Prospective Analysis
of Spring Chinook of the Snake River Basin

by Rick Deriso with assistance by
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April 1997

The low recent numbers of spring chinook spawners in the Snake River basin is a source of concern to many. Their fate depends on their ability to withstand many sources of mortality in the future. Of particular interest to the PATH group is the chinook's down-river passage mortality through the dam systems of the Snake River and Columbia River. We are interested in the degree to which passage mortality affects the fate of chinook. To address this issue, we develop a prospective analysis of chinook abundance for seven populations of the Snake River basin. The prospective analysis is the result of three workshops devoted to the issue in which several PATH members contributed substantial data, ideas, and concepts to the development of the current model and analysis.

Our evaluation of the fate of chinook takes into account two major kinds of uncertainties. Firstly, there are many alternative hypotheses about the dynamics of chinook and about their past levels of mortality. Secondly, future of chinook will be affected by many types of variability; some arising from basic stochasticity about the mean response of the populations to changes in spawner levels, but others because of variability in down-river passage mortality, and variability in harvest rates and other components of the chinook's returning up-river survival. We address both types of uncertainties in our analysis by employing a Bayesian statistical approach to the problem. The Bayesian approach has been found to be useful for many fisheries problems, as for example in the review paper by Punt and Hilborn (1997).

The Bayesian approach allows for the calculation of the probability distribution for alternative hypotheses about Chinook population dynamics by admitting uncertainty about the fundamental parameters governing our model of their dynamics. The admission of uncertainty extends over all 88 parameters of the model, which include parameters describing common year-effects (such as some portion of ocean mortality) that affect all analyzed chinook populations, parameters quantifying annual in-river passage mortality, parameters affecting the shape of a generalized three-parameter spawner-recruit model, and the overall process variance about the model.

Uncertainties about future events affecting chinook are addressed by development of a population projection model which contains many sources of stochasticity. Stochasticity is included foremost by the admission of a stochastic relationship between spawners and resultant recruits and by the admission of uncertainty about fundamental parameters governing their dynamics. Additional uncertainty is included by varying the time sequence of "year-effects", the initial-condition spawning stock abundance, and the time sequence of water transit times through the Columbia and consequent relation to in-river passage mortality. A number of sensitivity analyses are also presented where structural changes are made to either the input data or to the basic model framework.

Prospective analysis builds upon the model structures developed in the retrospective analysis (Deriso, Marmorek, and Parnell 1996) . In particular, the maximum likelihood models (MLE) developed in that paper provide a means to set up a Bayesian model (BSM) for the current problem. As in the MLE model, the current BSM model is based on analysis of spawner and recruitment data for thirteen spring/summer chinook stocks of the Columbia River. The model framework relies on a generalized Ricker spawner-recruit model in which the generalization is the incorporation of an additional parameter to allow for depensatory mortality at low spawning stock levels. Probability calculations are made by combining the generalized MLE model with a Monte Carlo Markov Chain (MCMC) algorithm and a population projection model. The resultant model framework produces probability estimates of stock recovery and survival as prescribed by the NMFS jeopardy standard criteria listed in Appendix I.

Methods

Spring and Summer Chinook Salmon Populations Examined (excerpt from Chapter 5)

Thirteen populations of Chinook salmon were analyzed in this study. They represent three down-river subbasins — those of the Wind River, Klickitat River , and Warm Springs River ; three populations in the John Day subbasin system — the John Day Main-stem, John Day Middle Fork, and John Day North Fork; and seven up-river subbasins all branching from the Snake River — those of the Imnaha, Minam, Bear Valley, Marsh Creek, Sulphur Creek, Poverty Flats, and Johnson Flats Rivers. Those thirteen populations represent the total number of populations on the lower to middle Columbia River system and Snake River system for which time series of spawner and recruitment information were available. Additional population time series are available for the Upper Columbia River, which we plan to analyze in a future report. Table 1 summarizes the number of main-river dams located below each river subbasin along with the number of years of spawner and recruitment information available.

Each of these subbasins are described in the report by Schaller and Petrosky (1996), and in more detail in Petrosky et al. (1995).

Table 1: Summary information on the thirteen chinook populations analyzed in this study.

Sub-basin	Brood Years of Paired Spawner-recruit Data	Number of Main-stem Dams Below Sub-basin
1. Wind	1973 - 1990	1
2. Klickitat	1966 - 1990	1
3. Springs	1969 - 1990	2
4. John Day Mainstem	1959 - 1990	3
5. John Day Mid Fork	1959 - 1990	3
6. John Day North Fork	1959 - 1990	3
7. Imnaha	1952 - 1990	8
8. Minam	1954 - 1990	8
9. Bear Valley	1957 - 1990	8
10. Marsh Creek	1957 - 1990	8
11. Sulphur Creek	1957 - 1990	8
12. Poverty Flat	1957 - 1990	8
13. Johnson Flat	1957 - 1990	8

Bayesian Model (BSM)

The Bayesian model is a method in which a generalized Ricker spawner-recruit (S-R) model is fitted to observations then population projections are made. The fitting of the model and the projections of the model are linked together by probability distributions for the parameters of the model, in which the distributions are based on the likelihood of the observations. The S-R model is described followed by a description of the method for calculation of probability distributions, and then followed by a description of the population projection model. Basic data and likelihood method of fitting observations to the model were described previously (Deriso *et al.* 1996).

Generalized Ricker Spawner-Recruit Model

The population model is based on Ricker type spawner-recruitment model, similar in structure to the Ricker models used in Deriso *et al.* (1996), except generalized to allow for depensatory mortality at low spawner levels, which can be written in generic form:

$$R = \alpha \beta S^{(1+p)} \boldsymbol{e}^{-\beta S}$$

Depensatory mortality occurs for low spawner values when $p>0$. The β and α parameters represent benchmark spawner-inverse and recruitment values: when $S=1/\beta$ and $p=0$ then $R=\alpha\, e^{-1}$, the maximum recruitment possible with the standard Ricker model. Therefore, α is e^{1} times the maximum recruitment of a Ricker model.

The year and area-specific terms of the S-R model are better seen in the logarithmic form of the model:

$$\ln(R_{t,i}) = a_i + \delta_t - m_{t,i} + \ln(\beta_i) + (1+p)\ln(S_{t,i}) - \beta_i S_{t,i} + \varepsilon_{t,i} \qquad (1)$$

Where:

	$R_{t,i}$	=	observed returns (recruitment) originating from spawning in year t and river sub-basin i,
	$S_{t,i}$	=	observed spawning in year t and river sub-basin i,
	a_i	=	transformed Ricker α parameter, which depends on river sub-basin i,
	β_i	=	Ricker β parameter, which depends on river sub-basin i,
	$m_{t,i}$	=	in-river passage mortality which depends on year t and river i,
	$\varepsilon_{t,i}$	=	normally distributed mixed process error and recruitment measurement error term N $(0,V_{\varepsilon})$
	p	=	depensation parameter ($p > 0$), and
	δ_t	=	year-effect parameter in year t.

In-river passage mortality $m_{t,i}$ is described by a two-level parameterization scheme as in the MLE model:

$$m_{t,i} = X{*}n + \mu_t$$

where n is the number of first level dams, X is the dam passage mortality per first level dam, and μ_t is the net dam passage mortality from the Snake River subbasins to John Day dam expressed as an instantaneous mortality rate for brood years t ≥ 1970. The μ term is a "net" effect mortality estimate because it reflects the overall impacts of dam passage over the complete life cycle, including the benefits of transportation by barge of some Snake River smolts down-river to below the Bonneville dam. The first level (number n of X's in each row of Table 2 below) treats mortality as a process proportional to the number of dams passed by a salmon during their transit to the ocean, excluding those dams and/or populations treated in the second level. At the second level (Y in Table 2) the incremental mortality experienced by upstream stocks is estimated by μ_t, which is usually estimated as a positive values, but it can sometimes be a negative value as for example when net benefit of barge transportation induces a total passage mortality below that experienced by down-river populations. Mortality in any given year for any given population is obtained in Table 2 by adding the number of Xs (number of first level dams passed) plus a second level annual term provided at least one Y is listed. A symbol is first listed on the diagram for a given dam for the year of initial service (lagged two years to standardize to brood year).

Table 2: Types of passage mortality estimates. (X = fixed estimate of mortality/dam; Y = annually varying estimates of mortality due to passage through 5 dams; BON = Bonneville; TDD = Dalles; JDA = John Day; McN = McNary; IHR = Ice Harbor; LOMO = Lower Monumental; LGS = Little Goose; LGR = Lower Granite) (adapted from Deriso *et al.* 1996).

	DAMS							
Brood Year	**BON**	**TDD**	**JDA**	**McN**	**IHR**	**LOMO**	**LGS**	**LGR**
1952 - 1954	X			X				
1955 - 1958	X	X		X				
1959 - 1965	X	X		X	X			
1966	X	X	X	X	X			
1967	X	X	X	X	X	X		
1968 -1969	X	X	X	X	X	X	X	
1970 - 1972	X	X	X	Y	Y	Y	Y	
1973 - present	X	X	X	Y	Y	Y	Y	Y

The population model (1) contains the potential for depensatory mortality at low spawner levels whenever (p>>0). In applications presented later, the likelihood of such mortality is quite low. A weakness of this approach is that the likelihood only evaluates the potential for depensatory mortality within the range of observed data. It is possible that at spawning levels below those observed in the past, depensation could occur. To address that possibility, a further level of depensation was added to the model (1) for a sensitivity analysis presented later. This additional depensation is modeled by assuming that recruitment survival (as given by R/S) declines below minimum observed spawning levels at a rate different than that given in (1). Specifically, this possibility is written as the equation,

$$R/S = R(\textit{as given in equation 1})^* \, (S/S_{min})^d \text{ for } S < S_{min} .$$

Figure 1 (a, b) show the different types of spawner-recruitment curves one obtains as the parameter d is varied. When d is set to zero then we obtain the original model (1).

