IN-SEASON FORECASTING OF REGIONAL SCALE ABUNDANCE OF NORTHERN BRITISH COLUMBIA COHO SALMON

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1. INTRODUCTION

Recent developments in in-season forecasting methodology for northern BC coho salmon have focused on predicting annual marine survival rates for indicator stocks based on coded-wire tag returns from Alaskan coho fisheries, as well as several mixed-catch indices from both Canada and Alaska (Cox et al. 2003, Cox et al. in revision). Implicit in this approach are two major assumptions: (i) that annual trends in marine survival for a few indicator streams are representative of trends experienced by hundreds of other spawning aggregations within a larger stock complex, and (ii) that marine survival rates are a good indicator of return abundance (i.e, pre-harvest abundance). Assumption (i) may not be appropriate for the management of northern BC coho salmon because harvest decisions are made at an aggregate- or mixed-stock level and there is a poor understanding of the scale of co-variation in marine survival among streams within a stock complex. Assumption (ii) is also problematic because management will likely fail to meet harvest and conservation objectives for years in which marine survival is high but total abundance is actually low due to low brood-year escapement and freshwater production.

Forecasting of regional-scale aggregate abundance indices could help address the current disconnect between the scale of monitoring and the scale of management for northern BC coho salmon. In this study, we conduct a preliminary investigation into the potential for mixed-stock catch indices from Alaskan fisheries to provide in-season forecasts of pre-harvest abundance levels. We use periodic visual survey data collected from hundreds of spawning aggregations within northern BC to develop regional-scale escapement indices and then expand these indices to pre-harvest abundance (escapement

+ catch) based on estimated exploitation rates. A key challenge of this approach is the need to extrapolate site-specific observations made on multiple streams, each of which are subject to variable trends in escapement and measurement error, up to a regional scale that is relevant for in-season decision-making.

Variation in escapement trends among streams arises from four major sources: (i) variation in freshwater productivity, (ii) variation in freshwater survival, (iii) variation in marine survival, and (iv) variation in exploitation rates. Freshwater productivity and survival for coho streams in the Pacific Northwest do not covary at a regional level suggesting that watershed-specific factors dominate variation in the freshwater stage of the life cycle (Bradford et al. 1997; Bradford 1999). Northern BC coho salmon move together though the ocean environment, which suggests that they are exposed to similar marine survival and harvest conditions (Weitkamp and Neely 2002). Covariation in marine survival is known to occur at regional scales for several salmonid species, including coho, in areas experiencing similar patterns in ocean conditions (e.g., Peterman et al. 1998; Coronado and Hilborn 1998; Quinn et al. 2005). There are however, exceptions to this generalization. Labelle et al. (1997) found no indication of similarity among the marine survival of coho stocks from adjacent streams on the east coast of Vancouver Island, British Columbia and concluded that genetic make-up, year, and the median smolt migration date were the major predictors explaining variation in survival. For northern BC coho indicator stocks, variability in smolt production and marine survival contribute almost equally to overall variability in return pre-harvest abundance (Shaul et al. 2007). Variation in exploitation rates among streams is the final contributor to variation in escapement trends. Stream location has been identified as a significant predictor of exploitation rate; however, genetic factors and run timing also play a significant role in explaining variation and can lead to stocks from neighbouring streams displaying no similarity in exploitation rates (Labelle et al. 1997).

In addition to variation in annual escapement levels among sites, the presence of measurement error in escapement estimates also complicates the extrapolation of observed, site-specific trends to a regional index. Measurement error in visual survey indices arises from variability in the proportion of fish seen by observers (referred to as "observer efficiency") and in the proportion of the total run present in the survey area during a count event. Observer efficiency can vary as a function of observer experience, fish behaviour, weather, and physical stream characteristics such as substrate-type, discharge level, and turbidity (Shardlow et al. 1987, Bue et al. 1998). The proportion of the total run present in the survey area during a count event is a function of the timing of fish entry into the survey area, the length of time fish remain alive in the survey area, and survey date (Korman et al. 2002, Holt and Cox 2008). As a result, observer efficiency can vary among streams, among years, and among surveys conducted on a single stream in a single year. When spatial or temporal patterns in observer efficiency exist, such as an increase in average observer efficiency through time or a higher average observer efficiency value for one watershed compared to another, regional indices of escapement can be biased because differences in the proportion of fish seen are misinterpreted as differences in escapement. When no pattern exists, variation in observer efficiency will not cause bias, but can reduce precision in regional escapement indices.

An additional complication for developing regional indices is the frequent occurrence of missing data points in long-term datasets. Fluctuating budgets for salmon monitoring programs and variable weather and stream conditions leads to certain sites not being monitored in some years. Comparisons of the number of fish counted within a specified sample will obviously give misleading results when this is the case. To reduce biases associated with missing data when developing regional indices, missing counts must be predicted based on assumptions about how escapement for that stream in that year is related to escapement in other streams and / or years that do have data. Several methods are available for infilling missing data points so that regional indices can be calculated that differ in assumptions made about the nature of this relationship (Ter Braak et al. 1994, Roy 2002). In general, larger percentages of missing data points in regional datasets result in lower levels of accuracy and precision (Roy 2002).

The primary objective of our research is to evaluate alternative methods for in-season forecasting of regional abundance of northern BC coho salmon based on historical relationships between in-season catch indices and regional-scale abundance indices derived from spawning ground surveys. Specifically, we address three questions related to assessing the need for regional-abundance indices (as opposed to continuing to rely on the indicator-stock approach) and identifying an adequate, abundance-based forecasting model:

1.) how well do northern BC coho indicator stocks represent the range of escapement to individual streams within a region?

2.) which of three alternative methods for combining stream-specific indices of escapement into regional-scale indices of escapement is most precise?

3.) can in-season indices of pre-harvest abundance from Alaskan mixed-stock fisheries reliably forecast regional patterns in coho salmon abundance?

Based on our observation that current indicator stocks only represent escapement for a small subset of streams within the same or neighbouring region, we conclude that monitoring of BC coho salmon would likely benefit from the development of regional-scale escapement indices that incorporate information collected from multiple streams within a region. Unfortunately, the poor performance of our in-season forecasting models suggest that currently available data are not sufficient for in-season management based on regional abundance. We discuss potential data gaps or weaknesses for northern BC coho salmon that limit the development of regional-scale forecasting models.

2. METHODS

In the first section, we examine among-stream variability in escapement indices for indicator and non-indicator streams. In the second section, we compare precision among three alternative methods for aggregating stream-specific indices into regional-scale escapement indices. Finally, in the third section we evaluate the ability of in-season mixed catch indicators to predict regional abundance trends. For the purpose of this study, we define regions based on the statistical areas currently used by DFO in the Pacific North Coast region (Areas 1-6 in Figure 1). Our methods are described in three sections.

2.1 Escapement indices for indicator and non-indicator streams

We first describe the data and methods used to develop stream-specific escapement indices for indicator and non-indicator streams. We then use correlation analyses to examine relationships among indicator stream escapement and non-indicator stream escapement within the same or neighbouring region.

2.1.1 Data Sources

Annual estimates of absolute escapement were obtained for each of the six indicator streams that were in operation between 1998 and 2006. Only two of the six indicators, Toboggan Creek and Deena Creek, were operated for all 9 years. The other four indicators were only in operation for a subset of years in the time series (Babine River: 1998-2001, 2003-2004, Lachmach River: 1998-2003, Zolzap Creek: 1998 – 2004, and West Arm Creek: 2002-2006).

Stream-specific indices of annual escapement for non-indicator streams were developed for 94 coho spawning aggregations in northern British Columbia using visual survey count data collected between 1998 and 2006. Visual survey escapement estimates exist for some northern BC coho streams as far back as the 1950's; however, we only used count data collected from 1998-onwards because the level of effort expended on coho visual surveys in this region increased in 1998. Visual survey data collected prior to 1998 are generally regarded as less reliable than those collected from 1998 onwards (Joel Sawada, Fisheries and Oceans Canada, North Coast Stock Assessment Division, personal communication).

Raw count data used to calculate escapement indices were obtained from Fisheries and Oceans Canada's Pacific Salmon Escapement Data System (nuSEDS). Annual indices of escapement for each of the 94 streams were developed using the mean-count method (Holt and Cox 2008), in which stream-specific escapement indices, $M_{t,j}$, were calculated as the mean-count value from N surveys conducted in stream j in year t,

(1) $$M_{t,j} = \frac{1}{N}\sum_{n=1}^{N} C_{t,j,n} \ .$$

$C_{t,j,n}$ in the above equation is the number of live fish counted by observers during survey $n = \{1, 2, \ldots N\}$. We defined N as the number of surveys conducted between the earliest and latest dates that salmon were observed in a given region between 1998 and 2006.

A potential source of bias and / or imprecision arises in visual survey indices when the segment of stream surveyed varies among years or among surveys within a given year in a non-random manner. Observer efficiency varies among stream habitat types (Shardlow et al. 1987). Therefore, if surveys were conducted in a segment with 75% riffle habitat (low observer efficiency) and 25% pool habitat (high observer efficiency) for the first three years of monitoring and in a different segment with 40% of riffle habitat and 60% pool habitat in the next three years, escapement indices in the first three years would be biased low relative to the last three. Furthermore, if 100% of available spawning habitat was surveyed one year and only 60% was surveyed in the second year, biases in the estimated difference between years would obviously occur. Using a stratified sampling scheme that accounts for habitat variation and ensuring that the length of stream inspected remains constant among surveys is a pro-active means to increase the accuracy of annual indices (Irvine et al. 1992). The selection of survey sites for northern BC coho has primarily been based on the judgement of field personnel in a given year however, making it necessary for us to take post-hoc measures when selecting survey events to include in our analysis. We only included a count event in our analysis if it covered the same segment of stream as all other surveys conducted in that year, as well as in all other years. Regional indices were only created for a given stream j in year t if $N_t \geq 2$ and if the total number of years with data was greater than or equal to 3. Not all streams had mean-count indices for each year in the time series of interest. On average, 37% of the stream-year combinations were missing.

2.1.3 Correlation analyses

To evaluate how well indicator streams represent escapement trends in non-indicator streams within the same or neighbouring region, we calculated Pearson correlation coefficients between escapement estimates from indicator stocks and mean-count indices from non-indicator stocks. Histograms of correlation coefficients for all combinations of indicator escapement and stream-specific mean-count indices were used to examine the distribution of correlation coefficients within a region.

2.2 Regional-scale escapement indices

We considered three alternative methods for computing aggregate escapement indices at regional scales. We defined the average-stream index as the average of scaled index values over all streams within a year. The other two index methods, referred to as GLM and GLM-OE, both used generalized linear models to identify year effects that were shared among all streams within a region. In section 2.2.1 we provide a more detailed description of each of the methods and in section 2.2.2 we compare the relative monitoring performance of the three methods based on the precision of their resulting annual escapement indices.

