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Case Study Applications of LRP Estimation Methods to Pacific Salmon Stock Management Units

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Foreword

This series documents the scientific basis for the evaluation of aquatic resources and ecosystems in Canada. As such, it addresses the issues of the day in the time frames required and the documents it contains are not intended as definitive statements on the subjects addressed but rather as progress reports on ongoing investigations.

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ABSTRACT

The revised *Fisheries Act* requires that Limit Reference Points (LRPs) be identified for all major fish stocks. For Pacific salmon, major fish stocks are represented by stock management units (SMUs). An SMU is composed of one or more salmon conservation units (CUs), which are the assessment units under the Wild Salmon Policy, WSP. We introduce methods to estimate LRPs at the SMU level that integrate statuses derived under the WSP at the CU level. We demonstrate and evaluate the LRPs for three case study SMUs: Interior Fraser Coho (*Oncorhynchus kisutch*), West Coast Vancouver Island (WCVI) Chinook (*O. tshawytscha*), and Inside South Coast Chum (*O. keta*) - excluding Fraser River. Methods are divided into two categories: CU status-based LRPs and aggregate abundance LRPs. CU status-based LRPs are recommended as the default method, and are based on the proportion of CUs above levels associated with increased risk of extinction (above 'Red' status) under the WSP. Aggregate abundance methods may be used supplementally to meet specific fisheries management requirements. Aggregate abundance LRPs are subdivided into logistic regression LRPs and projection LRPs. Both types of aggregate abundance LRPs are defined at the SMU-level abundances associated with a desired probabilty of all component CUs being above Red status, but they differ in that logistic regression LRPs are determined directly from historical data while projection LRPs are determined from projections of CU-level population dynamics. We discuss suitability and requirements for the application of the various LRP estimation methods, drawing from the range of data and information availability among the case studies. In general, the application of aggregate abundance LRPs may be limited to SMUs where the CU-level populations covary, as demonstrated for the Interior Fraser Coho case study, and where covariance has not changed over time or, for projection LRPs, those changes can be parameterized.

1. INTRODUCTION

Under recent amendments to Canada's *Fisheries Act*, Limit Reference Points (LRPs) will be required for all major fish stocks prescribed in regulation. Stocks that drop below their LRP will trigger the development of a rebuilding plan. For Pacific salmon, it is anticipated there will be more than 65 major fish stocks (or stock management units, SMUs), where the proposed functional definition of a SMU is a group of one or more Wild Salmon Policy (WSP) Conservation Units (CUs) that are managed together with the objective of achieving a joint status. LRPs have not yet been developed at the SMU-level for Pacific Salmon. This working paper summarizes the application of methods for estimating SMU-level LRPs to three Pacific salmon case study SMUs. These case study applications have been used to inform the development of guidelines for identifying LRPs for Pacific Salmon, which are presented in the companion paper by Holt et al. (2023).

While LRPs under the *Fisheries Act* are required at the SMU-level, monitoring and management under DFO's WSP occurs at the finer CU level. Under the WSP, a CU is defined as 'a group of wild salmon sufficiently isolated from other groups that, if lost, is very unlikely to recolonize naturally within an acceptable time frame, such as a human lifetime or a specified number of salmon generations' (DFO 2005). Methods to assess CU status have been identified for a range of data types, including WSP Integrated Assessment methods (hereafter called 'WSP assessments') that use expert opinion to combine multiple metrics into a single estimate of CU status (e.g., Grant et al. 2020). Metrics used to assess WSP CU status include spawner abundances, short- and long-term trends in abundance, and distribution of abundance (Holt et al. 2009). Lower and upper benchmarks on those metrics are used to assign status into one of three zones, with the zones Green, Amber and Red, representing increasingly depleted populations that require increasing management intervention (DFO 2005). A more fulsome description of these concepts is provided in Holt et al. (2023).

LRPs are defined within DFO's 'Precautionary Approach to Fisheries Decision-Making' as the stock status below which serious harm is expected to occur to the stock (DFO 2009). While LRPs are often based on metrics directly linked to productivity, such as spawning biomass or fishing mortality rates, the type of metric used to define an LRP can vary among species and data types, and may be related to other stock characteristics when appropriate. Since the CU is the fundamental unit of biodiversity that DFO aims to maintain under the WSP, it follows that metrics used to set LRPs for Pacific salmon should be linked to the status of component CUs within an SMU. Our companion paper (Holt et al. 2023) argues that the maintenance of CU-level spawning abundances above levels that would cause serious harm is the key biological requirement for Pacific salmon LRPs.

The specific goals of this working paper are to:

- apply proposed LRP methods to Pacific Salmon case studies over a range of data types and availabilities, and
- evaluate methods for developing LRPs using a combination of sensitivity analyses to key parameters and assumptions, and where possible retrospective analyses.

A full evaluation of LRPs using closed-loop simulation is beyond the scope of the current project. This type of evaluation is a high priority for future research.

The case studies considered include:

1. Interior Fraser Coho Salmon (*Oncorhynchus kisutch*),

2. West Coast Vancouver Island (WCVI) Chinook Salmon (*O. tshawytscha*), and

3. Inside South Coast Chum Salmon (*O. keta*), excluding Fraser River CUs.

Each of these SMUs consists of 3-7 CUs and was selected to represent a different level of data availability ranging from data rich (Interior Fraser Coho) to data-limited (Inside South Coast Chum and West Coast Vancouver Island Chinook). For each case study, the set of LRP estimation methods considered is a function of available data and previously developed assessment methods for the SMU.

The LRPs presented in this paper are for illustrative purposes only, and not meant to provide formal LRP estimates. The development of LRPs to support implementation of the *Fisheries Act* will require a more thorough review of data and assumptions with local analysts and partners.

2. LRP ESTIMATION METHODS

In this section, we provide an overview of methods used to develop LRPs for our three case studies. Detailed methods specific to each case study are provided in Sections 3 (Interior Fraser Coho), 4 (West Coast Vancouver Island Chinook), and 5 (Inside South Coast Chum, excluding Fraser). Links to GitHub repositories with the data and analysis code used for all three case studies are in Appendix A. An overview of the approaches applied to each of the three case studies are provided in Table 1.

Table 1. Overview of CU assessment methods and SMU assessment methods applied for each case study. Cells marked with '-' at the CU-Level Assessment level indicate that a method was not applied to CUs in that case study.

		Interior Fraser Coho	**WCVI Chinook**	**ISC Chum**
CU-level Assessment				
Composite Metric: (Salmon Scanner)		Yes (only for CU status-based LRPs)	Yes (only for CU status-based LRPs)	Yes (only for CU status-based LRPs)
Single Metric: Abundance relative to lower benchmark	Spawner-recruitment benchmark	Yes	-	*Attempted, estimates unreliable*
	Habitat-based benchmark	-	Yes	-
	Percentile benchmark	-	-	Yes
Single Metric: Distributional		Yes	-	-
SMU Assessment				
CU status-based LRP (Required for *Fisheries Act*)		Yes	Yes	Yes
Aggregate Abundance LRP (Supplemental)	Logistic Regression	Yes	*Attempted, data-deficient*	*Attempted, unreliable*
	Projection	Yes	Yes	*Not attempted, deemed unreliable*

2.1. OVERVIEW

We consider two types of LRPs based on two different metrics:

1. CU status-based LRPs use a proportion as the metric upon which LRPs are based. Specifically, they use the proportion of CUs within an SMU that are above the Red WSP status zone. We assume that in order for an SMU to remain above its CU status-based LRP, 100% of CUs must have status estimates above Red (i.e., either Amber or Green).
2. Aggregate abundance LRPs use the total SMU-level spawning abundance as the metric upon which LRPs are based. Two methods of developing aggregate abundance LRPs are applied: (i) Logistic Regression LRPs and (ii) Projection LRPs.

We propose that CU status-based LRPs are more appropriate for Pacific salmon SMUs because they more directly align with DFO's WSP objectives of maintaining salmon biodiversity; however, aggregate abundance LRP methods may be added to meet specific fisheries management requirements.

We implement CU status-based LRPs using approaches developed to assess CU status under DFO's WSP (DFO 2005; Holt et al. 2009) and implemented for a subset of priority CUs (DFO 2015; DFO 2016; Grant et al. 2020). These approaches use multiple metrics to evaluate status including trends in abundance and abundance metrics, and an expert-driven integration approach to combine statuses across metrics into a single status for each CU. In our case study applications, we apply the recently developed Pacific Salmon Status Scanner tool (also referred to as the 'Salmon Scanner'; Pestal et al., In prep[1]) as a way to rapidly approximate more detailed WSP status assessments. The Salmon Scanner allows us to rapidly generate up-to-date estimates of integrated CU status for all of our case study applications.

When developing candidate aggregate abundance LRPs, we aim to maintain consistency with the WSP by defining LRPs as aggregate abundance levels that have a high probability of all CUs being above their Red status zone. For these LRPs, estimates of CU status are approximated based on a comparison of spawning abundance to a single lower benchmark for each CU. Exceptions are described within specific case study applications below.

We also maintain consistency with the WSP by only including spawning streams without significant enhancement when evaluating CU and SMU status. We use the Proportionate Natural Influence metric, PNI,as a basis for defining 'significant enhancement'. PNI is a metric designed to estimate the relative strength of the hatchery and natural selective pressures resulting from gene flow between the two environments, and is used as a basis for determining genetic risk of hatcheries on natural populations. Values less than 0.5 indicate populations where most fish are hatchery origin (classified as integrated-hatchery populations) (Withler et al. 2018). We defined 'significantly enhanced' populations as those with PNI values < 0.5 and excluded them from case study analyses.

Systems with levels of PNI $\geqslant 0.5$ can still have hatchery influences; however, dynamics are predominately natural origin. Where time-series of the proportion of hatchery marked fish on the spawning grounds are available (e.g., Interior Fraser Coho case study), these proportions are used to inform assessments in two ways: first to develop time-series of natural-origin recruitment for benchmark estimation based on stock-recruitment relationships and second to develop time series of natural-origin spawners for status assessment against benchmarks. When reliable time-

[1] Pestal, G., MacDonald, B, Grant, S, and Holt, C., In prep. Rapid Status Approximations from Integrated Expert Assessments Under Canada's Wild Salmon Policy. Can. Tech. Rep. Fish. Aquat. Sci.

series of the proportion of hatchery influence are not available (WCVI Chinook), total spawners are used for LRP analyses provided that the threshold of assumed PNI $\geqslant$ 0.5 has been met. More detailed descriptions of LRP estimation methods are provided in the following sections, while guidance on when and how CU status-based and aggregate abundance LRPs should be applied is provided in Holt et al. (2023). We recommend that users consult Holt et al. (2023) before applying any of the methods described in this case study paper.

2.2. CU STATUS-BASED LRPS

A CU status-based LRP was set as 100% of CUs above their Red status zone. The LRP therefore acts as a trigger that is breached when one or more CUs in an SMU is assessed as having Red status. Rationale for this choice of 100% of CUs required to be above Red status is described in Holt et al. (2023).

We compare three different methods of assessing CU status when using CU status-based LRPs: (i) the proportion of CUs with a recent WSP status assessment above the Red zone (e.g., Grant et al. (2020)), (ii) the proportion of CUs with a recent Salmon Scanner status assessment above the Red zone (see below for more details), and (iii) the proportion of CUs with status estimated to be above a single CU lower benchmark (e.g., S_{gen}, percentile-based benchmarks, etc.). We recommend methods using composite metrics such as (i) and (ii) for CU assessments, and provide method (iii) for comparison purposes.

When assessing CU status relative to a single abundance-based lower benchmark in approach (iii), we compare generational mean spawner abundances to the benchmark, as described in Holt et al. (2023).

2.2.1. Multidimensional Approach to CU Status Assessments Within the Pacific Salmon Status Scanner

The Pacific Salmon Status Scanner (the Salmon Scanner) estimates statuses for individual WSP metrics and also integrates the statuses on multiple metrics into a single status estimate (e.g., Red, Amber, Green; Pestal et al., In prep). By automating this process, the Salmon Scanner supports implementation of Canada's WSP by rapidly approximating the more detailed, comprehensive WSP status assessment process. The Salmon Scanner's approach can be implemented annually and for a broader range of CUs, given it is less time and labour intensive that full WSP integrated status assessments. The Salmon Scanner was developed using Classification and Regression Tree (CART) analyses, and expert judgement gained from integrated status assessment processes, to create algorithms that approximate the integrated status assessment results.

Data inputs and outcomes from previous WSP assessment processes were used in analyses used to develop the Salmon Scanner: Fraser River Sockeye, Interior Fraser Coho, and Southern BC Chinook (DFO 2015, 2016, 2018; Grant et al. 2020). Briefly, the Salmon Scanner uses a decision tree to estimate CU status based on data type, quality, abundance, and trends (e.g., Figure 1). The decision tree algorithm was verified with data and local expertise (Pestal et al. In prep). As with other methods, an expert review of rapid status results for each CU is intended to be incorporated into the application of this tool (S. Grant, DFO, Vancouver, BC, pers. comm.). Such a review would help identify occurrences of false negatives or false positives in estimated CU status through expert opinion. When using this method in the case study, we took the outputs of the algorithms at face value and did not confirm them based on expert opinion. In practice, results from the Salmon Scanner will be validated against local expertise when implemented annually (S. Grant, DFO, Vancouver, BC, pers. comm.).

For absolute or relative abundance metrics, the Salmon Scanner uses the most recent generational mean spawner abundance (calculated as a running geometric mean) to compare to benchmarks, including absolute abundance thresholds (e.g., 1500 spawners), abundance-based lower benchmarks (e.g., S_{gen} or percentile), and abundance-based upper benchmarks (e.g., $0.8S_{MSY}$ or percentiles). Generational mean spawner abundances are also used when calculating trends in spawner abundances over time (Pestal et al., In prep.).

2.3. AGGREGATE ABUNDANCE LRPS

Aggregate abundance LRPs are based on the assumption that there is a predictable relationship between SMU-level abundance and the probability that all CUs will be above Red status. When estimating aggregate abundance LRPs, status relative to a single lower benchmark (LBM) is used a proxy for status above the Red zone. Aggregate abundance LRPs are then estimated by using the predicted relationship to find the SMU-level abundance at which there is a prescribed probability that 100% of CUs (the same proportion that was used for CU status-based LRPs) will be above the LBM.

The above definition of aggregate abundance LRPs requires a decision to be made about the required probability that 100% of CUs will be above their LBMs. We consider four alternative probability levels for our case studies that represent a range of calibrated probability categories developed by the Intergovernmental Panel on Climate Change (Mastrandrea et al. 2010): 50%, 66%, 90%, and 99%. The 50% value represents the mid-point of the “About as likely as not” category (33 - 66%), indicating that there is an equal probability that all CUs will be above their LBMs as there is that they will not. The 66% values represents the lower end of the “Likely” category (i.e., it is “Likely” that all CUs will be above their LBMs), the 90% value represents the lower end of the “Very Likely” category, and the 99% value represents the “Virtually Certain” category. A discussion of considerations for selecting the appropriate probability threshold when calculating abundance LRPs is included in Holt et al. (2023).

We consider two types of aggregate abundance LRPs in our case studies: logistic regression LRPs and projection LRPs. These two methods differ in the approach taken to estimate the underlying relationship between SMU-level aggregate abundance and the probability that all CUs will be above their LBMs. Logistic regression LRPs are estimated by fitting statistical models to historical data to estimate this relationship. In this case, LRPs are based on previously observed covariation in CU status, and thus implicitly assume the past is a reasonable approximation of the future. In comparison, projection LRPs use historical data as a basis for quantifying population dynamics, and then project population dynamics using stochastic simulations to identify an equilibrium state. Simulation outputs are then used to characterize the underlying relationship between aggregate abundance and the probability that all CUs will be above their LBMs.

The projection LRP approach allows uncertainty in current (or future) processes that might affect estimation of the LRP to be accounted for through alternative scenarios. For example, if there is evidence of recent changes in covariation among CUs, possibly due to a subset of CUs experiencing reduced productivity, this hypothesis can be modelled in projections. In comparison, logistic regression LRPs are limited to using historically observed data, which may not include enough observations of the new and emerging covariation structure.

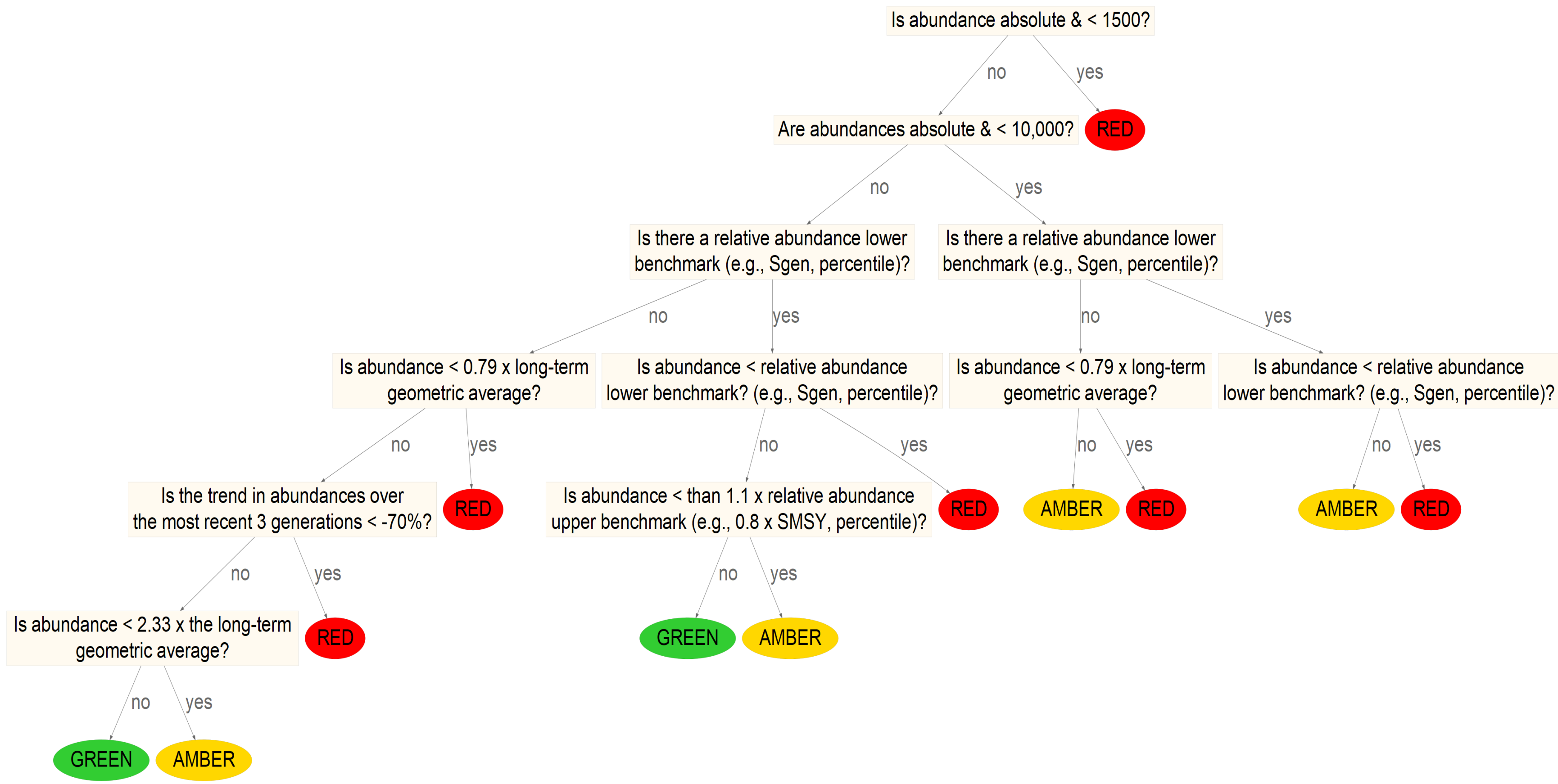

Figure 1. Decision tree (also referred to as the multidimensional algorithm) used in the Pacific Salmon Status Scanner to assess status of Conservation Units based on multiple metrics under the Wild Salmon Policy (Pestal et al. In prep.).

For both logistic regression and projection LRPs, we characterize annual CU status using a single metric, spawner abundances relative to a LBM, instead of using the status from the multi-dimensional algorithm within the Salmon Scanner tool. While in theory, estimates of CU status from the multidimensional approach could be used for logistic regression LRPs, we found little evidence of a statistical relationship between CU statuses from the Salmon Scanner and aggregate spawner abundances for the one case study where we considered this approach, Interior Fraser Coho. We provide further discussion of this result within the Interior Fraser Coho case study section of this paper. In addition, projection LRPs are derived from equilibrium conditions identified from projections that do not incorporate temporal dynamics required for assessment of trends in the multidimensional approach. While estimates of CU status relative to a single LBM such as S_{gen} is a readily available output from the Salmon Scanner tool, we calculated these metrics external to the tool for our case studies.

When assessing CU status for the purpose of estimating aggregate abundance LRPs, we used unsmoothed annual spawner abundances instead of generational averages. This approach was based on preliminary analyses of the logistic regression method that showed using unsmoothed spawner abundances improved the spread in the data used to establish a relationship between CU status and aggregate spawning abundance. Furthermore, using generational means in the logistic regression approach led to considerable autocorrelation in the aggregate abundance time series, violating assumptions of the logistic regression.

However, when assessing SMU status, we used generational running averages (geometric average) of aggregate spawner abundances. This approach reduced variability in annual decisions about whether an LRP had been breached arising from variability in cohorts within a generation. The decision to use generational averages of aggregate spawner abundances when determining whether an LRP is breached is consistent with the approach used for CU status-based LRPs. In both cases, the underlying metric being used to determine SMU status (either aggregate abundance or CU-level status of component CUs for the CU status-based approach) is based on generational-averaged values in order to reduce annual variability in status.

2.3.1. Logistic regression LRPs

Logistic regression LRPs are derived from an empirically estimated relationship between CU-level status and aggregate SMU abundance. Using this approach, the LRP represents the aggregate abundance level that has historically been associated with a given probability of 100% of CUs having status above a selected LBM. For each year of observed data, CU-level status is quantified as a Bernoulli variable: 1 (success) = all CUs have estimated status greater than their LBM and 0 (failure) = all CUs do not have status > LBM. A logistic regression is then fit to these outcomes to predict the probability that all CUs will have status > LBM as a function of aggregate SMU spawner abundance using the logistic regression equation:

$$\log(\frac{p}{1-p}) = B_0 + B_1 \sum_{i}^{i=nCUs} S_{i,t} \tag{1}$$

where, p is probability, B_0 and B_1 are estimated logistic regression parameters and $S_{i,t}$ is spawner abundance to CU i in year t. Equation 1 is then re-arranged to calculate the LRP as the aggregate spawner abundance associated with the pre-specified probability threshold of p^*,

$$LRP = \frac{log(\frac{p^*}{1-p^*}) - B_0}{B_1} \tag{2}$$

An example logistic regression fit is shown in Figure 2. We show the estimation of LRPs based on this fit for four possible probability thresholds: p^* = 0.5, 0.66, 0.90, and 0.99. For each p^* level, LRP estimates represent the aggregate abundance that is associated with that probability of all CUs having status greater than their LBM. LRPs were calculated from parameters of the logistic regression model (Eqn. 2), with uncertainty in the LRP quantified based on a 95% confidence interval on the maximum likelihood estimate, MLE.

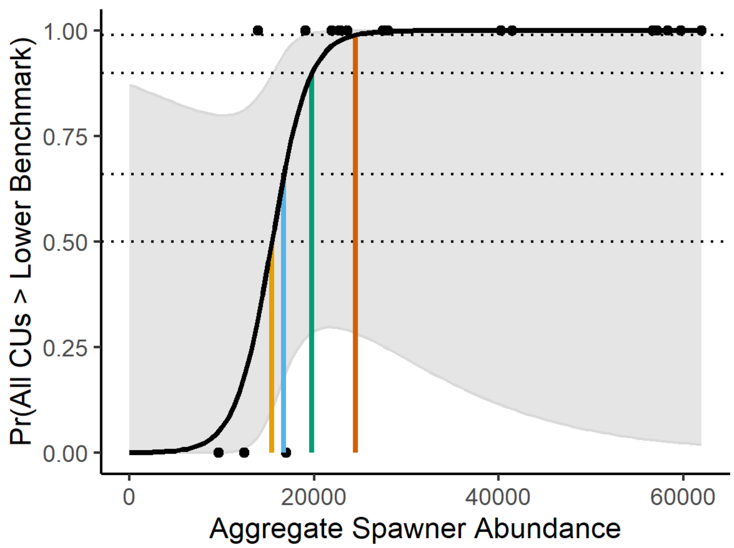

Figure 2. Logistic regression fit to annual Bernoulli data to predict the probability of all CUs being above their lower benchmark (LBM) as a function of aggregate SMU abundance. Each black dot represent a year in the observed time series as a Bernoulli indicator showing whether the requirement of all CUs above their LBM was met (success = 1) or not (failure = 0) as a function of aggregate spawning abundance to the SMU. The black solid line is the maximum likelihood model fit to indicator data, and the grey shaded region shows the 95% confidence interval around the fit model. Coloured lines illustrate aggregate abundance LRPs for 4 different probability thresholds: p = 0.5 (yellow), 0.66 (blue), 0.90 (green), and 0.99 (orange) probability that all CUs > LBM. Horizontal dotted lines intersect the y-axis at each probability threshold, while the solid vertical lines show the corresponding aggregate escapement that will represent the LRP.*

We initially considered an alternative approach to logistic regression in which the LRP represents the aggregate abundance that has historically been associated with a pre-specified proportion of CUs being above their lower benchmark. Using this approach, a logistic regression was fit to predict the proportion of CUs with status > LBM as a function of aggregate spawner abundance to the SMU (i.e., abundance from nCUs combined). We do not present this method for our case studies, however, due to inherent limitations when the required proportion of CUs above their lower benchmarks is 100%. Equation 2 cannot be solved directly for a threshold proportion of p^* = 100%, and LRP estimates were highly sensitive to the choice of p^* value used as a proxy. Using p^* = 99% vs. p^* = 99.9% vs. p^* = 99.99% gave very different LRP estimates.

The logistic regression model was implemented in TMB (Kristensen et al. 2016). The model was statistically integrated, which means that both the CU-specific lower benchmarks (S_{gen}) and the SMU logistic regression parameters were estimated within the same statistical model. The integrated approach allowed for the propagation of uncertainty in parameter estimates from the

CU level to the SMU level, resulting in uncertainty intervals that better capture uncertainty in benchmarks as well as the logistic model fit.

2.3.1.1. Logistic Regression Model Diagnostics

There are several assumptions associated with logistic regression, three of which are relevant for our application to LRPs and are listed below. Model diagnostics were applied to evaluate the extent to which those assumptions were met, as well as statistical significance of model coefficients, goodness-of-fit, and classification accuracy of LRPs developed from the logistic regression. The three assumptions are as follows:

1. The relationship between aggregate abundance and log-odds (the logarithm of the odds of all CUs being above their lower benchmark) is linear.
2. The observations are independent of each other (i.e., residuals are not autocorrelated).
3. There are no influential outliers.

Evaluating assumption of linearity (Assumption 1)

A Box-Tidwell test was used to evaluate linearity by assessing the significance of an additional interaction term in the logistic regression,

$$\log(\frac{p}{1-p}) = B_0 + B_1 \sum_{i}^{i=nCUs} S_{i,t} + B_2 \sum_{i}^{i=nCUs} S_{i,t} \times \log(\sum_{i}^{i=nCUs} S_{i,t}) \tag{3}$$

A significant interaction term B_2, indicates a non-linear relationship between aggregate abundance and log-odds, violating this assumption (Fox 2016).

Evaluating independence (Assumption 2)

Deviance residuals, d, were estimated for each year,

$$d = \pm\sqrt{-2(y\log(\frac{\mu}{y}) + (1-y)\log(\frac{1-\mu}{1-y}))} \tag{4}$$

where μ is the predicted probability of all CUs being above their lower benchmark and y is the observation (1 or 0, indicating all CUs above Red or not, respectively), in a given year (Fox 2016). Equation 4 reduces to (Ahmad 2011):

$$d = \begin{cases} -\sqrt{-2\log(1-\mu)} & \text{, if } y = 0 \\ \sqrt{-2\log(\mu)} & \text{, if } y = 1 \end{cases} \tag{5}$$

The magnitude of lag-1 autocorrelation was then estimated among deviance residuals and evaluated for statistical significance.

Evaluating outliers (Assumption 3)

We recommend identifying influential outliers using leverage statistics where possible. For our case studies, we identified outliers independent of their influence because the software used to estimate model parameters (TMB) does not provide the hat-matrix required to assess influence of individual points. Instead, we focused on identifying outliers based on the general rule of thumb that deviance residuals greater than 2 are considered to be outliers because 95% of the distribution is expected to be within 2 standard deviations of the mean. Further work to identify influential outliers is recommended when other statistical model fitting tools are used.

Statistical significance of model coefficients

Statistical significance of coefficients was evaluated using the Wald test statistic, calculated from the ratio of the B_1 model coefficient to the standard error of that coefficient, which is assumed to be normally distributed. Test statistics and significance were estimated within TMB (Kristensen et al. 2016).

Goodness-of-fit

The goodness-of-fit was evaluated by comparing the ratio of residual deviance to null deviance, similar to a likelihood ratio. This ratio is assumed to follow a Chi-square distribution with 1 degree of freedom derived from the difference in the number of parameters between full and null models. P-values <0.05 indicate significant lack of fit (Fox 2016).

In addition, the pseudo-R^2 was calculated to indicate the ratio of the model fit to the null model without an independent variable (Dobson and Barnett 2018),

$$\text{pseudo-}R^2 = 1 - \frac{\sum_t^{t=nYears} d}{\sum_t^{t=nYears} d_0} \tag{6}$$

where d_0 are the deviance residuals for the null model. The pseudo-R^2 is a measure of the strength of the relationship between aggregate abundances and probability of all CUs being above their lower benchmarks. Unlike R^2 values for linear models, the pseudo-R^2 does not represent the percentage of variance explained by the model and is not related to the correlation coefficient.

In addition, the length of available time-series will impact the power to detect significant model coefficients. Coefficient estimates may be biased when time-series are short. Peduzzi et al. (1996) recommend a minimum of 10 data points for the least frequent outcome to avoid biases in model coefficients, based on simulation study of epidemiological data. For example, if the frequency of outcomes were 0.5 and 0.5 (for 0 and 1, respectively), then a sample size of at least 10/0.5 = 20 would be sufficient. This minimum sample size would be higher if the data were skewed, e.g., if frequency of outcomes were 0.7 and 0.3, the minimum sample size would be 10/0.3 = 33. A similar evaluation of sample sizes to minimize biases in logistic regression LRPs for fisheries applications is warranted. Although it is possible to estimate LRPs with lower sample sizes, the risks of biases in model parameters (and LRPs) increases. We calculate minimum sample sizes for our case studies using the approach of Peduzzi et al. (1996).

Classification accuracy of LRPs

Classification accuracy was evaluated based on the ratio of successful classifications to total number of data points in the logistic regression, also called the hit ratio. Successful classifications were the number of years when the model successfully predicted that all CUs were above their lower benchmark plus the number years when the model successfully predicted that at least one CU was below its lower benchmark. The hit ratio tends to be biased towards optimistic classification rates when computed with the same sample used for fitting the logistic model. Therefore, we also considered an out-of-sample approach to classification accuracy, where the logistic regression was estimated iteratively removing a single data point and the occurrence of successes relative to observations were based on the model that did not contain that data point.

2.3.2. Projection LRPs

Projection LRPs are estimated using simulated CU abundances to characterize the relationship between aggregate SMU-level spawner abundance and the probability that all CUs will be above their lower benchmarks (e.g., S_{gen}). Parameters describing CU-level population dynamics are estimated from available data, and then individual CUs are projected forward under current exploitation rates (with sensitivity analyses used to explore alternative exploitation rates). This approach allows for explicit consideration of uncertainty as the user can specify various projection scenarios to reflect a lack of biological and/or fisheries information. Natural variability in recruitment and ages-at-maturity are incorporated into projections, as is implementation uncertainty in exploitation rates. As with logistic regression LRPs, we relied on status estimated from a single metric rather than multidimensional status estimates from the Salmon Scanner tool to develop LRPs.

For our case studies, we ran projections for 30 years after an initialization period to identify aggregate abundances characterized by an equilibrium state represented by stable distribution of projected abundances. We recommend that the initialization and number of years be chosen on an SMU-by-SMU basis to ensure the distribution of trajectories capture equilibrium conditions. These projections should not be interpreted as predictions of future abundance; rather, they are used to simulate the underlying relationship between SMU-level abundance and the probability that all CUs will be above their LBMs.

We used the samSim closed loop simulation modelling tool to conduct stochastic projections for our case study applications. samSim is an R package that was developed to evaluate fisheries rebuilding plans in simulation for Pacific salmon (Freshwater et al. 2020; Holt et al. 2020). We created a modified version of samSim to support LRP estimation. The LRP version of samSim is described in detail in Appendix B, and model code is available on GitHub (Appendix A).

Detailed descriptions of the parameterization of samSim for our two case study applications of projection LRPs (Interior Fraser Coho and WCVI Chinook) are presented in Sections 3 and 4, respectively. In both cases, we incorporated uncertainty into projected CU dynamics through the specification of empirically-derived probability distributions for key biological and management parameters, including stock-recruitment parameters, proportion of recruits at age, and exploitation rates (ER). Larger structural uncertainties in model formulation were represented through the use of sensitivity analyses and/or specification of alternative model structures. Observation error was not included in projections because derivation of LRPs was based on projected ‘true’ abundance levels rather than observed abundance.

The following steps were taken to calculate projection LRPs:

1. Use samSim to project spawner abundances forward for $nYears$ over $nTrial$ stochastic simulations, under current exploitation.
2. For each simulated year-trial combination, characterize abundances as follows:
   - Assign aggregate SMU level spawner abundance for each year-trial combination to an abundance bin ($AggS_{bin}$), based on intervals of 200 fish. E.g., $AggS_{bin}$ = 0:200 fish, 201:400 fish, 401:600 fish, ... etc.
   - Determine whether all CUs for that year-trial combination were above their CU-level lower benchmarks on abundances. If they were, the year-trial combination is scored as a success (1). If they were not, the year-trial combination is scored as a failure (0).
3. For each aggregate abundance bin, $AggS_{bin}$:

- Summarize the realized number of year-trial combinations that fell within that bin. For example, if a projection was run for 30 years with 1000 replicates, there might be 500 year-trial combinations that had an aggregate abundance in 10,000 - 10,200 fish bin.
- Summarize the number of 'successful' year-trial combinations that occurred for that bin. For example, 125 of 500 year-trial combinations in the aggregate abundance bin of 10,000 - 10,200 fish are successes with all CUs above their lower benchmarks.
- Calculate the probability that all CUs will be above their lower benchmarks as the ratio of the number of successes to the number of realizations for each bin:

$$Pr(AllCUs > LBM) = \frac{Number of successes in SAgg_{bin}}{Number of realizations in SAgg_{bin}} \quad (7)$$

  For example, if 125 of the 500 realizations that fell within the $SAgg_{bin}$ of 10,000 - 10,200 fish were 'successes', there would be a 25% probability (125 / 500 = 0.25) that all CUs would be above their lower benchmarks when aggregate abundances are between 10,000 and 10,200 fish.

4. Identify the LRP as the mid-point of the aggregate abundance bin, $AggS_{bin}$, that is closest to the desired probability threshold that all CUs are above their LBMs.

An example of the derivation of an LRP from the projected curve of aggregate abundance bins versus the probability of all CUs being > their lower benchmark is shown in Figure 3 for the four probability levels used in our case studies (p* = 0.5, 0.66, 0.90, and 0.99).

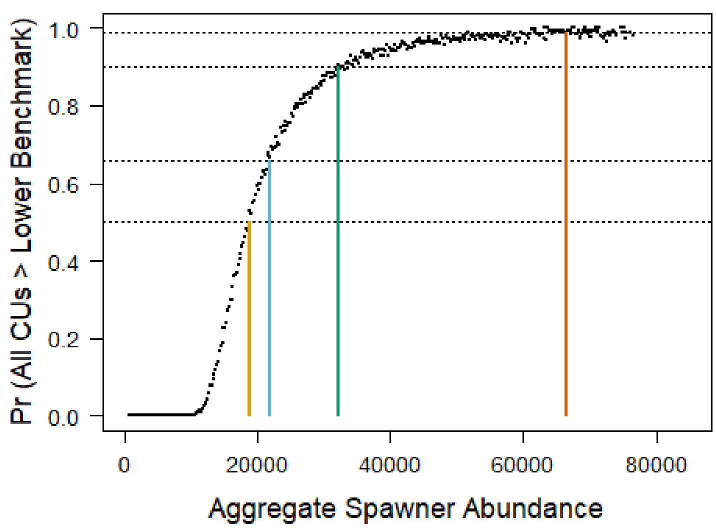

Figure 3. Example of projected probability curve derived from projections over 30 years and 10,000 MC trials. The curve shows the projected probability of all CUs being above their lower benchmark (LBM) as a function of aggregate SMU abundance, where aggregate spawning abundance is a bin of 200 fish (e.g., 0-200, 201-400, etc.). Each dot in the curve therefore represents a single 200-fish bin. Coloured lines demonstrate how aggregate abundance LRPs are calculated for 4 different probability thresholds: p = 0.5 (yellow), 0.66 (blue), 0.90 (green), and 0.99 (orange) for the probability that all CUs are greater than their LBM. Horizontal dotted lines intersect the y-axis at each probability threshold, while the solid vertical lines show the corresponding aggregate escapement that will represent the LRP.*

Uncertainty intervals for LRPs are not generated in this method because it does not include statistical estimation and projections integrate uncertainties in all underlying parameters to identify LRPs with specified probabilities of all CUs being above LBM. However, LRP estimates could be presented as a range based on the $SAgg_{bin}$ bin size.

3. CASE STUDY 1: INTERIOR FRASER COHO SALMON

3.1. CONTEXT

The Interior Fraser Coho SMU is well-suited for illustrating aggregate abundance LRPs due to the long history of using aggregate abundance-based recovery targets and fisheries reference points at the SMU scale. These rely on an underlying relationship between aggregate abundance and the distribution of abundance among sub-populations and CUs. Furthermore, it is a relatively data-rich SMU with spawner-recruitment time series available for all CUs starting in 1998.

The SMU includes Coho Salmon that spawn in the Fraser River and tributaries upstream of Hells Gate in the Fraser Canyon. Like most Coho Salmon, Interior Fraser Coho spend at least one full year in freshwater as fry before migrating to the ocean as smolts (Arbeider et al. 2020). Most (88%) Interior Fraser Coho have a 3-year life history, in which they leave freshwater in their second year and spend 18 months at sea prior to returning to their natal system to spawn. The remaining 12% have a 4-year life history in which they spend an additional year in freshwater before migrating as smolts in their third year. Both the 3-year and 4-year life histories spend 18 months at sea. Less than 1% of Interior Fraser Coho are believed to return as jacks (precocious mature males that spend only 6 months as sea) or at ages older than 4 years (Arbeider et al. 2020).

Five WSP CUs have been identified for Interior Fraser Coho based on genetics and geographic separation: Middle Fraser, Fraser Canyon, Lower Thompson, North Thompson, and South Thompson (Figure 4) (DFO 2015). Previous work by the Interior Fraser Coho Recovery Team (IFCRT) identified 11 sub-populations nested within the five CUs, and developed recovery objectives based on maintaining abundance above a 1000-spawner threshold in each of these sub-populations (IFCRT 2006, Table 2). The delineation of sub-populations was based on several factors, including the presence of natural barriers, the influence of large lakes on downstream discharge and thermal regimes, observations of spawner aggregations under differing discharge conditions, and genetic differentiation. The 11 sub-populations are described in detail by the IFCRT (2006).

Only the upper portion of the Fraser Canyon CU (upstream of Hells Gate on the Fraser River) is included in our delineation of Interior Fraser Coho. This delineation is consistent with previous analyses for this SMU (e.g. Arbeider et al. (2020)). As a result, Nahatlatch is the only sub-population included in our description of the Fraser Canyon CU. Kawkawa Creek, which is located below the Fraser Canyon near Hope, BC, is not included in the data we use.

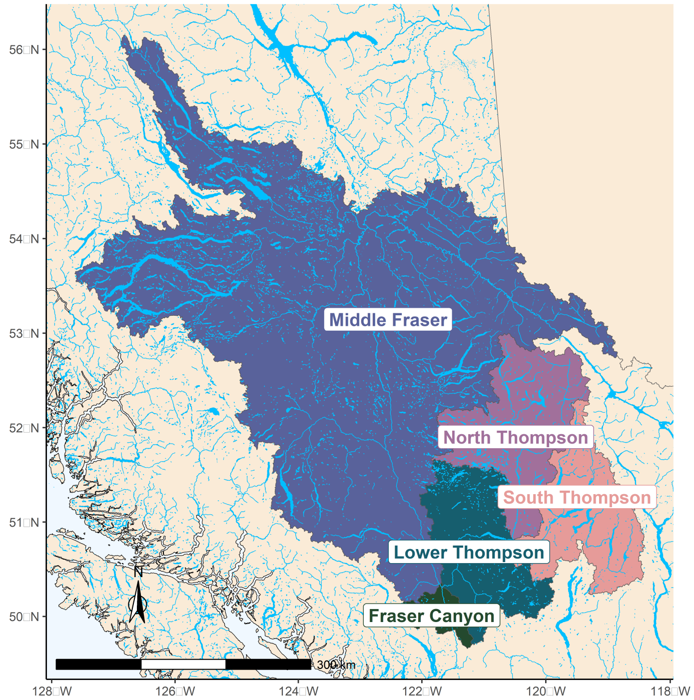

Figure 4. Distribution of the Interior Fraser Coho SMU, including the five CUs that make up the SMU. Only the upper portion of the Fraser Canyon CU (upstream of Hells Gate) is shown here to be consistent with the spatial scale of the data that was used for analyses.

Table 2. Interior Fraser Coho Conservation Units (CUs) and associated sub-populations. Note that the definition of these sub-populations, including mapped boundaries, are provided in IFCRT (2006).

Conservation Unit	Sub-populations
Middle Fraser	• Lower Middle Fraser • Upper Middle Fraser
Fraser Canyon	• Nahatlatch
Lower Thompson	• Lower Thompson • Nicola
North Thompson	• Lower North Thompson • Middle Thompson • Upper North Thompson
South Thompson	• Adams Drainage • Lower and Middle Shuswap Rivers • Shuswap Lake Tributaries

Hatchery enhancement has occurred, and continues to occur, in some parts of the Interior Fraser Coho SMU. Two CUs are currently considered wild populations based on the criteria developed by Withler et al. (2018) (i.e., do not have hatchery programs; strays from out-of-basin hatchery production are limited to <3% per year), while the other three are considered integrated-wild populations (i.e., with Proportionate Natural Influence (PNI) values most likely $\geq$ 0.72; M. Arbeider, pers. comm.). Within integrated-wild populations, most fish are considered 'wild' under the WSP with parents who were born in the natural environment. The Lower Thompson CU had higher levels of hatchery enhancement between 1998 and 2005, so would likely have been considered an integrated-transition population ($0.5 \leq$ PNI < 0.72) during this period.

The five Interior Fraser Coho CUs have historically shown relatively high levels of covariation in escapement among CUs, with an average correlation in spawner abundances among CUs of 0.56. Similarity among CU responses to environmental and anthropogenic drivers is further supported by application of the four criteria proposed by Holt et al. (2023) to evaluate the extent to which status of data deficient CUs can be inferred from CUs with data. A summary of our consideration of these criteria for Interior Fraser Coho are provided in Appendix C. Results showed that Interior Fraser Coho CUs have many shared characteristics. We found few significant indicators that would have prevented us from inferring CU status for one CU from neighboring CUs prior to our case study analyses.

Interior Fraser Coho is included in the first batch of major stocks proposed for regulation under the Fish Stocks provisions of the revised *Fisheries Act*, necessitating the development of LRPs for this SMU.

3.1.1. Previous Assessments

Declines in Interior Fraser Coho spawner abundance throughout the 1990's led to a suite of management actions to promote recovery, including significant fishery restrictions starting in 1998 (Decker et al. 2014). Evidence of a new, lower productivity regime starting in return year 1994 has been well documented, coinciding with declines in spawner abundances (Decker et al. 2014). In 2002, the Interior Fraser Coho stock management unit was designated 'endangered' by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC) based on the stock unit being assessed as a single 'Designatable Unit' (DU).

Subsequent work by the Interior Fraser Coho Recovery Team (IFCRT) led to a conservation strategy outlining short-term and long-term recovery objectives for the management unit (IFCRT 2006). In 2014, Decker et al. assessed status relative to the 2006 IFCRT objectives, and concluded that Interior Fraser Coho had been above the short-term recovery target in every year since 2008, and above the long-term recovery target in the most recent two return years (2012 and 2013). Also in 2014, Interior Fraser Coho were assessed under the framework of DFO's Wild Salmon Policy (WSP). The WSP Integrated Status Assessment classified three of these CUs as being Amber status (Middle Fraser, Fraser Canyon, South Thompson) and the remaining two CUs as Amber/Green status (Lower Thompson, North Thompson, DFO 2015). As part of the WSP assessment, S_{gen} and S_{MSY} were estimated for each CU and used along with other benchmarks when assigning integrated CU status. A subsequent COSEWIC assessment in 2016 upgraded the status assessment for the Interior Fraser Coho DU from 'endangered' to 'threatened' (COSEWIC 2016). In 2018, DFO undertook a Recovery Potential Assessment (RPA) for Interior Fraser Coho that described status, habitat, threats, limiting factors to recovery, candidate recovery targets, and abundance projections for the DU, as well as recommendations regarding mitigation and allowable harm (Arbeider et al. 2020).

3.1.2. History of Aggregate-Abundance Based Reference Points

Interior Fraser Coho show a strong positive relationship between their spatial distribution and overall abundance, which has been used as a basis for identifying aggregate abundance recovery targets and reference points for the stock group. Starting in 2006, the IFCRT identified a recovery goal of one or more viable sub-populations in each of the five 'populations', where their definition of populations aligns with CUs under the WSP (IFCRT 2006). Note that from this point on, we use the term CU instead of population when describing IFCRT recovery goals to be consistent with the WSP. The IFCRT identified a short-term recovery objective that the 3-year average escapement in at least half of the sub-populations within each of the five CUs was to exceed 1,000 natural-origin spawning Coho Salmon, excluding hatchery fish spawning in the wild. Based on analysis of the relationship between aggregate abundance and the number of CUs that met this objective based on historical data, the IFCRT identified an abundance short-term recovery target of 20,000 spawners as the level required to meet their distributional objective. In addition, the IFCRT identified a long-term recovery target of 40,000 spawners, which represented a level that was expected to maintain 1,000 or more wild Coho Salmon in all 11 sub-populations. Decker et al. (2014) updated the IFCRT's original analysis using a longer time series of escapement data. They also quantified the relationship between aggregate abundance and distribution by using a logistic regression to estimate the probability of meeting short-term and long-term recovery objectives as a function of aggregate abundance. They concluded that aggregate spawner abundance levels of 20,000 and 40,000 spawners would result in near 100% probability that the IFCRT's short-term objective and long-term recovery objectives would be met, respectively.

