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[Article]

# From Rags to Fishes: Data-Poor Methods for Fishery Managers

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*Abstract.*—Fishery managers often must make decisions regardless of data availability or completeness of scientific understanding. Existing and new legal mandates, such as the requirement to establish Annual Catch Limits for each United States fishery by 2011, as well as the ongoing need to improve understanding of fish stock dynamics, are driving efforts to develop new, more efficient ways to assess fish stocks when resources are insufficient for full stock assessments. Moreover, there is an increasing recognition of the need to assess stocks at smaller spatial scales. In December 2008, fishery scientists, fishermen, and managers convened at a workshop in Berkeley, California (USA), to discuss such methods. One goal of the workshop was to identify methods for estimating potential reference points for managing data-poor fisheries, such as science-based overfishing thresholds, allowable biological catch levels, and vulnerability indices. Here we review methods presented at the workshop, as well as some promising methods gleaned from the literature, for establishing reference points for data-poor situations. We present a new framework to help managers and stakeholders consider and choose appropriate analytical methods and alternative management approaches, based on available data (type, quantity, and quality) and feasibility constraints (scale, value, and implementation costs). We highlight limitations and considerations for each method and illustrate the use of our framework by presenting case-study examples. Too often, lack of data and/or proper data analysis results in lack of management. This status quo, however, poses risks to the economic and biological sustainability of fisheries. Application of data-poor methods, while subject to many caveats, can reduce these risks by providing scientific guidance for management.

Complex models that require large amounts of data are commonly used to inform fishery management decisions, such as setting allowable harvest levels or determining overfishing thresholds for species or species groups. Often, however, fishery managers must make such decisions without complex models, due to a lack of data quantity, data quality, understanding, technical capacity, or human capital. In California alone, approximately 70% of fished stocks (103 of 149 species) lack stock assessments and thus may be defined as data-poor fisheries (Botsford and Kilduff 2008).

Many, if not most fisheries in the United States and around the world, are data-poor due to lack of research funding and lack of support for monitoring and analysis. Many of these fisheries are important for economic and food security and/or because they affect vulnerable ecosystems or vulnerable stocks. It is important to assess and manage them — even when few data are available.

Fortunately, there are methods for assessing stock status and identifying management reference points for fisheries that are data-poor. Recently developed methods can be used to prioritize fisheries for research and management, as well as estimate overfishing thresholds, biomass levels, stock status, or catch or effort limits with limited information. Existing and new legal mandates, such as the requirement to establish Annual Catch Limits by 2011 for all targeted stocks in the United States, drive efforts to develop new, more efficient ways to assess and manage fish stocks when full stock assessments are infeasible. There is ongoing need to improve understanding of fish stock dynamics, given existing resources and information constraints.

When data are insufficient for a conventional stock-assessment, alternative methods can inform management tasks with science-based understanding. Further development of alternative assessment methods that can extract knowledge from relatively scarce data is

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one necessary step toward addressing the overall challenge of managing fisheries. Fishery managers must also weigh competing objectives, including the costs of management relative to the value of fisheries, in order to determine appropriate levels of investments in research and analysis.

When financial resources are scarce (as they often are for the management of data-poor stocks), every hour and dollar invested in stock management demands maximum return on investment. Therefore, managers of data-poor fisheries often face additional pressure to perform their responsibilities in a cost-efficient manner. They must extract as much scientific understanding as possible, given scarce data and resources to characterize population size, structure, and regional dynamics. Then, managers must apply values and control rules to manage fishing effort and catch. To achieve success within these data and resource constraints, the appropriate use of data-poor alternatives requires the decision maker to know about available options, as well as understanding which (if any) alternatives are most appropriate for a given fishery and management context.

In this paper, we present a framework to help managers and stakeholders identify alternative methods for assessing stock status and evaluate options for managing data-poor fisheries. We review a variety of data analysis methods and reference points for use in data-poor fisheries, while providing context and case-study examples of innovative and alternative approaches. We organize this range of data-poor methods in an intuitive way, within one framework, in order to make all tools and existing alternatives more accessible to fishery managers and stakeholders. Then, we discuss the specific needs, caveats, and limitations of each data-poor method and associated management approaches.

Many fisheries remain unassessed and unmanaged, not because they are unimportant economically and ecologically, but because insufficient resources and data exist to drive a complex stock assessment. Often, there is a lack of qualified stock assessment scientists for the work (Berkson et al. 2009). Therefore, our overall intent is to make data-poor methods more accessible and provide a framework that managers and stakeholders can use to evaluate the data-richness of their fisheries, the range of analytical methods available for assessing stock status, and some of the pros and cons of each method. We do not, however, provide exhaustive reviews of data-poor methods, so interested parties will need to conduct their own careful evaluation of the relevant primary literature on a case-by-case basis. We hope to stimulate increased development and use of data-poor methods, and ultimately the assessment and management of more fisheries in order to reduce risks to sustainability.

## Approach and Key Terms

We reviewed and summarized work presented at the "Managing Data-Poor Fisheries: Case Studies, Models, & Solutions" workshop in Berkeley, California, USA (December 1–4, 2008, co-sponsored by the California Department of Fish and Game and California Sea Grant College Program). Then, we augmented workshop materials with peer-reviewed literature and organized diverse alternative methods into a new framework in order to make the variety of data-poor methods more accessible to those managing data-poor fisheries.

In reference to data richness, this paper adopts the definition of "data-poor" fisheries shown in Text Box 1, as presented by Bentley and Stokes (2009, this volume). This definition emphasizes that data-poor fisheries can suffer from lack of data as well as from a lack of reliable data with adequate and appropriate analyses. Thus, data-poor fisheries can include fisheries with copious quantities of data, albeit unreliable or under-analyzed due to lack of resources. Transitioning from "data-poor" situations towards "data-rich" may result from any or all of the following: increasing the amount of data collected, improving data quality and analysis, or increasing technical capacity.

The term "data poor" is sometimes confounded with "small-scale" fisheries. While it is true that many small-scale fisheries are data poor, these terms are not synonymous. As Text Box 1 emphasizes, we interpret "small-scale" to refer exclusively to the size of a fishery (e.g., total landings or commercial value). Fishery size is independent of the "data-richness" of a fishery, which refers to the quantity and quality of available data and information sources. Many small-scale fisheries are data-poor because they generate relatively low revenues and hence receive low priority for data collection and assessment. Moreover, the fine-scale complexity of fish populations may render large-scale data collection systems inadequate for smaller scaled fisheries. Therefore, even though large amounts of data are collected, the fishery remains data-poor.

Fisheries vary tremendously in the kinds, amounts, and quality of data available for management. Consequently, fishery managers often classify data-poor situations into tiers, based on the severity of data limitations and uncertainty level (Smith et al. 2009, this volume). Tiers allow for the adjustment of harvest rules in response to data limitations in order to buffer against scientific uncertainty. Different tiers have different adjustment factors that coincide with different levels of data richness, ranging from data poor (e.g., only historical catch) to data rich (e.g., complex stage-structured models to estimate science-based reference points like $B_{msy}$ or $F_{msy}$ for maximum sustainable yield [MSY]). Government policy and management guide-

lines determine the application of these adjustment factors to harvest control rules based on public preferences and risk tolerances (Goodman et al. 2002; Smith et al. 2007; Smith et al. 2009, this volume).

Within the United States, technical guidelines are used to recommend adjustments to management goals like MSY, depending on data quality and quantity (Restrepo et al. 1998). To date, the North Pacific Fishery Management Council (NPFMC) has rigorously implemented and applied a tiered-management approach. The NPFMC approach evaluates data richness, adjusts harvest control rules commensurate with uncertainty, and maintains a buffer between the allowable biological catch (ABC) and the overfishing limit (OFL, or the upper limit of sustainable harvest (Thompson 1997). For example, in the Alaska crab fishery, the NPFMC organizes precautionary management into a five-tier system (NOAA Fisheries 2008). Other examples exist in Europe, Asia, Africa and Australia (O'Boyle 2003; Gonzalez-Laxe 2005; ICES 2007; Potts et al. 2008; Smith et al. 2009, this volume). In this volume, Smith et al. (2009) describe the four-tier approach used to manage Australia's Southern and Eastern Scalefish and Shark Fisheries (SESSF).

Within a tiered management context, we define a "data-poor method" as a method for informing a control rule or management action (qualitative or quantitative) that does not involve a full stock assessment. When a stock assessment exists for a fishery, then we consider this fishery to be data rich or data moderate for management. For our purposes in this paper, we define a "stock assessment" as a multistage process that uses (often sophisticated Bayesian) modeling approaches. Various types of data are combined to predict rates of change in stock biomass and productivity based on information about yield from fisheries and the rates at which fish enter the harvestable population (recruitment), grow in size, and exit the population (natural and fishing mortality, NRC 1998). Text Box 1 summarizes the multiple steps in the stock assessment process. Additionally, many books exist on stock assessment techniques that synthesize broadly used techniques (Hilborn and Walters 1992; National Research Council 1998; Walters and Martell 2004; Hoggarth et al. 2006). We intend for this work to be the beginning of a synthesis of "data-poor methods" and alternatives to multi-staged stock assessment, regardless the exact number of tiers or management context.

## A Framework for Existing Data-poor Methods

Our proposed framework organizes data-poor methods and matches them to the available data. We build on prior work, which summarizes and categorizes general characteristics of a stock assessment and approaches for various stock-assessment techniques (Hilborn and Walters 1992; Punt and Hilborn 2001; Hilborn 2003; Walters and Martell 2004; Hoggarth et al. 2006). Irrespective of data-richness, fisheries management involves two basic elements (Punt and Hilborn 2001):

(a) Fisheries science — involving data collection and analysis to develop an understanding of fish population dynamics, possible states of nature, environmental change, and scientific uncertainty analysis.

(b) Fisheries policy and management decision-analysis — involving the evaluation of alternative management strategies in order to gain insight into expected outcomes and trade-offs, assuming defined objectives, rules, and normative values of society.

When these two elements are coupled, better science leads to better management actions and outcomes.

TEXT BOX 1.—Key terms

**alternative method**: (see data-poor method).

**conventional method**: A management approach, often standard in industrialized commercial fisheries today that synthesizes available data and evaluates scientific knowledge with a stock assessment (or other single-species population model) to understand individual stock dynamics and estimate science-based reference points for a fishery. In response to science-based expectations, trends, and uncertainty, managers adjust fishing pressure for single-stock management (e.g., with quotas, effort reduction, partial seasonal closures, gear restrictions, and/or other harvest rules and regulations).

**data poor**: A condition to describe a fishery that lacks sufficient information to conduct a conventional stock assessment; this includes fisheries with few available data, as well as fisheries with copious amounts of data but limited understanding of stock status due to poor data quality or lack of data analysis.

**data-poor method** (also called "alternative method"): A method for fisheries data analysis and/or for informing a control rule or management action, which can be a qualitative or quantitative method, but is not a full, stage-structured stock assessment that requires data-rich or data-moderate conditions.

**data richness**: A relative index, combining data type, quantity, and quality, in order to qualitatively measure the amount of information that exists for a stock or fishery.

**meta-analysis**: A suite of quantitative techniques to statistically combine information across related, but independent, studies that can be field, experimental, or other information sources.

**small scale**: A small fishery (either in landings or value) that typically employs traditional gear and targets nearshore stocks. Most typically, small-scale fisheries harvest inshore stocks, often through traditional, artisanal, and/or subsistence methods without commercial sale or large-scale resale of harvest (Berkes et al. 2001).

**stock assessment**: A "stock assessment" is a multistage process that uses (often sophisticated Bayesian) modeling approaches to combine various types of data and predict rates of change in stock biomass and productivity based on information about yield from fisheries, and the rates at which fish enter the harvestable population (*recruitment*), growth in size, and exit the population (*natural* and *fishing mortality*). As defined by (NRC 1998) the multiple steps for a stock assessment are: (1) definition of the geographic and biological extent of the stock; (2) choice of data collection procedures and collection of data; (3) choice of an assessment model and its parameters and conduct of assessments; (4) specification of performance indicators and evaluation of alternative actions; and (5) presentation of results.

