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[Special Section: Data-Poor Fisheries]

Moving Fisheries from Data-Poor to Data-Sufficient: Evaluating the Costs of Management versus the Benefits of Management

NOKOME BENTLEY*
Trophia Ltd., Post Office Box 60, Kaikoura 7300, New Zealand

KEVIN STOKES
New Zealand Seafood Industry Council Ltd., Private Bag 24901, Wellington 6142, New Zealand

Abstract.—The data-poor status of a fishery usually occurs because the fishery is low in value and as such has the lowest priority for funding. However, there is often no formal evaluation of the cost of data collection versus the benefits it brings. In this article, we describe how the costs and benefits of data collection can be evaluated within the context of fisheries management procedures. Based on a data-poor fishery in New Zealand, we illustrate how to evaluate the utility associated with simple management procedures that incorporate no monitoring, fixed monitoring, or adaptive monitoring. We demonstrate that it is feasible to do formal evaluations of alternative data collection regimes by including their costs in a utility function that incorporates other performance measures. Our particular example demonstrates the potential benefits of monitoring even in low-value fisheries and shows, in principle, the gains that can be made through the use of management procedures that include adaptive monitoring.

Fisheries characterized as data poor usually attain this classification not because of some inherent biological characteristics but because the fisheries are low in value. Where there are fixed data collection budgets, low-value fisheries usually have a lower priority than their high-value counterparts. Even if management budgets are determined on a fishery-by-fishery basis, data collection is often considered to be prohibitive for low-value fisheries. However, such decision making is often ad hoc and subjective and tends to rely on convention or intuition more than evaluation (de la Mare 2006).

Evaluations of the precision of alternative data collection methods are relatively common (e.g., Francis 1984; Folmer and Pennington 2000; Helle and Pennington 2004). Fewer studies have estimated the cost required to achieve a given precision (e.g., McCormick and Choat 1987; Bogstad et al. 1995). However, in the fisheries management context, the benefit of data collection should not be measured in terms of the precision but in relation to the achievement of management objectives. A few studies have simulated the impact of parameter uncertainty or data errors on fisheries management (e.g., Restrepo et al. 1992; Reeves 2003; Bertignac and de Pontual 2007), but these studies have not explicitly answered the following question: "What type of data and how much data should be collected to maximize achievement of management objectives?" An example of a study that does answer this sort of question was conducted by Punt et al. (2002), who assessed the benefits of alternative levels of survey intensity in terms of achieving legislated fisheries management objectives.

In their review of this topic, Walters and Pearse (1996) noted that there had been no systematic studies of the management benefits of investing in alternative types of fisheries data collection. Caddy and Cochrane (2001) echoed this and highlighted the need for the development of fisheries management systems that are both cost effective and robust to the uncertainties inherent in fisheries management.

In this article, we illustrate an approach to evaluating alternative types and intensities of data collection. The approach is based on estimating the management benefits of data collection within the context of fisheries management procedures (de la Mare 1998; Butterworth and Punt 1999; Butterworth 2007; Rademeyer et al. 2007). When designing management, monitoring is often considered to be external, as a given constant stream of data. In contrast, we believe that monitoring is an attribute of the management procedure and that it should be evaluated just as other management attributes are—by simulating its consequences in terms of management objectives. We hope to show that data-poor fisheries need not be that way forever and that, through evaluation, they can be made "data sufficient." In some cases, this may require that more money be spent on data collection; in other cases, it

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* Corresponding author: nbentley@trophia.com

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may require that less money be spent on data collection. The aim should be to collect the type and amount of data that optimize the net value of the fishery.

We restrict our examination to what we call fisheries "monitoring": the collection and analysis of data required for the operation of a fisheries management procedure. For example, a management procedure may have as an input an estimate of the mean length of the catch (e.g., Campbell et al. 2007) and so would require some monitoring to provide this estimate. Monitoring is distinct from what we call fisheries "research": the collection and analysis of data to improve the knowledge of the dynamics and the current state of the fishery.

To illustrate our approach, we use an example fishery to evaluate alternative management procedures that encompass different forms of data collection. We nominally base our simulations on the fishery for tarakihi *Nemadactylus macropterus* along the east coast of the South Island of New Zealand (quota management area TAR3). This fishery can be considered to be data poor because a quantitative stock assessment has never been done and the only consistent data series available for it are commercial catch and effort data. In this study, we are not attempting to provide recommendations for this specific fishery or indeed for fisheries in general. Rather, by using a real-world example, we aim to illustrate that our approach is feasible. The second section of this article, "Evaluation Methods," describes the simulation model and methods used to evaluate alternative management procedures.

The third section, "Selection Methods," then describes the method that we use for selecting the management procedure that maximizes the achievement of management objectives. This method is the key to our approach because it provides a way of intrinsically weighing the cost associated with different management procedures against their benefits.

Because our emphasis is on evaluating the form of monitoring, we keep the management procedures that we evaluate very simple. As a baseline for comparison, we evaluate a management procedure with no monitoring that simply sets a constant total allowable catch (TAC). This is the "null" management procedure used for many data-poor fisheries. The other two types of management procedure that we evaluate simply apply a fixed exploitation rate to an estimate of biomass to determine the following year's TAC, but these two procedures differ in that one requires fixed (regular) monitoring while the other applies an adaptive monitoring rule.

Evaluation Methods

For simplicity, we used a delay-difference model to simulate the dynamics of the stock (Deriso 1980; Schnute 1985):

$$N_t = S_{t-1}N_{t-1} + R_t$$
$$B_t = S_{t-1}(\alpha N_{t-1} + \rho B_{t-1}) + \omega R_t,$$

where N_t is population abundance, S_t is survival, R_t is recruitment, B_t is biomass in year t, ω is the mean weight of recruits, and α and ρ are parameters of the Ford–Brody growth equation, which assumes that the growth in the mean weight of recruited fish is linear:

$$W_a = \alpha + \rho W_{a-1},$$

where W_a is the mean weight at age a.

It is assumed that the rate of natural mortality (M) is constant over time, is the same for all recruited fish, and that all recruited fish are equally vulnerable to fishing. Survival in a year (S_t) is thus the product of the natural survival rate and 1 minus the exploitation rate:

$$S_t = e^{-M}[1 - (C_t/B_t)],$$

where C_t is the catch taken in year t. Catch in a year is specified as a TAC by the management procedure being evaluated. It is assumed to be taken in full except when it exceeds the biomass, in which case it is set equal to biomass. In this case, the survival rate and biomass in subsequent years will be zero. In other words, the fishery would have been extinguished.

Recruitment in year t (R_t) is assumed to follow a Beverton–Holt stock–recruitment relationship, with deviations that are lognormally distributed with standard deviation σ:

$$R_t = \frac{B_{t-1}/B_0}{1 - [(5z-1)/4z](1 - B_{t-1}/B_0)} \mathrm{L}(1, \sigma),$$

where z is steepness, R_0 is the recruitment associated with virgin (unexploited) biomass B_0, and $\mathrm{L}(1, \sigma)$ is a lognormal distribution with mean 1 and standard deviation σ (Francis 1992).

