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A fisheries risk-assessment framework to evaluate trade-offs among management options in the presence of time-varying productivity

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Abstract

Empirically based simulation models can help fisheries managers make difficult decisions involving trade-offs between harvests and maintaining spawner abundance, especially when data contain uncertainties. We developed such a general risk-assessment framework and applied it to chum salmon (*Oncorhynchus keta*) stocks in the Arctic-Yukon-Kuskokwim region of Alaska. These stocks experienced low abundance in the 1990s, which led to declarations of economic disaster and calls for changes in harvest strategies. Our stochastic model provides decision makers with quantitative information about trade-offs among commercial harvest, subsistence harvest, and spawner abundance. The model included outcome uncertainty (the difference between target and realized spawner abundances) in the subsistence and commercial catch modules. We also used closed-loop simulations to investigate the utility of time-varying management policies in which target spawner abundance changed in response to changes in the Ricker productivity parameter (a), as estimated with a Kalman filter. Time-varying policies resulted in higher escapements and catches and reduced risk across a range of harvest rates. The resulting generic risk-assessment framework can be used to evaluate harvest guidelines for most salmon stocks.

Keywords: salmon management, trade-offs, Kalman filter, implementation error, management strategy evaluation

Introduction

Managers of most North Pacific salmon (*Oncorhynchus* spp.) populations have two management objectives, one related to achieving desired harvests and one related to desired spawner abundances (escapements). The two objectives are directly linked by the salmon life history. Theoretically, long-term maximum sustainable yield (MSY) is achieved by annually obtaining the escapement target or goal, S_m, that produces that yield and harvesting all fish above that target (Hilborn and Walters 1992). However, three factors make salmon management difficult in practice. First, salmon data are imperfect due to observation or measurement errors in both spawner abundance and stock identification of mixed-stock catches. Such errors make it difficult to reliably estimate S_m for a given population (Walters and Ludwig 1981). A second management challenge is created by harvesting. Even if the true S_m were known for a population, it usually cannot be obtained exactly because of (1) incomplete management control over the harvesting process (i.e., implementation error [Eggers and Rogers 1987] or outcome uncertainty [Holt and Peterman 2006]), and (2) trade-off decisions in mixed-stock fisheries regarding allocation of returning salmon to catch among different interest groups and spawning escapement (Wood et al. 1998). A third challenge to achieving target escapements consistently is that temporal changes occur in environmental conditions, particularly in the ocean, which greatly affect salmon survival rates and adult abundance each year (Francis et al. 1998; Mueter et al. 2002).

Given these pervasive uncertainties in salmon stock assessment and management created by imperfect data, outcome uncertainty, and environmental variation, methods that explicitly take these uncertainties into account are clearly needed to meet both management objectives listed above. Considerable work has been done on developing such methods, not only for salmon, but also for pelagic and groundfish species (Walters and Martell 2004). These methods include, among others, active adaptive management and formal quantitative decision analysis (Walters 1986), as well as stochastic closed-loop simulations or management strategy evaluations (MSEs) that simulate the parameter-estimation step that feeds into updating management actions (Walters 1986; Butterworth and Punt 1999). These methods differ in their approach but all essentially provide a framework for conducting risk assessments of management options, i.e., estimating the uncertain values of indicators of management objectives by explicitly modelling several sources of variation in fisheries systems.

The main objective of our research project was to develop a risk-assessment framework in a decision-analysis context for evaluating alternative management policies for salmon populations. We used the method of closed-loop simulations, or MSE. We developed this framework and applied it to four chum salmon populations (*O. keta*) in the remote Arctic- Fig. 1 Yukon-Kuskokwim (AYK) region of Alaska (Fig. 1) where trade-offs among harvesting and escapement objectives are prominent. Large and rapid decreases in abundance of chum and other salmon species in that region in the late 1990s-early 2000s not only greatly reduced economic value of commercial catches, but also caused severe shortages in subsistence catches for people living in this remote area, which forced difficult management trade-off decisions between allowing more spawners and achieving desired catches (AYK SSI 2006).

The low returns of chum salmon in the AYK region in the late 1990s occurred despite relatively low harvest rates, which suggests a decrease in productivity in that period (National Research Council 2004). Although the exact cause of this decrease in productivity remains unclear, it is hypothesized that chum salmon productivity is determined by environmental conditions during the early period of ocean residence (Kruse 1998, AYK SSI 2006). Regardless of the cause, this history prompted us to conduct our risk assessments across a wide range of scenarios of future temporal changes in productivity; escapement goals and harvests may need to respond in a timely manner to reflect such changes in the future.

Another key objective of our research was to quantitatively estimate trade-offs that would be incurred by any given choice of management policy. We define the latter term to mean an escapement goal (i.e., target) combined with a harvest rate that is applied to the number of returning salmon in excess of that goal. Due to logistical constraints, the realized harvest rate is rarely 100% in practice, as it should ideally be to achieve MSY (Hilborn and Walters 1992), so in our analyses, we allowed it to be set as a policy option. Fisheries managers everywhere are well aware of the unavoidable qualitative trade-off between increasing catch and maintaining numbers of spawners, as well as trade-offs implied by allocating catch among user groups. However, quantitative values of these trade-offs are difficult to estimate reliably due to the three sources of uncertainty described above: observation error in data, uncertainties about outcomes of implementing management regulations, and environmental variation. Our analysis includes these three sources of uncertainty so as to better estimate escapement and indicators of catches. Our method will help managers to consider more thoroughly the trade-offs inherent in their policy choices (e.g., how much increase would occur in one indicator for a given decrease in another).

To address our research objectives, we developed an empirically based stochastic simulation model (see Methods) for each of the four chum salmon populations. We used this model to evaluate the potential effectiveness of various harvesting/escapement goal policies at meeting management objectives. The model included not only salmon population dynamics and environmental influences on them, but also uncertainty in implementation of harvesting decisions, which caused realized escapements to differ stochastically from targets. We refer to those stochastic differences as "outcome uncertainty" (Holt and Peterman 2006), which is a general term that encompasses not only "implementation error/implementation uncertainty" (i.e., non-compliance with regulations by harvesters and/or imperfect knowledge of stock abundance), but also includes physical and biological dynamics that change vulnerability of fish to fishing gear. We also compared two types of management policies. In one version of the model (the closed-loop simulation or management strategy evaluation with a time-varying harvest/escapement goal policy), stock assessments were based on simulated catch and escapement data that assumed observation error existed, and the simulated management decision-making was based on the most recent simulated year's parameter estimates derived from the simulated stock assessment. In contrast, in the time-invariant version of the model, the escapement goal was constant over time (the most common situation in Pacific salmon fisheries). We modelled the dynamics of both commercial and subsistence fisheries and assessed risks (such as too few spawners, low upriver subsistence catches, and closure of commercial fisheries) associated with different management policies. In addition to informing salmon managers, this modelling framework is applicable to the management of other fish stocks that are subject to decadal-scale variations in productivity.

Methods

The AYK region is very large (Fig. 1) and the intensity of data collection is much lower than for other regions of Alaska and British Columbia. Four chum salmon stocks in the AYK region were selected for this analysis based on the duration of existing time series and availability of age-composition data to construct brood tables (spawner abundance by year and abundance of their offspring that survive to become adult recruits). The four stocks are the Yukon River fall chum, Anvik River, Andreafsky River, and the combined Kwiniuk and Tubutulik Rivers in the Norton Sound District. The Anvik and Andreafsky are tributaries of the Yukon River with summer runs of chum salmon (Fig. 1). Data on the number of spawners come from weirs and aerial surveys expanded to total escapement. Subsistence and commercial catches are attributed to stream of origin. Age-composition samples from weirs and test fisheries are applied to the escapement and catch data to determine the year of spawning (brood year). Brood tables for these stocks were compiled from catch, escapement, and age-composition data collected by the Alaska Department of Fish and Game (ADF&G). Brood tables for the four stocks contained the same data as used by Hilborn et al. (2007), except they were updated by ADF&G biologists (see Acknowledgments) to include more recent brood years, resulting in data series on spawners and resulting recruits ranging from 29 to 36 years in duration over brood years 1965-2002.

Spawner-recruit dynamics

There is considerable empirical evidence that productivity of salmon populations is influenced by variation in environmental (especially oceanographic) conditions at both high-frequency, interannual scales (Mueter et al. 2002) and at low-frequency, decadal scales (Beamish 1995; Mantua et al. 1997; Francis et al. 1998). Therefore, to generate spawner-to-recruit dynamics in our simulations, we used a standard Ricker model that was modified to have a time-varying a parameter to reflect that decadal-scale environmental variability in addition to the usual high-frequency variability:

(1) $$\log\left(\frac{R_t}{S_t}\right) = a_t - b\,S_t + v_t$$

where R_t is the total number of recruits resulting from S_t, spawners in year t, the time-varying parameter, a_t, represents density-independent productivity, and the b parameter reflects density-dependent effects (assumed constant for each stock). We refer to $v_t \sim N(0, \sigma_v^2)$ as "observation error", although technically speaking v_t is composed of two high-frequency sources of variation, observation error and high-frequency natural variability that is not autocorrelated over time. Given the way the data are collected, the observation error on recruits is expected to be higher than for spawners, because the latter are measured more directly. Variation in the a_t parameter was modeled as a random walk:

(2) $$a_t = a_{t-1} + w_t$$

with $w_t \sim N(0, \sigma_w^2)$.

To estimate the parameters of this time-varying component of the model, we applied a linear Kalman filter estimation procedure, with (1) as the observation equation and (2) as the system equation, to the historical stock-recruitment data for the four AYK chum salmon stocks. This procedure estimated past changes in the a_t parameter. Details of the Kalman filter method are provided in the Appendix of Peterman et al. (2000) and the computer code is available from the supplementary on-line material for Dorner et al. (2008). We used a Kalman filter estimation procedure because of its top-ranked performance in Monte Carlo simulation trials (Peterman et al. 2000) under a wide variety of scenarios for changes in underlying salmon productivity. In those simulations, this method performed better than the standard linear regression fitting to the Ricker model, which is the same as Eq. 1 except that a is not time-dependent. Peterman et al. (2003) also found that a random-walk system equation for Eq. 2 in the Kalman filter procedure produced estimates that tracked decadal changes in productivity better than a first-order autocorrelation function for Eq. 2. To estimate the other model parameters $\{b, \sigma_v^2$, and $\sigma_w^2\}$, our Kalman filter estimation procedure used the historical stock-recruitment data and maximized the concentrated likelihood by calling the S-plus function "ms" (Insightful Corp., 2001). The resulting series of a_t estimates was then recursively smoothed with a Kalman-filter fixed-interval smoother, as described in Peterman et al. (2003). Definitions of parameters of the simulation model are summarized in Table 1.

Table 1

To drive the variation in a_t in the forward simulations, we used a bounded random walk to simulate random series of a_t values that had the same statistical properties as the smoothed a_t values that were estimated from the historical data by the Kalman filter. To do so, we added a logistic penalty function to Eq. 2 in the forward simulations to constrain the random walk within the range of empirically estimated a_t values (Nicolau 2002). The penalty term p_t is:

(3) $$p_t = \frac{I\,m}{1 - e^{-\alpha(-I(a_t - \bar{a}) - \delta)}}$$

where I is an indicator variable such that $I = \{-1 \; if \;\; a_t > \bar{a} \; or \; 1 \; if \;\; a_t < \bar{a}\}$. The parameters m = 0.5, α = 10, and δ = 0.75, which define the shape of the logistic function, were optimized to match the variance, amplitude, and first-order autocorrelation of the observed a_t values.

Harvesting

To complete the model of the entire chum-salmon life cycle, we added a harvest dynamics function. We did not attempt to model the in-season dynamics of the chum salmon fishery because we are interested in the longer-term population dynamics and as well, there is little information available from the region to parameterize such a model. Instead, we used empirically based harvest rules that give preference to meeting escapement targets, subsistence fisheries, and commercial fisheries, in that order, which is what ADF&G uses. The harvest rule is specified by an escapement target (E, not to be confused with the actual realized spawners, S_t) and a harvest rate on the remaining run once the escapement target is met. In principle, these two quantities can be set independently; the escapement target is set to meet conservation objectives, whereas the harvest rate depends on harvesting capacity, duration of openings, etc.