Korman et al. (2019) also used logistic regressions of the relationship between the IFCRT's distributional objectives and aggregate abundance when evaluating how exploitation and smolt-to-adult survival rates affected the ability of Interior Fraser Coho to meet conservation targets. Their approach was similar to that of Decker et al. (2014), except they applied logistic regressions at the CU-level instead of the SMU-level. Using this approach, they calculated the probability that IFCRT sub-population objectives were met as a function of total escapement to the CU within their simulation evaluation. When evaluating how well conservation targets were met at the SMU-level, they chose to rely on the previous values of 20,000 and 40,000 identified by the IFCRT instead of updating these values. Finally, the 2018 RPA used an updated logistic regression to identify a long-term recovery target for Interior Fraser Coho that met the long-term IFCRT objective of 1000 spawners in all sub-populations (Arbeider et al. 2020). As a result, Arbeider et al. (2020) recommended that the long-term recovery target for Interior Fraser Coho should be a 3-year geometric mean abundance of 35,935 natural-origin spawners.

3.2. DATA

Data for this case study cover return years 1998-2020. Data prior to 1998 were not used due to inconsistent assessment methods and data quality. All Interior Fraser Coho data were provided by DFO's Fraser River Stock Assessment Unit (M. Arbeider, DFO, Kamploops, BC, pers. comm.). These data included: (i) annual spawner abundance by CU (1998-2020), (ii) annual natural origin recruits-at-age by CU (brood years 1998 - 2016), (iii) a hatchery-based smolt-to-adult survival rate index, (iv) annual exploitation rates, and (v) annual spawner abundances for 11 sub-populations nested within the 5 CUs.

Two types of spawner abundance series were provided: total spawners and natural-origin returns to the spawning grounds (sometimes called 'natural returns'). The first type, total spawners, includes both natural-origin spawners and spawners that originated from hatcheries but returned to spawn naturally, but excludes fish removed from the river for hatchery brood stock. When modelling spawner-recruit dynamics, total spawners was paired with natural-origin recruitment so that estimated productivity from all spawners was fully captured. The second type of spawner abundance series, natural-origin spawning returns, included only natural-origin fish that returned to spawn, with hatchery brood stock included. Natural-origin spawning returns were used when comparing spawning abundance to CU benchmarks or SMU-level LPRs in order to estimate CU or SMU status.

Data were similar to those previously described in Arbeider et al. (2020); data treatments, assumptions, infilling, and data quality are described in detail in that document. More recent updates that are not described in Arbeider et al. (2020) include the incorporation of three additional years of data (return years 2018-2020; brood years 2014-2016), updates to the SMU smolt-to-adult survival rate index to use a weighted average by release size, and increased data quality screening of scale ages used to calculate the proportion of recruits at age (M. Arbeider, DFO, Kamploops, BC, pers. comm.).

The exploitation rate time series is a large source of uncertainty for Interior Fraser Coho. Exploitation rates are only available at the SMU-level, so are assumed identical among all CUs. This assumption is unlikely to be true because of known differences in freshwater fisheries among CUs. Furthermore, models used to reconstruct exploitation rates require a large number of assumptions that are expected to be incorrect (Arbeider et al. 2020). Because exploitation rate time series are used to reconstruct recruitment time series, errors in exploitation rates will propagate through to estimates of stock-recruitment parameters, relative abundance benchmarks such as S_{gen}, and covariation in recruitment residuals. Additional sources of uncertainty in Interior Fraser Coho data sets include observation errors in spawner abundance estimates and estimates of age-at-escapement. Spawner abundance estimates are largely derived from visual surveys, for which observer efficiency is not estimated and survey life is difficult to estimate accurately. Scale sampling to determine age structure is incomplete at the CU-level with small sample sizes, missing data, and limited spatial representation within CUs in some years (Korman et al. 2019).

3.3. CU STATUS ESTIMATION

We use three alternative ways to characterize CU status when developing LRPs for Interior Fraser Coho: 1) multidimensional status estimates derived from the Pacific Salmon Status Scanner, 2) CU-level abundance relative to S_{gen} as a lower benchmark on abundance, and 3) distribution of spawning abundance relative to distributional targets developed by the IFCRT.

The first approach, which uses the Salmon Scanner tool developed by the State of the Salmon program (Section 2.2.1), is consistent with Canada's WSP. The other two approaches are primarily used to develop aggregate abundance LRPs in this case study, as well as for a point of comparison with the Salmon Scanner tool.

The second approach is based on comparing the current abundance of each CU to its CU-specific estimate of S_{gen}, where CU status is considered Red when abundance drops below S_{gen}. The value of S_{gen} represents the number of spawners required to recover to S_{MSY} (spawners at maximum sustainable yield) within one generation, under equilibrium conditions in the absence of fishing (Holt et al. 2009). S_{gen} is one of several benchmarks available for assigning multidimensional CU status in WSP Integrated Status Assessments and the Salmon Scanner; it represents a lower benchmark between Red and Amber status zones and was used as part of the 2014 Integrated Status Assessment for Interior Fraser Coho (DFO 2015). While estimates of CU status relative to S_{gen} are readily available outputs from the Salmon Scanner tool, we calculated this metric external to the tool for our case study.

The third approach is based on the distribution of spawning escapement among sub-populations nested within CUs (Table 2). We apply this approach for Interior Fraser Coho to maintain consistency with previous recovery planning processes for this SMU (IFCRT 2006; Arbeider et al. 2020). Since the distributional target we use was initially developed by the Interior Fraser Coho Recovery Team in 2006, we refer to it as “IFCRT distributional”. Specifically, we use the IFCRT’s short-term recovery objective that the 3-year geometric average escapement in at least half of the sub-populations within each of the five CUs is to exceed 1,000 wild-origin spawners, excluding hatchery fish spawning in the wild. We selected the short-term recovery target as a proxy for the lower benchmark in our case study because, as noted by Arbeider et al. (2020), the short-term target was designed as an immediate target when the population was endangered. As such, it was interpreted as a level expected to prevent extinction or loss of genetic diversity. We have included this third approach to defining CU status to demonstrate the range of approaches and metrics that can be used, and to demonstrate sensitivity of the LRP to choice of metrics for assigning CU-status. Future iterations of the Pacific Salmon Status Scanner approach could include distributional metrics such as those used in the IFCRT approach.

3.3.1. Estimation of S_{gen}

Estimates of S_{gen} are required when assessing CU status using both the multidimensional algorithm within the Pacific Salmon Status Scanner and the comparison of current CU-level abundance to S_{gen}. While the application of the Salmon Scanner to Interior Fraser Coho CUs in Pestal et al. (in prep) relies on peer-reviewed estimates of S_{gen} from the WSP Integrated Status Assessment (DFO 2015), we re-estimate S_{gen} here using data updated to 2020. In addition, we explore alternative stock-recruitment model formulations to better understand how model assumptions at the CU-level affect resulting LRP estimates.

Two different formulations of stock-recruitment model were used to estimate S_{gen}: (i) a base Ricker model, which includes a smolt-to-adult survival covariate, and (ii) an alternative form of the Ricker model in which an informative prior distribution is used to increase S_{REP} compared to the base model, labelled ‘Ricker_priorCap’. S_{REP} is the spawner abundance level at which the stock replaces itself; the relationship between S_{REP} and Ricker stock-recruitment model parameters is shown below (Equation 13). Both of these models have been previously developed and applied to Interior Fraser Coho CUs. The smolt-to-adult survival covariate used when fitting both models is a hatchery-based smolt-to-adult survival rate index. The index is not CU-specific; the same index is applied to all CUs. A third Ricker model, in which both an informative prior on S_{REP} and depensatory mortality were included, was also used by Korman et al. (2019) and Arbeider et al. (2020); however, we did not include it in our case study for simplicity. As noted by Korman et al. (2019), there is no indication in available data of depensatory dynamics, and the SR model fit with depensatory mortality required a highly uncertain assumption about the escapement level at which depensation occurs. Furthermore, formal model selection criteria showed that adding depensatory mortality into models lead to a reduction in model fit (Korman et al. 2019).

Korman et al. (2019) and Arbeider et al. (2020) used a hierarchical model structure for both the base Ricker and Ricker_priorCap models that assumed CU-level productivity parameters were sampled from a common, normal distribution shared by all CUs. Using formal model selection criteria (i.e., DIC), Korman et al. (2019) found higher support for the hierarchical structure than when productivity parameters were assumed independent among CUs. However, our initial examination of the hierarchical approach applied to the updated data set lead us to select the independent CU approach for our evaluation. Firstly, we found that LRP estimates were sensitive to the assumed standard deviation on the hyper-distribution prior for the productivity parameter. Using the individual model approach removed prior influence on model results. Secondly, a logistic regression fit to status estimates obtained using the hierarchical model was unable to converge on a solution in several years between 2015 and 2020, including the most recent year (2020).

Future stock-recruitment analyses for Interior Fraser Coho may wish to re-visit the hierarchical approach to modelling productivity. Bayesian posterior distributions of the productivity parameter from our individual model fits show some differences in productivity among CUs (particularly for the Fraser Canyon CU; Appendix C). However, there was substantial overlap in CU-level distributions for all other CUs. We do not expect our decision to apply an individual-stock modelling approach here will affect our general conclusions. In preliminary analyses, LRPs were similar between individual and hierarchical modelling approaches.

The formulations for the two stock-recruitment models are described below.

Model 1: Ricker

The base Ricker stock-recruit model formulation was:

$$R_{i,a,t} = P_{i,a,t-a} S_{i,t-a} e^{log(\alpha_i) + \gamma log(m_{t-1}) - \beta_i S_{i,t-a} - \sigma^2_{v_i}/2} \tag{8}$$

$$v_i \sim Normal(0, \sigma_{v_i}) \tag{9}$$

where,

$R_{i,a,t}$ = the predicted number of natural origin recruits from CU i of age a returning in year t (i.e., recruits that were produced by escapement in brood year $t-a$)

$P_{i,a,t-a}$ = the proportion of recruitment from CU i returning at age a from brood year $t-a$

$S_{i,t-a}$ = spawners from CU i in brood year $t-a$

α_i = productivity parameter for CU i

γ = smolt-to-adult survival co-efficient shared among CUs

m_{t-1} = hatchery smolt-to-adult survival index shared among CUs for sea entry in year t-1

β_i = density dependent term describing the rate of decrease in density dependent survival for CU i with increasing spawner abundance

σ_{v_i} = standard deviation of process error on recruitment deviations

Total recruitment from a brood year, BY, was calculated as the sum of age 3 and age 4 recruits in consecutive years,

$$R_{i,BY} = R_{i,a=3,BY} + R_{i,a=4,BY} \tag{10}$$

Observations of $ln(R_{BY}/S_{BY})$ were assumed to be normally-distributed random variables with a standard deviation of σ_{v_i}.

This model formulation is similar to the Ricker model used in Arbeider et al. (2020), but without a hierarchical structure imposed on $log(\alpha_i)$. We placed the following non-informative constraints on the likelihood function to replicate the Bayesian model fitting routine of Arbeider et al. (2020):

$$\gamma \sim Normal(0, 10) \tag{11}$$

$$\sigma_{v_i} \sim InverseGamma(0.1, 0.1) \tag{12}$$

Model 2: Ricker_priorCap

To maintain consistency with this previous work on Interior Fraser Coho, we also consider a version of the Ricker model that uses an informative prior distribution on S_{REP} to increase carrying capacity. Korman et al. (2019) suggested that the Ricker model with a smolt-to-adult survival co-variate (Model 1) over-estimated compensatory dynamics at high spawner abundances when applied only to data from 1998 onwards. They noted that spawner abundances since 1998 have been much lower than historic levels. Given that sparse data at high spawner abundances makes it difficult to estimate carrying capacity, base Ricker estimates of carrying capacity may be unreliable (Korman et al. 2019). Furthermore, they observed that one brood line had persisted at a relatively higher and more stable spawner abundance than the other two brood lines, which they viewed as evidence for a higher capacity than the base Ricker model estimates. Based on these concerns, Korman et al. (2019) proposed an alternative Ricker model that used an informative prior distribution to increase carrying capacity (represented as the spawner abundance at which the stock replaces itself, S_{REP}). Arbeider et al. (2020) followed the approach of Korman et al. (2019) by considering both the base Ricker model and a version of the Ricker model with an informative prior distribution on S_{REP} to be plausible when providing management advice.

$$\beta_i = \frac{\alpha_i + \gamma + log(\overline{m})}{S_{REP,i}} \tag{13}$$

$$S_{REP,i} \sim Normal(\mu_{SREP}, \sigma_{SREP}) \tag{14}$$

Arbeider et al. (2020) and Korman et al. (2019) set $\mu_{S_{REP}}$ at 1.5 times the S_{REP} value estimated from the base model fit without a prior on S_{REP}. For our model fits (described in Section 3.5.1.), we found that we needed to constrain μ_{SREP} at no more than 1.4 times the S_{REP} value to achieve model convergence, so we used the 1.4 times expansion instead. We set σ_{SREP} at $\sqrt{2} \times 1000 = 1414$ spawners, which is the same value used by Arbeider et al. (2020). Note that the "$\times 1000$" term is used to correct for scaling spawner abundance by 1/1000 when fitting models. The effect of adding the prior on S_{REP} when fitting individual models to available data is shown in Figure 5.

Calculation of Sgen

The inclusion of a smolt-to-adult survival co-variate in both stock-recruit models means that the realized productivity changes from year to year with changing survival. We incorporated this adjustment into our calculations of S_{gen} by first calculating the effective productivity for each CU as:

$$log(\alpha'_i) = log(\alpha_i) + \gamma log(\overline{m}) \tag{15}$$

where, $\overline{m}$ is the average smolt-to-adult survival rate over the available time series.

S_{MSY} was calculated as a function of log(α'_i) and β_i using:

$$S_{MSY,i} = 1 - \frac{W(e^1 - \alpha'_i)}{\beta_i} \tag{16}$$

where, W represents the Lambert W function (Scheuerell 2016). S_{gen} was then calculated numerically by solving the following equation:

$$S_{MSY,i} = \alpha'_i S_{gen,i} e^{-\beta_i \cdot S_{gen,i}} \tag{17}$$

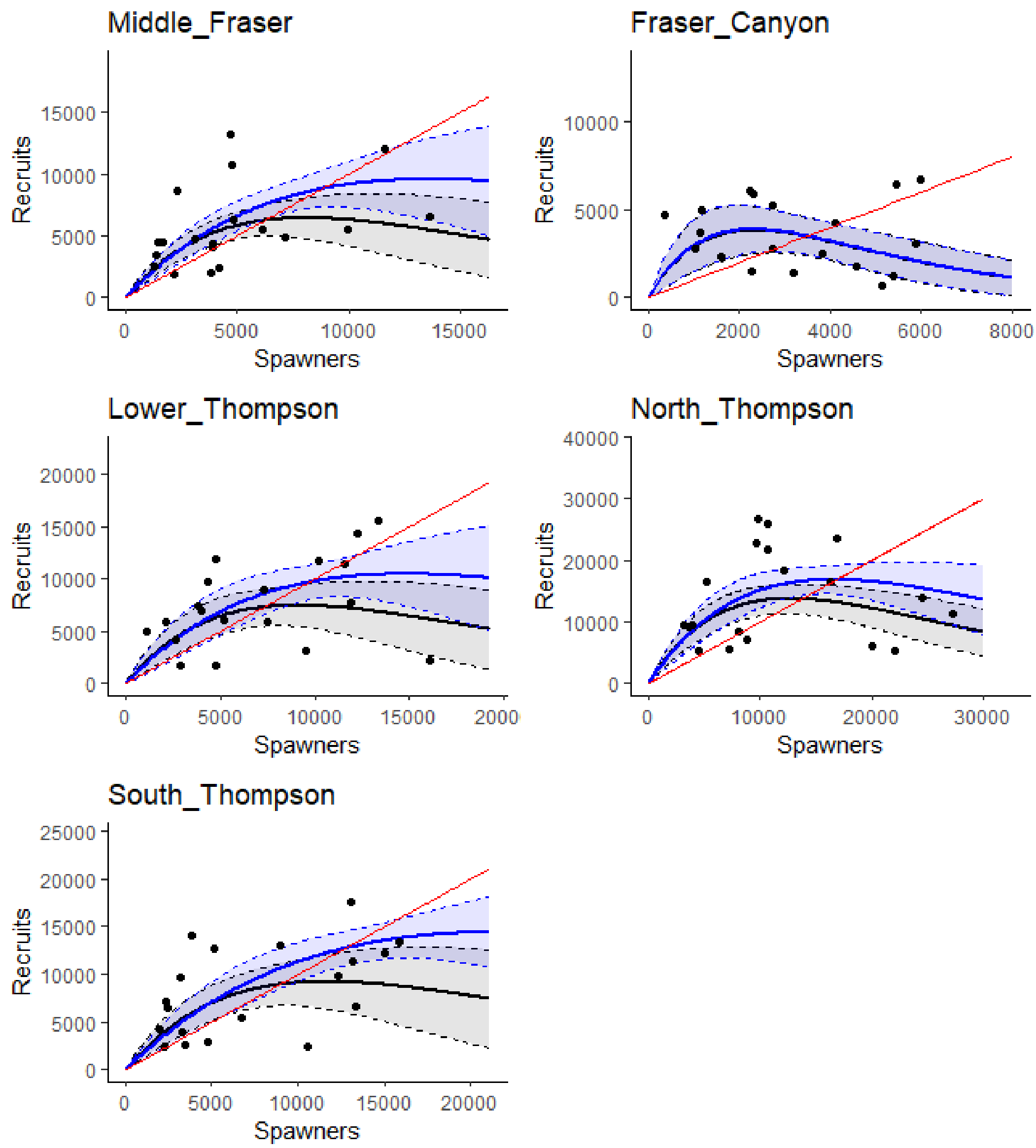

Figure 5. Spawner-recruitment curves fit to spawner and recruitment data using individual models for each CU. Solid black lines shows the MLE fit for the base Ricker model while solid blue lines shows the MLE fit for the Ricker_priorCap model. Associated black and blue shaded regions show the 95 percent confidence intervals on respective model fits using the average long-term smolt-to-adult survival rate from the available time series. The red lines show the replacement line.

3.4. LRP ESTIMATION: CU STATUS BASED

3.4.1. Methods

To derive CU status-based LRPs, we calculated the proportion of CUs that had multidimensional statuses from the Pacific Salmon Status Scanner above the Red zone. Status was assessed as being below the LRP in years in which one or more CUs assessed as having Red status. Both Ricker model formulations described above were used to estimate abundance-based benchmarks (lower benchmark = S_{gen} and upper benchmark = $0.8S_{MSY}$) when assessing status with the Pacific Salmon Status Scanner: the base Ricker model and the Ricker_priorCap model. Estimates of S_{gen} and S_{MSY} were estimated using all data available up to 2020.

For comparison, we also calculated LRPs from the proportion of CUs that had recent generational average (3-year) spawning abundance greater than S_{gen} and from the proportion of CUs that failed to meet the IFCRT distributional target of at least half of all sub-populations within each CU having more than 1000 spawners.

3.4.2. Results

Estimates of S_{gen} based on the Ricker_priorCap model were higher than those based on the base Ricker model for four of the five CUs (Middle Fraser, Lower Thompson, North Thompson, and South Thompson) and were approximately equal for the fifth CU (Fraser Canyon; Appendix C). As a result, generational average spawning abundance was more likely to drop below S_{gen} when it was estimated using the Ricker_priorCap model. Under the base Ricker model formulation, generational average spawning abundance remained above S_{gen} for all years between 2000 and 2020 (Figure 6). In comparison, under the Ricker_priorCap formulation, generational average abundance dropped below S_{gen} for 5 of the 21 years between 2000 and 2020. These occurrences included the Lower Thompson CU (2006), the Middle Fraser CU (2006, 2008), and the South Thompson CU (2000, 2006, 2007, 2015; Figure 7). All five CUs had spawning abundances above S_{gen} in 2020, regardless of which spawner recruitment model was used, indicating that the stock would be above a CU status-based LRP based on S_{gen}.

The frequency of years in which the IFCRT distributional target failed to be met for one or more CUs was similar to that observed when S_{gen} based on the Ricker_priorCap was used, with distributional targets not met in 4 of the 21 years between 2000 and 2020 (breached in 2006, 2015-2017). Eight of the 11 sub-populations had generational average escapement drop below the 1000 spawner threshold in one or more years (Figure 8). Sub-populations tended to differ in which years they dropped below the 1000 spawner threshold, which meant that the distributional target of at least half of the sub-populations within each CU with greater than 1000 fish was more often met than not. All 11 sub-populations had generational average spawning abundances above 1000 spawners in 2020, indicating that the stock would be well above a CU status-based LRP based on the IFCRT-distributional target (Figure 8).

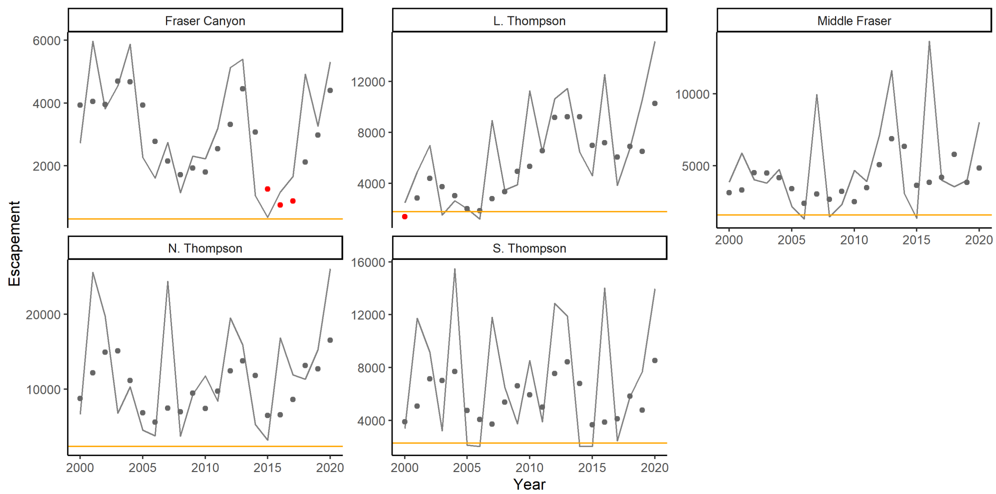

Figure 6. Escapement time series for Interior Fraser Coho CUs shown as annual escapements (lines) and 3-year geometric mean escapements (dots). First geometric mean includes years 1998-2000. Grey dots indicate years when all CUs had multidimensional Salmon Scanner assessments above Red when S_{gen} was estimated using the Ricker model, while red dots indicate when one or more CUs had assessments in the Red zone, which would trigger a breach of the LRP. Orange lines show estimated S_{gen}.

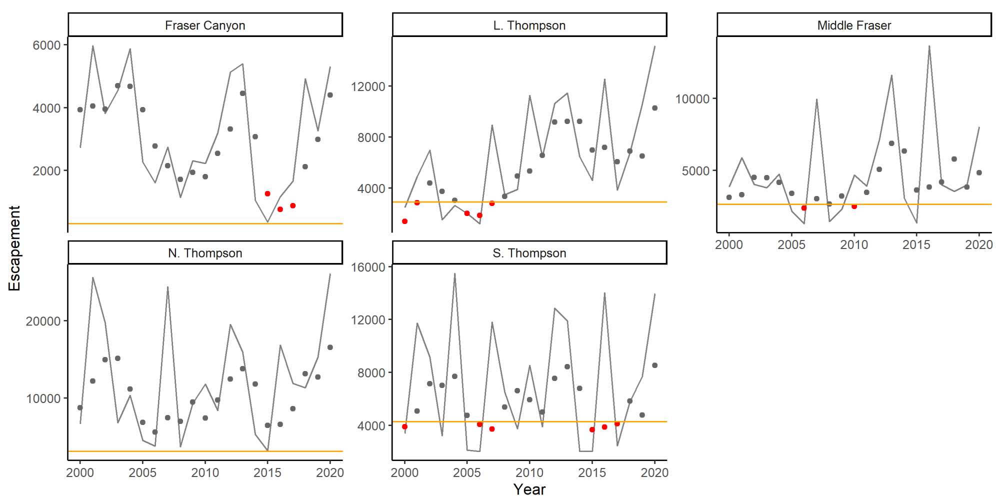

Figure 7. Escapement time series for Interior Fraser Coho CUs shown as annual escapements (lines) and 3-year geometric mean escapements (dots). Grey dots indicate years in which all CUs had multidimensional Salmon Scanner assessments above Red when S_{gen} was estimated using the Ricker_priorCap model, while red dots indicate years in which one or more CUs had assessments in the Red zone, which would trigger a breach of the LRP. Orange lines show estimates of S_{gen}.

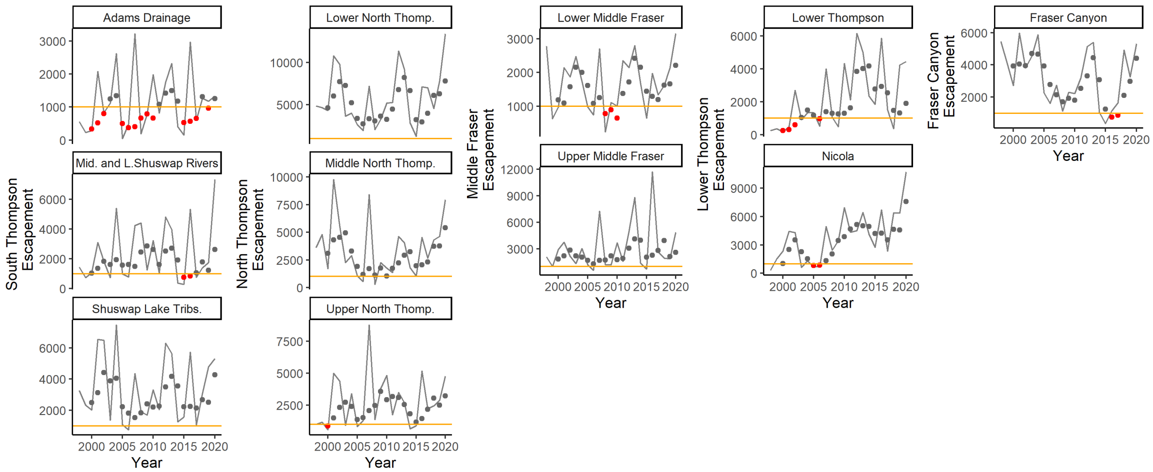

Figure 8. Escapement time series for 11 sub-populations of Interior Fraser Coho shown as annual escapements (lines) and 3-year geometric mean escapements (dots). First geometric mean includes years 1998-2000. Grey dots shows years in which the 3-year geometric mean escapement was above the 1000 fish threshold used to assess distributional status, while red dots show years in which the 1000 fish threshold was not met. CUs are represented by columns with labels long the y axis.

Multidimensional status derived from the Salmon Scanner is driven by abundance metrics for this SMU. Because absolute abundance data and benchmarks based on S_{gen} and S_{MSY} were available, the multidimensional algorithm within the Salmon Scanner (Figure 1) most often assigned CU status based on this metric (Figures 6 and 7). Though status in some cases was also influenced by absolute abundance relative to the threshold of 1500 spawners. This occurred in the Fraser Canyon CU between 2015 and 2017. In these years, the generational average of absolute spawning abundance was < 1500 spawners and the CU was assigned Red status under the first node of the decision tree even though spawning abundances are above S_{gen}.

The total number of years in which an LRP would have been breached using the multidimensional approach depended on which Ricker stock-recruitment model was used to estimate S_{gen}. When status was assessed using abundance-based benchmarks estimated from the base Ricker model, a CU status-based LRP for the SMU would have been breached in 4 of 21 years. For three of these years, the breach was based on Fraser Canyon spawning abundances dropping below 1500 spawners (2015-2017), while for the one additional year (2000) it was due to the Lower Thompson CU having spawning abundance < S_{gen} (Figure 6). In comparison, when status was assessed using abundance-based benchmarks from the Ricker_priorCap model, a CU status-based LRP would have been breached in 9 of 21 years (2000-2001, 2005-2007, 2010, 2015-2017; Figure 7). For both stock-recruitment models, multidimensional status from the Salmon Scanner was above Red for all CUs based on the most recent generational average, indicating that the SMU is currently above a CU status-based LRP, regardless of spawner recruitment model.

3.5. LRP ESTIMATION: AGGREGATE ABUNDANCE, LOGISTIC REGRESSION LRPS

3.5.1. Methods

We present aggregate abundance LRPs derived using logistic regressions with two of the Interior Fraser Coho benchmarks considered: S_{gen} and the IFCRT-distributional target. Because two stock-recruitment models were used to estimate S_{gen}, we distinguish these models as ‘Logistic:Sgen-

Ricker' and 'Logistic:Sgen-priorCap' for the Ricker and Ricker_priorCap models, respectively. We use the label 'Logistic:IFCRT' to denote the case in which the IFCRT distributional target was used to develop the aggregate abundance, logistic regression LRP. See Section 2.3.1 for an overview of the approach used to calculate aggregate abundance LRPs using logistic regression.

When estimating logistic regression LRPs using S_{gen}, we used an integrated modelling approach in which CU-level S_{gen} values and the SMU-level LRP were simultaneously estimated. The integrated S_{gen}-LRP models had two components:

(i) Stock-recruitment models fit to each of the 5 CUs to estimate CU-level S_{gen} (Equation 8 and Equations 15 - 17)

(ii) A logistic regression model fit to aggregated data to estimate the LRP as the aggregate abundance that has historically been associated with a specified probability of all CUs being above S_{gen} (Equations 1 - 2)

We initially considered a third version of the logistic regression model, in which we used the multidimensional algorithm within Salmon Scanner to characterize CU status. Preliminary model evaluations led us to exclude this model due to poor fit. The multidimensional algorithm relies on generational mean (smoothed abundances) to assess status of individual CUs against benchmarks, while our logistic regression approach uses raw (unsmoothed) aggregate abundance as a predictor variable. As a result, when logistic regressions were fit to multidimensional CU status estimates, there was a mismatch in the timing of abundance highs and lows. This mismatch led to a weak/nonexistent relationship between SMU status and the raw (unsmoothed) abundances. In addition, using the generational mean of aggregate abundance as the predictor variable in the logistic regression fit, instead of raw annual abundance values, introduced considerable autocorrelation in statuses.

Retrospective Analysis and Analysis Evaluating Impact of Missing CUs

We used retrospective analyses to examine the effect of time series length on logistic regression LRP estimates. For each year between 2010 and 2020, we used data only available up to that year to calculate LRPs and associated confidence intervals.

In addition, to examine the effect of missing CUs on retrospective LRP estimates, we calculated LRPs using data from only a subset of the five Interior Fraser Coho CUs. We limited our analysis to missing data from either one or two CUs so that we had at least three CUs of available data when calculating the proportion of CUs above their benchmarks. For each missing data case, we calculated SMU aggregate status as

$$AggStatus_t = \frac{\sum_i^{nCU} S_{i,t}}{LRP'_t} \tag{18}$$

where nCU is the number of CUs used (3, 4, or 5), $S_{i,t}$ is the abundance of natural-origin spawners returning to CU i in year t (including fish removed for brood), and LRP'_t is the LRP calculated in year t using only data from nCU. SMU-level status in a given year was calculated for all possible combinations of CUs available (5 combinations when nCU= 4 and 10 combinations when nCU = 3) to allow examination of the stability of status estimates among available combinations. Estimates of SMU status relative to LRPs were used to compare among missing CU scenarios instead of actual LRP estimates because the magnitude of the LRP will vary with the number and combination of CUs used. Since uncertainty estimates for spawner abundance are not available, confidence intervals on LRP status are based solely on estimated 95% confidence intervals for the LRP.

3.5.2. Results

LRP Estimates

Logistic regression model fits in 2020 from the integrated Logistic:Sgen-Ricker, Logistic:Sgen-priorCap and Logistic:IFCRT models are shown in Figure 9. All three logistic regression LRP methods were able to converge on a solution in 2020. Resulting LRPs for different *p* thresholds are shown on the regression curves, as well as in Table 3. There was considerable uncertainty around predicted curves as seen in the large areas of gray shading in Figure 9.

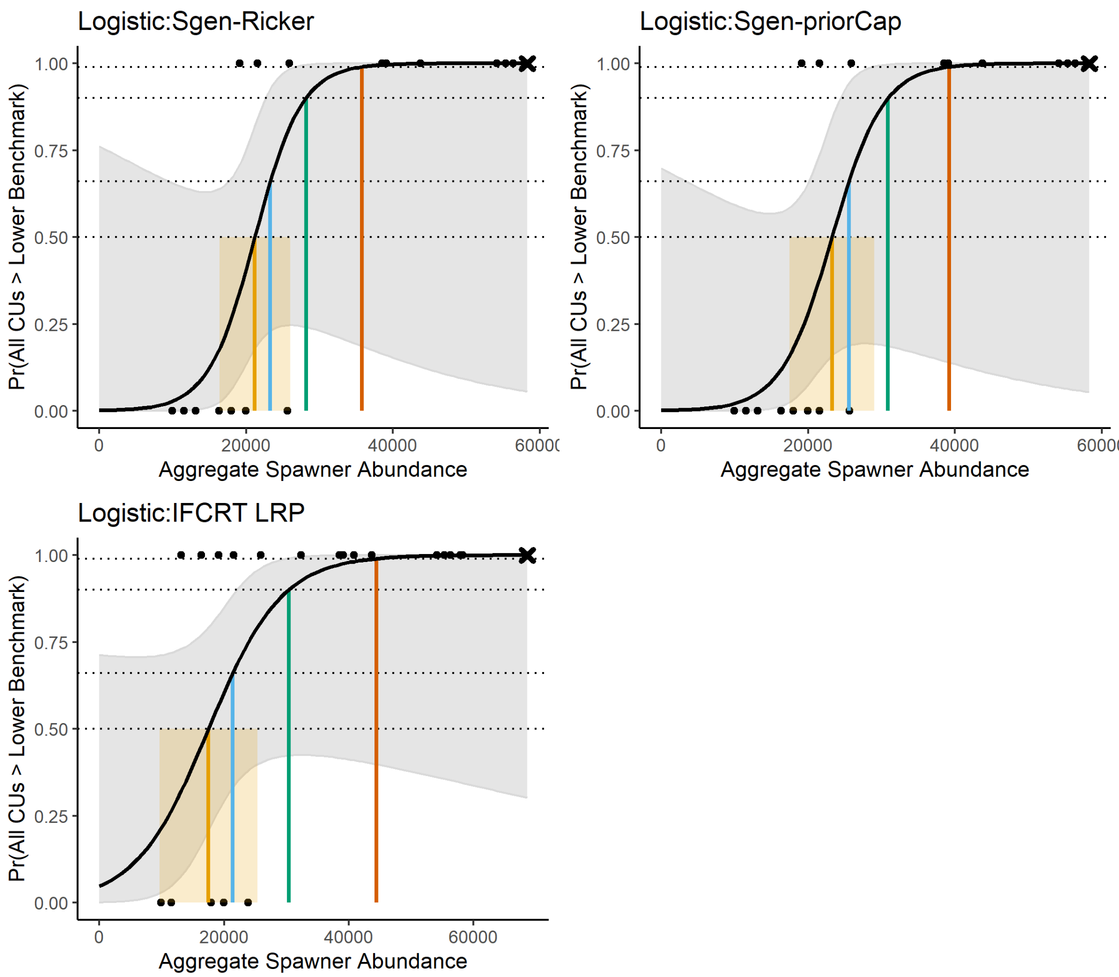

Figure 9. Logistic regression fit from the three logistic regression models (Logistic:Sgen-Ricker, Logistic:Sgen-priorCap and Logistic:IFCRT) using data from 1998 - 2020. Dots represent individual years and 'x' represents the latest year in the time series. The yellow vertical line shows the LRP estimate based on the requirement of a 50% probability of all CUs being above S_{gen}, while the yellow shaded region shows the associated 95% confidence interval around the LRP. LRPs for three alternative probability thresholds, 66%, 90%, and 99%, are shown in blue, green, and orange, respectively.

When the Logistic:Sgen-Ricker model was used, aggregate abundance LRPs ranged from 21,190 to 35,737 spawners, depending on whether the required probability of all CUs being above S_{gen} was moderate (50%) or very likely (99%) (Table 3). LRPs increased across all probability levels when the carrying capacity was assumed higher under the Logistic:Sgen-priorCap model

(Table 3). The higher S_{gen} values for most CUs under the alternative Logistic:Sgen_priorCap model formulation resulted in more historical years in which < 100% of CUs were above S_{gen}. The result was a shift of the logistic curve to the right (Figure 9). LRPs based on the Logistic:Sgen_priorCap model ranged from 23,245 to 39,200 spawners, depending on whether the required probability of all CUs being above S_{gen} was moderate (50%) or very likely (99%).

When CU status was based on the IFCRT distributional target, the fit of the logistic curve had a more gradual slope than the two S_{gen} models due to a greater overlap in 'successful' (all CUs > distributional target) and 'unsuccessful' (<100% of CUs above distributional target) years at low to moderate aggregate abundances. In 3 of the 6 years with aggregate abundances below 20,000 spawners, the distributional target was not met for all CUs (Figure 9). LRPs based on this model also became increasingly large at high probability thresholds (Table 3). The LRP based on a 99% probability was 44,403 spawners, with a 95% confidence interval extending from 15,102 - 73,703 spawners.

Table 3. Aggregate abundance based LRPs (with 95% confidence intervals) from three different logistic regression LRP models. For each probability level, the LRP estimate represents that probability that all CUs will be above their lower benchmark.

Probability	Sgen-Ricker	Sgen-priorCap	IFCRT
50% (As likely as not)	21,190 (16,383-25,996)	23,245 (17,456-29,034)	17,515 (9,695-25,336)
66% (Likely)	23,289 (17,364-29,215)	25,547 (18,158-32,937)	21,396 (13,418-29,375)
90% (Very likely)	28,145 (17,566-38,725)	30,874 (18,129-43,620)	30,372 (15,711-45,033)
99% (Virtually certain)	35,737 (16,525-54,949)	39,200 (16,922-61,479)	44,403 (15,102-73,703)

Logistic Regression Diagnostics

Logistic regression diagnostics showed that key regression assumptions were met, and that model fits were strong enough to support estimation of logistic regression LRPs from all three models (Table 4). The assumption of linearity was demonstrated based on the Box-Tidwell test. This test evaluates the significance of adding a non-linear interaction term to the logit regression. We found that this additional interaction term was not significant, supporting the linearity assumption (Table 4). An examination of deviance residuals did not show any large outliers, i.e., no residual values were greater than 2 standard deviations away from zero for all three models. Observations were also found to be independent at all year lags examined for all three models based on no significant autocorrelations among residuals.

The Wald test showed that the logistic model coefficient for aggregate abundance was marginally significant ($p < 0.10$). Pseudo-R^2 statistics indicated a moderately strong relationship between aggregate abundance and the probability of all CUs being above their lower benchmarks, and the goodness of fit statistics indicated a significant fit of the model with aggregate abundance relative to the null model based on p-values less than 0.01. Finally, 'out-of-sample' hit ratios representing classification accuracy as the proportion of successful predictions when one year of data was iteratively left out of the model fit, were relatively high at low probability thresholds, indicating good accuracy. This result was especially true for the Logistic:Sgen-Ricker and Logistic:Sgen-priorCap models which had hit ratios ranging between 0.83 and 0.87 at probability thresholds of 50% and 66%. Classification accuracy was lowest for all models at the 99% probability threshold.

Table 4. Model diagnostic statistics from Sgen:LRP, Sgen_priorCap:LRP, and Dist-LRP model fits. A description of diagnostic tests is provided in Section 2. Hit ratios are shown for all four probability thresholds considered. The symbol indicates a result that only marginally met the recommended criteria for demonstrating good model fit

Diagnostic Test	Sgen-Ricker	Sgen-priorCap	IFCRT
Box-Tidwell p-value	0.44	0.94	0.79
Max. deviance residual	1.98	1.81	1.66
AR-1	-0.07	0.09	0.05
Wald p-values	0.07^{*}	0.06^{*}	0.09^{*}
Goodness-of-fit p-value	<0.01	<0.01	<0.01
Pseudo-R^2	0.60	0.61	0.40
Hit Ratio (p= 50%, 66%, 90%, 99%)	0.87, 0.83, 0.74, 0.70	0.83, 0.83, 0.83, 0.74	0.76, 0.71, 0.76, 0.52

Sample sizes were small due to the short time series available for Interior Fraser Coho; only 23 years of observations were available to fit logistic regression models. Peduzzi et al. (1996) recommend a minimum requirement of 10 data points for the least frequent outcome based on their simulation studies in the field of clinical epidemiology. In our case, the least frequent outcome was the failure of all CUs to be above their benchmarks (i.e., 0). We were not able to make this minimum requirement for any of our model fits; we had only 7, 8, and 5 data points at the least frequent outcome for the Logistic:Sgen-Ricker, Logistic:Sgen-priorCap, and Logistic-IFCRT models, respectively. Based on the current ratio of successes and fails in the data, the estimated minimum sample sizes that would be required to meet the criteria of Peduzzi et al. (1996) ranged from 26 to 42 years. However, despite small sample sizes, hit ratios are high for all models at p = 50%. As a result, we suggest that logistic regression LRPs may still be useful for this SMU. We proceeded with retrospective analyses in order to examine how sensitive LRPs based on these model fits were to variations in the level of available data.

Retrospective Analysis and Analysis Evaluating Impact of Missing CUs

We started the retrospective analyses for the three logistic regression models in 2010. Throughout the time series, the Logistic:Sgen-Ricker did not converge when the estimates were truncated to 2013 and 2014. The Logistic:Sgen-priorCap model did not converge on an LRP estimate in 2018. All three models showed some fluctuations in LRP estimates over time (Figure 10). The Logistic:IFCRT model tended to produce the lowest estimates of LRPs over time, followed by the Logistic:Sgen-Ricker and the Logistic:Sgen-priorCap. However there was considerable overlap between the confidence interval of all three LRP estimates (Figure 10).

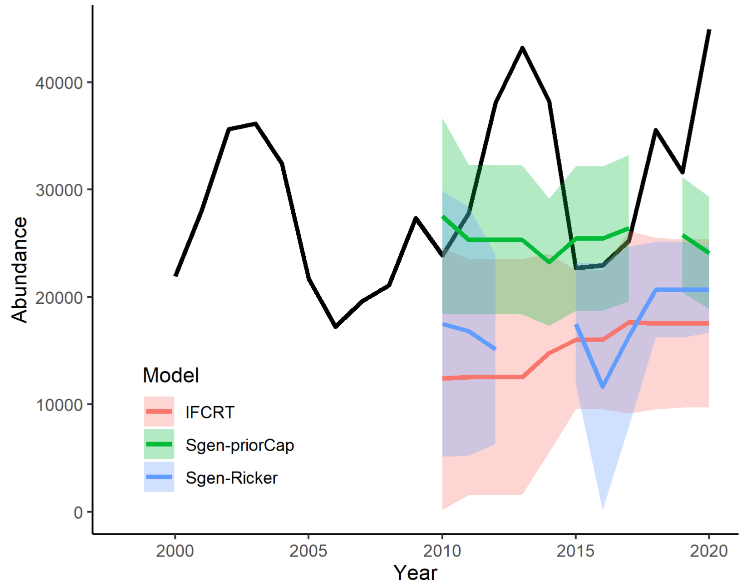

Figure 10. Three-year geometric mean of aggregate spawning abundance for the Interior Fraser Coho SMU (black line) and associated time series of retrospective LRPs from logistic regression estimation methods. LRPs are based on a 50% probability that all CUs will be above their lower benchmarks. Annual LRP estimates are shown as maximum likelihood values (coloured lines) and associated 95% confidence intervals (shaded areas).

When the Logistic:Sgen-Ricker model was applied retrospectively to missing data scenarios with 4 out of the 5 CUs, only a subset of scenarios had LRP estimates that converged on a solution (Figure 11). All five possible 4-CU combinations had estimates in 2017-2019, while only four combinations had estimates in 2020. For scenarios in which LRP estimates were possible, estimates of aggregate status (Equation 18) were often close to the estimate obtained when all 5 CUs were used, and always overlapped with the 95% confidence interval of the full data estimate. The Logistic:Sgen-Ricker model was less likely to converge on a solution when data from only 3 CUs were used. This pattern was especially true for 2020 when only six out of the ten possible combinations had estimates. For 3-CU scenarios that were able to converge, aggregate status estimates tended to be more uncertain than 4- and 5-CU scenarios, and showed larger deviations from estimated status when all CUs were used. One missing data scenario in 2019 had a status estimate that fell outside of the 95% confidence interval of the full data estimate.

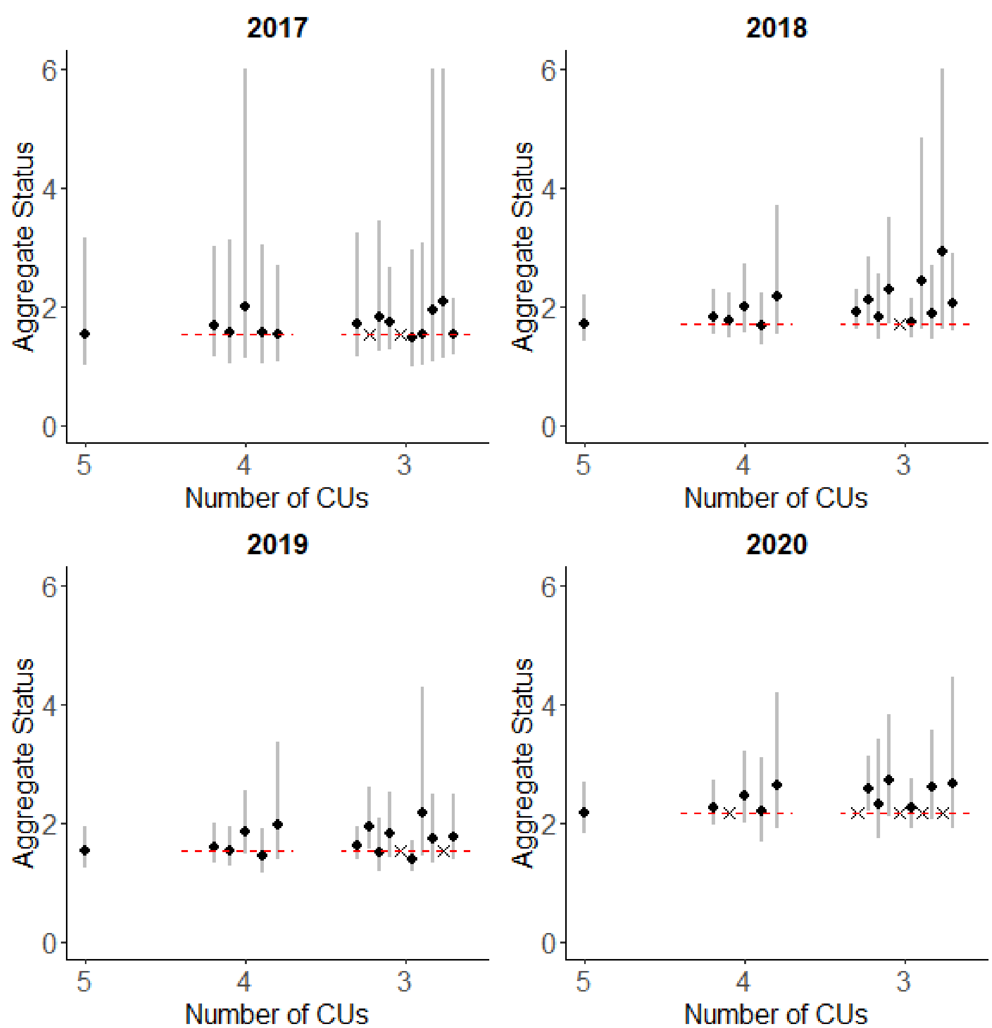

Figure 11. Estimates of SMU status (with 95% confidence intervals) from the Logistic:Sgen-Ricker model under different scenarios about missing CUs, where aggregate status is characterized as the recent generational mean of aggregate abundance / LRP. LRPs are based on a 50% probability that all CUs will be above their lower benchmarks. The set of status estimates associated with each number of CUs on the x-axis represents all possible combinations of CUs created by selecting that number from the 5 available CUs. Red dashed lines show the maximum likelihood estimate when no data is missing (i.e., all 5 CUs) for comparison with the missing data scenarios. Note that the y-axis has been truncated at 6, so the upper limits of some error bars are not shown.