Rather than making B_0 a parameter of the model, we parameterize the model in terms of current biomass ($\tilde{B}$) and the current state relative to B_0 (γ):

$$\tilde{B} = \gamma B_0.$$

The value of R_0 is determined numerically as the recruitment that produces B_0 under no exploitation; N_0 is also determined numerically as the population size under unexploited equilibrium. The initial state of the population for simulations is

$$N_1 = \gamma N_0, \qquad B_1 = \gamma B_0.$$

Catch per unit of effort (CPUE) of commercial fishing is simulated as

$$\mathrm{CPUE}_t = B_t^{\beta}\mathrm{L}(1, \tau).$$

TABLE 1.—Parameters for the simulation model used in the evaluation of fishery management procedures (for assumed distribution, U = uniform distribution specified by upper and lower bounds; N = normal distribution specified by mean and standard deviation; and L = lognormal distribution specified by mean and coefficient of variation [CV]).

Parameter	Description	Assumed distribution (mean, SD)	Notes
M	Annual rate of natural mortality	U (0.08, 0.15)	Based on Annala (1987)
α	Intercept of Ford–Brody growth equation (kg)	N (0.211, 0.01)	Derived from growth and weight parameters from Annala et al. (1990) and using a CV of 0.05.
ρ	Slope of Ford–Brody growth equation	N (0.849, 0.04)	
ω	Weight at recruitment (kg)	N (0.59, 0.03)	As above and assuming recruitment at 5 years
z	Steepness of stock–recruitment relationship	U (0.6, 0.9)	Arbitrary range
σ	SD of recruitment deviations	U (0.4, 0.6)	Arbitrary range
$\tilde{B}$	Current biomass (*t*)	L (10,000, 0.2)	Mean arbitrary; CV based on usual target for inshore trawl surveys in New Zealand.
γ	Current biomass relative to virgin biomass	U (0.2, 0.8)	Wide range representing uncertainty in the state of a data-poor stock
β	Hyperstability/depletion parameter	N (0.73, 0.10)	Based on Harley et al. (2001)
τ	SD of catchability	U (0.15, 0.25)	Based on Francis et al. (2001)

We do not include a catchability constant here because CPUE is used as a relative index of abundance in our simulations. The parameter β allows for CPUE to be proportional to biomass ($\beta = 1$), for hyperstability ($\beta < 1$) or hyperdepletion ($\beta > 1$) (Harley et al. 2001). The term $L(1, \tau)$ allows for annual variation in catchability or observation error.

The canonical parameters for the model (i.e., the parameters upon which all other model parameters and variables are dependent) are listed in Table 1. A probability distribution is defined for each parameter based on available research or is chosen to be reflective of the uncertainty typical in data-poor fisheries. When evaluating a management procedure, parameters of the simulation model are repeatedly drawn from these probability distributions to produce a parameter set (hereafter termed "a replicate"). Each replicate also incorporates a series of recruitment deviations. For each replicate, the operation of each candidate management procedure is evaluated and the performance variables (e.g., annual catch and biomass) are recorded. For this work, we evaluated each management procedure over a 100-year simulation period for 300 replicates. While this number of replicates is sufficient for this illustrative example, it would be inadequate for an evaluation of management procedures that are candidates for actual implementation in a fishery. For example, estimating the probability of rare events, such as very low biomass levels, would require far more replicates.

Selection Methods

A key element of what we term the procedural paradigm of fisheries management is evaluating many candidate management procedures and selecting the one that best achieves management objectives. However, fisheries management usually has multiple, often conflicting, objectives (e.g., Wattage et al. 2005; Nielsen and Mathiesen 2006; Hilborn 2007), and this can make it difficult to decide on which management procedure performs best. For example, a management procedure that has very precise data available to it may perform well in terms of maximizing yield but poorly in terms of management cost. Such trade-offs could be made informally by decision makers when the number of choices is small. When a selection has to be made from among a large number of candidate management procedures, a more formal method would be preferable.

Ideally, what is required is a function that combines multiple management objectives into a single value that represents the overall performance of fisheries management. This is what Crutchfield (1973) referred to as a "multiple social welfare function" but is more generally known as a utility function. There is a large body of literature on the construction and use of utility functions (e.g., Keeney and Raiffa 1993), including applications to fisheries (e.g., Keeney 1977; McDaniels 1995; Lane and Stephenson 1998; Dankel et al. 2007). Our aim is not to describe how to construct fisheries utility functions in general but rather to show one approach to this problem. In particular, our approach allows for a ranking of alternative data collection regimes within the framework of management procedure evaluation. We illustrate the approach by using the TAR3 fishery, but we re-emphasize that none of this work has been done in conjunction or consultation with stakeholders of the fishery, and this analysis is intended as an example only.

A common starting point for management procedure evaluation is to define a set of management objectives and associated performance measures. While this may not always be easy to do at the start of the process, it is necessary in order to define a minimum set of outputs from evaluations. The management objectives that we use for our example are as follows: yield (maximize catch); abundance (maximize abundance to improve fishing efficiency); stability (minimize variability in catch to reduce commercial uncertainty); efficiency (minimize the cost of management); and sustainability (minimize the probability of fishery collapse).

Associated with each of these objectives are performance measures that provide a quantitative measure of the success of achieving each objective. These performance measures are calculated by summarizing variables of the fishery, such as catch and biomass, over n years:

- yield (Y) = mean annual catch in year $t = \Sigma_{t=1}^{n} C_t/n$
- abundance (A) = mean ratio of CPUE to current CPUE $= \Sigma_{t=1}^{n}$ (CPUE$_t$/CPUE$_c$)/n
- variability (V) = mean annual variation in catch (%) $= 100\{\exp[\Sigma_{t=1}^{n} |\log_e(C_t/C_{t-1})|/n] - 1\}$
- cost (MC) = mean annual cost of management (\$) = $\Sigma_{t=1}^{n} X_t/n$
- collapse (L) = if biomass ever falls below 5% of B_0 (1/0) = minimum(B_t) $< 0.05B_0$,

where X_t is the monitoring cost in year t and $\tilde{B}$ is the assumed current biomass. Note that the performance measures that we have defined are aggregates of variables over time.

The set of management objectives and performance measures that we have chosen are typical of those used in management procedure evaluation. Perhaps the most important difference is that we include the cost of management (in this example, simply the cost of data collection) as a performance measure. Cost-efficient management is often stated as a fisheries objective (e.g., Smith et al. 1999) but is rarely reflected in a performance measure.

We use one biological reference point that is fundamentally required for evaluating fisheries management (Butterworth 2008): the biomass below which the stock is unable to replenish itself (i.e., stock collapse; Bravington et al. 2000). As we will show, such a performance measure is important because the expected value of the utility function can sometimes be highest for a management procedure that involves a significant risk of collapse. In this example, we have arbitrarily chosen 5% of B_0 for this reference point.

