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A Risk Assessment Framework for Alaska Chum Salmon

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Abstract

Pacific salmon (*Oncorhynchus* spp.) stocks in the Arctic-Yukon-Kuskokwim region of Alaska consistently experienced low returns in the late 1990s, which led to declarations of economic disaster, calls for more research, and changes in harvest strategies. We developed a risk-assessment framework to evaluate alternative harvest strategies for chum salmon (*O. keta*) in this region. We used a Kalman filter to fit a Ricker model with a time-varying productivity parameter (a), and the subsistence and commercial catch module included empirically estimated outcome uncertainty. The resulting salmon life-cycle model was placed in a risk-assessment framework to provide decision makers with quantitative information about trade-offs among commercial harvest, subsistence harvest, and spawner abundance. We also used closed-loop simulations to investigate the utility of time-varying harvest policies in which the escapement target (number of spawners) changed in response to the estimated change in productivity (a). The time-varying harvest policy could not improve on the best time-invariant policy for most performance measures. Our resulting generic risk-assessment framework can be used to evaluate harvest guidelines for the majority of salmon stocks.

Keywords: risk assessment, salmon management, trade-offs, Kalman filter, implementation error, outcome uncertainty, closed-loop simulations, management strategy evaluation, environmental variation

Introduction

Managers of most North Pacific salmon (*Oncorhynchus* spp.) populations use two management objectives, one related to achieving desired harvests and a conservation one related to target spawner abundances (escapements). Most often, the two objectives are directly linked. Theoretically, long-term maximum sustainable yield (MSY) is achieved by annually obtaining the escapement target that produces that yield, S_m (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 hard 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 is usually not met exactly because of (1) incomplete management control over the harvesting process (i.e., implementation error or outcome uncertainty – Eggers and Rogers 1987; Holt and Peterman 2006), and (2) management-trade-off decisions in mixed-stock fisheries about allocation of catch among different interest groups and spawners (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, productivity, and adult abundance. 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).

Given the pervasive uncertainties in salmon stock assessment and management created by imperfect data, outcome uncertainties, and environmental variation, there is a clear need for methods that provide scientific advice to managers that explicitly take these uncertainties into account. 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 (Walters 1986; Butterworth and Punt 1999). These methods 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 for evaluating alternative management policies for salmon populations, particularly in a relatively data-poor region. As a case example, we used several chum salmon populations (*O. keta*) in the Arctic-Yukon-Kuskokwim (AYK) region of Alaska (Fig. 1). Large and rapid decreases in abundance of chum and other salmon species in the 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 region (http://www.aykssi.org/About/index.htm). These two effects led to unprecedented declarations of economic disaster in western Alaska over the past decade and a subsequent injection of millions of dollars by the U.S. Congress into the AYK Sustainable Salmon Initiative (AYK SSI) for research and management (http://www.aykssi.org/About/index.htm). Two important planning documents emerged from this initiative, (1) the Arctic-Yukon-Kuskokwim Salmon Research and Restoration Plan (AYK SSI 2006), and (2) a report by the National Research Council (2004) on developing a research and restoration plan for this region. As well, in 2001, two significant policies were adopted by the Alaska Department of Fish and Game and the Board of Fisheries (2001a,b), the "Policy for the management of sustainable salmon fisheries" and the "Policy for statewide salmon escapement goals". These policies emphasize the paramount importance of setting escapement goals for achieving management objectives.

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 and/or additional sources of mortality. The cause of this major reduction remains unclear, but some evidence points to a reduction in survival of juveniles in the ocean. For instance, several separate chum salmon stocks in this region showed positively correlated temporal trends in productivity (the a parameter of the Ricker stock-recruitment model), and a general decrease in productivity beginning with mid-1980s brood years and ending with a more severe and rapid decline in the mid-to-late 1990s broods in which some stocks had productivity more than two standard deviations below the average (Dorner et al. 2008). These results suggest that a region-wide mechanism contributed more to the reduced salmon productivity than stock-specific problems. The area is relatively pristine habitat, so widespread simultaneous degradation of freshwater habitat is not likely the cause. Changing ocean conditions may be the main source of reduced salmon productivity but research is still ongoing. Regardless of the cause, we conducted our risk assessments across a wide range of scenarios of temporal changes in productivity because escapement goals and harvests need to respond in a timely manner to reflect such changes in the future.

Another key objective of our research was to estimate trade-offs that would be incurred by any given choice of harvest policy, which we define here to mean an escapement goal or target plus a harvest rate that is applied to the number of returning salmon in excess of that goal. Salmon fisheries managers everywhere are well aware of the unavoidable trade-off between increasing catch and reducing escapement, as well as the trade-off between catch allocated between one user group and others. 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. We therefore explicitly included these sources of uncertainty in our analyses so as to better estimate escapement and indicators of catches by sector to help managers more thoroughly consider the trade-offs inherent in their policy choices.

To address our research objectives, we developed an empirically based stochastic simulation model of several chum salmon populations in the AYK region of Alaska. We used this model to evaluate the potential effectiveness of various harvesting/escapement goal policies at meeting management objectives. The model was a closed-loop simulation that included salmon population dynamics and environmental influences on them, and implementation of harvesting decisions, which included uncertainty that caused realized escapements to differ stochastically from targets. In one version of the model (with a time-varying harvest/escapement goal policy), stock assessments were based on simulated catch and escapement data that assumed observation error existed, and 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 as specified by the user. We modelled the dynamics of both commercial and subsistence fisheries and assessed risks (such as too few spawners, closure of upriver native subsistence fisheries, and reduced commercial catches) associated with different harvesting guidelines. This modelling framework can also help inform managers about what could be done in the event of some future large decrease in productivity of AYK salmon populations, as was seen in the late 1990s.

Methods

Five chum salmon stocks in the AYK region were selected for this analysis, based on the length of existing time series and availability of age-composition data to construct brood tables. The five stocks are the combined Kwiniuk and Tubutulik Rivers in the Norton Sound District, Yukon River fall chum, the Anvik and Andreafsky Rivers, which are both tributaries of the Yukon River with summer runs of chum salmon, and the Kuskokwim River (Fig. 1). 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). The brood table for the Kuskokwim River was originally compiled by Shotwell et al. (2005); brood tables for the other four stocks were the same data as used by Hilborn et al. (2007). With the aid of ADF&G biologists, these tables were updated to include more recent brood years. These updated brood tables provide time series of spawning escapement and resulting recruitment data ranging from 25 to 36 years in duration.

Following Peterman et al. (2000, 2003), we used a Kalman filter to fit a time-varying Ricker model:

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

where R_t is the total number of recruits resulting from S_t, the spawners in year t, b is the density-dependent parameter (assumed constant for each stock), and we refer to $v_t \sim \mathrm{N}(0, \sigma_v^2)$ as observation error, although technically speaking it is the combination of both observation error and high-frequency natural variability that is not autocorrelated over time. Autocorrelated variation is accounted for below. The time varying parameter, a_t, measures the density-independent productivity of the stock; it is the average of the logarithm of recruits per spawner at low spawner abundance. Variation in the a_t parameter was modeled as a random walk:

$$a_t = a_{t-1} + w_t \tag{2}$$

where $w_t \sim \mathrm{N}(0, \sigma_w^2)$ is a process error. This choice of parameter estimation method for the Ricker model was based on its relatively good performance in Monte Carlo simulation trials (Peterman et al. 2000) under a wide variety of scenarios for changes in underlying salmon productivity. This Kalman filter model performed better than the standard Ricker model, which is the same as Eq. 1 except a is not time-dependent. Peterman et al. (2003) found that a random walk model for Eq. 2 was better able to track decadal changes in productivity than a first-order autocorrelation function. The model parameters $\{a_t, b, \sigma_v^2$, and $\sigma_w^2\}$ were estimated by maximizing the concentrated likelihood with 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).

In a separate analysis parallel to our main closed-loop simulation modelling, a limited number of Monte Carlo trials were run to test the ability of the Kalman filter to estimate a time series of a_t values from spawner-recruit data that were generated by fitting Eq. 1 to data. For each of our five stocks, we used the observed S_t and estimated a_t to define an operating model. Randomized sets of R_t were generated by drawing 500 v_t values from a normal distribution ($\sim\mathrm{N}(0, \sigma_v^2)$) with σ_v^2 set at its maximum likelihood estimate. The model parameters $\{a_t, b, \sigma_v^2$, and $\sigma_w^2\}$ were then re-estimated with the Kalman filter described above. The results of the 500 Monte Carlo simulations were used to calculate the mean bias and mean square error of the parameter estimates.

The Ricker *a* parameter is the slope of the spawner-recruit curve at low spawner abundance. However, since none of the five stocks has been reduced to very low levels of spawner abundance, this initial slope and even the shape of the spawner-recruit curve at low abundance remains uncertain. As an alternative "state of nature" to the Ricker model, we considered a depensatory Beverton-Holt model:

$$R_t^{'} = \frac{c\,S_t^d}{A^d + S^d} \tag{3}$$

which has declining recruits per spawner at low abundance for values of the exponent $d > 1$ (Peterman 1977). This depensatory model was not fit to the original data with the Kalman filter because it cannot be linearized as in Eq. 1. Instead, we used the Kalman filter results to "standardize" the original recruitment data to the recruitment that would be expected with average productivity ($\bar{a}$). The corrected recruitment data are $R_t^{'} = e^{-(a_t - \bar{a})} R_t$. The depensatory Beverton-Holt model (Eq. 3) was fit to these corrected spawner-recruit data with non-linear least squares and multiplicative log-normal errors.