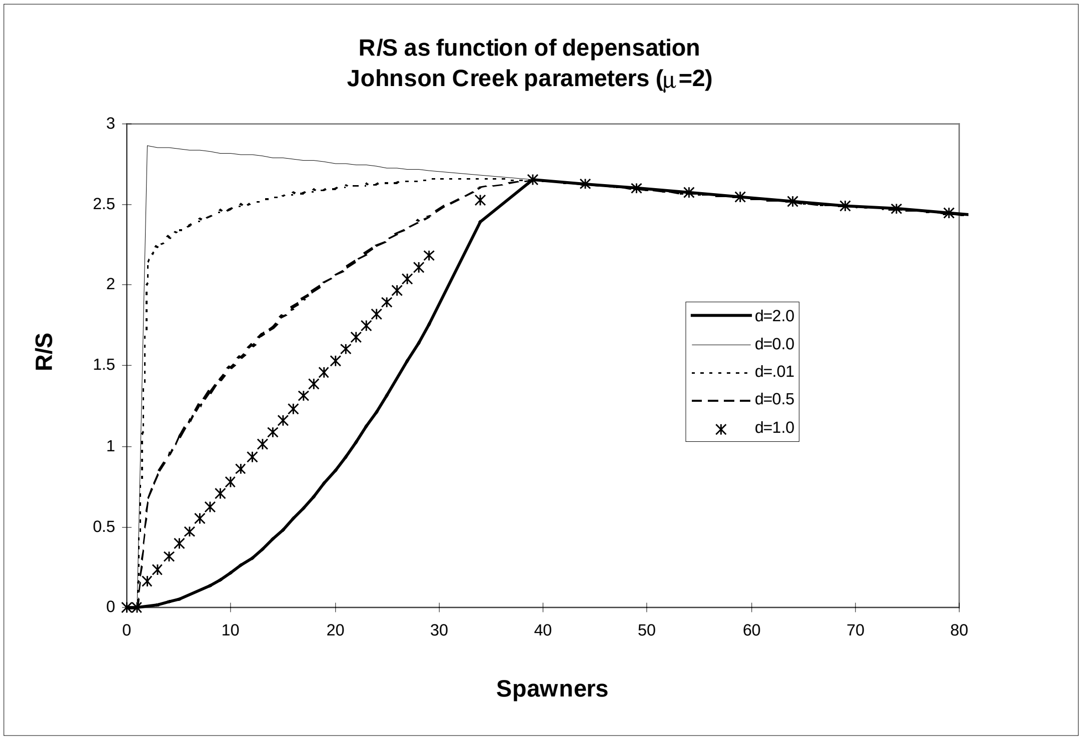

Figure 1(a): Recruitment survival (R/S) at low numbers of spawners for Johnson Creek. Spawner-recruit parameters are MLE estimates with parameter μ set to 2.0.

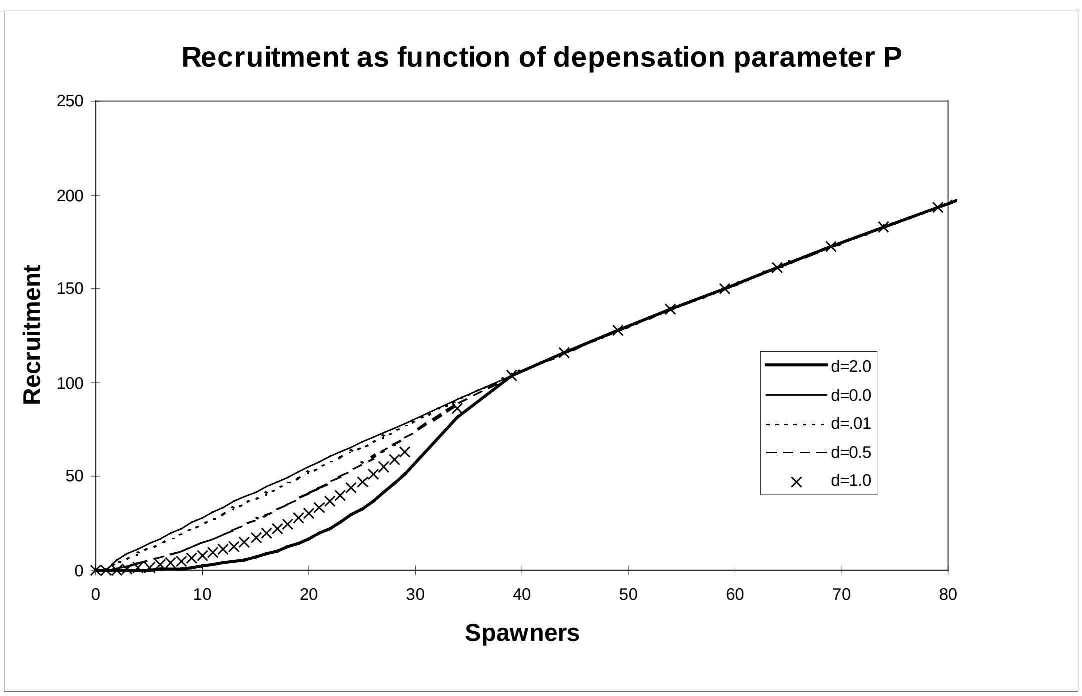

Figure 1(b): Recruitment at low numbers of spawners for Johnson Creek. Spawner-recruit parameters are MLE estimates with parameter μ set to 2.0.

Minimum observed spawning levels during years in which the likelihood function is calculated are given later in Table 5 along with other quantities of interest.

Bayesian Structure

Bayesian statistical conclusions about the probability of future events rely on two components: (1) probability statements about the parameters governing the population dynamics process; (2) probability statements about the population projections into the future conditional on a given set of parameter values. The first component, probability statements about parameters, is given by the posterior probability $p(\theta \mid \text{data})$ of the parameters, which is proportional to the likelihood $p(\text{data} \mid \theta)$ of the observed data and the prior distribution $p(\theta)$ for the parameters. In particular,

$$p(\theta|data) \propto p(\theta)\, p(data|\theta)$$

where the parameter vector θ contains 88 parameters for the application in this paper, which are δ's (year-effects) for brood years 1952-1989, μ's (Snake River to John Day passage mortality) for brood years 1970-1990, river-specific S-R parameters a, β, plus a first-level dam mortality parameter, the depensation parameter p, and a process error variance V_ε. Those parameters are all implemented in the Bayesian analysis as written in equation (1), except for the S-R parameters (β, p) and process error variance V_ε which are written on logarithmic scale. Note that the arithmetic scale chosen for the passage mortalities allows those parameters to take on either positive or negative values so that it is feasible (although it seldom occurred in application) that in some projected years, passage mortality actually benefits the population.

The uniform probability distribution U(-∞, ∞) is used for the prior distribution for all linear parameters (linear as described below); uniform U(-12,12) were used for prior distributions for the other parameters, where the number "12" is sufficiently large to allow parameters to span a range of meaningful values. The likelihood function for the problem is described in our retrospective paper; briefly, it is the normal likelihood function associated with equation (1). The second component to the Bayesian approach, regarding population projections, is described in detail below.

The two components interact in the following manner. First a random sample is drawn from the posterior probability of the parameters. A 100-year population projection is made with those parameters. Several annual sources of variation are introduced in that projection, as described later in the paper. This two-step process (select parameter from posterior then project) is repeated several thousands of times to insure good coverage of the posterior distribution and random distributions used in the projections.

The MCMC algorithm designed for this analysis takes advantage of the partial linear structure of the model. In particular, the year-effects parameters, the passage mortality rate parameters, and the S-R model a parameters occur linearly in the model. A two-step MCMC algorithm was constructed so that Gibbs steps are taken for the linear parameters (a conditional, multivariate normal posterior distribution is calculated) and Metropolis steps (with normal jump functions) are taken for the other parameters (Gelman *et al.* 1995). The MCMC approach works by forming a Markov chain of parameter values selected from the posterior distribution. The chain is calculated by stepping through the parameter space to obtain updates of parameters, which form the next step of the chain. The chain is updated 41,000 times in our application to insure good coverage of the posterior distribution. The first 1000 chain steps are not used to calculate posterior probabilities (the so-called "burn in" initialization period) and every 5th step thereafter is used as a sample from the cumulative distribution functions of the posterior distributions. Thus, 8000 samples are utilized. Several tests were made to insure convergence of the chain with respect to calculation of jeopardy standards; good convergence is expected because the model (1) could be written as a linear model (conditional on V_ε) if not for the log transformation applied to keep β and p within biologically feasible ranges.

