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Utility of escapement time series data for monitoring the response of salmon populations to habitat alteration

Josh Korman and Paul S. Higgins

Abstract: We provide a quantitative examination of the utility of escapement data for monitoring changes in salmonid populations caused by habitat alterations. We used Monte Carlo simulations to determine the precision, duration of monitoring, and the effect size required to achieve acceptable statistical inferences based on before-after (BA) and before-after-control-impact (BACI) comparisons. There was generally less than a 50% chance of detecting a population response unless the population change was large (more than a twofold increase) or the post-treatment monitoring period long (>10 years). Statistical power was improved by increasing the precision of escapement estimates, but the extent of improvement was dependent on the magnitude of population response to treatment, the duration of monitoring, and the extent of natural variability in abundance. BACI comparisons generally had a 10–15% lower probability of detecting a population change than BA comparisons unless the degree of covariation in survival rates between control and treatment stocks was very strong. Autocorrelation in error, simulating patterns of high and low survival rates over time, generally reduced power by 5–15%. Our results identify the conditions where escapement information can be used to make reliable inferences on salmonid population changes and provides a means for evaluating alternative monitoring designs.

Résumé : Nous présentons un examen quantitatif de l'utilité des données sur les échappées pour suivre les changements dans les populations de salmonidés causés par les modifications de l'habitat. Nous avons utilisé des simulations de Monte Carlo pour déterminer la précision, la durée de la surveillance et la taille de l'effet nécessaire pour pouvoir réaliser des inférences statistiques acceptables fondées sur des comparaisons avant-après (AA) et avant et après effet témoin (AAET). En général, il y avait moins de 50 % de probabilité de détecter une réaction de la population à moins que le changement touchant la population ait été important (augmentation supérieure à un facteur de deux) ou que la période de surveillance après traitement ait été longue (>10 ans). La puissance statistique a été améliorée en augmentant la précision des valeurs estimées de l'échappée, mais le degré d'amélioration dépendait de l'amplitude de la réaction de la population au traitement, de la durée de la surveillance et du degré de variabilité naturelle de l'abondance. En général, les comparaisons AAET présentaient une probabilité de détection d'un changement dans la population qui était de 10 à 15 % inférieure à celle des comparaisons de type AA, à moins que le degré de covariation dans les taux de survie entre les stocks témoins et traités ait été très élevé. L'autocorrélation de l'erreur, simulant des caractéristiques de taux de survie élevés et faibles dans le temps, réduisait généralement la puissance de 5 à 15 %. Nos résultats permettent de déterminer les conditions dans lesquelles l'information sur l'échappée peut être utilisée pour réaliser des déductions fiables sur les changements dans les populations de salmonidés et fournissent un moyen d'évaluer des plans de surveillance différents.

[Traduit par la Rédaction]

Introduction

Alteration of habitat in rivers and streams has been recognized as one of the primary causes of declines in anadromous salmonid populations on the Pacific coast of North America (e.g., Levings et al. 1989). With greater public scrutiny over fish habitat management there is increasing pressure to develop quantitative estimates of the effects of habitat alteration on salmon populations, to implement restoration programs, and to monitor the effectiveness of these programs for meeting

resource management goals. Impact assessment is undertaken to establish how an affected population has responded to habitat alteration and to determine the appropriate restoration actions. Monitoring, in theory, then serves to validate impact predictions and to establish whether mitigative actions meet management objectives for restoration (Millard et al. 1985; Stewart-Oaten et al. 1986; Walters et al. 1988; Peterman 1990; McAllister and Peterman 1992). However, in application, the absence of reliable historical population abundance data has forced fishery managers to use a combination of subjective judgment and relatively qualitative information to estimate the magnitude of salmon population response to habitat change. Monitoring has been typically neglected, presumably because of the high cost of implementing monitoring programs sufficient to reliably detect changes in population abundance. While this approach to habitat management may have functioned adequately in the past, greater legislative intervention (i.e., United States Endangered Species Act, Canadian Fisheries Act) into habitat issues now requires more quantitative assessment to ensure that acceptable standards for inference are

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attained (Thompson and Rueggeberg 1989). With a greater need be accountable, it is now recognized that relying on uncertain assessment information is not sufficient for inferring effects of habitat alteration on fish populations (Gordon 1995).

Salmon escapement data have been collected for more than 1400 rivers in British Columbia and represent the spatially and temporally most complete data set available to assess changes in population abundance (Williams and Brown 1994). Because these data have been routinely collected for fishery management purposes over the last four decades, a common approach for assessing impacts of habitat alterations on salmon populations has been to compare trends in abundance of spawning populations before and after a habitat change occurs (Pella and Myren 1974; Symons and Waldichuk 1984). Escapement data, however, can be an extremely misleading indicator of the response of populations to freshwater habitat changes. Recruiting adults are typically composed of both catch and escapement and if stock-specific catch statistics are not available or if marine survival is not constant through the monitoring period, estimates of spawning population size alone will not provide a reliable index of changes in freshwater survival or carrying capacity (Hilborn and Walters 1992). Moreover, the majority of escapement time series available for British Columbia salmon populations are based on visual surveys (stream walks, overflights; Symons and Waldichuk 1984; Williams and Brown 1994), which most often produce imprecise estimates of abundance (Bevan 1961; Becker 1962), further impairing the utility of these data for detecting population changes. Despite early warnings from researchers that escapement is too imprecise an indicator to detect population changes (Pella and Myren 1974), before-after comparisons using escapement time series are still one of the most common methods for inferring changes in the abundance of salmon populations.

