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Contribution to the Themed Section: 'Risk Assessment'

Original Article

Risk assessment of cartilaginous fish populations

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We review three broad categories of risk assessment methodology used for cartilaginous fish: productivity-susceptibility analysis (PSA), demographic methods, and quantitative stock assessments. PSA is generally a semi-quantitative approach useful as an exploratory or triage tool that can be used to prioritize research, group species with similar vulnerability or risk, and provide qualitative management advice. Demographic methods are typically used in the conservation arena and provide quantitative population metrics that are used to quantify extinction risk and identify vulnerable life stages. Stock assessments provide quantitative estimates of population status and the associated risk of exceeding biological reference points, such as maximum sustainable yield. We then describe six types of uncertainty (process, observation, model, estimation, implementation, and institutional) that affect the risk assessment process, identify which of the three risk assessment methods can accommodate each type of uncertainty, and provide examples mostly for sharks drawn from our experience in the United States. We also review the spectrum of stock assessment methods used mainly for sharks in the United States, and present a case study where multiple methods were applied to the same species (dusky shark, *Carcharinus obscurus*) to illustrate differing degrees of model complexity and type of uncertainty considered. Finally, we address the common and problematic case of data-poor bycatch species. Our main recommendation for future work is to use Management Strategy Evaluation or similar simulation approaches to explore the effect of different sources of uncertainty, identify the most critical data to satisfy predetermined management objectives, and develop harvest control rules for cartilaginous fish. We also propose to assess the performance of data-poor and -rich methods through stepwise model construction.

Keywords: chondrichthyans, demography, risk assessment, stock assessment, uncertainty.

Introduction

The field of risk assessment of chondrichthyan (sharks, skates, rays, and chimaeras) populations has lagged behind that of other vertebrate groups. This is due in large part to their comparatively low economic value, and as a consequence, their lack of basic life-history and fishery information. However, there is growing interest in this group, particularly sharks, sparked by the recent realization that many species have undergone substantial population declines (Stevens *et al.*, 2000; Baum *et al.*, 2003; Burgess *et al.*, 2005; Myers *et al.*, 2007; Dulvy *et al.*, 2008; Dulvy and Forrest, 2010; Cortés *et al.*, 2012). As a result, risk assessment of chondrichthyan populations, and the research to support it, is now drawing increased attention and resources.

The approaches used to assess the risk of various stressors, notably fishing, on chondrichthyan populations have been heavily influenced by both the quantity and quality of available data. This process takes different forms depending on the discipline and the questions being asked. In a conservation context, the objective is typically the avoidance of large population declines or extinction, whereas in fisheries the goal is to maintain a healthy population while allowing for its sustainable, long-term exploitation. In both cases, a common objective is estimating current status and projecting future trends of a population subjected to stressors or management intervention (e.g. fishing, habitat degradation, and improved water quality). Both current and future status will depend on the population's life-history characteristics; in addition, future status will depend on the type of management action that is implemented.

We consider the process of estimating vulnerability, population growth rates, or stock status and evaluating potential consequences of management actions to fall broadly under the category of "risk analysis" or "risk assessment". A more narrow distinction could be made between risk assessment and stock assessment; however, in this review, we treat stock assessment as part of the continuum of risk analysis methods, where the appropriate method depends on the amount of data available (Figure 1). Burgman *et al.* (1993) define risk assessment as the process of obtaining qualitative or quantitative measures of risk levels, or the probability of an adverse event. Rosenberg and Restrepo (1994) refer to an *ad hoc* working group that defined risk as the "expected loss of benefits from the resource" and risk analysis as "the analysis of benefit streams under uncertainty". A more comprehensive definition includes both the probability of an event and some measure of the severity of the event (Francis and Shotton, 1997). Furthermore, the International Organization for Standardization defines risk as the effect of uncertainty on objectives (ISO 31000, 2009). By reviewing both the methods to assess risk, and the types of uncertainty each method can account for, our review of risk assessment encompasses all these definitions to some extent.

We review three broad categories of risk assessment methodology that have been used for cartilaginous fish, noting the data required and the types of management products that are generated. We also discuss types of uncertainty, how they can be modelled, and which risk analysis methods can accommodate these uncertainties. Because risk analysis can have different objectives for different contexts, we discuss the approaches that have been traditionally used in the conservation arena and compare them with those followed in the field of fisheries. We then review the different types of stock assessments used mainly for sharks in the United States, showcasing a study where a comprehensive suite of methods were applied to Dusky shark (*Carcharhinus obscurus*). We conclude with considerations for bycatch species, review a framework for simultaneously

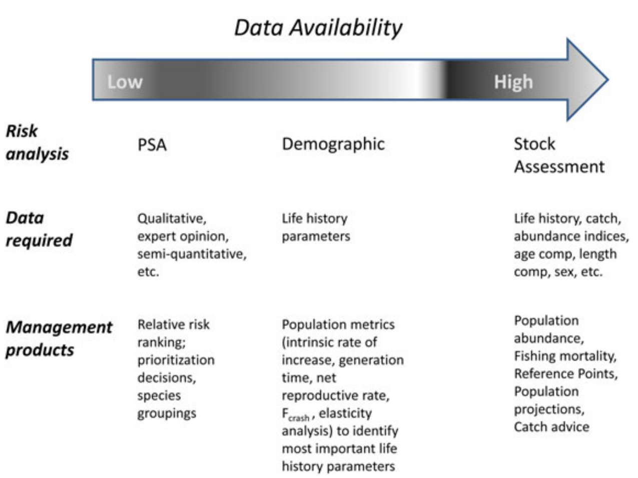

Figure 1. Continuum of risk assessment methods and the types of management products they generate. Although the figure presents the methods as a linear continuum, we recognize that there is overlap between the risk analysis categories.

exploring the effect of different sources of uncertainty, and make recommendations for future work.

Risk assessment methods

Productivity and susceptibility analysis

Data-poor situations are generally the norm when assessing risk of chondrichthyan populations. This group of fish is often taken as bycatch in many fisheries around the world and their biology is poorly understood. This situation gave rise to the use of productivity and susceptibility analysis (PSA, also known as ecological risk assessment or ERA), an approach initially designed to provide management advice when faced with cursory exploitation and biological information for a suite of species caught as bycatch (e.g. Stobutzki *et al.*, 2001). This approach ranges from purely qualitative to quantitative, and is designed to provide management advice by assessing the vulnerability to fishing of a species or population. Vulnerability is expressed as a function of productivity, or capacity of the stock to recover after it has been depleted, and of susceptibility, or propensity to be captured by fishing practices and not survive the interaction. In its most widely used application, PSA is a semi-quantitative approach wherein the productivity and susceptibility components are defined by several attributes that are scored based on a predetermined numerical scale. The attribute scores are then averaged for each component and displayed graphically on an x–y (PSA) plot (Figure 2). Although not generally done, the range or a measure of variability of the attribute scores from different experts can also be displayed to convey "inter-expert" uncertainty. From this, vulnerability can be computed, for example, as the Euclidean distance from the origin to the coordinates of the productivity and susceptibility scores on the PSA plot. Examination of these plots provides a quick, practical tool to assess the potential or risk of a stock to become overfished based on its biological characteristics and susceptibility to exploitation. These plots can be used by managers to adjust management measures to suitable levels given the stock's level of vulnerability. PSA can also be used to prioritize research efforts, for example, toward species that are very susceptible to fishing and for which the biology is poorly understood.

A two-step PSA has recently been developed that builds on existing approaches. In the first step, stock vulnerability is evaluated based on the usual life-history parameters to identify high-risk stocks; the second step evaluates the management risk by considering factors such as the existence of a stock assessment, management controls, and monitoring and compliance (Fleming *et al.*, 2012; Sant *et al.*, 2012; Lack *et al.*, 2014). The outcome for this approach is to identify specific management needs for high-risk stocks.