Population Projections Model

At present population projections are made for the seven Snake River chinook populations listed in Table 1 (stocks indexed 7-13). An overview of the general structure of the model is provided here. The projection model calculates posterior probabilities of survival and recovery in accordance with NMFS jeopardy standards listed in Appendix I. Each projection is made for 100 years beginning with 1996 as the first year of projection of spawner abundance. The initial values required to initiate each projection are based on projected age-specific returns for brood years beginning in 1991, except where actual estimates of returns are available. In each projected year, spawners $S_{t,i}$ are calculated as

$$S_{t,i} = \Sigma_a \; f_{t,a,i} \;\; s_{t,i} \, R_{t-a,i} \tag{2}$$

in which a fraction $f_{t,a,i}$ of total recruitment $R_{t-a,i}$ produced in brood year t-a returns in year t, and experiences an up-river survival to the spawning ground of $s_{t,i}$; the a subscript denotes age and the i subscript denotes sub-basin. Age 3 year-olds of the recruitment are not included in the spawning calculation because they are all males whereas the spawners in the model are taken to be an index of female spawners. Projected recruitment is based on equation (1) in which the "year-effects" and in-river passage mortalities are selected according to the rules described below. The stochasticity in the projections with equation (1) is smaller than characterized by the variance V_ε because of the removal of measurement error, as described below. The 100 year population projections are made 8000 times, one each for a sample from the posterior probabilities of the parameters, as discussed in the Section above.

A description of each component of the population projection model follows below.

Up-river survival of Recruits: the $s_{t,i}$ term in (2).

Many types of losses affect returning adults to the Columbia system. The losses can be placed in three categories: (1) a conversion factor from Bonneville dam through Lower Granite dam, which accounts for all non-fishery related losses of Snake River chinook during their up-river passage, (2) an exploitation fraction, which is the total loss of chinook due to in-river fisheries, (3) pre-spawn mortality, which accounts for non-fishery losses between Lower Granite dam and spawning grounds. The product of the conversion factor and (1 - exploitation fraction) and (1 - pre spawn mortality) equals up-river the survival fraction $s_{t,i}$. The three components are addressed separately.

Estimates of conversion rates were provided by H. Schaller in the form of an Excel worksheet and they are shown in Table 3. Based on analyses made by C. Paulsen in his memo dated Jan 6, 1997, the conversion rates in the population projections were chosen by random selection from conversion estimates from recent years. By inspection of loess regression plots, I decided to use the conversion estimates from the years 1985-1995 for the base case. Within that 11 year time frame, there is no significant autocorrelation in conversion estimates for Middle Fork or South Fork chinooks of the Snake River. More recent estimates for 1996 have not been structured in the form of Table 3, but they indicate a decline in conversion rates to values somewhat similar to the ones for 1995.

Table 3: Conversion rates for spring and summer chinook index stocks
(H. Schaller, unpublished data in SPRPROSS11.XLS)

Year	*Minam River*	*Imnaha River*	*John Day River(1)*	*Middle Fork(2)*	*South Fork(3)*	*Warm Springs*	*Klickitat River*	*Wind River*
1949								
1950								
1951								
1952		1.000						
1953		1.000						
1954	0.585	0.680						
1955	0.489	0.716						
1956	0.264	0.622						
1957	0.796	0.853						
1958	0.831	0.794						
1959	0.717	0.782	0.847	0.717	0.847			
1960	0.826	0.866	0.909	0.826	0.906			
1961	0.757	0.720	0.870	0.757	0.683			
1962	0.589	0.611	0.857	0.589	0.633			
1963	0.628	0.625	0.940	0.628	0.621			
1964	0.557	0.591	0.898	0.557	0.625			
1965	0.339	0.435	0.723	0.339	0.530			
1966	0.639	0.634	0.953	0.639	0.628		0.953	
1967	0.768	0.680	0.993	0.768	0.592		0.993	
1968	0.814	0.726	0.960	0.814	0.639		0.980	
1969	0.476	0.492	0.688	0.476	0.508	0.829	0.829	
1970	0.636	0.646	0.857	0.636	0.655	0.926	0.926	0.926
1971	0.385	0.497	0.590	0.385	0.608	0.768	0.768	0.768
1972	0.409	0.459	0.678	0.409	0.509	0.824	0.824	0.824
1973	0.739	0.660	0.900	0.739	0.580	0.949	0.949	0.949
1974	0.279	0.425	0.519	0.279	0.572	0.720	0.720	0.720
1975	0.295	0.492	0.517	0.295	0.689	0.719	0.719	0.719
1976	0.330	0.510	0.543	0.330	0.691	0.737	0.737	0.737

1977	0.685	0.646	0.856	0.685	0.607	0.925	0.925	0.925
1978	0.361	0.556	0.571	0.361	0.751	0.756	0.756	0.756
1979	0.410	0.568	0.692	0.410	0.726	0.832	0.832	0.832
1980	0.335	0.483	0.602	0.335	0.632	0.776	0.776	0.776
1981	0.577	0.566	0.750	0.577	0.556	0.866	0.866	0.866
1982	0.424	0.497	0.630	0.424	0.570	0.794	0.794	0.794
1983	0.526	0.561	0.846	0.526	0.596	0.920	0.920	0.920
1984	0.557	0.658	0.786	0.557	0.759	0.887	0.887	0.887
1985	0.735	0.754	0.913	0.735	0.773	0.956	0.956	0.956
1986	0.657	0.723	0.868	0.657	0.790	0.932	0.932	0.932
1987	0.745	0.654	0.897	0.745	0.562	0.947	0.947	0.947
1988	0.693	0.604	0.846	0.693	0.516	0.920	0.920	0.920
1989	0.476	0.584	0.712	0.476	0.693	0.844	0.844	0.844
1990	0.629	0.666	0.892	0.629	0.703	0.944	0.944	0.944
1991	0.488	0.587	0.787	0.488	0.686	0.887	0.887	0.887
1992	0.752	0.658	0.912	0.752	0.564	0.955	0.955	0.955
1993	0.743	0.810	0.899	0.743	0.877	0.948	0.948	0.948
1994	0.920	0.779	0.979	0.920	0.638	0.990	0.990	0.990
1995	0.538	0.637	1.000	0.538	0.737	1.000	1.000	1.000

(1) John Day applies to Middle fork John Day, Mainstem John Day and North Fork John Day/ Granite Creek
(2) Middle Fork Salmon applies to Bear Valley/ Elk, Marsh Creek, Sulphur Creek
(3) South Fork Salmon applies to Poverty Flat and Johnson Creek

Columbia River and tributary harvest rates were applied to population projections in accordance with the harvest rate policy followed by fishery management on the system. Harvest rules are established for mainstem and tributary harvest rates as a function of projected spawner abundance relative to MSP (maximum sustainable production) levels. The rules were provided by H. Schaller along with MSP levels currently in use by management, as listed below in Tables 4(a, b) and 5, respectively. In the current version of the model only Snake River populations are projected into the future and thus mainstem harvest rules were applied only to their aggregate abundance (rather than for the aggregate over down-river, up-river, and Snake River stocks). The rules differ by spring runs and summer runs. The Imnaha stock is a mixed spring/summer run ; in the BSM half of the population is treated as a spring run and half the population is treated as a summer run. Tributary harvest rules are based on projected escapement from the mainstem harvest, aggregated into spring chinook runs and summer chinook runs .

Table 4(a): Upriver Spring chinook Columbia River Fisheries Management Plan harvest rate schedule. (H. Schaller, unpublished data in SPRPROSS11.XLS)

Run Size % of MSP a/ b/	*C.R. Mainstem Harvest Rate*	*Tributary Harvest Rate*
< 22%	0.03	0
22%-44%	0.082	0
45%-112%	0.14	0
113%-125%	0.25	0.05
126%-175%	0.3	0.15
176%-200%	0.35	0.2
>200%	0.4	0.25

a/ run size adjusted for 77-90 average adult passage conversion and 90% pre-spawning survival
b/ average % of MSP for index stocks

Table 4(b): Upriver Summer chinook Columbia River Fisheries Management Plan harvest rate schedule. (H. Schaller, unpublished data in SPRPROSS11.XLS)

Run Size % of MSP a/	*C.R. Mainstem Harvest Rate*	*Tributary Harvest Rate*
< 25%	0.02	0
25%-49%	0.05	0
50%-99%	0.1	0
100%-129%	0.15	0
130%-149%	0.2	0.05
150%-169%	0.25	0.1
170%-200%	0.3	0.2
>200%	0.35	0.25

a/ run size adjusted for 77-90 average adult passage conversion and 90% prespawning survival

Table 5: Maximum sustainable production (MSP) and minimum observed spawners (through brood year 1990) in numbers of spawners for spring and summer chinook of the Snake River. (MSP estimates provided by H. Schaller, unpublished data in SPRPROSS11.XLS)

Sub-basin in Snake River	*MSP*	*minimum*
Bear Valley	1244	42
Marsh Creek	456	16
Sulphur Creek	333	12
Poverty Flat	3497	76
Johnson Creek	553	36
Imnaha River	1538	170
Minam River	810	41

Pre-spawning survival was assumed to equal 90% based on advice from the workshop participants.

Autocorrelation of year-effects.

There is a significant first-order auto-correlation present in the MLE estimates of δ (the year-effects parameters), as seen below in Figure 2. Regression of $\delta(t+1)$ versus $\delta(t)$ has an R-square = 0.271 (significant at p=.0008).