In this paper, we ask the question "Can escapement be used to monitor the response of salmon populations to habitat alteration?" Our objective was to define the conditions under which an escapement-based monitoring approach would provide statistically reliable results for assessing the effects of flow releases on the abundance of chinook salmon (*Oncorhynchus tshawytscha*) in the Cheakamus River, British Columbia. Computing the statistical power of monitoring programs is critical for determining the magnitude of effect that can be detected by available data and developing the appropriate design to achieve reliable inferences about habitat alteration (Peterman 1990; Mapstone 1995). We used a Monte Carlo simulation framework to determine the required precision, duration of monitoring, and effect size to achieve acceptable inferences about changes in stock abundance based on before-after (BA) and before-after-control-impact (BACI) comparisons (e.g., Green 1979; Underwood 1994). A priori, we expected that an escapement-based approach would not provide powerful inferences about population changes based on the typical precision of most of these time series (i.e., Pella and Myren 1974). However, we know of no studies that examine the interaction between variables of the monitoring program that can be controlled (i.e., estimation error, duration of monitoring) with extrinsic factors that cannot (i.e., serial correlation in survival rate, natural variation in fish survival rates, treatment effect size). Understanding how intrinsic and extrinsic factors affect the reliability of escapement-based comparisons

is a prerequisite for defining when it is appropriate to use these data as the indicator variable to monitor changes in the abundance of salmon populations resulting from habitat alterations.

Methods

The simulation framework uses an underlying stock-recruitment (SR) production model to evaluate the efficacy of escapement-based monitoring programs. Simulated escapement time series with random components designed to mimic environmental variability and measurement error were generated. Twenty years through each simulation, changes in carrying capacity were imposed on the underlying conditions to mimic the population response to habitat improvements. These simulated data were then used in statistical tests to evaluate whether the imposed biological changes could be detected using BA or BACI monitoring approaches. Our methodology consisted of two components: (i) an analysis of existing SR data to define the underlying production model, its error characteristics, and the degree of covariation between treatment (Cheakamus) and control (Mamquam) stocks used in our model simulations and (ii) Monte Carlo simulations to estimate the statistical power of escapement-based comparisons accounting for differences in the length of the monitoring period, the degree of biological change due habitat improvements, and the amount of environmental variation and measurement error that influence the number of returning spawners and estimates of their abundance.

Model parameterization

Chinook escapement estimates for the Cheakamus and Mamquam Rivers, British Columbia, were obtained from the Canadian Department of Fisheries and Oceans Salmon Escapement Database (G. Serbic, Pacific Biological Station, Department of Fisheries and Oceans, Canada, Nanaimo, B.C.). Both these rivers are part of the Squamish River watershed and are glacially fed systems characterized by high turbidity and low temperatures. The Mamquam River chinook stock was selected as a control to compare against the Cheakamus River stock because the Mamquam has similar physical characteristics to the Cheakamus, is in the same major watershed, and the juveniles from both rivers use the same areas for rearing in the lower Squamish River and its estuary. Escapement estimates have been reported for these systems based mostly on stream walks, spot checks, and (or) helicopter overflights.

Ricker SR functions were fit to the Cheakamus and Mamquam data sets. Because reliable catch data were not available, the SR curves were estimated using escapement data only, rather than using catch and escapement data for the recruit values, and escapement data for the stock values. Age-at-maturity information, estimated for these rivers based on a multiyear mark-recapture study (Schubert 1993), was used to compute the number of returns for each brood. The following form of the Ricker SR model was estimated by the regression of $\log_e(\text{returns/spawner})$ on spawners (Ricker 1975):

$$(1) \quad R_t = S_{t-x} e^{(\alpha - \beta)S_{t-x} + v_t}$$

where t is the return year, x is the total age-at-maturity, R_t is the returning spawners in year t , S_{t-x} is the returning spawners in year $t-x$, e^α is the maximum returns per spawner, β is the parameter of density dependence (α/β is the unfished equilibrium stock size), and v_t is the normally distributed error term with mean = 0 and SD = σ_{env} (hereafter referred to as process error). The model assumes lognormal process error (Allen 1973; Ricker 1975; Peterman 1981; Bradford 1995), and in this form the predicted returns for given values of α and S increase as the value of β decreases.

A quantitative measure of covariation between treatment and control stocks was required for our simulations of a BACI monitoring design. Residuals from the Cheakamus and Mamquam SR curves were correlated to provide an index of the temporal similarity in survival rates that is corrected for density dependent effects. In our

simulations, we used this level of covariation as well as higher values to examine the influence of the degree of similarity between control and treatment stock on the statistical power of a BACI design.

Monitoring program simulations

Parameters from the best-fit Ricker SR model for Cheakamus River chinook salmon were used to generate simulated escapement data series. Beginning the simulations at stock size = α/β , 20 years of data were generated using the best-fit Ricker α and β values to simulate pre-treatment data. The age of returning progeny was constant throughout the simulations and set based on the observed age-at-maturity data (Schubert 1993). For post-treatment years, carrying capacity was increased by arbitrary amounts to mimic the potential population response to habitat improvements by multiplying the β parameter of the underlying Ricker model by $1/X$, where X is the simulated post-treatment change in capacity.

The modelled population was simulated with random environmental effects (v_t in eq. 1), which were assumed to be lognormally distributed with a standard deviation of σ_{env} (process error). To simulate the effects of temporal patterns in process error that reflect sequences of good and bad survival-rate years, lognormal residuals were generated with different amounts of lag-1 autocorrelation using the following equation (Fogarty 1993):

$$(2) \quad W_t = \rho W_{t-1} + v_t(1 - \rho^2)^{1/2}$$

where W_t replaces v_t in eq. 1 and ρ is the lag-1 autocorrelation coefficient. The higher the value of the autocorrelation coefficient, the greater the correspondence between the environmental error in years t and $t - 1$.

