Abstract—Assessing the vulnerability of stocks to fishing practices in U.S. federal waters was recently highlighted by the National Marine Fisheries Service (NMFS), National Oceanic and Atmospheric Administration, as an important factor to consider when 1) identifying stocks that should be managed and protected under a fishery management plan; 2) grouping data-poor stocks into relevant management complexes; and 3) developing precautionary harvest control rules. To assist the regional fishery management councils in determining vulnerability, NMFS elected to use a modified version of a productivity and susceptibility analysis (PSA) because it can be based on qualitative data, has a history of use in other fisheries, and is recommended by several organizations as a reasonable approach for evaluating risk. A number of productivity and susceptibility attributes for a stock are used in a PSA and from these attributes, index scores and measures of uncertainty are computed and graphically displayed. To demonstrate the utility of the resulting vulnerability evaluation, we evaluated six U.S. fisheries targeting 162 stocks that exhibited varying degrees of productivity and susceptibility, and for which data quality varied. Overall, the PSA was capable of differentiating the vulnerability of stocks along the gradient of susceptibility and productivity indices, although fixed thresholds separating low-, moderate-, and highly vulnerable species were not observed. The PSA can be used as a flexible tool that can incorporate regional-specific information on fishery and management activity.

Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing

Wesley S. Patrick (contact author)[1]
Paul Spencer[2]
Jason Link[3]
Jason Cope[4]
John Field[5]
Donald Kobayashi[6]
Peter Lawson[7]
Todd Gedamke[8]
Enric Cortés[9]
Olav Ormseth[2]
Keith Bigelow[6]
William Overholtz[3]

Email address for contact author: Wesley.Patrick@noaa.gov

[1] Office of Sustainable Fisheries
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
1315 East-West Highway
Silver Spring, Maryland 20910

[2] Alaska Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
7600 Sand Point Way
Seattle, Washington 98115

[3] Northeast Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
166 Water Street
Woods Hole, Masssachusetts 02543

[4] Northwest Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
2725 Montlake Boulevard East
Seattle, Washington 98112

[5] Southwest Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
110 Shaffer Road
Santa Cruz, California 95060

[6] Pacific Islands Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
2570 Dole Street
Honolulu, Hawaii 96822

[7] Northwest Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
2030 South Marine Science Drive
Newport, Oregon 97365

[8] Southeast Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
75 Virginia Beach Drive
Miami, Florida 33149

[9] Southeast Fisheries Science Center
National Marine Fisheries Service
National Oceanographic and Atmospheric Administration
3500 Delwood Beach Road
Panama City, Florida 32408

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The need to ascertain the status of fish stocks is a common issue for fisheries management agencies the world over. Stock assessments are usually mandated by various national or international laws and frequently include an evaluation of a stock's current biomass and fishing mortality rate compared to some reference level, often maximum sustainable yield (MSY). Because of the data requirements for evaluating the status of stocks, however, a large proportion of the world's fishery managers and scientists lack the ability to adequately assess the status of their stocks (Mora et al. 2009). In the past, many of these data-poor stocks have been managed by using a "harvest control rule" that was based on the overfishing limit for, and biomass of, the stock. However, with little knowledge of a stock's status it is difficult to appropriately apply precautionary management (Restrepo and Powers, 1999; Katsukawa, 2004). Today, however, many managers and scientists are turning to risk assessments to try to better manage stocks for which there are directed measures of stock status (e.g., Lane and Stephenson, 1998; Peterman, 2004; Fletcher et al., 2005; Astles et al., 2006).

Risk assessments for data-poor stocks usually follow some type of semiquantitative method. In previous examples of semiquantitative risk assessments, scientists have evaluated fishery impacts on bycatch and targeted species (Francis, 1992; Lane and Stephenson, 1998; Stobutzki et al., 2001a,), extinction risk (Musick, 1999; Roberts and Hawkins, 1999; Cheung et al., 2005; Mace et al., 2008), and impacts on ecosystem viability (Jennings et al., 1999; Fletcher et al., 2005; Astles et al., 2006). These approaches allow for the inclusion of less quantitative information and a wide range of factors and can complement both stock and ecosystem assessments.

In the United States, scientists of the National Marine Fisheries Service (NMFS), National Oceanic and Atmospheric Administration, recently developed a risk assessment to assist managers and scientists in evaluating the vulnerability of stocks to overfishing (Patrick et al., 2009). Vulnerability is a measurement of a stock's productivity and its susceptibility to a fishery. Productivity refers to the capacity of the stock to recover rapidly when depleted, whereas susceptibility is the potential for the stock to be impacted by the fishery. In general, vulnerability is an important factor to consider when organizing stock complexes, developing buffers between target and limit fishing mortality reference points, and determining which stocks should be managed under a fishery management plan. This article describes the method developed by scientists at NMFS for determining vulnerability, explores the various caveats and nuances in its underlying calculations, and presents an overview of its application to six U.S. fisheries.

Materials and methods

Determining vulnerability of stocks

Several risk assessment methods were reviewed to determine which approach would be flexible and broadly applicable across fisheries and regions. A modified version of a productivity and susceptibility analysis (PSA) was selected as the best approach for examining the vulnerability of stocks, owing to its history of use in other fisheries (Milton, 2001; Stobutzki et al., 2001a, 2001b; Braccini et al., 2006; Griffiths et al., 2006; Zhou and Griffiths, 2008) and owing to recommendations by several organizations and working groups as a reasonable approach for determining risk (Hobday et al.[1],[2]; Rosenberg et al.[3]; Smith et al., 2007).

The PSA was originally developed to classify differences in bycatch sustainability in the Australian prawn fishery (Milton, 2001; Stobutzki et al., 2001b) by evaluating the productivity (p) of bycatch stocks and their susceptibility (s) to the fishery. The values for p and s were determined by providing a score ranging from 1 to 3 for a standardized set of attributes related to each index (i.e., 7 productivity and 6 susceptibility attributes). When data were lacking, scores could be based on similar taxa or given the most vulnerable score as a precautionary approach. The scores were then averaged for each index and displayed graphically on an x-y scatter plot (Fig. 1). The two-dimensional nature of the PSA leads directly to the calculation of an overall vulnerability score (v) of a species, defined as the Euclidean distance of productivity and susceptibility scores:

$$v = \sqrt{\left[(P - X_0)^2 + (S - Y_0)^2\right]}, \quad (1)$$

where x_0 and y_0 are the (x, y) origin coordinates, respectively.

Stocks that received a low productivity score and a high susceptibility score are considered to be the most vulnerable to overfishing, whereas stocks with a high productivity score and low susceptibility score are considered to be the least vulnerable.

Since 2001, the PSA has been modified by others to evaluate habitat, community, and management components of a fishery (Hobday et al.[2]; Rosenburg et al.[3]). In general, these modifications have included expanding the number of attributes for scoring, exploring additive and multiplicative models for combining scores, and examining a variety of alternative treatments for missing data. In the next section we review our application of a PSA to provide a uniform framework for evaluating the wide variety of fish stocks managed within the United States.

Identifying productivity and susceptibility attributes

With the expansion of the PSA to evaluate other management factors (e.g., habitat impacts, ecosystem considerations, management efficacy), the number of attributes that could be considered in a PSA has increased considerably—in some instances to approximately seventy-five (Hobday et al.[2]; Rosenberg et al.[3]). Although ~75 attributes have been recommended, Hobday et al.[2] noted that the use of more than six attributes per index

[1] Hobday, A. J., A. Smith, and I. Stobutzki. 2004. Ecological risk assessment for Australian Commonwealth fisheries, 172 p. Report R01/0934 for the Australian Fisheries Management Authority, Canberra, Australia.

[2] Hobday, A. J., A. Smith, H. Webb, R. Daley, S. Wayte, C. Bulman, J. Dowdney, A. Williams, M. Sporcic, J. Dambacher, M. Fuller, T. Walker. 2007. Ecological risk assessment for the effects of fishing: methodology, 174 p. Report R04/1072 for the Australian Fisheries Management Authority, Canberra, Australia.

