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THE CERTAINTY OF UNCERTAINTY IN MARINE CONSERVATION AND WHAT TO DO ABOUT IT

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ABSTRACT

The confounding effects of difficult sampling and dynamic systems make uncertainty the norm for managers of marine ecosystems. Thus managers need approaches that use relatively small amounts of information and account for a wide suite of biological and physical influences. Here we use a case study approach to review the use of several possible techniques for making decisions about marine ecosystems despite uncertainty. We describe the use of expert judgment in the rebuilding plans for data-poor US fisheries, models to manage the krill fishery in the Southern Ocean to account for both the impacts of climate change and the resource needs of krill predators, an integrated risk assessment framework to prioritize shark management in the Atlantic Ocean despite severe data limitations, and models to account for climate impacts on salmonid populations in California. Through this review, we show that with limited information, managers can use models to explore how highly variable systems might respond to management options under different scenarios. Expert judgment can help shape the assumptions that form the basis for those models and propose sensible boundaries within which management options can be developed. A weight of evidence approach can take advantage of small amounts of information from multiple sources, including models and expert judgment. Although none of these approaches is perfect, they can help provide a logical starting point for conservation and management, despite the certainty of uncertainty.

Ecosystem managers regularly confront the challenges of uncertainty. Ecosystems are subject to natural variations, such as changes in habitat, food availability, or exposure to pollutants and disease, that may be difficult for managers to anticipate (Charles 1998, Regan et al. 2002). Collecting data about many ecosystems can be challenging, especially if they are highly complex or difficult to access. Managers also face shifts in how social, political, and economic institutions and users value ecosystems and their resources.

Marine ecosystem management highlights the challenges of dealing with uncertain conditions. For example, fisheries managers aim to optimize catch for human use without causing target stocks to collapse (Botsford et al. 1997). Yet, there is still a great deal of uncertainty about how best to accomplish this goal (Larkin 1977, Ludwig et al. 1993). In part, this is due to the complexity of marine ecosystems and the difficulty in monitoring them (Norse 1993, Botsford et al. 1997, Thorne-Miller 1999). The abundance of fish stocks fluctuates over time and in different areas, and it can be difficult to determine baselines against which to measure progress (Pauly 1995). Tracking catch amounts, especially on the high seas, is challenging (Charles

1998, Watson and Pauly 2001, Flothmann et al. 2010). Fishing efforts can shift as stocks are depleted in one area or valuable stocks are found in another. For example, rising ocean temperatures due to climate change may cause stocks to shift to different habitats, and fishermen may follow them (Beaugrand et al. 2003, Perry et al. 2005, Cheung et al. 2009). The confounding effects of dynamic systems and difficult sampling thus make uncertainty the norm for managers of marine ecosystems.

Marine ecosystem managers, like other natural resource managers, have tried a variety of frameworks for managing despite uncertainty. These include adopting conservative, or precautionary, management measures (e.g., low catch limits) until more information is gathered, or the status of the stock or the ecosystem improves, but it is rarely easy to fill in the missing knowledge given natural variation and the monitoring limitations in the oceans (Ludwig et al. 1993, Charles 1998, Thorne-Miller 2003, Regan et al. 2005). Managers have also tried adaptive management, whereby they learn about a system through an iterative process of hypothesis testing and controlled management experiments (e.g., comparing population abundance in two areas that have different catch levels) so that emerging scientific results can inform subsequent management decisions (Holling 1978, Walters 1986, Halbert 1993). In practice, however, learning has been slow because of the difficulty and risks in implementing large-scale experiments (e.g., lowering current catch levels to find out if they promote better yields over the long term, but with no guarantee of future increases in yield; Halbert 1993, Johnson 1999). With ecosystem-based management, managers attempt to account for interactions among commercially valuable stocks, other species, and the physical environment that may be influencing management outcomes (Ludwig et al. 1993, Thorne-Miller 2003, Pikitch et al. 2004). Data, economic, and political constraints, however, can make implementation challenging. These approaches to managing under uncertain conditions are not mutually exclusive; precaution may often play a role in management decisions.

These management frameworks provide a helpful starting point to highlight a common thread: the effectiveness of approaches to address uncertainty is complicated by a lack of data and many potentially confounding variables. Thus managers still need ways of filling in information gaps and accounting for a wide suite of factors that could influence management outcomes, even if the underlying management framework is designed to address uncertainty. Here we focus on three possible options for supporting management efforts despite uncertainty: (1) expert judgment, which can fill in information gaps based on experts' experience; (2) modeling, which can be used to create representations of ecosystems and different management scenarios to address both information gaps and complex ecosystem interactions; and (3) integrated risk assessment, or a weight of evidence approach, which combines multiple lines of evidence to address a lack of information.