To generate "observed" data, we assumed that escapement was estimated with multiplicative errors as in Walters and Ludwig (1981) and Caputi (1988):

$$(3) \quad S_t = s_t e^{\sigma_{obs}}$$

where S_t is the observed spawners, s_t is the actual spawners, and σ_{obs} is the normally distributed random variable with mean = 0 and variance σ_{obs}^2 . We could not directly estimate the precision of Cheakamus River chinook escapement estimates and could find no comparative data sufficient to confidently estimate σ_{obs} for visual methods that have been predominantly used there in the past. Four levels of escapement estimate precision were therefore used in our simulations to reflect the expected quality of perfect ($\sigma_{obs} = 0$), moderate ($\sigma_{obs} = 0.3$, 5–95% confidence limits = 0.6–1.7 times the actual number of returns), poor ($\sigma_{obs} = 0.7$, 5–95% confidence limits = 0.3–3.2), and extremely poor ($\sigma_{obs} = 1$, 5–95% confidence limits = 0.2–4.8) counting methods. Because the difficult counting conditions (seasonal turbidity of tributaries), large relative wetted stream width (>10 m), and restricted access in some reaches would reduce the reliability of escapement estimates based on visual methods, we assumed a base σ_{obs} of 0.7 for our simulations but also examined the $\sigma_{obs} = 1.0$ condition as a worst case scenario.

Following each individual simulation, statistical power was estimated for both BA and BACI comparisons. For the former, the means of \log_e transformed pre- and post-treatment escapements were compared based on a one-tailed t test using a maximum acceptable type I error level of 20%. This value was chosen so that, when using a minimum acceptable power level of 80%, the probability of making a type II error would equal that of a type I error. We therefore assumed that the cost of not detecting a population change when it does occur is as great as the cost of falsely concluding that an improvement was detected. The \log_e transformation was used to normalize the distribution of escapements and reduce heteroscedasticity. This transformation was also selected to reduce nonadditivity between control and treatment stock abundance (effecting the BACI comparison) resulting from the multiplicative process error assumed in our simulations.

For the BACI comparison, an additional control stock was simulated for each trial based on the same Ricker parameters and error

levels as the treatment stock except the carrying capacity was not increased during the post-treatment period. For each trial, different random number sequences were used to simulate process and observation error for the two stocks. The process error between stocks was correlated at two levels, representing (i) the observed degree of similarity between the Cheakamus (treatment) and Mamquam (control) stocks based on the correlation of residuals among each stocks SR relationship ($r^2 = 0.1$) and (ii) a much stronger degree of covariation representing a greater similarity in control-treatment pairs ($r^2 = 0.8$). Once two sets of escapement time series were generated, a BACI comparison was performed following the method recommended by Stewart-Oaten et al. (1986). For each simulated year, the differences between the control and treatment stock's observed \log_e -transformed escapement values were computed. A one-tailed t test was used to test for significant differences in the mean before-treatment stock differences and the mean after-treatment differences.

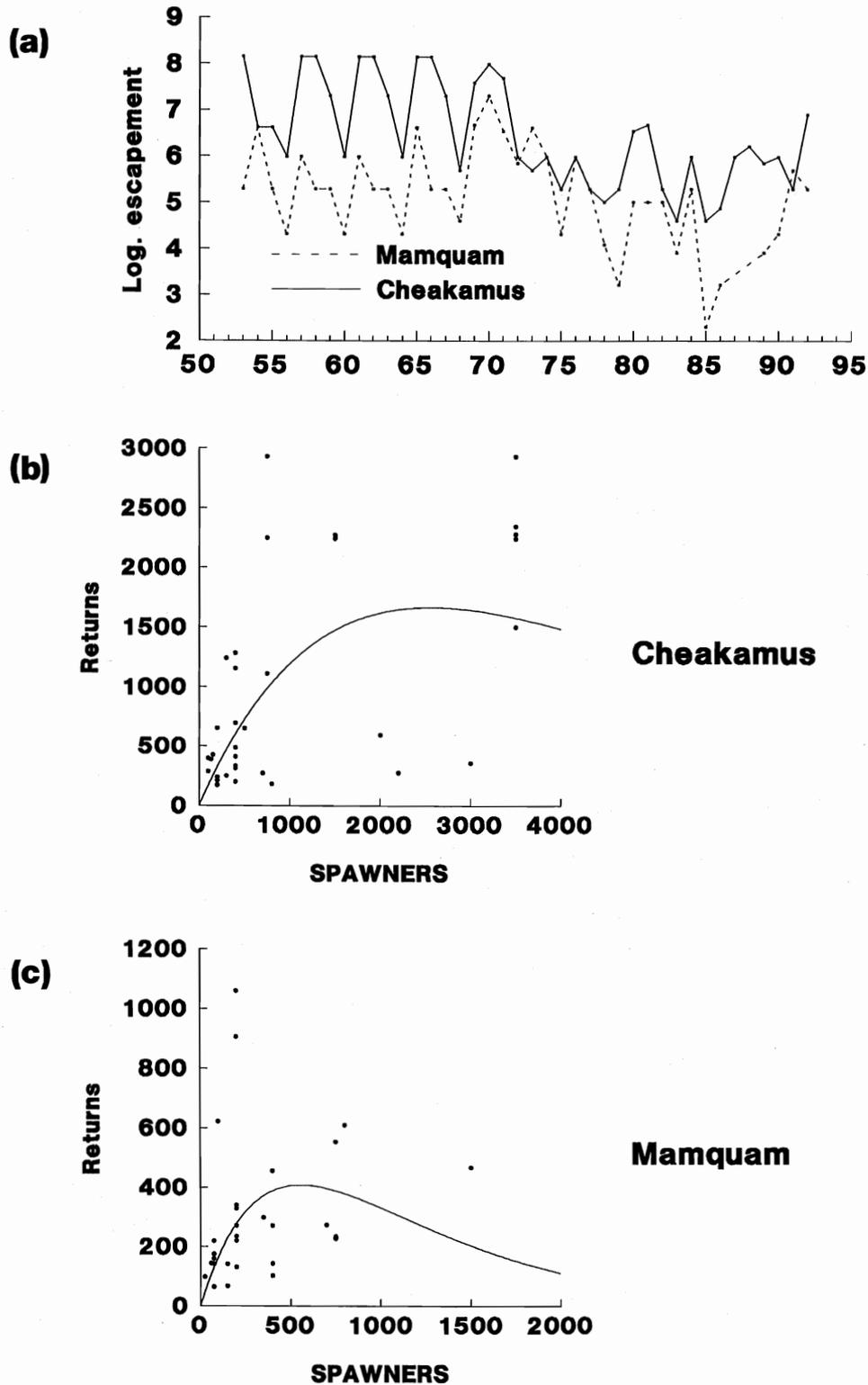
Statistical power was estimated by calculating the percentage of 1000 trials where a statistically significant positive increase in escapement had been detected. The effects of a variety of conditions on power were explored by assuming different (i) degrees of potential change in carrying capacity (zero- to three-fold increase in 0.25 increments); (ii) post-treatment monitoring periods (10–40 years in 10-year increments); (iii) amounts of environmental ($\sigma_{env} = 0.3$ and 0.6) and measurement ($\sigma_{obs} = 0, 0.3, 0.7$, and 1.0) error; and (iv) two levels of autocorrelation within the process error ($\rho = 0$ and 0.6). The default process error for our simulations was set at $\sigma_{env} = 0.6$. This value was selected so that, when combined with the assumed σ_{obs} value of 0.7 in the simulations, it resulted in an expected residual variance around the SR curve (computed from simulated data) equal to the empirical value from the Cheakamus River chinook SR relationship (SD of estimate = 0.8). To examine graphically how power varied as a function of these parameters, we used a distance-weighted least-squares smoothing procedure to plot isopleth diagrams showing the probability of detecting a statistical positive increase in the escapement based on the BA or BACI comparisons (Wilkinson 1990).