[3] Rosenberg, A., D. Agnew, E. Babcock, A. Cooper, C. Mogensen, R. O'Boyle, J. Powers, G. Stefansson, and J. Swasey. 2007. Setting annual catch limits for U.S. fisheries: An expert working group report, 36 p. MRAG Americas, Washington, D.C.

(e.g., productivity, susceptibility, habitat) does little to improve the accuracy of an assessment. Development of our PSA began with an initial examination and reduction of these 75 attributes to 35 after removing those perceived as redundant or not directly related to our definition of vulnerability. The remaining attributes were evaluated in two phases. In phase 1, our team provided individual scores (i.e., "yes," "no," or "maybe") to determine whether each attribute was 1) appropriate for calculating productivity or susceptibility of a stock; 2) useful at different scales (i.e., for stocks of various sizes and spatial distributions); and 3) capable of being calculated for most fisheries (i.e., for data availability). Attributes receiving a majority of "yes" scores for all three questions were retained. In phase 2, attributes receiving mixed scores, as well as new attributes not previously identified, were evaluated in a group discussion. Through this process, 18 (9 productivity, 9 susceptibility) of the 35 attributes were selected and four new attributes were added, including 1) recruitment pattern; 2) management strategy; 3) fishing rate in relation to natural mortality; and 4) desirability or value of the fishery. Overall, 22 attributes were selected for the analysis (10 productivity, 12 susceptibility). The large set of attributes to be scored, compared to previous versions of the PSA, is largely a result of the susceptibility index, including both catchability and management attributes (see *Susceptibility attributes* section below). We also recognized that the PSA would mainly be used to evaluate extremely data-poor stocks; thus, a larger set of attributes would be useful to ensure that an adequate number of attributes were scored.

Productivity attributes

Many of the productivity attributes are based on Musick's (1999) qualitative extinction risk assessment and the PSA of Stobutzki et al. (2001b). However, the scoring thresholds have been modified in many cases to better suit the distribution of life history characteristics observed in U.S. fish stocks (Table 1). Information on maximum length, maximum age, age-at-maturity, natural mortality, and von Bertalanffy growth coefficient were available for more than 140 stocks considered to be representative of U.S. fisheries (see Patrick et al., 2009). For these attributes, a range of scoring categories was evaluated by using analysis of variance (ANOVA) and *post hoc* tests to identify attribute scoring thresholds that produced significantly different bins of data. To ensure consistency in these attributes, the optimal scoring thresholds from the ANOVA were also compared to published relationships among maximum age and natural mortality (Alverson and Carney, 1975; Hoenig, 1983), von Bertalanffy growth coefficient (Froese and Binohlan, 2000), and age at maturity (Froese and Binohlan, 2000). Overall, we found this approach produced sensible categories compared to the approach of independently dividing each attribute into equal bins or using a quantile method. We defined the following 10 productivity attributes.

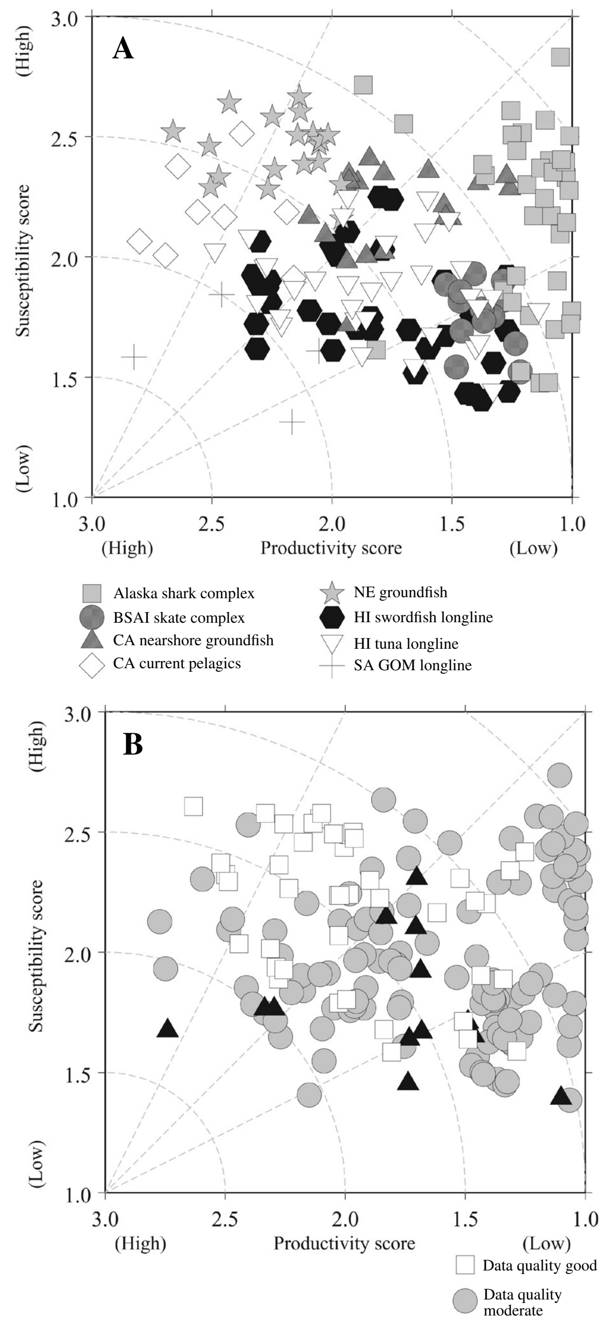

Figure 1

(**A**) Overall distribution of productivity and susceptibility x-y plot for the 166 stocks evaluated in this study, differentiated by fishery. BSAI=Bering Sea and Aleutian Islands. SA GOM= South Atlantic and Gulf of Mexico. (**B**) Associated data quality of each datum point of the 166 stocks evaluated in this study (see Appendix 1 for a list of the species in these fisheries).

Intrinsic growth rate (*r*) This is the intrinsic rate of population growth or maximum population growth that would occur in the absence of fishing at the lowest population size (Gedamke et al., 2007). Density-depen-

Table 1

Productivity attributes and rankings used to determine the vulnerability of a stock to becoming overfished.

Productivity attribute	Definition	Ranking High (3)	Ranking Moderate (2)	Ranking Low (1)
r	The intrinsic rate of population growth or maximum population growth that would occur in the absence of fishing at the lowest population size.	>0.5	0.16–0.5	<0.16
Maximum age	Maximum age is a direct indication of the natural mortality rate (M), where low levels of M are negatively correlated with high maximum ages.	<10 years	10–30 years	>30 years
Maximum size	Maximum size is correlated with productivity, with large fish tending to have lower levels of productivity, although this relationship tends to degrade at higher taxonomic levels.	< 60 cm	60–150 cm	>150 cm
von Bertalanffy growth coefficient (k)	The von Bertalanffy growth coefficient measures how rapidly a fish reaches its maximum size, where long-lived, low-productivity stocks tend to have low values of k.	>0.25	0.15–0.25	<0.15
Estimated natural mortality (M)	Natural mortality rate directly reflects population productivity; stocks with high rates of natural mortality will require high levels of production in order to maintain population levels.	>0.40	0.20–0.40	<0.20
Measured fecundity	Fecundity (i.e., the number of eggs produced by a female for a given spawning event or period) is measured here at the age of first maturity.	$>10^4$	10^2–10^3	$<10^2$
Breeding strategy	The breeding strategy of a stock provides an indication of the level of mortality that may be expected for the offspring in the first stages of life.	0	1–3	≥4
Recruitment pattern	Stocks with sporadic and infrequent recruitment success often are long lived and thus may be expected to have lower levels of productivity.	Highly frequent recruitment success (>75% of year classes are successful).	Moderately frequent recruitment success (between 10% and 75% of year classes are successful).	Infrequent recruitment success (<10% of year classes are successful).
Age at maturity	Age at maturity tends to be positively related with maximum age (t_{max}); long-lived, lower productivity stocks will have higher ages at maturity than short-lived stocks.	<2 year	2–4 years	>4 years
Mean trophic level	The position of a stock within the larger fish community can be used to infer stock productivity; lower-trophic-level stocks generally are more productive than higher-trophic-level stocks.	<2.5	2.5–3.5	>3.5

dent compensation is at a maximum in these depleted conditions and therefore r is a direct measure of stock productivity. The scoring thresholds were taken from Musick (1999), who stated that r should take precedence over other productivity attributes because it combines many of the other attributes defined below.

