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Estimating Risk of Management Error from Precautionary Reference Points (PRPs) for Non-targeted Salmon Stocks

by

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Alaska Department of Fish and Game Divisions of Sport Fish and Commercial Fisheries

Symbols and Abbreviations

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Weights and measures (metric)

centimeter	cm
deciliter	dL
gram	g
hectare	ha
kilogram	kg
kilometer	km
liter	L
meter	m
milliliter	mL
millimeter	mm

Weights and measures (English)

cubic feet per second	ft^3/s
foot	ft
gallon	gal
inch	in
mile	mi
nautical mile	nmi
ounce	oz
pound	lb
quart	qt
yard	yd

Time and temperature

day	d
degrees Celsius	°C
degrees Fahrenheit	°F
degrees kelvin	K
hour	h
minute	min
second	s

Physics and chemistry

all atomic symbols	
alternating current	AC
ampere	A
calorie	cal
direct current	DC
hertz	Hz
horsepower	hp
hydrogen ion activity (negative log of)	pH
parts per million	ppm
parts per thousand	ppt, ‰
volts	V
watts	W

General

Alaska Administrative Code	AAC
all commonly accepted abbreviations	e.g., Mr., Mrs., AM, PM, etc.
all commonly accepted professional titles	e.g., Dr., Ph.D., R.N., etc.
at	@
compass directions:	
east	E
north	N
south	S
west	W
copyright	©
corporate suffixes:	
Company	Co.
Corporation	Corp.
Incorporated	Inc.
Limited	Ltd.
District of Columbia	D.C.
et alii (and others)	et al.
et cetera (and so forth)	etc.
exempli gratia (for example)	e.g.
Federal Information Code	FIC
id est (that is)	i.e.
latitude or longitude	lat. or long.
monetary symbols (U.S.)	$, ¢
months (tables and figures): first three letters	Jan,...,Dec
registered trademark	®
trademark	™
United States (adjective)	U.S.
United States of America (noun)	USA
U.S.C.	United States Code
U.S. state	use two-letter abbreviations (e.g., AK, WA)

Measures (fisheries)

fork length	FL
mideye to fork	MEF
mideye to tail fork	METF
standard length	SL
total length	TL

Mathematics, statistics

all standard mathematical signs, symbols and abbreviations	
alternate hypothesis	H_A
base of natural logarithm	*e*
catch per unit effort	CPUE
coefficient of variation	CV
common test statistics	(F, t, χ^2, etc.)
confidence interval	CI
correlation coefficient (multiple)	R
correlation coefficient (simple)	r
covariance	cov
degree (angular)	°
degrees of freedom	df
expected value	*E*
greater than	>
greater than or equal to	≥
harvest per unit effort	HPUE
less than	<
less than or equal to	≤
logarithm (natural)	ln
logarithm (base 10)	log
logarithm (specify base)	log_2, etc.
minute (angular)	'
not significant	NS
null hypothesis	H_O
percent	%
probability	P
probability of a type I error (rejection of the null hypothesis when true)	α
probability of a type II error (acceptance of the null hypothesis when false)	β
second (angular)	"
standard deviation	SD
standard error	SE
variance	
population	Var
sample	var

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ABSTRACT

A procedure is described for estimating risks of management error, an unneeded management action or a mistaken inaction, when precautionary reference points (PRPs) are established for non-targeted stocks of Pacific salmon. Risks of error in a future year are estimated from past observations of abundance, and from what would be considered a worrisome decrease from those observations. Probability that future observations will be below a PRP is estimated from lognormal distributions modeling past observations. Not modeling serial correlation if present will understate risk of unneeded action and overstate risk of mistaken inaction. Twenty or more observations are sufficient to attain accurate estimates of risk with reasonable precision, and to detect at least strong serial correlation. Risk of unneeded action tends to be overstated and risk of mistaken inaction understated when estimated from a shorter series absent serial correlation. Missing observations are not a concern in the absence of serial correlation beyond the effect on sample size. Bayesian imputation of missing observations in a serially correlated series is described and demonstrated. Random measurement error in observations (say from mark-recapture experiments or from subsampling time when counting salmon) does not bias estimates of risk, but does decrease actual risk of unneeded action and increase actual risk of mistaken inaction. Depensatory measurement error (say in indices from foot or aerial surveys) in observed abundance exacerbates this effect on risk. Examples for Chinook and chum salmon counted from a weir and during aerial surveys are provided.

Key words: precautionary reference point (PRP), Pacific salmon, management error, risk, serial correlation, measurement error

INTRODUCTION

Management of a salmon fishery is often not intended to maximize sustained yield from every fished stock. For example, chum salmon *Oncorhynchus keta* in eastern Prince William Sound, Alaska are largely caught incidentally in fisheries targeting pink salmon *O. gorbuscha* (Ashe et al. 2005). Because purse seiners expect to make more money by targeting pink salmon, they target pink salmon, but of course still sell any chum salmon they catch. For this reason, goals for spawning abundance of pink salmon drive management of these fisheries, yet some protection for chum salmon stocks from gross overfishing is still desired. In another example, Chinook salmon *O. tshawytscha* from the Middle Fork of the Goodnews River in Southwest Alaska are caught in a marine gill net fishery for sockeye salmon *O. nerka* (Molyneaux and Brannian 2006). Managers consider sockeye salmon the targeted stock and manage their mixed-stock fishery accordingly. Because of budgetary priorities, statistics describing population dynamics of non-targeted salmon stocks are often limited to time series of observations (counts, estimates, or indices) of the abundance of migrating or spawning fish. In the context of the precautionary approach to fisheries management (see FAO 1996), management objectives for such stocks are not target or limit reference points per se, but lower thresholds called precautionary reference points (PRPs). To paraphrase Hilborn et al. (2001), a PRP represents a spawning abundance low enough to warrant reducing exploitation rates, but not so low as to engender stock collapse.

Use of PRPs for non-targeted salmon stocks implies a simple management plan. If one or more of recent observations are below the PRP for the stock, some management action will be taken to boost abundance in the future, usually by significantly reducing fishing effort in the mixed-stock fishery into the future. The presumption is that recent observations below the PRP portend a meaningful (worrisome) decrease in stock productivity, or a worrisome increase in the long-term exploitation on the non-targeted stock. If recent observations are above the PRP, no management action is taken at all, the presumption being that the non-targeted stock does not need protection.

Two types of management error arise under this simple plan: unneeded action and mistaken inaction. One inarguable fact is that annual salmon production is variable, often temporarily obscuring trends, or temporarily indicating non-existing trends, in stock productivity or in exploitation. Given this variability there is a probability of being below a threshold one or more years in the future without there being a decrease in the central tendency of productivity, or increase in the central tendency of exploitation. This probability is the risk of unneeded action and can be estimated by presuming future abundance will have the same central tendency and dispersion as past abundance. There is also a probability of having recent observations in spawning abundance above the PRP when there has been a meaningful decline in productivity or worrisome increase in the central tendency of exploitation. This probability is the risk of mistaken inaction.

Below we describe a method of estimating the two risks of management error that can arise from setting a PRP for a salmon stock known only through observation of its spawning abundance. Such observations represent a sample distribution of the recent history of production and of exploitation for the stock. Risk of unneeded action is estimated by presuming that this sample distribution represents the true distribution of abundance over the next few years as well, then using this distribution to estimate the probability of future observations being below the PRP. Risk of mistaken inaction is estimated by lowering the central tendency of the sample distribution by an amount deemed worrisome, then using the same dispersion of the sample distribution to calculate the probability of having future observations above the PRP. The method encompasses sample distributions with independent (uncorrelated) and with serially correlated observations. Issues of sample size, missing data, and measurement error in observations are addressed.