Realized escapements and harvest rates will differ from their targets because of outcome uncertainty, as defined above. However, year-by-year historical target harvest rates and escapement goals are not known for our four chum salmon stocks. Therefore, we could not estimate outcome uncertainty directly from the historically realized and target harvest rates, as has been done for some sockeye salmon stocks (Holt and Peterman 2006). Instead, following Eggers (1993), we used the observed data on run size (abundance of returning adult recruits), subsistence catch, and commercial catch to fit empirical harvest dynamics models that represented the harvesting process as realistically as possible. For each stock, a linear regression was fit between total catch and run size and between subsistence catch and run size. The regression error was modeled as a constant coefficient of variation (CV, i.e., standard deviation divided by the mean) of catch in relation to run size. This regression model was implemented with the generalized linear model function, glm, in the R language and the parameters were estimated by the method of quasi-likelihood (R Development Core Team 2008). The constant-CV model is specified with function arguments family = quasi, link = identity, and variance = mean squared.

Existing salmon harvest policies in Alaska are time invariant in that they are not routinely adjusted in response to perceived changes in salmon productivity. During the early years of salmon management, fisheries were opened and closed to regulate percentage harvest rates (Hilsinger et al. 2009). Starting in 1992, the Alaska Department of Fish and Game switched from largely passive harvest-rate management to more actively managing the salmon fisheries to meet fixed escapement goals (Hilsinger et al. 2009). To reflect this change that occurred in managing the AYK salmon fisheries, the total catch data were divided into two periods: before 1992 and 1992 and later. We then tested for different slopes and intercepts in the total-catch regressions in the two periods.

The fitted regression line can be interpreted as an empirical harvest policy in which the intercept on the *x* axis represents an escapement target (though not necessarily the target specified historically by managers) and the slope is the realized harvest rate on the remaining run once the escapement target is met. The residual variation around the regression lines is an empirical estimate of outcome uncertainty at the harvesting stage. The slopes and intercepts from the linear regressions were used to simulate the subsistence fisheries, but not the commercial fisheries. Instead, the total catch (commercial plus subsistence) was based on user-input escapement targets and harvest rates, as described below. The regressions were performed to characterize the general form of the harvest function and to estimate the likely levels of outcome uncertainty.

In the simulation model, the harvest rule is specified by a user-defined escapement target, E, a harvest rate for the subsistence fishery (h_s), a harvest rate (recall that this is for the number of fish surplus to the escapement target) for the combined subsistence plus commercial fisheries (h_c) and the corresponding coefficient of variation of the outcome uncertainty (CV_u^2). If T_t, the total chum salmon return in year t, is below the escapement target ($T_t < E$), there is only subsistence catch, with a harvest rate drawn from a uniform distribution, ranging from 0 to the maximum observed subsistence harvest rate for that stock. Following Eggers (1993), we used the uniform distribution such that subsistence catch is reduced, but not eliminated, when $T_t < E$ (Fig. S1). Above the escapement target, the subsistence catch is calculated from the regression line (parameters in Table 2) with normally distributed outcome uncertainty. Total catch (commercial plus subsistence) is calculated from the harvest rate, as specified by the user (h_c), applied to the fish that are surplus to the target, E:

Table 2

$$C_t = h_c\left(T_t - E\right)\cdot(1+u_t) \tag{4}$$

where C_t is catch and u_t~N(0, σ_u^2). The variance of the outcome uncertainty, σ_u^2, is related to the coefficients of variation estimated in the regression models, by $\sigma_u = CV_u$. The units of E, C_t, and T_t are thousands of fish. Finally, the commercial catch is the total catch minus subsistence catch, except there is no commercial fishery if this difference is negative. This sequence recognizes the priority of subsistence over commercial catch. The realized escapement is simply $S_t = T_t - C_t$. Because of outcome uncertainty, and in years of low adult returns, the escapement target is not met exactly each year. In model simulations, we mainly investigated the effects of using different escapement targets and total harvest rate occurring on the number of fish above those targets. The subsistence harvest rate and variance in outcome uncertainty were held constant, except for sensitivity analysis of harvest rules (see below). The complete harvest function and distributions of simulated catches are shown in the Supplementary Materials.

The stochastic life-cycle model is fully specified by combining the spawner-recruit function (Eq. 1 and 2) and harvest-dynamics function (Eq. 4) with random variability included in all equations (Fig. 2). The five most recent observed escapement values were used to initialize the model in order to estimate recruitment starting in year 1. To account for the long-term (decadal) variation in the a_t values, each simulation was run for 100 years. Preliminary simulations, conducted with between 100 and 1000 Monte Carlo replicates, indicated that the values of the performance measures described below stabilized at 500 replicates. Therefore, analysis of each combination of harvest parameters was repeated with 500 replicates. The population parameters used in the simulation model are listed in Tables 1 and 2.

Fig. 2

Management policies

We simulated two types of management policies, time-invariant and time-varying, each using the same core population dynamics and harvesting model (Fig. 2). For time-invariant policies, the user-specified harvest parameters (escapement target, harvest rate on the population exceeding that target) remained unchanged for the duration of the 100-year simulation. In contrast, for time-varying policies, the harvest rate on the population exceeding the escapement target remained fixed across years, but the target was updated each year in relation to the most recent estimate of the a_t value. Owing to the chum salmon life cycle, there is a five-year lag before a_t can be estimated from the returns at ages four and five. For these time-varying policies, each simulated year produced a new spawner-recruit data pair and the Kalman filter updated the estimate of the true a_t parameter. The following transcendental equation from Quinn and Deriso (1999) was then used to solve for the escapement that would generate the maximum sustainable catch (S_m),

(5) $$(1 - bS_m)e^{\hat{a}_t - bS_m} = 1.$$

Where $\hat{a}_t$ is the Kalman filter estimate of the true a_t. This new escapement target, S_m, was used in the time-varying management policy the following year. In this case, S_m replaced the fixed escapement target, E, in Eq. 4. This time-varying policy was compared against a time-invariant policy that used the value of S_m calculated from the mean a_t values (Table 2).

Performance measures were defined for escapement, subsistence, and commercial catch. For each of these categories, we calculated the average across 500 Monte Carlo trials of the mean and coefficient of variation over the 100 simulated years, as well as a measure of risk. For the spawning stock, the index of risk was the percentage of years that the run size was below the escapement target set by the user. Because we lacked a predefined measure of risk for the subsistence fishery, we used the percentage of simulated years in which the subsistence catch was in the lower quartile of historically observed subsistence catches for that stock. In years with low returns, the subsistence fishery is not closed, but it is assumed that low catches are undesirable. Finally, because commercial fishery closures can occur when run size is too low, the risk measure for the commercial fishery was the percentage of years with no commercial fishery.

Results

Estimated historical productivity

The Ricker a_t values estimated from the historical data by the Kalman filter indicate large-amplitude and substantial decadal-scale shifts in productivity (Fig. 3). There is a general pattern of high productivity in the 1970s, after which a_t dropped to its lowest in the mid-1990s. For brood years 1995-1997, the Andreafsky River a_t values approach zero, which is the replacement value for the spawning stock with no fishing (i.e., for $R/S = 1$, $\log_e(R/S) = 0$). Different productivity patterns were observed among stocks (Fig. 3). The a_t values for the Yukon River and its tributaries increased in the late 1990s with the highest value in that series estimated in brood year 2000 for Yukon fall chum. In contrast, there was no indication of increasing productivity for the Kwiniuk and Tubutulik Rivers as of brood year 2000.

Fig. 3

The Kalman filter decomposes each observed $\log_e(R/S)$ into three components: productivity (a_t), a density-dependent term ($-bS_t$), and an uncorrelated residual component (v_t), that reflects both observation error and short-term variability in productivity (Fig. 4). These bar plots illustrate that the reduction in productivity (low a_t) occurred during a period of relatively high stock abundance (large $-bS_t$,), and that low productivity was compounded by negative residuals (v_t), especially for the Yukon River and its tributaries. In contrast, the decline in productivities for the Kwiniuk and Tubutulik Rivers was more gradual with alternating positive and negative residuals (Fig. 4). The Yukon and Andreafsky Rivers had the largest signal-to-noise ratios (σ^2_w / σ^2_v) and the Kwiniuk and Tubutulik Rivers the lowest (Table 2).

Fig. 4

In a separate analyses, significant relationships were identified between estimated salmon productivity and a number of environmental variables (Supplementary Materials). Productivity was positively related to the Pacific Decadal Oscillation at a lag of three years and May sea surface temperature in the Bering Sea at lag 2. These lags correspond with the years of ocean residence of chum salmon. The a_t values were negatively related to Nome precipitation at lag of 1, which corresponds to the age of freshwater residence and migration to salt water. These relationships were not used in the life-cycle model but are reported here to indicate the environmental basis of decadal variability in these chum salmon stocks.

Harvest functions and outcome uncertainty

The empirical relationships between catch and run size were well approximated with linear regressions (Fig. 5). According to *F* tests on all four stocks, the best regression model for total catch (commercial plus subsistence) had a common intercept and different slopes for the two periods, before 1992 and 1992 and later. The significantly lower slopes for the latter period reflect the introduction of escapement targets and harvesting that was constrained by market forces. These empirically estimated relationships between total catch and run size can be interpreted as hybrid harvest policies: the *x* intercept can be considered an escapement target and the regression slope as the harvest rate on the run exceeding that target. The regression lines cross the *x* axis near zero (Fig. 5), well below the ADF&G escapement-goal range (Table 2) and the slopes are substantially less than one, which indicates that the empirical escapement policies differ from the theoretically optimal policy of harvesting all fish above the escapement target (Hilborn and Walters 1992). This result is not surprising given the logistical difficulty in any fishery of achieving a harvest rate that high and given that harvesting capacity is driven in part by market demand. The variance in residuals around these total catch-versus-run size functions showed substantial outcome uncertainty, or deviation between target and realized outcomes (Fig. 5). The Yukon River had the smallest scatter around the regression line for total catch ($CV_{u,T}$ in

Fig. 5

Table 2), whereas the Kwiniuk and Tubutulik Rivers had the highest. Subsistence catch alone also increased with increasing run size and was highest, as a fraction of the total catch, for the fall Yukon chum stock (Fig. 5). For subsistence fisheries, the *y*-intercepts of the regression lines were positive, which is consistent with policies to allow some level of subsistence fishing regardless of run size.

Constant management policies: trade-offs among multiple indicators

The nine performance measures from simulated time-invariant management policies illustrate trade-offs among measures of escapement, subsistence, and commercial catch (Fig. 6). Here we illustrate performance measures for Yukon fall chum salmon; we produced similar figures for the other three stocks (see Supplementary Materials). Each of the nine isopleth diagrams or contour plots in Figure 6 was generated by drawing isolines through the set of 121 values of a given indicator that resulted from running the model sequentially across 121 combinations of 11 different escapement targets and 11 different harvest rates (the latter applied to the number of salmon above those respective escapement targets). The latter harvest rates are those that managers aim to achieve through their choices of regulations, but due to outcome uncertainty, results will usually differ from the intended harvest rates. For each of those 121 management policies, 500 Monte Carlo trials were run and average values of indicators were used for plotting. A given (*x*,*y*) point on a graph corresponds to a particular management policy option, and that point is the same on all contour plots for the nine indicators. Thus, the quantitative trade-offs among indicators can be explored for any set of actions. For reference across the different performance measures, vertical gray lines indicate ADF&G's escapement

Fig. 6

goal range, and the horizontal gray lines are the slopes of the regression of total catch on run size ($slope.before_T$ and $slope.after_T$ in Table 2).

