found for other populations of blue shark on other Oceans. Consequently, analytically derived values of steepness were also high, with h=0.80-0.87. These estimates can be used as inputs into both Bayesian surplus production* (r_{max}) *and age-structured (steepness) stock assessment models.*

KEYWORDS: Blue shark, demographic models, population dynamics, stock assessment.

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1. Introduction

Blue shark (BSH, *Prionace glauca*) is a cosmopolitan species which can be captured by a variety of fishing gears, but most catches take place as bycatch in pelagic longlines targeting tunas and swordfish (Compagmo, 1984). Blue shark is the most prevalent shark captured in pelagic longline fisheries, in some cases blue shark catches can account for more than 50% of total fish catches and 80% of the total elasmobranch catch (Coelho *et al*., 2012, 2013).

Despite being regularly caught as bycatch, long-term catch and effort data is not readily available, which hinders stock assessment. Likewise, biological data, life history and population dynamics parameters in the Indian Ocean are still lacking. Two of the most fundamental parameters for stock assessment are the intrinsic rate of population change (r_{max}) and steepness (h), or the fraction of recruitment from an unfished population when the spawning stock size declines to 20% of its unfished level, for production models and age-structured models, respectively. These parameters are biologically derived and should therefore be estimated from the stock that is being assessed.

The first stock assessment for blue shark in the Indian Ocean was carried out in 2015 using various models, specifically 1) a stock reduction analysis, 2) a Bayesian state-space production model and, 3) a Stock Synthesis model. However due to uncertainties in catches and conflicting CPUEs, no absolute measures of biomass or yield were produced (IOTC–WPEB11, 2015). The next stock assessment for BSH n the IOTC region is scheduled to be conducted in 2017.

Given the lack of biologically derived parameters for the Indian Ocean, this study aims to generate values of r_{max} to use in constructing priors of this parameter in surplus production models, and values of h for use in the age-structured stock assessment models from biological data available for the Indian Ocean blue shark stock.

2. Materials and methods

Biological parameters were compiled from literature available for the Indian Ocean. The biological information available and used in the demographic model is summarized in **Table 1**.

The growth parameters (von Bertalanffy growth function) were taken from Jolly *et al.* (2013). Median age at maturity (A_{50}) was also taken from Jolly *et al*. (2013). Since no maturity ogive was available, maturity was assumed to be knife-edged at the observed age at maturity, i.e. 0 for ages lower than A_{50}, 0.5 for A_{50}, and 1 for ages higher than A_{50}. A one-year time lapse was added to account for the gestation period before females can contribute offspring to the population.

Fecundity was assumed to be 37 (litter size) based on Mejuto & Garcia-Cortés (2005). In an alternative scenario, a litter size (LS) vs. maternal length (ML) relationship from Castro & Mejuto (1995) was used: LS=-91.97+0.6052ML (cm FL). This accounts for increasing fecundity with increasing maternal size once maturity is achieved. A 1:1 female to male ratio at birth and an annual reproductive cycle were further used and litter size was divided by two to account for female pups only.

Table 1: Biological input values for blue shark (*Prionace glauca*) in the Indian Ocean, used in the demographic population dynamics model.

Parameter	Definition	Unit	Est.	CI		Reference
				25%	95%	
Growth						
L_{inf}	Theoretical max. age	cm TL	334.7	238.8	443.6	Jolly *et al.* (2013)
K	Growth coefficient	$year^{-1}$	0.11	0.06	0.27	
t_0	Age at zero length	year	-2.19	-3.49	-0.84	
Reproduction						
A50	Age at maturity	year	6			Jolly *et al.* (2013)
m_x	Litter size	N pups	37.1	36.7	37.5	Mejuto & Garcia-Cortés (2005)
	Sex ratio at birth	-	1:1			
	Reproductive cycle	year	1			
Reproduction (scenario 2)	Litter size	-	LS = -91.97 + 0.6052*ML			Castro & Mejuto (1995)
W-L						
a	Scalar coef. of W-L	-	$0.83*10^{-5}$			Romanov & Romanova (2009)
b	Power coef. of W-L	-	2.97			

Annual survival at age was obtained and converted through a series of mortality empirical equations. Those included age-independent equations such as Pauly (1980), Hoenig (1983) and Jensen (1996), and age-dependant equations such as Peterson and Wroblewski (1984) and Chen and Watanabe (1989).