We did not review all options for reducing uncertainty and their technical details. There is a rich literature on decision analysis (Raiffa 1997, Peterman and Anderson 1999), and multiple additional techniques that could maximize use of limited data for research managers, including Bayesian statistics (Ellison 2004) and genetic analysis, which can be used to recreate the historical abundance of populations or species (Alter et al. 2007). In addition, many researchers and managers are working on the challenges of effective resource management, and these approaches have been used before in various configurations (Holling 1978, Burgman et al. 1993, Ludwig et al.

1993, Johnson 1999, Cortés 2002, Ellison 2004, Halpern et al. 2006, 2009, Wintle 2007).

Instead, we focused on a case study approach and explored a few specific situations in greater detail. For these cases, we describe the management context, the uncertainty that needed to be addressed, the tools chosen to tackle the data gaps, and how the additional information gained informed managers. In describing these case studies, we hope to add to the existing suite of practical options for managing despite uncertainty.

An Expert Judgment Approach to Rebuilding Fish Stocks in the US—Setting Catch Limits in Data Poor Situations.

In the US, the Magnuson-Stevens Fishery Conservation and Management Act (MSA) is the primary law for marine fishery management. It established eight regional Fishery Management Councils (FMCs) to manage fisheries in different regions of US waters. The MSA has been amended several times since it was first adopted in 1976 to try to reverse the depleted state of many fisheries in US waters (Darcy and Matlock 1999). The most recent version, the Magnuson-Stevens Reauthorization Act (MSRA) of 2006, included a number of provisions designed to improve the accountability of fishery management plans and to prevent overfishing through the establishment of annual catch limits (ACLs).

Because of both scientific and management uncertainty, considerable ambiguity exists about the likelihood that overfishing is occurring. Assessments of stock abundance are complicated by a lack of data, errors in stock assessment models, and natural ecosystem variability. Even for stocks with extensive stock assessments, stock abundance estimates can depend on how well the fishery is controlled and monitored. For example, managers cannot be certain that limiting how long fishermen can fish (e.g., days at sea) will maintain catches near their target levels.

The FMCs are in charge of establishing catch limits for each fishery, although fishing levels may not exceed the recommendations of their Science and Statistical Committees, or SSCs (SSCs are a group of academic and government scientists, selected and appointed by a FMC to review relevant scientific information and advise Councils on their proposed management decisions). The US National Oceanic and Atmospheric Administration's National Marine Fisheries Service (NMFS) provides guidance to the FMCs and SSCs on setting catch limits and preventing overfishing through its National Standard 1 (NS1) guidelines. For example, NS1 guidelines provide direction on how much catch should increase as a stock rebuilds and biomass increases (Restrepo and Powers 1999). However, the sheer number and variety of stocks in US waters, coupled with large gaps in data, have made providing adequate detail difficult.

One way managers can overcome these challenges is to rely on expert judgment to fill in the gaps and give managers a better sense of risks (Halpern et al. 2007, Methot 2009). In the case of catch limits in the US, experts typically include SSC members, as well as scientists brought in to perform or review stock assessments and other analyses. These experts might use what they know about some fish stocks to fill in the blanks for those with data limitations. For example, experts could estimate the fishing mortality rate for a data-deficient stock based on a stock for which they have abundant information and that is biologically similar to the data-deficient one.

Expert judgment as "best available science" needs to be applied consistently and transparently so it is clear how decisions were made and where uncertainty lies (Halpern et al. 2007). Rosenberg et al. (2007) developed a risk assessment process using expert judgment to establish catch levels in data poor situations. The process is based on Productivity-Susceptibility Analysis (PSA), which adapts an ecological risk assessment tool developed in Australia for US fisheries (Fletcher 2005, Hobday et al. 2007). Experts estimate the ability of a fish stock to produce maximum sustainable yield (i.e., the largest annual catch or yield that can be taken from a stock given the current ecological and environmental conditions) under a given level of fishing pressure, based on its productivity and susceptibility to overfishing. Productivity is determined by life history characteristics, including the age when a stock first produces young, how frequently they reproduce, and how many young they produce, as well as habitat and community characteristics, such as whether the target stock lies at the top or bottom of the food chain. A stock's susceptibility to overfishing is influenced by factors such as the level to which fishing gear impacts essential habitat, stability of a stock's habitat, and the number and kind of gear types. Scientists rank each stock as to whether they have low to high productivity or susceptibility for each of these categories (from 1 to 3 for high to low productivity and from 1 to 3 for low to high susceptibility). The scores from each category are used to create an overall score and risk of overfishing for each stock (see Fig. 1; Rosenberg et al. 2007).

The PSA scores provide a starting point for setting precautionary catch limits. Once experts have assessed the vulnerability of each stock and the remaining uncertainty, they can estimate an overfishing limit for each stock based on the concept of maximum sustainable yield. Depending on the levels of uncertainty in knowledge about the stock and management effectiveness, experts can then estimate a target catch below the overfishing limit to help prevent overfishing, depending on the risk tolerance of the managers.