The top row of three isopleth diagrams (Fig. 6) shows indicators related to escapement. Realized mean escapement increases with increasing escapement target; the isopleths are diagonal because it is more difficult to meet escapement targets at high harvest rates, especially with outcome uncertainty. The coefficient of variation over time of escapement is fairly uniform across most combinations of escapement target and harvest rate, except that the CV increases rapidly when high harvest rates are combined with low escapement targets. The chance of not meeting the escapement target increases with the target—the higher the target, the more difficult it is to obtain. At higher harvest rates, the isopleths are again sloped because the higher harvest rates make it more difficult to attain the escapement target.

Subsistence catches are fairly similar over many combinations of escapement targets and harvest (second row of Fig. 6) rates because of the preference given to subsistence catches in the model's harvest rules; i.e., subsistence catch is reduced but not eliminated in years when the escapement target is not met (Fig. 5). Thus, the chance of the subsistence fishery falling below its threshold is high only at very low abundance—namely for low escapement targets and high harvest rates.

Indicators related to commercial catch (third row of Fig. 6) show that, as expected, mean commercial catch is maximized between ADF&G's escapement-goal range (vertical gray lines) with a harvest rate = 1 on fish exceeding the escapement goal. However, this maximum yield is associated with 33-49% of years with no commercial fishery ("bang-bang" control policy of Clark 1985). The chance of having no commercial fishery is minimized at low escapement targets and intermediate harvest rates. In contrast, the chance of no commercial fishery is maximized at low harvest rates and increases with the escapement target because of the preference for subsistence fisheries; in these cases, surplus salmon are not available for a commercial fishery.

Trade-offs are apparent when comparing across classes of performance measures (Fig. 6). The escapement and subsistence performance measures are largely compatible because the subsistence fishery has a low harvest rate. However, there are other obvious trade-offs. For instance, mean commercial catch is maximized at high harvest rates that produce an undesirable 65-71% of years in which escapement is below the escapement target and subsistence catch is reduced.

The range of harvest rates indicated by the two horizontal lines in Fig. 6 (0.23-0.53) appear fairly robust to the range of simulated variability in chum salmon productivity. Within those harvest rates and ADF&G's escapement-goal range of 300 to 600 thousand spawners, escapement goals are met in 60-90% of years, the subsistence fishery is unconstrained, and commercial fisheries would be allowed in 14-71% of years. Moving from the upper to lower bound of the escapement target range would sacrifice some escapement and very little subsistence catch, but would also increase the commercial catch, while reducing the year-to-year variability in that catch and drastically reducing the percentage of years with no commercial fishery (Fig. 6). These are just examples to illustrate interpretations of the contour plots (Fig. 6), which are intended to allow decision makers to visualize and quantify trade-offs in performance measures while exploring policy options (combinations of escapement target and harvest rate on the run exceeding that target).

The outcome uncertainty used in the simulations ($CV_{u,T}$ and $CV_{u,s}$) is the same order of magnitude as the correlated (σ_w) and uncorrelated (σ_v) recruitment variability (Table 2). To investigate the influence of outcome uncertainty on our results, we repeated the simulations with outcome uncertainty removed ($CV_{u,T}$ and $CV_{u,s}$ =0). For a given management policy, removing outcome uncertainty increased the mean levels of escapement, subsistence, and commercial catch (compare Fig. 7 with Fig. 6). In this case, the contour lines for the percent of years below the escapement target are almost vertical because, even at high harvest rates, there is reduced risk of not meeting the escapement target. In contrast, at low harvest rates the commercial fishery would be closed in most years to allow a subsistence fishery to occur.

Fig. 7

Time-varying management policies

In general, the time-varying management policy was able to improve on the best time-invariant management policy over a range of harvest rates (Fig. 8). The primary comparison is between the time-varying baseline policy (bold solid lines) and the time-invariant policy that had an escapement goal, S_m, that corresponded with the mean Ricker a_t parameter (thin solid lines). Both of these lines include outcome uncertainty and therefore represent the most realistic situation. The time-varying harvest policy resulted in higher mean escapement and subsistence catch across all levels of harvest rate, as well as higher commercial catch at high harvest rates. The CV of escapement was higher at high harvest rates, reflecting the fact that the escapement target was adjusted each year. With the time-varying harvest policy, the chance of not meeting the escapement target was reduced at low harvest rates and increased slightly at high harvest rates. The chance of low subsistence catches was reduced at all harvest rates and the chance of closing the commercial fishery was reduced at moderate and high harvest rates. In summary, with the levels of variability in the a values simulated with Equations 2 and 3 and with the

Fig. 8

parameter values in Table 2, the time-varying management policies were able to improve on the time-invariant policies.

To investigate the reasons for the relative performance of the time-varying and time-invariant policies, we did sensitivity analyses by selectively removing the main sources of error. Removing the combination of both observation error and high-frequency recruitment variability alone (i.e., by setting $v_t = 0$) had relatively little effect on most performance measures (not shown). In contrast, removing outcome uncertainty (i.e., by setting $CV_{u,T}$ and $CV_{u,s} = 0$) had the largest effect on changing the performance measures (dashed lines Fig. 8). In these cases, increases were observed in means for all three measures, but only at high harvest rates for catch. With no outcome uncertainty, the management policy would operate as designed by more frequently meeting escapement targets and keeping subsistence catches relatively high, while transferring recruitment variability into commercial catch. Therefore, at low harvest rates, the commercial fishery would be closed more often, and at high harvest rates, it would be closed less often.

With outcome uncertainty removed, the relative differences between the time-varying (bold dashed lines) and time-invariant (thin dashed lines) policies were similar to the differences with outcome uncertainty (Fig. 8). With the time varying harvest policy, mean escapement and catches were higher and percent risk lower. These differences were largest for escapement at low harvest rates, for subsistence catches at all harvest rates and for commercial catch at high harvest rates. Outcome uncertainty had a large effect on the performance measures, but for a given level of outcome uncertainty, the time-varying harvest policy could improve on the time-invariant policy.

Discussion

Arctic-Yukon-Kuskokwim chum salmon

We conducted simulations across stochastically generated decadal-scale trends in productivity because our empirical analysis confirmed that the four major chum salmon stocks in the Arctic-Yukon-Kuskokwim region have experienced large changes in productivity (Ricker a_t values), including major reductions in the mid-1990s brood years. To estimate the parameters of the Ricker stock-recruitment model to use in our simulations, we cast the fitting of that model in the form of a Kalman filter, which partitioned the high and low-frequency sources of variation. The resulting time trends in smoothed a_t values indicate that high-frequency year-to-year change in recruits per spawner (noise) is small relative to the larger, low-frequency decadal-scale time trend in the underlying a_t values (signal); the latter has greater long-term importance for managers. Such large underlying temporal changes in salmon productivity have been revealed in other empirical analyses for 120 pink (*O. gorbuscha*), chum, and sockeye (*O. nerka*) salmon stocks on the west coast of North America (Peterman et al. 2003; Dorner et al. 2008), including these AYK chum salmon stocks. Our Kalman filter results also identified a consistent upward trend in productivity starting in the mid-to-late 1990s brood years for the Anvik and Andreafsky summer chum stocks, and the Yukon fall chum salmon stocks.

General

We drew four main conclusions from our risk-assessment framework, which quantitatively compared various management policies and estimated the relative importance of different sources of uncertainty on outcomes from those policies. First, the harvest policies we investigated appeared robust to simulated decadal-scale variations in population productivity

(Ricker *a* values). For instance, time-invariant management policies (i.e., fixed-escapement target and fixed-percentage harvest rates on the fish above that target) maintained average escapements, subsistence, and commercial catches at high levels relative to past data. These averages, however, belie the large temporal variability, as measured by the coefficients of variation and risk measures. With a management policy that approximates the existing ADF&G escapement range and historical harvest rates, in about a third of the years the escapement target would not be met and the commercial fishery would be closed for about half the time. Our results suggest that fixed-escapement policies may not perform well at meeting competing objectives, and that the performance of alternative policies should be investigated.

Second, our simulations of both time-invariant and time-varying management policies were intended to determine the advantage, if any, of the latter type of policies. We found for AYK chum salmon that the time-varying policy did improve values of most performance indicators compared with the time-invariant policy, which is consistent with the earlier simulations of Peterman et al. (2000). Such time-varying policies are commonplace worldwide in fisheries of many marine fish stocks such as groundfish and pelagic fishes (Butterworth and Punt 1999; Butterworth 2007) and are one example of passive adaptive management in which parameters are updated annually as new data are collected (Walters 1986). Follow-up work could include analyzing the sensitivity of the time-varying management policy to different levels and patterns of environmental variability. Different algorithms (alternatives to Eq. 5) could also be investigated for updating the management policy with respect to the estimated value of a_t.

Third, regardless of whether time-invariant or time-varying policies are considered, we found that outcome uncertainties (which cause realized spawner abundances and harvest rates to differ from the targets) had a dominant effect on performance measures of different management policies. The direct implication is that, although stock assessment models might be improved in the future along with their parameter estimates, increases in precision and/or accuracy of the resulting scientific advice could be masked by large variations in the harvesting process that tend to cause catches and escapements to deviate substantially from values desired by managers. This result has also been found in other closed-loop simulations that included outcome uncertainty (Peterman et al. 2000; Kell et al. 2005; Dorner et al. 2009). Thus, an important conclusion is that to better achieve management objectives, considerable effort should be invested in reducing outcome uncertainty, which is usually referred to too narrowly as implementation error (Eggers and Rogers 1987) or implementation uncertainty (Rice and Richards 1996). This can be achieved through increased enforcement of regulations, educating users about the value of reducing that uncertainty, and improved in-season methods for updating abundance estimates and adjusting fishing effort.

Fourth, a key benefit of the contour plots that summarize large numbers of simulations is that managers can make well-informed decisions that involve more than one indicator. Trade-offs among indicators of escapement, subsistence catch, and commercial catch are quantified in a way that managers can use cross-hairs plotted at identical *x*-*y* coordinate locations for each of the nine contour plots to easily read off the contour plots the amount by which one indicator will increase when another decreases by a given amount as a result of a change in management policy. Each cross-hair represents a specific management policy defined by a target escapement and a harvest rate on the number of fish that exceed that target. Managers can also easily examine the effect of applying constraint regions that reflect unacceptable values of certain indicators. For instance, it may be unacceptable to have more than 50% of the years when escapement targets are not met or more than 30% of the years when the subsistence fishery is below the lowest 25th percentile of values achieved historically. Such constraints would create a small feasible region within the contour plots for acceptable management actions (target escapements and harvest rates). The effect of changing a constraint slightly will also become apparent in changes in other indicators. Due to the nonlinear nature of the contour surfaces, some cases will likely emerge in which a small change in a constraint on one indicator, along with the resulting change in size of the region of feasible management policies, can result in finding a policy associated with a large change in another indicator. Iterative explorations of such scenarios can serve as an effective focus for discussions among fisheries managers and interest groups. Software ("Vismon") has been developed to facilitate such group explorations of these simulation results (Booshehrian et al. 2011). This specialized software also permits examination of frequency distributions of indicators across the 500 Monte Carlo trials.

An additional source of uncertainty is structural uncertainty in the population model used in the simulations. For example, we investigated the possibility of depensatory recruitment by substituting a depensatory Beverton-Holt model for the Ricker model. The evidence of depensation in the stock-recruitment relationships was inconclusive, largely because these chum stocks have not been reduced to the levels at which depensation might become apparent if it were present. Thus, because those low abundances were not reached, it is likely that the period of reduced productivity in the 1990s was not caused by a depensatory mechanism. In simulations with depensation the general patterns in the performance measures were similar to the case without depensation (not shown). The main differences appeared at low escapement targets and high harvest rates, where the stock is likely to be reduced to low levels at which depensation becomes important.

It is clear that a quantitative framework for risk assessment and decision making, such as the one developed here, can provide powerful assistance to fisheries managers and various interest groups when dealing with today's challenging fisheries issues. Not only can several sources of natural and human-induced uncertainty be taken into account in analyses of management options, but results can be encapsulated in easily understood graphs that can assist with evaluations of trade-offs among multiple indicators. Furthermore, uncertainties can be identified that have higher priority for management actions to mitigate their effects. Such benefits can help improve achievement of fisheries management objectives.

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Table 1. Definitions of parameters used in the salmon life-cycle model. Listed in parentheses are the equations or figures where each parameter is derived or used.