An age structured Leslie matrix was used to estimate the finite rate of population change (λ) and r_{max}, assuming a birth-pulse, pre-breeding census (i.e., each element in the first row of the matrix is expressed as $fx=mxp0$, where $p0$ is the probability of survival of age-0 individuals and mx is fecundity or the number of female offspring produced annually by a female of age x, and a yearly time step applied to females only.

Uncertainty in life history variables was incorporated through Monte Carlo simulation (100,000 model runs) by randomly drawing values from statistical distributions for each of these variables. Specifically, uncertainty in the survivorships was introduced by generating age-specific random survivorship values from a Uniform distribution, with limits defined between the age-specific maximum and minimum empirical estimations. For the fecundity parameters uncertainty was incorporated by generating random age-specific fecundities following a Normal distribution with the expected value being the mean fecundity-at-age and the standard deviation the SD-at-age from the age-fecundity regression. To incorporate variability in the life history inputs described above, two stochastic scenarios were explored: 1) assuming constant fecundity and, 2) assuming increasing fecundity according to relation between litter size and maternal size.

Steepness was computed as $h = \hat{\alpha}/4 + \hat{\alpha}$, where $\hat{\alpha}$ is the maximum lifetime reproductive rate which in turn is the product of R0 (the net reproductive rate obtained from the Leslie matrix) and *p0* (Myers *et al*., 1999). A total of 100,000 iterations were run and descriptive statistics for λ, r_{max} and h computed, including the approximate 95% confidence intervals (expressed as the 2.5th and 97.5th percentiles of the distribution).

All analysis was conducted in R language for statistical computing (R Core Team, 2016). Matrix analysis used libraries "primer" (Stevens, 2009) and "popbio" (Stubben & Milligan, 2007). Library "reshape" (Wickham, 2007) was used for data and object manipulation in R.

3. Results and Discussion

For biology scenario 1, λ and r_{max} estimates were 1.37 yr^{-1} and 0.32 yr^{-1}, respectively. Steepness was estimated at 0.80, with 95% CI varying between 0.75-0.84 (Table 2, Figure 1).

Considering a constant vs. increasing fecundity with age had some effect on the estimated parameters, and predicted higher productivity of the population. Specifically, λ and r_{max} were estimated at 1.42 yr-1 and 0.35 yr^{-1}, respectively. Steepness was estimated at 0.87 (95% CI: 0.83-0.89).

Table 2: Productivity (λ and r_{max}) and steepness (h) descriptive statistics obtained through the stochastic simulations for the 2 biological scenarios, for blue shark (*Prionace glauca*) in the Indian Ocean.

Scenario	Parameter	Estimate	95% CI	
			Low	High
1	λ	1.37	1.33	1.41
	r_{max}	0.32	0.28	0.35
	h	0.80	0.75	0.84
2	λ	1.42	1.37	1.46
	r_{max}	0.35	0.32	0.38
	h	0.87	0.83	0.89

The values of intrinsic rate of population change and steepness found in this study are similar to those found in the Atlantic (Cortés, 2016) and the Pacific Oceans (Chen & Liu, 2013; Tsai *et al*., 2013; Liu *et al*., 2015). In the Pacific Ocean values of λ ranged from 1.25 to 1.67 (Tsai *et al.*, 2013) considering a 2-year reproduction cycle. When a 1-year reproductive cycle was considered, the values ranged from 1.15 to 1.16 (Tsai *et al*., 2013). For r_{max}, values ranged from 0.22 yr^{-1} to 0.51 yr^{-1} (Tsai *et al.*, 2013) considering a 2-year reproduction cycle. When a 1-year reproductive cycle was considered, the values ranged from 0.14 to 0.37 yr^{-1} (Tsai *et al*., 2013). For the Atlantic Ocean, Cortés (2016) estimated values of r_{max} ranging from 0.31 to 0.44 yr^{-1} and from 0.22 to 0.34 yr^{-1} for the North and South Atlantic, respectively.