METHODS

Risk of management error is related to the probability π_k of having to take a management action in the next *k* years. Assume that in the past, observations of spawning abundance have varied within acceptable limits, thereby providing empirical evidence for sustainability of average yields and for persistence of the stock. Such a series is said to be stationary if there is no meaningful temporal trend in its mean or variance (Box and Jenkins 1976, p. 26). Also, assume that over the next several years, productivity of the stock and general exploitation remain as experienced. That is not to say that annual production and annual harvest rates in the next *k* years will not vary, just that they will vary as they have done so in the past with a future observation of spawning abundance no more likely to be below the long-term median than above it. Under these circumstances, any management action is unneeded because observations will most likely rebound from low levels without any management action at all. Thus, the probability π_k of taking a management action is the risk of taking an unneeded action.

Now assume that over the next *k* years there will be a worrisome decline in stock productivity or a worrisome increase in exploitation, when compared against an acceptable record of past observations. An annual observation of spawning abundance will now more likely be below the median of past data than above. The probability π_k of taking a management action is greater than before. This increase in π_k is good because if a decline is worrisome, some management action is needed. However, even though management action is now needed, there is a probability, $1 - \pi_k$, of not getting it. Thus, $1 - \pi_k$ is the risk of mistaken inaction whenever there has been a worrisome trend in production or exploitation on a non-targeted stock.

Estimating the probability of a management action π_k begins with modeling variation in observed spawning abundance, and from those models estimating the probability of an observation being below the PRP. Because spawning abundance can not be less than zero, has a central tendency, and is on occasion quite large (Figure 1), variation in abundance can often be appropriately modeled with a lognormal probability distribution.

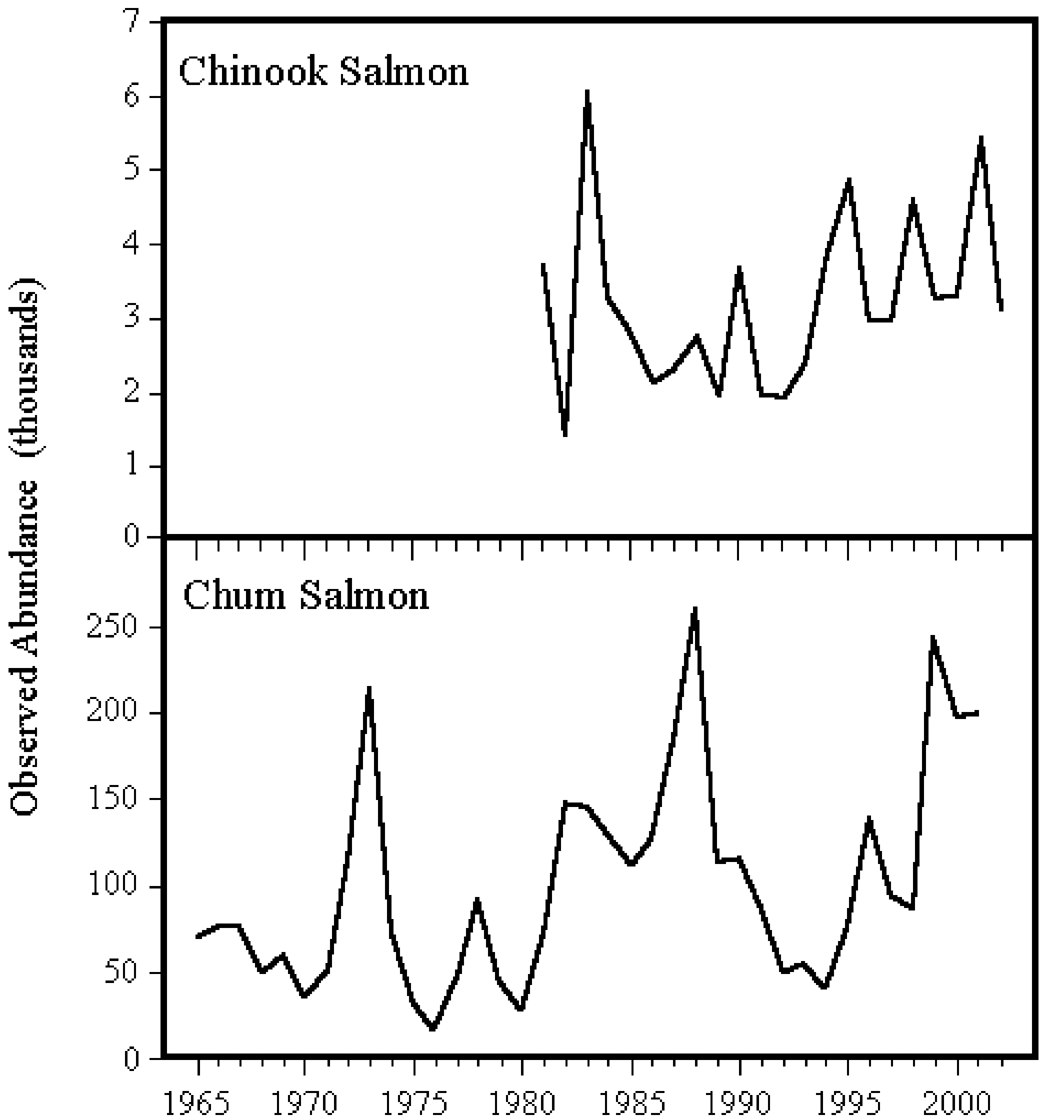

Figure 1.– Observed spawning abundance of Chinook salmon in the Middle Fork of the Goodnews River in Southwest Alaska, and of chum salmon in the eastern district of Prince William Sound, Alaska.

If individual observations are independent (not serially correlated), their lognormal model is:

$$y_i = \exp(\mu + a_i), \tag{1}$$

where y is an observation of abundance, i is the year, μ is the mean of log observations, and a_i follows a normal distribution with mean 0 and variance σ^2. Say that $x_i = \log_e(y_i)$. With this model the probability of seeing an observation below the PRP would be:

$$\mathrm{P}[y_i \le \mathrm{PRP}] = \mathrm{P}[x_i \le X] = \mathrm{P}[N : \mu, \sigma^2 \le X], \tag{2}$$

where $X = \log_e(\mathrm{PRP})$ and N is a normal variate. Usually, μ and σ^2 are unknown and must be estimated. From past observations:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \text{ and} \tag{3}$$

$$s^2 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}, \tag{4}$$

where $\bar{x}$ is the sample mean of the log observations, s^2 is the sample variance, and n the number of past observations. Equation (3) produces an asymptotically unbiased estimate for the mean $\hat{\mu}$. The asymptotically unbiased estimate of the variance is:

$$\hat{\sigma}^2 = s^2 (n+1) n^{-1}. \tag{5}$$

This adjustment to the sample variance represents the uncertainty in the estimate of the mean (see Steel and Torrie, 1980, p. 65). Because of this added uncertainty, the observations x_i would be expected to follow a Student's t distribution such that

$$\mathrm{prob}[y_i \le \mathrm{PRP}] = \mathrm{prob}[x_i \le X] = \mathrm{P}[t : (n\text{-}1) \le t_X : (n-1)], \tag{6}$$

where prob[…] signifies estimated probabilities, $n - 1$ are the degrees of freedom, and $t_X : (n - 1)$ is the t statistic corresponding to the $\log_e$ of the PRP (=X) such that

$$t_X : (n-1) = \frac{X - \bar{x}}{\sqrt{s^2 (n+1) n^{-1}}}. \tag{7}$$

The value of $\mathrm{P}[t : (n\text{-}1) \le t_X : (n-1)]$ for a set of past observations can be readily obtained from a cumulative distribution function with statistical software. The result is the estimated probability of an observation being at or below the PRP in a single year. The estimated probability of having k consecutive years with observations below the PRP is:

$$\hat{\pi}_k = \{\mathrm{P}[t : (n\text{-}1) \le t_X : (n-1)]\}^k \tag{8}$$

so long as observations are not serially correlated and represent a stationary series. If k consecutive years below the PRP is the criterion for a management action, $\hat{\pi}_k$ is the estimated probability of an action after k years.