2.2.1 Aggregate indices

Average-stream index

The average-stream index is derived by first scaling mean-count values for each stream j relative to the highest mean-count value observed in stream j over T_j years, where T_j refers to the total number of years in which a mean-count value exists for stream j. The resulting relative index of escapement for stream j in year t is

(2) $$P_{t,j} = \frac{M_{t,j}}{\max_{t=1}^{T_j}\left[M_{t,j}\right]}.$$

A regional escapement index for year t is obtained by scaling the average $P_{t,j}$ value from J index streams within the region relative to the average $P_{t,j}$ in the base year, 2003,

(3) $$I_{\mathrm{AVE},t} = \frac{\sum_{j=1}^{J} P_{t,j}}{\sum_{j=1}^{J} P_{t=2003,j}}.$$

All streams are weighted equally in the average-stream method, which means that escapement trends in low abundance streams contribute the same amount as those in high abundance streams to the aggregate index. A weakness of the average-stream method is the potential to obtain biased annual indices when T_j varies among streams due to missing data. This bias arises because one of the years with data will be forced to take a $P_{t,j}$ value of 1.0, which may not represent the $P_{t,j}$ value that would have occurred if one of the missing years actually had a higher escapement.

GLM Index

For the GLM index a generalized linear model (GLM) with a Poisson error distribution and log link function was fitted to mean-count values to estimate year-specific effects that were shared among all streams within a region. We used the following regression model:

(4) $$Y_{t,j} = Poisson\left(\lambda_{t,j}\right)$$

where the rate parameter, $\lambda_{t,i}$, was modelled as,

(5) $$\log\left(\lambda_{t,j}\right) = \theta_{1,1} + \beta_t + \delta_j + \log\left(\phi\right).$$

The notation in equation 5 is as follows: $\theta_{1,1}$ is the logarithm of the expected mean-count in year 1 at stream 1, β_t is the t^{th} year effect, δ_j is the j^{th} stream effect, and ϕ is a dispersion parameter. Estimated year-specific effects, β_t, were used to generate a regional escapement index relative the base year of 2003,

(6) $$I_{GLM,t} = \beta_t / \beta_{t=2003}.$$

We used a Poisson error distribution because it is well suited for dealing with count data (McCullough and Nelder 1989) and has been shown to be more precise for infilling missing data in spawning escapement estimates using generalized linear models than normal or Gamma distributions (Roy 2002). A preliminary inspection of mean-count values suggested that the data were over-dispersed ($\log(\phi) > 0$), so we treated ϕ as a free parameter to be estimated along with the regression coefficients. When over-dispersion is not believed to be a problem, $\log(\phi)$ is held constant at the value 0. The Poisson regression model was fit using maximum likelihood estimation with the iterative weighted least squares method (R software package, R Development Core Team, 2007).

A limitation of the additive generalized linear modelling approach is that it requires (i.) that year effects are the same for all streams and (ii.) that stream effects are constant over all years. While it is highly unlikely that these assumptions hold true in reality, they were necessary given that interactions terms cannot be estimated using datasets such as ours in which only one response metric is available for each stream in each year.

GLM Index with observer effects (GLM-OE)

The GLM-OE index also used a Poisson generalized linear model to estimate year effects that are shared among all streams. The key difference between the GLM and GLM-OE methods is that the GLM-OE model estimates observer effects (changes in effect size associated with the individual who conducted the counts) in addition to stream and year effects,

(7) $$Y_{t,j,v} \cong Poisson\left(\lambda_{t,j,v}\right)$$

(8) $$\log\left(\lambda_{t,j,v}\right) = \theta_{1,1,1} + \beta_t + \delta_j + \gamma_v + \phi$$

where, γ_v is the effect of the v^{th} observer. As with the GLM method, estimated year-specific effects, β_t, were used to generate a regional escapement index relative the base year (equation 12).

The inclusion of observer as a covariate in the generalized linear model is an important consideration because counts must be conducted under standardized conditions each year in order to produce precise annual indices. The ability of observers to detect fish is known to vary among individuals (Shardlow et al. 1987, Bue et al. 1998). Therefore, when the individual(s) conducting surveys on a given stream changes through time, the potential exists for trend detection to be distorted if different observers have different probabilities of detecting fish. The inclusion of observer-effects into models estimating population change through time has been shown to affect long-term estimates of population trend when monitoring bird populations with visual survey data (Link and

Sauer 1998). In our case, the inclusion of observer effects is possible because all counts conducted on a stream in a given year were either conducted by one individual or had one key individual who was present for all, or most, of the surveys and individuals often conducted surveys on multiple streams over multiple years. The mean-count dataset we used consisted of 536 year-stream combinations of counts that were conducted by 46 main observers.

2.2.2 Bootstrap estimates of precision

We measured relative performance for the three regional index methods (average-stream, GLM, and GLM-OE) based on the precision of annual index values. A non-parametric bootstrap approach was used to approximate precision by resampling individual streams for inclusion in the regional index. To implement the bootstrap, we selected a random sample of *N* streams with replacement from the original *N* streams within a region for each of 100 bootstrap replicates. For each replicate, all years of data from each of the sampled streams was used to calculate a regional index for the 9-year period 1998 – 2006. Because we sampled with replacement, it was possible for a single stream to occur more than once in a single bootstrap replicate. The precision of the three indexing methods was summarized using boxplots of the distribution of annual index values and the coefficient of variation for annual indices.

A key assumption of bootstrap sampling that is likely violated in our analysis is that all streams within a region were randomly selected for inclusion in the original sample. Visually monitored streams are often selected for primarily logistical reasons including accessibility, travel time to the site, proximity to other monitored streams, and physical characteristics that affect the ease of surveys such as turbidity and flow. We are therefore somewhat limited in our ability to make inferences about aggregate escapement trends experienced over an entire region. This limitation will not however affect our ability to make relative comparisons of precision among the three methods because all three methods are applied to the same sampled datasets within each bootstrap replicate.

2.3 In-season forecasting

We did not consider the GLM-OE index in our in-season forecasting models because annual escapement indices had low precision compared to the average-stream and GLM indices, and we suspected it would produce unreliable forecasts.

We evaluated the abilities of three different in-season catch indicators from Alaskan mixed-stock fisheries to predict regional trends in Northern BC coho pre-harvest abundance. The first two indices use CPUE of combined hatchery and wild coho salmon. The first index is mean weekly catch-per-boat-day for the Alaskan boundary troll fishery (BT index), while the second is cumulative catch-per-boat-day for the gillnet fishery located at Tree Point, Alaska (TP index). The third index was total pink salmon catch (in pieces) taken in commercial fisheries in southeast Alaska, which occurs prior to the opening of the Canadian coho fishery.

We used the following equation to expand regional average-stream and GLM escapement indices to pre-harvest abundance, R, for region a in year t,

$$R_{a,t} = \frac{I_{a,t}}{1 - H_{a,t}} \tag{9}$$

where $I_{a,t}$ is the aggregate escapement index and $H_{a,t}$ is the exploitation rate for fish in area a in year t. Regional-scale estimates of annual exploitation rates were obtained by extrapolating estimates from indicator stocks to a regional level (Appendix A). For example, exploitation rate estimates from the Deena Creek indicator stock were applied to all sub-areas and management areas within statistical area 2. These extrapolations were necessary because exploitation rate estimates for northern BC coho salmon are only available for indicator stocks as part of the coast-wide Pacific salmon coded-wire-tag program maintained between Canada and the United States (Johnston 2004).

Regional pre-harvest abundances in year *t* were modeled as a function of catch indices using the following power function

$$\hat{R}_{a,t,w} = \alpha_{a,w} \Theta_{t,w}^{\beta_{a,w}+\varepsilon_{a,t,w}}, \tag{10}$$

where, $\hat{R}_{a,t,w}$ is the regional index value predicted in week w for area a in year t, $\Theta_{a,t}$ is the mixed-catch index for year t, and $\alpha_{a,w}$ and $\beta_{a,w}$ are area- and week-specific forecast parameters, and the error $\varepsilon_{a,t,w}$ is assumed to be normally-distributed, i.e., $\varepsilon_{a,t,w} \sim N\left(0, \sigma^2_{a,w}\right)$. The regression coefficient β expresses the degree of curvature in the relationship between $\hat{R}$ and the in-season index. This parameter was added to the models after exploratory analyses revealed that many in-season catch indicators appeared to be non-linearly related to pre-harvest regional indices (Appendix B). In cases where the data do not support a non-linear hypothesis, the estimate of β will be close to 1 (i.e., linear).

Relative forecasting performance for all combinations of in-season catch indicator (Troll, Tree Point, and Pink), regional escapement index (average-stream and GLM), and area (Statistical Areas 2,4,5,6 and sub-areas 2E and 2W in Area 2 and 4A and 4B in Area 4) was quantified using the coefficient of determination (R^2) statistic obtained from the best-fit model. The R^2 statistic is a measure of model fit that represents the proportion of variability in the data set that is accounted for by the statistical model. The time series for this analysis extended over 8 years (1998 - 2005) with six weeks of in-season catch data available in each year. We use calendar week 27 as week 1, which is approximately the last week of June or the first week of July.

3. RESULTS

Correlation in escapement trends

Only two streams in each of Statistical Areas 1 and 3 met our criteria for developing mean-count indices (e.g., constant section of stream monitored each year, a minimum of two surveys conducted per year for at least three years). The small sample sizes in these regions limit our ability to make useful observations about within-region correlations in escapement indices and the precision of regional indices. As a result, we excluded these two regions from our analysis and instead focus on answering our research questions using data from Statistical Areas 2, 4, 5, and 6.

High variability existed in the degree of correlation between non-indicator streams and indicator streams within all Statistical Areas examined (Figure 2). Even within Statistical Areas for which the majority of streams were positively correlated with a given indicator stock (e.g., Toboggan Creek - Area 4, Figure 2), there were still a portion of streams that had near-zero or negative correlations. Average correlation values over all streams within a region never exceeded 0.29.

Area 4 streams tended to be better represented by previously operated or existing indicator stocks than other Statistical Areas, although only marginally. For example, Area 4 streams had average correlation values of 0.29 with Toboggan Creek, 0.27 with Babine Creek, and 0.29 with West Arm Creek. For many regions, the indicator stock that appeared to best represent the highest number of streams was not located in, or even near, the region (compare Figures 1 and 2). For example, West Arm is located in Area 6 and close to Area 5; however, it tended to be negatively correlated with non-indicator streams in both of these regions (average correlation coefficient = -0.20 and -0.26, respectively). Instead, escapement levels in Areas 5 and 6 were better represented by Babine and Lachmach indicator stocks located in the Skeena River watershed (average correlation coefficient for Babine-Area 5 = 0.19, Babine-Area 6 = 0.19, Lachmach-Area 5 = 0.13, Lachmach-Area 6 = 0.24; Figure 1). Similarly, non-indicator streams in Area 2 (Queen Charlotte Islands) had stronger positive correlations with Toboggan Creek on the mainland than with Deena Creek on the Queen Charlotte Islands (Figures 1 and 2).

