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

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# 1 INTRODUCTION

Under DFO’s New 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 > 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. 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 human lifetime or a specified number of salmon generations’ (DFO 2005). Thus, 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. Methods to assess CU status have been identified for a range of data types, and WSP Integrated Assessment methods (hereafter called ‘WSP assessments’) that use expert opinion to combine multiple metrics into a single estimate of CU status have been developed (e.g., [Grant et al.](#ref-grant2017FraserSockeye2020) ([2020](#ref-grant2017FraserSockeye2020))). Metrics used to assign WSP CU status include spawner abundances, short- and long-term trends in abundance, and distribution of abundance. At present, a key gap in our ability to develop LRPs under the Fisheries Act is that CU-level status assessments have not been aggregated to the SMU level.

LRPs are defined within DFO’s ‘Precautionary Approach to Fisheries Decision-Making’ as the stock status below which serious harm is occurring to the stock ([Government of Canada 2009](#Xc4c36b0d8a5ae98a4b852be6b7c89b80c7bc6df)). 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 methods for identifying LRPs should ensure that component CUs are maintained. The companion working paper to this one, *Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units* (Holt et al., in review), suggests that the maintenance of spawning abundance at the Conservation Unit (CU) level is a key biological requirement for Pacific Salmon LRPs.

The goal of this working paper is demonstrate and evaluate alternative LRP estimation methods for three case study SMUs: Interior Fraser Coho, West Coast Vancouver Island (WCVI) Chinook, and Inner South Coast Chum - excluding Fraser. Each of these SMUs is comprised of 3-7 CUs and has been selected to represent a different level of data availability ranging from data rich (Interior Fraser Coho) to data-limited (Inner South Coast Chum). Detailed guidelines for identifying LRPs for Pacific salmon SMUs informed by these three case study applications are available in the companion working paper *Guidelines for Defining Limit Reference Points for Pacific Salmon Stock Management Units* (Holt et al., in review). 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. Estimates presented in this paper are not meant to be definitive LRPs, which require more thorough review of data and methodology 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 (WCVI Chinook), and 5 (Inner South Coast Chum, excluding Fraser).

## 2.1 OVERVIEW

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

1. Proportion-based LRPs, which are based on the proportion of CUs within an SMU that are assessed as being above ‘poor’ status. We assume that in order for an SMU to remain above its proportion-based LRP, 100% of CUs must have status estimates above poor.
2. Aggregate abundance-based LRPs, which are based on total SMU-level spawning abundance.

While aggregate abundance-based LRPs are consistent with what is typically used for marine fish species, proportion-based LRPs have been proposed for Pacific salmon to align with DFO’s Wild Salmon Policy.

When developing aggregate abundance-based LRP options for salmon SMUs, 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 poor status. We use two different methods to identify these levels: (i) Logistic regression-based LRPs and (ii) Projection-based LRPs. More detailed descriptions of these methods are provided in the following sections, while guidance on when and how proportion-based and aggregate abundance-based LRPs should be applied is provided in Holt et al. (in review). We do not recommend that users apply any of the methods described in this case study paper without first consulting Holt et al. (in review). While aggregate-abundance based LRPs can be used as part of, or to inform harvest control rules for fisheries management, more complex harvest control rules that include for example, time-area closures to limit CU-specific harvests may better achieve the underlying objective of maintaining CU statuses above red (as described in Holt et al. (in review))

The above definitions hinge on what defines ‘poor’ CU status. In the case of WSP status assessments, in which multiple metrics are combined to assign CU status, poor status corresponds with the ‘red’ status zone ([*Canada’s policy for conservation of wild Pacific salmon* 2005](#ref-dfoCanadaPolicyConservation2005); [Grant et al. 2020](#ref-grant2017FraserSockeye2020)). While WSP assessments are typically intensive expert-driven processes, we demonstrate the application of a rapid multidimensional scanning tool that is being developed by DFO’s State of the Salmon Program to rapidly assess CU status under the WSP (Pestal et al., in prep). When developing aggregate abundance-based LRPs, we also consider cases in which CU status is based on spawning abundance relative to a single lower benchmark that has been identified as important by local experts. While the rapid multidimensional scanning tool better captures the multiple dimensions that are used to inform biological status under the WSP (e.g., abundances, short-term and long-term trends), we compare it to status derived from a single metric relative to a lower benchmark to demonstrate how in many cases the rapid multidimensional scanning tool reduces to this metric. Exceptions are described in the application to case studies. A variety of methods are available for estimating lower benchmarks on abundances depending on species and data availability ([Holt et al. 2009](#ref-holtIndicatorsStatusBenchmarks2009); [Holt et al. 2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f); [Grant et al. 2020](#ref-grant2017FraserSockeye2020)), as described in Holt et al. (in review).

## 2.2 PROPORTION-BASED LRPS

A proportion-based LRP is simply the proportion of CUs required to be assessed as being above poor status. In all three case studies, we default to 100% of CUs being required to be above poor status when setting the LRP. In this case, the LRP acts as a trigger that is breached when one of more CUs is assessed as having poor status. Rationale for the choice of 100% of CUs required to be above poor status in order for an SMU to be considered above its LRP is described in (Holt et al. in review).

We compare three different methods of assessing CU status when using proportion-based LRPs: (i) the proportion of CUs with a recent WSP status assessment above the red zone (e.g., [Grant et al.](#ref-grant2017FraserSockeye2020) ([2020](#ref-grant2017FraserSockeye2020))), (ii) the proportion of CUs with a recent rapid multidimensional status assessment above red (see below for more details), and (iii) the proportion of CUs with status estimated to be below a single type of CU lower benchmark (e.g., , percentile-based benchmarks, etc.). While we recommend applying methods (i) or (ii), approach (iii) is shown for comparison purposes to demonstrate consistency between rapid multidimensional status assessments and statuses derived from abundances relative to lower benchmarks.

When assessing CU status relative to a single abundance-based lower benchmark in approach (iii), we use generational mean spawner abundances as a basis for determining whether each CU is above or below its lower benchmark. This approach reduces noise in annual CU status determination due to annual fluctuations in CU abundances. It also makes our determination of CU status consistent with the approach taken for abundance-based benchmarks in WSP assessments and the rapid multidimensional scanning tool.

### 2.2.1 Rapid Multidimensional Scanning Tool

One of the methods we consider to estimate CU status for proportion-based LRP relies on a method of rapidly assessing CU status using multidimensional algorithms. We implement this approach using a scanner tool that has recently been developed by DFO’s State of the Salmon Program ([Pestal et al.](#ref-pestalAlgorithmsRapidStatus2021) ([2021](#ref-pestalAlgorithmsRapidStatus2021)), in prep). The scanning tool is intended to support implementation of Canada’s WSP by approximating the outcomes of full WSP Integrated Status Assessments on an more regular basis than the time-intensive WSP assessment approach allows. The rapid multidimensional scanning tool was developed using Classification and Regression Tree (CART) analyses to create algorithms that approximate the status of the integrated assessments. Data inputs and outcomes from thee WSP assessment processes were used in CART analyses: Fraser River sockeye, Interior Fraser coho, and Southern BC Chinook ([DFO 2015](#ref-dfoWildSalmonPolicy2015); [DFO 2016](#ref-dfoIntegratedBiologicalStatus2016), [2018](#ref-dfo2017FraserSockeye2018); [Grant et al. 2020](#ref-grant2017FraserSockeye2020)), and was further ground-truthed with data for Fraser River Chum and Pink Salmon (Pestal et al. in prep ). Essentially, the scanning tool uses a decision tree to estimate CU status based on data type, quality, abundance, and trends (e.g., Figure 2.1). An expert review of rapid status results for each CU is intended to be incorporated into application of this tool (S. Grant, pers comm). When using this method in the case study, we took the outputs of the algorithms at face value and did not confirm using expert opinion.