A different model and approach are required to estimate π_k when observations are serially correlated. Our experience has been that for salmon, serial correlation in spawning abundance often follows an autoregressive process with a lag of one year, a process where deviation from the mean of observations in the previous year affects the size of the deviation in the current year. When observations are expressed as natural logs, this autoregressive process is modeled as:

$$\varepsilon_i = \phi\varepsilon_{i-1} + a_i\,, \tag{9}$$

where $\varepsilon_i = x_i - \mu$ and ϕ is the parameter for autocorrelation ($0 \le \phi < |1|$ indicates a stationary series, from Abraham and Ledolter, 1983, p. 199, equation 5.10), and as before, a_i follows a normal distribution with mean 0 and variance σ^2. For salmon species with year classes that mature in more than one calendar year, ε_i and ε_{i-1} tend to be related such that $0 \le \phi < 1$, especially when two or more age groups dominate annual returns, exploitation rates are similar or negligible across years, and maturation schedules vary relatively little from year class to year class. In terms of observations with lognormal distributions, equation (9) becomes

$$x_i = \phi\, x_{i-1} + \mu(1-\phi) + a_i\,. \tag{10}$$

Most comprehensive statistical software packages have options to estimate parameters for stationary ARIMA (AutoRegressive Integrated Moving Average) models like the one above. Estimates for ϕ, σ^2, and c where $c \equiv \mu(1 - \phi)$ are then plugged back into equation (10), and parametric simulation used to estimate π_k. No simple density function can be used to estimate probabilities here because those probabilities are conditioned (dependent) on a prior observation. Simulations begin by first picking a value for the initial condition x_o [we suggest using the estimated mean $\hat{\mu} = \hat{c}(1-\hat{\phi})^{-1}$], then forecasting observed abundance for year i as functions of estimated parameters, predicted log of observed abundance for year i - 1, and a pseudo random number a_i . Using estimated parameters instead of ϕ, σ^2, and c adds uncertainty to the forecast (Box and Jenkins, 1976, Appendix A7.3) such that the variance of the forecast error is not σ^2, but $\sigma^2(n+1)n^{-1}$. A simple way to incorporate this added uncertainty is analogous to equation (5) such that $a_i \leftarrow t:(n-2)\sqrt{\hat{\sigma}^2(n+1)n^{-1}}$) in simulated forecasts where $t:(n$ - 2) is a randomly generated variate following the Student's t distribution with $n - 2$ degrees of freedom. Over the resulting simulated time series, an estimate of π_k can be calculated as per the decision rule:

$$\hat{\pi}_k = \frac{\sum_{i=k}^{M} \omega_i}{M-k+1}, \text{ where } \omega_i = \begin{cases} 1 & \text{if } \max\,(x_i, x_{i-1} \ldots x_{i-k+1}) \le X \\ 0 & \text{otherwise} \end{cases}, \tag{11}$$

where M is the number of simulated years, ω a flag, and again, $X = \log_e(\text{PRP})$. By making M large, most likely values of x are represented in the predicted series with the consequence that $\hat{\pi}_k$ becomes negligibly conditioned on prior observations.

The final consideration concerns how to incorporate a worrisome decline into calculations for $\hat{\pi}_k$, a requirement for estimating the risk of mistaken inaction. The probability of management action is estimated as described above, only this time with a reduction in the central tendency of the sample distribution. A postulated reduction in average observed abundance of ($\Delta \times 100$) per cent is attained with the substitutions

$$\bar{x} \leftarrow \bar{x}' = \log_e(1-\Delta) + \bar{x} \text{ and} \tag{12}$$

$$\hat{c} \leftarrow \hat{c}' = (1-\hat{\phi})\log_e(1-\Delta) + \hat{c}\,. \tag{13}$$

Equation (12) describes substitutions when individual observations are independent, and equation (13) when observations are serially correlated. Once substitutions are made, calculations to estimate π_k proceed as described above for a given PRP with the estimated risk of mistaken action now being $1-\hat{\pi}_k$.

RESULTS

EXAMPLES

Two examples involve Chinook salmon spawning in the Middle Fork of the Goodnews River in southwest Alaska and chum salmon spawning on the mainland just east of Prince William Sound, Alaska. Neither stock is directly targeted in the dominant fisheries in their areas. Chinook salmon are caught incidentally in a set gill net fishery for sockeye salmon in Goodnews Bay, and chum salmon in a purse seine fishery for pink salmon in bays and inlets of the eastern commercial fishing district in Prince William Sound. Chinook salmon have been counted through a weir on the Middle Fork every year since 1981 (Molyneaux and Brannian 2006; Table 1). Spawning abundance of chum salmon in streams issuing into the eastern district of Prince William Sound (Ashe et al. 2005; Table 1) has been estimated every year since 1965 by expanding counts from multiple, annual flights over spawning fish through area-under-the-curve calculations and independent estimates of stream life (Bue et al. 1998). Both time series of observations follow stationary lognormal distributions (Figure 2). For Chinook salmon, n = 22, $\bar{x}$ = 8.003, s^2 = 0.136, and $\hat{\sigma}^2$ = 0.143 with P_α = 0.996 in a one-sample Kolmogorov-Smirnov test with a null hypothesis that $(x_i-\bar{x})/\hat{\sigma} \sim t:(n-1)$. For chum salmon, n = 37, $\bar{x}$ = 11.326, s^2 = 0.427, and $\hat{\sigma}^2$ = 0.438 with P_α = 0.984. For Chinook salmon, $\hat{\phi}$ = -0.050; for chum salmon, $\hat{\phi}$ = 0.634.

Table 1.–Annual observations of abundance of Chinook salmon in the Middle Fork of the Goodnews River in Southwest Alaska (counts), and of chum salmon in the eastern district of Prince William Sound, Alaska (aerial index).

Year	PWS chum salmon	Year	Goodnews River Chinook salmon	PWS chum salmon	Year	Goodnews River Chinook salmon	PWS chum salmon
1965	69,180	1980		26,720	1995	4,836	75,655
1966	75,690	1981	3,688	71,560	1996	2,930	137,908
1967	74,570	1982	1,395	146,120	1997	2,937	93,146
1968	48,960	1983	6,022	143,800	1998	4,584	86,227
1969	58,690	1984	3,260	129,190	1999	3,221	242,713
1970	34,430	1985	2,831	111,310	2000	3,295	196,253
1971	49,730	1986	2,092	126,690	2001	5,404	198,683
1972	112,950	1987	2,272	183,620	2002	3,076	
1973	213,170	1988	2,712	258,560			
1974	72,010	1989	1,915	112,080			
1975	30,040	1990	3,636	115,100			
1976	16,260	1991	1,952	86,360			
1977	47,880	1992	1,903	48,804			
1978	90,250	1993	2,349	54,102			
1979	42,630	1994	3,856	40,476			

Source: Ashe et al. 2005; Molyneaux and Brannian 2006.