Maximum age (t_{max}) Maximum age is related to natural mortality rate (M), where M is inversely related to maximum age (Hoenig, 1983). The scoring thresholds were based on the ANOVA applied to the observed fish stocks considered to be representative of U.S. fisheries (see Patrick et al., 2009). The t_{max} for a majority of these fish ranges between 10 and 30 years.

Maximum size (L_{max}) Maximum size is also correlated with productivity, and large fish tend to have lower levels of productivity (Roberts and Hawkins, 1999), although this relationship varies phylogenetically and is strongest within higher taxonomic levels (e.g., genus, family). The scoring thresholds were based on the ANOVA applied to the observed fish stocks considered to be representative of U.S. fisheries (see Patrick et al., 2009). The L_{max} for a majority of these fish ranges between 60 and 150 cm total length (TL).

Growth coefficient (k) The von Bertalanffy growth coefficient measures how rapidly a fish reaches its maximum size. Long-lived, low-productivity stocks tend to have low values of k (Froese and Binohlan, 2000). The scoring thresholds of 0.15 and 0.25 were based on the ANOVA applied to the observed fish stocks considered to be representative of U.S. fisheries (see Patrick et al., 2009). This observed range of k is roughly consistent with the values obtained from Froese and Binohlan's (2000) empirical relationship $k=3/\ t_{max}$ of 0.1 and 0.3, based upon t_{max} values of 10 and 30.

Natural mortality (M) Natural mortality rate directly reflects population productivity because stocks with high rates of natural mortality will require high levels of production to maintain population levels. For several methods of estimating M, one must rely on the negative relationship between M and t_{max}, including Hoenig's (1983) regression based upon empirical data, the quantile method that depends upon exponential mortality rates (Hoenig, 1983), and Alverson and Carney's (1975) relationship between mortality, growth, and t_{max}. The scoring thresholds from the ANOVA applied to the fish stocks considered to be representative of U.S. fisheries were 0.2 and 0.4, roughly consistent with those produced from Hoenig's (1983) empirical regression of 0.14 and 0.4, based on t_{max} values of 10 and 30.

Fecundity Fecundity (i.e., the number of eggs produced by a female for a given spawning event or period) varies with size and age of the spawner; therefore we followed Musick's (1999) recommendation that fecundity should be measured at the age of first maturity. As Musick (1999) noted, low values of fecundity imply low population productivity, but high values of fecundity do not necessarily imply high population productivity; thus, this attribute may be more useful at the lower fecundity values. The scoring thresholds were taken from Musick (1999) and were fecundities values of 1,000 and 100,000.

Breeding strategy The breeding strategy of a stock provides an indication of the level of mortality that may be expected for the offspring in the first stages of life. To estimate offspring mortality, we used Winemiller's (1989) index of parental investment. The index ranges from 0 to 14 and is scored according to 1) the placement of larvae or zygotes (i.e., in a nest or in the water column; score ranges from 0 to 2); 2) the length of time of parental protection of zygotes or larvae (score ranges from 0 to 4); and 3) the length of gestation period or nutritional contribution (score ranges from 0 to 8). To translate Winemiller's index into our ranking system, we examined King and McFarlane's (2003) parental investment scores for 42 North Pacific stocks. These 42 stocks covered a wide range of life histories and habitats, including 10 surface pelagic, three mid-water pelagic, three deep-water pelagic, 18 near-shore benthic, and nine offshore benthic stocks. Thirty-one percent of the stocks had a Winemiller score of zero, and 40 percent had a Winemiller score of 4 or higher; therefore 0 and 4 were used as the scoring thresholds.

Recruitment pattern Stocks with sporadic and infrequent recruitment success often are long lived and thus might be expected to have lower levels of productivity (Musick, 1999). This attribute is intended as a coarse index to distinguish stocks with sporadic recruitment patterns and high frequency of year-class failures from those with relatively steady recruitment. Thus, the proportion of years in which recruitment was above average (e.g., the percentage of successful year classes over a 10-year period) was used for this attribute. Because this attribute was viewed as a coarse index, we chose 10% and 75% as the scoring thresholds, so that scores of 1 and 3 allowed us to identify relatively extreme differences in recruitment patterns.

Age-at-maturity (t_{mat}) Age at maturity tends to be strongly related to both maximum age (t_{max}) and natural mortality (M), where long-lived, lower-productivity stocks will have higher ages at maturity than short-lived stocks (Beverton, 1992). The scoring thresholds from the ANOVA applied to the fish stocks considered to be representative of U.S. fisheries were ages 2 and 4. These values are lower than those obtained from Froese and Binohlan's (2000) empirical relationship between t_{mat} and t_{max}, which were ages 3 and 9 based upon values of t_{max} of 10 and 30. However, Froese and Binohlan (2000) used data from many fish stocks around the world, which may not be representative of U.S. stocks. For the PSA, thresholds that were obtained from the ANOVA were applied to stocks considered representative of U.S. fisheries.

Mean trophic level The position of a stock within the larger fish community can be used to infer stock productivity; lower-trophic-level stocks are generally more productive than higher-trophic-level stocks. The trophic level of a stock can be computed as a function of the trophic levels of the organisms in its diet. For this attribute, stocks with trophic levels higher than 3.5 were categorized as low-productivity stocks and stocks with trophic levels less than 2.5 were categorized as high-productivity stocks, and moderate-productivity stocks would fall between these bounds. These scoring thresholds roughly categorize piscivores to higher trophic levels, omnivores to intermediate trophic levels, and planktivores to lower trophic levels (Pauly et al., 1998) and carry the assumption that the food web analysis did not consider microbial loops as an individual trophic level.

Susceptibility attributes

Previous applications have been focused on the catchability and mortality of stocks, and other attributes, such as management effectiveness and effects of fishing gear on habitat quality, have been addressed in subsequent analyses (Hobday et al.[2]). Our susceptibility index includes all these attributes in an effort to make the results of our analysis more transparent and understandable. We defined 12 susceptibility attributes; the first seven relate to catchability and the other five measure management factors.

Like the susceptibility attributes of Hobday et al.[2], catchability attributes provide information on the likelihood of a stock's capture by a particular fishery, given the stock's range, habitat preferences, behavioral responses, and morphological characteristics that may affect its susceptibility to the fishing gear deployed in that fishery. For management attributes, one must consider how the fishery is managed: for example, fisheries with conservative management measures in place that effectively control the amount of catch are less likely to overfish. For some of these attributes, the criteria are somewhat general in order to accommodate the wide range of fisheries and management systems.

Areal overlap This attribute pertains to the extent of geographic overlap between the known distribution of a stock and the distribution of the fishery. Greater overlap implies greater susceptibility, because some degree of geographical overlap is necessary for a fishery to impact a stock. The simplest approach to determining areal overlap is to evaluate, either qualitatively or quantitatively, the proportion of the spatial distribution of a given stock that overlaps that of the fishery, based on known geographical distributions of both.