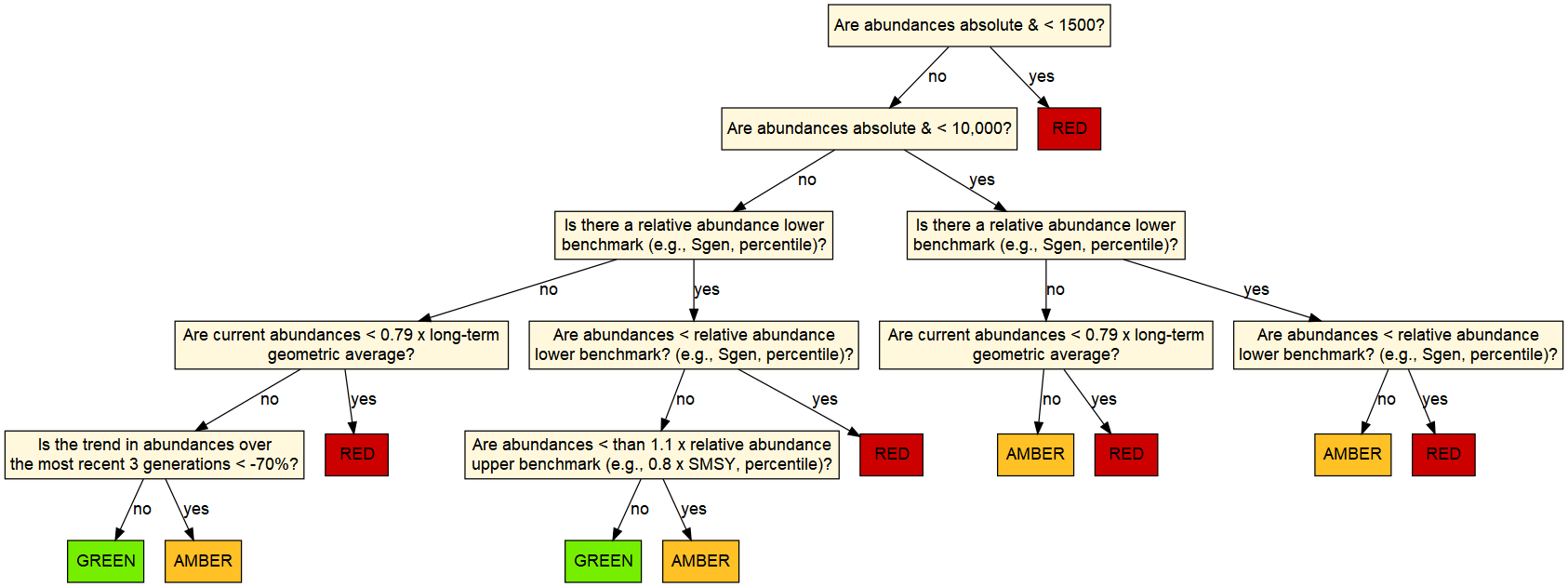


Figure 2.1: Decision tree to assess status of Conservation Units based on the Wild Salmon Policy, under development by State of the Salmon Program

The rapid multi-dimensional scanning tool uses generational mean spawner abundances as a basis for comparison at each node of the decision tree, including when comparing against absolute abundance thresholds (e.g., 1500 spawners), abundance-based lower benchmarks (e.g., or percentile), and abundance-based upper benchmarks (e.g., 0.8 or percentile). Spawner abundances are also smoothed using generational averages prior to calculating trends in spawner abundance over time (Pestal et al., in prep).

## 2.3 AGGREGATE ABUNDANCE-BASED LRPS

Aggregate abundance-based LRPs represent the SMU-level abundance at which there is a sufficiently high probability that 100% of CUs (the same % as used for proportion-based LRPs) will be above a single selected benchmark, which is a proxy for above the red zone in our case study applications. This definition requires a decision to be made about what represents a ‘sufficiently high probability’ that 100% of CUs will be above their benchmarks. 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 ([Frame et al. 2010](#ref-frameGuidanceNoteLead2010)): 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-based LRPs is included in (Holt et al. in review).

We consider two types of aggregate abundance-based LRPs in our case studies: Logistic regression-based LRPs and Projection-based LRPs. Logistic regression LRPs are estimated using historical data, and thus represent conditions that have been previously experienced by a SMU. In comparison, projection-based LRPs use historical data as a basis for quantifying population dynamics, but are based on projections of future states, and thus, allow uncertainty in future processes to be accounted for through alternative scenarios.

Within both the logistic regression- and projection-based LRP estimation routines, we characterize annual CU status using raw annual spawner abundances. This approach is based on preliminary analyses that showed using raw 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-based approach led to considerable auto-correlation in the aggregate abundance time series, which is a direct violation of the logistic regression assumptions. We therefore used raw annual spawner abundances within the estimation routines, but used generational averages of aggregate spawner abundances when assessing SMU-level status relative to the aggregate abundance-based LRPs to reduce noise in annual decisions about whether an LRP had been breached. The decision to use generational averages of aggregate spawner abundances when determining whether an LRP is breached is consistent with the approach used for proportion-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 proportion-based approach) is based on generational-averaged values in order to reduce annual fluctuations in decisions about about whether an SMU has dropped below its LRP.

### 2.3.1 Logistic regression-based LRPs

Logistic regression-based LRPs (also called 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 ‘poor.’ While in theory, estimates of CU status used in the logistic regression could come from the rapid multidimensional scanning tool, we found little evidence of a statistical relationship between between multidimensional CU status and aggregate spawner abundance for the one case study we considered this approach for: Interior Fraser Coho. As a result, we rely on status estimated from a single lower benchmark metric (e.g., ) rather than the multidimensional scanner tool to develop logistic-regression-based LRPs in our case studies. We provide further discussion of this result within the Interior Fraser Coho case study section of this paper.

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 lower benchmark (LBM) and 0 (failure) = all CUs did not have status > LBM. A logistic regression is then fit to predict the probability that all CUs will have status > LBM as a function of aggregate spawner abundance to the SMU using the logistic regression equation:

where, is probability, and are estimated logistic regression parameters and is spawner abundance to CU in year . Equation (2.1) is then re-arranged to calculate the LRP as the aggregate spawner abundance associated with the pre-specified probability threshold of ,

Annual spawner abundances at both the CU and SMU level for this analysis are on the raw scale (i.e., no generational averaging applied). An example logistic regression fit is shown in Figure 2.2. We show the estimation of LRPs based on this fit for four possible probability thresholds: = 0.5, 0.66, 0.90, and 0.99. For each level, LRP estimates represent the aggregate abundance that is associated with that probability of all CUs having status greater than their LBM. Logistic regression models were fit using TMB (citation), with resulting LRP estimates from equation (2.2) calculated within the code. Uncertainty in LRP estimates were quantified based on a 95% confidence interval on the MLE estimate.