Because the Kalman filter smoothing process tends to filter out high-frequency interannual variation in a_t, we attempted to identify potential sources of variability by using multiple regressions to fit the unsmoothed a_t values with a suite of environmental and biotic variables. These variables are categorized into five groups: climatic, temperature, wind, precipitation, and biotic (Table 1). 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 for inclusion in a step-wise regression. Only one variable was selected from each group because the variables in each group tend to be positively correlated. Forward stepwise regression was performed with variables retained based on minimizing the Akaike Information Criterion (AIC).

These step-wise regressions were performed to identify sets of environmental variables that were most strongly correlated 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. Instead, we used a bounded random walk to simulate random series of a_t values that had the same amplitude, variance, and autocorrelation as the smoothed a_t values estimated with the Kalman filter. We added a logistic penalty function to Eq. 2 to bound the random walk to prevent extremely high or extremely low simulated a_t values (Nicolau 2002). The penalty term p_t is:

$$p_t = \frac{I\,m}{1 - e^{-\alpha(-I(a_t - \bar{a}) - \delta)}} \qquad (4)$$

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 chosen to match the variance, amplitude, and autocorrelation of the observed a_t values.

A harvest dynamics function was needed to model the entire chum-salmon life history. Following Eggers (1993), we used the observed data on run size, subsistence, and commercial catch to fit empirical harvest dynamics models. Robust regressions were fit between total catch and run size and between subsistence catch and run size with function lmRobMM in S-plus (Insightful 2001). The intercept of the robust regression on the x axis defines a defacto escapement target (not necessarily the goal specified by managers) and the slope is the 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. This variance may be due to three main sources—natural variability in catchability of fish, imprecision in setting harvest regulations, and non-compliance with those regulations by harvesters (Holt and Peterman 2006).

We did not attempt to model the in-season harvest dynamics of chum salmon. Instead, we used empirically based harvest rules that give preference to meeting escapement targets, subsistence fisheries, and commercial fisheries, in that order. The harvest rule is specified by an escapement target (E, not to be confused with the actual realized spawners, S), a harvest rate for the subsistence fishery (h_s), a harvest rate for the combined subsistence plus commercial fisheries (h_c), and the corresponding variance of the outcome uncertainty (σ_u^2):

$$C_t = h\left(T_t - E\right)e^{u_t} \tag{5}$$

where C_t is catch, and h is either h_s or h_c depending on the fishery, T_t is the total chum salmon return in year t, and u_t~N(0, σ_u^2). The residuals from the robust regressions (above) were converted to multiplicative errors for the purpose of estimating σ_u^2. The units of E, C_t, and T_t are thousands of fish. If the total return is below the escapement target ($T < E$) there is only subsistence catch. Above the escapement target, the total catch (commercial plus subsistence) is calculated from the harvest rate specified by the user, but there is a preference for the subsistence fishery, which is calculated with the subsistence harvest rate (h_s) given in Table 2. The commercial catch is the total catch minus subsistence catch, with no commercial fishery if this difference is negative. Because of outcome uncertainty, 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. The subsistence harvest rate and outcome uncertainty variance were held constant, except for sensitivity analysis of time-varying harvest rules (see below).

The spawner-recruit function (Eq. 1) and harvest-dynamics function were combined in a stochastic life-cycle simulation model (Fig. 2) with random variability included in both functions. The five most recent observed escapement values were used to initialize the model, which was then simulated for 100 years. Analysis of each combination of harvest parameters was repeated with 500 Monte Carlo replicates. The population parameters used in the simulation model are listed in Table 2.

Two types of harvest policies were simulated—time-invariant and time-varying policies. For time-invariant policies, the harvest parameters (escapement target, harvest rate on the population exceeding that target) remained unchanged for the duration of the 100-year simulation. For time-varying harvest policies, the harvest rate remained fixed across years but the escapement target was updated each year in relation to the a_t value (Fig. 2). Each year a new spawner-recruit data pair was obtained. The Kalman filter was used to update the estimate of the a_t parameter, which was then used to solve for the escapement that would generate the maximum sustainable catch (S_m) with the transcendental equation Quinn and Deriso (1999),

$$(1-bS_m)e^{a_t-bS_m}=1\,. \tag{6}$$

This new escapement target was used in the harvest policy the following year.

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 median, mean, coefficient of variation over the 100 years, and a measure of risk. For the spawning stock, the 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 that the subsistence catch was in the lower quartile of the historically observed catches for that stock. Finally, because fishery closures can occur when the run size is too low, the risk measure for the commercial fishery was the percentage of years with no commercial fishery.

Results

The full set of analyses were applied to all five chum salmon stocks. However, the results for the Kuskokwim stock are considered less reliable because of remaining uncertainty in scaling the escapement index from one tributary, Kogrukluk River, to total escapement in the Kuskokwim River system (Doug Molyneaux, ADF&G, Commercial Fish Division, Bethel, Alaska, pers. comm.). Therefore, for Kuskokwim chum salmon, we do not present results of the Kalman-filter-estimated time series of Ricker *a* values, and we caution readers about interpreting other results presented here for Kuskokwim.

Estimated productivity

The Ricker a values estimated with the Kalman filter indicate large-amplitude and significant decadal-scale shifts in productivity (Fig. 3). There is a general pattern of high productivity in the 1970s, after which a values declined in the 1980s and dropped further to the lowest values in the mid-1990s. For brood years 1995-1997, the Andreafsky River a values approach zero, which is the replacement value for the spawning stock (i.e., for $R/S = 1$, $\log_e(R/S) = 0$). Different productivity patterns were observed among stocks (Fig. 3). The a values for the Yukon River and its tributaries increased in the late 1990s with the highest value in the 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.

In our separate Monte Carlo simulations of performance of the parameter estimation method, the Kalman filter was generally able to accurately reconstruct the temporal pattern of input a_t values as estimated from the original fits to the historical data (Fig. 3 dot-dashed lines compared with open circles). The bias in estimating the mean a for each stock ranged from -0.014 to +0.025 percent. However, the Kalman filter tended to smooth the temporal pattern in the a_t values, in some cases underestimating productivity in high-productivity years and overestimating it in low-productivity years. This pattern is shown most clearly in the Yukon River stock in its sharp decline in a_t values in the 1990s (Fig. 3). As a result, the variance of the random walk (σ_w^2 in Eq. 2) was underestimated. The Kalman filter performed better when the temporal change in a_t values was more gradual (e.g. the Kwiniuk and Tubutulik stock).

The Kalman filter decomposes each observed $\log_e(R/S)$ into three components: the productivity, a_t, a density-dependent term, $-bS_t$, and residual uncorrelated error, v_t (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 the 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_w/σ_v) and the Kuskokwim and Kwiniuk and Tubutulik Rivers the lowest (Table 2).

Significant correlations were found between the estimated Ricker *a* values and several environmental variables (Table 3). Productivity was positively correlated with the Pacific Decadal Oscillation (PDO) and negatively correlated with the Arctic Oscillation, which is itself negatively correlated with the PDO. The Ricker *a* values were positively correlated with May sea surface temperature (SST) in the Bering Sea at lags of 0 to 2 years. May SST is positively correlated with the annual PDO ($r = 0.35$). The *a* values were negatively correlated with Nome precipitation at a lag of 1 year, which corresponds to the age of freshwater residence and migration to salt water. Finally, chum salmon productivity was negatively correlated with the run size of East Kamchatka pink salmon, though the associated probabilities were > 0.05 (Table 3).

Harvest functions and outcome uncertainty

The empirical relationships between catch and run size were adequately described with linear relationships, as fit with robust regressions (Fig. 5). The regression lines for total catch (commercial plus subsistence) describe empirical constant-escapement policies; the *x* intercept is the escapement target and the regression slope is the harvest rate on the run exceeding that target. The *x* intercepts are considerably smaller than the ADF&G escapement range (Table 2) and the slopes are substantially less than one, which indicates that the empirical escapement policies differ from the theoretical policy of harvesting all fish above the escapement target (Hilborn and Walters 1992). The variance in the residuals around these total catch-versus-run size functions showed substantial outcome uncertainty, or deviation between the target and realized outcomes (Fig. 6). The Yukon River had the smallest scatter around the regression line (σ_u in Table 2), while 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, for the fall Yukon chum stock (Fig. 5). For the subsistence fisheries, the *x*-intercepts of the regression lines were negative, which is consistent with policies to allow some level of subsistence fishing regardless of run size.

Trade-offs among multiple indicators

The 12 performance measures from simulated harvest policies illustrate the trade-offs among measures of escapement, subsistence, and commercial catch (Fig. 6). Here we illustrate the performance measures for Yukon fall chum salmon, but similar figures exist for the other four stocks (see Appendix). Each of the 12 isopleth diagrams or contour plots in Figure 6 was generated by drawing isolines through the set of 121 values of a given indicator (median escapement, median subsistence catch, etc.) that resulted from running the model sequentially across 121 combinations of management actions (11 different escapement targets and 11 different harvest rates on the number of salmon above those respective 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 management actions, 500 Monte Carlo trials were run and average values of the indicators were used for plotting. A given (x,y) point on a graph corresponds to a particular management option, and that point is the same on all contour plots for the 12 indicators. Thus, the implications for trade-offs among indicators can be explored for any set of actions that managers might wish to explore. For reference across the different performance measures, the vertical gray lines indicate the ADF&G's escapement goal range, and the horizontal gray line is the slope of the total catch versus run size regression ($slope_t$ in Table 2).