The key challenge in constructing a utility function is to convert all performance measures into a common unit of utility. Perhaps the most obvious common unit to use is money. This is relatively straightforward for performance measures like yield and effort. For example, by using a survey of fleet economics, Holland et al. (2005) converted several performance measures into a net present value of the fishery. This aided decision makers in choosing among management alternatives by providing an implicit weighting between some of the chosen performance measures. For other performance measures, it is too difficult or too simplistic to convert them into monetary values (Hilborn and Walters 1992). For example, what is the monetary value of a 10% mean annual variation in catch? As another example, the negative utility of allowing a fishery to collapse may be more than the loss of monetary returns.

Without being able to consider the benefits of management in monetary terms, how can we meaningfully assess the worth of alternative data collection regimes with differing costs? We broach this impasse by using a utility function that combines (1) monetary partial utilities (hereafter, "part-utilities") for performance measures that can meaningfully be transformed into dollars (yield, abundance, and cost) with (2) a binary part-utility for the performance measure that cannot be expressed in dollars (variability). The remaining performance measure, collapse, is not included into the utility function but is used as a measure of risk. We consider each part-utility function separately and then describe how they are combined into an overall utility. All currency values are in New Zealand dollars.

Perhaps the easiest performance measure to convert into dollars is yield because generally the price per unit weight of fish is known. In New Zealand, the Ministry of Fisheries conducts annual surveys of the exvessel ("port") price of most of the commercially fished species. In 2006–2007, the exvessel price (P) for TAR3 was \$1.43 per kilogram or \$1,430 per metric ton. The part-utility for the yield performance measure Y (U_Y) is therefore calculated as follows:

$$U_Y(\$) = PY = 1,430Y.$$

The monetary value of alternative levels of abundance or biomass is harder to quantify. Higher abundance will increase CPUE, which will in turn reduce the cost of catching a unit weight of fish. Since our definition of the abundance performance measure is based on biomass relative to current levels, we could simply scale the current cost of catching a kilogram of fish according to abundance. Doubling abundance is unlikely to halve the cost of fishing because fixed costs such as vessel maintenance and the cost of capital are unaffected by fish abundance (Hilborn and Walters 1992). Here, we arbitrarily use a power function with a coefficient of 0.5 to express this lack of proportionality:

$$K = \tilde{K}/A^{0.5},$$

where K is the cost of catching a kilogram of fish given

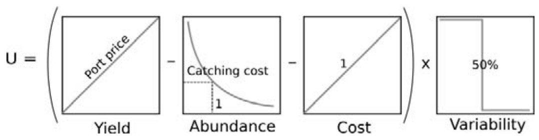

FIGURE 1.—Schematic representation of the utility function (U), which is a combination of the part-utilities from the performance indicators yield, abundance, and cost, which are transformed to dollars, and variability, which is transformed to 0 or 1.

an abundance A, and $\tilde{K}$ is the current cost of catching a kilogram of fish. How do we estimate this current cost? In New Zealand, Annual Catch Entitlement (ACE) is traded in an auction system and the ACE prices are available for each quota management area. For TAR3 in 2006–2007, the transaction-weighted ACE price (Q) was \$0.64 per kilogram. One model of the relationship between the ACE price and the exvessel price is that the ACE price represents what is left over after the costs of harvesting are taken into account. In other words, the ACE price is expected to trade up to a price at which

$$Q = P - K.$$

We therefore estimate the current fishing cost per unit weight as follows:

$$K = P - Q = 1,430 - 640 = \$790\,\text{per metric ton};$$

and the part-utility function for the abundance performance measure (U_A) is then the cost of catching a kilogram of fish times the yield performance measure:

$$U_A(\$) = K \times Y = (790/A^{0.5}) \times Y.$$

Since the management cost performance measure is already in dollars, its part-utility function is simply:

$$U_{\mathrm{MC}}(\$) = \mathrm{MC}.$$

As we have already stated, it is difficult or inappropriate to convert the variability performance measure into dollars. Instead, we use a binary part-utility function for variability (i.e., a part-utility that has a value of either 1 or 0). This is done by setting a standard on variability, above which performance of the management procedure is considered to be unacceptable. We use 50% as the standard for variability:

$$U_V(\{0,1\}) = \begin{cases} 0 & V > 50\% \\ 1 & V \leq 50\%. \end{cases}$$

Values lower than 50% were subjected to preliminary tests but were found to overly restrict the choice of management procedures in the final utility function, thereby reducing the illustrative value of the results. This decision in itself illustrates that the development of a utility function may be an iterative process with component parts being adjusted based on examination of what the simulated management procedures are capable of delivering in terms of performance measures.

The part-utilities are combined into an overall utility function. This is done by combining the monetary part-utilities to represent a net monetary utility of the fishery and then multiplying this by the binary part-utility for variability:

$$U = (U_Y - U_A - U_{\mathrm{MC}}) \times U_V.$$

When the U_V is zero (i.e., when $V > 50\%$), the overall utility is zero, regardless of the net monetary utility resulting from the other performance measures. Figure 1 provides a simplified schematic representation of the utility function.

To summarize the performance of a particular management procedure (m), we use the mean utility over all n replicates to calculate an expected utility:

$$U_m = \sum_{r=1}^{n} U_{m,r}/n.$$

TABLE 2.—Performance measures, part-utilities, overall utility, and risk for the best management procedure among the three types tested (TAC = total allowable catch; CV = coefficient of variation; E = exploitation rate; T = survey threshold; t = metric ton; all currency is in New Zealand dollars). Note that the values for performance measures are means over all replicates and are not the values used to calculate part-utilities. Similarly, the values for part-utilities are means over all replicates and are not the values used to calculate the utility.

		Performance measures (mean)				Part-utilities (mean)			
Procedure type	Attributes	Yield (t)	Abundance (relative)	Variability (%)	Cost (\$ million)	Yield (\$ million)	Abundance (\$ million)	Variability (prob ≤ 50%)	Cost (\$ million)
No monitoring	TAC = 250 metric tons	250	1.48	0	0.00	0.36	0.17	1.00	0.00
Fixed monitoring	CV = 0.28 E = 0.1	890	0.90	40	0.07	1.27	0.72	0.98	0.07
Adaptive monitoring	CV = 0.46 E = 0.11 T = 0.556	880	0.90	32	0.02	1.26	0.72	1.00	0.02

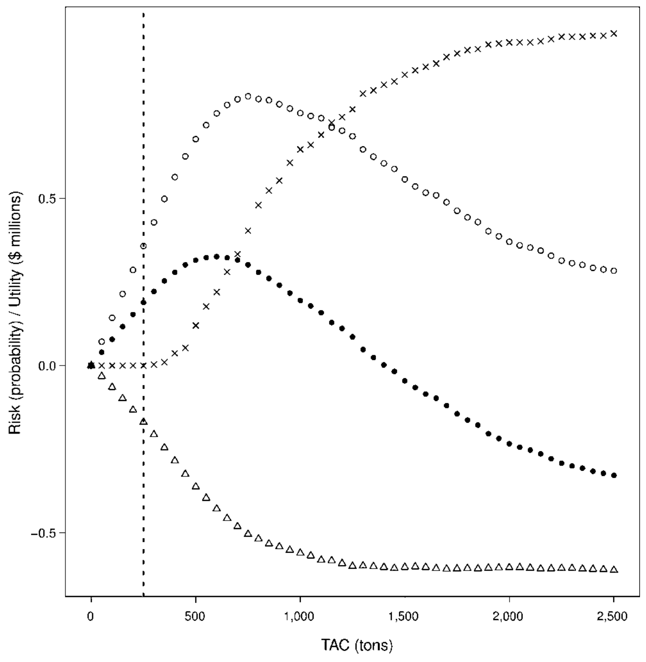

FIGURE 2.—Mean part-utilities (millions of New Zealand dollars) for yield (open circles) and abundance (open triangles), mean utility (filled circles), and risk (crosses) for alternative levels of constant total allowable catch (TAC; metric tons). The dashed vertical line indicates the TAC with the highest conditional utility (utility conditional on risk being less than 0.001). The mean part-utility for variability is not shown because it is always 1 due to constant TAC. The mean part-utility for cost is not shown because it is always 0 since no monitoring is done.