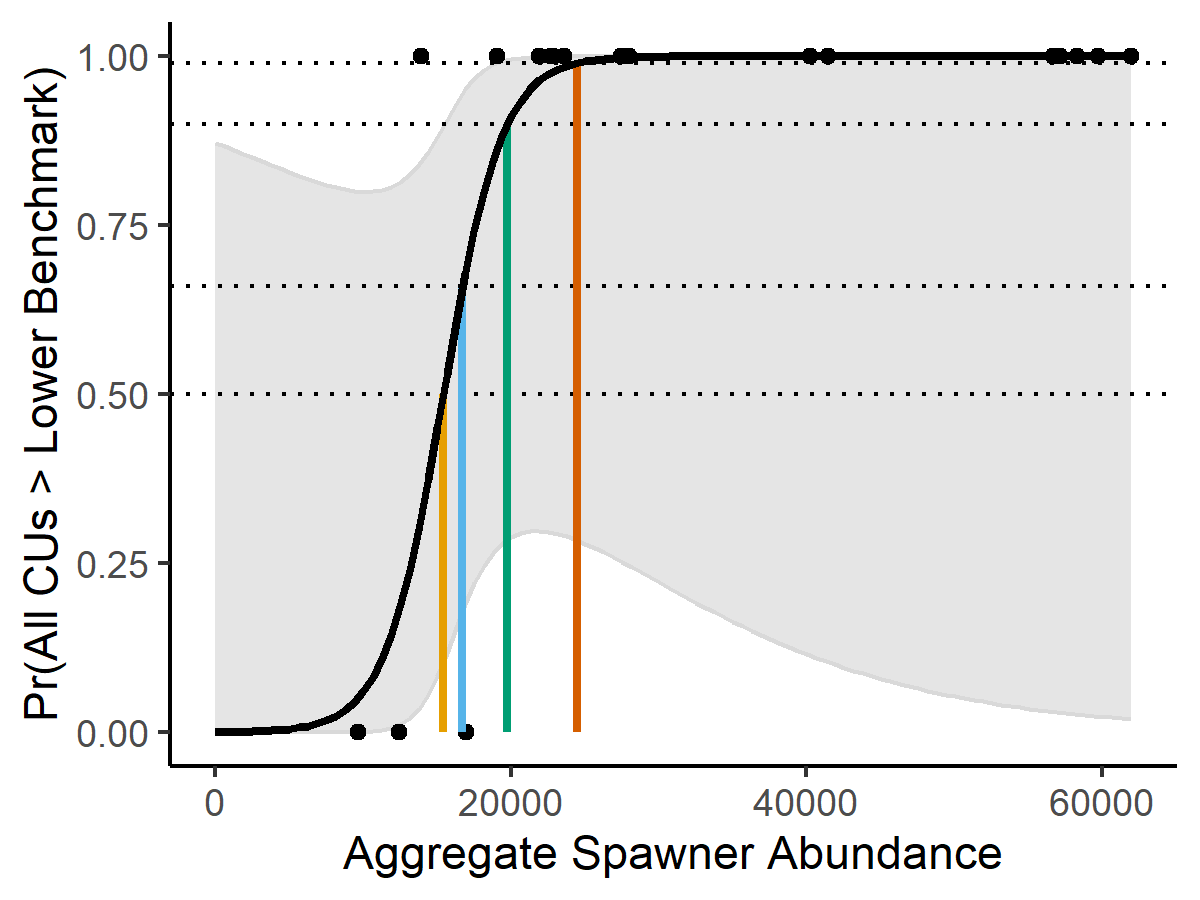


Figure 2.2: Logistic regression fit to annual Bernoulli data to predict the probability of all CUs being above their lower benchmark (LBM) as a function of aggregate SMU abundance. Each black dot represent a year in the observed time series as a Bernoulli indicator showing whether the requirement of 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 the 95-percent confidence interval around the fit model. 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) 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, CU-level status was quantified as the number or CUs with status > LBM for each year of observed data. A logistic regression was then 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 (2.2) cannot be solved directly for a threshold proportion of = 100%, and LRP estimates were highly sensitive to the choice of value used as a proxy. Using = 99% vs.  = 99.9% vs.  = 99.99% gave very different LRP estimates.

##### 2.3.1.0.1 Logistic Regression Model Diagnostics

There are several assumptions associated with logistic regression, of which four that are relevant for our application to LRPs 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. All analyses were implemented using R v.4.0.4 unless otherwise specified ([R Core Team 2021](#X7d7144c0a52ec3594cffc5fec0f425498533505)). 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,

A significant interaction term , indicates a non-linear relationship between aggregate abundance and log-odds, violating this assumption ([Fox 2016](#ref-foxAppliedRegressionAnalysis2016)).

**Evaluating independence (Assumption 2)**

Deviance residuals, , were estimated for each year,

where is the predicted probability of all CUs being above their lower benchmark and is the observation (1 or 0, indicating all CUs above or not, respectively), in a given year ([**fox\_applied\_2016?**](#ref-fox_applied_2016)). Equation (2.4) reduces to,

when , and to,

when ([**ahmad\_diagnostic\_2011?**](#ref-ahmad_diagnostic_2011)).

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 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 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\_tmb\_2016?**](#ref-kristensen_tmb_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, where 1 degree of freedom is based on the difference in the number of parameters between full and null models. P-values <0.05 indicate significant lack of fit ([Fox 2016](#ref-foxAppliedRegressionAnalysis2016)).

In addition, the psuedo- was calculated to indicate the ratio of the model fit to the null model without an independent variable,

where are the deviance residuals for the null model. The psuedo- is a measure of the strength of the relationship between aggregate abundances and probability of all CUs being above their lower benchmarks, but unlike values for linear models, it 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 power to detect significant model coefficients, and coefficient estimates may be biased when time-series are short. [Peduzzi et al.](#ref-peduzziSimulationStudyNumber1996) ([1996](#ref-peduzziSimulationStudyNumber1996)) 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, and 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 logistic-regression based 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.

**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-BASED LRPS

The projection-based LRP approach combines all the information known for individual CUs within an SMU and then uses that information to project abundance trends into the future. Projection-based LRPs are then estimated using projected future 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. ) at a given level of exploitation. This projection-based LRP approach allows for explicit consideration of uncertainty as the user can specify various projection scenarios to reflect lack of biological or fisheries information. As with logistic regression-based LRPs, we relied on status estimated from a single metric rather than the multidimensional scanner tool to develop LRPs using projections. Future extensions of this approach may want to consider applying the multidimensional scanner tool within forward projections to classify CU status.

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 quantify recovery potential for Pacific salmon populations ([Holt et al. 2020](#ref-holtQuantitativeToolEvaluating2020); [Freshwater et al. 2020](#X05d0642f7bbce859a84f3071e0897945c1c2212)). We created a modified version of samSim to support LRP estimation. The LRP version of samSim is described in detail in Appendix 8, while model code is available on GitHub at: <https://github.com/Pacific-salmon-assess/samSim/tree/LRP>.

Detailed descriptions of the parameterization of samSim for our two case study applications of abundance-based projected LRPs (Interior Fraser Coho and WCVI Chinook) are presented in Chapters 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 alternative operating models (OMs). 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 projected LRPs using samSim:

1. Use samSim to project spawner abundances forward for over stochastic simulations.
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 (), based on intervals of 200 fish . E.g., = 0:200 fish, 200:400 fish, 400:600 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, :
   * 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 a 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 for that bin as:
   * For example, if 125 of the 500 realizations that fell within the 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 1,200 fish.
4. Identify the LRP as the mid-point of the aggregate abundance bin, , that is closest to the required 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 2.3 for the four probability levels used in our case studies (p\* = 0.5, 0.66, 0.90, and 0.99). Uncertainty estimates for LRPs are not available based on this method, but the approach does integrate all uncertainties in underlying parameters to identify LRPs with specified probabilities of all CUs being above LBM. In addition, LRP estimates could be presented as a range based on the bin size.

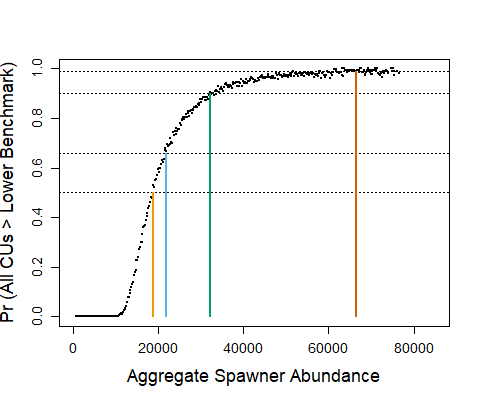


Figure 2.3: Example of projected probability curve derived from projections over 30 years and 10,000 MC trials. The curve shows the projected probability of all CUs being above their lower benchmark (LBM) as a function of aggregate SMU abundance, where aggregate spawning abundance is really a bin of 200 fish (e.g., 0-200, 200-400, etc). Each dot in the curve represents a single combination of year and simulation trial. 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) 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.

