Abstract

Keywords:

1. Introduction

Sharks are a highly diverse group of fishes and present an array of challenges for management and conservation due to their biological and ecological characteristics. Particularly since they are vulnerable to overexploitation and their populations are slow to rebuild. Like tuna pelagic sharks are widely distributed in Areas Beyond National Jurisdiction (ABNJ). However while five Regional Fisheries Management Organisations (RFMOs) were founded to management tuna stocks no such bodies have been established to manage fisheries of pelagic sharks. These species and fisheries for them are found within the convention areas of all the five tuna RFMOs where they are caught in artisanal, commercial, and recreational fisheries. Therefore the tRFMOs are increasingly taking responsibility for the management of commercial sahrks. However,in most cases, there is a general lack of data on catches, abundance, distribution, life history and interactions with fisheries. All of which hinders an accurate estimation of catch levels, assessment of impacts on their populations and management.

However, even when data are limited empirical studies have shown that there is significant correlation between the life history parameters such as age at first reproduction, natural mortality, and growth rate. This may mean that from something that is easily observable like the maximum size it is possible to infer other life history parameters, such as natural mortality. In this study we show how life history theory can be used to derive parameters for use in management where data and knowledge are limited. We do this three shark species short fin mako, blue and porbeagle.

- Construct simulation models with the life history characteristics of the three species
- Simulate time series of CPUE based on observer programmes

- Evaluate the power to detect trends useful for management

2. Material and Methods

2.1. Life History

Even when data are limited empirical studies have shown that in teleosts there is significant correlation between the life history parameters such as age at first reproduction, natural mortality, and growth rate **?**. This may mean that from something that is easily observable like the maximum size it is possible to infer other life history parameters, such as natural mortality that are less easy to observe. The biologically plausible parameter space is also restricted since size-spectrum theory and multispecies models suggest that natural mortality scales with body size **?**, **?** and **?**.

Kell et al (submitted) showed how life history relationships e.g. **?** can be used to help develop simulation tools for use in stock assessment. We extend this approach to pelagic sharks using the life history parameters for the three main shark species (Shortfin mako, Blue and Porbeagle) caught in Atlantic tuna fisheries.

Life history relationships were used to parameterise an age-structured equilibrium model, where SSB-per-recruit, yield-per-recruit and stockrecruitment analyses are combined, using fishing mortality (F), natural mortality (M), proportion mature (Q) and mass (W) -at-age with a stockrecruitment relationship.

SSB-per-recruit (S/R) is then given by

$$S/R = \sum_{a=r}^{n-1} e^{\sum\limits_{i=r}^{a-1} -F_i - M_i} W_a Q_a + e^{\sum\limits_{i=r}^{n-1} -F_n - M_n} \frac{W_n Q_n}{1 - e_{-F_n - M_n}} \tag{1}$$

where a is age, n is the oldest age, and r the age at recruitment. The second term is the plus-group (i.e. the summation of all ages from the last age to infinity).

Similarily for yield per recruit (Y/R)

$$Y/R = \sum_{a=r}^{n-1} e^{\sum\limits_{i=r}^{a-1} -F_i - M_i} W_a \frac{F_a}{F_a + M_a} \left(1 - e^{-F_i - M_i}\right) + e^{\sum\limits_{i=r}^{n-1} -F_n - M_n} W_n \frac{F_n}{F_n + M_n} \tag{2}$$

The stock recruitment relationship can then be reparameterised so that recruitment R is a function of S/R

e.g. for a **?**

$$S/R = (b + S)/a \tag{3}$$

S can then be derived from F by combining equation 3 or 4 with equation 1.

There are various models to describe growth, maturation and natural mortality and the relationships between them.

Here we model growth by applying (**?**)

$$L_t = L_\infty - L_\infty exp(-kt) \tag{4}$$

where L_∞ is the asymptotic length attainable, K is the rate at which the rate of growth in length declines as length approaches L_∞, and t_0 is the time at which an individual is of zero length.

Mass-at-age can be derived from length using a scaling exponent (a) and the condition factor (b).

$$W_t = a \times W_t^b \tag{5}$$

Natural mortality (M) at-age can then be derived from the life history relationship **?**.

$$log(M) = a - b \times log(L_\infty) + c \times log(L) + d \times log(k) - \frac{e}{T} \tag{6}$$

where L is the average length of the fish (in cm) for which the M estimate applies.