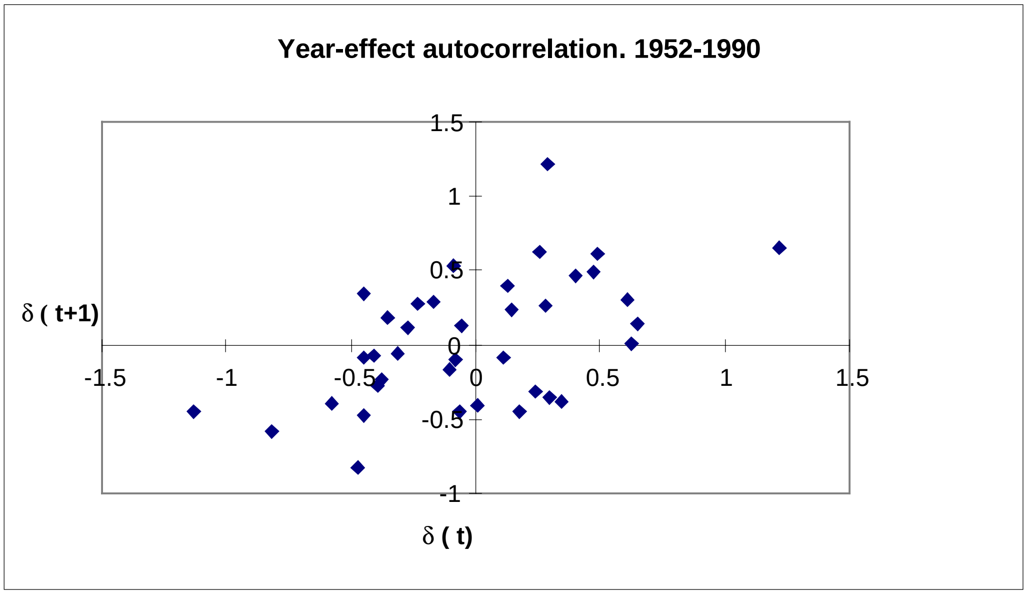

Figure 2: MLE estimates of year-effect parameters, the δ's, for 1952 - 1990.

The autocorrelation apparent in the year-effects parameters was captured in the population projections by a type of Markov process with empirical probability densities. The method implemented in the model consists of the following steps: for each 100 year population projection, a sample of the posterior density of the year-effect parameters is made. From that sample, MLE estimates are calculated for the multinomial probabilities that characterize the sign of a δ, such as, P(x(t)>0 | x(t-1)>0). Given such a P vector then each simulated year-effects follow the multinomial(P) for selection of positive and negative values. The actual positive (negative) values selected are chosen at random from the positive (negative) posterior sample of the year-effects selected for that particular 100 year projection.

Passage mortality relationship to water transit time WTT.

In our respective report, we showed that there was a weak correlation between WTT and passage mortality. As a first step toward modeling the relationship between those variables, I investigate whether there is an autocorrelation process within the WTT series themselves. The historical record of unregulated water transit times shows little autocorrelative relationship. There is no significant first-order autocorrelation of WTT(t+1) versus WTT(t) , R-square = 0.011 for the 1929-1990 data. This can be seen in the Figure 3 below.

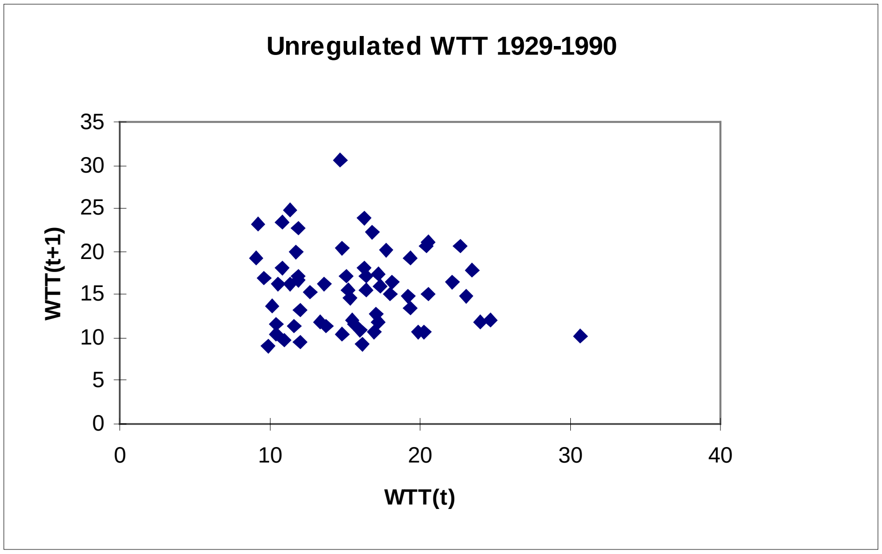

Figure 3: Unregulated WTT autocorrelation structure.

There is little structure revealed from a non-parametric view either: let w-bar be the average WTT for all years, then the P(WTT(t+1)>wbar given WTT(t)>wbar) = 0.467 and P(WTT(t+1)>wbar given WTT<wbar) = 0.50 . The only bias problem associated with a simple random selection of WTT year from the recent years is that there have been relatively few above average WTT years recently. For example 38% of the WTT values for 1972-1992 exceed wbar.

The relationship between passage mortalities and WTT was modeled by a two-step procedure. Population projections affected by this procedure are those projections made for the "recent condition" scenario, as defined in detail later in the paper, but it is one in which passage mortalities from the 1978-1992 water years are utilized. For the "recent" scenario, the first step of the procedure is random selection of WTT from the 1978-1992 period in proportion to the empirical CDF of long-term WTT's (water years 1929-1992). The method of selection is itself made in two steps: (1) randomly choose a 0.33 probability interval with ending point 0.33 to 1.0 from the CDF of the long-term WTT's; (2) from the chosen interval, randomly select one of the years 1978-1992 whose CD value falls within the chosen interval. For the selected year, the corresponding sample of the posterior density of in-river passage mortality is selected.

Maturity proportions.

The proportion of recruits returning to a given population vary by sub-basin and age of recruit, according to historical data. For each projected year, randomly selected proportions were chosen from those estimated for historical data (brood years 1963-1993) on each population. Those 31 historical years are the maximum number of historical data years in common for all Snake River populations, except Poverty Flats which has 30 years (no samples in 1984).

Other details of the projection model are as follows:

- The process error variance was deflated to 61% of the posterior variance contained in the likelihood function for the S-R data in order to account for confounding by observation error. The 61% estimate is based on a partitioning of the residual sum of squares (RSS) from the MLE analysis of Model (2) in our retrospective paper in which spawning measurement error is modeled. From that analysis, the RSS of total recruitment error is 76.4 and the RSS of spawning measurement error is 8.04. By assuming the RSS of spawning measurement error equals recruitment measurement error then the estimate 68.36 (=76.4-8.04) is the RSS for recruitment process error. The ratio of this last RSS to the RSS for equation (1) is .61 (=68.36/112.4). For each population and each projection year, a random process error is added to the logarithm of the recruitment model (1). The error is chosen from a normal distribution with mean 0 and variance selected from the posterior distribution of process error variance.
- Projections begin with the following initial conditions for the "recent condition" scenario: estimates of spawners for 1991-1995 and recruits produced by those spawners, where available. The estimates of spawners are multiplied by a 24% log-normal random variable to account for measurement error.

A complete listing of the fortran code used for the population projections is listed in Appendix II.

Jeopardy Standards

The jeopardy standard summary in Appendix I is used to guide development of appropriate output calculations. Some interpretation is needed to place the standards on a sound probability basis. With regards to the survival standard (item 1 of Appendix I), it is straightforward to estimate the probability that a given population is above a given threshold in any given year: one simply calculates the frequency of monte carlo projections for which the population is above the threshold in that given year. By averaging those probabilities over all projection years, one finds the average probability a given population is above a given threshold over all projection years. This "average probability" is the item (1c) for the 100-year projection time period; the 24-year time period is handled similarly. Threshold values for each of the Snake River populations are listed below in Table 6.

The jeopardy standards require calculation of the "average probability" for both recent and historical conditions in the Columbia River. We chose the passage mortalities for brood years 1976-1990 to represent recent conditions and we chose the passage mortalities for brood years 1952-1969 to represent historical conditions. Other parameters are not assumed to differ between scenarios, in particular, we assume that the δ year-effects or up-river survivals will not depend on whether a scenario is for "recent conditions" or "historical conditions".

Initial population conditions differ between scenarios. The “recent conditions” scenario uses initial populations during the 1990’s as described earlier. The “historical conditions” scenario were obtained by random selection from observed values for the 1957-1969 brood years.

Item 1d of Appendix I is the ratio of “average probability” for the recent conditions scenario relative to the historical conditions scenario. For example, a 90% ratio of average probability for a given population and given threshold means that the average probability for a “recent condition” scenario is 90% of the average probability for a “historical condition” scenario.