The PSA scores can also help address both scientific and management uncertainty. As additional information is gathered, the buffer between the overfishing limit and catch limit could decrease in a consistent way across all species. Rosenberg et al. (2007) recommended adjustments to the size of the buffer between the overfishing limit and annual catch limits, depending on whether the fishery adheres to the catch limit and achieves management goals. Knowing what information is available for the various indicators of productivity and susceptibility also allows managers to characterize existing sources of uncertainty more easily.

Expert judgment, however, will not resolve all the sources of uncertainty associated with setting precautionary catch limits. Expert judgment will likely be more accurate for data-rich species than it will be for data-poor stocks, for the same reasons that there are not more quantitative data available—even experts may not know much about the stocks. Likewise, some of the more variable attributes of a species or stock, like population size, may be difficult to extrapolate. Nor does the PSA process solve all of the information gaps. Although Patrick et al. (2009) found that PSA generally distinguished among stocks that faced different levels of fishing pressure, they found it difficult to find clear patterns in the demarcation between high, medium, and low vulnerability stocks. Indeed, other approaches will undoubtedly be employed to help develop appropriate catch limits. For example, reducing management uncertainty (e.g., via better real-time monitoring of catch) may be more effective for ensuring that targets are reached (Holt and Peterman 2008).

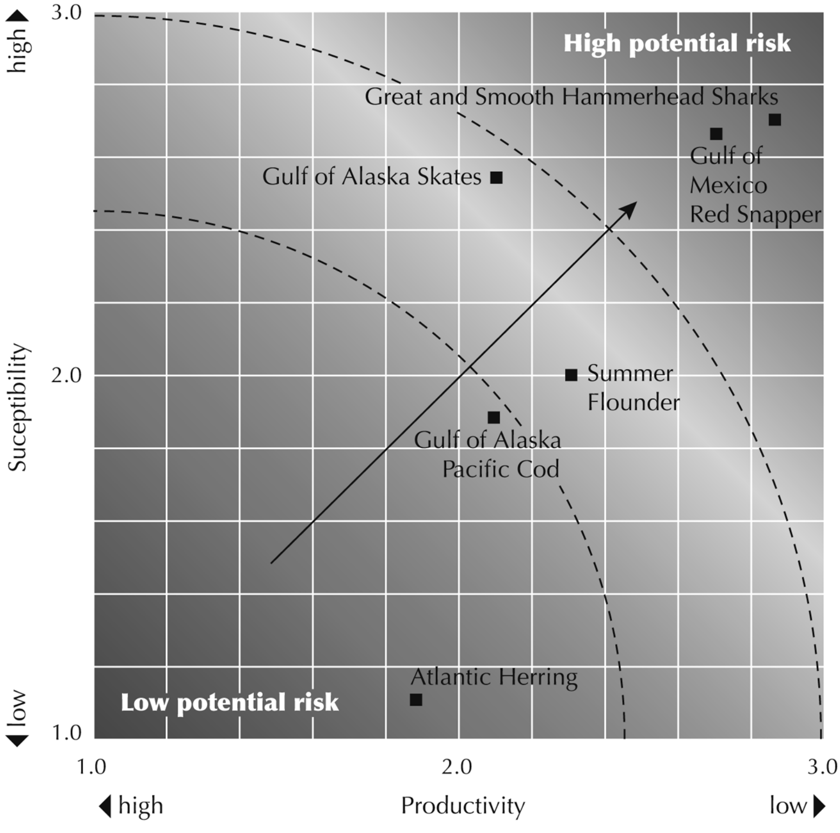

Figure 1. Productivity and susceptibility scores for selected US fisheries (Rosenberg et al. 2007). Risk increases from lower left to upper right.

Fishery management councils are still in the process of developing methods to set catch limits (Patrick et al. 2009). PSA has been part of the discussion in some fishery management councils, but there is a lack of consensus about how to incorporate it into the decision-making process (e.g., how to translate PSA scores into numerical buffers) and whether it should be used for both data-rich and data-poor stocks. One of the more promising uses of PSA involves grouping species with similar risks and biological characteristics for setting catch levels and monitoring efforts.

Expert judgment will inevitably play a role in the establishment of annual catch limits, and approaches such as PSA can allow for this type of information to be incorporated in a consistent manner. As long as expert judgment is used systematically and transparently, and takes account of a diversity of opinions, it can be a starting point for precautionary management when there is little information about the resource in question.

A Modeling Approach for Krill in the Southern Ocean—Precautionary Management in an Expanding Fishery

In the Southern Ocean, Antarctic krill, *Euphausia superba* (Dana, 1850), are the key prey for many predators like seals, penguins, and whales, as well as the target of an expanding commercial fishery mostly aimed at obtaining oil and meal for aquaculture (Nicol et al. 2000). Because no nation has exclusive fishing rights in this area, the fishery is cooperatively managed by the Commission on the Conservation of Antarctic Marine Living Resources (CCAMLR; henceforth "the Commission"). The Commission has adopted an ecosystem-based management approach to take account of the resource needs of both the predators and the fishery (Reid et al. 2005). However, new, more efficient harvesting techniques that allow krill to be continuously pumped from the water and the rising demand for aquaculture products may make conflicts between the fishery and the predators more likely. In many areas, the fishery operates in the main feeding grounds of breeding, krill-dependent predators, such as seals and penguins (Croxall and Nicol 2004). The Commission has established catch limits for the krill fishery in some areas, but concern remains that localized krill depletion could occur without more specific management plans in place. Thus the Commission is moving towards establishing smaller management units for which appropriate catch limits could be established, helping to avoid conflict between the predators' needs and the fishery (Constable and Nicol 2002, Hewitt et al. 2004).