When the Logistic:Sgen-priorCap model was applied to missing data scenarios in which 4 out of 5 CUs had data, LRP estimates were only available for two of the five CU combinations (Figure 12). For scenarios in which LRP estimates were available, status was poorly estimated with the estimate often falling outside of the 95% confidence interval of the full data estimate. While convergence was more frequent when only 3 CUs were used, estimates had high uncertainty and were variable among scenarios. Several of the status estimates from 3-CU scenarios fell outside of the 95% confidence interval for the full data case. In the year 2018 the model did not converge when all CUs were included, but estimates for missing CU scenarios were available.

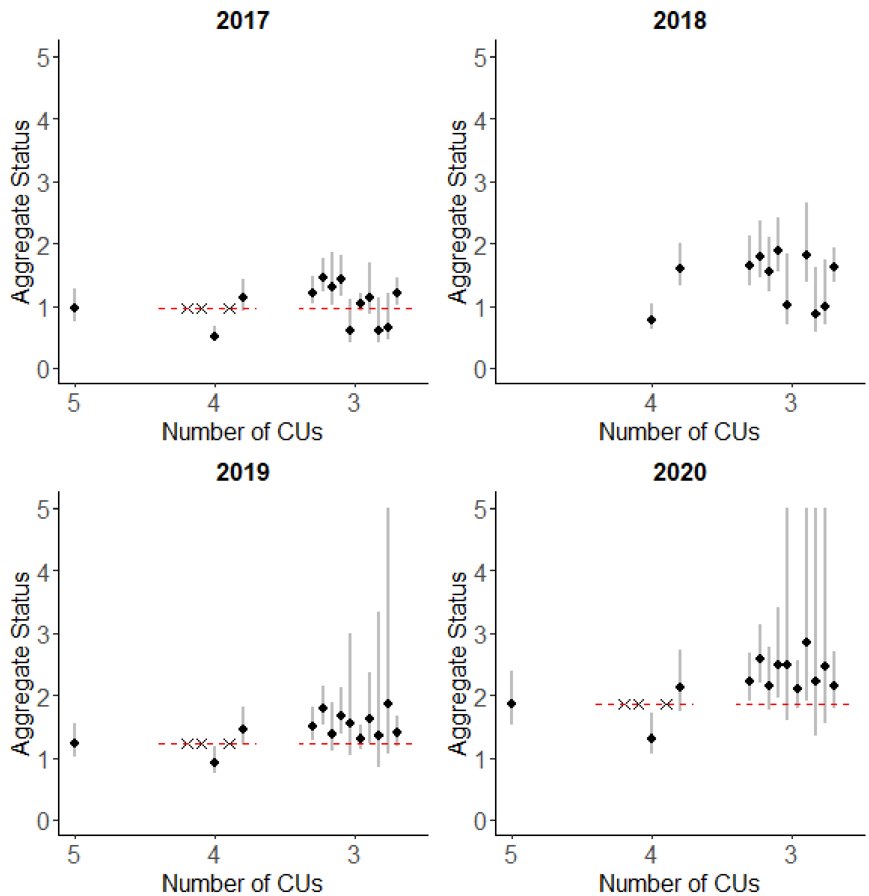

Figure 12. Estimates of SMU status (with 95% confidence intervals) from the Logistic:Sgen-priorCap model under different scenarios about missing CUs, where status is characterized as the recent generational mean of aggregate abundance / LRP. LRPs are based on a 50% probability that all CUs will be above their lower benchmarks. The set of status estimates associated with each number of CUs on the x-axis represents all possible combinations of CUs created by selecting that number from the 5 available CUs. Red dashed lines show the maximum likelihood estimate when no data is missing (i.e., all 5 CUs) for comparison with the missing data scenarios. The model with full data (5 CUs) failed to converge in 2018. Note that the y-axis has been truncated at 5, so the upper limits of some error bars are not shown.

LRPs based on the Logistic:IFCRT model could be estimated for all 4-CU data combinations in all years (Figure 13). Resulting estimates of SMU status were similar to the full data estimate for 4 of the 5 CU combinations. Status estimates were highest and most uncertain when the South Thompson CU was dropped from the analysis (i.e., the last of the five 4-CU combinations shown for each year in Figure 13). This pattern is due the 2015 data point for the South Thompson CU, which is an influential observation that has a large impact on the shape of the model fit. The South Thompson CU is the only CU that failed to meet the distributional target in 2015, which meant that its removal leads to a 'failure' year (i.e., at least one CU below its lower benchmark) becoming a 'success' (all CUs above lower benchmark). This shift results in a lower LRP and a higher status estimate. For missing data scenarios in which only 3 CUs were included, status estimates often had higher uncertainty than the 4-CU or full data scenarios, and showed high variability among scenarios in estimated status.

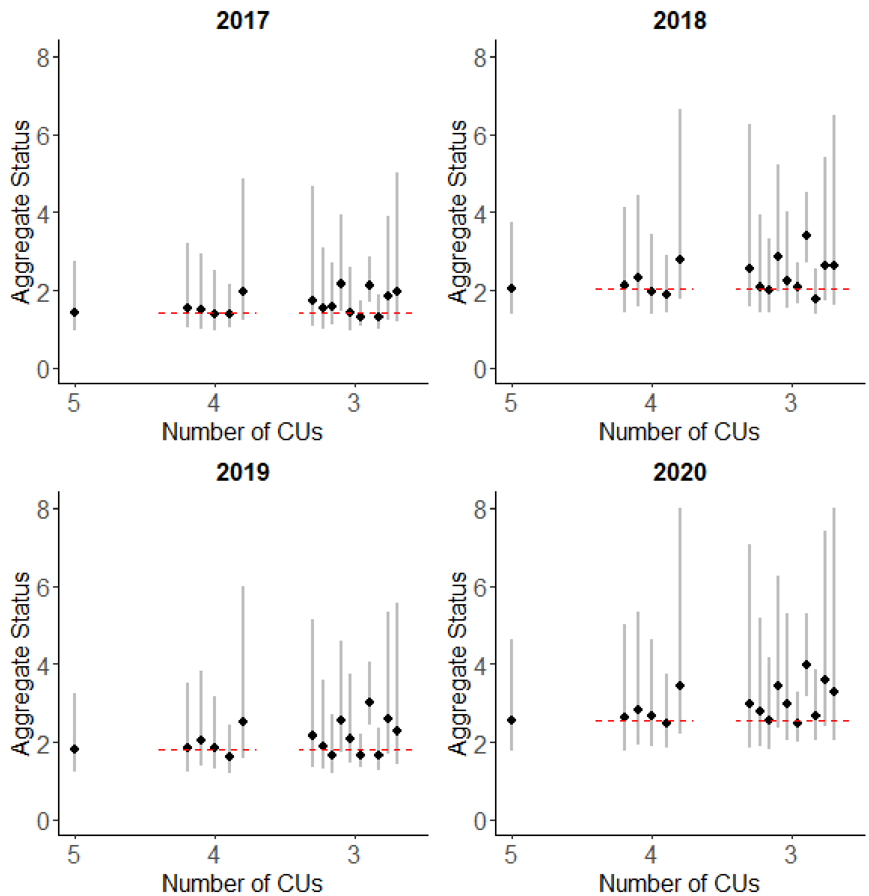

Figure 13. Estimates of SMU status (with 95% confidence intervals) from the Logistic:IFCRT model under different scenarios about missing CUs, where status is characterized as the recent generational mean of aggregate abundance / LRP. LRPs are based on a 50% probability that all CUs will be above their lower benchmarks. The set of status estimates associated with each number of CUs on the x-axis represents all possible combinations of CUs created by selecting that number from the 5 available CUs. Red dashed lines show the maximum likelihood estimate when no data is missing (i.e., all 5 CUs) for comparison with the missing data scenarios. Note that the y-axis has been truncated at 8, so the upper limits of some error bars are not shown.

3.6. LRP ESTIMATION: AGGREGATE ABUNDANCE, PROJECTION LRPS

3.6.1. Methods

Projections of each of the five CUs within the Interior Fraser Coho SMU were implemented using the `samSim` modelling tool (Appendix B). Finer-scale projections at the scale of sub-populations were not possible as spawner-recruitment data series were not available at this scale. As a result, projection LRPs using the IFCRT recovery target was not possible; we were restricted to estimating CU-level status based on S_{gen}. Parameters characterizing CU-level population dynamics, smolt-to-adult survival rates, and exploitation rates were derived directly from data sets described in Section 3.2. Base case parameters and alternative parameter values tested in sensitivity analyses are provided in Table 5. Additional details on key model parameterizations and sensitivity analyses are also described in text below.

Table 5. Parameters used for CU-specific projections of Interior Fraser Coho population dynamics.

Parameter	Value	Source
Ricker Parameters (α, β, γ,σ)	CU-specific (Appendix C)	Drawn from posterior from MCMC model fit to 1998-2016 brood years
Smolt-to-adult survival rate (all CUs)	Drawn from Lognormal(-4.83, 1.21), bound between [-9.21, -3.32]	Estimated from brood years 1998 - 2016, with bounds set at lowest and highest observations
Among-CU variability in smolt-to-adult survival coefficient γ	σ_γ = 0 (all CUs the same)	Assumed value when fitting models. Varied between 0 and 0.09 in sensitivity analyses
Ave age proportions at maturity (ages 3, 4)	MiddleFR, LThomp, SThomp = (0.86,0.14) , FRCanyon = (0.87, 0.13), NThomp = (0.88, 0.12)	Estimated from time-series of proportions of recruits at age
Interannual variability in age proportions (tau from multivariate logistic distribution)	MiddleFR, NThomp, SThomp = 1.0, LThomp = 0.9, FRCanyon = 0.8	Estimated from time-series of ppns of recruits at age
Average exploitation rate	0.125	Estimated from annual estimates, brood years 1998 - 2016. Varied in sensitivity analyses (0.05 - 0.35).
Interannual variability in exploitation rates	CV = 0.442	Estimated from annual estimates from brood years 1998 - 2016. Assumed to be Beta distributed.
Variability in exploitation rates among CUs	CV = 0.221	Assumed to be half of interannual variability. Varied in a sensitivity analysis (0-0.442).
Initial abundances	CU-specific	Based on spawner-recruit series

Projections were run for 30 years over 20,000 simulation trials, with projections initialized using spawner abundances from the most recent 4 return years, 2016 - 2020. The high number of simulation trials was required to stabilize LRP estimates given the binning of aggregate escapement in 200-fish intervals to identify LRPs based on probability thresholds. The distribution of projected trajectories were near equilibrium after 4 years of projections. During the first 4 years, trajectories depended primarily on the historical time-series (Figures C.6 and C.7).

Stock-recruitment dynamics

Stock-recruitment parameters for all five CUs were drawn from joint posterior distributions obtained by fitting the two stock-recruit models described in Section 3.3.1 (Ricker and Ricker_priorCap) to available spawner-recruit data using Bayesian Markov Chain Monte Carlo (MCMC) estimation. Bayesian estimation was done using 'tmbStan' (Kristensen et al. 2016), which is an R package that allows MCMC samples to be drawn from a TMB model object using 'rStan' (Stan Development Team 2020). Three MCMC chains were run for 14,000 iterations, with the first half of each chain excluded from the final posterior sample. Resulting joint posterior distributions included 21,000 samples. Posterior sampling was initiated at the MLE estimates for each model formulation. Neither model showed signs of convergence failure based on our examination of $\hat{R}$ and effective sample size diagnostics, as well as visual inspections of marginal posterior distributions. A summary of marginal posterior distributions for each stock-recruitment parameter (α, β, γ, and σ) is provided in Appendix C.

The two stock-recruitment models, Ricker and Ricker_priorCap, were treated as two alternative hypotheses about stock-recruitment dynamics, which we compare against each other. We also considered a simple model-averaging approach, in which we equally weighted the two stock-recruit models by combining projections prior to calculating a projection LRP as a demonstration of model averaging. Additional sensitivity analyses described below were applied to the base Ricker model.

Covariance in recruitment residuals

We parameterized correlations in recruitment residuals among CUs from MLE predictions of pairwise correlations from stock-recruitment model fits. The correlation matrix from the base Ricker model fit is shown in Figure 14. Correlation values for the Ricker_priorCap model were similar (not shown).

We initially attempted to reduce covariation in spawner abundances among CUs by scaling correlations in recruitment residuals (i.e., scalar < 1). However, we found that scalars had little effect on projected correlations in spawner abundances among CUs due to the shared smolt-to-adult survival rate coefficient dominating among-CU variability in recruitment. We therefore used sensitivity analyses of the level of variability in smolt-to-adult survival coefficients among CUs to drive patterns of covariation in spawner abundance, as described below. This approach differs from that taken for WCVI Chinook (Section 4).

Variability in smolt-to-adult survival coefficient among CUs

When fitting stock-recruit models to data, we followed the approach of Korman et al. (2019) and Arbeider et al. (2020) in assuming that all CUs experienced the same smolt-to-adult survival rate for given sea-entry year, and that the smolt-to-adult survival coefficient, γ, was constant both among CUs and among years. When projecting CUs forward, we maintained this assumption

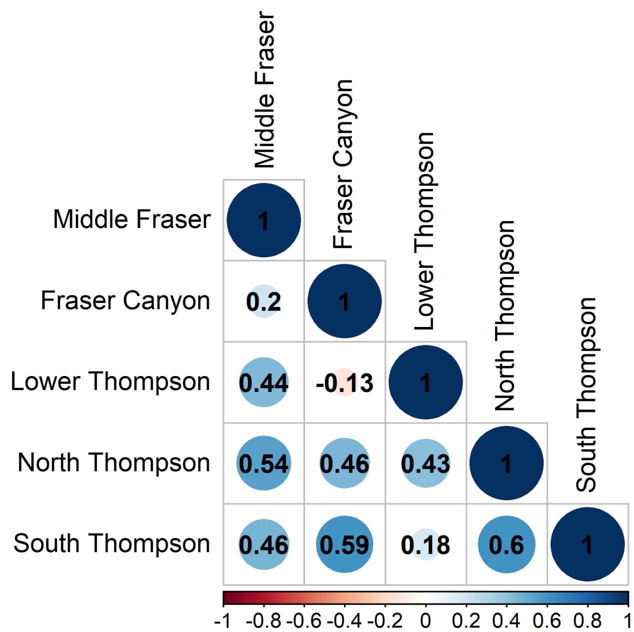

Figure 14. Bubble plot of pairwise correlation coefficient in recruitment residuals among CUs from base Ricker model fit.

in our base case by generating a single smolt-to-adult survival rate for each sea entry year and setting σ_γ = 0, where σ_γ is the standard deviation of among-CU variability in γ such that $\gamma_i \sim Normal(\bar{\gamma}, \sigma_\gamma)$. We used sensitivity analyses on σ_γ to test the effect of changes in spawner abundance covariation among CUs on projected LRP estimates. Three alternative levels of σ_γ were used in sensitivity analyses: σ_γ = 0.045, 0.0675, and 0.09. We selected these levels to cover a range between 0 and 0.09, where 0.09 was the standard deviation of the estimated marginal posterior distribution for γ from our Ricker stock-recruitment model fit.

The resulting correlations in spawner abundances from the projections are shown in Figure 15. In the forward projections, pairwise correlations in projected spawner abundances among CUs for the base case assumption of σ_γ = 0 were similar to observed pairwise correlations in spawner abundances among CUs. Increasing σ_γ resulted in decreased among-CU correlation in projected spawner abundances.

Variability in age proportions of recruitments among CUs

Annual variability in the age structure of returns was generated from a multivariate logistic distribution parameterized using CU-specific time series of proportions at age. The underlying average age structure for each CU was set at the average from the available time series (brood years 1998 - 2016), while annual deviations from underlying age-specific means were drawn from a multivariate logistic distribution. Annual deviations were held constant among all CUs; however, the scale of annual deviations was controlled by the variability parameter τ, which was estimated individually for each CU. This meant that while all CUs simultaneously experienced increases or decreases in a given year, the magnitude of the increase or decrease was CU-specific. Annual deviations were held constant among CUs to represent the strong covariation in proportions

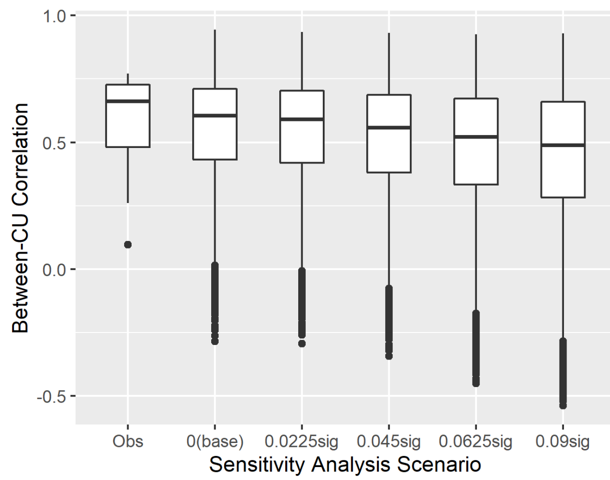

Figure 15. Distribution of correlations of spawner abundances among CUs for observed data between 1998 and 2020 and projected time-series under alternative assumptions about the standard deviation on the smolt-to-adult survival co-efficient among CUs for the base Ricker model formulation.

at age seen in available time series for Interior Fraser Coho, especially since 2010 (Figure 16). When the constraint of constant annual deviations was removed, generated proportion at age data was much more variable than observed data, which was considered to be unrealistic.

Annual variability in the age structure of recruitments has not been included in other recent projection analyses for this SMU. Both Korman et al. (2019) and Arbeider et al. (2020) assumed a constant age structure over time.

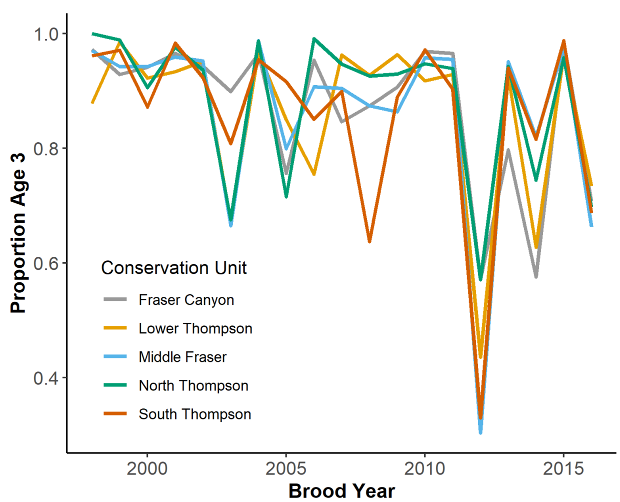

Figure 16. Proportion of recruits returning at age 3 for 1998 - 2016 brood years. Only two age classes (age 3 and age 4) are present in the age structure, so the proportion of recruits returning at age 4 will account for the remainder of returns from each brood year.

Covariance in exploitation

We assumed an average exploitation rate of 12.5% for all CUs in forward projections based on recent average values, with common interannual variability in exploitation rates due to shared fishery impacts among CUs each year. Interannual variability in exploitation rates was assumed to be Beta distributed (constrained between 0 and 1), with the standard deviation of the Beta distribution parameterized from estimated exploitation rates for 1998 - 2016 brood years. The corresponding coefficient of variation (CV) for interannual variability was 0.44.

Exploitation rates for Interior Fraser Coho are only available at the SMU-level due to limited coded-wire indicator programs (one to two CUs with indicators / year) that have been available for the Fishery Regulation Assessment Model used by the Pacific Salmon Commission for Coho Salmon (Pacific Salmon Commission et al. 2013). As a result, empirically-based estimates of among-CU variability in exploitation rates are not available. However, there are reasons to expect exploitation rates to vary among CUs in a given year, including differences in freshwater fisheries. We assumed that CU-specific variability in exploitation rates was half the common (SMU-level) interannual variability (CV=0.22), and varied this in sensitivity analyses from 0 and 0.44 to cover plausible bounds. Varying assumptions about variability in exploitation among CUs between CV = 0 and 0.44 in forward projections did not impact the distribution of correlations in spawner abundances in the projections (results not shown).

3.6.2. Results

LRP Estimates

Aggregate abundance LRPs estimated using the Ricker model as a basis for forward projections were lower than those obtained when the Ricker_priorCap model was used, regardless of which probability threshold was used (Table 6; Figure 17). This result is similar to the logistic regression LRPs, where LRPs derived using S_{gen} estimates from the Ricker_priorCap model were higher due to higher S_{gen} values. The projected curve showing the probability of all CUs being above S_{gen} had a slope that was more gradual and further from the origin for the Ricker_priorCap model compared to the base Ricker model (Figure 17). When projection outputs from both stock-recruitment model formulations were combined prior to binning in order to create a model-averaged scenario (with equal weight assigned to both scenarios), the resulting probability curve was mid-way between the curves from the two individual models. In all cases, projected curves had higher scatter with increasing aggregate abundance, such that LRP estimates at probability thresholds of p = 0.90 and p = 0.99 were unstable.

Projection LRPs were higher than logistic regression LRPs calculated using the same stock recruitment relationship. While we did not explore the underlying cause of this pattern, or whether it was a general result or specific to this case study, it may occur because projection LRPs account for more sources of uncertainty than logistic regression LRPs. Generational average spawning abundance (based on a 3-year geometric mean) remained above the projection LRP derived using the Ricker model with a probability threshold of p = 0.5 for most years between 2000 and 2020. There were two years when aggregate spawning abundance decreased below the LRP: 2006 and 2007 (Figure 18). In comparison, when projection LRPs were derived using the Ricker_priorCap model with p = 0.5, aggregate spawning abundance remained below the LRP for 11 out of the 21 years.

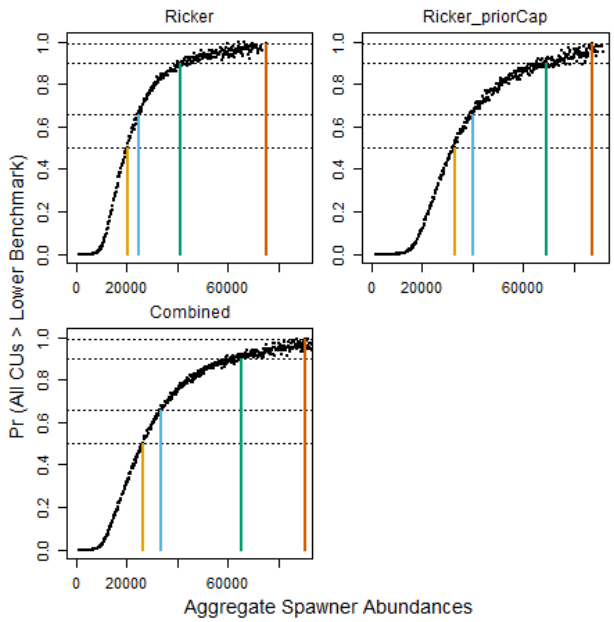

Figure 17. Probability of all CUs being above their lower benchmark of S_{gen} along a gradient in aggregate abundances within bins of 200 fish for two different stock-recruit model options (Ricker and Ricker_priorCap) as well as a model averaged case (Combined) in which results from both stock-recruitment models were equally weighted. Results are derived from projections over 30 years and 20,000 MC Trials. Each dot is the proportion of MC trials where all CUs were > lower benchmarks of S_{gen}. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue), 0.90 (green), and 0.99 (orange) are highlighted.

Table 6. Projection LRPs from forward projections under two different stock-recruit model options (Ricker and Ricker_priorCap), as well as a model averaged case (Combined) in which results from both stock-recruit models were equally weighted. For each probability level, the LRP estimate represents that probability that all CUs will be above their lower benchmark of Sgen.

Probability	Ricker	Ricker_priorCap	Combined
50%	20,100	32,700	26,500
66%	24,900	40,100	33,500
90%	41,100	68,900	65,300
99%	75,100	87,300	83,500

Sensitivity Analyses

Increasing σ_γ, which corresponded with reduced between-CU pairwise correlation in spawner abundances over time (Figure 15), resulted in a flattening of the projected relationship between aggregate spawner abundances and the probability of all CUs being above their lower benchmarks (Figure 19, where σ_γ is labelled ‘sigGamma’). LRP estimates corresponding to a given probability threshold increased as σ_γ increased due to curves shifting to the right and becoming more gradual (i.e., less steep). For the two highest σ_γ scenarios examined (σ_γ=0.0675 and 0.09), a 99% probability of all CUs being above their lower S_{gen} benchmark was never achieved. Increasing the average exploitation rate used in forward projections also led to a shift in projected curves to the right; however, the shift was more gradual over the range of exploitation rate scenarios we considered than the effect of increasing σγ (Figure 20). The effect of increasing exploitation rates was smallest at low probability thresholds. At p = 0.5, the LRP differed by 400 fish between the ER = 2.5% and ER = 12.5% scenarios (range = 19,700 - 21,000), and by < 4000 fish among all four scenarios (range = 19,700 - 24,000). Differences were much larger among the four exploitation rate levels examined for the p = 0.90 threshold. When the average exploitation rate was set at 22.5% or 32.5%, aggregate abundances barely exceeded 60,000 fish, and it was not possible to achieve a 99% probability of all CUs being above their lower Sgen benchmarks.

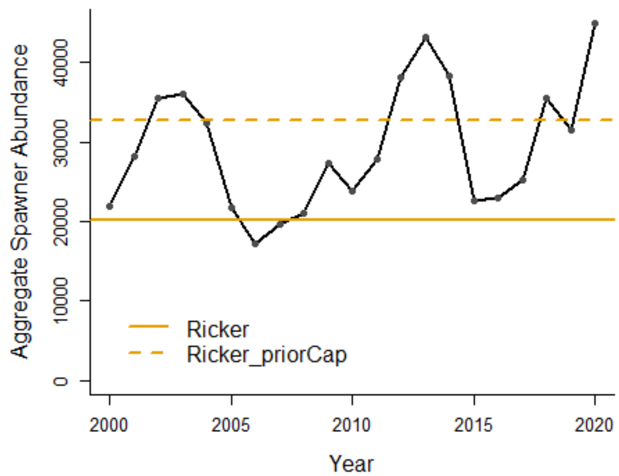

Figure 18. Three-year geometric mean of aggregate natural-origin spawning abundance for the Interior Fraser Coho SMU (black line) relative to projection LRP estimates using two different stock-recruitment model formulations, Ricker and Ricker_priorCap, with a probability threshold of p=0.5. Forward projections used to estimate reference points were parameterized using available 1998-2020 time series under base model assumptions.

3.7. HISTORICAL EVALUATION OF STATUS ACROSS LRP METHODS

We compared annual estimates of SMU status relative to LRPs for the range of LRP estimation options considered in this case study (Figure 21). For all aggregate abundance LRPs, we illustrate LRPs estimated from a probability threshold of p = 0.5 (i.e., a 50% probability that all CUs would have status above their lower benchmark). We used the following labeling convention when comparing historical status estimates across LRP estimation methods: *"Metric" : "LRP Method" : "CU Status Method"*. 'Metric' refers to the choice of whether to base an LRP on the proportion of CUs above Red CU status (CU status-based LRPs; labelled as 'CUbased') or on aggregate SMU-level abundance (Abund). The 'LRP' method only applies to aggregate-abundance based LRPs, which can be logistic regression (Logistic) or projection (Proj). Finally, the 'CU Status Method' can be based on the multidimensional algorithm within the Pacific Salmon Status Scanner in which CU abundance benchmarks are based on one of the two Ricker models (Scanner-Ricker or Scanner-priorCap). Alternatively, when only a single benchmark is used to characterize CU status, it can be based on S_{gen} estimated from one of the two Ricker models (Sgen-Ricker or Sgen-priorCap) or the IFCRT target (IFCRT). For example, when referring to an aggregate abundance LRP that is estimated via a logistic regression fit to historical CU status, with CU status estimated relative to S_{gen} from the base Ricker model, it was labelled as "Abund: Logistic: Sgen_Ricker". In the future, 21 could be expanded to include the number of CUs in the Red zone and / or the names of CUs in the Red zone. This type of information may help inform the development of rebuilding plans by highlighting CUs that are consistently in the Red zone.

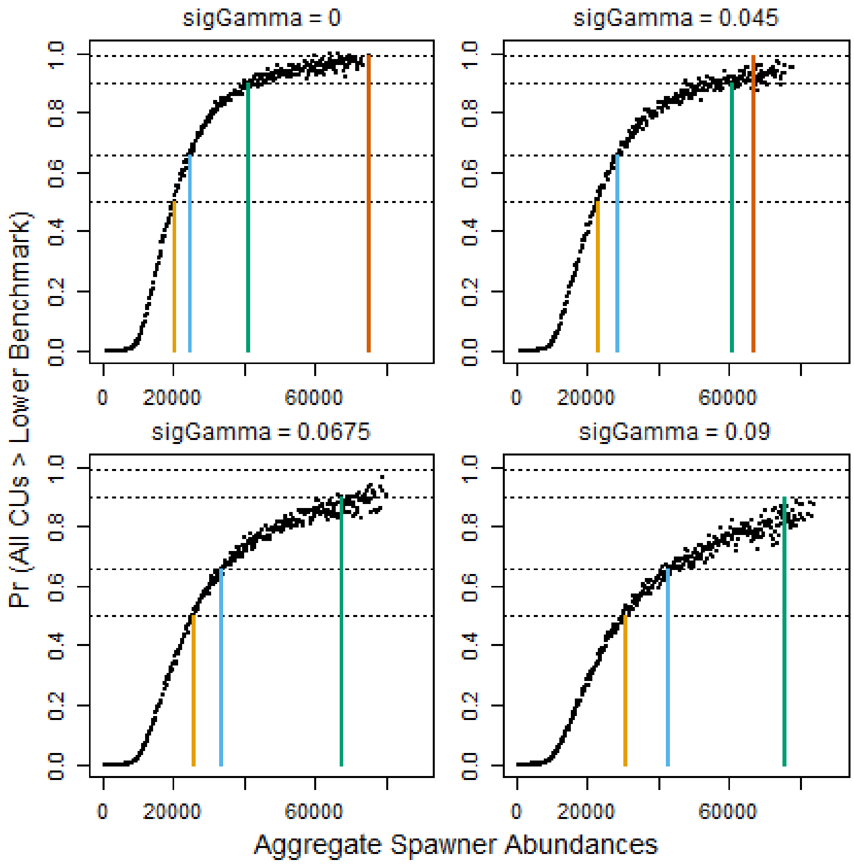

Figure 19. Probability of all CUs being above their lower benchmark of Sgen along a gradient in aggregate abundances (within bins of 200 fish) for alternative scenarios about the value of sigGamma. The baseline value used for forward projections was sigGamma = 0. Results are derived from projections over 30 years and 20,000 MC Trials. Each dot is the proportion of MC trials where all CUs were > S_{gen}. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue), 0.90 (green), and 0.99 (orange) are highlighted.

We show historical results for three types of CU status-based LRP methods: using the proportion of CUs with Pacific Salmon Status Scanner status > Red (e.g., CUbased: Scanner-Ricker), using the proportion of CUs with abundance > Sgen (e.g., CUbased: Sgen-Ricker), and using the IFCRT distributional target status (CUbased: IFCRT) . Holt et al. (2023) recommend CU statuses be derived from a multidimensional approach such as that used within the Salmon Scanner; however, we show results for the single metric S_{gen} and IFCRT approaches to demonstrate how these approaches impact SMU status. This comparison is of interest because our aggregate abundance LRPs use status estimates based on a single metric rather than a multidimensional approach.

In addition to the LRP estimation methods presented so far in this case study, we include the full WSP assessment that was conducted in 2014 as an option for estimating CU status for use in a CU status-based LRP. We label this case “CUbased : WSP-2014”. SMU status would have been assessed as being above the LRP at this time as all CUs were assessed as Amber or Amber/Green.

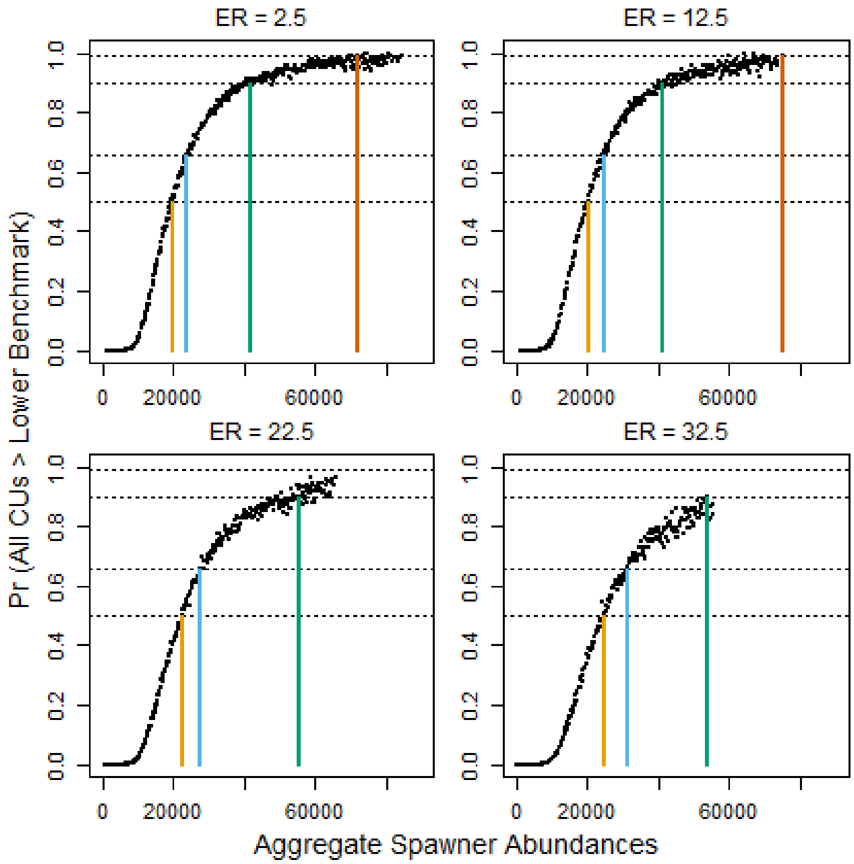

Figure 20. Probability of all CUs being above their lower benchmark of Sgen along a gradient in aggregate abundances (within bins of 200 fish) for alternative scenarios about average exploitation rates (ER) in forward projections. The baseline value used for forward projections was ER = 12.5%. Results are derived from projections over 30 years and 20,000 MC Trials. Each dot is the proportion of MC trials where all CUs were > S_{gen}. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue), 0.90 (green), and 0.99 (orange) are highlighted.

In general, estimated LRP breaches coincided with low points in the aggregate abundance time series (2000, 2005 - 2007 and 2015-2017). However, there were differences among methods in the years that SMU status was estimated to be below the LRP, as well as a couple methods for which status was never estimated to be below the LRP (CUbased: Sgen-Ricker and Abund: Logistic: IFCRT).

Comparison of SMU status estimates over time for all LRP estimation methods that used S_{gen} from the base Ricker model showed differences in statuses between the CU status-based and aggregate abundance methods (status bars 2-5 in Figure 21). Under the ‘CUbased: Scanner-Ricker’ method, the LRP was breached in years 2000 and 2015-2017, but for the ‘CUbased: Sgen-Ricker’ method, the LRP was only breached in the year 2000. The Salmon Scanner multidimensional algorithm includes a step in which CU status is designated as Red when the generational mean spawning abundance is less than 1500 spawners (Figure 1). Because estimated S_{gen} is less than 1500 spawners for the Fraser Canyon CU, it is possible for the criteria of <1500 spawners in a CU to be breached even though abundance exceeds Sgen.

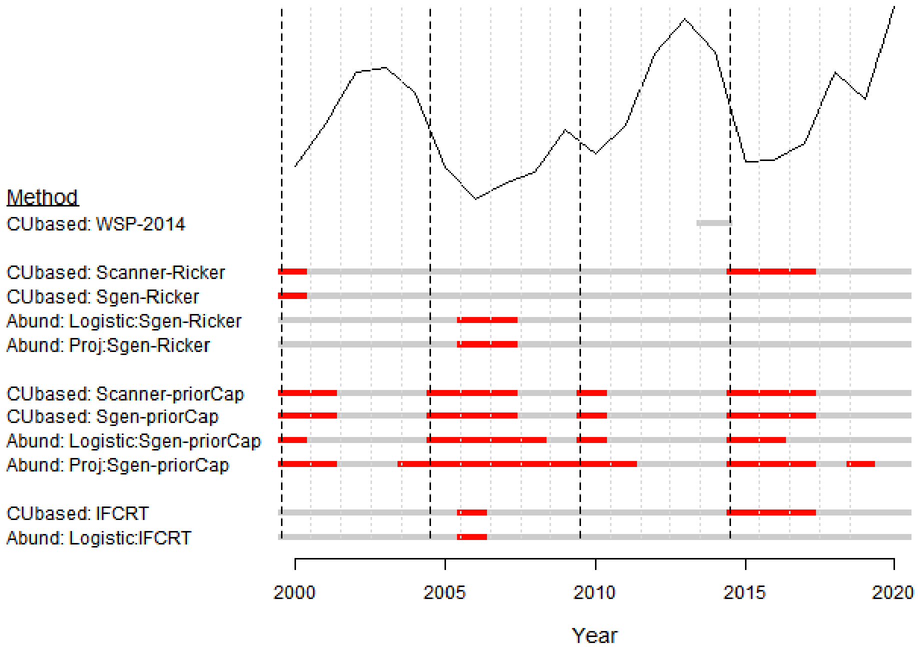

Figure 21. Historical evaluation of status relative to LRP options considered for Interior Fraser Coho. The black line shows the 2000-2020 generational mean aggregate spawning abundance to the SMU. Red bars indicate years in which SMU status would have been assessed as being below the LRP. Estimates of S_{gen} benchmarks and aggregate abundance LRPs were based on data available up to 2020

This situation occured for the Fraser Canyon CU in 2015-2017. Therefore, LRP methods that use the multidimensional approach to characterize CU status can be more precautionary than methods that rely on a single S_{gen} benchmark.

In the years 2005-2006, SMU status for both the 'Abund: Proj: Sgen-Ricker' and 'Abund: Logistic: Sgen-Ricker' methods fell below the LRP, while the CU status-based methods (labelled 'CUbased:') did not. Declines in aggregate SMU abundance in 2005-2006 were driven by declines in the four larger CUs (which, still remained above their individual S_{gen} estimates). Declines in the abundance of the Fraser Canyon CU were not as drastic. As a result, while SMU-level aggregate abundance dropped below the abundance LRP, the Fraser Canyon CU that triggered Red status in 2015-2017 exceeded 1500 spawners and did not trigger the CUbased: Scanner-Ricker method. The aggregate abundance LRP from the 'Abund: Proj: Sgen-Ricker' estimation method was higher than that from the 'Abund: Logistic: Sgen-Ricker', so only the former method triggered an LRP breach.

When the Ricker-priorCap model was used to estimate S_{gen} instead of the base Ricker model, both S_{gen} and LRP estimates were higher than under the base Ricker model formulation. This in turn resulted in more frequent LRP breaches when the Ricker-priorCap model was used (status bars 6-9 in Figure 21).

Among the 'priorCap' methods, status was most frequently estimated to be below the LRP when the 'Abund: Proj:Sgen-priorCap' method was used; for this method, the LRP was triggered in 14 out of the 21 years between 2000 and 2020. In comparison, the LRP was triggered in 9, 9, and 8 of the 21 years for the 'CUbased: Scanner-priorCap', 'CUbased: Sgen-priorCap' and 'Abund: Logistic:Sgen-priorCap' methods, respectively.

Finally, SMU status was below the LRP in four years (2006, 2015-2017) out of the 21 years for the 'CUbased: IFCRT' method, but was only triggered in 2006 under the 'Abund: Logistic: IFCRT method' (status bars 10-11 Figure 21). The 'Abund: Logistic: IFCRT method' produced the lowest LRP of all logistic methods (Figure 9 and Table 3), therefore the LRP tended to get breached less often.

Despite the differences in status estimates in some years for CU status-based and aggregate abundance LRPs highlighted above, estimated status tended to match in more years than not for CU status-based and aggregate abundance methods. Out of the 21 years available for comparison, the number of years with consistent status estimates for CU status-based and aggregate abundance LRPs ranged from 15 - 18 years (71 - 86% of years), depending on the exact methods being compared. For the Base Ricker models, the proportion of years with consistent status estimates was lowest when comparing the CUbased:Scanner-Ricker method to the Abund:Logistic:Sgen-Ricker and Abund:Proj:Sgen-Ricker methods (15 / 21 years; 72% for both comparisons). These proportions were higher when comparing among the Ricker_priorCap models (86% and 81% for the same comparisons).

3.8. DISCUSSION

The Interior Fraser Coho SMU is considered a data-rich SMU because it has stock-recruitment time series for all five CUs within the SMU, which allowed for the estimation of stock-recruitment based benchmarks (S_{gen}). However, time series were restricted to years after 1998, when spawner abundance data were collected with more consistent methodologies and regularity. This period also aligns with the low productivity period (Decker et al. 2014) when the SMU abundance is considered depressed relative to historical levels. Despite the short time series, Interior Fraser Coho are well-suited for looking at the application of aggregate abundance LRPs due to the long history of using aggregate abundance recovery targets and fisheries reference points (IFCRT 2006; Korman et al. 2019; Arbeider et al. 2020). While we were able to estimate aggregate abundance LRPs using a suite of CU-level benchmarks and LRP estimation methods (logistic regression and projection), our results highlight variability in status against aggregate abundance LRPs that in some cases deviates from status against CU status-based LRPs. Our results also highlight the sensitivity of logistic regression based LRPs to data availability.

3.8.1. CU Status-Based vs. Aggregate Abundance LRP Methods

Comparisons of status between the abundance-based methods and the CU status-based methods yielded mixed results. While there were differences in the years in which CU status-based and aggregate-abundance based methods dropped below LRPs, status tended to match in more years than not. Out of the 21 years available for comparison, the number of years with consistent status estimates for CU status-based and aggregate abundance LRPs ranged from 15 - 18 years (72-86% of years), depending on the exact methods being compared.

Consistency between CU status-based and aggregate abundance LRPs depended on the method used to assess CU status. For methods using the base Ricker model, status tended to drop below CU status-based LRPs when abundance of individual CUs was low (2000-2001, 2015-2017), and drop below aggregate abundance LRPs when aggregate abundances were low (2006-2007). As a result, CU status-based LRPs were breached in years with low abundance in only one CU (e.g, 2000, 2015-2017) whereas the aggregate abundance methods did not. In comparison, status was generally consistent for the scenarios in which the Ricker_priorCap model was used with LRPs breached in similar years. This result occurred because estimated S_{gen} and aggregate abundance LRPs were higher under the Ricker_priorCap model, which resulted in a more frequent occurrence of years with both aggregate abundance below the LRP and individual CUs below benchmarks. Finally, when the IFCRT distributional target was used, the CU status-based LRP was breached for 3 years in which the aggregate abundance was not (2015-2017) due to low abundance in one CU.

When considering CU status-based LRPs, comparisons between using a single metric benchmark to estimate CU status (i.e., S_{gen}) and using a multidimensional approach yielded similar results. This occurred because the multidimensional algorithm relies on S_{gen} benchmarks when those are available. Exceptions occur when an estimated S_{gen} is less than the absolute threshold of 1500 spawners, as occurred for the Fraser Canyon CU.

3.8.2. Structural Uncertainty in Spawner-Recruitment Dynamics

Most methods evaluated for the Interior Fraser Coho case study relied on the evaluation of CU status relative to S_{gen}. As a result, the method used to estimate S_{gen} had a large influence on results. S_{gen} estimates were higher for the Ricker_priorCap model compared to the base Ricker model, which meant that LRPs were more frequently triggered under this formulation. This pattern was observed for all four methods that relied on the Ricker_priorCap S_{gen} estimates.

We considered two alternative Ricker models for Interior Fraser Coho to represent different assumptions regarding carrying capacity, which in turn affected productivity. This approach has also been used in previous analyses for this SMU. Arbeider et al. (2020) used a model averaging approach with three SR models equally weighted when assessing recovery potential for the Interior Fraser Coho SMU (the base Ricker and Ricker_priorCap models we used, as well as a third depensatory mortality version that we did not consider). Korman et al. (2019) also considered multiple Ricker model formulations when estimating reference points for the Interior Fraser Coho SMU; however, they opted to focus on results for the base Ricker model instead of using model averaging approaches.

Future analyses to characterize Interior Fraser Coho dynamics and estimate biological reference points could further explore model structure by considering more varied approaches. For example, life-cycle models that partition the life cycle into separate marine and freshwater components allow for more direct representation of smolt abundance and subsequent marine survival than our current approach of using smolt-to-adult survival as a covariate in adult-to-adult spawner recruitment models (Bradford 1998). Treating smolt abundance as a latent variable within a life-cycle model would allow the smolt-to-adult survival rate index to be directly applied to smolt abundance (Ohlberger et al. 2018). Modelling frameworks that incorporate hatchery enhancement into spawner-recruitment models while allowing for differential productivity between hatchery- and natural-origin spawners could also be considered in the future (Falcy and Suring 2018).

The consideration of multiple model structures requires a decision on which model, or models, should be used to assess stock status. One approach to accounting for uncertainty in underlying model structure is to integrate estimates of LRP status over alternative structures. We demonstrate this approach when using projection estimates of aggregate abundance LRPs, in which we combine projections under each SR model scenario before calculating the LRP. This approach is basically a model averaging approach in which both scenarios are equally weighted. However, other methods of assigning weights among model are possible, such as weighting based on prediction skill (Kell et al. 2021). When model averaging, it is important to consider the plausibility of various models and the distribution of uncertain parameters (e.g., their variances and biases)(Millar et al. 2015; Dormann et al. 2018). It may be more appropriate to select one model instead of averaging over models when they provide competing hypotheses (i.e., bimodal distributions) with differing management implications (Millar et al. 2015).