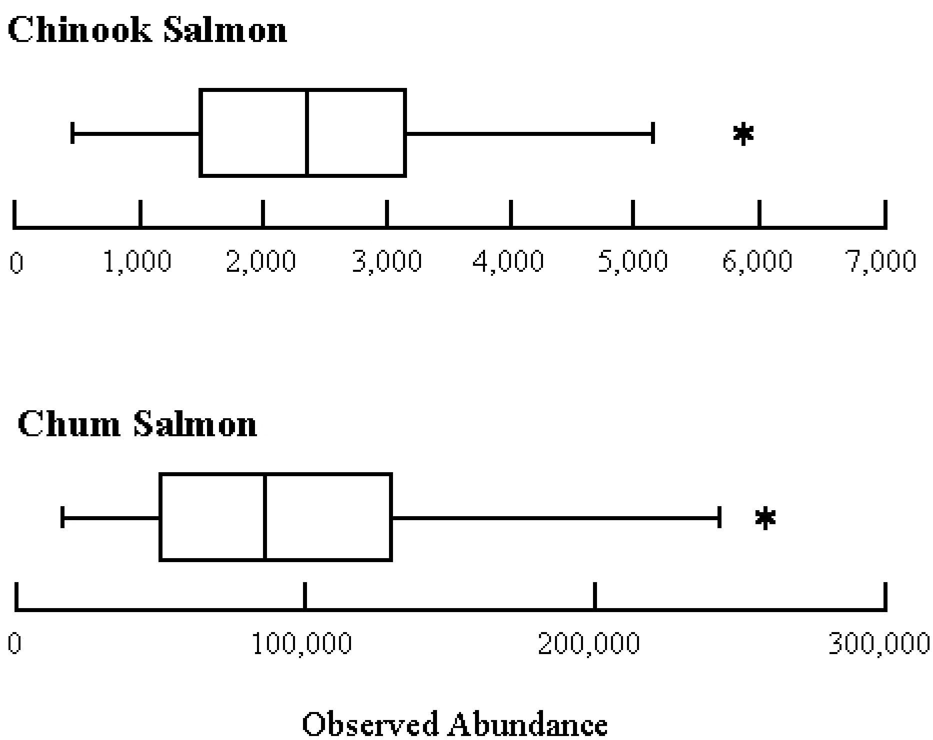

Figure 2.–Box plots of annual observations of abundance for Chinook salmon in the Middle Fork of the Goodnews River (1981-2002), and for chum salmon in the eastern district of Prince William Sound (1965–2001; see Table 1). Vertical lines are medians, boxes represent the interquartile range, whiskers 1.5 times the interquartile range above and below the box, and each asterisk represents a point beyond the whiskers, but less that 3 times the interquartile range.

The most important difference between these two stocks pertinent to the proposed method of estimating risks of management error is that observations of one stock are serially correlated, while those of the other are not (Figure 3). Autocorrelation and partial autocorrelation functions indicate no serial correlation among log observations of Chinook salmon in the Middle Fork of the Goodnews River (see Abraham and Ledolter 1983, Table 5.3 for rules to interpret plots of autocorrelation and partial autocorrelation functions). Because of this independence, equation (8) can be used directly to estimate π_k, the probability of meeting the criteria for a management action. Because Alaska's policy relating extraordinary management action to "escapement goals" requires five consecutive years with low observations, $k = 5$ in this example. Estimates of π_k for different PRPs were calculated with a cumulative distribution function in SYSTAT© 9.0 for the Student's t at $t_X : (n - 1)$ and together form the ascending curve in Figure 4, representing the estimated risk of an unneeded management action given a specific PRP. Also plotted in Figure 4 are two descending curves corresponding to postulated reductions in average abundance of 25 and 50%. The same cumulative distribution function was again used to estimate π_k, only this time with $\bar{x}$ displaced as per equation (12). The descending curves represent the estimated risk of mistaken inaction $(1-\hat{\pi}_k)$ for a specific PRP given the specified decline from the average of past observations.

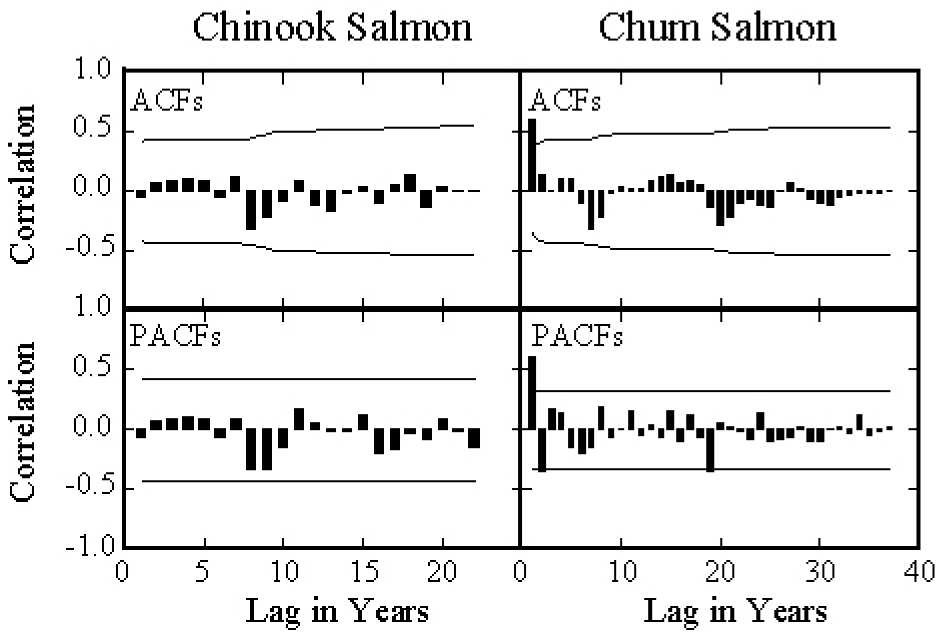

Figure 3.–Autocorrelation functions (ACFs) and partial autocorrelations functions (PACFs) for log annual observations of abundance for Chinook salmon in the Middle Fork of the Goodnews River and for chum salmon to the eastern district of Prince William Sound. Horizontal lines correspond to 95% confidence intervals for correlations.

In Figure 4 estimated risk of either type of management error can be read as a function of a PRP. In the example for the Goodnews River stock, a PRP of about 3,500 Chinook salmon entails a 10% estimated risk of unneeded management action (as read off the solid ascending curve). Put another way, if a year is picked at random, there is an estimated 10% chance that observed abundance will be below 3,500 in each of the next five years, provided there is no change from past central tendency in observations. If there is a decline from the average of past observations, say 25%, there is an estimated 45% ($=\hat{\pi}_k \times 100$) chance that observed abundance will be below the PRP of 3,500 in each of the five years and action taken. If such a 25% decline is considered worrisome, then action is needed, making the estimated risk of mistaken inaction the complement of $\hat{\pi}_k$, which from the thin, descending curve with the "25%" label is 55%.