Comparison of alternative regional index methods

We were unable to compute regional indices for Areas 1 and 3 (Northern Queen Charlotte Islands and Nass River) due to small sample sizes, so comparisons among regional index methods are based on Areas 2, 4, 5 and 6. Regional indices between 1998 and 2006 were usually consistent among methods; however, there are occasional years for which the indices produced by each method vary substantially (Figure 3). GLM and GLM-OE indices are almost identical for Statistical Areas 4 and 6, indicating that between-observer effects within these two areas were small or non-existent over the nine-year period. Observer effects were larger for Statistical Areas 2 and 5, as evidenced by the different index values for the GLM and GLM-OE methods in most years. For example, in Statistical Area 2 in 2005, the inclusion of an observer effect in the generalized linear model resulted in a much higher estimate of the year effect compared to when it was not included. Regional indices in Areas 4-6 had similarly large escapement indices in 2005 (i.e., 2005 values were larger than 2004), regardless of index method. This discrepancy suggests that the proportion of the fish counted in 2005 may have been lower than other in other years due to observers who collected counts in that year being less likely to detect fish.

The average-stream method for developing regional indices tended to produce more precise index values, based on estimated CVs from the bootstrap analysis, than the other two methods (Table 1). This observation did not hold true over all combinations of year and region. In Statistical Area 5, the GLM method produced more precise indices in 6 of the 8 years. Estimated coefficients of variation from the bootstrap analysis were higher for the GLM-OE index than for the other two indices in all regions in all years (Table 1).

An examination of the boxplots of annual index values obtained using bootstrap sampling suggests that the GLM method may be more susceptible to positive outliers than the average-stream method (Figure 4). For several combinations of year and region (e.g., 1998 and 2002 for Areas 2 and 4) the GLM method has a smaller interquantile range (25-75% range) than the average-stream method; however, the occurrence of a high number of outliers results in the average-stream method having a smaller CV (compare Figure 4 and Table 1).

Comparison of in-season forecasting model

We excluded the GLM-OE index method from our evaluation of in-season forecasting models because our bootstrap analysis showed it to be considerably less precise than the other two methods. Instead, we focus only on comparing how well the three mixed-stock catch indices (Tree Point CPUE (T), Alaskan boundary troll fishery

CPUE (B), and pink salmon commercial fishery catch (P)) predict regional indices developed using the average-stream and GLM methods.

The "best-fit" model for predicting regional-scale abundance indices (i.e., the model with the highest R^2 value) varied with both Statistical Area and the method used to calculate a regional index (Average-stream vs. GLM; Table 2, Appendix B). However, for almost all combinations of regional-index method and Statistical Area the predictor variable used in the best-fit model remained constant among weeks. In Areas 2 and 4, the best model almost always used boundary troll CPUE or pink salmon catch indices as predictor variables. Model fits in these two regions were often statistically significant ($\alpha \leq 0.05$) or marginally significant ($\alpha \leq 0.10$); however, a large proportion of the variation in regional-scale indices remained un-explained (maximum R^2 in the range of 0.40 to 0.66). All in-season mixed-catch indices performed very poorly at forecasting regional-scale abundance patterns in Statistical Areas 5 and 6. The maximum R^2 value for the best-fit model in these regions never exceeded 0.04 in any of the weeks examined.

4. DISCUSSION

Regional-scale approach to management

The results of our correlation analyses between northern BC indicator stocks and mean-count indices from individual streams highlight the large variation in annual escapement status that can exist within a management region. Based on our observation that current indicator stocks only represent escapement levels for a small subset of streams within the same or neighbouring region, we propose that management of northern BC coho salmon could benefit from the development of regional-scale escapement indices. Unfortunately, our preliminary investigation into the application of regional abundance indices to in-season forecasting procedures indicates that currently available data are not suitable for this purpose.

An assumption we have made in advocating the development of regional indices is that the low correlations we observed arise from underlying high variability in escapement trends among regions. An alternative explanation is that they are a result of poor data quality in indicator stock escapement estimates and / or visual survey mean-count indices. The latter is of particular concern because visual survey indices are less reliable than enumeration fences and mark recapture estimates that are used to estimate indicator stock escapement (Cousens 1982). We discuss the limitations of visual survey data, as well as other components of the in-season forecasting procedure, in more detail below.

Limitations to forecasting regional-scale abundance

Our in-season forecasting analysis shows that in-season catch data from Alaskan fisheries are unable to provide reliable predictions of regional abundance indices for northern BC coho salmon. This conclusion is especially relevant to Statistical Areas 5 and 6, for which R^2 values for best-fit regression models were less than 0.05 for all combinations of in-season catch index, regional indexing method, and statistical week examined. In these cases, less than 5% of the variation in pre-harvest regional abundance was explained by observed variation in in-season catch indices. The poor predictive ability of in-season catch indices could be attributable to several factors, including: (i) biased or imprecise estimation of regional escapement indices, (ii) uncertain exploitation rates used to extrapolate regional escapement to pre-harvest abundance, (iii) biased or imprecise in-season catch data, or (iv) some combination of the above. We briefly discuss components (i) to (iii) of this list to highlight areas in which data quality could be improved.

Regional escapement indices

Some sources of bias and precision in monitoring programs can be minimized through the selection of appropriate sampling designs and methods for data analysis (Paulsen et al. 1998, Larsen et al. 2001). We were unable to affect sampling design in this study because we were dealing with a limited amount of retrospective data. The approach we took of selecting a single subset of streams to be included in the index every year is referred to as a 'same site' or 'always revisit' design (Urquhart et al. 1998, Urquhart and Kincaid 1999). This design has high statistical power to detect trends in abundance within monitored streams; however, estimates of regional status are often less precise than those obtained from sampling protocols that use a combination of repeat surveys to old sites and new sites each year (rotating panel or augmented serially alternating designs; Urquhart et al. 1998). The increased precision of panel designs is due to increases in the total number of sites visited (i.e., sample size) over time. Ultimately, the most appropriate design choice is dependent on the specific objective of a monitoring plan. Our 'always revisit' method may be sufficient for plans seeking to estimate regional trends; however, if information on annual status is required to meet monitoring objectives, a panel design that distributes sampling effort more evenly through space and time will be more appropriate (Urquhart et al. 1998, Stevens and Olsen 2004). In our case, in which our motivation for developing regional indices was primarily in-season prediction, a sampling design that provided precise estimates of status would have been preferred.

The non-random selection of monitoring sites in our study is an additional sample design limitation that restricts the application of our regional indices to the entire region. Northern BC coho salmon streams have historically been selected for monitoring based on convenience and known fish abundance rather than on probability-based sampling methods (i.e., random sampling) that are more statistically valid. As a result, we are limited in our ability to make inference about regional escapement in unmonitored streams. Streams selected for monitoring due to convenience often represent disproportionately good habitat within a region, which can lead to positively biased escapement estimates when observed trends at monitored streams are extrapolated to all streams within a region (Paulsen et al. 1998). Previous work suggests that there is high potential for this bias to exist for the northern BC coho visual survey program. English et al. (2006) found that within Area 4, streams with the most complete time series of annual escapement estimates, which they called 'index streams' (a minimum of 17 out of 23 years between 1980 and 2002), represented only 14% of streams within the region, but accounted for 49-55 % of the total recruitment during this period. Of even greater concern to in-season prediction is the potential for the proportion of escapement represented to change over time. For example, within Area 6, English et al. (2006) found that their 'index streams' accounted for, on average, 15% of recruitment in the 1990's and 65% of recruitment between 2000 and 2002. This type of shift in representation could explain the poor performance of our in-season prediction models in Area 6.

The above two sampling design issues address the allocation of sampling effort among years and among streams; however, the allocation of sampling effort within a year is also an important design consideration that affects the bias and precision of calculated indices. The precision of annual escapement estimates generally increases with increasing numbers of surveys conducted in a year (referred to as "survey frequency"; Hill 1997, Bue et al. 1998). While some streams in our data set had eight or more surveys per year, the average survey frequency for all stream-year combinations was only 3.5. For any given survey frequency, the probability of correctly detecting a temporal trend in escapement is maximized by using the mean-count method to index escapement and holding survey dates constant among years (Holt and Cox 2008). We used the mean-count method to index escapement within individual streams; however, the strength of trend detection was likely reduced by high among-year variation in survey frequency and the spacing of surveys in the existing data set.

We considered three alternative analysis methods for calculating regional escapement indices from stream-specific mean-counts. Our bootstrap analysis showed that the average-stream index tended to be more precise than the two GLM methods. This precision may came at the cost of increased bias however, due to the equal weight placed on relative mean-count values for each stream in the average-stream method, regardless of level of abundance. A 50% decline in a stream with a highest observed mean-count of 100 fish is cancelled out by a 50% increase in a stream with a highest observed mean-count of 5000 fish in the average-stream index (net change in relative mean-count = 0%), despite the fact that the total abundance has increased by 48%. While this type of index may be desirable from a conservation point of view in which each stream is considered an equally valuable contributor to diversity within a stock complex, we wouldn't expect it to do well as an indicator of total abundance when there is high among-stream variability in escapement trends among years. The GLM-OE method is expected to reduce bias caused by variation in the ability of observers to see fish (Link and Sauer 1998); however, in our case, the potential reduction in bias came at the cost of decreased precision. This effect was likely due to the GLM-OE model being overparameterized, which means that the estimation of individual observer effects was not warranted given the limited data.

Exploitation rates

Our extrapolation of exploitation rates from indicator stocks to non-indicator stocks may also have contributed to the poor predictive ability of in-season forecasting models. The lack of stock-specific catch data made it necessary for us to assume that estimated exploitation rates for the few indicator stocks in northern BC were representative of all streams within their Statistical Area, and in some cases, even neighbouring Statistical Areas (Appendix B). This assumption is somewhat justified because stream location can be a significant predictor of exploitation rate; however, additional factors such as genotype and run timing can also be important predictors, which can lead to stocks from neighbouring streams displaying little or no similarity in annual exploitation rates (Labelle et al. 1997). The low R^2 values for several of our regression relationships between exploitation rates from different indicator stocks suggest that this assumption may not have been warranted for northern BC coho stocks (Appendix B). For example, both Toboggan and Babine indicator stocks are located in the mid-Skeena region (Sub-area 4C); however, the R^2 for the regression between annual exploitation rate estimates for these stocks was only 0.48.

In-season catch indices

Another possible explanation for the poor forecasting performance of in-season catch indices is the co-occurrence of fish from several regions, both in Alaska and northern BC, in fishery catches. Although marine survival rates and catch levels for southeast Alaska and northern BC stocks have been correlated during the past few decades, they have also shown periods of strong divergence (Shaul et al. 2007). Even within BC, interannual changes in predicted regional escapement levels differed among regions (Figure 3). For example, between 2003 and 2004 regional escapement levels decreased slightly in Area 4, remained constant in Areas 2 and 5, and increased in Area 5. The presence of fish from Area 6 in catches used to forecast Area 4 abundance could therefore mask the 2004 decline in Area 4 because forecasting models assume that the relative proportion of catch from different regions remains constant among years.

Conclusions

The degree to which indicator stocks can be relied upon to make inferences about escapement at broader spatial scales is dependent on how much trends vary among sites within a region. When variation among sites is high, any one individual stock is unlikely to provide a suitable basis for inference across all stocks within a region. The results of our correlation analyses suggest that this is the case for northern BC coho salmon populations. We attempted to address this concern by developing regional escapement indices that incorporate data from multiple sites into a single index value; however, the poor performance of in-season forecasting models indicated that these indices are not useful for management based.