# 3 CASE STUDY 1: INTERIOR FRASER COHO SALMON

## 3.1 CONTEXT

The Interior Fraser (IF) Coho Salmon Stock Management Unit (SMU) includes Coho Salmon that return to the Fraser River and tributaries upstream of Hell’s Gate in the Fraser Canyon. Like most coho salmon, IF Coho spend at least one full year in freshwater as fry before migrating to the ocean as smolts ([Arbeider et al. 2020](#ref-arbeiderInteriorFraserCoho2020)). Most (88%) IFC have a 3-year life cycle, 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 cycle in which they spend an additional year in freshwater before migrating as smolts in their third year. Both 3-year and 4-year life cycles spend 18 months at sea. Less than 1% of IF 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](#ref-arbeiderInteriorFraserCoho2020)).

WSP Conservation Units (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 [[DFO](#ref-dfoWildSalmonPolicy2015) ([2015](#ref-dfoWildSalmonPolicy2015)); Figure 3.1]. Previous work by the Interior Fraser Coho Recovery Team (IFCRT) identified 11 subpopulations nested within the five CUs, and developed recovery objectives based on maintaining abundance in each of these smaller subpopulation units [[IFCRT (Interior Fraser Coho Recovery Team)](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4) ([2006](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4)); Table 3.1]. The delineation of subpopulations 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 evidence. The 11 subpopulations are described in detail by the [IFCRT (Interior Fraser Coho Recovery Team)](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4) ([2006](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4)).

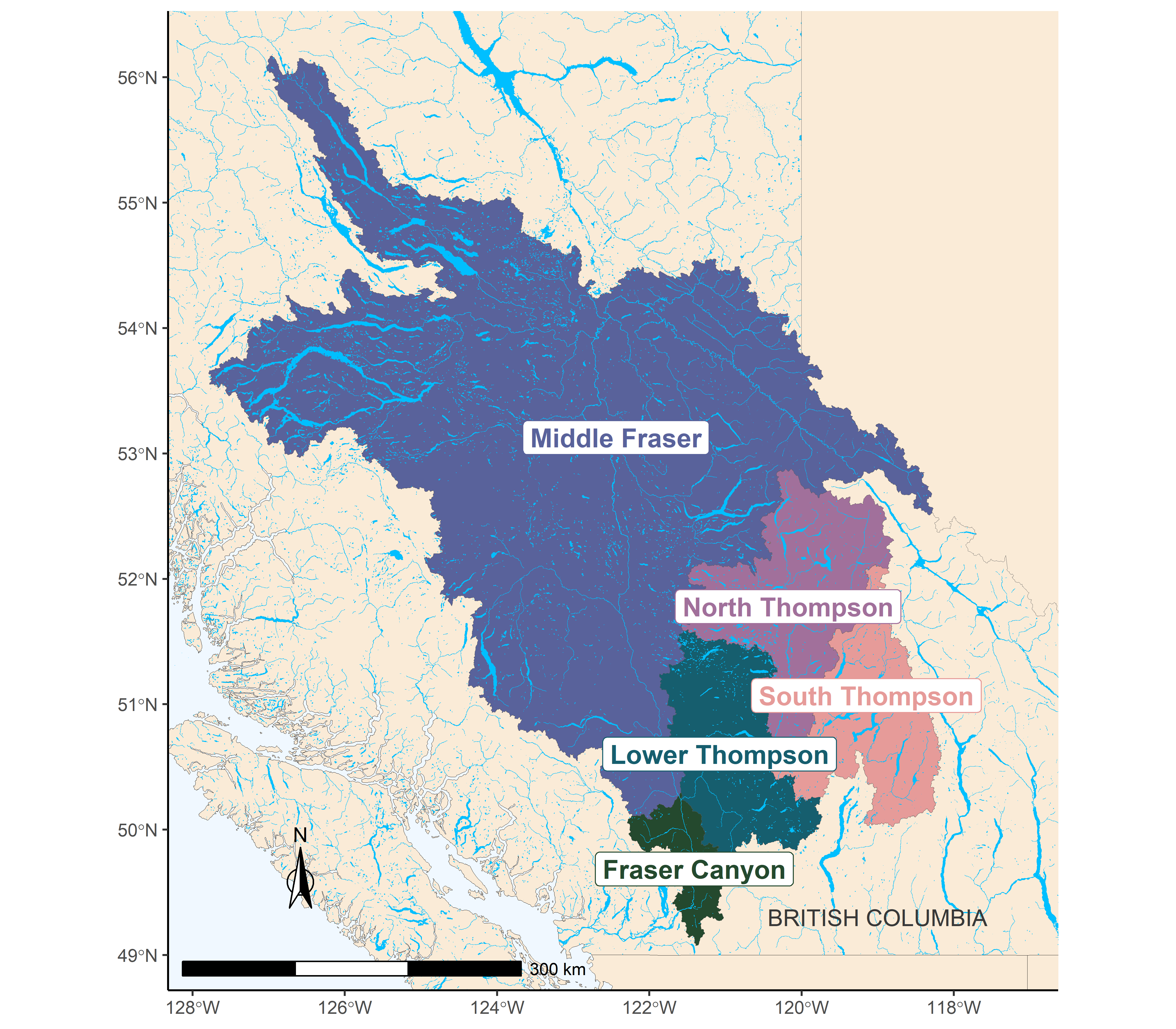


Figure 3.1: The five Conservation Units that make up the Interior Fraser Coho Stock Management Unit.

Table 3.1: 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 (Interior Fraser Coho Recovery Team)](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4) ([2006](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4)).

|  |  |
| --- | --- |
| 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 |

### 3.1.1 Previous assessments

Declines in IF 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](#ref-deckerAssessmentInteriorFraser2014)). Evidence of a new, lower productivity regime starting in return year 1994 has been documented ([Decker et al. 2014](#ref-deckerAssessmentInteriorFraser2014)) that coincides with declines in spawner abundances. In 2002, the IF 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) lead to a conservation strategy outlining short-term and long-term recovery objectives for the management unit ([IFCRT (Interior Fraser Coho Recovery Team) 2006](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4)). In 2014, [Decker et al.](#ref-deckerAssessmentInteriorFraser2014) ([2014](#ref-deckerAssessmentInteriorFraser2014)) assessed status relative to the 2006 IFCRT objectives, and concluded that IF coho had been above the short-term recovery target of 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](#ref-dfoWildSalmonPolicy2015))). As part of the WSP assessment, was estimated for each CU and used as one of several benchmarks considered when assigning integrated CU status. A subsequent COSEWIC assessment in 2016 upgraded the status assessment for the IF Coho DU from ‘endangered’ to ‘threatened’ ([**cosewic\_cosewic\_2016?**](#ref-cosewic_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](#ref-arbeiderInteriorFraserCoho2020)).

### 3.1.2 History of aggregate-abundance based reference points

Interior Fraser Coho show a strong positive relationship between spatial distribution and overall abundance, which has been used as a basis for identifying aggregate abundance-based 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 (Interior Fraser Coho Recovery Team) 2006](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4)); 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 wild-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-based 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.](#ref-deckerAssessmentInteriorFraser2014) ([2014](#ref-deckerAssessmentInteriorFraser2014)) 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. The 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.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) also used logistic regressions of the relationship between the IFCRT’s distributional objectives and aggregate abundance when evaluating how exploitation rates and marine survival rates affected the ability of Interior Fraser Coho to meet conservation targets. Their approach was similar to that of [Decker et al.](#ref-deckerAssessmentInteriorFraser2014) ([2014](#ref-deckerAssessmentInteriorFraser2014)), 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 MU-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](#ref-arbeiderInteriorFraserCoho2020)). As a result, [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) recommended that the long-term recovery target for the stock 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 concerns about inconsistent assessment methods and data quality. All Interior Fraser Coho data were provided by DFO’s Fraser River Stock Assessment Unit (M. Arbeider, pers. comm). These data included: (i) annual spawner abundance by CU (1998-2020), (ii) annual 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. Data were similar to those previously described in [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)); 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.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) include the incorporation of three additional years of data (return years 2018-2020; brood years 2014-2016), updates to the smolt-to-adult marine 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, 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 constant among all CUs, which is unlikely to be true. Furthermore, models used to reconstruct exploitation rates require a large number of assumptions that are expected to be incorrect ([Arbeider et al. 2020](#ref-arbeiderInteriorFraserCoho2020)). Because exploitation rate time series are used to reconstruct spawner-recruit time series, errors in exploitation rates will propagate through to estimates of stock recruitment parameters, relative abundance-based benchmarks such as , and covaration 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-maturity. Spawner abundance estimates are largely derived from visual surveys, for which observer efficiency is difficult to accurately estimate. Scale sampling to determine age structure is incomplete at at the CU-level with small sample sizes, missing data, and limited spatial representation within CUs in some years ([Korman et al. 2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)).