As Table 1 presents in an easy-to-reference format, we suggest a four-step framework for evaluating and managing data-poor fisheries:

**Step 1 — Gauge Data-richness.**
**Step 2 — Data-richness Informs Analytical Options.**
**Step 3 — Apply Fishery-evaluation Methods:**
*(ordered from high to low information requirements)*
(i) Sequential trend analysis (index indicators).
(ii) Vulnerability analysis.
(iii) Extrapolation.
**Step 4 — Apply Decision-making Methods:**
*(ordered from high to low expected practical use for data-poor management)*
(i) Decision trees.
(ii) Management Strategy Evaluation.

Given clear objectives and an understanding of existing data and methods, fishery managers can garner the most possible scientific understanding from available data. This becomes especially important when resources are scarce for science and management.

### Step 1 — Gauge Data-richness

Sources of available information determine the universe of options available to a fishery manager. A number of other constraints, such as those itemized in Table 2, require consideration. These constraints set the management context, within which our proposed framework operates.

As a general rule of thumb, managers facing data-poor decisions should first identify and qualitatively evaluate all information sources available to them. This evaluation of data should be conducted prior to choosing a method (or methods) for analyzing information (Hilborn and Mangel 1997). Data can then be organized in a way that facilitates the choice of appropriate analytical methods.

We recommend the use of a qualitative scorecard to assess data-richness by itemizing and organizing all available information sources into one intuitive and consistent layout for the manager (see sample scorecard, Figure 1). This approach is somewhat analogous to the quantitative scorecards used by Hilborn and Walters (1992) to assess management performance.

The example scorecard in Figure 1 presents only a part of the spectrum of potential information sources that may exist for a fishery classified as data poor. Fishery managers should develop their own scorecards to meet their needs. Data quantity and quality should both be incorporated into the scorecard since they both impact the usefulness of data-poor methods. Quantity can be characterized through simple check marks, with

TABLE 1.—Categories of data-poor methods

| | |
|---|---|
| We broadly group data-poor methods (i.e., alternative methods) into two general sets or categories to help make the full range of evaluation options visible and of use to managers who must manage stocks without the benefit of fishery stock assessments: | |
| **Fishery-Evaluation Methods** | • Less data and resource intensive.<br>• Often requires only one or two data types.<br>• Data-driven techniques to identify changes, trends, or priorities. |
| ***Types of fishery-evaluation methods:*** | |
| (i) Sequential trend analysis (index indicators). | |
| (ii) Vulnerability analysis. | |
| (iii) Extrapolation. | |
| **Decision-Making Methods** | • More data and resource intensive.<br>• Often requires several data types, plus assumptions about how to balance these different data inputs.<br>• Creates a framework for decision making. |
| ***Types of decision-making methods:*** | |
| (i) Decision trees. | |
| (ii) Management strategy evaluation (MSE). | |

TABLE 2.—Data-poor management considerations

| | |
|---|---|
| A manager must consider feasibility constraints and evaluative criteria to appropriately identify and implement assessment methods, especially when managing data-poor fisheries. | |
| **Feasibility constraints** | |
| ***Scale of the fishery*** | Index of fishery size, based on geographic range and/or economic importance. |
| ***Stakeholder incentives*** | Index to characterize the degree of incentives alignment (between industry profits and biological conservation), as well as stakeholder interest and co-management capacity. |
| ***Value-cost of new method*** | Index of cost feasibility (time, money, scalable/replicable), based on the fishery's present condition, existing resources/infrastructure, and specific context. |
| **Evaluative criteria** | |
| ***Nature of data available*** | Ranges from zero to perfect information. |

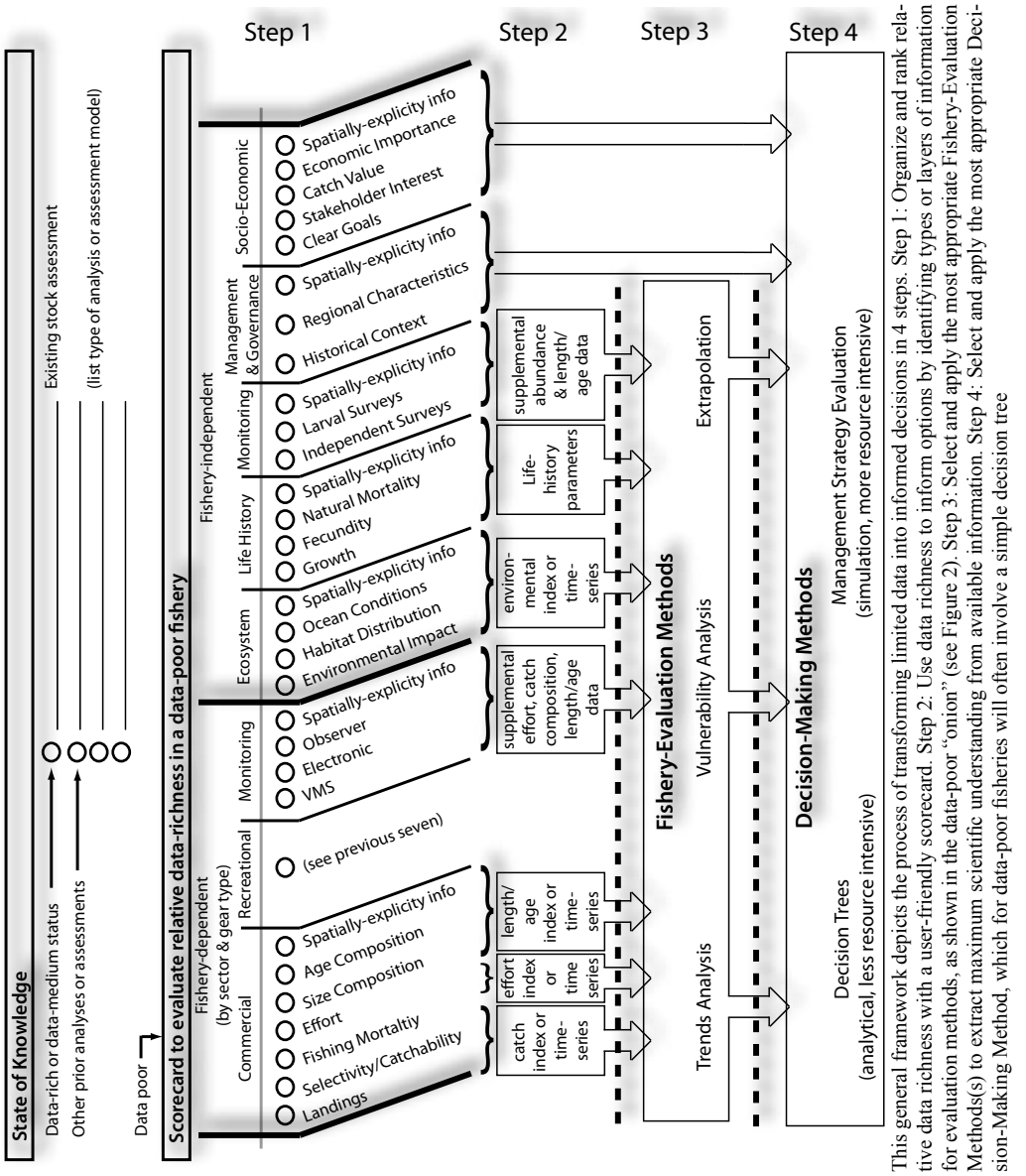



FIGURE 1.—Four-step framework to organize and link information with appropriate data-poor methods. This general framework depicts the process of transforming limited data into informed decisions in 4 steps. Step 1: Organize and rank relative data richness with a user-friendly scorecard. Step 2: Use data richness to inform options by identifying types or layers of information for evaluation methods, as shown in the data-poor "onion" (see Figure 2). Step 3: Select and apply the most appropriate Fishery-Evaluation Methods(s) to extract maximum scientific understanding from available information. Step 4: Select and apply the most appropriate Decision-Making Method, which for data-poor fisheries will often involve a simple decision tree

increasing check marks representing increasing richness. Zero checks indicate low richness, whereas 20 or more might indicate high richness. Data quality can be assessed with a coarsely-graduated rating system (e.g., low-med-high index of relative data quality or different marks, such as solid- or X-marks, to indicate different levels of data sufficiency). By evaluating the quality of data available, a manager can further gauge scientific confidence in trends, information, and decision based on the data driving the process. Regardless of specific layout, the aim of the scorecard is to provide an easy way for managers to identify, organize, and apply existing knowledge and available information for data-poor stocks.

If spatially explicit data exist, Geographical Information Systems (GIS) and other spatial tools can add another dimension of data-richness by addressing social and spatial complexity. GIS layering can enrich understanding by incorporating new or untapped fisheries information, such as regional knowledge of catch patterns, fleet behavior, habitat distribution, and other spatial variables like gear, seasonal, or social conflicts. GIS can also be used to explore spatially explicit relationships between layers and data sets that might affect the implementation of a management decision. Consideration of these elements may be included in a data richness scorecard.

### Step 2 — Data-richness Informs Analytical Options

After managers identify all their data and information sources for a given fishery, we recommend identifying all evaluation methods deemed feasible given the specific needs, strengths, and limitations of each data-poor method. Managers must recognize how different types and degrees of data-richness lend themselves to different evaluative frameworks and methods for data-poor fisheries.

Given the range of data-analysis methods potentially available, we grouped data-poor methods into five general categories based on shared analytical techniques and data requirements. As shown in Table 1, the five categories of data-poor methods bin into two distinct larger groups: Fishery-Evaluation Methods and Decision-Making Methods. These two groups of methods collectively span a wide range of data-richness levels, while paralleling the two-stage management process originally proposed by Punt and Hilborn (2001).

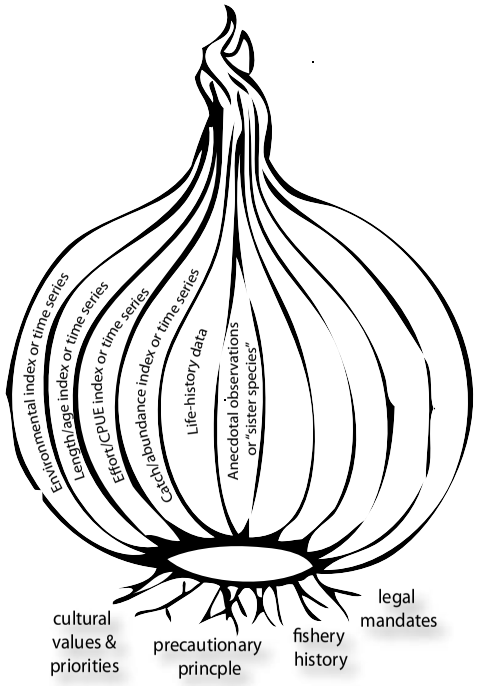
In Figure 1 (Step 2), we connect available data and data-richness levels from the scorecard to corresponding information types used as inputs for analysis of data-poor stocks. The scientific understanding generated from Fishery-Evaluation Methods (Step 3) then feeds into Decision-making Methods to guide management choice and action (Step 4).

This Step 2 links each of the various information types with approaches in the Fishery-Evaluation Methods currently available to managers. Using an onion analogy, Figure 2 illustrates how available information maps to recommended methods of analysis for data-poor fisheries. This onion has various layers, with each layer corresponding to a different type of information from the data-richness scorecard (see Step 1, Figure 1). Layers of the onion can be peeled back and removed, corresponding to the absence of individual types of information for the fishery of interest. The onion varies in quality and size for each individual fishery, commensurate with combinations of different data types, quantities, and qualities. It is rooted in the social and political context of the fishery, which provides the norms (e.g., social and economic goals, regulatory mandates, and risk tolerances) which guide the analyses, interpretation, and execution of fishery management. In this analogy, a full stock assessment requires a whole, large onion with all of the many different layers of fisheries time-series data and life-history information. Conversely, a data-poor fishery can be like a small pearl onion with fewer layers of data for consideration.

Aside from the onion in Figure 2, we list common pairings of data layers to guide managers towards the most appropriate data-poor methods, based on data types and data richness. We show how different layers and permutations lend themselves to analysis with different Fishery-Evaluation Methods, further discussed in Step 3. Methods that use several time-series layers (the outer layers) of the data onion typically provide more quantitative scientific knowledge, compared to methods that use only life-history or anecdotal information (the inner layers). For managers, more layers mean greater scientific knowledge, which typically translates into increasing scientific certainty and decreasing precautionary needs.