Curves representing estimated risks of management error associated with PRPs for chum salmon in the eastern district of Prince William Sound are displayed in Figure 4 as well. Interpretation of autocorrelation and partial autocorrelation functions for log observations for this stock (Figure 3) indicate an autoregressive process with lag one year (significant correlations only at lag one year common to both functions). Equation (10) was fit to log observations with the time series options in SYSTAT© 9.0 to provide estimates $\hat{c} = 4.141$, $\hat{\phi} = 0.634$, and $\hat{\sigma}^2 =$ 0.271. Residuals from this fit showed no further signs of serial correlation. A short QuickBasic© program was used to estimate π_k and 1 - π_k through simulation for prospective PRPs as per equations (10) and (11) with k = 5, M = 10,000, and M values of $t : (n - 2)$ generated using SAS© 8.2. Curves were determined for no change in central tendency to describe estimated risks of unneeded action, and with 25%, 50%, and 75% drops from the average of past observations as per equation (13) to describe estimated risks of mistaken inaction.

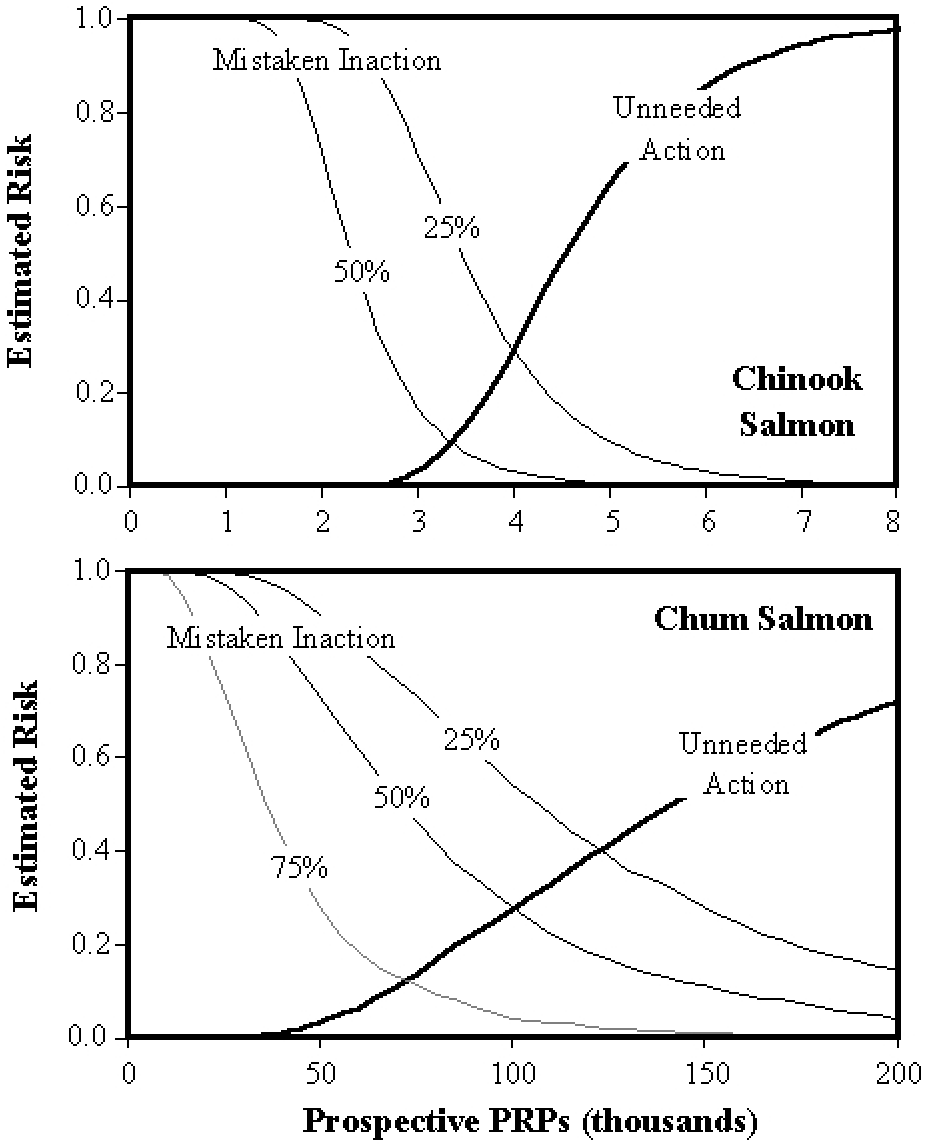

Figure 4.–Estimated risks of management error associated with possible PRPs for Chinook salmon in the Middle Fork of the Goodnews River, and for chum salmon in the eastern district of Prince William Sound. If expected variation in observations remains unchanged, management error occurs with a management action (ascending curves); if expected variation declines a worrisome percentage into the future, management error occurs with no a management action (descending curves).

This example with chum salmon can also be used to demonstrate the consequences of not adjusting calculations for serial correlation. Statistics $\bar{x} =$ 11.326 and $s^2 = 0.427$ were plugged into equation (7) and used to generate two new curves describing estimated risk of unneeded action and of mistaken inaction. Mean of observed spawning abundance was reduced 50% through equation (12) to produce the latter curve. These two new (dashed) curves are displayed in Figure 5 along with (solid) curves from Figure 4. Note that ignoring serial correlation shifts ascending and descending curves to the right, implying a bias of $\hat{\pi}_k < \pi_k$ in the dashed curves.

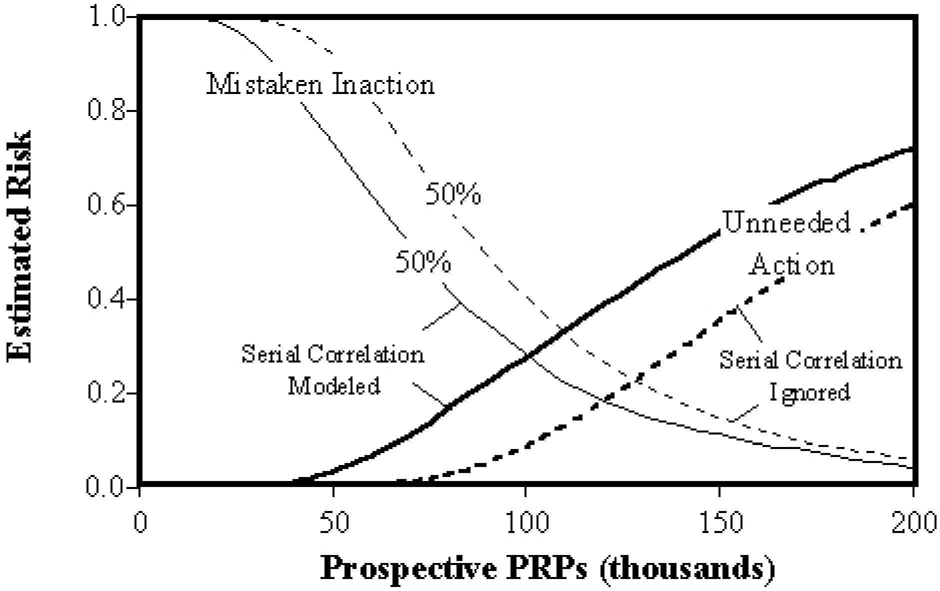

Figure 5.–Risks of management error for possible PRPs for chum salmon in the eastern district of Prince William Sound when existing serial correlation has (solid curves), and has not (dashed curves) been modeled.