PSA approaches fall short of providing quantitative management advice, such as appropriate levels of fishing mortality, effort, or catch (but see Zhou *et al.*, 2012 for an approach that combines PSA with indices of relative abundance trends). PSAs should thus be viewed as a first step or triage method in data-poor situations within the spectrum of risk analysis techniques that can be applied as more data become available (see Hobday *et al.*, 2011, for example). Nevertheless, it is being used in the United States to distinguish between fishery and ecosystem component stocks, identify and manage stock complexes based on similar vulnerabilities, and establish management (harvest) control rules that take into account scientific and management uncertainty and provide a larger buffer for species with increased vulnerability to overfishing (Patrick *et al.*, 2010). Several Regional Fishery Management Organizations have adopted this approach in recent years with the aim of providing

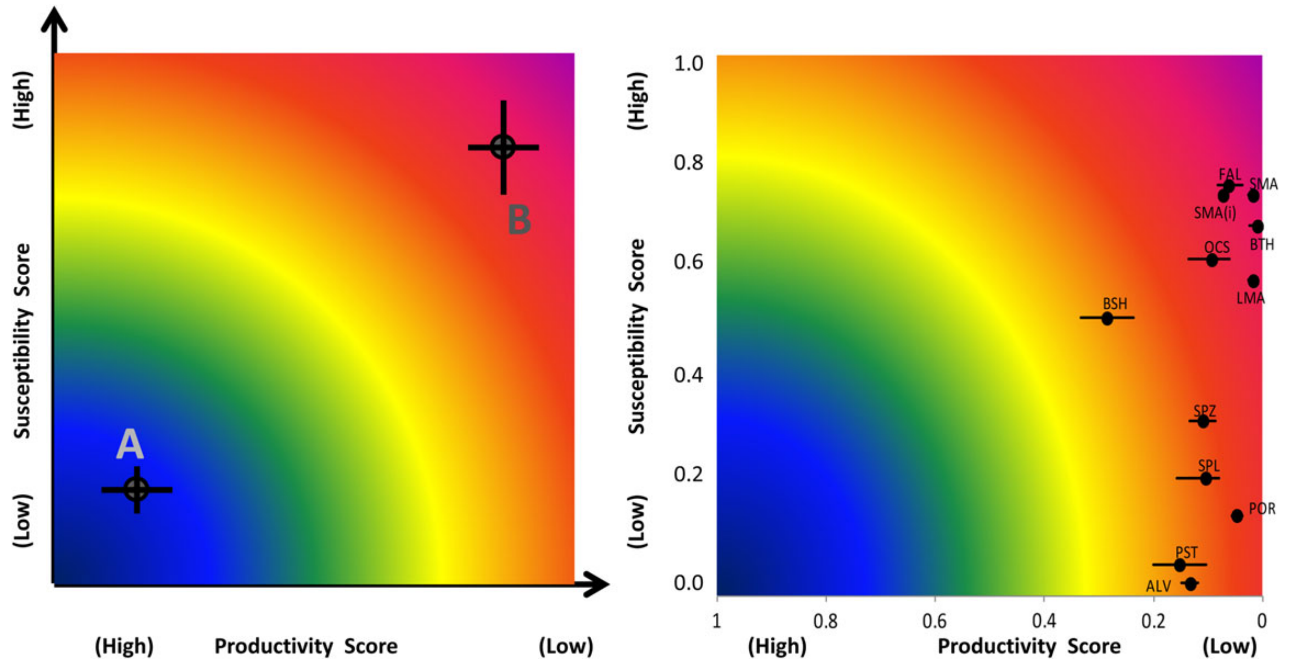

Figure 2. PSA plots. The left panel shows a theoretical example for two species (after Patrick *et al.*, 2009), where species A has high productivity and low susceptibility while species B has low productivity and high susceptibility. Species B would be considered to have higher risk (i.e. greater vulnerability) than species A. Error bars denote the range or a measure of variability of the attribute scores from different experts. The right panel shows a real application to 11 species of Atlantic pelagic elasmobranchs. Note that species greatly differ in their susceptibility score but all have relatively low productivities. Productivity scores incorporated uncertainty in input life-history parameters used to estimate the intrinsic rate of population increase (denoted by the error bars; after Cortés *et al.*, 2010).

management advice for data-poor species for which traditional stock assessments cannot be undertaken. The International Commission for the Conservation of Atlantic Tunas (ICCAT), for example, has recently adopted several management measures for pelagic sharks based on an ERA for the effect of pelagic longline fisheries (Cortés *et al.*, 2010; Figure 2b).

PSAs that compared different groups of fish or vertebrate taxa have consistently found that chondrichthyans were the most vulnerable. For example, Atlantic sharks and North Pacific skates were classified as the most vulnerable in a comparison of Northeast Atlantic groundfish, Atlantic sharks, California nearshore groundfish, California Current coastal-pelagic species, Bering and Aleutian Island skates, and Hawaiian tuna, swordfish, and pelagic sharks. Further, in the Hawaii-based longline fishery, pelagic sharks were more vulnerable than tunas, swordfish, and billfish (Patrick *et al.*, 2010). The same result was found in a comparison of Atlantic sharks, tunas, swordfish, and billfish (Rosenberg *et al.*, 2009). In the Western and Central Pacific Ocean, a PSA of birds, turtles, sharks, tunas, and billfish also found that sharks had the highest vulnerability (Manning *et al.*, 2009). Stobutzki *et al.* (2002) analysed the sustainability of elasmobranchs (sharks and rays) caught as bycatch in a tropical shrimp trawl fishery in Northern Australia and found that pristids (sawfish) and two species of rays have the highest risk. Cortés *et al.* (2008) included large coastal, small coastal, pelagic, and prohibited sharks in a PSA for the effect of fisheries in the Northwestern Atlantic off the United States, and found that coastal sharks were the most vulnerable, particularly larger species that tend to have low productivity and high susceptibility to multiple fishing gears.

In an extension of these more traditional PSAs, Chin *et al.* (2010) developed an integrated risk assessment to examine the vulnerability to climate change of sharks and rays on Australia's Great Barrier Reef. The assessment used three common components to measure vulnerability to climate change: exposure, sensitivity, and adaptive capacity. Freshwater, estuarine, and reef-associated elasmobranchs were found to be most vulnerable to climate change, with vulnerability being driven by species-specific interactions of multiple environmental and ecological factors. Changes in temperature, freshwater input, and ocean circulation tended to have the most widespread effects.

Demographic analysis

Demographic analyses, such as life tables and matrix population models, are another common approach to risk assessment of chondrichthyan species. These methods provide a quantitative estimate of the population intrinsic, or maximum, rate of increase (r_{max}) and other associated population metrics, such as generation time and net reproductive rate. They can be used to assess the level of fishing mortality (F_{crash}) that a stock can sustain before the population growth rate becomes negative and in theory leads to extinction. In some cases, mark-recapture methods have been used to estimate total fishing mortality (Z), from which F can be derived, and thus examine sustainability of shark fisheries (Simpfendorfer, 1999; McAuley *et al.*, 2007; Bradshaw *et al.*, 2013). A more complete accounting of uncertainty in demographic models is done by introducing variability in life-history traits such as fecundity, age at first reproduction, longevity, and natural mortality through Monte Carlo simulation or other resampling methods to generate probabilistic outcomes of the population metrics of interest or to predict extinction risk (also known *sensu lato* as population viability analyses, or PVAs; see, e.g. Fieberg and Ellner, 2001; Cortés, 2002a). The uncertainty introduced in these risk assessments is generally more epistemic than reflective of our knowledge of natural variability in life-history traits.

A notable shortcoming of demographic methods when applied to chondrichthyan fish is that they do not provide information on stock status. This is because the initial age-structured population abundance is not typically known, although the asymptotic stable age distribution (proportion at age) can be obtained from life tables or as the dominant right eigenvector of a matrix population model (Caswell, 2001). In the interest of exploring transient dynamics, rather than the asymptotic distribution, investigators have simulated an initial population size and age structure, allowed vital rates to vary annually, then compared the results of implementing different harvest levels (Cortés, 1999; Aires-da-Silva and Gallucci, 2007). The output of demographic analyses of shark populations has also been used to generate informative prior distributions of the population growth rate or related parameters, such as steepness (Mace and Doonan, 1988) or the maximum lifetime reproductive rate (Myers *et al.*, 1997), for use in Bayesian stock assessment models (e.g. McAllister *et al.*, 2001, 2008; Cortés, 2002b). It is important to note that productivity derived from demographic methods (expressed as $r_{\max}$) is typically based on density-independent theory, while productivity in fisheries models (e.g. steepness) is predicated on density-dependent premises. In both contexts, the productivity metric is intended to reflect the maximum realizable rate of population growth (Gedamke *et al.*, 2007; Cortés *et al.*, 2012).

Elasticity analysis is a common technique applied to matrix population models that can identify the life-history stages that most influence population growth rate, thereby providing a focus for management action (Benton and Grant, 1999). In the United States, for example, elasticity analysis was the basis for implementing minimum size limits for several shark species in an attempt to protect the vital rate (juvenile survival) that was found to be most important for population growth (Brewster-Geisz and Miller, 2000; Cortés, 2002a).

Stock assessment

In addition to PSA and demographic analyses, traditional stock assessment models have been used to analyse risk of chondrichthyan populations in the fisheries arena. The forms of these models range broadly in their level of complexity (Shertzer *et al.*, 2008; Cortés *et al.*, 2012), and ideally should be dictated by the data available. In general, more complex types of assessment models have greater data requirements. Perhaps most critical are data on catch and indices of abundance (developed from research surveys or catch-per-unit-effort). These data allow for annual estimates of population abundance and fishing mortality, which enables calculation of a population's current status.

Stock assessment models can be used to assess risk by providing probabilities of the stock or fishery exceeding biological reference points. In the United States, for example, these models commonly provide probabilities of the stock being overfished (i.e. biomass being below a threshold derived from B_{MSY}, the biomass level that produces MSY) or of overfishing occurring (i.e. fishing mortality being above F_{MSY}, the fishing rate that yields MSY). Once stock status with respect to these reference points has been established, projections can be performed to explore the likely effects of alternative harvest strategies (e.g. catch quotas) on future stock status (Francis and Shotton, 1997). These alternative projection scenarios can be considered by resource managers when making decisions on harvest levels, i.e. to help guide risk management.