## 3.3 CU STATUS ESTIMATION

We use three alternative ways to characterize CU status when developing LRPs for Interior Fraser Coho. The first approach, which uses the rapid multidimensional scanning tool developed by the State of the Salmon program (Section 2.2.1), is consistent with Canada’s WSP and is recommended by Holt et al. (in review) as the method that should be used to estimate CU status when using the proportional LRP approach. The other two approaches are primarily used to develop aggregate abundance-based LRPs in this case study, as well as for a point of comparison with the rapid multidimensional scanning tool.

1. Rapid multi-dimensional scanner tool
2. CU-level abundance relative to as a lower benchmark on abundance
3. Distribution of spawning abundance relative to distributional targets developed by the IFCRT

The second approach is based on comparing the current abundance of each CU to its CU-specific estimate of , where CU status is considered poor when abundance drops below . The value of represents the number of spawners required to recover to (spawners maximum sustainable yield) within one generation, under equilibrium conditions in the absence of fishing ([Holt et al. 2009](#ref-holtIndicatorsStatusBenchmarks2009)). is one of several benchmarks available for assigning multidimensional CU status in WSP Integrated Status Assessments; 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](#ref-dfoWildSalmonPolicy2015)).

The third approach is based on the distribution of spawning escapement among subpopulations nested within CUs (Table 3.1). We apply this approach for Interior Fraser Coho to maintain consistency with previous recovery planning processes for this SMU ([IFCRT (Interior Fraser Coho Recovery Team) 2006](#X3a9b2322ecf9aa099e5a3bc7325b931746d22c4); [Arbeider et al. 2020](#ref-arbeiderInteriorFraserCoho2020)). 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 average escapement in at least half of the sub-populations within each of the five CUs is to exceed 1,000 wild-origin spawning coho salmon, excluding hatchery fish spawning in the wild. We selected the short-term recovery target to represent poor CU status in our case study (e.g., below a lower benchmark) because, as noted by [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)), 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 multidimensional approach could include distributional metrics such as those used in the IFCRT approach.

### 3.3.1 Estimation of Sgen

Estimates of Sgen are required when assessing CU status using both the ‘Rapid Multidimensional Scanning Tool’ and the comparison of current CU-level abundance to . Two different formulations of stock recruitment model were used to estimate : (i) a base Ricker model, which includes a marine survival covariate, and (ii) a Ricker\_priorCap model in which an informative prior distribution is used to increase compared to the base model. is the spawner abundance level at which the stock replaces itself; the relationship between and Ricker stock recruit model parameters is shown below. Both of these models have been previously developed and applied to Interior Fraser Coho CUs. The marine 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 and depensatory mortality were included, was also used by [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) and [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)); however, we did not include it in our case study for simplicity. As noted by [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)), there is no indication in available data of depensatory dynamics, and the SR model fit with depensatory mortality required a highly uncertain assumption to be made about the escapement level at which recruitment is reduced to 50% of the value it would have been in the absence of depensatory mortality. Furthermore, formal model selection criteria showed that adding depensatory mortality into models lead to a reduction in model fit ([Korman et al. 2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)).

[Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) and [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) 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.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) 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). Thirdly, because all CUs had equal amounts of data, the commonly cited benefit of hierarchical models allowing data-poor systems to borrow information from data-rich systems did not apply. While future stock recruit analyses for Interior Fraser Coho may wish to re-visit the hierarchical model, we do not expect our decision to apply an individual modelling approach here will affect out general conclusions.

The formulations for our two stock recruitment models using the assumption of independent productivity among CUs are described below.

*Model 1: Ricker*

The base Ricker stock recruit model formulation was:

where,

= the predicted number of natural origin recruits from CU of age returning in year (i.e., recruits that were produced by escapement in brood year )

= the proportion of recruitment from CU returning at age from brood year

= spawners from CU in brood year

= productivity parameter for CU

= marine survival co-efficient shared among CUs

= hatchery marine survival index (smolt-to-adult) shared among CUs for sea entry in year t-1

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

= standard deviation of process error on recruitment deviations

This model formulation is similar to the Ricker model used in [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)), but without a hierarchical structure imposed on . We placed the following non-informative constraints on the likelihood function to replicate the Bayesian model fitting routine of [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)):

*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 to increase carrying capacity. [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) suggested that the Ricker model with a 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](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)). 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.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) 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, ). [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) followed the approach of [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) by considering both the base Ricker model and a version of the Ricker model with an informative prior distribution on to be plausible when providing management advice.

[Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) and [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) set at 1.5 times the value estimated from the base model fit without a prior on . For our integrated Sgen-LRP model fits (described in section xxx), we found that we needed to constrain at no more than 1.4 times the value to achieve model convergence, so we used the 1.4 times expansion instead. We set at spawners, which is the same value used by [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)). Note that the “” term is used to correct for scaling spawner abundance by 1/1000 when fitting models. [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) parameterized the distribution in terms of precision (), where . The effect of adding the prior on when fitting individual models to available data is shown in Figure 3.2.

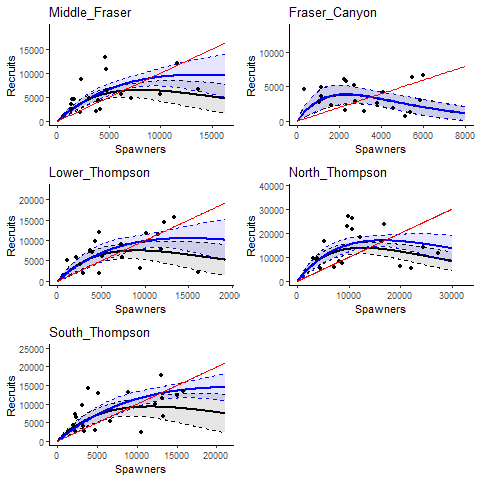


Figure 3.2: Stock recruit curves fit to spawner and recruitment data using individual models for each CU. Solid black lines shows the MLE fit for the base Ricker model while solid blue lines shows the MLE fit for the Ricker\_priorCap model. Associated black and blue shaded regions show the 95 percent confidence intervals on respective model fits. The red line show the replacement line.

*Calculation of Sgen*

The inclusion of a marine survival co-variate in all four spawner recuit models means that the realized productivity changes from year to year with changing marine survival. We incorporated this adjustment into our calculations of by first calculating the effective productivity for each CU as:

where, is the average marine survival rate over the available time series.

was calculated as a function of log() and using:

where, represents the Lambert W function ([Scheuerell 2016](#Xc42d04c48da523ac8df8573b3cd717b3dd480a5)). was then calculated numerically by solving the following equation:

## 3.4 LRP ESTIMATION: PROPORTION OF CUS

### 3.4.1 Methods

We looked at the proportion of CUs that had rapid multidimensional status assessments above the red zone to determine in which years between 1998 and 2020 the LRP would have been breached. 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 relative abundance-based benchmarks (lower benchmark = and upper benchmark = 0.8) when assessing multi-dimensional rapid status: the base Ricker model and the Ricker\_priorCap model. Estimates of and were made using all data available up to 2020.