Geographic concentration Geographic concentration is the extent to which the stock is concentrated into small areas. We included this attribute because a stock with a relatively even distribution across its range may be less susceptible than a highly aggregated stock. For some species, a useful measure of this attribute is the proportion of an area of interest occupied by a specified percentage of the stock (Swain and Sinclair, 1994), which can be computed if survey data exist (see Patrick et al., 2009). For many stocks, this measure gives a general index of areal coverage that relates well to geographic concentration. However, some stocks can be concentrated in a small number of locations throughout a survey area (i.e., a "patchy" stock that is distributed over the survey area). Thus, some refinements to the index may be necessary to characterize geographic concentration in these cases.

Vertical overlap Like geographic overlap, this attribute concerns the position of the stock within the water column (e.g., demersal or pelagic) in relation to the fishing gear. Information on the depth at which gear is deployed (e.g., depth range of hooks for a pelagic longline fishery) and the depth preference of the species (e.g., obtained from archival tagging or other sources) can be used to estimate the degree of vertical overlap between fishing gear and a stock.

Seasonal migrations Seasonal migrations either to or from the fishery area (i.e., spawning or feeding migrations) could affect the overlap between the stock and the fishery. This attribute also pertains to cases where the location of the fishery changes seasonally, and therefore may be relevant for stocks captured as bycatch.

Schooling, aggregation, and other behaviors This attribute encompasses behavioral responses of both individual fish and the stock in response to fishing. Individual responses may include, for example, herding or gear-avoidance behavior that would affect catchability. An example of a population-level response is a reduction in the area of stock distribution with reduction in population size, potentially leading to increases in catchability (MacCall, 1990).

Morphological characteristics affecting capture This attribute pertains to the ability of the fishing gear to capture fish according to their morphological characteristics (e.g., body shape, spiny versus soft rayed fins). On a population level, this attribute refers to gear selectivity as it varies with fish size and age. Scoring this attribute, one should take into consideration what portion of the population size or age composition is accessible to the fishing gear or gears in question. Particular attention should be paid to the size or age at maturity in relation to capture.

Desirability or value of the fishery For this attribute, one assumes that highly valued fish stocks are more susceptible to overfishing or becoming overfished by recreational or commercial fishermen because of increased fishing effort. To identify the value of the fish, we used the price per pound or annual landings value for commercial stocks (using the higher of the two values; see Table 2) or the retention rates for recreational fisheries.

Management strategy The susceptibility of a stock to overfishing may largely depend on the effectiveness of fishery management procedures used to control catch (Roughgarden and Smith, 1996; Sethi et al., 2005; Dankel et al., 2008). Stocks managed by using catch limits that allow for fishery closure before the catch limit is exceeded (i.e., in-season or proactive accountability measures) are considered to have a low susceptibility to overfishing. Stocks managed by using catch limits and reactive accountability measures (e.g., catch levels determined after the fishing season) are considered to be moderately susceptible to overfishing or to becoming overfished. Lastly, stocks that have neither catch limits nor accountability measures are considered to be highly susceptible to overfishing.

Fishing mortality rate (in relation to *M*) This attribute is applicable to stocks for which estimates of both fishing and natural mortality rates (F and M) are available. Because sustainable fisheries management typically involves conserving the reproductive potential of a stock, it is recommended that the average F on mature fish be used where possible, as opposed to the fully selected or "peak" F. We base our thresholds on the conservative rule of thumb that the M should be an upper limit of F (Thompson, 1993), and thus F/M should not exceed 1. For this attribute, we define intermediate F/M values as those between 0.5 and 1.0; values above 1.0 and below 0.5 are defined as high and low susceptibility, respectively.

Biomass of spawners Analogous to fishing mortality rate, a comparison of the current stock biomass ($B_{CURRENT}$) to expected unfished levels (B_0) offers information on the extent to which fishing has potentially depleted the stock and the stock's realized susceptibility to overfishing. If B_0 is not available, one could compare $B_{CURRENT}$ against the maximum observed biomass from a time series of population size estimates (e.g., from a research survey). If a time series is used, it should be of adequate length, and it should be recognized that the maximum observed survey estimates may not correspond to the true maximum biomass and that substantial observation errors in estimates may be present. Additionally, stocks may decline in abundance because of environmental factors unrelated to their susceptibility to the fishery, and therefore this situation should be considered by scientists when evaluating depletion estimates. Notwithstanding these issues, which can be addressed with the data quality score described below, some measure of current stock abundance was viewed as a useful attribute.

Survival after capture and release Fish survival after capture and release varies by species, region, depth, gear type, and even market conditions, and thus can affect the susceptibility of the stock (Davis, 2002). Considerations of barotraumatic effects, discarding methods, and gear invasiveness (e.g., gears with hooks or nets would likely be more invasive than traps) are particularly relevant.

Fishery impact on habitat A fishery may have an indirect effect on a species through adverse impacts on habitat (Benaka, 1999; Barnes and Thomas, 2005). Within the United States, a definition of the level of impact is the focus of environmental impact statements and essential fish habitat evaluations (see Rosenberg et al., 2000). To align with NMFS evaluations of impact, the scoring thresholds for this attribute were categorized as minimal, temporary, or mitigated.

Defining attribute scores and weights

Depending on the specific stock being evaluated, not all of the productivity and susceptibility attributes listed in Tables 1 and 2 will be equally useful in determining the vulnerability of a stock. In previous versions of the PSA, an attribute weighting scheme was used in which higher weights were applied to the more important attributes (Stobutzki et al., 2001b; Hobday et al.[1]; Rosenberg et al.[3]). We used a default weight of 2 for the productivity and susceptibility attributes, where attribute weights can be adjusted within a scale from 0 to 4 to customize the application to each fishery. In determining the proper weighting of each attribute, users should consider the relevance of the attribute for describing productivity or susceptibility rather than the availability of data for that attribute (e.g., data-poor attributes should not automatically receive low weightings). In some rare cases, it is also anticipated that some attributes will receive a weighting of zero, which cause them to be removed from the analysis, because the attribute has no relation to the fishery and its stocks. Some attributes (e.g., management strategy, fishing mortality rate, biomass of spawners, etc.) may also be removed from the analysis to avoid double-counting if they are considered in a more overarching risk analysis, for which the results of the PSA are only one component.

Like Milton (2001) and Stobutzki et al. (2001b), we defined the criteria for a score of 1, 2, or 3 to a productivity or susceptibility attribute (see Table 1). However, our approach provides users the flexibility to apply intermediate scores (e.g., 1.5 or 2.5) when the attribute value spans two categories. Owing to the subjective nature of semiquantitative analyses, scores should be applied in a consistent manner to reduce scoring bias (Lichtensten and Newman, 1967; Janis, 1983; Von Winterfeldt and Edwards, 1986; Bell et al., 1988), such as by employing the Delphi method (see Okoli and Pawlowski, 2004 and Landeta, 2006).

Data-quality index

As a precautionary measure for risk assessment scoring, the highest-level risk score can be used when data are missing to account for uncertainty and to avoid identifying a high-risk stock as low risk (Hardwood, 2000; Milton, 2001; Stobutzki et al., 2001b; Astles et al., 2006). Although precautionary, that approach also confounds the issues of data quality with risk assessment. For example, a data-poor stock may receive

Table 2

Susceptibility attributes and rankings used to determine the vulnerability of a stock becoming overfished.