While we illustrate data types and methods as separate layers, in fact there is considerable overlap. Data-poor methods are not always distinct, rarely mutually exclusive, and often complementary or nested within other methods. Such overlap and complexity confounds strict ranking based on data-richness criteria. Hence, our proposed framework should be considered to be a generalized organization scheme only, for convenience and simplicity.

This general framework should serve as a guiding reference to facilitate case-by-case evaluation of data-poor fisheries. We ask readers to interpret our proposed framework, method categories, and nested layers of information (Figures 1 and 2) as broad generalizations with malleability. Connections and recommendations between data-richness and data-poor methods are not intended to be immutable, prescriptive linkages. They




(Onion drawing adapted from http://tilz.tearfund.org)

**Recommended Fishery-Evaluation Methods, given data richness combinations:**
*(presented in order of high to low information requirements)*

| | | |
|---|---|---|
| **Stock Assessment** | ⇔ | All layers = the whole onion |
| **TRENDS ANALYSES** | | |
| **Environmental proxies** (e.g., Multivariate ENSO Index, MEI, as a biophysical indicator; see Aburto et al. 2008). | ⇔ | +Catch/Abundance time series<br>+Environmental time-series (best with length/age data) |
| **Per-recruit** (e.g., Fractional change in lifetime egg production, FLEP; see O'Farrell and Botsford 2005). | ⇔ | +Length-age time-series<br>+Catch time series<br>+Life-history data |
| **In-season population or length-based index** (e.g., In-season Depletion Estimator; see Maunder 2010, this volume). | ⇔ | +In-season CPUE or effort time series<br>+In-season catch<br>+Length-age data of in-season catch<br>+Life-history data |
| **Population or length-based index** (e.g., An-Index-Method, AIM; see Rago 2008). | ⇔ | +CPUE time series or abundance index<br>+Catch time series<br>+Life-history data |
| **Vulnerability Analysis** (e.g., Productivity-Susceptibility Analysis, PSA; see Field et al. 2010, this volume) | ⇔ | +Life-history data |
| **Extrapolation methods** (e.g., Robin-Hood approach, see Smith et al. 2009, this volume) | ⇔ | +Anecdotal observations or "sister species" data |

In this metaphor, the onion is a fishery or stock of management interest. Its roots provide the social context for scientific data analysis and, ultimately, the decisions that managers make. The core of the onion is a "no-data" minimum. It has some information value, which often comes from anecdotal observations and/or information borrowed from "sister species" or systems with similar characteristics. Each layer of the onion is a new time-series or source of information, available to the scientist or manager evaluating the fishery. There is no limit or cap to the number of layers within one onion. Sometimes, multiple layers of the same information type exist. For example, independent studies can generate different data sets on the same information type. Managers can elect to individually consider such multiple layers. Alternatively, they can collectively consider this information, using statistical techniques (e.g., average estimates, weighted average estimates, or meta-analysis) to combine several independent sources into one thick layer of integrated values. Given an understanding of existing data layers, a manager can then select most appropriate Fishery-Evaluation Methods for information analysis and increased scientific knowledge.

FIGURE 2.—The data-poor "onion" to connect information types with appropriate Fishery-Evaluation Methods.

are intended to guide managers towards methods that will help them overcome their data-poor challenges.

**Step 3 — Apply Fishery-evaluation Methods**

After choosing the most appropriate data-poor assessment method(s) given data types and richness, Fishery-Evaluation Methods are applied to extract as much scientific understanding as possible, given available information and resources. In this Step 3, we review Fishery-Evaluation Methods, which we divided into three general categories:

(i) Sequential trend analysis (index indicators).
(ii) Vulnerability analysis.
(iii) Extrapolation.

These are ordered by decreasing data-richness requirements (high to low), hence increasing need for management precaution. The application of Step 3 methods is useful for prioritizing fisheries for management and research by providing a "first look" at stock status or vulnerability to fishing mortality.

Meta-analysis, a statistical technique used to integrate and summarize results from multiple and independent studies (see Text Box 1), has potential to enhance the above Fishery-Evaluation Methods. Meta-analysis synthesizes available data sets to generate new and integrated results. When applied to fisheries, it is used most often to estimate parameters and/or prior probability distributions of parameters in a models (NRC 1998). The technique is common in stock assessments (Myers et al. 1995; Liermann and Hilborn 1997; Dorn 2002; Helser and Lai 2004; Helser et al. 2007).

The feasibility of meta-analysis for data-poor stocks may be less obvious because of the need for multiple, independent sources of information. Nonetheless, we see an important possibility for meta-analysis to estimate life-history parameters or coordinate the incorporation of data from on-going monitoring programs. For example, in the future, we expect that meta-analysis of nearshore studies (e.g., marine reserve monitoring) can help inform and guide state and federal management by developing fine-scale understanding from small-scale surveys. Good sources on the technique of meta-analysis itself, in addition to the ones above, are Gurevitch and Hedges (1999); Hedges et al. (1999); Osenberg et al. (1999), and Englund et al. (1999).

Below, we discuss each of the three Fishery-Evaluation Methods within our given framework with a summary paragraph of the method and example applications that demonstrate the use of the method. We then review and characterize minimum data needs, optimal data needs, and important cautions and caveats for the method. If available, we include references to original publications and peer-reviewed literature describing a method's implementation so interested parties can review the method in more depth.

***Fishery-Evaluation Methods — Type 1***
***Sequential Trend Analysis (Index Indicators)***

Sequential analysis comprises a broad suite of techniques used to analyze time series in order to detect a trend in a variable (or in various indices) and infer changes in the stock or population. By its nature, sequential analyses can encompass a wide range of data types and requirements. Some examples commonly used in data-poor fisheries are time series of catch statistics, survey/weight/length-based reference points, trophic indices, or spawning potential ratio (SPR) analogues.

A technique known as cumulative sum (CUSUM) is sometimes used to detect trends and discern significant changes (i.e., true positive or negative changes) from simple variations away from the mean (Manly and MacKenzie 2000; Manly 2001; Scandol 2003; Kelly and Codling 2006). Scandol (2003) demonstrates how the CUSUM method can determine if catch is increasing or decreasing from landed catch data only.

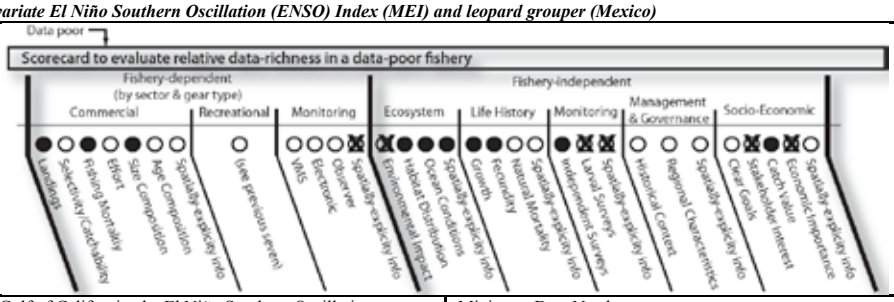
The main advantage of such relatively simple methods is their use of available or easy-to-collect data (e.g., lengths of landed fish as an index for fish stock size). The changes measured, however, only reflect relative change and not changes in (unknown) absolute values of the underlying population. Statistical correlations cannot be used to identify the mechanisms driving the observed changes. Therefore, especially for data-poor stocks, fishery managers must make assumptions about what changes in the measured variables mean for fish populations.

*Sequential Trends Analysis (1a): Environmental Proxies*

*Example technique (see Scorecard 1): biophysical indicators of fish abundance*.—Fish production and population abundance can be tightly linked to environmental processes. When such coupling exists, environmental indicators may be used, with proper scaling and lag factors, in order to evaluate the population, catch, and/or expected variations and uncertainty levels. Ideal environmental proxies are easy-to-measure indicators (e.g., salinity, ocean temperature, rainfall or fluvial runoff), which consistently and predictably lead to the same population-level response in a stock, regardless of other factors. This, however, rarely happens in complex marine ecosystems (Beamish and Bouillon 1993; Francis and Hare 1994; Polovina et al. 1994; Bakun 1996). Consequently, many environmental proxies for fisheries are associated with high levels of scientific uncertainty about whether or not an expected population-level response will (or will not)

SCORECARD 1.

***Environmental Proxy — Case-Study Example***
***Multivariate El Niño Southern Oscillation (ENSO) Index (MEI) and leopard grouper (Mexico)***




In the Gulf of California, the El Niño Southern Oscillation (ENSO) strongly affects the physical environment. Fluctuations in this climatic driver can have large effects on the Gulf's habitats and fish populations. Because of the strong influence of ENSO on the rocky reef habitat where larval and juvenile leopard grouper (*Mycteroperca rosacea*) live, environmental linkages exist between the Multivariate ENSO index (MEI), kelp-bed habitat cover, leopard grouper larval recruitment, and leopard grouper adult abundance (Aburto-Oropeza et al. 2007).

Scientists are now quantifying these relationships and determining their predictability, using visual survey data of kelp abundance, larval recruitment, and juvenile and adult abundances (Ballantyne et al., in review; Aburto-Oropeza et al. 2007). By accounting for the MEI index at the time of larval recruitment, model performance improves by more accurately predicting the abundance of juvenile or adult fish (Ballantyne et al., in review; Aburto-Oropeza et al. 2007). Environmental relationships, such as the one between fish abundance and the MEI index, can lead to general predictions of fishery yield on the basis of juvenile abundance, natural mortality, fishing mortality and catchability. This MEI example has been confirmed by model testing and verification for over a decade, but scientists continue to collect data and test models. On-going testing and updating is important because environmental relationships that influence fish productivity can change over time (e.g., ocean regime shifts).

Minimum Data Needs:
- Environmental time series.
- Abundance index time series (from CPUE or fishery-independent surveys, preferably with age-length information to estimate juvenile and adult abundances).

Optimal Data Needs:
- Underlying population model with known life-history data.
- The longer the time series, the better, especially if data-collection protocols remain consistent through time.
- Tight coupling (i.e., low noise) between environmental time-series data and catch/abundance time-series data.
- Mechanistic understanding of the process(es), which couple environmental parameters and fish production.

Cautions and Caveats:
- Vulnerable to misspecification of variable recruitment typical at low population sizes as environmentally driven.
- Past conditions assumed similar to current and future conditions (i.e., unchanged system dynamics).
- Multi-state systems or changes in system dynamics (e.g., regime shifts) can mask or misrepresent trends detected by this method. Said another way, the underlying relationship between environmental indices and indices can change as a result of regime shifts or oscillation changes in systems with multiple states.
- Relationships should be tested and updated regularly (e.g., annually) as new data emerge.
- Managers still must decide how detected trends affect harvest control rules.

References for environmental proxies:
(Ballantyne et al., in preparation; Vance et al. 1998; Aburto-Oropeza et al. 2007).

occur, given a detected change in the environment (Myers 1998). Another caveat arises from complex stock-recruitment relationships, which can obscure environmental drivers of population dynamics (Mace and Sissenwine 1993). Therefore, environmental proxies can be challenging (if not impossible) to implement for management use, especially when it comes to complex stock dynamics (e.g., those with highly variable recruitment or at low population sizes).

This method should not be a long-term replacement for direct monitoring of fishing effort and its effects. In some cases where abundance and life-history transitions (e.g., ontogenetic migrations) relate to environmental cues (e.g., salinity, temperature, fluvial runoff), environmental proxies can provide important information for management action. This is the case for some shrimp fisheries, where environmental factors influence season opening, closing, and closed areas (Vance et al. 1998).

