# Age-Structured Maturity for data-limited Carcharhinid sharks

# Introduction

* Why care about sharks?
  + Sharks are being overexploited on a global level (Worm et al., 2013)
  + Shark fisheries have long been important at local, regional, and international scales from social, cultural, and economic perspectives.
  + “The last decade has seen growing global concern about the status of elasmobranch populations, particularly due to their intrinsic sensitivity to fishing impacts and their very low population growth rates (Dulvy et al. 2014)”.
  + Sharks have declined in Australia (Robbins et al., 2006), the North Atlantic (Baum et al., 2003), the Mediterranean (Ferretti et al., 2008), the Gulf of Mexico (Shepherd and Myers, 2005), Asian waters (Lam and Sadovy De Mitcheson, 2011), Pacific reefs (Nadon et al., 2012) and on reefs around the world (MacNeil et al., 2020)
  + Global shark catches declining due to overfishing (Davidson et al., 2016), global stock status is overwhelmingly below sustainability reference points and without science-based management (Simpfendorfer and Dulvy, 2017)
  + There are examples of successful management of exploited shark populations, therefore worth striving for sustainable exploitation rather than no-take (Simpfendorfer and Dulvy, 2017)
  + Reef sharks therefore merit greater research attention to underpin science-based management and conservation action
* Sharks are hard to study and have no data…
  + chondrichthyan fishes are a particularly data limited group (Barker & Schuessel 2005.. others), which explains why most stocks worldwide have not been assessed with formal fisheries stock assessment methods (Cortés et al., 2012)
  + ‘Stock assessments take money and expertise (Geromont and Butterworth, 2015) which developing countries usually cannot afford’ (Evans, 2000) better reference for this?
  + “As such, the usual data-intensive stock assessment meth- ods are not applicable for a large diversity of bycatch, which has led to a recent increase in the development of tools for the assess- ment of data-poor species (Brooks et al., 2010)” Pardo
  + Catch reporting has been historically deficient leading to uncertainty in sustainability assessments and limiting the types of reference points that can be calculated (Clarke and Hoyle, 2014)
  + High degree of uncertainty in catch data for sharks both in magnitude and species id, can’t use stock assessment models that rely on catch data (Cortés et al., 2006)
  + Fishery-dependent indices of abundance for sharks are not as reliable (usually) as those for fish because the migratory nature and low density of sharks makes for low encounter rates with fishing vessels(Cortés et al., 2012)
  + The idiosyncrasies of tropical shark assemblages do not lend themselves to traditional fisheries assessment and monitoring approaches (Harry et al., 2011),
  + Although sharks have historically been a dominant component of the catch, they are generally not the target species in the Australia Coral Reef Finfish Fishery (Harry et al., 2016)

The poor quality of catch data from elasmobranch fisheries (FAO, 2008; Fischer, 2015) has thus far prevented use of traditional data-intensive methods for assessment and management of most stocks (Clarke and Hoyle, 2014; Cortés et al., 2006).