Susceptibility attribute	Definition
Areal overlap	The extent of geographic overlap between the known distribution of a stock and the distribution of the fishery.
Geographic concentration	The extent to which the stock is concentrated into small areas.
Vertical overlap	The position of the stock within the water column (i.e., whether is demersal or pelagic) in relation to the fishing gear.
Seasonal migrations	Seasonal migrations (i.e. spawning or feeding migrations) either to or from the fishery area could affect the overlap between the stock and the fishery.
Schooling, aggregation, and other behavioral responses	Behavioral responses of both individual fish and the stock in response to fishing.
Morphological characteristics affecting capture	The ability of the fishing gear to capture fish based on their morphological characteristics (e.g., body shape, spiny versus soft rayed fins, etc.).
Desirability or value of the fishery	The assumption that highly valued fish stocks are more susceptible to overfishing or to becoming overfished by recreational or commercial fishermen owing to increased effort.
Management strategy	The susceptibility of a stock to overfishing may largely depend on the effectiveness of fishery management procedures used to control catch.
Fishing rate relative to M	As a conservative rule of thumb, it is recommended that M should be the upper limit of F so as to conserve the reproductive potential of a stock.
Biomass of spawners (SSB) or other proxies	The extent to which fishing has depleted the biomass of a stock in relation to expected unfished levels offers information on realized susceptibility.
Survival after capture and release	Fish survival after capture and release varies by species, region, and gear type or even market conditions, and thus can affect the susceptibility of the stock.
Impact of fisheries on essential fish habitat or habitat in general for nontargeted fish	A fishery may have an indirect effect on a species by adverse impacts on habitat.

a high-risk evaluation either from an abundance of missing data or from the risk assessment of the available data, with the result that the risk scores may be inflated (Hobday et al.[1]). In contrast, we considered missing data within the larger context of data quality, and report the overall quality of data as a separate value.

A data-quality index was developed to represent the information quality of individual vulnerability scores based on five tiers, ranging from best data (or high belief in the score) to no data (or little belief in the score) (Table 3). The data-quality score is computed for the productivity and susceptibility scores as a weighted average and implies the overall quality of the data or belief in the score rather than the actual type of data used in the analysis. Like Hobday et al.[2], we divided the data-quality scores into three groupings (poor >3.5; moderate 2.0–3.5; and good <2.0) for display purposes. This information, along with more detailed descriptions of data quality (e.g., mean score, range), is a quick and useful means of providing decision-makers with details on the uncertainty of the vulnerability

Ranking		
Low (1)	Moderate (2)	High (3)
<25% of stock present in the area fished.	Between 25% and 50% of the stock present in the area fished.	>50% of stock present in the area fished.
Stock is distributed in >50% of its total range	Stock is distributed in 25% to 50% of its total range	Stock is distributed in <25% of its total range.
<25% of stock present in the depths fished.	Between 25% and 50% of the stock present in the depths fished.	>50% of stock present in the depths fished
Seasonal migrations decrease overlap with the fishery.	Seasonal migrations do not substantially affect the overlap with the fishery.	Seasonal migrations increase overlap with the fishery.
Behavioral responses of fish decrease the catchability of the gear.	Behavioral responses of fish do not substantially affect the catchability of the gear.	Behavioral responses of fish increase the catchability of the gear (i.e., hyperstability of catch per unit of effort with schooling behavior).
Species shows low susceptibility to gear selectivity.	Species shows moderate susceptiblity to gear selectivity.	Species shows high susceptiblity to gear selectivity.
Stock is not highly valued or desired by the fishery (<$1/lb; <$500K/yr landed; <33% retention).	Stock is moderately valued or desired by the fishery ($1–$2.25/lb; $500K–$10,000K/yr landed; 33–66% retention).	Stock is highly valued or desired by the fishery (>$2.25/lb; >$10,000K/yr landed; >66% retention).
Targeted stocks have catch limits and proactive accountability measures; nontarget stocks are closely monitored.	Targeted stocks have catch limits and reactive accountability measures.	Targeted stocks do not have catch limits or accountability measures; nontargeted stocks are not closely monitored.
<0.5	0.5–1.0	>1
B is >40% of B_0 (or maximum observed from time series of biomass estimates).	B is between 25% and 40% of B_0 (or maximum observed from time series of biomass estimates).	B is <25% of B_0 (or maximum observed from time series of biomass estimates).
Probability of survival >67%	33% < probability of survival <67%	Probability of survival <33%
Adverse effects absent, minimal or temporary.	Adverse effects more than minimal or temporary but are mitigated.	Adverse effects more than minimal or temporary and are not mitigated.

scores. Such uncertainty in the data would help with the interpretation of the overall vulnerability score and also help in targeting areas of further research and data needs.

Example case studies

To demonstrate the utility of our PSA scoring process, we evaluated six U.S. fisheries including the Northeast groundfish multispecies, highly migratory Atlantic shark complexes, California nearshore groundfish finfish assemblage, California Current coastal pelagic species, skates of the Bering Sea and Aleutian Islands (BSAI) management area (a bycatch fishery of the BSAI groundfish fishery), and the Hawaii-based pelagic longline fishery (both the tuna and swordfish sectors). In total, 162 stocks were evaluated (Appendix 1). These fisheries were chosen because they were expected to display varying degrees of productivity, susceptibility, and data quality. For descriptions of these fisheries and details on how our PSA scoring procedure was applied to each fishery, see Patrick et al. (2009).

Table 3

The five tiers of data quality used when evaluating the productivity and susceptibility of an individual stock.

Data quality tier	Description	Example
1	Best data. Information is based on collected data for the stock and area of interest that is established and substantial	Data-rich stock assessment; published literature for which multiple methods are used, etc.
2	Adequate data Information is based on limited coverage and corroboration, or for some other reason is deemed not as reliable as tier-1 data	Limited temporal or spatial data, relatively old information, etc.
3	Limited data. Estimates with high variation and limited confidence and may be based on studies of similar taxa or life history strategies	Similar genus or family, etc.
4	Very limited data. Information based on expert opinion or on general literature reviews from a wide range of species, or outside of region	General data not referenced
5	No data. When there are no data on which to make even an expert opinion, the person using the PSA should give this attribute a "data quality" score of 5 and not provide a "productivity" or "susceptibility" score so as not to bias those index scores. When plotted, the susceptibility or productivity index score will be based on one less attribute, and will be highlighted as such by its related quality score.	

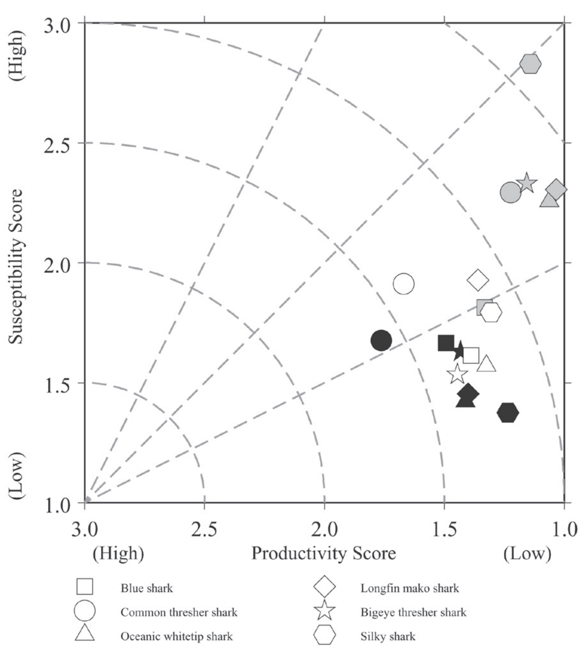

Figure 2

Comparison of vulnerabilities among common shark species in the highly migratory Atlantic shark complexes (gray), Hawaii-based pelagic longline—tuna sector (white), and Hawaii-based pelagic longline—swordfish sector (black).

Results and discussion

Range of vulnerability scores

The managed stocks evaluated in this report represent both targeted (n=71; 44%) and nontargeted species (n=91; 56%) that were included in fishery management plans to prevent overfishing and rebuild overfished stocks. The stocks generally displayed vulnerability scores greater than 1.0 (Fig. 1). Species evaluated within the Atlantic highly migratory shark complexes were found to be the most vulnerable, averaging vulnerability scores of 2.17, and California Current coastal pelagic species were the least vulnerable, averaging 1.29.