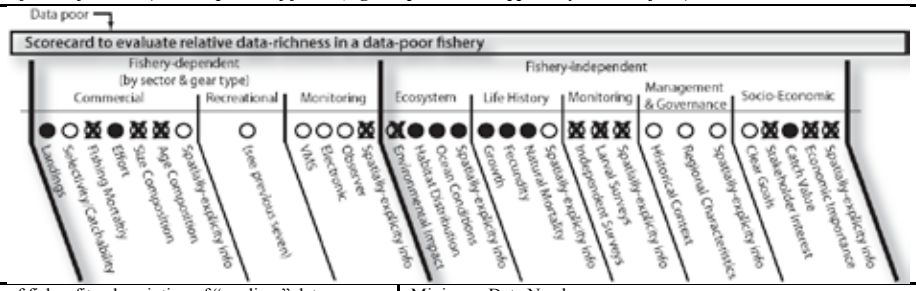
Some environmental proxies examine food web dynamics by evaluating a fishery's overall Mean Trophic Index (MTI), defined as the average trophic level of a region's entire landed catch (Pauly et al. 1998; Pauly and Palomares 2005). As with other index methods based on statistical correlations, environmental proxies provide little (if any) mechanistic insight as to why or how change occurs at the population-level of interest to fishery managers.

### *Sequential Trends Analysis (1b): Per-recruit Methods*

*Example technique (see Scorecard 2): fractional change in lifetime egg production.*—Frequently, long-term time series lack catch-at-age data or even aggregated catch data. Yet, species-specific estimates of demographic properties may be available, such as growth, mortality, and maturity. Coupled with yield- and biomass-per-recruit models, these life-history traits allow the estimation of optimal fishing mortality

SCORECARD 2.

***Per-Recruit Method — Case-Study Example***
***Stocks with "medium" quality data, including many temperate rocky reef fishes (e.g., Pacific rockfish, USA) and tropical reef fishes (e.g., Emperor red snapper, Seychelles, Africa)***




Many reef fishes fit a description of "medium" data richness with quality time-series data, so per-recruit methods are viable management options (Grandcourt et al. 2008). O'Farrell and Botsford (2005, 2006) applied these methods to rocky reef fish in nearshore California waters. Per-recruit methods can also apply to tropical reef fish and other stocks.

Reef fisheries are important resources and protein sources for many developing countries, regardless of whether or not a commercial industry exists. In many such fisheries, for example the Seychelles fishery for Emperor red snapper (*Lutjanus sebae*) in East Africa, scientific support for managers is lacking or nonexistent. Often, however, fishery managers can access basic life-history information. They also have time-series data from reef surveys or local catch. Relative measures (no absolute numbers) can be sufficient to detect a time-series trend and gauge population stock, structure, or change over space and/or time (Grandcourt et al. 2008).

Minimum Data Needs:
- Life-history data:
  - Mortality estimate.
  - Age-length relationship (e.g., von-Bertalanffy growth estimate).
  - Length-egg production relationship.
- Size-frequency distribution of virgin conditions (estimated from MPAs or other unfished areas, the earliest period of fishing exploitation known, or models).
- Size-frequency distribution of a recent population state.

Optimal Data Needs:
- Detailed knowledge of life-history parameters (ideally, informed with fishery-independent sources) to increase accuracy and confidence in model estimates and stock productivity.
- Known size-frequency distribution of unfished state.

Cautions and Caveats:
- Outputs sensitive to life-history assumptions (e.g., mortality particularly difficult to estimate).
- Uses the earliest catch distribution as an estimate of the unfished state.
- Past conditions should be similar to current and future.
- Managers still must decide how detected trends affect harvest control rules.

References for FLEP:
(O'Farrell and Botsford 2005, 2006; Grandcourt et al. 2008).

(*F*) and enable fishery managers to re-examine harvest targets with Yield-Per-Recruit (YPR), Spawning Stock Biomass Per Recruit (SSBPR), and in-season depletion metrics. Estimates of percentage of lifetime egg production (LEP), or egg production per recruit, can be used as a limit reference point in order to maintain a stock's persistence by maintaining the stock's reproductive capacity. Fractional change in lifetime egg production (FLEP) provides a less data-intensive alternative to spawning potential ratio (SPR) and SSBPR estimates. O'Farrell and Botsford (2005, 2006) convincingly show how nearshore species with length-frequency data, including Pacific rockfish (*Sebastes* spp.) along the U.S. West Coast, are good candidates for FLEP and per-recruit methods. Similar time-series information is also available for many tropical reef species that are classified as data-poor.

FLEP can be calculated using two size-frequency distributions — one from an unfished or early exploited state and the current one — with an age-length relationship (e.g., von Bertalanffy growth curve), a length-egg production relationship, and some estimate of mortality (*M*). If local management efforts include no-take marine reserves, these populations may serve as an appropriate proxy for an unfished state after populations have achieved a steady state inside the no-fishing area (Wendt and Starr 2009, this volume). LEP is calculated as the sum across size classes of each size class's abundance and fecundity. The fractional change can be determined as the ratio of the LEP of the recent catch-size distribution to the LEP of an unfished or early fishery state (see equation 4, O'Farrell and Botsford 2005).

Using this method, fishery managers still must make assumptions about what such a trend means for a given stock. Per-recruit methods rely on data correlations, so they offer little or no understanding into mechanistic processes that underlie trends and detected change. The length and quality (consistency) of time-series data strongly affects the value of this data-poor method. Per-recruit methods are most useful if the historical time series is reasonably expected to represent current and future conditions. If fisheries have been strongly affected by changes in fleet dynamics, oceanographic regimes, and/or climate change, then managers should proceed with caution when using this tool. It is important to avoid blindly applying such methods across time-series data that sample across heterogeneous peri-

ods with different environmental conditions. In these cases, fishery managers will need to use more sophisticated statistical techniques to filter data, appropriately parse time-series, and/or correct for biases.

*Sequential Trends Analysis (1c): Population and Length-Based Indices*

*Example technique (see Scorecard 3): In-season depletion estimator*.—The depletion estimator can be used to calculate near-real time stock abundance by analyzing in-season declines in CPUE, thus allowing management to adjust harvest rules (e.g., TAC) within the season. It can also be used as an alternative harvest rule when predicting pre-season abundance proves infeasible, so a seasonal TAC cannot be set. Using in-season statistics on the fishery's catch (e.g., by week) and estimates of the species growth, recruitment, and survival parameters, the depletion estimator compares CPUE and abundance estimates to provide a near real-time abundance level (see Equations 2 and 3; Maunder 2010, this volume). Compared to conventional stock assessment abundance estimates, the depletion estimator is accurate (less than 15% error; Maunder 2010, this volume), even though it only uses data from a year's first quarter. To correctly estimate biomass, however, the method requires up-to-date catch knowledge, as well as confident estimates of life-history characteristics (e.g., growth, recruitment, survival).

*Example technique (see Scorecard 4): An-index-method (AIM)*.—An-Index-Method (AIM) is used to explore relationships between catch statistics and stock abundance indices in order to estimate the scaling factor known as the catchability coefficient. AIM is a relatively new method, developed by Rago (2008) and the NOAA Fisheries Northeast Fisheries Science Center in Woods Hole, Massachusetts. It assumes a linear model of population growth to characterize stock response to different levels of fishing mortality. With an estimated catchability coefficient and the index of relative exploitation (i.e., catch/survey biomass), a manager can use catch data to infer stock status and estimate a relative mortality rate at which the population is likely to be stable. This method and AIM performance, when compared to the outputs and expectations of data-rich stock assessments, correctly tracks population trends but is still susceptible to misspecifying stock status (Rago 2008; Miller et al. 2009).

Population and length-based methods are analogous in many ways to per-recruit methods (discussed in the previous section), without additional assumptions or explicit estimates of fecundity and reproduction. This reserves AIM and similar length-based methods for stocks with medium-quality time-series information and data richness. These methods rely on two assumptions: (i) that the historical time series will represent present and future conditions; and (ii) that the model appropriately captures underlying population dynamics with linear assumptions. As is true with other index methods, the length and quality (consistency) of time-series data strongly affect the value of this data-poor method.

*Example technique: Depletion-corrected average catch (DCAC)*.—The depletion-corrected average catch (DCAC) by MacCall (2009, available from the NOAA Fisheries Toolbox http://nft.nefsc.noaa.gov) is an easy-to-use method that uses only catch time-series data, supplemented by educated guesses of a few supplementary parameters. Therefore, it is likely of practical use for many data-poor fisheries on long-lived species (e.g., natural mortality, $M < 0.2$). The ability of this method to identify sustainable yields from simple data input makes DCAC highly attractive for use, especially as a first-step estimate for an allowable catch level and/or in complement with other data-poor methods (discussed in this section, or in combination with the Decision-Making Methods of Step 4).

It has long been recognized that a simple average catch taken during some time period is probably sustainable if the underlying abundance has not changed. DCAC uses the potential-yield fishery model to extend this simple concept to situations where the underlying abundance is suspected to have changed. From historical catch records (or estimates) over a prolonged period, preferably 10 years or more, DCAC estimates two categories of fisheries yield: (1) a "sustainable yield component" and (2) an "unsustainable windfall component" associated with the one-time reduction in biomass as the stock transitions from higher abundance at the beginning of the time period to lower abundance at the end. In addition, this method can also correct for the less common case of an increasing biomass trend.

Inputs for DCAC are historical catch time series, and imprecise probability distributions of $M$, the ratio of FMSY to $M$ (typically in the range of 0.8 to 1.0), and the suspected relative change in abundance from the beginning to the end of the catch series (*deltaB,* which can be zero). The output from DCAC is a probability distribution of sustainable yield, after windfall harvest, which is expected to prevent over- fishing (MacCall 2009). The NOAA Fisheries Toolbox has a user-friendly DCAC software program, complete with Monte Carlo estimates of precision and available for public download at: http://nft.nefsc.noaa.gov.

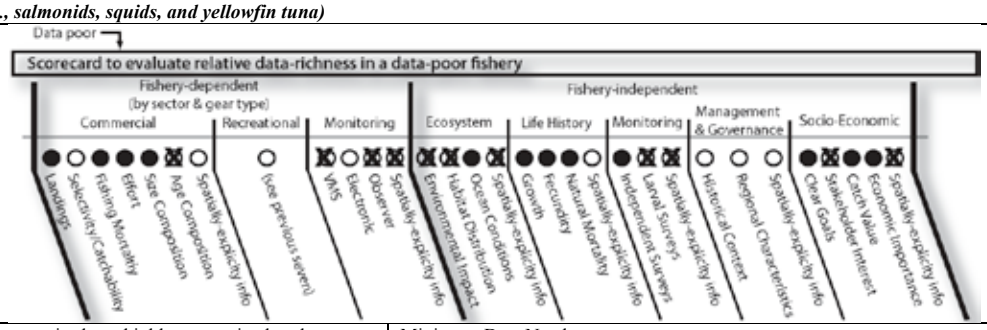
### *Fishery-evaluation Methods — Type 2*

*Vulnerability Analysis*

A variety of methods make use of general life-history characteristics and general species understanding to evaluate possible stock responses to fishing

SCORECARD 3.

***Population and Length-Based Indices — Case-Study Example (within-season)***
***In-Season Depletion Estimator: Stocks Driven by Variable Recruitment***
***(e.g., salmonids, squids, and yellowfin tuna)***




Many species have highly uncertain abundance estimates due to natural variability in annual recruitment, so new recruits sometimes comprise a substantial portion of total stock abundance. Frequently, this occurs for short-lived, fast-growing species and for species with highly variable and stochastic recruitment dynamics. Such stocks include salmonids, squids and fast-growing tuna.

Several decades ago, Walters and Buckingham (1975) proposed quantitative methods for in-season adjustments for the management of British Columbia salmon (*Oncorhynchus* spp.). Since then, these ideas have been refined and implemented for in-season management. Successful examples include fisheries for Alaska salmon (Walters 1996; Hilborn 2006) and Falkland Islands' squid (*Loligo gahi*; McAllister et al. 2004; Roa-Ureta and Arkhipkin 2006). Within this volume, Maunder (2010) presents a depletion estimator, using growth, recruitment, and survival estimates of eastern Pacific yellowfin tuna (*Thunnus albacares*) with in-season data to guide within-season management.

Minimum Data Needs:
- Life-history data.
- In-season catch time series (e.g., hourly, daily, or weekly data, depending on management goals and resources).

Optimal Data Needs:
- In-season CPUE or effort time series, at frequent intervals, using consistent data-collection protocols.
- Detailed life-history knowledge to correspond with the resolution of data collected.