The top row of four isopleth diagrams (Fig. 6) shows indicators related to escapement. Realized median and mean escapement increases with increasing escapement target but, in part because of outcome uncertainty, it becomes more difficult to meet escapement targets at high harvest rates. This latter effect causes the diagonal isopleths for median and average escapement. The coefficient of variation (CV, i.e., standard deviation divided by the mean) of escapement over time is fairly uniform and large across most combinations of escapement target and harvest rate, except that the CV increases rapidly with high harvest rates that 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. The isopleths are sloped because higher harvest rates make it more difficult to attain the escapement target.

In the second row of Figure 6, subsistence catches are fairly similar over many combinations of escapement targets and harvest rates because of the preference given to subsistence catches in the harvest rules; the 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 when escapement targets are not met—namely for low escapement targets and high harvest rates.

Indicators in the third row of Figure 6, related to commercial catch, show that, as expected, commercial catch is maximized between ADF&G's escapement-goal range (vertical gray lines) with harvest rate = 1 on fish exceeding the mean of the escapement-goal range (Hilborn and

Walters 1992). However, this maximum is associated with 45-57% of years with no commercial fishery (“bang-bang” control policy of Clark 1985). Therefore, the median commercial catch is maximized at substantially lower escapement targets and harvest rates. The chance of having no commercial fishery is minimized at low escapement targets and intermediate harvest rates. 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, there is no surplus salmon 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 obvious trade-offs between escapement and commercial catch; mean catch is maximized at high harvest rates corresponding to 70-77% of years in which escapement is below the escapement target.

The historical average harvest rate of 58% on the number of Yukon chum salmon above the target escapement appears fairly robust to the range of simulated variability in chum salmon productivity (Fig. 6). Within ADF&G's escapement-goal range of 300 to 600 thousand spawners, escapement goals are met in 25-45% of years, the subsistence fishery is unconstrained, and commercial fisheries would be allowed in 40-61% of years. Moving from the upper to lower bound of the escapement target range would sacrifice some escapement and subsistence catch, but would also increase the commercial catch, while reducing the year-to-year variability in that catch and percentage of years with no commercial fishery.

These are just examples to illustrate how to interpret the contour plots in Figure 6. These plots are intended to allow decision makers to visualize trade-offs in performance measures. The visualization process for Figure 6 can be facilitated by creating an overlay that has one cross-hair plotted at an identical *x-y* coordinate location for each of the 12 contour plots. For example, Peterman (1975) used a transparent plastic overlay. Each cross-hair represents a specific management option defined by a target escapement and a harvest rate on the number of fish that exceed that target. Then the overlay can be moved horizontally and vertically, to allow users to directly read off values of the 12 indicators for a given management strategy.

Depensatory spawner-recruit model

Empirical estimates of the depensation parameter (d in Eq. 3) ranged from 1.5 to 8.1 across our chum stocks. These results indicate that there is some evidence of depensation at low stock size, but that it is not strong except for the Anvik stock. To obtain parameter values for exploring depensation in our simulations, we fixed $d = 5$ and then re-estimated c and A in Eq. 2. These parameters (Table 2) ensured a degree of depensation that would distinguish the performance indicators from those obtained with the standard Ricker model (Fig. 6). With the depensatory spawner-recruit function, the general patterns in the performance measures (Fig. 7) are similar to the case without depensation. The main differences appear at low escapement targets and high harvest rates, where the stock is likely to be reduced to low levels with depensation. If depensation occurs, harvest policies in the upper left corner should be avoided because they are associated with low escapements and catches, high coefficients of variation, and increased chance of not meeting escapement targets and curtailing the fisheries. Projections below 200 thousand spawners in Figure 7 are uncertain because escapements within this range have not been observed.

Time-varying harvest policies

In general, the time-varying harvest policy was unable to improve on the best time-invariant harvest policy (Fig. 8). The primary comparison is between the time-varying baseline policy (solid lines) and the time-invariant policy that had an escapement goal, S_m, that corresponded with the mean Ricker *a* parameter (short-dashed lines). Both of these lines include outcome uncertainty and therefore represent the most realistic situation. For most performance measures, these two lines are very close over the range of harvest rates. Notable exceptions occurred, though. First, the temporal CV of escapement and percent of years when escapement falls below the escapement target were higher for the time-varying harvest policy because the escapement target is being adjusted each year. Second, the risk measures for the subsistence and commercial fisheries were reduced somewhat with the time-varying harvest policy.

To investigate the reasons for the lack of improvement over the time-invariant harvest policy (long dashed lines) associated with the time-varying policy, we did sensitivity analyses by selectively removing the main sources of error. Removing the observation errors alone (i.e., by setting $v_t = 0$) had relatively little effect on most performance measures (not shown).

Removing outcome uncertainty (i.e., by setting $u_t = 0$) had the largest effect on changing the performance measures (long-dashed lines and dotted lines in Fig. 8). The median performance measures all improved substantially, with the difference most pronounced at high harvest rates. Increases were also observed in the mean but only at high harvest rates for the catch measures. With no outcome uncertainty, the harvest policy operated as designed by more frequently meeting escapement targets and keeping subsistence catches relatively high, while transferring recruitment variability into the 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 time-varying (long-dashed lines) and time-invariant (dotted lines) policies were similar for most of the performance measures (Fig. 8). Again though, the CV of escapement and chance of not meeting the escapement target were higher for the time-varying policy, especially at high harvest rates, because the escapement target is adjusted each year. Conversely, the risk measures for the fisheries were reduced with the time-varying policy at low harvest rates for the subsistence fishery and at high harvest rates for the commercial fishery.

Further sensitivity analysis removed all sources of error except variation in the a values by setting both observation errors and outcome uncertainty to zero. In this sensitivity analysis, performance measures (not shown) for the time-varying policy were fairly similar to the case with only the outcome uncertainty removed (long-dashed lines). In summary, outcome uncertainty tends to dominate these performance measures. With the levels of variability in the a values simulated with Equations 2 and 4 and with parameter values in Table 2, the time-varying harvest policies were not able to improve substantively on the time-invariant policies.

Discussion

Our results show 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. Although this change in productivity has been suggested from the decreased abundances of adult returns in that period, the confounding effects of reduced productivity and reduced spawner abundance cannot be separated easily. However, by casting the estimation of parameters of the Ricker stock-recruitment model in the form of a Kalman filter, we estimated observation error variance and process variation separately. The resulting time trends in the smoothed a_t values indicate that the 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) that have 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. gorbushca*), 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. These Kalman filter results also identified a consistent upward trend in productivity starting in the mid-to-late 1990s brood years for the Anvik, Andreafsky, and Yukon fall chum salmon stocks. Data subsequent to the 2000 brood year would be necessary to extend these estimated series to determine whether those increases persisted.

After filtering out the high-frequency noise, the Kalman-filter-estimated Ricker a_t values correlated positively with sea-surface temperature (SST) in May and precipitation at Nome, Alaska, but negatively with the dominant Asian pink salmon stocks from East Kamchatka, Russia. The positive relation between Ricker a_t values and SST at the time of entry of juveniles into the ocean 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. Warmer conditions in the Bering Sea have led to early ice retreat and a later bloom with a large copepod biomass (Macklin and Hunt 2004). Thus, warmer conditions may enhance the feeding, growth, and survival for chum salmon stocks in the AYK region. These correlations are consistent with the hypothesis that chum salmon productivity is primarily determined by ocean survival (Kruse 1998). The negative associations between productivity of AYK chum salmon and abundance of the very abundant East Kamchatka pink salmon stocks suggest competitive interactions with AYK chums, analogous to those found by Ruggerone et al. (2003) for interactions between Asian pink salmon and Alaskan sockeye salmon.

The time-invariant harvest policies (escapement target plus harvest rate) appeared fairly robust to variation in *a* values, in the sense that average escapements, subsistence, and commercial catches could be maintained at high levels relative to past data. These averages, however, belie the large variability, as measured by the CVs and risk measures. With a harvest policy that approximates the existing ADF&G escapement range and historical harvest rate, in about half the years the escapement target would not be met and the commercially fishery would be closed. We found weak evidence of depensation in the stock-recruitment relationships, partly because these chum stocks have not been reduced to the levels at which depensation would become apparent. Thus, it is safe to conclude that the period of reduced productivity in the 1990s was not caused by a depensatory mechanism. The harvest policy simulations with depensation can be used to identify constraint regions (see below) to be avoided to prevent stocks from falling to low levels where depensation might become apparent.

Our simulations of both time-invariant (i.e., fixed escapement target and fixed percentage harvest rates on the fish above that target) and time-varying harvest policies were intended to determine the advantage, if any, of the latter type of policies. Such time-varying policies are commonplace worldwide in fisheries of many marine fish stocks such as groundfish and pelagic fishes (Butterworth 2007; Butterworth and Punt 1999) and are one example of passive adaptive management in which parameters are updated annually as new data come in (Walters 1986).

However, we found in this example that time-varying policies did not improve values of most of the performance indicators. Follow-up work could include analyzing the sensitivity of the time-varying harvest policy to different sources and levels of uncertainty. Different algorithms (alternatives to Eq. 6) could be investigated for updating the harvest policy with respect to the estimated value of a_t.

