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Methods For Assessing Harvest Rules For Fraser River Sockeye Salmon

Méthodes d'évaluation des règles de pêche du saumon rouge du fleuve Fraser

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Abstract

This paper is part of a long-term initiative to review and revise the management of Fraser River sockeye salmon. The Fraser River sockeye spawning initiative began in early 2002, and has since evolved through a series of workshops and feedback from stakeholders. In this application of formal policy analysis, we develop a quantitative modeling tool for assessing harvest rules for Fraser River sockeye salmon given conservation needs and other management objectives. The quantitative model allows stakeholders to assess objectives in a consistent framework. Through a series of different simulation runs, optimal exploitation rates at different abundance levels can be explored, given assumptions about stock dynamics and preferences for different objectives. This paper describes the details of the modeling methodology, illustrates the range of possible analyses for two example stocks (Chilko, Quesnel), and summarizes the results of preliminary sensitivity analyses using specified performance measures. The estimated optimal exploitation rate for a particular stock or stock aggregate depends on the underlying population dynamics model and the objectives being optimized. By performing a large number of simulations using different assumptions, the sensitivity of model performance to assumptions is assessed. The modeling tool was developed to allow users easy selection of options depending on assumptions and different choices he or she is willing to explore.

Résumé

Ce document s'inscrit dans un programme à long terme d'examen et de révision de la gestion du saumon rouge du fleuve Fraser. Le projet de reproduction du saumon rouge du fleuve Fraser a été entrepris au début de 2002 et a évolué depuis grâce à une série d'ateliers et aux commentaires des parties intéressées. Dans cette analyse officielle de l'orientation stratégique, nous élaborons un outil de modélisation quantitative pour évaluer les règles de pêche du saumon rouge du fleuve Fraser à la lumière des besoins de conservation et d'autres objectifs de gestion. Le modèle quantitatif permet aux parties intéressées d'évaluer les objectifs de façon cohérente. Il est possible d'étudier les taux d'exploitation optimaux pour différents niveaux d'abondance, selon diverses hypothèses de la dynamique du stock ou divers objectifs, en effectuant une série d'essais de simulation différents. Ce document présente de façon détaillée les méthodes de modélisation, illustre l'éventail des analyses possibles pour deux stocks (lacs Chilko et Quesnel) et présente un résumé des résultats des analyses préliminaires de sensibilité à l'aide de mesures de performance données. Le taux d'exploitation optimal estimé pour un stock ou un stock combiné donné dépend du modèle de dynamique des populations sous-jacent et de l'optimisation des objectifs. La sensibilité du modèle aux hypothèses est évaluée en effectuant un grand nombre de simulations fondées sur différentes hypothèses. L'outil de modélisation a été conçu de façon à permettre à chaque utilisateur de choisir facilement des options d'après différentes hypothèses ou choix qu'il est prêt à étudier.

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1 Introduction

This paper is part of a long-term initiative to review and revise the management of Fraser River sockeye salmon. The Fraser River sockeye spawning initiative began in early 2002, and has since evolved through a series of workshops and feedback from stakeholders.

In this application of formal policy analysis, we develop a quantitative modeling tool for assessing harvest rules for Fraser River sockeye salmon given conservation needs and other management objectives. Harvest rules generally specify target exploitation rates over a range of stock abundance levels, but can also be expressed as target escapement levels.

This modeling framework is intended to help assess the following questions:

- For each stock and stock aggregate, what are the optimal harvest rules given different management objectives and assumptions about population dynamics?
- How does performance compare between mixed-stock and selective fisheries?
- How do assumptions about potential cycle line interactions affect the optimal harvest rule?
- What are the implications of assumed conservation limits?
- What is the value of adaptive learning about stock characteristics and limits of capacity?
- How sensitive is the model to biases in stock-recruitment (S-R) parameter estimation?
- What is the expected effect of different future patterns of productivity and survival?
- How can annual fluctuations in catch be reduced?

The details of the rationale for the analysis are specified in the *Request For Working Paper* developed collaboratively between regional DFO resource managers and science staff (Appendix 1). Essentially, the quantitative model allows stakeholders to ask these questions and assess them in a consistent framework. Through a series of different simulation runs, optimal exploitation rates for a range of abundance levels can be explored, given different assumptions about stock dynamics and preferences for different objectives.

This paper describes the details of the modeling methodology, illustrates the range of possible analyses for two example stocks (Chilko and Quesnel), and summarizes the results of preliminary sensitivity analyses. It includes neither comprehensive sensitivity analyses nor recommended policy options. As part of the future analyses, stakeholders will be asked to provide feedback on all the components of the framework through workshops and consultation. Specific questions include:

- Which policies and objectives would you like explored?
- Which performance measures are most important to you?
- Does the model have the features or characteristics that would allow the technical group to model the Fraser system as you believe it to be?

The analysis follows four distinct steps:

1. *Capture management objectives* for Fraser River sockeye in a quantitative form useful for the analysis. This includes performance measures, benchmarks or reference points, and penalty weights for specifying preferences in a multi-attribute value function.

2. *Capture the population dynamics* of Fraser River sockeye in a quantitative form useful for the analysis. This step includes testing different S-R models and capturing parameter uncertainty using Bayesian inference.

3. *Solve for the optimal harvest feedback policy* (i.e. harvest rule) using simulation-estimation methods for policy optimization. Using the inputs 1 and 2 above, estimate the optimal exploitation rates over a range of stock sizes in a simulated fishery. More specifically, the model estimates the optimal harvest rule given uncertainty in the population dynamics represented by the Bayes posterior parameter distribution. It should be noted that throughout this document we refer to the term *harvest rule* and it is intended to be synonymous with the concept of exploitation rate and exploitation rate curve. These terms are well defined in fisheries literature and we do not feel it necessary to re-address their definitive meanings in this document.

4. *Evaluate the performance*. The optimal harvest rule determined in step 3 is applied either in a retrospective analysis or forward Monte Carlo simulations and summary performance measures are calculated.

The estimated optimal exploitation rate for a particular stock or stock aggregate depends on the underlying population dynamics model and the objectives being optimized. By performing a large number of simulations using different assumptions, the sensitivity of model performance to assumptions is assessed. The modeling tool was developed to allow users easy selection of options depending on assumptions and different choices he or she is willing to explore.

With the signing of the Pacific Salmon Treaty in 1985, a strategy was designed by Fisheries and Oceans Canada (DFO) to increase annual escapements incrementally from historical levels as part of a plan to increase the long-term economic value of the resource. The "Rebuilding Plan", as it came to be known, was implemented in 1987 (FRAP-FMG 1995), and was designed as an experiment for adaptive learning about stock characteristics, wherein short-term economic gains were foregone to increase the long-term value of the catch. The DFO task force evaluated historical catches, S-R relationships, spawning capacity and lake-rearing capacity to conclude that total returns of about 30 million Fraser River sockeye are possible. Interim goals between escapements observed at the time and optimal escapements were defined based on the available information and professional judgment (e.g. Table 1). These interim goals were set for individual cycle lines to account for recent escapement levels and make off-cycle targets more feasible. Rebuilding strategies, in the form of target harvest rates were evaluated individually for each cycle, based on average returns-per-spawner. Evaluation criteria for rebuilding options included:

- Net present value of projected Canadian commercial catch over 40 years
- Impact of harvest reductions on first cycle
- Effect of rebuilding one stock on other stocks

Results showed that reduced harvest rates ranging from 60 to 70% (compared to the observed 80-90%) on dominant stocks should bring the stocks to target levels within a few generations.

Accordingly, a plan was developed which identified:

- Lower bounds for annual target escapement designed to maintain escapements above brood year levels for Early Summer, Summer and Late Run aggregates.
- Lower bound for annual target escapement on the Early Stuart aggregate fixed at 66,000 spawners and then revised to 75,000 spawners through consultations.
- Upper bounds on annual target escapement for all aggregates based on a 65% exploitation rate ceiling.

A basic premise of the rebuilding plan was to increase escapements each year beyond brood year levels to maintain an increasing rebuilding trajectory towards interim escapement targets. The initial plan also specified exploitation rates for the first cycle of rebuilding. In subsequent years maintaining brood year escapements served as a lower bound for escapement planning. In periods of high or increasing survival, these escapement targets can be met with little short-term economic losses. To meet rebuilding targets during years of low survival, a higher fraction of the run is allocated to escapement rather than catch.

This implementation plan guided escapement management from 1987 to 2002. Despite the 15 years that have passed since its inception, the economic value of the resource didn't respond as hoped. Numerous factors contributed to this:

- Productivity fluctuated considerably, and has shown a marked decrease in recent years.
- Harvest opportunities on abundant and productive stocks were constrained by less productive or less abundant stocks intercepted in the same fisheries.

- Market conditions declined.

Since the Rebuilding Strategy was implemented, several challenges were identified through the consultation processes. Due to the wide range of available estimates of production potential, some stakeholder groups disagreed with the specified long-term and interim escapement goals. Some considered them too high, others too low. Similarly, stakeholders voiced their concerns that the prescribed rate of rebuilding was either too slow or too ambitious. Others pointed out that managing for a strictly increasing rebuilding trajectory is unrealistic under changing productivity levels. For example, if productivity declines then catches must decline proportionally to maintain the rebuilding trajectory. These fundamental disagreements among stakeholders were probably due to differing emphasis on the various management objectives, and differing value judgments regarding the trade-off between short-term and long-term benefits. Additional concerns were expressed regarding in-season implementation. The reactive response to changes in in-season run-size estimates increased uncertainty for harvesters and affected the overall performance of the escapement strategy. In summary, support for the rebuilding plan, as conceived in the 1980s, has diminished due to the recent decline in commercial catches, difficulty of accommodating multiple objectives, and the constraints of a strict rebuilding schedule.

The proposed approach is in many ways similar to the current escapement planning:

- Target exploitation rates (and hence catch, escapement) vary with estimated run size.

- Constraints on harvest rules may include a minimum run size with zero harvest, a maximum exploitation rate for aggregates to protect small co-migrating stocks with lower productivity, and possibly an escapement ceiling for individual stocks.

We are proposing several key modifications in this initiative, to address the challenges and concerns identified while implementing the Rebuilding Plan:

- Develop escapement plans based on optimal (target) exploitation rates rather than fixing target escapement derived from highly uncertain estimates of optimal escapement.

- Don't prescribe a strictly increasing rebuilding trajectory, (i.e. remove the constraint of not going below brood year escapement) but rather, balance the trade-off between catch and escapement in an objectives-based approach that considers the preferences of stakeholders.

With an approach based on target exploitation rates, it is not necessary to set annual escapement targets. The harvest rule directly responds to the best available run size estimates. However, heightened in-season reaction can lead to more variable target exploitation patterns than planned pre-season. Therefore, clear implementation guidelines for using this feedback policy in combination with changing run-size estimates need to be developed to avoid pressures to veer from established pre-season management rules.

2 Methods

2.1 Model Overview

The flow diagrams in Figures 1-4 show the steps and system components of the modeling framework. Figure 1 shows the overall, two-step process. Step 1 simulates the entire fishery system given assumptions and stakeholder preferences and estimates the optimal harvest rule using policy optimization techniques. Step 2 evaluates the performance based on key indicators by simulating the effects of applying the optimal harvest rule.

Figure 2 shows the detailed inputs and outputs at each of the two steps shown in Figure 1. The primary inputs in Step 1 are the management objectives that capture stakeholder preferences, and the stock dynamics that capture uncertainty in both the S-R model structure and the parameter estimates for each model. Stakeholder preferences are represented in an objective or value function. The value function can be modified by choosing different penalty weights to express different management priorities. The current model has options for three S-R relationships to account for different assumptions about cycle interaction. Uncertainty in the S-R model parameters for each S-R model is captured using Bayesian inference. The outputs from Step 2 are the values of the performance measures.

Figure 3 shows the details of the two-step, simulation-estimation process. Each input scenario specifies a S-R relationship and a value function. A systematic subsample of S-R parameter sets from the joint Bayes posterior distribution is used to represent the uncertainty in S-R parameter estimates for each stock. Annual catches and escapements resulting from harvest are simulated for each sampled S-R parameter set. The optimization routine iteratively simulates the fishery system with a new series of trial harvest rules and solves for the optimal harvest rule that maximizes the value function. Forward simulations can have multiple trials for each S-R parameter set. Each trial represents a single, probable realization of simulated time series of catch and escapement resulting from stochastic residual variation the S-R residuals. The mean of the value function is calculated over all S-R parameter sets and trials. The optimization routine, depicted in Figure 4, then solves for the optimal harvest rule that maximizes the mean of the value function across all S-R parameter sets and trials. Model choices that affect the harvest rule include the S-R model structure, form of the value function (linear versus non-linear), penalty weights for the value function and harvest rule shape. Two options for curve shape can be specified: 1) a sigmoid curve with a moderately descending limb and harvest potential at low run sizes, and 2) a sharply descending curve and zero harvest at low run sizes. Sections 2.3 to 2.7 describe the details of the simulation-estimation process. Appendix 2 contains a glossary of technical terms. Appendix 3 summarizes the notation used.

Schnute et al. (2000) examined a two-dimensional policy that results in contours of policy outcomes (i.e. scores of the value function) over a grid of incremental escapement targets and harvest fractions of surplus above the target. In their simulations, concepts of the precautionary approach were introduced because harvest rates were set to zero if the spawning escapement for any of the stocks fell below a specified target level. A more realistic multi-dimensional policy space was evaluated here, where the output is an optimal feedback harvest rule, specifying target exploitation rates as a function of run size. The extent to which the policy is precautionary is built into the objectives of the value function. In this analysis a high penalty weight can be assigned if spawning stock size falls below some benchmark. Ultimately, the penalty assigned will depend on expressed preferences for avoiding an undesirable event.

The model has the ability to do both forward and retrospective simulations. Retrospective simulations are appealing because they preserve the historical recruitment pattern so that alternative harvest rules can be directly compared to the performance of historical policies. However, there may be unique features in the observed time-series which could bias the optimal harvest rule. Forward simulations are useful for assessing stochastic effects beyond the range of historical observations, and provide the flexibility to test different assumptions about patterns of productivity changes. In this paper, only forward simulations are applied. The details are described in Section 2.4.

Simulating mixed-stock fisheries (Section 2.4.3) introduces additional complexities to deal with among-stock correlation and stock specific-performance evaluation. In the value function, some attributes are more appropriate for the aggregate (i.e. catch); whereas others need to be assessed for each component population (e.g. penalty for low stock size) and may even require different weights.

2.2 Data Sources

The primary data that describe the population dynamics are the estimates of annual spawning escapement and the number of adult progeny that are caught in fisheries or survive to spawn. Escapement is estimated directly using systematic surveys of the spawning population. Estimates of the catch removed from each stock and estimates of escapement are combined to estimate the total abundance of returning sockeye in a given year. The stock-recruitment data used in the analysis are maintained in a Microsoft Access database compiled by the Pacific Salmon Commission. Data for Chilko and Quesnel sockeye are listed in Appendices 4 and 5.

With increasing frequency in the 1990s there were large discrepancies between estimates of sockeye in the lower Fraser River measured at the hydro-acoustic site at Mission, B.C. (Banneheka et al., 1995) and estimates of the population at the spawning sites plus in-river catch above Mission. The discrepancies potentially arise from estimation error, unreported catch, and en-route mortality from adverse environmental conditions (MacDonald, 2000; MacDonald et al., 2000). Discrepancies are assumed to be real and therefore the recruitment data used in the stock-recruitment analysis includes an estimate of the discrepancy.

Since the late 1930s, escapements have been estimated annually for most of the individual spawning populations in the Fraser River watershed. Over 150 individual populations have been identified. The catch and spawning escapement data for these populations has historically been grouped into about 20 stocks for management purposes. Each stock is defined by: 1) the natal lake or stream, and 2) the migratory timing pattern of returns to the natal area within a year. For management purposes, stocks are further aggregated into four timing groups (Early Stuart, Early Summer, Summer and Late run) based on their peak date of abundance in coastal fishing. Each run timing group consists of one or more stocks. The timing distributions of the four timing groups overlap and cannot be harvested independently except in terminal areas near individual spawning sites. The present simulation model accommodates 12 stocks for which escapement and catch by brood year has been routinely measured since 1948. For purposes of this framework, the analysis is confined to spawning escapement and recruitment data for the two Summer run stocks: Chilko and Quesnel. In the future, if the model will be utilized in a 'gaming' context to aid policy development, the dataset needs to be updated to include other, less frequently sampled stocks and the most recent years of data available.

2.2.1 Spawning escapement data

Quesnel Lake sockeye spawn in about 22 tributaries of Quesnel Lake as well as near-shore areas in Quesnel Lake itself. Quesnel sockeye abundance has persistently fluctuated with a 4-year cycle (Figure 5). During the 1980s and early 1990s, returns of Quesnel sockeye averaged 1.1 million fish per year and peaked at 12.1 million in 1989. Chilko Lake sockeye mainly spawn in the Chilko River but also at various beach locations in Chilko Lake (Schubert 1998). Returns of Chilko sockeye averaged 1.3 million sockeye per year. Chilko sockeye do not exhibit persistent cyclic fluctuations (Figure 5).

Between 1937 and 1985, the International Pacific Salmon Fisheries Commission (IPSFC) was responsible for estimating spawner abundance at spawning sites in the Fraser watershed. Experimental work developed during the early years of the IPSFC led to a two-tiered approach for estimating escapement (Atkinson, 1944; Howard, 1948; Schaefer, 1951). Methods used by the IPSFC are described by Woodey (1984). For small populations (<25,000 fish), visual techniques were applied. For larger populations the estimates were based on mark-recapture experiments and to a lesser extent fence counts. With the signing of the Pacific Salmon Treaty in 1985, DFO assumed the responsibility and has generally followed the approach developed by the IPSFC (Schubert, 1998).

Visual surveys are either ground or aerial-based and are the least accurate of methods used to estimate salmon spawning escapement. Typically, visual surveys underestimate the known abundance based on fence counts by 2-12 times (Symons and Waldichuk, 1984). Expansion factors for Fraser sockeye have been developed by comparing visual estimates to known fence counts in an attempt to account for the bias in visual estimates (Woodey, 1984; Schubert, 1998). Schubert (1998) reports a factor of 1.8 has been used for Fraser sockeye to expand visual count data. Estimates of total escapement were calculated for river and lake spawning stocks as the product of the maximum daily count of live spawners, the cumulative recovery of carcasses to the day of peak live count and the expansion factor. In glacial systems or lake populations where live fish cannot be observed directly, escapement estimates were the product of the total carcasses recovered and an expansion factor that assumed that each person-day of survey effort recovered 5% of the population. For most populations, however, the reliability of visual survey estimates has not been verified and the uncertainty in accuracy and precision of the estimate is unknown but assumed to be large. Fence counts are considered the most reliable, but are used at relatively few locations for logistical and budgetary reasons (Schubert, 1998). Errors in fence counts result from counting/measurement errors, for example, if the fence is breached or damaged from obstructions or high river discharge.

Mark-recapture estimates are potentially positively biased as a result of tag shedding, tagging induced mortality and abnormal behavioral effects of tagged fish. In comparative studies on the Stellako River, mark-recapture estimate had estimation errors ranging from –1% to 18% compared to the fence counts (Schubert, 2000). This error is less than the error reported in other studies where errors of 2-3 times were typical (Simpson, 1984).

Sampling at the spawning sites provides estimates of the number of precocious males (jacks) and non-jack males and females. Female carcasses are sub-sampled to estimate the proportion of female spawners that contributed to spawning based on estimates of eggs retained in the sampled carcasses. The latter are categorized as "effective females".

In some stocks, anomalously low spawning success has occurred in some years as a result of high pre-spawning mortality. For example, estimated effective females for Chilko sockeye in 1963 only constituted 38% of the total female population. High pre-spawning mortality of Chilko sockeye in 1963 was associated with high water temperatures and anomalous early river entry (Anon., 1964). The two stocks showed slightly differing rates of spawning success over the 48 year time series (Chilko: mean=91% (SD 12%); Quesnel: mean=82% (SD 21%)). The Chilko stock has been much more stable and accordingly has a much smaller standard deviation. These differences are also reflected in the proportion of each time series below specific rates of spawning success:

<90% success: Chilko – 27%, Quesnel – 44%
<75% success: Chilko – 10%, Quesnel – 25%
<50% success: Chilko – 2%, Quesnel – 13%

2.2.2 Catch data

The historic catch estimates from commercial fisheries are based on landing records on fish tickets from U.S. fisheries and dock tallies and fish sales from Canadian fisheries. The Pacific Salmon Commission (PSC) and formerly the IPSFC were responsible for estimating the catch by age and stock (Woodey, 1987; Gable and Cox-Rogers, 1993). Historically, the contribution of individual stocks has been estimated mainly by comparing freshwater growth patterns on scales from catch samples with the pattern from stocks of known origin, based on samples from spawning sites (Henry, 1961; Gable and Cox-Rogers, 1993).

Catch estimation errors of individual stocks in the historical database are the result of insufficient discrimination in scale patterns among stocks, unrepresentative sampling of the catch or spawning sites, or incorrect assumptions about the stock mixture used in the assessment models (Cass and Wood, 1994; Gable and Cox-Rogers, 1993). Biased estimates result from misallocation of the catch of one or more stocks in a mixture to other stocks in the mixture. The bias is larger for small stocks because proportional errors in large stocks within a mixture result in larger absolute errors in catch of small stocks. Catch allocation bias overestimates the abundance and productivity of small populations in years when catch allocation is based on scale growth patterns.

Other information used in stock discrimination include differences in age and size composition and historical data on run timing and spawning ground arrival data (Gable and Cox-Rogers, 1993). The accuracy and precision in estimates of catch by stock depends on the number and size of stocks in the catch mixture and the uniqueness of scale patterns. The latter vary depending on variable annual juvenile growth conditions such as juvenile density (Goodlad et al., 1974).

Scale pattern analysis has been supplemented in recent years using parasite and genetic differences among stocks (Bailey and Margolis, 1987; Beacham et al., 1987). DNA-based methods for identifying individual stocks in mixed stock fisheries have improved stock identification accuracy and precision, and are now being used routinely (personal communication Mike Lapointe, Pacific Salmon Commission, Vancouver B.C.)

2.2.3 Recruitment data

The simulation model is age-structured and includes the main age classes present in the fishery. Recruits associated with a particular year of spawning can potentially return as adults 3 to 6 years from the year of spawning. Typically, after hatching, their progeny rear in a lake for one year and spend two summers in the north Pacific before returning to the Fraser River to spawn in the fall. The age of fish that spawn after one year in freshwater and two summers in the ocean is reported by convention as age 4_2 sockeye (Roos, 1991). For the Summer run, 93% of the returns (catch + escapement) since 1952 were age 4_2 sockeye. The remainder is almost exclusively age 5_2. The data used in the analysis are age 4_2 and 5_2 recruits hereafter referred to as age-4 and age-5 sockeye. Jacks contribute little to sockeye fisheries and their reproductive potential is unclear. Jacks are not used in the analysis. Because Quesnel sockeye have persistent four-year abundance cycles, the age-5 contribution from the dominant and sub-dominant cycle lines result in relatively large numbers on the following sub-dominant cycle line and the first off-cycle line. Recruitment data (Appendix 4 and 5) used in this analysis are for brood years 1949 (1953 age-4_2 return year) to 1995 (1999 age 4_2 return year).