The recovery standard (item 2 of Appendix I) is a standard based on the probability that an eight-year geometric-mean of spawners is above a given threshold in a given projection year; year 24 and year 48 probabilities are calculated. I calculated the average number of spawners for each population for all years of data on pre-1971 brood years as specified in Appendix I. The threshold values for the recovery standard are 60% of those historical averages, rounded to the nearest 50 spawners (due to bin sizes used to output results). The thresholds for both criterion are given in the table below. I went beyond the requirements of the jeopardy standard and calculate the eight-year geometric-mean spawners for both “recent condition” scenario and “historical condition” scenario. I also provide the ratio of probability for the “recent condition” scenario to probability for the “historical condition” scenario so as to make the results of item 2 more comparable to those in item 1.

Table 6: Survival and recovery thresholds prescribed the NMFS jeopardy standards for Snake River spring and summer chinook index populations. Average spawners listed are averages for all years of data prior to 1971 brood year.

Population	**Survival Standard Threshold**	**Recovery Standard Threshold**	**Historical Average Spawners**
Bear Valley/Elk	300	950	1611
Imnaha	300	900	1521
Marsh Creek	150	450	735
Minam River	150	500	823
Poverty Flats	300	1150	1884
Sulphur Creek	150	350	523
Johnson Creek	150	350	589

Projections with Change in future in-river passage mortality

Management actions to increase the chances of Snake River population survival and recovery can involve changes in future in-river passage mortality. A number of calculations were made to investigate consequences of changes in the in-river passage mortality by either fixed incremental units or by fixed units subject to a constraint. In previous PATH workshops this has been referred to as “change in mu” calculations, but the results pertain to any management action which results in an incremental decrease in the density-independent component of recruitment survival. In the projections, a fixed incremental change was implemented by altering the “recent condition” scenario so that in each simulated year, passage mortality m is replaced by m' where

$$m' = m - \Delta$$

in which Δ is the fixed increment change. In some simulated years, the fixed increment change can be so large as to change the sign of m' to a negative number. Such enhanced production by salmon is considered unlikely by some PATH participants and thus a sensitivity analysis was made in which the increments were constrained such that m' always remains a non-negative number. In both sets of calculations, there is a ten year linear “ramp-up” of Δ beginning in projection year 1 with an increment of 10% of Δ and linearly increasing to 100% in year 10 and thereafter.

Results of base case

Tables 7 (a - d) summarizes jeopardy standard probability results for the base case of the BSM, which is the version described in previous Sections. The NMFS Jeopardy Standards in Appendix I are vague regarding specific quantification of the standards. If we take the least stringent of the ones listed in Appendix I then the survival standard is satisfied if 80% of the populations have a probability of at least 70% in the right-hand column of Tables 7 (a, b). In Table 7(a) 14% (1 of 7) of the populations exceed 70% probability ratio and in Table 7(b) 43% (3 of 7) of the populations exceed 70% probability ratio. Therefore, the survival standard is not satisfied. The least stringent recovery standard is satisfied if 80% of the populations have a probability of at least 50% in the fourth column of Tables 7 (c, d). None of the populations have a 50% probability rate in Tables 7 (c, d) and therefore the recovery standard is not satisfied.

Jeopardy standards for survival and recovery can be met by making changes to passage mortality. Figures 4 (a-d) show how the probabilities are affected by fixed incremental changes in passage mortality. Reference lines are drawn on the graphs at roughly the mid-point of the range of options listed in Appendix I for each standard. If one adopted those mid-range reference values then some counter-intuitive results would occur: namely, the lower mid-range value for the recovery standard has the effect of allowing the recovery standard to be met at lower reductions in passage mortality than would be required for the survival standard to be met. Results similar to those in Figures 4 (a-d) were obtained for model simulations with constrained incremental changes; in those graphs replace fixed Δ with average Δ in which averaging takes place across all simulations of a given proposed fixed increment scenario.

Estimated posterior probability distributions for the 88 parameters are given in Table 8. As seen in the Table, 90% posterior quartiles are quite large for most of the parameters, which shows that the population projections are made over a wide range of parameter values. Of particular interest is the negligible amount of depensation, listed in logarithms as *ln(p)*, estimated from the observed data. The wide range of parameter values used in the projections lessens the sensitivity of jeopardy standard calculations to modest shifts in MLE estimates of the parameters, as shown by the sensitivity results given below.

Sensitivity analyses

Four different variations to the "base case" were developed in order to examine sensitivity of the results given above. The four models, along with the base case are more fully described below:

1. Base Case
2. Depensation is assumed to occur below minimum observed spawner levels. The model described in Figure 1 with depensation parameter $d = 1.0$ is applied.
3. Spawner measurement error was accounted for by application of model number 2 in our retrospective report. Estimated spawner values from that analysis were used instead of "observed" spawners – the data used in the base case. Recruitment process error was rescaled in the run to produce the same residual sum of squares as decided for the base case.
4. Age composition error was accounted for by application of the missing data algorithm described by me in the accompanying document. Estimated recruitment values from that analysis were used instead of "observed" recruitment – the data used in the base case. Recruitment process error was rescaled in the run to produce the same residual sum of squares as decided for the base case.
5. Year-effect parameters δ's were set to zero. This model had a very favorable BIC (Bayesian Information Criterion) score, as described in the recent paper by Paulsen.

Results of the sensitivity analysis are summarized in Table 9. The Table lists some summary statistics from the analysis, although complete results are available to anyone on request. Results in the Table show that the base case results are quite similar to results obtained from models 2-4. Model 5, the no year-effect model, gives a substantially more pessimistic view of the future of Snake River chinook salmon.

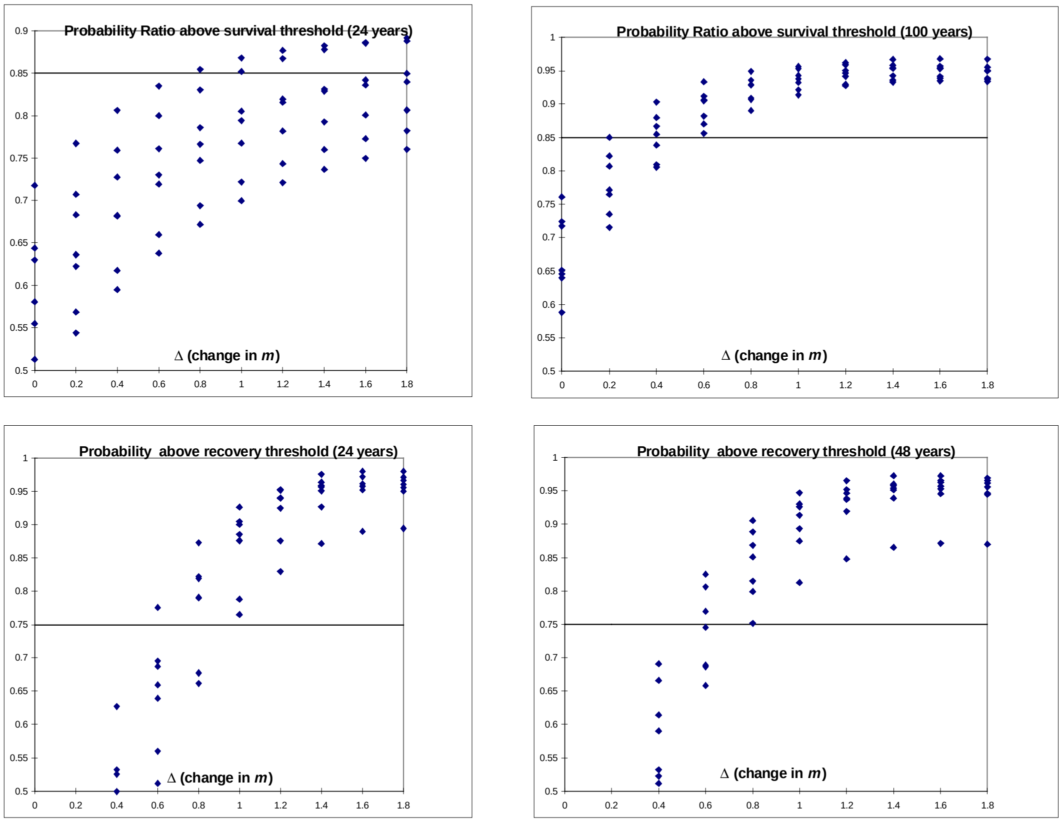

Figure 7 (a-d): Probability ratio for survival threshold standard and Probability for recovery threshold standard.

Table 7(a). Average probabilities of spawners being above survival threshold using 24 year simulation period.

Area	Survival Threshold	Average probability of being above threshold: Historical	Average probability of being above threshold: Recent	Recent prob./ historical prob.
Imnaha	300	0.984	0.706	0.718
Minam	150	0.967	0.609	0.630
Bear Valley	300	0.993	0.576	0.581
Marsh Creek	150	0.980	0.478	0.488
Sulphur Creek	150	0.900	0.462	0.513
Poverty Flat	300	0.974	0.628	0.644
Johnson Creek	150	0.946	0.525	0.555

Table 7(b): Average probabilities of spawners being above survival Threshold using 100 year simulation period.

Area	Survival Threshold	Average probability of being above threshold		Recent prob./ historical prob.
		Historical	Recent	
Imnaha	300	0.981	0.747	0.761
Minam	150	0.964	0.692	0.717
Bear Valley	300	0.992	0.718	0.724
Marsh Creek	150	0.979	0.637	0.651
Sulphur Creek	150	0.895	0.573	0.640
Poverty Flat	300	0.972	0.627	0.645
Johnson Creek	150	0.943	0.555	0.588

Table 7(c). Average probabilities of spawners being above recovery Threshold using 24 year simulation period.