Parameters of the Ricker stock-recruitment function	
$\bar{a}$	Mean value of the smoothed *a*-values (Eq. 1)
b	Ricker *b* parameter multiplied by 1000 (Eq. 1)
σ_v	Standard deviation of uncorrelated errors in the Ricker model (Eq. 1)
σ_w	Standard deviation of correlated errors in the random-walk model (Eq. 2)
σ^2_w / σ^2_v	Signal-to-noise ratio
Parameters of the total harvest	
$slope.before_T$	Slope of the total catch vs. run size before 1992 from regression (Fig. 5)
$slope.after_T$	Slope of the total catch vs. run size from 1992 and later from regression (Fig. 5)
$inter_T$	*y*-axis intercept of the total catch vs. run size regression (Fig. 5)
$CV_{u,T}$	Coefficient of variation of outcome uncertainty for total catch (Eq. 5)
Esc. range	ADF&G escapement target or range in thousands of fish (Fig. 6, 7)
S_m	Escapement for maximum sustainable yield based on Ricker parameters
Parameters of the subsistence harvest	
$slope_s$	Slope of the subsistence catch vs. run size from regression (Fig. 5)
$inter_s$	*y*-axis intercept of the subsistence catch vs. run size from regression (Fig. 5)
$CV_{u,s}$	Coefficient of variation of outcome uncertainty for subsistence catch (Fig. 5)
$0.25C_s$	Upper end of the lower quartile of observed subsistence catches (Fig. 6, 7, 8)

Table 2. Values of stock-specific parameters defined in Table 1 and used in the simulations of the AYK chum salmon populations.

Stock	Fall Yukon	Anvik	Andreafsky	Kwiniuk & Tubutulik
$\bar{a}$ [1]	1.046	1.045	1.144	1.026
b	1.103	1.243	3.171	17.393
σ_v	0.399	0.478	0.427	0.661
σ_w	0.283	0.237	0.301	0.183
σ^2_w / σ^2_v	0.503	0.246	0.497	0.077
$slope.before_T$	0.529	0.369	0.262	0.372
$slope.after_T$	0.228	0.133	0.082	0.056
$inter_T$	-17.803	-6.798	-0.163	0.315
$CV_{u,T}$	0.327	0.353	0.363	0.485
Escapement-goal range (1000s)	300-600	350-700	65-130	33.8
S_m	433	361	152.4	25.4
$slope_s$	0.180	0.011	NA	0.019
$inter_s$	2.934	26.446	NA	1.156
$CV_{u,s}$	0.405	0.196	NA	0.894
$0.25C_s$	24.346	23.747	NA	0.298

[1] $\bar{a}$ is the mean of a_t values over the entire time series.

Figure Captions

Figure 1. Map of the Arctic-Yukon-Kuskokwim region showing locations of chum salmon stocks used in this study. Map data from www.rivers.gov/maps.html.

Figure 2. Simulation framework and flowchart for the salmon life-cycle model. Starting with a "user-specified constant escapement goal," the arrows in the middle and to the left define the time-invariant management policy. Starting with an "annual escapement goal as estimated by Kalman filter," the arrows in the middle and to the right define the time-varying management policy. Numbers in parentheses refer to equations in the text.

Figure 3. Smoothed Kalman filter estimates of Ricker a_t values in units of $\log_e$(recruits/spawner) (solid dots) and their 95% probability intervals (gray areas) across years of spawning (brood years). (a) Fall Yukon, (b) Anvik, (c) Andreafsky, (d) Kwiniuk and Tubutulik chum salmon stocks.

Figure 4. Components of recruitment variation as estimated by Eq. 1 and 2. White bars are the estimated a_t values; gray bars are the density-dependent term, bS_t; and black bars are observation errors, v_t. The sum of bars for each brood year is the observed $\log_e$(Recruits/Spawner). (a) Fall Yukon, (b) Anvik, (c) Andreafsky, (d) Kwiniuk and Tubutulik.

Figure 5. Chum salmon catches as a function of run size: observed subsistence catches (+); total of commercial plus subsistence catch before 1992 (●) and 1992 and later (○). The straight lines are regression fits of catch on run size: dashed line, subsistence catch; solid line, total catch before 1992; dot-dash line, total catch 1992 and later. Variability of data around the lines is assumed to reflect outcome uncertainty. (a) Fall Yukon, (b) Anvik, (c) Andreafsky,

(d) Kwiniuk and Tubutulik. From the available data, it was not possible to partition the subsistence component of the Andreafsky chum fishery.

Figure 6. Performance measures for Yukon River fall chum salmon. Each combination of escapement target and harvest rate describes one time-invariant management policy. The vertical gray lines represent the current escapement-goal range for this stock; the horizontal gray lines are the regression slopes between total catch and run size, before 1992 and 1992 and later (Fig. 5, Table 2). The mean escapements, subsistence, and commercial catches over the 100-yr simulation are in thousands of fish. Coefficients of variation are percentages. The risk measures are, from top right to bottom right: the percentage of years in which the final realized escapement fell below the target set on the *x* axis; % of years in which subsistence catch was less than the lowest 25th percentile of the historically observed subsistence catches; and % of years in which the commercial fishery was closed due to an insufficient number of returning adults. All performance measures were averaged over 500 Monte Carlo trials.

Figure 7. Performance measures for the time-invariant management policies applied to Yukon River chum salmon with outcome uncertainty removed ($CV_{u,T} = CV_{u,s} = 0$). The vertical gray lines represent the current escapement-goal range for this stock; the horizontal gray lines are the regression slopes between total catch and run size, before 1992 and 1992 and later. The blank area below a harvest rate of 0.2 for the CV of commercial catch occurs because the commercial fishery would be closed in all years.

Figure 8. Performance measures for two types of management policies for Yukon River fall chum salmon. The time-varying policies (bold lines) update the escapement target each year in response to the most recent estimate of the Ricker a_t value, whereas the time-invariant

policies (thin lines) use a fixed escapement target S_m corresponding with the mean Ricker a_t value. The simulations were conducted both with (solid lines) and without (dashed lines) outcome uncertainty in the harvest control function.

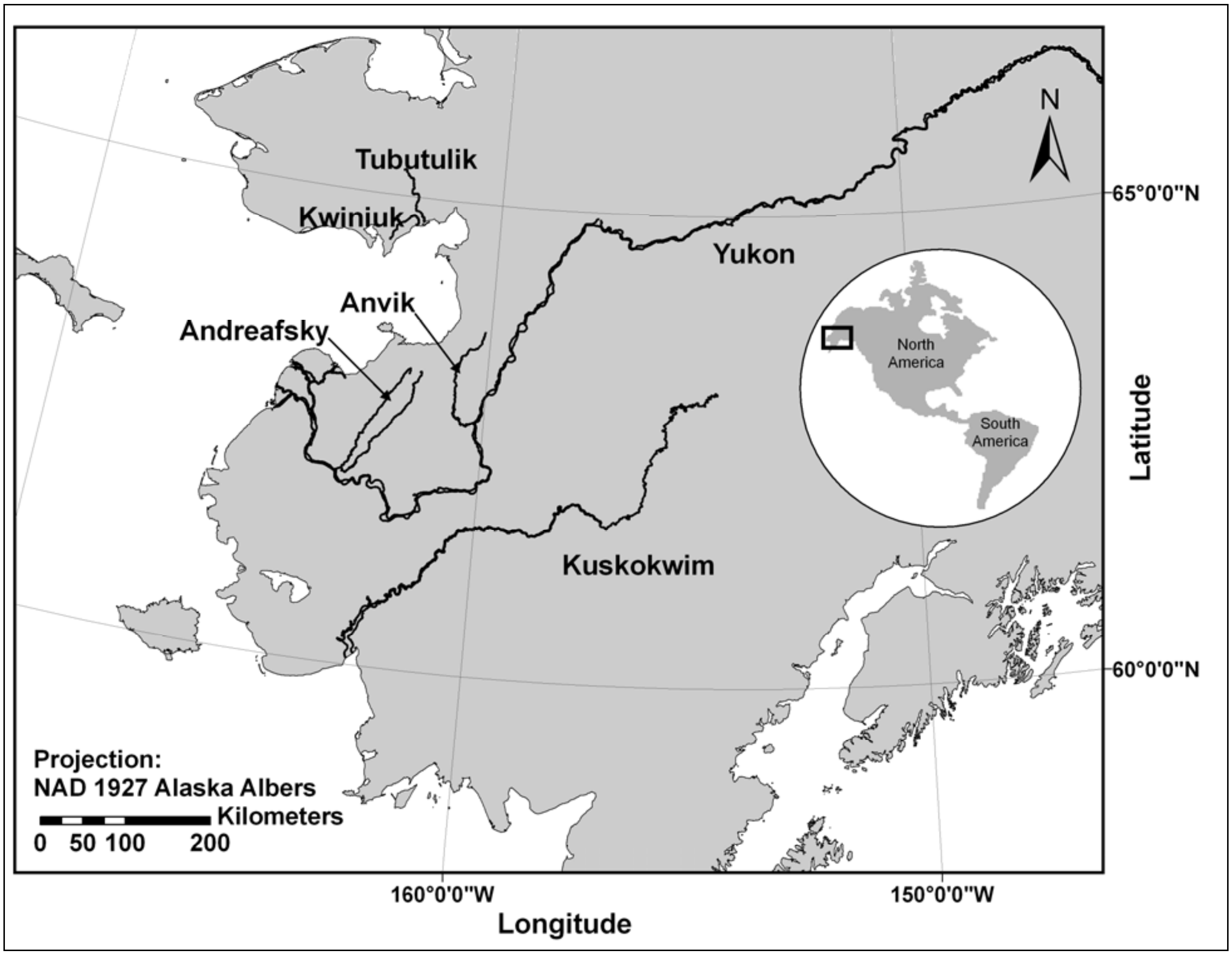

Tubutulik
Kwiniuk
Yukon
Anvik
Andreafsky
North America
South America
Kuskokwim
N
65°0'0"N
60°0'0"N
Latitude
Projection:
NAD 1927 Alaska Albers
Kilometers
0 50 100 200
160°0'0"W
150°0'0"W
Longitude

Figure1

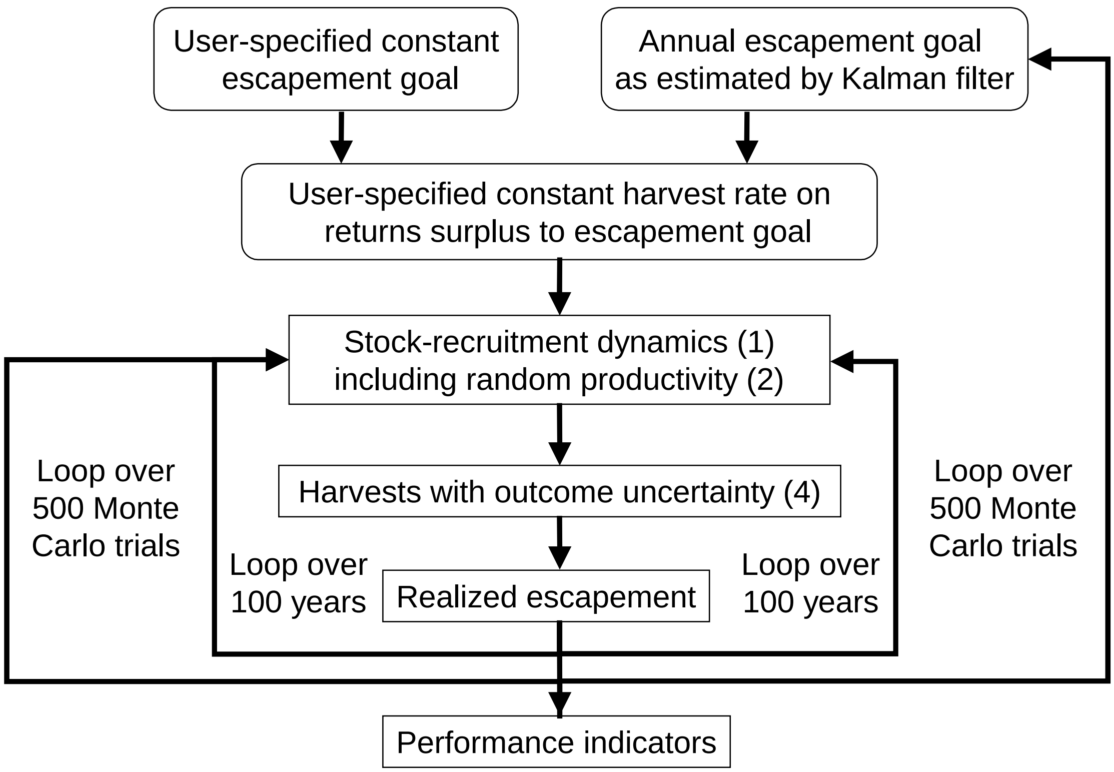

User-specified constant escapement goal
Annual escapement goal as estimated by Kalman filter
User-specified constant harvest rate on returns surplus to escapement goal
Stock-recruitment dynamics (1) including random productivity (2)
Harvests with outcome uncertainty (4)
Realized escapement
Loop over 500 Monte Carlo trials
Loop over 100 years
Loop over 100 years
Loop over 500 Monte Carlo trials
Performance indicators

Figure 2.