For comparison, we also looked at the proportion of CUs that had recent generational average (3-year) spawning abundance greater than in each historical year and 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 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 ??. As a result, generational average spawning abundance was more likely to drop below when it was estimated using the Ricker\_priorCap. Under the base Ricker model formulation, generational average spawning abundance remained above for all years between 2000 and 2020 (Figure 3.3). In comparison, under the Ricker\_priorCap formulation, generational average abundance dropped below in one or more years for Lower Thompson CU (2006), Middle Fraser CU (2006, 2008), and South Thompson CU (2000, 2006, 2007, 2015; Figure 3.4). As a result, at least one CU had stock status assessed as below for 5 of the 21 years between 2000 and 2020.

When CU status was assessed using the multidimensional scanning tool with lower and upper abundance-based benchmarks based on and 0.8 as inputs, CU status was always assessed as red for years in which the generational average spawning abundance dropped below , regardless of which stock recruit model was used to estimate benchmarks (Figures 3.3, 3.4). This result occurs because according to the multidimensional decision tree (Figure 2.1), status is derived from abundance-based benchmarks in most years, which means that being below is most often the trigger for a red CU status assessment. An exception occurs in the Fraser Canyon CU in years 2015-2017. In these years, the generational average of absolute spawning abundance is < 1500 spawners and CU is assigned red status under the first node of the decision tree even though spawning abundances are above (Figure 2.1). As a result, when multidimensional status was assessed using abundance-based benchmarks estimated from the base Ricker model, a proportion-based LRP for the SMU would have been breached in 3 of 21 years (2015-2017) based on Fraser Canyon spawning abundances dropping below 1500 spawners in theses years (Figure 3.3). When multidimensional status was assessed using abundance-based benchmarks from the Ricker\_priorCap model, a proportion-based LRP would have been breached in 7 of 21 years (2000, 2006-2008, 2015-2017) based on a combination of spawning abundances < 1500 in the Fraser Canyon CU and spawning abundances < in other CUs (Figure 3.4). Multidimensional status based on the rapid screening tool was above red for all CUs in the most recent year, 2020, indicating that the SMU is currently above a proportion-based LRP.

Overall, the proportion of CUs with red status differed between the multidimensional approach and the single metric approach of looking at status relative to lower benchmarks in only 2 or 3 of 21 years, depending on the Ricker model formulation.

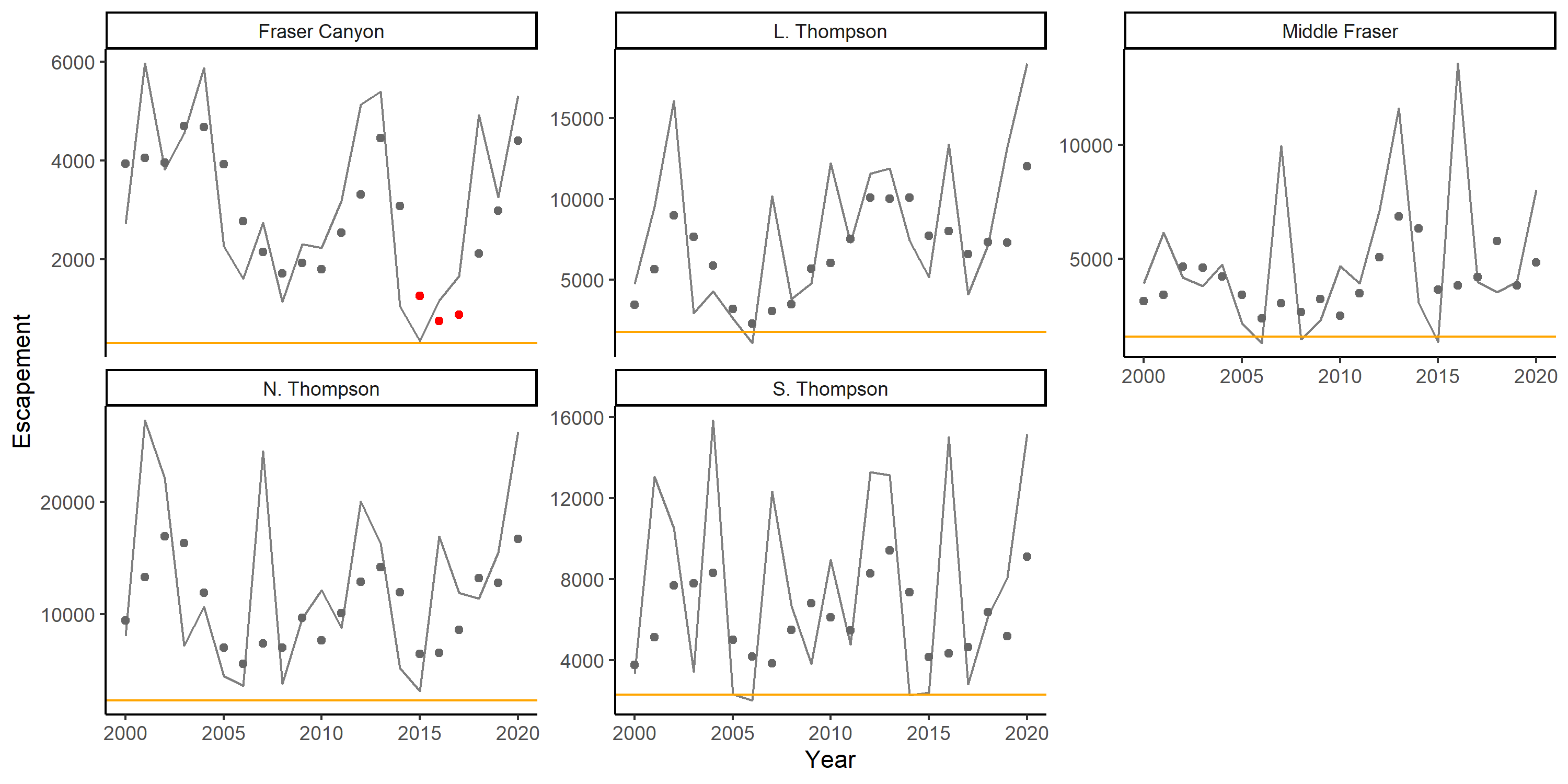


Figure 3.3: Escapement time series for five Interior Fraser Coho CUs shown as annual escapements (lines) and 3-year geometric mean escapements (dots). Grey dots indicate years in which all CUs had multidimensional rapid status assessments above red when Sgen was estimated using the Ricker model, while red dots indicate years in which one or more CUs had multi-dimensional status assessments in the red zone, which would trigger a breach of the LRP. Solid orange lines show estimates of Sgen from the Ricker model for comparison.