We discuss several plausible explanations for the observed poor forecasting performance of in-season models based on regional abundance indices that highlight potential data gaps in monitoring of northern BC coho salmon. For example, in recent years the number of indicator systems for northern B.C. coho salmon has declined from six to two and one of these systems is relatively new. Such a reduction represents a substantial loss of critical information about coho exploitation patterns in mixed-stock ocean fisheries and limits our ability to estimate regional exploitation rates that can be used to expand regional escapement estimates to pre-harvest abundance. An increase in the number of indicator stocks in northern BC is likely necessary to develop models for predicting exploitation rate on a finer scale. Second, the patchy nature of existing visual survey records, in which not all streams are surveyed in all years, required assumptions to be made about missing observations. Furthermore, the inclusion of multiple sites into a regional index does not necessarily increase the strength of inference over a single site if there is an unknown bias in site-selection. For this reason, we recommend that extensive visual survey programs for northern BC coho salmon should seek to develop standardized survey designs in which sites are selected using probabilistic sampling.

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TABLES

Table 1. Coefficients of variation (CV) estimated from 100 bootstrap replicates of mean-count data for the average-stream (Average), GLM, and GLM-OE methods of calculating regional escapement indices. Shaded cells indicate the minimum CV for a given combination of year and Area. A CV is not provided for 2003 because it was used as a base-year to standardize all other index values, making it always equal 1.0.

		Year							
Region	Method	1998	1999	2000	2001	2002	2004	2005	2006
Area 2	Average	0.38	0.32	0.48	0.35	0.37	0.37	0.46	0.72
	GLM	0.73	0.54	0.51	0.38	0.62	0.29	1.02	1.37
	GLM-OE	0.94	1.03	0.71	0.83	0.79	0.79	0.59	3.52
Area 4	Average	0.20	0.15	0.21	0.20	0.21	0.18	0.18	0.23
	GLM	0.21	0.26	0.24	0.35	0.34	0.17	0.44	0.32
	GLM-OE	0.36	0.28	0.36	0.40	0.48	0.18	0.46	0.32
Area 5	Average	0.21	0.35	0.42	0.35	0.31	0.22	0.27	0.44
	GLM	0.20	0.24	0.44	0.28	0.28	0.15	0.39	0.33
	GLM-OE	0.47	0.38	0.49	0.39	0.36	0.25	0.46	0.49
Area 6	Average	0.21	0.39	0.20	0.17	0.13	0.21	0.39	0.20
	GLM	0.23	0.28	0.25	0.26	0.25	0.23	0.28	0.25
	GLM-OE	NA	NA	NA	NA	NA	NA	NA	NA

Table 2. "Best" in-season forecasting model (i.e., highest R^2 value) and in-season catch predictor (B = boundary troll fishery CPUE, T = Tree Point CPUE, P = pink salmon catch) for each combination of week, Statistical Area, and regional index method (Average-stream versus GLM). [Stars indicate that a model is significant based on it's *p*-value ($\alpha \leq 0.05$) and dots indicate that a model is marginally significant ($\alpha \leq 0.10$)]. Note that the coefficients of the pink salmon forecasting model remain constant among weeks because the pink fishery occurs before the opening of the coho fishery, and thus, the total catch is used in all weeks.

		Average-stream Index			GLM Index		
Week	Area	Model	R^2	*p*	Model	R^2	*p*
1	2	$I = 2.81B^{0.75}$	0.28	0.18	$I = 3.62P^{0.86}$	0.43	0.08 ·
	4	$I = 3.53P^{1.46}$	0.66	0.01 *	$I = 1.58T^{1.05}$	0.42	0.08 ·
	5	$I = 3.71P^{0.18}$	0.02	0.75	$I = 3.78P^{0.11}$	0.01	0.78
	6	$I = 3.07B^{0.20}$	0.03	0.68	$I = 3.14B^{0.10}$	0.01	0.79
2	2	$I = 3.72B^{0.80}$	0.40	0.09 ·	$I = 3.62P^{0.86}$	0.43	0.08 ·
	4	$I = 3.53P^{1.46}$	0.66	0.01 *	$I = 3.96B^{0.65}$	0.39	0.10 ·
	5	$I = 3.71P^{0.18}$	0.02	0.75	$I = 3.78P^{0.11}$	0.01	0.78
	6	$I = 4.04B^{0.17}$	0.03	0.70	$I = 4.03B^{0.16}$	0.03	0.70
3	2	$I = 4.61B^{0.57}$	0.21	0.25	$I = 3.62P^{0.86}$	0.43	0.08 ·
	4	$I = 3.53P^{1.46}$	0.66	0.01 *	$I = 5.29B^{0.58}$	0.33	0.14
	5	$I = 3.71P^{0.18}$	0.02	0.75	$I = 3.78P^{0.11}$	0.01	0.78
	6	$I = 4.75B^{0.23}$	0.03	0.58	$I = 4.80B^{0.15}$	0.02	0.71
4	2	$I = 5.18B^{0.53}$	0.20	0.26	$I = 3.62P^{0.86}$	0.43	0.08 ·
	4	$I = 3.53P^{1.46}$	0.66	0.01 *	$I = 5.29B^{0.61}$	0.40	0.09 ·
	5	$I = 3.71P^{0.18}$	0.02	0.75	$I = 3.78P^{0.11}$	0.01	0.78
	6	$I = 5.33B^{0.19}$	0.04	0.64	$I = 5.41B^{0.08}$	0.01	0.84
5	2	$I = 5.53B^{0.57}$	0.34	0.13	$I = 3.62P^{0.86}$	0.43	0.08 ·
	4	$I = 3.53P^{1.46}$	0.66	0.01 *	$I = 5.29B^{0.61}$	0.54	0.04 *
	5	$I = 3.71P^{0.18}$	0.02	0.75	$I = 3.78P^{0.11}$	0.01	0.78
	6	$I = 5.73B^{0.15}$	0.04	0.64	$I = 5.41B^{0.08}$	0.01	0.85
6	2	$I = 5.85B^{0.49}$	0.36	0.12	$I = 3.62P^{0.86}$	0.43	0.08 ·
	4	$I = 3.53P^{1.46}$	0.66	0.01 *	$I = 5.96B^{0.51}$	0.57	0.03 *
	5	$I = 3.71P^{0.18}$	0.02	0.75	$I = 3.78P^{0.11}$	0.01	0.78
	6	$I = 6.01B^{0.14}$	0.04	0.65	$I = 6.06B^{0.07}$	0.01	0.79

FIGURES

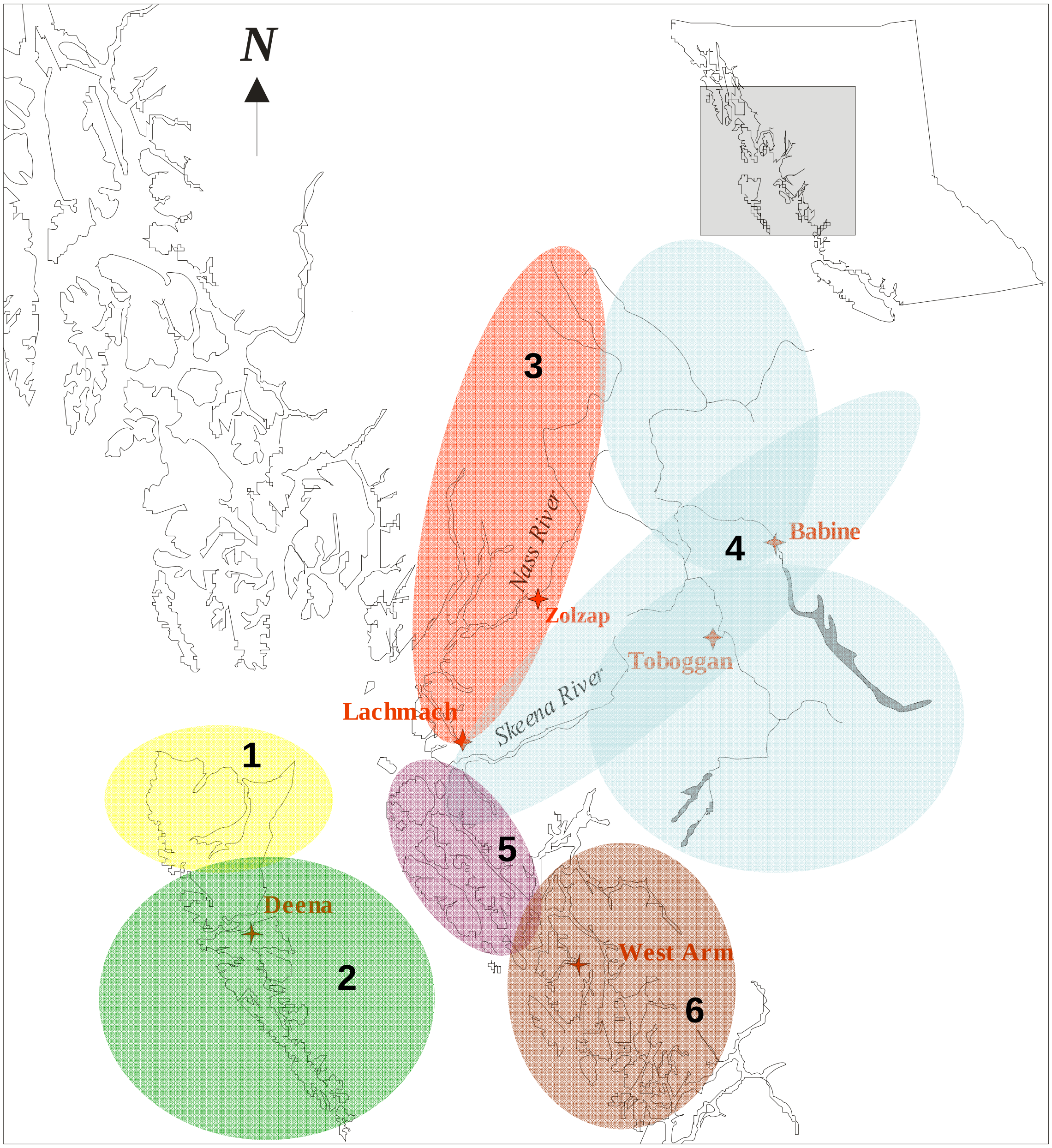


Figure 1. Locations of six northern B.C. coho indicator streams (indicated with stars) and approximate delineations of the six major Pacific Region statistical areas used by DFO. Some statistical areas are further broken down into sub-areas (e.g. Area 2 East and Area 2 West) and management areas, which are not shown on this map.