2.3 Population dynamics

2.3.1 Stock recruitment models

The stock-recruitment relationship is described by a quantitative model of the form:

$$R_{it} = g(S_{it}, \theta_i) \qquad \text{Equation 1}$$

where recruitment R_{it} of stock i at time t is produced by spawners S_{it} with suitable parameters θ_i.

The most widely applied model to quantify the population dynamics of Pacific salmon is the Ricker model (Ricker, 1954). The classical form of the Ricker model is:

$$g(S_{it}, \theta_i) = \alpha S_{it} e^{-\beta S_{it}} \qquad \text{Equation 2}$$

Parameters α and β respectively are the recruits-per-spawner at low spawning stock size and the density dependent parameter that describes the rate that the recruits-per-spawner drops as S_{it} increases. The Ricker model is dome-shaped with declining recruitment at higher stock sizes. Mechanisms that can lead to a Ricker-shaped stock-recruitment curve are cannibalism of juveniles by adults, disease transmission, over-crowding on the spawning sites and density-dependent growth coupled with size-dependent mortality (Hilborn and Walters, 1992).

A version of the Deriso-Schnute model proposed by Schnute and Kronlund (1996) and re-formulated by Schnute et al. (2000) is used here

$$g(S_{it}, \theta_i) = \frac{S_{it}}{1-h^*}\left[1 + \gamma h^*\left(1 - \frac{S_{it}}{S^*}\right)\right]^{1/\gamma} \qquad \text{Equation 3}$$

Parameters S^* and h^* represent the spawning stock size and harvest rate respectively associated with the maximum sustainable yield (MSY). The third parameter γ defines the curve shape. In our use of the classical Ricker model where γ=0

$$g(S_{it},\theta_i) = \frac{S_{it}}{1-h^*}\exp\left[h^*\left(1-\frac{S_{it}}{S^*}\right)\right] \text{.................... Equation 4}$$

The formulation of the Ricker model in Equation 2 was extended by Larkin (1971) to include cross-cycle interactions. Here the interaction terms are included in the reformulated Ricker model where:

$$g(S_{it},\theta_i) = \frac{S_{it}}{1-h^*}\exp\left[h^*\left(1-\frac{S_{it}}{S^*}\right) - \beta_1 S_{it-1} - \beta_2 S_{it-2} - \beta_3 S_{it-3}\right] \text{.......... Equation 5}$$

.

The recruits R_{it} are the result of the spawning stock S_{it} in year *t*, but also depend on stock size S_{it-1}, S_{it-2} and S_{it-3}. The extra lag terms ($\beta_1, \beta_2, \beta_3$) are surrogates for the effects of predators assuming that the abundance of predators is related to the abundance of prey in the initial year *t* and the preceding years *t-1*, *t-2* and *t-3*. The classical Ricker model is a subset of the Larkin model wherein the additional lag terms are zero. The Larkin model has no unique solution to the optimal spawning escapement S^* because of its dependence on S_{it}, S_{it-1}, S_{it-2} and S_{it-3}, but for consistency we maintain this notation.

Theoretically, substituting effective female spawners for total spawners in the stock-recruitment relationship reduces both uncertainty and negative bias in stock-recruitment parameter estimates if the reproductive potential is underestimated in years with a low proportion of effective females. The problem with using effective female escapement instead of total spawners is that recruitment and spawners are in different units. As shown by Collie and Walters (1987), the stock-recruitment parameters estimated using effective female spawners can be easily re-scaled to represent total sockeye in Equation 3.

Re-scaling the parameter estimates for the Larkin model is not straightforward because there is no unique solution to the optimal escapements in each of the four cycle lines. Collie and Walters (1987) showed that for Adams River sockeye, maximum catch occurs when all escapements are equal, but that the catch is only slightly less if escapement in one or both off-cycles were zero. Rather than re-scaling the parameter estimates, the stock-recruitment data was re-scaled to reduce potential bias and maintain the consistency in data used to fit Equations 4 and 5. The re-scaled escapement S_{it} is equal to:

$$S_{it} = S^T_{it} \frac{sr_{it}}{\overline{sr_i}} \frac{ef_{it}}{\overline{ef}_i} \qquad \text{Equation 6}$$

where the total escapement S^T_{it} is multiplied by the product of the sex ratio sr_{it} and the proportion of effective females ef_{it} in each year *t* and stock *i*, divided by the product of the mean sex ratio $\overline{sr}_i$ and mean proportion of effective females $\overline{ef}_i$. For Chilko sockeye, brood years 1987, 1989, and 1990-92 were subject to lake fertilization experiments to test for enhancement effects on juvenile sockeye (Hume et al., 1996; Bradford et al., 2000). These years were excluded from the Chilko data set to reduce potential bias in stock-recruitment parameter estimates. We assume that there was no carry-over of fertilization effects into the following years (e.g. 1988, 1993).

Because the time series of returning Chilko Lake sockeye do not show any evidence of persistent cycles (Figure 5), the population dynamics modeling is restricted to a Ricker model fit to all years of data. Highly cyclic populations present a more complex problem because the underlying mechanism causing cycles is not known. We therefore are less able to verify the assumptions underlying the choice of stock-recruitment model for highly cyclic populations such as Quesnel Lake sockeye. In addition to Ricker and Larkin model fits to all-years for highly cyclic stocks, we allow for a Ricker model fit separately to two subsets of stock-recruitment data. A Ricker model was fit to the set of years of persistent low abundance (i.e., the two adjacent low years) and the years of persistent high abundance (i.e., the two adjacent high years). We refer to this model as the Ricker cycle-aggregate (CA) model. The implicit assumption of the CA model is that the low and high years are completely independent.

2.3.2 Estimation of SR parameters

Parameter estimation is based on non-linear Bayesian estimation methods using software written in S-PLUS (www.insightful.com/splus/) originally developed by Schnute et al. (2000). The code was modified to include Equation 5. Uncertainty plays a major role in the analysis. The deterministic Equations 4 and 5 must be extended stochastically to account for the inherent noise in the data. A Bayes posterior inference function for parameter estimation is used to capture parameter uncertainty. The method uses the posterior sampling methods obtained by the Metropolis version of the Markov chain Monte Carlo (MCMC) algorithm (Gelman et al., 1995, chap. 11). The Bayesian approach is preferable over likelihood methods of parameter estimation because complex parameter distributions can be readily incorporated into policy evaluation. The proliferation of Bayesian techniques in recent fisheries literature illustrates the use of sampling with importance resampling (McAllister et al., 1994; Kinas, 1996; McAllister and Ianelli, 1997), Gibbs samplers (Meyer and Millar, 1999), and MCMC methods (Patterson, 1999, Schnute, 2000).

The MCMC approach considered by Schnute et al. (2000) is applied here. In summary, the method requires a random movement in step sizes proportional to the standard error for each parameter from a current parameter vector θ_i to a new acceptable point θ_i' specified by a defined probability of acceptance. An acceptable θ_i' becomes the next point in the sample sequence. The sampling algorithm is initialized with the modal $\hat{\theta}_i$ estimate and repeated until the desired sample size from the Bayes posterior distribution is obtained. Each sample parameter vector represents one possible version of the system dynamics (i.e. Equation 4 or 5). The population dynamics not only depend on the choice of underlying model but also on the error structure. A lognormal error model was adopted. Under the assumption of independent survival through sequential life history stages the random variation around a stock-recruitment curve is expected to be lognormal. Lognormal distributions are found in many stock-recruitment data sets (Hilborn and Walters, 1992). Peterman (1981) could not reject the assumption of log-normality for Skeena River sockeye.

For the lognormal distribution, the residuals η_{it} from the fitted curve are defined as:

$$\eta_{it}(\theta_i) = \left[\log R_{it} - \log g(S_{it}, \theta_i)\right] \text{..........Equation 7}$$

The inference function for θ_i depends on the residual sum of squares Q:

$$Q(\theta_i) = \sum_{t=1}^{N} \eta_{it}(\theta_i)^2 \text{ .... Equation 8}$$

where N is the number of (R_{it}, S_{it}) data points.

The standard deviation of the residuals σ is:

$$\sigma = \frac{1}{N+1}\sqrt{Q(\theta_i)} \quad \text{Equation 9}$$

Following methods presented in Schnute et al. (2000), the standard non-informative prior $P_0(\sigma_i) \propto 1/\sigma_i$ was chosen for the scale parameter σ_i so that $P_0(\log\sigma_i) \propto 1$. The posterior distribution $P(\theta_i, \sigma_i)$ is then specified by

$$P(\theta_i, \sigma_i) \propto \frac{1}{\sigma_i^{N_i+1}} \exp\left[-\frac{1}{2\sigma_i^2} Q_i(\theta_i)\right] P_0(\theta_i) \quad \text{Equation 10}$$

As in Schnute et al. (2000), the simple prior distribution $P_0(\theta_i)$ was adopted where the prior on each parameter is uniform across an admissible range and zero elsewhere. For h^* the admissible range is (0, 1). The lower limit of the prior for S^* is 0. The basis for choosing for the upper limit of S^* is less obvious. All previous stock-recruitment analyses of Fraser River sockeye indicate relatively low uncertainty in the productivity parameter h^* and high uncertainty in S^* due to high recruitment variation independent of density effects (Collie and Walters, 1987; Cass, 1989; Schnute et al., 2000; Cass et al., 2000). To assess the effects of constraining the upper range of S^*, the prior was first set sufficiently high to have a small effect on the posterior distribution. The upper limit was then constrained using independent estimates of spawning escapement that maximize sockeye lake rearing capacity (S_{max}). The independent estimates of S_{max} are those derived by Shortreed et al. (2000) from the correlation between estimates of photosynthetic rate and sockeye smolt biomass. The Larkin model lag terms ($\beta_1, \beta_2, \beta_3$) in Equation 5 were restricted to $(0,\infty)$ on the assumption that all the lag terms have a negative effect on future survival within the four year cycle.

2.4 Monte Carlo Simulations

The Bayesian approach for capturing parameter uncertainty and posterior sampling techniques, such as the MCMC approach of Gelman et al. (1995) used here, offer the advantage that complex parameter distributions can be naturally incorporated into policy analysis. To explicitly incorporate parameter uncertainty, a subsample of 250 stock-recruitment parameter vectors θ_i for each stock *i* was systematically sampled from the original 20,000 MCMC samples. In mixed-stock fisheries with n stocks, the complete parameter vector for all stocks 1 to n in the fishery is $\phi = (\theta_1, \ldots \theta_n)$

For each parameter vector θ_i sampled from the Bayes posterior distribution, the effect of fishing is simulated by sequentially generating streams of fake escapement and catch in annual time steps. The number of time steps in the simulated time series was set to 50 years in forward simulations or equal to the number of historical S-R data points for retrospective simulations. Each simulated time series is initialized from seed escapements. A trial set of curve parameters specify the initial harvest rule and exploitation rate trajectory to simulate the effects of fishing. This is repeated for each of the 250 parameter vectors θ_i times the number of trials in each parameter vector. The value function is calculated for each trial. Subsequent exploitation rate trajectories (i.e. harvest rules) are chosen by the optimization routine to maximize the mean of the value function calculated over all parameter vectors and trials. The output is a harvest rate – run size (*h-R*) curve that represents the optimal harvest rule given uncertainty in the population dynamics. The harvest rule is the optimal harvest policy that a manager could use to guide decision-making when setting harvest rates and escapement targets.

Both retrospective and forward simulations are useful for estimating optimal spawning escapement and harvest policies for a specified objective function. Both are available in this model, but only results for forward simulations are presented here. Schnute et al. (2000) retrospectively simulated catch and escapement by initializing the escapement with observed escapement at the start of the historical stock-recruitment time series (1949-52). They also confined the analysis to age-4 sockeye on the dominant cycle line. Subsequent years were reconstructed using the observed time series of residuals from the spawner-recruitment curve. In that way, they simulated what might have happened had fisheries been prosecuted differently over the time period of record given prevailing survival patterns (i.e. observed recruitment residuals). Retrospective simulation has the appealing advantage of preserving the historical survival pattern compared to forward simulations that typically assume a survival pattern sampled from parametric error distributions. Retrospective simulations also provide a benchmark to compare simulated performance measures such as average yield to the performance measures for the observed historical fishery. Alternatively, forward simulations avoid potential artifacts in the observed data which may introduce biases. Forward simulations add flexibility for exploring effects of survival variation outside the historical range, for example, to mimic El Nino effects on ocean survival, en-route losses of adult sockeye within the Fraser River due to adverse migratory condition, in particular, the recent high pre-spawning mortality of Late run sockeye.

The simulation software accommodates both retrospective and forward simulations. Forward simulations require estimates of the standard deviation of the residuals σ_i from which to sample from the parametric distribution $P(\theta_i, \sigma_i)$. Retrospective simulations use the non-parametric residuals $\log R_{it} - \log g(S_{it}, \theta_i)$. In retrospective simulations, the nuisance parameter σ_i can be integrated analytically from the right-hand side of Equation 10 to give the posterior distribution for the recruitment parameter θ_i alone (Schnute et al., 2000, Appendix A):

$$P(\theta_i) \propto [Q_i(\theta_i)]^{-N_i/2} P_0(\theta_i)$$

In the retrospective Ricker model case, the escapement S_{it} for t=1 to 4 is initialized with the observed escapement at the start of the historical time series (1949-52) for each stock i. The Ricker CA models are seeded with the first two years. For the Ricker model fit to the high years (CA-high), the last subdominant and dominant years are used. For the CA-low model, the first two low years are used. In the Larkin model case, the first 7 years (1949-55) are necessary to seed the simulation to account for the lag effects of spawning escapements in years *t-1*, *t-2*, and *t-3*. In forward simulations, the simulations are seeded with the most recent years rather than the first in the time series. For example, forward simulations that use the Ricker model were seeded with S_{it} = (1996-99). The simulation proceeds in annual time steps. The harvest process in each year occurs by first generating recruitment from the spawner-recruitment curve. For example, in the Ricker model case:

$$R'_{it} = g(S'_{it}, \theta_i)\exp(\eta'_{it}) \quad \text{......... Equation 11}$$

A prime accent $(')$ is used to distinguish simulated values from their historical counterparts. In the retrospective simulation the variable η'_{it} denotes the residual from the fitted spawner-recruit curve. In forward simulations, η_{it} is sampled from a parametric error distribution and depends on suitable autocorrelation and σ_i where:

$$\sigma_i = \frac{1}{N+1}\sum_{t=1}^{N}\eta_{it}(\theta_{it}) \quad \text{......... Equation 12}$$

In the absence of among-stock covariation (see Section 2.4.3), autocorrelation *r* in residuals is accounted for by:

$$\eta'_{it} = r_i\sigma_i\varepsilon_{i,t-1} + \sigma_i\varepsilon_{it} \quad \text{......... Equation 13}$$

where r_i is the coefficient of residual autocorrelation for stock *i* and ε is a random normal deviate with mean zero. Estimates of *r* for Fraser sockeye are typically low to moderate depending on the stock ($r \leq 0.2$). For Quesnel and Chilko sockeye *r* was low ($r \leq 0.04$).

Recent studies have shown positive covariation in temporal survival patterns among sockeye stocks (Adkinson et al., 1996; Mueter et al. 2002; Peterman et al., 1998). Peterman et al. (1998) showed that the survival correlation ρ among Fraser sockeye stocks is weak, but significantly positive. The average correlation ρ *was* 0.21 for 28 populations assessed by Peterman et al. The survival correlation for Chilko and Quesnel stocks was 0.23. For the two-stock example, the S-R residuals η'_{it} for Chilko sockeye (i=2) are correlated to Quesnel sockeye (i=1) according to ρ and autocorrelation *r* :

$\eta'_{i=2,t} = \rho\sigma_{i=1,t}\varepsilon_{it} + r\sigma_{i=2}\varepsilon_{i=2,t-1} + \sigma_{i=2}\varepsilon_{i=2,t}$ .... Equation 14

In our example two-stock simulations we set ρ to 0.23.

The escapement $S_{i,t-4}$ results in age 4 and age 5 recruits according to Equation 1 in years t and $t+1$, respectively. In the case of the retrospective analysis, the recruits are assigned to the year of return based on the observed proportion p at age in each year. For age 4 sockeye

$p_{it} = \dfrac{R_{it}}{(R_{it} + R_{i,t+1})}$ ....Equation 15

For age 5 sockeye $p_{i,t+1} = 1 - p_{it}$.

In forward simulations, p_{it} and $p_{i,t+1}$ are the mean values of age 4 and age 5 fish respectively in the historical time series.

Catch C'_{it} is computed as

$C'_{it} = h'_t R'_{it}$
....Equation 16

For mixed stock fisheries the harvest rate h'_t is assumed to impact all stocks equally in the stock mixture. Schnute et al. (2000) showed that harvest rates among the four Summer run stocks, including Chilko and Quesnel lake sockeye are strongly correlated.

The escapement S'_{it} is computed as

$S'_{it} = R'_{it} - C'_{it}$ ....Equation 17

The annual time step is then incremented and S'_{it} is used to generate recruitment in the next generation according to Equations 4 or 5.

Given a particular stock dynamic θ_i and trajectory of recruitment anomalies η'_{it}, the trajectory of harvest rates h'_t that maximizes the objective function is the optimal harvest policy given perfect information about future (or past) recruitment survival. In fact, the omniscient manager would recognize that the virtual world ends on the final time step of the simulation and harvest all the entire run in the last generation (h_N=1). The performance of alternative harvest policies was assessed based on *N*-4 years to avoid this problem.

2.4.1 Simulating depensatory mortality

The S-R models described so far ignores the possibility of depensatory mortality, which may occur when the population S' falls below some critical level S_c. Depensatory mortality results in declines in survival as population density declines (i.e. $R'/S' < 1$). This is known as the Allee effect (Allee et al. 1949). A number of factors could result in depensatory mortality. For example, inbreeding may occur and result in increased mortality, spawner densities may be so low that fish cannot easily find mates, and predation may result in high proportions of fish being killed when densities are low. Depensatory mortality will accelerate population declines and increase their probability of extinction (McElhany et al 2000).

Whether depensatory mortality is a significant factor for fish populations is not clear. Myers et al. (1995) found that 3 of 26 fish stocks had lower than expected recruits per spawner at low densities than would be expected using a Beverton-Holt model. Liermann and Hilborn (1997) examined the same data and found that the most likely values for the stock recruit relationship were usually close to or within the range of no depensatory mortality. However, since there was a significant amount of uncertainty about whether depensation existed, Liermann and Hilborn concluded that analyses of stock recruitment data should incorporate spawner recruit curves that allow for the possibility of depensation.

Several approaches have been used to incorporate possible depensatory effects in the analysis of stock recruit data. Hilborn and Walters (1992) recommended including a power term in the Beverton-Holt model to represent the effects of predators. Liermann and Hilborn (1997) used a Bayesian hierarchical model to estimate the distribution describing the variability of depensation within various taxa. Routledge and Irvine (1999) introduced a cut-off value to allow for the effects of possible depensation at low abundance and modified their formulas when $S' \le S_c$. Frank and Brickman (2000) were the first to introduce a S-R model that incorporated Allee effects by permitting a non-zero intercept representing recruitment failure. Chen et al. (2002) extended the standard Ricker function by incorporating an additional parameter and estimating the value of non-zero intercepts using S-R data. They found evidence for significant depensatory mortality in a northern BC coho population but not for Chilko sockeye.

Our purpose here is not to estimate depensatory mortality, but to simulate the potential effects on performance. If S' falls below a critically low value S_c, users can specify the value of the recruits-per-spawner R'/S' by assigning a higher mortality than prescribed by a standard S-R model. A stock, on average, will be unsustainable if $R'/S' < 1$. In our simulation model, if $S'_t < S_c$ then $R'_t = mS'_t$, where m is the proportion of S'_t that reproduces in the next generation after accounting for depensatory mortality. All else being equal, if m =1 then $R'_t = S'_t$ and the population will tend to sustain itself. If $m < 1$ then the population will tend to decline. The stochastic process defined in Equation 11 allows random variation in density-independent mortality in addition to depensatory mortality. At low stock densities, particularly where $m << 1$, the effect of random density-independent mortality can exacerbate or counter the effect of depensatory mortality. Once a year-class is driven to extinction it can only be repopulated by age-5 recruits from the preceding year-class. In a closed population (no straying between populations), two or more adjacent year-classes with low densities, high m and a run of several years of low density-independent mortality will inevitably result in a high probability of population extinction.

We chose an arbitrary value for S_c recognizing the difficulty in estimating it reliably from the S-R data. We set S_c to the lowest S value observed in the S-R data set. For both Chilko and Quesnel sockeye, S_c occurred early in the time series. The population was able to recover from S_c to much greater levels at least given prevailing survival conditions.

2.4.2 Simulating implementation error

Implementation error is associated with two factors: 1) the error in estimating abundance in-season from which an associate exploitation rate is chosen (targeted) and, 2) the actual exploitation rate realized versus the target exploitation rate given uncertainty in the catchability of fish. We allow model options for evaluating both or either of these factors on the optimal harvest rule solution and on performance measures. Estimates of adult abundance during the season are available for most years and timing groups since 1991.

Estimates of average measurement error in abundance E_i for timing group i were derived from the absolute value of the difference between the last in-season estimate (assumed to be the true abundance R^T_{it}) for timing group i and year t and the last estimate that a management action (R^E_{it}) was taken:

$$E_i = \frac{1}{n}\sum\frac{|(R_{it}^{\ T} - R_{it}^{\ E})|}{R_{it}^{\ T}} \quad \text{.......Equation 18}$$

The mean absolute error E_i for 1986-2000 was 0.08 when averaged across all four run timing group for which data is available.

To generate observed estimates of in-season abundance $\hat{R}^{E}{}_{it}$, where ^ differentiates the simulated estimate of abundance and that estimated historically in-season, we assume errors are multiplicative:

$$\hat{R}^{E}{}_{it} = \hat{R}^{T}{}_{it}e^{\sigma_v \varepsilon_t} \text{ ......Equation 19}$$

where, σ_v is the standard deviation of the error distribution set to achieve a mean error E_i.

Data to estimate implementation errors in target exploitation rates is not available and is confounded with errors in in-season abundance. We provide options for evaluating the effects of exploitation rate implementation error but have no prior information to bound the error. In the simulations, we assume exploitation rate errors are multiplicative in the same way that errors in in-season abundance are generated:

$$\hat{\upsilon}^{E}{}_{it} = \upsilon^{T}{}_{it}e^{\sigma_u \varepsilon_t} \text{ ......Equation 20}$$

where the actual exploitation rate applied $\hat{\upsilon}^{E}{}_{it}$ is related to the target exploitation rate determined stochastically according to σ_u.