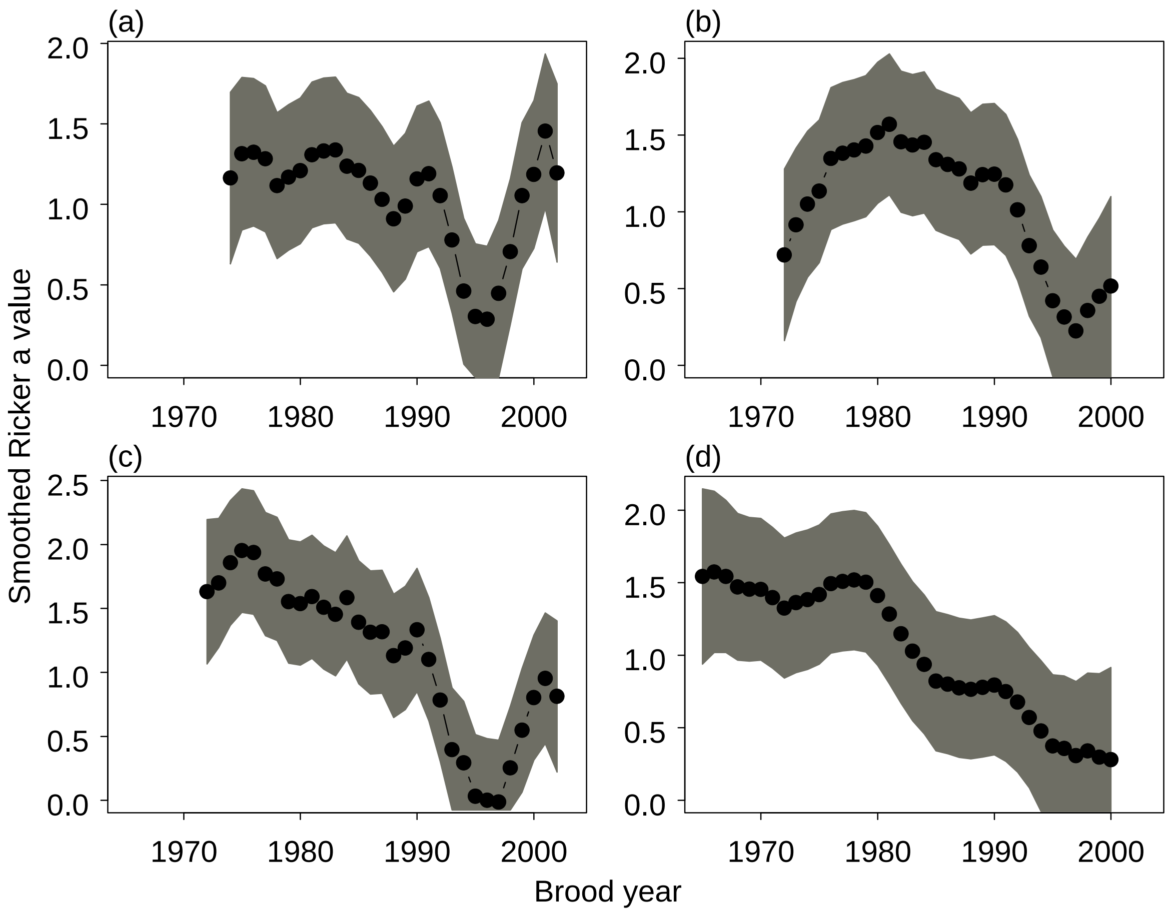
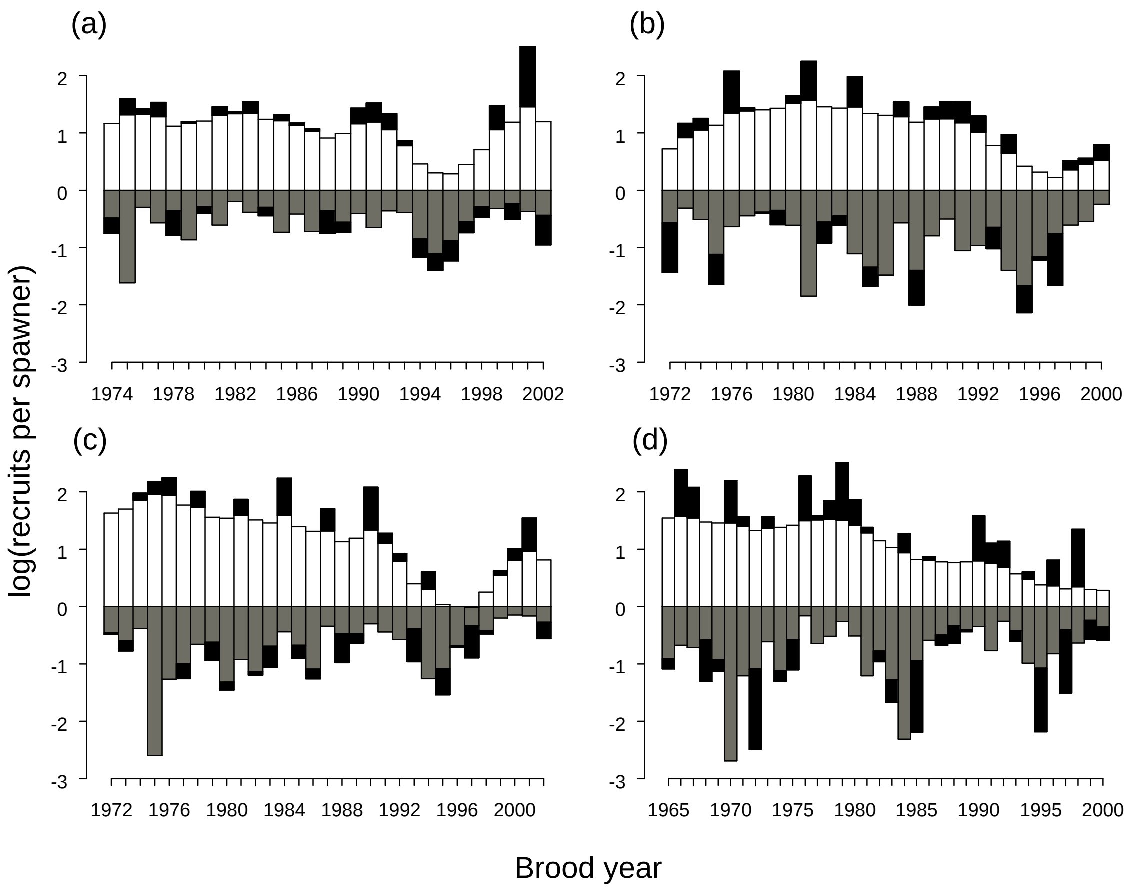

(a)
(b)
(c)
(d)
Smoothed Ricker a value
Brood year
0.0
0.5
1.0
1.5
2.0
2.5
1970
1980
1990
2000

Figure 3.

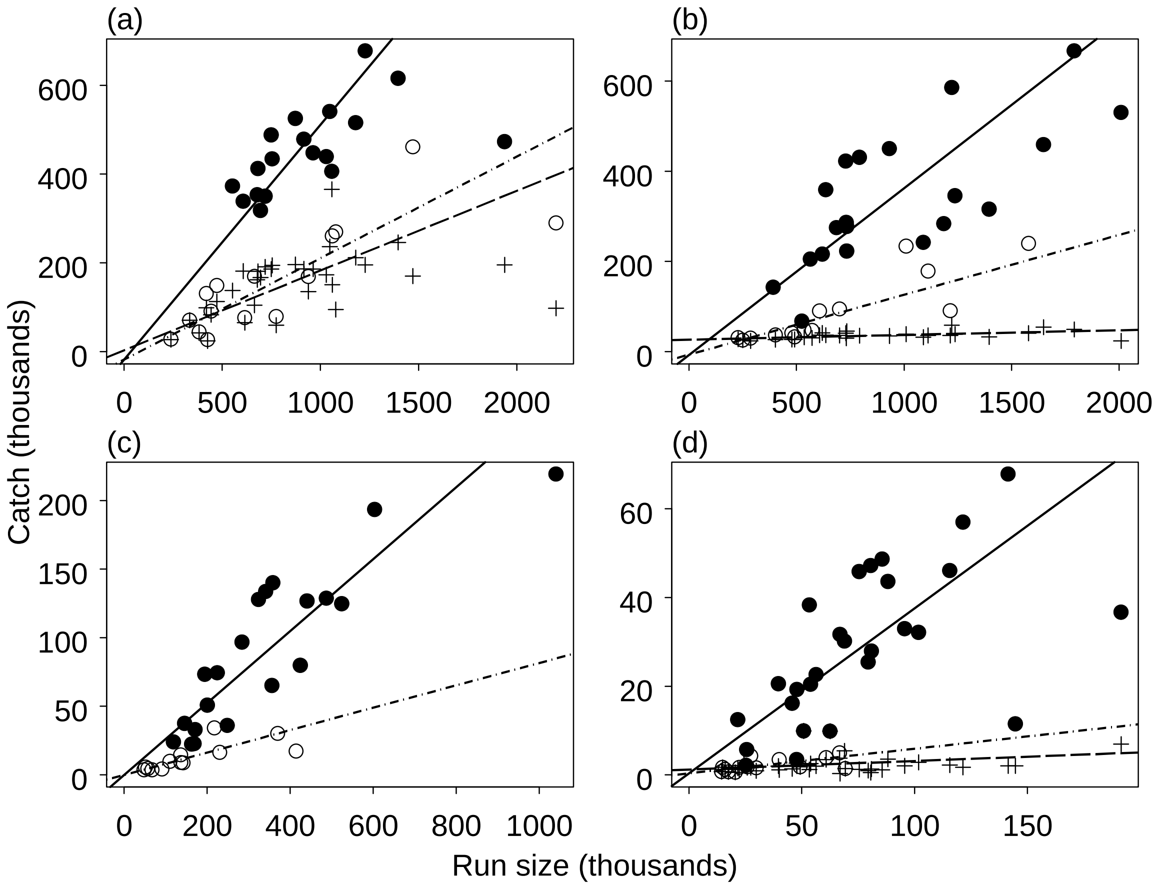
737



738

739 Figure 4.

740



(a)
(b)
(c)
(d)
Catch (thousands)
Run size (thousands)
0
200
400
600
500
1000
1500
2000
50
100
150
800
20
40
60

Figure 5.