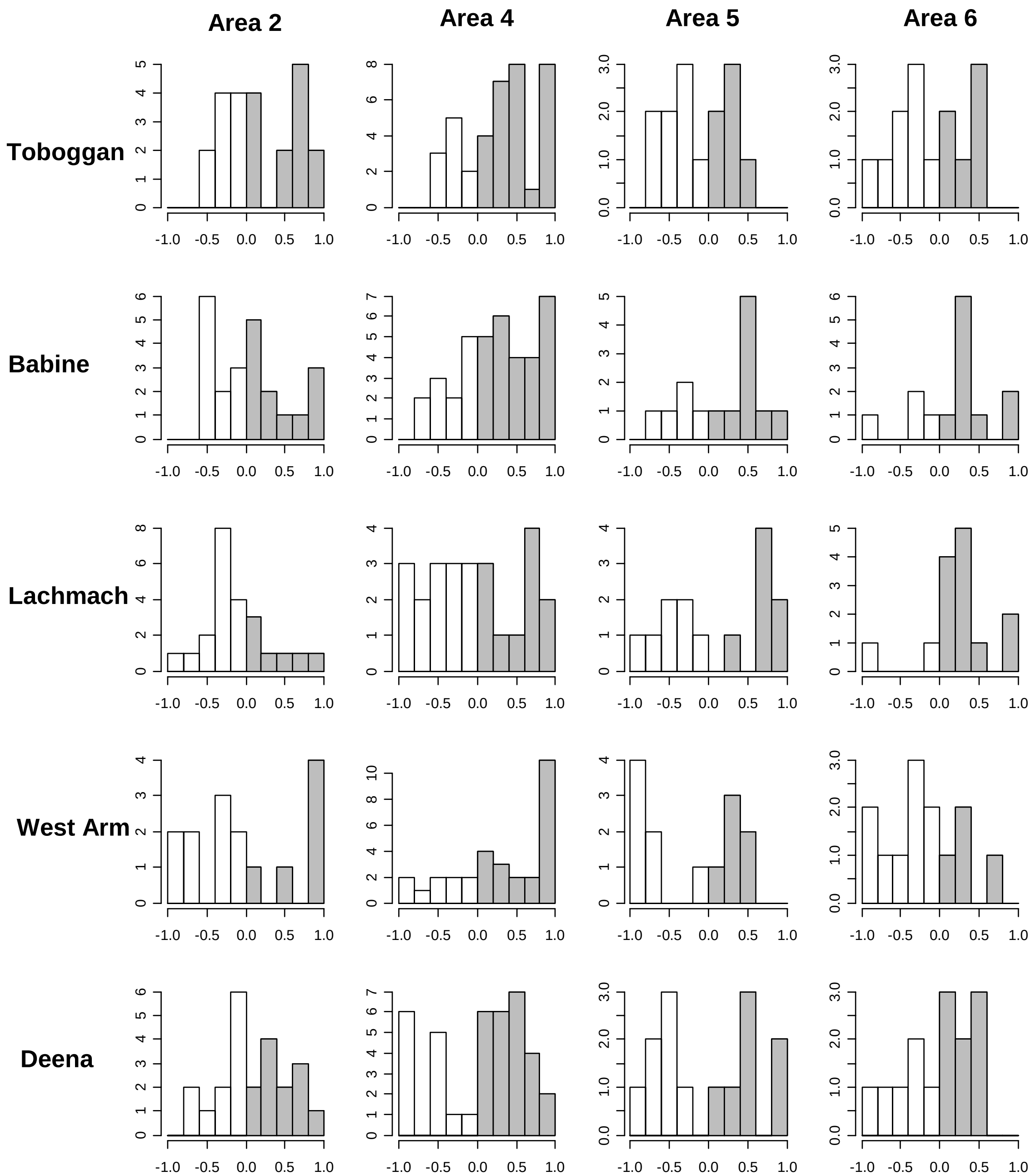


Figure 2. Distribution of correlation coefficients for each combination of stream-specific mean-count index, aggregated by Statistical Area (columns), and escapement estimates for each of five indicator stocks (rows) between 1998 and 2006. Shaded bars highlight positive correlative relationships. Statistical Areas 1 and 3 are excluded from this figure due to small sample sizes.

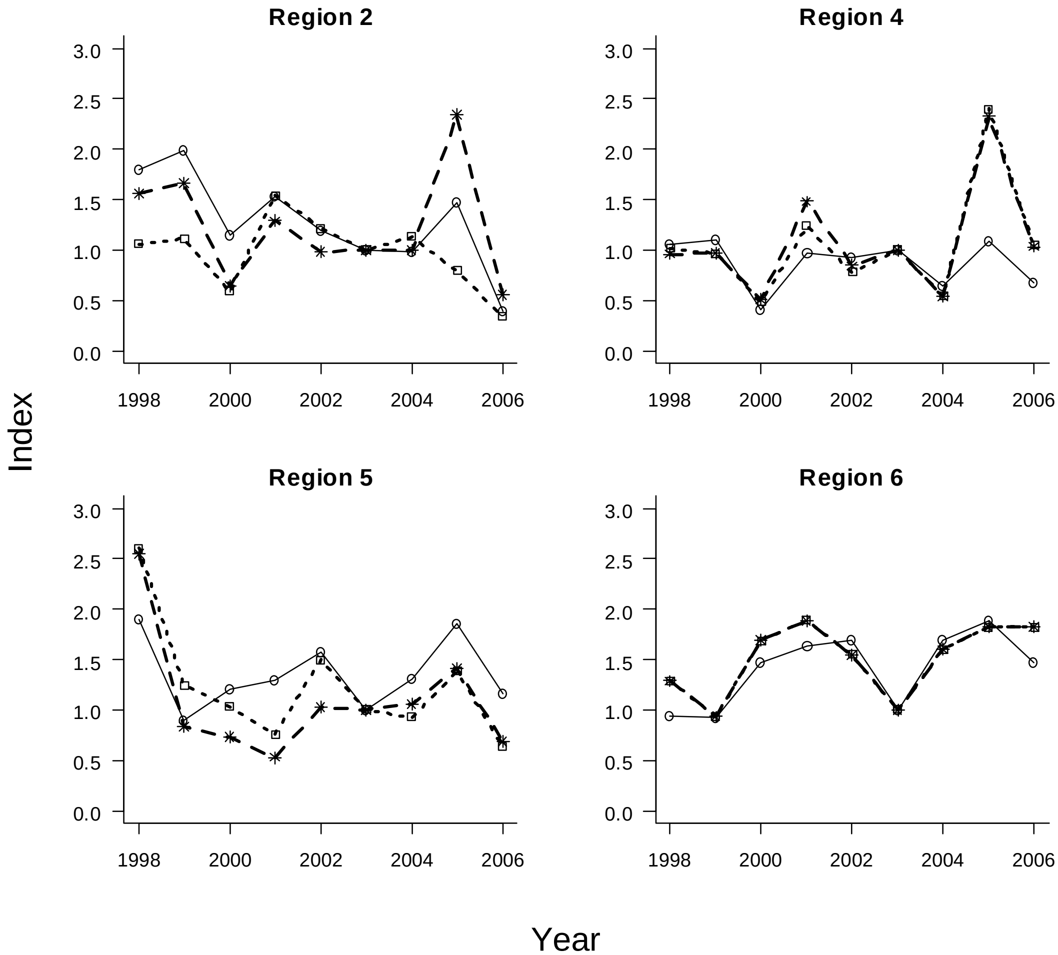


Figure 3. Regional indices of aggregate escapement for average-stream (circles-solid line), GLM (squares-dotted line), and GLM-OE (stars-dashed line) methods within statistical areas 2, 4, 5 and 6. Statistical Areas 1 and 3 are excluded from this figure due to small sample sizes.

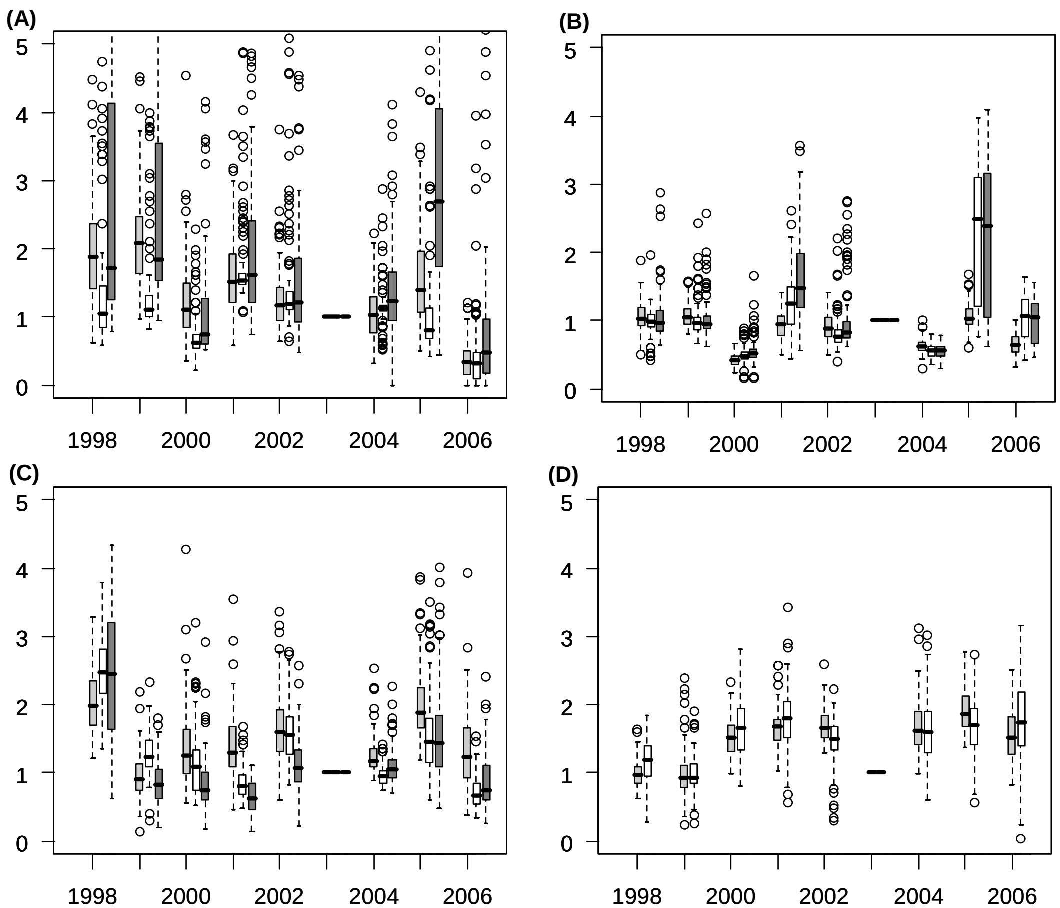


Figure 4. Estimated regional indices for 100 bootstrap replicates of the three aggregate methods (average-stream = light grey, GLM = white, and GLM-OE = dark grey) in Statistical Areas 2 (A), 4 (B), 5 (C) and 6 (D). For each year, the median of the distribution of index estimates is represented by a horizontal line, while the box surrounding the median shows the 25% to 75% quantile range. The whiskers on the boxplots are drawn to 1.5 times the interquantile range. The bootstrap procedure could not be applied to the GLM-OE method in Area 6 due to low contrast in the 'observer ID' variable that caused several bootstrap samples to have no overlap between different observers in different years.

Appendix A

Regional-scale estimates of annual exploitation rates were obtained by assuming that estimates from indicator stocks were representative of exploitation rates experienced over an entire region (Table A1). The pairing of regions with indicator stocks was based on geographic proximity. These assumptions were necessary because exploitation rate estimates for northern BC coho salmon are only available for the 6 indicator stocks that have historically been monitored using coded-wire-tags.

