Recent changes to federal law mandate that Fishery Management Councils implement annual catch limits for all United States stocks by 2011 (NOAA 2010). In order to establish catch limits and determine appropriate managerial actions however, stock assessments must first be conducted. For fisheries with little or no data, this is a significant challenge as traditional stock assessments are costly and demand large quantities of time and information. Fortunately, there are tools available to help assess data-poor fisheries using easily gathered data and/or data already on hand.

This paper reviews literature concerning data-poor stock assessment methods currently available to fishery managers. It provides a user-friendly guide to these assessment techniques and outlines the minimum and optimal data requirements, the results each model produces, and important caveats and limitations to each method. The following model descriptions are purposefully condensed; however, additional information can be found on NOAA's Fisheries Toolbox website (http://nft.nefsc.noaa.gov/) and in the primary literature, located in the references section.

Depending upon the method used, data-poor assessment models allow managers to calculate estimates of overexploitation risk, current population biomass, sustainable yield, optimal fishing mortality rate, stock status relative to reference points, or total allowable catch. Each of these parameters can then be used to determine appropriate catch limits for target populations.

Data-poor models fall into two distinct categories: fishery evaluation methods and decision-making methods. Fishery evaluation methods are generally less data- and resource-intensive and use data on species-specific life history, catch and size trends, and other relatively easy-to-obtain information to assess changes in fish populations or vulnerability to exploitation. Decision-making methods require more data but allow managers to not only assess changes in the population, but also establish sustainable catch levels. However, these categories are not exclusive as some models may fall under both, e.g., the Depletion-Corrected Average Catch method; a fishery evaluation model that also establishes sustainable yield levels.

This document outlines 11 examples of data-poor assessment models (nine evaluation methods and two decision-making methods) in order of least data-intensive to most data-intensive. Minimum data requirements, optimal data requirements, model results, and caveats for each are summarized in box format. Since continuous, long-term datasets do not exist for all fisheries, data-poor assessment methods provide managers with the tools they need to set appropriate catch limits and sustainably manage target stocks.

QUICK VIEW: DATA-POOR ASSESSMENT METHODS

Fishery Evaluation Methods
I. Extrapolation Method
   Example: Robin Hood Approach

II. Life-history Vulnerability Analysis
   Example: Productivity and Susceptibility Analysis (PSA)

III. Sequential Trend Analysis
   Type 1: Population or Length-Based Index
       Example 1: In-Season Depletion Estimator
       Example 2: Depletion-Corrected Average Catch (DCAC)
Example 3: Depletion-Based Stock Reduction Analysis (DB-SRA)
Example 4: An-Index-Method (AIM)
Example 5: Reserve-Based Spawning Potential Ratio (Dynamic SPR)

Type 2: Per-Recruit
Example: Fractional Change in Lifetime Egg Production (FLEP)

Type 3: Environmental Proxies
Example: Multivariate El Niño Southern Oscillation (ENSO) Index (MEI)

Decision-Making Methods
I. Decision Trees
Example 1: Length-Based Reference Point
Example 2: MPA-Based Decision Tree

Fishery Evaluation Methods

The following fishery evaluation methods are separated into three distinct categories, beginning with the least data-demanding assessment models: extrapolation methods, life-history vulnerability analyses, and sequential trend analyses.

Extrapolation Method

For stocks with little or no data, extrapolation methods may be the only assessment tools available for fishery managers. Using data from similar species and/or local knowledge from fishermen and other resource users, extrapolation methods provide managers with a starting point for the development of a precautionary management method. Due to assumptions associated with these techniques, managers should use extreme caution when extrapolating harvest limits for one stock based on an assessment of another stock, even when the stocks appear to be very similar.

Example: Robin Hood Approach
The Robin Hood approach uses observations and/or scientific understanding from similar, “sister” populations to help inform management decisions. Life-history characteristics and estimates for optimal fishing mortality can be “stolen” from related species or neighboring stocks and “given” to data-poor species. Model results vary as the Robin Hood Approach can be incorporated into any type of stock assessment model. Since life-history information from more data-rich species or regions will not always accurately transfer to target stocks, there is greater risk for management actions to lead to overfishing.