Outcome uncertainties (sometimes referred to narrowly as implementation errors) had the largest effect on the performance measures. In other words, stock assessment models can be improved along with parameter estimates, but that increased precision and/or accuracy in choice of management regulations can be offset by large variation in the harvesting process such that catches and escapements can deviate substantially from values desired by managers. This result has also been found by other closed-loop simulations that included outcome uncertainty (Peterman et al. 2000; Kell et al. 2005; Dorner et al. 2009). That uncertainty can completely mask improvements in scientific understanding of parameters of underlying dynamic models. Thus, an important conclusion is that considerable effort should be invested in reducing outcome uncertainty through increased enforcement of regulations and improved in-season methods for updating abundance estimates.

A key benefit of our succinct contour plots to 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 easily read off of the contour plots the amount by which one indicator will increase when another decreases by a given amount when a management action is changed (i.e., when the cross-hairs move). Managers can also easily examine the effect of applying constraint regions that reflect unacceptable values of certain indicators. For instance, it may not be acceptable 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 in the lower 25% of values achieved historically. Such constraints would create a limited sub-set of feasible regions in the contour plots for 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 region can result in a large change in one or more indicators, which could lead to more effective negotiations with interest groups. Software is being developed to simplify managers' use of such diagrams with cross-hairs and constraint regions to explore potential impacts of different management actions.

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We are grateful to the people who provided data on AYK chum salmon (Brian Bue, Doug Molyneaux, Dani Evenson, John Clark, Tracy Lingnau, and Bonnie Borba, and Kalai Shotwell), and Asian pink salmon (Greg Ruggerone). Milo Adkison, Michael Jones, and other members of the AYK-SSI Expert Panel on Escapement Goals made constructive comments on an earlier draft. Funding for this project was provided by the Arctic-Yukon-Kuskokwim Sustainable Salmon Initiative (http://www.aykssi.org/), project #708, and the Canada Research Chairs Program (http://www.chairs-chaires.gc.ca/home-accueil-eng.aspx).

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Table 1. 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-August	1
	Pacific Decadal Oscillation, Annual		1
	Alaska Index	Dec-March	1
Temperature	Air Temperature, St. Paul, Winter	Dec-March	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, Pribilofs	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	April-May	2
	Precipitation at Nome	April-May	2
Biotic	East Kamchatka Pink Salmon Returns		3

1. www.berring.climate.noaa.gov/data/index.php

2. www.wrcc.dri.edu/summary/Climsmak.html

3. Gregg Ruggerone, personal communication, Natural Resources Consultants, Inc., 4039 21st Avenue West, Suite 404, Seattle, Washington, USA, 98199.

Table 2. List of stock-specific parameters for salmon simulations. Listed in parentheses are the equations or figures where each parameter is derived or used.

Stock	Kuskokwim	Yukon	Anvik	Andreafsky	Kwiniuk & Tubutulik
$\bar{a}$	1.799	1.046	1.045	1.144	1.026
b	2.608	1.103	1.243	3.171	17.393
σ_v	0.560	0.399	0.478	0.427	0.661
σ_w	0.118	0.283	0.237	0.301	0.183
c	722.3	749.84	778.8	320.4	49.57
A	67.24	163.11	216	63.33	9.79
d	5	5	5	5	5
$slope_t$	0.480	0.583	0.282	0.238	0.516
$inter_t$	-9.393	-101.604	-14.745	-8.025	-9.422
$\sigma_{u,t}$	0.643	0.576	0.639	0.608	0.931
Esc. range	204-665[1]	300-600	350-700	65-130	33.8
$slope_s$	0.0591	0.157	0.0124	NA	0.00559
$inter_s$	37.615	34.979	24.642	NA	1.25
$\sigma_{u,s}$	0.364	0.490	0.206	NA	0.690
$0.25C_s$	39.97	24.346	23.747	NA	0.298

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)

Parameters of the depensatory Beverton-Holt function (Eq.

c maximum recruitment (Eq. 3)
A escapement level at which recruitment is one-half the maximum (Eq. 3)
d exponent that determines the degree of depensation (Eq. 3)

Parameters of the total harvest

$slope_t$ slope of the total catch vs. run size from robust regression (Fig. 5)
$inter_t$ y-axis intercept of the total catch vs. run size from robust regression (Fig. 5)
$\sigma_{u,t}$ standard deviation of outcome uncertainty for total catch (Eq. 5)
Esc. range ADF&G escapement target or range in thousands of fish (Fig. 6, 7)

Parameters of the subsistence harvest

$slope_s$ slope of the subsistence catch vs. run size from robust regression (Fig. 5)
$inter_s$ y-axis intercept of the subsistence catch vs. run size from robust regression (Fig. 5)
$\sigma_{u,s}$ standard deviation of outcome uncertainty for subsistence catch (Eq. 5)
$0.25C_s$ lower quartile of the historically observed subsistence catches (Fig. 6, 7, 8)

Table 3. Stepwise regressions of Ricker *a* values on environmental variables. Variables were retained according to the minimum Akaike Information Criterion. Top number for each variable is the lag period in years from the brood year; middle number is the regression coefficient; bottom number is the probability.

Variable	Kwiniuk & Tubutulik	Yukon	Andreafsky	Anvik	Kuskokwim
Arctic Oscillation, winter					
lag					1
coefficient					-0.094
probability					0.09
PDO, annual					
lag			3	3	
coefficient			0.281	0.376	
probability			0.039	<0.001	
May SST, SE Bering Sea					
lag	0	2	2		
coefficient	0.233	0.115	0.215		
probability	0.002	0.067	0.031		
Wind mixing, Mooring 2					
lag					2
coefficient					0.130
probability					0.032
Nome precipitation					
lag	1	1	1		
coefficient	-0.164	-0.177	-0.205		
probability	0.023	0.008	0.046		
Kamchatka pink salmon					
lag	0	1	0		0
coefficient	-0.004	-0.003	-0.006		-0.002
probability	0.063	0.069	0.076		0.178
Adjusted R^2 (%)	39	40	37	32	30

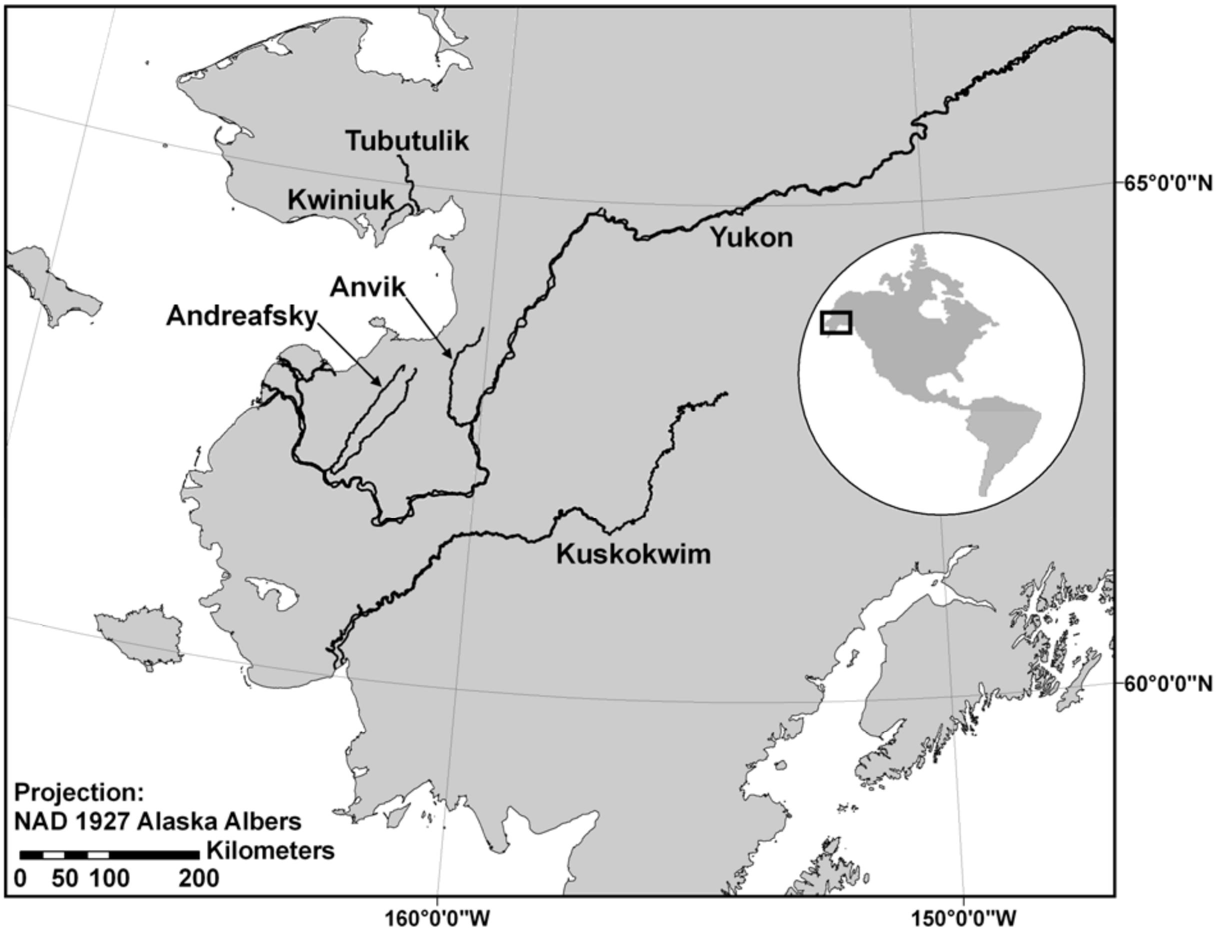

Figure 1. Map of the Arctic-Yukon-Kuskokwim region showing locations of chum salmon stocks used in this study. Map data from www.rivers.gov/maps.html.