Model options allow the following question to be answered:

1) What is the optimal curve for a particular objective given implementation errors?

2) What is the degradation in performance given an optimal curve (estimated without implementation errors) in the presence of implementation error?

2.4.3 Simulating mixed stock fisheries

Mixed-stock fisheries models are useful for assessing performance relative to single-stock models. In single-stock fisheries there is a direct feedback between the exploitation rate, future recruitment and ultimately conservation and socio-economic performance measures. Recruitment and performance in response to exploitation is only conditional on the underlying population dynamics of the stock. A common exploitation rate applied to a stock mixture potentially affects future recruitment and performance of the individual stocks differently for a number of reasons.

Productivity may vary among stocks to the extent that a common harvest rule is not optimal for some or any of the stock components. This, of course, is the weak-stock problem of mixed-stock fisheries. Differences in productivity among stocks are captured in the model using Bayesian inference. Temporal differences in productivity among stocks in mixtures, however, also affect performance, even though the long-term mean productivity may not vary among the stocks. The effect of temporal variation in survival patterns among stocks in mixed-stock fishery models therefore must be assessed.

Mixed-stock fisheries models are more complex than single-stock models and the complexity increases with the number of stocks in the mixture given differences in the degree of timing overlap and the recruitment survival patterns among stocks. Additional complications arise when assigning potentially conflicting values to socio-economic attributes in the value function for selective terminal fisheries versus ocean mixed-stock fisheries. Our purpose here is not to rigorously assess the sensitivity of performance measures to factors controlling stocks in mixed-stock fishery models. Our intention is to demonstrate that the model is general enough to allow an assessment of the full suite of factors that may be important in the assessment of mixed-stock models.

The question we pose here is: to what degree does performance of mixed stock-fisheries degrade compared to single-stock fisheries? A simulation of a simple hypothetical two-stock fishery model is developed to illustrate how performance compares to single-stock scenarios. Again we use Chilko and Quesnel Lake sockeye in a simulated mixed-stock fishery as the example. The timing of Chilko and Quesnel sockeye is very similar. Both stocks are managed together with Stellako and Late Stuart sockeye. The annual historical exploitation rates are also highly correlated (Schnute et al. 2000). We assume a common exploitation rate is equal to the exploitation rate on each stock.

Schnute et al. (2000) demonstrated that the MCMC samples of the posterior distribution are random with no evidence of initial burn-in. The sequential order in which they appear in the mixed-stock fishery model for the two-stocks is also random. More realistic mixed-stock models could inversely sort the sequential order of the S-R parameter vector θ_i based on the productivity parameter h^* to test sensitivity of performance measures in a worst-case scenarios. The productivity of each stock in that two-stock scenario would pair the highest h^* for one stock with the lowest h^* for the other stock.

2.5 Value Function

2.5.1 Incorporating Management Objectives

Choices regarding harvest policies depend on a wide range of conservation and socio-economic objectives. The relative importance placed on the different objectives is critical to determining the appropriate management actions that will ultimately determine future escapements and catches. For example, a conservation objective could be expressed as “Avoid low spawning abundances below which there is a high chance the population will collapse or result in low sustained future economic benefit”. An economic objective could be expressed as "Avoid the catch level below which an industry can no longer remain viable".

The objectives are introduced into the model as attributes in a value function for optimization and can include benchmarks or biological reference points such as desirable levels of run size, spawning escapement or catch. Conservation and economic objectives are included in the value function with appropriate penalty weights that affect the probability of an undesirable outcome occurring. The value function and population dynamics are the inputs for the simulation model. Additional performance measures can be assessed from the model output.

The value function, along with the parameters describing the population dynamics, is used in the simulation model to estimate the optimal harvest rule. Rather than requiring analysts and decision makers to compare the performance in many different combinations of simulated scenarios and harvest rules, the optimization procedure automatically searches for the specific harvest rule that performs best (i.e. maximizes the value function). Different weightings in the value function can be used to investigate how optimal exploitation rates and performance are affected by different management priorities. This process allows resource managers and stakeholders to see the effect of different weightings on conflicting objectives and often allows areas of common ground to be identified.

2.5.2 Capturing Objectives for Fraser River Sockeye

The policy context for the management of Fraser River sockeye is summarized at:

http://www.pac.dfo-mpo.gc.ca/ops/fm/Salmon/policy.htm

These general objectives need to be refined for the specific requirements of Fraser River sockeye management, and then translated into a form that can be formally evaluated. Quantitative performance measures are an attempt to capture the specific objectives in a form that can be easily compared and summarized. Carefully chosen performance measures can provide a comprehensive summary of the expected performance of different harvest guidelines. Many possible performance measures may be of interest to stakeholders. Some commonly used measures are listed in Table 2.

Benchmarks are simply specific levels of a performance measure used for quantitative assessment. For example, the benchmark identifying an undesirably low escapement in our example is defined as the escapement level that produces a recruitment of 10% of the mean maximum recruitment. Escapement levels below this benchmark are then penalized in the value function used to compare harvest rules. Benchmarks can also be based on independent considerations, such as negotiated limits. Relative benchmarks are more consistent with developing policy guidelines, but make it difficult to compare the performance between simulations when comparing different stock recruitment models. In this paper, only relative benchmarks are used. Earlier materials distributed for this initiative used the term "management reference points" to describe the benchmarks, which was inconsistent with the technical definition of reference points. Reference points can be trigger points for management actions. Thus, changes in state variables (e.g. run size) that cross a management reference point directly cause changes in management actions (e.g. fishery closure). Benchmarks only affect management actions indirectly by altering the valuation of particular system state such that another management action may produce a higher score of the value function. Some of the performance measures, particularly relating to catch, could be discounted over time, and future applications of this framework could be used to assess the effect of different discount rates.

2.5.3 Structure of the value function

The value function used in this analysis incorporates the trade-off between maximizing catches and escapement. Linear and exponential forms of the value function are used (Figure 6). In the linear form, the score or penalty for a given increase in an attribute does not depend on the level of the attribute. For example, 10,000 additional fish are valued equally whether the catch level is 20,000 or 1 Million fish. In the exponential form, the value of additional catch decreases as catch increases. Similarly, penalties are negligible when attributes are in the target range, but increase exponentially as undesirable events occur relative to the benchmarks.

Mathematically, the value (Z) of the linear value function is expressed as:

$$Z = uU - vV - wW - yY \qquad \text{Equation 21}$$

where:

$$U = \frac{1}{n}\sum \frac{C'}{C_{MSY}} \qquad \text{Equation 22}$$

V = Proportion of years where catch is less than a low catch benchmark (i.e. $Pr(C' < C_{low})$)
W = Proportion of years where catch is less than a high catch benchmark (i.e $Pr(C' < C_{high})$)
Y = Proportion of years where escapement is less than a low escapement benchmark (i.e $Pr(S' < S_{low})$)

In the current version of the model

C' = total catch for all harvester groups in one simulated year,
C_{low} = 10% of catch at MSY levels,
C_{high} = catch at MSY levels
S_{low} = Spawning escapement at 10% of the average spawner abundance producing maximum recruitment R_{max}.

The values u, v, w and y are the weights assigned to each component of the value function. The weight u is set to 1 in our simulations so that each unit of catch (in million) is assigned a value of 1. The weights v, w and y are penalty weights set to respectively avoid undesirable probabilities of falling below C_{low}, C_{high} and S_{low}.

In the exponential form (Keeney 1977)

$U^x = (1 - e^{-\alpha U})\gamma_1$ ....Equation 23

where α controls the slope of the curve and γ_1 is a scale parameter

$V^x = \left[-\frac{1}{\gamma_2} + e^{-\beta V} \right] / \gamma_2$ ....Equation 24

$W^x = \left[-\frac{1}{\gamma_2} + e^{-\beta W} \right] / \gamma_2$ ....Equation 25

$Y^x = \left[-\frac{1}{\gamma_2} + e^{-\beta Y} \right] / \gamma_2$ ....Equation 26

where β controls the slope of the curve and γ_2 is a scale parameter. In the absence of quantitative data for actual stakeholder preferences, arbitrary parameters were chosen for the exponential attributes (Figure 6)

By choosing different benchmarks and weightings for the four attributes in the value function, users can express a wide range of management objectives as input into the model. Many additional performance measures can be calculated from the model output, and may be of interest to users. However, these attributes are not included in the value function, because of the added complexity and increased potential for correlation between attributes. The effect of each component of the value function is additive and the overall score *Z* of the value function is the sum of all the components. Multiplicative value functions designed to admit interaction among the components are also possible (Keeney and Raiffa,1976) but were considered beyond the scope of this paper.

Choosing weights for the value function to accurately reflect preferences is not a trivial task. Weights need to be chosen in proportion to the unit change in each attribute and relative to the benchmarks associated with each attribute. In this initiative, stakeholder preferences will be elicited interactively by discussing the performance measures. For example, if the proportion of years with low catch is considered too high, the corresponding weight will be adjusted.

2.6 Harvest Rule Fitting

Until recently, the primary tool for solving complex decision problems was stochastic dynamic programming (Raiffa, 1968; Walters, 1981). Desktop computers are now powerful enough to solve high-dimensional problems using off-the-shelf numerical optimizers. The non-linear optimizer Solver developed by Frontline Systems Inc. (www.frontline.com) was used to estimate the optimal harvest rule. The Solver Dynamic Link Library (DLL) can be integrated directly into a variety of programming languages. In this case, the DLL was called from the Pascal visual programming language Delphi (www.borland.com/delphi).

Two fundamentally different approaches to fitting the optimal harvest rule were explored. The optimization step can be set up to calculate the optimal sequence of exploitation rates over all *t* time steps. This approach presents major challenges. The optimization calculations become very computing intensive, as each additional time step adds one more parameter to be estimated. For example, for a forward simulation of 50 years, a sequence of 50 different optimal exploitation rates h^o has to be estimated. Also, the likelihood of non-global optima increases as parameters are added. This can be overcome to some extent by using genetic algorithms in the optimization (Chen et al. 2000) or the multi-start function in Solver that systematically search for global optimal over the grid of gradient space. Both the genetic algorithm and multi-start cause enormous additional increases in computing time when the number of curve parameters are large. In the end, the objective is to calculate a single harvest rule that is representative of the overall distribution. However, fitting harvest rules through the resulting scatter plots may yield suboptimal harvest rules. The individual trajectories are optimal only for one specific sequence of simulated catch and escapement and averaging the cluster of h^o points at any given run size *R* does not preserve the complete set of results. A more efficient and tractable approach is to first choose a family of curves as possible harvest rules, based on theoretical considerations, and then optimize the curve parameters. This increases the probability of finding an optimal solution and drastically reduces the number of estimated parameters and hence computing time. The latter approach was used because, among other reasons described above, the increase in computation speed means that the modeling tool potentially can be used for real-time gaming.

We chose to use a flexible function developed by Schnute and Richards (1990) to estimate parameters for a range of curve types (e.g. shapes). The model equations are not reproduced here but see Schnute and Richards for a complete description. In summary, the curves are quantified using six parameters *b, c,* x_1, x_2, y_1, and y_2, subject to the constraints $0 < y_1 < y_2$ and $0 < x_1 < x_2$. In its present use, the parameters x_1 and x_2 represent two run size estimates and y_1 and y_2 are the associated exploitation rates. Although the model contains six parameters, x_1 and x_2 are redundant and are fixed. Parameters *b* and *c* are shape parameters and either one or the other is also redundant. This leaves three parameters (c, y_1, y_2) to be estimated. Schnute and Richards (1990) conclude that the model is more robust if *b* rather than *c* is fixed. We found through exploratory simulations (not shown) that by fixing b = (-1, 1) and freeing *c*, that the shape can be either sigmoid (i.e. with an inflection point) or possess a steeper descending limb at low run sizes with an x-intercept and no inflection point. Fixing *b* with more extreme values often resulted in pathological effects in *S-R* space with declining escapements *S* at high run sizes *R*. In the CA model case, the number of Schnute-Richards parameters increases to six. Two sets of (c, y_1,y_2) parameters are estimated simultaneously. One set for the low-cycle years (and low cycle dynamics) and one for the high-cycle years (and high cycle dynamics).

2.7 Performance evaluation and sensitivity analyses

In the final modeling step, the performance of a harvest rule was assessed using standard Monte Carlo simulations and the output from the optimization step Simulations were conducted over the complete set of 250 S-R parameters to evaluate the sensitivity of performance to assumptions (i.e. the value function, curve shape and population dynamics). Monte Carlo simulations were conducted by applying optimal harvest rules for one specific set of assumptions correctly and incorrectly. For example, an optimal harvest rule can be developed based on an assumed Ricker dynamics and performance can be evaluated under both the Ricker and the CA or Larkin model dynamics to assess the effect of correctly or incorrectly applying an optimal harvest rule assuming Ricker dynamics.

We illustrate five ways of comparing the results for these comparisons: 1) 2x2 table listing the actual performance measures, 2) Expected value for each harvest rule when applied correctly and incorrectly, 3) Percentage difference in expected value between the two harvest rules, 4) indicating the worst outcome for each performance measure, and 5) indicating the best expected value for each performance measure.

The expected value of each performance measure across alternative hypotheses, such as different S-R models, can be calculated by assigning probabilities to each hypothesis and calculating expected performance. These probabilities can be varied to investigate the effect of differing preferences or beliefs among stakeholders. Direct comparisons of expected performance for different harvest rules are easier when results are expressed as percentages. To assess whether these differences are important, decision makers need to assess whether small percentage differences, for example, translate into large absolute difference based on the simulation output. The choice between the two harvest rules could be based on “avoiding the worst outcome”, or “maximizing the expected outcome”, or some variation.

In this paper, only a few of the possible sensitivity analyses are summarized. The intent is to illustrate that the analytical framework can be used to assess the effects of alternate hypotheses or differing preferences. A much more exhaustive sensitivity analysis will be required before the analytical results can be used to inform policy development.

For the two populations used as examples, some core assumptions remain the same for all trials:

- Stock and recruitment data are measured without error.
- Bayesian inference with uniform priors to capture uncertainty.
- The simulated time-series is restricted to 50 years, of which the last 4 years are discarded because all fish will be harvested in the final year of each cycle (a function of the optimization component).
- Harvest rules are modeled using the Schnute-Richards (1990) family of curves.

A base-case scenario was developed for comparing effects of varying some key parameters in the stock-recruitment analysis, the value function and the harvest rules.

The base-case consists of:

- A Ricker stock-recruitment model.
- An uninformative upper limit on the S* prior.
- A single attribute value function to maximize catch.
- Curve shape parameters for harvest rule with fixed b = -1 and free c. Log-normal residual error with autocorrelation $r = 0$. The possible sensitivity analyses are summarized in Table 3.

3 Results

3.1 Effect of stock-recruitment parameter uncertainty

The influence of the constrained *S** prior on the joint *h*-S** posterior distribution for Chilko and Quesnel sockeye is compared to the base-case uninformative prior in Figure 7. The upper limit on the constrained prior is the point estimate of S_{msy} based on the PR model reported by Shortreed et al. (2000). The constrained *S** prior has a profound effect on the posterior distributions for both stocks but particularly for Quesnel sockeye. The uninformative prior results in a comet-shaped distribution. The constrained prior essentially collapses all the uncertainty in *S** revealed in the posterior distribution for the uninformative prior. The contour plots in the left panels in Figure 7 represent the approximate 20-80% confidence ellipses. For Chilko sockeye, the estimate of *h**, as represented by the 80% contour, ranges between 0.7-0.8 with a mean h* of 0.75. The estimate of *S** ranges from 0.3-0.7 million spawners with a mean of 0.51 million spawners (Figure7; Table 4). The posterior distribution for Chilko sockeye is well defined within the range of observed spawners (0.017 – 1.04 million).

For Quesnel Lake sockeye, the base-case Ricker model fit to all years of data reveals a highly uncertain estimate of *S** compared to Chilko sockeye (Figure 7). The joint *h*-S** posterior distribution has an extended tail at the upper range of *S**. The 80% probability contour extends well beyond the maximum observed spawner abundance of 2.6 million sockeye since routine data collection began in 1948. The uncertainty in *h** is small compared to *S** and, within the 80% contour, ranges from 0.67-0.77. As reported by Schnute et al. (2000), the modal *h** estimate tended to be greater than the mean and the modal *S** was considerably less that the mean for the Ricker model estimates (Table 4).

In the base-case scenario, the *h-R* harvest rule is the optimal feedback policy that maximizes long-term catch (Figure 8 A,C). Because the Schnute-Richards *b* parameter is fixed at -1, the harvest rule has an x-intercept with zero harvest if the run size falls below a particular abundance cut-off level determined by optimization. The x-intercept corresponds to a run-size R of 0.51 million spawners for Chilko sockeye and 3.7 million for Quesnel sockeye. The curve increases asymptotically thereafter. As revealed in the lower plot (Figure 8B), the harvest rule for Chilko sockeye results in an escapement policy with zero harvest at $R < 0.5$ million sockeye and slightly increasing escapements for $R \geq 0.5$ million spawners. Similarly for Quesnel sockeye (Figure 8D), there is also a positive slope in the escapement policy for the base-case scenario. In cases where environmental variation is random, it is well known that fixed escapement policies are optimal for management objectives designed to solely maximize long-term catch (i.e. base-case scenario) (Clark 1985; Mangel 1985). The slight increase in escapement for the base case over the range of returns explored in the simulations is directly related to the uncertainty in S^*. Simulations of fake stock-recruitment data with known Ricker parameters (not shown), uninformative upper limit on *S** priors and residual variation estimated for Fraser sockeye ($\sigma = 0.8$) result in high uncertainty in estimates of S^* and harvest rules for the MSY objective typical of those in Figure 8B & D for the uninformative S^* priors. The difference in policies for the informative (constrained) and uninformative S^* priors indicate how influential the uncertainty in S^* is in determining the optimal rule. The difference in the optimal harvest rule for Chilko is small compared to Quesnel sockeye where the uncertainty in S^* is much larger. The reliability of the PR model used to establish the informative prior is unknown and the variance of the estimate is not provided in Shortreed et al. (2000). Our point here is not to justify the use of either one of the priors, but to illustrate the effect on the harvest rule and performance measures.

The effect of the assuming different S^* priors on the performance measures for Quesnel sockeye is compared in Table 5 for Quesnel and for Chilko in Table 6. The first two columns are a 2 x 2 matrix (shaded) of performance measures. The upper left and lower right cells of the matrix are for simulations that correctly apply the harvest rule to the two choices of the S^* priors. The lower left and upper right cells in the matrix are the results when the harvest rules are incorrectly applied. Within each cell are the five performance measures used to evaluate the effect of correctly or incorrectly applying the alternative harvest rule. The next three columns are the expected value of each performance measure at an assumed 25%, 50% and 75% probability that either model is correct (informative versus uninformative). Table 5 also shows three types of decision aids, identifying for each performance measure (1) the best and worst outcome overall, (2) the best expected value for a range of probabilities assigned to alternative hypotheses, (3) the maximin criterion to choose the harvest strategy with the higher value for the worst outcome. The maximin criterion has been used to express risk-averse management objectives (e.g. Defeo and Seijo 1999).

For Quesnel sockeye, the expected value of the catch is highest if the harvest rule for priors $0 < S^* < 10$ million. The best performing harvest rule for all other performance measures is for priors set at $0 < S^* < 0.651$ million spawners. The relative effect of our choice of upper limit for the S^* prior is shown in the last three columns of Table 5. As discussed, they summarize the relative change in each performance measure relative to the base case for the 25%, 50% and 75% probability levels. Values near 100% indicate the performance measures are highly robust to assumptions. The greater the deviation from 100%, the more sensitive the outcome is to assumptions. In a real application of the model, both the absolute and relative difference need to be assessed. A large relative difference may not be important if the absolute values are small. As shown in Table 5 for Quesnel Lake sockeye, and assuming an equal (50:50) probability that either prior is correct, there is a 55% reduction in the expected value for long-term catch if the harvest rule for the priors $0 < S^* < 0.65$ is applied compared to the base case harvest rule. If the choice of harvest rule is based on the objective of avoiding the overall worst outcomes (marked by X), then the constrained prior ($0 < S^* < 0.65$) is chosen. All performance measures are at their worst level if the unconstrained prior is incorrectly applied (Table 5). If the choice of harvest rule is based on the objective of maximizing the expected value (marked by √), then the choice depends on the relative preference for the different performance measures. Expected catch is higher for the harvest rule based on the unconstrained prior, but all other performance measures are better for the harvest rule based on the constrained prior.

The information in Table 5 can be used to choose one harvest rule over the other. The worst outcome for all performance measures occurs when the harvest rule assuming high capacity (i.e. upper limit on S* is 10 million) is applied to stock dynamics with much lower capacity (i.e. the bottom left box). Given a policy of avoiding the worst outcome, the decision maker would choose the harvest rule based on the assumption that $0<S^*<0.65$ million. On the other hand, the expected value for long-term catch is higher for harvest rule based on the assumption that $0<S^*<10$ million. Another decision maker may be willing to take the chance of ending up with either the best or the worst outcome, as long as the average is better. When choosing among two options, the maximin criterion of choosing the strategy which performs best in the worst-case scenario results in the same choice as "avoiding the worst outcome" (Table 5).

The effect on performance measures for the Chilko example reveals little difference in average catch if either harvest rule is applied correctly or incorrectly given the two upper limits on S^* priors (Table 6). There is, however, substantial degradation in the other performance measures. Arguably, constraining S* based on Shortreed et al. (2000) is questionable given the relatively high confidence in the S* estimate determined from stock-recruitment data. Again, our point here is not to assess the reliability of the PR-based estimate of S_{MSY}, but to illustrate the effect of constraining S*.

3.2 Effects of stock-recruitment model uncertainty

The time series of returning Chilko Lake sockeye do not show any evidence of persistent cycles (Figure 5). The population dynamics for Chilko sockeye were therefore restricted to a Ricker model fit to all years of data. The returns for Quesnel Lake show a persistent 4-year periodicity (Figure 5). In addition to the base-case Ricker model, the present version of the model has options to assess the effects of two additional assumptions affecting the stock-recruitment dynamics of highly cyclic populations: 1) the Larkin model and 2) the cycle-aggregate (CA) model. The CA-low and CA-high are assumed to be independent, but some spill-over occurs due to the age structure.

Harvest rules for the base-case Ricker model, the Larkin model and the CA model for Quesnel sockeye are compared in Figure 9. The harvest rules for the Ricker model and the Ricker CA-high model are largely indistinguishable. In other words, the dominant and subdominant cycle years are the prime determinants affecting parameter estimates for the Ricker model. The harvest rules for the Larkin and Ricker CA-low model both result in higher harvest rates for a given *R* compared to the Ricker base-case and CA-high model.