In addition, we use the collapse performance measure to develop a measure of risk associated with each management procedure. Remember that this performance measure is a binary variable representing whether or not the fishery is considered to ever have collapsed in any single replicate evaluation. Thus, the risk or probability of collapse for a particular management procedure is as follows:

$$R_m = \sum_{r=1}^{n} L_{m,r}/n.$$

TABLE 2.—Extended.

Procedure type	Utility	Risk	Conditional utility
No monitoring	0.19	0.00	0.19
Fixed monitoring	0.47	0.00	0.47
Adaptive monitoring	0.52	0.00	0.52

The final criterion for selecting among candidate management procedures is what we call the conditional utility ($\breve{U}_m$), defined as the utility that is conditional upon the risk being less than 0.001:

$$\breve{U} = \begin{cases} 0 & R > 0.001 \\ U_m & R \leq 0.001. \end{cases}$$

In other words, the best management procedure is that which provides the maximum utility *and* that has at least a 99.9% probability of being sustainable. Due to the low number of simulations done in this study, this criterion is equivalent to experiencing no stock collapses in any of the replicates.

Evaluation of Alternative Monitoring Schemes

In this section, we evaluate three types of management procedures with respect to the utility function developed above. The management procedures evaluated illustrate contrasting schemes for monitoring.

No Monitoring

One alternative to manage a fishery is to use the most simple of management procedures—no monitoring and a TAC that does not change. We evaluated alternative levels of TAC from 0 to 2,500 metric tons in

50-metric-ton increments and calculated the mean part-utilities, mean utility, and risk for each of these levels (Figure 2). The part-utility for yield, representing fishing revenue, is maximized at a TAC of 750 metric tons and then declines due to higher TAC levels being unsustainable. The part-utility for abundance decreases (i.e., becomes more negative because fishing costs increase) with higher TAC, reflecting the increased cost of fishing when abundance is low. The part-utility for management cost is always zero because no monitoring is done, and the part-utility for variability is always 1 because the TAC is constant. The combined effect of the trends in the part-utilities of yield and abundance is that utility is maximized at a TAC of 600 metric tons. However, even at this level given the uncertainty in the dynamics of the population and variability in recruitment, there is a 22% risk that the fishery will collapse (by using our definition of collapse at 5% of B_0). To reduce the risk of collapse to 0.1% or less, it is necessary to reduce the constant TAC to 250 metric tons. This TAC produces a conditional utility of \$0.19 million (Table 2).

Fixed Monitoring

An alternative to a fixed TAC is a management procedure that invests in monitoring and alters TAC in response to the data collected. We use a very simple example of this type of management procedure. We assume that it is possible to do a trawl survey that produces unbiased estimates of absolute abundance based on area swept. Under this management procedure, a trawl survey with a specified target coefficient of variation (CV) is done each year, and the resulting biomass estimate, $\hat{B}$, is multiplied by a specified constant exploitation rate (E) to determine the TAC for the next year:

$$\mathrm{TAC}_{t+1} = \hat{B}_t E.$$

Therefore, this management procedure has two parameters or attributes that can be adjusted: the CV of the trawl survey and E. We would expect a priori that a survey with a lower CV would allow for a higher sustainable E and thus a higher yield because the TAC is set more precisely relative to the biomass. However, a more precise survey comes at the cost of higher annual monitoring costs.

In our simulations, the annual cost of the trawl survey (X_t) is based on the cost, sample size, and CV of an existing trawl survey conducted in part of the TAR3 quota management area. This trawl survey began in 1991, was discontinued in 2000, and then was reinstated in 2007. Under the cost recovery system that operates for New Zealand fisheries (Stokes et al. 2006), quota holders are charged part or all of the cost of fisheries data collection. For the 2007 survey, owners of the TAR3 quota were charged \$88,417, equivalent to 14% of the survey cost; the remainder of the cost was charged to quota holders of other fish stocks also benefiting from the survey. The trawl survey had 94 stations (within the 30–400-m depth stratum applicable to this fishery) and produced an estimated tarakihi biomass of 2,589 metric tons (CV = 24.5%). Using this information and basic statistics, we can derive an approximate formula for the cost of surveys with different numbers of stations and determine a target CV. The standard error (SE) of an estimate μ is as follows:

$$\mathrm{SE} = \mu\mathrm{CV} = \frac{\sigma}{\sqrt{n}},$$

where σ is the standard deviation and n is the sample size. Thus, the effective standard deviation of the estimate of biomass in 2007 is:

$$\sigma = \mathrm{SE}\sqrt{n} = \mu\mathrm{CV}\sqrt{n} = 6,150\,\text{metric tons}.$$

We can calculate the sample size (n_{cv}) that would have been required to achieve a specified CV in 2007:

$$n_{\mathrm{cv}} = (\sigma/\mathrm{SE})^2 = (6,150/2,589\mathrm{CV})^2.$$

We use this as the basis for calculating the fixed annual cost of a trawl survey with a specified CV based on the 2007 cost of \$941 per station:

$$X_t(\$) = 941 \times (6,150/2,589\mathrm{CV})^2.$$

The actual CV achieved for a given sample size in future surveys will of course depend upon many factors, including the biomass at the time of the survey. This formula is also only approximate because it ignores the fixed costs and other logistical considerations of operating a trawl survey.

We evaluated 2,500 management procedures of this type, having 50 levels of CV ranging uniformly from 0.1 to 1.1 combined with 50 levels of E ranging uniformly from 0.01 to 0.51. We summarize these evaluations by plotting the mean part-utilities, mean utility, risk, and conditional utility over each combination of CV and E (Figure 3). The plots show how each of the performance metrics varies with different combinations of the management procedure attributes.