A wide variety of stock assessment models exist from the very simple to the relatively complex. For simple models, one consideration is that the method supported by available data may not adequately reflect important biological processes. At the other extreme, model selection can be difficult when complex models include different dataseries, assumed error distributions, or data-weighting schemes. These issues all relate to uncertainty of one type or another, which we expand on below.

Types of uncertainty

Multiple types of uncertainty affect the stock assessment and fisheries management process. Francis and Shotton (1997) identified six types of uncertainty: process, observation, model, estimation, implementation, and institutions. We address each of these sources of uncertainty in the context of their consideration within risk assessment of chondrichthyan fish.

Process uncertainty

As noted by Francis and Shotton (1997), this type of uncertainty refers to natural variability in biological processes. It is often referred to as "process error" in state-space modelling to distinguish it from observation error (Hilborn and Mangel, 1997). Process error in recruitment is one of the most crucial and widely considered sources of uncertainty in modern stock assessments (Hennemuth et al., 1990; Quinn and Deriso, 1999). Because of their reproductive mode, sharks and chondrichthyan fish in general have a very limited number of offspring or eggs, and thus the spawner–recruit relationship is much more predictable than in teleost fish. This condition has led to reparameterizations of the spawner–recruitment curve into more biologically intuitive metrics, such as steepness, maximum lifetime reproductive rate, and pup survival at low population density (Brooks *et al.*, 2010). Process error can also occur in growth rate, maturation, and natural mortality; however, the range of fluctuation in these processes in chondrichthyan fish remains poorly understood. Process error is routinely incorporated into stock assessments and can also be introduced into demographic approaches.

Observation uncertainty

Measurement error is pervasive and almost impossible to avoid when collecting data. It occurs in scientifically designed surveys and in every source of fishery data, including landings, discards, ages of individual fish, and effort of fishers (Schnute, 1991). Observation error can be accounted for by demographic or stock assessment models to various degrees, from not at all to nearly fully through statistical techniques (e.g. maximum likelihood or Bayesian approaches). Even if the data contain no actual error, sampling itself is uncertain by definition because we are not observing the whole population.

Indices of abundance are particularly important when fitting models of population dynamics to data. Observation error in indices of abundance is now routinely taken into account in shark stock assessments through statistical standardization techniques, such as generalized linear models (GLMs) or analogous methods (Maunder and Punt, 2004). Despite efforts to account for all potential explanatory variables through statistical standardization, one recurring issue in shark stock assessments in the United States is that indices of abundance often show larger interannual variability than seems compatible with the life history of the species. This suggests that the GLMs do not always sufficiently account for all the noise in the data, including observation error.

An added problem when multiple indices are available is that different data sources can provide conflicting trends, leading to tensions among these indices when fitting the model. In such cases, the model might tend toward a compromising solution and not fit any index particularly well. As described by Francis (2011), this outcome is undesirable and probably not informative about the direction of population change. While the degree of reliability of the different indices can be conveyed through a variety of weighting schemes, these approaches still do not ensure that the indices track population abundance. For example, inverse CV weighting gives more weight and thus credibility to the most precise indices (those with lower CVs), but this may be reflective of larger sample size and not necessarily the ability to track relative abundance (e.g. NMFS, 2012). Conn (2010) developed a hierarchical approach that recognizes both process and observation errors in indices of relative abundance. This approach combines multiple indices into one, assuming that each index attempts to estimate the same underlying relative abundance. This approach has become one of several consistently in use for many shark stock assessments in the United States.

Observation error can also be reflected in estimates of life-history parameters such as growth rates, reproductive variables, or natural mortality, and can inform Monte Carlo or other resampling methods. Typically, analysts treat variability in life-history parameters as independent, when it may be that such variation is correlated. Brandon *et al.* (2007) review sampling schemes to obtain joint prior distributions that reflect realistic biological constraints between life-history parameters. This type of uncertainty can be incorporated into stock assessments and demographic analyses.

Model uncertainty

All models are necessarily simplifications of reality. Model uncertainty describes the degree to which the real system is adequately represented by the model. The uncertainty stems from an incomplete knowledge and characterization of the system, and it is introduced in two major forms: (i) model complexity and (ii) model structure.

Choosing the level of complexity requires balancing a trade-off: a simpler model will reduce the amount of data needed (thereby reducing other sources of uncertainty, such as observation error), whereas a more complex model can incorporate more processes important to describing population dynamics, but which may be poorly understood. We believe model choice should reflect a balance between data availability and parsimony—in some cases, compromising biological realism for a simpler model may be warranted, so long as the consequences of simplification are addressed when interpreting the results. As an example, shark stock assessments in the United States were typically conducted with surplus production models (Schaefer, 1954) in the 1990s when data available included only fragmentary catches, a few indices of abundance of relatively short duration, and little biological information. As time series of observed data increased in duration, and the knowledge of biological characteristics improved, age-aggregated production models were replaced by age-structured production models (Punt *et al.*, 1995) that more fully incorporate life history and better reflect the fisheries by accounting for size selectivity of different gear types.

Uncertainty in model structure stems from assuming a certain value and/or distribution for parameters and functional forms for variables (e.g. assuming natural mortality is constant vs. age- or time-dependent, dome-shaped vs. flat-topped selectivity curve, or lognormal vs. gamma error structure for process and observation error). The effect of some of these parameter and distribution choices on results can be explored through sensitivity analysis.

One can take the results of sensitivity analysis further by exploring the risk or consequence of applying alternative model structures on projections of future stock status. For example, conducting a stock assessment with three alternative model structures could produce three different estimates of allowable catch (or other management quantity) for the next year. A consequence analysis would take the advice from one model structure and evaluate the effect of implementing that catch advice in all three model structures (e.g. NEFSC, 2013). The results of a consequence analysis can be described graphically (Figure 3), and provide managers with a summary of the potential effects of basing management action on results from a particular model if the true (but unknown) model had a different structure. This technique differs from model averaging (Draper, 1995; Burnham and Anderson, 2002; Brodziak and Legault, 2005), where the results from different model structures (e.g. the diagonal elements in Figure 3) are weighted to obtain a single outcome.

In US stock assessment of sharks, the effect of using alternative values of parameter inputs that determine productivity (e.g. natural mortality, growth, and reproductive variables) is routinely

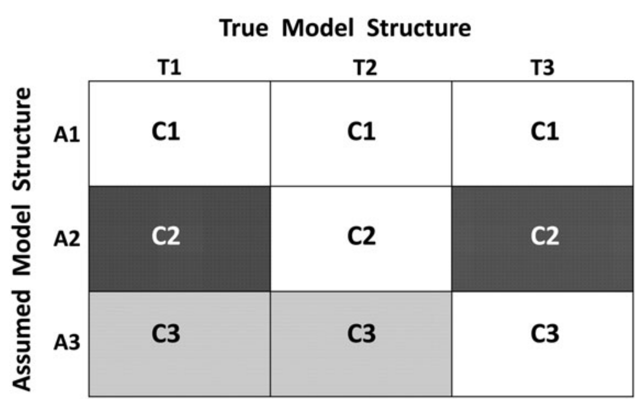

Figure 3. Example of results from a consequence analysis where three different model structures (A1, A2, and A3) are explored. Each model structure is used to perform a stock assessment, and some management quantity (e.g. catch) is estimated for each model (C1, C2, and C3) to achieve a specified goal (e.g. allow spawning biomass to increase). To evaluate the consequence of implementing catch advice from one model if in fact one of the other model structures were more appropriate, the catch from each assumed model structure is implemented in the full suite of models considered. In the above example, results are read across rows (and diagonal elements are self-consistent). The matrix of results is summarized in terms of the specified goal; e.g. if the goal was that spawning biomass would increase, then outcomes where spawning biomass either did not increase or decreased would increase the risk of implementing catch from that model structure. For this hypothetical example, a manager would conclude that the catch estimated for model structure 1 allows spawning biomass to increase regardless of whether or not it reflects the true (or most appropriate) structure. The catch estimated from model 2 only allows spawning biomass to increase if in fact model 2 is the true structure—thus that catch estimate should be considered a risky strategy. The catch estimate from model 3 allows spawning biomass to increase if model 3 is correct, but if not then the spawning stock is expected to remain at its current level (no increase or decrease). The shading of each cell reflects the positive (white), neutral (light grey), or negative (dark grey) outcome.

explored through the use of high and low productivity scenarios, as is the effect of assuming different distributions to describe virgin recruitment (e.g. NMFS, 2012). While performing sensitivity analysis has become routine in stock assessments, taking it further to perform consequence analysis can help managers realize the implications of their choices on future stock status with a more complete picture of model uncertainty. A full consequence analysis has not yet been considered in US shark assessments. This type of uncertainty is usually only considered in stock assessments, but not in PSA or demographic analyses.

Estimation uncertainty

This uncertainty relates to the process of parameter estimation and how well the parameters used for determining stock status represent the state of the stock. In shark stock assessments, uncertainty in parameter estimation is characterized in different ways according to the model used. The sampling-importance resampling (SIR) algorithm (e.g. McAllister *et al.*, 2008) or Markov Chain Monte Carlo (MCMC) (e.g. Cortés, 2002b) is used in Bayesian contexts, whereas bootstrapping (e.g. Simpfendorfer *et al.*, 2000; Hayes *et al.*, 2009) or delta methods (MacCall, 2013) are typically used in frequentist approaches. Accounting for estimation uncertainty results in distributions of model output rather than single point estimates. This type of uncertainty is often considered in stock assessments, much less frequently in demographic-type risk assessments, and not at all in PSAs.