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<thead>
<tr>
<th>MINIMUM DATA REQUIREMENTS</th>
<th>OPTIMAL DATA REQUIREMENTS</th>
<th>MODEL RESULTS</th>
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</thead>
<tbody>
<tr>
<td>Anecdotal observations/local knowledge about target stocks</td>
<td>Life-history characteristics from related “sister” species</td>
<td>Dependent on type of stock assessment used</td>
</tr>
</tbody>
</table>

Caveats

- Trend indicator only; does not determine causation
- Significant uncertainty concerning biological knowledge and management actions

Life-history Vulnerability Analysis

Life-history vulnerability analyses use basic life-history characteristics to determine potential stock responses to fishing pressure. Information such as growth rate, age at maturity, and fecundity can be used to assess vulnerability to fishing pressure and prioritize stocks for management. This model can also allow managers to better assess population models, and therefore make more informed decisions about optimal fishing levels. However, life-history vulnerability analyses only assess the relative vulnerability to fishing pressure and do not produce absolute population data about the risk of target stocks to harvest activities.

Example: Productivity and Susceptibility Analysis (PSA)
Using life-history data, the Productivity and Susceptibility Analysis (PSA) analyzes the risk, or vulnerability, of a stock to fishing pressure. Productivity, or the potential growth rate of the population, is ranked from low to high and based
upon a combination of the stock’s intrinsic rate of increase ($r$), von Bertalanffy growth coefficient ($k$), natural mortality ($M$), fecundity, average age at maturity, maximum length, and maximum age (Honey et al. 2010; Patrick et al. 2009). Susceptibility of the stock to fishing pressure is also scaled from low to high. Susceptibility is based upon the fishing mortality rate (including discards) and species behavior, such as schooling and seasonal migrations, which may alter catchability (Honey et al. 2010; Patrick et al. 2009). PSA can also be used as a baseline comparison within multi-species populations where varying amounts of data exist for each species (MRAG 2009). Although productivity and susceptibility analyses are useful in determining potential conservation measures and management decisions, as with any model, PSA model results are only as good as the original data inputs. The PSA model can be downloaded from the NOAA Fisheries Toolbox website (http://nft.nefsc.noaa.gov/).

### Sequential Trend Analysis

Sequential trend analyses utilize time-series data in order to identify trends in a variable (or multiple variables) and determine changes in a stock or population. While trend analyses require relatively easy-to-collect data, (e.g., catch records, length-based reference points, spawning potential ratio) any changes detected only reflect relative change and are not measured in absolute values. Also, statistical calculations can not be used to determine a causal relationship between variables and observed changes in the stock. The following discusses three types of sequential trend analyses, in order of least data-intensive to most data-intensive, along with example assessment models of each.

### Type 1: Population or Length-Based Index

Below are five examples of assessment models that use population or length-based data to calculate optimal catch limits.

#### Example 1: In-Season Depletion Estimator

Using up-to-date catch information, catch-per-unit-effort (CPUE) data, and life-history characteristics such as growth, survival, and recruitment parameters, the In-Season Depletion Estimator calculates the current stock biomass of target species. Abundance data from completed seasons is compared to current season information, allowing managers to apply harvest rates to biomass estimates to

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<th>OPTIMAL DATA REQUIREMENTS</th>
<th>MODEL RESULTS</th>
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<tbody>
<tr>
<td>Life-history characteristics</td>
<td>Detailed and accurate life-history characteristics and fishing mortality data</td>
<td>Estimates of overexploitation risk</td>
</tr>
<tr>
<td>Fishing mortality data</td>
<td>Multiple independent data sources to increase accuracy</td>
<td></td>
</tr>
</tbody>
</table>

#### CAVEATS

- Trend indicator only; does not determine causation
- Does not specify optimal harvest levels
- Only assesses relative, and not absolute, population vulnerability to fishing pressure
- Length and consistency of data strongly affects accuracy of model results

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<th>MODEL RESULTS</th>
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<tbody>
<tr>
<td>Life-history characteristics</td>
<td>In-season CPUE or effort time-series, at frequent intervals, using consistent data-collection methods</td>
<td>Estimates of real-time stock abundance/biomass</td>
</tr>
<tr>
<td>In-season/current catch time-series</td>
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</tbody>
</table>

#### CAVEATS

- Trend indicator only; does not determine causation
- CPUE is not always accurate due to effort creep, fishermen behavior, and/or stock dynamics
- Assumes ecosystem and fishery dynamics remain constant over time
determine appropriate catch limits (Maunder et al. 2008). As with other data-poor assessment methods, the In-Season Depletion Estimator assumes ecosystem and fishery dynamics remain constant over time.