3.8.3. Logisic Regression LRPs

Retrospective analyses of logistic regression LRP options showed that LRPs were sensitive to data availability, with LRP estimates changing over time as more data became available. In addition, relatively small shifts in estimated S_{gen} over time meant that logistic models based on S_{gen} were sometimes unable to converge on a solution even with more data. This failure to converge was a result of a lack of overlap between aggregate abundance levels associated with 'successes' and 'failures', which is a requirement for logistic models. This limitation did not occur for the IFCRT logistic regression approach, in which the absolute threshold used to define CU status was constant over time.

Missing data scenarios, in which 1 or 2 CUs were removed from the data set, further highlighted limitations in the ability of the logistic regression models to converge on a solution given small changes in the pattern of 'successes' and 'failures'. In addition, we found that removing CUs in logistic regression LRPs resulted in an increase in uncertainty of estimated status. However, despite these limitations, the 95% confidence intervals for the missing data scenarios usually overlapped with status based on all CUs being included. This result suggests that our assumption of CU representativeness for stock status within the Interior Fraser Coho SMU, as described in Appendix C, may be supported. Future work on this SMU (or, other SMUs wishing to apply these methods) could use retrospective analyses of CU status-based approaches to see whether status estimates remain stable when 1 or 2 CUs are removed from the data set. The extent to which this result can be applied to other SMUs is expected to be dependent on the level of covariation in CU status among CUs within an SMU.

Taken together, these retrospective results highlight that caution should be used when applying logistic regression LRPs. While they did provide similar estimates of SMU status as CU status-based methods for several (but not all) years in the historical comparison, they were sensitive to reductions in data availability. For the specific case of Interior Fraser Coho, retrospective performance may improve in the future as more data become available to improve the statistical power of logistic regression fits.

3.8.4. Projection LRPs

Projection LRPs have the advantage of being able to incorporate uncertainty about current (and future) population and / or fishery dynamics into LRP estimates, whereas logistic regression LRPs represent conditions that have been previously experienced, which may or may not persist into the future. Projection LRPs also allow key structural uncertainties to be incorporated into LRP estimates through the combination of multiple projection scenarios. For example, in the current application, we chose not to apply a third formulation of the Ricker model with depensatory mortality that has been used previously (Korman et al. 2019; Arbeider et al. 2020). However, future applications of projection LRP methods for Interior Fraser coho could easily incorporate depensation as an additional scenario in a model-average approach if this was considered a key uncertainty to be represented.

The sensitivity of projection LRPs to exploitation rate means that these LRPs are specific to the management context. In our Interior Fraser Coho projections, we set exploitation rates at the recent average as fishery restrictions since 1998 been stable. In this case, the LRP represents the level of aggregate abundance that would be required to ensure all CUs were above S_{gen} given that constant exploitation rate. However, Interior Fraser Coho are not managed using a fixed ER policy. While harvest has been relatively constant for several recent years, target harvest rates can vary among years for several reasons, including fishery plans for other species (e.g., Fraser Sockeye Salmon). For years in which target exploitation rates are increased, the LRP would also need be increased accordingly to ensure that the underlying objective of all CUs above S_{gen} could be achieved. This pattern arises due to variability in productivity among CUs; when higher exploitation rates are applied, some low productivity CUs will require higher spawning abundances to ensure that they remain above S_{gen}. This effect is demonstrated in Appendix D. As a result, projection LRPs are not static measures of serious harm, as commonly developed for other stocks and species.

Projection LRPs were also sensitive to the level of covariation in spawner abundances among CUs over time. Reductions in covariation resulted in increased LRP estimates. This pattern will result in higher LRPs as the relationship between aggregate abundance and CU status weakens because random dynamics among CUs will increase the probability of any one CU having Red status. We recommend that possible instabilities in projections be evaluated for this SMU, and other applications for projection LRPs, which could arise due to changes in covariation of spawner abundance among CUs due to CUs with different productivity levels responding differently to exploitation.

3.8.5. Distributional-Based Benchmarks

The distribution of spawning abundances among smaller populations or sub-populations within a CU is recognized as an important component of CU status (DFO 2005). We relied on previously established distributional targets for Interior Fraser Coho to demonstrate the development of LRPs based on finer-scale distributional metrics. These metrics were based on a short-term recovery target of of 1000 spawners in at least 50% of sub-populations (IFCRT 2006). While these targets were used for recent recovery planning analyses (Arbeider et al. 2020), they were not considered as part of the 2015 WSP Status Assessment for Interior Fraser Coho (DFO 2015) and are included in the Pacific Salmon Scanner Tool because formal distributional benchmarks have not been identified under the WSP. We recommend research on the development and evaluation of metrics and benchmarks of distribution of spawning within CUs, as well as the development of guidelines on how to incorporate these into CU-level assessments under the WSP.

4. CASE STUDY 2: WEST COAST VANCOUVER ISLAND CHINOOK

4.1. CONTEXT

The West Coast of Vancouver Island (WCVI) Chinook SMU is comprised of three CUs (Holtby and Ciruna 2007; DFO 2013; Pacific Salmon Commission Sentinel Stocks Committee 2018), 7 large inlets (or sounds), and 20 escapement indicators populations which have relatively complete time-series and consistent observation methodology (Figure 22, Table 7) (Riddell et al. 2002). Hatcheries produce a relatively large component of the total production for many of these populations, where they help achieve harvest, conservation and assessment objectives. However, hatcheries are also considered a risk factor for the long-term sustainability of CUs because they can reduce wild genetic diversity and fitness (Withler et al. 2018). As described in Holt et al. (2023), only escapement indicator populations without significant enhancement (i.e., populations with Proportionate Natural Influence, PNI, values $\geqslant 0.5$) were included in this analysis. Although most fish in these populations are of natural origin (i.e., they spawned in the wild), 'wild' fish, defined in the WSP as second generation natural-origin fish, may be in the minority (Withler et al. 2018).

Table 7. Overview of WCVI Chinook SMU. Italics represent escapement indicators with average PNI values $<$ 0.5 and are excluded from analyses. The inlets, San Juan and Nitinat do not contain escapement indicator populations with PNI $\geqslant$ 0.5 and are not included in these analyses.

CU	Inlets	Indicators
West Vancouver Island-South (CK-31)	San Juan	*San Juan*
	Nitinat	*Nitinat*
	Barkley	Nahmint , *Sarita*, *Somass*
	Clayoquot	Bedwell/Ursus , Megin , Moyeha , *Tranquil*
West Vancouver Island-Nootka & Kyuquot (CK-32)	Nootka/Esperanza	*Burman*, *Conuma*, *Gold*, *Leiner*, Tahsis
	Kyuquot	*Zeballos*, Artlish, Kaouk, Tahsish
West Vancouver Island-North (CK-33)	Quatsino	Cayeghle, Marble

This SMU was included as a case study, in part, to demonstrate the development of LRPs under data limitations when recruitment data are not available for deriving stock-recruitment based benchmarks, but habitat-based benchmarks exist, as is often the case for Chinook Salmon in BC. WCVI Chinook is also included in the proposed first batch of major stocks for regulation under the Fish Stocks provisions, necessitating the development of LRPs for this SMU. In addition, WCVI Chinook is highly enhanced yet does not have complete data on the proportion of hatchery-origin spawners contributing to total production, similar to many other Chinook Salmon SMUs. Furthermore, this SMU was unique among the case studies in the consideration of inlets within CUs as the level of assessment, demonstrating various spatial scales that can be integrated into SMU-level assessments. This scale is similar to the sub-population scale used in sensitivity analyses for the Interior Fraser River Coho case study.

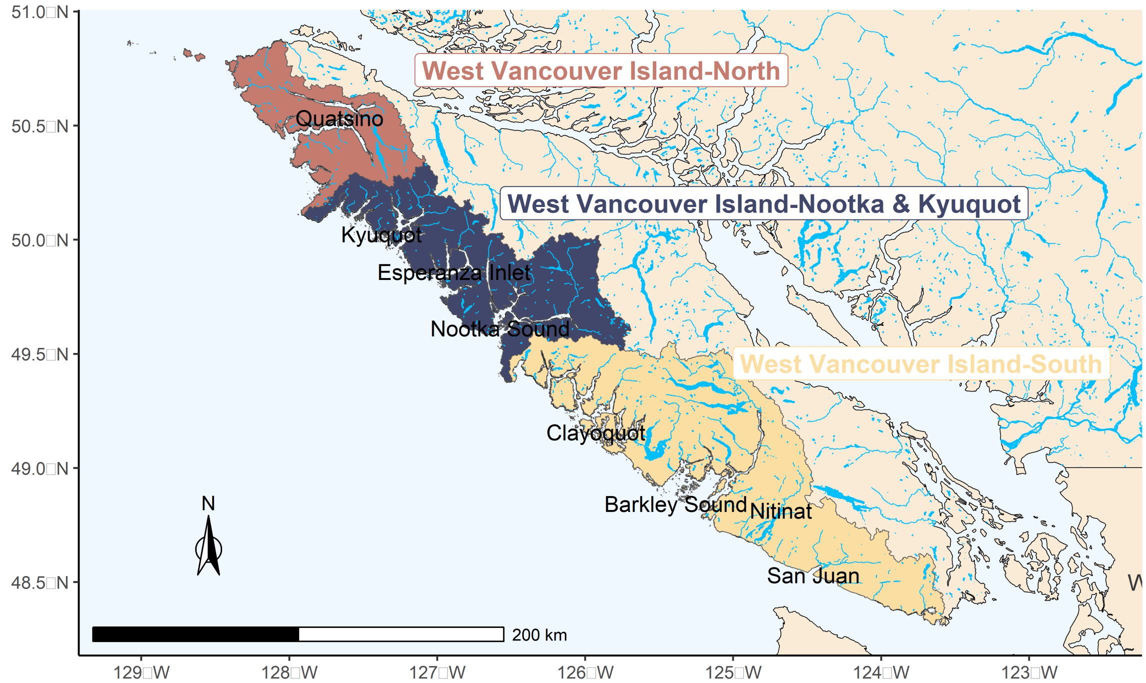

Figure 22. Map of the WCVI Chinook SMU, component CUs (coloured red, blue, and yellow), and inlets (labelled in black). Note, Designatable Units (DUs) defined by COSEWIC are aligned with CUs in this SMU.

Virtually all Chinook in this SMU are ‘ocean type’, entering the ocean 1 to 3 months after emergence from spawning gravel (DFO 2012). ‘Stream type’ Chinook, those that stay in the river for one year after emergence, are rare in this SMU. After entering the ocean, WCVI Chinook generally migrate into northern BC and southeast Alaskan waters to rear for 2 to 6 years, returning to spawn predominantly at ages 3, 4 and 5 (DFO 2012).

4.1.1. Previous Assessments

Two of the three CUs in this SMU, West Vancouver Island-South and West Vancouver Island-Nootka & Kyuquot, were assessed as Red status in an integrated Wild Salmon Policy assessment (DFO 2016). For these CUs, assessments were based on component populations without hatchery enhancement within the most recent 12 years, omitting populations with enhancement during that period. For West Vancouver Island-South, Red status was based primarily on threats of genetic introgression from strays from nearby large-scale hatcheries. For West Vancouver Island-Nootka & Kyuquot, Red status was based on a very low index of abundance for non-enhanced populations and threats of genetic introgression from strays from large-scale hatcheries.

The third CU, West Vancouver Island-North, was not assessed because the indicator site for this CU was enhanced over the most recent 12 years (other metrics of hatchery enhancement, e.g., Proportionate Natural Influence or PNI were not considered). A list of escapement indicator and non-indicator populations within each CU is available in Brown et al. (2020).

WCVI Chinook was identified as a stock of concern in the 2021 Integrated Fisheries Management Plan, IFMP, for South Coast Salmon, and a rebuilding plan is under development (DFO 2021a). Poor smolt-age 2 survival rates for WCVI Chinook and low spawner levels over the past two decades are reasons for conservation concern in the IFMP (DFO 2021a). Since the mid 1990s, a variety of management measures have been implemented to restrict harvest on WCVI Chinook and address these concerns, described in the IFMP (DFO 2021a).

For some Chinook Salmon populations including those on the west coast of Vancouver Island, habitat-based benchmarks have been used to derive status on spawner abundances (Parken et al. 2006). These benchmarks are estimated using an empirical relationship between watershed area of spawning habitat and two stock-recruitment benchmarks, spawner abundances at replacement, S_{REP} (also called spawners at equilibrium S_{eq}), and S_{MSY}, in a meta-analysis of 25 Chinook populations across North America (Parken et al. 2006; Liermann et al. 2010). Using this relationship, benchmarks can then be predicted for populations without stock-recruitment data from their watershed area.

In November 2020, COSEWIC (2020) designated the West Vancouver Island-South and West Vancouver Island-Nootka & Kyuquot DUs as Threatened, and West Vancouver Island-North as Data Deficient. Threatened statuses were determined primarily from genetic risks of hatcheries enhancement and habitat threats from forestry. The West Vancouver Island-North DU was designated data deficient because it contains only one escapement indicator population.

4.2. DATA

4.2.1. Spatial Scale

Under Canada's Wild Salmon Policy, CUs are identified at a spatial scale that allows for long-term sustainability of the species (Holtby and Ciruna 2007). For WCVI Chinook, inlets nested within CUs are another important spatial scale of diversity given the geographic separation of spawning habitats among inlets and limited straying among inlets (D. McHugh pers. comm. DFO South Coast Stock Assessment). We used a hybrid approach in which LRPs were developed to preserve inlet-scale diversity within CUs. However, only 5 of the 7 inlets on the west coast of Vancouver Island contained indicator populations without significant hatchery influence. Both Nitinat and San Juan inlets, which are the two most southern inlets within the WCVI-South CU, have large-scale hatcheries and infrequent monitoring of sites with natural spawning. These two inlets lack escapement escapement indicator populations without significant hatchery influence. Because the remaining five inlets with significant natural spawning are nested within the 3 WCVI Chinook CUs, preserving this inlet-scale biodiversity (5 inlets with data) will also preserve CU-scale biodiversity required under the Wild Salmon Policy. Future analyses could limit LRP estimation to the scale of CUs or extend it to include all 7 inlets with additional natural escapement indicators for Nitinat Lake and San Juan Bay, if they are developed.

4.2.2. Watershed Areas

To derive habitat-based benchmarks, watershed areas were updated for WCVI Chinook using methods described in Parken et al. (2006) by identifying 3rd order watershed areas that contain spawning habitat and omitting areas above obstacles to fish passage from the Provincial Obstacles to Fish Passage database. Only watershed areas for escapement indicator populations were included in the current analysis. These watershed areas were then summed within inlets to derive inlet-specific watershed areas (Table 8). As a result, inlet-level benchmarks presented in this case study are on a relative scale; they represent the abundance of select indicator streams. In future analyses, watershed areas of all known spawning populations could be included (omitting areas above obstacles to fish passage) to derive habitat-based benchmarks on an absolute abundance scale. These benchmarks could be compared against total abundances to each inlet. This approach was not used in this case study because of large uncertainties in abundances of non-indicator populations that precluded the development of reliable estimates of total absolute abundance.

Table 8. Sum of watershed areas for escapement indicator populations within inlets, km^2. Only indicator populations that are not highly enhanced (i.e., PNI $\geqslant$ 0.5) are included.

Inlet	Watershed Area, km^2
Barkley	42
Clayoquot	460
Kyuquot	336
Nootka/Esperanza	77
Quatsino	217

4.2.3. Spawner Abundances

Spawner abundances were provided for 20 WCVI escapement indicators populations (D. Dosbon and D. McHugh pers .comm.; Table 7; Figure 23). These time-series are compiled annually by DFO South Coast Area staff for local and international assessment and management (e.g., DFO 2021b). Missing values were not infilled and in some cases methodologies for monitoring changed over time, which limited the estimation of historical SMU status. Although some escapement time-series begin in 1953, others begin as late as 1995, limiting our analyses to these most recent years that are based on a consistent escapement methodology (Pacific Salmon Commission Sentinel Stocks Committee 2018). In future work, infilled time-series of escapement indicator populations within inlets (or CUs) could be developed to extend the available time-series. Spawner abundances for escapement indicators populations are estimated from a combination of snorkel, boat and aerial surveys, bank walks, and fence counts, which range in accuracy and precision (see DFO 2014 for a summary of monitoring and assessment methods). In particular, spawner estimates from visual surveys are a source of uncertainty for this SMU. Abundances are usually estimated using Area-Under-the-Curve (AUC) or associated maximum likelihood methods. For populations that are not surveyed continuously over the spawning season, abundances are estimated using peak counts or a combination of observations from multiple surveys, contributing additional uncertainties to the annual abundance estimates.

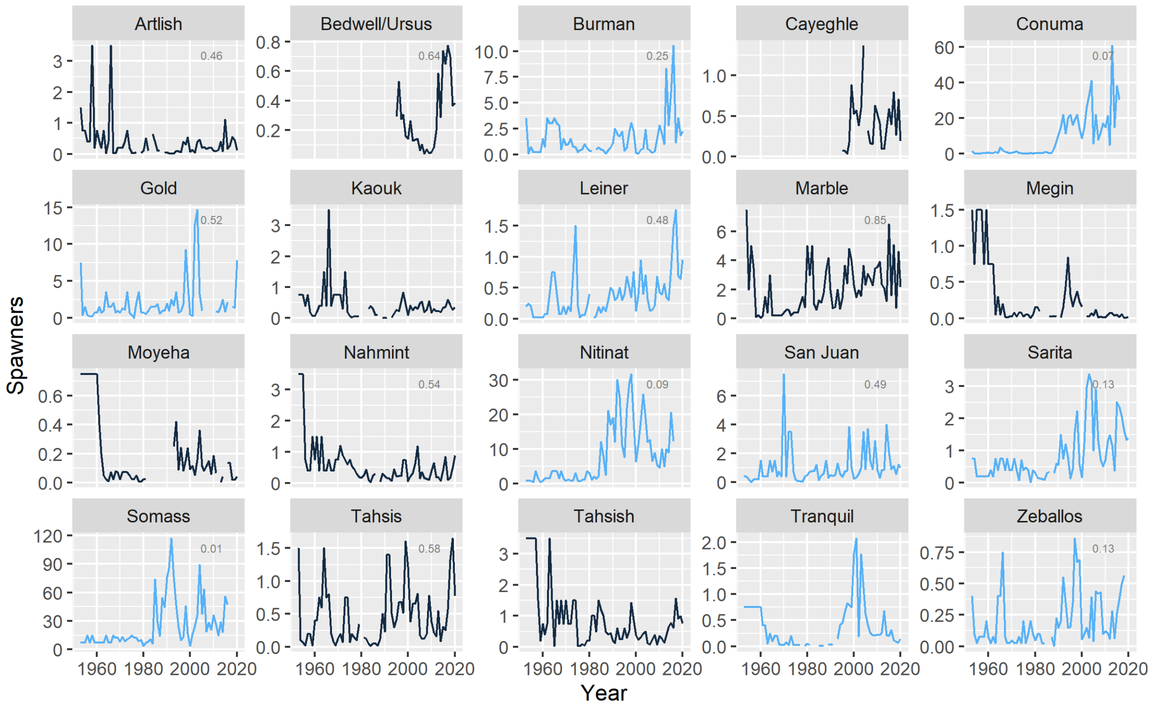

Figure 23. Time-series of spawner abundances by escapement indicator population, in units of 1000s. Dark blue time-series are escapement indicator populations where most production is from natural spawning and Proportionate Natural Index (PNI) values are generally $\geqslant$ 0.5; light blue time-series are escapement indicator populations where hatchery production is dominant, where PNI values are generally $<$ 0.5 over available time-series. Provisional average PNI values are provided in the top right corner of each panel, where they are available.

4.2.4. Proportionate Natural Influence, PNI

The metric, Proportionate Natural Influence, PNI is used to estimate the relative strength of the hatchery and natural selective pressures in hatchery-influenced populations (Withler et al. 2018). PNI values for 14 WCVI escapement indicator populations were provided to DFO South Coast Stock Assessment by DFO's Salmonid Enhancement Program (J. Bokvist, pers. comm., DFO South Coast Salmon Assessment). Populations were considered significantly enhanced and excluded from our analyses if average PNI values over the available time-series where hatchery objectives have remained constant were $<$ 0.5. Thermal marking was used to identify the proportion of hatchery-origin spawners on the spawning grounds to derive PNI values. When data on thermal marking were not available, coded-wire tags (CWTs) were used to identify hatchery-origin spawners. Although Gold River had average PNI values $>$ 0.5 (0.52), most of the unmarked spawners are thought to be second generation (or descendants of) hatchery-origin fish from the Robertson Creek hatchery. Thus, Gold River was excluded from our analyses. Also, although the average PNI of Artlish was marginally $<$ 0.5 (0.46), PNI estimates were only available for one year (2015) using CWTs, which was deemed to be unrepresentative of this population which is relatively unenhanced. Thus this population was retained in our analysis. Five of the remaining six escapement indicator populations without PNI data are not thought to be significantly enhanced: Cayeghle, Kaouk, Megin, Moyeha and Tasish (D. McHugh, pers. comm., DFO South Coast Stock Assessment), and were retained in the analysis. One escapement indicator population without PNI data, Tranquil, was considered significantly enhanced and was omitted from our analyses (D. McHugh, pers. comm., DFO South Coast Stock Assessment).

We initially considered a stricter definition of hatchery enhancement that included only populations with PNI values $\geqslant 0.72$. This stricter threshold resulted in excluding most data since reliable time-series of PNI values and spawner abundances are only available for exploitation-rate indicator populations where coded-wire tags have been applied and sampled for recoveries, which on the WCVI tend to be populations with hatcheries. The PNI threshold of $\geqslant 0.5$, a level associated with most fish being natural origin, accounts for the trade-off between assessing CU-level biodiversity and excluding significant hatchery impacts.

Guidelines and methods for estimating PNI values are currently being documented by DFO's Salmonid Enhancement Program (DFO, in review)[2]. Uncertainties in PNI values stem from low sample sizes on the spawning grounds to estimate proportion hatchery-origin spawners, large uncertainties from CWT estimates of hatchery-origin spawners due to insufficient marking of hatchery production, and lack of data on proportions of natural-origin brood stock (and assumption that proportions of natural-origin brood stock equal proportions of natural-origin spawners).

Because current and historical times-series of the proportion of hatchery-origin spawners were not consistently available for populations with PNI $\geqslant 0.5$, total spawner abundances (i.e., combined natural- and hatchery-origin spawners) were used in the assessment of CU and aggregate SMU level statuses. This may result in optimistic assessments of status. We recommend the design of hatchery marking and spawning ground sampling programs to collect data to estimate the contribution of hatchery-origin spawners to total production for these escapement indicator populations. The inclusion of hatchery-origin fish in estimates of status is a key source of uncertainty for this SMU, and likely many others in Pacific Region.

4.3. INLET AND CU STATUS ESTIMATION

Inlet status was derived by applying the multidimensional algorithm used within the Pacific Salmon Status Scanner to individual inlets (Pestal et al., in prep). We found that the status using this algorithm was equivalent to status on a single metric, abundances relative to an estimated lower benchmark for all inlets. When abundances are only available on a relative scale and abundance benchmarks can be estimated, status within the multidimensional algorithm reduces to spawner abundances relative to abundance-based benchmarks (as shown in Figure 1). Because the resulting LRPs were equivalent, in some cases we present only a single set of results, labeled as the single metric approach which also represents status based on the multidimensional algorithm in this case. Holt et al. (2023) recommend applying the multidimensional approach used in the Salmon Scanner to derive CU-level status.

S_{gen} is the spawner abundance required to achieve S_{MSY} within one generation without fishing under equilibrium conditions, and is the lower benchmark on abundances applied under the WSP. We derived S_{gen} by optimizing the Ricker equation with recruitment set to S_{MSY} (equation 17 repeated again here for transparency):

$$S_{MSY} = a \cdot S_{gen} \cdot e^{-b*S_{gen}} \tag{19}$$

[2]DFO in review. Guidelines for Calculating the Proportionate Natural Influence Index as a Metric of the Genetic Influence of Enhanced Pacific Salmon on Wild Populations. Report of the Salmonid Enhancement Program, Vancouver, BC

where,

$$b = \frac{\log(a)}{S_{REP}} \tag{20}$$

$$S_{MSY} = \frac{1 - We^{1-\log(a)}}{b} \tag{21}$$

and a is recruits-per-spawner at low productivity and *W* represents a Lambert function (Scheuerell 2016). Maximum likelihood estimates of S_{REP} values (and 95% CIs) were derived from the watershed-area model adapted from Parken et al. (2006), that included hierarchical structure in the underlying meta-analysis accounting for similarities in productivity among ocean-type and stream-type fish (Liermann et al. 2010, Table 9).

Ricker a values were approximated from a life-stage model that partitioned survival across freshwater and marine life-stages for ocean-type Chinook based on empirical data and expert opinion (W. Luedke pers. comm. DFO South Coast Stock Assessment). Life-stage specific survival rates were then combined to derive an overall survival from spawners to recruitment . Despite the relatively large uncertainties in the life-stage specific survival rates, this approach provides an approximation for productivity that is more realistic than the high estimate previously derived from the watershed-area model and reported for many other ocean-type Chinook populations ($>$ 7 recruits/spawner, Parken et al. 2006). From the life-stage model, mean a values were estimated at 2.7 recruits-per-spawner, with standard errors ranging from 1.6 to 4.5).

Our approach to estimating S_{MSY} (and S_{gen}) differed from that of Parken et al. (2006), because we derived productivity independently, whereas Parken et al. (2006) estimated both S_{MSY} and S_{REP} from the watershed-area model thereby inferring relatively high estimates of productivity, a. Those estimates of productivity were deemed unrealistically high for WCVI Chinook, necessitating the alternative approach adopted here.

Approximate confidence intervals of S_{gen} were estimated by repeated sampling of the normal distributions of S_{REP} and $\log(a)$, with standard deviations in log(S_{REP}) derived from the watershed-area model. This method does not account for covariance between productivity and capacity typically found in stock-recruitment relationships, and will overestimate uncertainty in derived benchmarks. In future analyses, we recommend Bayesian estimation of habitat-based benchmarks to facilitate integration of uncertainties from various sources.

Table 9. Benchmarks (in units of number of spawners) and approximate 95% confidence limits, CL (labelled to the right of each benchmark) for five inlets, including only escapement indicator populations that are not highly enhanced.

Population or Inlet	S_{gen}	upper 95%CL	lower 95%CL	S_{REP}	upper 95%CL	lower 95%CL
Barkley	120	28	430	640	290	1,400
Clayoquot	1,400	350	4,300	7,300	4,100	13,000
Kyuquot	1,000	240	3,200	5,300	2,900	9,600
Nootka/Esperanza	220	55	760	1,200	570	2,400
Quatsino	650	160	2,100	3,400	1,800	6,300

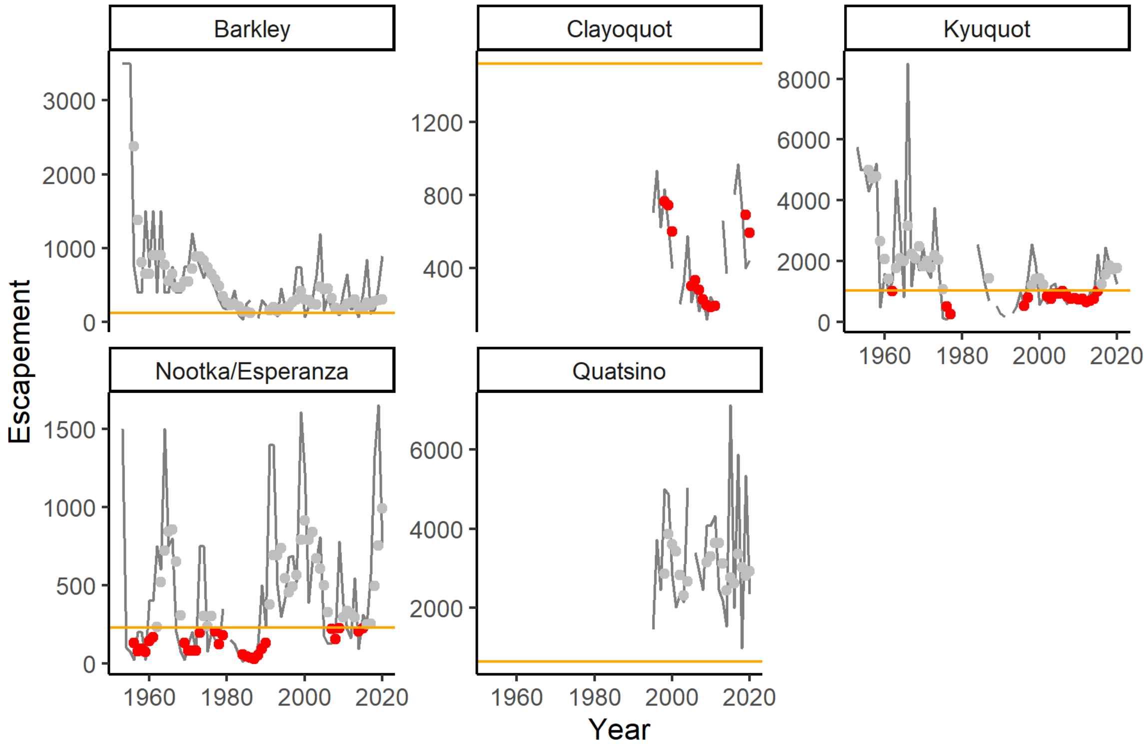

Figure 24. Time-series of spawner abundances by inlet, including only escapement indicator populations that are not highly enhanced. Horizontal yellow line is S_{gen} and dots are generational geometric average spawner abundances coloured by red (below S_{gen}) and grey (above S_{gen}).

CU status was derived from the proportion of component inlets above their lower benchmarks. Serious harm is expected to occur at levels where any one inlet within each of the three CUs dropped below its lower benchmark. Here we have assumed that the status of the one escapement indicator population in the West Vancouver Island-North CU (Marble River, in Quatsino Sound) is not significantly enhanced and is representative of the CU. However, further review of these assumptions by local experts is warranted.

4.4. LRP ESTIMATION: CU STATUS BASED

4.4.1. Methods

The LRP on the proportion of CUs was identified as all three CUs containing inlets with current statuses exclusively above Red status. Because inlets are nested within CUs, this LRP accounts for the distribution of spawning among inlets within CUs. If any CU contained an inlet with Red status, the LRP was considered breached. Status of component inlets was derived from the multidimensional approach used within the Pacific Salmon Status Scanner, which for this SMU reduced to a single metric of spawner abundances relative to the lower benchmark, S_{gen}.

We further considered a CU status-based LRP based on CU statuses derived from a previously published WSP integrated assessment (status in 2014 only, DFO 2016).

4.4.2. Results

In the most recent year with data, 2020, four of the five inlet had abundances above their abundance-based lower benchmark, S_{gen} (Figure 24). Therefore, two of the three CUs contained inlets with current statuses exclusively above their lower benchmarks. One CU, Southern Vancouver Island, contains an inlet, Clayoquot, with status that has been consistently below its lower benchmark throughout the available time-series. Therefore, this SMU falls below the LRP of 100% of CUs above Red status.

Only two of the three component CUs were assessed in the previously published WSP assessment, though those CUs were assessed as Red in 2014. For this year, the LRP would be considered breached because at least one CU had Red status.

4.5. LRP ESTIMATION: AGGREGATE ABUNDANCE, LOGISTIC REGRESSION LRPS

Logistic regression LRPs could not be identified for WCVI Chinook because there are no years when all inlets were above their lower benchmark in the historical record (Figure 24). In order to fit a logistic regression model to data, observations of successes (years when all inlets were $>$ lower benchmarks) and failures (years when all inlets were not $>$ lower benchmarks) are required. The estimation of logistic regression LRPs is limited to SMUs with historical records that demonstrate contrast in status over time.

4.6. LRP ESTIMATION: AGGREGATE ABUNDANCE, PROJECTION LRPS

4.6.1. Methods

Projection LRPs were derived for WCVI Chinook by projecting inlet-specific population dynamics using the `samSim` modelling tool (Appendix B). We chose to project inlet-specific rather than CU-specific population dynamics to reflect the relative demographic isolation of inlets. Population dynamics and exploitation parameters were derived from a previously developed CU-specific run-reconstruction for WCVI Chinook based on spawner abundances and age compositions from indicator populations, and exploitation rates from the Robertson Creek hatchery indicator population (D. Dobson & D. McHugh, pers. comm. DFO South Coast Stock Assessment). Because this run-reconstruction has not been peer-reviewed, it is not used to develop benchmarks, but can provide plausible distributions for parameters of projections. CU-specific parameters were applied across all component inlets. Inlet-specific population capacities, S_{REP}, were estimated from the watershed-area model (Parken et al. 2006) (Table 8) and applied in projections of recruitment with a Ricker stock-recruitment model. Base-case parameters are provided in Table 10 and sensitivity analyses are described in the text below.

The model was initialized at inlet-specific equilibrium abundances and projected for a 40-year initialization period to stabilize the distributions of spawner abundances. The model was then run for an additional 30 years and annual aggregate abundances and inlet-specific statuses were recorded. Because the projections identify long-term equilibrium abundances and statuses, the outputs are independent of initial abundances. Projections were summarized over 50,000 random Monte Carlo trials. A relatively large number of Monte Carlo trials was required for LRP estimation because the algorithm required a sufficient sample size within each 200-fish incremental bin of aggregate abundances along a range of realistic abundances (from near zero to carrying capacity). Projection LRPs were identified from the aggregate abundances with specified probabilities of all component inlets being above lower benchmarks. We recommend a review of model assumptions and parameters by local experts prior to adopting a projection LRP for this SMU. We provide an example for demonstration purposes.

Table 10. Parameters used for inlet-specific projections of WCVI Chinook population dynamics.

Parameter	Value	Source
Ricker $log(a)$ (mean)	WCVI-South = 1.14, WCVI-Nootka & Kyuquot =1.58, WCVI-North = 1.53	Run reconstruction for WCVI Chinook (1985-2019, D. Dobson & D. McHugh pers. comm.)
Ricker $log(a)$ (SD)	0.5	Approximate 95% CI and bounds from life-stage specific model (W. Luedke per. comm.)
S_{REP} (Spawners at replacement, mean)	Barkley = 637, Clayoquot = 7879, Nootka/Esperanza = 1184, Kyuquot = 5273, Quatsino = 3384	MLE estimate from watershed-area model
S_{REP} (SD)	Barkley = 0.40, Clayoquot = 0.30, Nootka/Esperanza = 0.37, Kyuquot = 0.31, Quatsino = 0.32	Derived from standard error of MLE estimate from the watershed-area model
SD in Ricker residuals (sigma)	WCVI-South = 0.80, WCVI-Nootka & Kyuquot = 0.69, WCVI- North = 0.68	Run reconstruction for WCVI Chinook (1985-2019, D. Dobson & D. McHugh pers. comm.)
Covariance in Ricker residuals among inlets	Equal to covariance in spawner time-series among inlets	Covariance in spawners among inlets from wild escapement indicator populations (D. Dobson & D. McHugh, pers. comm.)
Ave proportions of age-at-maturity (age 2, 3, 4 and 5). Ages 5 and 6 are grouped.	WCVI-South = 0.02, 0.14, 0.45, 0.38; WCVI-Nootka & Kyuquot = 0.01, 0.10, 0.48, 0.40; WCVI-North = 0.02, 0.15, 0.47, 0.36	Average proportions from run reconstruction (D. Dobson & D. McHugh pers. comm.)
Variability in age proportions (tau from multivariate logistic distribution)	WCVI-South = 0.7, WCVI-Nootka & Kyuquot = 0.6, WCVI-North = 0.7	Estimated from time-series of proportions of ages-at-maturity from the run reconstruction. Assumed variable over CUs and years.
Average exploitation rate	0.30	Average pre-terminal ERs 2010-2019 for Robertson Creek hatchery indicator (D. Dobson & D. McHugh pers. comm.). Varied in sensitivity analyses 0.05 - 0.45.

Parameter	Value	Source
Interannual variability in exploitation rates (CV)	0.17	Estimated from pre-terminal ERs 2010-2019 for Robertson Creek hatchery indicator. Assumed to be Beta distributed, constrained between 0-1.
Variability in exploitation rates among inlets (CV)	0.085	Assumed to be half of interannual variability, varied in a sensitivity analysis (0-0.17). Assumed to be Beta distributed, constrained between 0-1.
Initial abundances	S_{REP} (inlet-specific)	MLE from watershed-area model

We chose covariance parameters so that the resulting projections of inlet-specific spawner abundances exhibited correlations among inlets that were similar to those observed (Figure 25). Specifically, model parameters were tuned so that resulting correlations among inlets in projected spawner abundances approximated observed correlations in spawner abundances, described in more detail below.

Pairwise correlations between observed inlet-specific spawner time series were relatively strong in the 1990s and early 2000s, and have become slightly weaker since 2015. The correlations among inlets for running 20-year time periods are provided in Figure 25. Starting in 1995, the first boxplot displays the distribution of pair-wise correlations among the five inlets for the time period 1995-2015; the second boxplot displays correlations for 1996-2016, etc. A decline in correlations in evident in the last two time periods. The final boxplot shows the correlation over the entire time-series.

Within the forward projection model, correlations in spawner abundances among inlets are driven by three model components, each described in more detail below: (1) covariance in exploitation rates among inlets, (2) covariance in recruitment residuals among inlets, and (3) covariance in age proportions of recruits among inlets.

Covariance in exploitation

Covariance in exploitation rates among inlets is modelled as common interannual exploitation parameterized from pre-terminal exploitation on Robertson Creek hatchery Chinook, with additional inlet-specific variability. The common variability occurs due to their overlapping distribution in offshore fisheries, whereas inlet-specific variability results form inlet-specific vulnerability to exploitation in coastal waters and terminal fisheries within the inlets.

We assumed an average exploitation rate as observed for WCVI Chinook in recent years (2010-2019, Robertson Creek indicator, 30%, Figure 26). In projections, interannual variability in exploitation rates was assumed to be Beta distributed (constrained between 0 and 1), parameterized from estimated pre-terminal exploitation rates for Robertson Creek, with a coefficient of variation (CV) = 0.17 (Table 10).

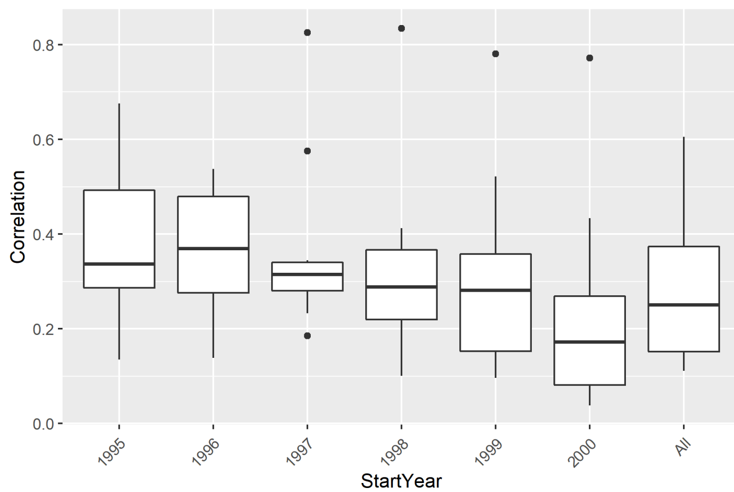

Figure 25. Running correlations in spawner abundances among inlets in 20-year time periods, with the start year of the 20-year period on the X-axis. Each boxplot shows the distribution of pairwise correlations among the five inlets (n=10 pairwise correlations).

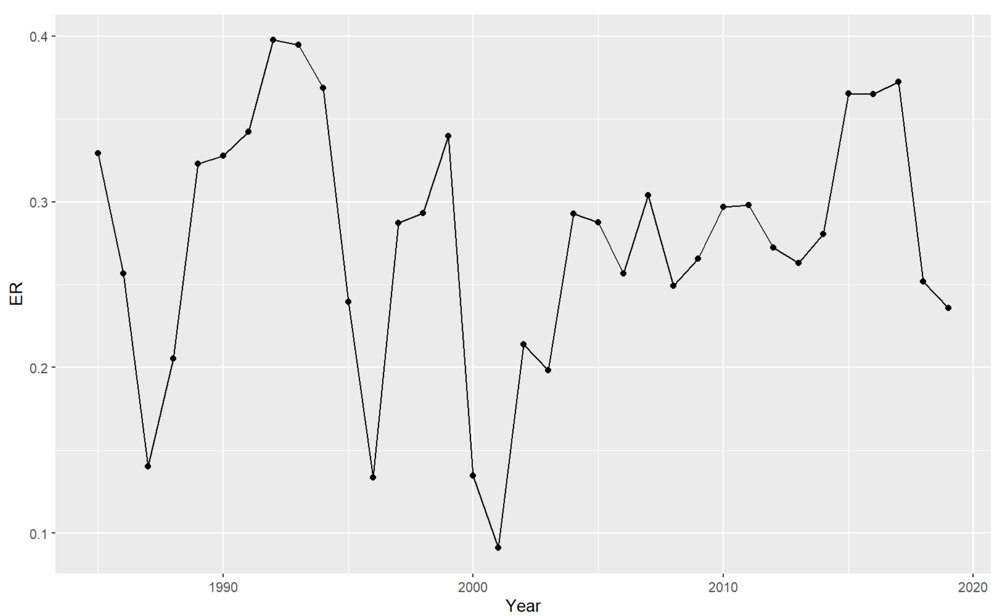

Figure 26. Pre-terminal exploitation rates for Robertson Creek CWT indicator population.

Without data to parameterize inlet-specific variability in exploitation rates, we assumed the inlet-specific variability was half the common (SMU-level) interannual variability (CV=0.085), and varied this in sensitivity analyses from 0 and 0.17 to cover plausible bounds (Figure 27). We assumed that inlet-specific deviations from the SMU-level average exploitation rate were consistent over years (e.g., due to the spatial and temporal variability in inlet-specific migration patterns affecting vulnerability to fisheries), but that this deviation changed over MC trials. Future analyses could include consistent biases in exploitation for specific inlets (e.g., positive biases for southern inlets and negative biases for northern inlets).

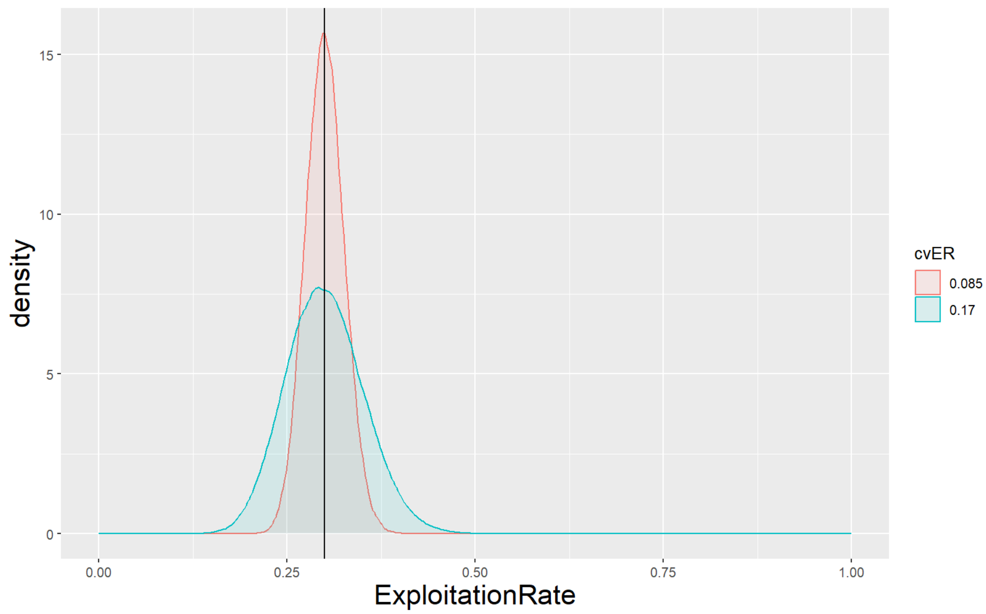

Figure 27. Variability in projected exploitation rates over time (cv=0.17) and among inlets (CV=0.085), from an average exploitation of 0.3.

In the forward projections, pairwise correlations in projected spawner abundances among inlets were similar to recent observed pairwise correlations in spawner abundances among inlets (Figure 28). Varying assumptions about variability in exploitation among inlets between CV= 0 and 0.17 did not impact the distribution of correlations in spawner abundances in the projections.

Covariance in recruitment residuals

We parameterized correlations in recruitment residuals among inlets from the observed correlations in spawner abundances among inlets derived from the WCVI Chinook run reconstruction (D. Dobson and D. McHugh, pers. comm. DFO South Coast Stock Assessment, Fig. 29). However, spawner abundances may be more weakly correlated than recruitment due to differences in exploitation among inlets and sub-populations within inlets.

In sensitivity analyses, we scaled pairwise correlations in recruitment residuals among inlets by 0.5 and 0 of the observed spawner correlations (0 representing recruitment residuals that were uncorrelated among inlets in the projections). We then compared the resulting correlations in projected spawner abundances to observed correlations, to evaluate the extent to which the model provided realistic projections under each assumption. When we scaled correlations in recruitment residuals to less than observed spawner correlations (i.e., scalar $<$ 1) the resulting correlations in spawner abundances from the projections were lower than observed correlations (Figure 28), but were roughly similar when recruitment residuals were scaled to 1. So, for our base case, we assumed correlations in recruitment residuals among inlets were equal to observed correlations among inlets.

Variability in proportions in age-at-maturity among inlets

For the base case, we assumed that proportions in age-at-maturity varied over time and among inlets parameterized from proportions of ages-at-maturity calculated for each CU in the WCVI

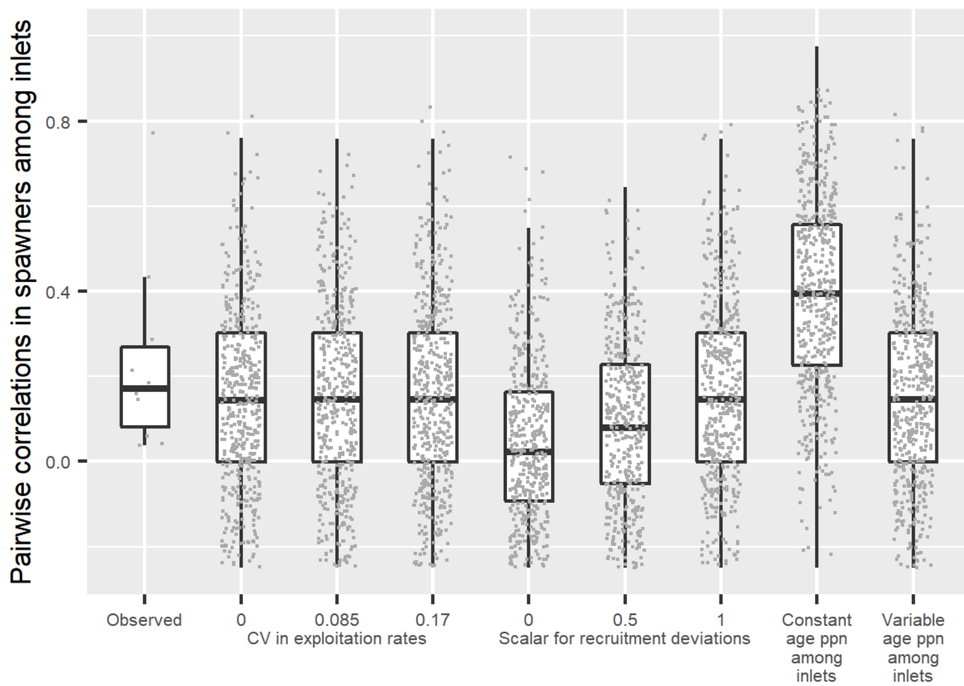

Figure 28. Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations, 1st boxplot) and projected time-series under various assumptions: with a CV in exploitation rates among inlets = 0, 0.085 or 0.17 (0.85 is the base case)(2nd-4th boxplots), with a scalar on covariance in recruitment residuals of 0 (no correlation in recruitment residuals), 0.5 and 1 (equal to observed spawner correlations, base case) (5th-7th boxplots), and variable or constant age proportions among inlets (variable is the base case) (8th-9th boxplot). For each set of assumptions the other variables were held constant at base-case values.