The effects of correctly and incorrectly assuming either a Ricker (base case) harvest rule or a Ricker CA (cycle independent) harvest rule on the performance measures are shown in Table 7. If the base-case harvest rule is applied, the expected value for long-term catch is higher than if the CA rule is applied. The trade-off is that all other performance measures are worse given the 25%, 50%, and 75% assumptions of being correct about the underlying dynamics. Essentially the fishery remains closed for two out of every four years if the base-case harvest rule is applied, because the returns are never high enough in low cycle years to open the fishery. In the worst case scenario, if the CA model is correct and the base-case harvest rule is used then $Pr(C<C_{low})=0.68$ and $Pr(C<C_{high})=0.85$. The probability $Pr(S<S_{low})$ is also degraded because the S_{low} benchmark of 0.1 S_{msy} is explicitly linked to the stock-recruitment dynamics, so that under the CA model different benchmarks are specified for the dominant/subdominant aggregate compared to the off-cycle aggregate. Again, for the worst case scenario, $Pr(S<S_{low})=0.19$ (Table 7).

3.3 Sensitivity to the harvest rule shape parameters

The effect of assuming a sigmoid shape (b=1) on the harvest rule and the performance measures for Chilko sockeye is compared to the base case in Figure 10 and Table 8. At $R \geq$ 1million fish, the optimal harvest rates at a given R are indistinguishable (Figure 10). At R < 1 million, the decline in harvest rate is not as steep if b=1 compared to b=-1. In the base-case scenario, the fishery is closed if R < 0.5 million fish whereas a sigmoid curve allows fishery removals as long as R > 0. A choice of b=1 reduces $Pr(C<C_{low})$ by 21% compared to the base case (Table 8). Also, the probability Pr(C=0) is zero for a sigmoid curve compared to a 2% for the base case. The effect on the three remaining performance measures is negligible. Similarly, for the Quesnel example, the greatest impact of a sigmoid harvest rule (Figure 10) compared to the base case is the reduction in Pr(C=0) from 28% to 4% due increased fishing opportunities at low R (Table 8).

3.4 Sensitivity to depensatory mortality

We found no effect of depensatory mortality on the performance for either stock if R/S is set to 0.1 if the stock falls below the assumed critical level S_c. The probability of falling below S_c was zero for the base case and a scenario with a high penalty assigned to the value function if the catch falls below C_{low} and $b=1$. In the base case, there is an x-intercept with zero harvest at low stock sizes to increase the long term catch. That level is well above S_c (i.e. 0.017 versus 0.5 million spawners for Chilko). A harvest policy that reduces the probability of the catch falling below C_{low} and a shape parameter b = 1, allows for catches (and fewer spawners) at low R. That scenario still resulted in a zero probability that stock size is less than S_c for both stocks.

3.5 Sensitivity to implementation error

3.5.1 Optimal harvest rule estimated without implementation error

Performance can degrade when optimal harvest rules are estimated from simulations that assume zero implementation error when, in reality, implementing error is non-zero. Two sources of implementation error were explored. The first source is associated with imprecise in-season run size estimation. Run size errors potentially degrade performance measures by assigning a suboptimal target exploitation rate given the true run size. The second source of error is from imprecise implementation of a target exploitation rate even when run size is measured without error.

Simulated effects of implementation error are shown in Figure 11 and Table 9 for base-case Chilko sockeye with and without implementation error. The distribution of the simulated data in control rule space shows the effect of an assumed ±8% mean error. Figure 11 (A,B) shows the error distribution when only run size error is assumed. Figure 11 (C,D) shows the error distribution when run size and exploitation rate errors are both applied with an assumed ±8% error rate. A ±8% error in run size estimation translates directly into an 8% decline in long-term catch compared to the base case. A similar level of degradation in mean catch occurs if a ±8% error in implementing a target exploitation rate is assumed. When both sources of error are simulated together, the effect on performance measures is similar to the results reported for the individual sources of error (Table 9).

3.5.2 Optimal harvest rule estimated with implementation error

Optimal harvest rules estimated with implementation error should out perform harvest rules that ignore implementation error. Optimal harvest rules were estimated for base-case Chilko sockeye using the same sources and amounts of implementation error described above. As reported, the fishery cut-off for the base-case is at a run size of 0.52 million sockeye with all sockeye allocated to escapement if $R \leq 0.52$ million fish. When the harvest rule is estimated with run size error only the cut-off is 0.38 million. Similarly, with target exploitation rate error only, the cut-off is 0.4 million sockeye. There is little additional change in the harvest rule when estimated with both sources of error. The cut-off in the latter case is 0.39 million fish (Fig 12). The shift to higher exploitation rates at low run sizes when the value function is simply to maximize catch is in response to the additional variation in catch at low run size due to implementation error. Performance measures were only slightly degraded when optimal harvest rules were estimated with either or both sources of error (Table 10).

3.6 Sensitivity to penalty weights in the value function

The choice of penalty weights expresses the value placed on the attributes in the value function. Exploratory simulations (not shown) indicate that there is little change in the impact on performance measures for penalty weights ≥ 10, indicating that any influence they might have diminishes quickly as weight is increased. A penalty weight of 10 was applied to each of the five attributes separately while setting all others to zero except for the attribute that values catch. Each unit of catch was assigned a value of 1 as in the base case. Some additional simulations were performed to assess the potential interaction when multiple penalty weights are applied.

3.6.1 Conservation attribute

From a conservation perspective, the most important attribute in our value function is the penalty weight *y* when $S<S_{low}$. However, the base-case value function that solely maximizes long-term catch for Chilko sockeye also results in $Pr(S<S_{low}) = 0$. For Quesnel sockeye, $Pr(S<S_{low}) = 0.027$ (Table 11). Applying a penalty *y* to that particular attribute had no effect on these two populations. Harvest rules and performance measures were indistinguishable from the base case. In other words, there is no disadvantage or trade-off from a conservation perspective of pursuing the objective of MSY. This occurs for two reasons: 1) the population is maintained at a level well above S_{low} in order to maximize catch and, 2) the residual variance results in survival rates that are high enough to maintain the population above S_{low} in all simulated years for Chilko sockeye and 39 of 40 years for Quesnel sockeye. The effect of penalty weight *y* could be much larger for a different benchmark, such as S_{low} = 30% of S_{max}.

3.6.2 Socio-economic attributes

The effects of applying high penalty weights (*v, w*) separately to each of the socio-economic attributes on harvest rules are shown in Figure 13 and Figure 14. Corresponding performance measures are shown in Table 11. Applying a high penalty *v* if $C<C_{low}$ has a greater effect on harvest rules and performance measures compared to attributes (*y, w*) for both stocks. A high penalty *v* results in higher harvest rates and lower escapements *S* at low run sizes *R*. With a penalty $v=10$, the fishery is closed (i.e. h=0) if $R \leq 0.18$ million fish for Chilko sockeye compared to the base case ($v=0$) where the fishery is closed if $R \leq 0.52$ million fish. The fishery cut-off for Quesnel with $v=10$ is at R=0.35 million fish compared to 3.65 million for the base case. The greatest effect of assigning a high penalty *v* on the performance measures is a reduction in $Pr(C<C_{low})$ and Pr(C=0). For Chilko sockeye, $Pr(C<C_{low})$ = 5% for the base case compared to $Pr(C<C_{low})$ = 1% if low catches are undesirable. The probability Pr(C=0) was 2% for the base-case Chilko stock compared to zero for $v=10$. There was also a slight (4%) declined in the long-term mean catch. For Quesnel sockeye, $Pr(C<C_{low})$ = 26% for the base case compared to 16% if $v=10$ and Pr(C=0) declined from 18% to 7%.The cost of maintaining catches above an undesirably low level (C_{low}) for Quesnel sockeye is a

slightly reduced long-term catch (6%). The effect of avoiding catches below MSY (i.e. *w*=10) had little effect of the harvest rule and performance measures compared to the base case for either stock (Fig. 14; Table 11).

3.6.3 Mixed conservation and socio-economic attributes

The analysis so far has focused on a single-attribute (base-case) and a two-attribute value functions (base case plus one additional attribute). More realistic mixes of penalty weights based on societal/stakeholder interests are possible depending on conservation, social and economic values. We investigated different mixes of penalty weights to assess effects on performance and potential interaction among attributes by assigning different penalty weights (*y, v, w)* to each of the attributes in the value function. A full treatment of potential effects was not explored but, as shown in Table 12, some attributes appear redundant.

Assigning weights of *y*=10 in addition to *v*=5 or *v*=10 within the same simulation, for example, had little additional effect on performance for either stock compared to simulations with *y*=0 and *v*=10. Because the simulated time series were seeded with recent escapements that are above the S_{low} benchmarks, the effect of a high penalty *y* and *v* on performance is inconsequential given the high productivity of Fraser sockeye. Additional penalties *y* >0 and v>0, therefore, result in performance measures that are only slightly different from *y*=0 and *v*>0, as discussed in Section 3.6.2. The effect of simultaneously assigning high penalties *v* and *w* was also explored (Table 12). The performance measures were very similar to those reported in Section 3.6.2, when high penalties for both *v* and *w* were not combined in a single simulation. Penalty *w*, in fact, is redundant at the arbitrary benchmark settings currently used in the value function.

3.7 Effect of a linear versus exponential value functions

The optimal harvest rules for base-case Chilko sockeye (linear value function) is compared in Figure 15 to an optimal curve when the exponential value function was applied. In both cases the penalty weights on proportional attributes (*v,w,y*) were zero (Equation 21). The fishery cut-off for the base-case harvest rule with the linear function was 0.52 million fish compared to 0.45 for the exponential function. This occurs because the penalty weight is higher at lower run sizes if an exponential function is used compared to the base-case linear function. At moderate to high run sizes the penalty is less than the linear function. As shown in Figure 6 (upper right panel), the weight is independent of the catch if the run size is maintained at a level that allows catches above the long-term mean. Overall the long-term mean catch was marginally less (3%) if an exponential value function was applied. There was also a slight reduction in the proportion of years with zero harvest if an exponential function was applied (1% versus 2%).

3.8 Mixed-stock models

Performance measures for base-case single stock fisheries are compared to a hypothetical base-case mixed stock fishery (Table 13). As discussed, the single-stock fishery example is the base-case for Chilko and Quesnel sockeye. The mixed-stock fishery includes both Chilko and Quesnel sockeye. Both stocks were subject to a common optimal harvest rule that maximizes the long-term catch (i.e. the base case). The mean long-term catch from the mixed-stock fishery was slightly less (4%) than the sum of the catch from the two single-stock fisheries. The economic performance measures for Chilko sockeye, however, were substantially degraded in the mixed-stock fishery compared to the single-stock fishery even though there was little difference for the total catches. This occurs because the assumed base case population dynamics, with little constraint on S^*, effectively means that the catch contribution from Chilko sockeye is small compared to Quesnel sockeye. The run size at which the mean optimal harvest rule is zero for the mixed-stock fishery was 5.5 million fish. This results in a very low harvest impact on Chilko sockeye because its capacity (i.e. mean S^*) is only 10% of the Quesnel capacity for the base case (Table 13). The implications of this for fisheries management are far reaching and attest to the importance of assumptions concerning stock capacity.

The probability $Pr(S<S_{low})$ for Chilko sockeye is zero for the single stock fishery and 2% in the mixed-stock fishery. $Pr(S<S_{low})$ for Quesnel in the mixed-stock fishery is unchanged and equal to 3%. Overall, $Pr(S<S_{low})$ = 4% for the combined stocks in the mixed-stock fishery scenario.

4 Discussion

This paper is in direct response to requests from fisheries managers for an objective-based approach for developing harvest rules for Fraser sockeye management. The harvest rules developed in the mid-1980s were designed to rebuild the most productive stocks by reducing exploitation rates to 60-70% from the historic mean of 80% or more. Opportunistic probing took place by increasing escapements beyond historic highs to test the spawning capacity of the large and most productive lake systems. The rebuilding plan also provided for rules that prevented the spawning escapement to drop below brood year estimates. The result was a feedback harvest policy with low exploitation rates a low run sizes and asymptotically increasing exploitation rates at high return levels. The resulting harvest policy, however, was not linked to specific conservation or socio-economic objectives. The tool developed here is designed to allow a consistent approach to assessing effects of different assumptions and multiple objectives on policy outcome. To that end, the tool is an objectives-based, systems approach to harvest policy analysis and decision-making. It is important to note that this is a methods paper and does not advocate a particular harvest policy. The tool is sufficiently general, however, to answer all the management questions posed in the "*Request for Working Paper*" (Appendix 1).

In our approach, three components of decision-making are considered: i) the information base that quantifies the population dynamics, ii) the societal values that determine the conservation, social and economic objectives for the resource, and iii) harvest rules and performance measures for assessing the outcome given a desired probability based on prescribed risk tolerances.

The central information base is the stock-recruitment data. The Bayesian machinery developed by Schnute et al. (2000) was extended here to investigate effects of model uncertainty. In the example stocks assessed here, the productivity (h^*) and capacity (S^*) of Chilko sockeye appear well determined from the stock-recruitment data. The estimate of capacity for Quesnel sockeye is, however, poorly determined. The use of independent capacity estimates (S_{max}) from lake productivity studies (Shortreed et al. 2000) as priors has a large impact on stock-recruitment parameter estimates. That uncertainty translates into high uncertainty in the optimal harvest policy and performance. More intensive assessment of factors limiting capacity would be useful to reduce the uncertainty in the capacity estimates for Fraser sockeye.

Formal decision theory requires a value function to solve for the optimal harvest control rule and ultimately to assess the performance measures of interest. We developed a multi-attribute value function to capture key conservation and socio-economic attributes that are potentially important for policy evaluation. Principles of the draft Wild Salmon Policy (WSP) are consistent with the framework developed here. In its present version, the model has the capacity to asses 12 stocks. Each stock corresponds to a particular lake rearing system and/or run timing component. The population groupings by stock therefore comply with the definition of Conservation Units in the draft WSP. There are about 35 individual lake rearing populations that could be added to the list but many of these are data limited. The S_{low} benchmark (S at $0.1R_{max}$) is also consistent with the intent of the draft WSP to reduce the probability $Pr(S< S_{low})$ that the stocks fall significantly below standards of best-use.

The socio-economic attributes were selected to assess trade-offs between maximizing catch and stabilizing annual catch variation by reducing the probability $Pr(C<C_{low})$ or $Pr(C<C_{high})$ should that be desirable. The values and penalty weights assigned to the attributes in the example analysis are completely arbitrary. The socio-economic benchmarks, values and the attributes themselves need to be developed through the consultation process. The analysis provided here however indicates that some attributes can be redundant in some scenarios (i.e. $Pr(C<C_{high})$ in the examples presented here).

The components of the value function are consistent with many published analyses of harvest strategies (e.g. Robb and Peterman 1998; Eggers 1993, Collie, Peterman, and Walters 1990, Walters 1975), In general, authors propose a set of measurable evaluation criteria (e.g. average catch over 30 years), compute the performance of a small set of alternative strategies (e.g. 10% , 20%, and 30% fixed exploitation strategy) with respect to each of these criteria, and consider all the evaluation criteria separately in their recommendations. In our analyses, we have taken the additional step of aggregating the performance measures into a single value function (i.e. an aggregate performance index), and applied that value function in an optimization step to directly compute the optimal harvest strategy for each set of specified starting conditions. The value function is simply an intermediate step in the calculations, and not intended capture all the nuances of stakeholder preferences. As in the published examples cited above, alternative harvest strategies will be assessed based on a summary of the individual performance measures. In addition, variations of the value functions (e.g. different weights) will be explored based on interactive feedback in a gaming environment. For example, starting with the output from a base case simulations, workshop participants will be asked a series of questions, such as "Which attributes are satisfactory at their current levels?" or "Which attribute is the most unsatisfactory?". Based on the responses, new simulations will be run with varied weights in the value function, and the output will once again be discussed with participants. Through this interactive approach, guided by facilitators, participants will identify key trade-offs and express their preferences. This approach is analogous to the current process used by the Fraser River Panel for developing fishing plans in Panel Area waters.

The Working Group chose this approach for several reasons. From a theoretical point of view, this exploratory search of all possible solutions may lead to suboptimal choices of harvest rules, but it is feasible with the available resources and the targeted timeframe. In actual implementation, when the harvest guidelines are used to develop fishing plans for the many fishing areas and gear types, subtle nuances achieved by fine-tuning the value function will likely be lost. Accurately capturing objectives is important when analysts intend to automate a decision-making process. However, within the consultation requirements for Pacific salmon management, the choice between alternative harvest strategies will always occur in a group setting, based on performance summaries. No generally accepted method for describing multiple objectives and preferences exists. Utility functions have a well documented theoretical basis, but proponents of other methods (e.g. Analytical Hierarchy Process, Choice Modeling) question the even the fundamental assumptions. Given the on-going debate in the literature, any interested party can find arguments to refute any preference model we care to put forward. No widely applied method describing multiple objectives and preferences exists. Several simple examples of utility functions for fisheries have been published, but we are not aware of any actual fisheries management decisions that have been made based on these. Even simple multi-attribute utility functions open up almost as many challenges as they are supposed to address. The questions needed to elicit utility statements are meaningless to laypersons (i.e. " Do you prefer a catch of 2 million for the commercial sector or a 50:50 gamble between 0 catch and 4 million catch"). Individual responses have to be aggregated and weighted, which is potentially very confrontational in a multi-sectoral stakeholder setting. Much of the criticism aimed at the value function in our analysis is based on its interpretation as a Multi-attribute Utility Function, which should ideally capture a realistic description of complex preferences. However, our use of an aggregate performance index is consistent with many published examples, which do not use complex utility functions.

The choice of the shape of the harvest rule (i.e. *b=-1 or 1*) was shown potentially to have a large effect on probability Pr(C=0) and negligible effect on any other attribute. Sigmoid-shaped curves reduce the frequency of closures. The choice of curve shape may be an important consideration for reducing undesirable effects of uncertain run size estimates. Steeply rising curves specified when *b=-1*, will result in larger errors in applied harvest rates compared to when *b=1*.

Evaluations of the performance measures are key to determining useful penalty weights for the attributes in a value function. The performance measures identify the probability of an undesirable outcome. We advocate that penalty weights should be chosen iteratively depending on the performance measures, rather than debating the level of weights independent of performance. Portraying the outcome of the model in a form that can be easily interpreted by stakeholders and managers is a challenging endeavor. We found the expected value calculations to be a simple way of summarizing the effects of applying alternative harvest rules in the face of alternative hypotheses. Other graphical methods may prove useful to interpret the results. Other tabular or graphical displays may also prove useful for interpreting the results in a group setting.

The model was designed to answer the questions posed in the *Working Paper Request* (Appendix 1). The harvest rule can be used explicitly to determine the optimal harvest rule and escapement curves given different management objectives and population dynamics assumptions as asked in Question 1.

The comparison of single- versus mixed-stock fishing scenarios using a two-stock fishery example shows how performance measures of a stock aggregate harvest rule undergoing mixed stock management compare with a selective, single stock scenarios. In answering this question, it is important to consider the complexity of mixed stock fisheries models. For example, harvest performance may be sensitive to such factors as the sequential order of the stock-recruitment parameters used in the simulations. The correlation in temporal survival (i.e. residuals) among stocks may also be important. The suboptimal exploitation of small stocks in mixed-stock fisheries, such as in the simple two-stock fishery example, illustrates how capacity assumptions (i.e. priors) affect the outcome.

This leads into the third question which asks how potential cyclic interactions influence the optimal harvest rules. Model uncertainty (i.e. interaction models vs. non- interaction models) can have a major influence on performance. In our example which compares performance using a Ricker all-year model and a Ricker cycle aggregate model, the model choice is important.

The fourth question asks: What are the implications of assumed conservation limits? Conservation objectives have yet to be specified but the tool explicitly requires that conservation limits be defined in the value function. The model output also presents the results in terms of the probability of not meeting the objectives. The latter is an important component of risk assessment.

Further simulations are required to assess the value of adaptive management (Walters, 1986) to experimentally determine the optimal policy. The framework could be used with minor modification to assess the value (and costs) of adaptive management. The appropriate experimental design could also be evaluated using the exiting model.

Question 6 asks: What is the expected effect of different future patterns of productivity and survival? The analysis in the Working Paper assumes environmental effects are completely random. The model has an option to assess the sensitivity of the harvest rule and performance indicators with respect to residual autocorrelation. Alternative residual temporal patterns such as alternating high and low productivity periods could also be modeled once the methodological concepts are reviewed.

Finally Question 7 deals with sensitivity to biases in stock-recruitment parameter estimation. It is well known that stock-recruitment parameter estimates are prone to several biases (e.g. Hilborn and Walters, 1992). Collie and Walters (1987) showed that stock-recruitment parameter estimates for Adams River sockeye were similar if simulated data generated by a Ricker model were fit with either a Ricker or Larkin model. If data generated by a Larkin model are fit with a Ricker model, the stock-recruitment parameters were negatively biased. The productivity parameter was underestimated by 35% and the capacity parameter was underestimated by 13% compared to a slightly positive bias when fitting a Larkin model correctly. As shown in this analysis, both parameter and model uncertainty for Quesnel sockeye has a large influence on the harvest rule and performance.

The modeling framework described here provides a comprehensive tool to develop harvest policies for Fraser sockeye stocks, and can be used to specifically address the questions raised in the Request for Working Paper. The effects of uncertainty in stock dynamics, different shapes of harvest rules, differing preferences, and mixed-stock concerns can be evaluated and the trade-offs associated with different choices and assumptions. (e.g. weights in the value function) can be quantified. However, before scientifically sound recommendations can be provided, additional work is required to perform comprehensive sensitivity analyses and clarify preferences.

5 Recommendations

The modeling framework described here was specifically designed to answer the questions raised in the Request for Working Paper. However, preliminary analyses show that the harvest rules can be quite sensitive to assumptions about cyclic interactions and capacity limits. Future extensions should focus on determining the benefits of adaptive experiments for improving our understanding of stock dynamics (i.e. value of learning).

The current analyses are based on the assumption that stock dynamics are uncertain, but with constant underlying mechanisms. However, to address the on-going debate regarding regime shifts in ocean productivity (e.g. Beamish and Bouillon 1993), the performance of harvest rules needs to be evaluated under different future patterns of productivity and survival (e.g. Peterman et al. 2000).

The family of curves described by Schnute and Richards (1989) proved very useful for estimating harvest rules in the optimization, but other shapes, such as step functions, need to be explored. Sensitivity to implementation error and changing in-season estimates of run-size will play a considerable role in choosing between candidate functions.

The biggest remaining challenge is to develop better ways for communicating the inner workings of this modeling framework to stakeholders, who will be asked to work with it in a gaming environment and will ultimately have to provide feedback on the resulting harvest policies.

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7 References

Allee, W.C., Emerson, A.E, Park, O., Park, T., and Schmidt, K.P. 1949. Principles of Animal Ecology, Saunders, Philadelphia.

Anon. 1964. Annual Report 1963. Intern. Pac. Sal. Fish. Comm. New Westminster, Canada. 46p.