Results

Model parameterization

The Mamquam escapement trend explained 40% of the trend in the Cheakamus data (Fig. 1a). Both time series show a similar decline in abundance starting in the early 1970s and stabilizing at lower levels by the end of that decade. Despite the significant correlation among the two stocks ($r^2 = 0.4$, $p < 0.001$, $n = 38$), any measure of covariation must be viewed with caution because of systematic errors that are inherent in escapement estimation methodologies applied in the past. For example, prior to the 1970s, escapement estimates in British Columbia were recorded using a categorical system (i.e., BC 16 form; Symons and Waldichuk 1984), and because continuous data are not available to determine the actual abundance during those years, the median value in the category is usually used to index spawning population. Depending on the actual abundance category, these biases can exceed 100% (Symons and Waldichuk 1984). Another possible source of bias is cross correlations among escapement estimates of stocks assessed by the same fisheries officer. Because access to coastal streams is usually difficult, budgets are limited, and fisheries officers have a large number of streams to survey, there may be a tendency for estimates obtained from one stream to inadvertently influence estimates made for subsequent rivers. For the Cheakamus and Mamquam chinook stocks, these two biases are probably the cause of the apparent cycles in the abundance data, which are not generally observed

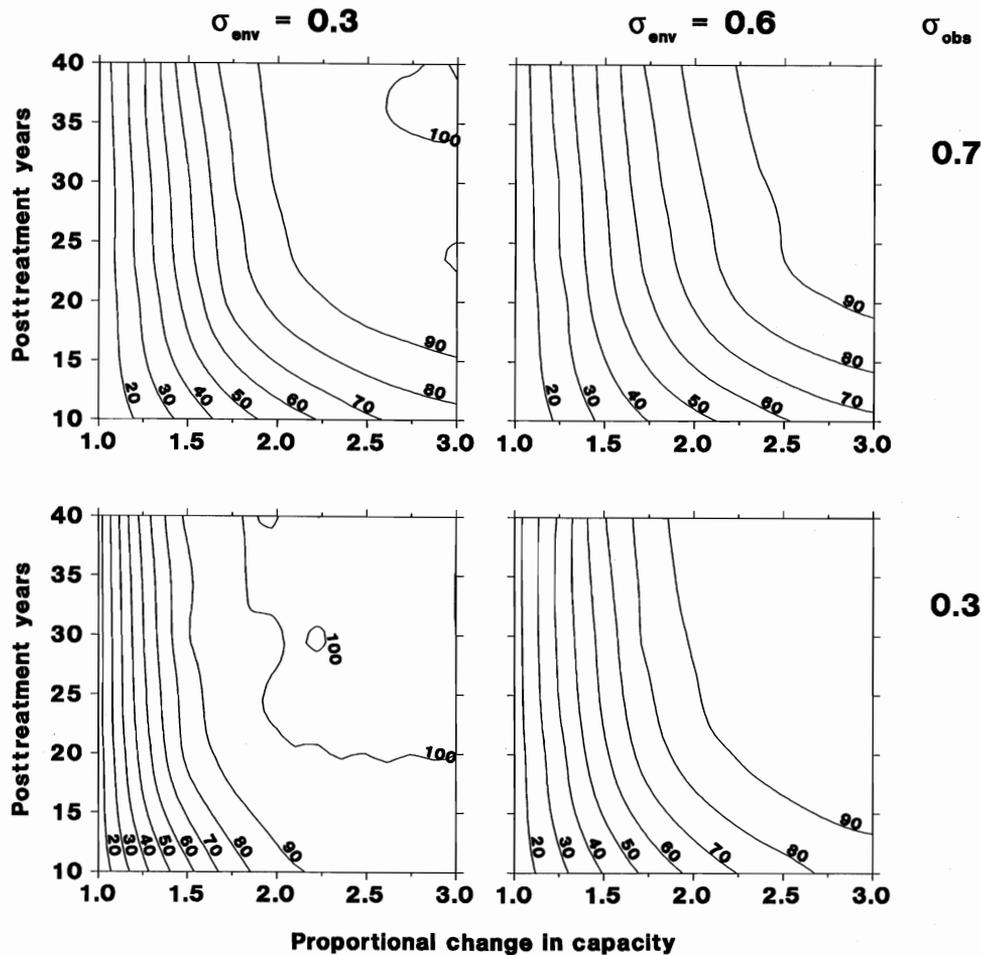
Fig. 1. Comparison of (a) chinook escapement time series for Cheakamus and Mamquam rivers and stock–recruitment relationships for the (b) Cheakamus River ($r^2 = 0.29$, $P_{\text{slope}} < 0.001$, $n = 38$, SE of estimate = 0.79, $\rho = 0.60$) and (c) Mamquam River ($r^2 = 0.42$, $P_{\text{slope}} < 0.001$, $n = 31$, SE of estimate = 0.69, $\rho = 0.61$).



for this species (J. Irvine, Department of Fisheries and Oceans, Canada, Pacific Biological Station, Nanaimo, B.C., personal communication).