Estimation uncertainty can be incorporated in the formulation of management control rules to help fishery managers establish fishing limits and allowable catches. For example, the estimated distributions from a stock assessment are used to define a distribution of catch that corresponds to F_{MSY}. This catch distribution, and specifically its central tendency, is referred to as the overfishing limit (OFL). A harvest control rule (HCR) can then be used to define the acceptable biological catch (ABC), which is some fraction of OFL that accounts for the degree of uncertainty in the OFL estimation (Figure 4). In US shark stock assessments, the ABC control rule sets a buffer of 30% between the OFL and ABC, i.e. the ABC is the 30th percentile of the OFL distribution, which corresponds to a $\geq$70% probability that overfishing will not occur.

Implementation uncertainty

Implementation uncertainty refers to how successfully management policies will be implemented (Patrick *et al.*, 2013). This is particularly problematic in developing nations or in the open oceans where enforcement is practically non-existent. This type of uncertainty could be incorporated into an HCR similar to estimation uncertainty. For instance, in the US example described above, estimation uncertainty defined the buffer between ABC and OFL. Implementation uncertainty could be used to create a second buffer that defines a lower annual catch limit (ACL). Exceeding the ACL can result in penalties, e.g. excess catch is "paid back" by subtracting it from next year's ACL. This can occur when in-season catch monitoring is imprecise or lags due to delays in reporting. To avoid a "payback" penalty, a third buffer can be defined between the ACL and a lower annual catch target (ACT; see Figure 4).

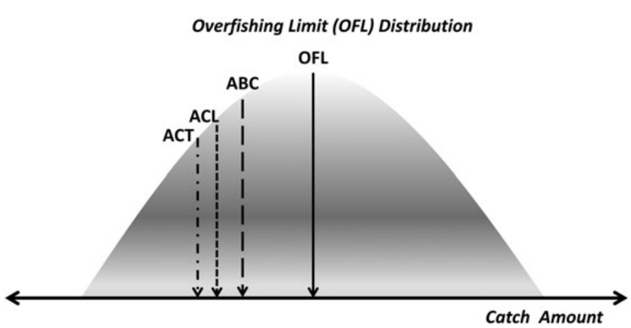

Figure 4. Summary of a type of HCR that determines a catch amount by considering estimation uncertainty (OFL → ABC) and management and implementation uncertainty (ABC → ACL). An additional buffer can also be accommodated (ACL → ACT) to avoid exceeding the ACL in a given year.

In US shark management, the ACL is set equal to the ABC. When the stock is overfished and rebuilding required, the ACL is defined as the projected catch level that produces $\geq$70% probability of stock biomass being above B_{MSY} by the end of the rebuilding time frame. The ACL is disaggregated into commercial, recreational, and discard components, and the commercial shark fishery can be closed when the quota reaches an ACT of 80% of the quota (NMFS, 2013b).

No formal HCRs have yet been developed in the United States to set ACLs and ACTs for managing lower tier (more data limited) shark stocks. In contrast, the southern and eastern scalefish and shark fishery in Australia developed a three-tier (1, 3, and 4) harvest strategy framework with an associated HCR for each tier that is used to determine a recommended biological catch (RBC) (AFMA, 2009). For tier-1 stocks (those with a well-established quantitative stock assessment), the RBC is calculated by applying F_{target} (the fishing mortality rate corresponding to a spawning biomass of B_{target}) to the current biomass to calculate the total catch in the next year. For tier-3 stocks (those without a quantitative stock assessment but with estimates of F and other biological information), the RBC is obtained from the current catch adjusted by the ratio of the intended and current exploitation rates, where the intended exploitation rate is based on the F for the RBC from the HCR. Tier 4 stocks are those corresponding to the most data-limited situations with no reliable information on current biomass or exploitation rate. For those stocks, the RBC is set based on a catch target derived from a historical period identified as a desirable target in terms of cpue, catches, and status of the fishery, the maximum level of catch that the HCR can set, target and limit cpues, and the average cpue over a given number of recent years. To further account for uncertainty in the lower tier stocks, a discount factor of 5 and 15% is applied to the RBC for the tier-3 and tier-4 stocks, respectively, to set a lower TAC (total allowable catch) with the aim of supporting stock recovery and preventing stocks from becoming overfished in the future.

Institutional uncertainty

Francis and Shotton (1997) further identified institutional uncertainty, arising from a lack of clear objectives for fisheries management and the interaction between different groups (scientists, managers, economists, fishers, and politicians). To some extent, the lack of clear objectives can arise from each group focusing on a different measure or consequence of risk (statistical probabilities, economic forecasts, future catch variability, and legal requirements of rebuilding). Reconciling these diverse considerations requires defining risk tolerance and the relative importance of each of these objectives. These decisions define risk management. In fisheries, the process of risk management is often qualitative and sometimes only loosely related to the risk assessment from which it stemmed (Francis and Shotton, 1997).

Comparing risk analysis across disciplines

Extinction risk in marine fish has been measured through a variety of methods. Dulvy *et al.* (2004) noted that there is variation in both the definition of extinction risk and the degree of precision and defensibility of the risk assessment methods used in conservation biology, leading them to recommend a two-step approach for defining and assessing extinction risk. First, simple methods would be used to triage a large number of populations, and second, only those populations identified as vulnerable would be subject to more rigorous analysis. This approach is analogous to using some "rapid assessment techniques," such as PSAs, to identify those species or stocks more at risk then for those stocks, to apply stock assessments of different complexity based on data availability.

There has been intense debate over whether to apply methods of assessing extinction risk vs. methods of stock assessment traditionally used in fisheries for highly catchable and productive marine fish species (Matsuda *et al.*, 1998; Punt, 2000; Hutchings, 2001). Dulvy *et al.* (2005) addressed this issue in a study of 76 stocks of exploited marine fish and invertebrate species, in which they applied two criteria defined by the International Union for the Conservation of Nature's Red List of Threatened Species (IUCN, 2004) based on decline rates and population viability, and a criterion defined by the American Fisheries Society (Musick, 1999) based on decline rates and productivity. They compared predictions of extinction risk with those of stock status reported in stock assessments, and found that results from the two approaches were consistent. Davies and Baum (2012) also reported that IUCN conservation metrics and fisheries metrics (whether the stock was above or below reference points) agreed well in assessing the status of marine fish despite basic differences in the methods used in both disciplines; they suggested that the only difference was in the divergent philosophy of how to manage species of mutual concern. This difference between disciplines is exacerbated by the fact that fisheries scientists do not generally consider overfished populations to be at risk of biological extinction and highlights that risk tolerance is not the same because of divergent goals.

The spectrum of stock assessment methods

Biomass dynamic (age-aggregated surplus production) models are the simplest form of model used for assessing marine fish stocks, including chondrichthyans, around the world. Bayesian surplus production (BSP) models have been used for assessing large and small coastal sharks in the United States since 1998 and 2002, respectively (NMFS, 1998; Cortés, 2002b). The BSP model (McAllister and Kirkwood, 1998a, b; McAllister and Babcock, 2006) is a Schaefer biomass dynamic model that considers observation error only and uses the SIR algorithm to draw the estimated parameters from their joint posterior distribution and project the population forward under constant quota- or fishing mortality-based policy options. Probabilistic statements about the condition of the stock with respect to various indices of policy performance are then generated for different projection time intervals thus conveying the uncertainty associated with alternative harvesting strategies. Meyer and Millar (1999) developed a Bayesian state-space model incorporating both process and observation errors, which has been used in several stock assessments of Atlantic sharks (Cortés *et al.*, 2002, 2006). This model is implemented in WinBUGS and uses MCMC for numerical integration (Spiegelhalter *et al.*, 2000). No formal projections of future stock condition were developed with this approach. Jiao *et al.* (2009) illustrated the use of hierarchical BSP models for situations when species-specific data are unavailable in a hammerhead shark complex stock assessment. They found that models incorporating a multilevel prior on the population maximum growth rate ($r_{\max}$) fitted the data better than non-hierarchical models, which tended to produce credible intervals for estimates of stock status that were unrealistically narrow as a result of ignoring variability among species. These narrow intervals could lead to adoption of high-risk management strategies. In a follow-up study, Jiao *et al.* (2011) further explored the use of hierarchical and non-hierarchical BSP models for assessing fish complexes in situations where species-specific data were available, but were of different quality and quantity, concluding that the hierarchical models outperformed the non-hierarchical formulations because the poor-data species could "borrow strength" from the species with better data.

