Management Strategies for AYK Salmon Stocks: Accounting for uncertainty

Final Report of an Expert Panel

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Arctic Yukon Kuskokwim Sustainable Salmon Initiative

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Executive Summary

In 2008 the Arctic-Yukon-Kuskokwim Sustainable Salmon Initiative (AYK SSI) called for an expert panel to evaluate methods to establish suitable escapement goals for AYK salmon stocks. This document summarizes the findings of the panel, which was formed in May 2009 and conducted its work between May 2009 and December 2010. The panel visited the AYK region to meet with managers and research biologists during summer 2009 and convened a broader meeting of Alaska salmon managers and biologists in October 2009 to seek advice on its activities. From this engagement emerged three distinct analyses that we present in this report. All three are examples of an approach to policy analysis referred to as Management Strategy Evaluation (MSE). MSE is a modeling approach that simulates the entire biological and management system while explicitly incorporating uncertainty in system structure, environmental stochasticity, observation errors in data collection, and errors in management implementation. The analyses focused on two stocks: Yukon River fall chum and Kuskokwim River Chinook salmon. We parameterized our simulations using estimates from Bayesian stock recruitment models fit to run reconstruction data from each stock.

The first analysis evaluated the effects of uncertainty on harvest policy trade-offs for the Yukon River fall chum and Kuskokwim River Chinook salmon stocks. We applied the general risk assessment approach of Collie et al. (2009) which treats policies as combinations of two policy choices: a target minimum escapement, and a commercial fishery exploitation rate on the surplus salmon run in excess of the minimum escapement and subsistence utilization. The magnitude of observation and implementation uncertainty was varied in the analysis to assess their effects on management trade-offs. Similar trade-offs existed for both stocks. Deviating from the conventional escapement policy (escapement goal centered on the escapement that produces MSY; i.e., harvest rate on surplus salmon = 1.0) by simultaneously reducing the minimum escapement target and the commercial harvest rate resulted in increased subsistence catch, reduced probability of commercial closure, and reduced probability of a stock of concern designation. However, these gains came at the expense of reduced average commercial catch. Harvest policy trade-offs were relatively insensitive to different assumptions regarding the magnitude of observation and implementation uncertainty. This is an important finding because it suggests that future deliberations regarding policy tradeoffs need not be overly concerned whether estimates of system uncertainty are highly accurate. Instead these deliberations can focus on the inherent trade-offs among objectives while encouraging stakeholders to find common ground on how these stocks should be managed.

The second analysis considered the performance of the percentile method for setting escapement goals based on historical escapement observations. Many AYK salmon stocks lack necessary data for fitting stock recruitment relationships. In these situations, an alternative approach called the percentile method is often used to set escapement goals. One such method sets an escapement goal range based on the 15th and 85th percentiles of the observed time series of escapements. We used an MSE model for Kuskokwim River Chinook to assess the effects of the historical exploitation status of the stock, the duration of the period in which initial escapement data were collected, and the magnitude of observation and implementation errors on the performance of the percentile method. Performance was strongly related to the initial exploitation status of the stock but not to the magnitude of uncertainty or the length of the initial escapement data time series. For lightly exploited stocks, the percentile method results in reduced catch and increased probability of commercial closure relative to what would be expected if an MSY policy was implemented. Under high initial exploitation, performance measures were generally within 50% of their respective MSY values as long as initial exploitation was not too high (escapement > 20% of MSY escapement) The escapement goals themselves drifted downward over time by up to 25% for stocks initially exploited at less than MSY, but were otherwise unchanged. We also evaluated the effects of stock productivity on performance of the percentile method. Our results suggest that the percentile method may be more robust for highly productive stocks.

The third analysis considered the challenges associated with the management of salmon harvest within a year (in-season management) for Yukon River fall chum salmon. Two critical aspects of in-season management that warrant investigation are (1) the statistical method used to combine the pre-season forecast and the in-season data when estimating the expected run size and (2) the degree of risk tolerance assumed by managers in prosecuting the fishery (e.g., how aggressively managers set fishery openings/closings). The method used to estimate the expected run size had no effect on fishery performance. The degree of risk tolerance had only modest effects on fishery performance measures such as average catch, probability of commercial closure, and average escapement, when integrated over all possible future run sizes. However, effects were more pronounced in years when the pre-season forecast was near the management thresholds of 300, 500, and 600 thousand salmon. In these cases, a risk averse manager would sacrifice substantial amounts of commercial and subsistence catch but with only relatively small gains in escapement. Thus, managers should carefully consider whether lost fishing opportunities due to a risk averse approach are justified considering the small expected gains in escapement objectives.

The panel believes that the analyses presented in this report show considerable promise as a means to facilitate discussions of how uncertainty and risk should be included in future policy deliberations for AYK salmon management. The models provide a rigorous, quantitative basis for estimating the potential benefits and risks of alternative policy choices by formally incorporating uncertainty into realistic models of the salmon populations and their fisheries. We have been encouraged by the positive response to our work from agency biologists and managers. The next steps will be to (a) continue working with managers and decision makers to promote effective use of the models; (b) development of effective tools for communication of the rationale, analytical approach, and management implications of our analysis to a wide range of audiences, including stakeholder groups; and (c) application of our approach to other AYK salmon fisheries.

Part 1: Introduction

In 2008 the Arctic-Yukon-Kuskokwim Sustainable Salmon Initiative (AYK SSI) called for an expert panel to consider and advise on methods to establish suitable escapement goals for AYK salmon stocks. The AYK SSI Steering Committee charged their Scientific and Technical Committee with appointing this panel in relation to Theme #4 of the AYK SSI Research and Restoration Plan: "Evaluation and development of management tools". This document summarizes the findings of the panel, which was formed in May 2009 and conducted its work between May 2009 and December 2010.

After a period of initial deliberation, the panel (Table 1) developed the following overarching research goal to guide its activities:

> *To provide advice on appropriate methods and strategies for establishing and evaluating escapement goals that support effective harvest policies for AYK salmon stocks, where that advice is based on:*
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> - *Consideration of a range of possible management objectives and the influence of management regimes on escapement goal decisions and options;*
> - *Assessment of the influence of uncertainty and risk on the performance of escapement goals;*
> - *Recognition of the wide variation in the quantity and quality of relevant data on AYK salmon stocks; and*
> - *Consideration of the potential influence of future environmental change on the performance of policies.*

This goal reflects four issues viewed by the panel as key to development of a scientifically defensible harvest policy for AYK salmon. First, there are usually many – potentially conflicting – interests associated with a salmon fishery. A policy that maximizes the expected sustainable yield from a fishery may not be the one that best meets as many of these interests as possible.

Instead, the expected performance of alternative policies should be evaluated by considering a variety of performance measures that reflect different interests in the fishery. Second, uncertainty is a pervasive feature of AYK salmon fisheries. We have far from perfect knowledge of salmon population dynamics and a limited ability to measure harvest and abundance. This uncertainty means that decisions we make will have uncertain outcomes, which creates risk. Sound policy should explicitly consider this risk, not simply ignore it or adjust for it arbitrarily. Third, our level of ignorance about many AYK stocks is higher than for many other salmon fisheries, which can preclude the use of data intensive methods for determining harvest policies. Finally, there is now strong evidence (Peterman et al. 1998) that the productivity of salmon populations can vary considerably over time, likely due to decadal-scale variations in oceanic conditions. A policy that appears to have performed well (or poorly) in recent years may lead to very different outcomes in the future. This gives rise to an additional element of risk in the policy analysis.

With this broad goal in mind, the panel visited the AYK region to meet with managers and research biologists during summer 2009 and convened a broader meeting of Alaska salmon managers and biologists in October 2009 to seek advice on our activities. From this engagement emerged three distinct analyses that we present in this report. All three are examples of an approach to policy analysis referred to as Management Strategy Evaluation (MSE; Smith et al. 1999). Briefly, MSE is a model-based analysis wherein the entire management process is simulated, including data collection (assessment), management, and the actual system dynamics. For AYK salmon this means collection of harvest and assessment data (to inform decisions and update models), implementation of a control rule (how much harvest to allow for commercial and subsistence fisheries), and salmon stock-recruit dynamics. The MSE model is used to compare the performance of alternative management procedures, including both data collection and harvest strategies. MSE models include uncertainty, which allows consideration of risk, but also means they can be used to examine the significance of differing levels of uncertainty, thereby enabling consideration of the value of better information (reduced uncertainty) to the management process.

The first analysis explicitly considers the effects of uncertainty on policy trade-offs that arise when one compares different harvest strategies. We followed the approach used by Collie et al. (2009) where they compared a range of minimum escapement levels and commercial harvest rates on the surplus production above this escapement level and expected subsistence harvest. Each combination of escapement level and harvest rate constitutes a single policy option. We used an MSE model to evaluate the performance of 121 policy combinations measured in terms of six performance measures that were intended to represent expected benefits and risks for commercial fishing, subsistence harvest, and escapement. We developed models for two case study stocks: Kuskokwim River Chinook salmon and Yukon River fall chum salmon. The details of this analysis are reported in Section 2 of this report.

The second analysis considered the performance of a method for setting escapement goals based on historical escapement observations (Bue and Hasbrouck 2001). It will not be possible to complete stock-recruitment analyses for many AYK salmon stocks in the foreseeable future, primarily because of difficulties determining stock-specific harvests in mixed-stock fisheries. We used an MSE model to simulate application of a historical escapement method across a wide range of conditions, mainly representing different initial levels of stock exploitation. We used a similar set of performance measures as was used in the first analysis. We also considered how differing levels of uncertainty, and the number of years of data used to determine the initial escapement goals, affected the method's performance. We used data for

Kuskokwim Chinook salmon as the basis for our analysis. The details are reported in Section 3 of this report.

The third analysis considered the challenges associated with the management of salmon harvest within a year (in-season management). Managers need to make decisions about whether to allow fishing in the face of high uncertainty about the actual run size in a given year, particularly early in the season. We used an MSE model of in-season management for Yukon fall chum salmon to consider alternative rules for combining pre-season forecasts with in-season data, and differing levels of precaution on the part of managers faced with an uncertain run size estimate. A similar set of performance measures was used for this analysis as well. The details of this analysis are reported in Section 4.

All three analyses required a model of the underlying population dynamics of the stocks being simulated. For both Kuskokwim Chinook and Yukon fall chum salmon we used run reconstructions for these aggregate stocks to conduct a stock-recruitment analysis using a Bayesian state-space method. This analysis enabled us to develop both point estimates of the stock-recruitment and maturation parameters and measures of the uncertainty associated with these estimates. We used the results of this analysis as the basis for the population dynamics component of each of our MSE models. The details of the stock-recruitment analysis are summarized in Appendix A, and the details of how the stock-recruit models were used in each MSE analysis are included in Sections 2-4.

Part 2. The effects of uncertainty on harvest policy tradeoffs for two AYK salmon stocks

Multi-objective tradeoffs are a fundamental aspect of fisheries management (Walters and Martell 2004). Tradeoffs occur when lesser achievement of one objective is accepted to attain better achievement of a competing objective (Clemen 1991). Naturally, tradeoffs cause conflict among resource user groups because users differ in the relative values they place on competing objectives. In other words, one user may be willing to give up much more of one objective to better attain a second objective than would another user. Explicit consideration of trade-offs can increase transparency of harvest policy decisions and ultimately lead to management that best balances competing objectives (Walters and Martell 2004).

Important tradeoffs in AYK salmon management lie in balancing the competing objectives of sustainability, subsistence fisheries, and commercial fisheries (Hilsinger et al. 2009). These objectives are hierarchical, with escapement as the first priority, followed by subsistence opportunities, and lastly commercial harvest. Sustainability is addressed by managing stocks for escapement goals representing a range of spawning escapements sufficient to provide for sustainable yield. Escapement goal policies are optimal if all surplus fish are harvested and there is no uncertainty (Hilborn and Walters 1992). However, commercial fisheries in the AYK region typically harvest only a fraction of the surplus run due to market and processing limitations (Bue et al. 2009) and uncertainty in in-season estimation of the run size. Thus, it is useful to think of AYK salmon harvest policies as a combination of two harvest management "levers": a minimum escapement target (E) and a commercial exploitation rate on surplus fish in excess of the escapement target and expected subsistence harvest. Harvest policy analyses for AYK salmon stocks are arguably more realistic if they explore the tradeoffs involved in choosing a particular escapement goal given the less than complete utilization of surplus salmon by commercial fisheries.

Desirable policies are those that not only balance tradeoffs but also are robust to system uncertainties (Walters 1986). Harvest policy decisions for AYK salmon must be made in the presence of large uncertainties in stock dynamics, data collection, assessment, and implementation of the fishery (Hilsinger et al. 2009). Accounting for uncertainty in policy decisions is critically important because the "best" policy choice could change depending on the types and amounts of uncertainties in the system. Uncertainties are best dealt with by formally incorporating them into harvest policy decisions using quantitative approaches such as decision analysis and risk assessment (Peterman 2004).

Collie et al. (2009) introduced a risk assessment framework for evaluating the performance of chum salmon harvest policies in the AYK region. They addressed tradeoffs among escapement, subsistence and commercial fishery objectives while accounting for key system uncertainties. These included decadal-scale variation in salmon returns related to changes in ocean productivity and uncertainty in the implementation of management actions. In this analysis, we build on the work of Collie et al. (2009) by evaluating the effects of changes in the magnitudes of different types of uncertainty on harvest policy tradeoffs. We ask the question: would harvest policy tradeoffs, and hence choices, change if the amount of a particular type of uncertainty changed or was under- or over-estimated? Our model attempts to account for additional sources of uncertainty not included in Collie et al.'s (2009) model, namely uncertainty in stock recruitment parameters, brood-year proportions returning at age to spawn, and observation/assessment errors on in-season estimates of the expected run size. We consider two AYK region fisheries: Kuskokwim River Chinook salmon and Yukon River fall chum salmon.

Methods

We used a simulation approach known as Management strategy Evaluation (MSE) which is a closed-loop simulation that models the entire management process and its interaction with a fish population (Butterworth et al. 1997; Cooke 1999). The model simulated a salmon fishery over a 50-year time horizon under management by a time-invariant harvest policy. Policies were a combination of two user-specified policy choices. The first was a target minimum escapement (E) to be allowed before harvesting. This value can be thought of as the lower bound of an escapement goal range, or the lowest possible escapement that would be allowed. The second was the commercial fishery exploitation rate (U) on the surplus salmon run in excess of the minimum escapement and expected subsistence harvest. A single 50-year simulation represents only one possible realization of how a given policy could perform because the model contained several stochastic elements to incorporate uncertainty. Thus we simulated the model 500 times and assessed the distribution of model outcomes over the repeated simulations. Outcomes were measured as the values of a suite of performance indicators, each of which was relevant to a fishery objective.

The model had three subcomponents: a process sub-model representing the simulated "true" dynamics of the salmon population, an observation model depicting the collection of data representing an in-season forecast of the run size, and a harvest sub-model that implemented the harvest (commercial and subsistence) according to the specified harvest policy (combination of E and U). The process sub-model was parameterized using estimates from an age-structured Bayesian stock-recruitment model fit to Kuskokwim Chinook (1974-2007) and Yukon fall chum (1976-2009) salmon data (Appendix A; Fleischman and Borba 2009).

The process sub-model simulated a self-sustaining salmon population returning to the river each year to spawn and exposed to a fishery. We assumed a Ricker stock recruitment function from which the run size was obtained as a function of the number of spawners in past years, stock-recruitment parameters alpha and beta, and a log-normally distributed annual recruitment deviate. The model allowed for temporal trends in stock productivity due to decadal-scale changes in the ocean environment by allowing the alpha parameter to vary over time according to a random walk process (Collie et al. 2009). Temporal variation in the proportion of salmon returning at age to spawn each year was modeled as random deviates of a Dirichlet distribution. All process error variances (recruitment, alpha random walk, spawning proportions) were obtained from the stock-recruit model (Table 2-1; Appendix A). Uncertainty in the dynamics of the salmon population (structural uncertainty) was considered by drawing parameter sets (i.e., a different set for each of the 500 simulations) from the posterior distribution of a Bayesian stock-recruitment analyses (Table 2-1, Appendix A).

The observation sub-model simulated the collection of in-season data for the estimation of the expected run size. The run size estimate was assumed to be collected relatively early in the run to mimic the use of a pre-season forecast and early in-season run size indicators to predict the expected run size in a given year. The run size estimate was generated as a log-normally distributed deviate of the true run size each year. The magnitude of the error variance was obtained from the in-season simulation model in Part 4 (In-season Analysis) as the average variance of deviations between in-season and post-season run size estimates at the first quarter point of the run over 500 model simulations.

The harvest sub-model implemented commercial and subsistence harvest taking into account the run size estimate, and the hierarchical objective of first meeting the minimum escapement target (E), followed by harvest amounts necessary for subsistence, then commercial catch. No commercial or subsistence harvest was allowed if the run size estimate was less than the minimum escapement target. The target subsistence harvest was the number of salmon in excess of the escapement goal up to a fixed upper limit that was the midpoint of the published ANS (amounts necessary for subsistence) range for each stock. Commercial harvest was taken by applying the specified commercial harvest rate (U) to the number of surplus fish available in excess of the sum of the minimum escapement target (E) and the target subsistence harvest. The order in which the commercial and subsistence harvests were taken differed between stocks. The commercial harvest was taken first for Yukon fall chum, and subsistence was taken first for Kuskokwim Chinook. Implementation error was incorporated into subsistence and commercial harvest by modeling actual harvests as log-normal deviations from the target harvest amounts.

Preliminary simulations suggested that the results were robust to differences in the order in which the commercial and subsistence fisheries were prosecuted. Nevertheless, we maintained the different respective orders of prosecution for the two stocks in the interest of building a realistic harvest sub model. Implementation error for the subsistence fishery strictly followed a lognormal distribution and therefore did not account for potential effort responses whereby fishers may reduce effort when run size is small. The harvest sub-model is clearly a simple representation of a complex process. Our goal was to capture the key elements of the process so that the entire run could be compressed into an annual time step.

Implementation error variance for the commercial fishery was obtained by fitting linear relationships between reconstructed annual run size estimates and observed commercial harvests (Collie et al. 2009). The implementation error variance was the estimated error variance of the linear models. Implementation error variance for the subsistence fishery was simply the variance around the recent mean subsistence catch because subsistence catch was not strongly related to run size. Variances were converted to the log scale for use in generating log-normally distributed implementation errors as described above. For both fisheries, we used only data from recent years (Yukon fall chum: 1992-2009; Kuskokwim Chinook: 1998-2007) because of changes in markets/processing capacity and subsistence utilization since the mid-1970s.

Analyses

The model was iterated 500 times to generate a distribution of outcomes, or different realizations of the simulation, for six performance measures. Performance measures were average commercial catch, average subsistence catch, probability of commercial closure, probability of subsistence catch exceeding minimum amounts necessary for subsistence (Kuskokwim Chinook: 64,500 salmon; Yukon fall chum: 89,500 salmon; Linderman et al. 2007), average escapement, and probability of a stock of concern designation (escapement < E 4 of the last 5 yrs). Averages for commercial and subsistence catch were calculated for each 50-year simulation. Probabilities of commercial closure and meeting minimum ANS were calculated as the proportion of years within each 50-year simulation that the respective closure or subsistence catch criterion was satisfied. Probability of stock of concern was calculated as the proportion of years within each 50-year simulation in which the escapement goal was not met in of the 5 previous years. The median value of each performance measure was calculated from the 500 outcomes. Contour plots were created to depict the median outcome for each performance measure for all possible combinations of E and U (n = 121 combinations). Comparison of contour plots of each of the performance measures revealed policy trade-offs. Trade-offs among performance measures were evident when policies (i.e., E and U combination) that favored a particular performance measure resulted in a less desirable value of another performance measure.

We evaluated the effects of uncertainty on harvest policy trade-offs by repeating the 500 simulations under different assumptions regarding the magnitude of different types of uncertainty. We first ran a baseline scenario in which the magnitude of uncertainties was based on our best estimates for each stock (as described above). We ran four additional scenarios in which a particular source of uncertainty was increased or decreased. The first scenario was one in which the observation error on the in-season run size forecast was reduced by 50%. The second scenario was one in which implementation error was reduced by 50% from the baseline value. In the third scenario, both implementation and observation error were doubled relative to the baseline value. The last scenario was one in which there was no uncertainty in observation and implementation error.

Results of the different uncertainty scenarios were compared to assess changes in the nature of the trade-offs under varying degrees/types of uncertainty. We were particularly interested in whether the relative performance of specific policies (E and U combinations) changed under different uncertainty scenarios. We focused on four example policies for each stock. The policies were chosen to encompass existing and hypothetical policy options and were not meant as prescriptive, but rather were meant to demonstrate the tradeoffs policymakers and stakeholders must confront. For Yukon fall chum, the Policy 1 represented the "ideal" case in which commercial fishing power was large enough to fully utilize the entire surplus run (U = 1.0) above a minimum escapement target chosen to maximize yield (E = 400,000). The Policy 2 represented the defacto policy from the 1970s to the early 1990s during which the commercial harvest rate was moderate (U = 0.51; see Appendix C) due to somewhat favorable market conditions compared to recent years, and the escapement target was 300,000 salmon. The Policy 3 was chosen to represent the recent fishery with a minimum escapement of 300,000 salmon and a commercial harvest rate of 0.16, which was the observed harvest rate for the 1992-2009 runs (excluding the period of low returns from 1998-2003). The Policy 4 (E=100,000, U=0.16) was a hypothetical case in which we sought to increase commercial and subsistence yield by reducing the minimum escapement target below 300,000 while keeping commercial harvest rates within the observed range (0.16 to 0.51) for the time series. Kuskokwim Chinook harvest policies were chosen in a similar manner to represent (1) the ideal MSY policy (U=1.0, E=80,000), (2) moderate commercial harvest rates from early in the observed time series (E=80,000, U=0.46; see Appendix C), (3) recent low commercial harvest rates (E=80,000, U=0.11; greater than the estimated recent harvest rate but representative of a low exploitation level), and (4) a reduced escapement target to maximize commercial yield while keeping U within the observed historical range (E=40,000, U=0.46). A minimum escapement target of 80,000 was chosen for scenarios 1-3 because this value was just below the minimum basin-wide escapement observed from 1974-2009. It should be noted that the Kuskokwim Chinook salmon stock has not in the past and is not currently managed for a basin-wide escapement goal. However, escapement goals exist for individual streams within the basin.

Results

Harvest policies strongly influenced the value of performance measures. For the baseline Kuskokwim Chinook scenario, mean subsistence catch was maximized at low minimum escapements and low commercial harvest rates (Figure 2-1). However, a large number of policy combinations produced mean subsistence catches near the maximum (Figure 2-1). For example, any exploitation rate within an escapement range of 20,000 to 100,000 produced mean subsistence catches within 80% of the maximum value. The maximum mean commercial catch in the baseline scenario occurred at a minimum escapement of 75,000 and a commercial harvest rate of 1.0 (Figure 2-1). When minimum escapement targets were reduced below 75,000 salmon, then commercial catch could be maximized only by reducing the commercial harvest rate. Obvious tradeoffs existed between commercial catch and subsistence fisheries because subsistence catch was maximized by reducing U and E whereas commercial catch was maximized at high U and moderate E values. Tradeoffs also existed between commercial catch and the probability of commercial closure because polices resulting in large commercial catches also resulted in greater probabilities of commercial closure. Policies that maximized mean commercial catch reflected a pulse fishery with occasional large catches followed by closures whereas reducing the harvest rate and the minimum escapement target allowed for lower probabilities of closure, but also lower overall average catches. No tradeoffs existed between the fisheries and escapement objectives. The probability of stock of concern designation was less than 0.05 for a large number of policies.

Tradeoffs between subsistence and commercial fisheries were stronger for Yukon fall chum than for Kuskokwim Chinook (Figure 2-2). For example, only 48% of the maximum mean subsistence catch of Yukon fall chum could be obtained at the policy producing the maximum commercial catch, at baseline uncertainty levels (Figure 2-2). In contrast, 87% of the maximum subsistence catch for Kuskokwim Chinook could be obtained at the policy producing the maximum mean commercial catch (Figure 2-1). Tradeoffs between commercial fishery and escapement objectives were also stronger for Yukon fall chum than for Kuskokwim Chinook. For example, the probability of a stock of concern designation was 0.37 at the policy producing the maximum mean commercial catch (U=1, E=400,000). Any policy change that would reduce the stock of concern probability to 0.1 would require nearly a 50% reduction in mean commercial catch. No tradeoffs existed between probability of meeting minimum ANS and probability of stock of concern; the former was maximized and the latter minimized by reducing E and U. Overall, the Yukon fall chum performance measures were more strongly influenced by temporal shifts in stock productivity, which were greater for this stock than for Kuskokwim Chinook. These productivity swings produced much more variable catches and increased the probability of closures, decreased the probability of meeting minimum ANS, and increased the probability of stock of concern designation.

Assessing the relative performance of the four example policies demonstrated tradeoffs and revealed the effects of changes in uncertainty. For Kuskokwim Chinook, policies 1 -3 demonstrated a weak tradeoff among commercial catch, probability of commercial closure, and probability of meeting minimum ANS (Figure 2-3). Moving from policy 1 to policy 3 would require a decrease in the commercial harvest rate and no change in the minimum escapement target. This policy shift resulted in small reduction in probability of commercial closure and a small increase in the probability of meeting minimum ANS; these gains could not be achieved without an 85% reduction in mean commercial catch (Figure 2-3, panel row 1). Policy 4, which represented a reduction in the minimum escapement target and an increase in commercial harvest rate relative to the current policy (Policy 3), produced a "win-win" situation. This policy resulted in the lowest probability of commercial closure, and the highest probability of meeting minimum ANS, and this was obtained with only a 30% reduction in commercial catch.

Only under extreme reductions in observation and implementation error, did the relative performance of these four policies change for Kuskokwim Chinook (Figure 2-3). Neither a 50%

reduction in observation uncertainty nor a 50% reduction in implementation error substantially changed the relative or absolute performance of the four policies (Figure 2-3, panel rows 2 and 3). A doubling of both sources of uncertainty substantially reduced mean commercial catches and the probability of meeting minimum ANS, but did not fundamentally alter the relative performance of the four policies (Figure 2-3, panel row 4). However, elimination of observation and implementation uncertainty made Policies 2-4 much less appealing because there was minimal improvement in probabilities of commercial closure and meeting minimum ANS despite a large reduction in commercial catch relative to Policy 1 (Figure 2-3, panel row 5).

For the Yukon fall chum, policies 1-3 demonstrated a clear tradeoff between commercial and subsistence fisheries (Figure 2-4). Policy 4, which required an increase in the harvest rate and a decrease in the escapement target relative to Policy 3, resulted in a 40% increase in commercial catch with no appreciable loss of subsistence catch or increases in commercial closure when compared to Policy 3. Similar to Kuskokwim Chinook, changes in uncertainty regimes altered the absolute value of the performance measures, particularly the catch indicators, but did not alter the relative performance of the four policies.