Cautions and Caveats:
- CPUE does not always track actual population because of effort creep, targeting behavior of fishermen, and/or stock dynamics.
- Use with caution for schooling species or aggregate spawners.
- Within-season comparisons assume consistency across a fishing season:
  - Method may not be appropriate (requires correction) for fisheries with effort or regulatory changes within one fishing season.
  - Method may not be appropriate (requires correction) if anomalous conditions differentially impact different times within one season (e.g., algal blooms or hypoxic zones).
- Managers still must decide how detected trends affect harvest control rules.

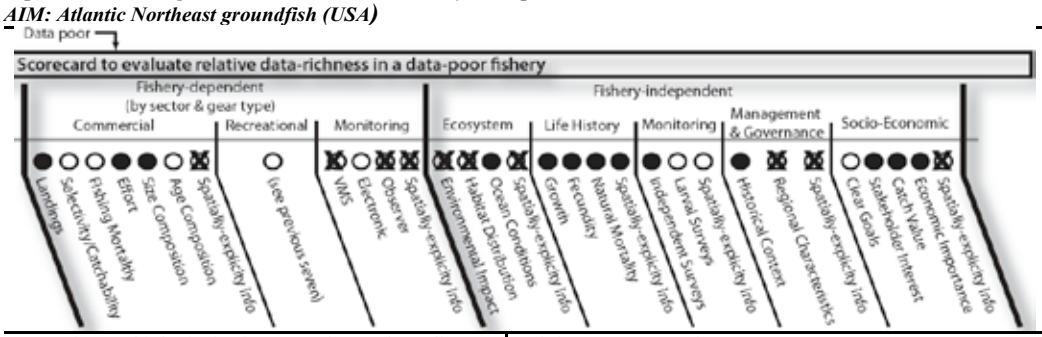
References for depletion estimator for in-season management:
(Hilborn and Walters 1992; Maunder 2010, this volume).

pressure. Knowledge of basic vital statistics (e.g., survival, growth, intrinsic rate of increase, age of maturity, fecundity) can inform simple population dynamic models and fishery management models in a heuristic — albeit imperfect — way (Winemiller and Rose 1992; Alonzo and Mangel 2005; Winemiller 2005). Musick (1999b) identifies intrinsic rate of increase and age at maturity as two key traits, which strongly influence degree of vulnerability. Such life-history parameters can be used to assess species vulnerability and prioritize stocks for research and management (Winemiller and Rose 1992).

*Example technique (see Scorecard 5): Productivity and susceptibility analysis of vulnerability.*—The Productivity and Susceptibility Analysis of vulnerability (PSA) method is used to assess a stock's vulnerability to overfishing, based on relative scores derived from life-history characteristics — "productivity" — and species' responses to fishing pressure — "susceptibility." Productivity, which represents the potential for rapid stock growth, is ranked semi-quantitatively from low to high on the basis of the stock's intrinsic rate of increase ($r$), von Bertalanffy growth coefficient ($k$), natural mortality rate ($M$), mean age at maturity, and other metrics (Patrick et al. 2009; Field et al. 2010, this volume). The low to high scores of susceptibility refer to overall impacts of fishing on the stock's abundance and habitat. Susceptibility scores are based on the expected fishing mortality rate, discard mortality, and behavioral responses (e.g., schooling) that can make a stock more or less vulnerable to fishing effort. Table 1 of Field et al. (2010, this volume) provides a systematic framework for applying the PSA method to a multi-species fishery or stock-specific fishery with a high diversity of bycatch. This method can be used to make a preliminary characterization of overall risk of overfishing. It offers a way to evaluate multiple bycatch stocks and identify species of priority or for protec-

SCORECARD 4.

***Population and Length-Based Indices — Case-Study Example***
***AIM: Atlantic Northeast groundfish (USA)***




AIM estimates biological reference points, using a linear model of population growth to fit a time-series relationship between catch data (fishery-dependent data) and a relative abundance index (from CPUE or fishery-independent data). If the underlying population model is valid, AIM enables managers to identify levels of relative fishing mortality that will achieve a stable or targeted stock size. This data-poor method continues to undergo additional peer review (Palmer 2008; Miller et al. 2009). To date, it has been applied to U.S. Atlantic stocks, such as haddock (*Melanogrammus aeglefinus*). The New England groundfish case study demonstrates the application of AIM to stock complexes where certain species may be overlooked and unassessed, despite the large amounts of data and stock assessments focused on a few well-studied species in the same complex.

Minimum Data Needs:
- Life-history data.
- Catch time series.
- Abundance index time series (from CPUE or fishery independent surveys).

Optimal Data Needs:
- Detailed population data and length-age information, in order to calibrate the AIM index with independent quantitative assessments.

Cautions and Caveats:
- Underlying linear model assumptions are not appropriate for all stocks.
- Susceptible to problems with misspecification (i.e., use of catch series from long overfished periods, recruitment pulses, or noisy data), resulting in bias.
- Past conditions should be similar to current and future conditions.
- Managers still must decide how detected trends affect harvest control rules.

References for AIM:
(Palmer 2008; Rago 2008; Miller et al. 2009).
AIM model downloadable from NOAA Fisheries Toolbox Version 3.0, 2008.
AIM Internet address: *http://nft.nefsc.noaa.gov/AIM.html*.

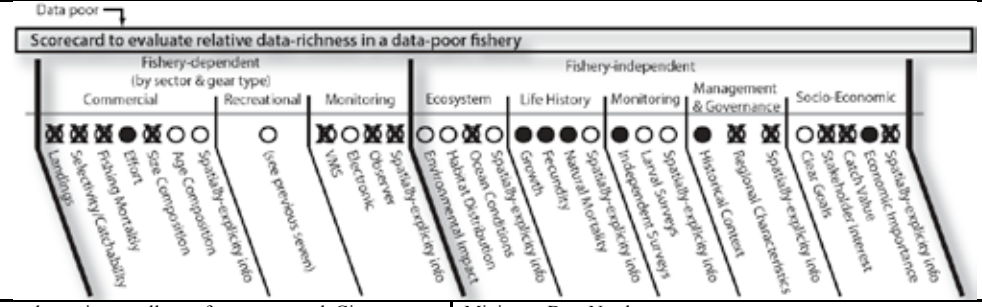
tion (Simpendorfer et al. 2008). Patrick et al. (2009) demonstrate the application of the PSA method for six federally managed fisheries in the United States.

The American Fisheries Society's (AFS) extinction risk criteria (i.e., endangered, threatened, vulnerable) are based on similar principles as the productivity analysis in the PSA (Musick 1999a; Musick et al. 2000). It uses many of the same productivity parameters, such as intrinsic rate of increase ($r$), von Bertalanffy coefficient ($k$), fecundity ($Fec$), age at maturity ($T_{mat}$), and maximum age ($T_{max}$) to determine a species productivity level (e.g., high, med, low, very low; see Table 3, Musick 1999a). Thus when a species is thought to be at risk by expert opinion or due to drastic decline, the productivity ranking of the species is first assessed (Musick 1999a). This productivity ranking provides a qualitative decline threshold that describes the degree of decline the stock can likely withstand (Musick 1999a). If the observed decline rate exceeds the suggested threshold based on the stock's productivity characteristics, the stock's vulnerability status may be upgraded to threatened or endangered. It is important to note, however, that results from this data-poor method provide only a relative measure. This method does not generate absolute numbers or index estimates of stock size, but estimates population extinction risk relative to other species.

As with all models, the outputs and management recommendations from a life-history vulnerability analysis can only be as good as the life-history science and data inputs into the analysis (Hilborn and Mangel 1997). Therefore, managers should be confident of the life-history parameters used, and check assumptions that life-history data from laboratories and/or other geographic regions will hold true across space and/or time for the region and stock of interest to the fishery manager (Cope 2006). This is not necessarily the case and the failure of this assumption can, of course, lead to misspecification of stock status, productivity, and vulnerability (e.g., West Coast rockfish species; Clark 1991, 1993, 1999)

SCORECARD 5.

***Productivity & Susceptibility Analysis — Case-Study Example***
***Bycatch and Other Species of Low Value or Low Priority to Management***
***(e.g., Atlantic pelagic sharks and rays, USA)***




Bycatch species are all too often unassessed. Given some basic life history and fishing mortality estimates, however, methods like Productivity and Susceptibility Analysis (PSA) can estimate individual species vulnerability to fishing pressure, relative to other species. By simultaneously accounting for estimated stock productivity and stock susceptibility to fishing effort, PSA produces estimates of overexploitation risk. Target and nontarget species can all be evaluated. Therefore, PSA can be a good choice for managers with bycatch concerns (e.g., in fisheries that are managed to protect weak stocks or stock complexes mixed with productive stocks).

A recent evaluation of Atlantic pelagic sharks and rays shows the advantage of life-history vulnerability analyses when managing bycatch species. Simpfendorfer et al. (2008) assess the risk of overexploitation for elasmobranchs caught as bycatch in the Atlantic swordfish fishery (longline). To evaluate population vulnerability, they used multivariate statistics to analyze information using three primary data metrics: (1) Ecological Risk Assessment, (2) the inflection point of the population growth curve (a proxy for $B_{msy}$), and (3) the World Conservation Union (IUCN) Red List status (Simpfendorfer et al. 2008). Integrated results provide a relative measure of overexploitation risk for each nontarget species of management concern.

Minimum Data Needs:
- Life-history data to estimate stock productivity.
  - Typically, done with estimates of von Bertalanffy growth coefficient, natural mortality rate, and mean age at 50% maturity.
- Fishing mortality data to estimate stock susceptibility.
  - Typically, done with estimates of the catchability coefficient and bycatch rates, which may be affected by fleet dynamics and/or fish behavior like schooling.

Optimal Data Needs:
- Detailed and accurate knowledge of life-history parameters to increase accuracy and confidence in model estimates of stock productivity.
- Detailed and accurate knowledge of fishing mortality.
- Multiple independent data sources and/or expert knowledge to corroborate estimates for calculated parameters (see above).

Cautions and Caveats:
- Only assesses expected, relative vulnerability to fishing pressure (not absolute population numbers).
- Will not specify harvest guidelines (i.e., Total Allowable Catch [TAC] or target catch limits).
- Managers still must decide how detected trends affect harvest control rules.

References for PSA:
(Simpfendorfer et al. 2008; Patrick et al. 2009; Field et al. 2010, this volume)

### *Fishery-evaluation Methods — Type 3 Extrapolation ("Robin Hood" Management)*

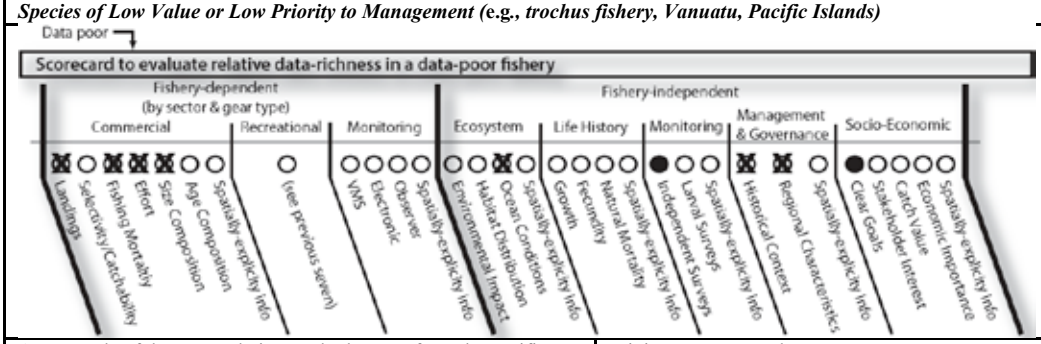
When virtually no data are available for a stock or specific species in a specific region, then managers may need to rely on extrapolation methods to inform decisions. Frequently, low-value stocks are subject to such data constraints. This method is termed the "Robin Hood" approach in Australia because it "steals" information and scientific understanding in data-rich fisheries to "give" inferences to the data-poor fisheries (see Scorecard 6; Smith et al. 2009, this volume).

Even with zero-available scientific data for a given fishery, managers still have access to information from: (1) the local knowledge of the fishers and resource users; and/or (2) scientific research and ecosystem understanding from "sister" systems thought to be similar. Extrapolation from similar systems or related "sister" species may offer an informed starting point from which managers can build precautionary management. In these situations, life-history characteristics, potentially sustainable harvest levels, spawning behavior, and other information can be gleaned from nearby stocks, systems, or related species.