The expected part-utility for yield, representing revenue, is highest when CV is 0.10 and E is 0.18. As expected, long-term yield is maximized at an intermediate E. Generally, yield decreases as CV is increased because often the TAC is set too high when biomass is low and the TAC is set too low when

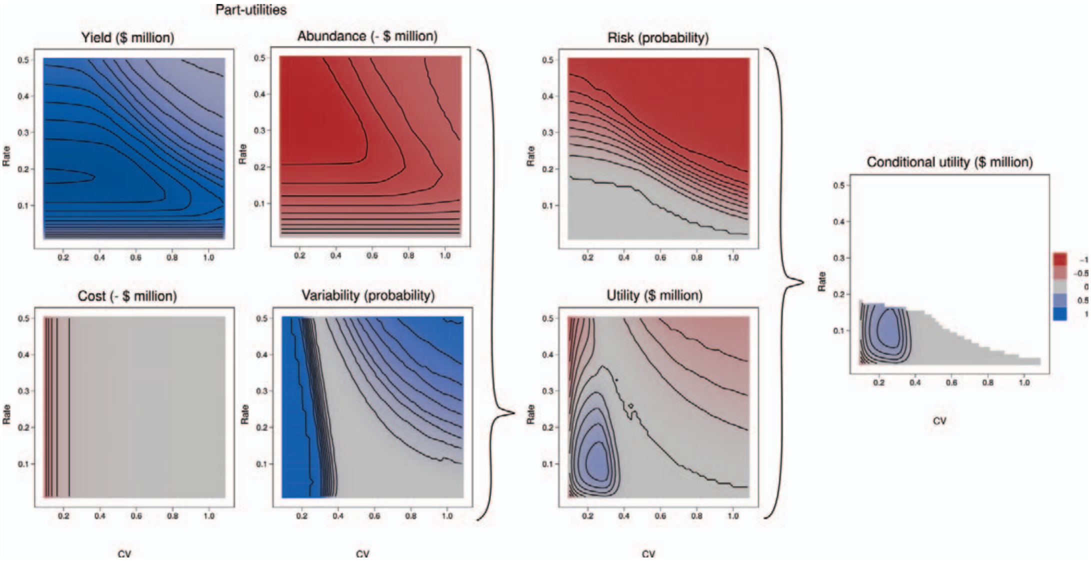

FIGURE 3.—Expected part-utilities (millions of New Zealand dollars), expected utility, risk, and conditional utility for the fixed-monitoring management procedure with alternative levels of exploitation rate (rate) and survey coefficient of variation (CV). Note that part-utilities for each performance measure are shown rather than the performance measure values themselves. For example, the part-utility for abundance is in units of negative dollars, representing the increased cost of fishing when abundance is reduced. Color scales are equivalent in all plots (red = negative utility; blue = positive utility). For the conditional utility plot, cells are white when the combination of exploitation rate and survey CV does not meet the risk criterion (risk $\leq$ 0.001).

biomass is high. However, at low *E*, yield is relatively insensitive to CV.

The expected part-utility for abundance, representing fishing cost, is greatest at high *E* because biomass levels are depressed and so more effort is required to take a given catch. At high *E* and high CV, expected fishing costs actually decrease because there is a high probability that the TAC is set higher than the biomass, in which case the fishery is extinguished and catch and effort are both zero for all subsequent years.

The expected part-utility for variability, representing the probability of variability being less than 50%, is highly sensitive to CV but not to *E*. However, because this is a binary part-utility (i.e., one that uses a knife-edged function), there are few gains from reducing CV below about 0.2.

Cost is dependent only on CV and increases rapidly when CV is reduced to low levels because the survey sample size required becomes disproportionately large.

When these part-utilities are combined into an overall expected utility, a clear peak emerges with a maximum at a CV of 0.28 and an *E* of 0.1. In each direction, utility falls away from this peak for the following main reasons: when CV is increased due to increased variability; when CV is decreased due to increased cost; when *E* is increased due to reduced abundance; and when *E* is decreased due to reduced yield. Note that the expected utility is actually negative when CV and *E* are both low because the cost of the survey is greater than the net value of the catch.

Risk is sensitive to both CV and *E* and is close to zero (very low probability of stock collapse) for low CV and low *E* and close to 1.0 (very high probability of stock collapse) at high CV and high *E*. Although our risk criterion of 0.001 restricts the conditional utility (Figure 3, far right panel) to less than a quarter of the attribute space that we evaluated, it does not exclude the peak expected utility. For this type of management procedure, the conditional utility is maximized at a value of $0.47 million when CV is 0.28 and when *E* is 0.1 (Table 2). This is $0.28 million greater than the best no-monitoring, fixed-TAC management procedure, principally because the $68,000 investment required to produce a survey with a CV of 0.28 is more than compensated for by a yield that is on average more than three times higher. To reduce risk to an acceptable level, a fixed-TAC strategy has to be far more conservative than one that varies TAC according to the available biomass.

Adaptive Monitoring

The monitoring component of a management procedure need not be fixed. As we have shown, benefits in terms of yield (and thus revenue) are

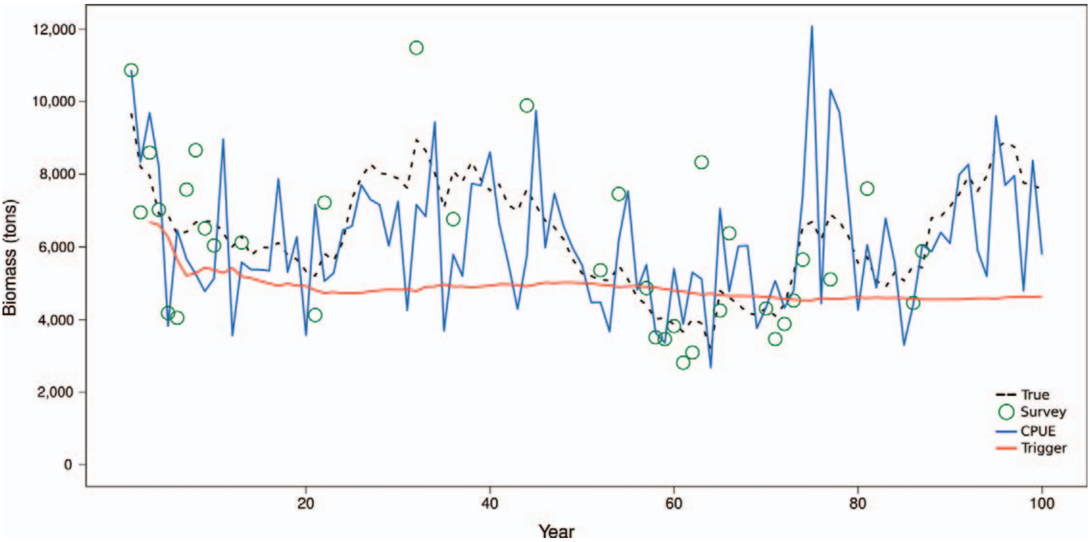

FIGURE 4.—Operation of an example of the adaptive monitoring management procedure. This example has an exploitation rate of 0.1, a survey coefficient of variation of 0.2, and a survey threshold of 0.75. The dashed black line (true) is the true but unknown biomass (metric tons). The red line (trigger) is the biomass below which a survey is triggered in the subsequent year and is equal to 75% of the running mean of biomass estimates. The blue line is catch per unit effort (CPUE). This plot represents the outcome from one replicate in which β was 0.725 and τ was 0.218. β = hyperstability/depletion parameter. τ = SD of catchability (see Table 1).

obtained from a management procedure that adjusts TAC in response to indicators of biomass. Similarly, benefits in terms of management costs may be achieved by adjusting the monitoring as part of a management procedure. We illustrate this by using a modification of the previous fixed-monitoring management procedure.