Age-structured production models are a bridge between the simpler production models and the more complex fully age-structured models (ASMs). The underlying dynamics are age-structured, but predicted values are aggregated across ages and compared with observed data that lack age information. The state-space age-structured production model (Porch, 2003a) is one example that can incorporate both observation error in the data variables (catches, cpue, and effort) and process error in state variables (effort, recruitment, and catchability deviations) and has been used to assess shark stocks in the United States since 2002 (e.g. Cortés *et al.*, 2002). Future projections of stock status initially included process error in recruitment only (Porch, 2003b); however, current projection methodology incorporates additional sources of variability in initial abundance, fishing mortality, pup survival at low density, and equilibrium recruitment. This approach also allows one to calculate probabilities of the stock being overfished and overfishing occurring for alternative levels of fixed removals each projection year (NMFS, 2013a). For overfished stocks in the United States, the population is first projected forward at $F = 0$ to determine the year when the stock recovers ($B/B_{MSY} > 1$) with a 70% probability. If that year is >10, then the stock must be rebuilt by the estimated rebuilding time $+1$ generation (Restrepo *et al.*, 1998). Fixed *F* and catch strategies can then be used to find the level that allows for the stock to be rebuilt with a 70% probability by the target year.

Porch *et al.* (2006) developed a variant of the age-structured production model for situations with no reliable catch history, a condition that is common in shark assessments. The state-space age-structured catch-free production model (ASCFPM) expresses the population dynamics on a relative scale (relative to virgin levels), to account for the lack of catch in the model. Model inputs include the usual age-specific vital rates, indices of abundance, and specification of a form for the stock–recruit curve, which for sharks can be parameterized in terms of maximum lifetime reproductive rate ($\hat{\alpha}$). The model estimates relative biomass trends, fishing mortality rates, predicted values for indices, and MSY-based reference points (abundance-related values are expressed relative to the unexploited level) and has been used for assessing dusky (*Carcharhinus obscurus*) sharks (Cortés *et al.*, 2006; NMFS, 2010), porbeagle (*Lamna nasus*) (ICCAT, 2010), and shortfin mako (*Isurus oxyrinchus*) (ICCAT, 2013).

Statistical catch-at-age models are the most complex form of model used for assessing shark stocks. Through "Integrated Analysis" (Maunder and Punt, 2013), these models attempt to make use of multiple data sources simultaneously, generally including information on catch and indices of abundance, as well as age and/or length composition. These models can take many different forms (e.g. sex structure in addition to age structure), and their flexibility allows them to accommodate nearly any additional type of data that might be deemed important (e.g. tagging data). Punt and Walker (1998) used a statistical catch-at-age model, along with Bayesian inference and the SIR algorithm, to generate posterior distributions of virgin equilibrium biomass and a parameter determining the magnitude of density dependence in a stock assessment of the school shark (*Galeorhinus galeus*) off southern Australia. They also conducted a risk analysis consisting of probabilistic projections under alternative *F* levels.

Length-based ASMs are also being increasingly used to take advantage of the fact that lengths are often recorded in many fisheries and surveys for chondrichthyan fish. Age information is very scarce, in part because of insufficient sampling of catches, but also because cartilaginous fish are inherently difficult to age. Pribac *et al.* (2005) used a variant of integrated analysis wherein catch, catch rate, length and age compositions, and tagging data were used to assess the status of the gummy shark off the Bass Strait and South Australia within a maximum likelihood estimation framework. Frisk *et al.* (2010) developed an ASM that was fit to catch rate and length composition data to assess trends in winter skate (*Leucoraja ocellata*) abundance, biomass, and exploitation, testing hypotheses to explain the population dynamics of this species in the Georges Bank region.

Stock synthesis (SS), a widely used programme for integrated analysis, is a very flexible assessment framework that accommodates input of many different types of data, including both sex-specific length and age compositions (Methot and Wetzel, 2013). Gertseva (2009) used SS to assess the status of the longnose skate (*Raja rhina*) in the northeast Pacific Ocean, and more recently, Rice and Harley (2012) used SS to assess the status of the oceanic whitetip (*Carcharhinus longimanus*) shark in the western and central Pacific Ocean. As more and better data become available, we expect that shark assessments will rely less on data-poor methods and will transition toward integrated analysis, at least for some species.

Case study: the dusky shark

The dusky shark off the Northwest Atlantic Ocean provides a good example to illustrate the suite of analytic tools that can be used to determine the status of a stock under multiple sources of uncertainty. The dusky shark is a large coastal-pelagic species designated in 1997 as a candidate for listing under the Endangered Species Act in the United States, and classified as vulnerable in the western North Atlantic Ocean under World Conservation Union IUCN criteria in 2004. Capture of dusky sharks off the US East Coast has been prohibited since 2000. Data from a variety of sources and a portfolio of quantitative methods were used to assess the status of the dusky shark population in the western North Atlantic Ocean (Cortés *et al.*, 2006; Table 1). Trends in average size and catch rates (cpues) from five sources standardized through GLM statistical techniques were all found to have declined, many of them significantly. A demographic analysis was conducted in which uncertainty in life-history traits (age, growth, reproduction, and natural mortality) was incorporated through Monte Carlo simulation of life tables, which allowed consideration of a wide range of plausible parameter values. That analysis found dusky sharks to have long generation times (30 years), as well as very low population growth rates ($r_{max} < 0.023$ year^{-1}) and steepness ($h = 0.29$). Some of these estimated population parameters were later used to inform priors in Bayesian stock assessments. Elasticity analysis identified juvenile survival as the main contributor to population growth.

A broad spectrum of stock assessment methods was applied to evaluate stock status. Three complementary approaches of increasing complexity were used: BSP models, the catch-free age-structured production model; and an ASM that incorporated catch. Three Bayesian variants of Schaefer's biomass dynamic model were applied that allowed incorporation of different assumptions about observation and process error and numerical integration techniques: a BSP model with the SIR algorithm (McAllister and Kirkwood, 1998a, b; McAllister and Babcock, 2006), another version of the BSP model with the SIR algorithm but incorporating process error in the projections (Cortés, 2002b), and a state-space BSP model implemented in WinBUGS (Meyer and Millar, 1999).

Table 1. Methods used by Cortés *et al.* (2006) to estimate the status of the dusky shark (*Carcharhinus obscurus*) stock in the western North Atlantic Ocean.

Method	Type of uncertainty	Results	Conclusion
Trends in size		All decreasing (4 of 5, $P = 0.05-0.001$)	Heavily exploited, particularly immature stages
Trends in cpue	Observation	All decreasing (3 of 5, $P = 0.001$)	Declines >50% of virgin likely
Demographic analysis	Observation, model structure	Low productivity ($r < 3\%$ per year); long generation time (30 years)	Can withstand only very low *F*
Elasticity analysis	Observation, model structure	Juvenile (immature) stage most influential to productivity	Should protect immature sharks
Bayesian SPM	Observation, model structure, estimation	$B_{current}/B_{virgin} = 0.03-0.21$; stock overfished; overfishing occurring	Heavily depleted stock in need of rebuilding
Bayesian SSSPM	Observation, process, model structure, estimation	$B_{current}/B_{virgin} = 0.16$; stock overfished; overfishing not occurring[a]	Heavily depleted stock in need of rebuilding
SPMs (combined)	Observation, process, model complexity, model structure, estimation	$B_{current}/B_{virgin} = 0.03-0.21$; stock overfished; overfishing occurring	Heavily depleted stock in need of rebuilding
ASCFPM	Observation, process, model structure, estimation	$B_{current}/B_{virgin} = 0.04-0.13$; stock overfished; overfishing occurring	Heavily depleted stock in need of rebuilding
ASM	Observation, model structure, estimation	$B_{current}/B_{virgin} = 0.21-0.37$; stock overfished; overfishing occurring	Heavily depleted stock in need of rebuilding

The main results and conclusions from application of each method are listed for comparison along with the type of uncertainty that each method addressed. SPM, surplus production model; SSSPM, state-space surplus production model (WinBUGS); ASCFPM, age-structured catch-free production model; ASM, age-structured model.
[a]Only in terminal year.

While the data for production models were certainly available, these models are not able to incorporate important information about age-specific quantities, protracted maturation schedules, or generation time.

Estimates of age-specific vital rates for dusky shark from limited studies were used to derive inputs for ASMs to better capture the biology of the species. The ASCFPM (Porch *et al*., 2006) and the ASM of Apostolaki *et al*. (2006) were both used. The ASCFPM was a convenient approach because it re-scales the model population dynamics as proportional to unexploited conditions, thereby eliminating dependence of model results on catch levels, which are poorly known. The ASM is sex specific, a feature that is considered important for describing population dynamics of dusky and other sharks.

Use of the three modelling approaches thus addressed several sources of uncertainty: observation, process, model, and estimation uncertainties. Model uncertainty was further addressed directly through model complexity (the type of model used) and model structure (via sensitivity analyses of several parameter input values or distributions). Uncertainty in data inputs was investigated through extensive sensitivity analyses. Estimation uncertainty was addressed through the use of different algorithms for numerical integration (SIR vs. MCMC) or the importance function used in the SIR algorithm (changing it from the priors to a multivariate *t*-distribution).

Despite the diversity of assumptions, required model inputs, and sources of uncertainty considered, the multitude of methods used provided a consistent picture of heavy fishing impact and high vulnerability to exploitation of dusky sharks in the western North Atlantic Ocean (Cortés *et al*., 2006). All three stock assessment models generally estimated large depletions of at least 80% with respect to virgin levels. Such convergence of results suggests that the data, particularly the biological information and the indices of abundance, were robust and led to conclusions that were largely independent of the method used, despite the acknowledged sources of uncertainty.

