Evaluation of quota management policies for developing fisheries

Carl Walters

Abstract: Losses can be measured as deviations from a desired reference trajectory of quotas that would be taken if there were no uncertainty and are highly dependent on assessments prior to and during development. Simulations of assessment and quota setting under various quota setting rules indicate that variability in relative abundance indices can cause substantial losses, especially considering cumulative effect of early quota errors on later departures of biomass from that needed to produce the desired quotas, even if optimum fishing mortality rate is known in advance. Conservative assessments (low biomass estimates for which there is only a small probability that biomass is actually lower) are favored during development when loss is measured as the relative departure from the best quota for each year. But if loss is measured as absolute departure from the best quota, it is generally better to base the quota on the biomass estimate for which there is nearly a 50% chance that the stock is smaller. Deliberate overfishing (probing) is not favored under either loss measure. Losses can be reduced with minimum biomass surveys and closed areas that directly cushion fishing mortality rates from being more than 50% too low or high.

Résumé : Les pertes peuvent être mesurées comme écarts par rapport à une courbe de référence souhaitée des quotas qui seraient pris en l'absence d'incertitude, et elles sont fortement dépendantes des évaluations faites avant et après le développement de la pêche. Les simulations de l'évaluation et de l'établissement des quotas selon diverses règles indiquent que la variabilité des indices de l'abondance relative peuvent causer des pertes substantielles, surtout lorsqu'on tient compte de l'effet cumulatif des erreurs initiales dans les quotas sur les écarts ultérieurs de la biomasse par rapport à celle qui serait nécessaire pour produire les quotas souhaités, même si on connaît à l'avance le taux optimal de mortalité par pêche. Il est conseillé d'avoir recours à des évaluations prudentes (estimations basses de la biomasse pour lesquelles n'existe qu'une faible probabilité que la biomasse soit effectivement plus basse) pendant la phase de développement lorsque la perte est mesurée comme écart relatif par rapport au meilleur quota pour chaque année. Toutefois, si on mesure plutôt l'écart absolu par rapport au meilleur quota, il vaut généralement mieux baser le quota sur l'estimation de la biomasse pour laquelle il y a près de 50% de chances que le stock soit plus petit. Quelle que soit la méthode de mesure des pertes, il n'est pas recommandé d'avoir recours délibérément à la surpêche (à titre exploratoire). On peut réduire les pertes en effectuant des relevés de la biomasse minimale et en fermant des zones qui permettent directement d'éviter que les taux de mortalité par pêche soient de 50% trop haut ou trop bas.

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Introduction

There is surprising demand today for development of new fisheries due to desperation of fishers displaced from collapsed fisheries and to emergence of New World markets for edible products from aquatic ecosystems. From a stock assessment perspective, new fisheries can no longer be studied at leisure by counting on efforts and catch to develop slowly enough to provide clear signals of stock decline well in advance of serious overfishing. Usually, surplus fishing capacity and technology are more than capable of quickly doing very severe damage to almost any natural population.

As capacity for destructive development has grown, so has public demand for sustainable management and for new cost and risk sharing arrangements (Troadec 1989; Pearse and Walters 1992; Walters and Pearse 1996; Starr et al. 1998). Fishers are often expected to share the costs of "proving" potential through investment in exploratory fishing, regular surveys, basic biological research, and better record keeping. Fishers are demanding better value for their money: there is less tolerance for basic research, poorly designed surveys, and inept assessments. Also, there is growing demand by both fishers and fishery managers for output controls (quota management), with obvious economic and administrative advantages but dangerous in a world where fishing technologies are capable of taking quotas that are grossly too high.

This paper uses simulation of data gathering and assessment (Smith 1993) to define when improved information gathering is likely to result in substantially improved management for developing fisheries, defined here as situations where (*i*) fishing mortality has historically been low or negligible, (*ii*) a stock is near an unfished level most often involving considerable biomass accumulation that cannot be sustained under harvesting, and (*iii*) there is enough economic demand for growth in fishing mortality to eventually cause overfishing. Performance is measured by deviations of yield from a desirable reference trajectory that would be taken given no uncertainty about stock size; both positive and negative deviations from the desirable trajectory are

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C. Walters. Fisheries Centre, University of British Columbia, Vancouver, BC V6T1Z4, Canada. e-mail: walters@fisheries.com

treated as loss. I argue that such errors arise less from uncertainty about productivity (best fishing mortality rate) than from uncertainty about total stock size. Three approaches are suggested for reducing the impact of assessment errors on long-term performance: (*i*) progressive exposure to increasing fishing mortality, with only a small part of any stock exposed at first to risk of harvest, (*ii*) limits on fishing mortality independent of stock size assessments via spatial closures that reduce the proportion of fish exposed to harvest risk, and (*iii*) surveys by industry to provide minimum estimates of occupied area and density that can be used to set quota "floors" or "proven production potential" directly.

Modeling development as an adaptive process

Presumably, management for new fisheries aims to regulate harvests so the stock(s) will move to a most productive level for sustaining yield without passing through a costly period of collapse. Usually, we cannot tell how large a stock is without exploiting it, and we cannot be sure that a most productive level has been reached without obtaining observations from stock sizes below that level (Hilborn and Sibert 1988). In short, developing fisheries live and die by the quality of information used to learn about sustainability: new management strategies for developing fisheries should be based on understanding limits to learning and on regulatory tactics to prevent destruction before good information becomes available.

Can we resolve the dilemma posed by Hilborn and Sibert (1988) by breaking down the problem of assessing long-term quotas into simpler subproblems and by making judicious use of previous fishery development experience? A best long-term regime is defined by average catch quota C_l, average biomass B_l, and optimum fishing mortality rate F_{opt} so that $C_1 = F_{opt}B_1$. Thus the adaptive process of learning about sustainable catch has two subproblems: (*i*) F_{opt}, which depends on growth, natural mortality, and recruitment compensation parameters, and (*ii*) B_1, which depends on many factors ranging from simple habitat size to life history characteristics that define how good fish are at utilizing resources and dealing with risks in the habitat.

We can obtain bounds on F_{opt} from basic information on growth and natural mortality rates M. Empirical experience suggests that F_{opt} is generally less than or equal to M and, at least for pelagic species, is most likely to be on the order of $2/3M$ (Patterson 1992). Further, setting a target F somewhat lower than optimum (e.g., $2/3M$ when $F_{opt} = M$) is not costly in terms of lost harvest opportunity, since this lower F will result in a higher average biomass so the product FB is not substantially lower than $F_{opt}B$. In short, we can solve "half" of the problem of assessing an optimum long-term quota C_1 quickly by investing in acquisition of good growth and natural mortality information very early in (or as a precondition for) fishery development. That is, we can avoid part of the dilemma posed by Hilborn and Sibert (1988) by accepting modest losses in potential yield, without determining F_{opt} precisely by seeing what happens if it is exceeded. Considering progress in methods for sampling and aging aquatic organisms, there are few potential fisheries for which the investments needed to obtain this information would be too costly for fishers and public agencies.

Given good estimates of F_{opt} from previous fisheries experience and knowledge about aquatic organisms, the difficult problem is then to either estimate the stock size B_t over time or find a way to directly regulate F (e.g., through large marine protected areas). Quota management appears to preclude the second of these options, leaving estimation of B_t as the main adaptive learning problem. Unlike F_{opt}, population dynamics theory and experience tell us almost nothing about what B_1 values to expect (although that experience does provide likely values for the ratio of B_1 to unfished stock size B_0).

Seldom can we economically estimate biomass through direct enumeration. The B_t is a product of mean density per unit habitat area, $(B/A)_t$, and area occupied, A_t, i.e., $B_t = (B/A)_t A_t$. We can rarely afford to obtain large enough samples of $(B/A)_t$ to estimate mean density accurately, and in most developments, A_t is also highly uncertain and is "discovered" by fishers in search of better fishing opportunities. Experience and trophic theory may provide bounds for density $(B/A)_t$ but not for A_t. Further, A_t can change rapidly due to environmental influences, and factors like shoaling behavior can cause A_t to decrease as B_t declines. Fishery-independent biomass surveys help guard against errors in assessment of $(B/A)_t$ due to nonrandom targeting of high-density sites by fishers, but it is usually not economical to spread survey sampling over large enough areas to insure against errors in assessment of A_t; further, if surveys represent only areas of major fish concentration, survey abundance indices can show the same "hyperstability" (Hilborn and Walters 1992) as commercial catch rate during stock declines, if occupied range area contracts into the surveyed area.

Because of technical difficulties and costs of assessing $(B/A)_t$ and A_t, B_t must usually be estimated with some generalized "removal method": we compare measured total removals (catches) with survey or catch rate indices of relative abundance so as to reconstruct how large the stock had to have been to produce both the removals and the observed trend in relative abundance. Such comparisons involve fitting population models to the relative abundance data, where we "drive" the models with observed removals and also correct the abundance predictions for effects of production processes (growth, recruitment, natural mortality). Models range from simple biomass dynamics equations based on surplus production or delay-difference relationships to complex age-structured models that simulate losses either forward over time ("synthesis" models: Fournier and Archibald 1982; Deriso et al. 1985; Megrey 1989; Methot 1990; Schnute and Richards 1995) or backward (virtual population models, e.g., ADAPT: Gavaris 1988; Walters and Punt 1994). There are pitfalls with all of these removal models, particularly in relation to violation of assumptions about the abundance index being proportional to B_t. And generally, the more complex age-structured models do not perform all that much better than the simple ones (Hilborn 1979; Ludwig and Walters 1985; NRC 1997; Punt 1997); the massive increase in apparent information associated with age composition data is useful mainly for estimating recruitment variation and age–size selectivity.