As with the previous management procedure, the adaptive monitoring management procedure determines an annual TAC based on an annual estimate of biomass and a specified E:

$$\mathrm{TAC}_t = \hat{B}_t E.$$

The difference with the adaptive procedure is that, in an attempt to reduce the cost of monitoring, it uses the CPUE from the commercial fishery as an index of biomass. However, in years when the biomass is low, the procedure triggers a trawl survey in the following year. This design attempts to reduce costs while remaining precautionary at low biomass levels.

The operation of the procedure begins by doing a trawl survey each year for 10 years so that a scalar (λ) between CPUE and absolute biomass can be estimated:

$$\lambda = \exp\left[\sum_{t=1}^{n} \log_e(\hat{B}_t^s/\mathrm{CPUE}_t)/n\right],$$

where $\hat{B}_t^s$ is the biomass estimate from the trawl survey in year t. The scalar is updated each time that a trawl survey is done, and λ is used to estimate absolute biomass from CPUE:

$$\hat{B}_t^c = \lambda \mathrm{CPUE}_t.$$

In subsequent years, the CPUE-based biomass estimate is used unless a survey is done:

$$\hat{B}_t = \begin{cases} \hat{B}_t^s & \text{if survey done} \\ \hat{B}_t^c & \text{otherwise.} \end{cases}$$

The running mean ($\tilde{\hat{B}}$) of these biomass estimates is calculated each year; after the first 10 years, the procedure triggers a trawl survey in the subsequent year if the estimated biomass is less than a specified proportion, which we call the survey threshold (T) of that running mean.

The annual monitoring cost of the management procedure consists of a fixed annual cost of a CPUE standardization analysis plus the cost of a trawl survey if one is done in that year. We use the same CV–cost function as for the fixed-monitoring management procedure, and we assume a cost of $15,000 for CPUE standardization. Figure 4 provides an example of the operation of this type of management procedure.

We evaluated 15,625 management procedures of this type, having 25 levels of CV ranging uniformly from 0.1 to 1.1; 25 levels of E ranging uniformly from 0.01 to 0.51; and 25 levels of T ranging uniformly from 0.1 to 2.0.

We determined a conditional utility profile for the E

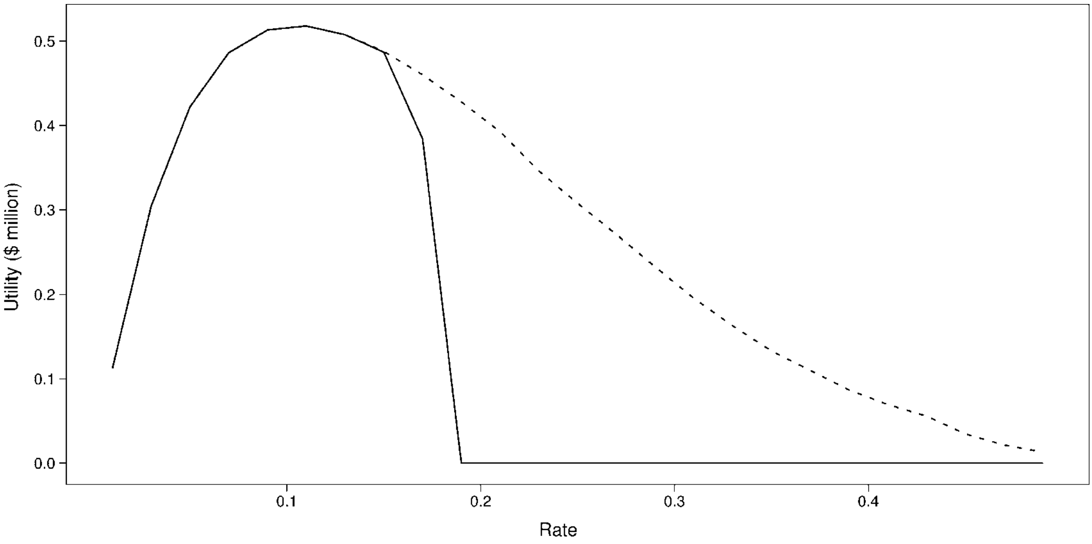

FIGURE 5.—Profiles of utility (dashed line; millions of New Zealand dollars) and conditional utility (solid line) for the exploitation rate parameter (rate) of the adaptive monitoring management procedure. Each profile represents the maximum expected utility or conditional utility associated with a given exploitation rate across all levels of the other attributes of the management procedure.

attribute of the evaluated management procedures (Figure 5). The profile represents the maximum expected conditional utility associated with a given *E* across all levels of the other attributes of the management procedure. The maximum expected conditional utility is achieved by a procedure having an *E* of 0.11, which is very similar to that for the best-performing fixed-monitoring management procedure.

To simplify presentation, Figure 6 is restricted to management procedures where *E* is 0.11. Figure 6 is similar to Figure 3 except that it shows the sensitivity of performance metrics to CV and *T*. The expected part-utilities for yield and abundance show very little sensitivity to either of these attributes. These results are consistent with those for the fixed-monitoring management procedures when *E* was around 0.1 or lower (Figure 3).

In contrast, the monitoring cost is sensitive to both *T* and CV. More precise surveys cost more and surveys need to be done more often when *T* is higher. The part-utility for variability is also sensitive to both parameters, being close to 0 (0% probability of variability being less than 50%) when CV is greater than 0.5 and when *T* is greater than 1 (i.e., imprecise surveys done often). The two-dimensional surface for expected utility primarily reflects the part-utilities for monitoring cost and variability and has a peak when CV is 0.46 and *T* is 0.55.

Risk is relatively insensitive to either attribute but is elevated when CV is high and *T* is high. The fact that higher levels of risk are not apparent in Figure 6 reflects the relatively low *E* to which these plots are restricted. Again, risk does not constrain the choice of management procedure, with conditional utility being maximized at a value of $0.52 million when *E* is 0.11, CV is 0.46, and *T* is 0.556 (Table 2).

Adaptive monitoring is able to reduce management costs by over 70% from fixed monitoring while maintaining other performance measures at similar levels (Table 2). It does this by triggering a relatively imprecise survey when biomass levels are at about half of the long-term mean. This should be considered in the context of the simulation model that uses a CV of the CPUE ranging from 0.15 to 0.25 and a biomass–CPUE relationship that is usually hyperstable (Table 1). Thus, the benefit from the trawl survey comes not from its precision but from its proportionality to biomass at low biomass levels.

Discussion

As we have stated from the outset, this work is not meant to provide recommendations on the design of data collection programs or management procedures for any specific fishery. What we have attempted to do is to illustrate an approach to evaluating fisheries data collection within the context of fisheries management procedures. In the real world, for any given case, there could be numerous improvements made to the management procedures, evaluations, and utility functions that we have presented in this article.