All extrapolation methods require the very careful testing of assumptions. As previously noted, it is not necessarily the case that life-history data from laboratories and/or other geographic regions will hold true across space and/or time (see PSA discussion, above). The assumption that data-poor stocks behave like data-rich stocks has been proven wrong in the past, resulting in unintentional overfishing (e.g., West Coast rockfish species; Clark 1991, 1993, 1999). Due to uncertainty from the extrapolation of scientific information with "Robin Hood" methods, fishery managers should consider building in a precautionary buffer.

SCORECARD 6.

***Extrapolation Method — Case-Study Example***
***Species of Low Value or Low Priority to Management* (e.g., *trochus fishery, Vanuatu, Pacific Islands)***




An example of the extrapolation method comes from the Pacific Islands country of Vanuatu, where a sea snail — the trochus (*Trochus niloticus*) — is fished. Despite its "data-less" status, for years Vanuatu officials have successfully managed the trochus fishery for years (Johannes 1998). To do this, fishery officials use generalized growth rates determined by the government. The fishery managers emphasize one central principle: trochus stocks should be harvested about once every three years (Johannes 1998). After successes in villages that initially implemented this three-year rule, neighboring villages extrapolated this control rule for managing their own local stocks (Johannes 1998). Ultimately, many communities implemented similar control rules based on generalized growth knowledge for stocks beyond the *Trochidae* family, including octopus, lobster and other species (Johannes 1998).

While the lack of explicit conservation goals in such traditional management systems has been criticized, more recent empirical evaluations suggest that the application of traditional knowledge, marine tenure, and other traditional management techniques can result in sustainable conservation outcomes (Cinner et al. 2005a, 2005b).

Minimum Data Needs:
- Anecdotal observations or related "sister" species and systems with similar characteristics that are known.

Optimal Data Needs:
- The more information from sources above, the better.
- Life-history data to supplement observations and test underlying assumptions in the extrapolations.

Cautions and Caveats:
- Large scientific and management uncertainty.
- Risk of misspecifying stock status, vulnerability, sustainable harvest levels; this risk can be potentially serious and lead to overfishing, especially (e.g., if the data-poor stock of interest is less productive than its data-rich "sister" species; Clark 1991, 1993, 1999).
- Not a replacement for quantitative management.
- Managers still must decide how detected trends affect harvest control rules.

References for extrapolation and "Robin Hood" methods:
(Johannes 1998; Prince 2010, this volume; Smith et al. 2009, this volume).

**Step 4—Apply Decision-making Methods**

In the previous steps of our framework, managers select and apply as many Fishery-Evaluation Tools as deemed appropriate, based on the data richness, available resources, and fishery context. Here, in Step 4, we review two general categories of Decision-Making Methods available to evaluate alternative management options, trade-offs, and expected outcomes without a full stock assessment:

(i) Decision trees.
(ii) Management Strategy Evaluations (MSEs).

These are decision-making tools that combine scientific knowledge with management knowledge (and value judgments), in order to identify preferable actions or recommendations for a fishery. Both decision trees and MSEs use multistage frameworks to arrive at conclusions about stock status, harvest recommendations, and/or alternative control rules. Often, several different outputs from several different Fishery-Evaluation Methods (Step 3) serve as inputs into Decision-Making Methods (Step 4, see Figure 1). In comparison to methods previously reviewed, these Step 4 methods typically require greater information inputs and technical resources, including greater human capital.

These methods are highly flexible. They are fully capable of incorporating diverse sources and types of information to generate new understanding and management guidance from limited information.

Below, we introduce each of these two Decision-Making Methods with a summary paragraph and an example application. We reference case-study examples to show how each method can be applied, while briefly reviewing minimum data requirements, optimal data needs, and important cautions and caveats for the method within our example context. We include references to original publications and peer-reviewed literature describing a method's implementation, so interested parties can review this method in more depth.

### *Decision-making Methods — Type 1*
### *Decision Trees (Analytical Approach)*

Decision trees provide a systematic, hierarchical framework for decision-making that scales to any spatial, temporal, or management context in order to address a specific question. A decision tree may be customized to meet virtually any need.

In this volume, other authors propose several innovative decision trees. Their uses include: identification of reference points based on stock characteristics and vulnerability (Cope and Punt 2009, this volume); fostering fine-scale, transparent, and local management (Prince 2010, this volume); and estimating and refining an appropriate Total Allowable Catch (TAC) level (Wilson et al. 2010, this volume). These examples are discussed further below.

Given only available catch records and trends, managers of data-poor fisheries can use this information to infer stock change. This generally works well for high-value species because their catch records tend to have detailed information of good quality. Fishery scientists have previously suggested index-based management approaches for high-value stocks, including Atlantic cod (*Gadus morhua*, Froese 2004), white grouper (*Epinephelus aeneus*, Froese 2004), and blacktip abalone (*Haliotis rubra*, Prince 2010, this volume). When the resolution of data collection corresponds to an appropriate scale for management decisions, then trend changes in fisheries data can feed into decision-tree approaches to inform management choice.

When developing or using decision trees, fishery managers must know their data sources and how information is logged and recorded. Importantly, catch data are often aggregated over space and time at a scale that may not necessarily match biological processes and mechanisms of change. In these cases, the decision-tree approach may fail to detect trends and can mask underlying uncertainties.

*Example technique: Length-based reference points set by decision tree.*—A length-based decision tree allows for the interpretation of easy to collect catch-length data to provide indicators of stock status and the fishery's sustainability. Froese (2004) outlined a simple way to characterize fisheries at low risk of growth or recruitment overfishing based on catch–length data: (1) catch-length compositions consisting solely of mature individuals ($P_{mature}$ or $P_{mat}$); (2) catch-length compositions consisting largely of fish of the size at which the highest yield from a cohort occurs ($P_{optimal}$ or $P_{opt}$); and (3) catch-length compositions to conserve megaspawners that are large, highly fecund individuals ($P_{megaspawners}$ or $P_{mega}$). Cope and Punt (2009, this volume; see Case-Study Example, p. 175) extend the method by examining its sensitivity to life history traits, recruitment patterns, and fishery selectivity (i.e., what fraction of each length class is taken by the fishery). They establish a critical link between the identification of trends and the design of harvest control rules with a decision tree.

Using a simulation model based on West Coast groundfish population dynamics and data, Cope and Punt found that overfishing could occur using Froese's guidelines under some scenarios, depending on assumptions of life-history traits and fishery selectivity. According to simulation runs, even when $P_{mat}$ and $P_{opt}$ are very low, fishing can be sustainable. Simulations also suggest that major stock decline could result even when $P_{opt} = 1$ is the ideal situation for a fishery. The Cope and Punt decision tree interprets catch-length data and stock status, using a new parameter $P_{obj}$ (the sum of $P_{mat}$, $P_{opt}$, and $P_{mega}$, see Figure 10 in Cope and Punt 2009, this volume). This decision tree can be applied even if direct information on mortality, fishery selectivity, and recruitment is lacking. While this provides a flexible management tool, the authors are careful to point out a number of caveats concerning the use of $P_{mat}$ and $P_{opt}$ with this method (Cope and Punt 2009, this volume).

*Example technique: marine reserve-based decision tree.*—This decision tree by Wilson et al. (2010, this volume; see Case Study Example p. 176) makes use of data from no-take marine reserves to improve assessments of stock status. It provides an alternative method to set and refine a TAC by comparing CPUE and the size structures of a species inside and outside reserves. This method assumes reserve conditions are a proxy for natural abundance or as conservation targets for management. Since it uses inside/outside reserve comparisons, this method requires survey sites with comparable habitat both inside and outside reserve boundaries. As is true for any method that assumes reserves are a baseline or proxy for unfished conditions, the amount of movement and mixing of species across reserve boundaries is an important source of uncertainty.

This decision tree is designed for the analysis of data collected on relatively small scales, in order to develop TAC levels at those local scales. The initial TAC estimate is calculated from the slope of the line connecting current CPUE to a target CPUE level. Further branches in the decision tree allow the user to update and adjust the TAC by determining whether CPUE or size distributions of the fished population are above or below an expected level (e.g., as observed within the reserve) for an unfished, equilibrium population. Because this method is intended to be updated regularly by incorporating new and easy-to-acquire data (e.g., CPUE trends and size), the reserve-based decision tree is naturally dynamic and adaptable to changing environmental or biological conditions.

***Length-Based Decision Tree — Case-Study Example***
***Australia's Eastern Tuna and Billfish Fishery***

Australia's Eastern Tuna and Billfish Fishery (ETBF) is a high-value but low-information fishery for bigeye and yellowfin stocks near Tasmania (Prince 2010, this volume). Regional data exist, particularly fishery-dependent time series, but information is insufficient for a stock assessment. ETBF data-poor challenges arise from unresolved population structure and resulting implications for quantitative stock assessment techniques, since the population connectivity is unknown between tuna stocks in the Tasman Sea and the Western Central Pacific Ocean (Prince 2010, this volume).

A decision-tree approach to management is appropriate for this kind of fishery, especially if used in conjunction with other data-poor methods. For example, CUSUM and other Fishery-Evaluation methods (see Step 3) can be used to verify the statistical significance of detected change in time-series data.

To develop a formal harvest policy for ETBF under Australia's Harvest Strategy Guidelines (DAFF 2007), fishery managers adopted an innovative empirical strategy for regional stock management in the Tasman Sea (Prince 2010, this volume). They use regional fisheries data as "local" indicators for stock status. Time-series data from regional fleet effort, landings, and length distributions of catch are quantitative inputs into a decision tree, designed to inform ETBF management in a manner responsive to local change in stock status and fishing trends. Inputs are size-based indicators of stock status with a determined level of Spawning Potential Ratio (SPR)* for local stocks. Then, relative to local SPR, managers can evaluate and adjust the proportion of the catch comprised of "mature" (small), "optimum" (medium), and "megaspawner" (large) fish. Using detected trends over time, this decision tree organizes information and frames expected outcomes to recommend action for local management.

Minimum Data Needs:
- Life-history data.
- Catch time series.
- Length-age data for catch size distribution to estimate:
  - Size-frequency distribution of virgin conditions (i.e., unfished state).
  - Size-frequency distribution for the fished population.

Optimal Data Needs:
- Detailed knowledge of life-history parameters (ideally, informed with fishery-independent sources) to increase accuracy and confidence in model estimates and stock productivity.
- Scientific knowledge of critical size classes with detailed length-age data (e.g., length at maturity, megaspawning size).
- Known size-frequency distribution of unfished state.

Cautions and Caveats:
- Depletion of megaspawners from fishing can falsely suggest the fishery is catching "optimum" (medium) individuals.
- May not be appropriate for stocks with low steepness** because of little difference between "mature" (small) and "optimum" (medium) individuals.
- Simple assessment methods like this (based on maintaining conservative levels of spawning biomass, SPR*) are helpful, but do not directly translate to harvest control rules.
- The accuracy and statistical power of decision-tree outputs depends strongly on the quality of data inputs and underlying model assumptions.

*SPR is the number of eggs that could be produced by an average recruit in a fished stock, divided by the number of eggs that could be produced by an average recruit in an unfished stock.
**Steepness is conventionally defined as the proportion of unfished recruitment produced by 20% of unfished spawning biomass.

References for length-based reference points set by decision tree:
(Froese 2004; Cope and Punt 2009, this volume).

Comparisons of fish density inside and outside reserves might also be used to inform season length and other effort controls through a reserve-based "density-ratio" method (Babcock and MacCall, in review). Currently in California, researchers, fishermen, and stakeholders are engaged in collaborative efforts to test, implement, and expand this method (Wilson et al. 2010, this volume). Other collaborative efforts, such as the California Collaborative Fisheries Research Program, also gather fishery-independent data to monitor populations and assess marine reserve performance across a broad range of species across 250 coastal miles (see Wendt and Starr 2009, this volume). As California continues to develop its statewide network of marine reserves and other types of marine managed areas under the Marine Life Protection Act, expansion opportunities seem likely for data-collection (and analysis) efforts like those of the California Collaborative Fisheries Research Program. Such efforts appear well poised for future integration with innovative data-poor methods, particularly methods that rely on marine-reserve monitoring data to infer conditions about an unfished population state (e.g., the "density-ratio" method or the decision tree by Wilson et al. 2010, this volume).