It has proven complicated, however, to find an appropriate way to subdivide the catch among these smaller units. Much of this uncertainty is driven by questions about how the warming of the Antarctic due to climate change will affect krill, their predators, and the fishery (Murphy 1995, Reid et al. 1999, Wiedenmann et al. 2009). So far, scientists have shown that krill growth could change as sea surface temperature increases, and there are important connections between krill population dynamics and ice cover (krill depend on ice for resources and shelter; Kawaguchi and Satake 1994, Siegel and Loeb 1995, Loeb et al. 1997, Quetin and Ross 2003, Atkinson et al. 2004). However, the mechanisms by which variability in sea ice cover affects krill population dynamics remain poorly understood. In addition, krill biomass can vary substantially from year to year and place to place, yet little information is available about factors that could drive this variability, like climate change (Mangel 1994, Wiedenmann et al. 2008). Current management models also include only fishing and predation sources of mortality (Watters et al. 2006). However, krill mortality due to increased UV radiation from the ozone hole above the Antarctic could be an important component of their population dynamics (Naganobu et al. 1999). Finally, some key aspects of how predators may respond to the rapidly changing conditions in this ecosystem because of warming trends and the expanding fishery remain uncertain (Cresswell et al. 2008). These gaps have made it difficult to develop comprehensive, predictive models that can help the Commission manage the krill fishery and the ecosystem appropriately.

We review the use of several models aimed at establishing more specific linkages among krill abundance and patchiness, predator condition, and changes in the physical environmental. First, Wiedenmann et al. (2008) approached the issue of how temperature changes could affect variability in krill biomass. Current management models do not use temperature as an influential factor; however, temperature changes over time could affect the growth of individuals within cohorts, which in turn could affect total biomass available to the fishery and predators (Rosenberg et al. 1986, Constable and Mare 1996). Wiedenmann et al. (2008) projected growth trajectories for individuals within groups of krill of the same age (i.e., a cohort) and estimated the variation in total biomass due to fluctuations in temperature. They used an existing temperature-dependent growth model and a time series of temperature data from the vicinity of the Antarctic Peninsula and the island of South Georgia. The growth model predicted increasing individual size (length and weight) with increasing temperature in the cooler Antarctic Peninsula region and decreasing individual size with increasing temperature in the warmer South Georgia region. Given that more than half of the krill stocks in the Southern Ocean are found in the latter region, changes over time in Southern Ocean temperatures may have profound effects on total krill biomass available to both predators and the fishery. Moreover, the model predicts that the effects of a potentially warming Southern Ocean on krill biomass will likely be more pronounced in the currently warmer regions occupied by krill. These results suggest the importance of including temperature variability when estimating krill biomass.

Second, Wiedenmann et al. (2009) explored the relationship between changes in ice extent due to climate change and krill recruitment (i.e., the process of adding young to a population). Previous assessments of the relationship between recruitment and sea ice used a relative measure of krill recruitment, the fraction of recruits collected in a particular region (Siegel and Loeb 1995, Quetin and Ross 2003). The annual fraction of recruits is easily calculated from scientific survey data, and it has therefore been used as a proxy for recruitment since its introduction (de la Mare 1994). However, because it is not an absolute measure of recruitment, it is limited in its ability to predict changes in total biomass in response to changes in sea ice. Therefore, Wiedenmann et al. (2009) developed an age-structured model for krill near the Antarctic Peninsula. This model allowed an estimate of the magnitude of recruitment events that reproduce observed trends in krill abundance and age structure. These estimates of recruitment show a nonlinear relationship between recruitment and sea ice area from the previous winter and spring, with large recruitment events occurring over a narrow range of ice area, and minimal recruitment otherwise. This result suggests that the ecosystem may change dramatically once ice area drops below a recruitment threshold. These results also show that it may be possible to predict recruitment, and in turn, biomass, from the extent of ice cover. This could help reduce some of the uncertainty in current management models about temporal and spatial variability in krill biomass.

Third, scientists have suspected that fewer krill survive with increased UV exposure, but very few data are available to support this hypothesis (Naganobu et al. 1999, Newman et al. 1999, Ban et al. 2007). Mangel et al. (2010) developed a model for krill mortality caused by UV exposure using the limited empirical data available. They illustrated the utility of this method for krill in the Livingston Island area and showed: (1) that it is possible to estimate the changes in natural mortality due to UV-induced damage; and (2) individuals in the same age groups with different levels of UV exposures are predicted to have had different survival rates (with a 10% predicted decline in survival between 1979 and 1997; for details of the model, see Mangel et al. 2010). This model can allow a potentially important source of krill mortality to be incorporated into management models.