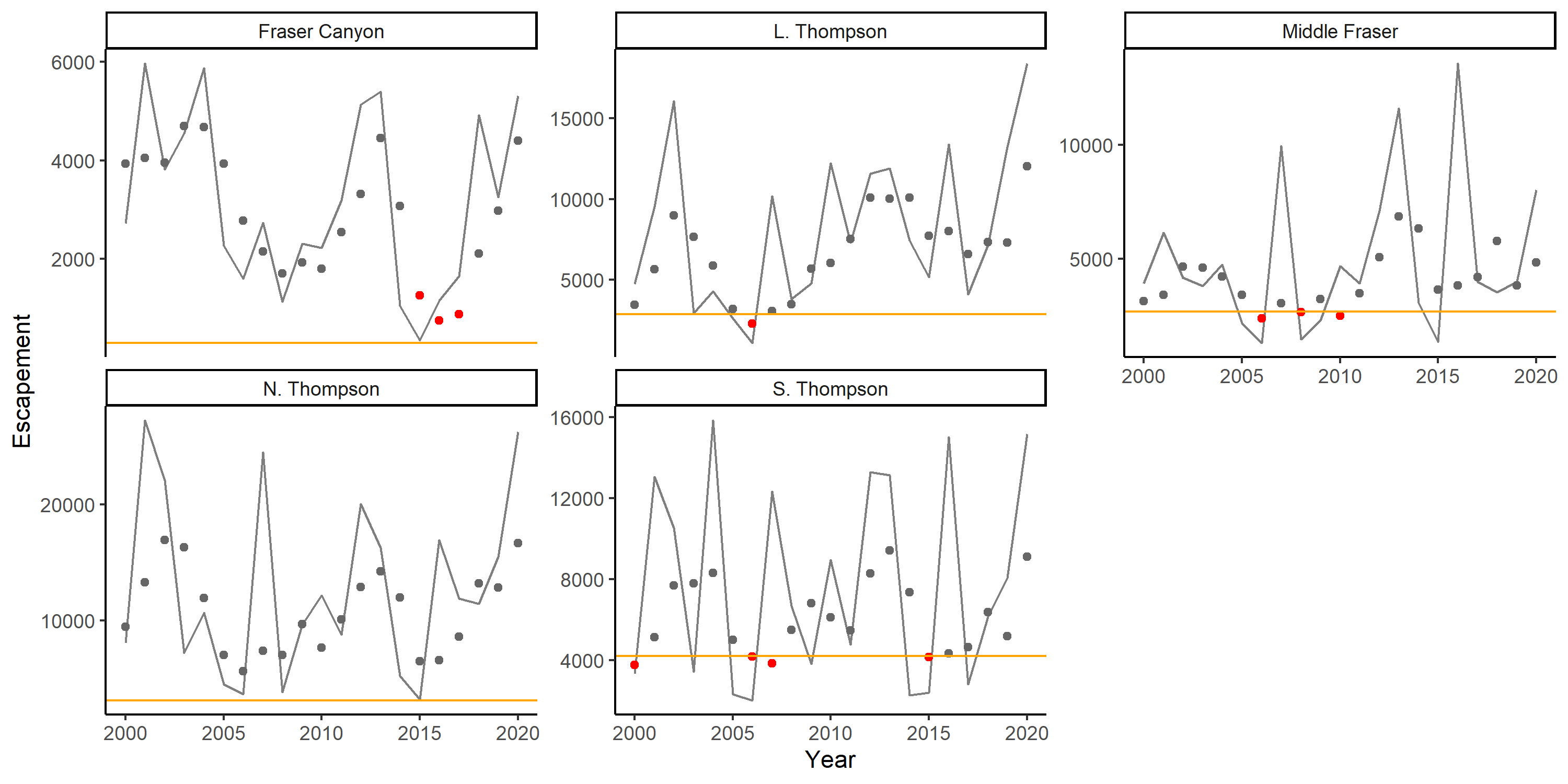


Figure 3.4: Escapement time series for five Interior Fraser Coho CUs shown as annual escapements (lines) and 3-year geometric mean escapements (dots). Grey dots indicate years in which all CUs had multidimensional rapid status assessments above red when Sgen was estimated using the Ricker\_priorCap model, while red dots indicate years in which one or more CUs had multidimensional status assessments in the red zone, which would trigger a breach of the LRP. Solid orange lines show estimates of Sgen from the Ricker\_priorCap model for comparison.

As a point of comparison, if a proportion-based LRP was based on all CUs being above the IFCRT distributional target, the LRP would have been breached in 4 of the 21 years between 2000 and 2020. Eight of the 11 sub-populations had generational average escapement drop below the 1000 spawner threshold in one or more years (Figure 3.5). 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 subpopulations within each CU with greater than 1000 fish was more often met than not. All 11 subpopulations had generational average spawning abundances above 1000 spawners in 2020, indicating that the stock would be well above a proportion-based LRP based on the IFCRT-distributional target (Figure 3.5).

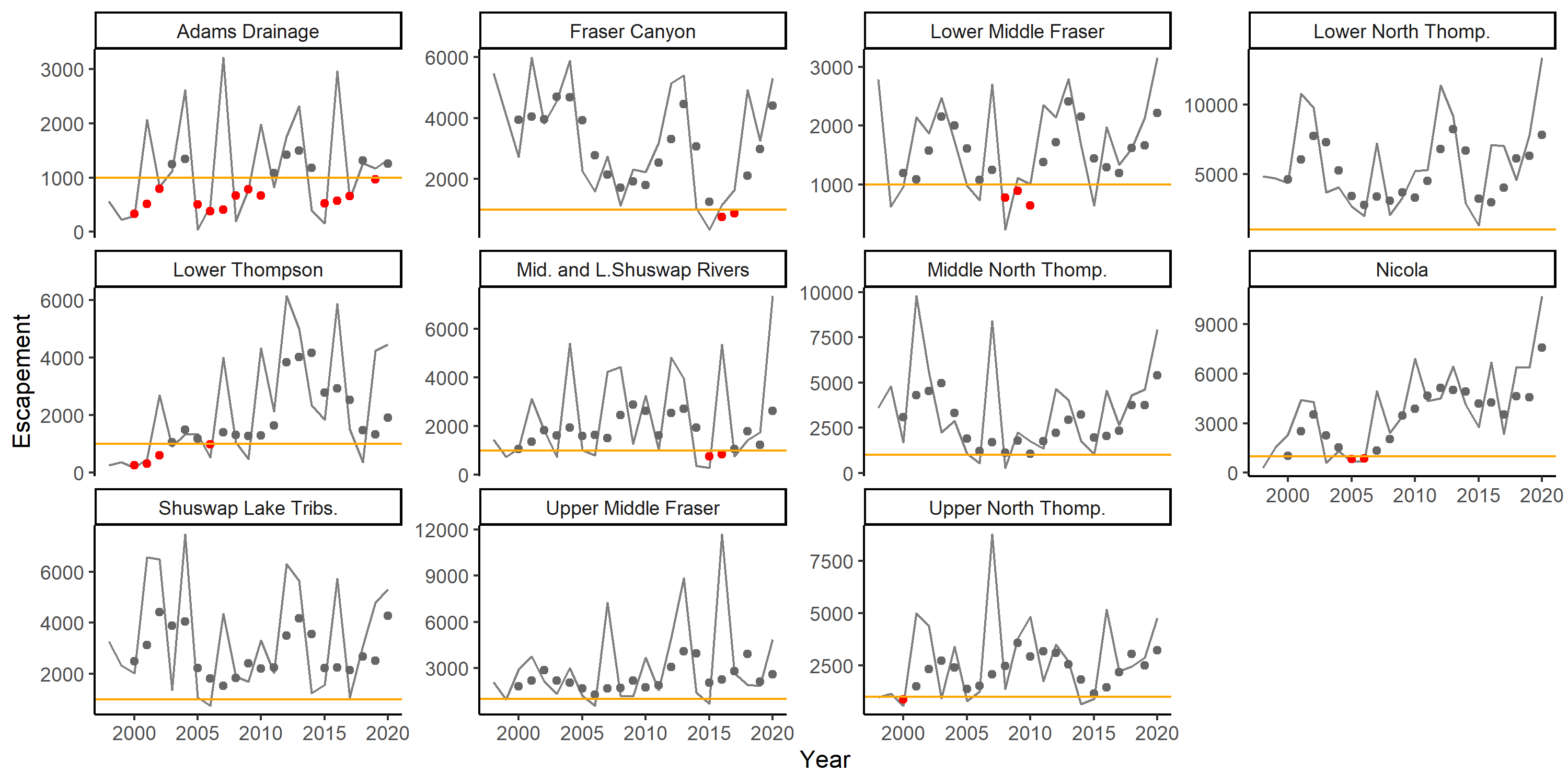


Figure 3.5: Escapement time series for 11 subpopulations of Interior Fraser Coho shown as annual escapements (lines) and 3-year geometric mean escapements (dots). Gray dots shows years in which the 3-year geometric mean escapement was above the 1000 fish threshold used to assess distributional status, while red dots show years in which the 1000 fish threshold was not met. CUs to which each subpopulation belong to are shown in Table 1.