### *Decision-making Methods — Type 2*
### *Management Strategy Evaluation (Simulation Approach)*

Management Strategy Evaluation (MSE) is a general modeling framework designed for the probabilistic evaluation of the performance of alternative management strategies for pursuing different management objectives. This approach promotes a high degree of flexibility. It simulates the fishery's response to different management strategies (e.g., different TAC levels, seasonal closures, or other effort reductions). Assuming sufficient and quality data exist, MSE proves useful for assessing the effectiveness of diverse policy options. Given a single set of objective function(s) and modeling assumptions, the method informs the choice of the optimal management decision.

MSE offers a strategic approach to organize information within one model, often made with linked submodels to collectively and systematically evaluate the system as one whole. Using any variety of predefined metric(s) and goal(s), managers can explore various management options and expected outcomes with MSE — whether biological, economic, and/or social outcomes of interest. It uses and integrates numer-

***MPA-Based Decision Tree — Case-Study Example***
***Nearshore stick fishery in Southern California (USA)***

The California stick fishery is a part of California's nearshore finfish fishery (further discussed below, see box with the MSE case-study example). The stick fishery in Southern California targets cabezon (*Scorpaenichthys marmoratus*) and grass rockfish (*Sebastes rastrelliger*), using selective "stick" gear that minimizes bycatch of nontarget species. In the Santa Barbara Channel Islands region, local fishermen and researchers are collaborating to collect spatially explicit data, inside and outside of marine reserves (Wilson et al. 2010, this volume). Currently, they are evaluating the management potential for establishing an experimental program for the Santa Barbara Channel Islands, based on a framework using an innovative marine reserve-based decision tree (Wilson et al. 2010, this volume).

This decision tree uses a data-driven model that is spatially scale-less and based on length-age catch data, inside and outside of the reserves (Wilson et al. 2010, this volume). The reserve-based decision tree is integrated within a MSE simulation, so it responds dynamically to simulated changes in environmental conditions. For the basic decision tree, data inputs are life-history parameters: species growth rates, size/age at maturity, fecundity at age, and selectivity to fishing. Conditions inside the reserves serve as a proxy for virgin conditions and are used to estimate unfished biomass. This decision tree uses similar size-based criteria and spawning biomass targets, as described above (see previous scorecard with the decision-tree case-study example, highlighting Prince 2010, this volume). Time series of individual length data are compared with current catch and effort data. Using these relationships, the decision-tree makes recommended harvest adjustments, either up or down, to maintain the spawning biomass and stock at specified levels (Wilson et al. 2010, this volume).

*(for this MPA-based decision tree)*

Minimum Data Needs:
- Life-history data.
- CPUE time series.
- Length-age data, inside/outside MPAs, to estimate:
  - Size-frequency distribution of virgin conditions (i.e., unfished state). If estimated from MPAs, this often requires 5 to 10 years (minimum) of data without fishing, although it varies widely by species and species-specific life histories. In the absence of no-take MPAs, models can estimate virgin conditions.
  - Size-frequency distribution for the fished population.
- Environmental time series.

Optimal Data Needs:
- The longer the time series for inside/outside reserves, the better, because it improves virgin estimates.
- Detailed knowledge of life-history parameters (ideally, informed with fishery-independent sources) to increase accuracy and confidence in model estimates**.**
- Scientific knowledge of critical size classes with detailed length-age data (e.g., length at maturity, mega-spawning size).
- Known size-frequency distribution of unfished state.

Cautions and Caveats:
- Assumes reserve conditions as an appropriate proxy for the unfished state.
- Requires enforcement of reserves.
- Interpretation of CPUE can be difficult, if standardized methods are not used inside/outside reserves.
- Depletion of megaspawners from fishing can falsely suggest the fishery is catching "optimum" (medium) individuals.
- May not be appropriate for stocks with low steepness** because of the lack of contrast between "mature" (small) and "optimum" (medium) individuals.
- Simple assessment frameworks, like this (based on maintaining conservative levels of spawning biomass, SPR*) are helpful, but do not directly inform harvest control rules.
- The accuracy and statistical power of decision-tree outputs depends strongly on the quality of data inputs and underlying model assumptions.
- Outputs from combined methods, such as a decision tree and MSE (as used here), are powerful but fairly data intensive. This decision-tree-MSE approach is suited for "data-medium" and "data-rich" fisheries. It is not recommended for "data-poor" stocks on the low end of the data-richness spectrum.

*SPR is the number of eggs that could be produced by an average recruit in a fished stock, divided by the number of eggs that could be produced by an average recruit in an unfished stock.
**Steepness is conventionally defined as the proportion of unfished recruitment produced by 20% of unfished spawning biomass.

References for MPA-based decision tree:
(Prince 2010, this volume; Wilson et al. 2010, this volume).

ous data inputs, ranging from biological to socioeconomic criteria along the entire data-richness spectrum. Depending on model design, it can simulate various system attributes including stock status, fleet dynamics, and/or socioeconomic utility. For example, in a minimal case, the model may only simulate stock status or socioeconomic utility. MSE modelers, however, can also incorporate other data types like environmental factors and indices to increase model realism and further test policy alternatives with added context. This amalgamation of diverse datasets under a single modeling framework provides valuable understanding of various tradeoffs and indirect effects that exist within management objectives (Aranda and Motos 2006).

Because of the breadth of the MSE method, its value can only be realized if management objectives are clear and performance metrics are well defined (Punt et al. 2001). This is critical to the systematic evaluation and relative weighting of alternative scenarios and hypotheses (Punt et al. 2001). The assessment of the fishery's performance in achieving predetermined target goals is measured through metrics most appropriate for the established goal; for example, stock status for biological criteria or industry value for socioeconomic criteria. Clearly defined goals and their metrics allow for the use of MSE to test the robustness of the management system to uncertainty (Aranda and Motos 2006).

The application of MSE spans the spectrum of data-poor to data-rich fisheries but it is effort- and resource-intensive. The complexity of MSE can be limiting, since simulation-focus requires specialized expertise

in modeling (Aranda and Motos 2006). MSE synthesis is particularly challenging, yet fruitful, for complex fisheries like multi-species fisheries or those with heterogeneous socioeconomic objectives (see case-study example box). Nonetheless, Butterworth et al. (2010, this volume) successfully applied the method in a data-poor situation with only a time series of mean-catch length. Outputs improve with greater data quantity and quality (i.e., data richness), yet MSE still has potential use as a method for data-poor fisheries (Butterworth et al. 2010, this volume).

*Example technique: MSE Monte Carlo simulation*.— Quantitative fishery scientists have long used MSE approaches, often incorporating Monte Carlo simulation (Southward 1968; Hilborn 1979; Punt et al. 2001). Monte Carlo methods are computational algorithms, using repeated random sampling to simulate probabilistic outcomes, which can be used to evaluate the stock's, as well as the system's, responses to management actions. In practice, managers have used MSE for over a decade in Australia's fisheries, guiding quota management decisions in a multi-species fishery with a multi-sector trawl fleet (Punt et al. 2001). More recently, Butterworth et al. (2010, this volume) apply MSE to develop management decision rules with limited empirical information for the Patagonian toothfish fishery in the sub-Antarctic. MSE also seems appropriate for California's nearshore finfish fishery (see Case-Study Example p. 178).

MSE is of particular use for systems that are data medium or data rich and of high value or political interest, yet the fishery dynamics are too complex and challenging for managers to evaluate with back-of-the-envelope techniques. For example, consider a multi-species fishery. Some stocks (regardless of scale) fall lower than others on the data-richness spectrum because not all species are an equal focus of fishery dependent and independent studies (CDFG 2002). Even for the most data-poor stocks, however, some fishery dependent and independent biological data likely exist. In addition, socioeconomic data from industry, research, and monitoring efforts likely exists for associated ports (CDFG 2002; 2007; 2008). Evaluated independently, this available information may not appropriately or sufficiently address management goals. Often, for un-assessed species, existing data are limited by the small-scale, short-term scope of scientific efforts. Data may not easily scale up or translate into coast-wide understanding of a stock, which is most relevant for federal or state management. By integrating all these various types of data considerations — across species and across scales — within one coherent framework, MSE methods have the potential to assimilate and evaluate multiple considerations to inform and guide management decisions. One critical challenge for such MSE application, however, involves unresolved stock structure at the local or regional scale, which potentially impacts data quality and techniques for quantitative stock assessment at the larger coast-wide scale (Wendt and Starr 2009, this volume).

## Discussion

Many fisheries can be thought of as data poor, and many remain under-managed or not managed at all due to lack of data, assessment, and analysis. Conventional stock assessments require large amounts of data and are conducted at large scales. New methods are required to more simply and quickly assess stock status and develop management reference points, given data and resource limitations. This is especially apparent at smaller scales in data-poor fisheries (Fujita et al. 2010).

In the United States and globally, impending deadlines exist to end overfishing. For example (under the reauthorized U.S. Magnuson-Stevens Act of 2006), National Standard 1 (NS1) guidelines and regulatory revisions establish Annual Catch Limits and bring new priority and attention to data-poor methods and management. Federal Fishery Management Plans (FMPs) cover nearly all managed species in the United States, at least as part of a FMP species complex. Still, however, many landed species remain un-assessed. The pertinence of improved data-poor assessment and management to fisheries is clear.

As managers move forward to achieve NS1 mandates and end overfishing, they can combine the methods presented in this review with available information and resources to improve assessment and outcomes for data-poor stocks. Data-poor methods are likely to be most informative when used in complement with each other, as well as with on-going data analysis and (re) evaluation. The robustness of results from individual methods increases when information is evaluated by different means and subsequent results corroborate each another. This is especially true if each of the data-poor methods draws on different information sources (independent or quasi-independent data sources).

Looking to the future, we anticipate the increased use of flexible decision trees to make informed decisions with limited information (Prince 2010, this volume; Wilson et al. 2010, this volume). Decision trees are simple, adaptable, and transparent. They step the user through a sequence of logical steps, based on explicit assumptions to generate knowledge and/or management recommendations. They can be used to organize and evaluate fisheries information that otherwise might not be used by managers. Arguably most importantly, decision trees are tractable. They use data, resources, and technical capacity frequently available to fishery managers — even those of data-poor fisheries.

MSE is a powerful method for testing different expected outcomes and management strategies. It also

***Management Strategy Evaluation (MSE) — Case-Study Example***
***California's nearshore finfish fishery (USA)***

California's nearshore finfish fishery is a multi-species fishery with 19 nearshore species, collectively managed by a complex process with overlapping jurisdictions between federal and state regulatory agencies (Weber and Heneman 2000). The Marine Life Management Act (MLMA) of 1999 is a precautionary law to manage state fisheries and achieve multiple objectives, including: conservation, habitat protection, the prevention of overfishing and the rebuilding of depressed stocks. Current regulatory efforts use total allowable catch (TAC), limited entry, trip limits, gear restrictions, fish-size limits, seasonal closures and area closures (e.g., no-take marine reserves). Most stocks, however, are data-poor; only five species in this fishery are formally assessed with a stock assessment (CDFG 2002; Field et al. 2010, this volume). Regulatory consequences of data-poor status are large cuts in allowable catch (Kaufman et al. 2004). This approach to precautionary management makes California's nearshore finfish fishery of great political interest.

For unassessed species, several data-poor methods are available for use by California fishery managers (see Field et al. 2010, this volume). With minimal information, data-poor methods rely on general life-history understanding to inform vulnerability assessments and extrapolation methods (see Life-History Vulnerability Analyses in the Fishery-evaluation Methods section, above). On the other side of the "data-richness" spectrum, a limited number of nearshore species have full stock assessments. Given the uneven distribution of data and information constraints, a MSE provides a method to organize and synthesize the multi-species and patchy data-rich information.

Recently, such a MSE effort was initiated for nearshore fisheries management in Port Orford, Oregon (see Bloeser et al. 2010, this volume). In the future, outputs will likely help to define priorities and guide management decisions.

*(for this example MSE application)*

Minimum Data Needs:
- Life-history data.
- Catch time series.
- Length-age data for catch size distribution to estimate:
  - Size-frequency distribution of virgin conditions (i.e., unfished state).
  - Size-frequency distribution for the fished population.
- Defined goals and objective functions (with known constraints and metrics to evaluate success, whether defined by biological, social and/or economic goals).
- Clear rules about how these various goals and objective functions interact. This requires some understanding of regulatory options, societal preferences and/or regulatory priorities to define acceptable trade-offs and recognize unacceptable outcomes.