Finally, Cresswell et al. (2008) explored how changes in krill patchiness due to climate change and krill fishing may affect predator abundance. Macaroni penguins, *Eudyptes chrysolophus* (Brandt, 1837), are one of the key krill predators and have evolved to cope with highly variable conditions in the Southern Ocean (Fraser et al. 1992, Clarke et al. 2007). However, changes in prey abundance and patchiness may be now occurring too rapidly for them to adapt, and there is very little information available about how those changes may affect breeding penguin behavior and condition. Thus Cresswell et al. (2008) used a state-dependent life history model (sensu Mangel and Clark 1988, Clark and Mangel 2000), which allowed them to explore how life history characteristics, such as reproductive rates over an organism's lifetime, depend on the organism's physiological state, as well as environmental influences like climate change. This model allowed the authors to examine how the density and patchiness of krill supply affect the foraging decisions and breeding success of female macaroni penguins at South Georgia. Through this analysis, Cresswell et al. (2008) predicted that rapid changes in the mean supply of prey will have more of an effect on the condition of the female and chick than changes in prey patchiness, and that foraging behavior can compensate for changes in prey up to a threshold point, beyond which breeding success is likely impacted. The analysis showed that the ability of the penguins to compensate does depend on the adaptability of the penguin to foraging in a changing environment. A female encountering a prey density reduced to half of what she had adapted to results in a perceptibly worse condition for the female and her chick. If the female does not respond to new conditions, she and her chick are predicted to receive, on average, 20% less of their daily energetic requirement. While modified behavior may buffer against the decreases in krill abundance in terms of energy intake, it may make penguins more susceptible to additional stressors not considered in this work, and thus predictions may be overly optimistic. Nevertheless, this work suggests one possible avenue through which macaroni penguins may be adversely affected by climate change and increases in fishing effort.

This work on krill, climate change, and penguins shows that models can be a convenient tool for predicting outcomes for management interventions. However, while models are intended to address uncertainty, they also represent simplifications of a system. It can be difficult to determine whether all relevant variables have been considered in the model, or whether the predictions will hold in other environments.

Regardless, models can provide a reasonable place to start thinking about management options. Discussion continues on how best to set catch limits for krill in the Southern Ocean. This and other modeling work on krill, climate change, and penguins may help to resolve some of the key information gaps in current CCAMLR management.

Using an Integrated Risk Assessment Approach—Precautionary Catch Limits for Sharks

Evidence is accumulating that shows that many of the world's pelagic, or open ocean, shark species are declining (Dulvy et al. 2008). Many of these sharks produce only a few young at a time or over their life time, which means that recovery from overfishing can be particularly prolonged (Walker 1998, Cortés 2002, Smith et al. 2008, Simpfendorfer and Kyne 2009). Pelagic shark species also tend to be highly migratory, which means they do not fall under any one nation's management jurisdiction. In the Atlantic Ocean, these species are managed by the International Commission for the Conservation of Atlantic Tunas (ICCAT), which is focused on the conservation of tunas and tuna-like species (e.g., swordfish), but also gathers information on some species taken as bycatch during longlining. Indeed, longline fisheries for tuna and swordfish catch large numbers of pelagic sharks. In addition, targeted shark fisheries are growing due to the value of shark fins and meat (Campana et al. 2002, Simpfendofer et al. 2008). Yet, there are few—if any—catch limits in place for pelagic sharks, in part because of lack of information about them (Simpfendofer et al. 2008).

In response to these information gaps, Simpfendorfer et al. (2008) developed a process using an integrated risk assessment (or weight of evidence approach) to estimate and prioritize risks of overfishing for a number of data-deficient shark species. Three tools were used to assess the risks of overfishing to twelve pelagic shark species: (1) ecological risk assessment, or productivity susceptibility analysis (PSA); (2) the position of the inflection point in population growth curves; and (3) the species' status according to the International Union for the Conservation of Nature (IUCN) Red List of Threatened Species. Simpfendorfer et al. (2008) combined the risk estimates from each of these approaches to estimate the overall risk of overfishing for each species. This "weight of evidence" approach allowed for the inclusion of multiple lines of evidence (Simpfendorfer et al. 2008).

Simpfendorfer et al. (2008) first used the ecological risk assessment approach developed by Hobday et al. (2007) and others to estimate the vulnerability of these shark species to overfishing based on PSA. This is similar to the PSA process adapted for US fisheries and is based on estimating the susceptibility of the species to fishing pressure as well as its productivity (e.g., population growth rate; Braccini et al. 2006, Hobday et al. 2007). In this case, the group calculated productivity using a model that estimates a species' rate of population increase while accounting for variability in birth rates and environmental influences. Susceptibility was calculated as the product of four factors: (1) availability: the proportion of a species' geographic range over which the pelagic longline fisheries operate in the Atlantic Ocean; (2) encounterability: the proportion of the species' depth range over which encounters with pelagic longline fishing gear are likely; (3) selectivity: the proportion of the total population that is susceptible to being caught in the fishing gear; and (4) post-capture mortality: the proportion of the individuals captured that died (retained or discarded).