Chinook run reconstruction (D. Dobson pers. comm. DFO Science; inlet-specific age-proportions were not available) (Figure 30). We used the CU-specific mean proportions at each age from the run reconstruction with annual deviations in those proportions based on a multivariate logistic distribution, parameterized from the estimated time-series of age proportions.

For these analyses, recruitment was calculated from total spawner abundances (i.e., combined natural- and hatchery-origin spawners) and catches, which may result in biased proportions for hatchery-influenced populations if hatchery-origin adults return at different (younger) ages than natural-origin salmon (Larsen et al. 2019). As mentioned above, the inclusion of hatchery-origin fish in estimates of status is a key source of uncertainty for this SMU. We ran a sensitivity analysis under an alternative assumption where age proportions varied over years but were constant among CUs. Under this assumption, we found that pairwise correlations of spawner abundances in projections were much higher than those observed (Figure 28), generating time-series that were unrealistic.

4.6.2. Results

Projection LRPs were developed under the base-case assumptions of (1) interannual variability in exploitation rates among inlets with a CV = 0.085, (2) correlations in recruitment residuals among inlets equal to observed spawner correlations among inlets, and (3) variability in age

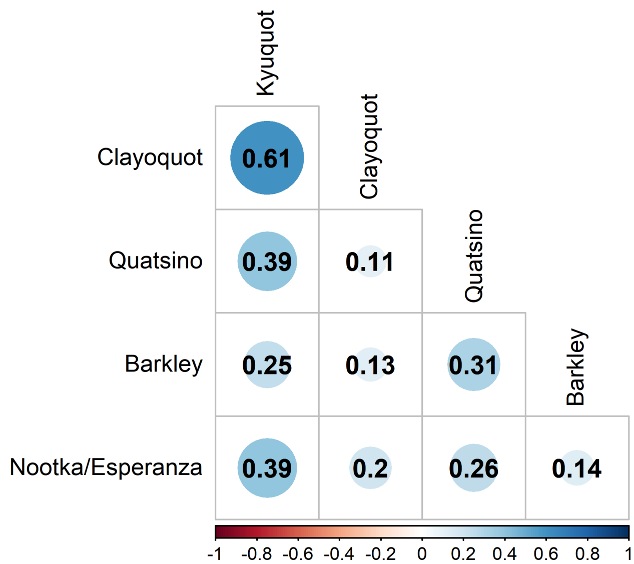

Figure 29. Bubble plot of correlations in spawner abundances among inlets over time, 1994-2020.

proportions among CUs and years. We identified a provisional aggregate abundance LRP with p=0.5 (50% probability of all inlets being greater than their lower benchmark) equal to 11300 (Figure 31). Provisional LRPs at p=0.66 ("likely" that all inlets are above their lower benchmarks) is also shown, near 20,000 (Figure 31). Probabilities that all inlets were above their lower benchmarks never exceeded 0.9, so LRPs at higher p values could not be estimated. Note that the LRP at p=0.66 required more MC trials for full stabilization and is shown here for demonstration purposes only. Candidate projection LRPs were compared against time-series of aggregate abundances observed for WCVI Chinook salmon (sum of escapement indicator populations with PNI $>$ 0.5), showing that abundances are currently below these LRPs and have been near or below them over the available time-series (Figure 32).

4.6.3. Sensitivity Analyses

We considered sensitivity analyses on interannual variability in exploitation rates among inlets with a CV = 0 and 0.17 (Figure 33), and found LRPs at 50% probability were not sensitive to interannual variability in exploitation rates over the range of values we considered. We further considered sensitivity analyses on average exploitation rates from 5-45% (Figure 34), where 30% exploitation was the base case. As exploitation increased, the LRP associated with a specified probability of all inlets being above their lower benchmark also increased. At high exploitation, individual inlets dropped below their lower benchmarks more frequently despite often relatively high aggregate abundances on the remaining inlets. To explain the initially counter-intuitive result of the sensitivity of projection LRPs to exploitation rates, we ran additional analyses for a hypothetical SMU where the spawner-recruitment parameters were either varied or kept constant over component inlets (or CUs) and Monte Carlo trials, and a range of exploitation rates were applied (Appendix D). Based on these sensitivity analyses, we found that differences in productivity among component inlets results in inlet-specific variability in sensitivity to exploitation rates.

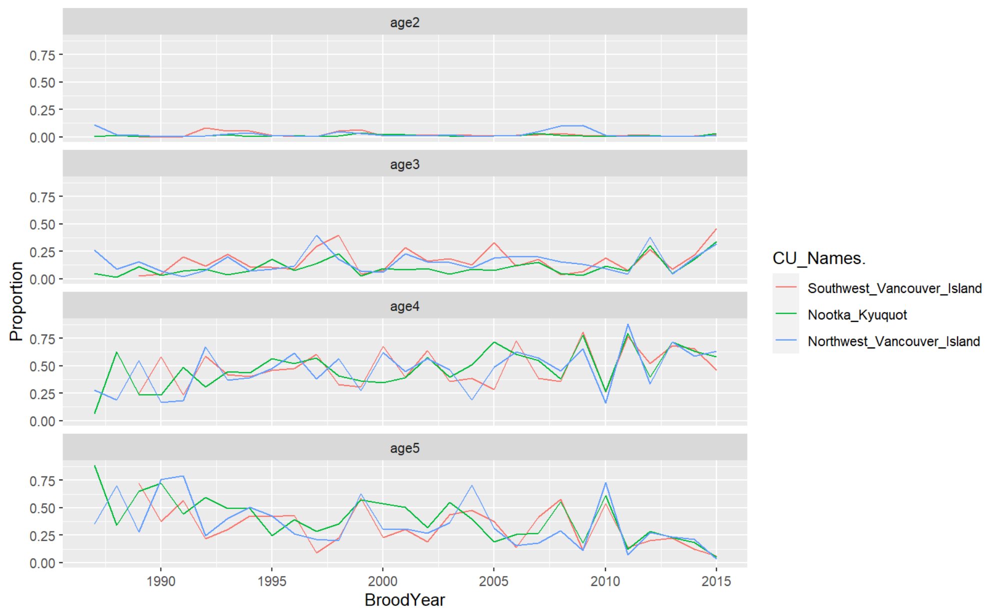

Figure 30. Time-series of proportions at age in recruitment aligned by brood year, calculated from run reconstruction for WCVI Chinook by CU.

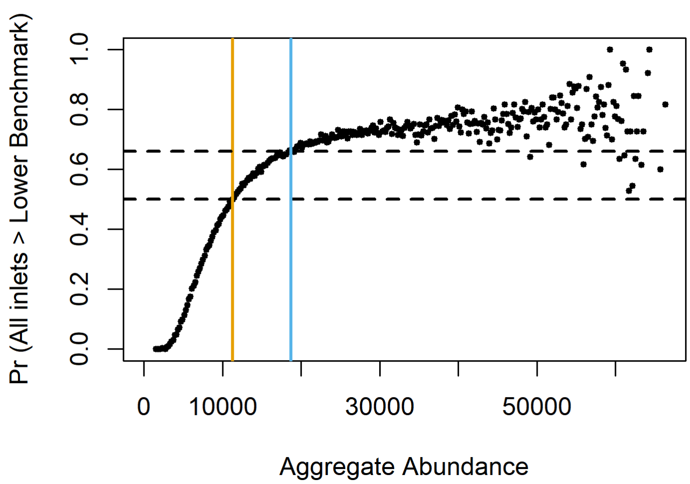

Figure 31. Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials. Each dot is the proportion of MC trials where all inlets were > lower benchmarks. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue) are highlighted, where p is the probability of all inlets being > their lower benchmarks.

Inlets with relatively low productivity fall below lower benchmarks more frequently. This effect is accentuated when exploitation rates are high resulting in divergences in status among inlets and higher aggregate abundances required for all inlets to be above their lower benchmarks (i.e., higher LRP).

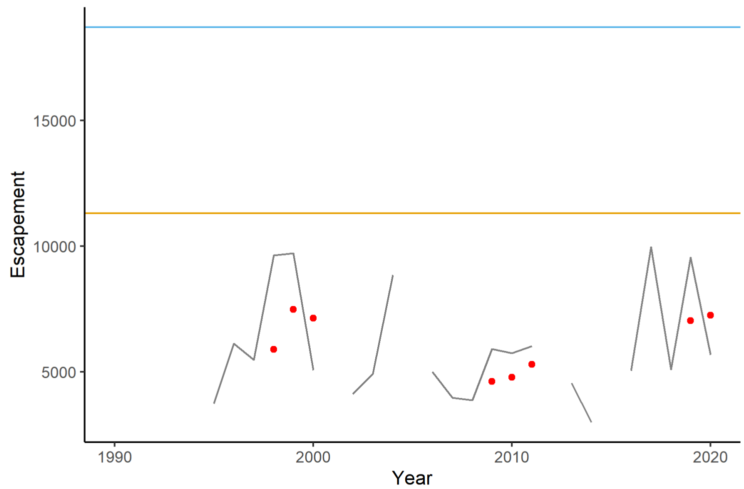

Figure 32. Time-series of aggregate escapement for WCVI Chinook (indicator populations with PNI >= 0.5), with projection LRPs associated with component inlets being > lower benchmarks at p=0.5 (yellow) and p=0.66 (blue). Red points are the generational average escapement (geometric mean), indicating status below LRPs

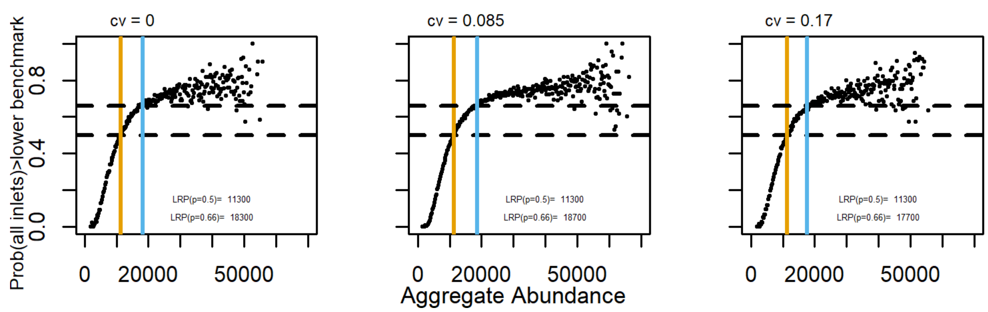

Figure 33. Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials. The projections assumed variability in ERs among inlets with a CV=0, 0.085, and 0.17.

Given uncertainty in current and anticipated productivity, projection LRPs were further evaluated under a range of productivities from 75% - 150% of base case estimates, under current exploitation. Scenarios with lower productivity ($<$ 0.75x current estimates) had a large proportion of trajectories with productivity below replacement, for which LRPs could not be estimated.

Projection LRPs tended to increase under low productivity and vice versa (Figure 35), a trend that was expected due to the inverse relationship between productivity and inlet-specific S_{gen} values (Holt and Folkes 2015). At low productivity, S_{gen} tends to increase, thereby becoming more precautionary. The sensitivity of LRPs to productivity highlights the value of updating benchmarks and projection LRPs as productivity changes. Our results also show that uncertainty in projections increased under low productivity, likely requiring more random Monte Carlo trials for stabilization at p=0.5. The probability of all inlets being above their lower benchmark rarely met or exceeded 0.66 ('likely' category, Mastrandrea et al. 2010) when productivity was low, so LRPs at this level could not be estimated. When productivity was high, the probability of all inlets being above their lower benchmark rarely dropped below 0.66. At high productivity, LRPs at the p=0.5 level could not be estimated. More detailed analyses of LRPs along the entire range of productivities and exploitation was beyond the scope of this case study.

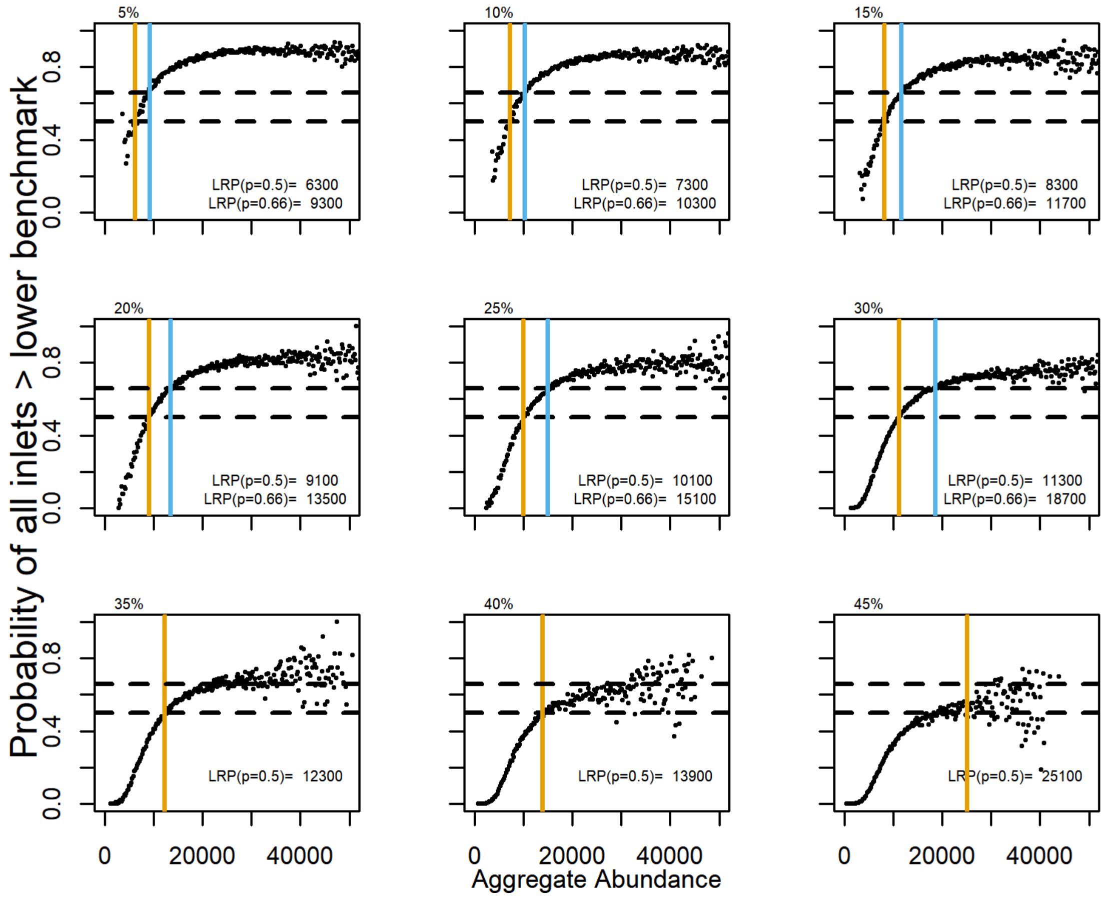

Figure 34. Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials, under a range of average exploitation rates from 5-45%. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue) are highlighted.

4.7. HISTORICAL EVALUATION OF STATUS ACROSS LRP METHODS

We evaluated the status of WCVI Chinook using LRPs estimated using CU status-based and projection methods. We show status against three types of CU status-based LRPs: an LRP based all component inlets having status above Red using the multidimensional algorithm in the Salmon Scanner, an LRP based all component inlets having spawner abundances above S_{gen}, and status based on the previously published WSP integrated assessment of CUs (status in 2014 only, DFO 2016, Figure 36). The results from the multidimensional approach and abundances against S_{gen} are identical, but are shown separately for clarity. Although the Salmon Scanner can equally provide status on a single metric of abundances, we have differentiated them here to highlight the unique approach to multidimensional assessments provided within the Scanner.

All methods indicate this SMU being below its LRP for years where data are available. We use the same nomenclature as for Interior Fraser River Coho Salmon, where ‘CUbased’ indicates CU status-based LRPs, ‘Abund’ indicates aggregate abundance LRPs, ‘Scanner’ indicates CU-level assessments derived from multidimensional approach within the the Pacific Salmon Status Scanner, ‘Sgen’ indicates CU assessments derived on a single metric, (e.g., abundances relative to the lower benchmark Sgen), and ‘Proj’ indicates projection LRPs.

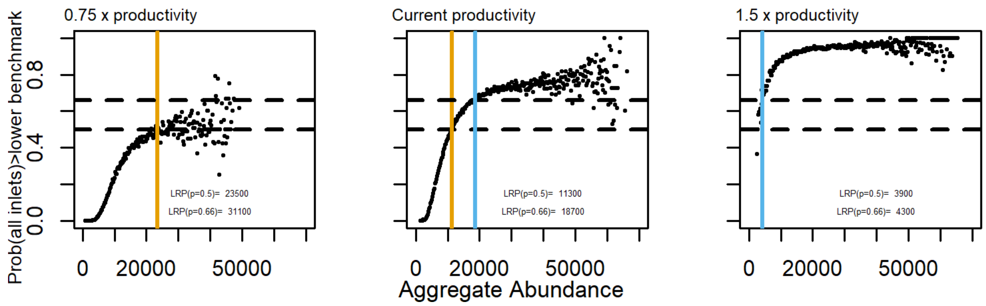

Figure 35. Projection LRPs estimated under assumptions of reduced productivity (0.75x of current levels) and increased productivity (1.5x current levels). Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue) are highlighted. More Monte Carlo trials are required for stabilization of LRPs at low productivity. LRPs at p=0.66 could not be estimated at low productivity, and LRPs at p=0.5 could not be estimated at high productivity

4.8. DISCUSSION

A few key conclusions from this case study are highlighted for broader relevance. Status was consistent across the LRP methods that were available, and with a previously published assessment. This SMU is generally managed at scales smaller than the SMU supporting the application of CU status-based LRPs to allow management decisions to be responsive to CU- or inlet-level statuses. However, aggregate abundance, projection LRPs were also estimated here for demonstration purposes. It was not possible to estimate a logistic regression LRP due to lack of contrast in the time-series.

Projection LRPs were highly sensitive to average exploitation for this SMU. LRPs derived assuming current exploitation rates cannot be used as an indicator of serious harm if the management procedure changes. Projection LRPs were also highly sensitive to underlying population productivities. As productivity declined, LRPs increased, becoming more precautionary, reflecting trends of underlying benchmarks. Projection LRPs at probabilities levels of 90% and 99% could not be estimated for this SMU because of the relatively low covariation in population dynamics among CUs. The probability of all CUs exceeding their lower benchmarks was never high, even at high aggregate abundances.

A key uncertainty for this SMU is the contribution of hatcheries to total abundances. Although only escapement indicator populations where most of the production was from natural spawning were included, hatchery production likely biases abundance estimates upwards, providing an optimistic characterization of status compared to if the hatchery contribution were removed. Furthermore, hatchery production can result in optimistic estimates of recruitment and productivity, resulting in LRPs that are biased low. Time-series of hatchery-origin spawners were not available for most of the populations we considered, precluding the ability to account for enhancement quantitatively in abundance estimates.

We recommend a few areas for further research relevant to this SMU:

- The projection LRPs illustrated here should further be evaluated for sensitivity to key structural assumptions, such as the stock-recruitment model, and the presence and magnitude of depensation, among other assumptions. This evaluation is especially important for this SMU because of the lack of peer-reviewed stock-recruitment models. We based our assumption of a Ricker form of the stock-recruitment relationship from its application to other Chinook populations in BC (Parken et al. 2006), but this form may not represent the high observed variability and declining productivity that are now common for Chinook salmon.

- In the development of CU status-based and projection LRPs, inlets were chosen as the spatial scale of biodiversity required for the sustainability for the SMU. In future analyses, alternative assumptions could be considered, including LRPs derived to maintain diversity at the CU scale by projecting CU-level abundances. In addition, we recommend research on the development and evaluation of metrics and benchmarks of distribution of spawning within CUs, and guidelines on how to incorporate these into CU-level assessments under the WSP.
- Future iterations of the multidimensional status assessments used within the Pacific Salmon Status Scanner could include information on the distribution of spawners across inlets within CUs to incorporate this finer scale of biodiversity.
- Further evaluation of the influence of hatcheries on spawner abundances, including the extent and magnitude of straying among basins is warranted for this, and other Chinook SMUs.

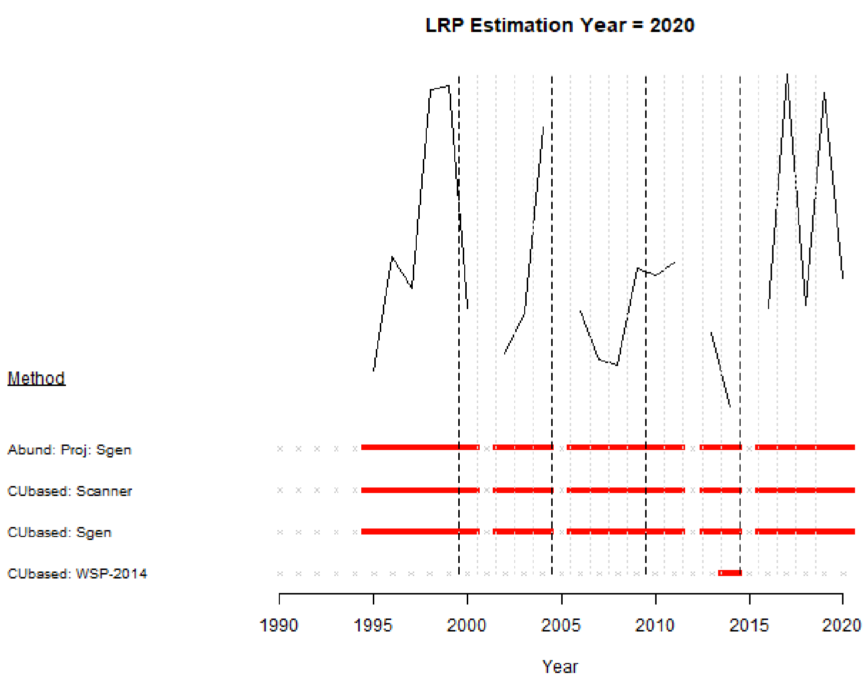

Figure 36. Historical evaluation of status using available methods for estimating LRPs. Red bars indicate status below LRP; grey x's indicate status not available

5. CASE STUDY 3: INSIDE SOUTH COAST CHUM - NON-FRASER

5.1. CONTEXT

The Inside South Coast Chum - Non-Fraser SMU (abbreviated as ISC Chum) includes seven CUs of Chum Salmon from rivers that drain into Johnstone Strait and the Salish Sea along the mainland of British Columbia and the east coast of Vancouver Island (Figure 37; Holtby and Ciruna (2007)). This area includes deep fjords, glaciers, large rivers, and small coastal streams. Chum salmon CUs spawning in the Fraser River watershed are not included in this SMU. They have been categorized as a separate 'Inside South Coast Chum - Fraser' SMU. While these two SMUs have substantial overlap in ocean fisheries, they have been separated into two SMUs based on differences in terminal fishery impacts and freshwater habitats.

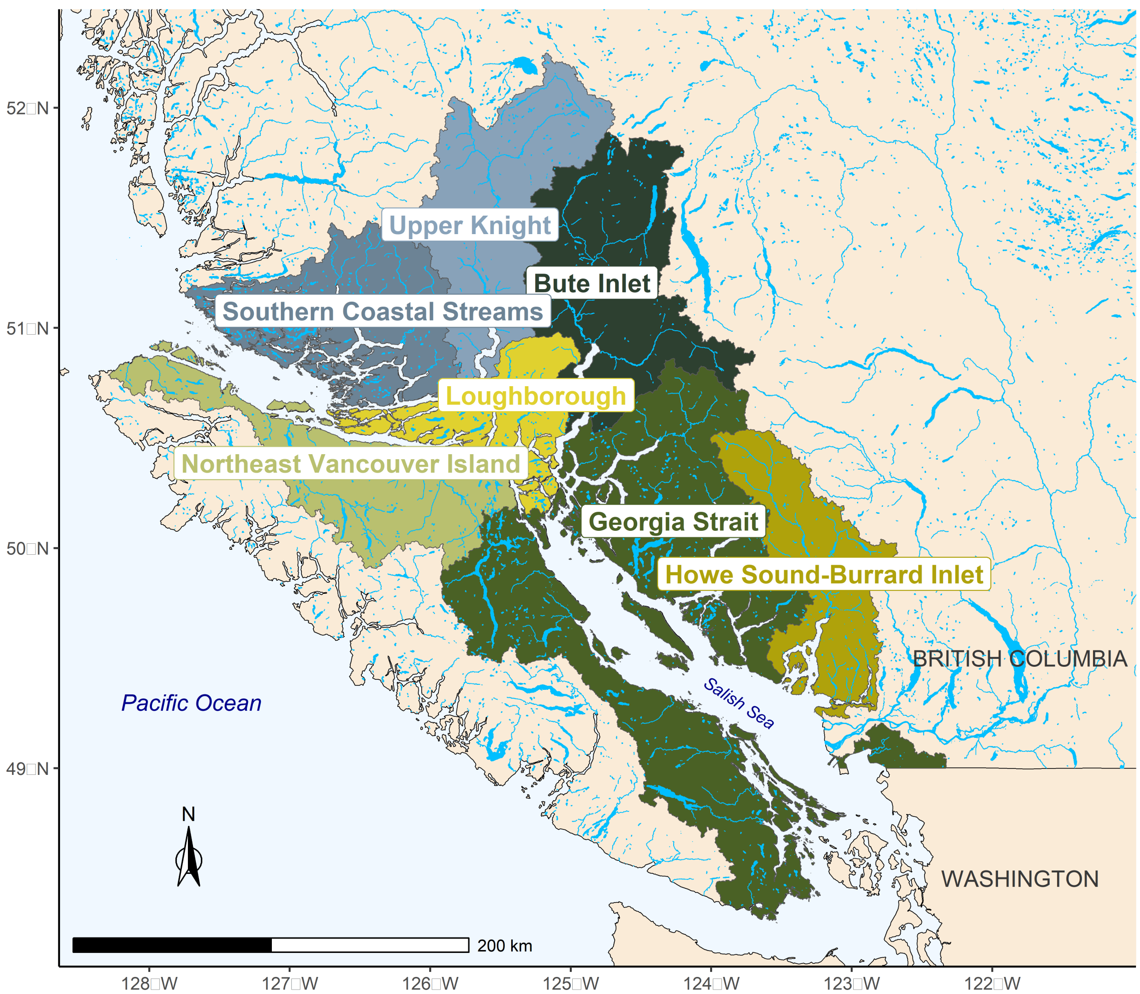

Figure 37. The seven Conservation Units that make up the Inside South Coast Chum Stock Management Unit (not including Lower Fraser and Fraser Canyon Conservation Units).

The ISC Chum SMU is considered data-limited. While escapement time series are available for many streams starting in 1953, several series are incomplete and require infilling assumptions (i.e., not all streams counted each year, some CUs have no counts in some years). In addition, run reconstructions of recruitment are uncertain, making the development of benchmarks based on spawner and recruitment data problematic. There are also no data on marine survival (although there are some scale/growth data in Debertin et al. 2017). Other unique characteristics of this SMU include high contrast in abundance among CUs and relatively low correlation in abundance among CUs over time. The SMU covers a large area with many diverse watersheds, flow regimes, and ocean entry locations. Wild Salmon Policy status assessments have not been done on any ISC Chum CUs. Godbout et al. (2004) identified long-term increases or variable abundance in Georgia Strait and Howe Sound-Burrard Inlet and declines in Northeast Vancouver Island and especially in the Southern Coastal Streams CU (from 1953-2002). Holt et al. (2018) found similar results in a provisional assessment of status. At this time, a peer-reviewed WSP status assessment has not been developed for ISC chum.

Holt et al. (2023) provide steps for applying LRPs to salmon SMUs, one of which is to identify if the status of data-deficient CUs can be represented by other data-rich CUs. This is relevant for the ISC Chum case study because two CUs have no observations in some years (Upper Knight and Bute Inlet). To infer status of data-deficient CUs from data-rich CUs, Holt et al. (2023) recommend providing evidence for similar threats, environmental drivers, biological characteristics, and population capacity among CUs.

Upper Knight and Bute Inlet CUs are both associated with long fjords that run from the Broughton Archipelago through the Coast Mountains. They include rivers with headwaters in the Cariboo region farther inland than other CUs in the SMU (Figure 37). Southern Coastal Streams, Georgia Strait, and Howe Sound-Burrard Inlet also include portions of the Coast Mountains and some glaciers, but to a lesser extent and their inlets are shorter and their watersheds do not go as far inland. Upper Knight and Bute Inlet are unique in that they are the only CUs in the SMU that only include watersheds that drain into the upper end of long inlets. They are both more remote than the other CUs, which is partly why there are fewer observations over time for Chum with fall run timing.

Chum from the Upper Knight and Bute Inlet CUs are exposed to different threats to habitat, survival and productivity than the other five CUs in both the freshwater and the early marine phase. While these two CUs have, on average, lower impacts from forest harvest, impervious area, and roads, they have larger impacts from forest defoliation and pests (Pacific Salmon Foundation 2021). They may also have different levels of risk from disturbances such as glacier melt, avalanches, debris flows, and floods because they have large melting glaciers associated with lakes, steep slopes, and unstable terrain. In the Bute Inlet CU, the glacial lake outburst flood that caused a debris flow in the Southgate River in November 2020 is one example of such an event. These events are capable of killing an entire brood year of eggs/alevins and reshaping habitat with impacts on spawning habitat and stream ecosystems for many years. They can also change water quality in near shore marine habitats. These catastrophic events may be less likely in watersheds with gentler topography and that lack glaciers and glacial lakes.

Environmental drivers, biological characteristics, and population capacity for Upper Knight and Bute Inlet CUs also differ from the other five CUs. The hydrology of these two CUs likely differs from that of other CUs with more low-lying topography. The two largest watersheds in these CUs (Homathko and Klinaklini) fall within their own Freshwater Adaptive Zone, which indicates unique freshwater habitat conditions (Figure 76 and Table 52 in Holtby and Ciruna (2007)). These watersheds have large glaciers and high amounts of snowmelt, compared to more low-elevation coastal watersheds with more rain-dominant hydrographs. Marine conditions when smolts enter the ocean in these systems may vary from that of the other five CUs, as they are entering the upper ends of large fjords. Competition with other salmon in the ocean and ocean conditions affect chum salmon in this SMU (Debertin et al. 2017; Litz et al. 2021), although declines in Pink salmon populations in this general area may suggest that these factors are not affecting these CUs only. Regarding biological characteristics, Bute Inlet and Upper Knight have a higher proportion of summer-run populations of Chum (Table 11). Recruits per spawner of the Upper Knight and Bute Inlet CUs (estimated using CU-level infilling, which introduces error) are more variable than for other CUs in this SMU, exhibiting very productive years (>100 recruits per spawner) and years with very low productivity. These CUs also have lower habitat capacity, with fewer streams with fall timed Chum spawners than the other CUs (Table 11). Based on these differences, we cannot infer the status for Bute Inlet and Upper Knight from the other CUs. Note that these criteria used to evaluate whether status can be inferred for these CUs extends to whether reliable spawner escapement data can be infilled using escapement in the other CUs. Thus, these CUs are dropped for years with no spawner data in this case study.

Table 11. The seven Conservation Units in the Inside South Coast Chum Non-Fraser Stock Management Unit, and the number of streams in the fall and summer runs. Note that only fall run streams were used in this study due to run reconstruction methods. LBM = Lower Benchmark, UBM = Upper Benchmark derived using the percentile method.

CU Name	Fall run streams	Summer run streams	LBM	UBM
Southern Coastal Streams	23	8	NA	NA
North East Vancouver Island	17	0	50%	50%
Upper Knight	3	2	50%	50%
Loughborough	37	0	50%	50%
Bute Inlet	4	1	NA	NA
Georgia Strait	125	1	25%	50%
Howe Sound-Burrard Inlet	66	0	25%	50%

Previous evaluations of WSP benchmarks for Inner South Coast Chum have shown that percentile benchmarks can be comparable to those based on stock-recruitment relationships when productivity is relatively high and harvest is relatively low (Holt et al. 2018). However, in some cases, percentile benchmarks may be inappropriate due to low productivity or high harvest, resulting in a shifting baseline (Holt et al. 2018).

We chose the ISC Chum SMU as a case study because we were interested in exploring LRP options for a data-limited SMU without stock-recruitment or habitat-based benchmarks. We applied LRPs based on two methods: proportions of CUs above Red status, and aggregate abundance LRPs estimated using the logistic regression approach.

5.2. DATA

We used the same data used in Holt et al. (2018), but updated with five additional years of data. Available data included spawner abundance time series from 1959 - 2018 and corresponding CU-level recruitment estimated from run reconstruction. Spawner abundance series rely heavily on infilling; 60% of observations (count of spawners for an individual stream, in a given year) were missing and needed to be infilled. We chose to apply infilling procedures for this SMU when possible to develop metrics of wild spawner abundance since infilling methods for this SMU have been previously peer reviewed (Holt et al. 2018). This differs from the approach taken for WCVI Chinook, in which infilling methods were not implemented due to high and variable hatchery influences. Recruitment data are considered highly uncertain for all ISC Chum CUs due to uncertain assumptions required to assign mixed-fishery catch to CUs within the run-reconstruction model. As a result, we did not consider recruitment time-series to be reliable enough to estimate stock-recruitment based benchmarks such as S_{MSY} and S_{gen}. We did however use spawner recruitment model fits to provide approximate estimates of CU-level productivity, which are used to inform the application of percentile-based benchmarks.

Van Will (2014) provides more details on the data sources, infilling procedures and run reconstruction, which were reproduced for this study. We did not include the Lower Fraser or Fraser Canyon Chum CUs. More details can be found in Appendix E. We removed three systems with extensive enhancement (Qualicum River and Little Qualicum River from spawning channels, and Puntledge River from hatchery production, all within the Georgia Strait CU). It is assumed that the enhanced contribution to spawning was near 100% for these systems.

5.3. CU STATUS ESTIMATION

For this case study, we consider two approaches for characterizing CU status: (1) Multidimensional algorithm within the Pacific Salmon Scanner Tool, or Salmon Scanner (Pestal et al. in prep.) and (2) CU-level abundance relative to a percentile lower benchmark.

The first approach is a multidimensional approach consistent with Canada's WSP, as recommended by Holt et al. (2023) for estimating CU status when using the CU status-based LRP approach. The second approach is presented for comparison with the multidimensional approach.

When applying the multidimensional algorithm used within the Salmon Scanner to ISC Chum, we used percentile benchmarks when they were available for a CU. For CUs in which percentile benchmarks were not appropriate, the multidimensional algorithm used trends in spawner abundance as a basis for assessing CU status (Figure 1). As a result, both of our approaches to CU status estimation depend at least partially on percentile benchmarks.

Percentile benchmarks can be applied to assess status of CUs when other data - like benchmarks based on productivity or habitat - are not available or reliable (Clark et al. 2014; Holt et al. 2018). The suitability of percentile benchmarks was evaluated for ISC Chum by Holt et al. (2018), who tested how well percentile benchmarks matched benchmarks from stock-recruitment parameters, using retrospective and simulation analyses. Holt et al. (2018) also calculated benchmarks based on stock-recruitment model parameters for ISC Chum CUs, but did not recommend them due to uncertainty in spawner and recruitment data. They tested how well a 25% percentile benchmark (and higher values up to 50%) compared to estimates of S_{gen} for these CUs. They found that percentile benchmarks (from 25-50%) under moderate to high harvest rates and low to moderate productivity tended to underestimate 'true' S_{gen} values (estimated from the same data), which would lead to optimistic and incorrect status assessments. More work on alternatives to percentile benchmarks were needed in this case.

For this case study, percentile benchmarks were calculated using the raw infilled time series of annual escapement (i.e., not smoothed). In contrast, status for year i was determined by comparing the generational mean (geometric mean on a 4 year window, ending with year i) spawner abundance with the benchmark. This approach of using raw (unsmoothed) escapements when calculating benchmarks, and generational smoothed escapements when estimating CU status relative to benchmarks, is consistent with the approaches taken for our other two case studies for proortional LRPs.

*Table 12. Selected percentile-based lower and upper benchmarks identified to be similar or higher in value than stock-recruitment based benchmarks under the WSP, along gradients in productivity (Ricker α) and average harvest rates. * denotes the low-productivity scenario where lower and upper Ricker-based benchmarks are very close to one another, resulting in lower and upper percentile-based benchmarks that are the same. Adapted from Table 6, Holt et al. 2018.*

		Harvest rate		
		<20%	20-40%	40-60 %
Productivity (Ricker α)	>4	25th (lower) 50th (upper)	25th (lower) 50th (upper)	25th (lower) 50th (upper)
	2.5-4	25th (lower) 50th (upper)	25th (lower) 50th (upper)	Further evaluation required
	1.5-2.5	*50th (lower and upper)	Further evaluation required	Further evaluation required

Based on recommendations in Holt et al. (2018) (Table 12), Georgia Strait and Howe Sound-Burrard Inlet fall in the category of using 25% as a lower benchmark and 50% as an upper benchmark (Ricker α 2.5-4, harvest rate 20-40%). Loughborough, Northeast Vancouver Island, and Upper Knight (α 1.5-2.5 and harvest rate 0-20%) had a 50% lower and upper benchmark recommended. Bute Inlet (α 1.5-2.5, harvest rate 20-40%) needed further evaluation and percentile benchmarks were not recommended. Percentile benchmarks were also not recommended for Southern Coastal Streams due to low productivity (α <1.5; Table 11).

The methods for multidimensional assessments within the Salmon Scanner are described in Section 2. In applying the multidimensional approach to ISC Chum, we used percentile benchmarks as recommended in Holt et al. (2018) for lower and upper benchmarks for the five CUs that have appropriate percentiles benchmarks identified (as described above). Percentile benchmarks were not available for Bute Inlet and Southern Coastal Streams, in which case the multidimensional algorithm used trends to assess CU status (Figure 1).

5.4. LRP ESTIMATION: CU STATUS BASED

5.4.1. Methods

To derive CU status-based LRPs, we calculated the proportion of CUs that had status estimates above the Red zone (or, above the lower percentile benchmark). As with the Interior Fraser Coho and WCVI Chinook case studies, we required all CUs to be above the Red zone for the ISC Chum SMU to be classified as being above the LRP.

The single-metric approach to assessing CU status based on percentiles has specific data requirements (Holt et al. 2018) while the multidimensional approach can be applied to any CU with at least a consistent time-series of spawner abundances. To compare LRPs based on CU assessment from these two approaches we compared data subsets including those that used the same data for each method, and all appropriate data for each method. We evaluated six different combinations of data and LRP methods (Table 13).

Table 13. Scenarios using different subsets of data (CU names abbreviated) and methods to assign LRP status. 'Y' indicates a full time series, 'YP' indicates a time series was included but is partial (missing years that required CU-level infilling which wer omitted). Bute Inlet and Southern Coastal Streams do not have appropriate percentile benchmarks. 'Full' scenarios use only years with full time series (no CU-level infilled CUs) and 'partial' scenarios include CU-level infilled CUs but drop years with CU-level infilling for those CUs.

Scenario Name	Southern Coastal Streams	North East Vancouver Island	Upper Knight	Loughborough	Bute Inlet	Georgia Strait	Howe Sound-Burrard Inlet
1. CUbased: Scanner: 4CUs full	-	Y	-	Y	-	Y	Y
2. CUbased: Percentile: 4CUs full	-	Y	-	Y	-	Y	Y
3. CUbased: Scanner: 5CUs partial	-	Y	YP	Y	-	Y	Y
4. CUbased: Percentile: 5CUs partial	-	Y	YP	Y	-	Y	Y
5. CUbased: Scanner: 5CUs full	Y	Y	-	Y	-	Y	Y
6. CUbased: Scanner: 7CUs partial	Y	Y	YP	Y	YP	Y	Y

When describing ISC Chum LRP scenarios in Table 13 and throughout this case study, we use the following labeling convention: *Metric : CU Status Method : Data Scenario*. 'Metric' refers to the choice to base all ISC Chum LRPs on the proportion of CUs above Red CU status (CUbased). The 'CU Status Method' can be based on the multidimensional algorithm within the Salmon Scanner (Scanner) or on a single percentile benchmark used to characterize CU status (Percentile). Finally, 'Data Scenario' labels indicate both the number of CUs represented (4, 5, or 7) and the completeness of the time series (Full or Partial). 'Full' scenarios only included CUs with complete time series (no CUs with missing years). 'Partial' scenarios included CUs with incomplete time series (years that did not have observations in those CUs were omitted). When using percentile benchmarks in these scenarios, we used percentiles based on Holt et al. (2018). The benchmarks were estimated using the entire time series.

For Scenarios 2 and 4 in Table 13, we used CU status based on percentile benchmarks that are determined by productivity and historical exploitation, as outlined in Holt et al. (2018). This method used annual escapement values to calculate benchmarks and the generational mean of escapement (geometric mean over 4 years) to assess status in each year. Scenario 2 includes the four CUs that had complete time series (observations in each year, no CU-level infilling) and that also had appropriate percentile benchmarks (Table 13). For example, Upper Knight was excluded because it did not have a complete time series, Southern Coastal Streams was excluded because it does not have an appropriate percentile benchmark, and Bute Inlet was excluded for both of these reasons. We then relaxed this requirement for all CUs to have data in all years and included all CUs that meet the constraints of Holt et al. (2018) even if they had missing data for some years (Scenario 4). This scenario included Upper Knight in some years, which meant that it had five CUs in some years and four in others. Thus, the power to detect Red status varied among years in Scenario 4, using more of the available data than Scenario 2.

For Scenarios 1, 3, 5 and 6 in Table 13, we used status based on the multidimensional algorithm within the Salmon Scanner. To compare results between status on a single metric (abundance relative to percentile benchmarks) and the multidimensional approach, we applied the multidimensional algorithm to the same two data sets used for percentiles, i.e., using same CUs and years. For examples, Scenarios 1 and 2 use the same data, and Scenarios 3 and 4 use the same data. Because the multidimensional assessments do not require abundance-based benchmarks to assign status, this method could also be used for CUs that did not have appropriate percentile benchmarks (Southern Coastal Streams and Bute Inlet). Scenario 5 only included CUs with a full time series, and Scenario 6 included Upper Knight and Bute Inlet, which had some missing years.

5.4.2. Results

CU Status Based on the Multidimensional Approach within the Salmon Scanner

Using the CU status based on the multidimensional approach within the Salmon Scanner, two out of five CUs with data in the most recent year of data (2018) would be above their lower benchmark (Amber or Green zone) and three would be below (Red zone; Figure 38). Over the time series, status for Howe Sound-Burrard Inlet and Georgia Strait has improved, while status in other CUs has declined or switched from Green to Red several times.

CU Status Based on Percentile Benchmarks

Two out of four CUs were below their percentile lower benchmark in 2018 (Figure 39). Howe Sound-Burrard Inlet and Georgia Strait had status above their lower benchmarks, and Upper Knight did not have observations in 2018. Status for North East Vancouver Island and Loughborough was occasionally above the Red zone before the 2000s, but has been mainly Red for the past $\sim$ 20 years. Georgia Strait and Howe Sound-Burrard Inlet have been above Red status in every since $\sim$ 1970. Upper Knight has been mainly Red status except for two short periods in in the 1960s and 1970s, and did not have any observations since 2004. In supplementary analyses, we evaluated percentile benchmarks retrospectively for each year in the time series using only data prior to that year. As more years of data were included, percentile benchmarks increased over time for Georgia Strait (especially the 50th percentile) and had modest increases for Howe Sound-Burrard Inlet (Figure E.5). Percentile benchmarks decreased by a small amount for Loughborough and North East Vancouver Island. Southern Coastal Stream shows evidence of shifting baselines, as the percentiles decrease over time following a general decline in abundances (Figure E.5). Upper Knight also shows this pattern but to a lesser extent.

5.5. LRP ESTIMATION: AGGREGATE ABUNDANCE, LOGISTIC REGRESSION LRPS

5.5.1. Methods

We evaluated whether the proportion of CUs above their lower benchmark could be predicted by aggregate abundance using logistic regression models. We tested this using percentile benchmarks. While we initially considered logistic regression LRPs that used Sgen as a lower CU benchmark instead of percentiles, we decided to drop this approach due to unreliable stock-recruitment data. Using recruitment data would not satisfy reliability principles in Holt et al. (2023). These methods used four CUs with over 50 years of data and appropriate percentile benchmarks (North East Vancouver Island, Loughborough, Georgia Strait, and Howe Sound-Burrard Inlet). Aggregate abundance (predictor variable) was calculated using only these four CUs. We omitted Bute Inlet and Upper Knight (both had CU-level infilling in recent years) and Southern Coastal Streams (no appropriate percentile benchmark). Refer to Section 2 for more details.

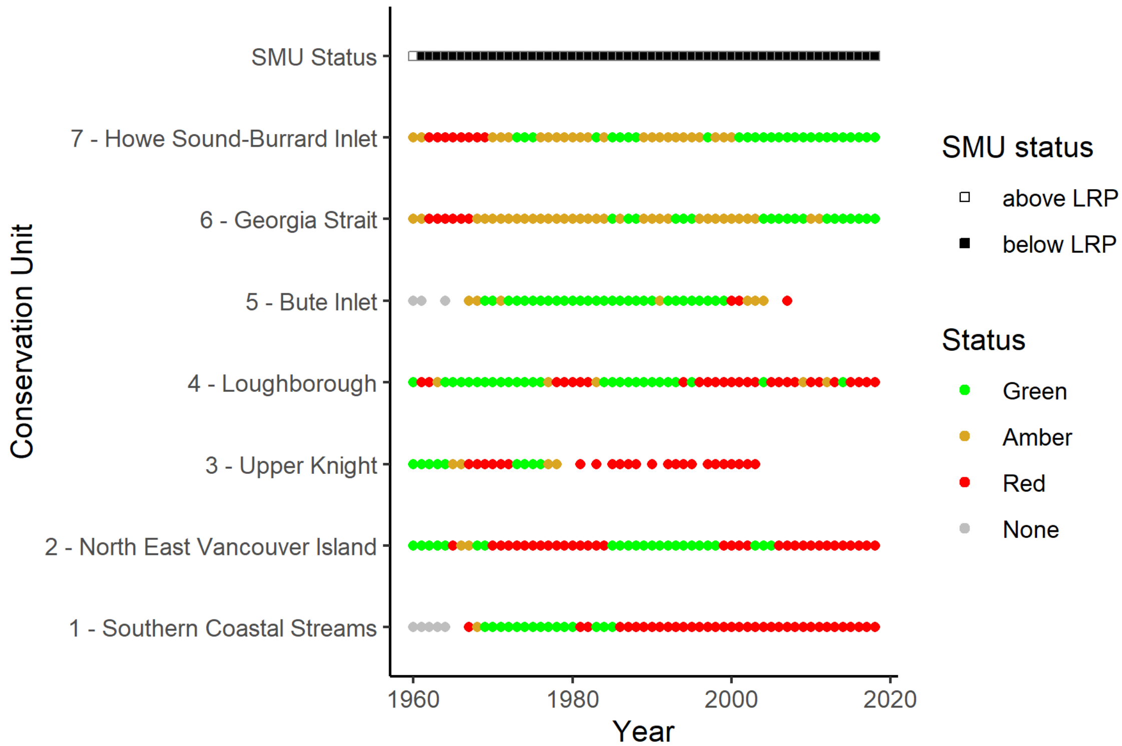

Figure 38. Status of CUs based on multi-dimensional Salmon Scanner. Years with CU-level infilling were not included. The top row shows the overall SMU status based on the CU status-based LRP of all CUs being above Red status.