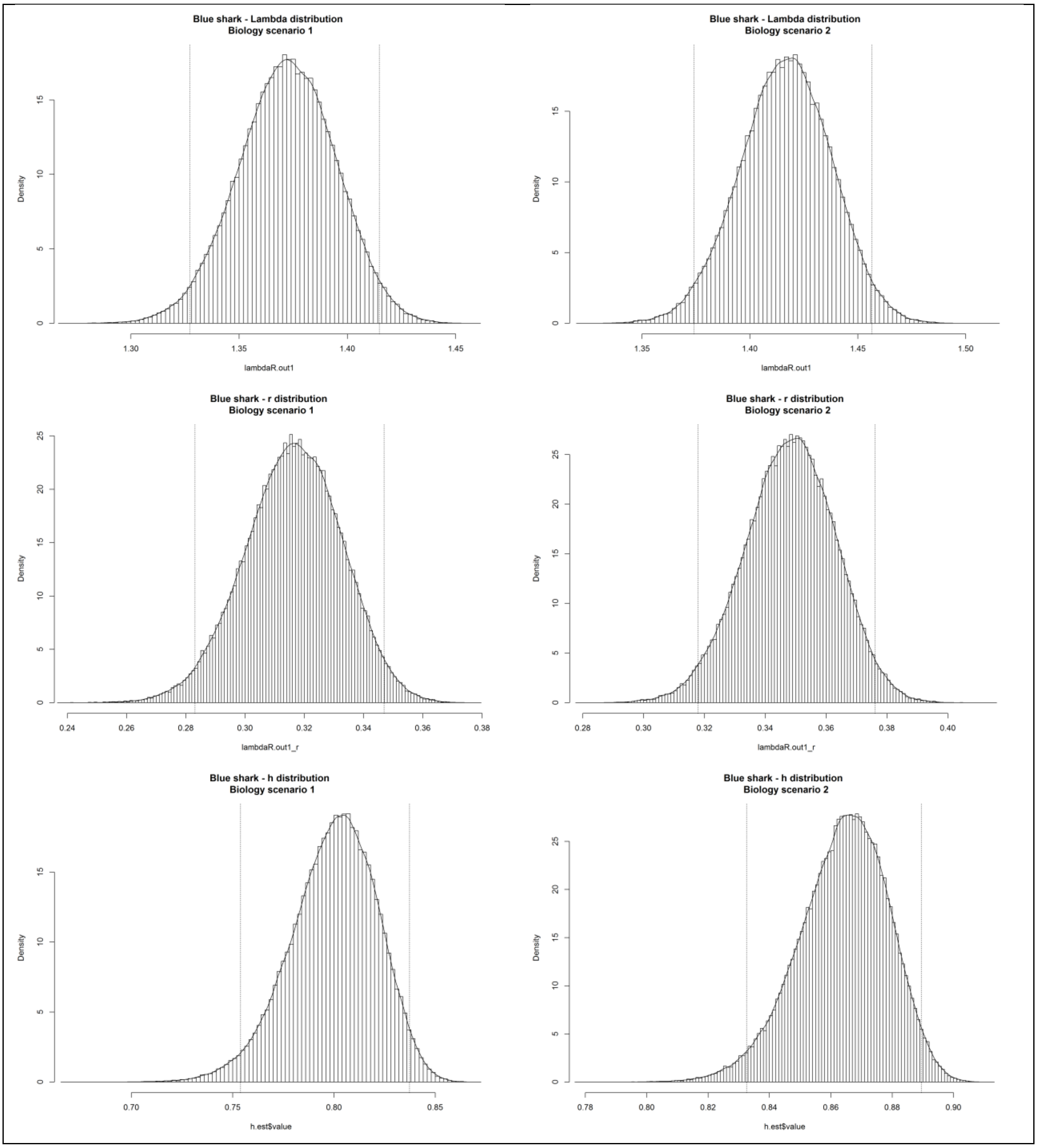

Figure 1: Distribution of productivity (λ and r_{max}) and steepness (*h*) estimates obtained through the stochastic simulations for the 2 biological scenarios, for blue shark (*Prionace glauca*) in the Indian Ocean.

One important shortcoming of this study is that part of the biological parameters used in the demographic model, particularly the age, growth, and fecundity, come from a study with samples only from the SW Indian Ocean (Jolly *et al*., 2013). A recommendation for the future is that a wider ranging biological study should be carried out, so that biological parameters across a wider Indian Ocean area can be used to update these results.

Nonetheless, and even considering this shortcoming in the biological parameters, this is the first study that calculates population dynamic parameters from the Indian Ocean blue shark.

Those parameters could now be considered in future stock assessments, specifically the use of *h* in integrated models as SS3 and r_{max} as priors for Bayesian production models.

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