While maturity (Q) can be derived as in **?** from the theoretical relationship between M, K, and age at maturity a_Q based on the dimensionless ratio of length at maturity to asymptotic length (**?**).

$$a_Q = a \times L_\infty - b \tag{7}$$

2.2. Stock Recruitment Relationships

Stock recruitment relationships are needed to formulate management advice, e.g. when estimating reference points such as MSY and F_{crash} and making stock projections. Often stock recruitment relationships are reparameterised in terms of steepness and virgin biomass, where steepness is the ratio of recruitment at 40% of virgin biomass to recruitment at virgin biomass. However, steepness is difficult to estimate from stock assessment data sets: there is often insufficient range in biomass levels to allow the estimation of steepness **?**.

We use a Beverton and Holt stock recruitment relationship reformulated in terms of steepness (h), virgin biomass (v) and $S/R_{F=0}$.

Where steepness is the proportion of the expected recruitment produced at 20% of virgin biomass relative to virgin recruitment (R_0). For the Beverton & Holt stock-recruit formulation, this equals

$$R = \frac{0.8 \times R_0 \times h \times S}{0.2 \times S/R_{F=0} \times R_0(1-h) + (h-0.2)S} \tag{8}$$

For future studies however, it may be more appropraite to alter the stock recruitment relationship used here. For some species, particularly those with low fecundity, a more appropriate stockrecruitment relationship may be one that is expressed in terms of offspring survival rather than recruitment. Unlike fish producing millions of eggs, species with low fecundity (e.g. sharks), produce few offspring per litter and exhibit relatively little variability in litter size among spawn- ers. This suggests both low productivity in general and a more direct connection between spawning output (which is commonly expressed in numbers of eggs or embryos) and recruitment than for many species. The commonly used BevertonHolt and Ricker models can be stated in terms of pre-recruit survival, with two parameters controlling the shape of the function. Both models, however, would result in survival decreasing fastest at low stock size (concave decreasing survival) even though it is reasonable to expect that for low fecundity species, offspring survival would instead decrease faster due to competition when the population approaches carrying capacity (convex decreasing survival). New methods such as the a , flexible three-parameter stockrecruitment model (MaunderTaylor-Methot stock recruitment model), based on pre-recruit survival should be investigated. This new model enables the description of a wider range of pre-recruit survival curves than either BevertonHolt or Ricker, including those that correspond to shapes ranging from convex to concave **?**.

2.3. Observer Programmes

2.4. Power Analysis

A power analysis is conducted to determine the ability to detect trends in abundance for different life histories, population distributions and sampling levels. . The power analysis is conducted for a range of survey CVs based on different observer sampling levels and evaluates the number of years required before an given change in the population can be detected. The power of a change abundance being detected is calculated using linear regression given i) estimates of survey variability (CV), ii) the number of annual surveys, iii) the relationship between CV and population density and iv) the percent rate of change (see Gerrodette, 1987 and 1991).

Conducting a power analysis requires choosing appropriate power and significance levels. The power of a statistical test is the probability of correctly rejecting a null hypothesis (H_0) when the hypothese is false (in this case the H_0 is that there has been no increase in the population). As the power increases, the chances of a Type II error (i.e. a false negative) occurring decrease (Greene 2000). Conventionally a test with power greater than 0.8 level (or $\beta <= .2$) is considered statistically powerful.

The statistical power determines the ability of a test to detect an effect, if the effect actually exists (High 2000). The significance level is chosen depending on the acceptable risk of drawing the wrong conclusion. Smaller levels of α increase confidence in the determination of significance, but run an increased risk of failing to reject a false null hypothesis (a Type II error, or "false negative"), and so have less statistical power. The selection of the level α thus inevitably involves a compromise between significance and power, and consequently between the Type I error and the Type II error.

It was also assumed i) that the survey CV was independent of population size (i.e. consistent with the stock assessment assumptions) and ii) that the population increase was linear (since the stock is recovering to B_{MSY} and so density dependence will limit population increase).

Table X show the the population increase required to detect a significant upward trend (at the 95% level) with a power of 80%, while figure Y shows the spawning stock biomass (SSB) for the six projection trajectories used to provide management advice to the Commission by the SCRS (values are relative to the 2012 level). While table Z summaries the CVs by area for the different survey designs.

These table and figures allow important questions to be answered for example e.g. If stock is a single stock what CV will be required to detect a doubling of the population within 10yrs?

Table X shows that if the CV is 25% then it will take 11 years whilst if the CV is 20% it will take 6 years, so the answer would be a CV of 20-25%. The next question would be what survey design would provide a CV of between

20

The CV of the survey is a factor that can be controlled to some extent by the design of and the funding for a survey. The population increase is determined by the biology of a stock and managment. Even with perfect managment as assumed by the Commission and the SCRS there is however considereable uncertainty about the response of the stock to managment, i.e. the SCRS projections predict that stock may increase between 50

All modelling was conducted in R using the /pkgfishmodels and /pkgFLR packages