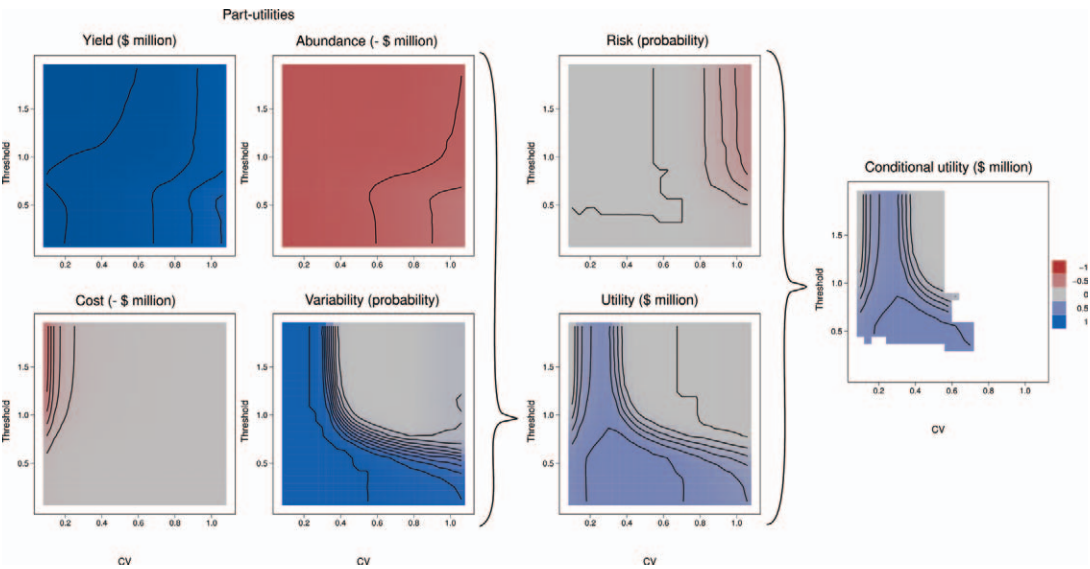

FIGURE 6.—Expected part-utilities (millions of New Zealand dollars), expected utility, risk, and conditional utility for the adaptive monitoring management procedure, with alternative levels of survey threshold and survey coefficient of variation (CV). See Figure 3 for additional details.

The management procedures that we chose to evaluate are intentionally simplistic. We chose the basic management procedure design based on absolute biomass estimates and a target *E* to illustrate the benefits that can arise when those biomass estimates are made more precise. It is notoriously difficult to obtain unbiased estimates of absolute biomass, and procedures that are based on indices of relative biomass may perform better (Hilborn 2002). In the real world, logistics may play an important role when considering adaptive monitoring. For example, it may not be logistically possible to sporadically trigger a biomass survey for the subsequent year. To reflect such considerations, management procedures need to be designed in consultation with those doing the data collection.

Cross-fishery considerations may also be important for some data collection programs. For example, trawl surveys often provide data for—and thus confer benefits to—more than one fishery. In our example, we took this into account by only using the part of the trawl survey cost that is attributed to the TAR3 fishery. However, to properly determine the optimum precision of that survey, it would be necessary to combine the results of similar evaluations for all fisheries for which the trawl survey provides data.

When evaluating management procedures, it is important that the simulations accurately reflect the uncertainty around the dynamics and state of the stock. We applied relatively large uncertainty to most of the parameters of our simulation model to reflect a relatively data-poor stock. Underestimating uncertainty will usually result in overestimates of performance. For example, if we underestimated uncertainty, the performance of the constant TAC (no monitoring) management procedure would be overestimated because the calculated risk associated with higher TAC would be reduced. Some management procedures will be more robust to this uncertainty. For example, in our simulations, the management procedures that involve monitoring will be more robust to uncertainty around the current biomass because they update this estimate via additional surveys, CPUE indices, or both.

Our utility function could easily be criticized as back-of-the-envelope economics. For example, for simplicity, we ignore discounting. Depending on the case, incorporation of more sophisticated economics may be more or less important. In general, however, we think it is most important to explicitly incorporate economics in the selection of management procedures, albeit roughly, than to not incorporate economics at all. Also, it must be remembered that our utility function is in no way intended as a means of estimating the absolute net monetary value of the fishery. We simply use monetary units as the means for implicitly weighting several performance measures to produce a utility value that is reflective of monetary value and therefore allows meaningful comparison of management options. We caution against the use of complicated utility functions that are difficult for stakeholders to interpret.

In this example, again for simplicity, we assumed that only the commercial sector benefits from the fishery. We based our part-utilities on the monetary return to owners of the fishing quota. We did this for two reasons. First, under the New Zealand cost recovery regime, it is quota owners that pay for data collection via levies (Stokes et al. 2006). Second, data on the economics of commercial fishing are most readily available. Fisheries often have noncommercial stakeholders and in real-world evaluations of management procedures, those stakeholders' performance measures should be reflected in utility functions. The framework that we have presented does not exclude this possibility. For example, the interests of recreational fishers might be represented in binary part-utilities on abundance (similar to the approach used for risk of collapse) or the mean size of fish. Dankel et al. (2007) provided a simple illustration of how utility functions can be used to incorporate the different weights that alternative stakeholder groups place on performance measures.

Of course, utility functions do not necessarily require that monetary units be used at all. For example, decision makers could decide to base a utility function on a part-utility for yield (measured in metric tons of fish) along with binary part-utilities for other performance measures. Such a utility function would be more reflective of a traditional approach to fisheries management, but it ignores the subtle trade-offs that exist between management objectives. Although feasible, we would not recommend such an approach.

This article examined fisheries monitoring—that is, data collection and analyses—required for the operation of a management procedure. We evaluated alternative forms of monitoring by simulating the benefits produced via the operation of a management procedure. However, monitoring accumulates data that may also be used to improve knowledge of the fishery, which in turn allows the design of management procedures that perform better because they are more finely tuned to the particular dynamics of the fishery. Thus, if anything, our evaluations underestimate the value of monitoring.

We do not suggest that absolutely all decisions on fisheries data collection should be based on formal evaluations (which have a cost that needs to be informally weighed). There is a trade-off between scientists doing what they think is important and what can be demonstrated as important (Apostolaki et al. 2008). Sometimes, the convention and intuition we noted in our introductory paragraph may in fact provide the best basis for deciding which data collection is worthwhile. Nonetheless, even in these cases, evaluations similar to those presented here can support the decision-making process.

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References

Annala, J. H. 1987. The biology and fishery of tarakihi, *Nemadactylus macropterus*, in New Zealand waters. Fisheries Research Division Occasional Publication 51.

Annala, J. H., B. A. Wood, J. D. Hadfield, and D. A. Banks. 1990. Age, growth, mortality and yield–per–recruit estimates of tarakihi from the east coast of the South Island during 1987. MAF Fisheries Greta Point Internal Report 138.

Apostolaki, P., G. M. Pilling, M. J. Armstrong, J. D. Metcalfe, and R. Forster. 2008. Accumulation of new knowledge and advances in fishery management: two complementary processes? Pages 229–254 *in* A. Payne, J. A. Cotter, and T. Potter, editors. Advances in fisheries science. Wiley, New York.