Discussion

Policy choices regarding minimum escapements and commercial exploitation rates strongly affected the values of performance measures. For both stocks, tradeoffs existed among commercial, subsistence, and escapement objectives. Increased subsistence catch and reduced probability of commercial closure could be obtained by simultaneously reducing the minimum escapement target and the commercial harvest rate. These gains would come at the expense of reduced average commercial catch but not at the expense of escapement objectives.

The current minimum escapement targets combined with low commercial exploitation rates on Yukon River fall chum and Kuskokwim Chinook salmon favors subsistence fishery objectives at the expense of commercial catch. Although this policy may reflect current priorities of ADF&G and some stakeholders, it is not the result of an explicit choice based on formal policy deliberations. Our analysis could inform explicit policy choices because the results clearly show where the current policy lies in the context of the broader tradeoffs across a wide range of policies. Stakeholders will need to consider the full range of policy options to properly evaluate the tradeoffs involved under the current policy. Policy makers will need to also consider the feasible limits on commercial exploitation rate and constrain policy choices accordingly. For both stocks, a move toward a lower minimum escapement target and an increase in commercial exploitation rate to levels observed in the 1970s and 1980s could result in increased commercial catch with little sacrifice of subsistence and escapement objectives.

Harvest policy trade-offs were relatively insensitive to changes in the magnitude of uncertainties. For the four example policies we evaluated, the amount of uncertainty would likely not change the tradeoffs enough to warrant the selection of a different policy. Thus the policy trade-offs (and decisions based on them) suggested by the baseline scenario are robust to changes in uncertainty or errors in our estimation of uncertainty. This is an important finding because it suggests that future deliberations regarding policy tradeoffs need not be overly concerned whether estimates of system uncertainty are highly accurate. These deliberations can focus rather on the inherent trade-offs in the system while encouraging stakeholders to find common ground on how these stocks should be managed.

Our analysis suggests that there are many sustainable policies for both salmon stocks. Our model assumed a compensatory Ricker stock recruitment in which per capita reproductive rates always increase as escapement decreases. Thus a stock with an assumed Ricker-type stock recruitment relationship should be sustainable under higher exploitation rates. Collie et al. (2009) considered depensatory stock recruitment models for AYK chum salmon stocks and found that incorporating depensation resulted in greater risks of not meeting escapement and harvest objectives. We were primarily interested in the effects of implementation and observation uncertainty on policy tradeoffs and therefore did not consider depensatory stock-recruitment dynamics. However, any formal policy deliberation undertaken for these stocks should consider uncertainty in the form of the stock-recruitment relationship.

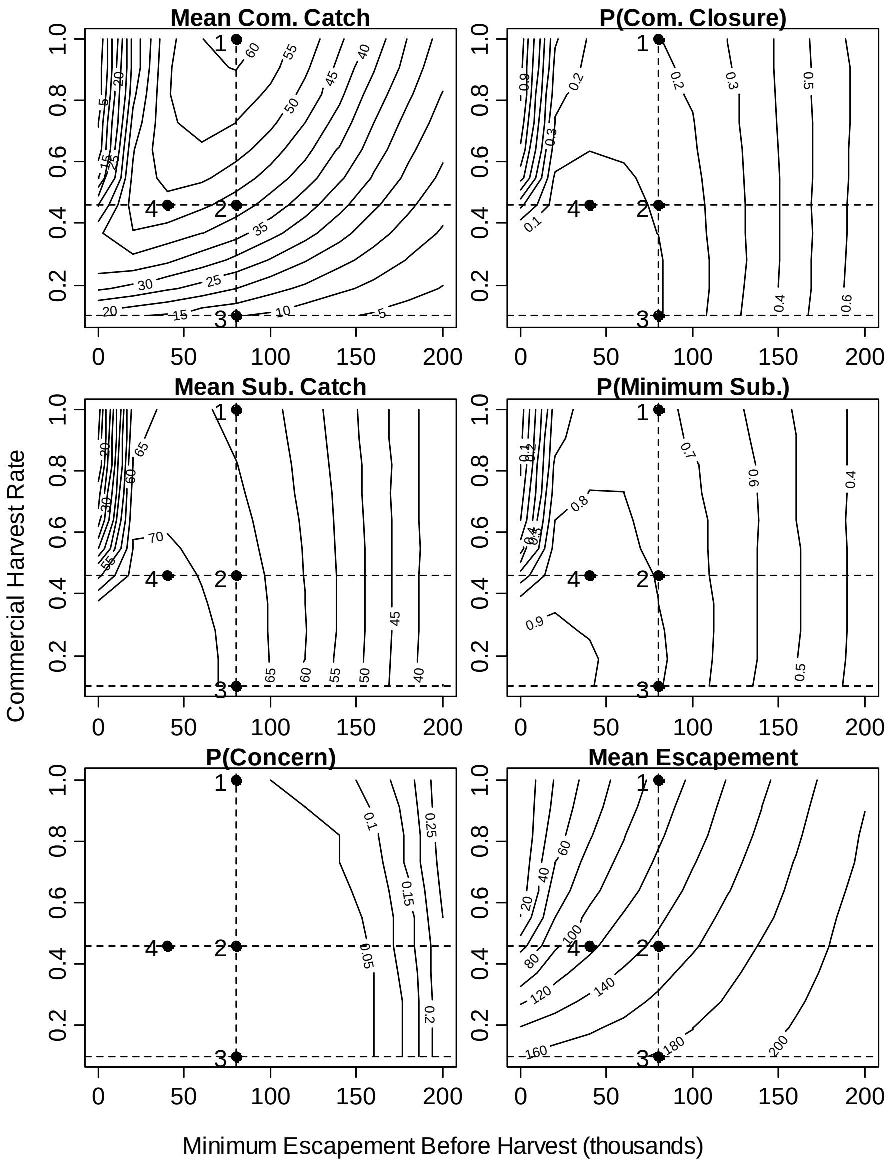

Figure 2-1. Contour plots for the Kuskokwim River Chinook salmon stock showing the median values of performance indicators from 500 simulations across combinations of a minimum escapement target and commercial harvest rate for the baseline uncertainty scenario. Performance indicators for escapement and catch are in units of thousands of salmon. Four example policies are shown as solid circles to depict tradeoffs among specific policy choices. Policy 1 represents the MSY policy in which 100% of surplus fish are harvested by the commercial fishery. Policy 2 is the defacto policy from the 1970s to the early 1990s with a moderate commercial harvest rate (U = 0.46) and an escapement target was 80,000 salmon. Policy 3 represents the recent fishery with a minimum escapement of 80,000 salmon and a commercial harvest rate of 0.11. The fourth policy (E=40,000, U=0.46) sought to increase commercial and subsistence yield by reducing the minimum escapement target below 80,000 while keeping commercial harvest rates within the observed range for the time series.

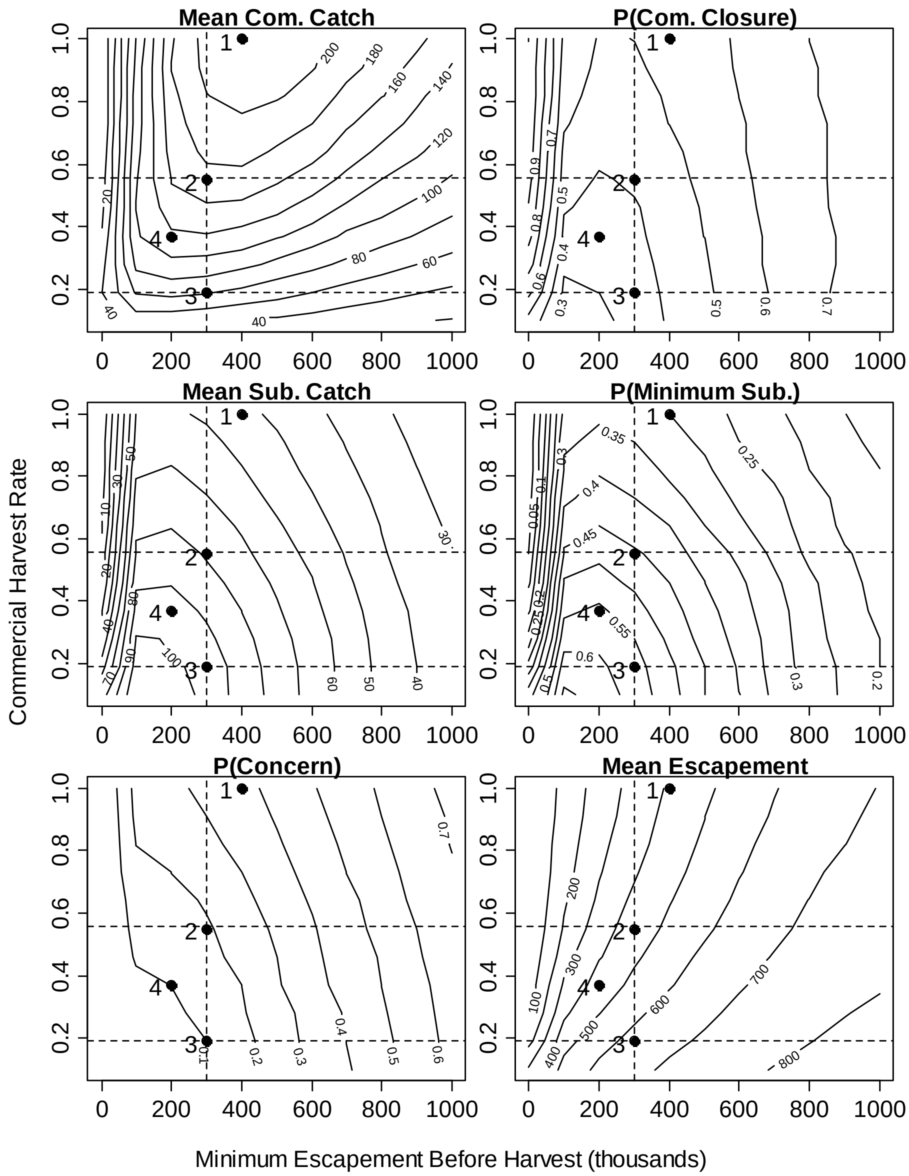

Figure 2-2. Contour plots for the Yukon River fall chum salmon stock showing the median values of performance indicators from 500 simulations across combinations of a minimum escapement target and commercial harvest rate for the baseline uncertainty scenario. Performance indicators for escapement and catch are in units of thousands of salmon. Four example policies are shown as solid circles to depict tradeoffs among specific policy choices. Policy 1 represents the MSY policy in which 100% of surplus fish are harvested by the commercial fishery. Policy 2 is the defacto policy from the 1970s to the early 1990s with a moderate commercial harvest rate (U = 0.55) and an escapement target was 300,000 salmon. Policy 3 represents the recent fishery with a minimum escapement of 300,000 salmon and a commercial harvest rate of 0.19. The fourth policy (E=100,000, U=0.19) sought to increase commercial and subsistence yield by reducing the minimum escapement target below 300,000 while keeping commercial harvest rates within the observed range for the time series.

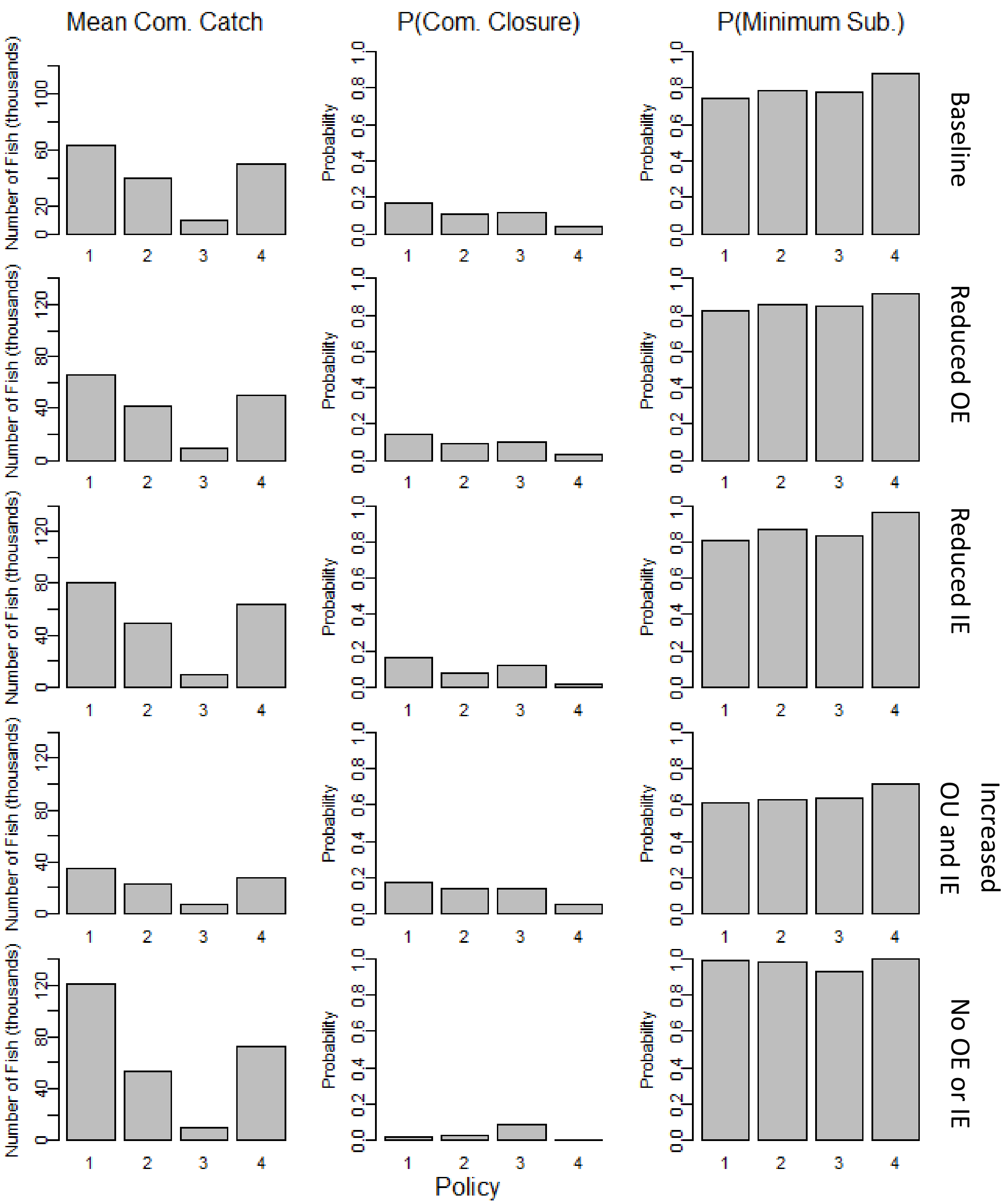

Figure 2-3. Kuskokwim River Chinook salmon average commercial catch (median from 500 simulations of the model), probability of commercial closure, and probability of meeting minimum ANS for four individual harvest policies. Each policy is a combination of a minimum escapement target and a commercial exploitation rate. Each row of panels represents a different uncertainty scenario: baseline (row 1), reduced observation error (row 2), reduced implementation error (row 3), increased observation and implementation error (row 4), and no observation or implementation error (row 5).

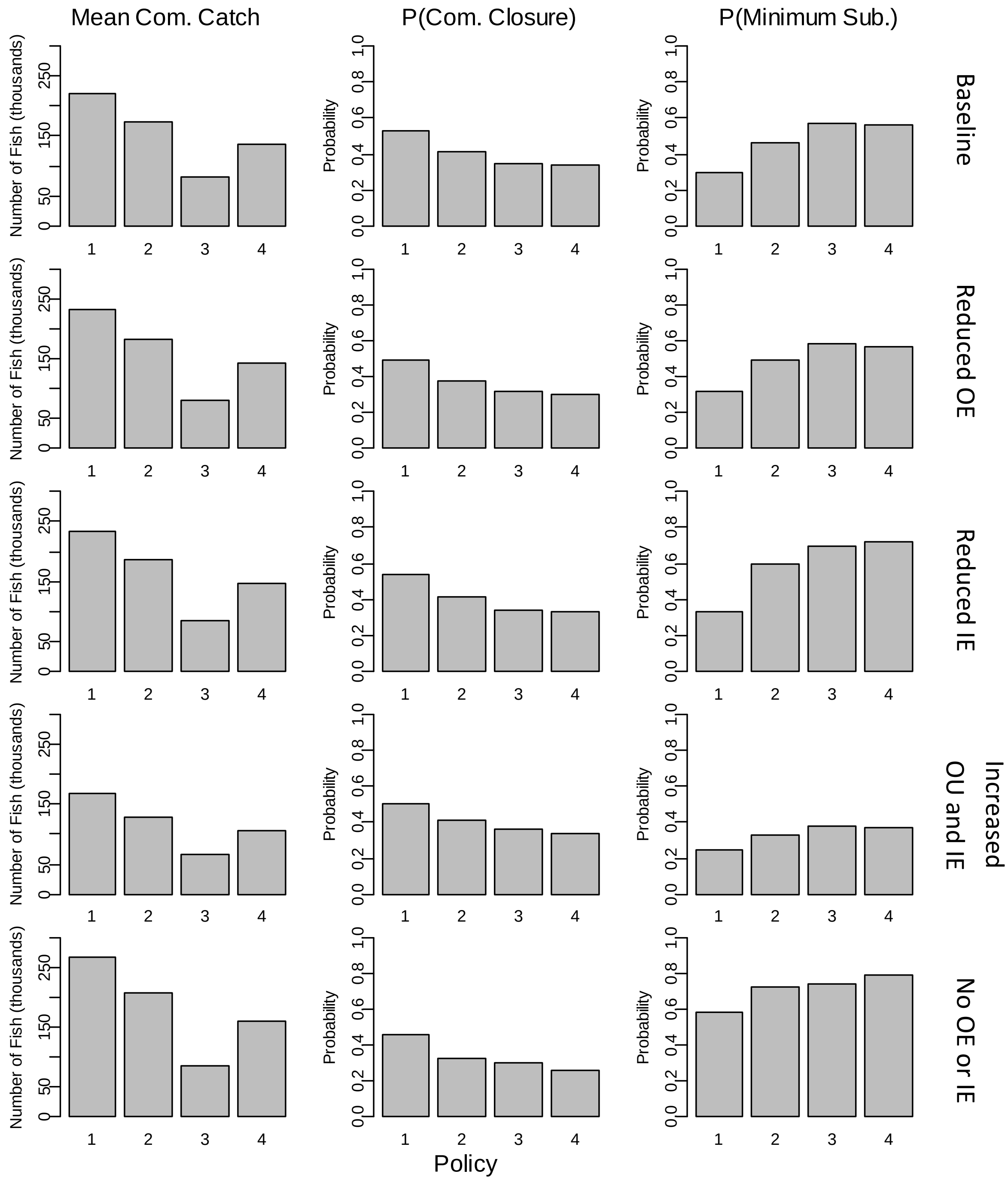

Figure 2-4. Yukon River fall chum salmon average commercial catch (median from 500 simulations of the model), probability of commercial closure, and probability of meeting minimum ANS for four individual harvest policies. Each policy is a combination of a minimum escapement target and a commercial exploitation rate. Each row of panels represents a different uncertainty scenario: baseline (row 1), reduced observation error (row 2), reduced implementation error (row 3), increased observation and implementation error (row 4), and no observation or implementation error (row 5).

Part 3. Evaluating the use of historical escapements to set escapement goals for data-poor salmon stocks

Salmon escapement goals are set to meet management objectives such as maximum sustainable yield. When data permit, these goals have been established by fitting stock-recruitment models to time series of harvest and escapement data and using the resulting parameter estimates to determine the escapement that best meets the management objective (Hilborn and Walters 1992). Recruitment in these models is rarely directly observed but is instead inferred as the sum of observed harvest and escapement. Escapement data are obtained from salmon counts at weirs, counting towers, or from aerial surveys of spawning reaches. Harvest data are usually available from mandatory commercial catch reports and post-season subsistence surveys. For mixed-stock fisheries, where harvest occurs on an aggregate pool of fish from many stocks, each destined for a different spawning tributary, it is often difficult to determine the stream of origin of harvested fish. In such cases, stock-recruitment models cannot be fitted for individual stream-specific stocks because the harvest cannot be attributed to the stream of origin, and hence recruitment cannot be inferred by summing harvest and escapement (Begg et al. 1999).

In western Alaska, many salmon fisheries occur on mixed-stocks in which harvest is not attributable to stream of origin and thus stock-recruitment models cannot be used to set escapement goals (Hilsinger et al. 2009). However, escapement is often measured for salmon stocks of important spawning tributaries with varying degrees of accuracy (Hilsinger et al. 2009). These salmon stocks have high social and economic values (Wolfe and Spaeder 2009) and are managed for a hierarchical set of objectives with sustainability (adequate escapement) as the first priority, followed second by subsistence harvest opportunities, and third commercial harvest

(Hilsinger et al. 2009). Thus there is a strong impetus for the use of escapement goals to manage these stocks despite the lack of data that could be used to estimate biologically-based escapement goals. Management agencies have sought alternative methods for setting escapement goals for these stocks.

One method that has become pervasive throughout the AYK region is the use of observed historical escapements to set a range of acceptable escapements using what is called the "percentile method" (Bue and Hasbrouck 2001). The percentile method identifies an escapement goal range that coincides with the 15th and 85th percentiles of observed historical escapements for a particular stock. The method is predicated on the assumption that observed historical escapements represent sustainable escapements so long as the time series does not indicate a downward trend in escapement over time. Despite its frequent use to set escapement goals in western Alaska, the performance of method has not been formally evaluated.

Two potential problems have been identified with the use of the percentile method for setting escapement goals. The most obvious is that the method could perpetuate the exploitation status of a stock even when escapement is far from an optimal level. Stocks with low escapements due to overexploitation would yield an erroneously small escapement goal using this method, and overexploitation would be continued if the stock were managed for the goal. Escapement goals for many salmon stocks serve as a post-season management performance indicator rather than an in-season management target (Hilsinger et al. 2009). For these stocks, low escapements would fail to prompt regulatory action to reduce harvest for stocks with erroneously small escapement goals. Thus the historical exploitation status of the stock might be expected to have a substantial effect on the performance of the percentile method.

Decadal-scale variation in stock productivity has been documented for western Alaska salmon stocks (Peterman et al. 1998), and this variability could affect performance of the percentile method. Escapement goals set using data from periods of high stock productivity would be unrealistically large if productivity were to decrease in the future. The length of the data series used in setting the escapement goal could be important because a longer data collection period should encompass more temporal variation in stock productivity.

We used a simulation analysis to evaluate the performance of managing salmon stocks for escapement goals obtained from observed historical escapements. Specifically we evaluated the percentile method as an algorithm for using historical escapement to set escapement goals. We were particularly interested in three factors that could affect the performance of the percentile method: (1) the exploitation status of the stock during the initial period of escapement data gathering, (2) the duration of the initial escapement data gathering period, and (3) the magnitude of observation and implementation uncertainty.

Methods

Model

We used a simulation approach known as Management Strategy Evaluation (MSE) to assess the performance of the percentile method for setting escapement goals. Management strategy evaluation is a closed-loop simulation approach that models the entire management process and its interaction with a fish population (Butterworth et al. 1997; Cooke 1999). The model simulated a salmon fishery during the first 50 years under management for an escapement goal that was obtained using the percentile method. The model had four subcomponents: a process sub-model representing the simulated "true" dynamics of the salmon population, an observation model depicting the collection of data (run size, escapement, catch) from the population, an assessment sub-model that used the observed data to set the escapement goal (using the percentile method), and a harvest sub-model that implemented the harvest (commercial and subsistence) on excess fish above the escapement goal. Fish not removed by harvest formed the spawning stock that gave rise to returns in the next generation. The model was parameterized using estimates from an age-structured Bayesian stock-recruitment model fit to Kuskokwim River Chinook salmon data from 1976-2009 (Table 3-1; Appendix A; Fleischman and Borba 2009).

The process sub-model simulated a self-sustaining Chinook salmon population with life history parameters estimated from data for the aggregate Kuskokwim River stock. We assumed a Ricker stock-recruitment function from which the annual run size was obtained as a function of the number of spawners in past years, stock-recruitment parameters alpha and beta, and a log-normally distributed annual recruitment deviate. The model allowed for temporal trends in stock productivity due to decadal-scale changes in the ocean environment by allowing the alpha parameter to vary over time according to a random walk process (Collie et al. 2009). Temporal variation in the proportion of salmon returning at age to spawn each year was modeled as random deviates of the Dirichlet distribution. Measures of process uncertainty (recruitment variation, alpha random walk, spawning proportions) were obtained from fits of the Kuskokwim River Chinook stock-recruit model (Table 3-1; Appendix A). Uncertainty in the dynamics of the salmon population (structural uncertainty) was considered by drawing parameter sets (i.e., a different set for each model iteration) from the posterior distribution of the parameters from the Bayesian stock-recruitment analysis (Table 3-1, Appendix A).

The observation sub-model simulated the collection of two types of data from the salmon population: an early season run size estimate and annual escapements. The run size estimate was assumed to be collected relatively early in the run to mimic a pre-season forecast and in-season run size indicators. The run size estimate was generated as a log-normally distributed deviate of the true run size each year with observation error variance based on estimated deviations between in-season and post-season run size estimates at the first quarter point of the run as calculated in Part 4, below. Escapement data were generated as log-normally distributed deviates of the true escapement and were meant to represent counts of salmon from weirs, counting towers, aerial surveys. Observation error variance on escapement was taken from a basin-wide run reconstruction (Bue; Table 3-1).

The harvest sub-model implemented commercial and subsistence harvest taking into account the escapement goal, the run size estimate, and the hierarchical objective of first meeting the escapement goal, followed by subsistence opportunity, then commercial catch. No harvest was allowed if the run size estimate was less than the escapement goal. Subsistence harvest was taken in excess of the escapement goal up to a fixed amount necessary that was midpoint of the published ANS range for Kuskokwim Chinook salmon. Commercial harvest was taken as the number of surplus fish available in excess of the sum of the escapement goal and average subsistence need. Implementation error was incorporated into subsistence and commercial harvest by modeling actual harvests as log-normal deviations from the target harvest amount. The variance of implementation error was based on the estimated error variance of linear models relating commercial and subsistence catches to estimated run sizes (Table 3-1; ADF&G unpublished data).

The assessment sub-model estimated the escapement goal from the escapement data provided by the observation model. The percentile method was the method by which the escapement goal was obtained. The percentile method defines the escapement goal as a range encompassing the 15^{th} and 85^{th} percentiles of the observed escapements (Bue and Hasbrouck 2001). Our model assumed the escapement goal was the median of the observed escapements to facilitate simulation of the harvesting process within the model.

Each iteration of the model consisted of three time periods. The first period was a ten year burn-in to remove effects of initial conditions. The burn-in was followed by a 5 or 15-year (see *Analyses*, below) period during which the initial escapement data were gathered for the setting of an escapement goal. We will refer to this period hereafter as the initial period. After setting the escapement goal using the percentile method, the stock was managed for this goal for 50-years, during which time the escapement goal was updated every five years by including any new escapement data in the calculation.