Further considerations and recommendations

The case study described for dusky sharks, where multiple methods were applied to the same stock, is not possible for most chondrichthyans. These species tend to be bycatch, thus both the data and the range of applicable methods is limited (Stevens *et al*., 2000). As a consequence, fisheries impacts on bycatch species are particularly difficult to quantify, and management objectives often lack specific bycatch reduction targets (Moore *et al*., 2013). In these typically data-poor situations, multiple limit reference points based only on catch and life-history data have been proposed to identify sustainable levels of bycatch for non-target populations of marine megafauna. Moore *et al*. (2013) cite the potential biological removal (PBR) reference point used in the Marine Mammal Protection Act as an example of a precautionary approach to incorporating uncertainty directly into the reference point estimator to ensure relatively high population levels or a high probability of rapid recovery. However, for several elasmobranch species that are relatively abundant but of low economic value, depletion to lower abundance levels or a higher risk tolerance to a given level of bycatch may be a reasonable option (Zhou *et al*., 2011). Even if a given bycatch or exploitation level in general exceeds the prescribed reference point (e.g. PBR), it could still be sustainable but with a lower degree of certainty (i.e. higher risk tolerance).

Concerns related to the ability of data-poor methods to accurately reflect the complex dynamics and protracted population response times are valid. Furthermore, the inherent uncertainty in data for bycatch species can complicate management decisions about buffer size, rebuilding targets, and how strictly to regulate the fisheries responsible for bycatch. A convenient framework for simultaneously exploring the effect of different sources of uncertainty is management strategy evaluation (MSE; Butterworth and Punt, 1999). In this approach, the entire assessment and management process is evaluated, from data collection to the application of HCRs, using Monte Carlo simulation where parameter or data values are sampled from relevant probability distributions (Little *et al*., 2011). Typically, an MSE comprises an operating model that describes the "true" population dynamics of the stock, including process error; an observation/estimation model that generates data and estimates reference points considering observation (sampling) error and uncertainty in the operating model; and an assessment/management model that implements HCRs in response to the estimated stock status relative to reference points to define the level of catch each year (e.g. Smith, 1994; Wayte and Klaer, 2010; Moore *et al*., 2013). MSE thus allows exploration of the likely effect of alternative management strategies and the ability of those strategies to satisfy quantifiable management objectives (Smith, 1994).

Punt *et al*. (2005) used MSE to evaluate the relative benefits of alternative harvest strategies to set annual TACs for school and gummy shark (*Mustelus antarcticus*), finding that the uncertainties that most affected performance measures (related to average catches, catch variability, and resource conservation) were the technical interaction between fishing for school and gummy shark, the productivity of the school shark, and the magnitude of tag loss or shark death immediately after tagging. Little *et al*. (2011) used MSE to evaluate a catch- and cpue-based HCR for the southern and eastern scalefish and shark fishery of Australia for situations with limited data, finding that fishery objectives could be achieved reasonably well when target catch was a function of a predefined historical reference period characterized by relatively stable cpue and catches.

The effort needed to conduct an MSE is incomparably greater than required for a PSA. However, it may be possible to conduct an MSE for a representative species to develop an HCR that incorporates decisions about risk tolerance, then use that HCR for species that scored similarly in a PSA. Such stopgap measures may be a practical management approach until data are sufficient for species-specific applications.

In general, we recommend a stepwise approach wherein the model used to assess risk is determined by the data available. Initially, this can be a simple model that requires few data. As more and better data become available, more complex models can be explored in tandem with identifying the types of data that are most crucial for satisfying predefined management objectives through MSE or similar simulation approaches.

When using simple models like PSA to rank species by risk of overfishing, it would be advisable to explore the use of additional measures of vulnerability and compare them to the more traditionally used Euclidean distance. When using demographic models, it is also important to make sure that the life history inputs (growth, mortality, reproduction) correspond to those that would be expected of a population growing at its maximum rate.Finally, we also recommend testing model performance through stepwise construction. The performance of data-poor methods can be assessed for their ability to recreate results obtained with more data-rich approaches. A simple model can also be built up to a more complex model by adding data that support the next level of complexity. This sequential model building exercise could identify which steps cause model results to diverge, pointing towards aspects of the data or model structure that are important to refine with targeted future research. In addition, simulation testing can help identify applications where data-limited approaches will not be appropriate.

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References

AFMA (Australian Fisheries Management Authority). 2009. Harvest Strategy Framework for the Southern and Eastern Scalefish and Shark Fishery. Australian Government. 25 pp.

Aires-da-Silva, A. M., and Gallucci, V. F. 2007. Demographic and risk analyses applied to management and conservation of the blue shark (*Prionace glauca*) in the North Atlantic Ocean. Marine and Freshwater Resources, 58: 570–580.

Apostolaki, P., Babcock, E. A., and McAllister, M. K. 2006. Contrasting deterministic and probabilistic ranking of catch quotas and spatially and size-regulated fisheries management. Canadian Journal of Fisheries and Aquatic Sciences, 63: 1777–1792.

Baum, J. K., Myers, R. A., Kehler, D. G., Worm, B., Harley, S. J., and Doherty, P. A. 2003. Collapse and conservation of shark populations in the northwest Atlantic. Science, 299: 389–392.

Benton, T. G., and Grant, A. 1999. Elasticity analysis as an important tool in evolutionary and population ecology. Trends in Ecology and Evolution, 14: 467–471.

Bradshaw, C. J. A., Field, I. C., McMahon, C. R., Johnson, G. J., Meekan, M. G., and Buckworth, R. C. 2013. More analytical bite in estimating targets for shark harvest. Marine Ecology Progress Series, 488: 221–2232.

Brandon, J. R., Breiwick, J. M., Punt, A. E., and Wade, P. R. 2007. Constructing a coherent joint prior while respecting biological realism: Application to marine mammal stock assessments. ICES Journal of Marine Science, 64: 1085–1100.

Brewster-Geisz, K., and Miller, T. J. 2000. Management of the sandbar shark, *Carcharhinus plumbeus*: implications of a stage-based model. Fishery Bulletin, 98: 236–249.

Brodziak, J., and Legault, C. M. 2005. Model averaging to estimate rebuilding targets for overfished stocks. Canadian Journal of Fisheries and Aquatic Sciences, 62: 544–562.

Brooks, E. N., Powers, J. E., and Cortés, E. 2010. Analytical reference points for age-structured models: application to data-poor fisheries. ICES Journal of Marine Science, 67: 165–175.

Burgess, G., Beerkircher, L., Cailliet, G. M., Carlson, J. K., Cortés, E., Goldman, K. J., Grubbs, D., *et al.* 2005. Is the collapse of shark populations in the northwest Atlantic and Gulf of Mexico real? Fisheries, 30: 19–26.

Burgman, M. A., Ferson, S., and Akçakaya, H. R. 1993. Risk Assessment in Conservation Biology. Chapman and Hall, London.

Burnham, K. P., and Anderson, D. 2002. Model Selection and Multimodel Inference. Springer-Verlag, New York.

Butterworth, D. S., and Punt, A. E. 1999. Experiences in the evaluation and implementation of management procedures. ICES Journal of Marine Science, 56: 985–998.

Caswell, H. 2001. Matrix Population Models, 2nd edn. Sinauer Associates, Inc., Sunderland, MA. 722 pp.

Chin, A., Kyne, P. M., Walker, T. I., and McAuley, R. 2010. An integrated risk assessment for climate change: analysing the vulnerability of sharks and rays on Australia's Great Barrier Reef. Global Change Biology, 16: 1936–1953.

Conn, P. B. 2010. Hierarchical analysis of multiple noisy abundance indices. Canadian Journal of Fisheries and Aquatic Sciences, 67: 108–120.

Cortés, E. 1999. A stochastic stage-based population model of the sandbar shark in the western North Atlantic. *In* Life in the Slow Lane: Ecology and Conservation of Long-lived Marine Animals, pp. 115–136. Ed. by J. A. Musick. Symposium 23, American Fisheries Society, Bethesda, MD. 265 pp.

Cortés, E. 2002a. Incorporating uncertainty into demographic modeling: application to shark populations and their conservation. Conservation Biology, 16: 1048–1062.

Cortés, E. 2002b. Stock assessment of small coastal sharks in the U.S. Atlantic and Gulf of Mexico. Sustainable Fisheries Division Contribution SFD-01/02-152. National Oceanographic and Atmospheric Administration, Panama City, FL. 133 pp.

Cortés, E., Arocha, F., Beerkircher, L., Carvalho, F., Domingo, A., Heupel, M., Holtzhausen, H., *et al.* 2010. Ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. Aquatic Living Resources, 23: 25–34.

Cortés, E., Brooks, E. N., Apostolaki, P., and Brown, C. A. 2006. Stock assessment of dusky shark in the U.S. Atlantic and Gulf of Mexico. Sustainable Fisheries Division Contribution SFD-2006-014, NOAA Fisheries, Miami, FL. 155 pp.