Due to poor logistic model fits using the entire 1953-2018 time series, we did not conduct retrospective analyses of logistic regression LRPs for this SMU as was done for the Interior Fraser River Coho case study. The characteristics of the data that led to poor logistic model fits are highlighted in the results section below.

Projection LRPs are an alternative aggregate abundance LRP that we did not consider for this SMU due to lack of reliable stock-recruitment parameter estimates for component CUs. However, this approach could be considered in future analyses given consensus on model structure and parameterization that provide realistic uncertainties in projections of population dynamics.

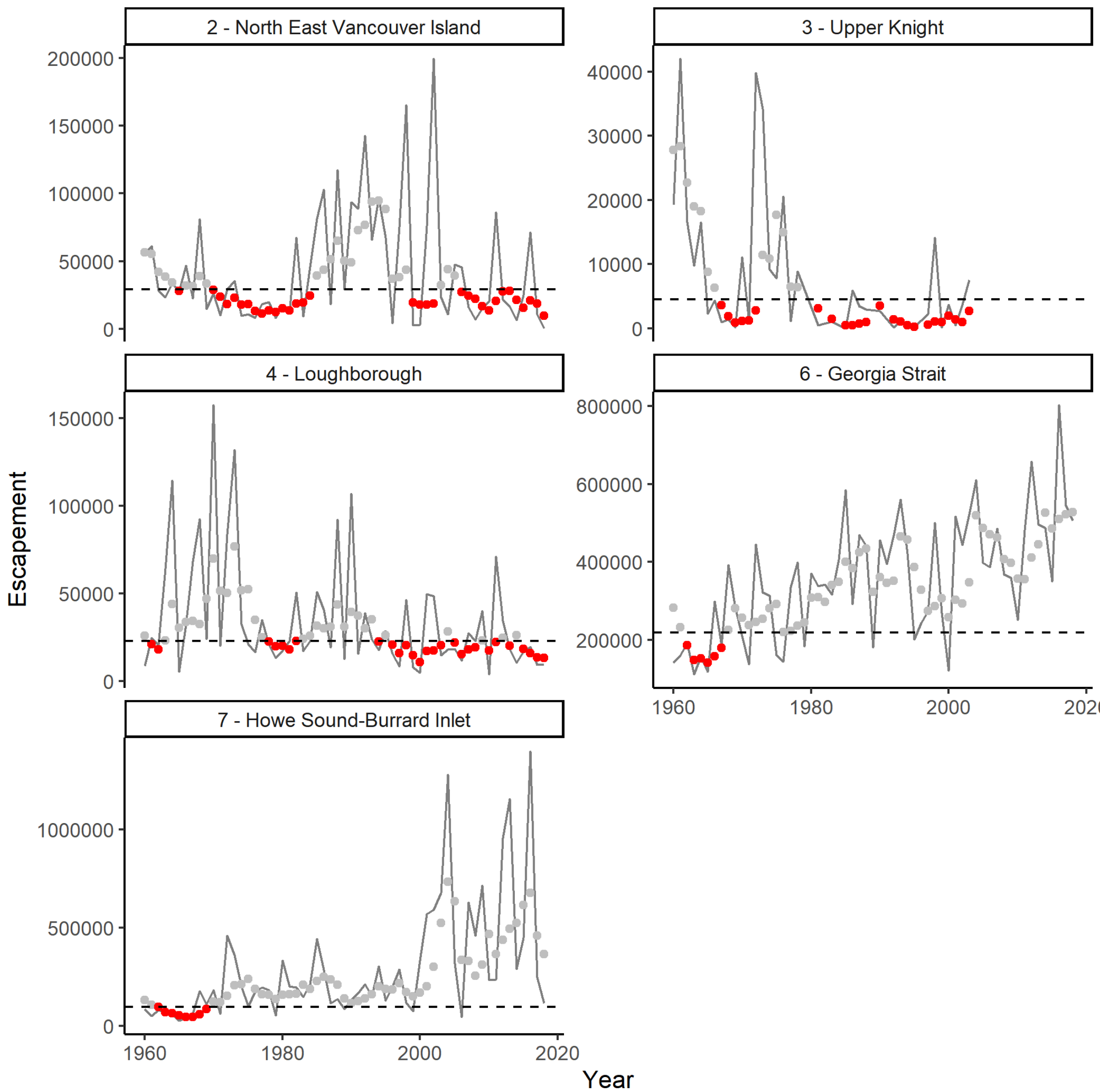

Figure 39. Spawner escapement (solid black line) with generational mean (4 year rolling geometric mean) of escapement in points. Dashed lines indicate percentile lower benchmarks. Red points indicate years when the generational mean of abundance was below the lower benchmark, and gray points indicate when it was above. Southern Coastal Streams and Bute Inlet are omitted because they do not have appropriate percentile benchmarks due to low productivity and moderate to high harvest. Note that Upper Knight is missing observations in 1979-1980, 1982, 1984, 1989, 1991, 1996, and 2004-2018.

5.5.2. Results

The logistic model predicting whether all CUs were above their benchmark based on aggregate abundance fit the data poorly (Figure 40). The sum of abundance for all CUs in a given year was not a good predictor of whether those CUs were above their benchmarks in that year. Years with high aggregate abundance but with some CUs below their benchmark make a logistic model unsuitable for the purpose of estimating which aggregate abundance is linked to a high probability of each component CU being above its lower benchmark.

The diagnostics for the logistic regression indicated that the model fit was poor (Table 14, Figure 40). Pseudo R^2 was low (0.03), indicating a poor fit. The Box-Tidwell test indicated a significant lack of linearity in the relationship between aggregate abundance and log-odds (p-value = 0.02), which means that the assumption that the relationship between aggregate abundance and log-odds is linear was not met. Including aggregate abundance in the model did not improve fit over the null model based on a Goodness of fit p-value of 0.13 (>0.05). The ratio of correct classifications (above below LRP) relative to all classification was 0.7 based an LRP at p=0.5. Note that this method tends to have overly optimistic values when the data used to fit the logistic model and to evaluate classification accuracy are the same. The Wald p-value was not significant for B_1 (p=0.19, the coefficient for aggregate abundances). There was no evidence of outliers or autocorrelation in residual deviations. Despite meeting the last two assumptions (no autocorrelation or outliers), they were not enough to overcome the deficiencies identified by the other diagnostic criteria. Therefore, logistic regression LRPs are not presented here.

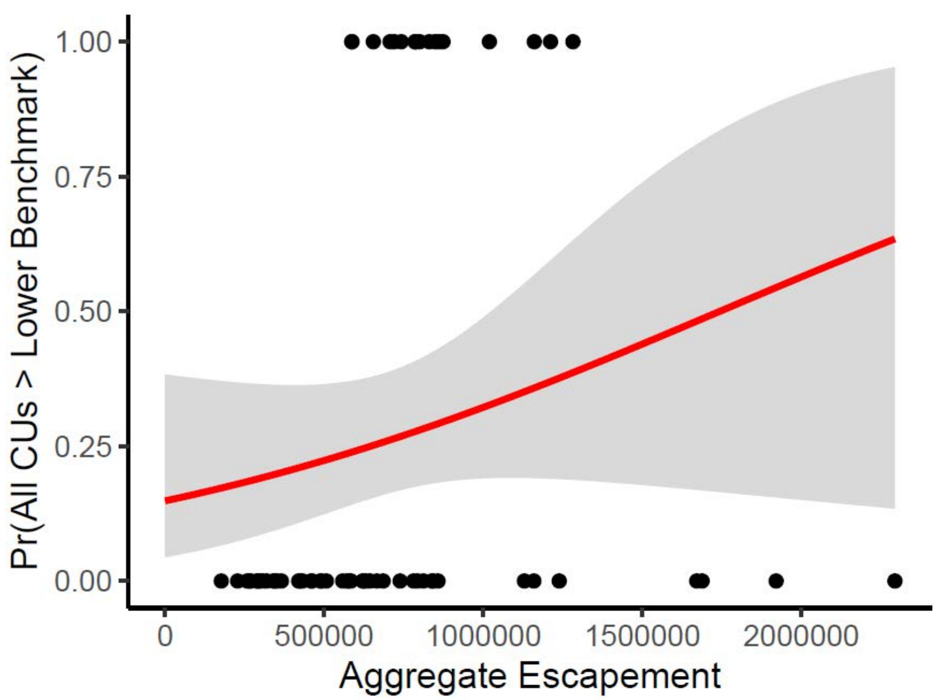

Figure 40. Logistic regression of whether escapement of all component CUs were above their percentile benchmarks based on aggregate abundance, for Inside South Coast Chum SMU. Includes CUs where percentile benchmarks were appropriate (no Bute Inlet, Upper Knight, or Southern Coastal Streams).

Table 14. Model diagnostic statistics from logistic regression LRP using percentile benchmarks. A description of diagnostic tests is provided in Section 2. Hit ratios are shown for p=0.5.

Diagnostic Test	Value
Box-Tidwell p-value	0.02
Max. deviance residual	1.69
AR-1	0.14
Wald p-value	0.19
Goodness-of-fit p-value	0.13
Pseudo-R^2	0.03
Hit Ratio (p= 50%)	0.7

Several factors led to these poor model fits. The Inside South Coast Chum SMU is made up of seven CUs that vary in their escapement abundance. In many years, escapement in Georgia Strait and Howe Sound-Burrard Inlet is greater than in other CUs by two orders of magnitude (Figure E.2). In addition, the correlation in escapement among these seven CUs is low (Figure 41). These characteristics mean that the aggregate abundance may be high due to one or more CUs with high escapements, while one more smaller CUs are below their benchmark. High aggregate escapements do not mean that all CUs are above their benchmark. The low pairwise correlations in CU escapements are likely due to the SMU covering a large area, with varying numbers of populations affected by both local and regional factors, as described in Section 5.1

In a preliminary retrospective analysis, the logistic model fits were more appropriate using a truncated portion of the data that ended in the 1980s. Although logistic regression may be used to estimated LRPs based on aggregate abundance in SMUs where abundance is more even among CUs and escapements are more correlated, these relationships may not remain static and could break down over time.

5.6. HISTORICAL EVALUATION OF STATUS ACROSS LRP METHODS

The ISC Chum SMU was consistently below the LRP for large portions of the historical time series, regardless of LRP estimation method (Figure 42). While the aggregate abundance of the SMU increased over time, SMU status remained below the LRP in every year of the past two decades except 2004 for all estimation methods. These results were mainly due to the tendency of Georgia Strait and Burrard Inlet-Howe Sound CUs to have high and increasing abundances while smaller CUs, such as North East Vancouver Island, Loughborough, and Southern Coastal Streams, remained low (Figures 39, E.1).

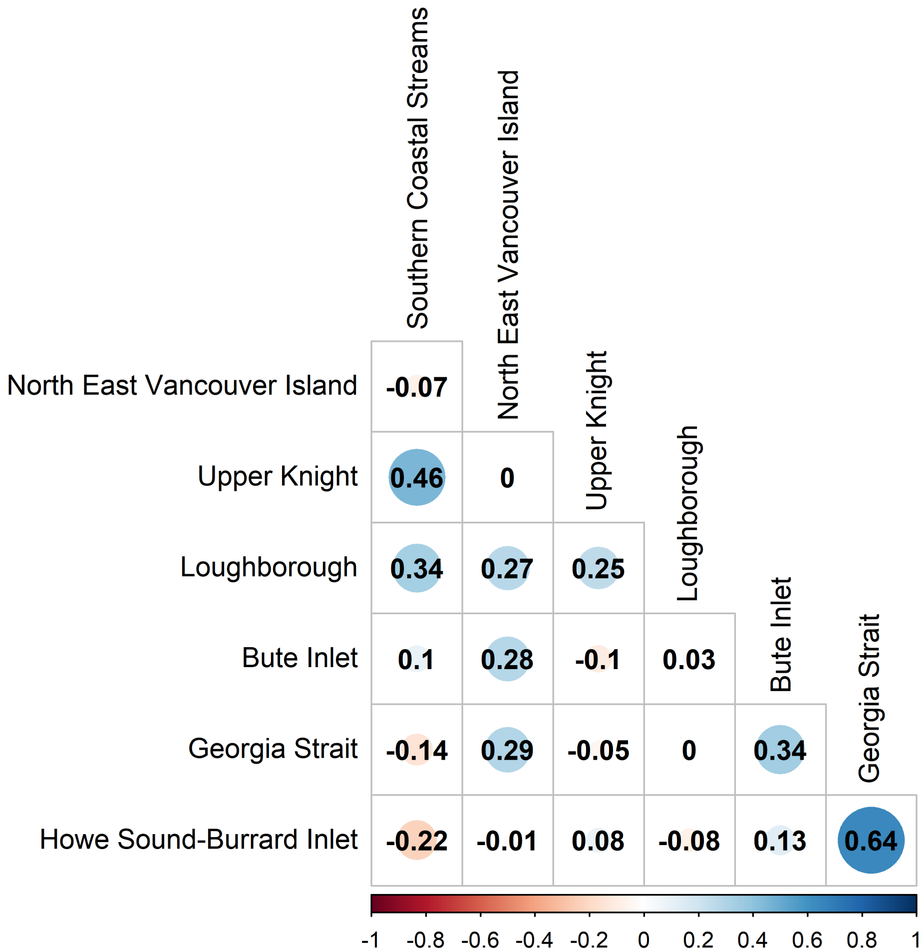

Figure 41. Pairwise correlations of spawner abundance between Inside South Coast Chum Conservation Units.

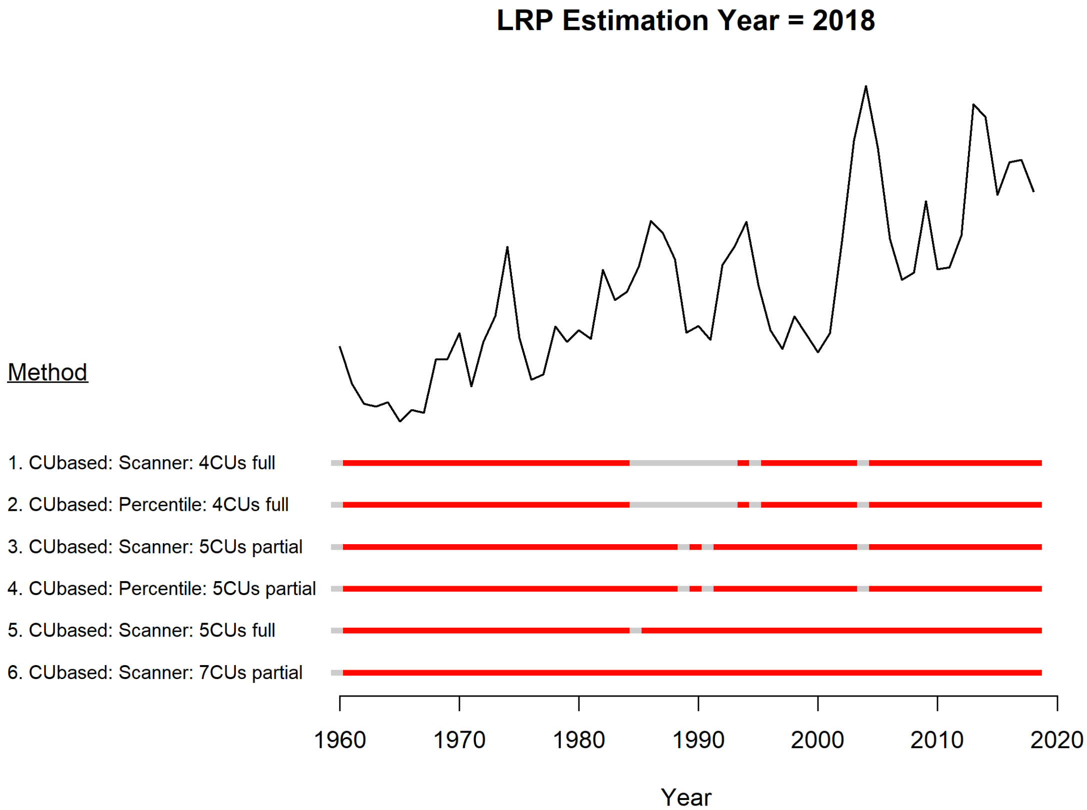

Figure 42. Comparison of LRP status (red = below LRP, gray = above LRP) for six scenarios. The black line shows aggregate abundance. Scenarios 1-3 and 6 do not include Bute Inlet or Southern Coastal Streams (no appropriate percentile benchmarks). 'Full' scenarios use only years with full time series (no CU-level infilled CUs) and 'partial' scenarios include CU-level infilled CUs but drop years with CU-level infilling for those CUs.

When using the same data, LRP status based on a single metric on abundances relative to percentile benchmarks and the multidimensional approach within the Salmon Scanner were identical (Figure 42). This result can be seen by comparing Scenario 1 and 2 and Scenario 3 and 4. These identical results occur because all CUs in Scenarios 1-4 have percentile benchmarks and never drop below 1500 fish, which means that the multidimensional approach relies on percentile benchmarks to assess CU status for all CUs in all years. If some CUs did not have percentile benchmarks, requiring trends to be used instead, or if their absolute abundances dropped below 1500 spawners, then the two approaches could have led to different results.

In this case study, adding more data changed the number of years that the SMU was below the LRP. Scenario 6 (most data) had the most years below the LRP, with every year after the first being below the LRP (Figure 42, Table 13). A comparison of Scenarios 2 and 4, which are both based on percentile benchmarks, shows that including more data (Scenario 4) results in more years below the LRP. A comparison of Scenarios 5 and 6 (Salmon Scanner), shows that including more observations results in one year switching from above the LRP to below it, with the addition of data from two CUs with partial time series. Finally, a comparison of Scenarios 4 and 6 (where Scenario 6 had two more CUs than Scenario 4), shows that three years switched from above the LRP to below, as the two CUs without percentile benchmarks are added.

We found that SMU status can be below the LRP even if the aggregate abundance increases (Figure 42). For ISC Chum, this is mainly due to years with high abundances of Georgia Strait and Howe Sound-Burrard Inlet and low abundances and Red status in other, smaller CUs, such as Southern Coastal Streams. The moderate correlation in spawner abundances in Georgia Strait and Howe Sound-Burrard Inlet exacerbates this pattern (Figure 41). This highlights the importance of including metrics of status at the CU level, which influence the overall SMU status.

5.7. DISCUSSION

As a data-limited SMU, the ISC Chum case study had unique characteristics to inform the guidelines for LRP development. We found that only the CU status-based LRP were applicable to this SMU, which is based on individual CU status. Because there were no reliable stock-recruitment parameter estimates, we relied on data-limited methods to estimate CU status. We assessed CU status based on abundance relative to percentile benchmarks alone, or on a combination of percentiles and trends using the multidimensional algorithm within the Salmon Scanner. The use of the multidimensional algorithm was particularly valuable because percentile benchmarks were not appropriate for two of the CUs (Bute Inlet and Southern Coastal Streams, Table 11). Missing data also required decisions to be made about which CUs to include in which years. We used this case study to explore how sensitive CU status-based LRPs were to the decisions on number of CUs, and years of data to include in the analysis.

Using a multidimensional approach allowed us to include two CUs that did not have appropriate percentile benchmarks (Bute Inlet and Southern Coastal Streams). It allowed all seven CUs to be included when assessing SMU status by allowing alternative trend-based metrics to be considered. The seven-CU partial case provided the most pessimistic status of the scenarios considered as this approach used the most data. It resulted with the most years of the SMU being below the LRP (Figure 42). This multidimensional approach is especially useful for SMUs with a mix of data qualities and benchmark types, including those with and without relative abundance benchmarks. Like any approach to assess LRPs, the underlying data, and benchmarks applied (if abundance benchmarks can be used) should be verified by experts.

In its current form, the multidimensional algorithm within th Salmon Scanner relies on whether abundance is < 0.79× the long-term geometric average and whether abundances are > 1500 in the absence of abundance-based benchmarks. It is worth noting that this long-term geometric average may also be sensitive to shifting baselines. This is another reason for experts to thoroughly review the data before any status assessment is made.

This case study highlighted requirements and limitations of percentile benchmarks on data-limited CUs. Shifting baselines are one of the challenges of applying this method. If abundance has decreased over time, the resulting percentile benchmark will also decrease as more data is included (Figure E.5). This can arise from a decrease in abundance in the period of data or by an unrecorded high level of abundance before the period of data followed by a decrease before data are available. Thus, a CU with low abundance could be Green status based on the current benchmark, but would be Red using a benchmark with data before decreases in abundance. The result is an overly optimistic view of current status that does not reflect the reality of long-term declines. Two CUs (Southern Coastal Streams and Upper Knight) showed evidence of shifting baselines as abundances decreased over the last several decades (Figure E.5). Decreasing productivity can exacerbate this pattern. As productivity decreases, a larger abundance of spawners would be required to produce the same number of recruits. Experts should thoroughly review historical abundance data and determine where shifting baselines may be occurring, and can adjust benchmarks accordingly. In some cases it may be appropriate to choose benchmarks based on historical data or information prior to declines to avoid shifting baselines (Holt and Folkes 2015). Thus, while they are useful for CUs that lack reliable stock-recruitment information, they cannot be used universally on data-limited CUs.

Existing guidelines and cautions should be incorporated into any LRP analysis using percentile benchmarks. We followed guidelines from Holt et al. (2018) and did not use percentile benchmarks for CUs with low productivity and high exploitation rate (Tables 11, 12). In their simulation study, percentile-based benchmarks overestimated status with harvest rates >40% and α <4, or harvest rates 20-40% and α <2.5. In these cases of low productivity and high harvest rates, more exploration could be done on alternative benchmarks. These could include benchmarks based on Traditional Ecological Knowledge, habitat availability, or other information. If productivity and/or harvest is unknown, low contrast in escapement time-series could be indicators of cases where percentile benchmarks may not be appropriate (Holt et al. 2018). We also note that cases with identical lower and upper benchmarks carry the risk of moving immediately from Green to Red status with time in the Amber status zone (North East Vancouver Island, Upper Knight, Loughborough, Table 11). CUs with shorter time series also have the risk of unreliable percentile benchmarks. Confidence intervals for percentile benchmarks can also be derived by bootstrapping escapement data, accounting for autocorrelation in time-series (Holt et al. 2018; Peacock et al. 2020).

Clark et al. (2014) applied a similar percentile-based approach for Alaskan salmon populations, where applicability of percentiles was categorized in into 3 tiers based on contrast in spawner abundances, harvest rate, and precision of escapement data. They tested the suitability of this tiered approach with theoretical, simulation, and meta-analysis methods using 76 stock-recruitment data sets from Alaska covering all 5 species of Pacific salmon. The goal of these tiers was to choose a Sustainable Escapement Goal (SEG; an upper and lower percentile) as a proxy for keeping escapement within a range that includes S_{MSY} (Clark et al. 2014). Moving to British Columbia, Hilborn et al. (2012) adopted the percentile-based thresholds for evaluating the status of Inside South Coast Chum in BC for the purpose of certification with the Marine Stewardship Council (Hilborn et al. 2012).

Percentile benchmarks are used differently in Alaska and BC. In BC, percentiles are used at the CU scale, while in Alaska they are applied to each river (McKinley et al. 2020). ISC chum includes 296 streams among the seven CUs, with 126 in Strait of Georgia alone. Aggregating over river systems within CUs ignores the distribution of spawning within the CU and may not capture the loss of some less productive streams, rivers, or sub-populations within the CU. This risk is especially relevant in this case study because the data is infilled assuming correlation in spawning escapement within CUs.

An additional source of uncertainty stems from spawner time series that may include the influence of enhancement, which introduces the risk of inflating wild spawner numbers and providing an overly optimistic status assessments. We removed three systems that are highly enhanced (Qualicum and Little Qualicum from spawning channels, and Puntledge from a hatchery) before infilling stream escapements, but hatchery influence may impact time-series for the remaining systems through production and/or straying (Lynch et al. 2020).

We showed that increasing the number of CUs included in CU status-based LRP status assessment gave a more pessimistic status. This is not surprising given the low correlation of CUs within this SMU; we do not expect CUs to be interchangeable. Therefore, using as much data as possible will provide more realistic assessments of status, where those data are reliable. For this SMU where the status of two data-limited CUs, Upper Knight and Bute Inlet, cannot be inferred from data-rich CUs (see Section 5.1), omitting the data-limited CUs from analyses can result in either an SMU status that is data deficient or below the LRP depending on status of remaining data-rich CUs. When the status of at least one of the data-rich CUs is in the Red zone, the CU status-based LRP of 100% of CUs above the Red zone is considered breached. However, if the status of all data-rich CUs are above the Red zone, the SMU is considered data deficient if status of data-limited CUs is unknown because it cannot be inferred. In our case, we could assess status based on trends for these data-limited CUs as applied in the Salmon Scanner. However, in other SMUs, there may be cases where data to estimate trends are not available.

We were not able to estimate aggregate abundance logistic regression LRPs for ISC Chum due to poor model fits of the underlying data. The data were not suited to logistic regression, and aggregate abundance was not a good predictor of the status of component CUs. Abundance for two CUs was regularly two orders of magnitude larger than the smaller CUs (Figure E.2), and correlation in abundances between CUs was generally low (Figure 41). Thus, aggregate abundance can be high mainly due to high abundance CUs while low abundance CUs have Red status, and the SMU is thus below the LRP. This pattern is exacerbated because the two most abundant CUs have the highest correlation in escapement with each other, and generally low correlation with the other CUs (Figure 41). This pattern is also the reason why SMU status can be below the LRP even as aggregate abundances increase (Figure 42). The large geographical range of the SMU, different numbers of populations within each CU, and variation in productivity, threats, and ecosystem conditions help explain these characteristics of the data.

The CUs that were missing observations in some years and required CU-level infilling (Upper Knight and Bute Inlet) were not used in the aggregate abundance LRP analysis because the assumption that escapement is correlated between CUs ignores diversity between CUs and the potential for uncorrelated escapements. Unlike CU status-based LRPs, we did not consider status based on the multidimensional algorithm in the Salmon Scanner for aggregate abundance LRPs. It should also be noted that Upper Knight and Bute Inlet do not represent a random subset of the seven CUs in the Inside South Coast Chum SMU due to their location, watershed characteristics, near-shore marine environment, threats, and environmental conditions (Section 5.1).

6. LESSONS LEARNED FROM CASE STUDY APPLICATIONS

The three SMUs used as case studies were selected to represent a range of levels of data availability, ranging from data-rich to data-limited. For each case study, the set of LRP estimation methods considered (Table 1) was a function of available data and previously developed assessment methods for the SMU. Each case study section includes its own discussion section highlighting conclusions from that case study. In this section, we provide an summary of key lessons learned when looking across all three case studies. These lessons were used to inform the development of guidelines for defining LRPs for Pacific Salmon SMUs, as described in Holt et al. (2023).

Lesson 1: CU status-based LRPs based on the multidimensional algorithm within the Salmon Scanner could be readily estimated for all SMUs over a wide range of data availabilities, and were consistent with the multidimensional approach that has been developed for Wild Salmon Policy assessments. This was not the case for aggregate abundance LRPs.

CU status-based LRPs based on the Salmon scanner could be applied in all three case studies; whereas aggregate-abundance methods required a strong positive relationship between observed aggregate abundance and the log-odds of all CUs being above their lower benchmarks (logistic regression LRP) and / or sufficient data to parameterize a population dynamics model (projection LRP). While the Interior Fraser Coho case study met both of these requirements, WCVI Chinook could only meet the second, and ISC Chum could not meet either of them. The use of the Pacific Salmon Scanner tool to estimate multidimensional statuses for CU status-based LRPs was especially valuable for data-poor SMUs because it allowed a mix of data quality and benchmark types to be applied, depending on what was available for a given CU in a given year. For example, in the ISC Chum case study, applying the Salmon Scanner to develop CU status-based LRPs allowed all seven CUs to be included when assessing SMU status by using alternative trend-based metrics for CUs without percentile benchmarks. The ability to assess CUs lacking abundance-based lower benchmarks is particularly important when SMUs are composed of CUs with low levels of synchrony in which data deficient CUs cannot be represented by proxy, as was the case for ISC Chum.

Lesson 2: The development of metrics and benchmarks on the distribution of spawning within a CU is a high priority to support WSP status assessments, which in turn will support the development of CU status-based LRPs at the SMU-level.

Both the Interior Fraser Coho and WCVI Chinook case studies applied LRP estimation methods that considered the distribution of spawning abundance among smaller sub-units within CUs; however, different approaches were used in each case. For Interior Fraser Coho, we relied on previously established distributional targets that recognized the biological importance of maintaining spawning abundance within 11 identified sub-populations nested within the 5 CUs. For WCVI Chinook, expert opinion brought into the development of the case study identified inlets as an important spatial scale of diversity for the SMU (D. McHugh pers. comm. DFO South Coast Stock Assessment). As a result, LRPs were developed to preserve inlet-scale diversity for this case study instead of CU-scale diversity.

Future research is needed to develop and evaluate distributional metrics and associated benchmarks that delineate WSP status zones. The establishment of distributional benchmarks would allow the distribution of spawning abundance within a CU to be directly incorporated into multidimensional

WSP status assessments, which in turn would enable a standardized approach to considering finer-scale spawning distribution when identifying LRPs at the SMU-level.

Lesson 3: Annual status estimates from aggregate abundance LRPs and CU status-based LRPs will differ from each other in some cases.

While annual status estimates from aggregate abundance methods were generally consistent with estimates from CU status-based methods using the recommended Salmon Scanner tool, they did not always match. For the Interior Fraser Coho case study, status tended to drop below CU status-based LRPs when abundance of individual CUs was low, and drop below aggregate abundance LRPs when aggregate abundances were low. While these conditions corresponded in most years, they did not always. For our case study on Interior Fraser River Coho, we found that the proportion of years with matching status estimates for CU status-based and aggregate abundance LRPs ranged from 72-86%, depending on the method used to estimate CU status.

Lesson 4: Data from all component CUs should be used whenever possible. When data are missing from one or more CUs, careful consideration should be given to the question of whether status can be inferred from other CUs within the SMU. While there may be cases where inference is possible, uncertainty in resulting status estimates will increase, and this uncertainty should be clearly communicated in status assessments.

In the case of ISC Chum, using data from all seven CUs when available (even if only a subset of years) resulted in status dropping below the LRP more frequently than when only a subset of CUs was used in all years. This result occurs because, for CU status-based LRPs, there is an asymmetry in how missing CUs may affect SMU status relative to the LRP. Adding additional CUs may decrease status from above to below the LRP if the additional CU is Red and all other CUs are Amber or Green. However, adding an additional CU will never increase status from below to above an LRP because if a Red CU already exists; the 100% threshold for all CUs to be above Red cannot be met in this case. Given that ISC Chum CUs have low correlations in among-CU spawner abundances over time, and experience different environmental drivers in their freshwater habitats, inferring status of missing CUs from other CUs with data is not recommended. Therefore, status estimates that only include a portion of CUs are potentially biased.

In the case of Interior Fraser Coho, results from missing data scenarios for the logistic regression approach showed that it may be possible to use data-rich CUs as indicators for CUs with missing data. However, logistic regression-based LRPs were more uncertain when more than 1 CUs was missing, and the logistic regression model frequently failed to converge, so caution should be used when applying this method to SMUs with missing data. Furthermore, Interior Fraser Coho display higher levels of among-CU correlations in spawner abundances over time that ISC Chum, so the extent to which this result can be applied to other SMUs is expected to be dependent on the level of covariation in CU status among CUs within an SMU.

Lesson 5: Logistic regression LRPs have several limitations and should only be used when (i) aggregate abundance LRPs are required and (ii) all assumptions of the logistic regression model can be met.

Logistic regression LRPs are empirically derived from past observations of SMU abundance and CU statuses. By fitting a logistic regression to historical data, we identified historical abundance levels associated with probabilities that all component CUs have statuses above their lower benchmarks. Similar to the CU status-based LRP, this aggregate abundance method depends on the outcomes of individual CU assessments, which are sensitive to structural assumptions underlying the CU-level benchmarks and data availability.

Logistic regression-based LRPs could only be estimated for one of our three case study SMUs, which suggests that they may only be an option for a small proportion of SMUs. Even for Interior Fraser Coho where a logistic regression fit was possible, estimates did not converge for all retrospective years, and status estimates were sensitive to missing data. Taken together, our exploration of logistic regression LRPs for our three case studies highlighted some limitations of this approach.

First, logistic regression LRPs are limited to conditions that have been historically observed. This can be a problem when there is poor contrast in historical data, as was the case for WCVI Chinook. In this case, there were no years when all component inlets exceeded their lower benchmarks. However, similar challenges could occur in cases where no CUs drop below their lower benchmarks. The dependence on historically observed conditions is a further limitation when there have been changes in the correlation in populations dynamics among CUs over time such that current (or future) correlations are not represented by historical data.

Second, model diagnostics do not support logistic regressions and their associated LRPs when CU-level abundances are not correlated or only weakly correlated. Here, we found that logistic regression LRPs could be estimated for Interior Fraser Coho (average correlation in spawner abundances among CUs of 0.56), but not for Inside South Coast Chum (average correlation among CUs of 0.12). Also, the wide range in productivities and capacities among CUs for the Inside South Coast Chum case study contributed to the weak relationship between aggregate abundances and CU-level statuses. In general, model diagnostics as described in Section 2 can be used to support or reject logistic regression LRPs. We illustrate how these diagnostics are used to evaluate model fit in Sections 3 and 5.

Finally, preliminary analyses of logistic regression LRPs for Fraser River Sockeye Salmon (not presented in this paper) showed that the method was not easily applied to cyclic stocks.

Lesson 6: Stochastic projections can be used to estimate aggregate abundance LRPs under various assumptions about population dynamics and covariance in dynamics among CUs. This approach allows uncertainties in our understanding of population dynamics to be represented in a more comprehensive way than other LRP methods.

Projection LRPs rely on closed-loop simulation models to quantify the emergent relationship between aggregate SMU abundances and the probabilities that all CUs are above their lower benchmarks, given a predefined level of exploitation. The most important requirements for this approach are CU-specific estimates of stock-recruitment parameters (productivity and capacity) and covariance in recruitment among CUs. Parameter estimates for productivity and capacity can be based on posterior distributions from stock-recruitment analyses (see Interior Fraser Coho case study, Section 3) or more qualitatively from expert input, life-stage models, or watershed-area model estimates (see WCVI Chinook case study, Section 4).

Furthermore, we demonstrated an approach to choosing parameters and model assumptions used in the projections so that correlations in spawner abundances in projections were similar to observed correlations. We recommend that correlations in CUs within projections are explored under various model assumptions, and that model parameters are tuned to derive realistic correlations.

The projection LRP approach is flexible in that allows for consideration of structural uncertainty in SMU population dynamics through the consideration of alternative scenarios. For example, for the WCVI Chinook case study, sensitivity analyses were performed to assess the impacts of correlations in recruitment residuals and variability in exploitation among inlets. For the Interior Fraser Coho study case, structural uncertainty in the formulation of the stock-recruit model was considered through alternative projection scenarios. In this case, we demonstrated how a model-averaging approach could be used to combine projections from these two scenarios into a single LRP.

Future implementations of projection LRPs could also consider temporal shifts in stock-recruitment parameters, the potential for depensatory population dynamics at low population size, and future variability in fishery exploitation rates. Decisions about which scenarios to consider should be made on a case-by-case basis, and should be dependent on current understandings of key uncertainties for each SMU.

Lesson 7: Projection LRPs are highly sensitive to exploitation rates

Sensitivity analyses showed that projection LRPs are sensitive to the assumed levels of exploitation in the projections. Higher exploitation rates resulted in higher required SMU aggregate abundance to ensure that all CUs remain above their lower benchmarks. The sensitivity to exploitation rate increases as variability in stock-recruitment parameters among CUs increase and as uncertainty in parameter estimates increase. This property of projection LRPs is explored in Appendix D. Therefore projection LRPs developed under historical and current exploitation rates cannot necessarily be used as a basis for evaluating alternative management procedures. However demonstrating the changes in aggregate abundances required for all CUs to be above lower benchmarks (i.e. changes in projection LRP) under different exploitation scenarios may help analysts and managers understand the implications of changing exploitation rates on the ability to achieve WSP objectives.

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APPENDIX A. DATA AND ANALYSIS LINKS

Code for data and analysis for the case studies are available on the Git Hub repository:

pacific-salmon-assess/SalmonLRP_RetroEval

Code for the samSim closed loop simulation modelling tool used to conduct stochastic projections are available on the 'LRP' branch of the following Git Hub repository:

pacific-salmon-assess/SalmonLRP_samSim

Code for the write-up of this report are available on the Git Hub repository:

pacific-salmon-assess/SalmonLRP_csasdown

APPENDIX B. SAMSIM MODEL DOCUMENTATION

`samSim` is the closed loop simulation modelling tool used for calculation of the projection-based LRPs. An overview of `samSim` and the code can be found in the LRP project github page. samSim has been previously used to evaluate harvest control rule performance relative to recovery potential (Freshwater et al. 2020; Holt et al. 2020). We created a modified version of samSim to support LRP estimation for this paper.

Updated functionality for the LRP version of samSim include:

- The option to sample stock-recruitment parameter sets directly from an estimated Bayesian joint posterior distribution.
- The addition of a stock-recruitment function that includes an environmental co-variate, as well as specification of future variability in the environmental co-variate (required for Interior Fraser Coho case study).
- The option to initialize population dynamics for individual CUs at unfished equilibrium when historical recruitment data are not available. While this option would not be appropriate for projections aimed at estimating recovery from a current state, it can be used to estimate projection-based LRPs because we are only interested in the underlying relationship between aggregate abundance and the probability individual CUs will be above their lower benchmark at equilbrium levels.
- The option to include a log-normal bias-correction factor of $-\sigma^2/2$ to recruitment projected using one of the two available Ricker stock-recruit models. This option was added to accommodate cases in which samSim is parameterized using stock-recruitment parameters that have been corrected for log-normal bias to represent expected (mean) parameters. The log-nomral bias correction is commonly applied in stock-recruit modelling because the expected value of e$\hat{}\sigma$ is e$\hat{}\sigma^2/2$ rather than zero when recruitment deviations are normally distributed (Cox et al. 2019; Ohlberger et al. 2019; Olmos et al. 2019; Forrest et al. 2020). When input parameters have been corrected for this log-normal bias, the bias correction must also be added to projections (as in Weir et al. (in press))[1]. We use a log-normal bias correction factor for all of our case study analyses.
- Specification of variability in exploitation rates as a function of both variability among years and variability among CUs.

This appendix describes the `samSim` model equations and the structure. We focus on providing detailed descriptions of the modeling options used for LRP study cases but include brief mentions of other model extensions already implemented within `samSim`. `samSim` includes two population scales, which can be applied to one Conservation Unit (CU) with component spawning populations or one Stock Management Unit (SMU; referred to as Management Unit, MU, in the `samSim` code and this appendix) with component CUs. For the projection-based LRP analysis two SMUs and their component CUs were used as study cases: the West Coast of Vancouver Island (WCVI) Chinook SMU (with three CUs) and the Interior Fraser Coho Salmon SMU (with five CUs). The following sections in this appendix are organized similarly to the `samSim` code, for this reason the subheadings of this appendix can be read as pseudo code. The simulation model has two main phases: Model Priming and Projections. The model priming phase recreates data for past years, either by populating objects with observed data or by generating population trends

[1]Weir, L., et al. Recovery Potential Assessment for 11 Designatable Units of Chinook Salmon, Oncorhynchus tshawytscha, Part 2: Elements 12 to 22. DFO Can. Sci. Advis. Sec. Res. Doc. In press

based on input parameters. The projection phase generates data for future years based on the input data and parameters as well as the user defined scenarios and management procedures. Model indicies are defined in Table B.1, model parameters and inputs are defined in Table B.2 and the modeled quantities are defined in Table B.3. Detailed definitions of the input data and parameters are provided in the repository's README file.

Table B.1. List of `samSim` model indexes.

Notation	Definition
y	year
$nPrime$	number of years in the priming phase
Y	number of years in the projection phase
j	age
J	maximum age
i	Conservation Unit (CU)
I	Number of conservation units
n	Nation: U.S. or Canada

Table B.2. List of `samSim` model parameters and user input variables.

Notation	Definition
α_i	Ricker productivity parameter
β_i	Ricker inverse capacity parameter or 1/spawners at maximum recruitment
σ_i	Standard deviation for recruitment error
ρ	Temporal autocorrelation coefficient in recruitment residuals
γ	Survival covariate scalar
$covMat$	Covariance matrix used to generate recruitment deviations with correlation among CUs
$\overline{ER}_n$	Nation specific long term average exploitation rate
$\overline{p}_{i,j}$	Mean proportions of recruits at age
τ_i	Multivariate logistic variability parameter for proportions of recruits at age
$\overline{sv}$	Mean survival covariate
σ_{sv}	Standard deviation for survival covariate
Υ	Scalar to cap recruitment values
φ	Multivariate logistic variability parameter for observed proportions of recruits at age
$\overline{\omega}$	mean for forecast lognormal error
σ_ω	variance for forecast lognormal error
$CV(\overline{ER}_n)$	CV for MU-specific exploitation rate variability
$CV(ER_{y,i,n})$	CV for CU-specific exploitation rate variability
ψ	Proportion of the catch associated with mixed-stock catch
$ERagg_{y,i}$	Total exploitation rates
κ	multivariate logistic variability parameter associated with assigning catch in mixed-stock fisheries to the correct CU
$\hat{\alpha}_{y,i}$	Estimated Ricker productivity parameter
$\hat{\beta}_{y,i}$	Estimated Ricker inverse capacity parameter

Table B.3. List of `samSim` model variables.

Notation	Definition
$S_{y,i}$	Spawners
Seq_i	Equilibrium spawners
$RY_{y,i}$	Calendar year recruitments (returns)
$p_{y,i,j}$	Proportions of returns at age
$R_{y,i}$	Brood year recruits
$Ra_{y,i,j}$	Age specific brood year recruits
$w_{y,i}$	Recruitment deviations with temporal auto-correlation
$v_{y,i}$	Recruitment deviations
$sv_{y,j}$	Brood year survival covariate
$svCY_y$	Calendar survival covariate
wsv_y	Survival covariate without bias correction
$Smsy_i$	Spawners that produce the maximum sustainable yield
$Sgen_i$	Number of spawners required to recover to $Smsy_i$ in one generation in the absence of fishing
α'_i	Adjusted α_i parameters for calculation of time invariant management benchmarks
$obsp_{y,i,j}$	Observed proportions of recruits at age
$f(R_{y,i})$	Forecast of calendar year recruitment
$ER^{MU}_{y,n}$	Exploitation rate including only MU-specific variability
$d1$, $d2$	Shape parameters for Beta distribution used to generate MU-specific variability
ϑ	Standard deviation for MU-specific exploitation rate variability
$ER_{y,i,n}$	Exploitation rate including MU- and CU-specific variability
$o1$, $o2$	Shape parameters for Beta distribution used to generate CU-specific variability
$\phi_{y,i,n}$	Standard deviation for CU-specific exploitation rate variability
$C_{y,i,n}$	Catch
$mC_{y,i}$	Mixed-stock Canadian catches
$sC_{y,i}$	Single-stock Canadian catches
$ERagg_{y,i}$	Aggregate exploitation rates
$obsC_{y,i,n}$	Observed nation-specific catches
$obsmC_{y,i}$	Observed mixed-stock Canadian catches

Notation	Definition
$obssC_{y,i}$	Observed single-stock Canadian catches
$u_{y,i,n}$	Lognormal error component of observed catches
$pCU_{y,i}$	Proportion of catches from each CU
$obspCU_{y,i}$	Observed proportion of catches from each CU
$obsS_{y,i,n}$	Observed spawners
$z_{y,i}$	Lognormal error component of observed spawners
$obsRY_{y,i,n}$	Observed calendar year recruits
$obsER_{y,i,n}$	Observed exploitation rates

B.1. MODEL PRIMING

The priming phase, or model initialization, represents the past data for CUs being modeled. It is used to represent true and observed abundances before starting the projection trials. This phase loops over a number of past years ('nPrime') and reconstructs recruitment time series for past years. The simulations can be initialized in two ways: with existing recruitment data or with user defined parameters, if recruitment data are not available.

B.1.1. Recruitment Data are Available

If spawner-recruitment data are available, the number of initialization years 'nPrime' is defined based on the length of the longest CU time series available. The spawners, recruits, catch and exploitation rate objects are populated with the input data. If catch and/or exploitation rate data are not available, those values are set to zero.

B.1.2. Recruitment Data are not Available

When Recruitment data are not available, the 'nPrime' is set to 10 times the maximum age of recruits. The first step on this routine is to retrieve the stock-recruitment parameters. The user has the option of providing either one set of values to be used across all trials or many sets of parameter estimates, typically from MCMC samples. If MCMC samples are provided, a different set of parameters is used for each simulation trial.

The stock-recruitment parameters can be altered according to the user defined scenarios, e.g., to simulate regime shifts. `samSim` includes options to adjust the productivity parameter, α_i, the capacity parameter β_i, and the recruitment standard deviations, σ_i. The LRP case studies do not include adjustments or changes in productivity over time, therefore we will not describe the parameter adjustment options in this appendix. Recruitment is assumed to be correlated between the CUs, where the variance-covariance matrix is calculated based on CU-specific recruitment variances and the correlation matrix in recruitment residuals specified in an input files.