The exploitation status of the stock during the initial period was specified by defining an initial escapement goal (S_{init}). Harvesting during the initial period was implemented as described above using this initial escapement goal as the management target. A high initial escapement goal would mimic a stock with a low initial harvest rate, and vice versa.

Analyses

The model was iterated 500 times to generate a distribution of outcomes, or different realizations of the system dynamics over time. The performance of the percentile method was assessed by evaluating the distribution of outcomes over 500 iterations with respect to six performance measures. Performance measures were average commercial harvest, average subsistence harvest, probability of commercial closure, probability of meeting the lower bound of the minimum amounts necessary for subsistence (64,500 salmon; Linderman et al. 2007), probability of stock of concern designation, and average escapement. We added an additional performance measure to assess the change in the escapement goal over the course of the simulation (goal in year 50 minus the goal in year 1). This performance measure was established to assess so-called escapement goal "drift" that is a concern of ADF&G managers.

We used the model to assess the effects of the initial exploitation status of the stock, the duration of the initial period, the magnitude of observation and implementation errors, and stock productivity on the performance of the percentile method. We assessed the effects of initial exploitation status by varying the initial escapement goal across a range from 0.1 to 3.0 times the escapement that produces maximum sustainable yield (S_{msy}). The duration of the initial period for these baseline scenarios was 15 years and was chosen to represent a realistic time series of data that would be used to set an initial escapement goal using the percentile method. We assessed the effect of the duration of the initial period by repeating the baseline simulations described above but setting the duration of the initial period at 5 instead of 15 years. The effects of observation and implementation error on the performance of the percentile method was evaluated by repeating the baseline scenarios but with a 100% increase in observation error variance and another set of simulations with a 100% increase in implementation error variance. We assessed the effects of stock productivity by repeating the baseline uncertainty scenario under low (alpha = 2.0) medium (alpha=5.2; baseline value), and high (alpha = 10) stock productivity.

Results

Performance measures at baseline uncertainty levels were generally within 50% of their respective MSY values as long as escapements during the initial period exceeded 20% of S_{msy} (Figure 3-1). Commercial catch was 68,000 salmon at S_{msy}, but declined to 33,000 salmon under high initial escapements representing a lightly exploited population during the initial period. Similarly, commercial catch declined to 51,000 salmon when initial escapements were at 25% of the value that produces MSY (Figure 3-1, panel a). Commercial catch declined rapidly as initial escapements dropped below 25% of S_{msy}. Probability of commercial closure was highest at initial escapements that produced the largest average commercial catches (Figure 3-1, panel c). Subsistence catch was more robust to low escapements during the initial period than was commercial catch. Subsistence catch at an initial escapement of 10% resulted in catches that were 70% of the catch when initial escapements were at S_{msy} (Figure 3-1, panel b). Probability of a stock of concern designation was low across the range on initial escapements (Figure 3-1, panel f).

The escapement goals themselves remained unchanged over time (i.e., within a simulation; i.e., no "drift") as long as the initial escapements were less than or equal to S_{msy} (Figure 3-1, panel e). Escapement goals drifted downward over time (i.e., over 50 years) by up to 25% if initial escapements exceeded 1.25 times S_{msy} (Figure 3-1, panel e). Escapement goal drift increased harvest and reduced the probability of closure without increasing the risk of low returns due to overharvest.

Increasing the magnitude of observation and implementation error and reducing the duration of the initial period had weak effects on performance measures relative to the effects of the initial exploitation status. An increase in observation error on escapement did not appreciably affect the median values of performance measures (Figure 3-2). Increasing the magnitude of implementation error resulted in a 10,000-fish increase in commercial catch at low initial escapements and a 5,000-fish decrease when initial escapements were near S_{msy}. Most notably, downward escapement goal drift increased by 12,000 relative to the baseline scenario when the duration of the initial period was reduced to 5 years (Figure 3-2, panel e).

Changes in stock productivity strongly affected performance of the percentile method. At high stock productivity, performance measures were near MSY values even at initial escapements that were 10% of the MSY escapement (Figure 3-3).

Discussion

The performance of the percentile method was strongly related to the initial exploitation status of the stock. Obviously, the initial exploitation status is not known for stocks to which the percentile method is applied. Although these findings are not unexpected, our modeling approach provided quantitative estimates of the expected performance across a range of initial exploitation rates (i.e., escapements). For example, we demonstrated the amount of commercial catch that would be foregone on stocks that are lightly exploited initially. We also found that nearly 50% of the MSY commercial catch could be obtained so long as initial escapements were greater than 20% of the level that produces MSY. These quantitative estimates are preferable to subjective "best guesses" regarding the performance of escapement goals obtained via the percentile method.

The relationship between initial exploitation status and performance of the percentile method depended on the strength of density dependent compensation. Although our results pertain only to Kuskokwim River Chinook salmon, by assessing the effects of stock productivity our analysis may have broader implications. Our results suggest that stocks with strong compensation (large alpha parameter) should be more robust to high initial exploitation rates because they can more rapidly replace themselves under low escapements than low productivity stocks. Conducting these types of analyses for a wide range of stocks would provide more certainty in potential responses to varying productivity. Another important factor regarding stock productivity could be the amount of temporal variation in stock productivity, which is likely to vary among stocks.

As our results show, and as one might intuitively suspect, the initial exploitations status of a stock is very important to the performance of the percentile method-based escapement goals. Although fishery performance was suboptimal in cases with low initial exploitation, the most obvious concerns toward meeting escapement and harvesting objectives occurred for stocks under relatively high initial exploitation. Thus, management would benefit from alternative methods to identify highly exploited stocks. Methods have recently been developed to relate equilibrium stock size to watershed characteristics (Liermann et al. 2010). Perhaps these approaches could be used as a screening tool to identify stocks for which percentile method-based escapement goals are unlikely to be sustainable due to high initial exploitation rates. These cases would be identified as those with very low escapement relative to predicted stock size from watershed characteristics. Nevertheless, it is important to consider that few stocks to which the percentile method is applied have exploitation rates high enough to be a concern for sustainability. Most of these stocks are lightly exploited because heavily exploited stocks tend to have much more intensive data collection programs.

Downward drift in escapement goals has been a concern associated with using the percentile method to set escapement goals. Our results suggest that downward drift is a major concern only for stocks that are lightly exploited initially. In such cases downward drift should improve performance of the percentile method as the escapement goal would trend closer to the escapement that produces MSY.

In systems with percentile based escapement goals, escapement data are often used as a post-season indicator of management performance and are therefore not used to regulate harvest in-season. Nevertheless, failure to consistently meet these goals typically results in some sort of management action in the future that would limit harvest on downstream mixed stocks, particularly if several sub-stocks failed to meet goals. One important question facing managers is when escapements consistently fail to meet a percentile-based goal; do we update the goal to include recent years of escapement data (i.e., adjust the goal downward), or do we make a stock of concern designation? If stock of concern is called for, then restrictions will be made on the downstream mixed stock fishery, which could have negative financial and social consequences for fishers. Our analysis suggests that in the absence of auxiliary information on exploitation rates, recalculating the escapement goal to include recent data should not result in substantial negative consequences for management performance. However, our analysis did not assess performance of the percentile method when setting escapement goals under increasing harvest rates. Thus managers should take care that reductions in escapement are not the result of recent increases in harvest rates or fishing effort.

Table 3-1. Parameter values used in the management strategy evaluation. Upper and lower 95% credible intervals are shown for parameters obtained from a basin-wide stock-recruitment analysis from Kuskokwim Chinook (Appendix A). Structural uncertainty was incorporated into simulations by drawing parameter sets (one set for each model iteration) from the posterior distribution of the stock recruitment parameters.

Parameter	Symbol	Estimate	Lower 95%	Upper 95%
Process Error				
alpha	α	8.26	4.91	9.24
beta	β	$9.08e^{-06}$	$6.3e^{-06}$	$1.3e^{-05}$
recruitment variance	σ^2_R	0.063	0.026	0.14
alpha random walk variance	σ^2_α	0.01	0.002	0.08
proportion returning at age 1	γ_4	0.17	0.09	0.31
proportion returning at age 2	γ_5	0.37	0.26	0.47
proportion returning at age 3	γ_6	0.42	0.30	0.54
proportion returning at age 4	γ_7	0.04	0.01	0.10
Observation Error				
escapement observation error variance	σ^2_S	0.01		
run size observation error variance	σ^2_N	0.11		
Implementation Error				
commercial implementation error variance	σ^2_{com}	0.94		
subsistence implementation error variance	σ^2_{sub}	$6.8e^{-3}$		

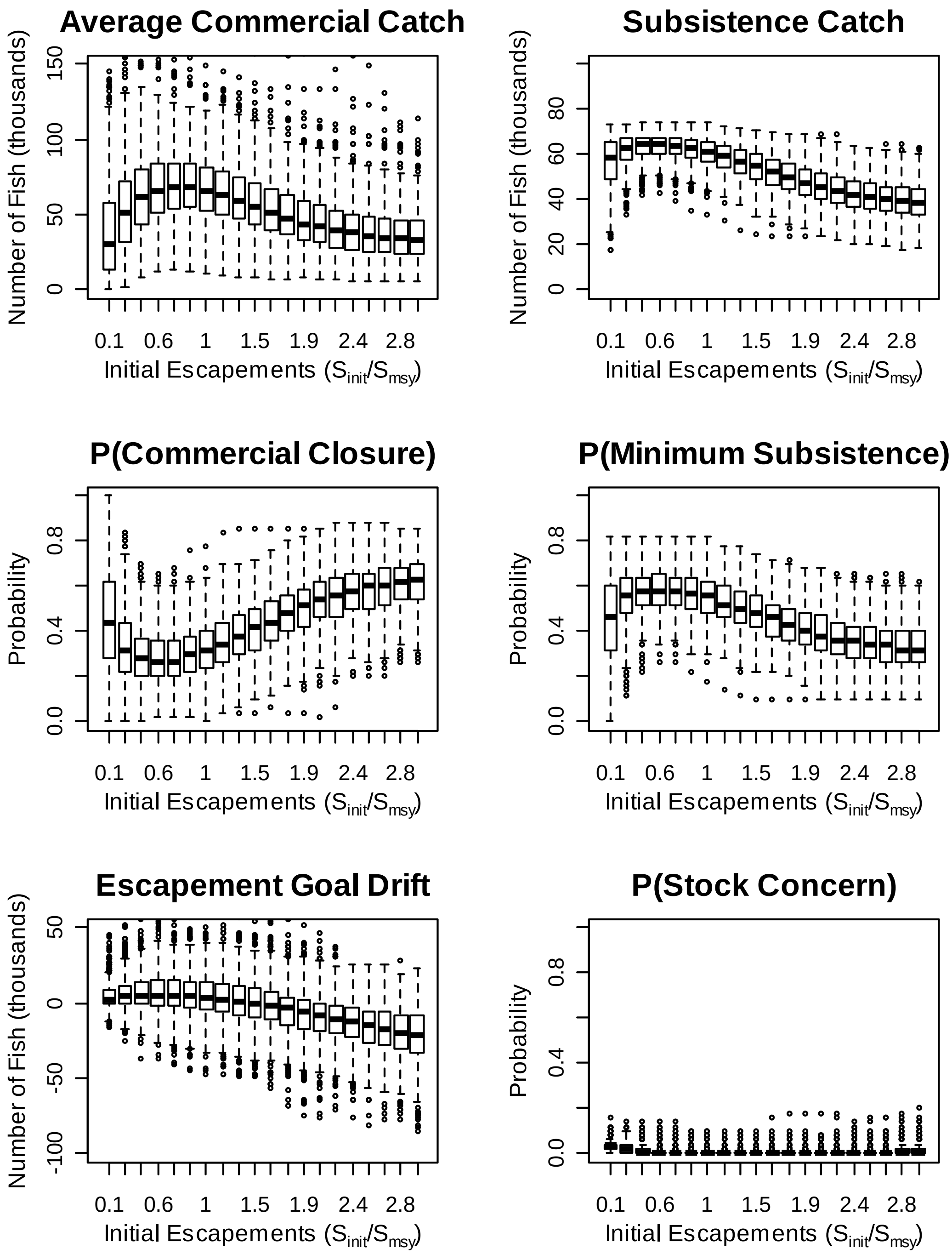

Figure 3-1. Baseline uncertainty scenario. Box and whisker plots showing the distribution of performance measures (y axis) vs. the exploitation status of the stock during the initial period (x axis). Boxes represent the median and inter-quartile range, and whiskers depict the 95% outcome interval.

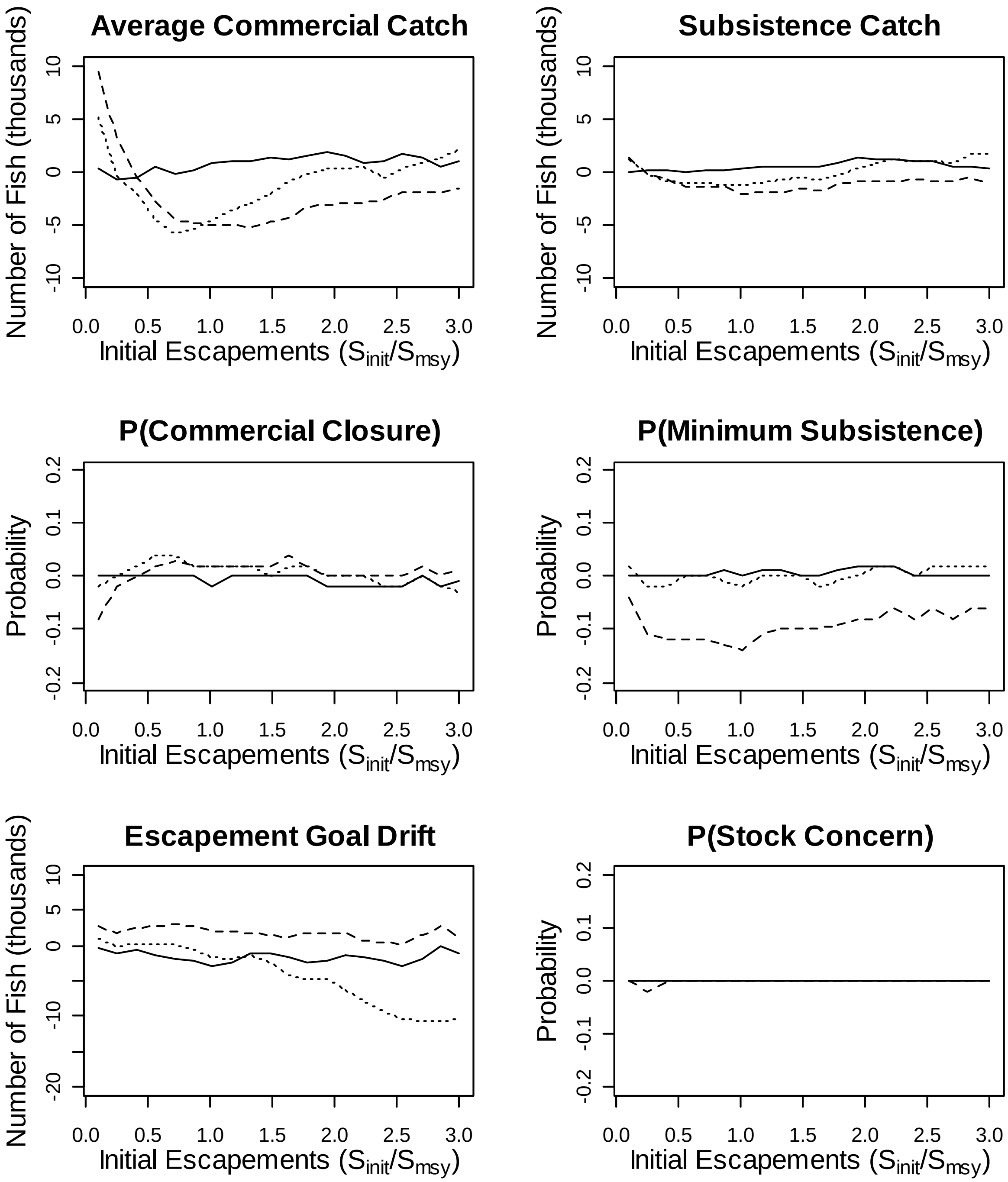

Figure 3-2. The change in the median value of performance measures relative to the baseline scenario under a 100% increase in escapement observation error (solid line), 100% increase in implementation error (dashed line), and a reduction in the duration of the initial period from 15 to 5 years (fine dashed line).

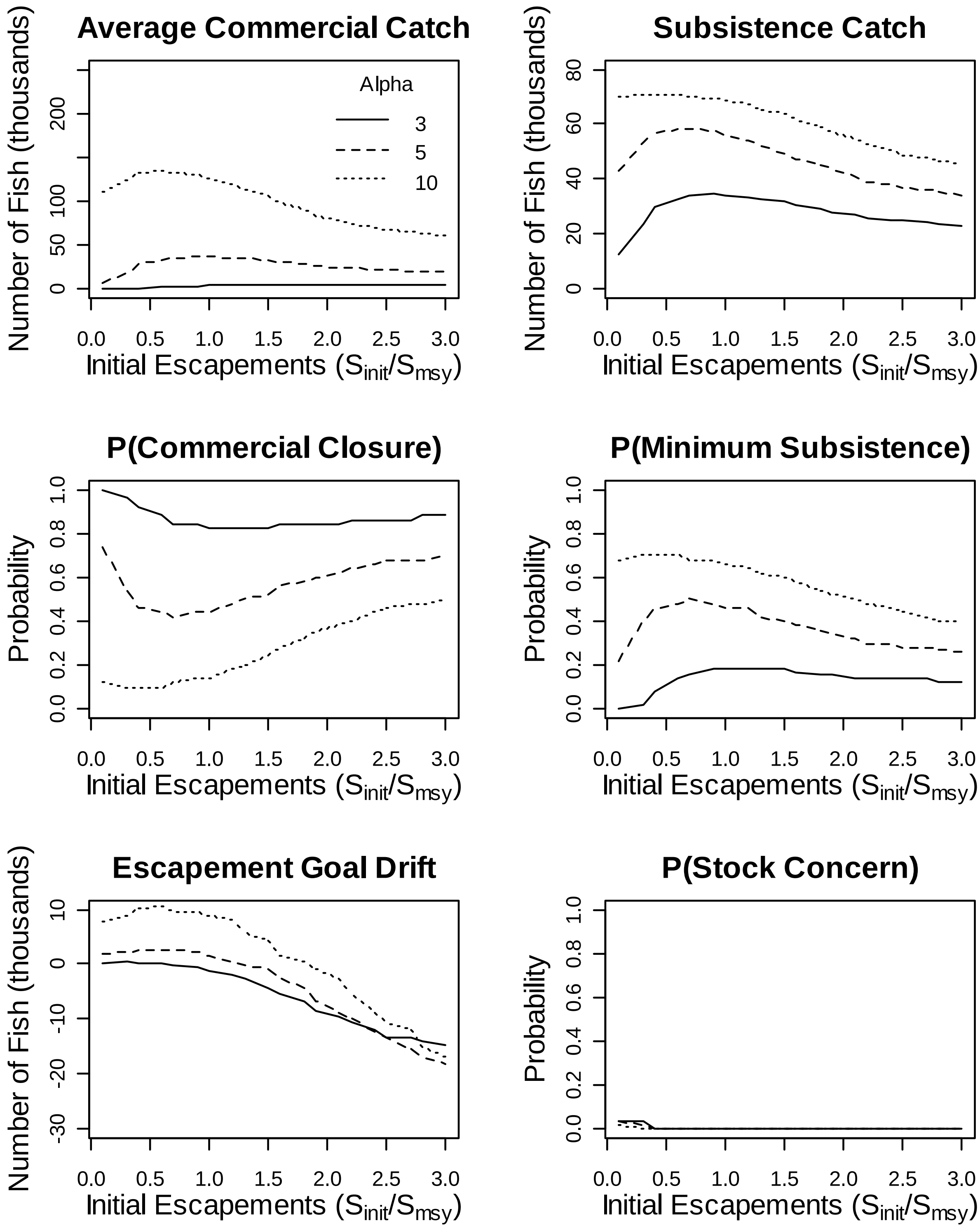

Figure 3-3. Median posterior values of performance measures as a function of the initial escapements for three different levels of stock productivity (alpha parameter): 3.0 (solid line), 5.0 (dashed line; baseline value), 10.0 (fine dashed line). The results are from the baseline uncertainty scenario but with no time-varying productivity.

Part 4. The relative performance of in-season management strategies for Yukon fall chum salmon

In-season salmon harvest management decisions must be made on the basis of imperfect estimates of the expected run size and with imperfect management control over outcomes. Run timing and size are confounded such that cumulative indices of the run on a given day of the season may poorly predict total run size (Hyun et al. 2005). In large river systems such as the Yukon River, Alaska, time lags exist between when harvest management decisions are made and when the outcomes of those decisions can be measured (Hilsinger et al. 2009). For example, decisions on downriver fisheries must be made early in the season when the run size is least certain. As another example, escapement data cannot be used in managing harvest because fisheries have concluded long before salmon reach spawning tributaries where escapement is measured. In such cases, managers must rely on uncertain pre-season forecasts and in-season data from test fisheries, downstream sonar or weir projects, and commercial harvest data (Hilsinger et al. 2009).

In-season data sources are combined with a pre-season forecast using informal or formal procedures to estimate the expected run size (Walters and Buckingham 1975; Fried and Hilborn 1988; Hyun et al. 2005). Daily decisions on fishery openings and closures are based on the expected run size and its uncertainty relative to pre-determined run size thresholds. Two critical aspects of this process that warrant investigation are (1) the statistical method used to combine the pre-season forecast vs. the in-season data when estimating the expected run size and (2) the degree of risk tolerance assumed by managers in prosecuting the fishery (e.g., how aggressively managers set fishery openings/closings).

Managers may use different methods for weighting pre-season forecasts and in-season data when estimating the expected run size. Formal methods make use of Bayes' Theorem where the pre-season forecast is treated as the prior and the in-season information as the data from which the likelihood is calculated (Fried and Hilborn 1988). The weights of the prior (forecast) and the data (in-season) are proportional to the precision of the estimates. However, most managers use less formal procedures that rely on rules of thumb and intuition derived from experience. For example, they may choose to rely on a pre-season forecast until some arbitrary estimated proportion of the run has entered the river. Other managers may rely on the forecast only during the first fishing period and still others may use forecasts throughout the season if they suspect in-season data are not reliable. Regardless of the method, certainty in the run size generally increases through time within the season as more data become available.

Managers must adopt a degree of risk tolerance toward escapement objectives to make in-season decisions. Risk tolerance refers to the degree of confidence a manager must have that the run size exceeds some pre-determined (e.g., by law or management council) threshold before harvest is allowed. Risk tolerance can be expressed as a probability. We will refer to these probabilities as "confidence thresholds" throughout this paper. For example, if a manager adopted a confidence threshold of 0.7 and by rule no commercial harvest should be allowed for run sizes below 500,000 fish, then the commercial fishery would remain closed until the data suggested the run size exceeds 500,000 with a probability of at least 0.7. Consider two managers that differ in their tolerance for failing to meet escapement goals. We will define a conservative manager as one who puts a high premium on meeting escapement goals and would therefore adopt a high confidence threshold value (e.g., 0.95). In contrast, we define a liberal manager as one who is willing to assume more risk toward meeting escapement goals in the interest of allowing more harvest. Thus, the liberal manager would prefer a lower confidence threshold (e.g., 0.5). Confidence thresholds may be a function of recent management performance. For example, managers of stocks that have recently failed to meet escapement goals might become more conservative and adopt higher confidence thresholds. These thresholds may also differ between subsistence and commercial fisheries. Confidence thresholds could be explicitly declared prior to the season, but typically are implicit in pre-season harvest outlooks declared by management agencies.

Evaluating the relative performance of different methods for weighting pre-season forecasts vs. in-season data and setting confidence thresholds would aid salmon management. Identifying methods that result in the best long-term management performance would assist managers in using the available data to make in-season management decisions. Moreover, if these analyses suggest robust rules of interpreting in-season and pre-season data, then the loss of institutional knowledge could be reduced when experienced managers leave management agencies. In this study, we used a simulation model of the in-season dynamics of the Yukon fall chum salmon run and fishery to evaluate the relative performance of (1) using different methods for weighting forecasts vs. in-season data and (2) assuming different degrees of risk tolerance in prosecuting the fishery.

Methods

We constructed a model that simulated a self-sustaining salmon population returning annually to spawn at ages 3-5 and exposed it to a downstream commercial and an upstream subsistence fishery. Although assuming this amount of spatial segregation between fisheries is somewhat unrealistic for Yukon fall chum, we aimed for the model to capture the prevailing pattern in which commercial harvest is concentrated in the lower river and subsistence fisheries are more common upstream. A single iteration of the model comprised a 50-year time series of salmon returns and associated outcomes for harvest and escapement. The model was iterated 500 times to generate a distribution of outcomes (over the 50 years) for a particular management scenario. The different management scenarios reflected different levels of risk tolerance and different methods for estimating the expected run size. The relative performance of each of the scenarios was then evaluated by comparing the distribution of performance outcomes among scenarios. Uncertainty in the dynamics of the salmon population was considered by drawing parameter sets (i.e., a different set for each model iteration) from the posterior distribution of a Bayesian stock-recruitment analysis (Table 4-1).

The Model

For each year of a simulation, a true run size was generated as a function of the number of spawners in the last generation using point estimates of stock recruit parameters from an age-structured stock-recruitment analysis for Yukon River fall chum salmon (Table 4-1; Fleischman and Borba 2009). The stock-recruitment function allowed for time-varying stock productivity to simulate decadal-scale changes in the ocean environment and their effects on survival rates of Yukon River fall chum stocks. The daily number of fish entering the river was calculated as the product of the true run size and the proportion of the run entering the lower river on that date. The daily proportions of the run entering the river (i.e., within-year run timing) were determined by re-sampling from 22 observed Yukon fall chum run timings from 1986 to 2007 (B. Borba, ADF&G, unpublished data; Figure 4-1). The observed run timings were determined by averaging the run timings from test fisheries and Pilot Station sonar. Run timings were standardized to the timing at the Middle Mouth/Big Eddy test fishery by lagging Pilot Station timings by 3 days and the Mountain Village test fishery by 2 days. The fate of salmon as they migrated upstream was simulated using a simple “box-car” representation (Starr and Hilborn 1988) that divided the river into 30 reaches, each representing one day of upstream travel. All individuals entering the river on the same day were assumed to move upstream at the same rate and experience commercial harvest within the first 10 days in the river and subsistence harvest from day 11 to 30. Fish surviving to day 31 were counted as escapement.

The model simulated the process of obtaining daily estimates of the total expected run size ($\hat{N}_d$) by combining a pre-season forecast ($\hat{H}_y$) with a daily run estimate based on in-season data ($\hat{I}_d$). The point estimate of the pre-season forecast ($\hat{H}_y$; i.e., median forecasted run size) was generated as a bias-corrected lognormal random deviate of the true run size with variance based on observed historical deviations between pre-season forecasts and reconstructed run sizes from 1990-2009 (Table 4-1; ADF&G unpublished data).