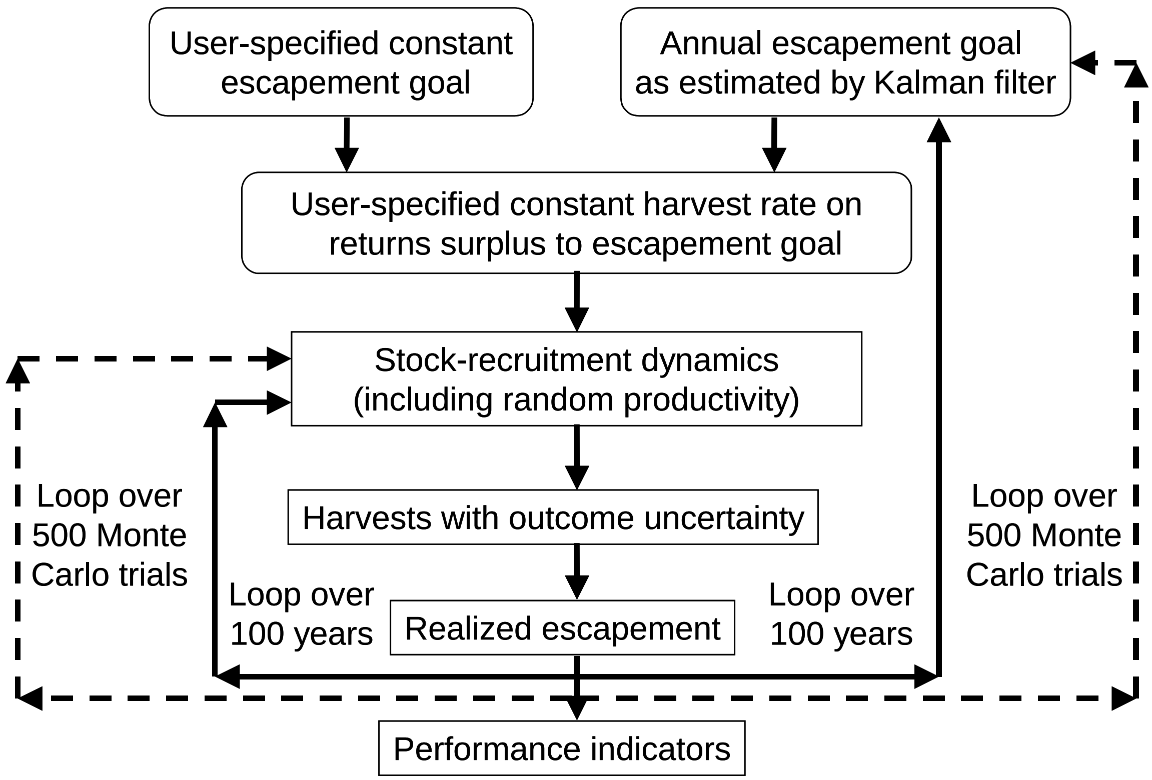

Figure 2. Simulation framework and flowchart for the salmon life-cycle model. Starting with a "user-specified constant escapement goal," the arrows in the middle and to the left define the time-invariant harvest policy. Starting with an "annual escapement goal as estimated by Kalman filter," the arrows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

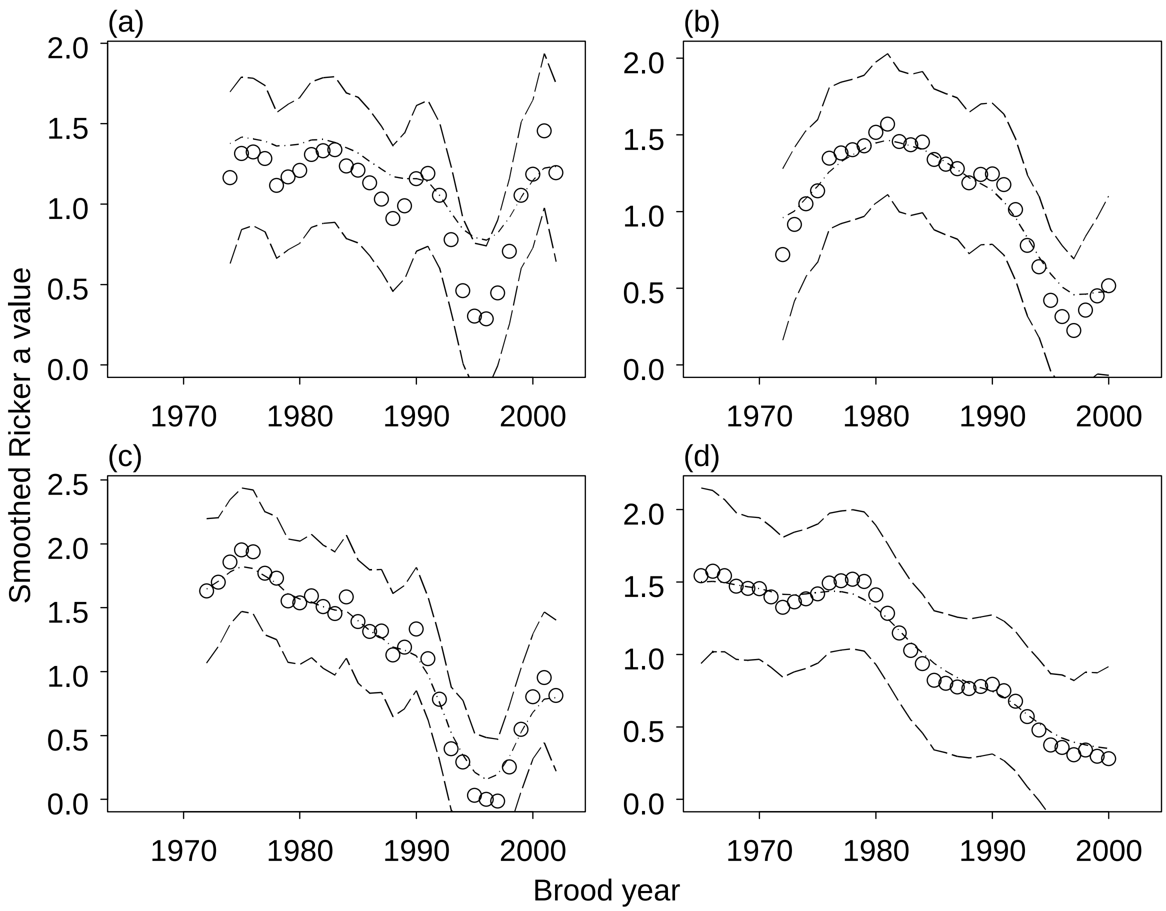

Figure 3. Estimates of smoothed Ricker *a* values (dots) and their 95% probability intervals (dashed lines) across years of spawning (brood years). The dot-dashed lines in the center are means of 500 Monte Carlo simulations of the Kalman filter estimation with the dots being the true underlying values as estimated from the original data. (a) Fall Yukon, (b) Anvik, (c) Andreafsky, (d) Kwiniuk and Tubutulik.

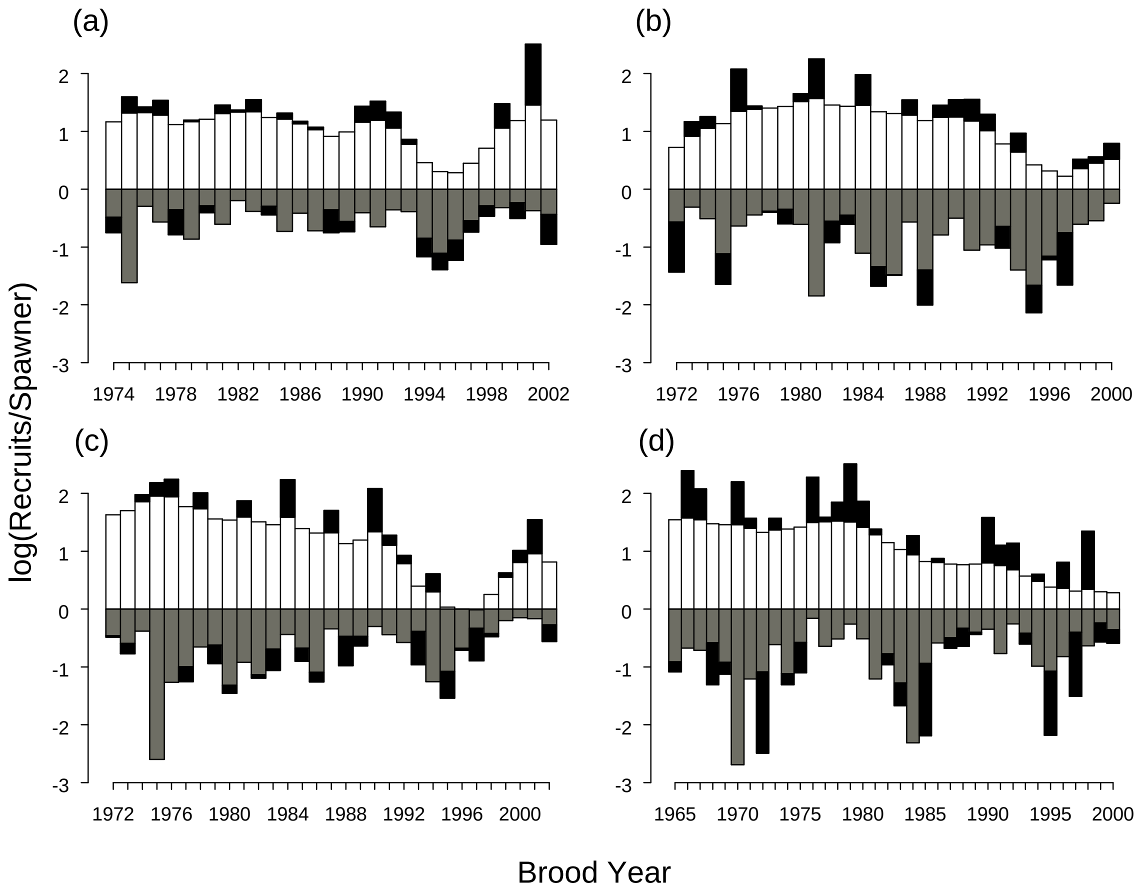

Figure 4. Components of recruitment variation as estimated by Eq. 1. White bars are the estimated a_t values; gray bars are the density-dependent term, bS_t; and black bars are observation errors, v_t. The sum of the bars for each brood year is the observed $\log_e$(Recruits/Spawner). (a) Fall Yukon,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