Cortés, E., Brooks, E. N., and Gedamke, T. 2012. Population dynamics, demography, and stock assessment. *In* Biology of Sharks and Their Relatives, 2nd edn, pp. 449–481. Ed. by J. C. Carrier, J. A. Musick, and M. R. Heithaus. CRC Press, Boca Raton, FL. 633 pp.

Cortés, E., Brooks, E. N., and Scott, G. 2002. Stock assessment of large coastal sharks in the U.S. Atlantic and Gulf of Mexico. Sustainable Fisheries Division Contribution SFD-02/03-177. National Oceanographic and Atmospheric Administration, Panama City, FL. 222 pp.

Cortés, E., Heupel, M., Ribera, M., and Simpfendorfer, C. A. 2008. Productivity and susceptibility analysis (ecological risk assessment) of Atlantic sharks. 88th Annual Meeting of the American Society of Ichthyologists and Herpetologists (ASIH), 24th Annual Meeting of the American Elasmobranch Society (AES), Montreal, Canada, July 23–28.

Davies, T. D., and Baum, J. K. 2012. Extinction risk and overfishing: reconciling conservation and fisheries perspectives on the status of marine fishes. Nature, 2: 561.

Draper, D. 1995. Assessment and propagation of model uncertainty. Journal of the Royal Statistical Society Series B, 57: 45–97.

Dulvy, N. K., Baum, J. K., Clarke, S., Compagno, L. J. V., Cortés, E., Domingo, A., Fordham, S., *et al.* 2008. You can swim but you can't hide: the global status and conservation of oceanic pelagic sharks and rays. Aquatic Conservation, 18: 459–482.

Dulvy, N. K., Ellis, R. J., Goodwin, N. B., Grant, A., Reynolds, J. D., and Jennings, S. 2004. Methods of assessing extinction risk in marine fishes. Fish and Fisheries, 5: 255–276.

Dulvy, N. K., and Forrest, R. E. 2010. Life histories, population dynamics, and extinction risks in chondrichthyans. *In* Biology of Sharks and Their Relatives II, 1st edn, pp. 639–679. Ed. by J. C. Carrier, J. A. Musick, and M. R. Heithaus. CRC Press, Boca Raton, FL. 713 pp.

Dulvy, N. K., Jennings, S., Goodwin, N. B., Grant, A., and Reynolds, J. D. 2005. Comparison of threat and exploitation status in Northeast Atlantic marine populations. Journal of Applied Ecology, 42: 883–891.

Fieberg, J., and Ellner, S. P. 2001. Stochastic matrix models for conservation and management: a comparative review of methods. Ecology Letters, 4: 244–266.

Fleming, L. V., Goodman, G., Williams, J., Crook, V., Littlewood, A., Oldfield, T., and Sant, G. 2012. Addendum to JNCC Report No 453 Fish and Multilateral Environmental Agreements: developing a method to identify high risk commercially-exploited aquatic organisms in trade and an analysis of the potential application of

MEAs. Report of an expert review workshop. Aberdeen, Scotland 26–27 September 2011.

Francis, R. I. C. C. 2011. Data weighting in statistical fisheries stock assessment models. Canadian Journal of Fisheries and Aquatic Sciences, 68: 1124–1138.

Francis, R. I. C. C., and Shotton, R. 1997. "Risk" in fisheries management: a review. Canadian Journal of Fisheries and Aquatic Sciences, 54: 1699–1715.

Frisk, M. G., Martell, S. J. D., Miller, T. J., and Sosebee, K. 2010. Exploring the population dynamics of winter skate (*Leucoraja ocellata*) in the Georges Bank region using a statistical catch-at-age model incorporating length, migration, and recruitment process errors. Canadian Journal of Fisheries and Aquatic Sciences, 67: 774–792.

Gedamke, T., Hoenig, J. M., DuPaul, W. D., Musick, J. A., and Gruber, S. H. 2007. Using demographic models to determine intrinsic rate of increase and sustainable fishing for elasmobranchs: pitfalls, advances and applications. North American Journal of Fisheries Management, 27: 605–618.

Gertseva, V. V. 2009. The population dynamics of the longnose skate, *Raja rhina*, in the northeast Pacific Ocean. Fisheries Research, 95: 146–153.

Hayes, C. G., Jiao, Y., and Cortés, E. 2009. Stock assessment of scalloped hammerheads in the western North Atlantic Ocean and Gulf of Mexico. North American Journal of Fisheries Management, 29: 1406–1417.

Hennemuth, R. C., Palmer, J. E., and Brown, B. E. 1990. A statistical description of recruitment in eighteen selected fish stocks. Journal of Northwest Atlantic Fisheries Science, 1: 101–111.

Hilborn, R., and Mangel, M. 1997. The Ecological Detective. Princeton University Press, Princeton, NJ. 315 pp.

Hobday, A. J., Smith, A. D. M., Stobutzki, I. C., Bulman, C., Daley, R., Dambacher, J. M., Dend, R. A., *et al.* 2011. Ecological risk assessment for the effects of fishing. Fisheries Research, 108: 372–384.

Hutchings, J. 2001. Conservation biology of marine fishes: perceptions and caveats regarding assignment of extinction risk. Canadian Journal of Fisheries and Aquatic Sciences, 58: 108–121.

ICCAT. 2010. Report of the 2009 porbeagle stock assessments meeting. Collective Volume of Scientific Papers ICCAT, 65: 1909–2005.

ICCAT. 2013. Report of the 2012 shortfin mako stock assessment and ecological risk assessment meeting. Collective Volume of Scientific Papers ICCAT, 69: 1427–1570.

ISO 31000. 2009. Risk Management – Principles and Guidelines. International Organization for Standardization.

IUCN. 2004. Guidelines for using the IUCN Red List categories and criteria. World Conservation Union, Gland, Switzerland.

Jiao, Y., Cortés, E., Andrews, K., and Guo, F. 2011. Poor-data and data-poor species stock assessment using a Bayesian hierarchical approach. Ecological Applications, 21: 2691–2708.

Jiao, Y., Hayes, C., and Cortés, E. 2009. Hierarchical Bayesian approach for population dynamics modelling of fish complexes without species-specific data. ICES Journal of Marine Science, 66: 367–377.

Lack, M., Sant, G., Burgener, M., and Okes, N. 2014. Development of a Rapid Management-Risk Assessment Method for Fish Species through its Application to Sharks: Framework and Results. Report to the Department of Environment, Food and Rural Affairs. DEFRA Contract No. MB0123. 108 pp.

Little, L. R., Wayte, S. E., Tuck, G. N., Smith, A. D. M., Klaer, N., Haddon, M., Punt, A. E., *et al.* 2011. Development and evaluation of a cpue-based harvest control rule for the southern and eastern scalefish and shark fishery of Australia. ICES Journal of Marine Science, 68: 1699–1705.

MacCall, A. D. 2013. Use of the delta method to evaluate the precision of assessments that fix parameter values. Fisheries Research, 142: 56–60.

Mace, P. M., and Doonan, I. J. 1988. A generalized bioeconomic simulation model for fish population dynamics. New Zealand Fisheries Assessment Research Document 88/4.

Manning, M. J., Bromhead, D. B., Harley, S. J., Hoyle, S. D., and Kirby, D. S. 2009. The feasibility of conducting quantitative stock assessments for key shark species and recommendations for providing preliminary advice on stock status in 2010. Western and Central Pacific Fisheries Commission. WCPFC-SC5-2009/EB-WP-08. 32 pp.

Matsuda, H., Takenaka, Y., Yahara, T., and Uozumi, Y. 1998. Extinction risk assessment of declining wild populations: the case of the southern bluefin tuna. Research in Population Ecology, 40: 271–278.

Maunder, M. N., and Punt, A. E. 2004. Standardizing catch and effort data: a review of recent approaches. Fisheries Research, 70: 141–159.

Maunder, M. N., and Punt, A. E. 2013. A review of integrated analysis in fisheries stock assessment. Fisheries Research, 142: 61–74.

McAllister, M. K., and Babcock, E. A. 2006. Bayesian surplus production model with the Sampling Importance Resampling algorithm (BSP): a user's guide. http://www.iccat.int/en/AssessCatalog.htm (last accessed May 2006).

McAllister, M. K., and Kirkwood, G. P. 1998a. Bayesian stock assessment: a review and example application using the logistic model. ICES Journal of Marine Science, 55: 1031–1060.

McAllister, M. K., and Kirkwood, G. P. 1998b. Using Bayesian decision analysis to help achieve a precautionary approach to managing newly developing fisheries. Canadian Journal of Fisheries and Aquatic Sciences, 55: 2642–2661.

McAllister, M. K., Pikitch, E. K., and Babcock, E. A. 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.

McAllister, M. K., Pikitch, E. K., and Babcock, E. A. 2008. Why are Bayesian methods useful for the stock assessment of sharks? *In* Sharks of the Open Ocean, pp. 351–368. Ed. by M. D. Camhi, E. K. Pikitch, and E. A. Babcock. Blackwell Publishing, Oxford. 502 pp.

McAuley, R. B., Simpfendorfer, C. A., and Hall, N. G. 2007. A method for evaluating the impacts of fishing mortality and stochastic influences on the demography of two long-lived shark stocks. ICES Journal of Marine Science, 64: 1710–1722.