There was considerable variability around the Ricker SR relationships fitted to escapement data from the Cheakamus and Mamquam Rivers (Figs. 1b and 1c). For the Cheakamus

Fig. 2. The effect of the process (σ_{env}) and observation (σ_{obs}) error on statistical power. The isopleths show the percentage of simulations where a significant increase in the post-treatment escapement level was correctly detected based on a type I error level of 20% and $\rho = 0$.



relationship, which was used as the underlying production model for our simulations, mean stock productivity was 1.8 returns/spawner and carrying capacity was 1456 fish. The estimate of stock productivity is an underestimate of the true value because the recruitment component of the SR curve does not include catch. The SD of residuals around the recruitment curve was relatively large (0.8) and showed a high degree of lag-1 autocorrelation ($\rho = 0.6$). The relationship between the standardized residuals from the SR curves for the Cheakamus and Mamquam Rivers was marginally significant ($r^2 = 0.1$, $p = 0.098$) and for 19 of 31 years the recruitment anomalies were either both negative or positive values.

Monitoring program simulations

As expected from basic statistical theory, estimated power was sensitive to the amount of variation used in the simulations, depending on the assumed levels of (i) natural variability in freshwater and marine survival rates (process error) or (ii) the extent of the observation error in measuring escapement (Fig. 2). Based on a BA comparison of simulated \log_e -transformed escapement data, power increased at larger effect sizes or longer post-treatment monitoring periods. For example, it would take 15 years of post-treatment monitoring to detect a statistically significant increase in escapement 80% of the time

resulting from an actual threefold increase in carrying capacity ($\sigma_{\text{env}} = 0.6$, $\sigma_{\text{obs}} = 0.7$). However, this same level of power could be achieved with only a twofold increase in capacity if the duration of monitoring program was increased to 35 years. An increase in power was obtained by repeating the simulations at a lower process error level ($\sigma_{\text{env}} = 0.3$), but the extent of this improvement was dependent on the degree of observation error. At high levels of observation error ($\sigma_{\text{obs}} = 0.7$) the decline in power due to higher natural variation in recruitment was quite small. For example, a 1.5-fold increase in capacity could be detected within 20 years over 50% of the time based on the low σ_{env} simulations, while at the higher process error level, the same change would be detected about 45% of the time. However, when observation error was reduced ($\sigma_{\text{obs}} = 0.3$), power was greater than 80% with low process error and was reduced by a much greater extent (55%) when process error was increased. The improvement in power gained by reducing observation error is therefore highly sensitive to the amount of natural variation in returns. Under a more conservative type I error level (10%) these general results were similar except power was decreased by about 10% for most combinations of monitoring period and effect size, with a slightly greater loss of power for shorter monitoring periods.

Improvements in power resulting from reduced observation

Table 1. Effect of observation error on statistical power.

Proportional change in capacity	Post-treatment years	Observation error (SD)			
		1.0	0.7	0.3	0
Statistical power (%)					
1.25	10	18	21	27	30
	20	24	27	37	39
2	10	38	47	62	69
	20	58	71	85	88
Power relative to $\sigma_{\text{obs}} = 0.7$ (%)					
1.25	10	-14	0	26	40
	20	-13	0	35	44
2	10	-19	0	32	46
	20	-18	0	20	25

Note: Power represents the proportion of simulations where a significant increase in \log_e -transformed escapement between the pre- and post-treatment periods was detected based on a type I error level of 20% and $\rho = 0$.

error were also influenced by the extent of the population change and the length of the post-treatment monitoring period. The assumed level of observation error in our simulations was $\sigma_{\text{obs}} = 0.7$ and was used to represent the amount of error associated with escapement estimates based on visual surveys in a relatively wide stream with some reaches having poor visibility. When σ_{obs} was reduced to zero to represent estimates obtained from a well-maintained fish counting weir, statistical power generally increased by 25–44% (Table 1). This improvement was dependent on the proportional increase in capacity of the simulated population and the post-treatment monitoring period; for small population changes (e.g., 1.25-fold increase in capacity), power increased by a greater extent over a longer monitoring period (20 years) than a shorter (10 years) one. However, when the population change was relatively large (e.g., a doubling in capacity), the largest increase in power resulting from reduced observation error occurred over the shorter monitoring period. While the proportional increase in power caused by reducing observation error was generally higher when the change in capacity was low (e.g., 1.25-fold), power was not increased to acceptable levels even when observation error was completely eliminated. When the change in capacity was higher (e.g., twofold), power increased from unacceptable (47%) to reasonable (69%) values over a 10-year post-treatment monitoring period, and from reasonable (71%) to excellent (88%) levels over the 20-year period.