The consequences can be demonstrated with a PRP set at 100 thousand chum salmon. By ignoring serial correlation, a biased $\hat{\pi}_k = 0.08$ from the ascending, dashed curve (no change from past variation), indicating management actions, all unneeded, about once every 12 years ($\cong 1/\hat{\pi}_k$). However, future observations should be serially correlated as in the past, so management action is more likely to occur on average once every 4 years (≅1/ 0.24 from the ascending, solid curve). A similar bias in $\hat{\pi}_k$ occurs with a worrisome change from past variation, only now error occurs in a year without a management action. From the descending, dashed curve in Figure 5, chance of no management action is an estimated 40% at a PRP = 100 thousand chum salmon. Because the descending, solid curve is germane to future observations (not the dashed curve), 28% is a better estimate of the actual risk of mistaken inaction. In short, more management actions than expected will probably occur if serial correlation is ignored when estimating risk at a given PRP. Estimated risk of unneeded action will be understated, while estimated risk of mistaken action will be overstated.

SAMPLE SIZE, MISSING OBSERVATIONS, AND MEASUREMENT ERROR

Results from parametric simulations indicate that effects of sample size on the accuracy and precision of $\hat{\pi}_k$ wane and moderate as sample size nears 20 years (Figure 6). One thousand series of 20 observations each were drawn from the standard normal distribution. Statistics $\bar{x}$ and s^2 were calculated at n = 2, 3, 4 … 20 years within each series to create 19,000 samples. The statistic $t_X : (n-1)$ was calculated thrice for each sample with X = -1 (for π_k = 0.159, k=1), with X = -1.645 (for π_k = 0.050, k = 1), and with X = -0.5 (for π_k = 0.029, k = 3.). Each estimate of π_k was obtained from the cumulative density function for the Student's t distribution as per equation (8) with k = 1 or 3. Results indicate that the effect of using estimates $\hat{\mu}$ and $\hat{\sigma}^2$ when estimating risk becomes negligible as sample size *n* nears 20 years, at least with simple decision rules for management action. Marginal improvement in the dispersion of $\hat{\pi}_k$ begins to noticeably tail off between 10 and 15 years of observations. At low sample sizes there is considerably better than a 50/50 chance that $\hat{\pi}_k > \pi_k$, meaning that for a given PRP, fewer management actions will probably occur than expected from the estimate, the opposite effect from ignoring serial correlation. At low sample sizes estimated risk of unneeded action will be overstated at a given PRP, while estimated risk of mistaken inaction will be understated.

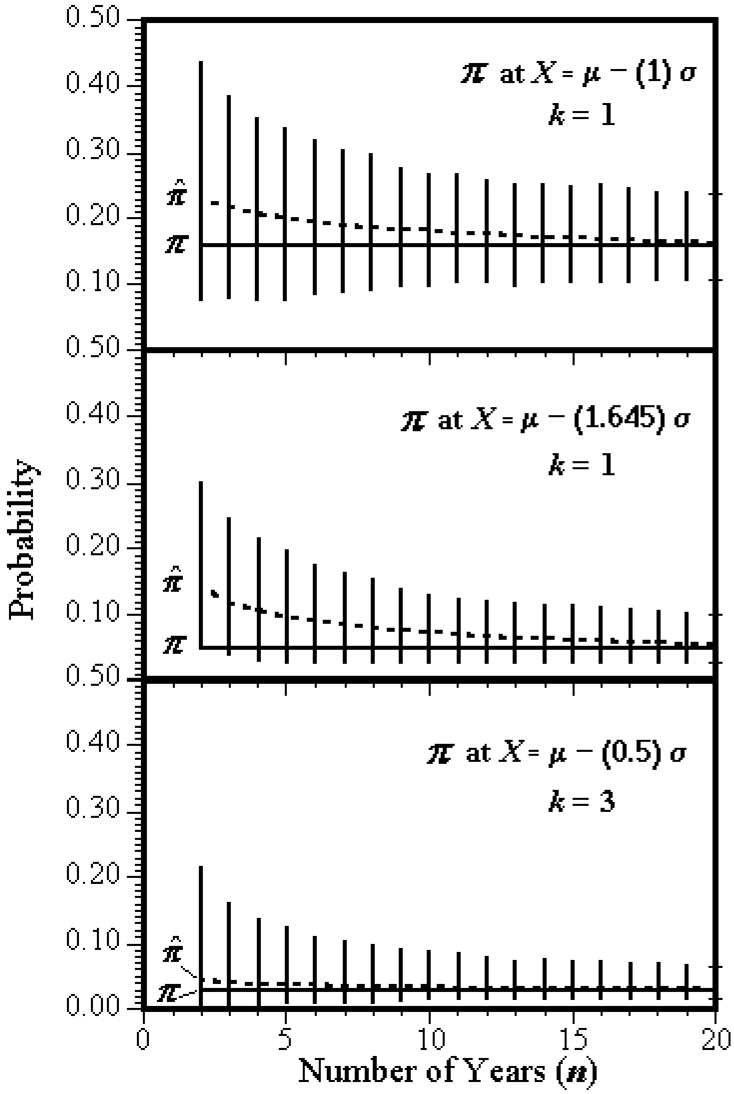

Figure 6.–Precision and accuracy of $\hat{\pi}$ as functions of sample size *n* for three scenarios: π_k = 0.159 and 0.050 with k = 1, and 0.029 with k = 3. Values of π_k correspond to 1, 1.645, and 0.5 SDs below the mean. Smoothed dashed curves connect medians of $\hat{\pi}_k$ over a 1000 simulated samples at each sample size; each vertical bar corresponds to 34% of simulated estimates above and 34% of estimates below the median estimate.

Sample size should also be large enough to detect significant serial correlation in observations. The minimal sample size to do so depends upon the magnitude of the correlation (Figure 7). Twenty years is sufficiently long to consistently detect strong (ϕ = 0.8) serial correlation against the null hypothesis $H_o : \phi \leq 0$ (one-tailed test at 80% power, probability of a type I error = 0.05). Minimal length increases to 25 years when ϕ = 0.6, 30 years at ϕ = 0.5, and 35 years when ϕ = 0.4 for the same precision and power. As shown in the example with chum salmon above, more management actions than expected will probably occur if serial correlation is not detected when it exists.

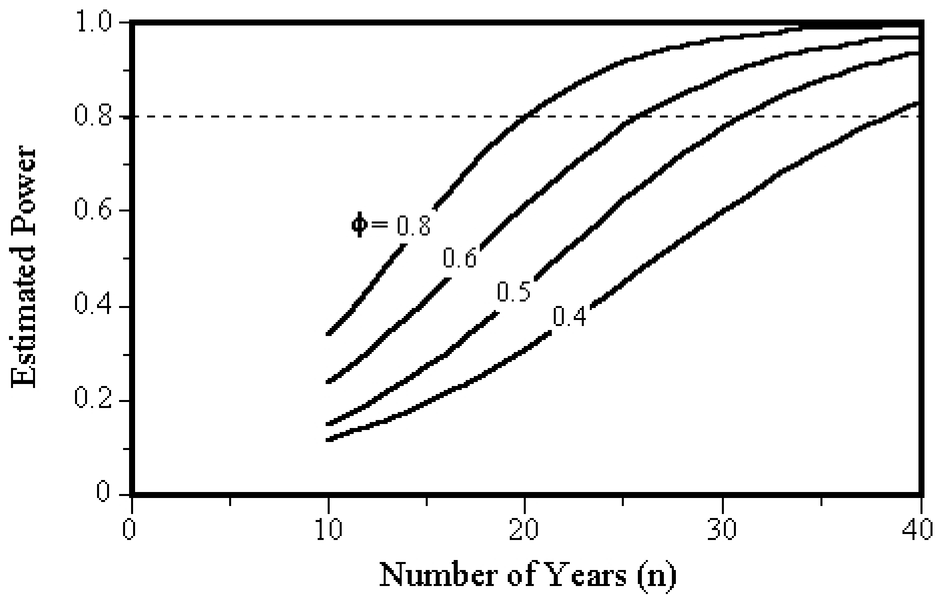

Figure 7.–Estimated power for detecting an autoregressive process with lag one year in a time series of *n* observations. Two hundred, 35-year series of log observations were simulated, each with $\mu = 0$, $\sigma = 1$ or 0.33, and ϕ as specified. Each series was analyzed at length 10, 15, 20, 30, and 35 years to detect a significant estimate ($H_o : \phi \leq 0$ and $H_a : \phi > 0$ with the probability of a type I error at 0.05) with the fraction of significant results in each analysis being an estimate of power. Value of σ did not affect estimates of power. Curves were developed by using linearized logistic equations fit to individual estimates of power; coefficients of determination (R^2) were greater than 99%.