Atkinson, C.E. 1944. The problem of enumerating spawning populations of sockeye salmon, p. 37-44 *In*: International Pacific Salmon Fisheries Commission Annual Report 1943. New Westminster, B.C.

Adkison, M.D., Peterman, R.M., LaPointe, M.F., Gillis, D.M. and Korman, J. 1996. Alternative models of climate effects of Sockeye salmon, *Onchorynchus nerka*, productivity in Bristol Bay, Alaska, and the Fraser River, British Columbia. Fish. Oceanogr. 5: 137-152.

Bailey, R.E., and Margolis, L. 1987. Comparison of parasite fauna of juvenile sockeye salmon (*Oncorhynchus nerka*) from southern British Columbia and Washington State lakes. Can. J. Zool. 65:420-431.

Banneheka, S.G., Routledge R.D., Guthrie, I.C., and Woodey, J.C. 1995. Estimation of in-river fish passage using a combination of transect and stationary hydro-acoustic sampling. Can. J. Fish. Aquat. Sci. 52: 335-343.

Beacham, T.D., Gould, A.P., Whithler, R.E., Murray, C.B., and Barner L.W. 1987. Biochemical genetic survey and stock identification of chum (*Oncorhynchus keta*) in British Columbia. Can. J. Fish. Aquat. Sc. 44: 1702-1713.

Beamish, R.J. and Bouillon, D.R. 1993. Pacific salmon production trends in relation to climate. Canadian Journal of Fisheries and Aquatic Sciences 50:1002-1016

Bradford, M.J., Pyper, B.J. and Shortreed, K.S. 2000. Biological responses of sockeye salmon to fertilization of Chilko Lake, a large lake in the interior of British Columbia. N.Am. J. Fish. Manage. 20: 661-671.

Cass, A.J. 1989. Stock status of Fraser River sockeye. Can. Tech. Rep. Fish. Aquat. Sci. 1674. 101p.

Cass, A.J., and Wood, C.C. 1994. Evaluation of the depensatory fishing hypothesis as an explanation for population cycles in Fraser River sockeye salmon (*Oncorhynchus nerka*). Can. J. Fish. Aquat. Sci. 51:1839-1854.

Cass, A.J., Schnute, J.T., Richards, L.J. and MacDonald, A. 2000. Stock Status of Fraser River sockeye. Canadian Stock Assessment Secretariat Research Document 2000/068. 52p. Available at the web site: http://www.dfo-mpo.gfc.ca/csas/.

Chen, D.G., Hargreaves, N.B., Ware, D.M. and Liu, T. 2000. A fuzzy logic model with genetic algorithm for analyzing fish stock-recruitment relationships. Can. J. Fish. Aquat. Sci. 57: 1878-1887.

Chen, D.G., Irvine, J.R. and Cass, A.J. 2002. Incorporating allele effects in fish stock-recruitment models and applications for determining reference points. Can. J. Fish. Aquat. Sci. 59: 242-249.

Clark, C. W. 1985. Bioeconomic modelling and fisheries management. John Wiley interscience, New York, NY. 291p.

Collie, J.S. and Walters, C.J. 1987. Alternative recruitment models of Adams River sockeye salmon *Oncorhynchus nerka*. Can. J. Fish. Aquat. Sci. 44: 1551-1561.

Collie, J.S., Peterman R.M., and Walters, C.J. 1990. Experimental Harvest Policies for a Mixed –Stock Fishery: Fraser River Sockeye Salmon, *Oncorhynchus nerka* Can. J. Fish. Aquat. Sci. 47: 145-155.

Defeo, O. and Seijo, J.C. 1999. Yield-mortality models: a precautionary bioeconomic approach. Fisheries Research 40(1): 7-16

Frank, K.T. and Brickman, D. 2000. Allee effects and compensatory population dynamics within a stock complex. Can. J. Fish. Aquat. Sci. 57:513-517.

FRAP-FMG. 1995. Fraser River Sockeye Salmon. Prepared by the Fraser River Action Plan – Fishery Management Group. Dept. of Fisheries and Oceans. 55p.

Gable, J. and Cox-Rogers, S. 1993. Stock identification of Fraser River sockeye salmon: methodology and management application. Pacific Salmon Commission. Tech. Rep. 5. 36p.

Gelman, A., Carlin, J.B., Stern, H.S., and Rubin, D.B 1995. Bayesian data analysis. Chapman and Hall, London, U.K.

Goodlad, I.C., Gjernes, T.W., and Brannon, E.L. 1974. Factors affecting sockeye salmon (*Oncorhynchus nerka*) growth in four lakes in the Fraser River system. J. Fish. Res. Board Can. 31: 871-892.

Henry, K.A. 1961. Racial identification of Fraser River sockeye salmon by means of scales and its application to salmon management. Int. Pac. Salmon Fish. Comm. Bull. XII: 97p.

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

Holland, J. 1975. Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor, Mich.

Howard, G.V. 1948. Problems in enumeration of populations of sockeye salmon. Part 1. A study of tagging methods in the enumeration of sockeye salmon populations. International Pacific Salmon Fisheries Commission Bulletin II: 4-66.

Hume, J.M.B., Shortreed, K.S., and Morton, K.F. 1996. Juvenile sockeye rearing capacity of three lakes in the Fraser River System. Can J. Fish. and Aquat. Sci: 53: 719-733

Keeney...1977. A utility function for examining policy affecting salmon on the Skeena River. J. Fish. Res. Board Can. 34: 49-63.

Keeney, R.L. and Raiffa, H. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Wiley & Sons, New York.

Kinas, P.G. 1996. Bayesian fishery stock assessment and decision making using adaptive importance resampling. Can. J. Fish. Aquat. Sci. 53: 414-423.

Larkin, P.A. 1971. Simulation studies of the Adams River sockeye salmon, *Oncorhynchus nerka*. J. Fish. Res. Board Can. 28: 1493-1502.

Liermann, M., and Hilborn, R. 1997. Depensation in fish stocks: a hierarchical Bayesian meta-analysis. Can. J. Fish. Aquat. Sci. 44: 1976-1984.

McElhany, P., Ruckelshaus, M.H., Ford, M.J., Wainwright, T.C., and Bjorkstedt, E.P. 2000. Viable salmonid populations and the recovery of evolutionarily significant units. U.S. Dept. Commer., NOAA Tech. Memo. NMFS-NWFSC-42, 156 p.

MacDonald, J.S. 2000. Mortality during the migration of Fraser River sockeye salmon (*Oncorhynchus nerka*): a study of the effect of ocean and river environmental conditions in 1997. Can. Tech. Rep. Fish. Aquat. Sci. 2315: 120 p.

MacDonald, J.S., Foreman, M.G.G., Farrell, T., Williams, I.V., Grout, J., Cass, A., Woodey, J.C., Enzenhofer, H., Clarke, C., Houtman, R., Donaldson, E.M., and Barnes, D. 2000. The influence of extreme water temperatures on migrating Fraser River sockeye salmon (*Oncorhynchus nerka*) during the 1998 spawning season. Can. Tech. Rep. Fish. Aquat. Sci. 2326: 117 p.

McAllister, M.K., Pikitch, E.K., Punt, A.E. and Hilborn, R. 1994. A Bayesian approach to stock assessment and harvest decisions using the sampling/importance resampling algorithm. Can. J. Fish. Aquat. Sci. 51: 2673-2687.

McAllister, M.K. and Ianelli, J.N. 1997. Bayesian stock assessment using catch-age data and the sampling-importance resampling algorithm. Can. J. Fish. Aquat. Sci. 54: 284-300.

Mangel, M. 1985. Decision and control in uncertain resource systems. Academic Press Series on Mathematics in Science and Engineering. No. 172. Orlando, FL. 255p.

Meyer, R. and Millar, R.B. 1999. Bayesian stock assessment using a state-space implementation of the delay difference model. Can. J. Fish. Aquat. Sci. 56: 37-52.

Myers, R. A., Barrowman, N. J., Hutchings, J. A., and Rosenberg, A. A. 1995. Population dynamics of exploited fish stocks at low population levels. Science (Washington, D.C.) 269: 1106-1108.

Mueter, F.J., Ware, D.M., and Peterman, R.M. 2002. Spatial correlation patterns in coastal environmental variables and survival rates of Pacific salmon in the Northeast Pacific Ocean. Fisheries Oceanography. 11(4):205-218.

Patterson, K.R. 1999. Evaluating uncertainty in harvest control law catches using Bayesian Markov chain Monte Carlo virtual population analysis with adaptive rejection sampling and including structural uncertainty. Can. J. Aquat. Sci. 56: 208-221.

Peterman, R.M. 1981. Form of random variation in salmon smolt-to-adult relations and its influence on production estimates. Can. J. Fish. Aquat. Sci. 38: 1113-1119.

Peterman, R.M., Pyper, B.J., and Grout, J.A. 2000. Comparison of parameter estimation methods for detecting climate-induced changes in productivity of Pacific salmon (Oncorhynchus spp.). Can. J. Fish. Aquat. Sci. 57:181-191.

Peterman, R.M., Pyper, B.J., LaPointe, M.F., Adkison, M.D., and Walters, C.J. 1998. Patterns of covariation in survival rates of British Columbia and Alaska sockeye salmon (*Oncorhynchus nerka*) stocks. Can. J. Fish. Aquat. Sci. 55: 2503-2517.

Raiffa, H. 1968. Decision analysis. Addison-Wesley, Reading, Mass.

Robb and Peterman, R.M. 1998. Application of Bayesian decision analysis to management of a sockeye salmon (*Oncorhynchus nerka*) fishery. Can. J. Fish. Aquat. Sci. 55: 86-98.

Ricker, W.E. 1950. Cyclic dominance among the Fraser River sockeye. Ecology, 31: 6-26.

Ricker, W.E. 1954. Stock and Recruitment. J. Fish. Res. Board Can. 11: 559-623.

Roos, J.F. 1991. Restoring Fraser River Salmon. Canada. Pacific Salmon Commission, Vancouver, B.C. 438 p.

Routledge, R. D. and Irvine, J. R. 1999. Chance fluctuations and the survival of small salmon stocks.Can. J. Fish. Aquat. Sci. 56: 1512-1519.

Saila, S.B. 1996. Guide to some computerised artificial intelligence methods. *In* Computers in fisheries research. *Edited by* B.A. Megrey and E. Mokksness. Chapman and Hall, London. Pp. 8-40.

Schaefer, M.B. 1951. A study of the spawning populations of sockeye salmon in the Harrison River system, with special reference to the problems of enumeration by means of marked members. International Pacific Salmon Fisheries Commission Bulletin IV: 207p.

Schnute, J.T., Cass, A.J., and Richards, L.J. 2000. A Bayesian decision analysis to set escapement goals for Fraser River sockeye salmon. Can. J. Aquat. Sci. 57: 962-979.

Schnute, J.T and Kronlund, A.R.. 1996. A management oriented approach to stock recruitment analysis. Can. J. Fish. Aquat. Sci. 53: 1281-1293.

Schnute, J.T. and Richards, L.J. 1990. A unified approach to the analysis of fish growth, maturity, and survivorship data. Can. J. Fish. Aquat. Sci: 47 24-40.

Schubert, N.D. 1998. The 1994 Fraser River sockeye salmon (*Oncorhynchus nerka*) escapement. Can. Tech. Rep. Fish. Aquat. Sci. 2210: 62p.

Schubert, N.D. 2000. The 1994 Stellako River sockeye salmon (*Oncorhynchus nerka*) escapement: evaluation of poled Petersen and stratified mark-recapture estimates of a known population. Can. Tech. Rep. Fish. Aquat. Sci. 2303. 56p.

Shortreed, K.S., Hume, J.M.B., and Stockner, J.G. 2000. Using photosynthetic rates to estimate the juvenile sockeye salmon rearing capacity of British Columbia lakes, p. 505-521 *In:* Knudsen, E.E., Steward, C.R., MacDonald, D.D., Williams, J.E., and D.W. Reiser (eds). Sustainable fisheries management: Pacific salmon. CRC Press LLC.

Shortreed, K.S., Morton, K.F., Malange, K. and Hume, J.M.B. 2001. Factors limiting juvenile sockeye production and enhancement potential for selected BC nursery lakes. Canadian Science Advisory Secretariat Research Document 2001/098. (Available on-line at www.dfo-mpo.gc.ca/csas/)

Simpson, K. 1984. The accuracy of mark-recapture estimates of escapement. *In* P.E.K. Symons and M. Waldichuk (eds). Proceedings of the workshop on stream indexing for salmon escapement estimation, West Vancouver, B.C., 2-3 February 1984. Can. Tech Rep. Fish. Aquat. Sci. 1326: 209-225.

Symons, P.E.K. and Waldichuk, M. (eds). 1984. Proceedings of the workshop on stream indexing for salmon escapement estimation, West Vancouver, B.C., 2-3 February 1984. Can. Tech Rep. Fish. Aquat. Sci. 1326. 258p.

Walters C.J. 1975. Optimal harvest strategies for salmon in relation to environmental variability and uncertain production parameters. J. Fish. Res. Board. Can. 32: 1777-1784.

Walters, C.J. 1981. Optimum escapements in the face of alternative recruitment hypotheses. Can. J. Fish. Aquat. Sci. 88: 678-689.

Woodey, J.C. 1984. Escapement estimation in the management of Fraser River sockeye salmon, p. 121-132 *In*: Symons, P.E.K., and M. Waldichuk (eds.) Proceedings of the workshop on stream indexing for salmon escapement estimation, West Vancouver, B.C., 2-3 February 1984. Can. Tech. Rep. Fish. Aquat. Sci. 1326.

Woodey, J.C. 1987. In-season management of Fraser River sockeye salmon (*Oncorhynchus nerka*): meeting multiple objectives., p. 367-374. *In*: H.D. Smith, L. Margolis, and C.C. Wood (eds). Sockeye salmon (*Oncorhynchus nerka)* population biology and future management. Can. Spec. Publ. Fish. Aquat. Sci. 96.

Table 1. Estimates (millions) of optimal escapement (S_{MSY}) for Quesnel and Chilko sockeye.

	Stock	
	Quesnel	**Chilko**
Interim Spawning Escapement Goal (FRAP-FMG 1995) (2001, 2002 cycle year)	2.20	0.224
Optimum escapement based on stock-recruit analysis		
Larkin	2.353	NA
Ricker	4.860	0.507
Cycle Aggregate low	0.151	NA
Cycle Aggregate high	4.197	NA
Optimum escapement – based on lake rearing capacity (Shortreed 2000)	0.651	0.362
Observed maximum escapement	2.620	1.038

Table 2. Examples of management objectives, performance measures, benchmarks and components of the value function.

Objective	Possible Performance Measure	Possible Benchmarks	Possible Value Function Components
• Ensure conservation of stock units • Ensure long-term sustainability of populations • Maintain existing levels of genetic and phenotypic diversity • Maintain abundance at levels needed to maintain ecosystem processes	• Smallest escapement observed over next 40 years • Average long-term escapement • Variability in spawning escapement • Average long-term returns • Variability in returns •	• Spawning escapement level which produces 10% of the maximum recruits on average	• Proportion of simulated years in which spawning escapement level falls below the benchmark.
• Provide sustainable fishing opportunity for all harvesters	• Smallest annual catch observed over next 40 years • Long-term average total catch • Variability in total catch • Maximum decrease in catch from one year to the next • Harvest reduction over status quo during first four years • Measure of short-term economic viability (e.g. 4-year moving average of catch)	• Recent average of total catch • 10% of Catch at MSY • 50% of recent average	• Average catch • Proportion of simulated years in which total catch falls below the benchmark. • Proportion of years with 0 catch •

Table 3. Model components and options to be investigated in sensitivity analyses

Stock Dynamics

	S-R model	Shape of capacity prior (S*)	S-R parameter uncertainty[1] Upper limit on prior for capacity (S*)
Options	• Ricker – All years • Ricker -Cycle Aggregate • Larkin	• Uniform • Normal	• Observed Maximum • Based on Photosynthetic rate (Shortreed et al., 2000)[2] • Non-informative limit[3]

[1] S-R models are specified in terms of S^* and h^*, as in Schnute, Cass and Richards (2000)
[2] Fraser sockeye stocks tend to be limited by spawning ground capacity, rather than rearing lake capacity. Hence the estimated optimal spawning level based on Shortreed et al. (2000) is likely an over-estimate, and provides a reasonable upper limit.
[3] A non-informative upper limit for the prior S^* is chosen based on visual assessment of the joint posterior distribution of h^*. The prior for h* is uniform [0,1].

Harvest Rule Fitting

	Calculation method	Shape of harvest rule[4]
Options	• Estimate parameters of harvest rule in optimization • Estimate time sequence of optimal h, and then fit the harvest rule	• For all harvest rules the minimum stock size for harvest (x-intercept) is >0 • 0, 1, or 2 inflection points. Inflection points are estimated. • Maximum exploitation rate (asymptote) is either fixed at 1 or estimated

[4] Harvest rule fitting is based on the family of curves presented by Schnute and Richards (1989).

Table 3 continued

Value Function

	Structure	Benchmarks: S_{low}	Benchmarks: C_{low}	Benchmarks: C_{high}	Weights
Options	• simple additive	• 10% S_{max}[6] • 50% S_{max}	• 10% C_{MSY} • 50% C_{MSY}	• Recent average • Half recent average • Double recent average • C_{MSY}	• Mean C only • Mean C and 1 other • All 5 with varying weights • Interactions

[5] The value function contains four attributes: Mean C, P(C<Clo), P(C<Chi), P(S<Slo)

[6] S_{max} is defined as the spawning escapement which maximizes the number of recruits.

Type of Simulation

	Aggregation	Forward simulation	Retrospective simulation
Options	• Single stock unit • 2 stock units in mixed fisheries • 3 or more units	• Mean productivity is constant over time for each simulated unit • Different levels of temporal autocorrelation for each simulated unit • Split posterior of h^* into three ranges (low, medium, high) and sample parameter sets from each. • Specified periodic patterns in mean productivity	• Use observed deviations from S-R relationship over last 40 years

Table 4. Mean and modal Bayesian stock-recruitment parameter estimates for Chilko and Quesnel sockeye. *S** is in millions of fish.

		Mean			Mode			Benchmarks		
Stock	Model	h*	S*	sigma	h*	S*	sigma	S_{low} (10% S_{max})	C_{low} (10% C_{msy})	C_{high} (100% C_{msy})
Chilko[a]	Ricker	0.737	0.507	0.695	0.751	0.434	0.665	0.032	0.143	1.427
Chilko[b]	Ricker	0.775	0.345	0.705	0.772	0.362	0.674	0.017	0.118	1.180
Quesnel[c]	Ricker	0.707	4.860	0.940	0.718	2.059	0.895	0.262	1.180	11.803
Quesnel[d]	Ricker	0.733	0.631	1.074	0.739	0.651	1.023	0.032	0.177	1.772
Quesnel[e]	Ricker CA-low	0.696	0.151	0.996	0.718	0.071	0.887	0.008	0.034	0.337
Quesnel[f]	Ricker CA-high	0.733	4.197	0.793	0.753	1.873	0.719	0.211	1.158	11.580
Quesnel[g]	Larkin	0.772	2.353	0.888	0.773	2.586	0.820	0.205	0.942	9.422
	Larkin interaction Terms	β_1 = 0.255	β_2= 0.583	β_3 = 0.548	β_1 = 0.148	β_2 = 0.616	β_3 = 0.488			

a: S* prior = 0 < S* < 1.20
b: S* prior = 0 < S* < 0.362
c: S* prior = 0 < S* < 10.0
d: S* prior = 0 < S* < 0.651
e: fit to low cycle years only with S* prior = 0 < S* < 10.0
f: fit to high cycle years only with S* prior = 0 < S* < 10.0
g: all lagged escapements for Larkin model = 0 < S 10.0

Table 5. Effect of correctly and incorrectly applying harvest rules developed based different assumptions about the *S** prior for Quesnel Lake sockeye. *S** and Catch are in millions of fish.

Harvest Rule	Performance measure	S* prior		Expected value at probability ratio			Comparison of expected values		
		0<S*<0.651	0<S*<10.0	25:75	50:50	75:25	25:75	50:50	75:25
0<S*<0.651	Catch	3.45	5.86	5.26	4.66	4.05	41.32%	53.29%	85.38%
	P(C<Clow)	0.18	0.07	0.10	0.12	0.15	23.25%	21.63%	20.70%
	P(C<Chigh)	0.52	0.29	0.35	0.41	0.46	48.40%	50.18%	51.61%
	P(C=0)	0.13	0.05	0.07	0.09	0.11	21.49%	18.57%	17.06%
	P(S<Slow)	0.01	0.01	0.01	0.01	0.01	23.23%	12.17%	8.21%
0<S*<10.0	Catch	0.76	16.71	12.73	8.74	4.75			
	P(C<Clow)	0.89	0.26	0.42	0.57	0.73			
	P(C<Chigh)	0.99	0.64	0.72	0.81	0.90			
	P(C=0)	0.81	0.18	0.34	0.50	0.65			
	P(S<Slow)	0.14	0.00	0.04	0.07	0.10			

Decision Criteria

Harvest Rule based on	Performance measure	Avoid worst possible outcome (X) or Pick best outcome (√) S* prior		Choose best expected outcome (marked by √) At probability ratio			Worst outcome for each harvest rule	Maximin (Best of the worst)
		0<S*<0.651	0<S*<10.0	25:75	50:50	75:25		
0<S*<0.651	Catch						3.45	√
	P(C<Clow)			√	√	√	0.18	√
	P(C<Chigh)			√	√	√	0.52	√
	P(C=0)			√	√	√	0.13	√
	P(S<Slow)			√	√	√	0.01	√
0<S*<10.0	Catch	X	√	√	√	√	0.76	
	P(C<Clow)	X	√				0.89	
	P(C<Chigh)	X	√				0.99	
	P(C=0)	X	√				0.81	
	P(S<Slow)	X	√				0.14	

Table 6. Effect of correctly and incorrectly applying harvest rules developed based different assumptions about the S^* prior for Chilko Lake sockeye. S^* and Catch are in millions of fish.

Harvest Rule based on	Performance measure	S* prior		Expected value at probability ratio			Comparison of expected values		
		0<S*<0.362	0<S*<1.2	25:75	50:50	75:25	25:75	50:50	75:25
0<S*<0.362	Catch	1.66	1.59	1.61	1.61	1.61	96.36%	96.36%	96.36%
	P(C<Clow)	0.04	0.02	0.03	0.03	0.03	42.82%	42.82%	42.82%
	P(C<Chigh)	0.49	0.48	0.48	0.48	0.48	85.42%	85.42%	85.42%
	P(C=0)	0.01	0.01	0.01	0.01	0.01	34.47%	34.47%	34.47%
	P(S<Slow)	0.00	0.00	0.00	0.00	0.00	0.00%	0.00%	0.00%
0<S*<1.2	Catch	1.44	1.74	1.67	1.67	1.67			
	P(C<Clow)	0.10	0.05	0.06	0.06	0.06			
	P(C<Chigh)	0.64	0.54	0.57	0.57	0.57			
	P(C=0)	0.05	0.02	0.03	0.03	0.03			
	P(S<Slow)	0.00	0.00	0.00	0.00	0.00			

Table 7. Effect of correctly and incorrectly applying harvest rules developed based different assumptions about the S-R model for Quesnel Lake sockeye. Catch in millions of fish.