Once stock-recruitment parameters are defined, the number of spawners is initialized. The number of spawners is set at equilibrium for the first 6 years (the maximum possible number of age classes) and then calculated based on recruitment and exploitation rates in the previous years (Equation B.1). If the calculated number of spawners is lower than the user inputted extinction threshold, then the number of spawners is set to zero. Recruitment error is given by a multivariate normal distribution reflecting the recruitment covariance among CUs.

$$S_{y,i} = \begin{cases} Seq_i & \text{if } y = \leq 6 \\ RY_{y,i} \cdot (1 - \overline{ER}_n) & \text{otherwise} \end{cases} \tag{B.1}$$

$$Seq_i = \alpha_i / \beta_i \tag{B.2}$$

The age structure of the recruitment by brood year is computed following a multivariate logistic error structure based on the long term average age structure for each CU, $\overline{p}_{i,j}$ and the CU-specific variability parameter τ_i (Schnute and Richards 1995) (Equation B.3. The age structure error can vary or be held constant among CUs. Calendar year recruitment is then calculated after the sixth year of the priming phase. It is the product of the brood year recruitment and the age structure of the recruits (Equation B.4.).

$$p_{y,i,j} \sim \text{Multivariate Logistic}(\overline{p}_{i,j}, \tau_i) \tag{B.3}$$

if y>6:

$$RY_{y,i} = \sum_j (R_{y-j,i} \cdot p_{y-j,i,j}) \tag{B.4}$$

The computation of brood year recruitment follows the recruitment curve of choice. For the LRP version of `samSim`, three options for the recruitment curve are available: a simple Ricker curve (equation B.5 when $\rho = 0$), Ricker curve with temporal autocorrelation in recruitment error (equation B.5), and Ricker curve with a smolt-to-adult survival covariate (Equations B.8 and B.9, also described in Chapter 3). Recruitment error is assumed to be correlated among CUs for all versions of the Ricker curve. Random recruitment deviates can be generated with multivariate t or multivariate normal distributions, that can be symmetric or skewed. The study cases used in this report all assume that recruitment deviates come from a symmetrical multivariate normal distribution (Equation B.7).

$$R_{y,i} = S_{y,i} \cdot e^{\alpha i - \beta i \cdot S_{y,i} + w_{y,i} - \frac{\sigma_i^2}{2}} \tag{B.5}$$

$$w_{y,i} = \begin{cases} v_{y,i} & \text{if } y = 1 \\ w_{y-1,i} * \rho + v_{y,i} & \text{if } y > 1 \end{cases} \tag{B.6}$$

$$v_{y,i} \sim N(\mu = 0, covMat) \tag{B.7}$$

$$Ra_{y,i,j} = p_{y,i,j} \cdot S_{y,i} \cdot e^{\alpha_i - \beta_i \cdot S_{y,i} + \gamma_i \cdot sv_{y,j} + v_{y,i} - \frac{\sigma_i^2}{2}} \tag{B.8}$$

$$R_{y,i} = \sum_j Ra_{y,i,j} \tag{B.9}$$

For the Ricker model with the smolt-to-adult survival covariate, the covariates for each calendar year are generated following a normal distribution with user defined mean and variance (Equation B.12). The distribution of survival covariates is truncated between maximum and minimum values provided in the input files. The brood year survival covariates, $Surv_{y,j}$, are currently populated following the dominant life history types from Interior Fraser Coho. For that stock, fish with a 3-year life cycle differ from those with a 4-year life cycle in the number of years spent in freshwater as juveniles, i.e., 18 months vs 30 months; both life cycles spend 18 months at sea before returning to spawn. Fish with a 2-year life cycle spend 18 months in the freshwater environment and only 6 months at sea before returning as jacks. This life history results in the survival covariate being lagged by one year for ages 2 and 3 Equation B.10). The exception is the first two years of the priming loop, when no lag is applied to the covariates.

$$sv_{y,j} = \begin{cases} svCY_{y-1} & \text{if } j \leq 3 \\ svCY_y & \text{otherwise} \end{cases} \tag{B.10}$$

$$svCY_y = wsv_y - \frac{{\sigma_{sv}}^2}{2} \tag{B.11}$$

$$wsv_y \sim N(\overline{sv}, \sigma_{sv}) \tag{B.12}$$

Recruitment numbers produced with either formulation of the Ricker model are capped. The default maximum recruitment value is $3 \cdot S_{eq}$, but the scalar can be modified by the user via the variable (Equation B.13). In addition, if the generated recruitment is lower than the user defined extinction threshold, then recruitment is set to zero.

$$R_{y,i} = min(R_{y,i}, \Upsilon \cdot Seq_i) \tag{B.13}$$

Although in our implementation of `samSim` for Interior Fraser Coho with smolt-to-adult survival covariate, data were used to prime the model, equations for simulating dynamics during this period are provided here for completeness. The equations for simulating population dynamics are also used in the projection phase of the model (see below).

B.1.3. Compute Management Quantities and Benchmarks

In the priming loop, the management quantities and benchmarks are only calculated in the last two generations. The management benchmarks are calculated according to three options: “stockRecruit”, “percentile” and “habitat”. `samSim` has the capability of estimating management quantities and benchmarks on a yearly basis, relying on the data obtained from the beginning of the time series to the current simulation year. However for the purpose of the LRP study cases, time invariant management benchmarks were used. For this reason we omit the time index, y, from the notation used for the management quantities.

If the “stockRecruit” option is used, the management quantities are $Smsy_i$ and $Sgen_i$ calculated based on the stock-recruitment parameters. When the model with the survival covariate is used, the α_i parameter is modified to incorporate the survival component (Equation B.14). In order to keep the management benchmarks constant through time, the long term average of the survival covariate is used. $Smsy_i$ is calculated following the explicit solution provided by Scheuerell (2016) using the Lambert W function (Equation B.15). $Sgen_i$ is estimated by solving Equation B.16 numerically, as described by Holt et al. (2009). The lower benchmark is set to $Sgen_i$ and the upper benchmark is set to 80% of $Smsy_i$.

$$\alpha'_i = \begin{cases} \alpha_i + \gamma_i \cdot \overline{sv} & \text{for Ricker with survival} \\ \alpha_i & \text{for simple Ricker} \end{cases} \tag{B.14}$$

$$Smsy_i = \frac{1 - W(e^{1-\alpha'_i})}{\beta_i} \tag{B.15}$$

$$Smsy_i = Sgen_i \cdot e^{\alpha'_i - \beta_i \cdot Sgen_i} \tag{B.16}$$

If the "percentile" benchmark option is chosen, the upper benchmark is set to the 50th percentile of historical spawners ($S_{1:y,i}$). The lower benchmark is set to the 25th percentile of historical spawners. Note, percentile-based benchmarks were not implemented in our case studies for projection-based LRPs. Future applications could vary the percentiles used as lower and upper benchmarks as recommended in Holt et al. (2018). If the "habitat" benchmark option is chosen, the benchmarks are computed using the same approach as in the "stockRecruit" option. The difference is in the origin of the stock-recruit parameters, i.e., from the habitat model instead of spawner-recruitment curve.

B.1.4. Infill Missing Data

The last step of the model priming is infilling, which is only relevant if stock-recruitment data are available and there are gaps in the last 12 years of the time series. Any gaps in the last 12 years of the Spawners and Recruits time series are infilled with a geometric mean of the entire priming period. In the priming phase, we assume that all variables are known without error, therefore all observations are set to the true simulation values, i.e., no observation error is added.

B.2. MODEL PROJECTIONS

The model projection phase is used to represent future potential outcomes. The steps in this phase will depend on the scenarios and management procedures selected by the user, and therefore will vary depending on the model application. In the following section, we list all steps in the order they appear in the code and indicate in the text if the step was used for the LRP case studies. Similarly to the priming phase, the subheadings in this section can be read as pseudocode. The projections run for each trial from year `nPrime + 1` to `Y`, the latter being the number of projection years defined by the user.

B.2.1. Specify Stock Recruitment Parameters

Similarly to the priming phase, the first step on the projection loop is to define the stock-recruitment parameters. The β_i and σ_i parameters are fixed through time and were already defined in the priming phase. However, if the user specifies productivity changes through time, then the productivity parameter $\alpha_{y,i}$ is adjusted every year following a linear trend. A detailed description of the algorithm used to generate productivity trends is out of the scope of this report as the study cases do not include scenarios with productivity changes. As the productivity parameter is held constant in the study cases, we will continue to use the time-invariant notation (α_i) for the parameter in the sections to follow.

B.2.2. Project Management Benchmarks

Once α_i is specified, the true management quantities $Smsy_i$ and $Sgen_i$ for the projection year are computed following Equations B.15 and B.16. The management benchmarks can be re-estimated every year or set by the normative period, i.e., last year of the priming phase, `nPrime`. The study cases in this report use the normative period management benchmarks.

B.2.3. Project Observed Recruitment

In this step, we compute the observed proportions of returns at age and the observed recruitment for each brood year. The observation error for the proportions of returns at age is given by a multivariate logistic error structure as described by Schnute and Richards (1995). Observation error for the proportions of returns at age is not included in the LRP study cases, i.e., the variability parameter, φ, is set to zero.

$$obsp_{y,i,j} \sim \text{Multivariate Logistic}(p_{y,i,j}, \varphi) \tag{B.17}$$

The observed recruitment by brood year is retrieved by multiplying the true recruitment at age for each calendar year by the vector of observed proportions at age in the returns (Equation B.18).

$$obsR_{y-j,i} = \sum^{j}(RY_{y-j,i} \cdot obsp_{y-j,i,j}) \tag{B.18}$$

B.2.4. Project Recruitment Forecast

When forecast error is included in the projection scenarios, it is generated by adding lognormal error around the calendar year recruitment (Equations B.19 and B.20). The error distribution is also truncated between the 0.0001 and 0.9999 quantiles to avoid extreme forecast values. Forecast error is not considered in the LRP study cases.

$$f(RY_{y,i}) = RY_{y,i} \cdot exp(\omega_{y,i}) \tag{B.19}$$

$$\omega_{y,i} \sim N(\overline{\omega}, \sigma_{\omega}) \tag{B.20}$$

B.2.5. Project Realized Catches

The next step is to calculate the realized catches following a harvest control rule. Both study cases in this report use the fixed exploitation rate harvest control rule. In this option, the catch is the product of calendar year recruits and fixed exploitation rate over all projection years (Equation B.29). However, even though the harvest control rule specifies fixed exploitation rate, the realized exploitation rates vary from year to year due to changes in population distribution and fisheries dynamics. In this section we describe the layers of variability added to the simulated catches. Two layers of variability are considered in `samSim`, these represent MU-specific variability and CU-specific variability. Both uncertainty layers are implemented through draws of exploitation rate values from beta distributions. Currently only the Canadian catches include the annual added variability. In the LRP study cases, both U.S. Catches and Canadian single-stock catches are set to zero, therefore only the Canadian mixed-stock catches are implemented.

The first layer of catch variability is implemented at the MU level. The error is assumed to be the same for all CUs within an MU. The mean and variance for the MU level error are defined in the input files and then transformed into shape parameters for the Beta distribution draw (Equations B.21-B.22).

$$ER^{MU}_{y,n} \begin{cases} \sim Beta(d1, d2) & \text{n=Canada} \\ = \overline{ER}_n & \text{n=U.S.} \end{cases} \tag{B.21}$$

$$d1 = \overline{ER_n}^{\,2} \cdot \left(\frac{1 - \overline{ER_n}}{\vartheta^2} - \frac{1}{\overline{ER_n}} \right) \tag{B.22}$$

$$d2 = d1 \cdot \frac{1}{\overline{ER_n} - 1} \tag{B.23}$$

$$\vartheta = CV(\overline{ER_n}) \cdot \overline{ER_n} \tag{B.24}$$

In the second layer, CU-specific exploitation rates are drawn from a beta distribution using the output exploitation rate from the first layer as mean and CU-specific CV defined in the input files. The mean and CVs are transformed into shape parameters for the Beta distribution draws (Equations B.25-B.28). The Catches are then computed by multiplying the CU specific ER and the calendar year recruits Equation B.29.

$$ER_{y,i,n} \begin{cases} \sim Beta(o1_{y,i}, o2_{y,i}) & \text{n=Canada} \\ = \overline{ER_n} & \text{n=U.S.} \end{cases} \tag{B.25}$$

$$o1_{y,i} = (ER^{MU}_{y,n})^2 \cdot \left(\frac{1 - ER^{MU}_{y,n}}{\phi^2_{y,i,n}} - \frac{1}{ER^{MU}_{y,n}} \right) \tag{B.26}$$

$$o2_{y,i} = o1_{y,i} \cdot \frac{1}{ER^{MU}_{y,n} - 1} \tag{B.27}$$

$$\phi_{y,i,n} = CV(ER_{y,i,n}) \cdot ER^{MU}_{y,n} \tag{B.28}$$

$$C_{y,i,n} = ER_{y,i,n} \cdot RY_{y,i} \tag{B.29}$$

The catch for Canada is further divided in two components, mixed-stock fishery and single-stock fisheries (Equations B.30 and B.31). Single-stock fisheries were not included in our LRP analyses, setting $psi_{y,i}$ =1, where:

$$mC_{y,i} = C_{y,i,n=Canada} \cdot \psi_{y,i} \tag{B.30}$$

$$sC_{y,i} = C_{y,i,n=Canada} \cdot (1 - \psi_{y,i}) \tag{B.31}$$

The next step is to compute the aggregate exploitation rate and the remaining number of spawners (Equations B.32 and B.33).

$$ERagg_{y,i} = \frac{\sum^n C_{y,i,n}}{RY_{y,i}} \tag{B.32}$$

$$S_{y,i} = RY_{y,i} \cdot (1 - ERagg_{y,i}) \tag{B.33}$$

B.2.6. Project Observed Data

In this step, observation error is added to the quantities calculated in the current time step. Observation errors were not included in our implementation for LRPs because LRPs were derived from true underlying population dynamics without observation errors and the management procedure applied (constant exploitation rates) did not require information on observed abundances.

Catch observation error is given by a log normal distribution (Equations B.34-B.36), the distribution is truncated between the 0.0001 and 0.9999 quantiles. If the catch is taken in a mixed-stock fishery, additional multivariate logistic error is incorporated to account for uncertainty in the stock assignment process (Equation B.38).

$$obsC_{y,i,n} = \begin{cases} C_{y,i,n} \cdot u_{y,i,n} & \text{n=U.S.} \\ obsmC_{y,i} + obssC_{y,i} & \text{n=Canada} \end{cases} \tag{B.34}$$

Canadian mixed-stock fisheries observed catches:

$$obsmC_{y,i} = mC_{y,i} \cdot u_{y,i,n} \cdot obspCU_{y,i} \tag{B.35}$$

Canadian single-stock fisheries observed catches:

$$obssC_{y,i} = sC_{y,i} \cdot u_{y,i,n} \tag{B.36}$$

$$u_{y,i,n} \sim logN(0, \sigma_C) \tag{B.37}$$

$$obspCU_{y,i} \sim \text{Multivariate Logistic}(pCU_{y,i}, \kappa) \tag{B.38}$$

$$pCU_{y,i} = \frac{mC_{y,i}}{\sum^{i} mC_{y,i}} \tag{B.39}$$

Observed number of spawners is given by a log normal distribution truncated between the 0.0001 and 0.9999 quantiles (Equation B.40). The observed recruitment is the sum of observed catches and observed spawner numbers (Equation B.42). The observed exploitation rate is directly calculated by dividing the observed catches by the observed recruitment (Equation B.43).

$$obsS_{y,i} = S_{y,i} \cdot \cdot z_{y,i} \tag{B.40}$$

$$z_{y,i} \sim logN(0, \sigma_S) \tag{B.41}$$

$$obsRY_{y,i} = \sum^{n} obsC_{y,i,n} + obsS_{y,i} \tag{B.42}$$

$$obsER_{y,i} = \frac{\sum_n obsC_{y,i,n}}{obsRY_{y,i}} \tag{B.43}$$

B.2.7. Run Stock Assessment and Calculate Management Quantities

This next phase of the projection loop simulates salmon stock assessment analysis. The linearized simple Ricker stock-recruit curve is fit to the observed data and $\hat{a}_{y,i}$ and $\hat{b}_{y,i}$ are estimated. Again, this step was not implemented for LRP analyses, which used benchmarks calculated from true underlying parameters provided as inputs (i.e., from a normative period).

$$log\left(\frac{obsR_{1:y,i}}{obsS_{1:y,i}}\right) = \hat{\alpha}_{y,i} - \hat{\beta}_{y,i} \cdot obsS_{y,i} \tag{B.44}$$

The management quantities, i.e., $Sgen$ and $Smsy$ or Spawners quantiles, can then be recalculated based on the estimated stock-recruitment parameters and the observed time series of spawners using the same procedure described in section B.1.3.

B.2.8. Project Population Dynamics

In this section the brood year recruitment for the current projection year is computed. The first step is to generate the smolt-to-adult survival estimates which are used to project recruitment when the Ricker model with survival covariates is applied. The survival covariates are generated using the method described in Section B.1.2 and Equations B.12 and B.10. Smolt-to-adult survival covariates are considered to be constant across CUs.

The following step is to compute the age structure of the returns with random error, which follows the same procedure described in Section B.1.2. The age structure follows a distribution with mean age structure and standard deviation for each CU given in the input files.

In the next step generates recruitment deviations, which are computed with multivariate normal distribution, reflecting the recruitment covariance among C Us. Recruitment is then calculated following the same procedure described in SectionB.1.2 and using Equation B.5 for the simple Ricker model, or Equation B.8 for the Ricker model with survival covariates.

The last step of the projection loop is to compute the true and observed upper and lower benchmarks, which are based on the management quantities described in the previous section (Section B.2.7. These are either stock-recruit or percentile benchmarks, as described in section B.1.3 computed based on the true and observed spawner abundances.

APPENDIX C. SUPPORTING INFORMATION FOR INTERIOR FRASER COHO CASE STUDY

C.1. ASSESSMENT OF CU REPRESENTATIVENESS BASED ON GUIDELINES CRITERIA

We considered the 4 criteria identified in Holt et al. (2023) to evaluate if status of any one CU within this SMU could be inferred from the remaining CUs; these criteria included similarity in (i) threats, (ii) environmental conditions and drivers, (iii) life history and (iv) population capacity. Although statuses are available for all CUs in this SMU, we consider the application of these criteria to evaluate how decisions about whether CU status can be inferred from other CUs based on these criteria differ from the results of sensitivity analyses presented in the main paper. As part of these sensitivity analyses, we explored how removing one or two CUs affected LRP estimation and status assessments against the LRP.

In an assessment of threats for Interior Fraser Coho completed as part of the 2018 Recovery Potential Assessment, Arbeider et al. (2020) ranked a comprehensive set of threats on a scale of high, medium, low, and unknown. The dominant threats to this SMU are from activities related to forestry, forest fires, agriculture, and urban and rural development. Specific threats arising from these activities included the modification of catchment surfaces, effluents from agriculture and forestry, and linear development, which is defined as the straightening and channelization of streams (Arbeider et al. 2020). While impacts from a given activity may be higher in some CUs than others, the interconnected threats stemming from multiple activities, as well as cumulative impacts, mean that it is hard to isolate one CU that experiences threats differently than another. Furthermore, extensive agricultural and linear development in the lower Fraser River, which all Interior Fraser Coho smolts migrate through, and a proportion of juveniles rear in, means that there is a possibility that all CUs are affected by threats stemming from agriculture and linear development.

When evaluating the similarity of environmental conditions and drivers among CUs, we looked to multiple ecosystem classification schemes. The first scheme, Marine Adaptive Zones, applies to the riverine, estuarine, and marine habitats utilized by juveniles, and were used to inform CU delineation (Holtby and Ciruna 2007). For Interior Fraser Coho, all CUs belongs to the same Marine Adaptive Zone, Georgia Strait, suggesting that environmental conditions and drivers in these habitats are shared among all CUs. The second scheme, Freshwater Adaptive Zones (FAZ), represents the freshwater ecological drainage units, and was also used to delineate CUs (Holtby and Ciruna 2007). For Interior Fraser Coho, each CU belongs to a unique FAZ, which is often (but not always) the case with CU delineation. Finally, we looked at Biogeoclimatic Zones derived from vegetation classification. All five Interior Fraser Coho CUs included a mix of Biogeoclimatic Zones with Interior vegetation, including Interior Douglas Fir, Bunchgrass, Montane Spruce, and Engelmann Spruce. The Middle Fraser CU included some boreal vegetation zones, such as Sub-Boreal Pine and Sub-Boreal Pine–Spruce. The Fraser Canyon CU was the only CU that included a more coastal vegetation type, Coastal Western Hemlock. However, it is not well understood how this difference would affect environmental conditions and drivers. More work is needed to better understand whether these differences are substantial enough to affect the representativeness of CUs.

All Interior Fraser Coho CUs have the same predominantly 3-year life history, with the proportion maturing at age 3 similar among CUs.

Finally, we use the estimated S_{REP}, which is the spawner abundance at which the stock replaces itself, from a base Ricker model fit (described in the main body of the paper) to look for differences in habitat capacity among CUs. S_{REP} values ranged from 4023 (Fraser Canyon CU) to 14,595 (North Thompson CU), with S_{REP} values for the other three CUs evenly spaced within this range (Middle Fraser = 6925, Lower Thompson = 8614, South Thompson = 10,498). Given that there was no clear outlier in terms of extremely low or extremely high capacity, it is unclear whether these five CUs would respond differently to threats based on habitat capacity alone.

Based on similarities in threats, life history, population capacity, and some shared environmental drivers (i.e., lower Fraser River, estuary, and marine environments), we found few significant indicators that would have prevented us from inferring CU status for one CU from neighboring CUs prior to our case study analyses, especially when data from several other CUs are available to represent the missing CU. However, the large diversity in environmental conditions on land, Biogeoclimatic zones, and unique weather events, combined with the generally large areas encompassed by each CU, does require careful consideration when inferring CU status. For example, consideration may be required when environmental catastrophes occur that only impact individual CUs, or parts of CUs, such as landslides, floods, droughts, and forest fires; depending on the duration of the impacts of such events. An example of a recent catastrophic event is the Big Bar landslide, which only impacted one subpopulation within the Middle Fraser CU.If the impacts of this slide persist without mitigation, the status of the Middle Fraser CU would likely not be coupled with adjacent CUs. We also note that the Fraser Canyon CU may be the most unique in terms of it having the smallest capacity and a more coastal dominated biogeoclimatic zone, so special consideration may be given to cases in which CU-level data is missing from Fraser Canyon.

C.2. BAYESIAN STOCK-RECRUITMENT MODEL PARAMETER ESTIMATES

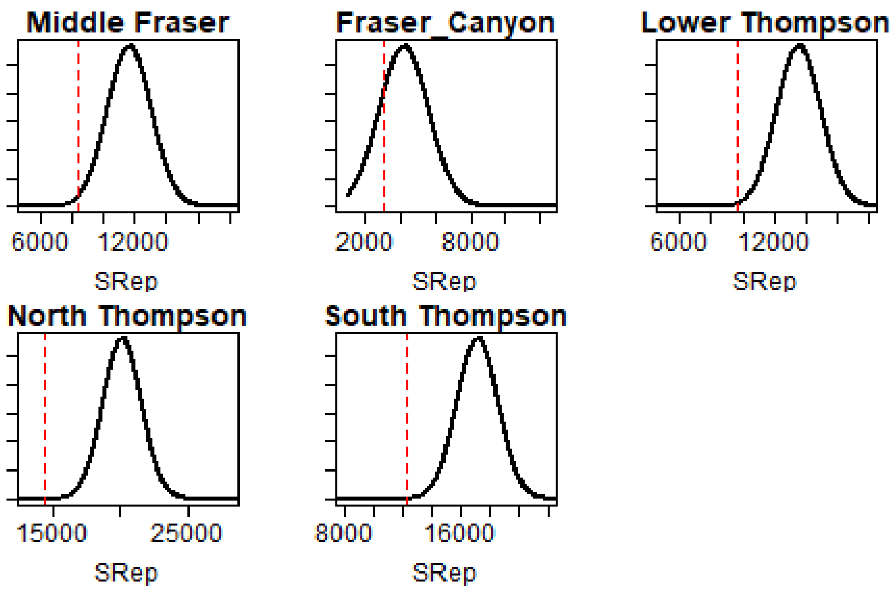

Figure C.1. Prior distribution for S_{REP} (the spawner abundance level at which the stock replaces itself) used when fitting the Ricker_priorCap model. The red dashed line shows the maximum likelihood estimate of S_{REP} from the base Ricker model stock-recruitment fit. The mean of the SRep prior was set to 1.4 times the maximum likelihood estimate.

Table C.1. *Summary of posterior distribution mean and quantiles (5%, 50%, and 95%) for stock-recruit model parameters and Sgen lower benchmark from the Ricker model fit. The 'adjProd' parameter is the effective productivity, α', from Equation 15 in the main document.*

CU	Variable	Mean	P05	P50	P95
Middle Fraser	adjProd	2.3800	1.7300	2.3200	3.2000
	alpha	2.8800	2.2000	2.8700	3.6200
	beta	0.0001	0.0001	0.0001	0.0002
	gamma	0.4200	0.2900	0.4200	0.5600
	Sgen	1,646.0000	870.0000	1,576.0000	2,663.0000
	sigma	0.4500	0.3400	0.4400	0.6000
Fraser Canyon	adjProd	6.2600	3.1600	5.6700	11.2100
	alpha	3.7900	2.9200	3.7700	4.7300
	beta	0.0004	0.0003	0.0004	0.0006
	gamma	0.4200	0.2900	0.4200	0.5600
	Sgen	314.0000	52.0000	266.0000	748.0000
	sigma	0.7600	0.5700	0.7400	1.0100
Lower Thompson	adjProd	2.5600	1.5700	2.4500	3.9600
	alpha	2.9300	2.2000	2.9300	3.6900
	beta	0.0001	0.0000	0.0001	0.0001
	gamma	0.4200	0.2900	0.4200	0.5600
	Sgen	1,977.0000	970.0000	1,841.0000	3,429.0000
	sigma	0.5900	0.4500	0.5800	0.7800
North Thompson	adjProd	3.1700	2.2900	3.0900	4.2900
	alpha	3.1700	2.5100	3.1600	3.8700
	beta	0.0001	0.0000	0.0001	0.0001
	gamma	0.4200	0.2900	0.4200	0.5600
	Sgen	2,482.0000	1,557.0000	2,409.0000	3,650.0000
	sigma	0.4100	0.3100	0.4100	0.5500
South Thompson	adjProd	2.4700	1.5900	2.3700	3.6600
	alpha	2.9100	2.1700	2.8900	3.7000
	beta	0.0001	0.0000	0.0001	0.0001
	gamma	0.4200	0.2900	0.4200	0.5600

CU	Variable	Mean	P05	P50	P95
	Sgen	2,573.0000	1,291.0000	2,365.0000	4,667.0000
	sigma	0.5700	0.4300	0.5600	0.7500

Table C.2. Summary of posterior distribution mean and quantiles (5%, 50%, and 95%) for stock-recruit model parameters and Sgen lower benchmark from the Ricker_priorCap model fit. The 'adjProd' parameter is the effective productivity, α', from Equation 15 in the main document.

CU_Name	Variable	Mean	P05	P50	P95
Middle Fraser	adjProd	2.29	1.64	2.22	3.19
	alpha	2.58	1.87	2.57	3.35
	beta	0.00	0.00	0.00	0.00
	gamma	0.37	0.23	0.36	0.51
	Sgen	2,515.00	1,339.00	2,452.00	3,932.00
	sigma	0.52	0.39	0.50	0.69
Fraser Canyon	adjProd	6.36	3.24	5.80	11.27
	alpha	3.55	2.68	3.53	4.49
	beta	0.00	0.00	0.00	0.00
	gamma	0.37	0.23	0.36	0.51
	Sgen	304.00	53.00	258.00	715.00
	sigma	0.75	0.57	0.74	1.00
Lower Thompson	adjProd	2.64	1.57	2.47	4.24
	alpha	2.70	1.93	2.68	3.53
	beta	0.00	0.00	0.00	0.00
	gamma	0.37	0.23	0.36	0.51
	Sgen	2,781.00	1,241.00	2,654.00	4,767.00
	sigma	0.67	0.51	0.66	0.89
North Thompson	adjProd	3.20	2.15	3.09	4.62
	alpha	2.91	2.19	2.90	3.66
	beta	0.00	0.00	0.00	0.00
	gamma	0.37	0.23	0.36	0.51
	Sgen	3,171.00	1,771.00	3,051.00	5,017.00
	sigma	0.50	0.37	0.49	0.66
South Thompson	adjProd	2.35	1.54	2.22	3.56
	alpha	2.59	1.83	2.57	3.41
	beta	0.00	0.00	0.00	0.00
	gamma	0.37	0.23	0.36	0.51

CU_Name	Variable	Mean	P05	P50	P95
	Sgen	4,050.00	2,130.00	3,978.00	6,247.00
	sigma	0.64	0.48	0.62	0.84

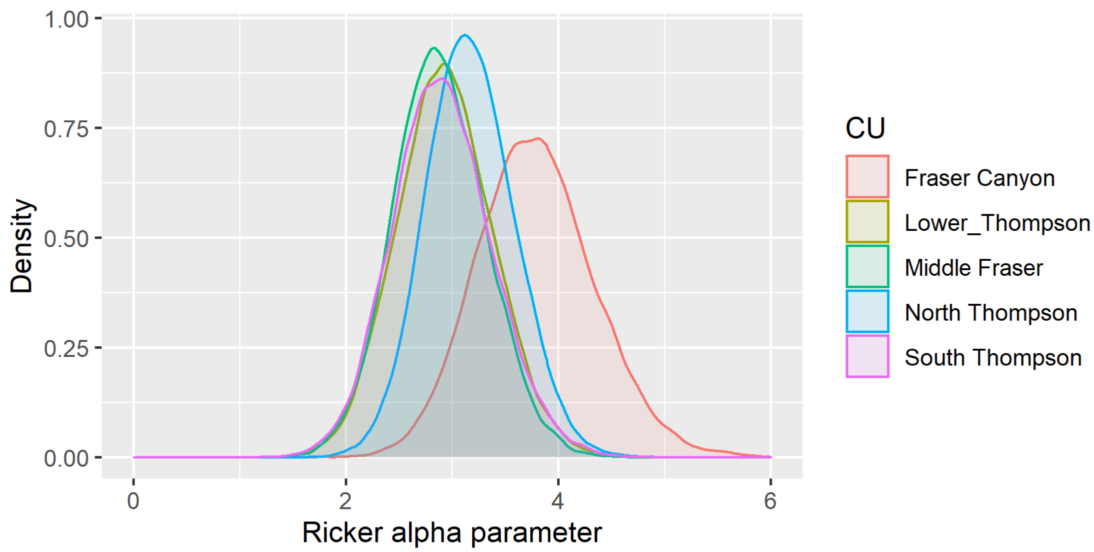

Figure C.2. Posterior distributions for Ricker α parameters, by CU, obtained from fitting the base Ricker stock-recruitment model.

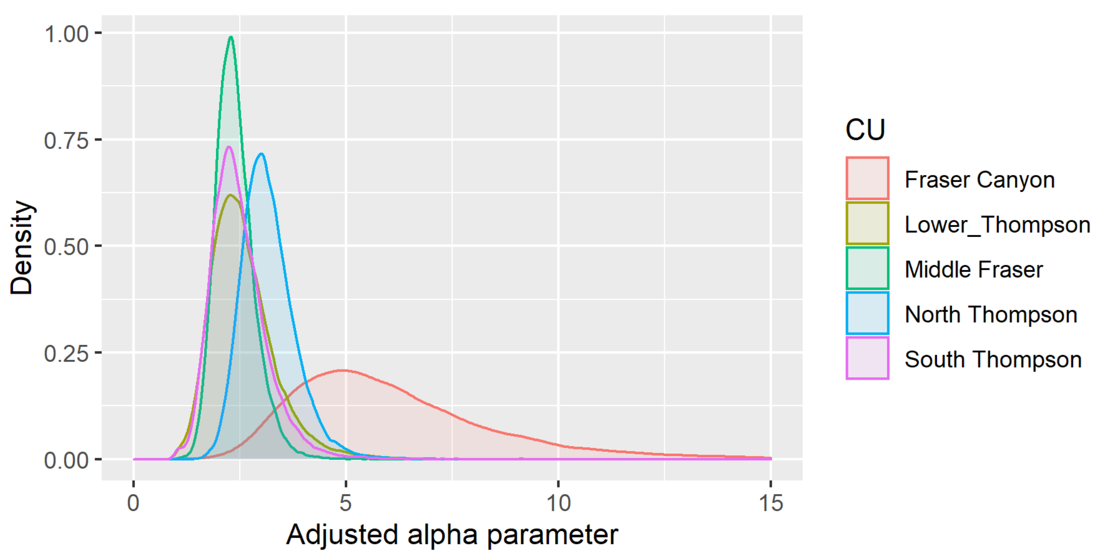

Figure C.3. Posterior distributions for effective productivity (α') parameters, by CU, obtained from fitting the base Ricker stock-recruitment model.

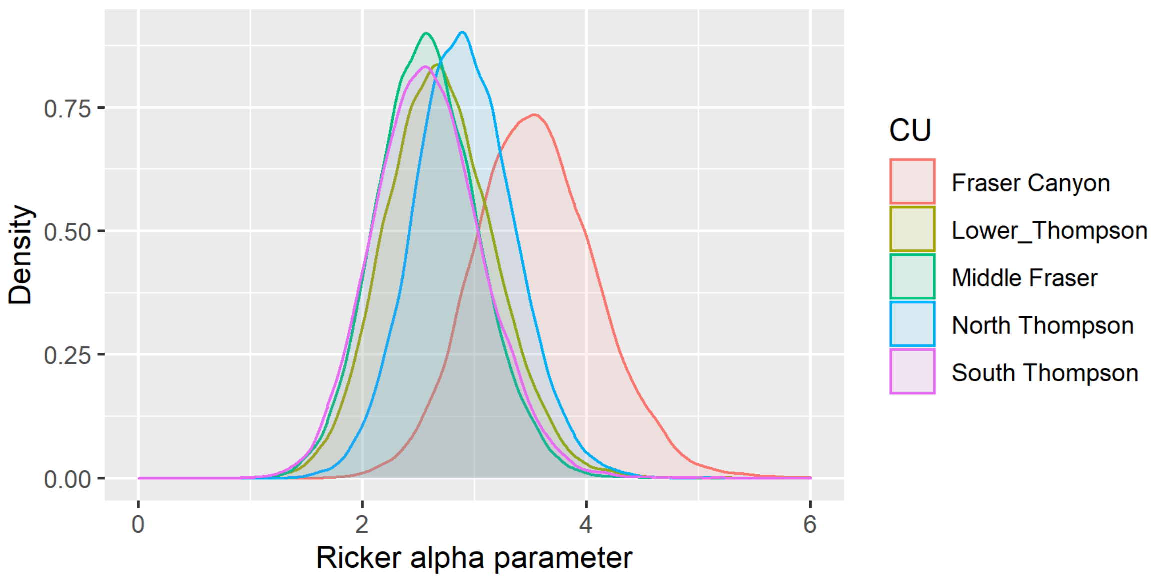

Figure C.4. Posterior distributions for Ricker α parameters, by CU, obtained from fitting the Ricker_priorCap stock-recruitment model.

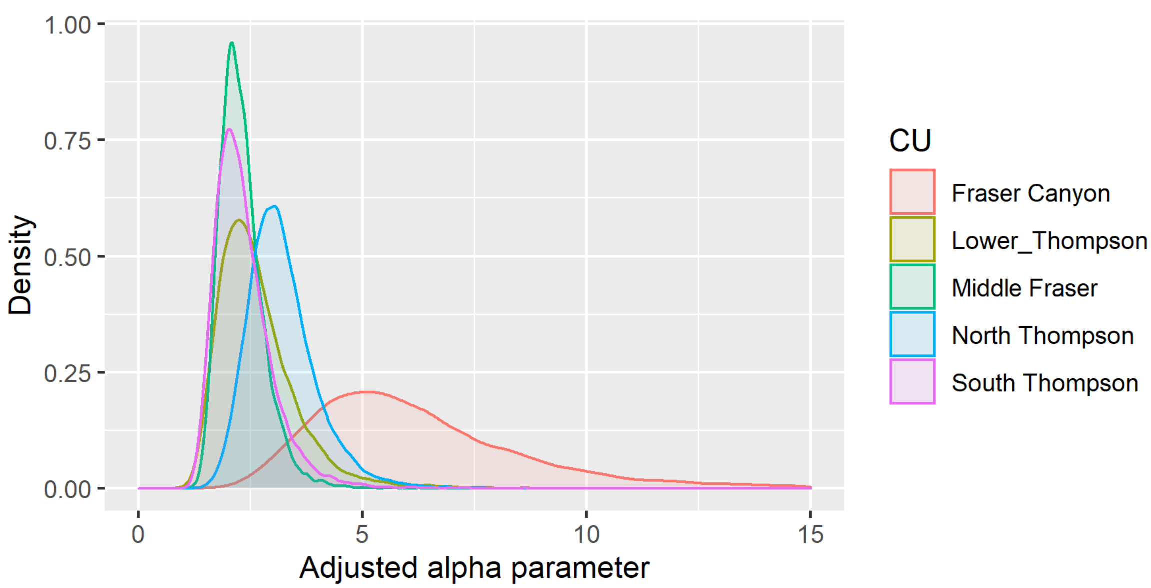

Figure C.5. Posterior distributions for effective productivity (α') parameters, by CU, obtained from fitting the Ricker_priorCap stock-recruitment model.

C.3. PROJECTED SPAWNER ABUNDANCES USED FOR THE PROJECTION LRP METHOD

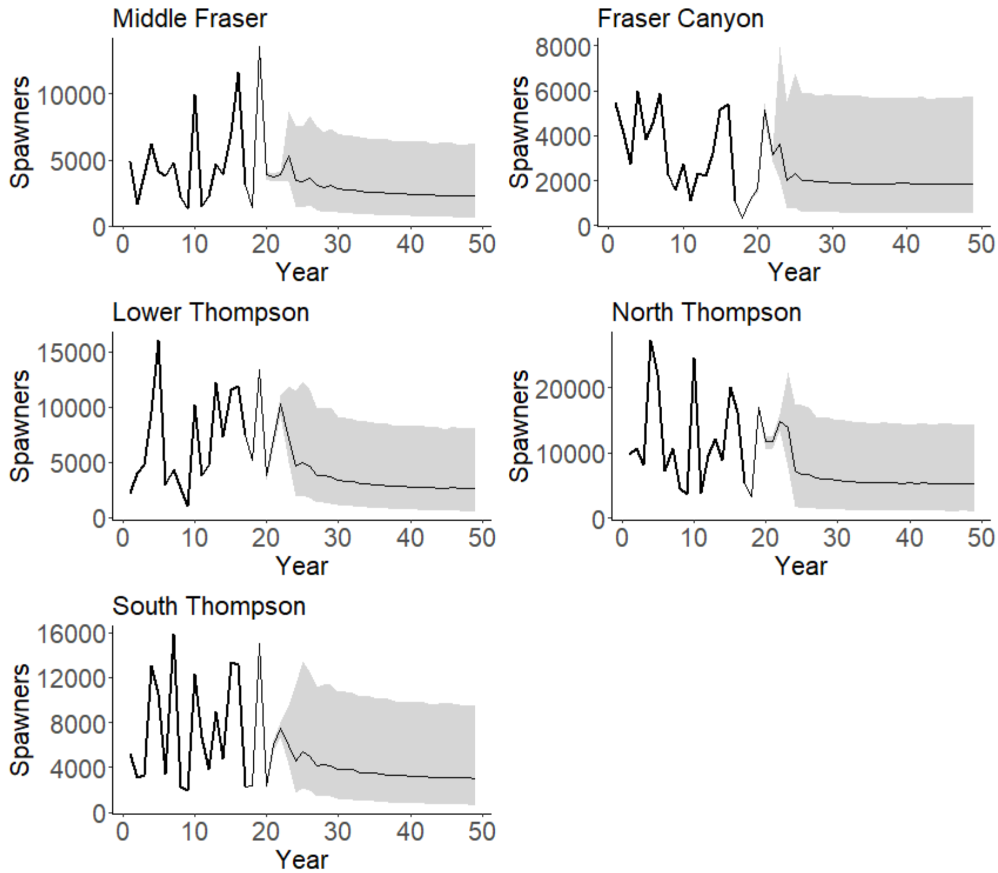

Figure C.6. Projected spawner abundances, for each of the five Interior Fraser Coho CUs, used to develop projection LRPs under the base Ricker model. The solid line shows the median spawning abundance in a projection year while the grey shading shows the 10th and 90th percentiles of spawner abundance.

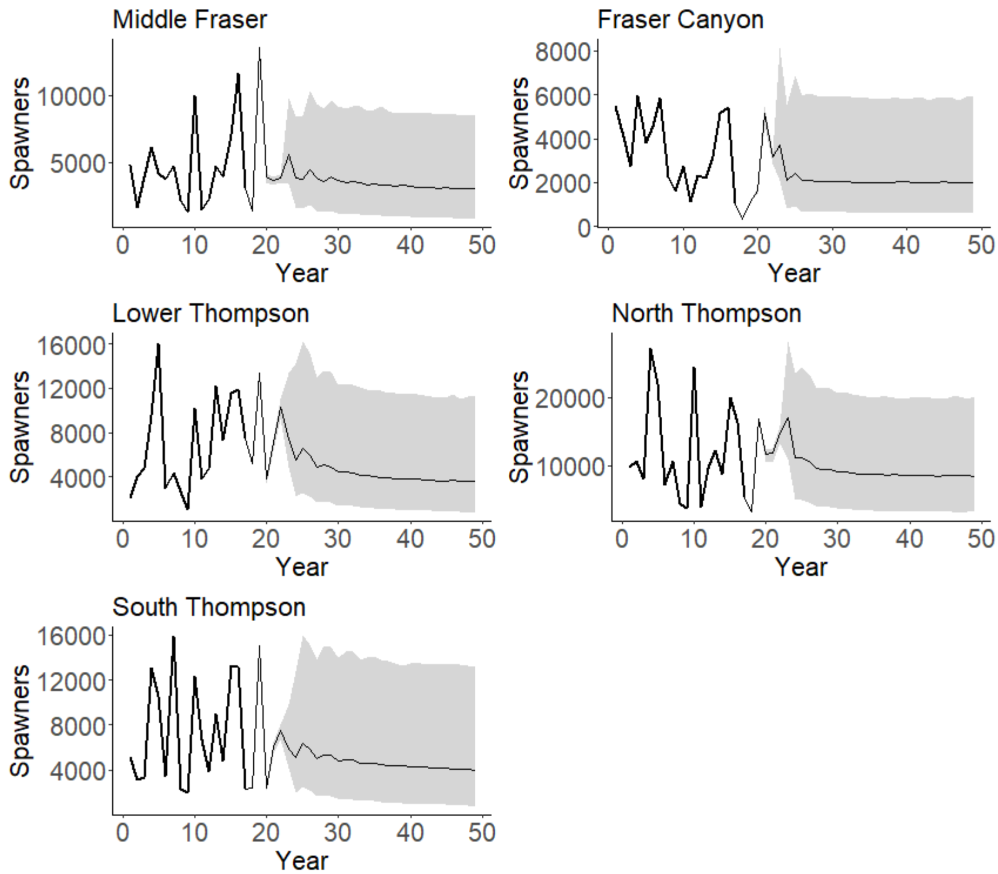

Figure C.7. Projected spawner abundances, for each of the five Interior Fraser Coho CUs, used to develop projection LRPs under the Ricker_priorCap model. The solid line shows the median spawning abundance in a projection year while the grey shading shows the 10th and 90th percentiles of spawner abundance.

APPENDIX D. SENSITIVITY OF PROJECTION-BASED LRPS TO EXPLOITATION RATES

To explain the initially counter-intuitive result of the sensitivity of projection based LRPs to exploitation rates, we ran an additional analysis where the spawner-recruitment parameters, productivity (log($alpha$)) and spawners at replacement, S_{REP} (log($alpha$)/$beta$) were either varied or kept constant over inlets and Monte Carlo trials.

Specifically, we evaluated the sensitivity of aggregate projection-based LRPs to exploitation rates under three alternative scenarios, as applied to the case study on WCVI Chinook Salmon:

1. All component inlets were assumed to have stock-recruitment parameters drawn from the same distributions (the mean and standard deviation for productivity and S_{REP} as estimated for Quatsino, west coast Vancouver Island) but a unique set of stock-recruitment parameters was drawn for each inlet and trial (i.e., each inlet was a replicate of each other with random variability). We chose to draw S_{REP} from a random distributions instead of Ricker $beta$ or S_{MAX} (1/$beta$) because the spawner-recruitment relationship was parameterized with S_{REP} for this case study. In preliminary sensitivity analyses, we sampled from a random distribution of $beta$ values and found similar results. We assumed strong positive covariation in recruitment residuals among inlets with pairwise correlations equal to 0.7.
2. The productivity parameter was fixed at the mean of the assumed distribution for all inlets and trials. S_{REP} was drawn from its distribution and allowed to vary across inlets and trials. The same distribution of S_{REP} was used across inlets and trials, as in Scenario 1.
3. S_{REP} was fixed at the mean of the distribution across inlets and across trials. The productivity parameter was drawn from the distribution and allowed to vary across inlets and trials. The same distribution of productivity was used across inlets and trials, as in Scenario 1.

We found that the sensitivity of projection-based LRPs to exploitation rates was due to variability in productivity and to a lesser extent S_{REP} among inlets. In Scenario 1, when we applied a relatively high exploitation rate (45%), productivity and S_{REP} tended to be lower for random trials and inlets that dropped below the lower benchmark in at least one year (Fig. D.1). Random trials and inlets with abundances that remained above the lower benchmark over the time-series tended to be more productive and slightly larger.

Inlets and Monte Carlo trials with low productivity tended to have relatively high S_{gen} (lower benchmark) values (as described in Holt and Folkes (2015)), and therefore a higher frequency of dropping below the lower benchmark. This variability in productivity among inlets was associated with projection-based LRPs that were sensitive to exploitation rates (Fig. D.2).

When productivity was fixed at the mean value among random trials and inlets in Scenario 2, the distribution of spawner-recruitment parameters for trials in which abundances dropped below the lower benchmark was the same or similar for trials that remained above it (Fig. D.3), and the LRP was insensitive to exploitation rate (Fig. D.4).

When S_{REP} was fixed at the mean value among inlets and random trials in Scenario 3, productivity was higher for inlets and trials that remained above benchmarks compared to those that dropped below them, similar to the scenario when both S_{REP} and productivity varied (Scenario 1) (Fig. D.5). LRPs varied with exploitation rates but to a lesser extent than when both productivity and S_{REP} varied (Fig. D.6).