Simpfendorfer et al. (2008) then estimated the population abundance, relative to unfished levels, associated with the maximum population production (Cortés 2008). This "inflection point" estimates how far a population can be depleted from unfished levels before its ability to sustain a fishery starts to decline. Species with a higher inflection point are at greater risk of overfishing, because their populations must be closer to the unfished level in order to sustain a fishery. This is not an exact measure of maximum population production, but shows where this point lies in relation to other species.

Finally, Simpfendorfer et al. (2008) incorporated a third risk assessment metric: status on the IUCN Red List. The IUCN uses specialist groups to review the conservation status of species and determine which are in greatest need of conservation action (Akçakaya et al. 2000, IUCN 2001). Experts classify species according to their risk of extinction using the terms: (1) "Threatened," or high risk species, which includes the categories "Critically Endangered," "Endangered," or

"Vulnerable," from most to least vulnerable; (2) "Near Threatened," or those species which may soon become "Threatened" if conservation action is not taken; (3) "Least Concern," or those species with a low risk of extinction; and (4) "Data Deficient," or species for which there is insufficient information for assessment. In order to compare the IUCN Red List status with the ecological risk assessment scores and inflection points, Simpfendorfer et al. (2008) assigned a value between 0 and 1 to each threat category, with Critically Endangered assigned the highest value and Least Concern worth the least (i.e., 0.2). Data Deficient species were classified in the mid-range of values as a conservative way to assign these species to a score.

Simpfendorfer et al. (2008) used several statistical techniques (including cluster analysis and multidimensional scaling) to combine the risk scores from the three approaches and estimate an overall risk of overfishing for each pelagic shark species. These techniques allowed grouping of species with similar risk levels. The authors used blue sharks as a reference point, because there is more extensive information available about these sharks.

The sharks studied fell into two main risk clusters. Most of the sharks were grouped into a higher risk cluster. Within this cluster, bigeye thresher, *Alopias superciliosus* (Lowe, 1841), shortfin mako, *Isurus oxyrinchus* Rafinesque, 1810, and longfin mako, *Isurus paucus* Guitart Manday, 1966, sharks were found to be most at risk from overfishing (see Fig. 2). A second subset of the higher risk cluster, which included common thresher, *Alopias vulpinus* (Bonnaterre, 1788), porbeagle, *Lamna nasus* (Bonnaterre, 1788), and oceanic whitetip, *Carcharhinus longimanus* (Poey, 1861), had moderately high risks of overfishing. Simpfendorfer et al. (2008) found that the silky shark, *Carcharhinus falciformis* (Muller and Henle, 1839), had a risk level similar to the moderately high risk cluster, but was not grouped with those species because it is in a lower IUCN Red List category (Near Threatened). The lower risk cluster included scalloped hammerheads, *Sphyrna lewini* (Griffiths and Smith, 1834), and pelagic stingrays, *Pteroplatytrygon violacea* (Bonaparte, 1832), as well as blue sharks, *Prionace glauca* (Linnaeus, 1758). However, the scalloped hammerhead is classified by IUCN as Endangered, partly because of particularly intense fishing pressure on it.

Although this analysis was useful as a first step at teasing apart the risks of overfishing for a number of data-poor pelagic shark species, it also emphasized the need for more data about them (Cortés et al. 2009). For example, the analysis may underestimate the overfishing risks for pelagic sharks, such as porbeagles and hammerheads, which also occur in coastal waters, because data on them were too limited to be included in the analysis. A lack of data also limited the assessment of the risks to crocodile sharks, *Pseudocarcharhias kamoharai* (Matsubara, 1936), and smooth hammerheads, *Sphyrna zygaena* (Linnaeus, 1758). Further, the process did not provide information about the actual abundance of the shark stocks (Cortés et al. 2009).

This risk assessment approach has begun to inform some management recommendations for sharks. For example, although there are still no catch limits for sharks agreed to by ICCAT, ICCAT members have agreed to zero-retention policies for several of the sharks identified as at risk by the integrated risk assessment framework. In 2008, ICCAT recommended that bigeye thresher sharks be released if caught alive (this species has a low survival rate when caught and released), based on recommendations from its technical advisory committee, the Standing Committee on Research and Statistics, or SCRS (ICCAT 2010). The SCRS recommended precautionary management measures for this species, largely because it was identified by the risk assess-