Toboggan Creek was the only indicator stock monitored consistently during the time period we are interested in for in-season forecasting (1998 to 2005), making it necessary to predict missing exploitation rate estimates for all other stocks (Table A2). For each indicator stock with missing values, we used a simple linear regression between exploitation rate estimates for years with data and corresponding Toboggan Creek estimates to predict missing values (Figures A1-A4). Implicit in this approach is the assumption that the average relationship between Toboggan Creek exploitation rates and exploitation rates for all other indicator stocks remains constant between years. While this assumption seems unlikely, it was necessary given the limited data on exploitation rates for northern BC coho salmon.

Table A1. Eight regions (four statistical areas and four sub-areas) for which in-season forecasting models were examined and indicator stocks used to provide annual exploitation rate estimates for each region.

Region	Indicator stock
Area 2	Deena Creek
Sub-area 2E	Deena Creek
Sub-area 2W	Deena Creek
Area 4	Toboggan Creek
Sub-area 4A	Lachmach River
Sub-area 4B	Toboggan Creek
Area 5	Lachmach River
Area 6	West Arm River

Table A2. Exploitation rate estimates for northern BC indicator stocks between 1988 and 2006. Shaded cells indicate that values were predicted based on a regression relationship with exploitation rate estimates for Toboggan Creek (Figures B1-B4). Dashed lines indicate that we did not calculate a predicted exploitation rate because it was not necessary for our evaluation of in-season forecasting models between 1998 and 2005.

Year	Toboggan	Babine	Lachmach	Zolzap	West Arm	Deena
1988	0.406	-	0.659	-	-	-
1989	0.663	-	0.623	-	-	-
1990	0.727	-	0.764	-	-	-
1991	0.665	-	0.728	-	-	-
1992	0.692	-	0.756	-	-	-
1993	0.687	-	0.651	0.632	-	-
1994	0.690	0.860	0.712	0.745	-	-
1995	0.470	0.871	0.698	0.699	-	-
1996	0.740	0.670	0.719	0.665	-	-
1997	0.535	0.548	0.562	0.559	-	0.223
1998	0.282	0.601	0.464	0.466	0.326	0.102
1999	0.222	0.457	0.487	0.496	0.267	0.062
2000	0.513	0.492	0.223	0.521	0.552	0.254
2001	0.418	0.346	0.350	0.495	0.459	0.192
2002	0.152	0.368	0.286	0.235	0.198	0.016
2003	0.229	0.331	0.320	0.387	0.144	0.039
2004	0.372	0.430	0.473	0.467	0.416	0.352
2005	0.222	0.414	0.373	0.396	0.424	0.561
2006	0.199	-	-	-	0.216	0.151

Figure A1. Estimated linear regression relationship between Toboggan Creek and Babine River exploitation rates used to predict missing exploitation rate estimates for the Babine River fish in 2002 and 2005.

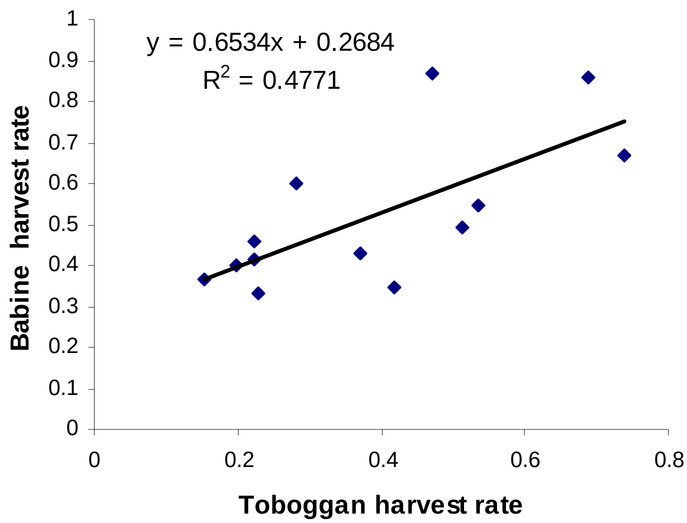


Figure A2. Estimated linear regression relationship between Toboggan Creek and Lachmach River exploitation rates used to predict missing exploitation rate estimates for Lachmach River fish in 2004 and 2005.

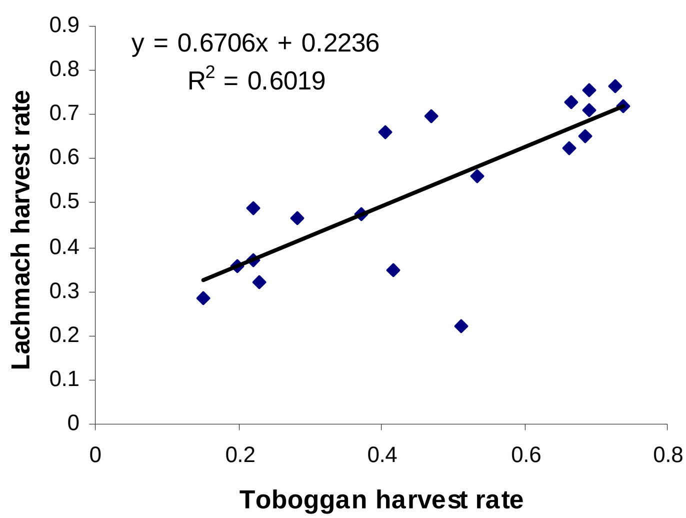


Figure A3. Estimated linear regression relationship between Toboggan Creek and Deena River exploitation rates used to predict missing exploitation rate estimates for Deena River fish in 1998 - 2002.

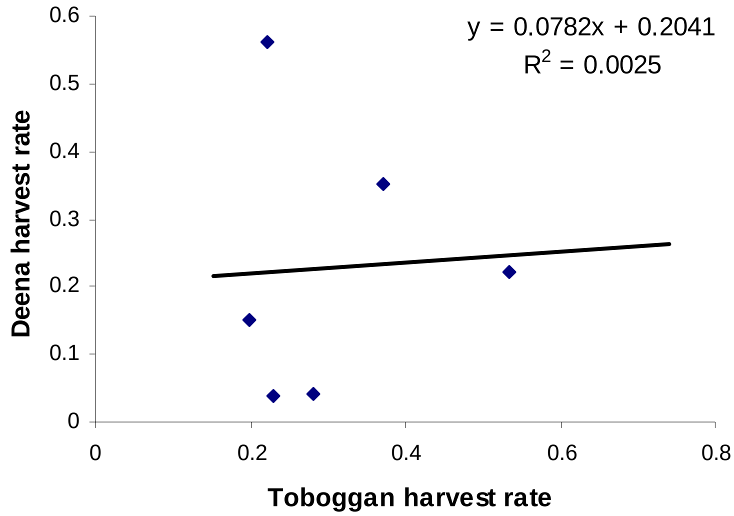
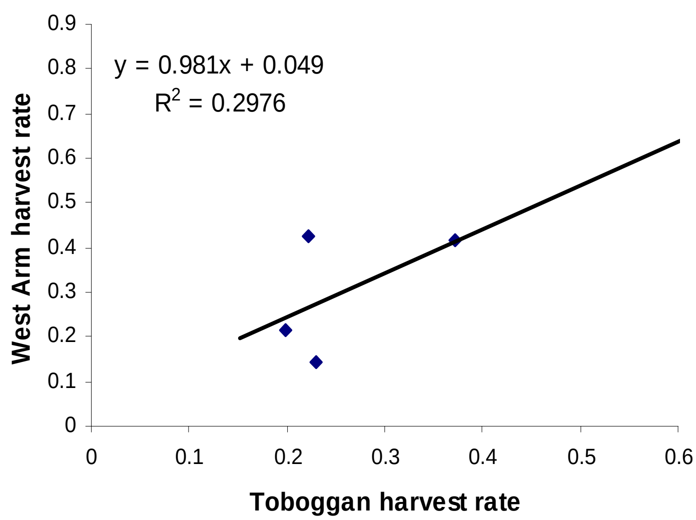


Figure A4. Estimated linear regression relationship between Toboggan Creek and West Arm Creek exploitation rates used to predict missing exploitation rate estimates for West Arm Creek fish in 1998 to 2002.



Appendix B

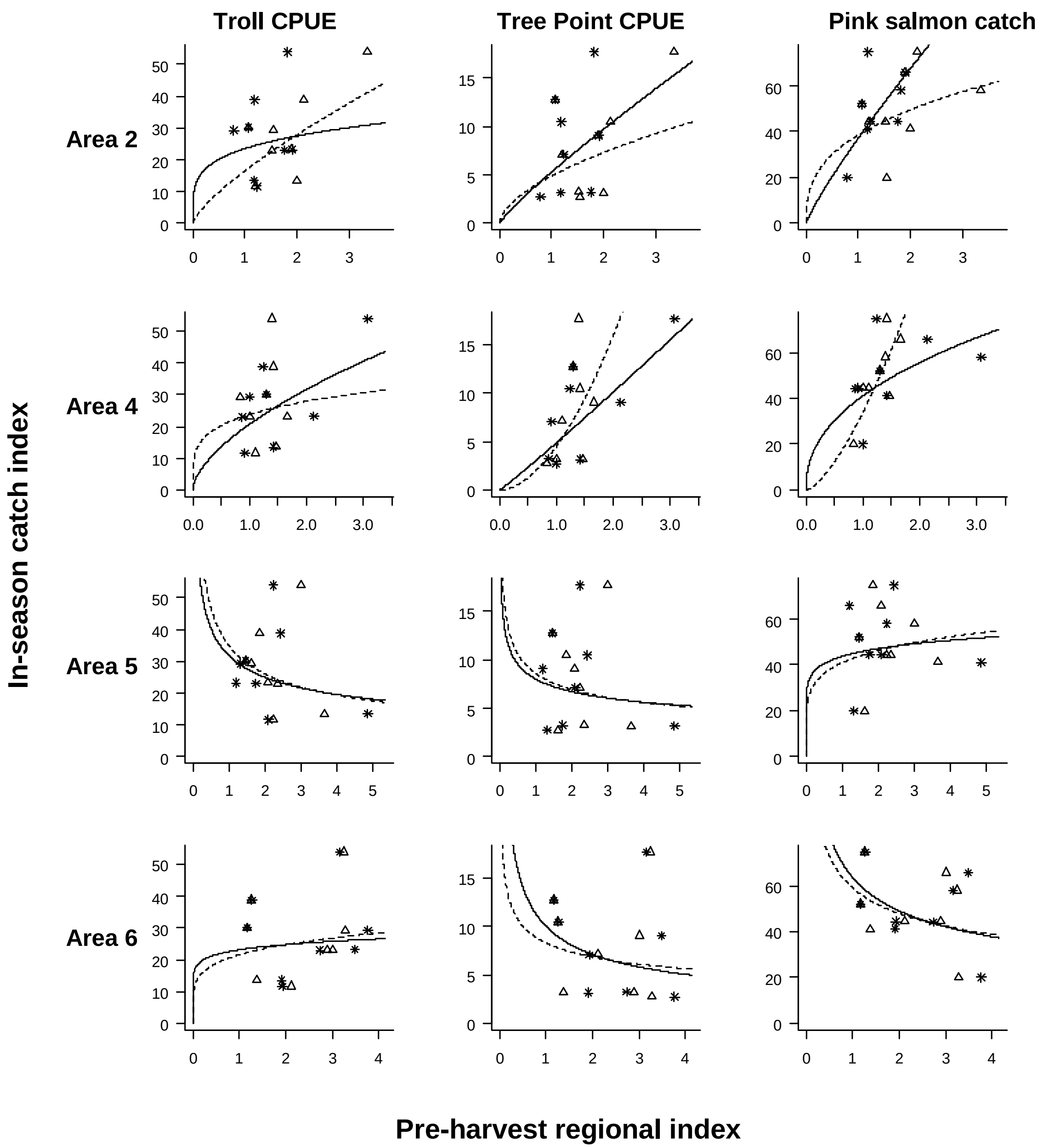


Figure B1. Pre-harvest regional abundance indices for average-stream (triangles) and GLM (stars) index methods in Statistical Areas 2, 4, 5, and 6 versus in-season mixed-catch indices (Boundary Troll cumulative CPUE, Tree Point cumulative CPUE, Pink salmon catch) in week 1 between 1998 and 2005. The dashed line shows the best-fit model for the average-stream method and the solid line shows the best-fit model for the GLM method.