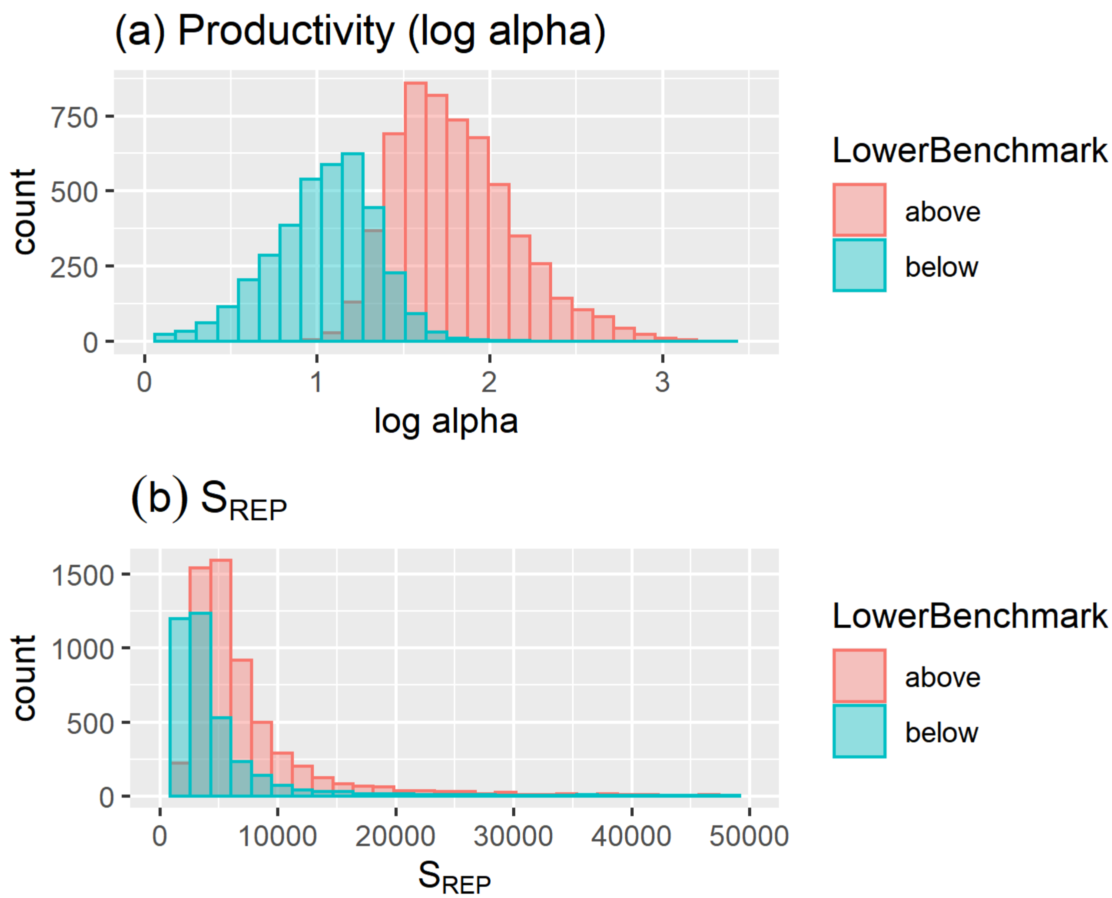

Figure D.1. Distribution of (a) productivity (log alpha) and (b) spawners at replacement, S REP among MC trials, shaded according to whether abundances in that trial remained above the lower benchmark (red) or not (blue), under a 45% exploitation rate. Productivity and S REP varied among inlets and trials and were drawn from common distributions.

Based on these sensitivity analyses, we conclude that variability in productivity among inlets results in inlet-specific variability in sensitivity to exploitation rates. Inlets with relatively low productivity fall below lower benchmarks more frequently. This effect is accentuated when exploitation rates are high resulting in divergences in statuses among inlets and a higher aggregate abundance is required for all inlets to be above their lower benchmarks resulting in a higher LRP. These results are generalizable to other SMUs to the extent that productivities differ among component CUs.

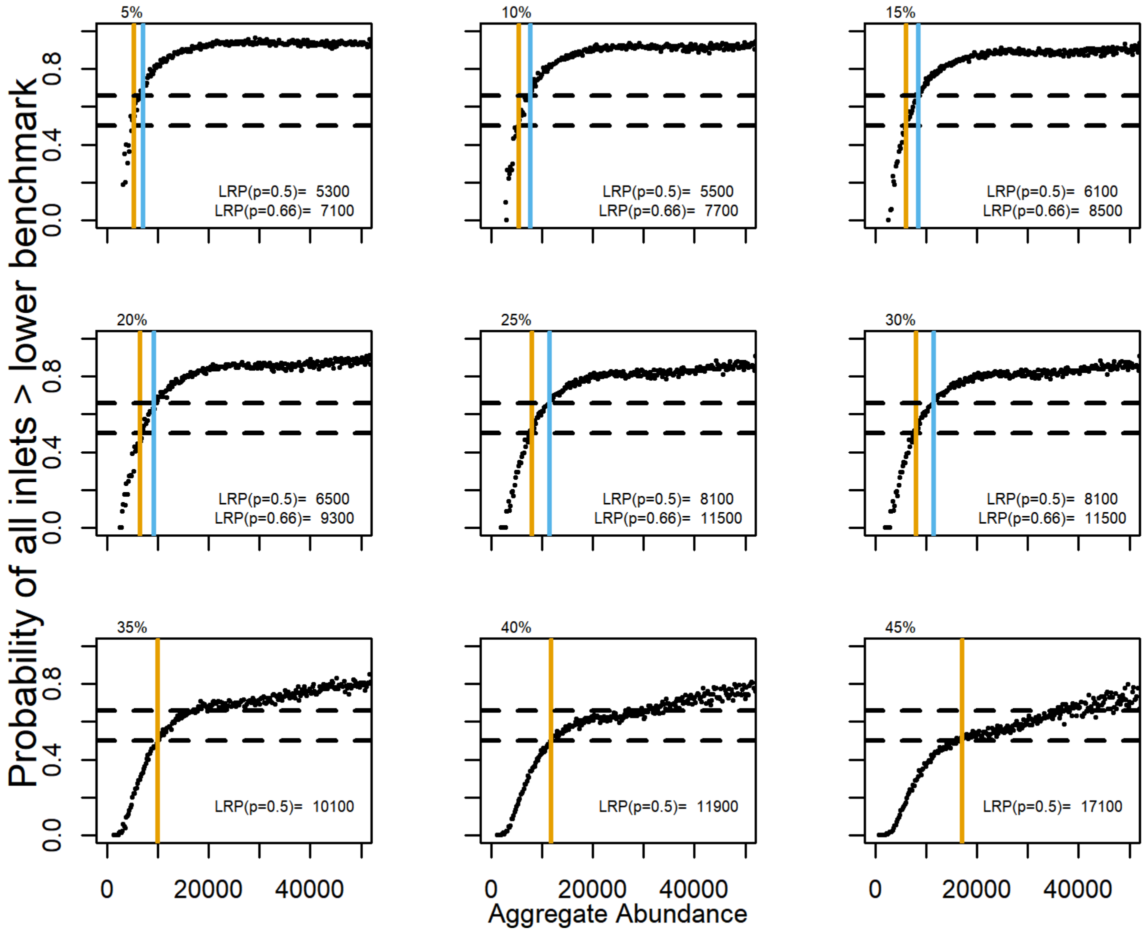

Figure D.2. Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 10,000 MC Trials, under a range of average exploitation rates from 5-45%, assuming productivity and S REP varied across inlets and trials, and are drawn from common distributions. Horizontal dashed lines are at 50% and 66%. Orange and pale green vertical lines are the LRPs associated with 50% and 66% probability of all inlets being above their lower benchmarks, respectively. LRPs at 66% probability are not shown for exploitation rates greater than 30% because of large uncertainty in projections at high aggregate abundances.

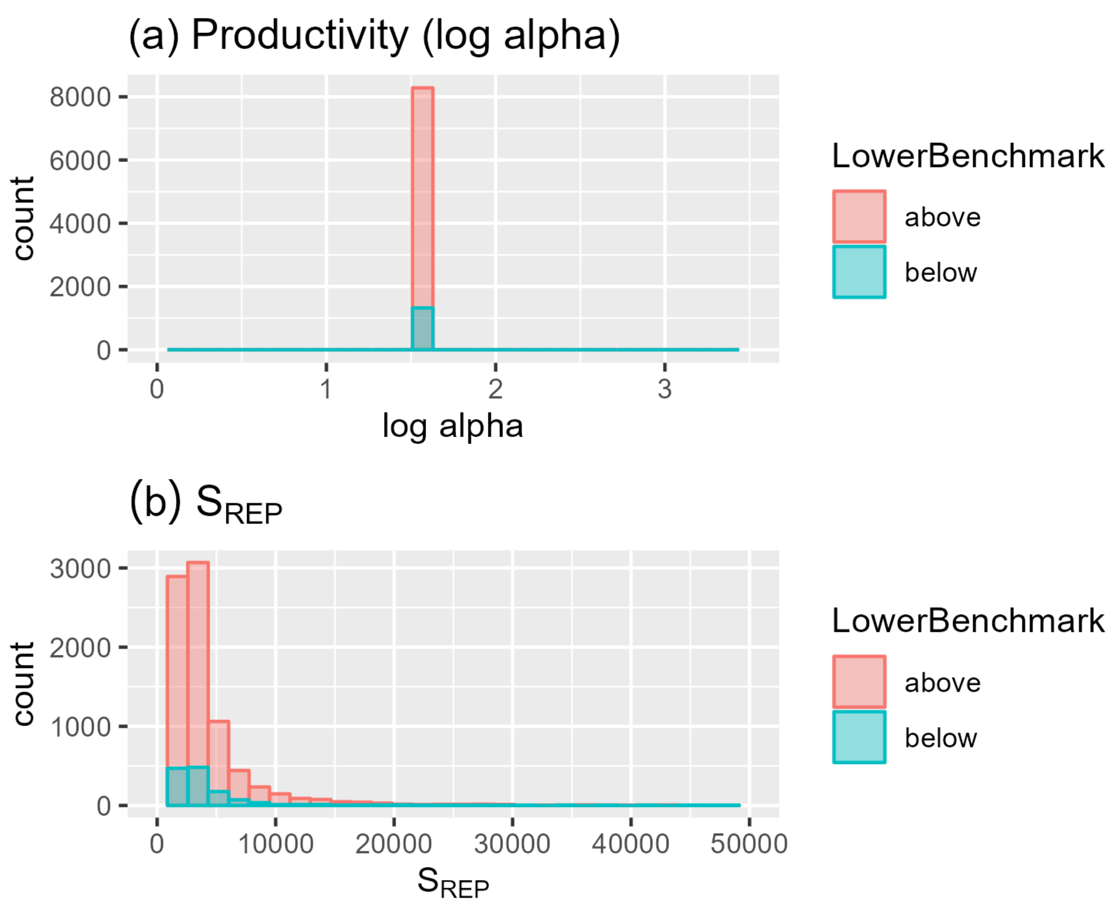

Figure D.3. Distribution of (a) productivity (log alpha) and (b) spawners at replacement, S REP among MC trials, coloured by whether abundances in that trial remained above the lower benchmark (red) or not (blue), under a 45% exploitation and constant productivity among inlets and trials. S REP was drawn from a common distribution across inlets and trials.

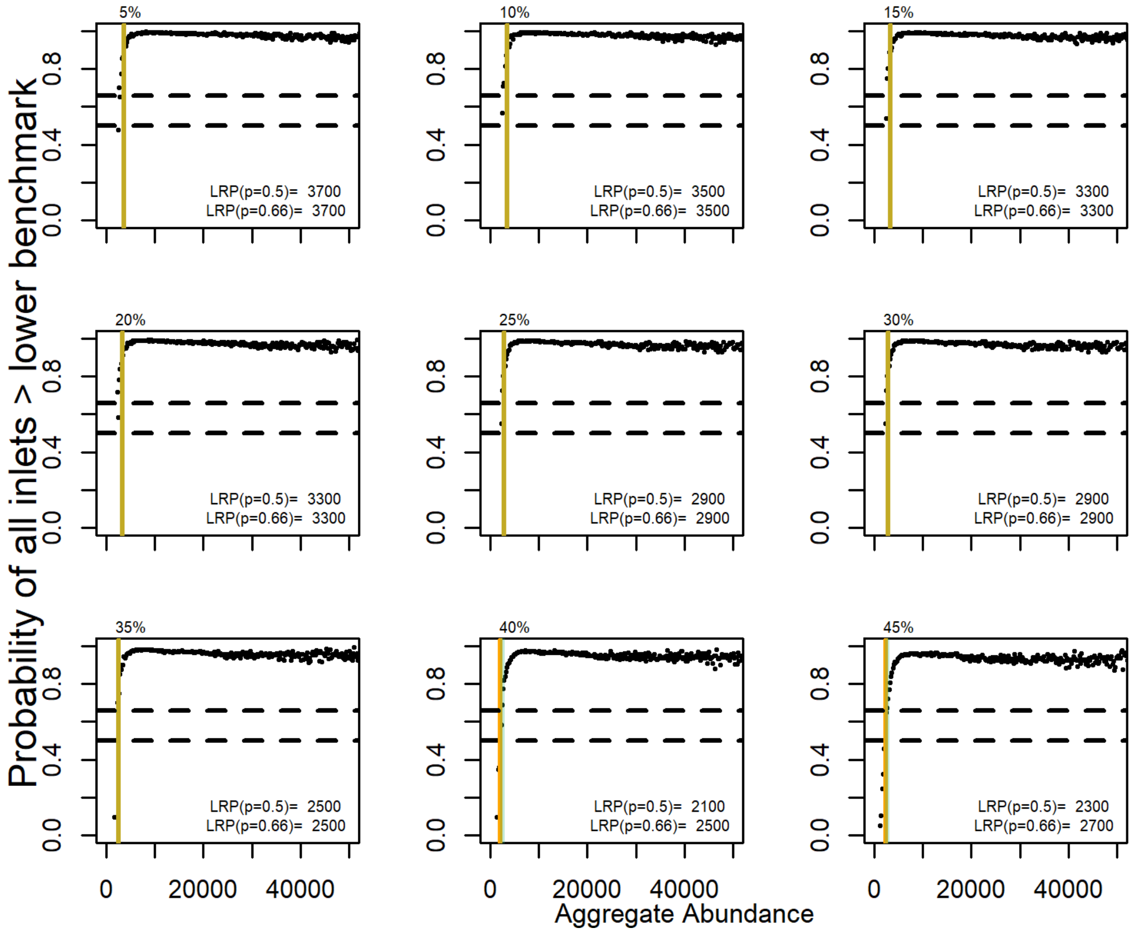

Figure D.4. Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 10,000 MC Trials, under a range of average exploitation rates from 5-45% (across 9 panels), assuming the same productivity for each inlet and trial, and an S REP that varied across inlets and trials, drawn from a common distribution. Horizontal dashed lines are at 50% and 66%. Orange and pale green vertical lines are the LRPs associated with 50% and 66% probability of all inlets being above their lower benchmarks, but are indistinguishably here.

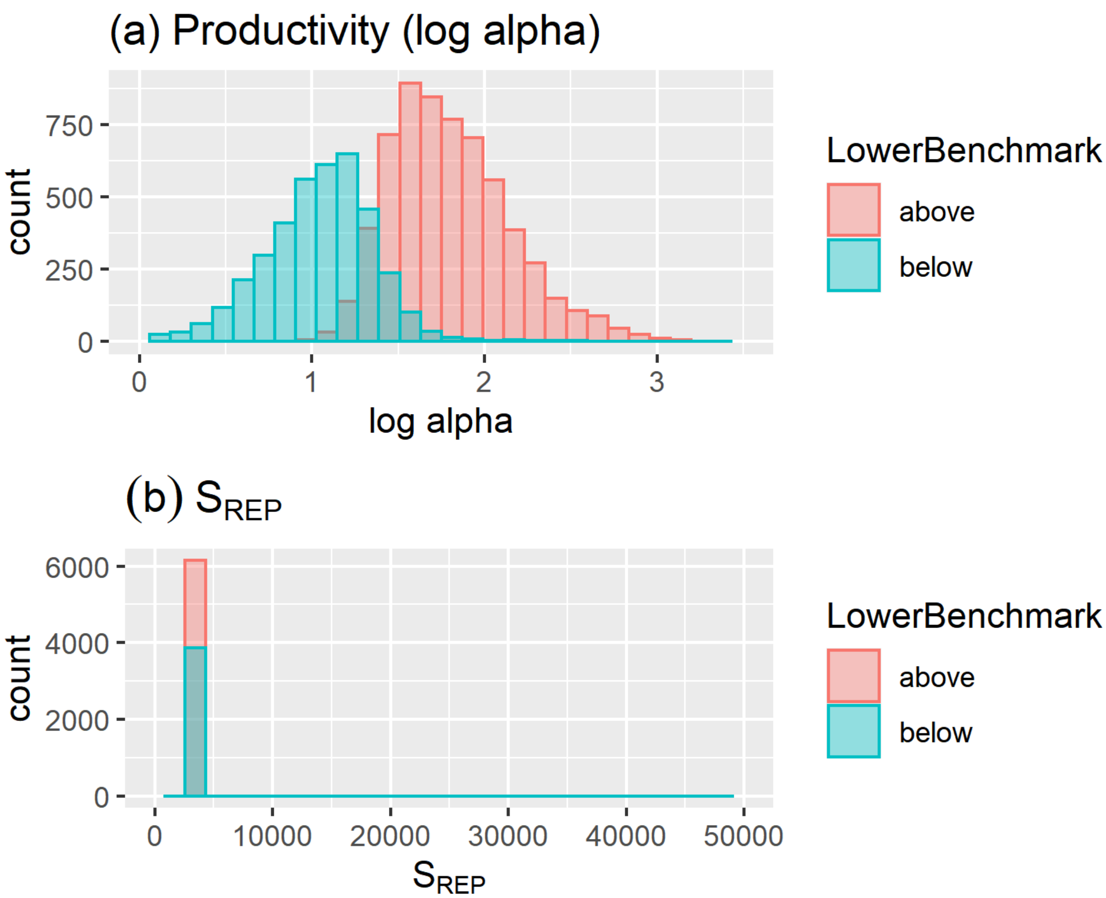

Figure D.5. Distribution of (a) productivity (log alpha) and (b) spawners at replacement, S REP among MC trials, coloured by whether abundances in that trial remained above the lower benchmark (red) or not (blue), under a 45% exploitation and constant S REP among inlets and trials. Productivity was drawn from a common distribution across inlets and trials.

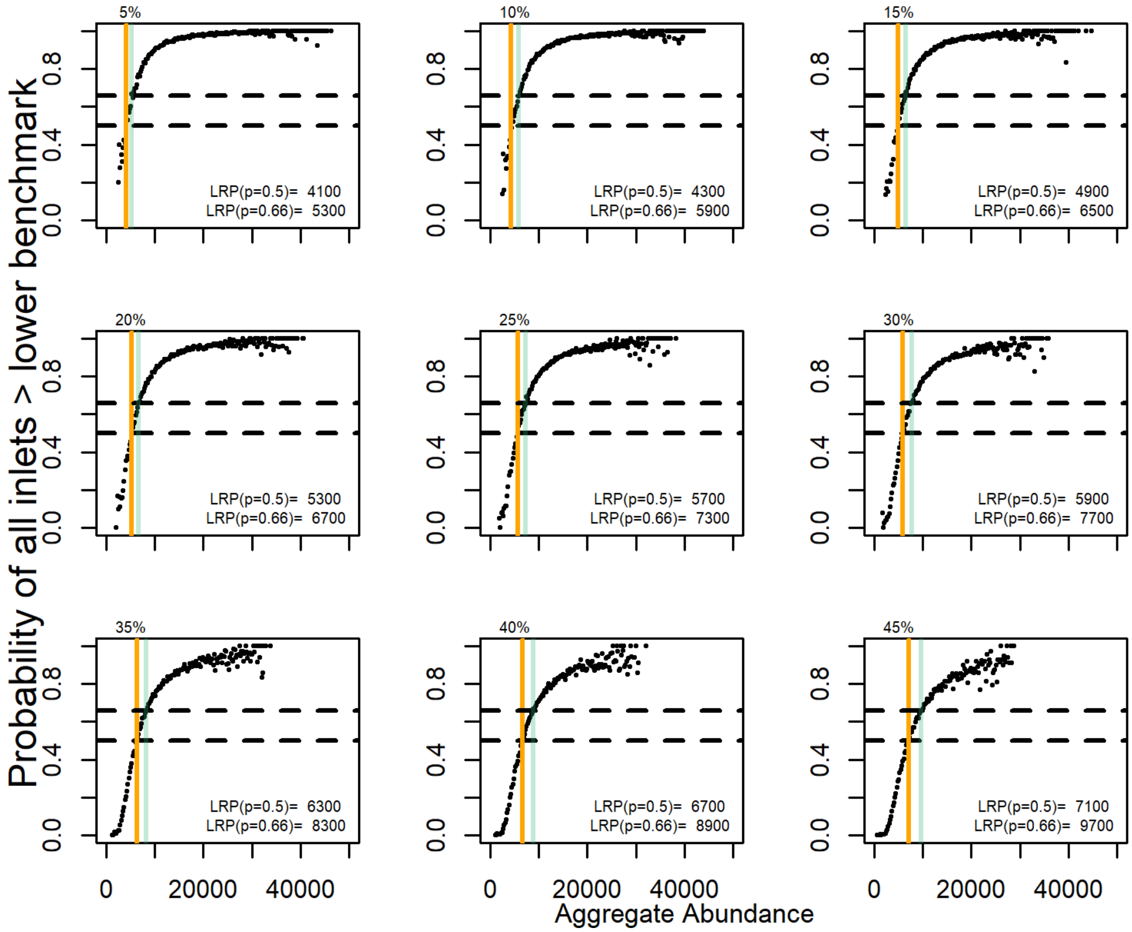

Figure D.6. Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 10,000 MC Trials, under a range of average exploitation rates from 5-45% (across 9 panels), assuming the same S REP for each inlet and trial, and productivity that varied across inlets and trials, drawn from a common distribution. Horizontal dashed lines are at 50% and 66%. Orange and pale green vertical lines are the LRPs associated with 50% and 66% probability of all inlets being above their lower benchmarks, respectively.

APPENDIX E. SUPPORTING INFORMATION FOR INSIDE SOUTH COAST CHUM SALMON CASE STUDY

E.1. DATA SOURCES AND TREATMENT

E.1.1. Spawner Escapement

We used spawning escapement data from 1953-2018. Most of the escapement data comes from the NUSEDS database (a small amount from Lower Fraser Stock Assessment for Areas 28 and 29, FSC in-river catch from some First Nations, and enhanced escapement from DFO Salmon Enhancement Program). The number of Chum salmon that return to spawn is typically counted using visual surveys, and using fences or weirs on some rivers. Total escapement for each stream is usually a peak count or estimated using the area under the curve (AUC) method.

E.1.2. Fishery Harvest, Genetics, and Age

The number of Chum caught in fisheries in the Inside South Coast area were taken from the DFO Clockwork Database, which includes the DFO Fishery Operating System and Sales slip databases and Genetic Stock Identification data. Age distributions for each year were taken from the Johnstone Strait fishery aggregate, as age data for specific CUs or streams was not available. Harvest data was available for 1954-2018. Age composition data was available for 1958-2018.

E.1.3. Data Selection and Infilling

We removed summer-run fish because all of the data that goes into the run reconstruction work is associated with populations that return in the fall. Summer-run fish are relatively minor portion of the total abundances for these CUs (Table 11). Because hatchery fish are not visibly marked, time-series of proportion of hatchery-origin and natural origin-fish were not available. However, we removed three systems because of high enhancement: Qualicum River and Little Qualicum River (spawning channels), and Puntledge River (hatchery production). These systems have been nearly 100% enhanced at least since enhancement began at these locations. It is assumed that hatchery enhancement is a relatively small component of total production in the remaining systems (Lynch et al. 2020). Brood take and rack abundances were also removed from spawner abundances to derive time-series of 'natural' escapement.

After these removals, the steps for preparing the data for analysis were:

- Infill total and wild escapement by CU and Area, (by stream for CUs with observations, by CU for years with no observations in a CU)
- Run reconstruction, required to estimate CU-specific productivity from stock-recruitment models:
  - Add fishery catch by CU and Area to total escapement to estimate total returns
  - Use proportion of natural escapement:total escapement (which includes brood stock and rack abundances and the three large hatchery systems), by CU and Area to estimate number of wild returns
  - Use age proportions of catch to estimate age of returns and get recruits by brood year for each CU. Result is wild spawners and corresponding recruits by brood year for each CU

E.1.4. Infilling of Spawner Escapement Data

The data we used had years where not all streams were counted. Missing escapement values require infilling for two purposes:

1. To ensure that all CUs have annual estimates of wild returns for input to the run reconstruction model, which allows recruits for each brood year to be estimated.
2. To create CU-level time series of wild escapement that can be used to calculate status relative to CU-level benchmarks, as well as LRPs based on CU status.

Two levels of infilling have previously been used for ISC Chum CUs (Holt et al. 2018, Figure E.1). The first level, infilling by stream, is used when a CU has some streams counted in a year. In this case, stream-level infilling is done by borrowing information from other streams within the same CU. The second level, infilling by CU, is used when there are no counts of spawners for a CU in a given year. We had to infill by CU to get total spawners to use for the run reconstruction, but we did not use CUs with CU-level infilling to calculate LRPs because the infilling procedure assumes that escapement is correlated between CUs in a given year.

E.1.4.1. Infilling by Stream

This applies to CUs and years when there were counts in some streams in the CU in a given year. For each stream, the geometric mean of escapement over all years was calculated as the stream's average escapement. Then the total average escapement for each CU in each year was the sum of the average escapements from all streams. Then a proportion of monitored escapement in each year was the sum of average escapement of all streams with counts in a year divided by the sum of the average escapements for all streams (counted and uncounted) in that CU. The infilled escapement for a CU in given year was the sum of the observed escapements for that CU and year divided by the proportion of the monitored escapement for that CU and year.

Infilling by stream typically made up a small proportion of the total escapement for each CU, with the exception of Howe Sound-Burrard Inlet. This was partly due to increasing escapements in the Cheakamus River and Indian River since 2000. This method assumes that escapement among streams is correlated, which is not always the case (see Figure 41 for correlations among CUs).

E.1.4.2. Infilling by CU

If there were no counts of any streams in a CU in a given year, a second round of infilling was done with data set that had already been infilled by stream. This was the case for two CUs: Upper Knight (22 years: 1979-1980, 1982, 1984, 1989, 1991,1996,2004-2018) and Bute Inlet (13 years: 2005-2006, 2008-2018). We describe this level of infilling below, though it was not applied for development of LRPs as it violates assumptions of independence among CUs.

Using by-stream infilled escapement summed for each CU, the CUs and years with missing data were infilled assuming the total CU escapement was correlated between CUs. The procedure was similar to that for infilling by stream, but a geometric average for each CU across all years was used to calculate the proportion of the average for each year, and then that was used to estimate escapement for the two CUs with no observations.

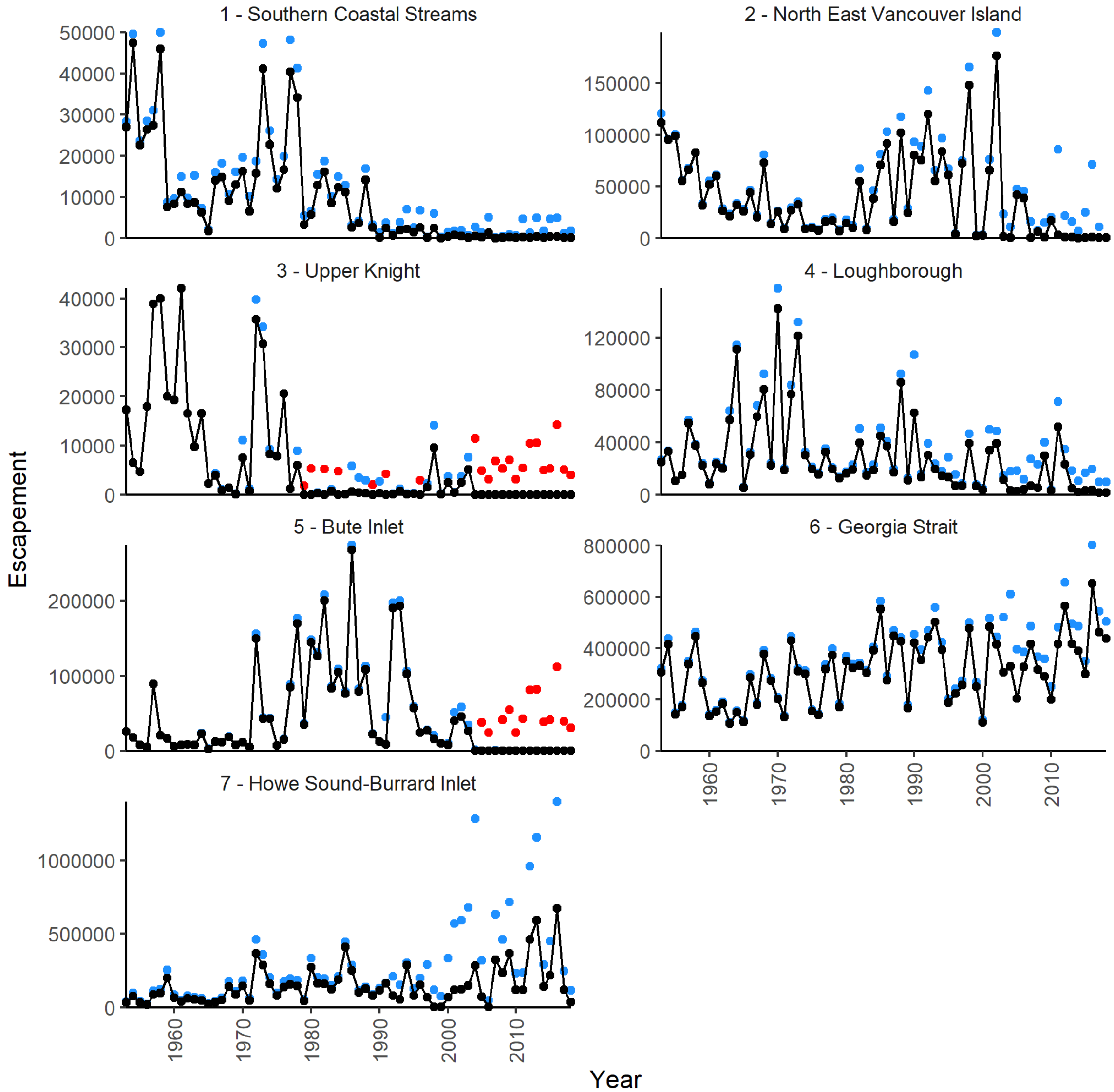

Figure E.1. Chum salmon escapement for the seven Conservation Units. Black points indicate actual counts, blue points are infilled by stream, and red points are infilled by Conservation Unit.

E.1.5. Run Reconstruction to Estimate Recruitment

We reconstructed the returns for each brood year to give recruits for brood years 1955-2012 (age composition data from 1958-2018, minimum fish age was 3 years, maximum fish age was 6 years). In prelminiary analyses we estimated stock-recruitment based benchmarks for these CUs. Using CU benchmarks based on stock-recruit parameters - in this case, S_{gen} - requires knowing the spawners and recruits (adult offspring produced by each brood year of spawners) for each brood year (spawning year). Estimating recruits requires knowing wild spawner escapement, number of wild fish caught in fisheries, and the age of these fish.

To get these estimates, total (wild and hatchery origin) spawners based on the infilling methods above (both stream and CU level infilling) were calculated for each CU and Fishery Management Area (Figure 37). The number of fish harvested in fisheries (wild and hatchery, by CU and Fishery

Management Area) were added to the total escapement to get an estimate of total adult returns by CU and Fishery Management Area for each spawning year. This total returns number was multiplied by the proportion of wild spawners in each CU and Fishery Management Area based on the infilled wild and total spawner escapement. The product was an estimate of wild returns (spawner escapement plus fishery harvest) by CU and Fishery Management Area for each brood year. Finally, the age composition of Chum harvested in the Johnstone Strait aggregate fishery (ages 3, 4, 5 and 6) were used to assign fish from wild returns to brood years. As such, this analysis does not account for age diversity between CUs or streams.

Note that the two CUs requiring CU-level infilling correspond to only one Fishery Management Area each, which allows the run reconstruction using fishery harvest data at this level.

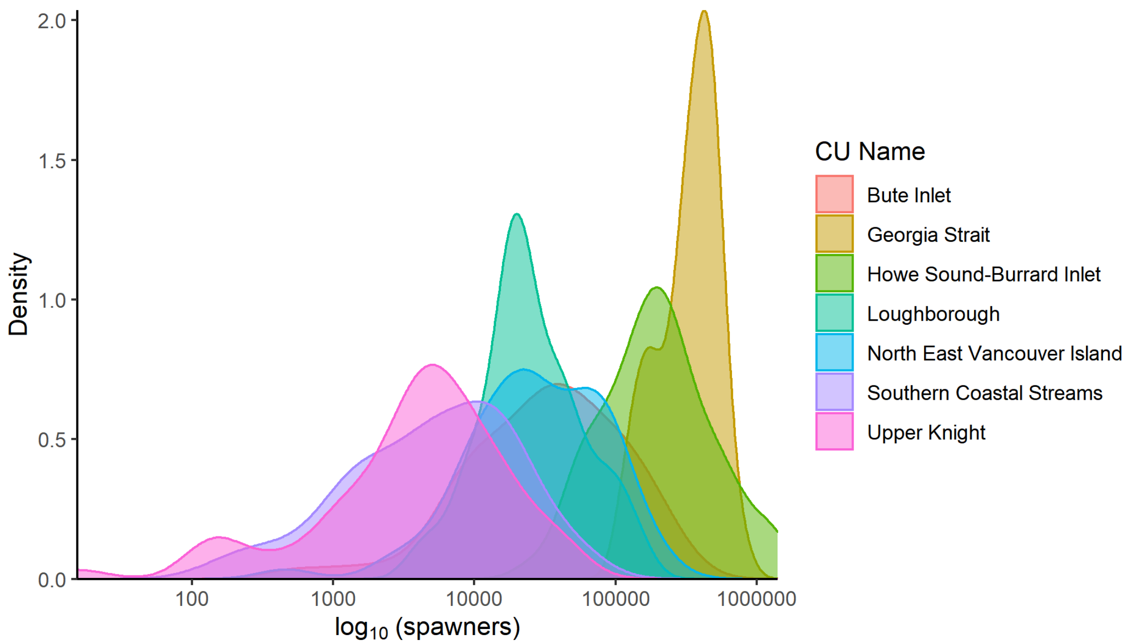

Figure E.2. Density (smoothed histogram) of chum escapement for the seven Conservation Units. Note that x axis is on logarithmic scale.

E.2. RETROSPECTIVE ANALYSIS OF CU BENCHMARKS

We conducted a retrospective analysis using the data for the Inside South Coast Chum to evaluate how stock-recruitment parameters and benchmarks, S_{gen} and percentile benchmarks, changed over time. When α, β, and S_{gen} were estimated annually using only data prior to that year, values changed over time as progressively more years of data were included (Figures E.3). Note that these are not estimates based on a model that accounts for time-varying parameters. Rather, the estimates of α, β, and S_{gen} in a given year come from fitting a Ricker model to spawners and recruits for all years up to and including that year, for each CU. Each subsequent year includes another year of data. Thus, as more data is included, the estimates of α, β, and S_{gen} may change. These results should be interpreted with caution due to the large residuals in observed vs. predicted recruits. Since α and β are correlated, the meaning of any trends in one parameter should be interpreted with the other parameter in mind, especially when model fits have large residuals. Similarly, since α and β determine S_{MSY} and S_{gen}, changes in these derived parameters can be challenging to interpret and can be due to changes in α, β, and their relative values. Retrospective estimates of α and β for Southern Coastal Streams show declines over time. S_{MSY} and S_{gen} increase sharply in the first few years due to large decreases in α and β. S_{MSY} then decreases over time, while S_{gen} stays relatively stable. This is because as α decreases below approximately 2.5, S_{gen} decreases, but as β decreases, S_{gen} decreases, so that a simultaneous decrease in α and β can cancel out. However, the lower alpha is below 2.5, the less influence β has on S_{gen}.

Increasing S_{gen} for North East Vancouver Island is mainly due to an increase in α from <1.5 to >2 and then a decrease in β. α for Loughborough showed modest decreases over time, and S_{gen} was fairly stable. The Georgia Strait CU shows evidence of increasing α, and its S_{gen} estimate was fairly stable. Howe Sound-Burrard Inlet S_{gen} was fairly stable, and then increased due to decreases in α and β.

Despite large uncertainties in the underlying recruitment data and stock-recruitment benchmarks, we estimated a logistic regression model based on aggregate abundances vs. CU status from abundances relative stock-recruitment benchmarks. Similar to our results for the logistic regression model based on percentile benchmarks, the model fit was poor and cannot be used as a basis for estimating LRPs (Figure E.4). We further evaluated status based on percentile-based benchmarks retrospectively, where status was evaluated annually based on benchmarks estimated from data prior to that year (Figure E.5).

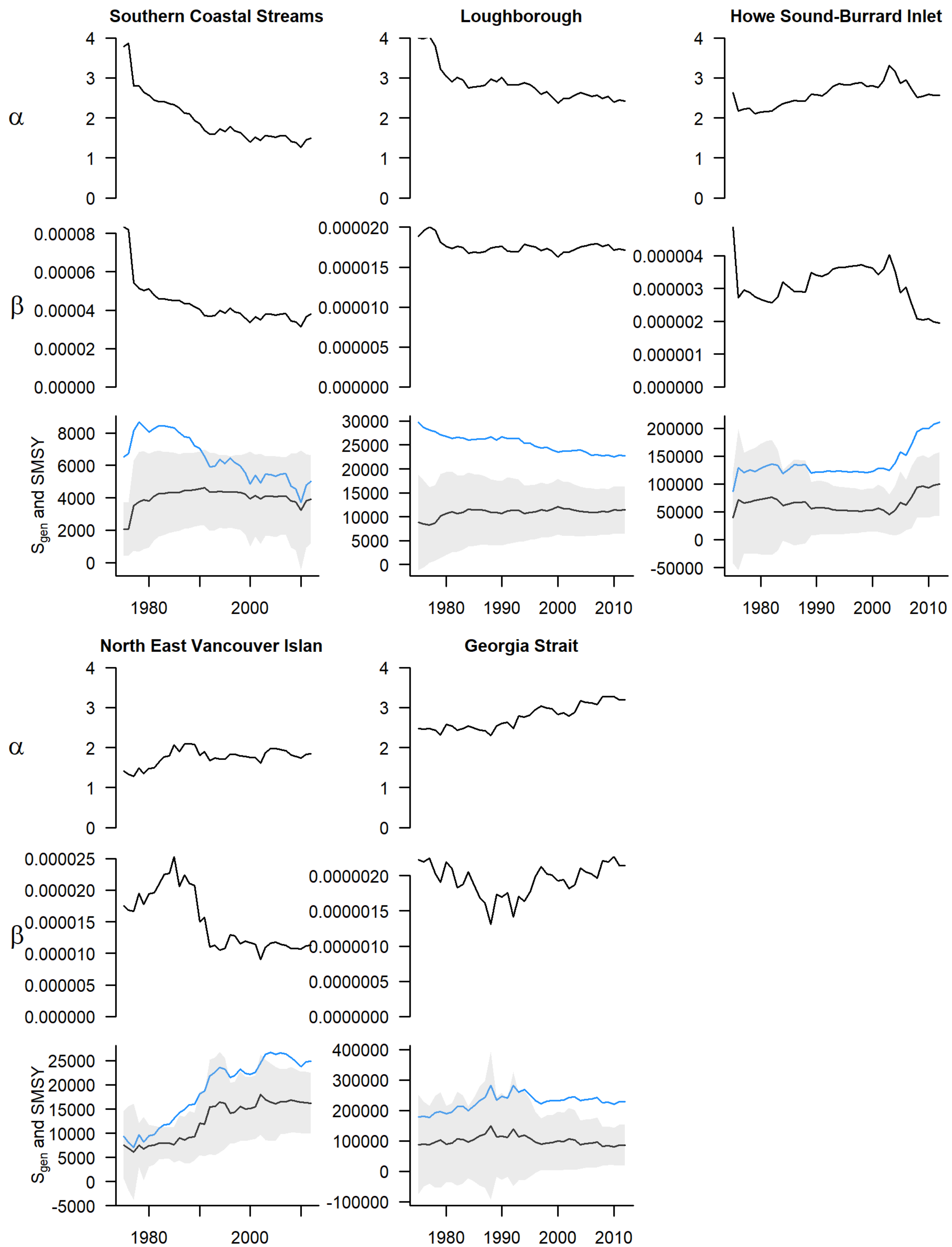

Figure E.3. Retrospective estimates of α, β, S_{gen} (black line with grey confidence intervals) and S_{MSY} (blue line) for five CUs in the Inside South Coast Chum SMU. Note y axis is identical across CUs for α but varies for other parameters.

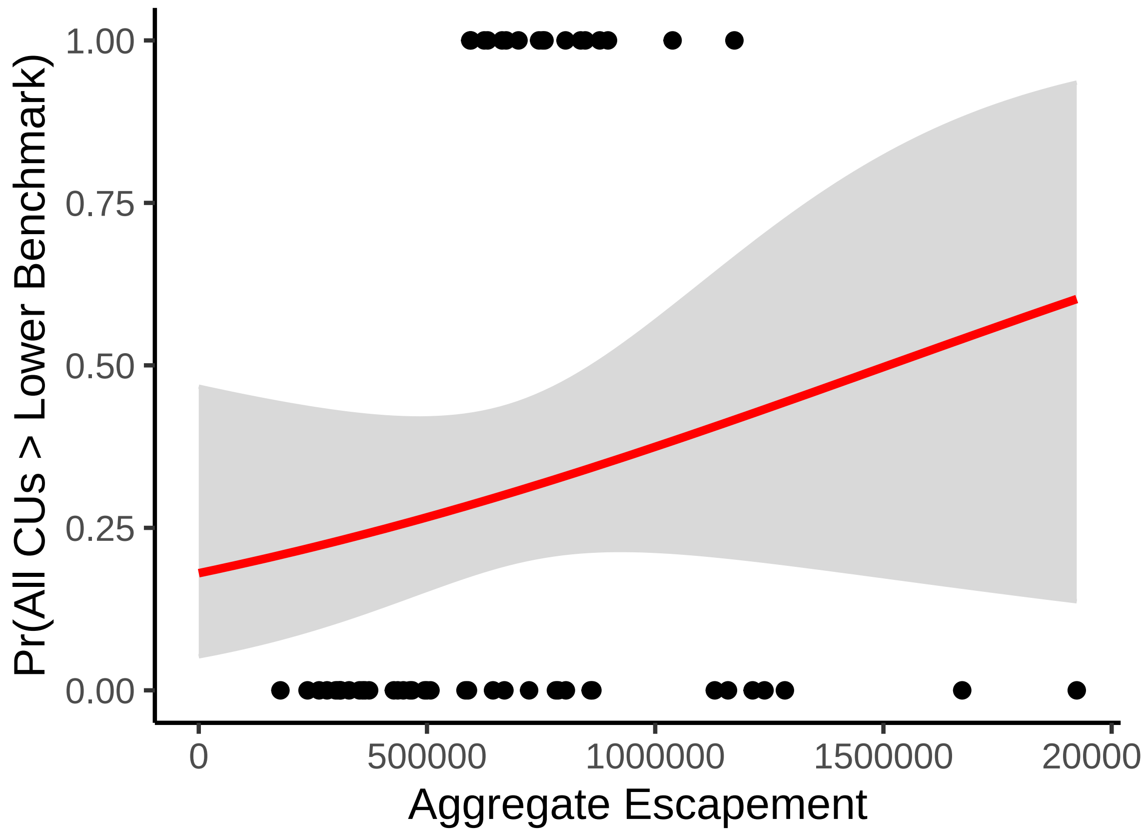

Figure E.4. Logistic regression of whether escapement of all component CUs were above their S_{gen} benchmarks based on aggregate abundance, for Inside South Coast Chum SMU. Includes the 5 CUs without CU-level infilling (no Bute Inlet or Upper Knight).

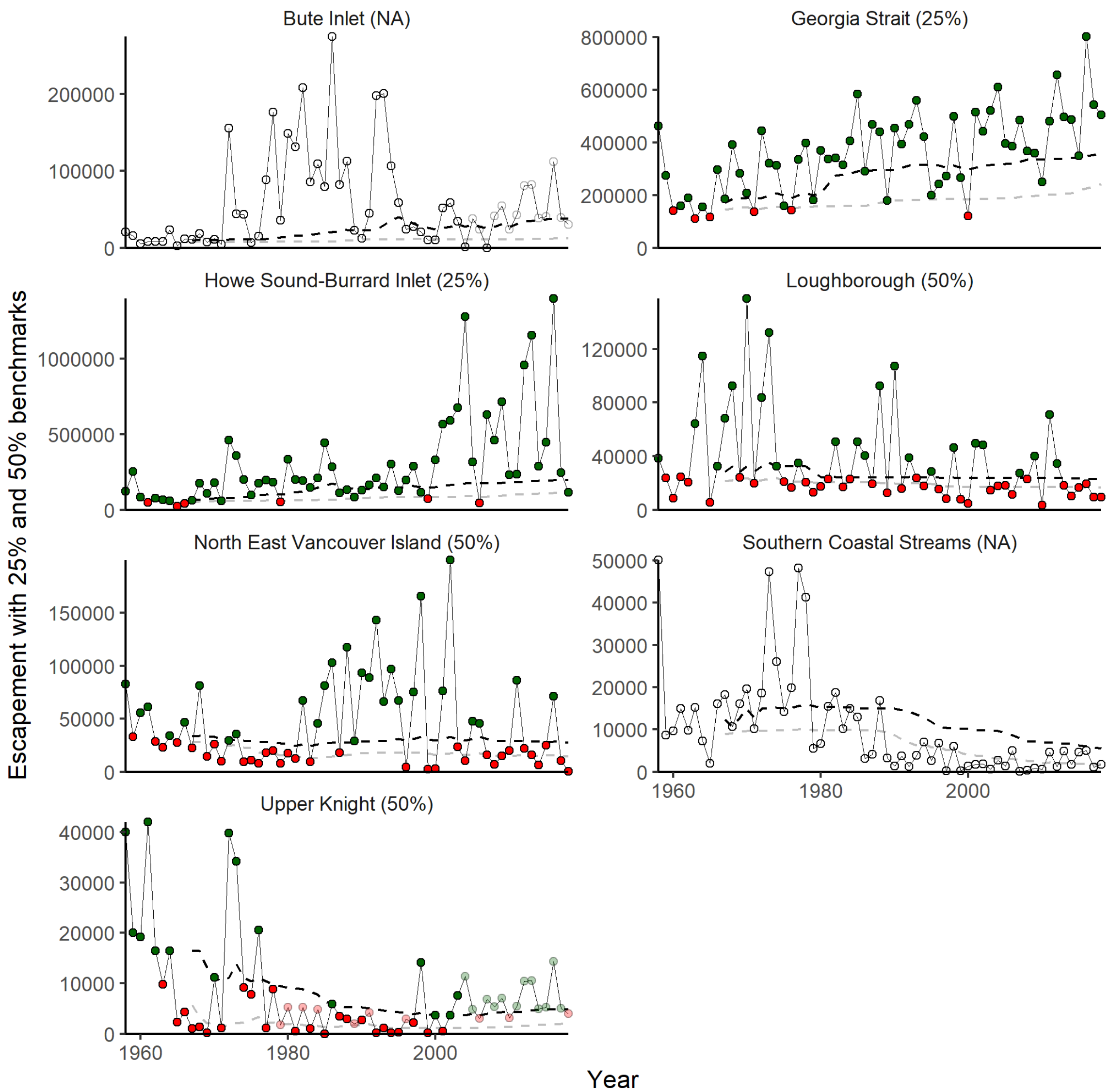

Figure E.5. Escapement with 25th and 50th percentile benchmarks shown by grey and black dotted lines, respectively. Benchmarks are calculated using escapements up to the given year. Values following the CU names indicate the appropriate percentile benchmark. Green and red points indicate status above or below benchmark, respectively. Transparent points are years with CU-level infilling.