Although different groups of species will exhibit different ranges of productivity and susceptibility scores, it is interesting to note that in some cases even the same species may exhibit different productivity scores. For example, the productivity scores for the blue (*Prionace glauca*), bigeye thresher (*Alopias superciliosus*), longfin mako (*Isurus paucus*), oceanic whitetip (*Carcharhinus longimanus*), silky (*C. falciformis*), and common thresher (*A. vulpinus*) sharks differed between the highly migratory Atlantic shark complexes and the Hawaii-based pelagic longline fishery example applications (Fig. 2). These differences are likely related to intraspecific variations in life history patterns (Cope, 2006) and to the use of different weightings in the vulnerability analysis (see Patrick et al., 2009).

In contrast, the species in the Hawaii-based pelagic longline fishery (both the tuna and swordfish sectors) showed an expanded range of productivity and suscep-

Table 4

Summary of the productivity and susceptibility scoring frequencies and correlations to the overall index or category score. Correlations were based on stock attributes scores (1–3) (see Tables 1 and 2) that were compared to a modified categorical score for the stock, the latter of which did not include the related attribute score.

Category	No. scored	Frequency scored	Pearson correlation coefficient	*P*-value
Productivity				
r	128	96%	0.596	<0.001
Maximum age	126	95%	0.674	<0.001
Maximum size	128	96%	0.592	<0.001
von Bertalanffy growth coefficient (*k*)	129	97%	0.656	<0.001
Estimated natural mortality (*M*)	127	95%	0.785	<0.001
Measured fecundity	126	95%	0.509	<0.001
Breeding strategy	133	100%	0.568	<0.001
Recruitment pattern	84	63%	−0.211	0.054
Age at maturity	125	94%	0.802	<0.001
Mean trophic level	132	99%	0.439	<0.001
Susceptibility				
Catchability				
Areal overlap	123	92%	0.333	<0.001
Geographic concentration	133	100%	0.345	<0.001
Vertical overlap	133	100%	0.772	<0.001
Seasonal migrations	49	37%	0.058	0.692
Schooling, aggregation, and other behavioral responses	87	65%	0.340	0.001
Morphology affecting capture	132	99%	0.319	<0.001
Desirability or value of the fishery	133	100%	0.504	<0.001
Management				
Management strategy	133	100%	0.154	0.077
Fishing rate in relation to *M*	79	59%	0.510	<0.001
Biomass of spawners (SSB) or other proxies	78	59%	0.389	<0.001
Survival after capture and release	126	95%	0.201	0.024
Fishery impact to essential fish habitat (EFH) or habitat in general for nontargeted fish	133	100%	0.286	0.001

tibility scores. The swordfish sector overall exhibited a slightly reduced susceptibility when compared to the tuna sector, probably due to the higher level of targeting in the tuna sector of the fishery (Fig. 1). The restricted range in some of the example applications may reflect the species chosen for these examples, and a more expanded range may be observed if the PSA were applied to all species in a fishery management plan (FMP). For example, BSAI skate complexes are managed as bycatch within the BSAI Groundfish FMP, which includes a range of life-history types, including rockfish and flatfish, and the productivity and susceptibility scores for these species would likely contrast with those obtained for skates.

A restricted range of scores from a PSA may motivate some to modify the attribute scoring thresholds to produce greater contrast. But because the overall goal of the present PSA is to estimate vulnerability in relation to an overall standard appropriate for the range of managed species, a lack of contrast in vulnerability scores may simply reflect a limited breadth of species diversity. It may be advantageous in some cases to modify the attribute scoring thresholds to increase the contrast within a given region or FMP (see Field et al., in press), while recognizing that the vulnerability scores for that particular fishery no longer represent the risk of overfishing based on the original scoring criteria described here.

Data availability and data quality

From our example applications, data availability was relatively high for the majority of the attributes evaluated, averaging 88% and ranging from 37% to 100% in scoring frequency (Table 4). However, the quality of these data was considered moderate (i.e., medium data quality scores of 2–3), except for the Northeast multispecies groundfish fishery (Fig. 1). The high degree of data quality for those targeted stocks reflects the relatively long time series of fishery and survey data. In general, a relationship between susceptibility and data quality is intuitive (i.e., valuable stocks are likely the most susceptible owing to targeting, and priority is therefore given to the collection of data for valuable target fisheries).

The degree of consistency within the productivity and susceptibility scores was determined from correlations of a particular attribute to its overall productivity or susceptibility score (after removal of the attribute being evaluated). In this analysis, susceptibility attributes related to management were separated from other susceptibility attributes. All but two of the attributes had relatively high correlation coefficients, with an overall average correlation of 0.43 and ranging from –0.21 to 0.80 (Table 4). The correlation coefficients for recruitment pattern (–0.21) and seasonal migration (0.06) were unusually low and could reflect the narrow range of observed recruitment patterns or seasonal migrations, as is evident from each attribute being scored 90% of the time as a moderate risk. Although these attributes were not informative for the majority of the stocks we examined, we anticipate that these attributes may prove to be more useful for other fisheries. As previously noted, in these cases the attribute weight can be adjusted to reflect its utility.

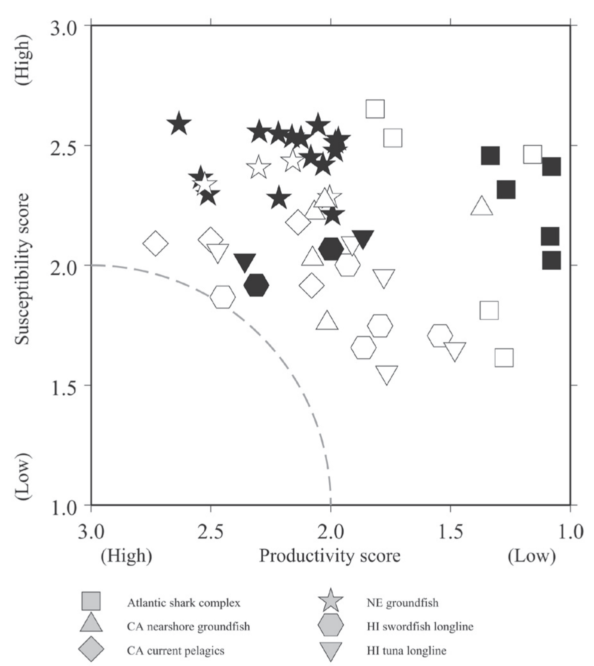

Figure 3

A subset of the stocks from the example applications (n=50) for which the status (stock is either overfished [$F_{CURRENT}$>F_{MSY}] or is being overfished [$B_{CURRENT}$<B_{MSY}]) could be determined between 2000 and 2008. Productivity and susceptibility analysis scores increase with distance from the origin, as does the vulnerability score. The dashed line references the minimum vulnerability scores observed among the 162 stocks evaluated in the applications.

Relationship of stock vulnerability to fishing pressure

To evaluate the efficacy of the PSA in identifying stocks that are vulnerable to overfishing, we examined a subset (n=50) of the example stocks for which status determination criteria were available to assess whether the stock's maximum sustainable fishing mortality rate (i.e., whether it is being overfished) or minimal stock size threshold (i.e., whether it was overfished) had been exceeded between the years of 2000 and 2008 (Fig. 3). Kruskal-Wallis tests indicated significant differences in susceptibility (P=0.001) and vulnerability (P=0.002) scores between stocks that had been overfished or that were being overfished in the past (i.e., Northeast groundfish multispecies and highly migratory Atlantic shark complexes) and those that had not. However, productivity scores were not found to be significantly different (P=0.891). Stocks that had been overfished or that were being overfished in the past generally had susceptibility scores greater than 2.3 and vulnerability scores greater than 1.8.

To further examine the efficacy of the PSA to identify vulnerable stocks, we evaluated four lightly fished nontarget species (i.e., minor bycatch species) that were unlikely to be impacted by fishing activities in their region according to their average landings (<5 metric tons/yr), price value (<$1.00/lb), and suspected high productivity rates. These minor bycatch species, from the South Atlantic and Gulf of Mexico snapper-grouper longline fishery, represented stocks that should have substantially lower vulnerability scores (<1.0) compared to the other species that are considered either targeted species or major bycatch species. Three of the four nontarget species received vulnerability scores of less than 1.0 (Fig. 1), but the other stock (sand tilefish, *Malacanthus plumieri*) received a vulnerability score of 1.1 because of its moderate productivity (2.1) and susceptibility (1.9).