For removal models to perform well, catches must cause large changes in relative abundance. In adaptive management terms, this means that there is a strong "dual effect of control" (Walters 1986): harvests produce both direct value and information value in the form of impacts on relative abundance. There is a conflict between the dual effects: harvesting harder promotes faster learning, but also increases risk of overfishing. Little progress has been made toward solving the formal dynamic optimization problem of how to best balance the dual effects; suggestions about how to approach this problem have ranged from dynamic programming methods (Walters 1986) to management "metagaming" (Walters 1994).

Some assessments of overharvesting risk during development have ignored the dual effect of harvesting on information. For example, one practice has been to simulate alternative future quota sequences while assigning probabilities to various estimates of unfished biomass and productivity and then report the resulting probabilities of reducing stock size below some arbitrary threshold level. A fisher or manager could ask "but if unfished biomass is in fact low, will relative abundance not decline more quickly and give opportunity to correct the quotas much sooner than in your simulations?" This is a valid question; there is no good excuse to ignore future data gathering and response to new information. We can predict, or specify as investment options, the data gathering and analysis methods that will be used, and we have enough experience with variability in survey and catch rate data to simulate likely patterns of stochastic variation. Thus, we can simulate future observations of relative abundance (and age composition, etc.) and assessment calculations based on these. Such "closed-loop" simulations (Smith 1993) of future management performance have other benefits; in particular, they allow us to compare various decision rules for responding to uncertainty. That is, using closed-loop simulations, we can answer questions like "what if future decisions are based on setting the quota each year to $F_{opt}B_{0.1}(t)$ where $B_{0.1}(t)$ is the 10% point on the cumulative probability distribution for B_t (value of B for which there is a 90% chance that B_t is actually larger) and how will expected yields from this option compare with harvesting $F_{opt}B_{0.5}(t)$?"

Procedures for assessing performance of development strategies

One way to compare closed-loop policies is to simulate development performance for a range of alternative hypotheses about unfished stock size and then use a weighted average of performance over this range as an overall measure. The function used to measure performance under each alternative hypothesis is a "loss function" and the weighted average of this function over hypotheses is the "risk" (Mood and Graybill 1963). Statistical decision theory encourages us to use Bayes prior probabilities $P_0(B_0)$ for unfished biomasses B_0 as weights for calculating risk; leaving out such weights (just averaging performance over a wide range of B_0 values) is equivalent to assuming equal prior probabilities for all values of B_0 admitted in analysis. This raises an important basic issue and warning to the reader: we cannot measure or quantify risk for any particular development opportunity without at least placing bounds on possible B_0 outcomes, and the choice of bounds is necessarily subjective. Hence, any procedure for assessing risk is vulnerable to abuse: analysts can paint an unduly conservative or rosy picture of future risk by appropriate choice of B_0 bounds.

Performance simulations need six basic components: (*i*) bounds on uncertainty in the form of parameters that are taken to be known or given (not treated as part of the simulated learning process) and prior range for B_0, (*ii*) a population response submodel for predicting how any catch sequence would influence B_t, given any B_0, (*iii*) an observation submodel for generating simulated future observations given any B_t, (*iv*) a procedure to simulate how future observations will be used to update a probability distribution $P_t(B_t)$ for biomass (and perhaps other uncertain quantities), (*v*) a procedure for translating the probability distribution $P_t(B_t)$ into specific quota decision choices C_t (i.e., a procedure for applying decision rules based on P_t), and (*vi*) a procedure for calculating performance from each simulation trial over $t = 1,..., T$ years. Results presented here are based on simulation component assumptions described in the following subsections.

The procedures described below are not meant to represent the best modeling or Bayesian data analysis. Various procedural simplifications are used to make it computationally practical to compare very large numbers of simulation trials. I tried to use simplifications that avoid overly optimistic estimates of future uncertainty, although most modern procedures would deal explicitly with some uncertainties that I ignore or lump with others. Unfortunately, even the relatively optimistic assumptions used below are not enough to rescue some commonly held beliefs about the value of assessment information during fishery development; I show that even where these optimistic assumptions are valid, assessment information cannot usually be gathered quickly or accurately enough to prevent substantial risk during development.

Baseline information assumed to be available at the start of development

There are at least two ways to set a good simulation estimate of F_{opt}: (*i*) obtain an estimate of natural mortality rate M and take $F_{opt} = 0.6M$ (Patterson 1992; Mertz and Myers 1998) and (*ii*) obtain an estimate of M and of the Ford–Brody growth parameters α and ρ (intercept and slope of the body weight Walford plot) and use these along with recruitment parameters in an equilibrium delay-difference model to calculate F_{opt} (Walters and Parma 1996). Since information on recruitment compensation will generally not be available at the start of development, the second of these approaches is most likely to be "tuned" (by varying the ratio of maximum to unfished recruitment per biomass) so as to give F_{opt} on the order of 0.6–1.0M. I assume below that F_{opt} has been correctly estimated from early biological sampling and analysis efforts. Thus the pathological estimates of expected losses presented below are due only to biomass estimation problems; including effects of errors in estimation of F_{opt} would result in even higher loss estimates.

I also assume that there has been enough exploratory fishing or surveys to provide swept area or local depletion estimates of density and bounds for the area occupied. Products of these estimates are assumed to provide bounds B_{min} and B_{max} for unfished biomass B_0. The prior distribution $P_0(B_0)$ is then assumed to be uniform over B_{min} to B_{max}. The evaluation examples presented below are generally based on very wide limits, e.g., from $1 \times C_0$ to $300 \times C_0$, where C_0 is average catch over a few years prior to the first risk analysis.

Alternative loss functions for comparing development policies

Many measures can be used to compare performance of alternative information gathering and regulatory policies for developing fisheries, ranging from simple output measures like total catch over an arbitrary development period, to discounted economic value, to risk of having the stock fall below some arbitrary threshold value relative to B_0. Comparison of simple biological or economic output measures is complicated by failure of these measures to recognize some development objectives that are difficult to quantify. For example, total catch is generally maximized by a policy that takes high catches initially so as to drive the stock to an optimum level as quickly as possible and then much lower catches afterward; however, there are social and economic drawbacks to such a boom–bust trajectory. Likewise, it is hard to justify policies based on avoiding arbitrary biomass levels; we generally cannot decide objectively what a "dangerous" biomass level is, nor can we expect full consensus from fisheries stakeholders on an acceptable probability (or risk) of falling below any such level.

One way to represent complex temporal objectives is to measure performance as a loss relative to some arbitrary trajectory of catches that would be chosen by stakeholders if they had perfect knowledge of stock size and future production. That is, suppose we knew B_0 and F_{opt} exactly, along with future recruitment anomalies. Then, I expect that we could obtain consensus on an optimum quota development trajectory of the form

$$C_{opt}(t) = D(t)F_{opt}B_t,\ t = 1,\ldots,\ T \tag{1}$$

where $D(t) \leq 1.0$ represents a "fractional development" or progressive development function set to increase over time so that catch approaches $F_{opt}B_t$ in the long term. Note that constraining D to be <1.0 means insisting that F never exceed F_{opt} and hence that expected biomass B_t never be driven below the optimum equilibrium resulting from B_t, i.e., eq. 1 with $D < 1$ implies a mandatory concern for long-term sustainability, whatever stakeholders might feel about how rapidly development should proceed.