Daily run estimates from in-season data ($\hat{I}_d$) were simulated to approximate estimates that would be obtained from test fisheries and Pilot Station sonar. The point estimate of the expected run size from in-season data was generated as the observed cumulative passage to date in the current year (c_d) divided by the average cumulative proportion of the run returning to date ($\bar{p}_d$) based on historical run timing data:

(4-1) $$\hat{I}_d = \frac{c_d}{\bar{p}_d}.$$

Observed cumulative passage estimates were generated as log-normal deviates of the true cumulative passage with a variance taken as the estimated variance of deviations between annual passage estimates at Pilot Station sonar and reconstructed run sizes from a basin-wide stock-recruitment model (Fleischman and Borba 2009; Table 4-1). Variance of the in-season run estimates (${\sigma_{\hat{I}_d}}^2$) was a function of the variance in the historical cumulative proportions returning on a given day of the season (${\sigma_{p_d}}^2$;Walters and Buckingham 1975):

(4-1) $${\sigma_{\hat{I}_d}}^2 = \frac{c_d^2 \sigma_{\bar{p}_d}^2}{\bar{p}_d^4}\left(1 + 2\frac{\sigma_{\bar{p}_d}^2}{\bar{p}_d}\right)$$

Daily total run size estimates ($\hat{N}_d$) were generated by combining the pre-season forecast ($\hat{H}_y$) with the in-season run estimates ($\hat{I}_d$). We evaluated the relative performance of two methods for estimating $\hat{N}_d$. The first method used Bayes' theorem to obtain the posterior distribution of the expected run size by taking the weighted average (and variance) of the forecast (prior) and in-season data (likelihood), with the weights proportional to the precision of the estimates (Fried and Hilborn 1988). The second method used the forecast exclusively until the day on which the first 25% of the run had historically entered the river, after which the in-season data were used exclusively. We will refer to this method hereafter as the quartile method. Yukon River fall chum salmon managers within ADF&G currently use what could be described as a hybrid of these two approaches. The quartile method is used periodically by ADF&G depending on the magnitude and uncertainty in the pre-season forecast and depending on any available auxiliary data. The Bayesian method is not used explicitly (i.e., the computations are not formally carried out), but ADF&G managers frequently attempt to balance the forecast and the in-season data depending on how confident they are in either estimate, although this is typically done in a subjective manner.

Daily decisions on commercial and subsistence harvest rates were made depending on run size estimates relative to pre-determined run size thresholds. The rules were based on current ADF&G harvest run size thresholds for Yukon River fall chum: no harvest if

($\hat{N}_d$)<300,000 fish, limited subsistence if ($\hat{N}_d$)>300,000, full subsistence if ($\hat{N}_d$)>500,000, commercial harvest if ($\hat{N}_d$) >600,000 fish. Harvest was allowed if the probability that the run size exceeded a particular run size threshold was greater than an assumed confidence threshold probability (*P**). *P** represents the risk tolerance assumed by managers with values close to 1.0 representing a very risk averse (i.e., conservative with respect to meeting escapement goals) approach to management and values close to zero being very risk tolerant (i.e., aggressive). For example, a *P** of 0.5 means that harvest for a particular fishery will be allowed if the median of the total run estimate on a given day ($\hat{N}_d$) exceeds the corresponding harvest threshold for that fishery.

Harvest was taken by setting daily exploitation rates for each fishery such that the total harvest summed over the entire fishing season would match the expected surplus available to each fishery (+/- implementation error) if harvest was allowed on all possible days. Daily exploitation rates for the commercial fishery were determined by first dividing the number of surplus fish available for harvest above 600,000 ($\hat{N}_d$-600,000) by the total run size estimate, then converting this quantity to an instantaneous rate, and converting to a daily rate by dividing the instantaneous rate by the number of days each migrating cohort of fish is exposed to the commercial fishery (i.e., 10 days). Similarly, harvest rates for the subsistence fishery were determined by dividing the average amount necessary for subsistence (midpoint of the published ANS range of 89,500-167,100: 128,500 salmon; Linderman et al 2007) by the expected number of fish available for subsistence harvest ($\hat{N}_d$-target commercial harvest) and converting to an instantaneous daily rate (divide by 20 days exposed to the subsistence fishery) as was done for the commercial harvest rates. This harvesting algorithm is likely realistic for the subsistence fishery, which is typically regulated simply based on the current estimate of expected total run because real-time catch data are not available. For commercial fisheries, managers obtain real-time catch data which can be used to adjust fishing effort by comparing cumulative catches to the expected surplus to the commercial fishery given run size estimates. Preliminary simulations that allowed for adjustment of commercial effort via real time catch data allowed for an unrealistic ability for the commercial fishery to "catch up" late in the season if catches were too low early in the run.

We evaluated the performance of three approaches for setting confidence threshold values. The first approach involved using a constant P* between fisheries and over time. We evaluated a range of constant P* values from 0.5 to 0.9. The second scenario used a liberal confidence threshold for the subsistence fishery (P* = 0.5) and a conservative one (P* = 0.9) for the commercial fishery, and P* was constant over time. Subsistence fisheries have priority, therefore we wished to assess whether management performance could be improved by adopting a more conservative threshold for the commercial fishery. The third scenario used a liberal confidence threshold for both fisheries (P* = 0.5), but switched to a conservative one (P* = 0.9) for the commercial fishery when a stock of concern designation was declared by failing to meet the minimum escapement goal in four of the last five years. This scenario was important to consider because managers typically become more conservative in implementing the commercial fishery if recent management performance (or run size) has been poor. Each of these four scenarios was evaluated using the Bayesian method for estimating the run size.

Relative performance of the different management strategies was evaluated by considering differences in the distribution of outcomes for several performance measures over 500 model iterations for each strategy. Recall that each iteration represents one realization of a

50-year time series of salmon returns and harvests. The performance measures were the mean subsistence catch, mean commercial catch, the probability of commercial closure, the probability of providing minimum amounts necessary for subsistence (lower bound of the ANS range: 89,500; Linderman et al 2007), the probability of a stock of concern designation (failure to meet the minimum escapement goal for 4 of the most recent 5 years), and the probability of meeting the minimum escapement goal of 300,000 salmon. Mean catch performance indicators were calculated as the mean catch over each 50-year model iteration. Probability performance measures were calculated as the proportion of the 50-years of simulated salmon runs satisfying a particular criterion (e.g., commercial closure, minimum ANS, minimum escapement).

Fishery performance should be most sensitive to the value of P* when the run size is in the neighborhood of the management thresholds of 300,000, 500,000 and 600,000. Therefore we conducted an additional set of analyses to determine whether a liberal or conservative P* might perform better when run sizes were between 300,000 and 800,000. We obtained the results of the individual year simulations from each of the 500 model iterations (500 iterations × 50 years/iteration = 25,000 individual years). We then focused on the subset of those years in which the preseason forecast was between 300,000 and 800,000 salmon. Basing the subset on the value of the forecast and not the true run size was an attempt to make the analysis relevant to managers, who do not know the true run size and must make decisions based on noisy forecasts and in-season run estimates. We divided the forecast range (300,000-800,000) into five 100,000-fish intervals and assessed differences in the performance measures under different P* values and among intervals.

Results

The values of performance measures varied substantially among model iterations regardless of the probability threshold level or method used to calculate daily run estimates. For example, the inter-quartile range of the average commercial catch for the Bayesian method and a conservative confidence threshold ranged from 129,000 to 418,000 salmon (Figure 4-2, panel a). This variability was attributable to variation in salmon returns, which resulted from temporal variation in stock productivity and stationary process error.

The Bayesian and quartile methods for obtaining daily estimates of the expected run size performed similarly (Figure 4-2). The average subsistence catch (median of the average 50-year catch over 500 model iterations) was 94,000 salmon for both methods (Figure 4-2, panel b). Probability of commercial closure was 0.35 for the quartile and 0.41 for the Bayesian method (Figure 4-2, panel c). Probability of meeting minimum amounts necessary for subsistence of 89,500 salmon was 0.61 for both methods (Figure 4-2, panel d). All other performance measures were similar between the two methods (Figure 4-2).

Although the two methods performed similarly overall, their relative performance varied among individual year simulations (Figure 4-3). For example, run estimates obtained with the two methods agreed strongly in some years, resulting in similar subsistence and commercial catches (Figure 4-3, panels a-c). In other years, performance of the two methods differed substantially when in-season data from early in the run diverged from the forecast. In such cases, the estimated run size changed substantially when shifting from the forecast to the in-season data (Figure 4-3, panels d-f). Nevertheless, the distribution of outcomes over 500 model iterations suggested that the two methods performed similarly over the 50 year time horizon and across simulations.

Confidence threshold probabilities (*P**) modestly affect fishery performance measures (Figure 4-4). Adopting a constant aggressive *P** of 0.5 resulted in an average commercial catch of 257,000 salmon and subsistence catch of 97,000 salmon (Figure 4-4, panels a, b). A relatively conservative constant *P** of 0.9 for both fisheries resulted in an average commercial catch of 263,000 salmon and subsistence catch of 88,000 salmon (Figure 4-4, panels a, b). The 4,000 fish increase in commercial catch despite a more conservative P* was attributable to larger average returns when *P** = 0.9 (returns = 654,000 salmon) than when P* = 0.5 (620,000 salmon), which allowed for larger commercial catches in years with very large runs. The probability of commercial closure increased from 0.40 at a *P** of 0.5 to 0.54 at a *P** of 0.9 (Figure 4-4, panel c). The probability of meeting subsistence needs decreased with increasing *P** (Figure 4-4, panel d). Escapement increased from 410,000 to 448,000 when moving from a *P** of 0.5 to 0.9 (Figure 4-4, panel e). The probability of a stock of concern designation was less than 0.1 for all scenarios and decreased from 0.04 to 0.01 with increased *P** (Figure 4-4, panel f).

When *P** was allowed to differ between fisheries, an aggressive stance toward the subsistence fishery (*P**=0.5) coupled with a conservative stance toward the commercial fishery (*P**=0.9) resulted in the largest average subsistence catch (102,000 salmon; Figure 4-4, panel b) but also the highest probability of commercial closure (0.56; Figure 4-4, panel c). Allowing for a time varying *P** with a baseline value of 0.5 and switching to a conservative value (*P**=0.9) for the commercial fishery under a stock of concern designation resulted in minimal changes in performance measures relative to the baseline constant *P** of 0.5 for both fisheries (Figure 4-4). This finding was not unexpected given the low probability of stock of concern designation.

Although performance measures were modestly influenced by choices of the value of P* on average over the 50-year time horizon, differences were evident in individual year simulations, particularly when the run size was near the management thresholds. As an example, Figure 4-5 shows the daily time series of run size estimates, commercial harvest, and subsistence harvest for a single year example simulation. The true run size for this example was 620,000 salmon and the pre-season forecast indicated a run of 825,000 +/- 330,000. Assuming an aggressive P* resulted in a subsistence catch of 124,000 and a commercial catch of 68,000. Not unexpectedly, a conservative *P** resulted in a complete commercial closure. Interestingly, the conservative *P** resulted in a greater subsistence catch (129,000) than the aggressive P* because more fish were available in the upstream subsistence zone due to the commercial closure.

In years when the pre-season forecast was near the management thresholds of 300, 500, and 600 thousand salmon, the effects of changes in *P** were more pronounced for some of the performance measures (Figure 4-6). For example, when the forecast was between 600 and 700 thousand salmon, commercial catch decreased from 41,000 to zero salmon with increasing *P** from 0.5 to 0.9 (Figure 4-6, panel a), but these losses were not accompanied by substantial increases in other performance indicators such as subsistence catch (Figure 4-6, panel b). As another example, when the forecast was between 500 and 600 thousand salmon, increasing P* resulted in a substantial reduction in the probability of meeting minimum ANS (Figure 4-6, panel d) and an increase in the probability of commercial closure (Figure 4-6, panel c), but with minimal improvement in escapement indicators (Figure 4-6, panels e, f). Only at forecasts between 300 and 400 thousand was a conservative P* advantageous. In this case, moving to a conservative P* of 0.9 resulted in a nearly 50% complete reduction in the probability of failing to meet the minimum escapement of 300,000 (Figure 4-6, panel f) and this improvement was not accompanied by less desirable values of the other performance indicators. Thus, only when forecasts were very low, did performance benefit from a conservative rather than liberal management approach.

Discussion

Poor Yukon River fall chum salmon runs from 1998-2002 caused significant hardship for subsistence users and commercial fishers along the river. Processing capacity that was lost during these small runs has yet to fully return. Another lasting effect of the poor runs has arguably been on salmon managers' approach to prosecuting the commercial fisheries. Managers have become quite averse to the risk of failing to meet escapement and subsistence objectives. Risk aversion has led managers to delay commercial openings until in-season run estimates were more certain. Our analysis suggests that, integrated over the possible future states of the stock, this conservative approach results in small gains in escapement and subsistence objectives while modestly increasing the probability of commercial closures, with minimal effect on subsistence performance. Armed with this information, policymakers could formalize the degree of management conservatism by choosing a P* value that best reflects stakeholder tolerance for reduced commercial catch in the interest of improved escapements. Our model suggests that any change in performance due to selection of a particular P* value will be modest at best.

We expected the degree of management conservatism to have more effect when the run size was in the neighborhood of the management thresholds of 300, 500, and 600 thousand salmon. Our analysis supports this prediction. However, close examination of the trends in performance measures at low run sizes suggests that a conservative approach that results in reduced fishery performance is not necessarily accompanied by substantial gains toward escapement objectives. Because these are relatively small run sizes, the amount of additional commercial harvest allowed under a liberal approach is also likely to be small during most years and commensurate increases in escapement were equally small. Thus, there may be little to gain by a conservative approach, even in years with poor runs. Only when the forecast was between 300 and 400 thousand salmon was there a substantial gain in probability of meeting the escapement goal under a more conservative approach.

Management performance was similar between using the Bayesian approach or the quartile method to estimate the expected run size. Generally, the in-season data become more informative around the first quarter point of the run. The Bayesian method was mostly weighted toward the in-season data after the quarter point because precision of in-season estimates began to exceed the pre-season forecast at that time. Therefore it was not surprising that the two methods perform similarly. Two conclusions could be drawn from this finding. The first is that adopting the Bayesian approach results in no loss of performance. The other possible conclusion is that there is nothing to gain by switching to the Bayesian approach. Although either of these conclusions in valid given our findings, there could be additional advantages of the Bayesian approach not accounted for in our analysis.

The Bayesian method provides a quantitative, defensible, and transparent method for estimating the expected run size when compared to the quartile method or some other more subjective weighting scheme. In essence, the Bayesian method attempts to model a manager's thought process in assessing the relative merits of the forecast and in-season data. For example, most reasonable managers would not base decisions on a highly uncertain forecast when a relatively precise in-season estimate is available, nor would a Bayesian. Furthermore, a Bayesian approach lends itself to increased and more structured thinking about uncertainty, which could foster improved communication with stakeholders and ultimately increased stakeholder "buy-in" of the management process.

The in-season modeling approach we present here provides a platform for continued evaluation of alternative management strategies for Yukon fall chum and for other stocks such as Yukon River Chinook salmon. The harvest rules we simulated were relatively simple. Further evaluation of specific opening or closing schedules could be incorporated into future modeling efforts. Future harvest policies could incorporate formal rules governing the duration and location of openings or closings, and the rules that are adopted should be those that have been shown to best balance the existing tradeoffs in a simulation framework. In addition, modeling efforts could incorporate additional complexity such as stock composition from genetics studies to test management strategies that could increase the probability meeting escapement objectives for Canadian stocks. A continued iterative process involving stakeholders, managers and policy-makers could result in enhanced understanding of trade-offs, the uncertainties facing managers, and could improve fishery outcomes.

Table 4-1. Parameter values used in the in-season simulation model. Upper and lower 95% credible intervals are shown for parameters obtained from a basin-wide stock-recruitment analysis for Yukon River fall chum (Appendix A). Structural uncertainty was incorporated into simulations by drawing parameter sets (one set for each model iteration) from the posterior distribution of the stock recruitment parameters.

Parameter	Symbol	Estimate	Lower 95%	Upper 95%
Process Error				
alpha	α	2.63	1.06	4.87
beta	β	9.10e^{-07}	3.10e^{-07}	1.64e^{-06}
recruitment variance	σ^2_R	0.13	0.01	0.38
alpha random walk variance	σ^2_α	0.12	0.01	0.40
proportion returning at age 1	γ_3	0.04	0.02	0.05
proportion returning at age 2	γ_4	0.70	0.66	0.73
proportion returning at age 3	γ_5	0.27	0.23	0.31
Observation Error				
pre-season forecast variance	σ^2_H	0.38		
cumulative passage observation error variance	σ^2_c	0.04		
Implementation Error				
commercial implementation error variance	σ^2_{com}	0.51		
subsistence implementation error variance	σ^2_{sub}	0.13		

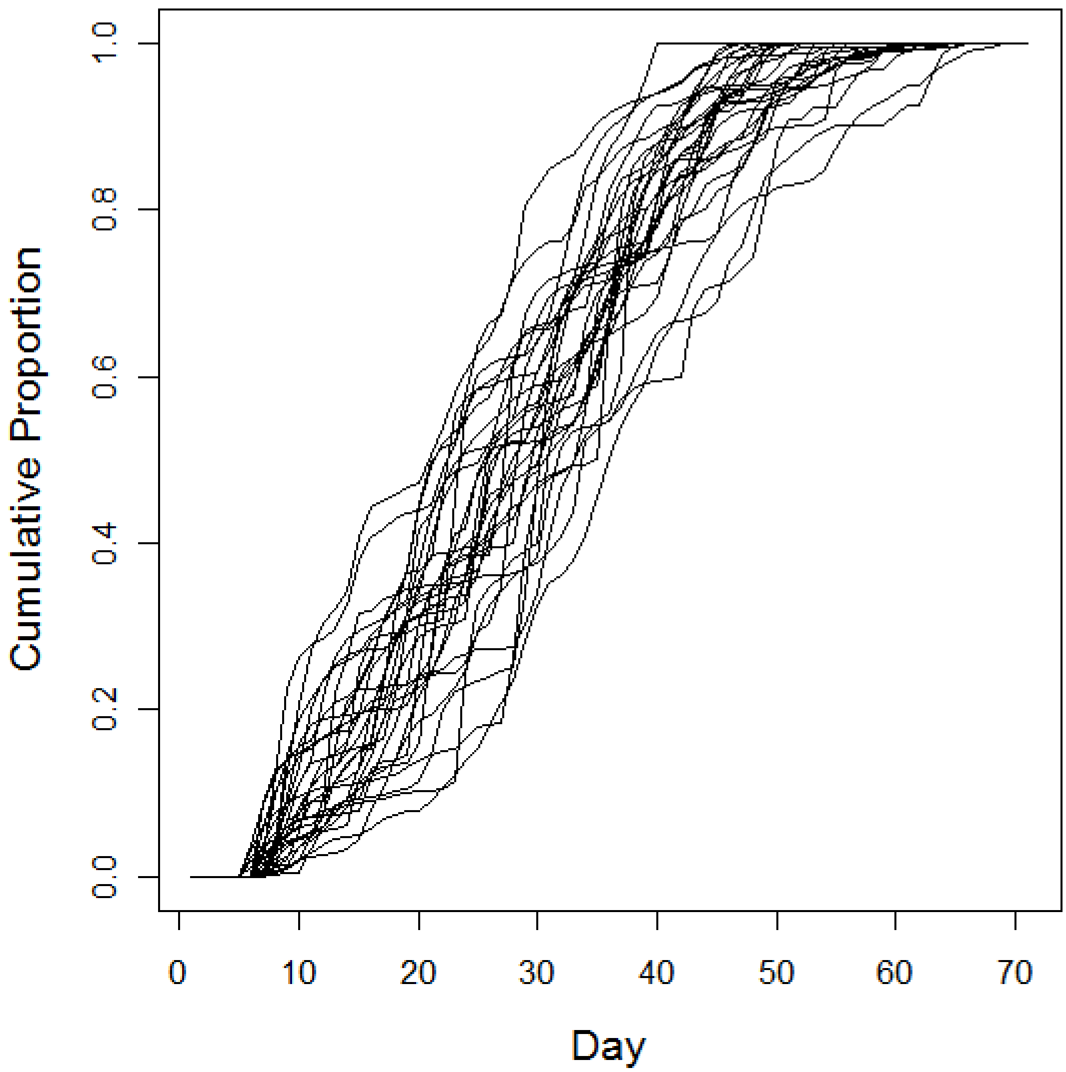

Figure 4-1. The daily proportions of the run entering the river (i.e., within-year run timing) from 22 observed Yukon fall chum run timings from 1986 to 2007 (B. Borba, ADF&G, unpublished data). Run timings were determined by averaging the run timings from test fisheries and Pilot Station sonar. Run timings were standardized to the timing at the Middle Mouth/Big Eddy test fishery by lagging Pilot Station by 3 days and the Mountain Village test fishery by 2 days.

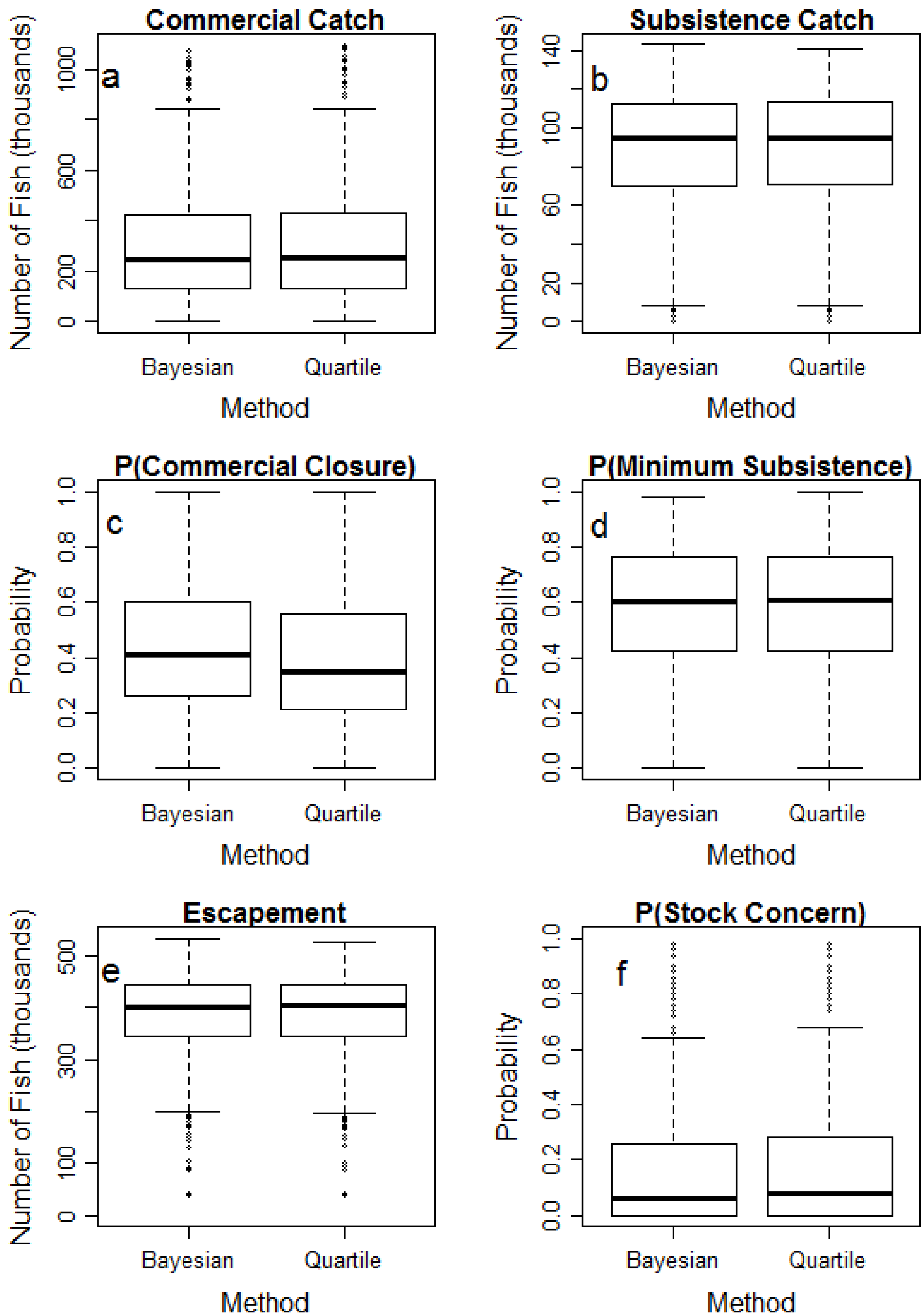

Figure 4-2. Boxplots showing the distribution of performance measures from 500 model iterations for two methods (Bayesian and quartile methods) used to obtain daily in-season estimates of the expected run size. The confidence threshold (P*) was 0.5 for these simulations.