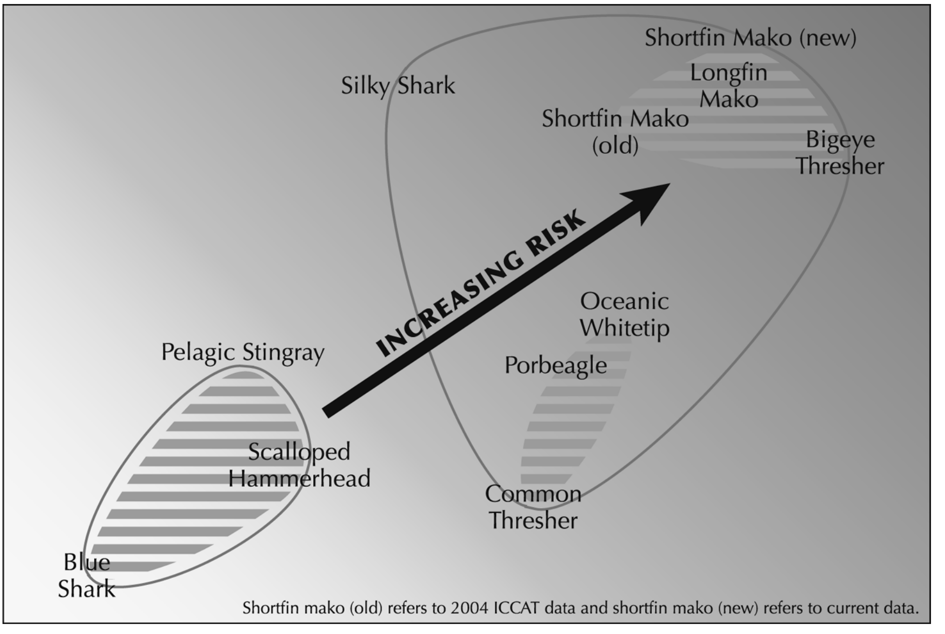

Figure 2. Results of an integrated risk assessment for Atlantic shark and ray species taken in pelagic fisheries (Simpfendofer et al. 2008). Risk increases from lower left to upper right, and represents the risk of overexploitation by pelagic longline fisheries in the Atlantic Ocean. The axes are dimensionless, because the results are derived from multi-dimensional scaling.

ment developed by Simpfendorfer et al. (2008) as the shark species with the highest vulnerability. In 2010, ICCAT took action on several additional sharks identified as vulnerable by the integrated risk assessment. ICCAT agreed to prohibit the fishing, retention, and sale of oceanic whitetip sharks, in part, because it was identified as high risk by the Simpfendorfer et al. (2008) risk assessment (ICCAT 2010). ICCAT also agreed that it needed better data on the shortfin mako to assess appropriate catch levels (ICCAT 2010). This decision was informed by findings that this species has low productivity and a high susceptibility to overfishing. Thus, this risk assessment approach appears to be providing a helpful framework within which to discuss management options for pelagic sharks in the Atlantic Ocean.

Using Models to Integrate Climate Impacts into the Management of Salmonids in California

Natural resource management, of course, is not solely concerned with harvest. Interventions in natural systems often are intended to improve the status of populations that have declined because of other anthropogenic influences (Fowler 2009, Mangel 2010). California once supported a thriving recreational fishery of steelhead trout [*Oncorhynchus mykiss* (Walbaum, 1792); henceforth steelhead], but they have been eliminated from at least 95% of their former habitat, in large part because of altered river flows (McEwan 2001). Indeed, many populations of salmonids in California have been listed as endangered or threatened under the US Endangered Species Act, including steelhead (Busby et al. 1996).

Managers aim to preserve some life history diversity (i.e., both resident and migratory forms), both to maintain the endangered and threatened fish populations and to take advantage of the buffering effect of diversity (e.g., Hilborn et al. 2003). Yet, because steelhead display a remarkable diversity of life history strategies that can be affected by changes in the environment, there is a great deal of uncertainty about how best to manage them. For example, steelhead can migrate to the ocean at a variety of ages, remain in fresh water for their entire life, or vary the age at which they mature (Smith-Gill 1983, Thorpe et al. 1998). The steelhead that remain in fresh water and do not migrate become smaller rainbow trout. The timing of these conversions depends on complex interactions between their genes and the environment (Satterthwaite et al. 2009). Variation in river flows is one of the largest environmental influences on these fish, because steelhead, like other salmonids, require specific kinds of flows (e.g., quantity and temperature) for growth, migration, and reproduction (Quinn 2005). Thus whether or not endangered steelhead are present in a specific area can depend on the kinds of river flows (e.g., quantity and rate) occurring (e.g., Cramer and Beamesderfer 2006). Climate change is likely to exacerbate water supply and quality issues, and place additional pressure on many salmonids (Palmer et al. 2008).

Modeling salmonid response to climate change, however, requires understanding the patterns of migration and life history variation simultaneously, particularly the major life-history events of migration from fresh water to the sea and back. Yet, so far, this has been challenging for managers, in large part because of the high degree of variability in both life history strategies of steelhead and the large swaths of river through which steelhead travel.