For simulation tests, I assume that stakeholder consensus will result in a $D(t)$ that increases asymptotically toward 1.0 (F starts low and approaches F_{opt} over time), and for simulation tests, I assume that D can be approximated by a function of the form

$$D(t) = (t/t_h)/[1 + (t/t_h)]. \tag{2}$$

In this formulation, t_h is the number of years until the fishing mortality rate would be allowed to reach $1/2F_{opt}$; setting high values for t_h would result in "smooth" development without an initial overshoot of C_t to values above the long-term sustainable level C_1. Then, suppose that an information gathering/response policy results in the catch sequence $C_{real}(t)$, where the policy accounts for development objectives represented in $D(t)$ but differs from C_{opt} due to errors in assessment of B_t, use of deliberately cautious B_t estimates, and cumulative impacts of past C_{real} quota choices on B_t. We can measure the loss L due to using this policy in at least two simple ways:

Sum of absolute quota errors:

$$L_{abs} = \sum_{t=1}^{T} \left| C_{opt}(t) - C_{real}(t) \right|. \tag{3a}$$

Sum of relative quota errors:

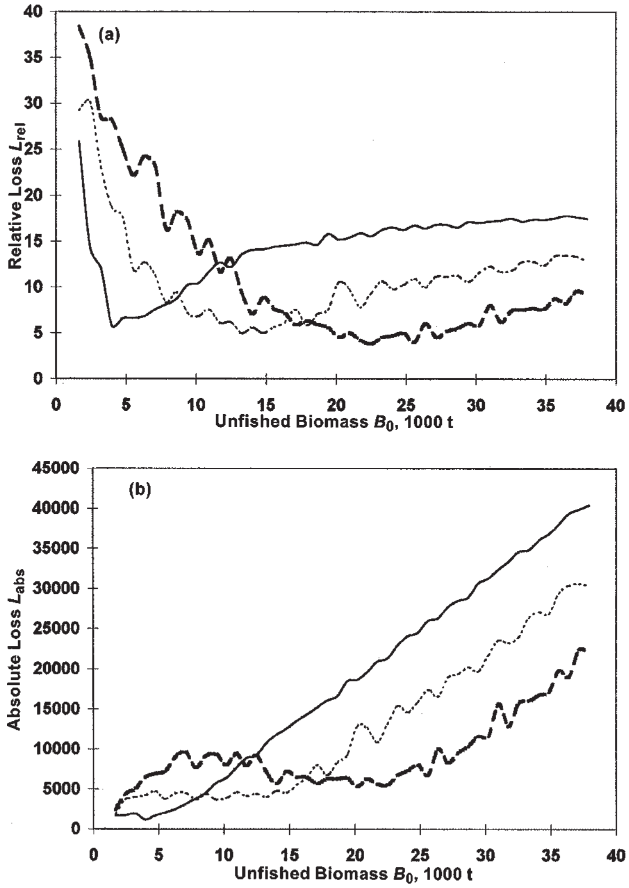
$$L_{rel} = \sum_{t=1}^{T} \left| C_{opt}(t) - C_{real}(t) \right| / C_{opt}(t). \tag{3b}$$

Both of these loss measures are based on two key presumptions: (*i*) future losses are as important as present ones, at least for T years (i.e., no discounting of future losses), and (*ii*) quota overages ($C_{real} > C_{opt}$) are as undesirable as missed opportunities ($C_{real} < C_{opt}$), whether or not the overages result in any long-term impairment of capability to achieve C_{opt} due to impact on B_t. Simulation trials indicate that inclusion of low discount rates (0.01–0.03 per year) does not substantially affect policy comparisons based on L, but differential weighting of overages and underages can have a profound effect (failing to penalize overages makes aggressive development policies look better unless T is large enough for long-term losses due to overfishing to become clearly evident).

Although eqs. 3*a* and 3*b* appear to weight over- and under-fishing equally, the absolute and relative loss measures result in profoundly different relationships between loss and initial population size B_0 and hence very different weighting of over- versus under-harvesting when risk or expected loss is calculated as a weighted sum of losses over the prior probability distribution for B_0. The basic difference (Fig. 1) is that the relative loss measure strongly penalizes quota overages early in development and (or) for low values of B_0 (cases when C_{opt} is in fact small) but "unweights" losses when C_{opt} is in fact large (if B_0 is in fact large, or later in development). In contrast, the absolute loss measure is small for low B_0 whether or not the quota policy wipes out this small biomass but is large for high B_0 when the quota policy does not fully capitalize on the harvest opportunity represented by this high B_0. In short, the relative measure penalizes overharvesting relative to whatever potential the stock turns out to have (whatever B_0 really is) whereas the absolute measure places much more weight on losses in total catch. Hence the relative measure tends to favor cautious policies (do not risk overharvesting in the event that B_0 is small) whereas the absolute measure tends to favor "certainty equivalent" (Walters 1986) policies (assume that B_0 is somewhere in the middle of its probable range).

There are reasons for preferring either absolute or relative loss as performance measures. An "ecologically" oriented stakeholder might argue for the relative measure on the grounds that development should aim to bring fishery resources to their best potential whatever that potential might happen to be, with relatively low risk of overfishing during the development. But a "socially" oriented stakeholder

Fig. 1. Simulated variation in 20-year (*a*) relative and (*b*) absolute losses measured as differences between quotas realized and reference or target quotas. Note that relative loss is higher for low unfished biomass (overfishing risk weighted heavily), while absolute loss is highest for high stock size (underfishing risk weighted heavily). Each point along a curve is mean of 10 simulation trials. Quotas were set each simulated year using the biomass estimate for which assessment indicated probability ξ that the stock size was actually smaller. Solid line, $\xi = 0.1$; dotted line, $\xi = 0.3$; heavy broken line, $\xi = 0.5$.



might equally well argue that total yield (and the economic development potential it represents) is what really matters to people and that the risk of overharvesting a resource that cannot support much development should not be considered important. This is a debate that proponents and regulators of development must somehow resolve. Absent better arguments to the contrary, agency regulators today are becoming more likely to adopt relative loss measures that reflect public concern about biological diversity and the protection of vulnerable species and stocks.

For simulation tests, I elected to use relatively short planning horizons T of 20–40 years for two reasons. First, if major deviations (losses) from a desired development pattern are going to occur because of inadequacies in information gathering and assessment methods, these deviations will be concentrated in the first few decades of development. Second, I tested longer horizons and found that these did not affect predicted loss patterns and relationships between loss and policy variables intended to reduce loss.

Representation of uncertainty as development proceeds

As noted above, we generally represent uncertainty about current biomass B_t by measures of how well alternative hypotheses about the biomass trajectory (removal pattern) agree with observed indices Y_t of relative abundance. Here, I assume that relative abundance will be measured over time (using standardized catch-per-unit-effort (CPUE) or surveys) so as to follow the multiplicative observation error model

$$(4)\qquad Y_t = qB_t^{\beta}\exp(v_t\sigma_v)$$

where v_t is normally distributed with unit standard deviation and the nuisance parameters q, β, and σ_v are unknown except for the following prior probability statements: (*i*) all values of $\ln(q)$ are equally likely, (*ii*) the prior probability for σ_v is proportional to $1/\sigma_v$ (Jeffreys prior), and (*iii*) all values of β between β_{min} and β_{max} are equally likely (the worst case is hyperstability: $\beta_{min} = 0$, $\beta_{max} << 1$). Under these assumptions, the marginal likelihood (integrated over nuisance parameters) of Y ($Y = \{Y_1,..., Y_T\}$) for any value B_0 is proportional to

$$(5)\qquad L(Y|B_0) = \int_{\beta=\beta_{min}}^{\beta=\beta_{max}} SS(\beta, B_0)^{-(T-1)/2}$$

where $SS(\beta,B_0)$ is the conditional (on β, B_0) sum of squared deviations

$$(6)\qquad SS(\beta, B_0) = \sum_{t=1}^{t=T}[z(t) - \bar{z}]^2$$

and

$$(7)\qquad z_t = \ln(Y_t) - \beta\ln[B_{B(0)}(t)].$$

Here, the notation $B_{B(0)}(t)$ refers to the most likely value of B_t given B_0, which we would most simply calculate by a deterministic simulation starting at B_0 and proceeding forward in time with removal at each t of observed catch. Equations 5–7 are simple extensions of derivations in Walters and Ludwig (1994). For simulation studies of estimation performance, note that Y_t is generated from eq. 4 with an arbitrary true q and biomass sequence $B_{trueB(0)}(t)$ and note that SS can be calculated efficiently at each simulated t by updating the sufficient statistics

$$(8)\qquad \begin{aligned} S_1(\beta, B_0) &= \sum z_t^2 \\ S_2(\beta, B_0) &= \sum z_t \end{aligned}$$

and using the familiar statistical relationship $SS = S_1 - S_2^2/T$. For the results presented below, I stored S_1 and S_2 values for a 10 × 50 grid of β,B_0 combinations ($\beta = (\beta_{min} + \beta_{max} - \beta_{min})i/9$, $i = 0,..., 9$; $B_0 = (B_{min} + B_{max} - B_{min})j/49$, $j = 0,..., 49$) as each simulation proceeded and took the integral in eq. 5 to be just the sum of $SS^{-(T-1)/2}$ values over the β grid elements for each B_0. Further, I generally used $\beta_{min} = 0$, $\beta_{max} = 1$; this assumption ignores the possibility of hyperdepletion in the relative abundance index due to "mining" high-density fish aggregations that do not reform rapidly due to shoaling behavior, but does admit a risk of hyperstability in the relative abundance data. It is not assumed that the simulated manager knows the arbitrary q used to generate Y_t; information about q at each time t is available through the mean of z_t in eq. 7, which is the maximum likelihood estimate of $\ln(q)$, but this information is not used directly in setting simulated quotas.