Simulations based on $\sigma_{\text{obs}} = 0.3$ represent the statistical power that might be expected based on escapement estimates derived from mark-recapture methods or more rigorous visual methods (i.e., observation towers, additional stream overflights, better information on spawner distribution). Substantial gains in power (20–35%) were achieved at $\sigma_{\text{obs}} = 0.3$ compared with $\sigma_{\text{obs}} = 0.7$, but the result of the improvement only provided adequate or near-adequate levels of power when the degree of population change was large (e.g., twofold). An σ_{obs} value of 1.0 represents a lower bound on our estimate of the precision of escapement data for the Cheakamus system. Increasing observation error to this level resulted in a loss of power ranging from 13 to 19% relative to power at $\sigma_{\text{obs}} = 0.7$, moving the power of even the most optimistic scenario (twofold change monitored for 20 years) from good (71%) to weak (58%).

The power of the BACI comparisons were strongly dependent on the degree of covariation in process error between control and treatment stocks (Fig. 3, $\rho = 0$ column). The weak correlation case ($r^2 = 0.1$) represents the degree of covariation between the Cheakamus and Mamquam chinook stocks. At this level of covariation, power is about 10–15% less using a BACI comparison than one based on a BA comparison except under very low power scenarios where the differences are less. Under the very strong covariation case ($r^2 = 0.8$), power from a BA design is only marginally greater than that from a BACI comparison.

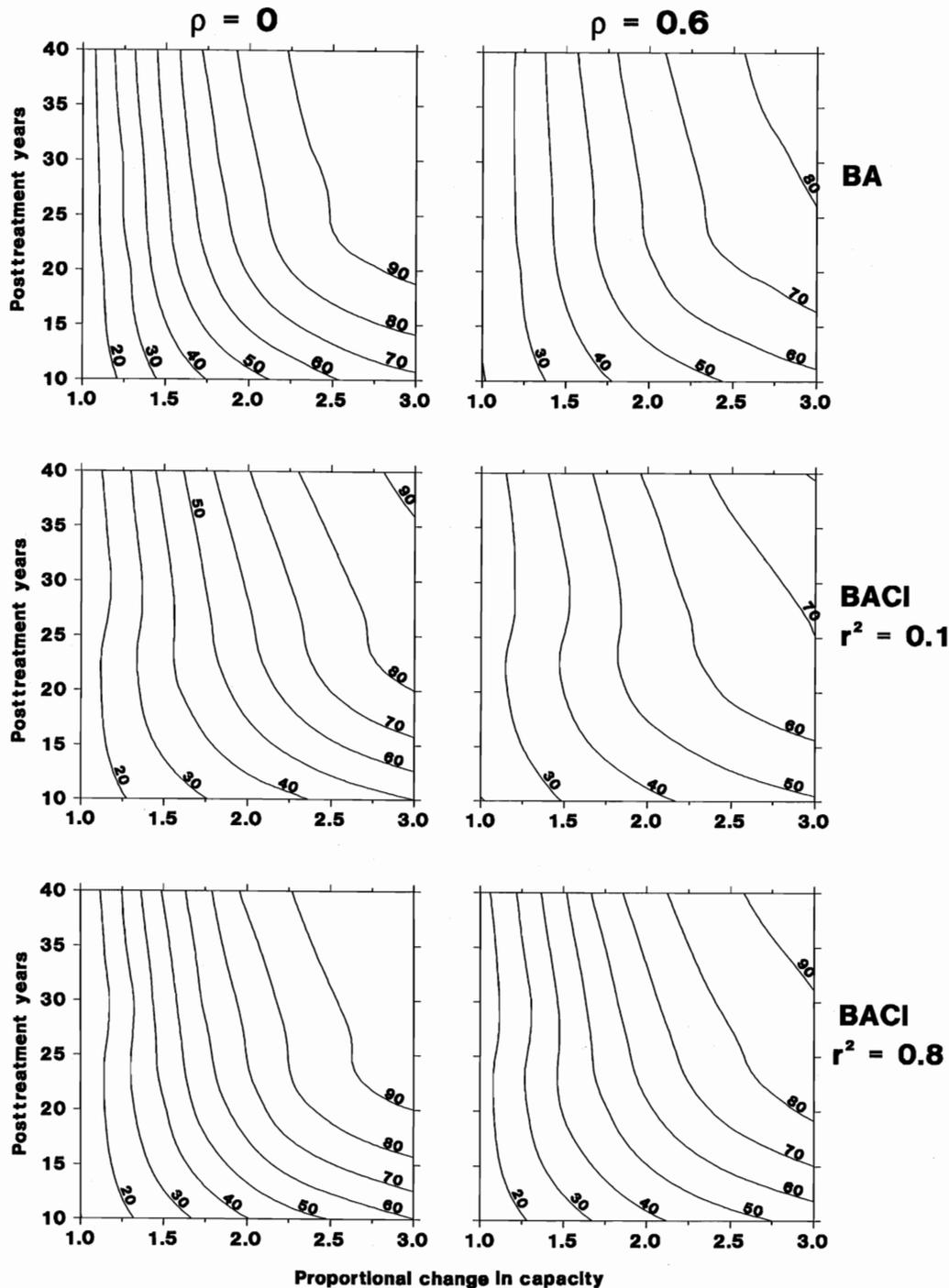
Simulation results to this point have been based on the assumption that there is no autocorrelation in process error over time. Including autocorrelation in the simulations allowed us to assess how trends in environmental conditions that affect survival rates influence power. High levels of autocorrelation reduced the statistical power of both BA and BACI comparisons by 5–15% (Fig. 3, $\rho = 0.6$ column). The greatest losses in power occurred when there were large changes in carrying capacity; this effect was not mitigated by using a BACI design, even with a high degree of covariation between control and treatment stocks. Autocorrelation increased the probability of determining that a significant increase in escapement had occurred when carrying capacity was not increased during the post-treatment period (power under a 1.0 proportional change); this is the realized type I error rate ($\alpha = 20\%$) of the t test used to compare abundance levels in the simulated data. For the BA and BACI ($r^2 = 0.1$) comparisons, 25–30% of the simulations showed a significant increase in returns when capacity was not changed at $\rho = 0.6$ compared with a 15% type I error rate at $\rho = 0$. However, when the degree of covariation between control and treatment stocks in the BACI design was high ($r^2 = 0.8$), the resulting type I error rate was maintained below 20% at $\rho = 0.6$. Thus, a well-paired control treatment stock in a BACI design can lower the probability of making type I errors because of autocorrelation in errors.