Consequences of missing observations in a stationary series at random depend on the presence of serial correlation in spawning abundance. If available observations are too few to reasonably detect even strong serial correlation ($n < 20$), the only option is to assume that serial correlation is not present when not detected, proceed, and suffer the consequences if the assumption is wrong. If there are ≥ 20 available observations, there are options with a moderate amount of missing data. Skipping or imputing missing observations may produce unbiased estimates of μ and ϕ, but will underestimate σ^2 (Little and Rubin 2002). Unbiased estimates of μ, ϕ, and σ^2 can be obtained using an EM algorithm to impute missing values (Little and Rubin 2002, p. 246-248), so long as available observations are numerous enough to exhibit the underlying serial correlation. If not, the recursive EM procedure will fail to converge to a solution. Degrees of freedom for estimating π_k would be decremented for each missing observation imputed. A Bayesian fit to equation (10) provides an alternative method of imputing missing observations by considering them as extra parameters (see Gelman et al. 1995). Table 2 shows mean values for the posterior marginal distributions of μ, ϕ, and σ^2 from the chum salmon example when 0, 5, 8, and 10 observations were removed at random from the series; non-informative priors were used in this imputation. As is evident in the table there is very little change in posterior means through imputing 10 missing observations. However, attempts to imput 15 missing observations failed in that the SDs from the posterior distributions of ϕ and σ^2 ballooned with the former becoming bimodal with a mode on zero. Considering the power estimates described in Figure 7, the 22 remaining observations after 15 had been censored probably did not contain enough information to consistently detect serial correlation when $\phi \cong 0.6$.

Table 2.–Means from posterior marginal distributions for μ, ϕ, and σ^2 from Bayesian imputation of censored observations of spawning abundance of chum salmon in the eastern district of Prince William Sound, Alaska. Estimates were from fits of an AR(1) model in WinBUGS1.3© beginning with non-informative priors. Corresponding estimates from minimizing sums of squared deviations for all 37 observations and the model are 11.31, 0.63, and 0.27. Standard deviations of posterior distributions are in parentheses.

Censored Observations:			Parameters:	
Number	Years	μ	ϕ	σ^2
0	-	11.38	0.68	0.29
		(0.60)	(0.14)	(0.07)
5	1966 1981	11.40	0.61	0.28
	1970 1985	(0.42)	(0.16)	(0.08)
	1976			
8	1968 1984	11.37	0.61	0.30
	1972 1992	(0.64)	(0.16)	(0.09)
	1974 1996			
	1980 1999			
10	1966 1984	11.34	0.59	0.30
	1969 1988	(0.50)	(0.17)	(0.09)
	1972 1992			
	1974 1996			
	1980 2000			

Measurement error in observations does not affect estimated risk of management error per se, but does affect the risk itself. Several models of random and systematic measurement error typical of observing spawning abundance of salmon are given in Table 3.

Table 3.–Models, parameters, and expected standard normal variates *Z* that can be used to estimate probability of management action from observations of spawning abundance with different types of measurement error. Notation is defined in the text; *A* represents actual abundance. Parameter values have the following ranges: $0 < \alpha \le 1$, $0 < \beta < 1$, $\mu > 0$, $\sigma^2 \ge 0$.

NO MEASUREMENT ERROR	**RANDOM/SYSTEMATIC MEASUREMENT ERROR**	
	Proportional Error	Depensatory Error
Model:		
$y_{i(1)} = A_i$	$y_{i(2)} = \alpha A_i \exp(\delta_i)$ $\delta_i \sim N : 0, \sigma_\delta^2$	$y_{i(3)} = \alpha A_i^\beta \exp(\delta_i)$ $\delta_i \sim N : 0, \sigma_\delta^2$
Transformed Model :		
$x_{i(1)} = \log_e A_i$ $x_{i(1)} \sim N : \mu_{(1)}, \sigma_{(1)}^2$	$x_{i(2)} =$ $\log_e \alpha + \log_e A_i + \delta_i$	$x_{i(3)} =$ $\log_e \alpha + \beta \log_e A_i + \delta_i$
Mean of *x*:		
$\mu_{(1)}$	$\mu_{(2)} = \log_e \alpha + \mu_{(1)}$	$\mu_{(3)} = \log_e \alpha + \beta \mu_{(1)}$
Variance of *x*:		
$\sigma_{(1)}^2$	$\sigma_{(2)}^2 = \sigma_{(1)}^2 + \sigma_\delta^2$	$\sigma_{(3)}^2 = \beta^2 \sigma_{(1)}^2 + \sigma_\delta^2$
Expected Standard Normal Variate:		
$\mathrm{E}[Z_{(1)}] =$ $(x_{(1)} - \mu_{(1)}) / \sigma_{(1)}$	$\mathrm{E}[Z_{(2)}] =$ $\mathrm{E}[Z_{(1)}] \left[\frac{\sigma_{(1)}}{\sqrt{\sigma_{(1)}^2 + \sigma_\delta^2}} \right]$	$\mathrm{E}[Z_{(3)}] =$ $\mathrm{E}[Z_{(1)}] \left[\frac{\sigma_{(1)}}{\sqrt{\sigma_{(1)}^2 + \sigma_\delta^2 / \beta^2}} \right]$

Counts of all fish by species passing through a weir, past a sonar, or from a tower would theoretically produce observations with no, or at least negligible, measurement error. Subsampling time when counting at weirs, towers, or sonars; capture-recapture experiments; and catch-at-age analyses entail a sampling variance, and thus produce observations with random measurement error. Note that models in the middle column in Table 3 represent this type of measurement error when $\alpha = 1$. A proportional index of abundance is implied when $\alpha < 1$. A count or an estimate from only one spawning tributary when members of the stock spawn in several tributaries are examples of proportional indices. Some indices, such as counts from aerial, foot, or snorkel surveys, may not be strictly proportional to abundance, but are depensatory with a smaller fraction counted at a larger abundance (Eicher 1953; Shardlow et al. 1987; Jones et al. 1998; and others). The depensatory model in the third column of Table 3 is the power function from Jones et al. (1998). From the bottom row of Table 3, note that terms in brackets $[\sigma_{(1)} \big/ \sqrt{\sigma_{(1)}^2 + f(\sigma_\delta^2)}]$ are less than 1 when $\sigma_\delta^2 > 0$, making the expected value of the standard normal variate Z smaller whenever observations have measurement error. Since in this demonstration $\pi_k = \mathrm{P}[Z \le Z_X]^k$, smaller expected values of *Z* mean smaller values of π_k at a given PRP. There will be less management action with measurement error, resulting in a lower risk of unneeded action, but with a worrisome decline, more risk of mistaken inaction. To demonstrate this effect, random measurement error was added to variation observed for Chinook salmon returning to the Middle Fork of the Goodnews River. These salmon were counted through a weir ostensibly with no measurement error at all. Because calculations for estimating risk are in terms of logs while sampling variances are not, $\mathrm{CV}^2(\hat{y})$ was used to approximate expected sample variance for $\log_e \hat{y}_i$ by applying the delta method (Seber 1982, p. 8) to the transformation. Coefficients of variation were set at 0.15, which is common for estimates from capture-recapture experiments, and at a larger 0.30 for comparison. Remembering that originally $\hat{\sigma}^2 = 0.143$ for this stock, additions of measurement error create new variances at 0.166 and 0.233 for estimating risk. The result is that both curves describing estimated risk are shifted to the right (Figure 8), implying less risk of unneeded action and more risk of mistaken inaction. These effects are small when random measurement error represents 14% of variation (CV = 0.15) in the example, and are more pronounced when it represents 39% of variation (CV = 0.30) (Figure 8). The bracketed term $[\sigma_{(1)} \big/ \sqrt{\sigma^2_{(1)} + \sigma^2_\delta / \beta^2}\,]$ in the last row of Table 3 confirms that importance of measurement error is relative to underlying variation $\sigma^2_{(1)}$ in abundance with importance enhanced as depensation in observations increases (as β falls below 1).