Area	Recovery Threshold	Average probability of being above threshold		Recent prob./ historical prob.
		Historical	Recent	
Imnaha	850	0.945	0.280	0.297
Minam	450	0.884	0.196	0.222
Bear Valley	900	0.961	0.202	0.211
Marsh Creek	450	0.933	0.127	0.136
Sulphur Creek	300	0.833	0.166	0.200
Poverty Flat	850	0.904	0.147	0.163
Johnson Creek	300	0.926	0.202	0.218

Table 7(d). Average probabilities of being above recovery Threshold using 48 year simulation period.

Area	Recovery Threshold	Average probability of being above threshold		Recent prob./ historical prob.
		Historical	Recent	
Imnaha	850	0.945	0.292	0.309
Minam	450	0.880	0.211	0.239
Bear Valley	900	0.961	0.284	0.295
Marsh Creek	450	0.936	0.238	0.254
Sulphur Creek	300	0.822	0.220	0.268
Poverty Flat	850	0.906	0.154	0.170
Johnson Creek	300	0.925	0.215	0.232

Table 8: posterior probability distributions for the 88 estimated parameters in the BSM model.

parameter		highest posterior densities (analogous to quartiles) 5%	25%	median	75%	95%
a for area	1	6.397	6.71	7.087	7.405	7.66
a for area	2	6.99	7.389	7.805	8.126	8.383
a for area	3	8.804	9.316	9.837	10.236	10.556
a for area	4	7.539	7.904	8.351	8.748	9.066
a for area	5	7.948	8.361	8.843	9.24	9.557
a for area	6	9.017	9.515	10.062	10.498	10.847
a for area	7	8.904	9.736	10.344	10.969	11.776
a for area	8	8.39	9.242	9.833	10.44	11.258
a for area	9	9.177	9.948	10.612	11.219	12.197
a for area	10	8.586	9.394	10.056	10.642	11.665
a for area	11	8.068	8.921	9.524	10.119	11.008
a for area	12	8.782	9.627	10.224	10.847	11.615
a for area	13	7.821	8.677	9.268	9.859	10.75
δ for year	1952	-0.716	-0.006	0.493	1.003	1.725
δ for year	1953	-1.3	-0.585	-0.079	0.424	1.141
δ for year	1954	-1.42	-0.825	-0.426	-0.022	0.546
δ for year	1955	-0.744	-0.241	0.118	0.466	0.989
δ for year	1956	-1.243	-0.733	-0.388	-0.046	0.455
δ for year	1957	-0.48	-0.101	0.162	0.422	0.809
δ for year	1958	0.07	0.427	0.678	0.924	1.279
δ for year	1959	0.165	0.377	0.529	0.688	0.912
δ for year	1960	0.118	0.344	0.501	0.654	0.868
δ for year	1961	0.07	0.289	0.44	0.593	0.807
δ for year	1962	-0.274	-0.053	0.1	0.25	0.468
δ for year	1963	-0.402	-0.18	-0.027	0.125	0.339
δ for year	1964	-0.689	-0.469	-0.315	-0.164	0.057
δ for year	1965	-0.013	0.221	0.37	0.521	0.741
δ for year	1966	-0.178	0.015	0.152	0.288	0.484
δ for year	1967	0.225	0.46	0.631	0.799	1.036
δ for year	1968	0.751	1.046	1.261	1.473	1.779
δ for year	1969	-0.218	0.073	0.271	0.471	0.763
δ for year	1970	-0.683	-0.391	-0.181	0.031	0.316
δ for year	1971	-0.589	-0.284	-0.078	0.122	0.403
δ for year	1972	-0.556	-0.265	-0.057	0.147	0.433
δ for year	1973	-0.378	-0.102	0.086	0.271	0.544

δ for year	1974	-0.701	-0.429	-0.244	-0.06	0.201
δ for year	1975	-0.882	-0.61	-0.419	-0.226	0.047
δ for year	1976	-1.056	-0.781	-0.582	-0.398	-0.117
δ for year	1977	-1.295	-1.022	-0.841	-0.653	-0.387
δ for year	1978	-0.936	-0.663	-0.479	-0.293	-0.023
δ for year	1979	-0.888	-0.625	-0.442	-0.257	0.008
δ for year	1980	-0.491	-0.215	-0.026	0.16	0.42
δ for year	1981	-0.831	-0.558	-0.373	-0.194	0.081
δ for year	1982	-0.445	-0.164	0.024	0.205	0.47
δ for year	1983	0.179	0.454	0.639	0.83	1.106
δ for year	1984	-0.168	0.101	0.286	0.468	0.744
δ for year	1985	-0.175	0.107	0.297	0.493	0.777
δ for year	1986	-0.707	-0.436	-0.25	-0.063	0.2
δ for year	1987	-0.95	-0.664	-0.463	-0.259	0.042
δ for year	1988	-0.231	0.073	0.28	0.484	0.784
δ for year	1989	-0.932	-0.654	-0.47	-0.281	-0.022
X dam effect		-0.004	0.153	0.254	0.354	0.515
μ for year	1970	-0.387	0.143	0.509	0.867	1.404
μ for year	1971	0.746	1.274	1.651	2.021	2.535
μ for year	1972	1.315	1.851	2.226	2.596	3.116
μ for year	1973	-0.273	0.243	0.609	0.955	1.498
μ for year	1974	0.876	1.384	1.746	2.104	2.619
μ for year	1975	1.825	2.364	2.733	3.099	3.635
μ for year	1976	0.378	0.89	1.256	1.617	2.129
μ for year	1977	-0.088	0.416	0.771	1.127	1.634
μ for year	1978	0.62	1.12	1.479	1.839	2.34
μ for year	1979	0.348	0.874	1.232	1.597	2.113
μ for year	1980	-0.7	-0.17	0.191	0.551	1.072
μ for year	1981	-0.706	-0.189	0.175	0.528	1.034
μ for year	1982	-0.277	0.257	0.614	0.97	1.486
μ for year	1983	-0.427	0.101	0.457	0.823	1.339
μ for year	1984	0.714	1.242	1.606	1.969	2.515
μ for year	1985	1.205	1.73	2.093	2.453	2.985
μ for year	1986	0.125	0.647	1.016	1.378	1.882
μ for year	1987	0.916	1.455	1.836	2.208	2.759
μ for year	1988	0.984	1.506	1.874	2.249	2.774
μ for year	1989	0.767	1.297	1.67	2.034	2.536
μ for year	1990	1.852	2.381	2.749	3.114	3.649
ln β area	1	-6.102	-5.859	-5.559	-5.291	-5.076
ln β area	2	-6.768	-6.291	-6.011	-5.677	-5.381

ln β area	3	-8.008	-7.282	-6.951	-6.565	-6.146
ln β area	4	-6.359	-6.168	-5.93	-5.622	-5.289
ln β area	5	-7.229	-6.98	-6.724	-6.406	-5.981
ln β area	6	-8.999	-8.234	-7.875	-7.443	-6.994
ln β area	7	-7.953	-7.739	-7.471	-7.138	-6.65
ln β area	8	-7.306	-7.107	-6.857	-6.536	-6.11
ln β area	9	-8.692	-7.992	-7.676	-7.32	-6.791
ln β area	10	-8.472	-7.457	-7.146	-6.816	-6.297
ln β area	11	-7.122	-6.643	-6.4	-6.134	-5.671
ln β area	12	-7.885	-7.655	-7.366	-6.984	-6.585
ln β area	13	-7.21	-6.616	-6.349	-6.015	-5.649
ln(p)		-11.672	-10.29	-8.492	-6.67	-4.828
ln(V)		-1.178	-1.104	-1.035	-0.96	-0.893

Table 9: Results of sensitivity analysis of jeopardy standard probability calculations to alternative models. See text for description of the models implemented.

	Model				
Probability average across stocks	**1 Base Case**	**2 Depensate *d* = 1.0**	**3 Spawner error**	**4 Age error**	**5 Year-effect δ = 0**
24 year survival threshold	0.59	0.57	0.61	0.60	0.45
with Δ = 0.4	0.68	0.66	0.70	0.69	0.56
with Δ = 0.8	0.76	0.74	0.78	0.78	0.67
100 year survival threshold	0.68	0.65	0.71	0.69	0.50
with Δ = 0.4	0.85	0.84	0.88	0.86	0.76
with Δ = 0.8	0.92	0.91	0.94	0.92	0.87
24 year recovery threshold	0.19	0.17	0.23	0.19	0.05
with Δ = 0.4	0.49	0.46	0.56	0.49	0.26
with Δ = 0.8	0.78	0.75	0.84	0.79	0.62
48 year recovery threshold	0.23	0.22	0.29	0.23	0.07
with Δ = 0.4	0.59	0.57	0.68	0.59	0.38
with Δ = 0.8	0.84	0.83	0.89	0.84	0.75

References

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Hilborn, R. and C. J. Walters. 1992. Quantitative Fisheries Stock Assessment. Chapman & Hall. London. 570p.

Punt, A. E. and R. Hilborn. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. Rev. Fish Bio. And Fisheries (7): 1-29.