### Sequential Trend Analysis

#### Type 1: Population or Length-Based Index

**Example 2: Depletion-Corrected Average Catch (DCAC)**

Depletion-Corrected Average Catch (DCAC) uses historical catch data (preferably ten years or more) and an estimated natural mortality rate (preferably 0.2 or smaller) to determine potential sustainable yield (MacCall 2009). An extension of potential-yield models, DCAC is based on the theory that average catch is sustainable if stock abundance has not changed substantially. The method differs from simple extrapolation of average catch to estimate sustainable yield by correcting for the initial depletion in fish abundance typical of many fisheries. DCAC divides the target stock into two categories: a sustainable yield component and an unsustainable “windfall” component, which is based upon a one-time drop in stock abundance for a newly established fishery. DCAC calculates a sustainable fishery yield, provided the stock is kept at historical abundance levels. The DCAC model can be downloaded from the NOAA Fisheries Toolbox website (http://nft.nefsc.noaa.gov/).

#### Type 2: Depletion-Based Stock Reduction Analysis (DB-SRA)

Combines DCAC with a probability analysis to more closely link stock production with biomass and evaluate potential changes in abundance over time. Using Monte Carlo simulations, DB-SRA provides probability distributions for stock size over a given time period, under varying recruitment rates (Walters et al. 2006). The addition of a probability analysis increases the reliability and decreases uncertainties associated with historical biomass estimates generated from DCAC.

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<th>MODEL RESULTS</th>
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</thead>
<tbody>
<tr>
<td>Historical catch time-series</td>
<td>Data gathered at frequent intervals, using consistent data-collection methods</td>
<td>Estimates of sustainable yield</td>
</tr>
<tr>
<td>Natural mortality rate (M)</td>
<td></td>
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</tbody>
</table>

**Caveats**

- Trend indicator only; does not determine causation
- Assumes ecosystem and fishery dynamics remain constant over time

#### Type 4: An-Index-Method (AIM)

Based on a linear model of population growth, An-Index-Method (AIM) estimates biological reference points from catch and abundance data. By estimating catchability and harvest rates, managers can use AIM to determine stock size, and therefore the fishing mortality rate for a stable population. Since the length and consistency of input data strongly affects the outputs, AIM should be reserved for data-medium stocks where a linear growth model
appropriately reflects the target species. The AIM model can be downloaded from the NOAA Fisheries Toolbox website (http://nft.nefsc.noaa.gov/).

### Sequential Trend Analysis

#### Type 1: Population or Length-Based Index

**Example 5: Reserve-Based Spawning Potential Ratio (Dynamic SPR)**

Currently in development, the Reserve-Based Spawner-per-Recruit (SPR) Assessment Model is an especially effective tool for data-poor species with highly irregular recruitment patterns (e.g., bocaccio and many invertebrate species along the West Coast) (Honey and He in prep). The model combines age or length data from inside and outside no-take marine reserves with life-history characteristics to estimate sustainable yield from spawning potential ratios. Depending on the species, this method requires data from an established no-take marine reserve (typically four to ten years without any fishing) before it produces meaningful results distinguishable from background noise (Honey and He in prep). Additionally, as the recruitment variability in a population increases, more data are required for the model’s dynamic methods to work. The Dynamic SPR method is not suitable for species that lack data over their full range of life cycle stages, for example species that are only monitored nearshore but move offshore as individuals grow larger in length and age. In such cases, population development and ontogenetic growth shifts may lead to skewed data and assumptions about unfished biomass, thereby misrepresenting the structure of the target stock. Finally, such methods assume that marine reserve populations accurately represent an unfished biomass.

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<th>OPTIMAL DATA REQUIREMENTS</th>
<th>MODEL RESULTS</th>
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</thead>
<tbody>
<tr>
<td>Life-history characteristics</td>
<td>Detailed population and age-length data</td>
<td>Relative fishing mortality rate</td>
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<tr>
<td>Catch time-series</td>
<td></td>
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<tr>
<td>Abundance data (from CPUE or independent surveys)</td>
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</tbody>
</table>

### CAVEATS

- Trend indicator only; does not determine causation
- Linear model assumptions are not appropriate for all stocks
- Length and consistency of data strongly affects accuracy of model results
- Assumes ecosystem and fishery dynamics remain constant over time

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<th>MODEL RESULTS</th>
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</thead>
<tbody>
<tr>
<td>Life-history characteristics</td>
<td>Age-length data from an established (10+ years) no-take marine reserve</td>
<td>Estimates of sustainable yield</td>
</tr>
<tr>
<td>Catch time-series</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age-length data from inside and outside no-take marine reserve boundaries</td>
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</table>