A posterior probability distribution for B_0 is defined from the likelihood eq. 5 and prior probabilities $P_0(B_0)$ by

$$(9) \qquad P_t(B_0|Y) = L(Y|B_0)P_0(B_0) \Big/ \int_{B_0=B_{\min}}^{B_0=B_{\max}} L(Y|B_0)P_0(B_0)\mathrm{d}B_0$$

Assuming that the P_0 and L values have been stored or calculated for a reasonably fine (e.g., 50-point) grid of discrete B_0 values, the posterior P_t for each discrete B_0 is found simply by summing the LP_0 values for all these B_0 and then dividing the LP_0 for each B_0 by that sum. For the assumptions outlined above, generally, P_t as a function of B_0 has a lognormal shape but is truncated at the biomass limits $B_{\min}$ and $B_{\max}$. Further, admitting a wide range of possible values for β results in higher P_t for lower values of B_0, i.e., the admission that stock size may have decreased due to historical catches C_t much more than would be indicated by assuming Y_t proportional to biomass.

Accumulating the P_t values from eq. 9 as they are calculated results immediately in estimates of another important probability distribution, namely $P(B_t \geq X)$, which is the total of all P_t for which $B_{B(0)}(t) \geq X_t$, i.e., the odds that B_0 was high enough that B_t exceeds X given the history of catches up to time t. Then from this cumulative distribution, it is easy to pick out critical biomass estimates $B_\xi(t)$ for which the probability that $B_t \geq B_\xi(t)$ is ξ. For example, $B_{0.1}(t)$ is a "risk-averse" or conservative biomass estimate (only 0.1 probability that $B_t < B_{0.1}(t)$), while $B_{0.5}(t)$ is a "median" biomass estimate for which there is a 50:50 chance that biomass is actually lower.

An efficient computational technique when many simulations need be conducted for risk analysis is to simultaneously calculate the conditional biomass trajectories $B_{B(0)}(t)$ for all B_0 grid points as each simulation proceeds (Walters 1994). The delay-difference model for these trajectories is

$$(10) \qquad B_{B(0)}(t) = S_{B(0)}(t-1)[\alpha N_{B(0)}(t-1) + \rho \mathrm{B}_{B(0)}(t-1)] + w_k R_{B(0)}(t)$$

$$(11) \qquad N_{B(0)}(t) = S_{B(0)}(t-1)N_{B(0)}(t-1) + w_k R_{B(0)}(t)$$

where the conditional survival rate $S_{B(0)}(t-1)$ is given by

$$(12) \qquad S_{B(0)}(t-1) = \max\{0,[1 - C_{t-1}/B_{B(0)}(t-1)]\mathrm{e}^{-M}\}$$

and recruitment $R_{B(0)}(t)$ is predicted from a stock–recruitment relationship of the form

$$(13) \qquad R_{B(0)}(t) = aB_{B(0)}(t-k) / [1 + bB_{B(0)}(t-k)]^c \exp(w_t).$$

Here, a, b, and c are recruitment parameters, k is age at recruitment/maturity, and w_t is an arbitrary recruitment "anomaly" sequence with mean 0 over time. For simulation years 1 to k, R is initialized at $R_{B(0)}(0) = N_{B(0)}(0)(1 - \mathrm{e}^{-M})$ (i.e., recruitment to the unfished stock just balances natural mortality on average) where $N_{B(0)}(0)$ is calculated from B_0 and predicted mean body weight for the unfished state as $N_{B(0)}(0) = B_{B(0)}(0)/\{[\mathrm{e}^{-M}\alpha + w_k(1 - \mathrm{e}^{-M})]/[1 - \rho\mathrm{e}^{-M}]\}$ (Hilborn and Walters 1992). For results below, c is set to 1.0 (Beverton–Holt recruitment function), a is set to $5 \times R_{B(0)}(0)/B_0$ (recruits/spawner can increase to 5 times the unfished ratio if B is low), and b is calculated from a and $R_{B(0)}(0)$ so as to predict $R_{B(0)}(0)$ when $B_{B(0)}(t) = B_0$. The recruitment anomaly sequence w_t is either set to 0.0, in which case the "observation errors" v_t in eq. 4 are "contaminated" by correlated effects of historical recruitment anomalies (B_t varies from the mean prediction of the deterministic model; effect seen in deviations along with index measurement errors), or set to a sequence w_t assumed known from independent analysis of recruitment variation using age composition or recruitment index sampling.

Decision rules for relating quotas to uncertainty: biomass probabilities, progressive exposure plans

Any quota choice C_t can be thought of as arising from or rationalizing a particular probabilistic stock size estimate $B_\xi(t)$, in the sense that we can always express that choice C_t as a product, $C_t = D(t)F_{\mathrm{opt}}B_\xi(t)$, and provided the target fishing mortality rate $D(t)F_{\mathrm{opt}}$ is defined in advance as a desirable exploitation rate for year t. Recall from above that $B_\xi(t)$ is the stock size for which assessment procedures indicate a probability ξ that B_t is actually smaller. That is, ξ is the probability that if quota C_t is taken, the ratio C_t/B_t will exceed $D(t)F_{\mathrm{opt}}$ at least for year t.

Thus, alternative decision rules for setting C_t can be expressed as choices of the progressive exposure function $D(t)$ and the acceptable overharvest "risk" ξ, along with rules for processing the historical data so as to arrive at the estimator $B_\xi(t)$ for each year. An important point is that $B_\xi(t)$ is not a point biomass estimate based only on information (e.g., a survey) gathered prior to fishing in year t; the probability distribution for B_t from which $B_\xi(t)$ is calculated should reflect (summarize) all information gathered up to time t concerning B_t. Generally, such probability distributions cannot be represented completely by one or a few "information state" statistics, precluding the possibility of using optimization methods like dynamic programming to calculate an optimum feedback relationship between the quota choice C_t and current information state. To define decision rules for management practice, we are forced to guess at the likely form of the feedback relationship, and an obvious guess is that this relationship would involve acting as though ξ were constant, i.e., operate with the same overfishing risk each year.

Treating the risk measure ξ as a decision rule constant, with ξ << 0.5, does not mean that quotas will always be much lower than if the best biomass point estimate (roughly, $B_{0.5}(t)$) were used to calculate the quota. If good information is gathered during the development (accurate relative abundance data, informative biomass depletion pattern prior to time t), the probability distribution for B_t will become progressively more peaked around $B_{0.5}(t)$, so that $B_\xi(t)$ will approach the most likely estimate over time. Hence the simple decision rule $C_t = D(t)F_{\mathrm{opt}}B_\xi(t)$ will "automatically" adjust for improving stock information over time, with $B_\xi(t)$ moving closer and closer to $B_{0.5}(t)$. This means that we probably do not need to evaluate policy rules that involve varying ξ over time (e.g., start with a low, risk-averse ξ and then move toward $\xi = 0.5$ as better information becomes available), except to the extent that we should be concerned whether low values of ξ and (or) $D(t)$ may prevent the distribution of B_t from improving over time (lack of informative impact of quotas on relative abundance).

Using a constant ξ decision rule, $\xi < 0.5$, creates an economic incentive for gathering information that will narrow the B_t distribution, moving $B_\xi(t)$ closer to $B_{0.5}(t)$. There is, of course, always a risk that better information will reveal B_t to be near the lower end of the B_t distribution, but on average, at least some investment should be a good gamble. The possibility that ξ should be set very low, so that $B_\xi(t)$ represents a "proven production potential", has been discussed by Pearse and Walters (1992) and Walters and Pearse (1996). The effect of such incentives on information gathering to reduce σ_v or provide direct biomass estimates B_t is not represented in the analysis below. However, I do consider the impact on expected loss due to having industry invest in independent information gathering to provide a lower bound or "proven" estimate $B_{\min}(t)$ represented as a proportion $R_{\min}B_t$. Surveys to establish quota floors are different from surveys to provide trend indices Y_t for routine stock assessment; surveys for trend information must be done in a consistent way every year, while surveys to estimate a minimum proven production potential might vary greatly in area surveyed and survey methods depending on how much investment in "proving up" biomass is economically worthwhile. Such surveys affect likelihood calculations by setting the minimum B_0 and B_t for which nonzero likelihood should be assigned, but should not otherwise affect likelihoods assigned to higher B_t values based on trend data.

Likewise, I consider the impact of using regulatory measures like marine protected areas to provide an upper bound on the realized exploitation rate, $R_{\max}F_{\text{opt}}$, where $R_{\max} > 1$. The idea here is that measures like large spatial closures can limit the fraction of the stock exposed to significant risk of capture, except perhaps for highly migratory species.

While fixed exploitation rate policies of the form $C_t = FB_t$ may assure near-optimum long-term harvest performance in the face of variation in recruitment due to environmental changes (Walters and Parma 1996; Engen et al. 1997), it is not clear that such policies are best for dealing with the contingency $B_t << B_t$, i.e., accidental reduction of stock size to far below the optimum level for long-term production. Fisheries scientists often advocate using decision rule with some "conservation threshold", expressed as a minimum biomass or minimum ratio $R_{\text{cutoff}} = B_t/B_0$, below which it is considered best to stop fishing entirely until the stock has recovered to a more productive level (Smith et al. 1993; NRC 1997). Below, I provide limited evaluation of the impact of alternative choices for R_{cutoff} on the loss measures (eqs. 3*a* and 3*b*).