These *post hoc* results involving stocks with status determinations and lightly fished nontarget species, although limited, indicate that the PSA can differentiate between low- and highly vulnerable stocks. However, a fixed threshold for delineating between the varying levels of vulnerability was not observed in all situations because a gradient of vulnerabilities existed. Therefore, determination of appropriate thresholds for low-, moderate-, and highly vulnerable stocks will likely reflect the nature of each particular fishery and the management action that will be applied. In some cases, managers may prefer to use the results of the PSA in a contextual or qualitative manner to determine management decisions rather than as a basis for specifying rigid decision rules. When thresholds are desired, we recommend that managers and scientists jointly determine appropriate thresholds on a fishery-by-fishery basis.

Comparisons between target and nontarget stocks

Comparisons of productivity and susceptibility between target and nontarget stocks were made in the Hawaii-

Table 5

Nonparametric statistical analysis of targeted versus non-targeted species productivity, susceptibility, and vulnerability scores in the highly migratory Atlantic shark complexes and Hawaii-based pelagic longline sector fisheries.

		Kruskal-Wallis P-values		
Fishery	Number	Productivity	Susceptibility	Vulnerability
Hawaii-based pelagic longline—tuna	33	0.026	0.373	0.072
Hawaii-based pelagic longline—swordfish	33	0.026	0.153	0.058
Highly migratory Atlantic shark complexes	37	0.150	<0.001	0.380
Combined	103	0.752	<0.001	0.160

based pelagic longline (tuna sector), Hawaii-based pelagic longline (swordfish sector), and the highly migratory Atlantic shark complexes (nontarget stocks are identified in Appendix 1). Kruskall-Wallis tests revealed that the productivity scores were significantly different between the target and nontarget stocks in each of the two sectors of the Hawaii-based pelagic longline fishery ($P=0.026$), whereas the susceptibility scores were significantly different ($P<0.001$) in the highly migratory Atlantic shark complexes (Table 5). None of these cases showed significant differences in both axes, and no significant differences were observed in vulnerability. Like others, these results indicate that nontarget stocks can be as vulnerable to overfishing as the target stocks of a fishery and reinforce the need for a careful examination of the vulnerability of nontarget stocks when making management decisions (see Alverson et al., 1994; Hall, 1996; Kaiser and de Groot, 2000).

Conclusions

Although many qualitative risk analyses are used by fisheries scientists and managers, the PSA is a particularly useful method for determining vulnerability because it permits an evaluation of both the productivity of the stock and its susceptibility to the fishery. The output from this relatively simple and straightforward tool provides managers and scientists an index of how vulnerable target and nontarget stocks within a fishery are to becoming overfished. Even when specific values for many life history parameters are not well known, the categorical bins of low, medium, and high values are often distinct enough to allow scores for even the most data-poor species. The bins also help in determining the needed strength of conservation measures and the degree of precaution to apply in management measures. They can also identify those stocks or fisheries that warrant further, more complicated analytical attention.

Our analyses indicate that the PSA is generally capable of distinguishing the vulnerability of stocks that experience differing levels of fishing pressure, although fixed thresholds separating low-, medium-, and high-vulnerability stocks were not developed. When fixed thresholds of vulnerability are desired, it is recommended that managers and scientists determine thresholds between low-, medium-, and high-vulnerability stocks on a fishery-by-fishery basis, using cluster analysis or other techniques that identify groups of similar species.

Like those of Shertzer and Williams (2008), our example applications showed that current stock complexes exhibit a wide range of vulnerabilities (e.g., highly migratory Atlantic shark complexes). Therefore, managers should consider reorganizing complexes that exhibit a wide range of vulnerabilities, or at least consider choosing an indicator stock that represents the more vulnerable stock(s) within the complex. If an indicator stock is found to be less vulnerable than other members of the complex, management measures should be conservative so that the more vulnerable members of the complex are not at risk from the fishery.

It is also important to note that PSA scores will likely vary between sectors of a targeted fishery (e.g., gear type, user group) or among fisheries that capture the stock as bycatch. For example, the susceptibility score for "survival after capture and release" may differ greatly between trawl and gill net gears. Thus, it is recommended that a vulnerability evaluation be performed for all or a majority of sectors interacting with the stock when the overall vulnerability of stock is needed (e.g., for setting control rule buffers, identifying sectors where stocks are particularly vulnerable, etc.). An overarching vulnerability evaluation score could then be calculated by using a weighting system based on average landings by sector over some predetermined time frame.

Scientists have begun using the PSA in developing control rules for fisheries management. For example, the South Atlantic Fishery Management Council is considering an acceptable biological catch control rule that is based on a tiered system that reduces the probability of overfishing from 50% (i.e., the overfishing limit) to as low as 20% based on 1) the uncertainty in the stock assessment, 2) the status of the stock, and 3) the vulnerability score from the PSA (SAFMC[4]). Additional control rule frameworks are being developed

[4] SAFMC (South Atlantic Fisheries Management Council). 2009. Briefing book–attachment 10: Scientific and Statistical Committee's draft ABC control rule, 11 p. South Atlantic Fisheries Management Council Meeting, Stuart, FL.

within NMFS (Witherell[5]). We assert that as fishery scientists and management advisors begin to explore the use of risk analysis, that the PSA is one approach that could demonstrably help managers to make more informed decisions, particularly in instances where data are limited.

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Appendix 1

List of example stocks and associated fisheries used to evaluate the efficacy of the productivity and susceptibility indices in determining vulnerability of stocks to becoming overfished.

Fishery	Stock	Scientific name
Highly migratory Atlantic shark complexes	Sixgill shark*	*Hexanchus griseus*
	Sharpnose sevengill shark*	*Heptranchias perlo*
	Bigeye sandtiger shark*	*Odontaspis noronhai*
	Whale shark*	*Rhincodon typus*
	Caribbean sharpnose shark*	*Rhizoprionodon porosus*
	Angel shark*	*Squatina dumeril*
	White shark*	*Carcharodon carcharias*
	Basking shark*	*Cetorhinus maximus*
	Sandtiger shark*	*Carcharias taurus*
	Blue shark*	*Prionace glauca*
	Smalltail shark*	*Carcharhinus porosus*
	Nurse shark	*Ginglymostoma cirratum*
	Galapagos shark*	*Carcharhinus galapagensis*
	Dusky shark*	*Carcharhinus obscurus*
	Porbeagle*	*Lamna nasus*
	Common thresher shark*	*Alopias vulpinus*
	Oceanic whitetip shark*	*Carcharhinus longimanus*
	Blacknose shark	*Carcharhinus acronotus*
	Lemon shark	*Negaprion brevirostris*
	Shortfin mako*	*Isurus oxyrinchus*
	Longfin mako*	*Isurus paucus*
	Tiger shark	*Galeocerdo cuvier*
	Smooth hammerhead shark	*Sphyrna zygaena*
	Caribbean reef shark*	*Carcharhinus perezi*
	Blacktip shark	*Carcharhinus limbatus*
	Scalloped hammerhead shark	*Sphyrna lewini*
	Sandbar shark	*Carcharhinus plumbeus*
	Bigeye thresher shark*	*Alopias superciliosus*
	Finetooth shark	*Carcharhinus isodon*
	Night shark*	*Carcharhinus signatus*
	Bignose shark*	*Carcharhinus altimus*
	Bonnethead shark	*Sphyrna tiburo*
	Spinner shark	*Carcharhinus brevipinna*
	Bull shark	*Carcharhinus leucas*
	Great hammerhead shark	*Sphyrna mokarran*
	Atlantic sharpnose shark	*Rhizoprionodon terraenovae*
	Silky shark	*Carcharhinus falciformis*
Bering Sea and Aleutian Islands skate complexes	Alaska skate*	*Bathyraja parmifera*
	Aleutian skate*	*Bathyraja aleutica*
	Commander skate*	*Bathyraja lindbergi*
	Whiteblotched skate*	*Bathyraja maculata*
	Whitebrow skate*	*Bathyraja minispinosa*
	Roughtail skate*	*Bathyraja trachura*
	Bering skate*	*Bathyraja interrupta*
	Mud skate*	*Bathyraja taranetzi*
	Roughshoulder skate*	*Amblyraja badia*
	Big skate*	*Raja binoculata*
	Longnose skate*	*Raja rhina*
	Butterfly skate*	*Bathyraja mariposa*
	Deepsea skate*	*Bathyraja abyssicola*
California nearshore groundfish finfish assemblage	California sheephead	*Semicossyphus pulcher*
	Cabezon	*Scorpaenichthys marmoratus*
	Kelp greenling	*Hexagrammos decagrammus*

continued

Appendix 1 (continued)