The effect of the uncertainty in assumed parameter values of the underlying Ricker production relationship on power was investigated by repeating the simulations at the lower and upper 95% confidence limits of the best-fit α and β estimates for the Cheakamus chinook stock. Changing β had no effect on the results; contour plots generated at the lower 5% and upper 95% confidence values for β were identical to those based on the mean value. Changing stock productivity (e^α) had little effect on power for small changes in carrying capacity during the post-treatment period; however, power changed substantially when large changes in carrying capacity were simulated (Table 2). A more productive stock will reach its increased equilibrium population level more quickly than a less productive one; hence, power is reduced under larger changes in capacity at lower α values compared with higher ones. Conversely, power increases for more productive stocks. The extent of this effect was most evident when the benefits of a higher intrinsic population growth rate could be realized; that is, when the post-treatment monitoring period was short and the capacity change was large.

Discussion

Our simulations lead to two main considerations about the utility of monitoring escapement to assess the response of

Fig. 3. The effects of the degree of covariation between control and treatment stocks (expressed as the r^2 between residuals of control and treatment stock–recruitment curves) and autocorrelation in process error (ρ) on the statistical power of before-after (BA) and before-after-control-impact (BACI) designs. The isopleths show the percentage of simulations where a significant increase in the post-treatment escapement level was correctly detected based on a type I error level of 20%.



salmon populations to habitat alteration. First, it is unlikely that assessments using escapement time series of typical precision will provide managers with the level of confidence they require to make immediate decisions on the implications of habitat modifications or other management actions on salmon populations. For example, even after 10 years of monitoring

following a habitat improvement measure that resulted in a doubling of population abundance for the Cheakamus chinook population, there is less than a 50% chance of correctly inferring that there was a significant increase in abundance. For the Cheakamus River chinook example, low statistical power may result in decisions to increase flows when fish protection

Table 2. Sensitivity of power estimates to stock productivity (maximum returns/spawner = e^α).

Proportional change in capacity	Post-treatment years	$\alpha = 0.21, e^\alpha = 1.3,$ lower 5% limit	$\alpha = 0.57, e^\alpha = 1.8,$ mean	$\alpha = 0.93, e^\alpha = 2.5,$ upper 95% limit
1.5	10	31	32	31
	30	53	50	48
2.5	10	44	59	68
	30	79	92	94

Note: Type I error = 20%, $\sigma_{env} = 0.6$, and $\rho = 0$.

objectives have already been met or terminating additional flows when they are effective in increasing stock size. Thus, our results provide a quantitative example of the common perception among fisheries resource managers that, under the expected responses of populations to habitat change (more than doubling of carrying capacity) and time horizons of current management (<10 years), standard escapement estimates are generally too imprecise to detect population changes.

A second, and more encouraging, conclusion was that the statistical reliability of monitoring programs can be substantially improved by increasing the precision of escapement estimates. While this conclusion may be obvious, we are unaware of any other methodology that quantifies (i) how much the precision of escapement estimates need to be increased to attain acceptable power; and (ii) how statistical power is influenced by the magnitude of the biological response to a treatment effect, the length of the monitoring period, and the extent of apparent natural variation in abundance. For the Cheakamus River chinook stock, it is valuable to know that, in theory, the chances of detecting a realistic change in the population resulting from flow changes (e.g., an increase of 25%) nearly double if error in escapement estimates can be substantially reduced or eliminated. However, if the variation in density-independent mortality (i.e., process error) is the dominant component of the total variance of estimated adult returns, improving the precision of escapement estimates will have less of an effect on power. Because the biological costs of not releasing enough water may be significant and the economic costs of instream flow releases into the Cheakamus are large (i.e., more than \$500 000 per year), there is strong justification for investing in more precise escapement estimates to make sure that water released to protect or enhance fish meets its intended objectives. Our conclusion underscores the need for managers to be aware of the sensitivity of monitoring to process and measurement errors and to assess the costs and benefits of collecting more precise escapement data.

Our results are important to fishery managers who may consider using escapement time-series data for post hoc BA assessments of the effects of habitat alterations on population abundance. An escapement-based approach relies on the assumptions that harvest rate and environmental factors effecting stock productivity remain constant throughout the assessment period. Walters et al. (1989) concluded that the use of a BA design is a risky and potentially misleading way to study salmon population responses, because these assumptions are not usually true. In rare cases, environmental variable(s) can explain a significant proportion of the variability in recruitment of fish populations (e.g., Stocker et al. 1985); such knowledge would reduce the risk of making an incorrect decision about the treatment effect and could be used to block pre- and post-treatment data into similar periods of environmental

conditions to reduce natural variation and increase statistical power. Because fishing mortality is not likely a random process, differences between average harvest rates in pre- and post-treatment periods may also confound escapement-based assessments. For most salmon stocks in British Columbia, the absence of reliable, stock-specific catch data makes it impossible to accurately reconstruct recruitment to account for potential changes in harvest rates. Caution must be taken when conducting post hoc BA comparisons, and assumptions about time-invariant extrinsic factors, such as fishing mortality rates and environmental effects, must be validated before BA comparisons can legitimately be used to support resource management decisions.