To summarize, many alternative decision rules for regulating quotas during development in relation to probabilistic stock size assessments can be represented as alternative choices for the policy variables $R(t)$, ξ, $R_{\min}$, $R_{\max}$, and R_{cutoff}. The $R(t)$ regulates the acceptable rate of development relative to long-term optimum fishing rate F_{opt}. The ξ sets an acceptable probability for short-term overfishing (C_t/B_t > optimum for year t only). The $R_{\min}$ and $R_{\max}$ set minimum and maximum ratios of fishing rate F_t to the optimum rate $R(t)F_{\text{opt}}$. The R_{cutoff} defines a biomass ratio B_t/B_0 such that the fishery will be closed if there is a probability of ξ or larger that the actual ratio is smaller than this ratio.

Simulation method for comparing policy options

A relatively simple simulation procedure can be used to estimate the loss functions (eqs. 3*a* and 3*b*). Define a grid of B_0 values over the range $B_{\min}$ to $B_{\max}$. For each B_0, calculate the reference catch trajectory $C_{\text{opt}}(t)$ and then perform a set of time simulations $t = 1,..., T$, with each simulation having random choices for β (uniform over the range $\beta_{\min}$ to $\beta_{\max}$) and v_t (normal with mean 0 variance 1.0, possibly autocorrelated to represent mixed process/observation error effects). For each simulated year t, (*i*) generate an abundance index Y_t from eq. 4 and use this in eqs. 5–9 to provide an updated estimate of the probability distribution for B_t, the ξ *C*-risk biomass $B_\xi(t)$, and the associated quota C_t, (*ii*) apply this C_t in the state dynamics relationships (eqs. 10–13) to provide updated conditional predictions $B_{B(0)}(t + 1)$ for all B_0 grid values (including the "true" value chosen for the simulation), and (*iii*) update estimated losses (eqs. 3*a* and 3*b*). Average the summed losses over trials to provide loss curves like Fig. 1, and average these over the prior probability distribution for B_0 to provide expected loss or risk for whatever $R(t)$, ξ, $R_{\min}$, $R_{\max}$, and R_{cutoff} policy is being evaluated.

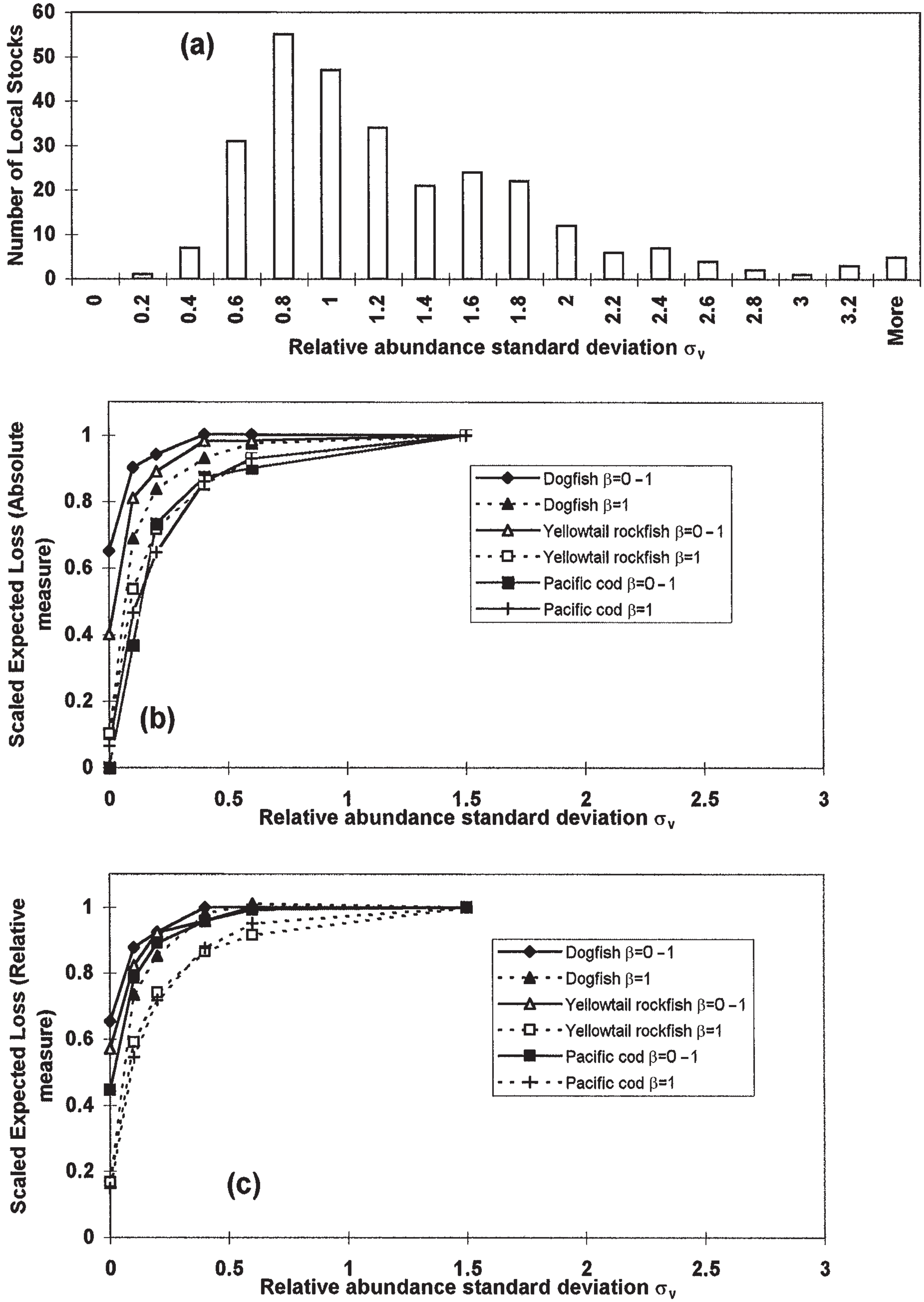
It only takes around 10 simulation trials for each B_0 to provide quite stable estimates of the loss "profiles" L_{abs} and L_{rel} versus B_0, provided $T \geq 20$. For 10 trials and $T = 20$, each profile takes less than a minute to compute with a Pentium PC. (Computing speed is an important consideration if many policy options ($R(t)$, ξ, $R_{\min}$, $R_{\max}$, and R_{cutoff}) are to be compared.) The procedure described above could be readily extended to represent somewhat more complex assessment methods such as use of Kalman filtering (Pella 1993; Schnute 1994) to provide better conditional estimates B_t given B_0 for situations where there is high process (recruitment) variation. However, I believe it is unlikely that such assessment methods will provide much more precise estimates of B_t than the method defined by eqs. 5–9, unless there is some method (as yet undiscovered) for providing really precise independent estimates of the recruitment anomalies w_t.

Results

I applied the closed-loop simulation procedure described above to a variety of British Columbia groundfish stocks for which there are developing trawl fisheries and that vary widely in longevity (F_{opt} ranging from 0.035 for spiny dogfish (*Squalus acanthias*) to 0.25 for Pacific cod (*Gadus macrocephalus*)). These patchily distributed, mainly long-lived species are quite representative of developing fisheries today, having escaped earlier attention by fishers for economic or technological (e.g., extreme depth) reasons. They are also typical of modern development situations in that existing trawl capacity is large enough to quickly generate high fishing mortalities, and a species-area quota management system was initiated in 1997 to manage the fishery better.

For the British Columbia data, patchy distributions and rapid changes in trawl targeting methods are reflected in typ-

Fig. 2. Frequency distribution of measured standard deviation of relative abundance indices (σ_v) for (*a*) British Columbia groundfish stocks compared with (*b* and *c*) simulated effect of increasing σ_v on expected 20-year loss for three British Columbia stocks representing a range in productivity and longevity: (*b*) absolute expected loss measure; (*c*) relative expected loss measure. Dotted lines show expected loss patterns if the relative abundance index is known to be proportional to biomass (β = 1), while solid lines show



higher loss expected if the abundance index may be hyperstable (β anywhere between 0 and 1 with equal probability). Each expected loss estimate was evaluated at best (minimum loss) choice for the overfishing risk probability ξ.

ically variable catch rate and survey abundance index data; based on fitting time series for various stocks to catch rate data using eqs. 5–13, σ_v values range from around 0.2 to over 3.0 (Fig. 2). Note that even the minimum σ_v in Fig. 2 is near the upper end of the range of observation error used in some recent evaluations of stock assessment methods based on relative abundance data (e.g., Polacheck et al. 1993; Chen and Andrew 1998). I have assisted with stock assessments for dozens of developing fisheries around the world, particularly in Mexico and Australia, and on the basis of this experience, I consider the σ_v pattern in Fig. 2 to be quite representative of developing fisheries in general. Values of $\sigma_v < 0.2$ give good visual fits to data, but are uncommon in development practice (Stanley 1992).