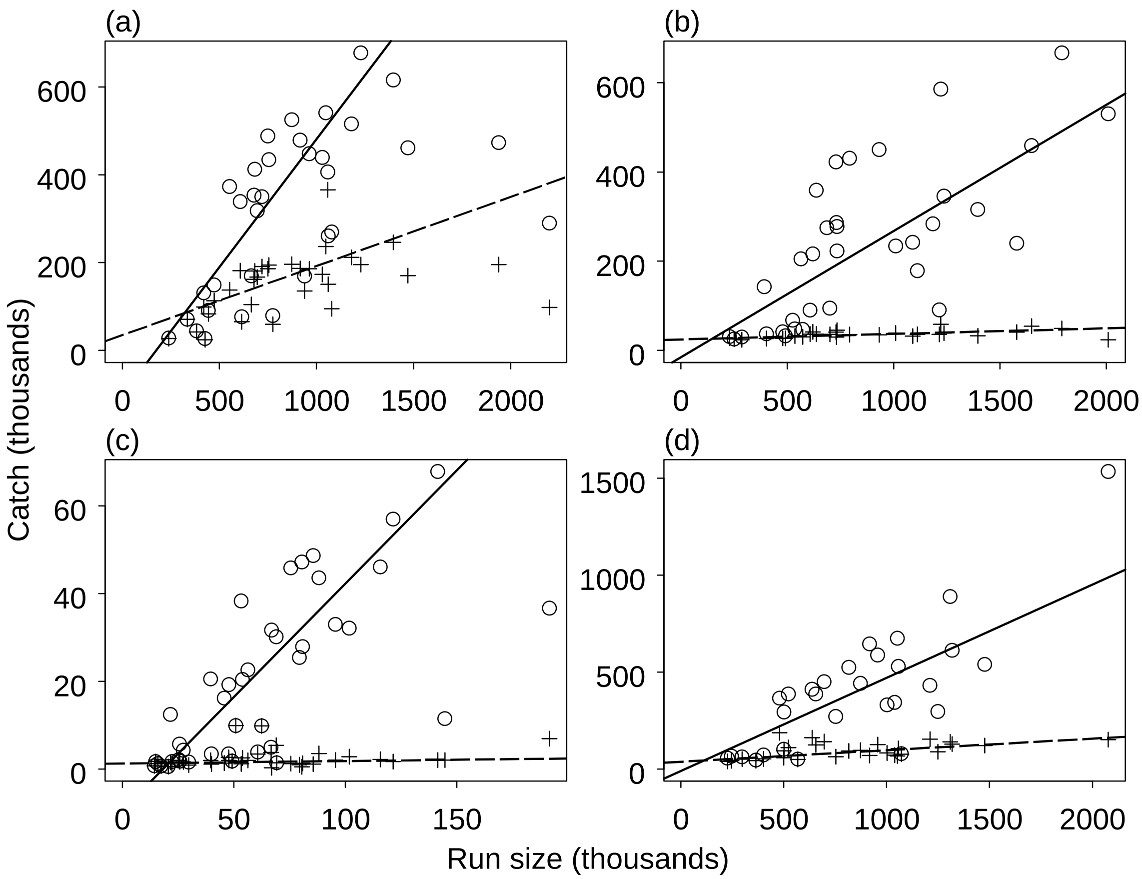

Figure 5. Observed subsistence (+) and total of commercial plus subsistence (○) chum salmon catches as a function of run size. The straight lines are robust regression fits of catch on run size. Variability of data around the lines reflects outcome uncertainty. (a) Fall Yukon, (b) Anvik, (c) Kwiniuk and Tubutulik, (d) Kuskokwim. From the available data, it was not possible partition the subsistence component of the Andreafsky chum fishery.

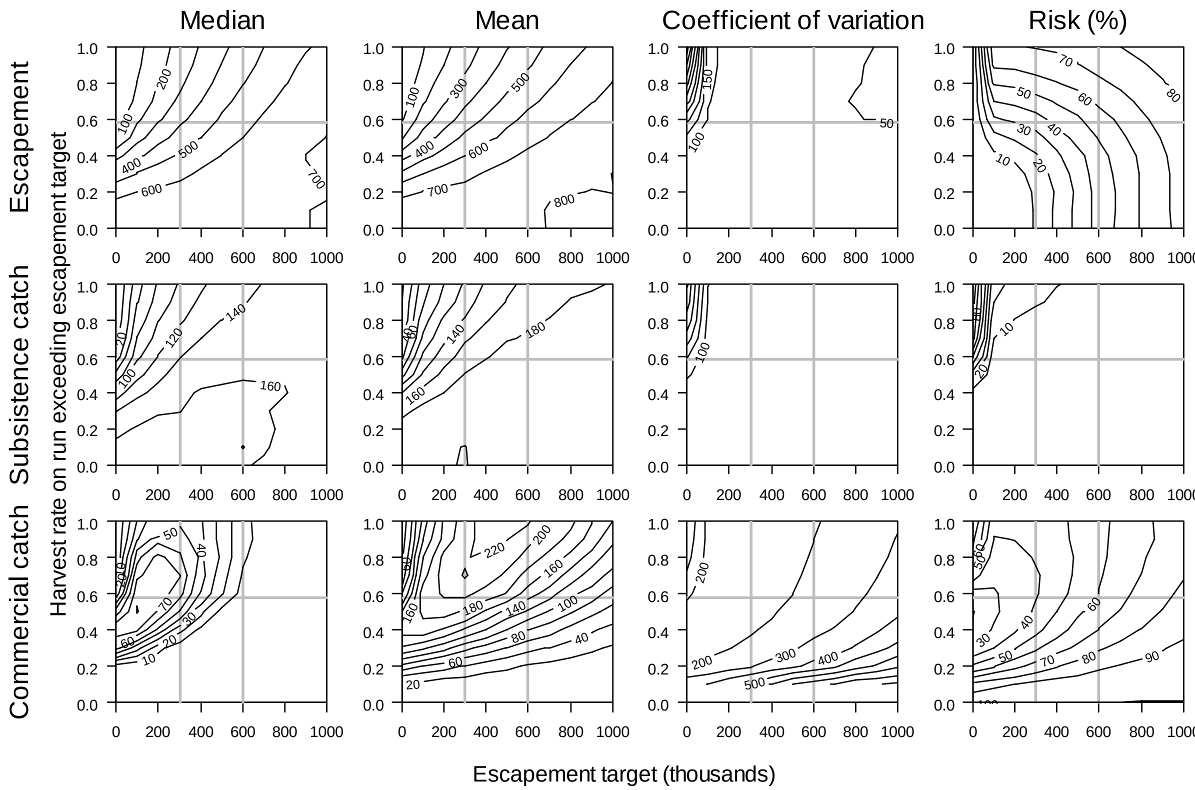

Figure 6. Performance measures for Yukon River fall chum salmon. Each combination of escapement target and harvest rate describes one time-invariant harvest policy. The vertical gray lines represent the current escapement-goal range for this stock; the horizontal gray line is the average observed harvest rate. The median and 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: 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 insufficient number of returning adults. All performance measures were averaged over 500 Monte Carlo trials.