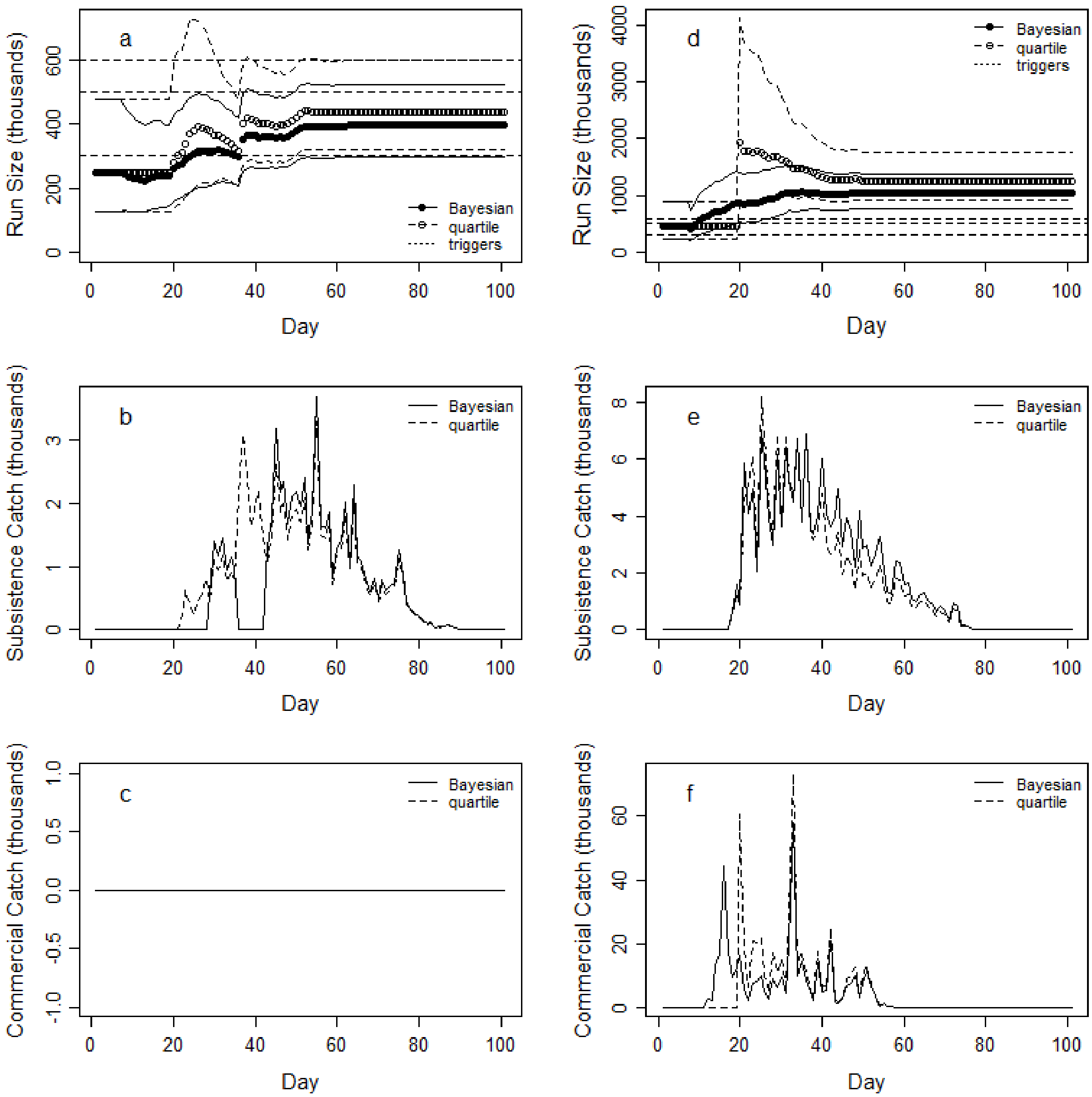

Figure 4-3. Two example in-season time series of the daily run size estimates (+/- 90% credible interval; panels a and d), daily subsistence catches (panels b and e), and daily commercial catches (panels c and f). Solid lines represent time series in which the Bayesian method was used to estimate the run size whereas dashed lines represent the quartile method. Horizontal dashed lines in panels a and d represent the management threshold run sizes for escapement (300,000 salmon), full subsistence harvest (500,000 salmon) and full commercial harvest (600,000 salmon). For each time series, an identical random seed was used for the two methods so that the results are comparable between methods.

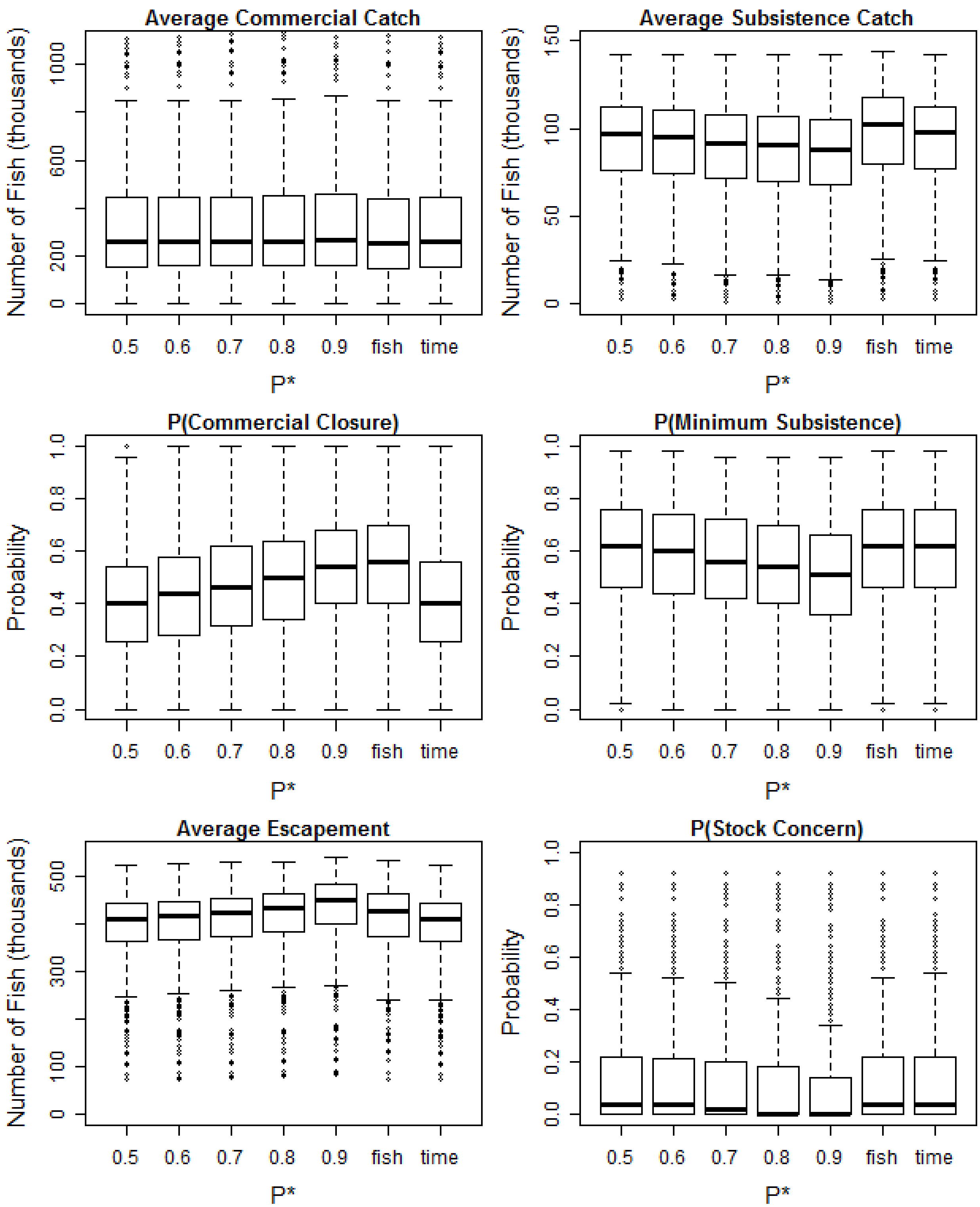

Figure 4-4. Boxplots showing the distribution of performance measures from 500 model iterations for a range of P* values from 0.5 to 0.9, and for variable P* between fisheries ('fish') and variable P* over time as a function of stock of concern designation ('time').

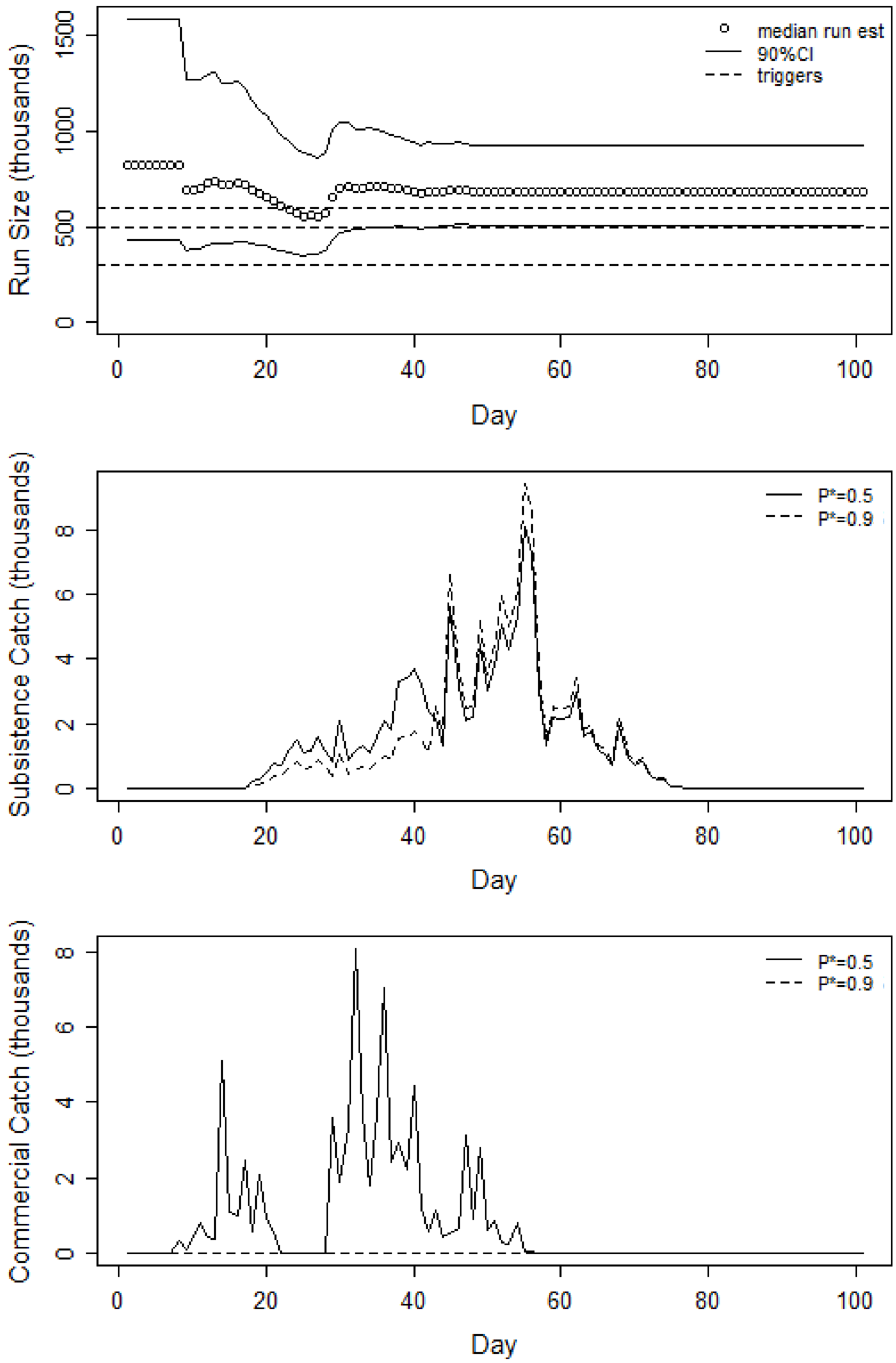

Figure 4-5. Example time series of a single year in-season simulation showing the daily run size estimates (+/- 90% credible interval; panel a), subsistence catch (panel b), and commercial catch (panel c). Solid lines in panels b and c represent the outcomes of using an aggressive P* of 0.5 whereas dashed lines represent a conservative P* of 0.9. Horizontal dashed lines in panel a show the management threshold run sizes for escapement (300,000 salmon), full subsistence harvest (500,000 salmon) and full commercial harvest (600,000 salmon). An identical random seed was used for both P* values so the results of the two simulations are comparable.

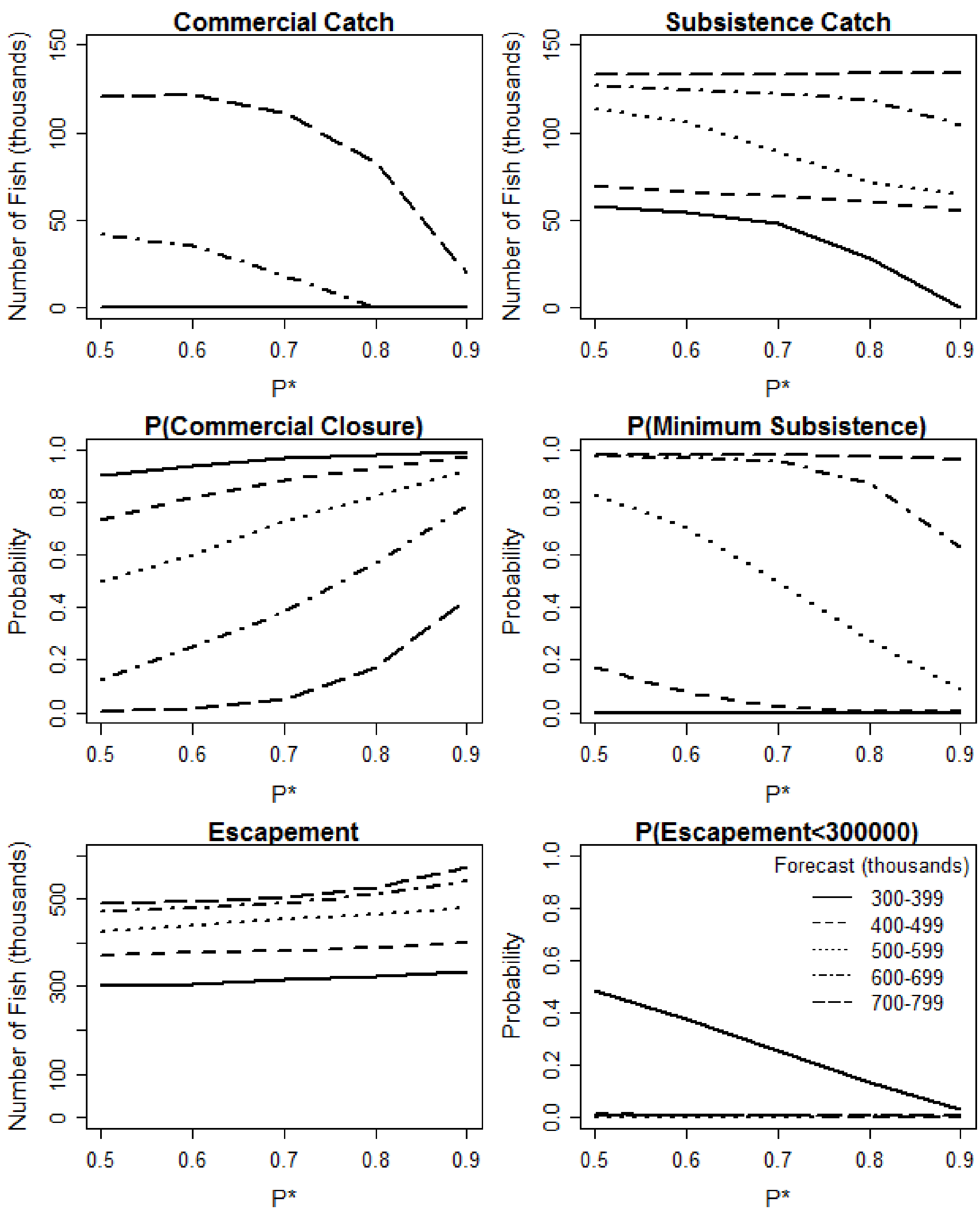

Figure 4-6. Average values of performance measures as a function of the confidence probability threshold (P*) for a range of values of the pre-season forecast (different line types). For example, the solid line represents the values of performance measures when the pre-season forecast was between 300,000 and 399,999 salmon. The averages were calculated across each of the individual year simulations and across the 500 model iterations (500 iterations X 50 years/iteration = 25,000 individual years).

Appendix A. Stock recruitment analysis for Yukon River fall chum and Kuskokwim River Chinook salmon

We obtained estimates of life history parameters and associated uncertainty for the Yukon River fall chum and Kuskokwim River Chinook salmon stocks using an age-structured Ricker stock-recruitment model. Our analysis closely followed the methodology of Fleischman and Borba (2009), although we made a few modifications. Fleischman and Borba's (2009) analysis took a Bayesian state-space approach, which allowed estimation of process and observation uncertainty. Markov Chain Monte Carlo simulation was used to obtain estimates of uncertainty by integrating over population states and parameters using the Metropolis-within-Gibbs algorithm as implemented by WinBUGS software. Process errors were incorporated in the form of inter-annual recruitment variation, temporal variation in stock productivity (alpha parameter) to represent decadal-scale changes in ocean productivity, and temporal variation in salmon maturation schedules (proportions returning at age). The model incorporated observation errors on escapement, commercial harvest, and subsistence harvest. The primary difference between Fleischman and Borba (2009) and our model is that they accounted for time varying productivity by modeling serially autocorrelated recruitment residuals (AR(1) process) whereas we allowed the alpha parameter to vary over time as a random walk process. We modeled commercial and subsistence harvest separately whereas Fleischman and Borba (2009) pooled the two harvests. Finally, Fleischman and Borba (2009) included observed passage data from the Pilot Station Sonar because they were interested in estimating the bias and uncertainty of the Pilot passage estimates, whereas our model did not use Pilot Station data. The model was fitted to annual escapement and harvest estimates, as well as annual age counts from 1974-2009 for Yukon fall chum and 1976-2007 for Kuskokwim Chinook (Tables A-1, A-2).

We used a Ricker stock recruitment function to obtain predicted brood year recruitment ($\bar{R}_y$) as a function of escapement (S_y):

(A-1) $$\bar{R}_y = \alpha_y S_y e^{-\beta S_y},$$

where α_y are brood year-specific productivity parameters and β is the density-dependent parameter. Unknown brood year recruitments (R_y) were assumed drawn from a log-normal distribution:

(A-2) $$R_y = \bar{R}_y \varepsilon_{R_y}$$

(A-3) $$\varepsilon_{R_t} \sim LN(1, \sigma_R),$$

where σ_R is the process error standard deviation of high-frequency interannual recruitment variation.

The natural log of α was allowed to vary over time according to a random walk with normally distributed annual deviations:

(A-4) $\ln(\alpha_y) = \ln(\alpha_{y-1}) + \varepsilon_{\alpha_y}$

(A-5) $\varepsilon_{\alpha_y} \sim N(0, \sigma_\alpha)$,

where σ_α is the process error standard deviation of the random walk.

Unknown recruitments in the first several years (R_{init_y}) could not be linked with prior escapements. Therefore, these recruitments were modeled hierarchically, as individual draws from a common log-normal distribution:

(A-6) $R_{init_y} = \bar{R}_{init_y} \varepsilon_{init_y}$

(A-7) $\varepsilon_{init_t} \sim LN(1, \sigma_{init_R})$,

where $\bar{R}_{init_y}$ and σ_{init_R} are the parameters of the distribution.

The abundance of age-*a* salmon from brood year *y* in calendar year *t* was the recruitment for brood year *y* multiplied by the proportion of that cohort returning at age *a*:

(A-8) $N_{t,a} = R_{t-a} p_{t-a,a}$

The proportion ($p_{y,a}$) of each brood year *y* returning at age *a* was modeled hierarchically assuming the proportion vectors (e.g., $\boldsymbol{p_y} = \{p_{y,3}\ p_{y,4}\ p_{y,5}\}$) were drawn from a common Dirichlet(γ_3, γ_4, γ_5) distribution. The hierarchical approach facilitated estimation of expected proportions returning at age (π_a) while allowing for temporal variation in return proportions across brood years (i.e., process error).

The brood year-specific age proportions ($p_{y,a}$) were a function of brood year parameters ($g_{y,a}$) via:

(A-9) $p_{y,a} = \frac{g_{y,a}}{\sum_a g_{y,a}}$

The $g_{y,a}$ were assumed drawn from a gamma distribution:

(A-10) $g_{y,a} \sim gamma(shape = \gamma_a, rate = 1)$,

which ensures that the brood year age proportions ($p_{y,a}$) are Dirichlet distributed (Evans et al. 1993). The gamma rate parameter acts simply as a scaling factor and therefore has no effect on the variance of the age proportions. The γ_a are age-specific hyperparameters of the Dirichlet distribution that determine the expected proportions returning at age (and their variance across brood years):

(A-11) $\pi_a = \frac{\gamma_a}{\sum_a \gamma_a}$

The total return in calendar year t was the sum over ages of the individual brood year returns in that year:

(A-12) $$N_t = \sum_a N_{t,a}$$

Abundances ($N_{t,a}$) were fitted to observed age composition data $n_{t,a}$ taken from scale samples of fish captured annually in test fisheries in the lower portion of each river. Observed age compositions were multinomially distributed:

(A-13) $$n_{t,a} \sim multinomial\left(\frac{N_{t,a}}{N_t}\right),$$

where $\frac{N_{t,a}}{N_t}$ is the proportion of the run in year t that is age a. We assumed the effective sample size of the observed age composition data was 100 salmon per year.

Annual escapement S_t was obtained by subtracting annual commercial (H_{c_t}) and subsistence (H_{s_t}) harvest from total abundance:

(A-14) $$S_t = N_t - H_{c_t} - H_{s_t}$$

Subsistence harvest $H_{s_t}$was assumed to occur before commercial harvestH_{c_t} for the Kuskokwim Chinook fishery:

(A-15) $$H_{s_t} = N_t \mu_{s_t}$$

(A-16) $$H_{c_t} = N_t(1 - \mu_{s_t})\mu_{c_t},$$

but the opposite was true for Yukon fall chum. The ordering of the two fisheries affected exploitation estimates but had no effect on all other parameters.

Observed data included estimates of annual escapement (s_y), estimates of annual harvest for the commercial (h_{c_t}) and subsistence (h_{s_t}) fisheries, and annual age counts determined from scale samples ($n_{t,a}$).

Observed escapements (s_t) were assumed to have a log-normal sampling distribution:

(A-17) $$s_t = S_t \varepsilon_{s_t}$$

(A-18) $$\varepsilon_{s_t} \sim LN(1, \sigma_{s_t})$$

where σ_{s_t} are year-specific observation error standard deviations. Observed escapements were escapement estimates from basin-wide run reconstruction models (Bue 2008, Fleischman and Borba 2009). The error standard deviations were assumed known and were taken from the estimated standard errors of the reconstructed escapement estimates (Bue 2008, Fleischman and Borba 2009).

Observed commercial harvest (h_{c_t}) was assumed to have a log-normal sampling distribution:

(A-19) $$h_{c_t} = H_{c_t}\varepsilon_{c_t}$$

(A-20) $$\varepsilon_{c_t} \sim LN(\mu = 1, \sigma = \sigma_c),$$

where σ_c is a time-invariant observation error standard deviation of the commercial harvest that was assumed known and was set at 0.05. This small value was chosen because observation errors in commercial catch should be small due to the mandatory daily reporting of total catch by all permit holders.

Observed subsistence harvest (h_{s_t}) was assumed to have a log-normal sampling distribution:

(A-21) $$h_{s_t} = H_{s_t}\varepsilon_{s_t}$$

(A-22) $$\varepsilon_{s_t} \sim LN(\mu = 1, \sigma = \sigma_s)$$

Observation error standard deviation for subsistence harvest (σ_s) was assumed known and was taken from the standard error of recent estimates of basin-wide subsistence harvest (Yukon fall chum = 0.12, Kuskokwim Chinook = 0.10; cite)

Non-informative priors (chosen to have a minimal effect on the posterior) were used for all parameters. Normal priors with mean zero and very large variances ($1+e^6$), were used for $\ln(\alpha_1)$, β, and for the natural log of $\bar{R}_{init_y}$. Diffuse conjugate inverse gamma priors were used for $\sigma_R, \sigma_\alpha, \sigma_{init_R}$, and γ_a. Annual exploitation rates μ_{s_t} and μ_{c_t} were given diffuse beta (0.1, 0.1) prior distributions.

Markov-Chain Monte Carlo samples were drawn from the joint posterior probability distribution of all unknowns in the model. For each of two Markov chains initialized, a 50,000-sample burn-in period was discarded, thinning by a factor of 50 was initiated, and 100,000 additional updates were generated. The resulting 1,000 samples were used to estimate the marginal posterior means, standard deviations, and percentiles. The diagnostic tools of WinBUGS were used to assess mixing. Convergence was assessed with the Gelman-Rubin R statistic. Diagnostics indicated the chains converged and mixing was adequate. Bayesian credible intervals were obtained from the percentiles of the posterior distribution of each unknown.

Results

Yukon River Fall chum salmon have low stock productivity that has varied substantially over the last 20 years. The median α over the time series was 2.86 and ranged from 1.06 to 4.87 (Table A-1) and the error standard deviation of the alpha random walk (σ_α) was 0.34 (95% credible interval: 0.1, 0.63). High frequency inter-annual recruitment variation had an error standard deviation (σ_R) of 0.36 (0.1, 0.62). The posterior median of β was $9.1e^{-7}$ ($3.1e^{-7}$, $1.64e^{-6}$). Low productivity of the 1994-1997 brood years caused well-documented poor returns from 1998 to 2002 (Figure A-1, panel d). The runs were dominated by age-4 fish. The expected proportions returning at ages 3 to 5 (π_a) were 0.04 (0.02, 0.05), 0.70 (0.66, 0.73), and 0.27 (0.23, 0.31), respectively. However, the proportions returning at age for individual brood years ($p_{y,a}$) were variable (Table A-1), resulting in weak sibling relationships for the stock. The model fit the observed data reasonably well (Figure A-1, panels a-c; Figure A-2). Exploitation rates ranged from 0.0 to 0.4 for the commercial fishery and from 0.05 to 0.36 for subsistence (Table A-1).

Kuskokwim River Chinook salmon have greater and less variable stock productivity than Yukon fall chum. The median α over the time series was 8.26 and ranged from 4.91 to 9.24 (Table A-2). The error standard deviation of the alpha random walk was 0.10 (0.04, 0.27). The magnitude of σ_R was 0.25 (0.16, 0.38), which was similar to Yukon fall chum. The posterior median of β was $9.08e^{-6}$ ($6.3e^{-6}$, $1.3e^{-5}$). The runs were dominated by age-5 and 6 fish. The expected proportions returning at ages 4 to 7 (π_a) were 0.17 (0.09, 0.31), 0.37 (0.26, 0.47), 0.42 (0.30, 0.54), and 0.04 (0.01, 0.10), respectively. The proportions returning at age for individual brood years were less variable than for Yukon fall chum (Table A-2). The model fit the observed data reasonably well (Figure A-3, panels a-c; Figure A-4). Exploitation rates ranged from 0.0 to 0.23 for the commercial fishery and from 0.16 to 0.43 for subsistence (Table A-2).

Table A-1. Posterior median and 95% credible intervals (parentheses) for time-specific unknowns of the age-structured stock-recruitment model for Yukon River fall chum salmon. Recruitment (millions; R_y), proportions returning at age (p_a), and productivity (α_y) are brood year unknowns whereas commercial (μ_c) and subsistence (μ_s) exploitation rates are calendar year unknowns. Recruitment is expressed as millions of salmon.