Methot, R. D., and Wetzel, C. R. 2013. Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. Fisheries Research, 142: 86–99.

Meyer, R., and Millar, R. B. 1999. BUGS in Bayesian stock assessments. Canadian Journal of Fisheries and Aquatic Sciences, 56: 1078–1086.

Moore, J. E., Curtis, K. A., Lewison, R. L., Dillingham, P. W., Cope, J. M., Fordham, S. V., Heppell, S. S., *et al.* 2013. Evaluating sustainability of fisheries bycatch mortality for marine megafauna: a review of conservation reference points for data-limited populations. Environmental Conservation, 40: 329–344.

Musick, J. 1999. Criteria to define extinction risk in marine fishes: the American Fisheries Society initiative. Fisheries, 24: 6–14.

Myers, R. A., Baum, J. K., Shepherd, T. D., Powers, S. D., and Peterson, C. H. 2007. Cascading effects of the loss of apex predatory sharks from a coastal Ocean. Science, 315: 1846–1850.

Myers, R. A., Mertz, G., and Fowlow, P. S. 1997. Maximum population growth rates and recovery times for Atlantic cod, *Gadus morhua*. Fisheries Bulletin, 95: 762–772.

NEFSC. 2013. 55th Northeast Regional Stock Assessment Workshop (55th SAW) Assessment Report. US Department of Commerce, Northeast Fisheries Science Center Reference Document 13–11. 845 pp.

NEFSC. 1998. Report of the shark evaluation workshop. National Oceanographic and Atmospheric Administration. Panama City, Florida. 109 pp.

NMFS. 2010. Southeast Data, Assessment and Review (SEDAR) 21: Stock assessment report—Sandbar, dusky and Gulf of Mexico blacknose shark. NMFS, North Charleston, SC.

NMFS. 2012. Southeast Data, Assessment and Review (SEDAR) 29: stock assessment report—Gulf of Mexico blacktip shark. NMFS, North Charleston, SC.

NMFS. 2013a. Southeast Data, Assessment and Review (SEDAR) 34: stock assessment report—Atlantic sharpnose shark. NMFS, North Charleston, SC.

NMFS. 2013b. Amendment 5a to the 2006 Consolidated Atlantic Highly Migratory Species Fisheries Management Plan. Office of Sustainable Fisheries, Silver Spring, MD.

Patrick, W. S., Morrison, W., Nelson, M., and Gonzalez Marrero, R. L. 2013. Factors affecting management uncertainty in U.S. fisheries and methodological solutions. Ocean and Coastal Management, 71: 64–72.

Patrick, W. S., Spencer, P., Link, J., Ormseth, O., Cope, J., Field, J., Kobayashi, D., *et al.* 2009. Use of productivity and susceptibility indices to determine stock vulnerability, with example applications to six U.S. fisheries. NOAA Technical Memorandum NMFS-F/SPO 101. 90 pp.

Patrick, W. S., Spencer, P., Link, J., Ormseth, O., Cope, J., Field, J., Kobayashi, D., *et al.* 2010. Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing. Fishery Bulletin, 108: 305–322.

Porch, C. E. 2003a. A preliminary assessment of Atlantic white marlin (*Tetrapturus albidus*) using a state-space implementation of an age-structured production model. Collective Volume of Scientific Papers, International Commission for the Conservation of Atlantic Tunas, 55: 559–527.

Porch, C. E. 2003b. Pro-2Box v.2.01 User's Guide. 40 pp.

Porch, C. E., Ecklund, A. M., and Scott, G. P. 2006. A catch-free stock assessment model with application to goliath grouper (*Epinephelus itajara*) off southern Florida. Fishery Bulletin, 104: 89–101.

Pribac, F., Punt, A. E., Taylor, B. L., and Walker, T. I. 2005. Using length, age and tagging data in a stock assessment of a length selective fishery for gummy shark (*Mustelus antarcticus*). Journal of Northwest Atlantic Fishery Science, 35: 267–290.

Punt, A. E. 2000. Extinction of marine renewable resources: a demographic analysis. Population Ecology, 42: 19–27.

Punt, A. E., Butterworth, D. S., and Penney, A. J. 1995. Stock assessment and risk analysis for the South Atlantic population of albacore *Thunnus alalunga* using an age-structured production model. South African Journal of Marine Science, 16: 287–310.

Punt, A. E., and Walker, T. I. 1998. Stock assessment and risk analysis for the school shark *Galeorhinus galeus* (Linnaeus) off southern Australia. Marina and Freshwater Research, 49: 719–731.

Punt, A. E., Pribac, F., Taylor, B. L., and Walker, T. I. 2005. Harvest strategy evaluation for school and gummy shark. Journal of Northwest Atlantic Fishery Science, 35: 387–406.

Quinn, T. J., and Deriso, R. B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York. 542 pp.

Restrepo, V. R., Thompson, G. G., Mace, P. M., Gabriel, W. L., Low, L. L., MacCall, A. D., Methot, R. D., *et al.* 1998. Technical guidance on the use of precautionary approaches to implementing National Standard 1 of the Magnuson–Stevens Fishery Conservation and Management Act. NOAA Technical Memorandum NMFS-F/SPO 31. 54 pp.

Rice, J., and Harley, S. J. 2012. Stock assessment of oceanic whitetip sharks in the western and central Pacific Ocean. Western and Central Pacific Fisheries Commission. WCPFC-SC8-2012/SA-WP-06. 53 pp.

Rosenberg, A. A., Acosta, A., Babcock, E., Harrington, J., Hobday, A., Mogensen, C. B., O'Boyle, R., *et al.* 2009. Use of Productivity-Susceptibility Analysis (PSA) in setting annual catch limits for US fisheries: a workshop report. MRAG Americas report to the Lenfest Ocean Program, Washington, DC. 18 pp.

Rosenberg, A. A., and Restrepo, V. R. 1994. Uncertainty and risk evaluation in stock assessment advice for U.S. marine fisheries. Canadian Journal of Fisheries and Aquatic Sciences, 51: 2715–2720.

Sant, G., Goodman, G., Crook, V., Lack, M., and Oldfield, T. E. E. 2012. Fish and Multilateral Environmental Agreements: developing a method to identify high risk commercially-exploited aquatic organisms in trade and an analysis of the potential application of MEAs. JNCC Report No 453.

Schaefer, M. B. 1954. Some aspects of the dynamics of populations important to the management of commercial marine fisheries. Inter American Tropical Tuna Commission Bulletin, 2: 247–285.

Schnute, J. T. 1991. The importance of noise in fish population models. Fisheries Research, 11: 197–223.

Shertzer, K. W., Prager, M. H., Vaughan, D. S., and Williams, E. H. 2008. Fishery Models. *In* Population Dynamics. Vol. 2 of Encyclopedia of Ecology, pp. 1582–1593. Ed. by S. E. Jorgensen, and B. D. Fath. Elsevier, Oxford.

Simpfendorfer, C. A. 1999. Demographic analysis of the dusky shark fishery in southwestern Australia. *In* Life in the Slow Lane: Ecology and Conservation of Long-Lived Marine Animals, pp. 149–160. Ed. by J. A. Musick. Symposium 23, American Fisheries Society, Bethesda, MD. 265 pp.

Simpfendorfer, C. A., Donohue, K., and Hall, N. G. 2000. Stock assessment and risk analysis for the whiskery shark (*Furgaleus macki* (Whitley)) in south-western Australia. Fisheries Research, 47: 1–17.

Smith, A. D. M. 1994. Management strategy evaluation – the light on the hill. *In* Population Dynamics for Fisheries Management, pp 249–253. Ed. by D. A. Hancock. Australian Society for Fish Biology Workshop Proceedings, Perth, 24–25 August, 1993.

Spiegelhalter, D., Thomas, A., and Best, N. 2000. WinBUGS User Manual Version 1.4. MRC Biostatistics Unit, Cambridge, UK.

Stevens, J. D., Bonfil, R., Dulvy, N. K., and Walker, P. A. 2000. The effects of fishing on sharks, rays, and chimaeras (chondrichthyans), and the implications for marine ecosystems. ICES Journal of Marine Science, 57: 476–494.

Stobutzki, I. C., Miller, M. J., and Brewer, D. T. 2001. Sustainability of fishery bycatch: a process for assessing highly diverse and numerous bycatch. Environmental Conservation, 28: 167–181.

Stobutzki, I. C., Miller, M. J., Heales, D. S., and Brewer, D. T. 2002. Sustainability of elasmobranchs caught as bycatch in a tropical prawn (shrimp) trawl fishery. Fishery Bulletin, 100: 800–821.

Wayte, S. E., and Klaer, N. L. 2010. An effective harvest strategy using improved catch-curves. Fisheries Research, 106: 310–320.

Zhou, S., Milton, D. A., and Fry, G. C. 2012. Integrated risk analysis for rare marine species impacted by fishing: sustainability assessment and population trend modelling. ICES Journal of Marine Science, 69: 271–280.

Zhou, S., Smith, A. D. M., and Fuller, M. 2011. Quantitative ecological risk assessment for fishing effects on diverse non-target species in a multi-sector and multi-gear fishery. Fisheries Research, 112: 168–178.

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