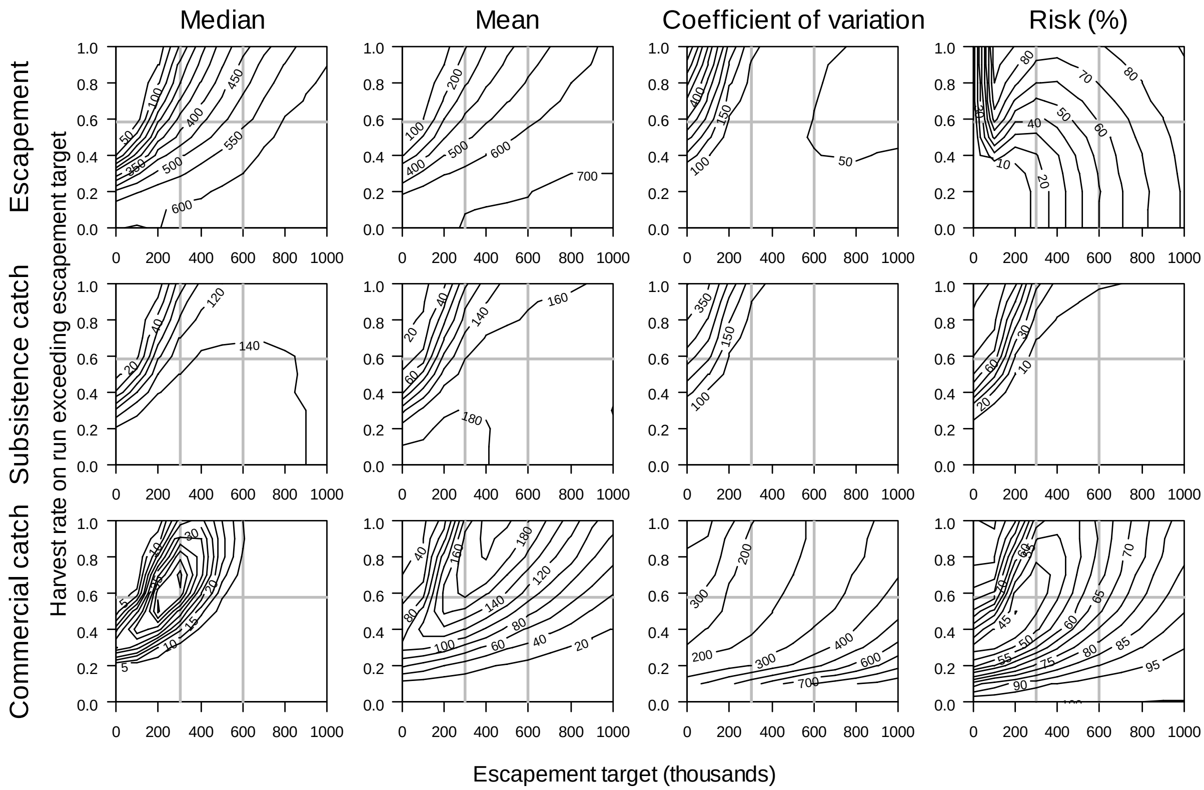

Figure 7. Performance measures for time-invariant harvest policies applied to Yukon River fall chum salmon with a depensatory stock-recruitment model (Eq. 3), as opposed to the non-depensatory model in Figure 6. The plot features are as described in the caption for Figure 6.

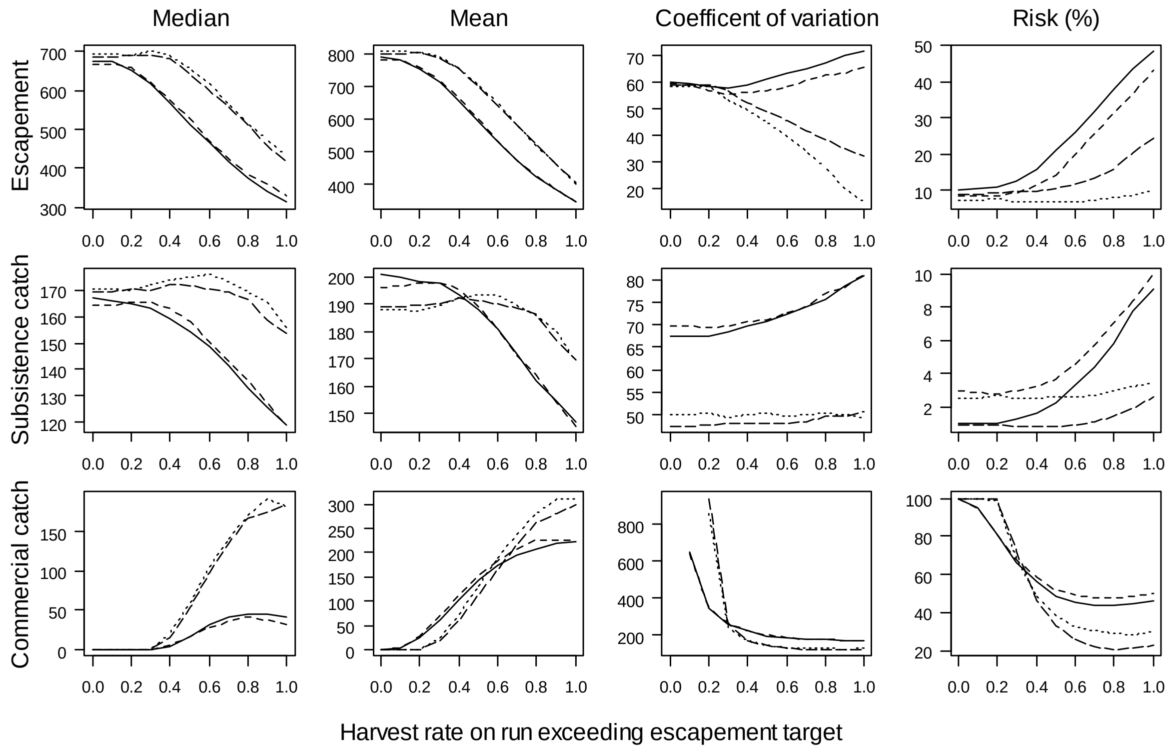

Figure 8. Performance measures for the time-varying and time-invariant harvest policies for Yukon River fall chum salmon. The time-varying harvest policies update the escapement target each year in response to the most recent estimate of the Ricker a_t value; the time-invariant policies use the escapement target S_m corresponding with the mean Ricker a_t value. The scenarios are: time-varying harvest policy with outcome uncertainty (solid line), time-invariant harvest policy with outcome uncertainty (short-dashed line), time-varying harvest policy without outcome uncertainty (long-dashed line), and time-invariant harvest policy without outcome uncertainty (dotted line). The 12 measures are in units defined in Figure 6.

Appendix

Contour plots of 12 performance indicators for four other populations of chum salmon in the AYK region: Andreafsky (Figure A1), Anvik (Figure A2), Kuskokwim (Figure A3), Kwiniuk and Tubutulik (Figure A4). See Figure 6 for full explanation of performance measures and *x* and *y* axes.

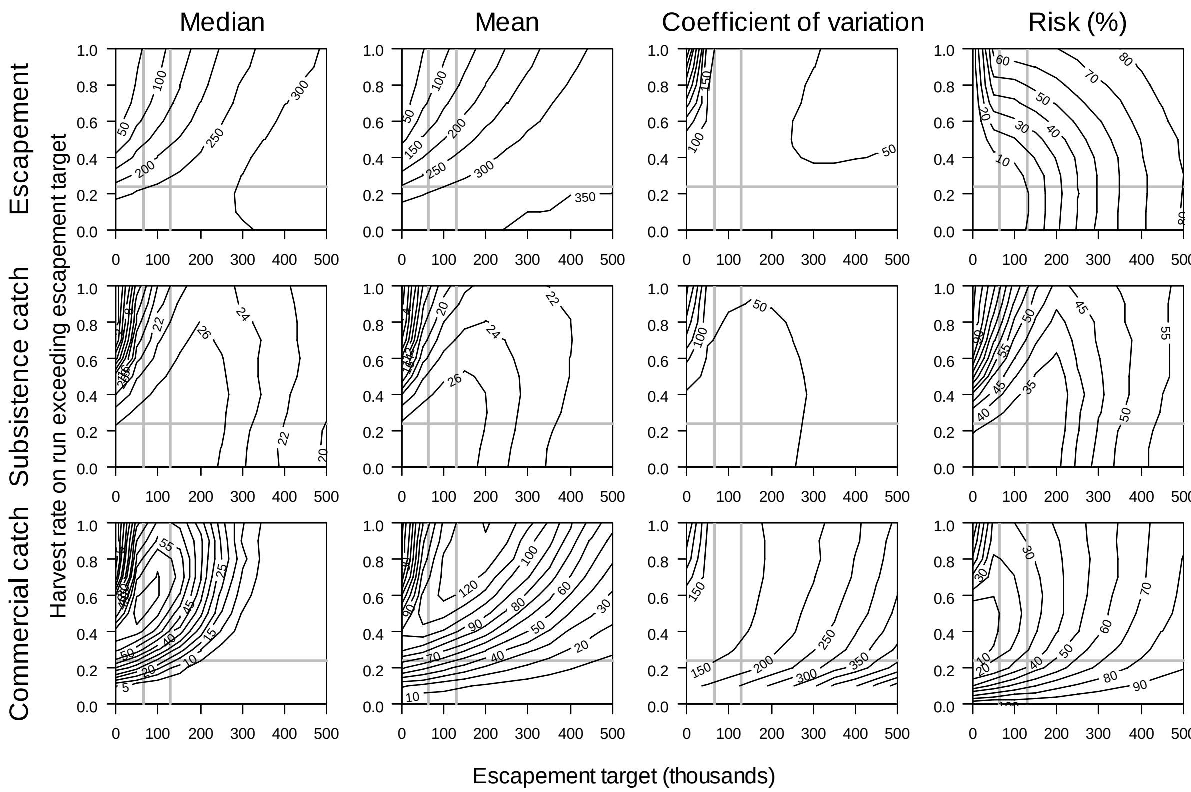

Figure A1. Performance measures for timeinvariant harvest policies applied to Adreafsky River chum salmon.