The problem of time trends in extrinsic factors that affect stock abundance can be controlled to some extent by a BACI design. By including pre-treatment information for both control and treatment stocks, the design allows inferences regarding the response of the treatment stock relative to an untreated stock to be made (i.e., Smith et al. 1993; Bradford 1994). The rationale for this design is that several experimental units in the same region will respond similarly to uncontrolled changes that would affect simple BA comparisons, and this control reduces the chance that confounding factors will alter conclusions of the assessment (Underwood 1994). The limitation of the BACI design is the difficulty of finding suitable control stocks, and the degree to which common changes can be factored out depends on the strength of stock covariation (Smith et al. 1993). For the Squamish River tributaries, our analyses suggest that the strength of covariation among stocks is not strong enough to provide more reliable results than the simpler BA comparison. A BACI design provides added confidence that observed abundance changes are the result of the treatment effect but at the cost of substantially lower power due to poor covariation between treatment and control.

The biological response of the population to habitat alteration can influence the required precision of escapement estimates, and the duration of monitoring and this response is regulated by the SR relation. Together, process error and measurement error make it difficult to differentiate between alternative SR models and to obtain unbiased parameter estimates (Walters and Ludwig 1981; Hilborn and Walters 1992). For the Cheakamus chinook population, we were unable to statistically differentiate between Ricker and Beverton-Holt SR model forms. Despite the difference in the shape of these functions, estimates of power based on both forms were comparable; however, the Ricker model was selected because power estimates were marginally more conservative (5% less) than those computed using the Beverton-Holt model. By varying parameter estimates for the Ricker model we observed that much greater statistical power could be achieved in shorter monitoring programs when the simulated stock was assumed

to be more productive. Time-series bias in SR parameters results in an overestimate of stock productivity (Walters 1985), which in turn could lead to underestimates of both the length of the required monitoring period and the magnitude of effect that can be detected. Because the apparent performance of monitoring programs can depend on assumptions about the form and, more importantly, the parameters of the underlying SR model, we encourage managers to take this uncertainty into account when estimating statistical power of alternative monitoring designs.

Incorporating autocorrelation into our simulations allowed us to determine how trends in environmental variables affecting fish survival rates may confound monitoring comparisons. Environmental effects such as variation in freshwater discharge into nearshore marine environments and the average surface temperature in the Pacific Ocean (Beamish et al. 1994; Hare and Francis 1995) are examples of extrinsic factors that have been demonstrated to cause serial correlations in marine survival rates of Pacific salmon populations. The simulation of estimated levels of autocorrelation in process error resulted in a moderate (5–15%) reduction in the power for detecting population responses. Estimates of ρ are typically too low, especially for short time series (Walters 1985). The ρ estimate for the Cheakamus stock is based on a relatively long data series and includes the effects of increasing fishing effort over time and, therefore, would not be substantially negatively biased. Increasing the lag-1 autocorrelation coefficient increases the probability of having a disproportionate number of good survival years in the pre-treatment period or bad survival years in the post-treatment period. Either of these scenarios could result in failure to detect a simulated population increase; this is why power was reduced at higher values of ρ . The opposite scenarios (more bad years in the pre-treatment period or more good years in the post-treatment period) are also possible and were evident in our results. At higher autocorrelation levels, the probability of detecting a significant increase in escapement in the post-treatment period when no population change was simulated increased beyond the specified type I error level. Thus, trends in environmental conditions can act like a double-edged sword on the utility of BA and BACI comparisons using escapement time-series data, inflating the probabilities of both incorrectly rejecting the null hypothesis (type I error) and incorrectly accepting it (type II error). One possible way to avoid this problem would be to focus exclusively on freshwater effects and base monitoring comparisons on smolt or presmolt production to avoid confounding factors caused by shifts in the marine environment.

A key assumption of the parametric tests used in our BA and BACI comparisons is that observations are temporally independent. Positively correlated observations will inflate the value of the t statistic because the variance component of t (denominator) will underestimate the true variance of the mean (Stewart-Oaten et al. 1986). Thus, for some simulations with t values close to the specified significance level, an incorrect rejection of H_0 (falsely concluding that there was an increase in escapement in the post-treatment period) could have occurred, resulting in an overestimate of statistical power for the parameter combination in question. By using an SR model in our simulations, we are explicitly stating that the escapement in year $t + x$ is dependent on the escapement in year t . However, because of the large degree of process variation we also

simulated, the observations appear to be independent enough so that the bias is not evident. For the basic BA and BACI (Fig. 3, $\rho = 0$) comparisons, the probabilities of detecting a significant increase in escapement when no post-treatment change was simulated were always well below the specified type I error level of 20%. However, when autocorrelation was introduced into the simulations (Fig. 3, $\rho = 0.6$), power increased beyond the type I error level when no change in the population was simulated. This result does not change our general conclusions that, when large changes in the population are simulated, there is a moderate loss in power as ρ is increased; accounting for the positive bias in the t statistic provides an even more pessimistic appraisal of the effect of temporal correlation in errors on the power of a monitoring program to detect population changes, although it does increase the odds of incorrectly rejecting H_0 . In situations where time-series effects are greater than those shown here, formal time-series methods should be employed. Intervention analysis (Noakes 1986; Wei 1990) is a time-series technique used to statistically evaluate the effect of time-series interventions (e.g., habitat alterations) such as those considered in this paper.

One of the most significant challenges for contemporary fisheries managers is predicting the response of fish populations to changes in freshwater habitat. In the past, habitat-management decisions were based mostly on professional judgment and experience with other rivers or stocks, and monitoring was typically not undertaken because managers were content to believe their prescriptions were effective in meeting management goals. Much research has been undertaken to develop methods to predict impacts of habitat changes; however, it still is not possible to provide accurate predictions regarding the impacts of habitat alteration on salmon population abundance. Because of uncertainty in predictive tools, monitoring, in conjunction with experimental policies, is currently the only defensible way that managers can infer the response of a population to habitat change. We suggest that, given the significant biological and economic costs of implementing incorrect restoration actions, managers and politicians must be willing to make greater investments in monitoring and be able to accept substantial delays before these investments pay off. Without this investment, public pressure, political will, and the random outcomes of the legal process may become the primary determinants of environmental protection, and this will certainly not add to our understanding on how to best protect natural habitats that are subjected to human influences.

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