Fishery	Stock	Scientific name
California nearshore groundfish finfish assemblage (cont.)	Rock greenling	*Hexagrammos lagocephalus*
	California scorpionfish	*Scorpaena guttata*
	Monkeyface prickelback	*Cebidichthys violaceus*
	Black rockfish	*Sebastes melanops*
	Black-and-yellow rockfish	*Sebastes chrysomelas*
	Blue rockfish	*Sebastes mystinus*
	Brown rockfish	*Sebastes auriculatus*
	Calico rockfish*	*Sebastes dallii*
	China rockfish	*Sebastes nebulosus*
	Copper rockfish	*Sebastes caurinus*
	Gopher rockfish	*Sebastes carnatus*
	Grass rockfish	*Sebastes rastrelliger*
	Kelp rockfish	*Sebastes atrovirens*
	Olive rockfish	*Sebastes serranoides*
	Quillback rockfish	*Sebastes maliger*
	Treefish rockfish	*Sebastes serriceps*
California Current coastal pelagic species	Pacific sardine	*Sardinops sagax*
	Northern anchovy	*Engraulis mordax*
	Pacific mackerel	*Scomber japonicus*
	Jack mackerel	*Trachurus symmetricus*
	Market squid	*Doryteuthis opalescens*
	Pacific herring	*Clupea pallasii*
	Pacific bonito	*Sarda chiliensis*
	Pacific saury	*Cololabis saira*
Northeast groundfish multispecies	Gulf of Maine cod	*Gadus morhua*
	Georges Bank cod	*Gadus morhua*
	Gulf of Maine haddock	*Melanogrammus aeglefinus*
	Georges Bank haddock	*Melanogrammus aeglefinus*
	Redfish	*Sebastes marinus*
	Pollock	*Pollachius virens*
	Cape Cod/Gulf of Maine yellowtail flounder	*Limanda ferruginea*
	Georges Bank yellowtail flounder	*Limanda ferruginea*
	Southern New England yellowtail flounder	*Limanda ferruginea*
	American plaice	*Hippoglossoides platessoides*
	Witch flounder	*Glyptocephalus cynoglossus*
	Gulf of Maine Winter flounder	*Pseudopleuronectes americanus*
	Georges Bank Winter flounder	*Pseudopleuronectes americanus*
	Southern New England/Mid-Atlantic winter flounder	*Pseudopleuronectes americanus*
	Gulf of Maine/Georges Bank windowpane	*Scophthalmus aquosus*
	Southern New EnglandMid-Atlantic windowpane	*Scophthalmus aquosus*
	Ocean pout	*Zoarces americanus*
	White hake	*Urophycis tenuis*
	Atlantic halibut	*Hippoglossus hippoglossus*
Hawaii-based pelagic longline—swordfish	Albacore	*Thunnus alalunga*
	Bigeye tuna	*Thunnus obesus*
	Black marlin*	*Makaira indica*
	Bullet tuna	*Auxis rochei rochei*
	Pacific pomfret*	*Brama japonica*
	Blue shark*	*Prionace glauca*
	Bigeye thresher shark*	*Alopias superciliosus*
	Blue marlin*	*Makaira mazara*
	Dolphin fish (mahi mahi)*	*Coryphaena hippurus*
	Brilliant pomfret*	*Eumegistus illustris*
	Kawakawa*	*Euthynnus affinis*
	Spotted moonfish*	*Lampris guttatus*
	Longfin mako shark*	*Isurus paucus*

continued

Appendix 1 (continued)

Fishery	Stock	Scientific name
Hawaii-based pelagic longline—swordfish (cont.)	Salmon shark*	*Lamna ditropis*
	Striped marlin*	*Tetrapturus audax*
	Oilfish*	*Ruvettus pretiosus*
	Northern bluefin tuna*	*Thunnus orientalis*
	Roudi escolar*	*Promethichthys prometheus*
	Pelagic thresher shark*	*Alopias pelagicus*
	Sailfish*	*Istiophorus platypterus*
	Skipjack tuna	*Katsuwonus pelamis*
	Shortfin mako shark*	*Isurus oxyrinchus*
	Shortbill spearfish*	*Tetrapturus angustirostris*
	Broad billed swordfish	*Xiphias gladius*
	Flathead pomfret*	*Taractichthys asper*
	Dagger pomfret*	*Taractichthys rubescens*
	Sickle pomfret*	*Taractichthys steindachneri*
	Wahoo*	*Acanthocybium solandri*
	Yellowfin tuna	*Thunnus albacares*
	Oceanic whitetip shark*	*Carcharhinus longimanus*
	Silky shark*	*Carcharhinus falciformis*
	Common thresher shark*	*Alopias vulpinus*
	Escolar*	*Lepidocybium flavobrunneum*
Hawaii-based pelagic longline—tuna	Albacore	*Thunnus alalunga*
	Bigeye tuna	*Thunnus obesus*
	Black Marlin*	*Makaira indica*
	Bullet tuna	*Auxis rochei rochei*
	Pacific pomfret*	*Brama japonica*
	Blue Shark*	*Prionace glauca*
	Bigeye thresher shark*	*Alopias superciliosus*
	Blue marlin*	*Makaira mazara*
	Dolphin fish (mahi mahi)*	*Coryphaena hippurus*
	Brilliant pomfret*	*Eumegistus illustris*
	Kawakawa*	*Euthynnus affinis*
	Spotted moonfish*	*Lampris guttatus*
	Longfin mako shark*	*Isurus paucus*
	Salmon shark*	*Lamna ditropis*
	Striped marlin*	*Tetrapturus audax*
	Oilfish*	*Ruvettus pretiosus*
	Northern bluefin tuna*	*Thunnus orientalis*
	Roudi escolar*	*Promethichthys prometheus*
	Pelagic thresher shark*	*Alopias pelagicus*
	Sailfish*	*Istiophorus platypterus*
	Skipjack tuna	*Katsuwonus pelamis*
	Shortfinned mako shark*	*Isurus oxyrinchus*
	Short bill spearfish*	*Tetrapturus angustirostris*
	Broad billed swordfish*	*Xiphias gladius*
	Flathead pomfret*	*Taractichthys asper*
	Dagger pomfret*	*Taractichthys rubescens*
	Sickle pomfret*	*Taractichthys steindachneri*
	Wahoo*	*Acanthocybium solandri*
	Yellowfin tuna	*Thunnus albacares*
	Oceanic whitetip shark*	*Carcharhinus longimanus*
	Silky shark*	*Carcharhinus falciformis*
	Common thresher shark*	*Alopias vulpinus*
	Escolar*	*Lepidocybium flavobrunneum*
South Atlantic and Gulf of Mexico snapper-grouper longline	Sand tilefish*	*Malacanthus plumieri*
	Rock sea bass*	*Centropristis philadelphica*
	Margate*	*Haemulon album*
	Bar jack*	*Caranx ruber*

*Nontarget stocks.