Optimal Data Needs:
- Detailed knowledge of life-history parameters (ideally, informed with fishery-independent sources) to increase accuracy and confidence in model estimates and stock productivity**.**
- Detailed socioeconomic knowledge, potentially with high-resolution, spatial data**.**
- The more data and longer the time series, the better, especially if data-collection protocols remain consistent through time.
- The higher the quality of input data, the better.

Cautions and Caveats:
- The statistical power of MSE outputs depends strongly on the quality of data inputs and underlying model assumptions.
- Choice about objective function(s) and evaluation criteria drive outcomes.
- MSE outputs rely on multiple sub-model assumptions and assumptions about sub-model integration, which potentially compounds modeling errors and uncertainty.
- Assumptions about how to link MSE sub-models with one another are critically important, but potentially hidden from view. Be wary of "black box" outputs.
- MSE is powerful but data intensive. It requires careful design and appropriate development to individually match the MSE with stock characteristics, fishery context and management goals.
- MSE is suited for "data-medium" and "data-rich" fisheries, yet often limited by the method's need for large time investment and highly skilled technical work. It is not recommended for "data-poor" stocks on the low end of the data-richness spectrum.

References for MSE:
(Sainsbury et al. 2000; Gunderson et al. 2008; Bentley and Stokes 2009, this volume; Butterworth et al. 2010, this volume; Dewees 2010, this volume; Dichmont and Brown 2010, this volume; Smith et al. 2009, this volume).

holds promise for the quantitative testing and evaluation of expected performance by various data-poor methods (qualitatively reviewed here). MSE application to data-poor fisheries is most appropriate for the high end of the data-richness spectrum, particularly where multiple sources of high quality information exist but lack integration and holistic evaluation. It requires significant data, time, and specialized modeling expertise, often unavailable for data-poor fisheries. Therefore, for many data-poor managers with scarce resources, simulation-modeling techniques like MSE will be intractable.

When considering any of these methods, particularly MSE for data-poor fisheries, it is critical that managers remember that the use of sparse and/or inaccurate information as inputs for data-demanding methods will mislead. For data-poor fisheries, if employing MSE, we suggest using it in tandem with other methods and heuristic approaches like decision trees, to help check and ground-truth MSE outputs. This can help identify and avoid wildly erroneous expectations for data-poor stocks, if and when managers explore data-poor fisheries with MSE simulation. The simultaneous use of multiple, alternative data-poor methods allows managers to contextualize model outputs and gain understanding about the robustness of these different approaches. This can be done with formal analysis of alternative models and sensitivity analysis (Hilborn and Mangel 1997; Walters and Martell 2004).

It is important to note that risks and limitations are givens with these methods, due to the inherent scientific uncertainty and data constraints in managing fish stocks. Thus, it is important for fishery managers to think about how to best pair the available data with appropriate methods that can make the most use of the data, given management goals. This coupling of data with optimal methods requires science-based recommendations on appropriate assessment methods. In the absence of scientific advisers, the presented framework should help decision makers and stakeholders organize scientific information and identify available alternatives.

Overall, the framework we present should aid anyone interested in assessing local stocks and/or improving the scientific basis for fisheries management, regardless of the amount of data available. Both managers and stakeholders can benefit from the application of data-poor methods, and from the framework we provide here to pair methods with fishery goals and available data. With better knowledge of the methods and their respective data requirements, stakeholders can actively drive research and better engage in management. Recently, this engagement has expanded with growing cooperative efforts, such as fishery independent data collection for marine-reserve monitoring for stock assessments, Marine Stewardship Certification, and FMP development (e.g., California's abalone, lobster, and urchin fisheries). Ultimately, such efforts will help to overcome the barriers of inadequate resources, lack of sensitivity to scale, and lack of information flow between managers and stakeholders.

## Conclusion

On-going collection of high quality data, combined with appropriate and comprehensive data analysis, are the ideal solutions to the dilemma of data-poor fisheries management. In the absence of sufficient resources to collect and analyze more fisheries data, however, responsible fishing practices and management are still required. Such challenges seem particularly common and acute in low-value fisheries, many of which are also small-scale fisheries, which do not generate sufficient revenue to justify large, costly data acquisition programs.

Data-poor and small-scale fisheries need not be ignored. New methods are available for extracting more useful information from scant data. Data-poor methods include trend analysis of indicators, vulnerability analysis, extrapolation, decision trees, and MSE methods, as summarized in Tables 3 and 4 (see pp. 183, 184). Each makes valuable contributions to overcoming different fishery management challenges. Trend analysis and extrapolation methods, such as DCAC (see our page 165 and MacCall 2009) can provide a "first look" at stock status from extremely limited data. For new and emerging fisheries, vulnerability analyses and extrapolation can yield information useful for prioritizing research and management efforts. Decision trees and MSE facilitate the systematic evaluation of available data and management options. None are mutually exclusive, as all five of these general categories may be used together in synergistic and complementary ways.

We see our work as a step toward organizing existing information and resources, with a target audience of fishery managers and stakeholders, to improve management choices given limited information. On-going collaborative partnerships can extend this effort by making information on data-poor alternatives more accessible to a larger audience of stakeholders, including fishermen themselves.

Ignorance in fisheries management is not bliss, but a risk. Data-poor methods can reduce our ignorance given what we know now, even if that is relatively little. Their appropriate application reduces the risks of overfishing, fishery collapse, and lost economic yields. This improves prospects for biological sustainability and economic viability in all fisheries — large and small, data poor and data rich.

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TABLE 3.—Fisherey-Evaluation Methods at a glance.

*(Fishery-Evaluation Methods presented in order of high to low information requirements).*

| Method Type | Minimum Data Needs | Optimal Data Needs | Cautions and Caveats |
|---|---|---|---|
| **Sequential trend analysis (index indicators)**<br><br>Sub-category types include:<br>○ ***Population and length-based indices***<br>○ ***Per-recruit methods***<br>○ ***Environmental proxies*** | • Series data (most commonly time-series data), although data requirements vary by type of trend analysis.<br>• Common requirements are:<br>○ Life-history data.<br>○ Catch time series.<br>○ Abundance index time series (from CPUE or fishery independent surveys). | • The more data and longer the time series, the better.<br>• The higher the input-data quality, the better (e.g., consistent data-collection protocols through time).<br>• As a broad generalization, 30+ data points in a series is preferred (e.g., 30+ years of time-series data for annual catch), although this varies with system dynamics. | • Trend indicator only.<br>• Managers still must decide how detected trends affect harvest control rules.<br>• Assumes system dynamics and assumptions remain constant for the period over which data are analyzed (e.g., no environmental regime shifts; no major change in fleet dynamics or technologies).<br>• Relationships should be tested and updated regularly (e.g., annually) as new data emerge. |
| *References for CUSUM control charts and statistical methods:*<br>(Manly and MacKenzie 2000; Manly 2001; Scandol 2003; Kelly and Codling 2006)<br>*References for multivariate El Niño Southern Oscillation index (MEI), which is an example of an environmental proxy:*<br>(Ballantyne et al., in review; Aburto-Oropeza et al. 2007)<br>*References for fractional change in lifetime egg production (FLEP), which is a per-recruit method:*<br>(O'Farrell and Botsford 2005, 2006)<br>*References for depletion estimator for in-season management:*<br>(Hilborn and Walters 1992; Maunder 2010, this volume)<br>*References for an-index-method (AIM), which is a population and length-based index:*<br>(Palmer 2008; Rago 2008; Miller et al. 2009) | | | |
| **Life-history vulnerability analyses** | • Life-history data to estimate stock productivity.<br>• Fishing mortality data to estimate stock susceptibility. | • Detailed and accurate knowledge of life-history parameters.<br>• Detailed and accurate knowledge of fishing mortality.<br>• Multiple data sources, fishery independent sources of information, and/or expert knowledge to corroborate estimates for calculated parameters. | • Only assesses expected, relative vulnerability to fishing pressure (not absolute population numbers).<br>• Will not specify harvest guidelines (i.e., Total Allowable Catch [TAC] or target catch limits).<br>• Managers still must decide how detected trends affect harvest control rules. |
| *References for productivity and susceptibility analysis (PSA), an example of life-history vulnerability analyses:*<br>(Simpfendorfer et al. 2008; Patrick et al. 2009; Field et al. 2010, this volume) | | | |
| **Extrapolation methods** or "Robin Hood" management (in Australia) | • Ecological understanding of stock from:<br>• Anecdotal observations.<br>• Local knowledge.<br>• Related "sister" species and systems with similar characteristics that are known. | • The more information, the better, from observations or similar systems.<br>• Life-history data. | • Large scientific and management uncertainty.<br>• Risk of misspecifying stock status, vulnerability, and sustainable harvest levels if the data-poor stock of interest differs from its data-rich "sister" population.<br>• Not a replacement for quantitative management.<br>• Managers still must decide how detected trends affect harvest control rules. |
| *References for extrapolation and "Robin Hood" methods:*<br>(Johannes 1998; Prince 2010, this volume; Smith et al. 2009, this volume) | | | |

TABLE 4.—Decision-Making Methods at a glance.

*(Decision-Making Methods presented in order of expected practical use for data-poor management).*

| Method Type | Minimum Data Needs | Optimal Data Needs | Cautions and Caveats |
|---|---|---|---|
| *Decision-tree approach* | • Clear fishery goals and metrics with evaluation criteria.<br>• Depending on decision-tree design (highly flexible) and manager goals, exact metrics and data requirements vary.<br>• Common data inputs to evaluate metrics and decision points are:<br>  ○ Life-history data.<br>  ○ Catch time series.<br>  ○ CPUE time series.<br>  ○ Socioeconomic context and data. | Given defined metrics and evaluation criteria, the biological, social and/or economic data have:<br>• Multiple information sources to increase the robustness of and confidence in information.<br>• Long time series.<br>• Quality data. | • Decision trees are flexible tools, requiring appropriate design to individually match the decision tree with stock characteristics, fishery context and management goals.<br>• A decision tree can provide a simple assessment method, helpful for management (e.g., to maintain conservative levels of spawning biomass, SPR), although it may not directly address harvest control rules.<br>• The accuracy and statistical power of decision-tree outputs depends strongly on the quality of data inputs and underlying model assumptions. |
| *References for length-based reference points set by decision tree:* (Froese 2004; Cope and Punt 2010, this volume)<br>*References for MPA-based decision tree:* (Prince 2010, this volume; Wilson et al. 2010, this volume) | | | |
| **Management strategy evaluation (MSE)** | • Highly skilled technical expertise, time, and resources for advanced programming and simulation modeling.<br>• Clear fishery goals and metrics with evaluation criteria.<br>• Depending on MSE design (highly flexible) and manager goals, exact metrics and data requirements vary.<br>• Common data inputs to evaluate metrics and decision points are:<br>  ○ Life-history data.<br>  ○ Catch time series.<br>  ○ CPUE time series.<br>  ○ Environmental context and data.<br>  ○ Socioeconomic context and data. | Given defined metrics and evaluation criteria, the biological, social and/or economic data have:<br>• Multiple information sources to increase the robustness of and confidence in information.<br>• Long time series.<br>• Quality data. | • MSE is powerful but data intensive. It requires careful design and appropriate development to individually match the MSE with stock characteristics, fishery context and management goals.<br>• MSE is suited for "data-medium" and "data-rich" fisheries, yet often limited by the method's need for large time investment and highly skilled technical work. It is not recommended for "data-poor" stocks on the low end of the data-richness spectrum.<br>• The statistical power of MSE outputs depends strongly on the quality of data inputs and underlying model assumptions.<br>• Choice about objective function(s) and evaluation criteria drive outcomes.<br>• Assumptions about how to link MSE sub-models with one another are critically important, but potentially hidden from view. Be wary of "black box" outputs. |
| *References for MSE:* (Sainsbury et al. 2000; Bentley and Stokes 2009, this volume; Butterworth et al. 2010, this volume; Dewees 2010, this volume; Dichmont and Brown 2010, this volume; Smith et al. 2009, this volume). | | | |