Year	R	p_3	p_4	p_5	α	μ_c	μ_s
1969	0.95(0.04,3.76)	0.02(0.00,0.16)	0.71(0.48,0.88)	0.26(0.10,0.47)			
1970	1.07(0.07,1.96)	0.02(0.00,0.15)	0.67(0.43,0.87)	0.29(0.11,0.53)			
1971	2.48(1.32,3.63)	0.02(0.00,0.15)	0.75(0.61,0.88)	0.21(0.09,0.34)			
1972	0.33(0.09,0.87)	0.02(0.00,0.19)	0.75(0.51,0.89)	0.21(0.08,0.43)			
1973	1.09(0.86,1.43)	0.02(0.00,0.16)	0.84(0.71,0.90)	0.13(0.08,0.21)			
1974	0.82(0.64,1.06)	0.11(0.06,0.19)	0.73(0.62,0.82)	0.15(0.08,0.26)	2.95(1.38,6.44)	0.28(0.21,0.36)	0.24(0.16,0.35)
1975	1.71(1.36,2.24)	0.10(0.06,0.15)	0.85(0.79,0.90)	0.05(0.03,0.09)	3.47(1.57,7.32)	0.13(0.09,0.18)	0.10(0.07,0.15)
1976	0.88(0.73,1.07)	0.11(0.05,0.20)	0.71(0.62,0.79)	0.18(0.11,0.26)	3.09(1.65,6.28)	0.19(0.14,0.25)	0.27(0.18,0.38)
1977	1.35(1.17,1.58)	0.08(0.05,0.11)	0.77(0.71,0.82)	0.16(0.11,0.20)	3.20(1.78,5.93)	0.24(0.19,0.31)	0.23(0.16,0.33)
1978	0.52(0.42,0.64)	0.04(0.01,0.11)	0.72(0.61,0.81)	0.24(0.15,0.34)	2.51(1.19,5.25)	0.26(0.20,0.33)	0.29(0.20,0.41)
1979	1.23(1.04,1.45)	0.03(0.01,0.06)	0.72(0.66,0.78)	0.24(0.19,0.31)	2.86(1.41,5.56)	0.22(0.16,0.29)	0.19(0.13,0.27)
1980	0.62(0.49,0.76)	0.02(0.00,0.06)	0.65(0.55,0.75)	0.33(0.23,0.43)	2.92(1.62,5.33)	0.37(0.31,0.43)	0.36(0.27,0.47)
1981	1.33(1.12,1.57)	0.04(0.02,0.07)	0.71(0.64,0.78)	0.25(0.19,0.32)	3.43(2.02,6.01)	0.40(0.33,0.47)	0.27(0.20,0.36)
1982	0.66(0.52,0.82)	0.02(0.00,0.06)	0.71(0.60,0.80)	0.27(0.18,0.37)	3.37(1.97,5.71)	0.38(0.32,0.44)	0.36(0.27,0.46)
1983	1.11(0.92,1.37)	0.02(0.00,0.04)	0.78(0.71,0.84)	0.20(0.15,0.27)	3.26(1.88,5.35)	0.32(0.27,0.38)	0.29(0.21,0.37)
1984	0.60(0.49,0.75)	0.02(0.00,0.07)	0.68(0.58,0.77)	0.29(0.20,0.40)	2.88(1.66,5.00)	0.31(0.25,0.36)	0.36(0.27,0.46)
1985	1.23(1.05,1.44)	0.04(0.02,0.07)	0.70(0.63,0.77)	0.26(0.20,0.33)	3.03(1.79,5.20)	0.26(0.21,0.32)	0.25(0.19,0.33)
1986	0.86(0.71,1.05)	0.00(0.00,0.03)	0.60(0.50,0.69)	0.40(0.31,0.49)	2.80(1.60,5.01)	0.19(0.15,0.23)	0.25(0.19,0.33)
1987	0.97(0.82,1.17)	0.02(0.00,0.05)	0.64(0.56,0.71)	0.34(0.27,0.42)	2.60(1.50,4.69)	0.04(0.03,0.05)	0.36(0.27,0.44)
1988	0.42(0.33,0.54)	0.08(0.03,0.16)	0.54(0.42,0.65)	0.38(0.28,0.49)	2.21(1.18,4.31)	0.28(0.23,0.33)	0.33(0.25,0.43)
1989	0.68(0.53,0.86)	0.01(0.00,0.04)	0.48(0.37,0.58)	0.51(0.41,0.62)	2.42(1.36,4.39)	0.30(0.25,0.35)	0.32(0.25,0.41)
1990	1.07(0.86,1.32)	0.00(0.00,0.01)	0.61(0.52,0.71)	0.39(0.29,0.48)	2.91(1.67,5.10)	0.19(0.15,0.23)	0.28(0.20,0.36)
1991	1.43(1.22,1.65)	0.00(0.00,0.02)	0.72(0.65,0.78)	0.28(0.22,0.34)	3.20(1.85,5.55)	0.27(0.22,0.32)	0.24(0.18,0.31)
1992	0.87(0.72,1.02)	0.01(0.00,0.04)	0.75(0.68,0.81)	0.24(0.18,0.31)	2.64(1.55,4.53)	0.06(0.05,0.08)	0.21(0.16,0.28)
1993	0.57(0.48,0.66)	0.02(0.00,0.07)	0.79(0.72,0.84)	0.19(0.14,0.25)	1.98(1.15,3.64)	0.02(0.01,0.02)	0.18(0.13,0.24)
1994	0.37(0.32,0.44)	0.02(0.00,0.07)	0.60(0.52,0.68)	0.38(0.30,0.46)	1.28(0.58,3.13)	0.03(0.03,0.04)	0.14(0.10,0.19)
1995	0.34(0.29,0.40)	0.01(0.00,0.04)	0.77(0.71,0.83)	0.21(0.15,0.28)	1.06(0.46,2.95)	0.20(0.17,0.23)	0.15(0.12,0.18)
1996	0.30(0.25,0.36)	0.00(0.00,0.03)	0.58(0.49,0.66)	0.42(0.33,0.50)	1.06(0.47,2.90)	0.10(0.09,0.12)	0.16(0.13,0.20)
1997	0.37(0.31,0.44)	0.01(0.00,0.03)	0.67(0.58,0.74)	0.32(0.25,0.41)	1.35(0.75,3.04)	0.10(0.08,0.12)	0.17(0.14,0.21)
1998	0.33(0.27,0.41)	0.00(0.00,0.03)	0.78(0.68,0.87)	0.21(0.13,0.31)	1.86(1.09,3.42)	0.00(0.00,0.00)	0.21(0.17,0.26)
1999	0.89(0.79,1.00)	0.03(0.01,0.06)	0.77(0.71,0.82)	0.20(0.15,0.25)	3.00(1.81,4.88)	0.08(0.07,0.09)	0.27(0.22,0.32)
2000	0.44(0.34,0.56)	0.02(0.00,0.07)	0.68(0.55,0.81)	0.30(0.16,0.44)	3.02(1.88,5.12)	0.01(0.00,0.01)	0.11(0.09,0.14)
2001	2.69(2.42,2.98)	0.05(0.03,0.07)	0.72(0.67,0.76)	0.24(0.20,0.28)	4.87(2.27,10.14)	0.01(0.00,0.01)	0.11(0.09,0.14)
2002	0.71(0.57,0.86)	0.01(0.00,0.05)	0.64(0.54,0.73)	0.35(0.26,0.45)	3.04(1.87,5.38)	0.01(0.01,0.01)	0.06(0.05,0.08)
2003	1.26(1.13,1.42)	0.02(0.00,0.05)	0.65(0.59,0.70)	0.33(0.28,0.39)	2.81(1.65,4.94)	0.03(0.02,0.03)	0.08(0.06,0.10)
2004	0.50(0.42,0.61)	0.01(0.00,0.05)	0.69(0.61,0.77)	0.30(0.22,0.38)	1.94(0.95,4.50)	0.02(0.02,0.02)	0.11(0.09,0.14)
2005	0.55(0.42,0.78)	0.01(0.00,0.06)	0.71(0.50,0.87)	0.27(0.10,0.48)	1.81(0.59,4.87)	0.09(0.08,0.11)	0.05(0.04,0.07)
2006	0.69(0.24,2.07)	0.04(0.01,0.12)	0.69(0.48,0.87)	0.26(0.09,0.48)	1.95(0.50,5.50)	0.16(0.14,0.19)	0.10(0.08,0.12)
2007						0.09(0.08,0.10)	0.10(0.08,0.12)
2008						0.15(0.13,0.17)	0.15(0.12,0.18)
2009						0.04(0.04,0.05)	0.14(0.11,0.16)

Table A-2. Posterior median and 95% credible intervals (parentheses) for time-specific unknowns of the age-structured stock-recruitment model for Kuskokwim River Chinook salmon. Recruitment (millions; R_y), proportions returning at age (p_a), and productivity (α_y) are brood year unknowns whereas commercial (μ_c) and subsistence (μ_s) exploitation rates are calendar year unknowns. Recruitment is expressed as millions of salmon.

Year	R_y	p_3	p_4	p_5	p_6	α_y	μ_c	μ_s
1969	0.22(0.05,0.65)	0.17(0.08,0.28)	0.37(0.25,0.50)	0.42(0.30,0.55)	0.03(0.01,0.10)			
1970	0.17(0.03,0.30)	0.17(0.09,0.28)	0.37(0.26,0.50)	0.41(0.29,0.53)	0.04(0.01,0.10)			
1971	0.25(0.16,0.39)	0.17(0.08,0.28)	0.34(0.24,0.45)	0.39(0.28,0.49)	0.09(0.06,0.16)			
1972	0.31(0.23,0.42)	0.15(0.08,0.24)	0.33(0.23,0.43)	0.47(0.37,0.59)	0.04(0.01,0.10)			
1973	0.13(0.07,0.21)	0.17(0.09,0.28)	0.33(0.22,0.46)	0.45(0.32,0.58)	0.04(0.01,0.10)			
1974	0.21(0.13,0.30)	0.16(0.10,0.23)	0.39(0.28,0.50)	0.40(0.29,0.52)	0.05(0.02,0.09)			
1975	0.33(0.25,0.45)	0.17(0.10,0.27)	0.33(0.23,0.43)	0.46(0.37,0.57)	0.03(0.01,0.05)			
1976	0.27(0.22,0.34)	0.15(0.08,0.24)	0.35(0.28,0.43)	0.46(0.38,0.54)	0.03(0.01,0.09)	5.35(3.30,8.79)	0.15(0.12,0.18)	0.29(0.22,0.37)
1977	0.16(0.12,0.20)	0.15(0.10,0.22)	0.37(0.29,0.46)	0.43(0.32,0.54)	0.05(0.03,0.08)	5.07(3.04,8.11)	0.16(0.12,0.20)	0.26(0.18,0.35)
1978	0.14(0.11,0.18)	0.12(0.08,0.18)	0.39(0.28,0.50)	0.44(0.35,0.54)	0.04(0.02,0.08)	4.91(2.92,7.79)	0.19(0.15,0.23)	0.16(0.12,0.21)
1979	0.20(0.16,0.24)	0.17(0.09,0.26)	0.38(0.30,0.46)	0.40(0.34,0.48)	0.05(0.03,0.08)	5.08(3.11,8.08)	0.18(0.14,0.22)	0.26(0.20,0.34)
1980	0.16(0.13,0.19)	0.17(0.12,0.23)	0.39(0.32,0.46)	0.40(0.32,0.47)	0.04(0.01,0.11)	5.21(3.21,8.27)	0.15(0.11,0.20)	0.26(0.18,0.36)
1981	0.22(0.17,0.28)	0.15(0.11,0.21)	0.36(0.29,0.45)	0.42(0.32,0.53)	0.06(0.03,0.10)	5.58(3.48,8.75)	0.17(0.14,0.21)	0.22(0.17,0.29)
1982	0.18(0.14,0.24)	0.10(0.06,0.15)	0.40(0.29,0.52)	0.45(0.35,0.55)	0.05(0.02,0.08)	5.74(3.68,8.93)	0.23(0.19,0.28)	0.29(0.22,0.36)
1983	0.31(0.26,0.38)	0.16(0.09,0.26)	0.38(0.31,0.45)	0.43(0.36,0.51)	0.02(0.01,0.04)	6.23(4.19,9.44)	0.20(0.15,0.24)	0.30(0.22,0.39)
1984	0.19(0.16,0.22)	0.17(0.12,0.22)	0.41(0.33,0.48)	0.39(0.31,0.46)	0.04(0.02,0.07)	6.34(4.22,9.48)	0.19(0.15,0.23)	0.34(0.26,0.43)
1985	0.32(0.28,0.37)	0.13(0.10,0.18)	0.43(0.37,0.50)	0.41(0.35,0.47)	0.02(0.01,0.04)	6.79(4.55,10.18)	0.21(0.17,0.26)	0.25(0.19,0.32)
1986	0.26(0.22,0.31)	0.23(0.18,0.29)	0.33(0.27,0.40)	0.39(0.32,0.45)	0.05(0.03,0.08)	6.98(4.67,10.60)	0.11(0.09,0.14)	0.31(0.23,0.40)
1987	0.25(0.21,0.29)	0.13(0.09,0.18)	0.38(0.31,0.45)	0.46(0.39,0.53)	0.04(0.02,0.07)	7.26(4.70,11.23)	0.16(0.12,0.21)	0.30(0.22,0.41)
1988	0.31(0.26,0.37)	0.23(0.18,0.30)	0.31(0.24,0.37)	0.44(0.37,0.50)	0.02(0.01,0.04)	7.87(5.05,12.55)	0.23(0.19,0.27)	0.29(0.23,0.37)
1989	0.57(0.50,0.66)	0.16(0.13,0.20)	0.40(0.34,0.45)	0.38(0.33,0.44)	0.06(0.04,0.09)	8.56(5.27,14.89)	0.17(0.14,0.20)	0.32(0.25,0.40)
1990	0.28(0.24,0.33)	0.17(0.12,0.23)	0.39(0.32,0.46)	0.42(0.34,0.49)	0.02(0.01,0.04)	8.38(5.08,13.92)	0.19(0.15,0.23)	0.31(0.24,0.39)
1991	0.38(0.33,0.45)	0.18(0.14,0.23)	0.35(0.29,0.41)	0.44(0.38,0.50)	0.02(0.01,0.04)	8.42(5.09,14.20)	0.15(0.12,0.17)	0.34(0.27,0.42)
1992	0.23(0.19,0.28)	0.15(0.10,0.21)	0.36(0.29,0.43)	0.46(0.39,0.54)	0.02(0.01,0.05)	8.24(4.76,14.60)	0.17(0.14,0.20)	0.24(0.19,0.31)
1993	0.36(0.31,0.42)	0.25(0.20,0.31)	0.36(0.30,0.43)	0.37(0.31,0.43)	0.02(0.01,0.03)	8.66(4.75,16.92)	0.03(0.02,0.03)	0.29(0.23,0.37)
1994	0.15(0.12,0.18)	0.14(0.09,0.20)	0.38(0.31,0.45)	0.43(0.36,0.50)	0.05(0.03,0.09)	8.48(4.20,16.78)	0.04(0.03,0.05)	0.23(0.17,0.29)
1995	0.20(0.17,0.23)	0.10(0.06,0.15)	0.33(0.27,0.39)	0.53(0.46,0.60)	0.04(0.02,0.07)	8.38(4.36,16.81)	0.08(0.06,0.09)	0.24(0.19,0.31)
1996	0.21(0.18,0.25)	0.12(0.09,0.16)	0.41(0.35,0.48)	0.42(0.36,0.49)	0.04(0.02,0.07)	8.30(4.28,16.27)	0.02(0.02,0.03)	0.25(0.19,0.31)
1997	0.20(0.18,0.24)	0.16(0.11,0.21)	0.40(0.34,0.46)	0.41(0.35,0.48)	0.03(0.01,0.06)	8.28(4.37,15.85)	0.03(0.02,0.04)	0.24(0.18,0.30)
1998	0.29(0.25,0.33)	0.18(0.14,0.22)	0.39(0.33,0.44)	0.41(0.35,0.47)	0.02(0.01,0.05)	8.44(4.69,15.35)	0.06(0.05,0.08)	0.31(0.23,0.41)
1999	0.32(0.28,0.36)	0.17(0.13,0.21)	0.39(0.33,0.45)	0.39(0.33,0.45)	0.05(0.03,0.08)	8.57(5.01,14.85)	0.02(0.02,0.03)	0.35(0.27,0.45)
2000	0.46(0.41,0.52)	0.32(0.27,0.37)	0.36(0.31,0.41)	0.31(0.26,0.36)	0.02(0.01,0.03)	8.93(5.21,15.38)	0.00(0.00,0.00)	0.43(0.34,0.51)
2001	0.27(0.23,0.31)	0.23(0.18,0.29)	0.38(0.32,0.45)	0.34(0.28,0.40)	0.04(0.01,0.11)	8.75(4.90,15.12)	0.00 (0.00,0.00)	0.31(0.24,0.38)
2002	0.33(0.25,0.43)	0.27(0.20,0.34)	0.27(0.20,0.35)	0.42(0.30,0.54)	0.04(0.01,0.11)	8.99(4.97,16.33)	0.00 (0.00,0.00)	0.29(0.24,0.35)
2003	0.36(0.24,0.59)	0.20(0.13,0.29)	0.36(0.24,0.48)	0.4(0.29,0.52)	0.04(0.01,0.10)	9.24(5.00,17.71)	0.00 (0.00,0.00)	0.27(0.22,0.33)
2004							0.01(0.01,0.01)	0.20(0.17,0.25)
2005							0.01(0.01,0.02)	0.20(0.16,0.25)
2006							0.01(0.01,0.01)	0.19(0.15,0.23)
2007							0.00 (0.00,0.00)	0.30(0.24,0.37)

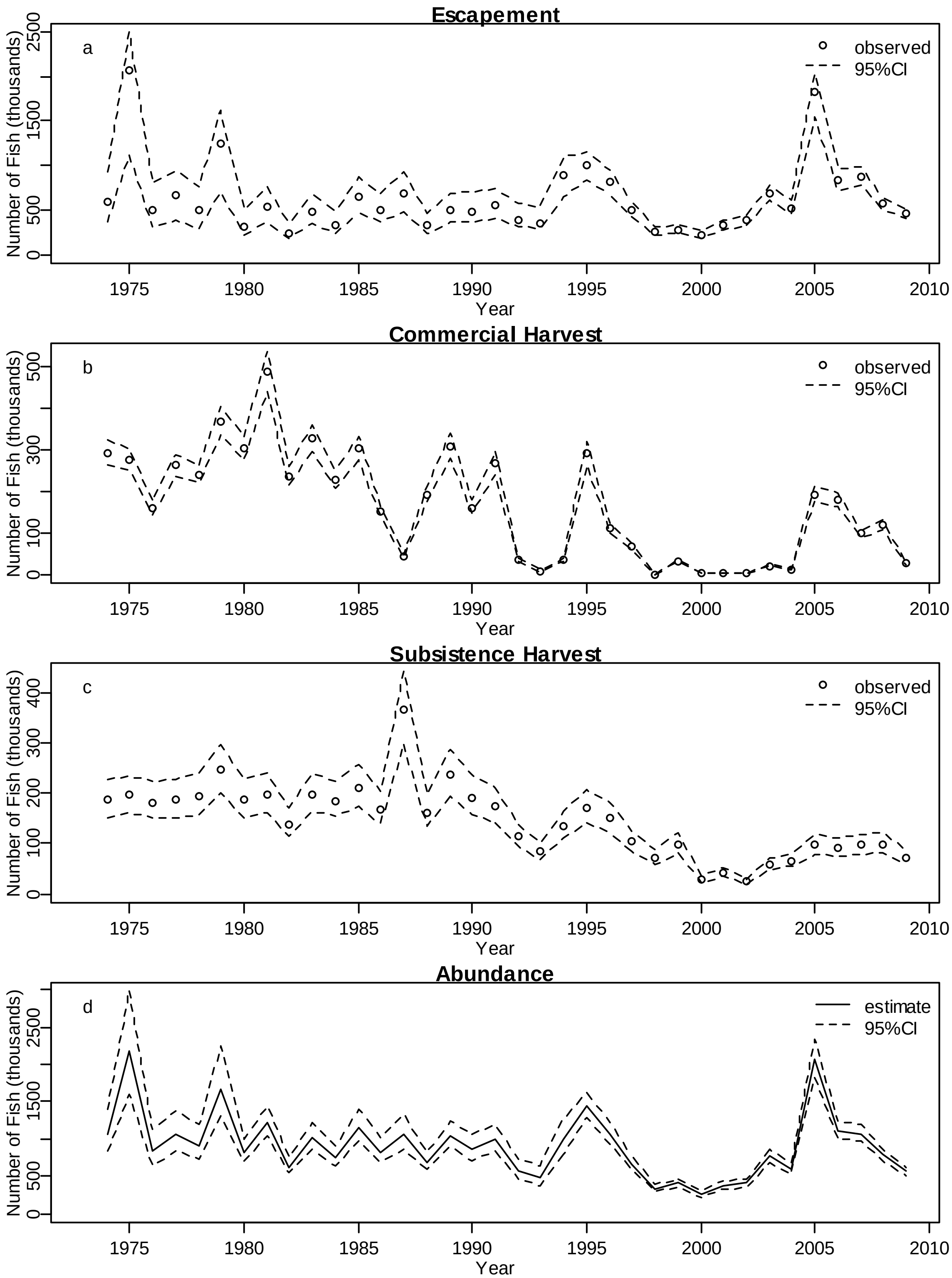

Figure A-1. Escapement, commercial harvest, subsistence harvest, and total abundance of Yukon River fall chum salmon from 1974-2009. Solid and dashed lines represent the posterior median and 95% credible intervals whereas dots in panels a-c depict observed data.

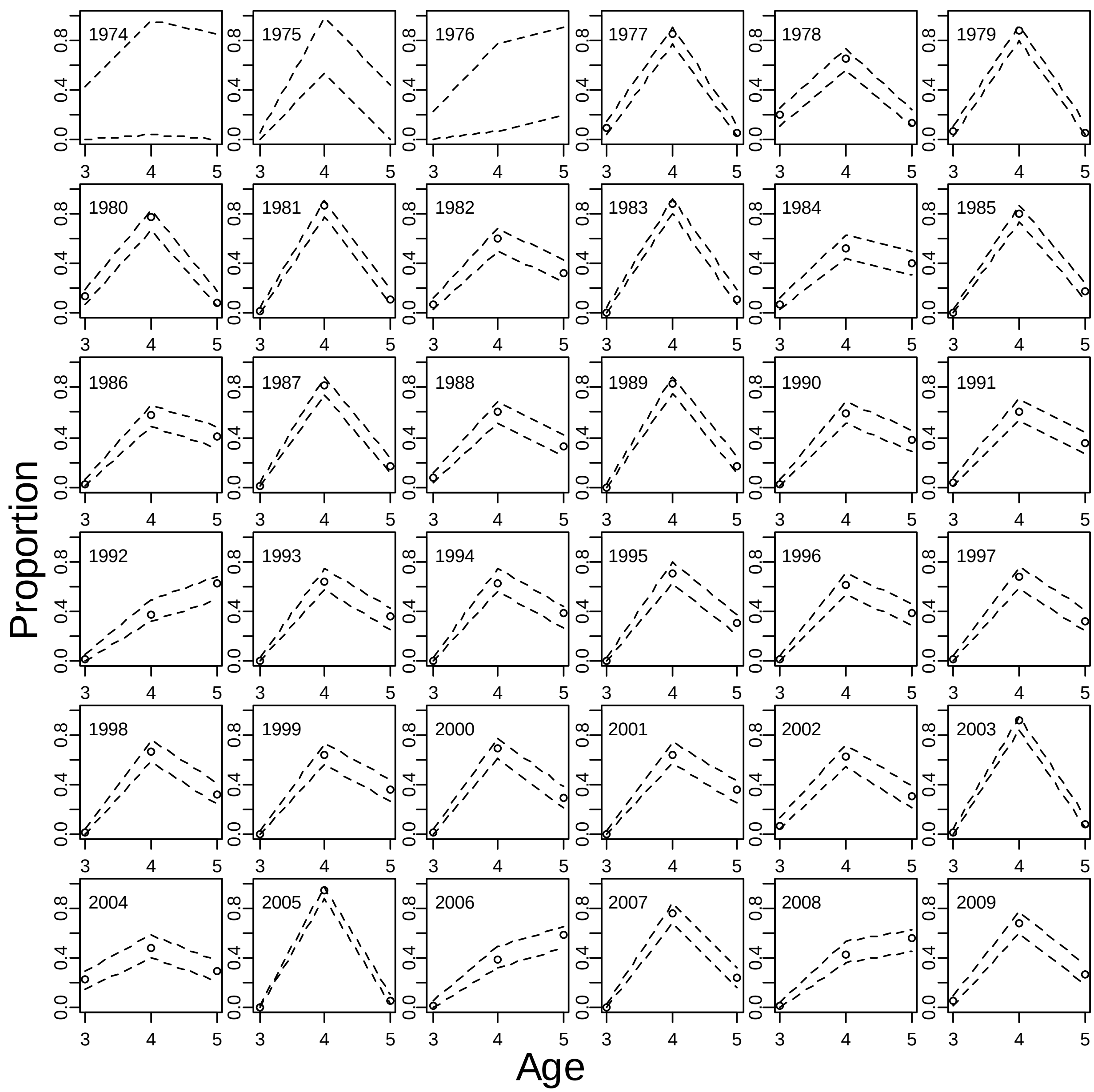

Figure A-2. Observed (dots) age composition along with 95% credible intervals (dashed lines) of the 1974-2009 Yukon River fall chum salmon runs. Age data were not collected from 1974 to 1976.

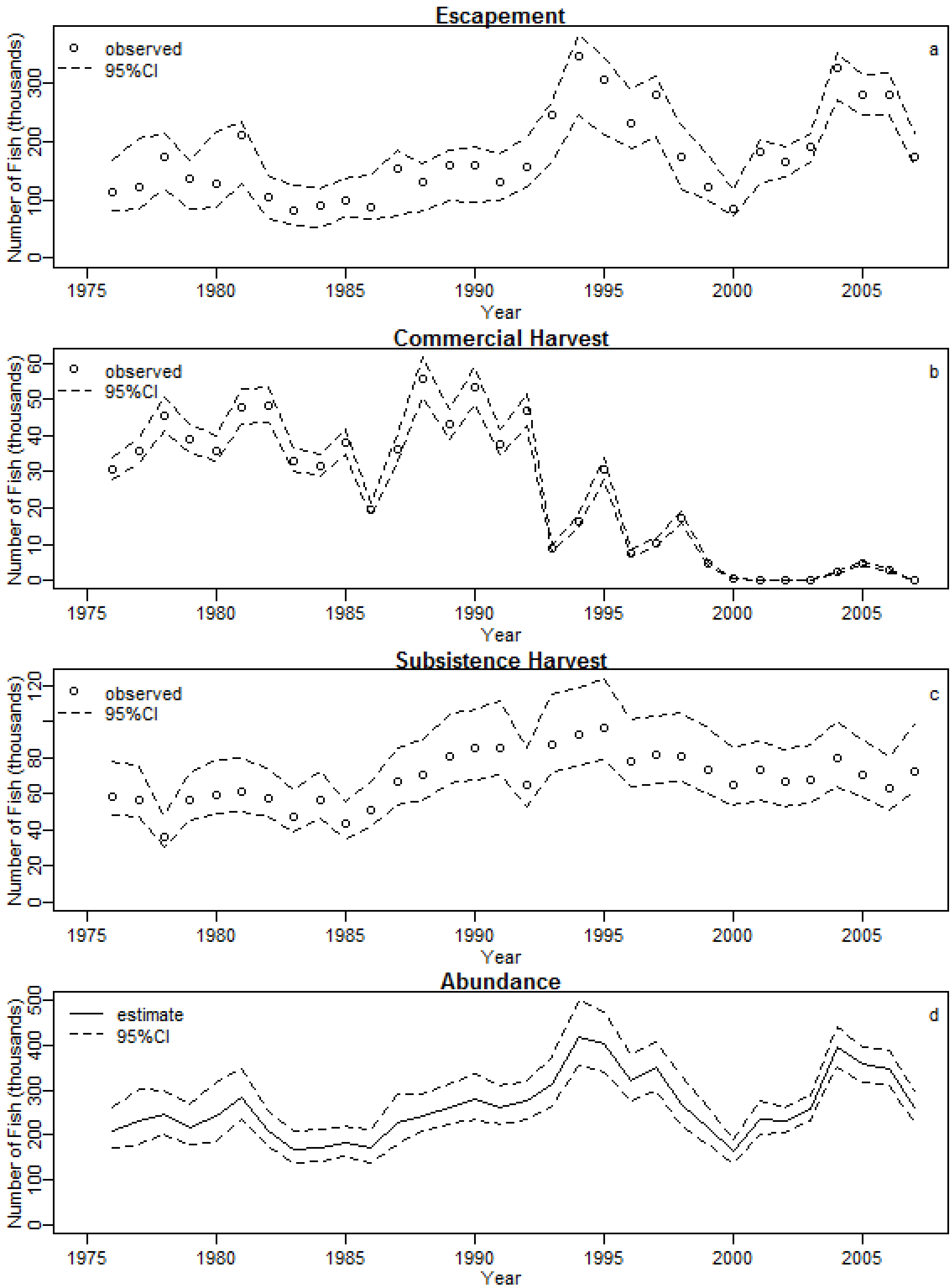

Figure A-3. Escapement, commercial harvest, subsistence harvest, and total abundance of Kuskokwim River Chinook salmon from 1976-2007. Solid and dashed lines represent the posterior median and 95% credible intervals whereas the dots in panels a-c depict observed data.