Appendix I: Spring/Summer Chinook "Jeopardy Standard" Summary (from C. Toole)

1. Survival Standard

a. Set threshold levels for each population. BRWG estimates were used by NMFS for the following stocks:

Population	Number of Spawners Annually
Bear Valley/Elk	300
Imnaha	300
Marsh Creek	150
Minam River	150
Poverty Flats	300
Sulphur Creek	150

Recently, Johnson Creek run reconstructions were completed. According pers. comm. with Schaller, Petrosky, and Wilson:

Johnson Creek	150

b. Using simulation models, project population levels over 24 years into the future and 100 years into the future.

c. Determine likelihood that each population will be above its threshold level over each of the two time periods. This is determined from the cumulative distribution of all simulations encompassing the time period.

For example, if 500 simulations each projected population levels for a 100-year period, the resulting distribution would consist of 50,000 values.

d. Express probability in step c. as a proportion of probability of being above threshold during a historical period in which stocks were believed to be relatively healthy. NMFS did not define this historical period, but accepted model results based on all available years prior to 1976 for the Biological Opinion.

Estimation of the historical probability follows the same process described in step c., except the simulation model is calibrated only to observations during the historical period.

e. NMFS' jeopardy standard is that a "high percentage" of available populations must have a "high likelihood," relative to the historical probability, of being above the threshold level over each time period.

NMFS defined "high percentage" as 80% of available populations.

NMFS did not define "high likelihood." I suggest that 70% be considered an approximation of this standard. Other PATH members have suggested reporting results for a range of probabilities between 70%-95%.

For example:

Probability	% of Stocks At or Above Probability	
	24-Year	100-Year
0.70	_______	________
0.75	_______	________
0.80	_______	________
0.85	_______	________
0.90	_______	________
0.95	_______	________

2. Recovery Standard

a. Set recovery population level. Relevant population recovery goal in NMFS' "Proposed Recovery Plan" is eight-year geometric mean of annual redd counts equivalent to 60% of the pre-1971 brood-year average redd counts. Although the NMFS draft recovery level is expressed as redd counts, analyses for the biological opinion converted these to estimates of number of spawners.

Values used in previous analyses have changed for some stocks as the run reconstruction procedure has been refined. The recovery levels should be calculated after the Petrosky et al. run reconstruction manuscript is completed, so that the "final" historical estimates are used.

b. Using simulation models, project population levels 48 years into the future. [Note: 48 years is the proposed NMFS recovery standard. Some PATH members would also like to see population projections 24 years into the future.]

c. Determine likelihood that the 8-year geometric mean of each population will be above its recovery level in the 48th year of a simulation (i.e., geometric mean of years 41-48). This is determined from the cumulative distribution of all simulations.

For example, if 500 simulations each project an 8-year geometric mean population level for the 48th year of the simulation, the resulting distribution would consist of 500 values.

[Note: Based on recommendation of some PATH members, probability should also be estimated for the 24th year of the simulation.]

d. NMFS' jeopardy standard is that a "high percentage" of available populations must have a "moderate to high likelihood" of being above the recovery level within 48 years.

NMFS defined "high percentage" as 80% of available populations.

NMFS did not define "moderate to high likelihood." I suggest that 50% be considered an approximation of this standard. It would be good to report results for a range of probabilities from 50-95% in a similar table to that described for threshold levels.

3. Considerations For the Simulations

NMFS commented on some of the assumptions used in simulations in our discussion of the jeopardy standard. Several of these comments are only pertinent to the specific simulation models used for biological opinion analyses (i.e., CRiSP vs FLUSH reach survival estimates) or to specific scenarios that were simulated (i.e., predator removal effectiveness).

One general consideration that would apply to any simulation model and any future scenario is NMFS' conclusion that survival/recovery probabilities based on simulation models that include depensatory effects are more reasonable than those from models lacking such effects. However, there is a substantial debate over the proper method of implementing depensation in life-cycle models, which Charlie Paulsen is tasked with laying out for PATH to review and, hopefully, resolve. [My understanding, in a nutshell, is when SLCM included depensation in both the calibration and projection for biological opinion scenarios, the effect was very small for most stocks; i.e., results were similar to simulations in which depensation was not implemented at all. ELCM included depensation in the forward projection only, and there was a greater difference between simulations with and without depensation.] NMFS did not take a position on the best method.