### CAVEATS

- Survey data may not accurately portray the stock structure due to development/growth shifts in the population
- Assumes reserve conditions represent an unfished biomass
- Assumes reserve regulations are well enforced
- Assumes ecosystem and fishery dynamics remain constant over time

### Sequential Trend Analysis

#### Type 2: Per-Recruit

In data-poor or data-medium situations where long-term, comprehensive catch data does not exist, per-recruit models can be used to determine estimates of optimal fishing mortality. By focusing on yield-per-recruit (YPR) or spawning stock biomass per recruit (SSBPR), managers can maintain a stock’s population by preserving its reproductive capability. Calculations of lifetime egg production (LEP),
also known as egg production per recruit, can be used as reference points for harvest targets. As fishing pressure increases, the stock’s age structure changes, which reduces LEP and the equilibrium egg production (the level of egg production needed to balance fishery mortality). Eventually equilibrium egg production reaches zero and the population collapses. Unfortunately this point is often unknown due to lack of data, larval source-sink dynamics, and environmental variability (Botsford et al. 2004).

Example: Fractional Change in Lifetime Egg Production (FLEP)
Fractional change in lifetime egg production (FLEP) can be used as an alternative to more data-intensive per-recruit models such as SSBPR. Length-frequency data from an unfished (or early exploited) population and the current population, along with information on growth and maturity, are used to determine a limit reference point that represents the persistence of a population. The fractional change is calculated as the ratio of LEP between the unfished and current populations (O’Farrell and Botsford 2005). While FLEP analyses help calculate optimal fishing mortality, this method only indicates population trends and correlations, forcing managers to make assumptions about the target stock.

Sequential Trend Analysis

Type 3: Environmental Proxies
Environmental proxies use ecosystem indicators such as salinity, ocean temperature, rainfall, or river runoff to predict stock biomass and/or potential changes in a population for species whose life cycle is tightly linked to environmental variables. Due to the complexity of marine systems, however, a high degree of uncertainty is associated with the use of environmental proxies as it is often unclear whether or not a change in the environmental variable led to a direct change in population structure or abundance. Although environmental proxies can provide important data for management, they should not replace long-term monitoring of the fishery.

Example: Multivariate El Niño Southern Oscillation (ENSO) Index (MEI)
Recruitment of larvae to nursery habitats and/or recruitment of young fish to adult populations have significant effects on overall fishery dynamics and stock biomass. For example, studies conducted in the Gulf of California on leopard grouper (Mycteroperca rosacea) show that the density of larval recruits decreases exponentially with increasing water temperature caused by ENSO events (Aburto-Oropeza et al. 2007). Environmental fluctuations produced by ENSO events can alter the availability of suitable habitat as the biomass of Sargassum algae decreases with increasing water temperatures (Aburto-Oropeza et al. 2007). Including the MEI during larval recruitment phases improves the accuracy of assessment models to predict juvenile and adult biomass, creating adaptive management opportunities and improving fishery management techniques.

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<th>OPTIMAL DATA REQUIREMENTS</th>
<th>MODEL RESULTS</th>
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</thead>
<tbody>
<tr>
<td>Length-frequency distribution for an unfished or early exploited population and for the current population</td>
<td>Detailed life-history characteristics to increase accuracy</td>
<td>Limit reference point</td>
</tr>
<tr>
<td>Age-length relationship (von Bertalanffy growth curve)</td>
<td>Known length-frequency distribution for an unfished population</td>
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<tr>
<td>Length-egg production relationship</td>
<td></td>
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<tr>
<td>Natural mortality rate (M)</td>
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</table>

CAVEATS
- Trend indicator only; does not determine causation
- Length and consistency of data strongly affects accuracy of model results
- Model results are sensitive to life-history assumptions
- Assumes ecosystem and fishery dynamics remain constant over time
The following discusses two types of decision-making methods, both of which fall under the category of decision trees.

**Decision Trees**

Decision trees are step-by-step decision-making tools that can be scaled to fit any management framework and stock size. Given catch data and life-history characteristics, managers can use decision trees to examine trends in the population and better implement harvest control rules. In order to accurately determine stock trends, however, it is important for the resolution of input data to properly match underlying biological assumptions about the stock. For example, nearshore groundfish in Northern California exhibit sub-population dynamics characterized by short dispersal distances, small adult home ranges, and little connectivity between populations. Model inputs should reflect regional information rather than biological parameters that average data across the entire coastline.