Harvest Rule based on	Performance measure	Dynamics model		Expected value at probability ratio			Comparison of expected values		
		CA	base case	25:75	50:50	75:25	25:75	50:50	75:25
CA	Catch	6.68	9.25	8.61	7.97	7.32	61.18%	69.70%	83.34%
	P(C<Clow)	0.15	0.10	0.11	0.12	0.13	32.13%	27.81%	24.99%
	P(C<Chigh)	0.71	0.50	0.55	0.61	0.66	80.14%	81.58%	82.84%
	P(C=0)	0.12	0.09	0.10	0.10	0.11	34.62%	27.21%	22.88%
	P(S<Slow)	0.03	0.02	0.02	0.03	0.03	48.57%	25.51%	17.41%
base case	Catch	6.15	16.71	14.07	11.43	8.79			
	P(C<Clow)	0.63	0.26	0.35	0.45	0.54			
	P(C<Chigh)	0.85	0.64	0.69	0.74	0.79			
	P(C=0)	0.57	0.18	0.28	0.38	0.48			
	P(S<Slow)	0.19	0.00	0.05	0.10	0.15			

Table 8. Effect of changing the shape of the harvest rule by stock. Catch is in millions of fish.

Performance measure	Quesnel: Harvest rule shape parameter b=-1	Quesnel: Harvest rule shape parameter b=1	Chilko: Harvest rule shape parameter b=-1	Chilko: Harvest rule shape parameter b=1
Catch	16.71	16.68	1.74	1.74
P(C<Clow)	0.26	0.25	0.05	0.03
P(C<Chigh)	0.64	0.64	0.54	0.54
P(C=0)	0.18	0.02	0.02	0.00
P(S<Slow)	0.00	0.00	0.00	0.00

Table 9. Effects of implementation error on performance for Chilko sockeye. Harvest rules were estimated without implementation error and then applied in simulations with a mean error of ±8%. In-season run size estimation and exploitation rate implementation error is shown separately and then for both combined. Catch is in millions of fish.

Performance Measure	Base Case	Run size error only	Exploitation rate error only	Combined
Catch	1.74	1.605	1.63	1.62
P(C<Clow)	0.05	0.030	0.08	0.08
P(C<Chigh)	0.54	0.500	0.58	0.58
P(C=0)	0.02	0.010	0.04	0.04
P(S<Slow)	0.00	0.000	0.00	0.00

Table 10. Effects of implementation error on performance when harvest rules were estimated with and without implementation error assuming a mean error of ±8% for Chilko sockeye. Catch in millions of fish.

Performance Measure	Simulated with run size error		Simulated with exploitation rate implementation error		Simulated with both run size error and exploitation rate implementation error	
	Base-case optimal harvest rule	Optimal HR estimated with run size error	Base-case optimal Harvest rule	Optimal HR estimated with exploitation rate error	Base-case optimal Harvest rule	Optimal HR estimated with both run size and exploitation rate error
Catch	1.74	1.74	1.66	1.66	1.65	1.65
$P(C<C_{low})$	0.00	0.00	0.00	0.00	0.00	0.00
$P(C<C_{high})$	0.54	0.55	0.57	0.57	0.57	0.57
$P(C=0)$	0.02	0.00	0.03	0.01	0.03	0.01
$P(S<S_{low})$	0.00	0.00	0.00	0.00	0.00	0.00

Table 11. Performance measures for simulations with penalty weights (v,w,y) separately applied to attributes in the value function compared to the base case. Each simulation was run with one of the penalty weights set to a value of 10. All other weights were set to zero except for the value of each unit catch. The value of each unit of catch was set to 1. Catch is in millions of fish.

A. Quesnel

Performance Measure	base case	v=10		w=10		y=10	
		value	% diff	value	% diff	Value	% diff
Catch	16.71	15.64	-6.4%	16.50	-1.3%	16.54	-1.1%
P(C<Clow)	0.26	0.16	-37.6%	0.25	-2.8%	0.26	-1.3%
P(C<Chigh)	0.64	0.65	1.4%	0.63	-0.8%	0.64	0.2%
P(C=0)	0.18	0.07	-63.3%	0.18	1.0%	0.17	-2.4%
P(S<Slow)	0.00	0.03	576.0%	0.03	576.0%	0.03	576.0%

B. Chilko

Performance Measure	base case	v=10		w=10		y=10	
		value	% diff	value	% diff	value	% diff
Catch	1.74	1.67	-4.3%	1.74	-0.1%	1.74	0.0%
P(C<Clow)	0.05	0.01	-86.6%	0.04	-10.1%	0.05	0.0%
P(C<Chigh)	0.54	0.56	3.5%	0.54	0.0%	0.54	0.0%
P(C=0)	0.02	0.00	-98.6%	0.01	-13.9%	0.02	0.0%
P(S<Slow)	0.00	0.00	0.0%	0.00	0.0%	0.00	0.0%

Table 12. Performance measures for simulations with penalty weights (*v*,*w*,*y*) applied in combination to attributes in the value function compared to the base case (*v*=0, *w*=0,*y*=0). Catch is in millions of fish.

A. Quesnel

Performance Measure	**base case**	**v=10,y=10**		**v=10,w=10**		**v=5,w=10**	
		value	**% diff**	**value**	**% diff**	**value**	**% diff**
Catch	16.71	15.64	-6.4%	15.61	-6.6%	15.64	-6.4%
P(C<Clow)	0.26	0.16	-37.6%	0.16	-37.4%	0.16	-37.6%
P(C<Chigh)	0.64	0.65	1.4%	0.65	1.5%	0.65	1.4%
P(C=0)	0.18	0.07	-63.3%	0.07	-63.0%	0.07	-63.3%
P(S<Slow)	0.00	0.03	576.0%	0.03	578.1%	0.03	576.0%

B. Chilko

Performance Measure	**base case**	**v=10,y=10**		**v=10,w=10**		**v=5,w=10**	
		value	**% diff**	**value**	**% diff**	**value**	**% diff**
Catch	1.74	1.70	-2.2%	1.67	-4.3%	1.68	-3.6%
P(C<Clow)	0.05	0.01	-75.3%	0.01	-86.6%	0.01	-83.9%
P(C<Chigh)	0.54	0.55	1.8%	0.56	3.5%	0.56	3.2%
P(C=0)	0.02	0.00	-93.1%	0.00	-98.6%	0.00	-98.6%
P(S<Slow)	0.00	0.00	0.0%	0.00	0.0%	0.00	0.0%

Table 13. Comparison of performance measures for hypothetical single-stock and mixed (two-stock) fisheries. Catches are in millions of fish. Catch is in millions of fish.

Performance Measure	Single-stock fishery			Two-stock fishery		
	Chilko	Quesnel	Total	Chilko	Quesnel	Total
Catch	1.74	16.71	18.46	0.81	16.38	17.61
P(C<Clow)	0.05	0.26	-	0.19	0.23	0.21
P(C<Chigh)	0.54	0.64	-	0.76	0.64	0.64
P(C=0)	0.02	0.18	-	0.12	0.12	0.12
P(S<Slow)	0.00	0.00	-	0.02	0.03	0.04

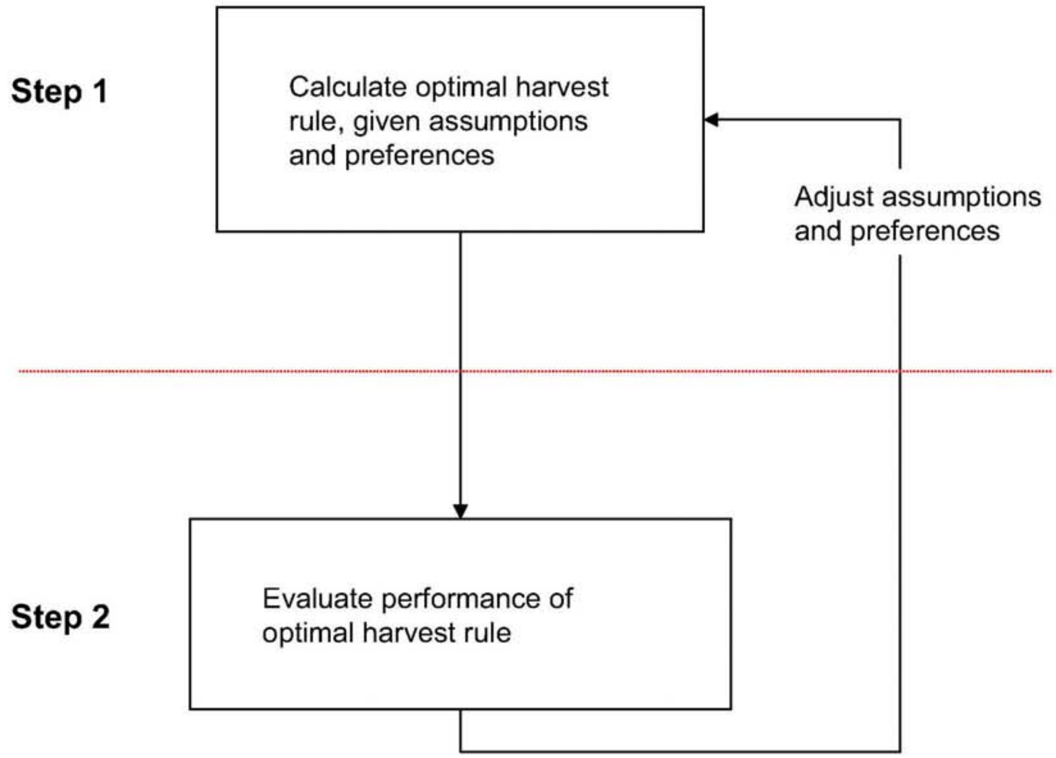

Figure 1. Flow diagram of the simulation model showing the overall, two-step simulation-estimation process for estimating optimal harvest rule and evaluating performance.

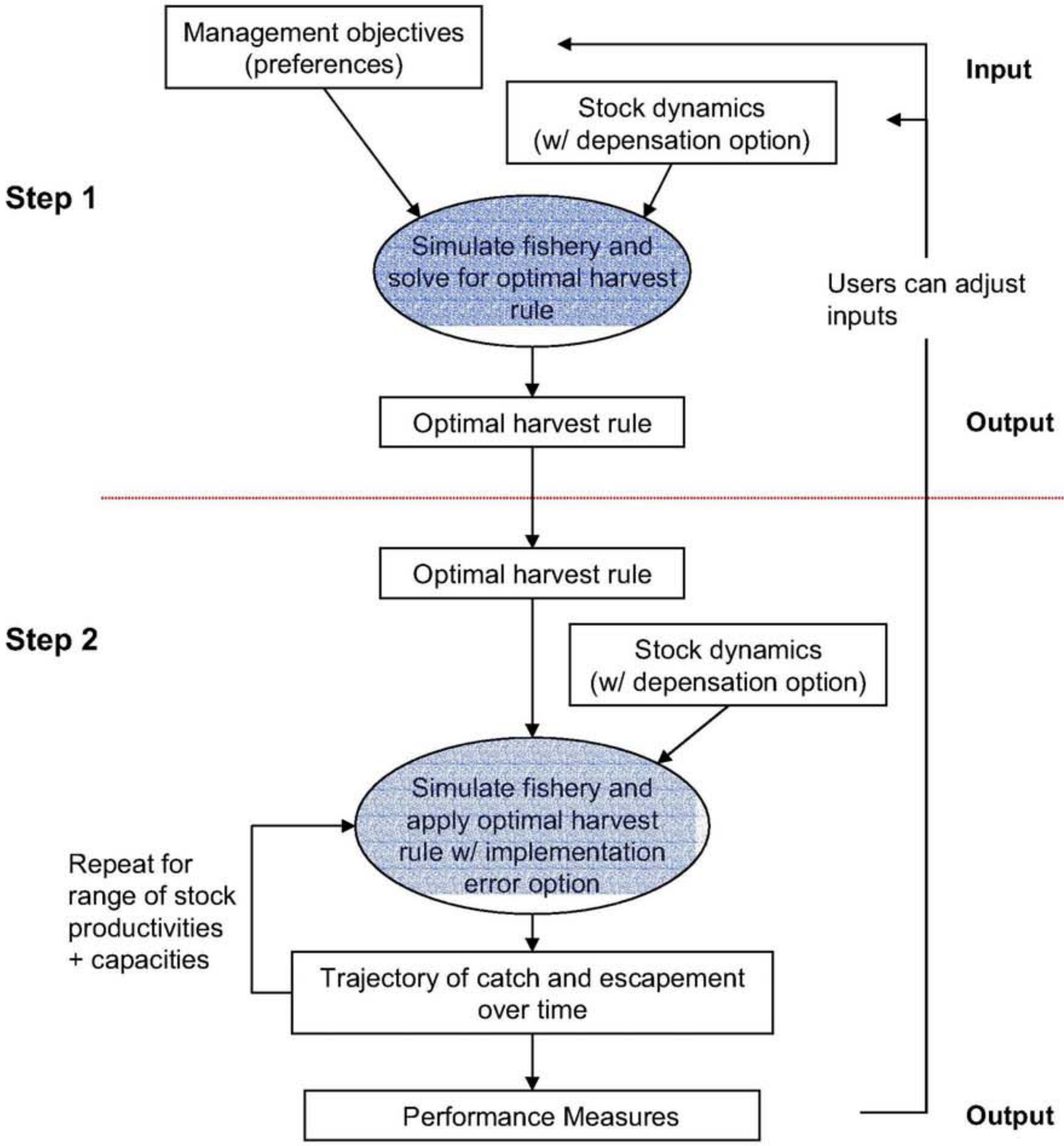

Figure 2. Flow diagram showing specific model inputs and outputs of the two-step framework shown in Figure 1.

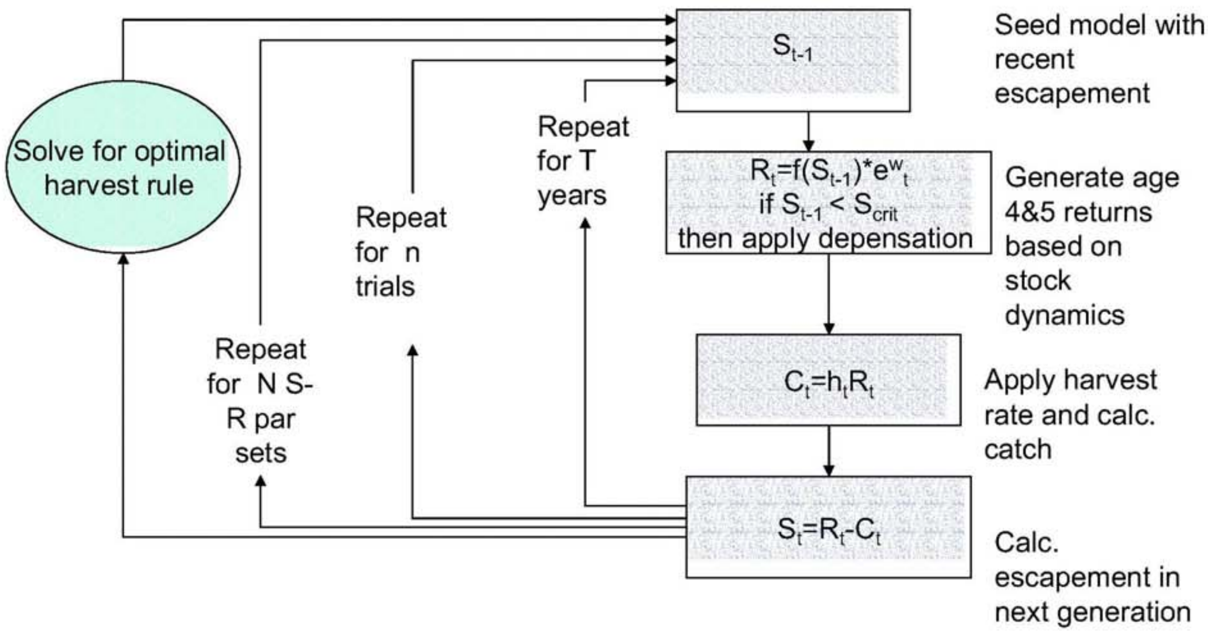

Figure 3. Flow Diagram showing the details of the simulation-estimation process in step 1 (see Figures 1 and 2).

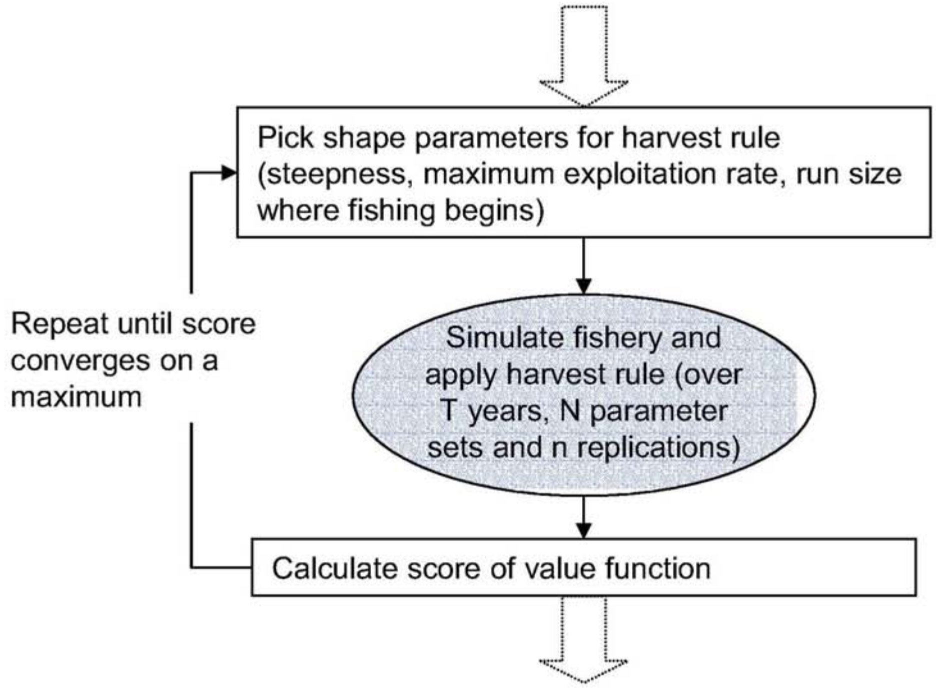

Figure 4. Flow diagram showing the iterative policy optimization process in the outer loop of the simulation-estimation routine of Step 1 shown in Figure 3 for estimating an optimal harvest rule.

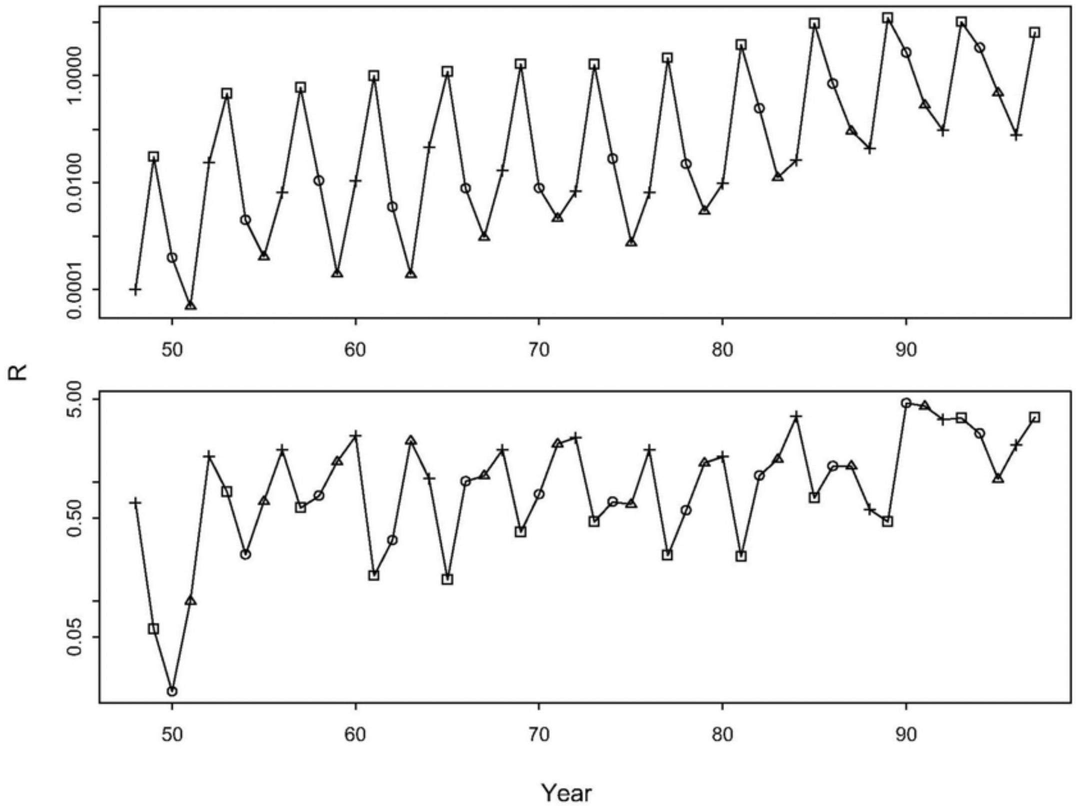

Figure 5. Time series of returns R for Quesnel (upper) and Chilko Lake sockeye (lower). Note is R is plotted on logarithmic scale. Symbols (+,□, ○, Δ) denote the 1996, 1997, 1998, 1999 cycle lines.