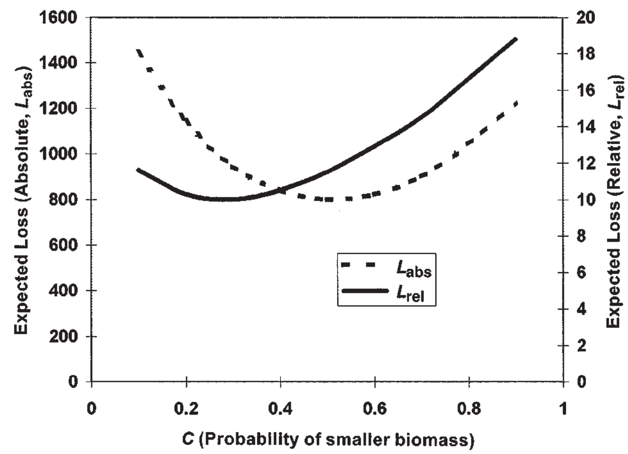
Figure 2 presents the most disturbing finding of this study. For a typical assortment of the British Columbia stocks, it shows how the minimum expected 20-year loss from eqs. 3*a* and 3*b*, averaged over prior probability distributions $P_0(B_0)$, varies with the abundance index standard deviation σ_v. Here the minimization is over choices of the acceptable overfishing probability ξ, so the results are optimal with respect to that policy choice. For these tests, I used a relatively rapid development objective (t_h = 3 years in eq. 2). The minimum risk ξ was found to be around 0.5 for L_{abs} in all cases examined and to be between 0.1 and 0.3 for L_{rel} for all cases, i.e., it is best to use certainty equivalent quota choices to minimize absolute loss but very risk-averse quota choices to minimize relative loss (as expected). Typical patterns of variation in expected loss with ξ are shown in Fig. 3; generally the "optimum" value of ξ is quite well defined once a choice between L_{abs} and L_{rel} has been made. The best choice of ξ is not sensitive to development rate as measured by t_h.

The disturbing result in Fig. 2 is that expected loss rises very quickly with σ_v, from a minimum set by how much damage can be done in even the first few years before any index data become available to a maximum where data gathered over the 20 years are so noisy as to have little impact on ability to reduce loss through improved assessment of B_t. Almost all of this increase in loss occurs over a range of σ_v less than even the minimum found in the British Columbia catch rate data; in other words, the catch rate and survey data that have been available so far are not good enough to have any significant impact on expected loss over the next 20 years.

The pessimistic pattern in Fig. 2 is not due simply to using too conservative a likelihood function, in particular assuming the possibility of severe hyperstability in relative abundance indices ($0 < \beta < 1$). The dotted loss lines in Fig. 2 show the effect of using simulated survey or carefully screened catch rate data for which it is safe to assume $\beta = 1$. This certainly helps for $\sigma_v < 0.5$, i.e., the dotted loss lines are well below corresponding lines calculated with $0 < \beta < 1$. But for the majority of the stocks for which σ_v are shown in the top panel, even knowing $\beta = 1$ would not make a substantial difference to expected loss.

The main reason why expected loss during development increases so rapidly with σ_v is that noise in the relative

Fig. 3. Variation in expected loss, averaged over the prior probability distribution for unfished biomass B_0, with choice of the overfishing risk probability ξ. The quota was calculated each year from the optimum fishing mortality rate for that year times the biomass estimate for which the probability was ξ that true biomass was lower than the estimate.

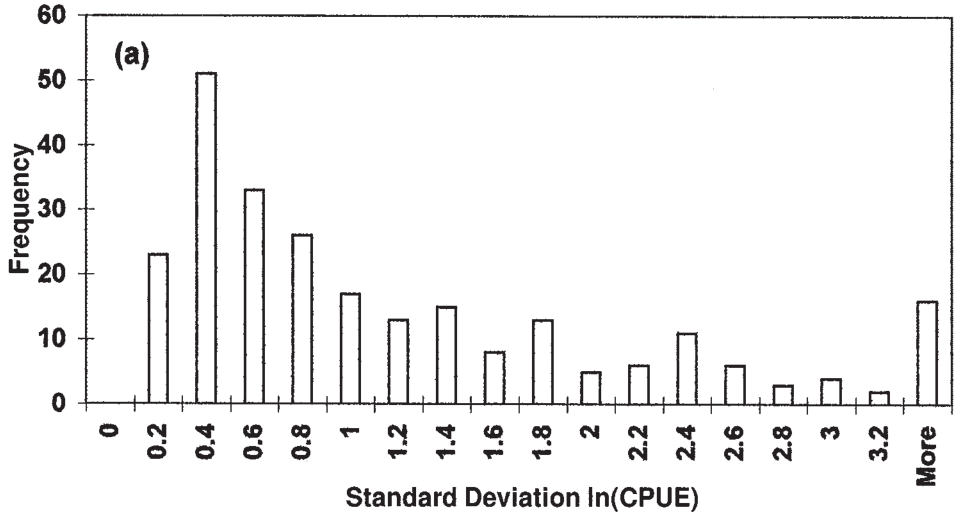


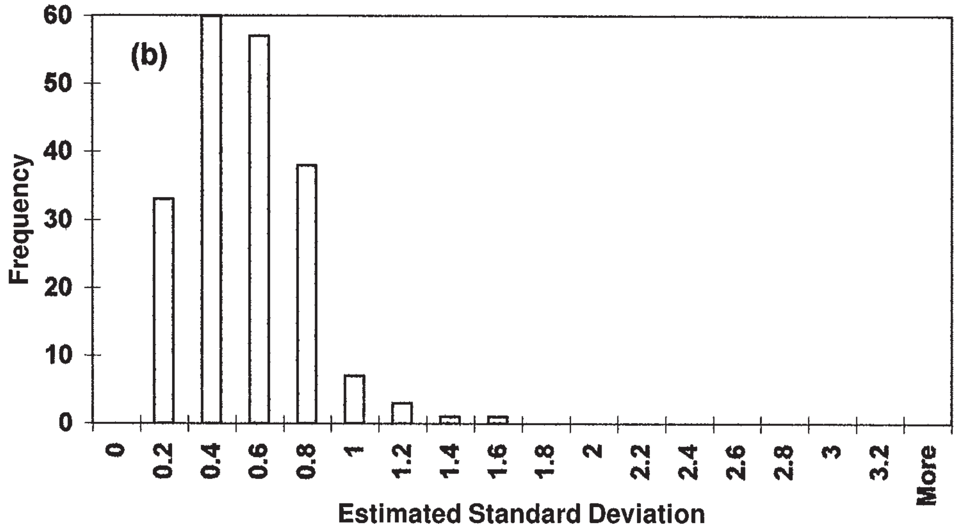
abundance indexing system causes delays in correctly estimating B_0 and hence B_t. Such delays can have a large cumulative effect on B_t through incorrect C_t choices.

This observation leads immediately to a question about whether to use a more "forgiving" loss measure, such as one proportional to $|B_\xi(t) - B_t)|$ rather than to $|B_\xi(t) - B_{opt}(t)|$, i.e., ignore cumulative effect of past errors on the difference $B_t - B_{opt}(t)$. We could use such measures for development planning, but we would in effect be saying "it is acceptable to make large quota setting errors early in development, so long as we eventually manage whatever B_t is left wisely." It is doubtful that conservation-oriented stakeholders would accept such arguments.

The distribution of σ_v in Fig. 2 is based on crude catch per effort data that are "contaminated" with process error (recruitment variation) effects and have not been subject to spatial analysis based on accurately georeferenced logbook catches. Figure 4 shows a distribution of σ_v estimates for the same British Columbia stocks but calculated from interannual variation in spatial mean catch rate from detailed logbooks ("exact" georeferences for every shot) that are available for 1994–1996 (around 18 000 shots per year). For each stock each year, the spatial mean catch rate was calculated by assigning shots to 1 square nautical mile grid blocks or strata and then taking the best estimate for each block to be an inverse-distance weighted average of the shot observations for the block and neighboring blocks within 3 nautical miles (Walters and Bonfil 1999). The details of this spatial statistics procedure are not of concern here; the point of Fig. 4 is that substantial variance reduction may be possible by "filtering" fishery data so as to correct for variations caused by changes in spatial distributions of fish and fishing effort, implying considerable value for management of insisting on detailed logbook reporting even in developing

Fig. 4. (*a*) Frequency distribution of measurement error standard deviation (σ_v) estimates for British Columbia groundfish stocks, based on spatial analysis of CPUE data from detailed 1994–1996 logbooks. Interannual variation in spatial mean CPUE is shown only for long-lived stocks that are likely to have had stable biomass over the 3-year period. (*b*) Variation in estimated σ_v expected by chance alone for such short time series.





fisheries. Results like Fig. 2 provide a direct way to estimate this value.