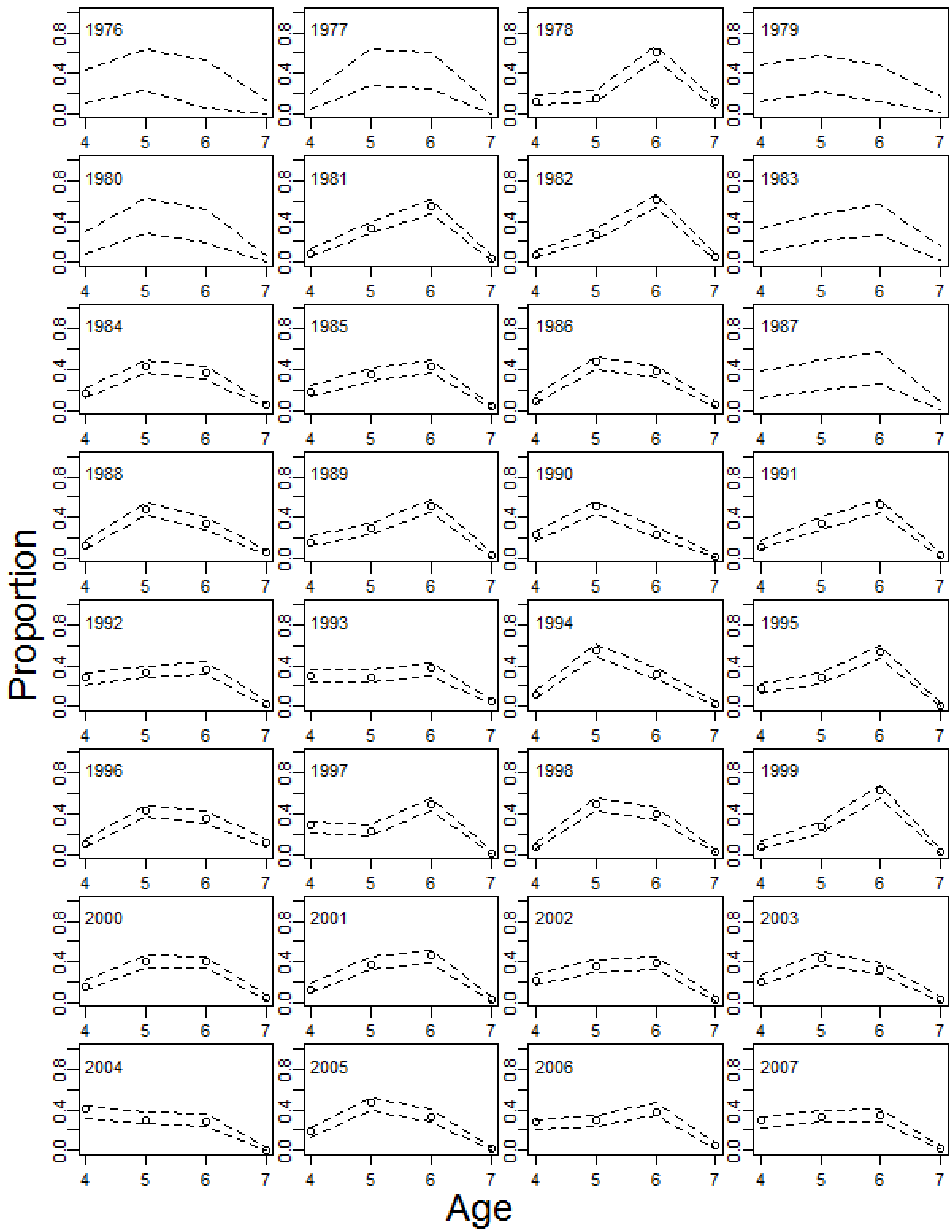

Figure A-4. Observed (dots) age composition along with 95% credible intervals (dashed lines) of the 1974-2009 Kuskokwim River Chinook salmon runs. Age data were not collected from in 1976-77, 1979-80, 1983, and 1987.

Appendix B. Additional contour plots of harvest policy tradeoffs under different uncertainty scenarios.

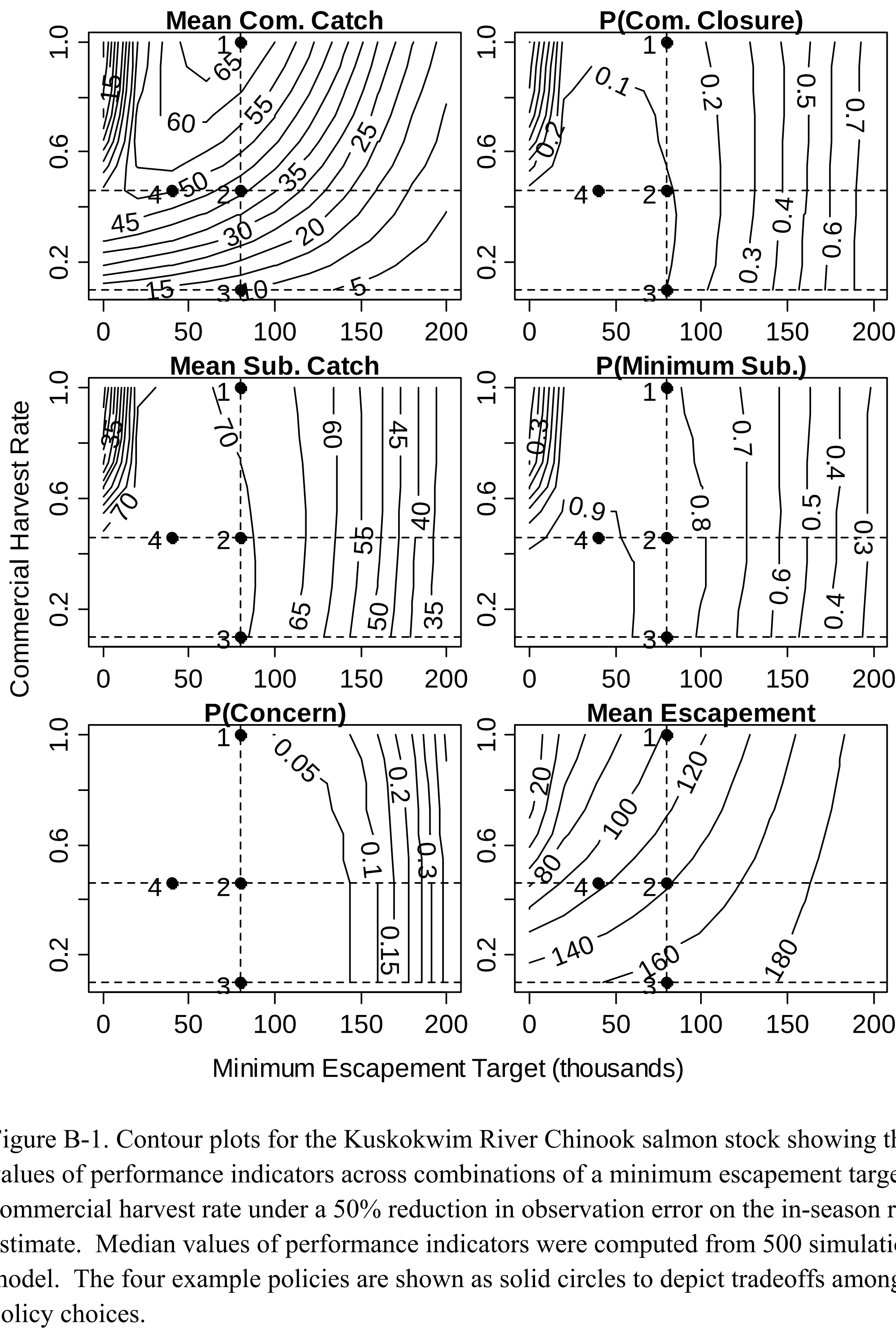

Figure B-1. Contour plots for the Kuskokwim River Chinook salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under a 50% reduction in observation error on the in-season run estimate. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

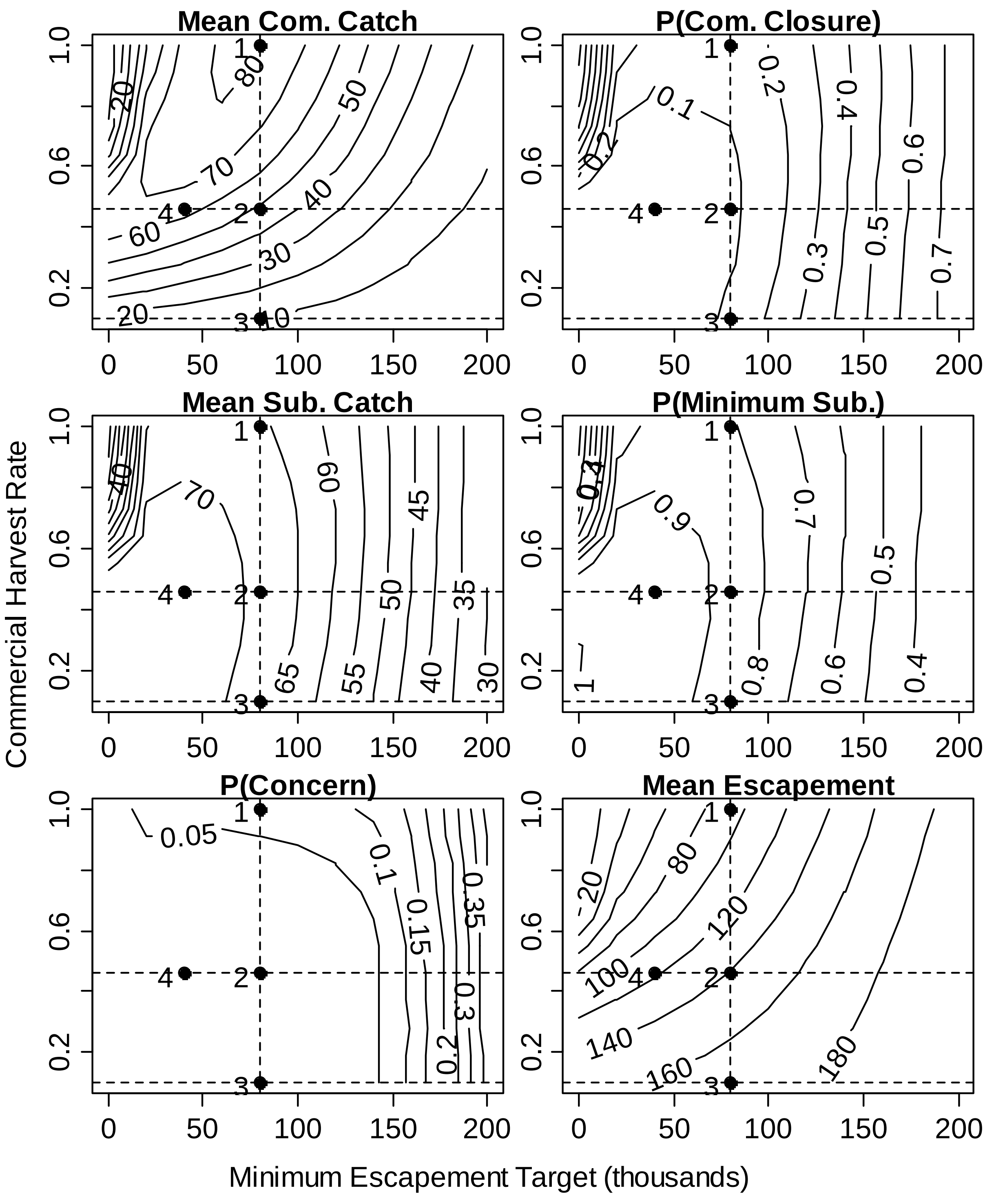

Figure B-2. Contour plots for the Kuskokwim River Chinook salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under a 50% reduction in implementation error. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

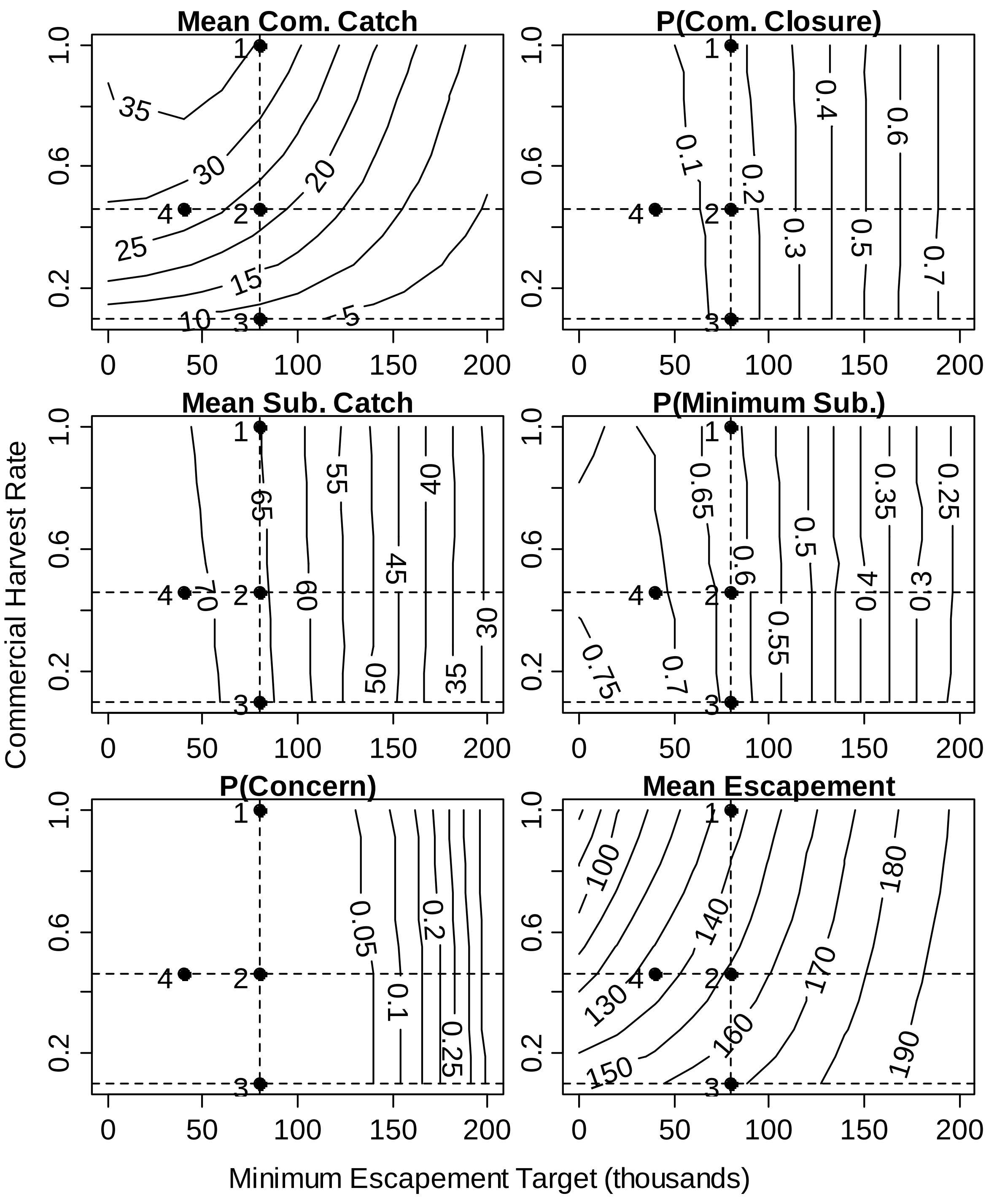

Figure B-3. Contour plots for the Kuskokwim River Chinook salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under a 100% increase in implementation error and observation error. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

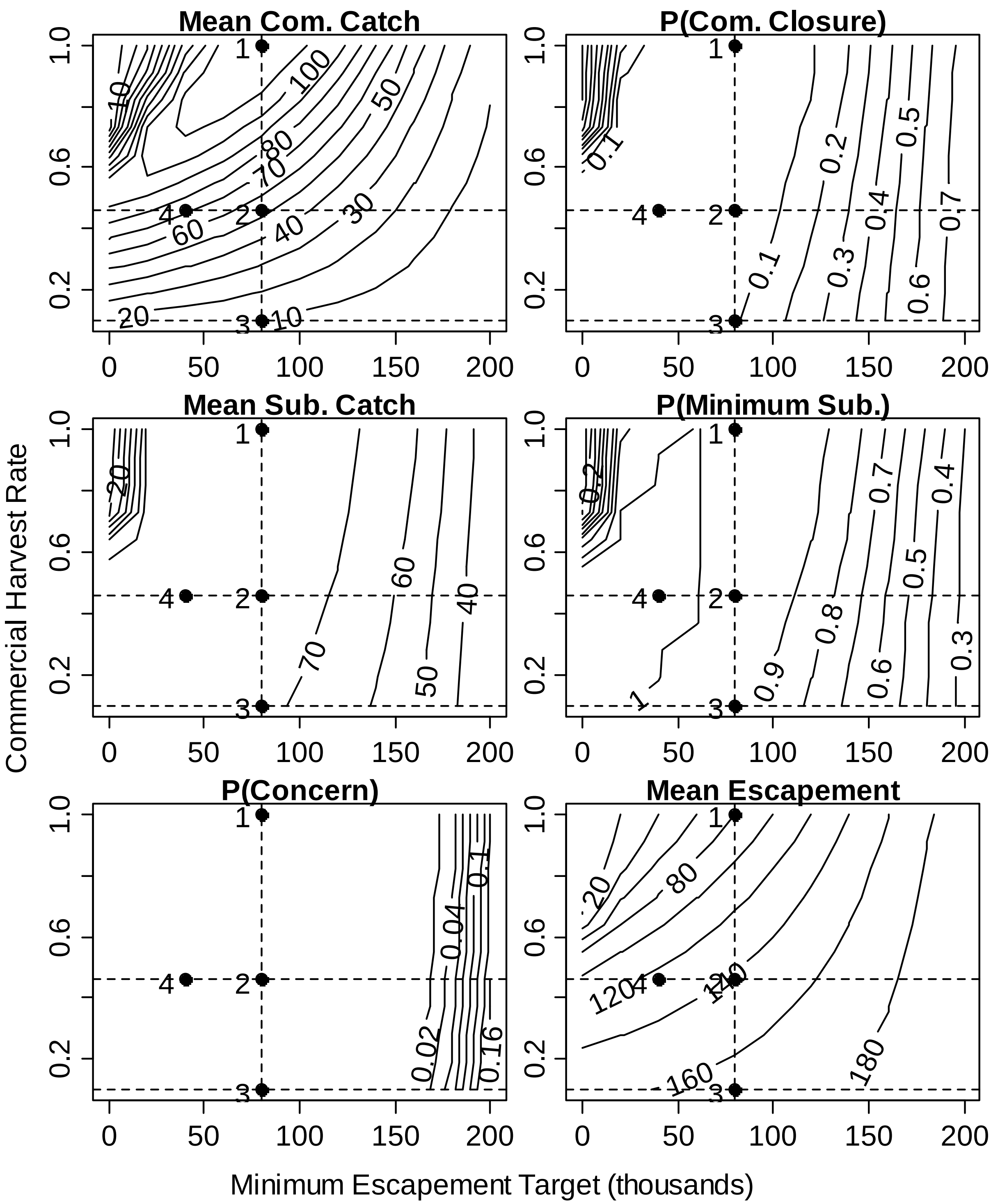

Figure B-4. Contour plots for the Kuskokwim River Chinook salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under no implementation or observation error. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

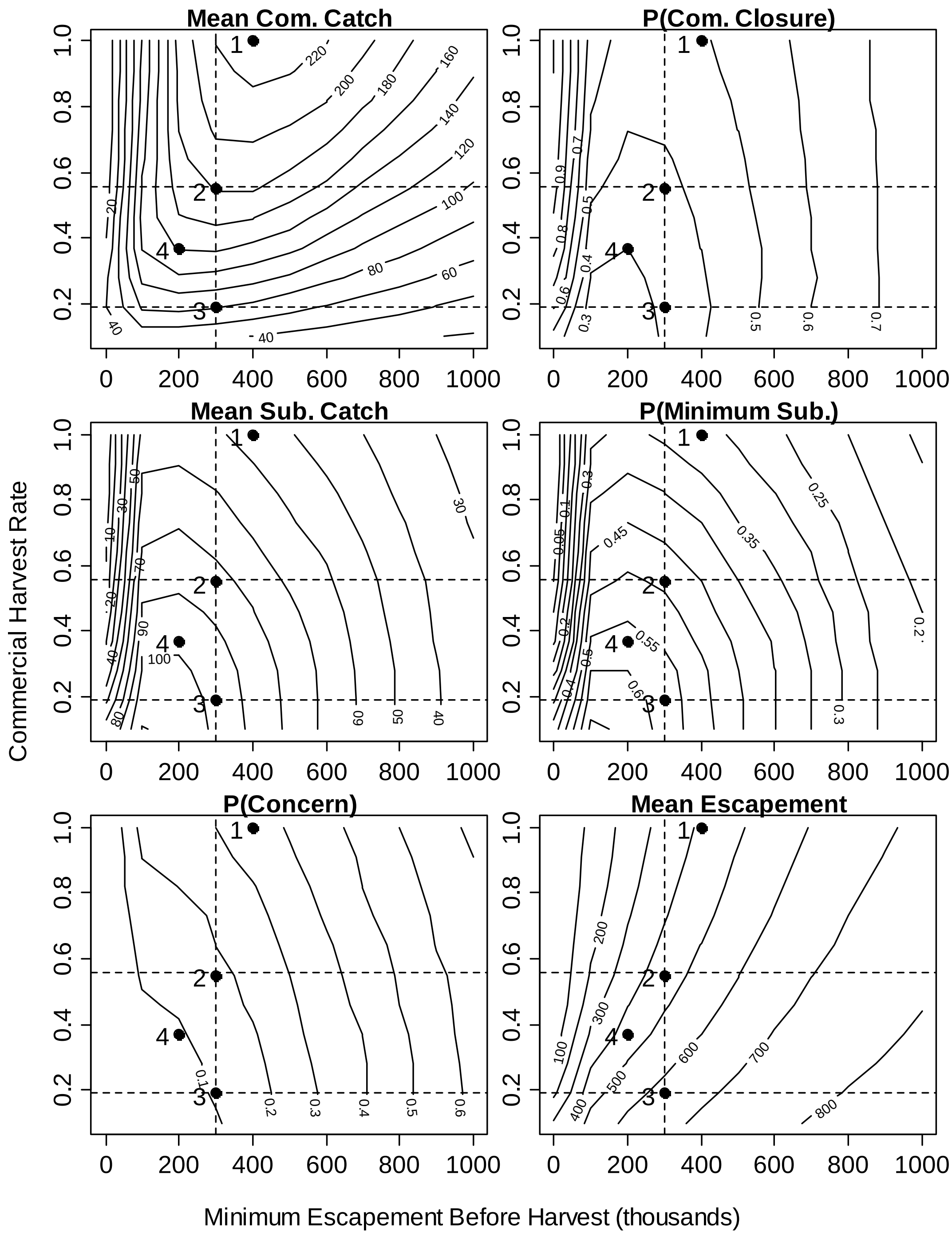

Figure B-5. Contour plots for the Yukon River fall chum salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under a 50% reduction in observation error on the in-season run estimate. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

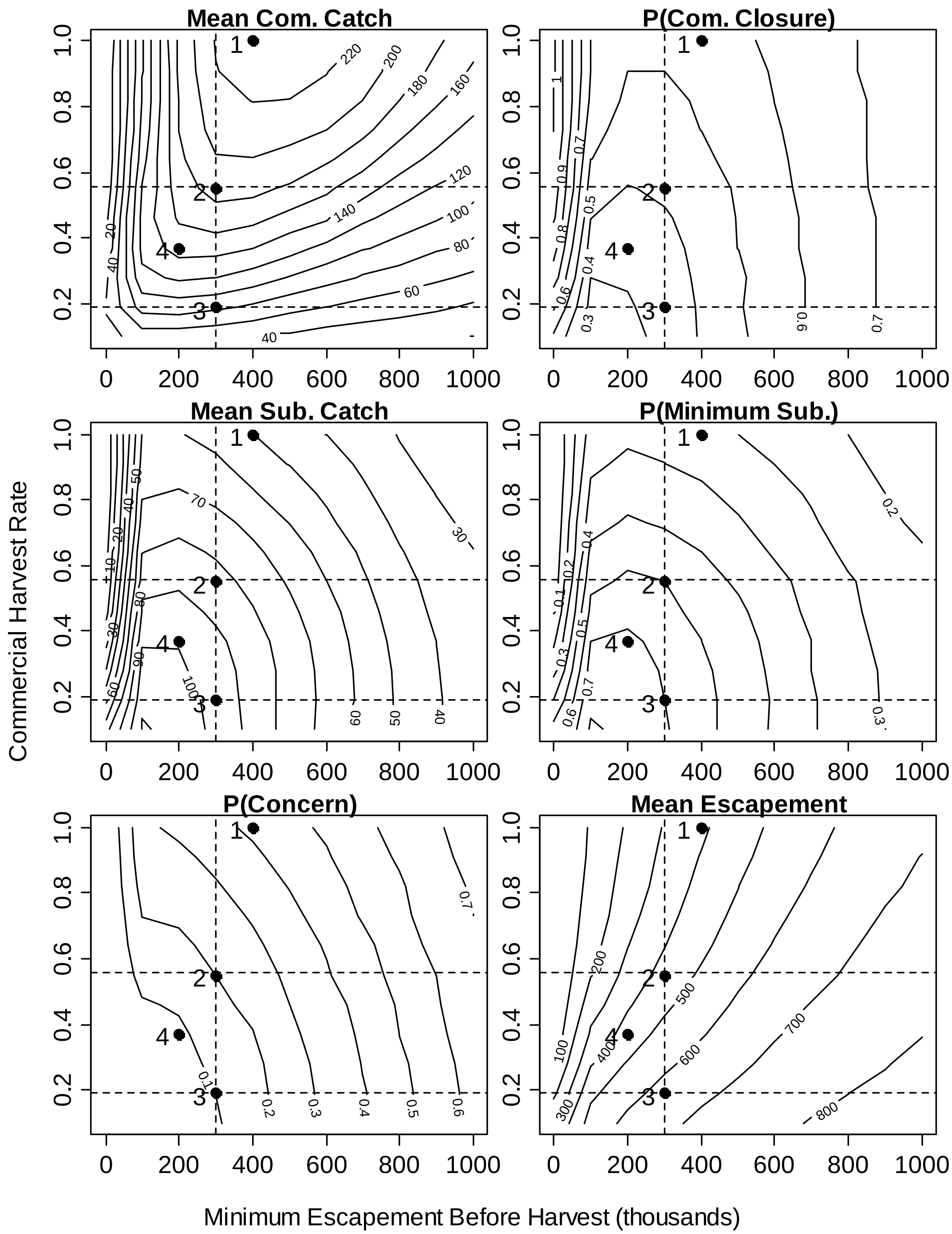

Figure B-6. Contour plots for the Yukon River fall chum salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under a 50% reduction in implementation error. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