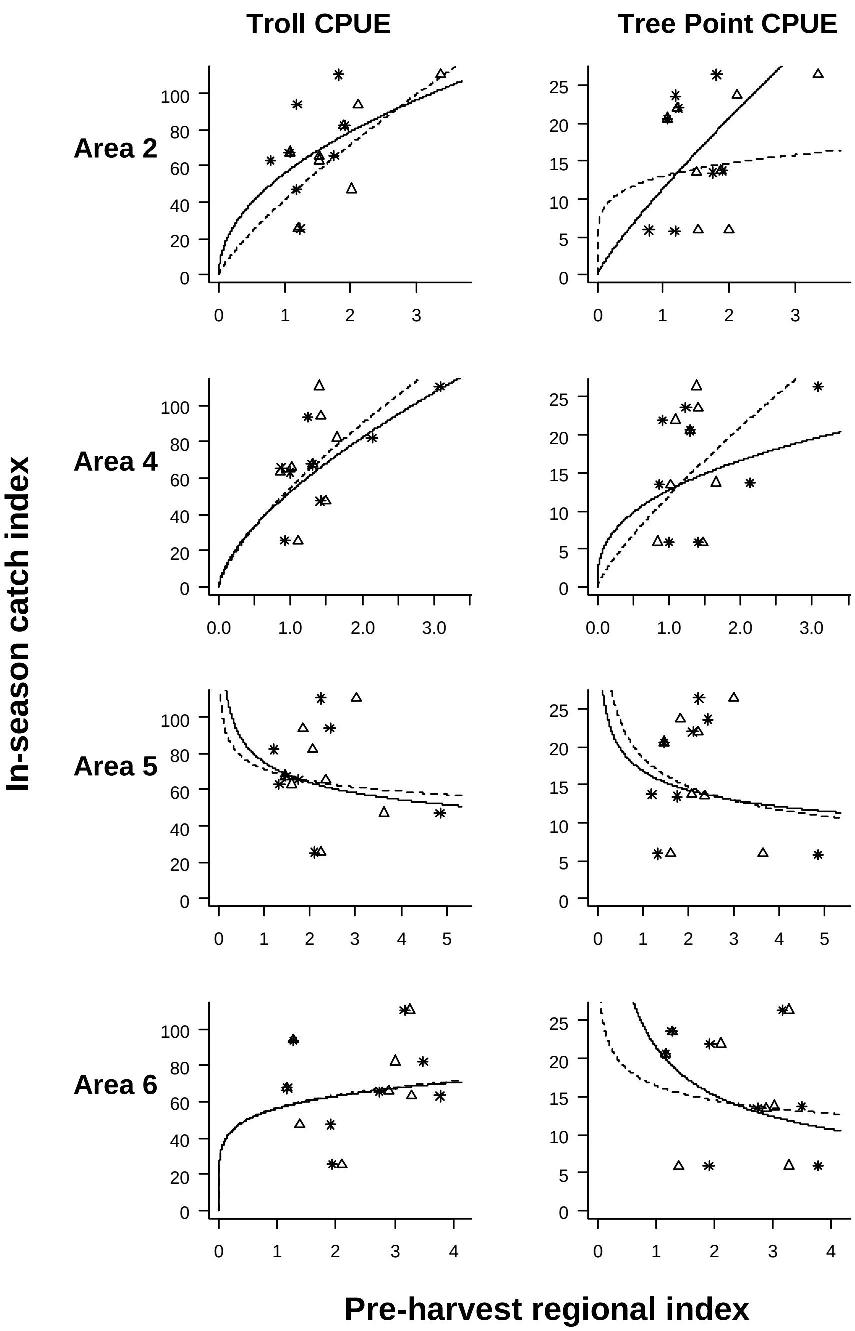


Figure B2. Pre-harvest regional abundance indices for average-stream (triangles) and GLM (stars) index methods in Statistical Areas 2, 4, 5, and 6 versus in-season mixed-catch indices (Boundary Troll cumulative CPUE and Tree Point cumulative CPUE) in week 2 between 1998 and 2005. The dashed line shows the best-fit model for the average-stream method and the solid line shows the best-fit model for the GLM method. Plots are not shown for Pink salmon in-season catch indices because the fishery occurs prior to week 1 and there an no weekly updates for weeks 2 to 6.

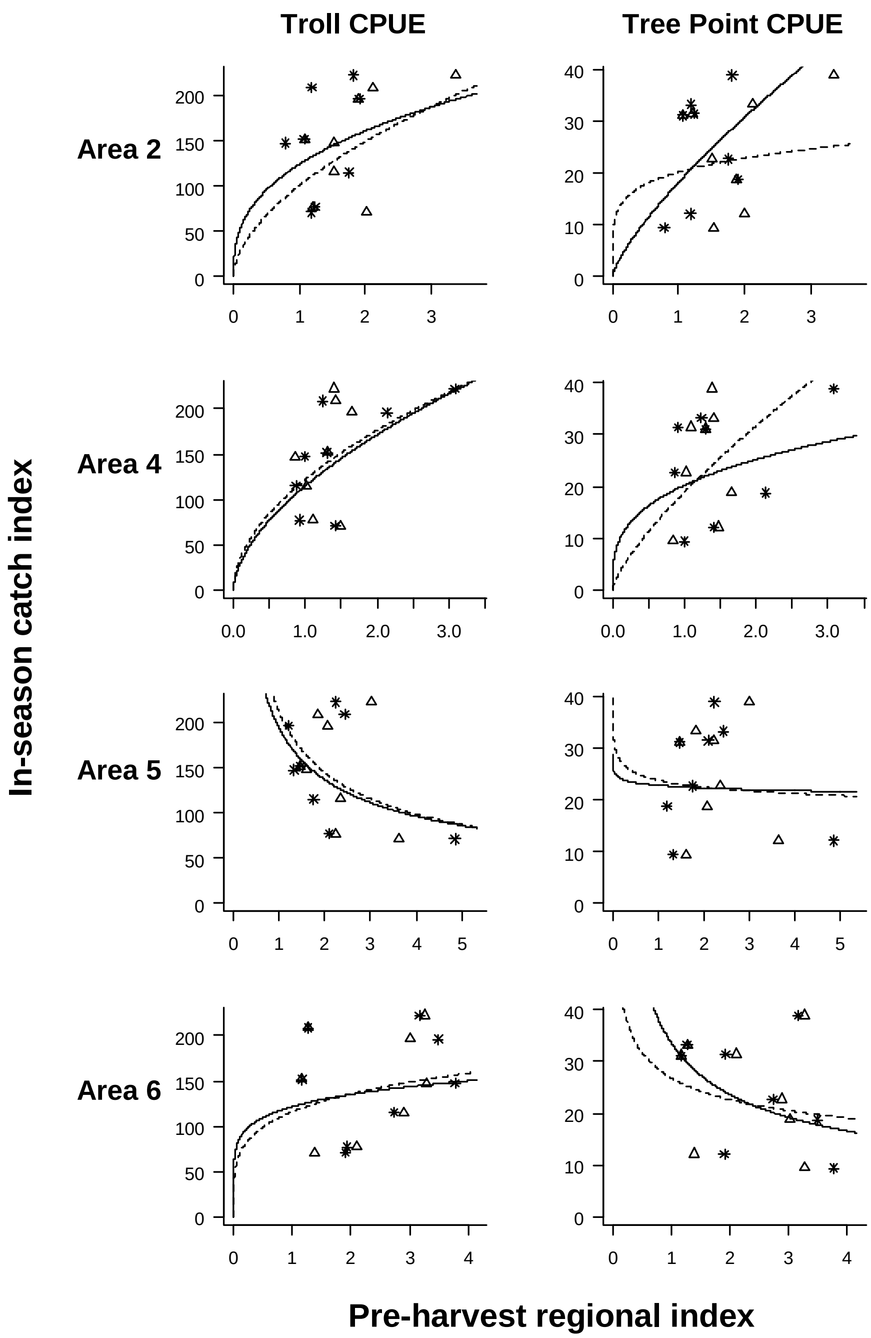


Figure B3. Pre-harvest regional abundance indices for average-stream (triangles) and GLM (stars) index methods in Statistical Areas 2, 4, 5, and 6 versus in-season mixed-catch indices (Boundary Troll cumulative CPUE and Tree Point cumulative CPUE) in week 3 between 1998 and 2005. The dashed line shows the best-fit model for the average-stream method and the solid line shows the best-fit model for the GLM method. Plots are not shown for Pink salmon in-season catch indices because the fishery occurs prior to week 1 and there an no weekly updates for weeks 2 to 6.