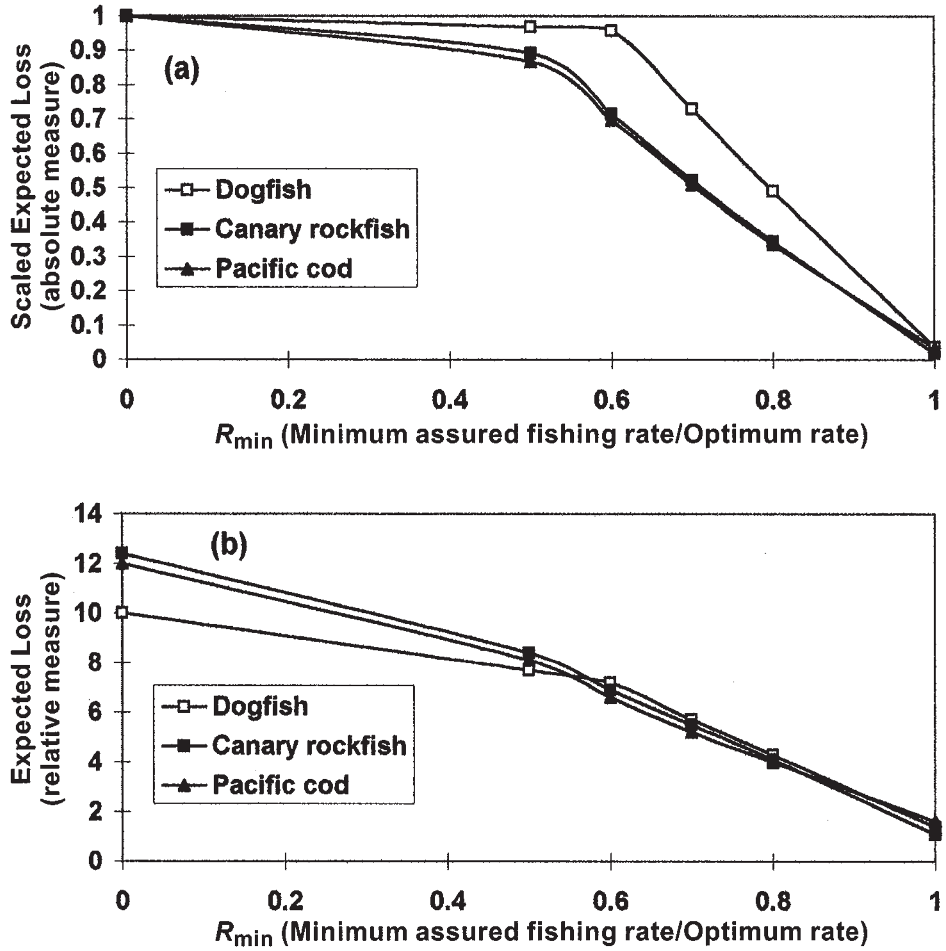
Another way to reduce apparent σ_v in situations like British Columbia groundfish is to aggregate the data over larger spatial areas; this practice usually results in smoother trends to which tighter model fits can almost always be obtained. It is a justifiable practice for highly migratory and dispersive species, but for relatively sedentary species, it can mask a variety of nonsustainable pathologies like sequential depletion of local substocks.

Narrowing the initial range of uncertainty: surveys to establish proven potential

Suppose fishers (or the public) were convinced to invest in an annual survey aimed at providing a minimum density estimate $(B/A)_{\min}(t)$ and a minimum estimate of the area $A_{\min}(t)$ currently occupied at density $(B/A)_{\min}$. A “floor” quota could then be set at $R(t)F_{\text{opt}}B_{\min}(t)$ with $B_{\min}(t) = R_{\min}B_t$, overriding the quota calculated from $B_\xi(t)$ in years when $B_{\min} > B_\xi$. Without asking whether it would be economical to survey so as to achieve high $R_{\min}$ (approaching 1.0), we can at least ask the question how big would $R_{\min}$ have to be to make substantial difference to expected loss during development. Figure 5 shows the effect of $R_{\min}$ on expected minimum loss for three representative British Columbia groundfish stocks, where as in Fig. 2 the minimum loss presented is with respect to choice of the overfishing risk ξ. Increasing $R_{\min}$ causes the optimum ξ to decrease, since there is no “cost” to using a more conservative ξ when surveys will assure that unduly low $B_\xi(t)$ estimates will not be used in quota setting.

Figure 5 implies that surveys to demonstrate minimum biomass are likely to have little impact on expected loss dur-

Fig. 5. Variation in expected loss, averaged over the prior probability distribution for unfished biomass and evaluated at best overfishing risk ξ, with increases in R_{min}, a minimum assured ratio of fishing rate each year to the optimum rate for that year. Higher values of R_{min} represent larger investments in surveys aimed at "proving" a minimum biomass (e.g., R_{min} = 0.5 means that surveys have demonstrated biomass to be at least 50% of its actual value). (*a*) Absolute loss measure; (*b*) relative loss measure.



ing development unless such surveys are intensive (accurate *B*/*A*) and extensive (*A* covered) enough to "prove" at least 50% of the actual stock size B_t. This is not a promising result, since it is unusual in fisheries to have density estimation methods capable of guaranteeing to see even half the fish (e.g., higher but unknown proportions typically escape survey trawls), and there is usually considerable ambiguity about the area occupied *A* (especially for parts of the stock range that are large but are occupied at low or very erratic densities). However, at least it is useful to know what standards that surveys for minimum stock size would have to meet in order to substantially reduce expected loss.

Effect of setting upper bounds on fishing mortality with marine protected areas

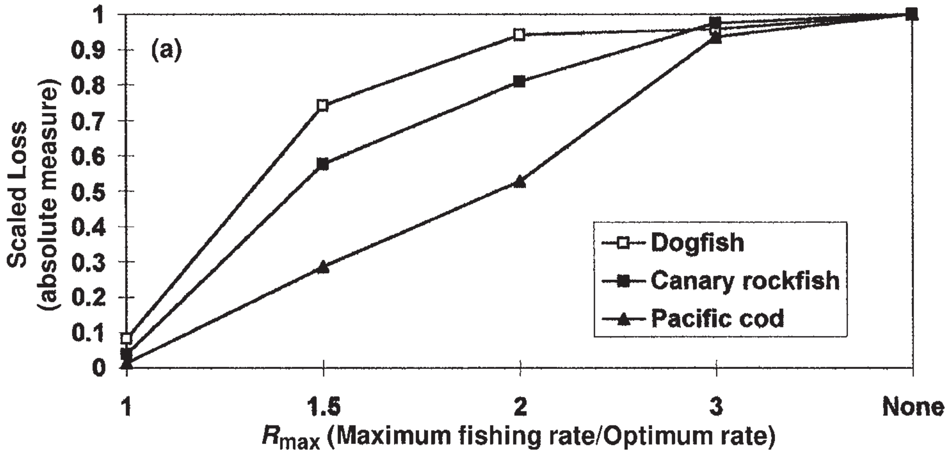
At the opposite extreme from surveys for proven production potential, suppose fishery regulators elect to close large enough areas during the development so as to insure that fishing mortality rate F_t cannot exceed $R_{max}F_{opt}$. The question then becomes how small would R_{max} have to be in order to substantially reduce expected loss during development. Note that if F_{opt} is small in the first place (e.g., around 0.05 for many long-lived rockfish in British Columbia), then even guaranteeing $R_{max} = 2$ ($F < 0.1$) might have to involve closing 90% of the grounds to fishing every year.

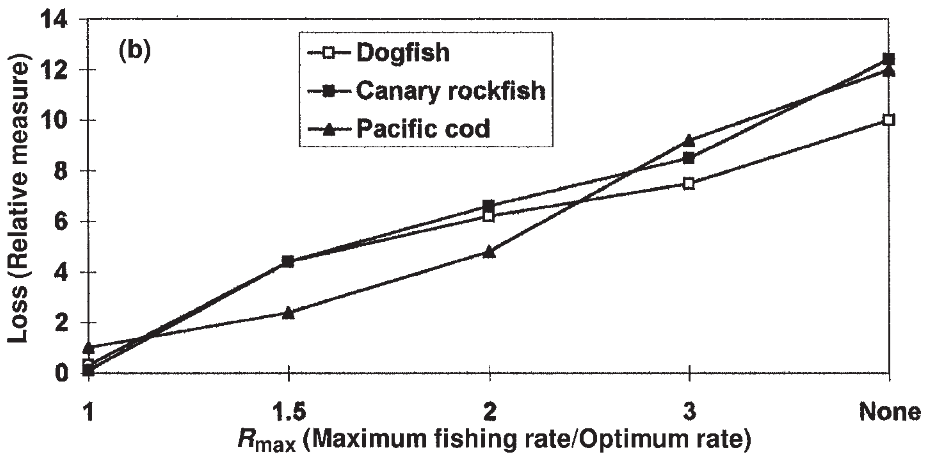
If $R_{max} = 1$, closed areas "guarantee" that fishing mortality rate cannot exceed optimum, and the only losses as measured by eqs. 3*a* and 3*b* can be due to setting an unnecessarily low fishing rate by basing quota decisions on a low-ξ biomass estimate. Hence, for R_{max} near 1.0, the best ξ policy is $\xi = 1.0$, i.e., ignore the probability distribution for biomass B_t. Then as R_{max} is increased (progressively larger open areas that could allow F_t to exceed F_{opt} by progressively larger proportions), the optimum ξ decreases and expected loss evaluated at the best ξ increases (Fig. 6). The pattern of increase is not sensitive to stock productivity characteristics or loss measure, and a robust prediction is that R_{max} exceeding 3.0 (areas open to fishing large enough to allow $F > 3F_{opt}$ in event of bad a overestimate of biomass) provides essentially no protection in terms of reduction in expected loss. In short, the results in Fig. 6 indicate that marine protected areas must be very large indeed to provide a significant hedge against losses for unproductive stocks.