* Therefore many sharks are assessed using risk-based methods, dependent on life history traits…
  + “Identifying which life history traits affect resilience to a range of fishing pressures is crucial for averting over-exploitation or extinc- tion of data-poor species (Reynolds, 2003; Kindsvater et al.,2016).” Pardo 2017
  + “Life history traits are interrelated due to the evolutionary constraints imposed by energy acquisition and processing (Law, 1979; Charnov, 1993). Some of these relationships, widely known as Beverton–Holt dimensionless ratios, can be used to predict other life history parameters and tied to population dynamics, albeit with considerable uncertainty (Dulvy and Forrest, 2010).” Pardo 2017
  + “The link between life histories and demography allows the use of life history traits to quantify a species’ intrinsic sensitivity (Frisk et al., 2001; Dulvy et al., 2004; Reynolds et al., 2005),” Pardo 2017
  + Life history traits related to body size, growth, age and reproduction are known to be correlated with each other (Cortés, 2000; Hutchings et al., 2012) and thus may be use to predict related parameters such as rate of intrinsic increase or lifetime reproductive output (Frisk et al., 2001; Jennings et al., 1998; Reynolds et al., 2005)
  + ‘the most fundamental parameter in population biology is the reproductive rate at low population size (ã)’. … It is ‘central to calculating r (population growth), reference points, and estimation of long term anthropogenic impacts (Myers et al., 1999)
  + Body size and age at maturity can be used to predict Rmax (Hutchings et al., 2012)
  + Life history characteristics are related to each other (Cortés, 2000; Thorson et al., 2017)
  + Life history traits are related to extinction vulnerability/risk (Dulvy et al., 2014; Dulvy and Reynolds, 2002; García et al., 2008; Hutchings, 2002; Walls and Dulvy, 2020)
  + Despite the greater focus on risk-based methods relative to data-intensive methods like stock assessments, risk assessment methods for chondrichthyans has lagged behind methods for other kinds of fish because of their low economic value and lack of life history and fishery information (Cortés et al., 2015)
* Why a50?
  + Maturity is an essential component to understanding the productivity of a species or population, which in turn indicates how vulnerable it may be to fishing
  + Knowing maturity is necessary to calculate certain reference points, in particular catch-free analytical reference points which may be the only option for species which are not well studied and also have poor quality catch data (see chapter 4 notes)
  + Maturity often expressed as a single value (a50) but in reality varies on a slope – more insightful/faithful to reality to express maturity as an ogive (Brooks paper?)
* Why age-structured data?
  + age-structured data on growth, natural mortality and reproduction are very important for modelling species Rint and (therefore) sensitivity to fishing, but that age-structured data is lacking for many sharks (Gedamke et al., 2007)
  + papers that have used age-structured data for sharks (Cortés, 2002; Frisk et al., 2005; Mollet and Cailliet, 2002)
  + Unstructured = model with single values for life history traits. Structured = age- or size- structured data. Examples of age structured studies for intrinsic rate of increase: (Cortés, 2002; Mollet and Cailliet, 2002)
  + Elasmobranch pop. models often rely on demographic rates which are not age-specific due to data or sampling limitations (Cortés et al., 2012)
  + Many studies assume knife-edge maturity because they haven’t tried to fit a maturity ogive (assume all females mature at the same time) (Cortés et al., 2012)
  + reference points such as catch-free analytical reference points can be calculated for data-limited stocks but depend (for one thing) on age-structured maturity data (Brooks et al., 2010; Cortés and Brooks, 2018)
* Why use modelling to predict unknown life history traits ?
  + Life history traits, while more commonly available than catch data/stock assessments, are still not available for many of the more obscure species which are for example, of less commercial interest or occur in lower-income countries
  + Shark stock assessments often borrow data from similar species/use species complexes because there is not enough species-specific data available (NMFS, 2006)
  + It’s ok to calculate parameters you don’t have based on known relationship to parameters you do have, based on previous empirical work (Kacev et al., 2017)
  + Previous studies have also used data from better-studied species to model life history parameters of data-poor shark species (Jiao et al., 2011; Thorson et al., 2017) robin hood approach (Kacev et al., 2017)
  + Bayesian hierarchical methods are great for data-poor species bc they allow you to borrow strength from species with good-quality data (Jiao et al., 2011)
  + Predictive models are useful to estimate vital parameters for species lacking directly observed demographic or life history data. Sharks are particularly lack in this info as they are so hard to age accurately. Luckily thre are predictable relationships between certain life history traits, for example a50 and K (Frisk et al., 2001)
* In this paper…
  + We specified a Bayesian Hierarchical model to describe the maturity ogives of Carcharhinid sharks, using species where age-structured maturity data were available
  + We then predicted maturity ogives for less-studied species
  + I will focus on a group of species which are understudied, even in the shark world, but nevertheless urgently require science-based management and conservation action
  + The family Carcharhinidae forms a relatively speciose group which includes both well studied species like the bull shark, and lesser-known ones such as the Brazilian sharpnose. We included only Carcharhinids in order to limit phylogenetically derived variation.
  + Risk Assessment methods (such as estimating reference points with life history data) for elasmobranchs has lagged behind that of other vertebrate groups (Cortés et al., 2015), therefore this paper fills a hole in the literature