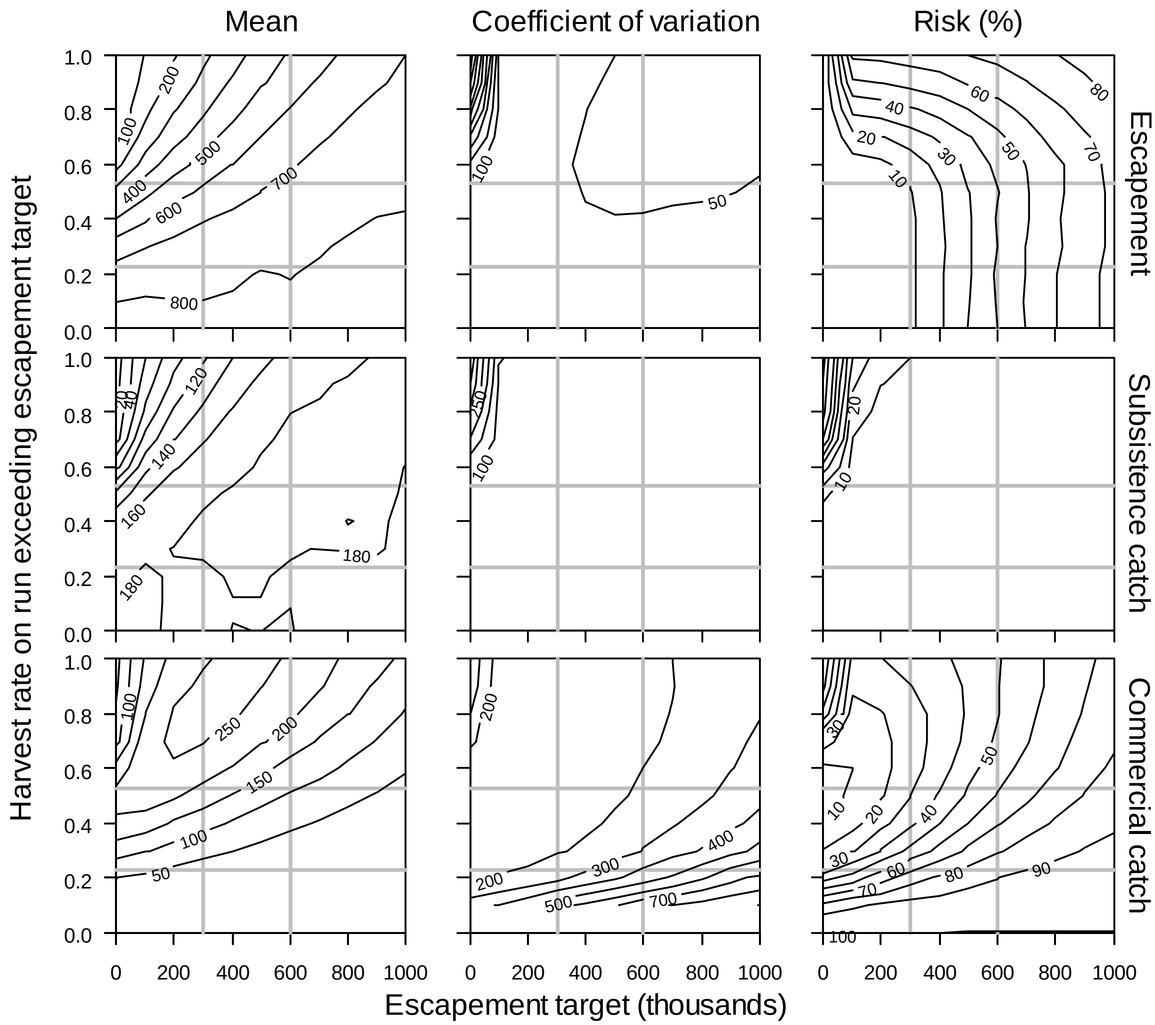

Mean
Coefficient of variation
Risk (%)
Escapement
Subsistence catch
Commercial catch
Harvest rate on run exceeding escapement target
Escapement target (thousands)
0.0
0.2
0.4
0.6
0.8
1.0
0
200
400
600
800
1000

Figure 6.

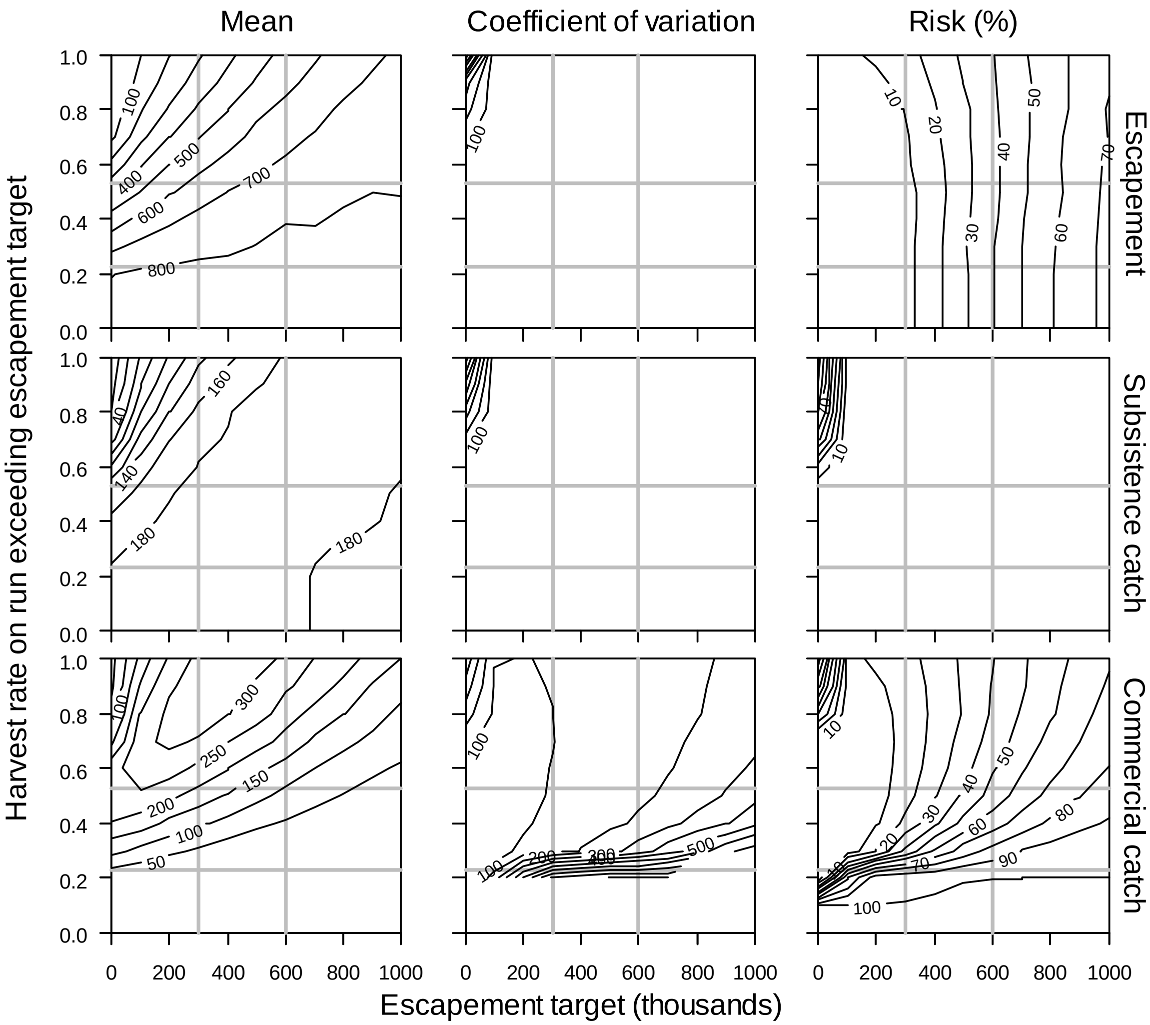

Mean
Coefficient of variation
Risk (%)
Escapement
Subsistence catch
Commercial catch
Harvest rate on run exceeding escapement target
Escapement target (thousands)
0.0
0.2
0.4
0.6
0.8
1.0
0
200
400
600
800
1000
100
400
500
600
700
800
40
140
160
180
300
250
200
150
50
10
20
30
60
70
80
90

Figure 7.

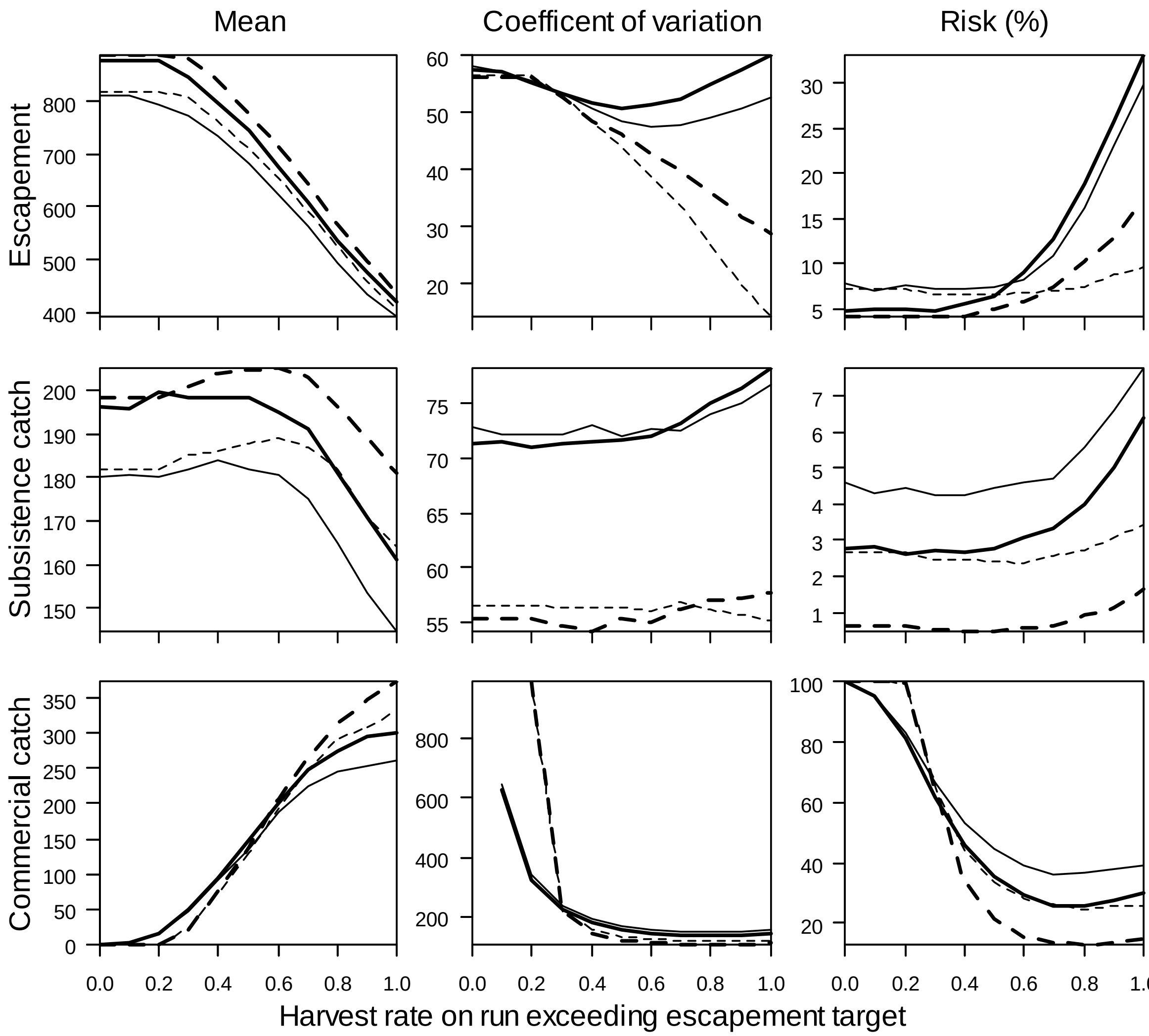

Mean
Coefficent of variation
Risk (%)
Escapement
Subsistence catch
Commercial catch
Harvest rate on run exceeding escapement target

Figure 8.