Is progressive exposure a wise strategy?

There are a variety of reasons for insuring that fisheries

Fig. 6. Variation in expected loss, averaged over the prior probability distribution for unfished biomass and evaluated at best overfishing risk ξ, with increases in R_{max}, a maximum assured ratio of fishing rate each year to the optimum rate for that year. Assuring low R_{max} values would generally have to involve large closed areas (exposing only a low proportion of the stock to risk of capture). (*a*) Absolute loss measure; (*b*) relative loss measure.





develop slowly ($R(t)$ increases slowly toward 1.0), beyond just making sure that assumptions of equilibrium catch–effort models are not violated too badly. Is slowing down development sufficient to insure that enough data are gathered for reliable assessment of B_t, without incurring unacceptable losses along the way? Absolute loss as defined in eq. 3*a* certainly is reduced by reducing $R(t)$, whether or not accurate assessment ever becomes possible (lower catch goals mean lower absolute loss in general). But can the relative or "ecological" loss be reduced substantially by slowing development? To answer these questions, I ran a series of expected loss calculations for the same British Columbia stocks as in Figs. 5 and 6, assuming relatively uninformative relative abundance data ($\sigma_v = 0.5$, $\beta = 0–1$) while varying t_h in the calculation of $R(t)$. I also tried using two distinctive values for t_h: a base "stakeholder concensus" value for assessment of $C_{opt}(t)$ and a larger (more conservative, slower development) value for calculation of annual simulated quotas. For all cases, I sought the minimum expected loss achievable over choices of the overfishing risk ξ.

I found no evidence of substantial decrease in expected relative loss (L_{rel}) from slowing development (high t_h) or from using a more conservative t_h for annual quota setting than for setting the reference catch development trajectory. For the more productive stock examples (Pacific cod, canary rockfish (*Sebastes pinniger*)), there was a very slight decrease (3%) in L_{rel} for slower development and a similar slight decrease in L_{abs} for larger t_h values. Increasing t_h generally causes the best choice of ξ to increase (no gain from being doubly conservative). Increasing the time planning horizon (T = 40 years instead of 20 years) did not reveal more substantial long-term benefits of initial caution in development. There are at least two reasons for these discouraging results: (*i*) slowing development slows the process of learning about B_0, quite a different effect than slowing development in order to avoid violating equilibrium assumptions of catch–effort assessment methods, leading to larger average errors in quota setting later in development and (*ii*) increasing "opportunity loss" due to taking lower quotas than would (on average) be safe (slow development does reduce odds of immediate overfishing for low B_0, but also leads to underfishing for higher B_0 values).

Is it critical to have a conservation limit B_t/B_0 below which fishing is stopped?

A potentially contentious issue in planning is whether to include a contingency rule for stopping the fishery in the event that assessment methods indicate high odds that B_t/B_0 is too small. While it would seem only responsible to stakeholders concerned with conservation to make sure that planning is "up front" about this contingency, other stakeholders may misinterpret discussions about such rules as an attempt to sneak unnecessary closures into the plan.

Using the same stocks and measurement assumptions as in the previous subsections, I tested the effect on expected loss of various values between 0 and 0.5 for the cutoff ratio $R_{cutoff} = B_\xi(t)/B_\xi(0)$ below which simulated quota was set to 0. Somewhat surprisingly, R_{cutoff} values > 0 generally resulted in increasing loss by both the absolute and relative measures. The increasing loss occurs because there is a good chance that any particular application of the rule (at any particular time t, risk level ξ) will be the incorrect thing to do (set C_t to zero when it need not be), and such losses more than compensate for instances when relief from fishing helps put the stock "back on track" (nearer the optimum biomass trajectory $B_{opt}(t)$). Hence, it may be unwise to risk stakeholder distrust by putting much planning emphasis on good choice of R_{cutoff}.

Discussion

There are two very different viewpoints about investment in information gathering during fishery development. One is that information gathering should roughly recapitulate the history of stock assessment modeling: start first with catch–effort data and models and then move toward more detailed age-structured analyses. This view is justified by the idea that some development should occur to prove economic potential, before substantial research and assessment are justifiable. The opposite viewpoint is that the most important scientific investments, in analysis of productivity (F_{opt}), bounds for biomass, and sound indices of relative abundance, are most important at the outset of development (e.g., FAO 1995). This paper has concentrated mainly on predictions about performance of the second approach because we have much experience in fisheries that suggests that the first approach is unreliable and because the sort of slow, progressive, and relatively "safe" economic development that it assumes is just not how modern fisheries develop. The second view also reflects the frustration that many of us have felt when working with the "one-way trip" data obtained during typical historical developments (Hilborn and Walters 1992), where assessment results can be highly sensitive to the first few data points, which we usually cannot trust.

Losses can be large during fishery development, even if development is "front loaded" with investment in research to provide biomass bounds and a good estimate of the optimum fishing rate. The value of initial investment can be negated by inadequacy of trend index data used for ongoing assessment. Still, potential for high loss should not be used as an excuse for development to proceed as a free-for-all, with scientists having to base assessments only on crude catch and effort statistics. Management for sustainability is an investment for all concerned (Troadec 1989).

It is particularly worrisome that for many fisheries, there may be no practical way to reduce σ_v into the 0.1–0.2 range where assessment becomes really helpful at reducing losses. High variance in catch rate and survey series is common even when the data have been carefully analyzed to account for gear effects, spatial density patterns, and other causes of variation in relative abundance. For fisheries that are developing today, unpredictability in spatial distribution and availability to both survey and fishing gear may be the norm rather than the exception (the predictable fishing opportunities have long since been developed). But we also see high σ_v even in apparently well-understood situations like the northern Atlantic cod (*Gadus morhua*) stock off Newfoundland (Hutchings 1996), and coefficients of variation for biomass estimates based on trend data are generally >0.25 (Punt and Butterworth 1993). In some circumstances, it may be possible to substantially reduce losses by using age-structured data and assessment methods (NRC 1997; Punt 1997), but even these methods are vulnerable to high σ_v and $\beta \neq 1.0$ (Patterson and Kirkwood 1995).

Could it be that the rather dismal track record of fisheries assessment and management worldwide is due at least in part to not recognizing the fundamental weaknesses in assessment information suggested by Fig. 2? Certainly the published literature on fisheries assessment methods has been highly selective; we tend to publish case examples with relatively low random variation, where the methods at least appear to work. Has this selective process led fisheries managers to expect too much from our assessments and to assume that the methods have been working when in fact they have contributed to overfishing by providing excuses not to take precautionary measures like large marine protected areas? Particularly in relation to quota management, it certainly does not appear that fishery managers have yet started to heed warnings like Walters and Pearse (1996) about the dependence of output control performance on stock assessments and the difficulty (and expense) of obtaining accurate enough assessments to make output controls effective.

The most disappointing results above are not those about risk of poor assessment performance, but rather about efficacy of measures to reduce impact of assessment errors (surveys for proven production potential R_{min}, protected areas to limit fishing mortality R_{max}, and contingency plans for severely depleted situations R_{cutoff}). Unless innovative methods to reduce survey costs are found, it may be unusual for fishery stakeholders to invest enough to insure $R_{min} > 0.5$. Likewise, protected areas and related measures severe enough to insure $R_{max} < 3.0$ are not economically palatable, at least for species where F_{opt} is low in the first place. Figures 5 and 6 suggest that it will often be best to invest in improved information gathering for assessment, rather than "backstop" measures.

What should scientists advise fisheries stakeholders about the best investments to make prior to fisheries development? There are two basic options for reducing expected losses due to stock assessment errors: (*i*) spend more before development starts, to narrow the range of possible unfished biomasses (reduce the B_{max}–B_{min} range) and (or) (*ii*) spend more as development proceeds, to provide better indices of change in relative abundance (smaller σ_v) and (or) higher estimates of proven production potential (R_{min}). We could provide much better advice about how to trade off between these assessment investment options if we could better quantify the relationship between B_{max}–B_{min} and exploratory survey effort and the relationship between routine survey effort and σ_v. Unfortunately, we cannot safely estimate these relationships from statistical quantities like sample size for which unit costs can be readily assessed; variances actually achieved are often larger than expected from such quantities, implying important sources of variation that are not easy to anticipate in survey design (e.g., interannual variation in proportion of stock “exposed” in the survey frame, variation in survey efficiency due to seasonal changes in spatial aggregation patterns).

For developing fisheries on species that are not highly migratory or dispersive, perhaps we should be seeking development policies that make better use of spatial structure and “replication” of local development opportunities so as to treat development as a sequence of local depletion experiments (e.g., Walters and Collie 1989). Many populations consist of relatively isolated subpopulations, and progressive development across such subpopulations can provide much information on parameters like survey catchability without exposing too large a fraction of the overall stock to overfishing risk early in development. The main barrier that needs to be overcome to make such policies practical is in fact an attitude, among fishers and some managers, that freedom of movement and fishing location choice are a basic right.

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