Appendix II: Fortran computer code for population projections.

```
          subroutine project
$INCLUDE:'MARCOM.DAT'
          character*12 srname
          common /srlabel/ srname(406),indxsp(200,13),pmature(40,13,6)
          common /readit/ recrt(200,13),spawn(200,13),gammay,gammae,ians
          common /idone/ idonit,icatopt,iyrmx,iareamx,gamavg
          common /save/ savest(100),fxn,ihistory,nspwn(50,100,0:10,5),
     &    zobs(mob),avgit(200,21),ihisflag,muflag
          common /crisp/ riverm(200,13),icrisp
          common /projec/ sdata(200,13),recage(200,13,6),conver(11,2)
     &             ,hrule(9,2),urule(9,2,2)
          common /pass/ prec(200,13),bcoef(13),rm(200,13)
     &         ,delt(200),strue(200,13),amean(13)
      common /depcom/ depen,spmin(13)
      dimension wttp(15),msp(7:13),rtemp(13),convert(2)
     &         ,msptot(2),rttot(2),utrib(13),umain(2)
     &         ,zjack(200,13),iwttp(15),iwtt(15)
      data wttp/.25,.313,.328,.344,.39,.406,.453,.468,.484,.64,.75,
     &         .765,.828,.844,.938/
      data iwttp/82,84,80,83,78,89,86,79,85,81,90,91,88,87,92/
          data msp/1538,810,1244,456,333,3497,553/
c-- ihistory is looped 0,1,..,10 ; 0=historical scenario; 1=recent;
c--  2-10 are iterations on changing MU by fixed maximum increments
          if(ihistory.ge.1) then
                    idum=idumsav
          else
                    idumsav=idum
c-- ihisflag is flag; when =0 use 1957-1969 initial conditions; =1 use recent initial conditions
                    if(ihisflag.eq.0) ihisyr= 5.0 + 11.0*ran0(idum)    !used to initial historical scenario
                    idum=idumsav
          endif
          deltamu=0.2*(ihistory-1)      ! MU = MU +DELTAMU; maximum change allowed
c--go get parameters
          call calcfg
          p=exp(theta(87))
c-- year-effect parameters modeled as a Markovian process; find structure
c--select year for year-effect from coded year 1 to 39 ('52-'90)
          pplus=0.0
          pminus=0.0
          plus=0.0
          zminus=0.0
          do 22 i=1,38
          if(delt(i).ge. 0.0) then
                    plus=plus+1.
                    if(delt(i+1).ge. 0.0) pplus=pplus+1.
          else
                    zminus=zminus+1.
                    if(delt(i+1).ge. 0.0) pminus=pminus+1.
          endif
22      continue
```

```
            if(plus.gt. 0.) pplus=pplus/plus
            if(zminus.gt. 0.) pminus=pminus/zminus
c-- zero vector and re-use it. Note it is in exponential form in this subroutine
            do 1 i=1,200
            do 1 j=7,13
            zjack(i,j)=0.0
1       strue(i,j)=0.0
c--simulation begins
c--start in year 1991 calculate future returns. use rec input where available
c--start spawner calculations in 1996; first 5 years to initialize process
            istart=1990-1951
            do 10 isim=1,105
            iyr=istart+isim
            if(ihisflag.eq.0) ihisyr=ihisyr+1
            iramp=isim-5
c-- ramp change in mu linearly over 10 years; dramp is maximum feasible
c-- change in mu for a given simulation year
            if(iramp.gt.0 .and. iramp.lt.10) then
                        dramp=float(iramp)/10.*deltamu
            else
                        dramp=deltamu
                        if(iramp.le.0) dramp = 0.0 ! don't ramp during initial conditions
            endif
c--select year for year-effect from coded year 1 to 39 ('52-'90)
c-- use Markov parameters given above to select year-effect
            if(isim.gt.1) then
                        ptemp=ran0(idum)
                        if(delta.ge. 0.0) then
                                    if(ptemp.le.pplus) then
15                     iselyr=1.0+(iyrmx)*ran0(idum)
                                    dtmp=delt(iselyr)
                                    if(dtmp.lt. 0.0) goto 15
                                    else
12                     iselyr=1.0+(iyrmx)*ran0(idum)
                                    dtmp=delt(iselyr)
                                    if(dtmp.ge. 0.0) goto 12
                                    endif
                        else
                                    if(ptemp.le.pminus) then
13                     iselyr=1.0+(iyrmx)*ran0(idum)
                                    dtmp=delt(iselyr)
                                    if(dtmp.lt. 0.0) goto 13
                                    else
14                     iselyr=1.0+(iyrmx)*ran0(idum)
                                    dtmp=delt(iselyr)
                                    if(dtmp.ge. 0.0) goto 14
                                    endif
                        endif
            else
            iselyr=1.0+(iyrmx)*ran0(idum)
            dtmp=delt(iselyr)
            endif
            delta=dtmp + 0.01  ! bias correction --see bayavg.out to see it works
            if(ihistory.ne.0) then
```

```
c--select mu from one of the 1976-present values. Note lag 2 for byr vs H2Oyr
c--- even up the selection wrt WTT years by using empirical WTT CDF 1929-92
c-- stored cdf and year in data arrays wttp and iwttp
              rtmp=0.33 + 0.67*ran0(idum)
              nhat=0
              do 25 i=1,15
              if(wttp(i).le.rtmp .and. wttp(i).gt. rtmp-.33) then
              nhat=nhat+1
              iwtt(nhat)=iwttp(i)
              endif
25              continue
              iselec= 1 + nhat*ran0(idum)
              iselec=iwtt(iselec)-51-2
c-- constrain delta mu
                        if(muflag.eq.0) then !flag to use mu-star approach or not
                        dtmp=dramp
                        else   ! constrains delta mu to keep from sign change on rmort
                        dtmp=dmin1(rm(iselec,7),dramp)
                        dtmp=dmax1(dtmp,0.0d0)
                        endif
                        rmort=rm(iselec,7) - dtmp
            else
c--select mu from one of the 1969-1952
                        iselec= 1.0+(18.0)*ran0(idum)
                        rmort=rm(iselec,7)
            endif
c-- calculate up-river survival
            rttot(1)=0.0
            msptot(1)=0
            rttot(2)=0.0
            msptot(2)=0
c---first get recruits to mouth adjusted for average losses upriver
c---note that recruits do not include the jacks (age 3's)
c              and relative to MSP levels
            do 30 iar=7,13
            j=1
            if(iar.gt.11) j=2  ! S fork
            iy1=iyr
            if(ihisflag.eq. 0 .and. ihistory.eq.0) iy1=ihisyr
            if(isim.le.5) then
                        strue(iyr,iar)=sdata(iy1,iar)/.6  ! initial harvest conditions
            endif
            tmp=.659        ! 1977-1990 average conversion Sfork
            if(j.eq.1) tmp=0.558 ! 1977-1990 average conversion mid Fork
            rtemp(iar)= strue(iyr,iar)*tmp*0.9  ! 0.9 pre-spwn survival
            rtemp(7)= strue(iyr,iar)*0.9*(.659+.558)/2.
            if(iar.ne.7) then  !Imnaha is a combo su/sp and treated special
            rttot(j)=rtemp(iar)+rttot(j)
            msptot(j)=msptot(j) +msp(iar)
            endif
            utrib(iar)=0.0
30      continue
            rttot(1)=(rttot(1)+0.5*rtemp(7))/(msptot(1)+0.5*msp(7))
            rttot(2)=(rttot(2)+0.5*rtemp(7))/(msptot(2)+0.5*msp(7))
```

```
c-- calculate conversion for BN to IH: randomly select from 1985-1995 estimates
        iselec= 1.0+(11.0)*ran0(idum)
        convert(1)=conver(iselec,1)
        convert(2)=conver(iselec,2)
c-- apply exploitation; from harvest rules - mainstem  & tributary
        umain(1)=0.0
        umain(2)=0.0
        do 41 iar=7,13
        j=1
        if(iar.gt.11) j=2
        do 40 i=2,9
        hrul1=hrule(i-1,j)
        hrul2=hrule(i,j)
        if(rttot(j).gt.hrul1.and. rttot(j).le. hrul2)
     &          umain(j)=urule(i,j,1)
40    continue
        do 44 i=2,9
        hrul1=hrule(i-1,j)
        hrul2=hrule(i,j)
        rescape=rttot(j)*(1.0-umain(j))   ! trib harvest rules apply to escape
        if(rescape.gt.hrul1.and. rescape.le. hrul2)
     &          utrib(iar)=urule(i,j,2)
44    continue
41    continue
c-- calculate escapement and future recruits; note jacks don't spawn
c-- "strue" variable is used for recruits and spawners
        do 11 iar=7,13
        j=1
        if(iar.gt.11) j=2
        conv=convert(j)
        umai=umain(j)
        utri=utrib(iar)
        if(iar.eq.7) then   ! treat Imnaha as average
                conv=(convert(1)+convert(2))/2.
                umai=(umain(1)+umain(2))/2.
                utri=(utrib(7)+utrib(13))/2.
        endif
        surviv=(1.0-umai)*(1.0-utri)*conv*0.9
        iy1=iyr
        if(ihisflag.eq.0 .and. ihistory.eq.0) iy1=ihisyr
        if(isim.le.5) then              ! initial conditions
                strue(iyr,iar)=sdata(iy1,iar)*(1.+znorm(idum)*.24)
        else
                strue(iyr,iar)=strue(iyr,iar)*surviv
c               strue(iyr,iar)=(strue(iyr,iar)-zjack(iyr,iar))*surviv
        endif
c-- add process error; the .600 shrinks process error because of measure err
        epsilon=znorm(idum)*sqrt(exp(theta(88))*0.6)
        if(strue(iyr,iar) .ge. 1.0) then
        prec(iyr,iar)= dexp(amean(iar)+delta-rmort+epsilon)*bcoef(iar)
     &   *strue(iyr,iar)**(1.+p)/(1000.**p)
     &   *dexp(-bcoef(iar)*strue(iyr,iar) )
c-- depensation possible below min obs spawn
      if(strue(iyr,iar).lt.spmin(iar)) then
```

```
        tmp=(strue(iyr,iar)/spmin(iar))**depen
        prec(iyr,iar)=prec(iyr,iar)*tmp
        endif

                  else
          prec(iyr,iar) = 0.0
          endif
c--calculate some averages for graphs etc
          if(ihistory.ge.1) then
          isim1=isim
          if(isim.ge.15) isim1=15
          avgit(isim1,8+ihistory)=avgit(isim1,8+ihistory)+ dtmp
          if(iar.ge.7 .and. iar.le.9) avgit(isim1,12+iar) =
     &                  avgit(isim1,12+iar)+ strue(iyr,iar)
          avgit(isim1,8)=avgit(isim1,8)+ 0.1
                  if(iar.eq.7 .and. ihistory.eq.1) then
                  avgit(isim,1)=avgit(isim,1)+1.0
                  avgit(isim,2)=avgit(isim,2)+rmort
                  avgit(isim,3)=avgit(isim,3)+delta
                  avgit(isim,4)=avgit(isim,4)+surviv
                  avgit(isim,5)=avgit(isim,5)+conv
                  avgit(isim,6)=avgit(isim,6)+umai
                  endif
          else
                  if(iar.eq.7) then
                  avgit(isim,7)=avgit(isim,7)+rmort
                  endif
          endif
c-- future returns; do not include jacks (3 year-olds)
c---select randomly one of the maturity schedules
          iselec=34*ran0(idum) + 1.0
          do 20 iage = 4,6
          rectmp = pmature(iselec,iar,iage)*prec(iyr,iar)
          if(ihistory.ne.0 .and. recage(iyr,iar,iage).gt.0.0
     &            .and. isim.le.5) then
                  rectmp=recage(iyr,iar,iage)
          endif
          strue(iyr+iage,iar)=strue(iyr+iage,iar) + rectmp
c         if(iage.eq.3) zjack(iyr+iage,iar)=zjack(iyr+iage,iar) + rectmp
20     continue
c--calculate jeopardy stuff
c--criterion 1: Are spawners above threshold values
          i1=ihistory
          do 100 ifreq=1,40
          x=ifreq*50.
          if(ifreq.eq. 40) x=10000000.
          if(strue(iyr,iar).le. x .and. isim.gt. 5) then
                  if(isim.le.29) then
                  nspwn(ifreq,iar,i1,1)=nspwn(ifreq,iar,i1,1)+1
                  endif
                  nspwn(ifreq,iar,i1,2)=nspwn(ifreq,iar,i1,2)+1
          endif
c--- criterion 2: recovery standard, 8-year geometric mean spawners
          if(isim.eq.29) then
```

```
                geo=0.0
                do 129 jsim=22,29
                jyr=istart+jsim
                geo=geo+log(strue(jyr,iar)+.000001)
129         continue
                geo=exp(geo/8.)
                if(geo.le. x ) then
                nspwn(ifreq,iar,i1,3)=nspwn(ifreq,iar,i1,3)+1
                endif
        endif
        if(isim.eq.53) then
                geo=0.0
                do 153 jsim=46,53
                jyr=istart+jsim
                geo=geo+log(strue(jyr,iar)+.000001)
153         continue
                geo=exp(geo/8.)
                if(geo.le. x ) then
                nspwn(ifreq,iar,i1,4)=nspwn(ifreq,iar,i1,4)+1
                endif
        endif
c--calculate once per call, some frequencies of parameters
        if(isim.eq.100.and. i1.eq.0 .and. iar.eq.7) then
                do 154 jpar=1,np
                deltmp=.1
                deltmp=max(.1*abs(savest(jpar)),deltmp)
                deltmp=deltmp*(ifreq-15) +savest(jpar)
                if(ifreq.eq.40) deltmp=10000.0
                if(theta(jpar).le.deltmp) then
                nspwn(ifreq,jpar,i1,5)=nspwn(ifreq,jpar,i1,5)+1
                endif
154         continue
        endif

100    continue
11     continue
10     continue
c      write(*,110) ihistory,(strue(iyr,j),j=7,13)
c      write(8,110) ihistory,(strue(iyr,j),j=7,13)
c      write(*,110) iyr,(amean(j),j=1,6)
c      write(*,110) iyr,(bcoef(j),j=1,6)
        return
        end
```