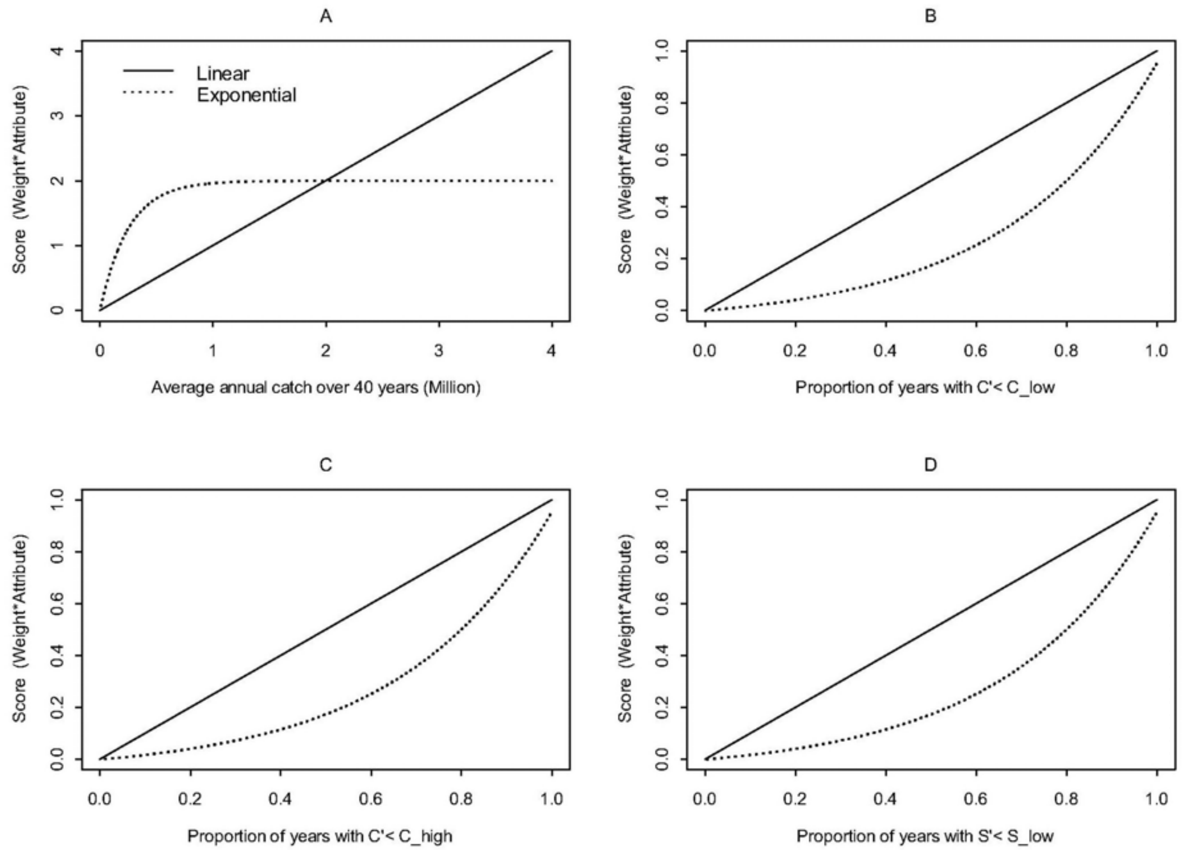

Figure 6. Linear and exponential components of the additive value function. The aggregate score for each scenario is the sum of attribute scores (Equation 21). Attribute scores are calculated based on the attribute value (e.g. $Prop(S'<S_{low})$), the shape of the attribute function (linear or exponential) and the weight for each component. The example shown uses $u = v = w = y = 1$, $\alpha = 8$, $\gamma_1 = 2$, $\beta = 8$, $\gamma_1 = 2$. The exponential value function for average catch puts a greater emphasis on increasing catch to 1 Million, but adds no additional score for larger catches (Panel A). For the proportional attributes, the exponential value function puts a greater emphasis on reducing high proportions. (Panels B,C,D). The penalty scores for proportional attributes can be adjusted relative to the average catch score by changing the weights *v,w,y*.

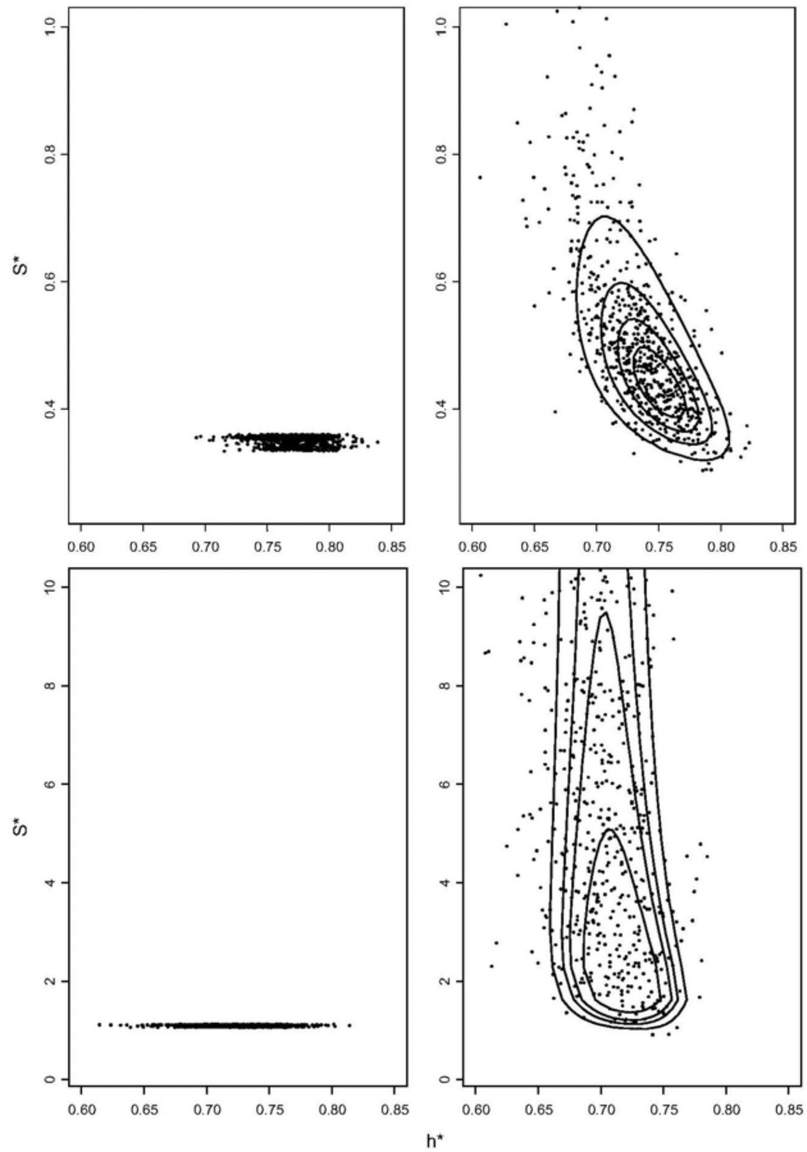

Figure 7. Joint probability distribution of Bayesian stock-recruitment parameter estimates (S*, h*) for Chilko Lake (upper) and Quesnel Lake (lower) sockeye. Contour lines in each panel are computed exactly from the posterior function, corresponding to 20, 40,60, and 80% posterior confidence regions. The left panels show the distribution for uniform prior for S*, Chilko: (0 < S* < 0.360), Quesnel: (0 < S* < 0.93). The upper limits on the *S** priors were set equal to the S_{max} value estimated from the PR model (Shortreed et al., 2000). The right panels show the distributions for a uniform prior for S*; Chilko: (0 < S* < 1.2), Quesnel: (0 < S* < 10). The upper limits on the S* priors set so that its influence on parameter estimation was negligible (i.e. uninformative).

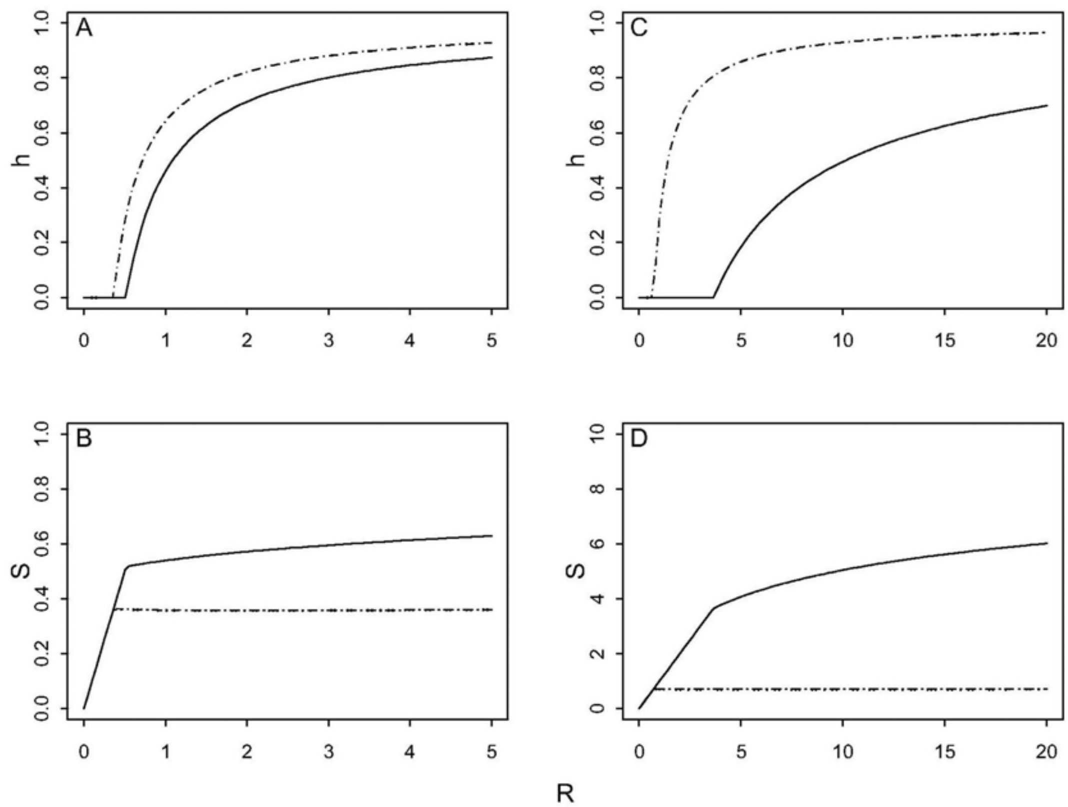

Figure 8. Harvest rules for Chilko (A, B) and Quesnel (C, D) sockeye based on the mean Schnute-Richards parameter estimates from fishery simulations with curve shape parameter b fixed (b=-1) for different upper limits on S* priors. The solid line represents the rule for dynamics with an uninformative upper limits on *S** prior (base case). The dashed line is for the prior set to equal the point estimate of S_{MSY} based on the PR model of Shortreed et al. (2000). Note that different scales apply to each stock (R,S in millions).

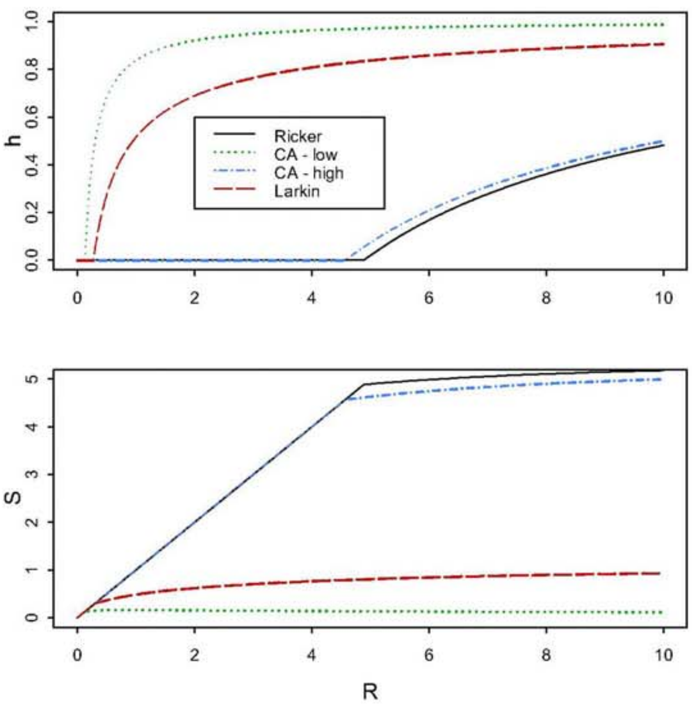

Figure 9. Optimal harvest rule for Quesnel sockeye based on the mean Schnute-Richards parameter estimates from fishery simulations with different S-R models and an uninformative S* prior. The Ricker model is fit to all years (Ricker), or to cycle line groupings (CA-low and CA-high). (R,S in millions).

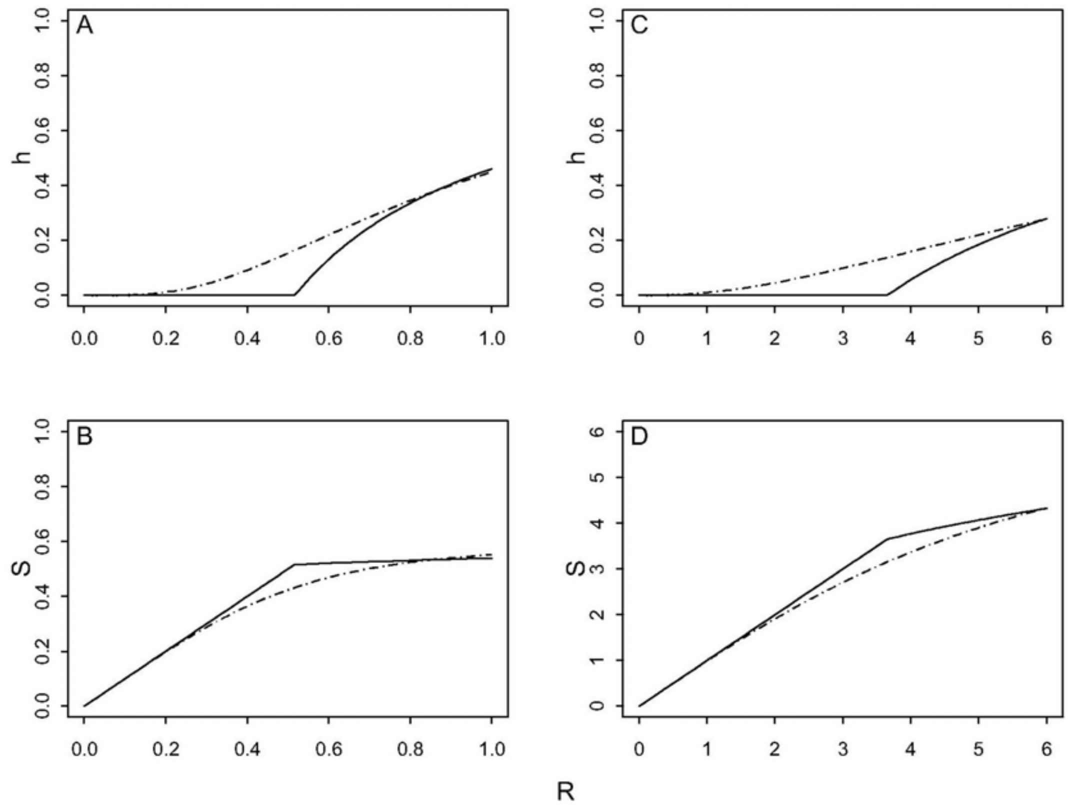

Figure 10. Harvest rules for Chilko (A, B) and Quesnel (C, D) sockeye based on the mean Schnute-Richards parameter estimates from fishery simulations with variable curve shape parameter b. The solid line represents the rule for *b*=-1. The dashed line is for b=1. All other parameters are for the base case. Note that different scales apply to each stock (R,S in millions).

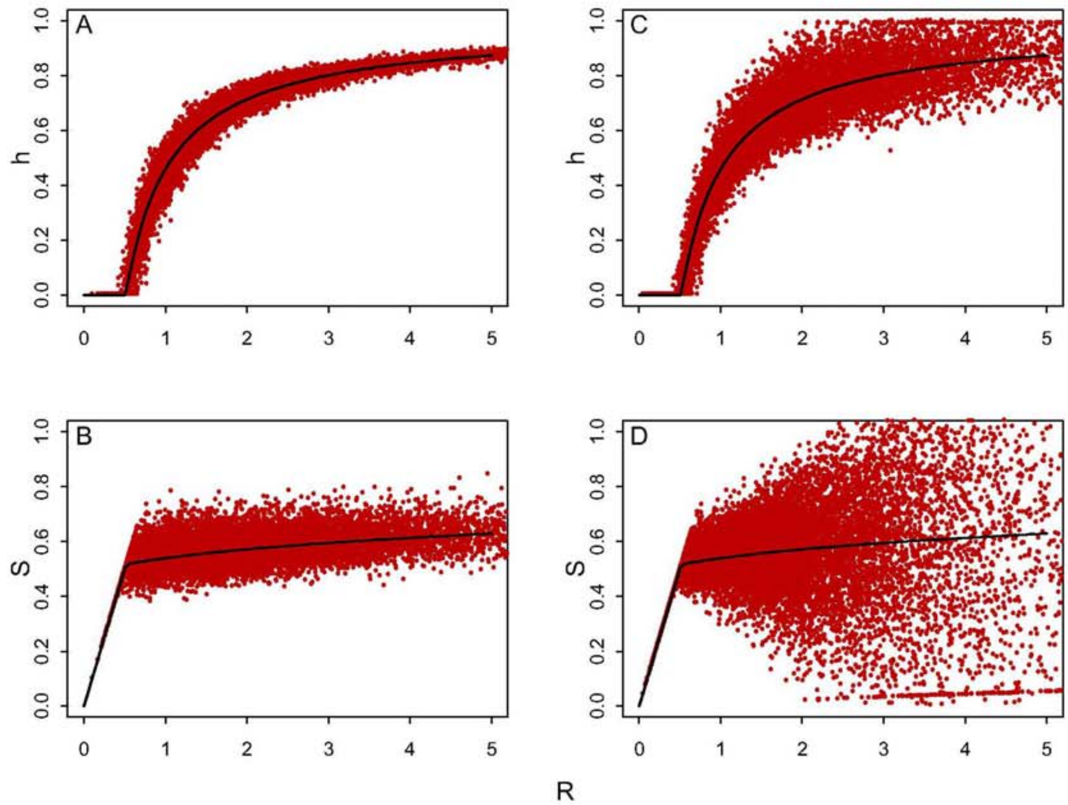

Figure 11. Simulated effects of run size error only (A,B) and additional exploitation rate implementation error (C, D) for base-case Chilko sockeye. Each dot represents the exploitation rate estimate (A,C) and corresponding escapement estimate (B, D) with the assumed error. The solid lines are the optimal curves in the absence or error. Both run size and implementation error assumed an average error of ±8% (R,S in millions).

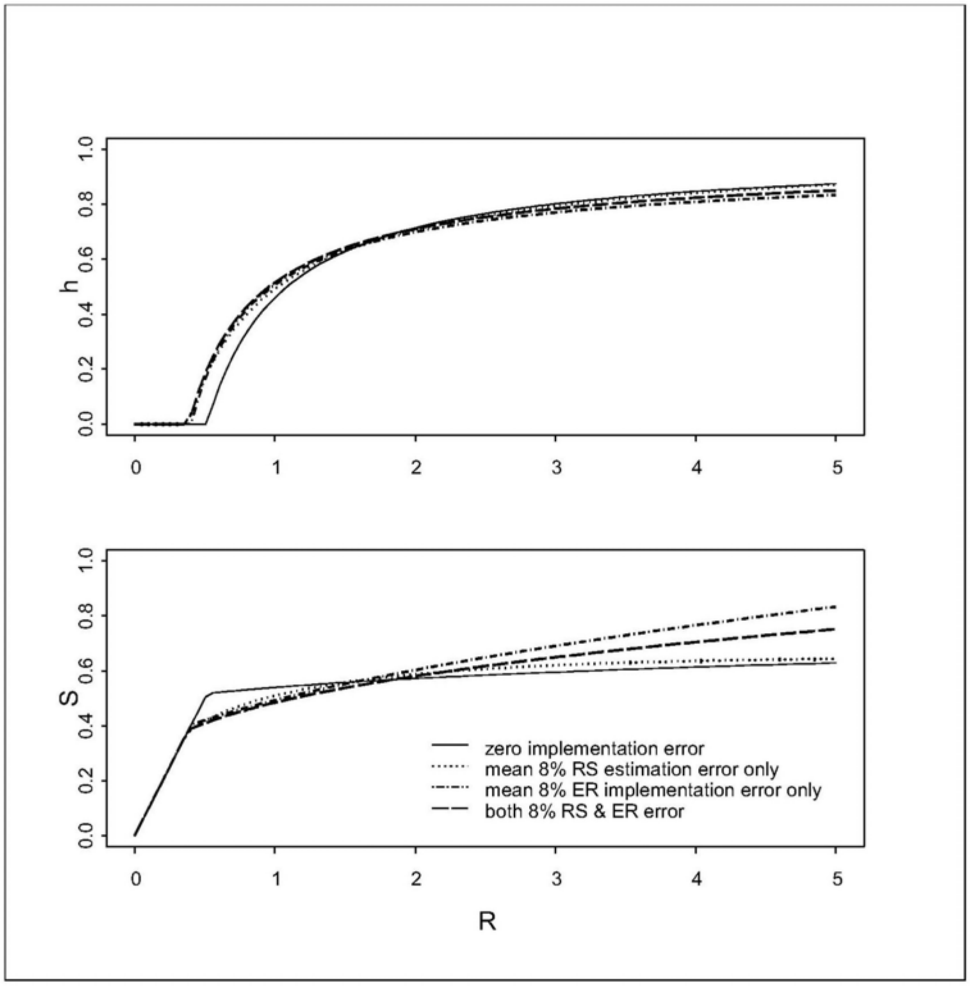

Figure 12. Optimal harvest rules for different assumptions for run size (RS) estimation error and target exploitation rate (ER) implementation error for base-case Chilko sockeye (R,S in millions).

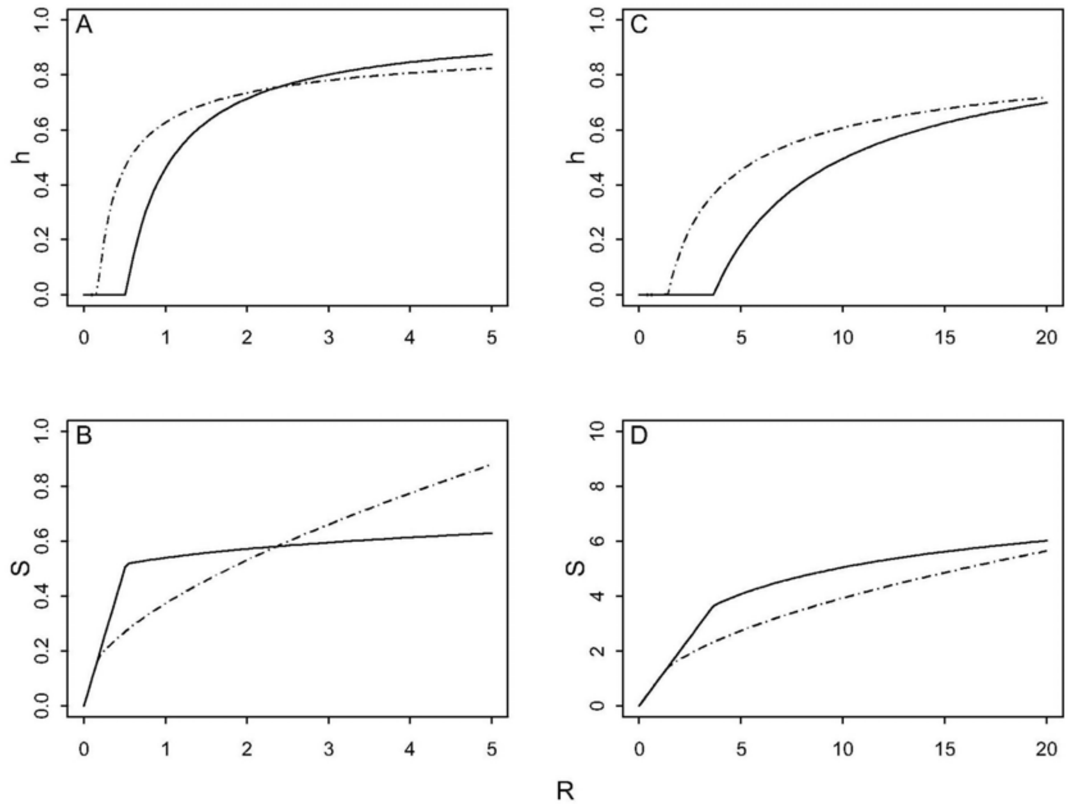

Figure 13. Optimal harvest rule for Chilko (A,B) and Quesnel (C,D) sockeye based on the mean Schnute-Richards parameter estimates from fishery simulations with a high penalty (v=10) for catch falling below C_{low} (broken lines) compared to the base case (solid line). (R,S in millions).