Supplementary Materials for Collie et al., *in press* in CJFAS (3 Oct. 2011)

Environmental variables

To identify potential sources of variation in chum salmon productivity, we investigated a suite of abiotic and biotic variables that characterize the marine environment of the Bering Sea and/or have been linked with Pacific salmon dynamics in other studies. Because the Kalman filter smoothing process tends to filter out high-frequency, interannual variation in a_t, we used the unsmoothed a_t values of chum productivity for our correlation and regression analyses with environmental variables. Those variables were categorized into five groups: climatic, temperature, wind, precipitation, and biotic (Table S1). Following Shotwell et al. (2005), we used a two-stage process to screen the environmental variables. First, we calculated the correlation coefficients between each variable and a_t at lags of 0 (year of spawning) to 3 (ocean residence) years. From each group of environmental variables, we selected the variable and lag with the highest correlation across stocks for potential inclusion in a mixed-effects regression with first-order autocorrelated residuals (Venables and Ripley 2002). Only one variable was selected from each of the five groups because the variables within each group tend to be positively correlated. A mixed-effects model is appropriate for these data because Pacific salmon stocks have been shown to have coherent responses to environmental variability over the spatial scale of the AYK region (Mueter et al. 2002, Dorner et al. 2008). This regression was performed to identify a set of environmental variables that were most strongly associated with the observed shifts in chum salmon productivity and that should be investigated further in future field research programs. However, these environmental variables were not used directly in the salmon life-cycle simulation model.

Significant relationships were identified between estimated productivity of AYK chum salmon and a number of environmental variables (Table S2), showing the influence of those conditions on variation in population dynamics of the chum salmon stocks. None of the random effects were significant; only the fixed-effect parameter estimates are reported. The model intercept was very close to 1.0, which is expected because it is related to the mean a_t (Table 2). Productivity was positively related to the Pacific Decadal Oscillation (PDO) at a lag of three years and May sea surface temperature (SST) in the Bering Sea at lag 2. These lags correspond with the years of ocean residence of chum salmon. The a_t values were negatively related to Nome precipitation at lag of 1, which corresponds to the age of freshwater residence and migration to salt water. Finally, chum salmon productivity was negatively related to the run size of East Kamchatka pink salmon in the year of spawning, although this effect was not statistically significant. All correlations among regression parameters were low except for the positive correlation between the coefficients for the PDO and May SST (Table S2).

The positive relation between Ricker a_t values and SST during the period of ocean residence is consistent with the positive association found by Mueter et al. (2002) for all chum, pink, and sockeye salmon in Alaska. Sea-surface temperature is not likely a direct physiological limiting factor on survival rate, but rather is more likely an indirect surrogate for oceanographic conditions that reflect predator abundance and/or food supply for chum salmon. Recent warmer conditions in the Bering Sea have led to earlier ice retreat and a later bloom with a large copepod biomass (Macklin and Hunt 2004). Thus, warmer conditions may enhance feeding, growth, and survival of chum salmon stocks in the AYK region. These correlations are consistent with the hypothesis that chum salmon productivity is primarily determined by ocean survival, as opposed to freshwater survival (Kruse 1998). The negative association between the Ricker a_t values and precipitation at Nome, Alaska, contrasts with the results of Shotwell et al. (2005) in which the best model for Yukon River chum salmon included a positive effect of spring precipitation at Tanana, Alaska during the freshwater stage. Precipitation affects flow conditions within the rivers during out-migration as well as the degree of stratification in estuaries.

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Table S1. List of environmental variables and their sources. Month ranges are inclusive.

Category	Index	Months	Source
Climatic	Arctic Oscillation Index, winter	Dec.-Feb.	1
	Arctic Oscillation Index, summer	June-Sep.	1
	Pacific Decadal Oscillation, summer	June-Aug.	1
	Pacific Decadal Oscillation, annual		1
	Alaska Index	Dec.-Mar.	1
Temperature	Air temperature, St. Paul, winter	Dec.-Mar.	1
	Air temperature, St. Paul, annual		1
	Sea surface temp. in SE Bering Sea	May	1
	Sea surface temperature, Mooring 2	Jan.-Apr.	1
	Sea surface temperature, Pribilof Is.	Jan.-Mar.	1
Wind	Wind mixing index, St. Paul	May	1
	Wind mixing index, Mooring 2	June-July	1
	Along Peninsula wind stress	Nov.-Apr.	1
	Along Peninsula wind stress	May-June	1
Precipitation	Precipitation at Bethel, Alaska	Apr.-May	2
	Precipitation at Nome, Alaska	Apr.-May	2
Biotic	East Kamchatka pink salmon returns		3

1. www.bering.climate.noaa.gov/data/index.php
2. www.wrcc.dri.edu/summary/Climsmak.html
3. Gregg Ruggerone, Natural Resources Consultants, Inc., 4039 21st Avenue West, Suite 404, Seattle, Washington, USA, 98199. Personal communication, 2008.

Table S2. Linear mixed-effects model fit by restricted maximum likelihood. The dependent variable is the unsmoothed a_t value for each stock and year. Independent variables are the annual Pacific Decadal Oscillation, May sea surface temperature, Nome precipitation, and abundance of Kamchatka pink salmon, as listed in Table S1.

Parameter estimates:

Variable	**Lag (yr)**	**Value**	**Std.Error**	**t-value**	**p-value**
Intercept	NA	0.971	0.153	6.363	<0.0001
Annual PDO	3	0.110	0.031	3.353	0.0006
May SST	2	0.067	0.022	3.089	0.0025
Nome precip.	1	-0.063	0.020	-3.161	0.0020
Pink salmon	0	-0.0002	0.0004	-0.351	0.7263

First-order autocorrelation coefficient of the residuals: 0.887

Parameter correlations:

	Intercept	**Annual PDO**	**May SST**	**Nome precip.**
Annual PDO	-0.071			
May SST	-0.036	0.355		
Nome precip.	-0.013	-0.150	0.080	
Pink salmon	-0.074	0.149	-0.132	-0.104

Number of observations: 120, Number of groups: 4, Degrees of freedom: 112, r^2: 0.21

Harvest Control Function

```
get.catch <- function(ret) {
    # Function to calculate catch as a function of run size (ret)
    # Written by Jeremy Collie on 26 February 2008 at SFU
    # Modified on 28-Feb-08 to include outcome uncertainty
    # This example uses the parameters for the Anvik stock from Table 2.
    # Parameters of the harvest rules
    #
    # Total fishery (commercial plus subsistence)
    # input total harvest rate (slope of total catch on return regression)
    slope1 <- 0.369
    # input escapement target (x-intercept) for the time-invariant policy
    x1 <- 154.644
    # maximum total harvest rate is needed because of outcome uncertainty
    hr.tot <- 1.0
    #  coefficient of variation of outcome uncertainty for the total fishery
    sigma.t <- 0.353
    #
    # Subsistence fishery
    # subsistence harvest rate (slope of catch on return regression)
    slope2 <- 0.0105
    # y-intercept of subsistence catch on return regression
    inter2 <- 26.446
    # maximum observed subsistence harvest rate
    hr.sub <- 0.121
    # CV of outcome uncertainty for the subsistence fishery
    sigma.s <- 0.197
    #
    # Set commercial catch to zero if the return is below the target
    commercial <- 0
    # If the return is below x1 there is only subsistence catch
    # with a random uniform outcome uncertainty after Eggers (1993)
    if(ret <= x1) subsistence <- ret * runif(1, max = hr.sub)
    #
    # If the return exceeds x1 there is subsistence and commercial catch
    # with normal outcome uncertainty
    if(ret > x1) {
        subsistence <- (inter2 + ret * slope2) * (1+rnorm(1, sd = sigma.s))
        hrate <- subsistence/ret
        if(hrate > hr.sub)
            subsistence <- hr.sub * ret
        total <- (ret - x1) * slope1 * (1+rnorm(1, sd = sigma.t))
        hrate <- total/ret
        if(hrate > hr.tot)
            total <- hr.tot * ret
        commercial <- max(0, total - subsistence)
    }
    c(subsistence, commercial)
}
```

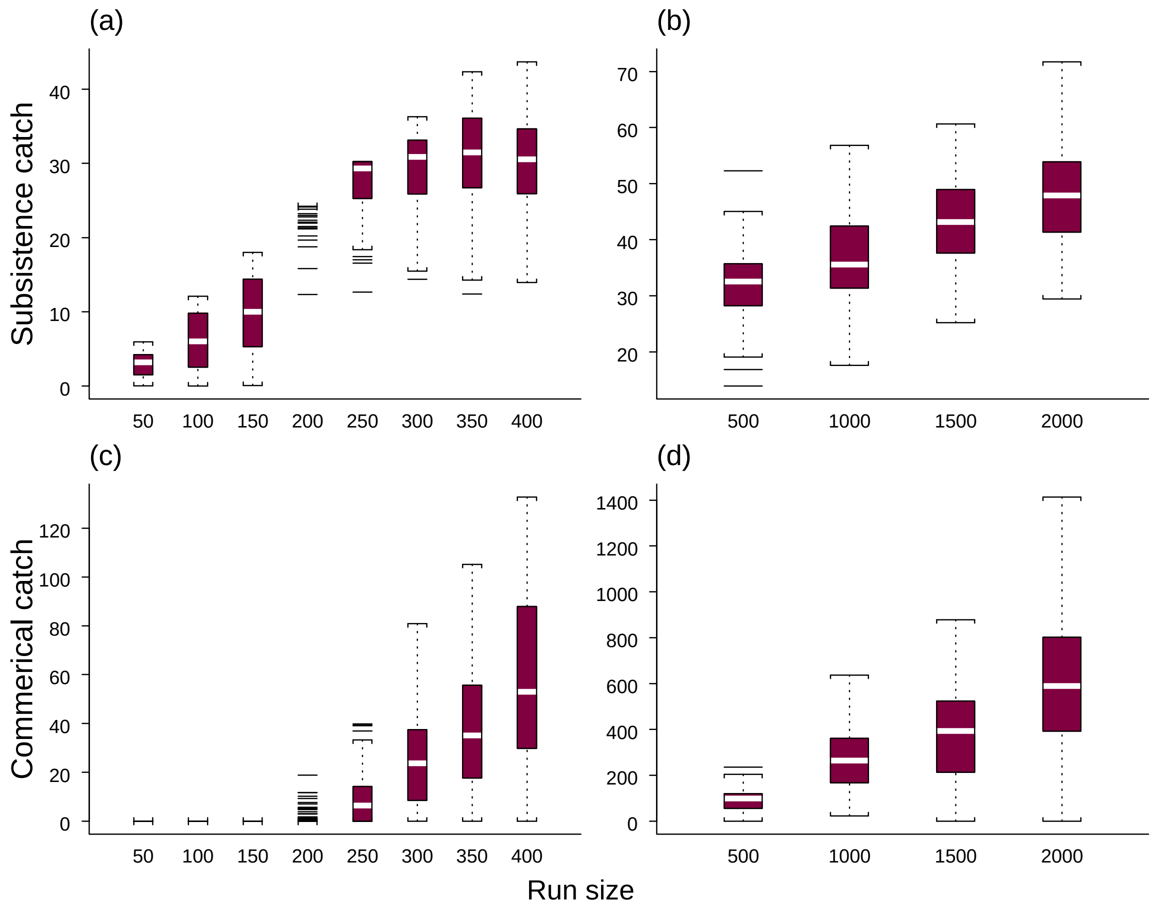

Figure S1. Simulated subsistence (a,b) and commercial (c,d) catches as a function of run size for the Anvik stock. All units are thousands of salmon. Run size is plotted on two scales: below (a,c) and above (b,d) 500 thousand. Below the escapement target (in this example 155,000 spawners) there is only subsistence catch, with the harvest rate calculated from a uniform distribution. Above the escapement target, there is both subsistence and commercial catch, calculated from the input harvest rates with normally distributed outcome uncertainty. The box plots summarize the results of 100 random simulations: white lines are median catches; solid boxes are interquartile ranges; whiskers extend to 1.5 times the interquartile range; horizontal lines beyond the whiskers are outliers.

Supplementary Contour Plots

Contour plots of nine performance indicators for the three other populations of chum salmon in the AYK region: Andreafsky (Figure S2), Anvik (Figure S3), and Kwiniuk and Tubutulik (Figure S4). See Fig. 6 for full explanation of performance measures and *x* and *y* axes.