A first step in addressing uncertainty about how life history variation may interact with environmental cues is to demonstrate the importance of different flow types to steelhead. In order to do so, Mangel and Satterthwaite (2008) used a modeling approach that allowed simultaneous consideration of various physiological and environmental considerations—stochastic dynamic programming (Mangel and Clark 1988, Clark and Mangel 2000). With this model, Mangel and Satterthwaite (2008) predicted that different types of water flows can be important determinants of growth and timing of smoltification (i.e., the rapid phase of growth fish go through before returning to fresh water from the ocean).

In the Central Valley of California, that growth phase occurs in the summer, coinciding with the greatest demand for water by humans. Current US Department of the Interior water policy (Cramer and Beamesderfer 2006) is to release cold water for steelhead in the summer and early fall and to release cool water in the late fall for returning chinook salmon, *Oncorhynchus tshawytscha* (Walbaum, 1792). Thus, the management challenge is to minimize the amount of cold water released in summer and early fall so that there is more cool water available for chinook in late fall. Cramer and Beamesderfer (2006) showed that residency (i.e., non-migration) is more common when there are dependable flows and cool water in summer and thus concluded that releasing too much cool water in summer and early fall may reduce the occurrence of anadromy or migration in steelhead. However, they were unable to consider how changes in the environment due to climate change might affect their predictions.

To address this gap, Satterthwaite et al. (2010) used a state-dependent model to predict life history strategies of female steelhead in altered riverine environments. As a case study, they applied this model to the American and Mokelumne Rivers in central California. Both rivers have highly regulated flows and a history of introducing fish from other rivers, which may dilute local adaptation. This model successfully predicted life history strategies of fish on the American River (all anadromous, with young smolts) and on the Mokelumne River (a mix of anadromy and residency). Thus, Satterthwaite et al. (2010) were able to use this modeling strategy to understand how increases in water temperature and changes in flow might influence whether steelhead migrated. They also used sensitivity analyses (a way of testing the robustness of the model) to predict likely shifts in life history strategies under changed environments. For example, they considered two scenarios for the American River. In the first, the model was modified so that the period of high food availability was extended into the fall and water temperatures were reduced by 3 °C for October and November. They discovered that anadromy was still predicted under altered growth conditions for five out of the six cases in which it was predicted under baseline conditions. For this scenario, a shift to resident life histories is predicted only if freshwater survival is low. In the second scenario, Satterthwaite et al. (2010) modified the model so that summer temperatures (i.e., June 21–September 2) were reduced and survival over the summer was increased by 30%. In this scenario, they predicted no freshwater maturity, although if freshwater survival was high to begin with, some of the slowest growing parr (the stage before smoltification) might delay smolting and migrate at older ages. Satterthwaite et al. (2010) concluded that the greatest management concern with respect to preserving migration is reduced survival of emigrating smolts. They also suggest that steelhead need sufficient water flows for growth during the migration period and control of predators of juvenile fishes (e.g., other fishes, such as bass, *Morone saxatilis* (Walbaum, 1792).

Modeling is only one tool among the many being used to find workable solutions to water policy challenges in California under conditions of uncertainty. Given their limitations, models cannot resolve all sources of uncertainty. However, the models discussed in this section provide specific predictions about timing of water needs for maintaining migration potential for steelhead. These results may help inform some of the complicated and ongoing negotiations about water supply and climate impacts in California.

Conclusions

This review provides some practical approaches for dealing with uncertainty in resource management. With limited information, managers can use models to explore how highly variable systems might respond to management options under different environmental scenarios. Expert judgment can help shape the assumptions that form the basis for those models and propose sensible boundaries within which management options can be developed. A weight of evidence approach can take advantage of small amounts of information from multiple sources, including models and expert judgment.

Of course none of these techniques is perfect, and all of them could benefit from additional information. Models can be difficult to understand by a non-technical audience and can be complicated to implement. Expert judgment is limited by the specific experiences of the experts. Ecological risk assessments do not provide abundance estimates and experts may disagree about how to score the risks of species. Combining multiple lines of evidence can be complicated by lack of comparability among the different assessments used. Thus transparency and consistency will be crucial in moving forward efforts to manage in the face of uncertainty.

So far, only some of these attempts to reduce uncertainty have led to changes in management. This is not surprising. Uncertainty about some aspect of the decision at hand will always remain, and such remaining uncertainty can provide plenty of fodder for arguments about how best to manage or conserve a resource (Sarewitz 1996, Pielke 2007). In addition, decision makers and managers are juggling many competing demands and may decide against conservation action for any number of reasons. Thus no single approach to reducing uncertainty can guarantee that increased scientific certainty will turn into desired policy changes.

Still, more information can help managers move beyond "blind precaution" to more informed management (Kaufman et al. 2004). With increasing concern for the status of many of the world's ocean ecosystems, decisions need to be made about conservation and management priorities. To do so, managers need approaches that require relatively small amounts of information that can account for a wide suite of ecosystem influences on a target resource. None of these approaches can address all sources of uncertainty or yield complete information, but they help provide a logical starting point for conservation and management efforts despite the certainty of uncertainty.

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