Bertignac, M., and H. de Pontual. 2007. Consequences of bias in age estimation on assessment of the northern stock of European hake (*Merluccius merluccius*) and on management advice. ICES Journal of Marine Science 64:981–988.

Bogstad, B., M. Pennington, and J. H. Vølstad. 1995. Cost-efficient survey designs for estimating food consumption by fish. Fisheries Research 23:37–46.

Bravington, M. V., T. K. Stokes, and C. M. O'Brien. 2000. Sustainable recruitment: the bottom line. Marine and Freshwater Research 51:465–475.

Butterworth, D. S. 2007. Why a management procedure approach? Some positives and negatives. ICES Journal of Marine Science 64:613–617.

Butterworth, D. S. 2008. Why fisheries reference points miss the point. Pages 215–222 *in* J. Nielsen, J. J. Dodson, K. Friedland, T. R. Hamon, J. Musick, and E. Vespoor, editors. Reconciling fisheries with conservation: proceedings of the Fourth World Fisheries Congress. American Fisheries Society, Symposium 49, Bethesda, Maryland.

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

Caddy, J. F., and K. L. Cochrane. 2001. A review of fisheries management past and present and some future perspectives for the third millennium. Ocean and Coastal Management 44:653–682.

Campbell, R., J. Prince, C. Davies, D. Kolody, N. Dowling, M. Basson, P. Ward, K. McLoughlin, I. Freeman, and A. Bodsworth. 2007. Development of an empirical-indicator based harvest strategy for the Australian eastern tuna and billfish fishery. Working Paper ME-SWG/WP-4 presented to the third meeting of the Western and Central Pacific Fisheries Commission Scientific Committee.

Crutchfield, J. A. 1973. Economic and political objectives in fisheries management. Transactions of the American Fisheries Society 2:481–491.

Dankel, D. J., U. Dieckmann, and M. Heino. 2007. Success in fishery management by reconciling stakeholder objectives in Hilborn's "zone of new consensus". ICES CM 2007/O:17.

de la Mare, W. K. 1998. Tidier fisheries management requires a new MOP (management oriented paradigm). Reviews in Fish Biology and Fisheries 8:349–56.

de la Mare, W. K. 2006. What is wrong with fisheries and wildlife management? An engineering perspective. Pages 309–320 *in* D. M. Lavigne, editor. Gaining ground: in pursuit of ecological sustainability. International Fund for Animal Welfare, Guelph, Canada; and University of Limerick, Limerick, Ireland.

Deriso, R. B. 1980. Harvesting strategies and parameter estimation for an age-structured model. Canadian Journal of Fisheries and Aquatic Sciences 37:268–282.

Folmer, O., and M. Pennington. 2000. A statistical evaluation of the design and precision of the shrimp trawl survey off West Greenland. Fisheries Research 49:165–178.

Francis, R. I. C. C. 1984. An adaptive strategy for stratified random trawl surveys. New Zealand Journal of Marine and Freshwater Research 18:59–71.

Francis, R. I. C. C. 1992. Use of risk analysis to assess fishery management strategies: a case study using orange roughy (*Hoplostethus atlanticus*) on the Chatham Rise, New Zealand. Canadian Journal of Fisheries and Aquatic Sciences 49:922–930.

Francis, R. I. C. C., R. J. Hurst, and J. A. Renwick. 2001. An evaluation of catchability assumptions in New Zealand stock assessments. New Zealand Fisheries Assessment Report 2001/1.

Harley, S. J., R. A. Myers, and A. Dunn. 2001. Is catch-per-unit-effort proportional to abundance? Canadian Journal of Fisheries and Aquatic Sciences 58:1760–1772.

Helle, K., and M. Pennington. 2004. Survey design considerations for estimating the length composition of the commercial catch of some deep-water species in the northeast Atlantic. Fisheries Research 70:55–60.

Hilborn, R. 2002. The dark side of reference points. Bulletin of Marine Science 70:403–408.

Hilborn, R. 2007. Defining success in fisheries and conflicts in objectives. Marine Policy 31:153–158.

Hilborn, R., and C. J. Walters. 1992. Quantitative fisheries stock assessment: choice, dynamics and uncertainty. Chapman and Hall, New York.

Holland, D. S., N. Bentley, and P. Lallemand. 2005. A bioeconomic analysis of management strategies for rebuilding and maintenance of the NSS rock lobster stock in southern New Zealand. Canadian Journal of Fisheries and Aquatic Sciences 62:1553–1569.

Keeney, R. L. 1977. The utility function for estimating policy affecting salmon on the Skeena River. Journal of the Fisheries Research Board of Canada 34:49–63.

Keeney, R. L., and H. Raiffa. 1993. Decisions with multiple objectives: preferences and value trade-offs. Cambridge University Press, Cambridge, UK.

Lane, D. E., and R. L. Stephenson. 1998. A framework for risk analysis in fisheries decision-making. ICES Journal of Marine Science 55:1–13.

McCormick, M. I., and J. H. Choat. 1987. Estimating total abundance of a large temperate-reef fish using visual strip-transects. Marine Biology 96:469–478.

McDaniels, T. L. 1995. Using judgment in resource management: a multiple objective analysis of a fisheries management decision. Operations Research 43:415–26.

Nielsen, J. R., and C. Mathiesen. 2006. Stakeholder preferences for Danish fisheries management of sand eel and Norway pout. Fisheries Research 77:92–101.

Punt, A. E., T. I. Walker, and J. D. Prince. 2002. Assessing the management-related benefits of fixed-station fishery-independent surveys in Australia's southern shark fishery. Fisheries Research 55:281–295.

Rademeyer, R. A., E'. E. Plaga'nyi, and D. S. Butterworth. 2007. Tips and tricks in designing management procedures. ICES Journal of Marine Science 64:618–625.

Reeves, S. A. 2003. A simulation study of the implications of age-reading errors for stock assessment and management advice. ICES Journal of Marine Science 60:314–328.

Restrepo, V. R., J. M. Hoenig, J. E. Powers, J. W. Baird, and S. C. Turner. 1992. A simple simulation approach to risk and cost analysis with applications to swordfish and cod fisheries. U.S. National Marine Fisheries Service Fishery Bulletin 90:736–748.

Schnute, J. 1985. A general theory for the analysis of catch and effort data. Canadian Journal of Fisheries and Aquatic Sciences 42:414–429.

Smith, A. D. M., K. J. Sainsbury, and R. A. Stevens. 1999. Implementing effective fisheries-management systems: management strategy evaluation and the Australian partnership approach. ICES Journal of Marine Science 56:967–979.

Stokes, K., N. Gibbs, and D. Holland. 2006. New Zealand's cost-recovery regime for fisheries research services: an industry perspective. Bulletin of Marine Science 78:467–485.

Walters, C., and P. H. Pearse. 1996. Stock information requirements for management systems in commercial quota fisheries. Reviews in Fish Biology and Fisheries 6:21–42.

Wattage, P., A. Mardle, and S. Pascoe. 2005. Evaluation of the importance of fisheries management objectives using choice-experiments. Ecological Economics 55:85–95.