**Example 1: Length-Based Reference Point**

Using easy-to-gather catch-length data, the Length-Based Reference Point Model provides managers with an assessment tool that evaluates whether a stock's spawning biomass is at or above a specified target reference point (Cope and Punt 2009). This information can then aid managers when determining optimal harvest levels. Data inputs include the proportion of the catch in a given length-class \( L \), length at 50% maturity, maximum length, and the length at which a stock's cohort provides the highest yield. These inputs are then used to calculate the proportion of mature fish, optimally sized fish, and large, highly fecund females in a population (Froese 2004). The length-based reference point method can be used even if data concerning mortality, fishery selectivity, and recruitment does not exist. Due to the use of specific size classes, this model may not be appropriate for stocks that exhibit little difference between mature (small) and optimum (medium) individuals.

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<th>MODEL RESULTS</th>
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<tbody>
<tr>
<td>Time-series data concerning stock abundance from CPUE or fishery-independent surveys</td>
<td>Population model with life-history characteristics</td>
<td>Changes in population structure, biomass, and/or abundance over time in relation to changes in environmental variables</td>
</tr>
<tr>
<td>Time-series data concerning environmental proxies such as water temperature, rainfall, or river runoff</td>
<td>Understanding of processes that connect environmental parameters and fish production</td>
<td></td>
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</tbody>
</table>

**CAVEATS**

Trend indicator only; does not determine causation
**Decision Trees**

*Example 2: MPA-Based Decision Tree*

Similar to the Length-Based Reference Point method, the Marine Protected Area-Based Decision Tree uses spatially explicit, easy to gather catch and age-length data to set and further refine total allowable catch (Wilson et al. 2010). Additionally, data gathered from inside no-take marine protected areas (MPAs) are used as a baseline for an unfished population. Model inputs are life-history characteristics such as size and age at maturity and natural mortality, catch-per-unit effort (CPUE) information, and age-length data collected from inside and outside marine reserves. Total allowable catch (TAC) is calculated using the current CPUE and target CPUE levels, and then further adjusted with each successive step of the decision tree. Although the MPA-Based Decision Tree allows managers to set and refine TAC, the model assumes populations within MPAs are representative of an unfished baseline. Also, because marine reserves are usually relatively small compared to fishing grounds, care must be taken when extrapolating results to areas that are significantly larger than the MPAs used as reference areas.

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<th><strong>MINIMUM DATA REQUIREMENTS</strong></th>
<th><strong>OPTIMAL DATA REQUIREMENTS</strong></th>
<th><strong>MODEL RESULTS</strong></th>
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<tbody>
<tr>
<td>Life-history characteristics</td>
<td>Detailed life-history characteristics to increase accuracy</td>
<td>Total allowable catch (TAC)</td>
</tr>
<tr>
<td>Catch-per-unit-effort (CPUE)</td>
<td>Knowledge of critical size classes with detailed age-length data</td>
<td></td>
</tr>
<tr>
<td>Age-length data inside and outside no-take marine reserves</td>
<td>Known age-length frequency distribution for unfished population</td>
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</tr>
</tbody>
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**CAVEATS**

- Not appropriate for stocks with low “steepness” — little difference between mature (small) and optimum (medium) individuals
- Assumes reserve conditions represent an unfished biomass
- Assumes reserve regulations are well enforced

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**CONCLUSION**

Many fisheries throughout the United States currently lack enough data to accurately assess target stocks using conventional stock assessment methods. However, continuing to fish stocks that are not assessed poses risks to the biological and economic sustainability of fisheries. Fortunately, new methods have been developed and tested that can allow managers to estimate a stock’s vulnerability to fishing, stock abundance and productivity, sustainable yield levels, overfishing thresholds, and other important management reference points even when few data are available.

While these methods are relatively new, they have already been successfully used to assess several U.S. fish stocks, including Atlantic wolfish, New England red crab, and 50 groundfish species on the West Coast. The data-poor methods described here provide regional councils with the tools they need to develop assessments and set annual catch limits for all council-managed fisheries by the quickly approaching 2011 deadline. These methods, while subject to many caveats and qualifications, are generally much faster and less expensive than traditional stock assessments. While having long-term, continuous datasets for each species is the ultimate goal, data-poor methods can help managers extract more useful information from readily available data and reduce risks associated with fishing in ignorance.