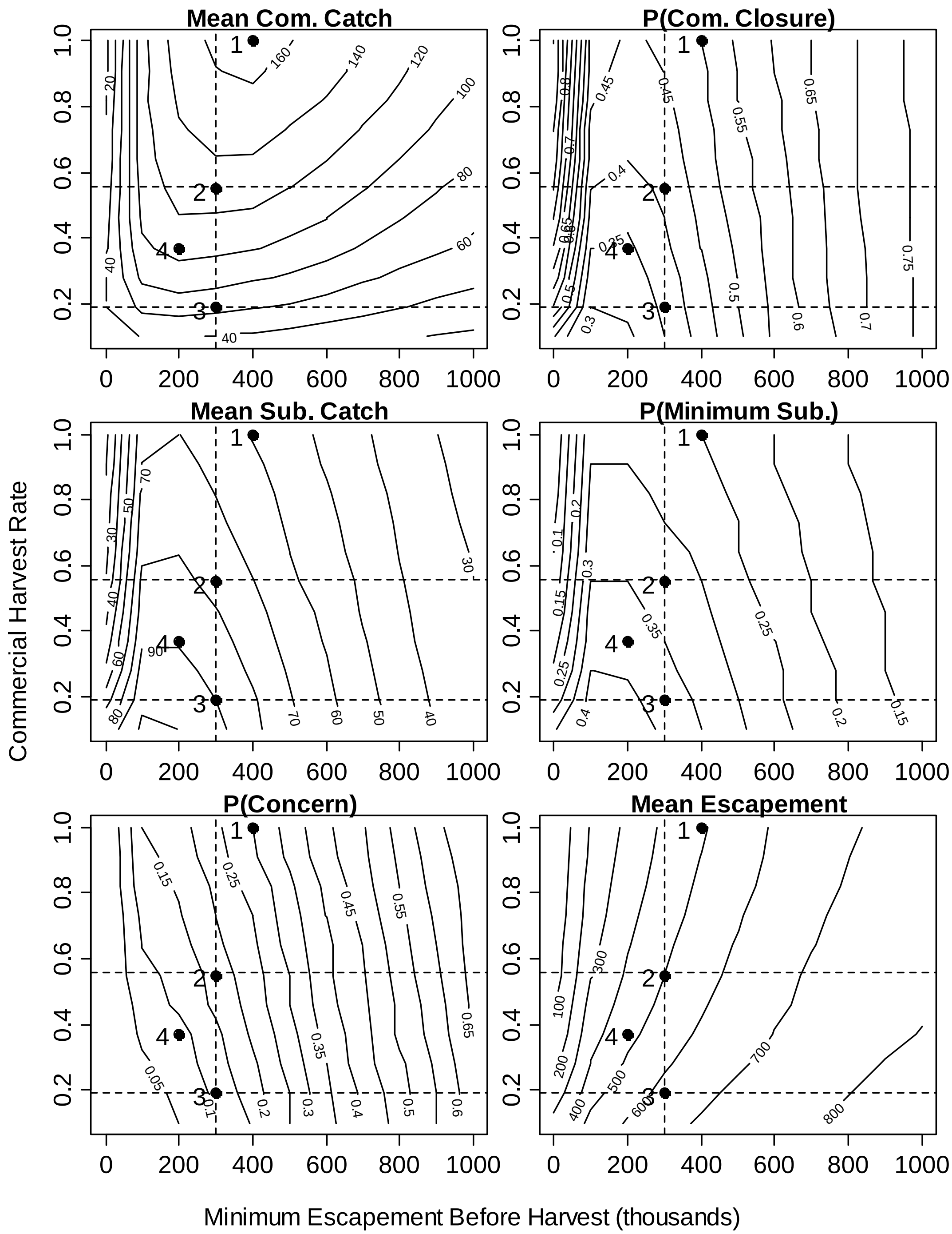

Figure B-7. Contour plots for the Yukon River fall chum salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under a 100% increase in implementation error and observation error. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

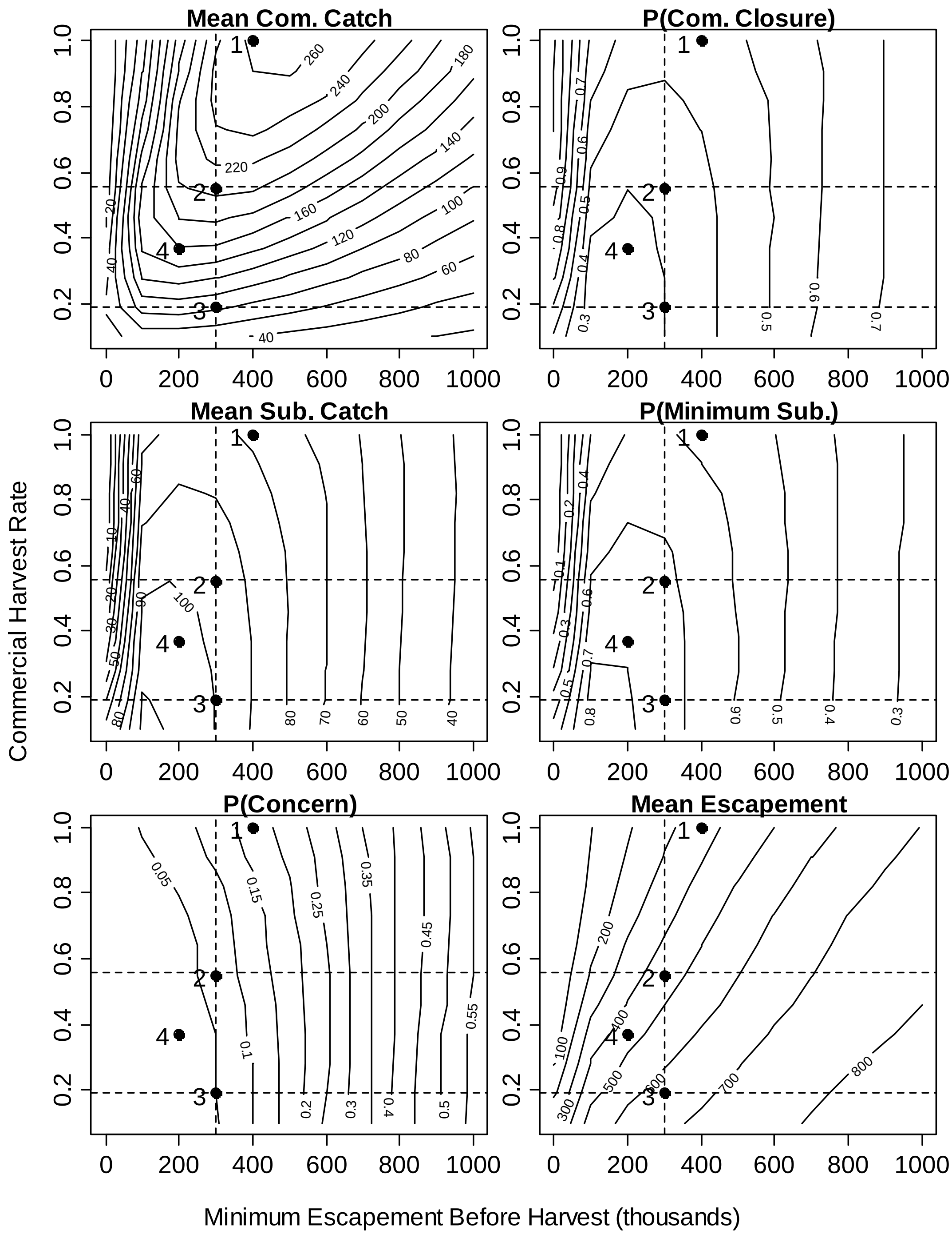

Figure B-8. Contour plots for the Yukon River fall chum salmon stock showing the median values of performance indicators across combinations of a minimum escapement target and commercial harvest rate under no implementation or observation error. Median values of performance indicators were computed from 500 simulations of the model. The four example policies are shown as solid circles to depict tradeoffs among specific policy choices.

Appendix C. Plots of commercial catch as a function of the surplus run.

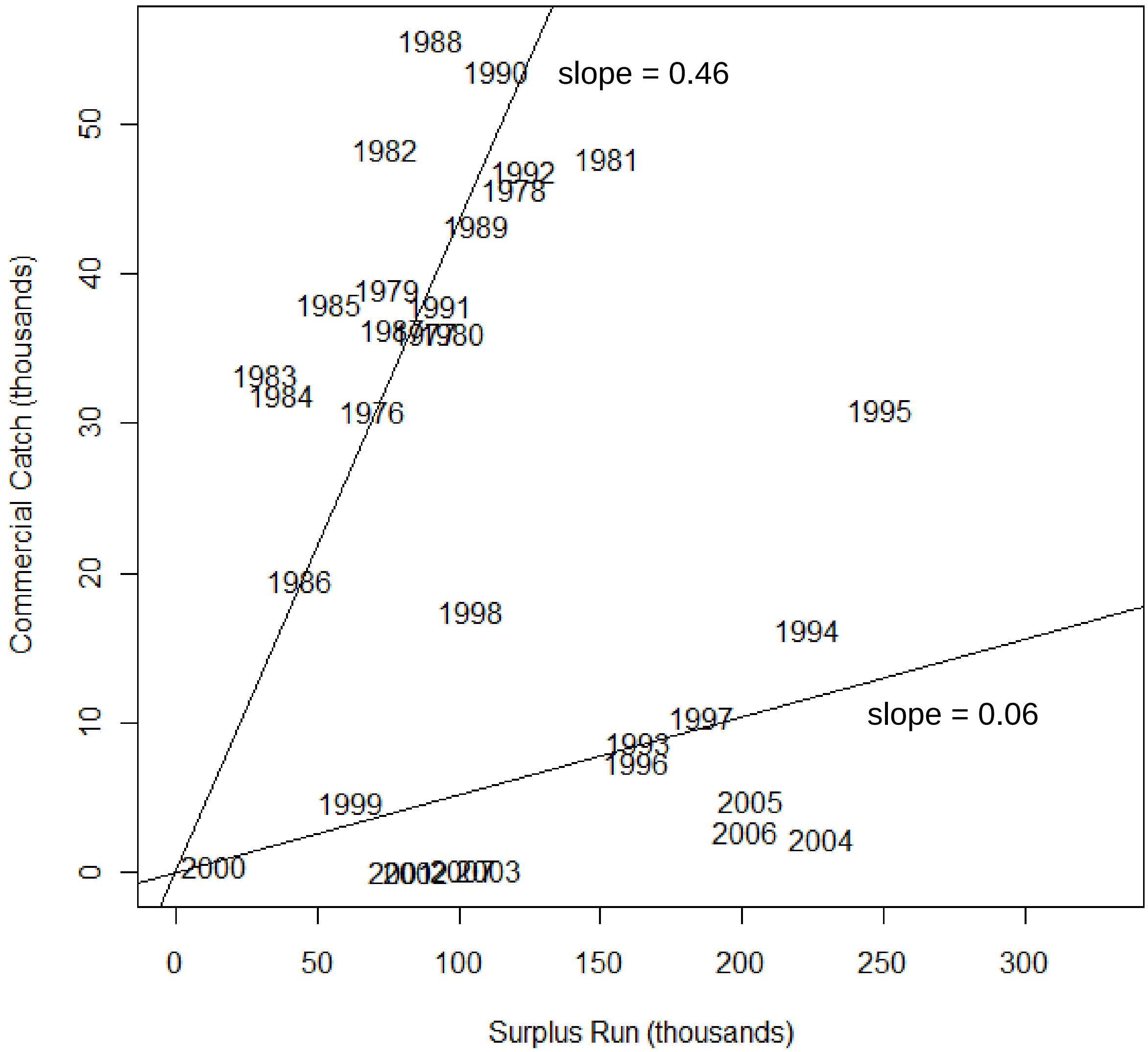

Figure C-1. Kuskokwim River Chinook salmon commercial catch (thousands of salmon) vs. the surplus run from 1976 to 2007. Solid lines show zero intercept linear models for two time periods: early and late. The early period was from 1976 to 1992 and was a period with good markets and processing capacity. The later period was after 1992 and was the period with poor markets and fishery closures due to small runs.

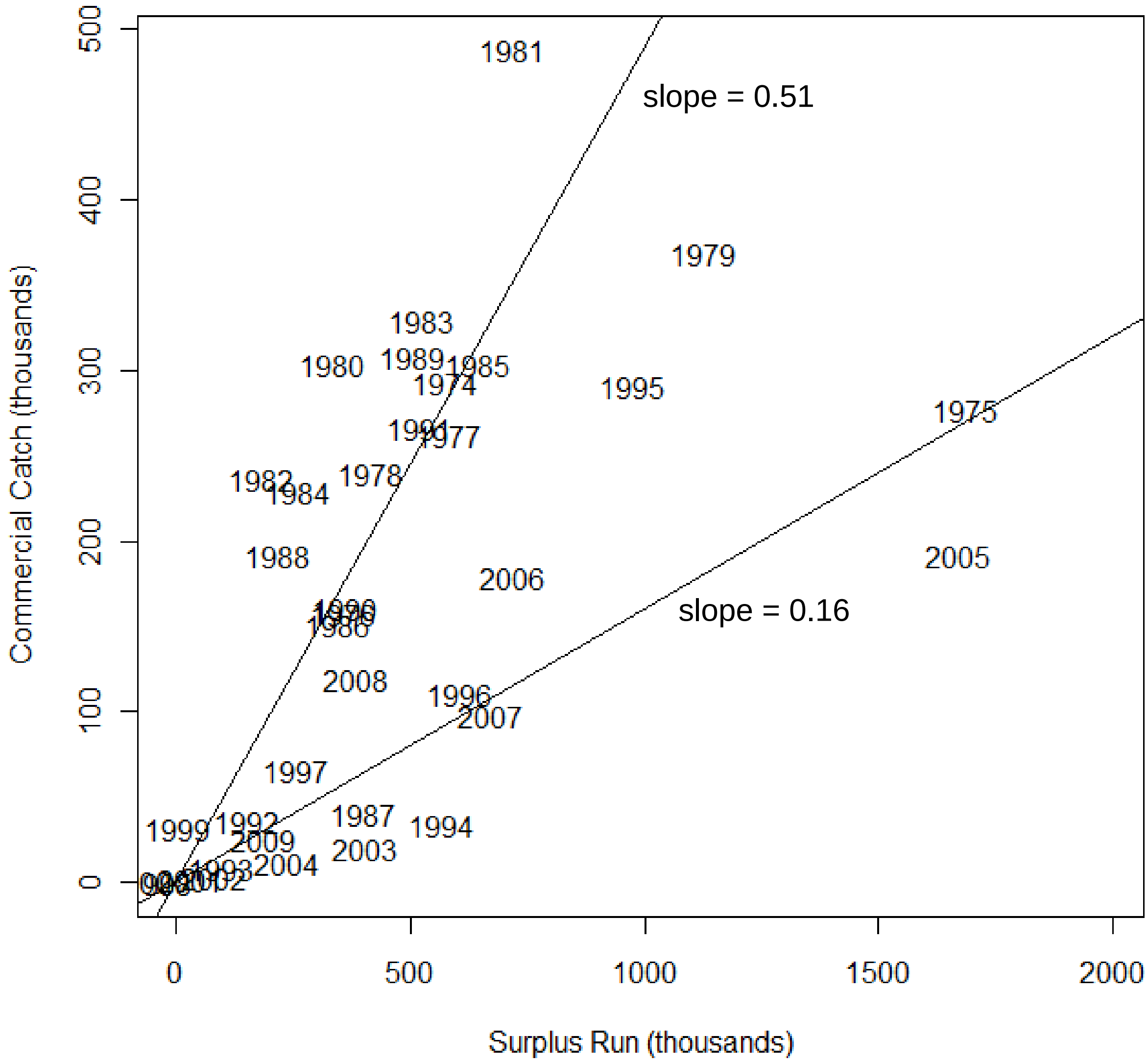

Figure C-2. Yukon River fall chum salmon commercial catch (thousands of salmon) vs. the surplus run from 1974 to 2009. Solid lines show zero intercept linear models for two time periods: early and late. The early period was from 1974 to 1992 and was a period with good markets and processing capacity. The later period was after 1992 and was the period with poor markets and fishery closures due to small runs.

Appendix D. We explored the effects of implementation error bias in the commercial fishery on performance measures. We simulated two levels of positive bias, meaning that on average more catch was taken than intended. We chose this approach because we sought to mimic situation in which managers consistently manage the commercial fishery for the lower bound of the escapement goal range rather than the midpoint of the range. As shown in Figure D-1, large positive implementation bias resulted in substantial downward escapement goal drift relative to other scenarios. The bias also pushed the stock to a less productive state, which reduced average commercial catches.

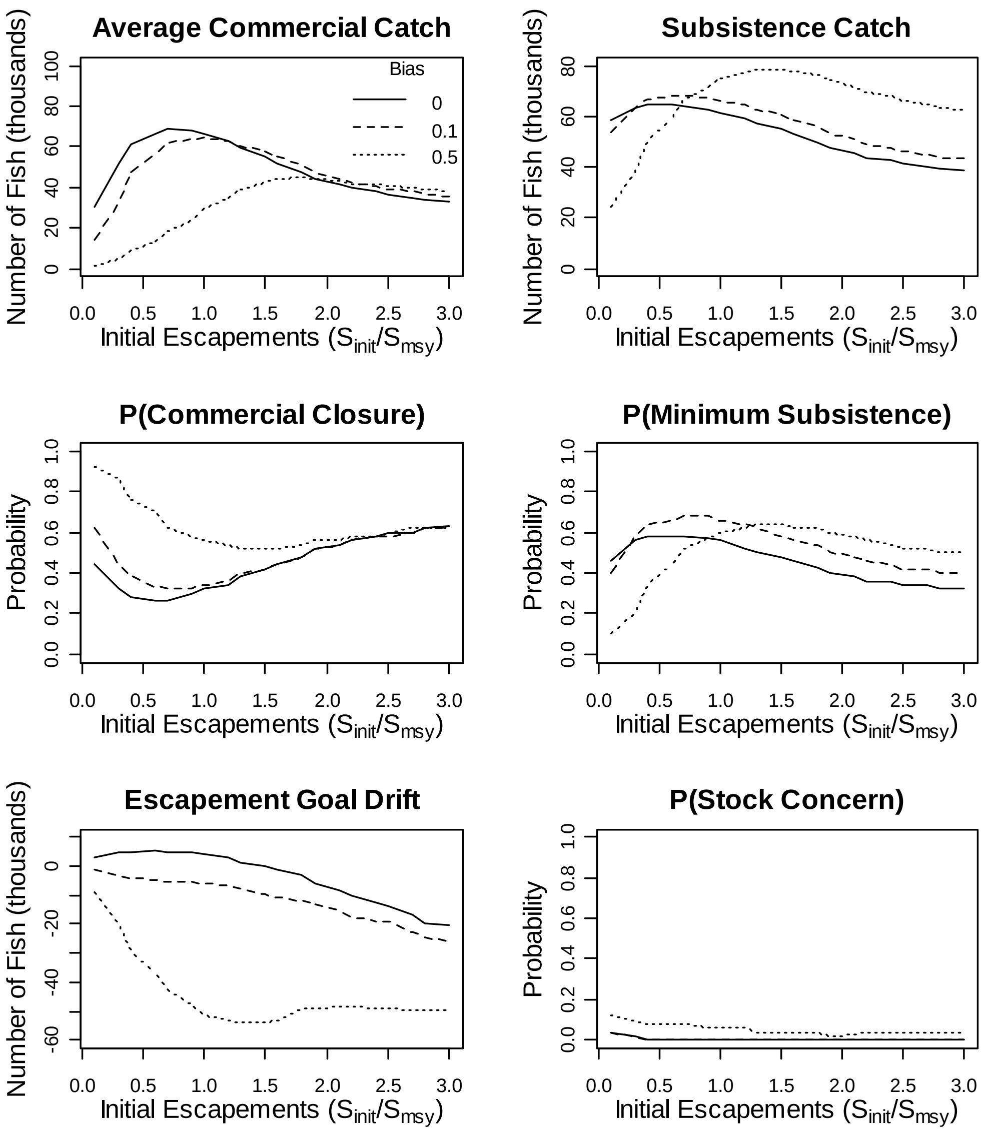

Figure D-1. Median posterior values of performance measures for Kuskokwim Chinook as a function of the initial escapements for three different levels of implementation bias: 0 (solid line; baseline value), 0.1 (dashed line), 0.5 (fine dashed line). The results are from the baseline uncertainty scenario.

References

Begg, G.A., Friedland, K.D., and Pearce, J.B. 1999. Stock identification and its role in stock assessment and fisheries management: an overview. Fish. Res. **43**: 1-8.

Bue, B.G., and Hasbrouck, J.J. 2001. Escapement goal review of salmon stocks of Upper Cook Inlet, Alaska Department of Fish and Game, Report to the Board of Fisheries, Anchorage.

Bue, F.J., Borba, B.M., Cannon, R., and Krueger, C.C. 2009. Yukon River Fall Chum Salmon Fisheries: Management, Harvest, and Stock Abundance. *In* Salmon Management in the Arctic-Yukon-Kuskokwim Region of Alaska: Past, Present, and Future. *Edited by* C.C. Krueger and C.E. Zimmerman, American Fisheries Society, Bethesda, Maryland.

Butterworth, D.S., Cochrane, K.L., and Oliveria, J.A.A.D. 1997. Management Procedures: A Better Way to Manage Fisheries? The South African Experience. *In* Global Trends: Fisheries Management. American Fisheries Society Symposium 20. *Edited by* E.K. Pikitch, D.D. Huppert and M.P. Sissenwine. pp. 83-90.

Clemen, R.T. 1991. Making Hard Decisions: An Introduction to Decision Analysis. PWS - Kent, Boston.

Collie, J.S., Peterman, R.M., and Zuehlke, B.M. 2009. A risk assessment framework for AYK salmon. Final Report to Arctic Yukon Kuskokwim Sustainable Salmon Fund.

Cooke, J.G. 1999. Improvement of fishery management advice through simulation testing of harvest algorithms. ICES J. Mar. Sci. **56**: 797-810.

Evans, M., Hastings, N., and Peacock., B. 1993. Statistical Distributions, 2nd edition. Wiley and Sons, New York.

Fleischman, S.J., and Borba, B.M. 2009. Escapement estimation, spawner-recruit analysis, and escapement goal recommendation for fall chum salmon in the Yukon River drainage.

Fried, S.M., and Hilborn, R. 1988. Inseason forecasting of Bristsl Bay, Alaska, sockeye salmon (*Oneorhynchus nerka*) abundance using Bayesian probability theory. Can. J. Fish. Aquat. Sci. **45**: 850-855.

Hilborn, R., and Walters, C.J. 1992. Quantitative fisheries stock assessment: choice dynamics and uncertainty. Kluwer Academic Publishers, Boston, Massachusetts.

Hilsinger, J.R., Volk, E., Sandone, G., and Cannon, R. 2009. Salmon Management in the Arctic-Yukon-Kuskokwim Region of Alaska: Past, Present, and Future. *In* Pacific Salmon: Ecology and Management of Western Alaska's Populations. *Edited by* C.C. Krueger and C.E. Zimmerman, American Fisheries Society, Bethesda, Maryland.

Hyun, S.-Y., Hilborn, R., Anderson, J.J., and Ernst, B. 2005. A statistical model for in-season forecasts of sockeye salmon (Oncorhynchus nerka) returns to the Bristol Bay districts of Alaska. Can. J. Fish. Aquat. Sci. **62**: 1665-1680.

Liermann, M.C., Sharma, R., and Parken, C.K. 2010. Using accessible watershed size to predict management parameters for Chinook salmon, Oncorhynchus tshawytscha, populations with little or no spawner-recruit data: a Bayesian hierarchical modelling approach. Fish. Manage. Ecol. **17**: 40-51.

Peterman, R.M. 2004. Possible solutions to some challenges facing fisheries scientists and managers. ICES J. Mar. Sci. **61**: 1331-1343.

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 Columbian and Alaskan sockeye salmon (Oncorhynchus nerka)stocks. Can. J. Fish. Aquat. Sci. **55**: 2503-2517.

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

Starr, P., and Hilborn, R. 1988. Reconstruction of harvest rates and stock contribution in gauntlet salmon fisheries: application ts British Columbia and Washington sockeye (Onchorhynchus nerka). Can. J. Fish. Aquat. Sci. **45**: 2216-2229.

Walters, C.J. 1986. Adaptive Management of Renewable Resources. MacMillan Pub. Co, New York, USA.

Walters, C.J., and Buckingham, S. 1975. A control system for intraseason salmon management. *In* Proceedings of a Workshop on Salmon Management. International Institute for Applied Systems Analysis, Laxenburg, Austria.

Walters, C.J., and Martell, S.J.D. 2004. Fisheries Ecology and Management. Princeton University Press, Princeton, New Jersey.

Wolfe, R.J., and Spaeder, J. 2009. People and Salmon of the Yukon and Kuskokwim Drainages and Norton Sound in Alaska: Fishery Harvests, Culture Change, and Local Knowledge Systems. *In* Pacific Salmon: Ecology and Management of Western Alaska's Populations. *Edited by* C.C. Krueger and C.E. Zimmerman, American Fisheries Society, Bethesda, Maryland.