# Methods

Part 1: Data Collection

1. Age-structured maturity data
   1. Stock assessments
   2. Papers
2. Trait covariates
   1. How chose candidate traits – papers describing relationships between shark or fish maturity and related factors.
   2. How collected candidate traits
      1. fishbase
      2. shark traits
      3. shark refs
      4. google scholar
      5. fill in from closely related species (life history is phylogenetically constrained so that closely related species will have more similar parameters than distantly related species (Frisk et al., 2005))

Part 2: Modelling

We developed a Bayesian hierarchical model to quantify the relationship between Carcharhinid maturity ogives and candidate life history variables at the family and at the stock scale. Maturity ogives are specified by two variables *a50* and *s* (equation 1), where *a* isage, *a50* is the age at which 50% of a population of sharks achieves sexual maturity, and *s* describes the steepness of the ogive (ref).

Both response variables were described using Normal distributions and were estimated simultaneously as two levels within the same model. The distribution of *a50* values were defined by a mean *Ga50* and a standard deviation Ϭa50 (equation 2). *Ga50* was described as a Uniform distribution and allowed to vary between 0 and 30, as the range of known Carcharhinid ages at maturity are 1 and 21 (FishBase2020). Ϭa50 was described using an Exponential distribution decaying from 1.

The distribution of steepness values was defined by a mean *Gs* and a standard deviation *Ϭs* (equation 6). The mean values of *S* where described using a Uniform distribution and allowed to vary between 0.01 and 10, meaning all curves must describe an increasing % maturity as age increases but can do so at different rates.

Covariates were applied at the level of *Ga50* and *Gs* as shown in equations 9 and 10.

Xx Life history traits were initially related to a50 and S because of previous research investigating various relationships between shark growth and other aspects of ecology and life history (go into more detail here, run through the papers cited in list of model params).

Explain how initial list of covariates was refined down to final list

* + - * + Ran a series of model versions
        + Removed covariates with no effect
        + Ran models with S and a50 separately

Summary table of input data? With candidate and chosen covariates, sources for mat data

The outcome space defined by these prior distributions combined with age-structured maturity data and related life history traits was sampled using a Hamiltonian Markov Chain Monte Carlo sampler. Modelling was carried out in Python using the PyMC3 package. Model performance was assessed by looking at convergence (Gelman-Ruben’s R-hat statistic), and through examining posterior traces for full exploration of the potential outcome space. Model fit was evaluated using Widely Acceptable Information Criterion (WAIC) and by plotting observed maturity values against the posterior distribution of maturity ogives.

Part 3: Predicted Ogives:

* Describe prediction method
* Describe process of assessing results
* Use Pardo et al 2018 to justify use of mean/median values for life history traits in prediction dataset. There is uncertainty around maximum age etc for shark species but generally this does not change the median value of calculated parameters such as Rmax (Pardo et al., 2018)

# Results

### Part 1: discuss model performance

* Maybe put a table of parameters, model versions with different parameters, WAIC values

Chart

Description automatically generated

### Part 2: talk about effect of covariates

* Go through each of the s and a50 parameters and discuss the effect direction and size
* Why is it that a50 is easier to predict than s?

Chart, box and whisker chart

Description automatically generatedChart

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Chart

Description automatically generatedPart 3: predicted a50s and ogives

* Talk about performance of prediction script – why some species were able to predict more precisely than others (smaller range of values)
* Talk about species where observed a50 is outside the range of predicted a50. What traits probably contributed to this happening, and what does this tell us about the potential usefulness of this prediction exercise for future applications to other species?
* Remember to take out or mark the species from the model input data

Chart, scatter chart

Description automatically generated

* One more figure about out-of-sample species where the model fails?

# Discussion

* discuss the effects of all the covaraites on s and a50 and how the effect direction and matches/doesn’t match the existing literature
* Why some of the out of sample results don’t work – what traits do tigers have e.g.g that make them hard to predict?

# Supplementary

Possible maturity ogives described by the null model and priors were visualised using prior predictive simulation (figure 1)

Chart

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Describe alternative models

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Figures

Tables