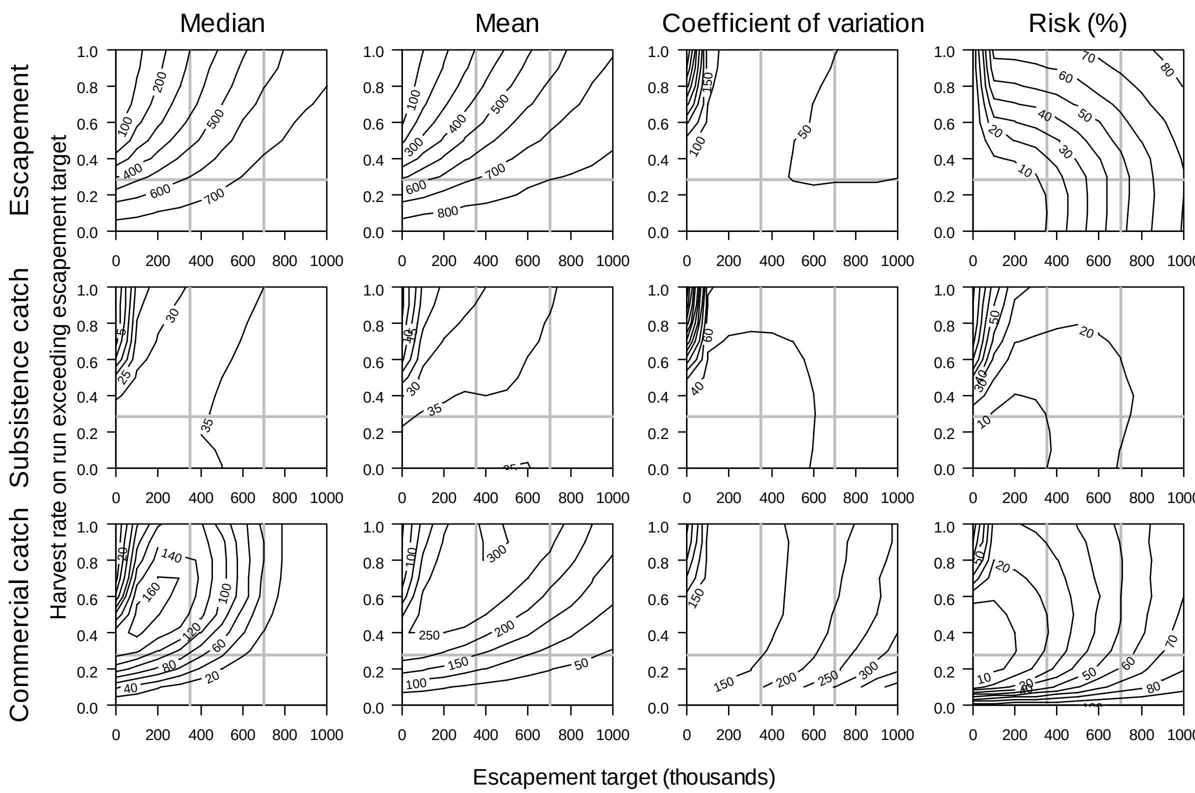

Figure A2. Performance measures for time-invariant harvest policies applied to Anvik River chum salmon.

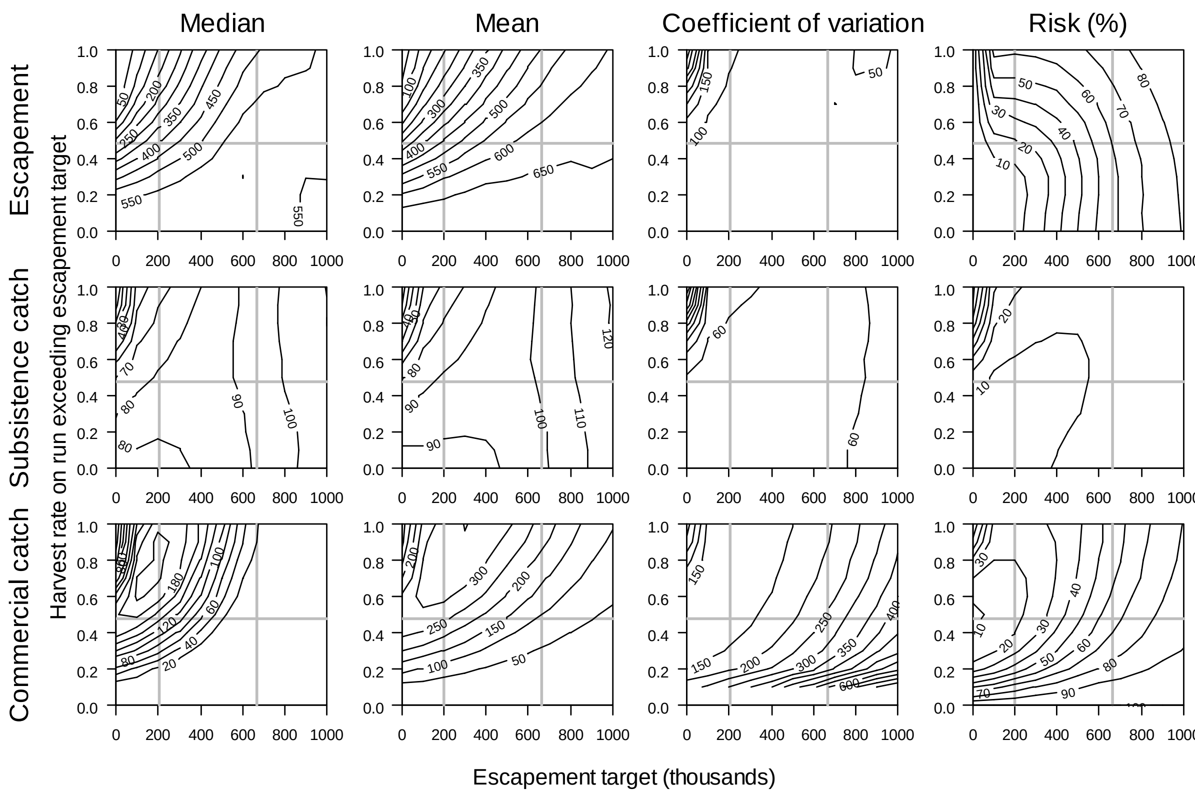

Figure A3. Performance measures for time-invariant harvest policies applied to Kuskokwim River chum salmon.

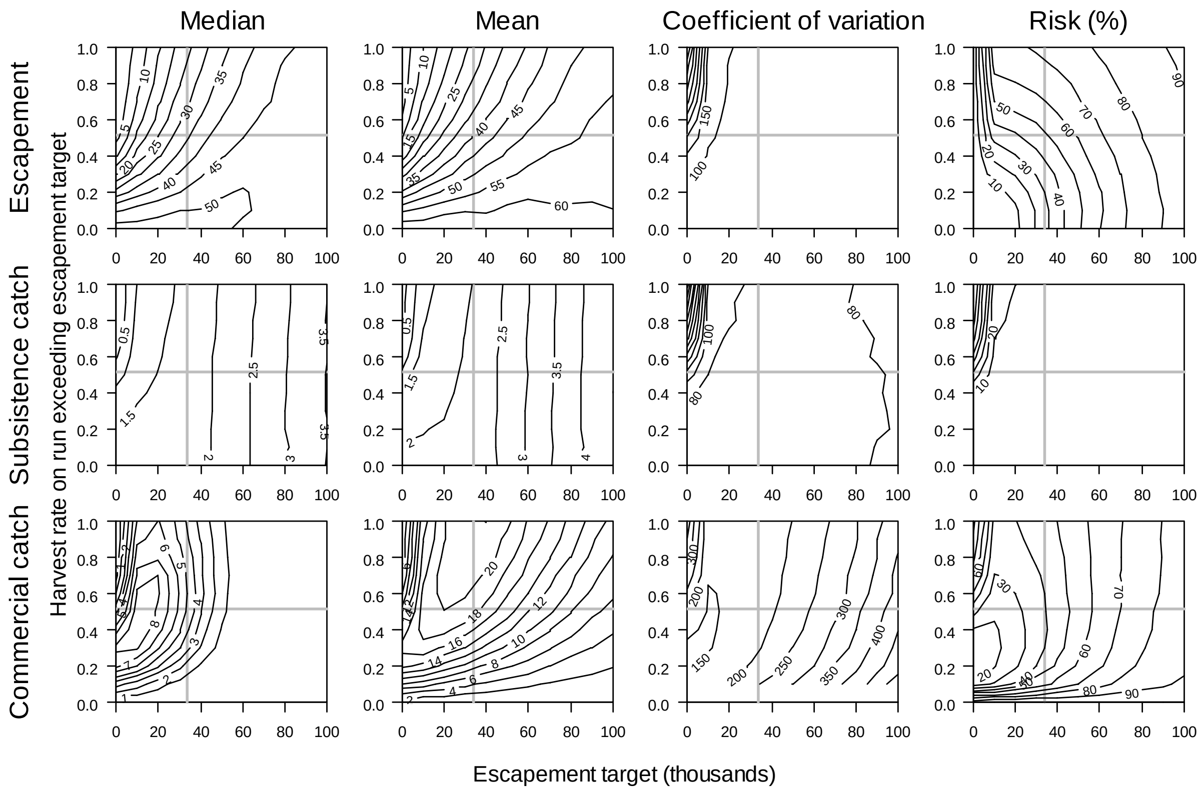

Figure A4. Performance measures for time-invariant harvest policies applied to Kwiniuk and Tubutulik River chum salmon.

(AYKPaperD9)