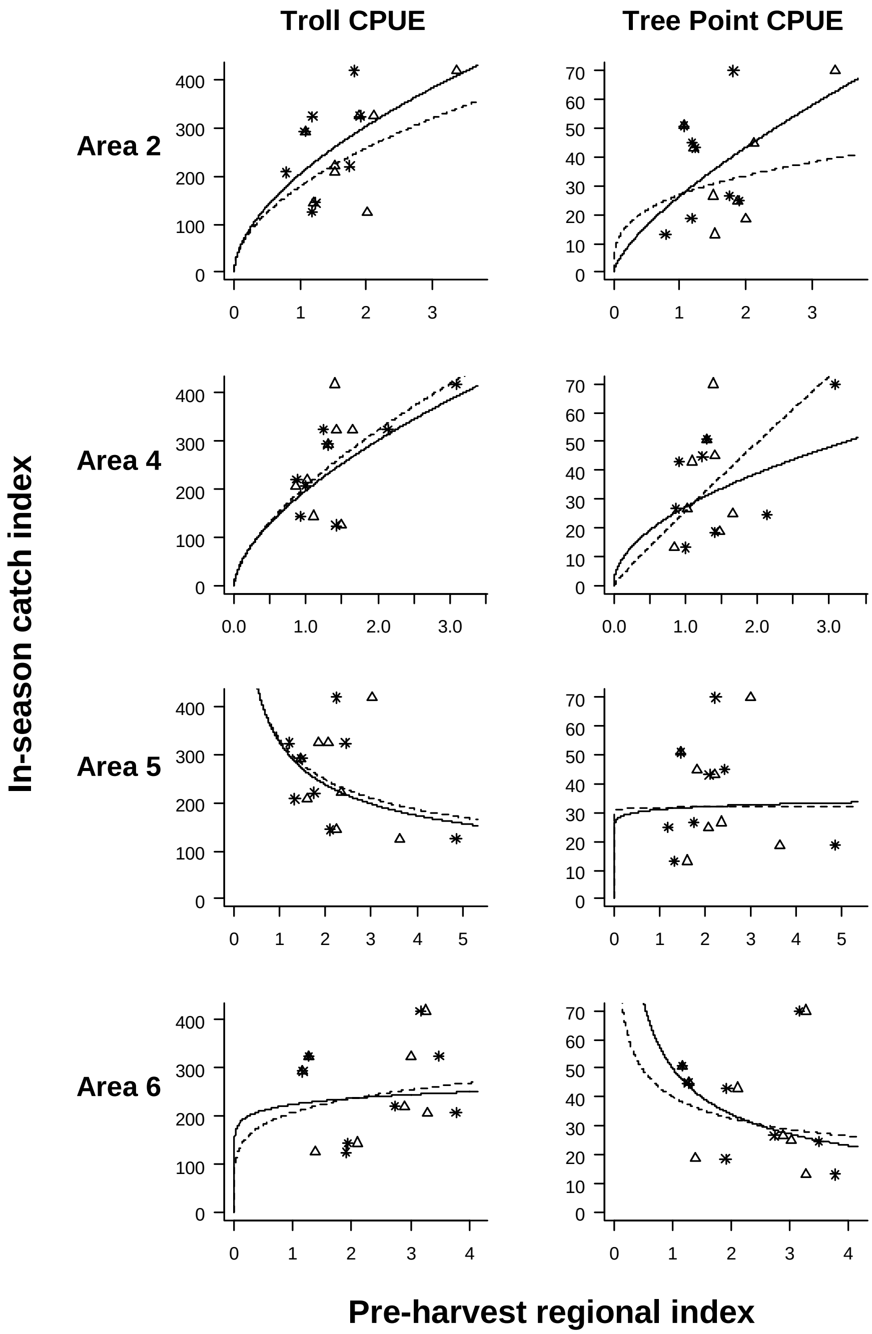


Figure B4. Pre-harvest regional abundance indices for average-stream (triangles) and GLM (stars) index methods in Statistical Areas 2, 4, 5, and 6 versus in-season mixed-catch indices (Boundary Troll cumulative CPUE and Tree Point cumulative CPUE) in week 4 between 1998 and 2005. The dashed line shows the best-fit model for the average-stream method and the solid line shows the best-fit model for the GLM method. Plots are not shown for Pink salmon in-season catch indices because the fishery occurs prior to week 1 and there an no weekly updates for weeks 2 to 6.

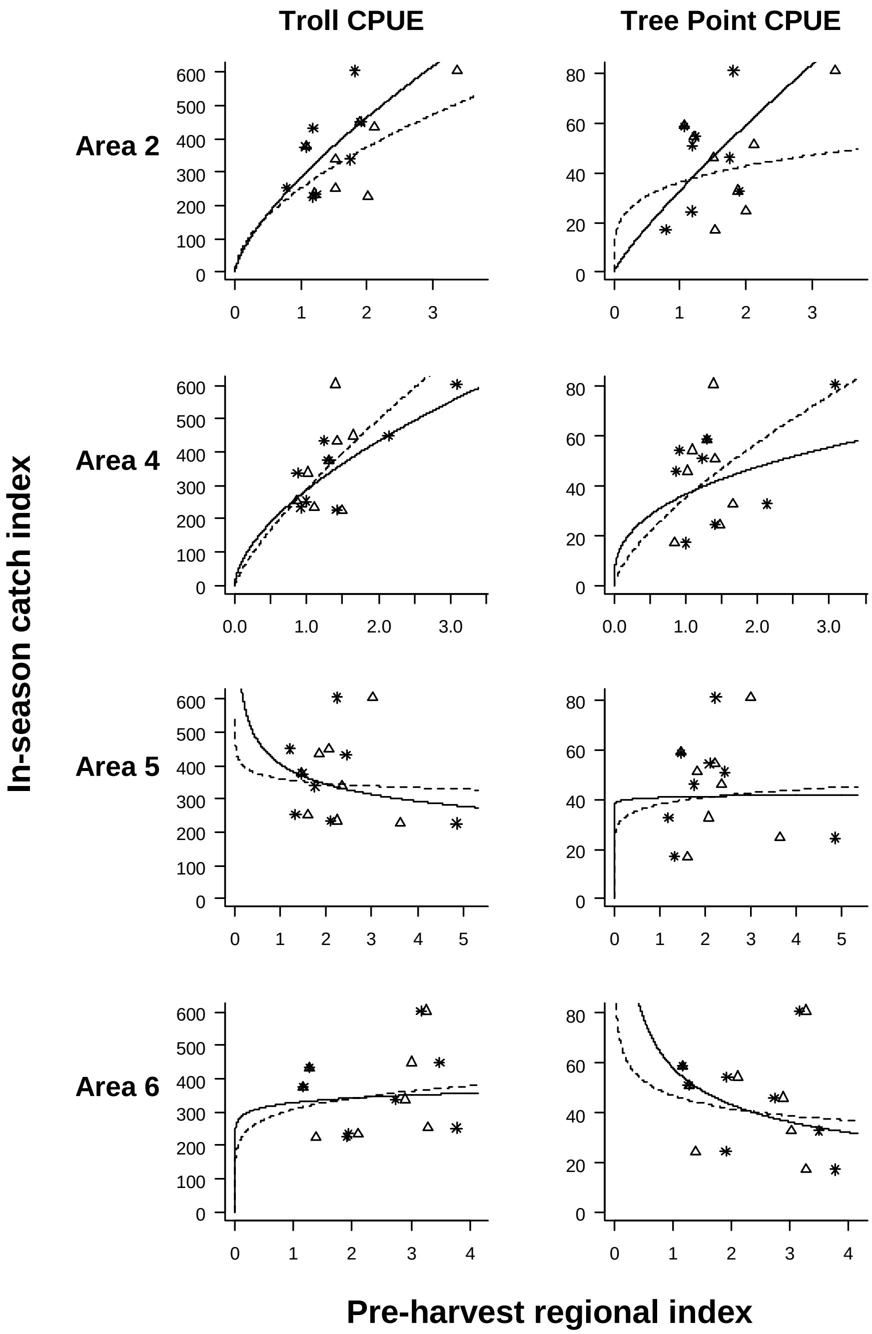


Figure B5. Pre-harvest regional abundance indices for average-stream (triangles) and GLM (stars) index methods in Statistical Areas 2, 4, 5, and 6 versus in-season mixed-catch indices (Boundary Troll cumulative CPUE and Tree Point cumulative CPUE) in week 5 between 1998 and 2005. The dashed line shows the best-fit model for the average-stream method and the solid line shows the best-fit model for the GLM method. Plots are not shown for Pink salmon in-season catch indices because the fishery occurs prior to week 1 and there an no weekly updates for weeks 2 to 6.

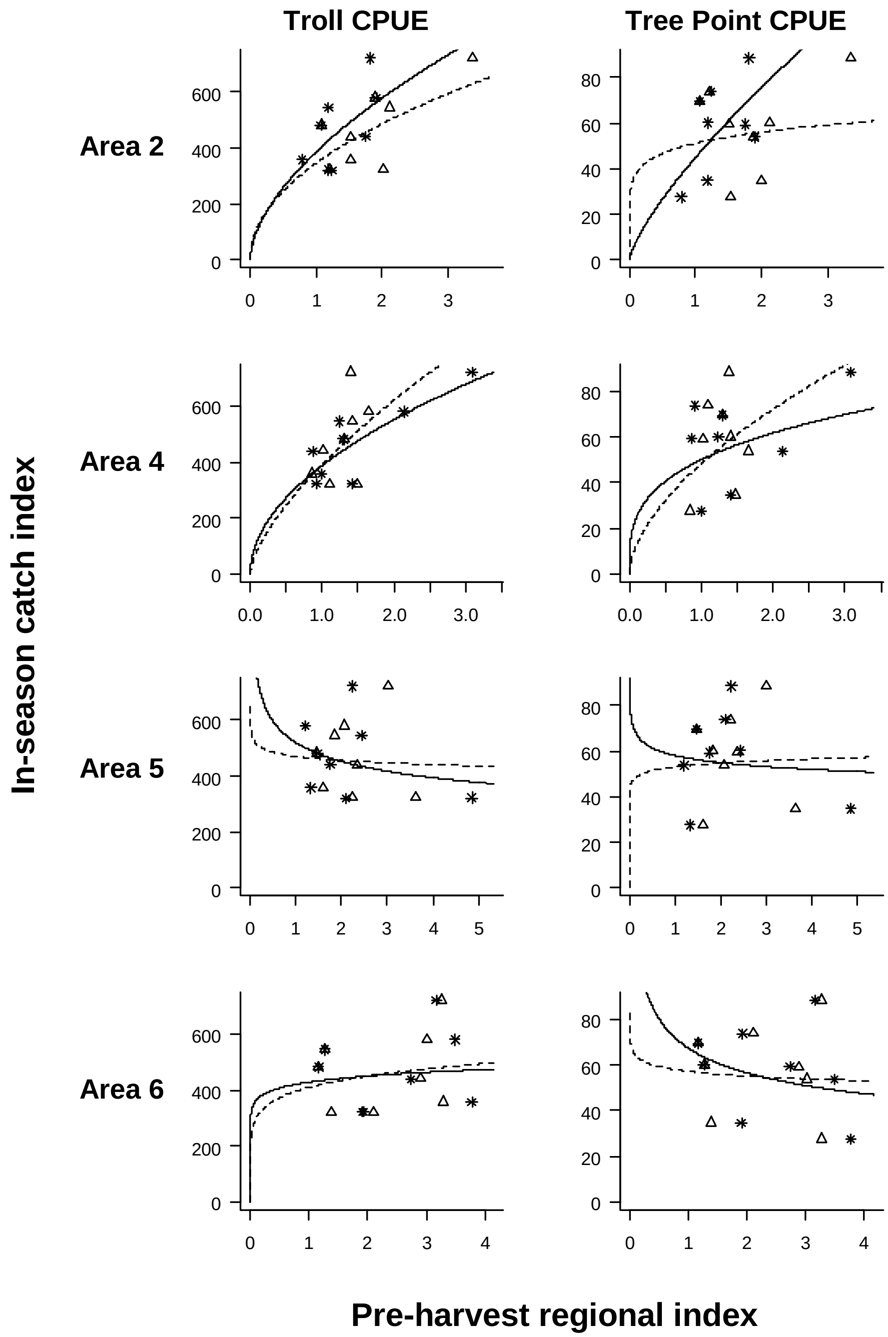


Figure B6. Pre-harvest regional abundance indices for average-stream (triangles) and GLM (stars) index methods in Statistical Areas 2, 4, 5, and 6 versus in-season mixed-catch indices (Boundary Troll cumulative CPUE and Tree Point cumulative CPUE) in week 6 between 1998 and 2005. The dashed line shows the best-fit model for the average-stream method and the solid line shows the best-fit model for the GLM method. Plots are not shown for Pink salmon in-season catch indices because the fishery occurs prior to week 1 and there an no weekly updates for weeks 2 to 6.