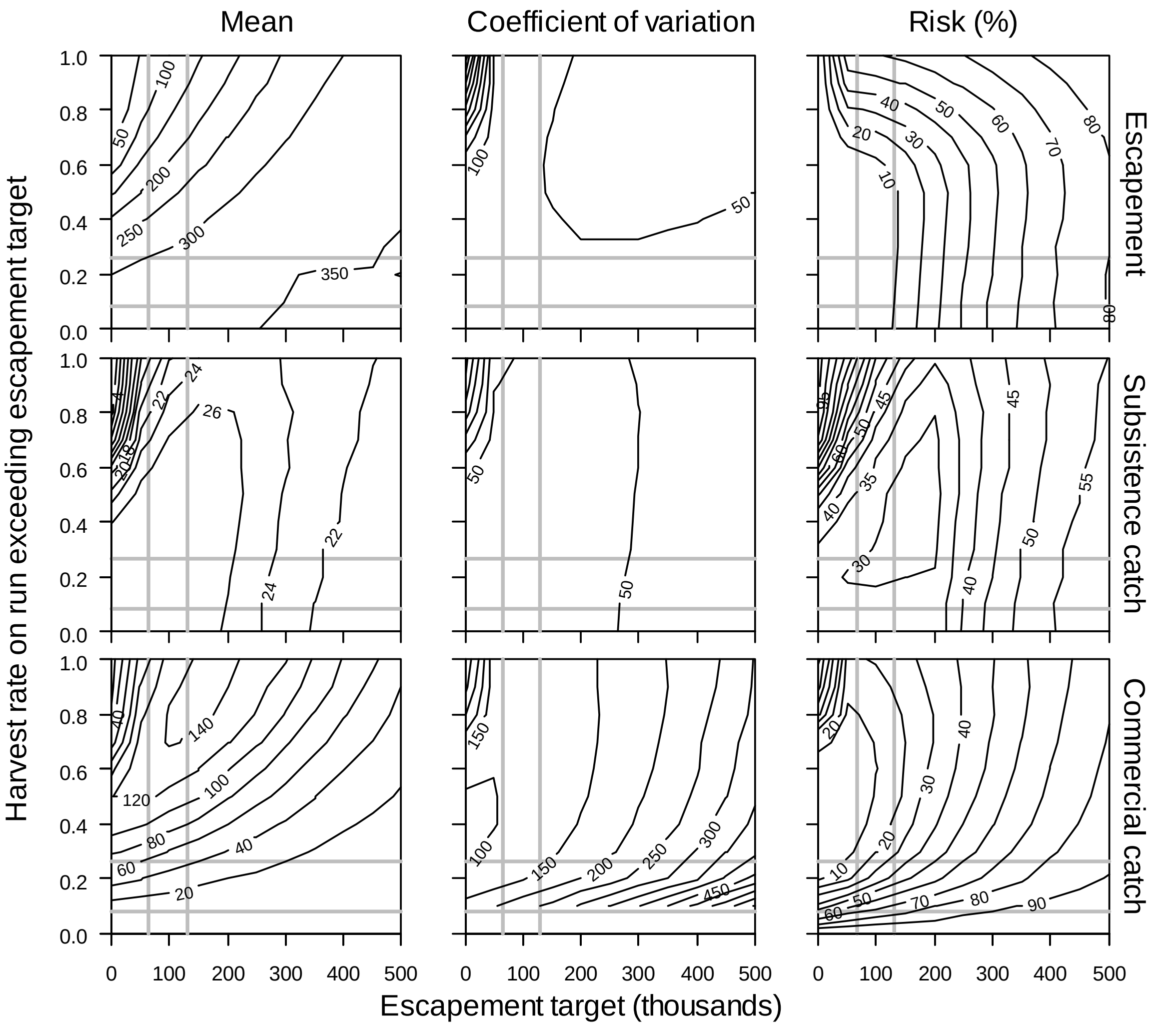

Figure S2. Performance measures for time-invariant management policies applied to Andreafsky River chum salmon. The harvest parameters for the subsistence fishery were assumed to be the same as those for the neighboring Anvik stock because empirical data for the subsistence catch of the Andreafsky stock were not available.

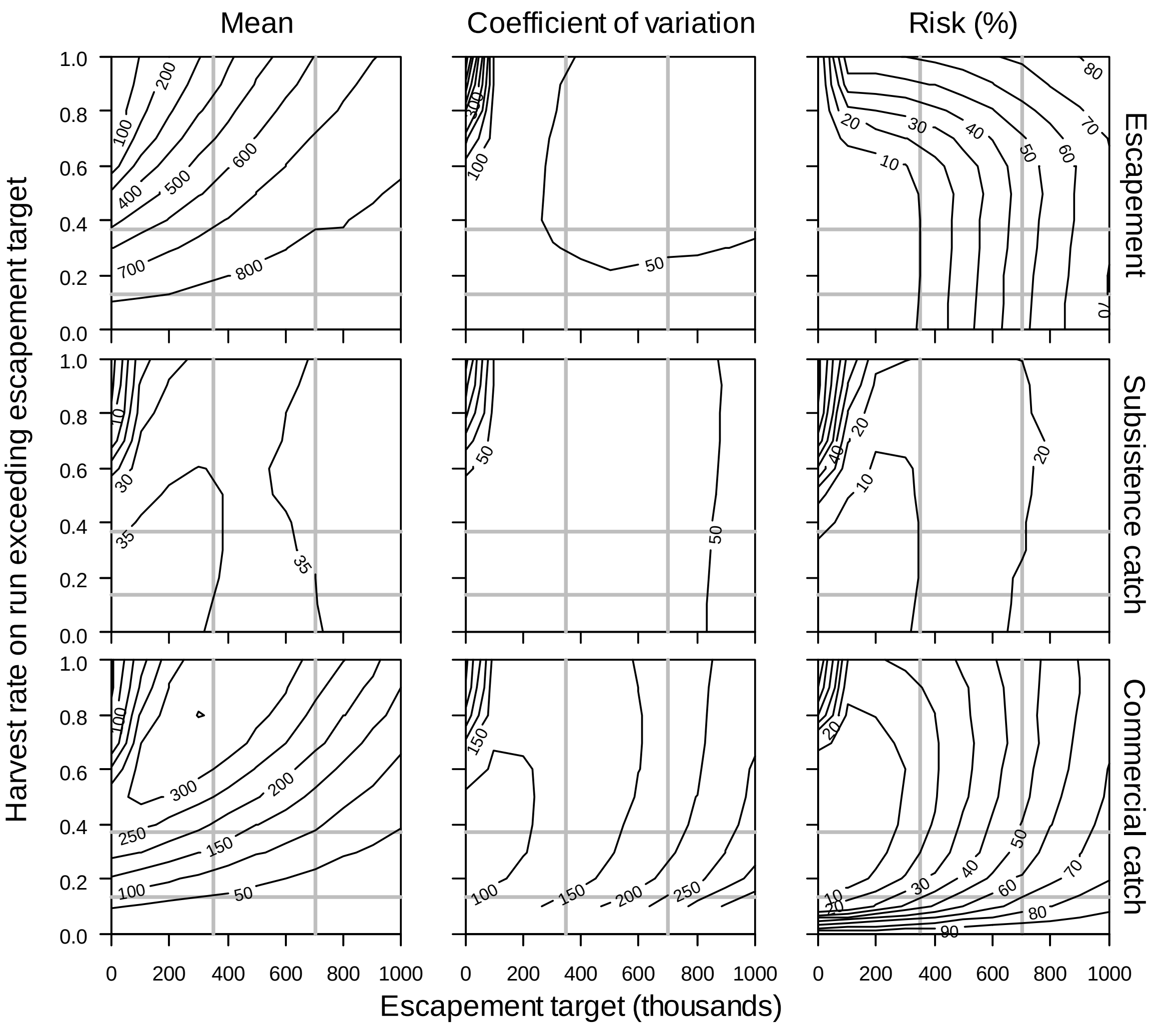

Figure S3. Performance measures for time-invariant management policies applied to Anvik River chum salmon.

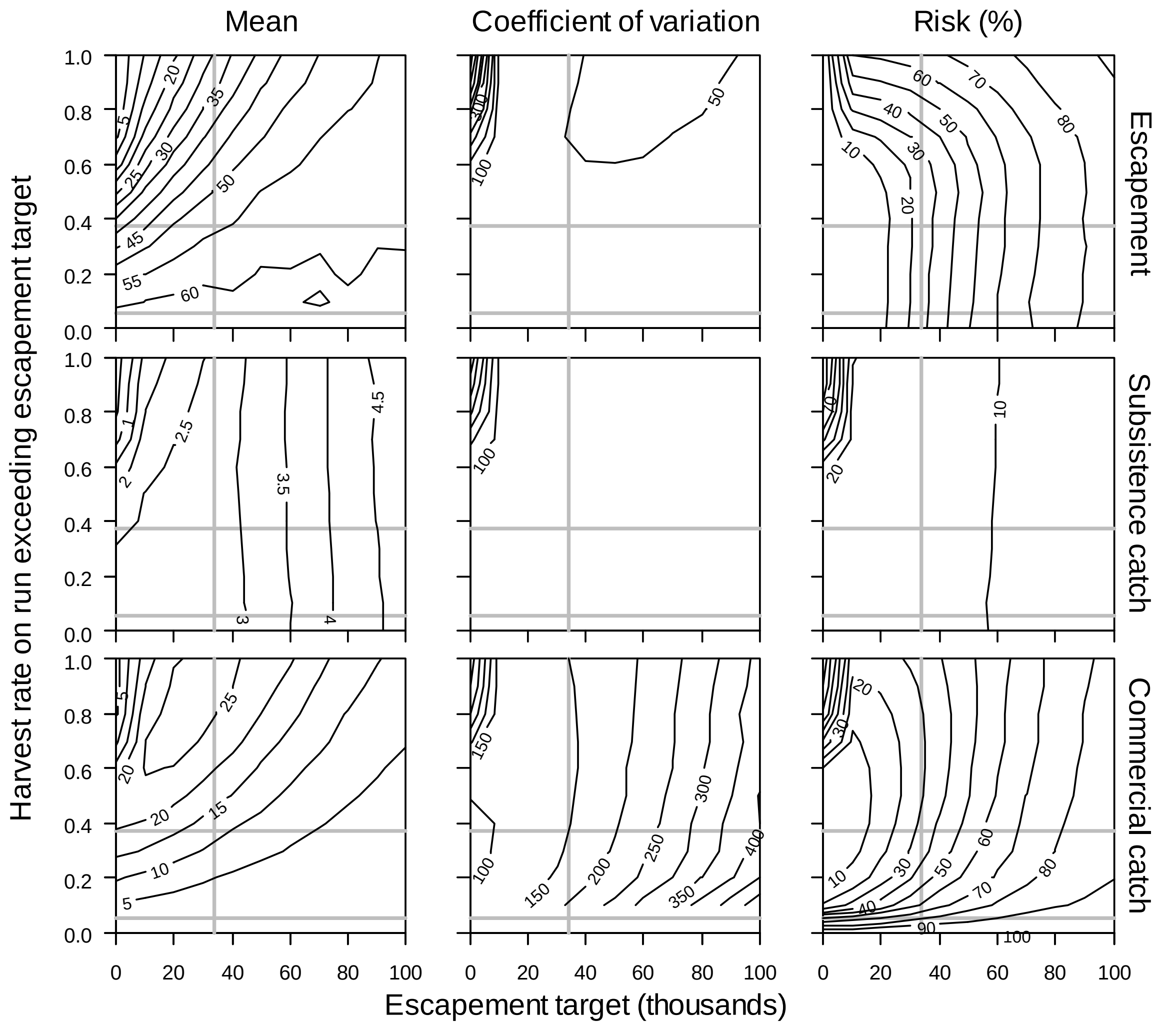

Figure S4. Performance measures for time-invariant management policies applied to the combined Kwiniuk River and Tubutulik River chum salmon.