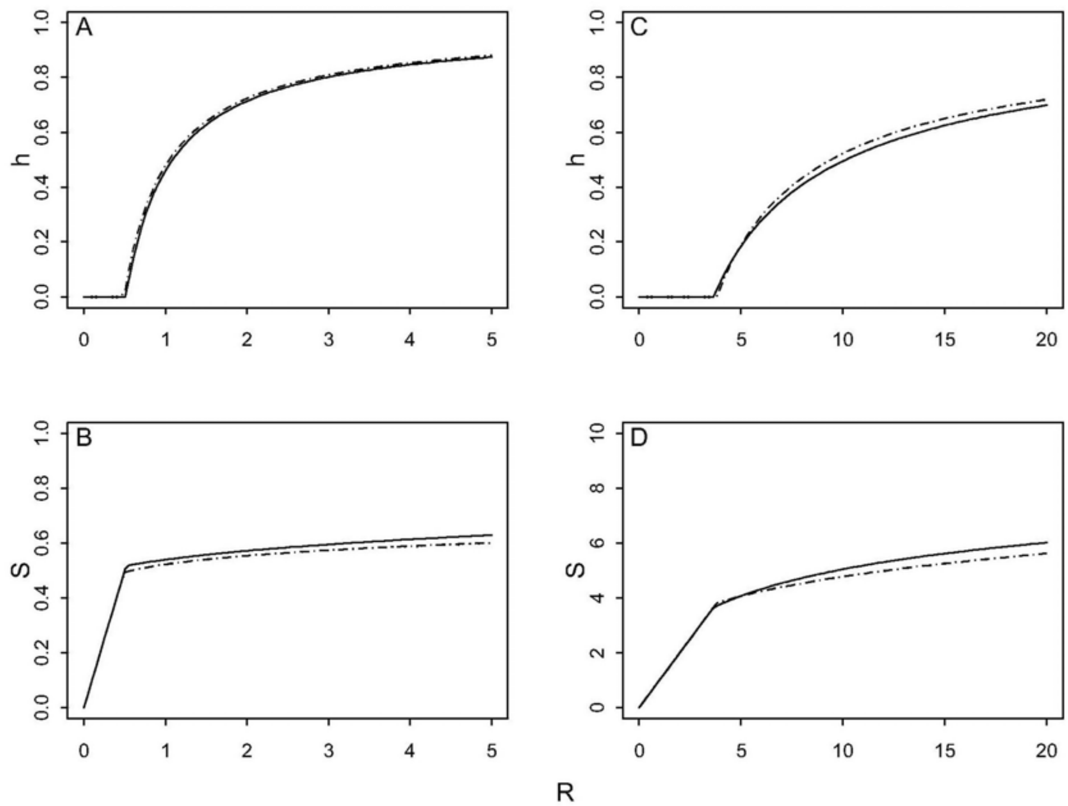

Figure 14. Optimal harvest rule for Chilko sockeye (A,B) and Quesnel (C,D) sockeye based on the mean Schnute-Richards parameter estimates from fishery simulations with different penalties for catch falling below C_{high} (R,S in millions).

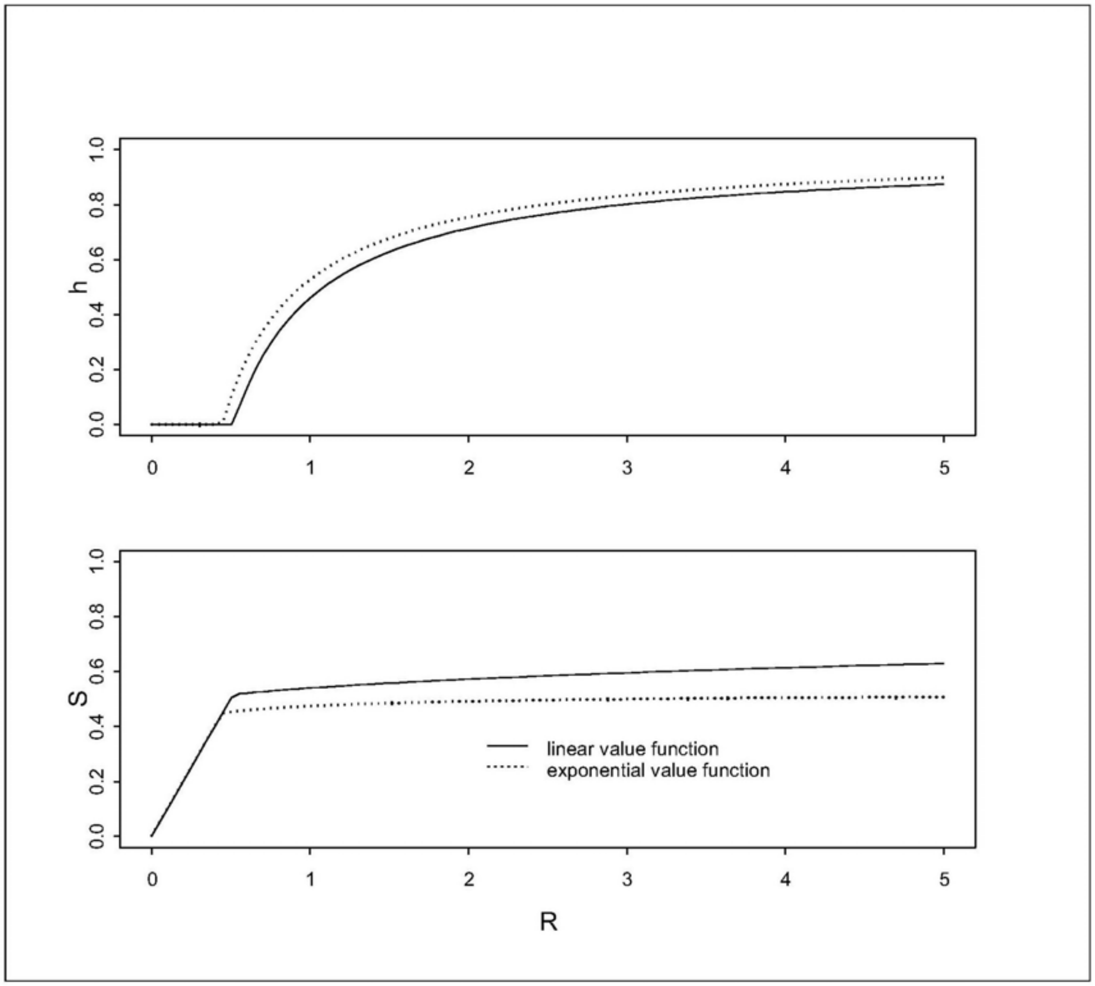

Figure 15. Optimal harvest rules for an additive linear (base-case) and exponential value function for Chilko sockeye (R,S in millions).

Appendix 1: PSARC Request for Working Paper

Fraser Sockeye Harvest Plan

Date Submitted: March 13, 2003

Individual or group requesting advice:
(Fisheries Manager/Biologist, Science, SWG, PSARC, Industry, Other stakeholder etc.)

- Paul Ryall (Area Chief Resource Management Lower Fraser Area) and Les Jantz (A/Area Chief Resource Management B.C. Interior)
- Steering Committee of the Fraser Sockeye Spawning Initiative

Proposed PSARC Presentation Date: June 23, 2003

Subject of Paper (title if developed): A decision framework for modelling management options of Fraser River Sockeye.

Stock Assessment Lead Author: Al Cass

Fisheries Management Author/Reviewer: Michael Folkes and Gottfried Pestal

Rationale for request:
(What is the issue, what will it address, importance, etc.)
The management of Fraser River sockeye is under review through the direction of the *Fraser River Sockeye Spawning Initiative* (here on referred to as *the initiative).* The current approach to managing Fraser River sockeye is target escapement driven. The management approach will likely shift to utilization of target exploitation rates curves which are driven by run size. However, the optimal exploitation rates curves are not to be derived solely from the stock-recruitment dynamics. We wish to have an ER curve which is estimated from stock recruitment analysis but is also an optimized balance of conservation requirements, stakeholders' priorities, and considers the range of productivities that Fraser stocks have endured during the last forty years. This initiative requires an analytical tool which attributes an empirical value to all stakeholder priorities and utilizes those priorities in the construction of an exploitation rate curve.

Objective of Working Paper:
(To be developed by FM & StAD for internal papers)
The main objective of the working paper will be to produce an analytical tool which will allow the *initiative* to assess optimal exploitation rate curves under the constraint of various management objectives and assumptions about factors controlling population dynamics. Harvest curves need to be produced for individual stocks and stock aggregates. The model should address, separately, selective harvest on individual stocks, and harvest at the mixed-stock level. The uncertainty surrounding implementation error (i.e. in-season run size estimation & management application) should be considered in the model.

Question(s) to be addressed in the Working Paper:
(To be developed by initiator)
While immediate results are not expected for review in PSARC, the framework should be have the capacity to address the following questions:

- For each stock and stock aggregate, what are the optimal exploitation rate and escapement curves given different management objectives and population dynamics assumptions?
- How do performance measures of a stock aggregate curve undergoing mixed stock management compare with a selective, single stock model?
- How do potential cyclic interactions influence the optimal exploitation rate curves?
- What are the implications of assumed conservation limits?
- What adaptive management experiments could one use if there are differences in terms of stock characteristics and capacity limits?
- What is the expected effect of different future patterns of productivity and survival?
- How sensitive is the model to biases in SR parameter estimation?

Stakeholders Affected:
The results of from this PSARC paper will be key in the development of Fraser River sockeye harvest and conservation strategies. As such all harvesters will be impacted

How Advice May Impact the Development of a Fishing Plan:
The *Initiative* will be the forum that utilizes the results of the working paper. Specifically, the tool will be used to 'game' given different objectives and population dynamics. The *initiative* is expected to give help in the decision-making process used to develop fishing plans.

Timing Issues Related to When Advice is Necessary
Results from this document will serve a guiding role in meetings of the *Initiative*. Meetings are tentatively planned for September 24/25, 2003.

Appendix 2. Glossary.

Benchmark	Specific level of a performance measure, used for quantitative assessment.
Control rule	See harvest rule
Exploitation rate	Exploitation rate is calculated based on estimated spawning stock (S) and total run size (R). The general calculation is (R-S)/R, but the specifics may differ by stock.
Exploitation rate curve	See harvest rule
Fixed Escapement Targets	Escapement targets do not change as run size estimates are updated. Fixed escapement generally refers to long-term targets, but in the Fraser system they are generally set before the season, and maintained throughout.
Gross Escapement	Salmon escaping all marine and intertidal fisheries and starting the up-river migration past Mission.
Harvest rate	Harvest rate is the proportion of fish in a given area removed by a specific fishery over a specific timeframe. Harvest rates from all fisheries combine result in the overall exploitation rate.
Harvest rule	Graphical representation of a management policy, commonly expressed as target exploitation rates for different run sizes. Target levels of catch and escapement vary accordingly. Denoted *H*.
Objective function	See value function
Spawning Escapement	Adult salmon reaching the spawning grounds. Denoted *S*.
S-R	Spawner-Recruit
Value Function	Weighted aggregate of performance measures used to evaluate harvest rules in the optimization

Appendix 3. Table of Symbols

α	Ricker model: Recruitment at low stock size
β	Ricker model: density dependent parameter
$\beta_1, \beta_2, \beta_3$	Lag-terms in the Larkin model
γ	Shape parameter in general S-R model. $\gamma = 0$ specifies a Ricker curve, while $\gamma = -1$ defines the Beverton-Holt model (Schnute et al 2000)
$\eta_{i,t}(\theta_i)$	Residuals from fitted S-R relationship with parameter vector θ_i
θ_i	Vector of S-R parameters for stock *i*
r	Coefficient of residual autocorrelation
ρ	Coefficient of among-stock correlation
C_{low}	Low benchmark for assessing annual catch
C_{high}	High benchmark for assessing annual catch
C_{MSY}	Catch at maximum sustainable yield (MSY)
ef_{it}	Proportion of effective females for stock *i* and time *t*
$\overline{ef}_i$	Mean proportion of effective females for stock *i* and time *t*
H	Harvest rule specifying target exploitation rate as a function of run size
H^o	Optimal harvest rule
h	Exploitation rate
h^*	*h* at MSY
h'	Simulated *h*
$h^o(R)$	Optimal exploitation rate for a given run size
R	Returns of adult salmon
$R_{i,t}$	*R* for stock *i* and time *t*
$P_o(\theta_i)$	Uniform prior distribution on θ_i
$P_o(\sigma_i)$	Non-informative prior on σ_i

R_{max}	Maximum number of recruits
S	Spawning escapement
$S_{i,t}$	S for stock i and time t
$S^{T}_{i,t}$	*Total* S for stock i and time t before rescaling
S_{max}	S which produces maximum number of recruits.
S^{*}	Spawning stock size at MSY
S_{low}	Low benchmark for assessing annual spawning escapement
S_{c}	Lowest spawning stock size observed (1948-1999)
sr_{it}	Sex ratio for stock i and time t
$\overline{sr}_{i}$	Mean sex ratio for stock i

Appendix 4. Spawning escapements and returns for Chilko Sockeye.

Brood	Spawning escapement				Brood year returns by age					
year	jack	male	female	% spawn	3_2	4_2	5_2	4_3	5_3	6_3
1948	403	277,737	392,885	0.93	32,000	1,643,062	11,182	6,131	254,316	1,282
1949	63	24,056	34,191	0.97	3,732	560,635	10,368	621	46,358	1,424
1950	9,139	9,815	7,493	0.87	1,489	183,278	4,705	954	15,449	0
1951	17,994	41,982	58,134	0.99	3,925	644,911	20,763	5,004	74,115	3,609
1952	4,480	224,256	261,329	0.89	18,732	1,763,929	35,975	114	38,833	893
1953	554	91,350	109,341	0.86	1,172	514,554	14,004	2,583	86,362	781
1954	3,447	12,459	21,837	0.97	12,234	632,132	4,415	2,844	58,891	2,233
1955	10,979	40,578	80,589	0.94	32,418	1,407,963	31,011	1,373	40,510	0
1956	862	260,525	386,381	0.95	13,905	2,379,854	16,684	75	25,152	0
1957	2,301	54,952	83,512	1.00	76	117,362	3,149	63	17,578	0
1958	16,977	49,600	70,504	1.00	4,055	278,320	13,613	1,711	130,581	5,091
1959	8,102	189,677	273,383	1.00	23,792	2,080,497	18,659	1,272	88,363	0
1960	61	179,209	247,337	0.99	5,472	958,877	5,980	1,045	81,961	0
1961	1,214	15,515	23,586	0.64	256	52,713	11,583	409	4,492	0
1962	14,754	28,212	49,501	0.85	10,657	960,609	13,582	0	696	18
1963	4,021	454,959	543,272	0.38	37,579	1,112,861	4,045	3,971	47,006	841
1964	329	103,777	134,495	0.98	7,252	1,818,921	55,810	1,343	156,756	0
1965	4,567	12,294	23,041	0.90	1,787	138,555	2,360	1,782	14,460	0
1966	17,083	94,921	114,698	0.94	26,456	744,469	27,636	1,479	89,160	0
1967	1,622	72,563	102,152	0.88	28,734	1,933,329	23,351	5,300	8,770	0
1968	584	173,238	240,624	0.76	46,952	2,335,183	21,925	1,108	55,581	1,128
1969	5,616	28,491	42,411	0.60	4,126	369,954	15,839	294	12,070	0
1970	9,661	63,483	71,905	0.71	16,775	627,337	1,084	4,296	39,119	0
1971	17,073	57,727	99,466	0.91	24,353	571,260	0	2,592	4,183	0
1972	1,815	225,935	336,715	0.99	37,001	1,861,092	12,635	902	27,052	0
1973	6,032	24,786	30,889	0.98	7,640	180,432	4,843	2,879	17,949	0
1974	18,568	36,569	72,994	0.97	18,667	547,007	4,748	2,309	27,910	0
1975	20,815	81,685	118,054	0.86	8,131	1,406,022	7,375	3,960	56,488	390
1976	2,559	146,424	215,328	0.98	7,798	1,572,025	25,168	161	13,897	0
1977	4,783	20,671	28,868	0.69	2,708	189,574	2,743	0	0	0
1978	8,433	60,269	83,133	1.00	8,307	1,125,918	77,743	44	9,789	0
1979	5,370	80,701	154,223	0.87	5,962	1,459,307	67,538	113	4,377	7,804
1980	846	169,437	298,375	0.93	8,842	3,496,336	473,961	414	28,408	2,375
1981	1,549	12,919	21,441	0.94	1,220	177,561	4,547	1,633	16,386	0
1982	2,360	99,437	140,466	0.97	47,921	1,300,458	115,688	0	28,961	1,412
1983	2,290	138,690	190,530	0.94	43,205	1,215,599	36,418	1,461	228,478	4,399
1984	350	223,925	228,693	0.96	3,915	324,216	2,890	316	125,657	5,802
1985	14,685	36,373	35,062	0.99	331	308,815	184,400	1,563	18,862	1,136
1986	28,626	112,924	168,847	0.94	21,355	4,413,216	282,507	335	54,505	5,033
1987	2,102	88,974	150,627	0.93	11,552	4,036,989	316,979	863	56,111	2,975
1988	514	115,629	139,039	0.97	2,697	2,979,547	157,353	797	154,472	0
1989	5,480	17,444	35,595	0.98	11,841	3,139,648	80,689	0	0	0
1990	7,476	316,764	509,073	0.98	13,265	2,480,876	153,178	3,056	15,371	0
1991	1,887	420,297	617,440	0.97	4,425	891,508	128,918	1,140	123,021	0
1992	4,396	190,554	320,713	1.00	4,633	1,781,463	79,236	614	9,774	0
1993	6,639	230,736	324,490	0.99	18,173	3,401,545	470,430	208	13,659	0
1994	1,494	188,475	262,270	0.97	10,606	1,142,007	73,494	184	4,593	0
1995	4,709	219,798	314,761	0.93	2,778	1,056,481	180,012	36	45,038	2,416

Appendix 5. Spawning escapements and returns for Quesnel Sockeye.

Brood	Spawning escapement				Brood year returns by age					
year	Jack	male	female	% spawn	3_2	4_2	5_2	4_3	5_3	6_3
1948	0	50	50	0.95	0	1,132	0	0	0	0
1949	0	10,438	20,226	0.95	22,455	463,409	0	0	0	0
1950	0	121	277	0.95	34	2,014	0	0	0	0
1951	0	27	22	0.40	0	413	0	0	0	0
1952	6,833	92	92	0.56	0	562	0	0	0	0
1953	8	47,485	63,432	0.75	5,902	604,123	220	0	0	0
1954	0	149	150	0.97	0	10,692	0	0	0	0
1955	0	31	32	0.95	0	180	0	0	0	0
1956	2,588	40	41	0.95	18	2,535	0	0	0	0
1957	0	82,023	141,644	0.95	8,359	989,580	144	0	30	0
1958	0	574	1,289	0.98	27	3,362	23	0	0	0
1959	11	35	30	0.97	0	165	0	0	0	0
1960	2,765	128	164	0.75	6	1,469	0	0	0	0
1961	9	118,506	184,059	0.38	44,481	1,195,807	509	0	93	0
1962	0	462	616	0.92	30	7,257	0	0	0	0
1963	3	36	47	0.85	0	956	0	0	0	0
1964	15,447	162	92	0.83	0	2,812	0	0	0	0
1965	10	166,919	197,787	0.53	14,161	1,652,107	821	0	83	0
1966	0	616	1,137	0.91	28	7,038	396	0	0	0
1967	0	59	60	0.40	11	1,750	0	0	0	0
1968	5,064	349	350	0.95	0	497	0	0	0	0
1969	5	115,242	163,719	0.48	6,413	1,626,582	7,768	0	0	0
1970	5	461	907	0.42	0	20,339	0	0	0	0
1971	0	65	106	0.15	0	747	0	0	0	0
1972	3,377	40	71	0.64	9	1,383	0	0	0	0
1973	0	124,663	153,398	0.73	5,114	2,153,882	2,429	0	0	0
1974	0	1,846	2,613	0.99	79	19,886	1,143	0	114	0
1975	8	88	105	1.00	0	1,713	0	0	0	0
1976	1,892	96	209	1.00	0	1,233	0	0	0	0
1977	24	248,303	267,896	0.60	8,446	3,810,786	54,029	0	5,261	0
1978	0	4,194	4,420	0.98	142	186,073	10,473	0	36	0
1979	0	243	268	0.89	0	2,103	3,908	0	0	0
1980	2,902	154	154	0.64	0	2,446	0	0	0	0
1981	31	346,412	402,209	0.81	19,608	9,553,856	213,188	0	0	0
1982	0	19,279	20,562	0.98	0	499,074	60,605	0	0	156
1983	0	701	1,454	0.76	33	32,959	8,864	0	0	0
1984	5,272	323	591	0.93	85	6,868	0	0	0	0
1985	0	605,659	712,092	0.95	28,135	12,137,665	334,171	0	17,706	993
1986	6	79,927	101,540	0.93	41	2,364,628	164,686	0	0	0
1987	13	7,600	12,946	0.84	11	116,727	0	0	0	0
1988	20,202	2,151	4,681	0.88	0	0	0	0	0	0
1989	13	913,798	957,022	0.98	0	10,119,506	334,546	51	13,605	0
1990	7	225,272	262,987	0.99	570	2,995,905	371,837	0	0	0
1991	0	20,885	25,374	0.98	37	111,274	48,185	0	268	0
1992	0	0	0	1.00	0	28,058	0	0	0	0
1993	303	1,075,708	1,544,746	0.98	1,642	6,465,519	429,754	0	3,304	0
1994	7	314,749	371,662	0.98	248	2,437,332	214,504	0	352	0