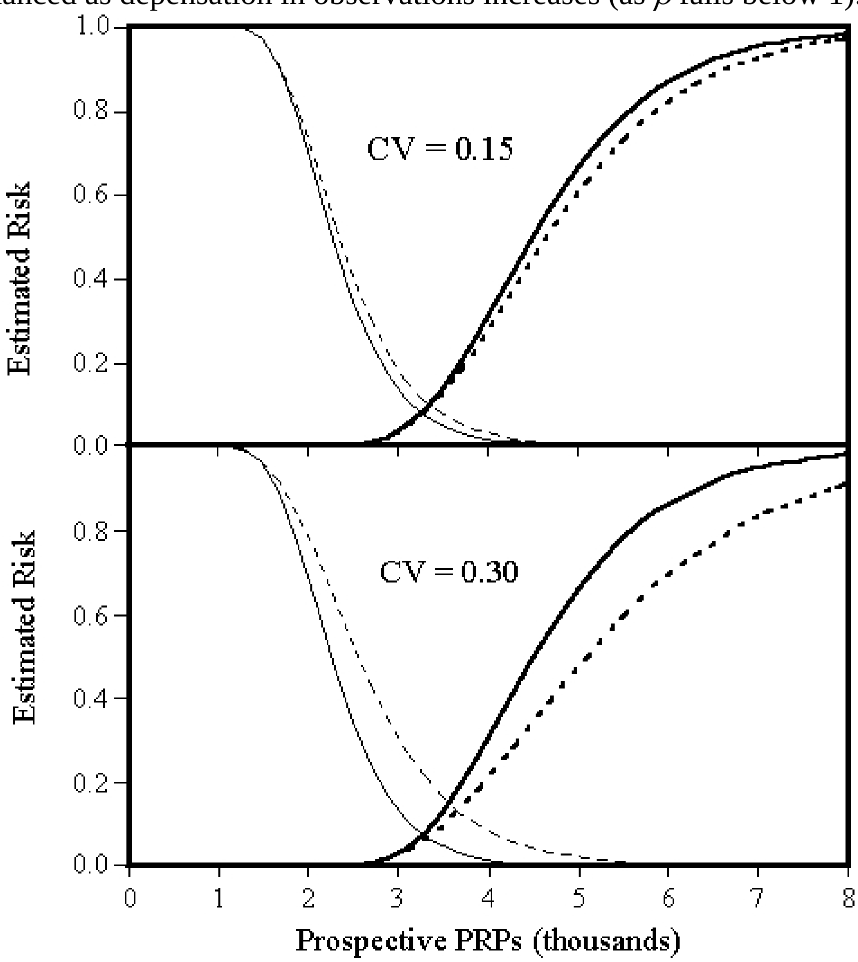

Figure 8. Estimated risks of management error for possible PRPs for Chinook salmon in the Middle Fork of the Goodnews River without (solid curves) and with the addition of random measurement error (dashed curves) with CVs of 0.15 and 0.30.

DISCUSSION

Small sample size presents the biggest difficulty to inference when estimating risk of management error from observed abundance of a non-targeted stock. Measurement error in observations is not a problem for estimating risk of management error per se, but does increase the risk inherent in management. Observations missed because of random events such as flooding and inclement weather reduce effective sample size, and small sample size imparts bias to estimates of risk. The difficulty arises because the direction of small-sample bias will be unknown. At sample sizes under 20 years, particularly 10 or fewer, uncertainty in parameter estimates tends to inflate expectations of management actions while undetected serial correlation, if present, tends to deflate those expectations. There is no way to determine which is the case without information beyond the available observations. Of course, patience would provide more observations, eventually resolving the dilemma.

Sample size is also related to the effective length of a time series. Times series in the examples above for Chinook salmon and chum salmon are demonstrably stationary, that is, they do not exhibit a temporal trend in central tendency or in variation. However, not all time series are stationary; some series will have a prominent downward or upward shift in observations. If long enough, such a non-stationary series might be decomposed into one or more subseries with each stationary subseries being empirical evidence for persistence of the stock at the corresponding level of abundance. Given the data, protection of a non-targeted stock with minimal disruption of the mixed-stock fishery would be achieved with estimates calculated from the stationary subseries with the low mean. If this subseries is also the recent subseries, presumably extending into the near future, estimated risk for a given PRP should be unbiased within limits of sample size. If the recent subseries of observations, stationary or not, has a higher mean, estimates of risk calculated from an earlier subseries that is stationary with a lower mean will be biased with probably fewer management actions in the future than expected ($\pi < \hat{\pi}$). However, this bias is mitigated because a non-targeted stock is not in need of protection in this situation. If recent observations constitute a slide to the lowest observations on record, risk can still be estimated from an earlier stationary subseries with higher observations. More management actions will probably occur than “expected” at a given PRP ($\pi > \hat{\pi}$), not surprising since a worrisome decline in observations has already occurred. In this last case, estimated risks of management error will be more germane once management action and long-standing regulation has changed the mixed-stock fishery to increase spawning abundance in the non-targeted stock. Of course, a series of observations may be too short to contain a stationary subseries, in which case estimating risk of management error based on a period of stability becomes problematic. Our method of estimating risk of management error is in some ways just a start at risk assessment or risk management for non-targeted stocks of salmon. We addressed process uncertainty (lognormal variation), observation uncertainty (measurement and sampling error), model uncertainty (serial correlation), and estimation uncertainty (sample size and missing data) in management error as described in Francis and Shotton (1997), but did not address implementation or institutional uncertainty in decisions to take management actions with PRPs, as did Prager et al. (2003) for target reference points. Nor did we discount the risk of management error by perceived consequences, though we did address the risk of unneeded action as a disruption of the mixed-stock fishery, as suggested by Hilborn (2002). We concentrated on risk involved with stocks that are often ignored when managing fisheries, stocks for which there is usually limited information. Taking further steps into risk assessment would involve expanding that focus to estimating risk and consequences of management actions for targeted stocks as well, a subject that has been well explored (see Francis and Shotton 1997). As for risk management, estimated risk of management error at a given PRP could be used to establish a risk averse PRP for management. However, putting such risk aversion into perspective requires covering more than just non-targeted stocks in a mixed-stock fishery, again getting away from our focus of providing a useful tool related to a special, but common situation.

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