## 3.5 LRP ESTIMATION: AGGREGATE ABUNDANCE LOGISTIC REGRESSION LRPS

### 3.5.1 Methods

We present aggregate abundance-based LRPs derived using logistic regressions with two of the Interior Fraser Coho benchmarks considered: and the IFCRT-distributional target. Because two different spawner recruit models were used to estimate , 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 an LRP. See Section 2.3.1 for an overview of the approach used to calculate aggregate abundance-based LRPs using logistic regression.

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

1. Stock-recruit models fit to each of the 5 CUs to estimate CU-level Sgen (Equation (3.1) and Equations (3.3) - (3.5))
2. 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 Sgen (Equations (2.1) - (2.2))

We did initially consider a third version of the logistic regression model, in which we used the rapid multidimensional scanning tool to characterize CU status. Initial model evaluations led us to exclude this model due to poor fit. There were two factors limiting the establishment of a statistical relationship between multidimensional estimates of CU status and aggregate spawner abundance. First, the rapid multidimensional scanning tool 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 CU status estimates from the multidimensional tool, there was a mismatch in the timing of abundance highs and lows. This mismatch lead to a weak/non-existent relationship between SMU status and the raw (not smoothed) abundances. Using the generational mean of aggregate abundance as the predictor variable in the logistical regression fit instead of raw, annual abundance values introduced considerable auto-correlation. Future explorations of aggregate abundance logistic regression-based LRPs based on the rapid multidimensional scanning tool could account for the auto-correlation by including an AR(1) covariace structure. However, longer time-series and a wider spread of the data would be required to compensate for the additional parameter in the model. The second limiting factor in establishing a statistical relationship between rapid multidimensional estimates of CU status and aggregate spawner abundance is that the rapid multidimensional scanning tool includes criteria that are not continuously tied to the CU abundance. For example, CU status can be determined based on trends, which is not congruent with logistic regression goal of identifying underlying relationship between aggregate abundance and CU statuses. In addition, the rapid multidimensional scanning tool includes absolute abundance thresholds (e.g. generational mean should be above 1500 fish) that are not proportional to the size of a CU. These absolute benchmarks introduce a disconnect between the SMU abundance and status, even when there is high correlation between CUs, because small CUs will be more likely to be below the absolute threshold despite high aggregate abundances.

***Retrospective Analysis***

We used retrospective analyses to examine the effect of time series length on logistic regression-based LRP estimates. Retrospective analyses were restricted to the most recent 6 years (2015-2020) because logistic model fits prior to 2015 were unable to converge on an LRP estimate. For each year between 2015 and 2020, we used data only available up to that year to calculate LRPs and associated confidence intervals.

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

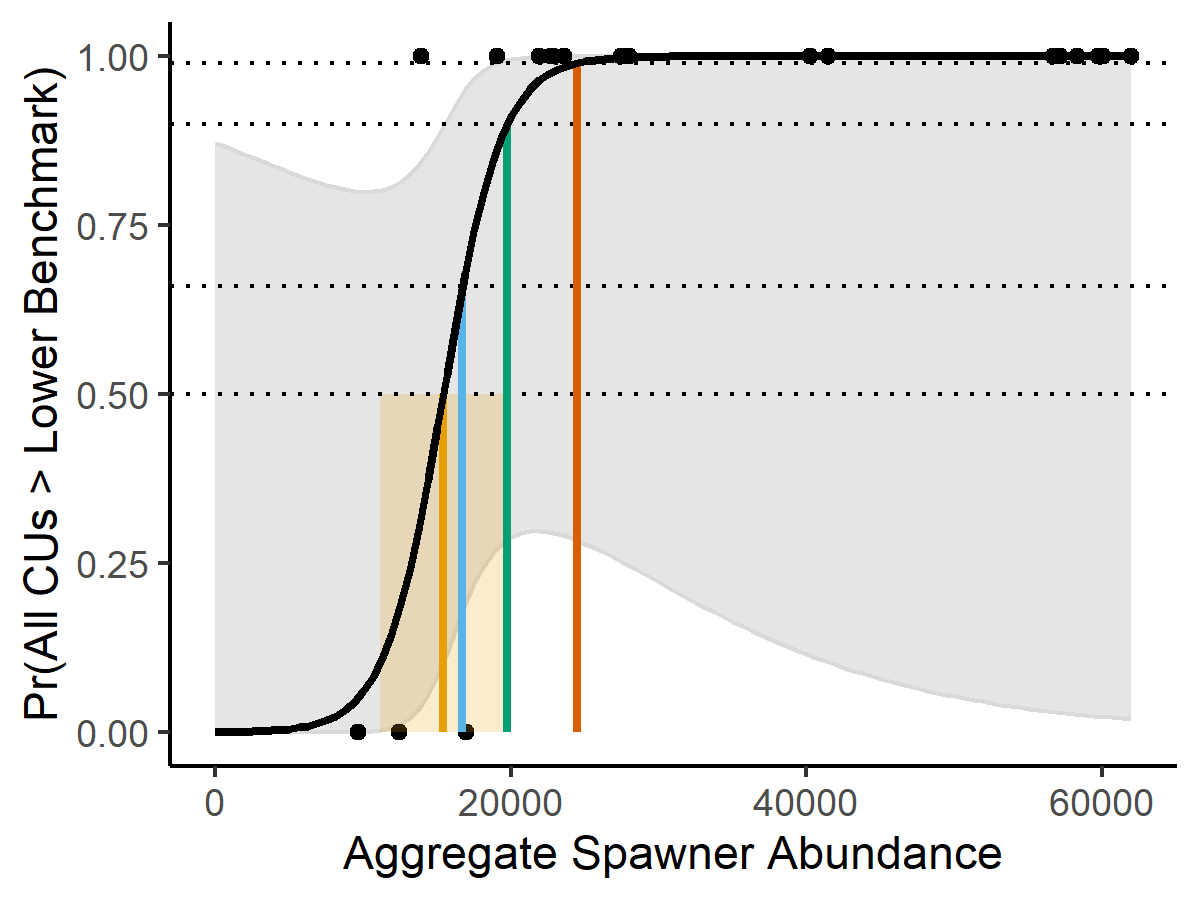
where is the number of CUs being used (3 or 4) and is the LRP calculated in year using only data from . SMU-level status in a given year was calculated for all possible combinations of CUs available (5 combinations when nCUs = 4 and 10 combinations when nCUs = 3) to allow examination of the stability 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.

### 3.5.2 Results

***LRP Estimates***

Logistic regression model fits in 2020 from the integrated Logistic:Sgen-Ricker and Logistic:Sgen-priorCap models are shown in Figures 3.6 and 3.7, respectively. The logistic regression model fit to status estimates based on the IFCRT-distributional benchmark is shown in Figure 3.8.

All three logistic regression-based 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 3.2. There was considerable uncertainty around predicted curves as seen in the large areas of gray shading in Figures 3.6 - 3.8.



When the Logistic:Sgen-Ricker model was used, aggregate abundance-based LRPs ranged from 15,395 to 24,331 spawners, depending on whether the required probability of all CUs being above Sgen was moderate (50%) or very likely (99%) (Table 3.2).

LRPs increased across all probability levels when the carrying capacity was assumed higher under the Logistic:Sgen-priorCap model (Table 3.2). The higher values for most CUs under the alternative Logistic:Sgen\_priorCap model formulation resulted in more historical years in which < 100% of CUs were above . Several years with aggregate abundances between 19,000 - 30,000 spawners that had met the threshold of all CUs > using the Ricker model no longer met this threshold. The result was a shift of the fit curve to the right and higher LRP estimates. LRPs based on the Logistic:Sgen\_priorCap model ranged from 25,677 to 40,637 spawners, depending on whether the required probability of all CUs being above Sgen was moderate (50%) or very likely (99%).

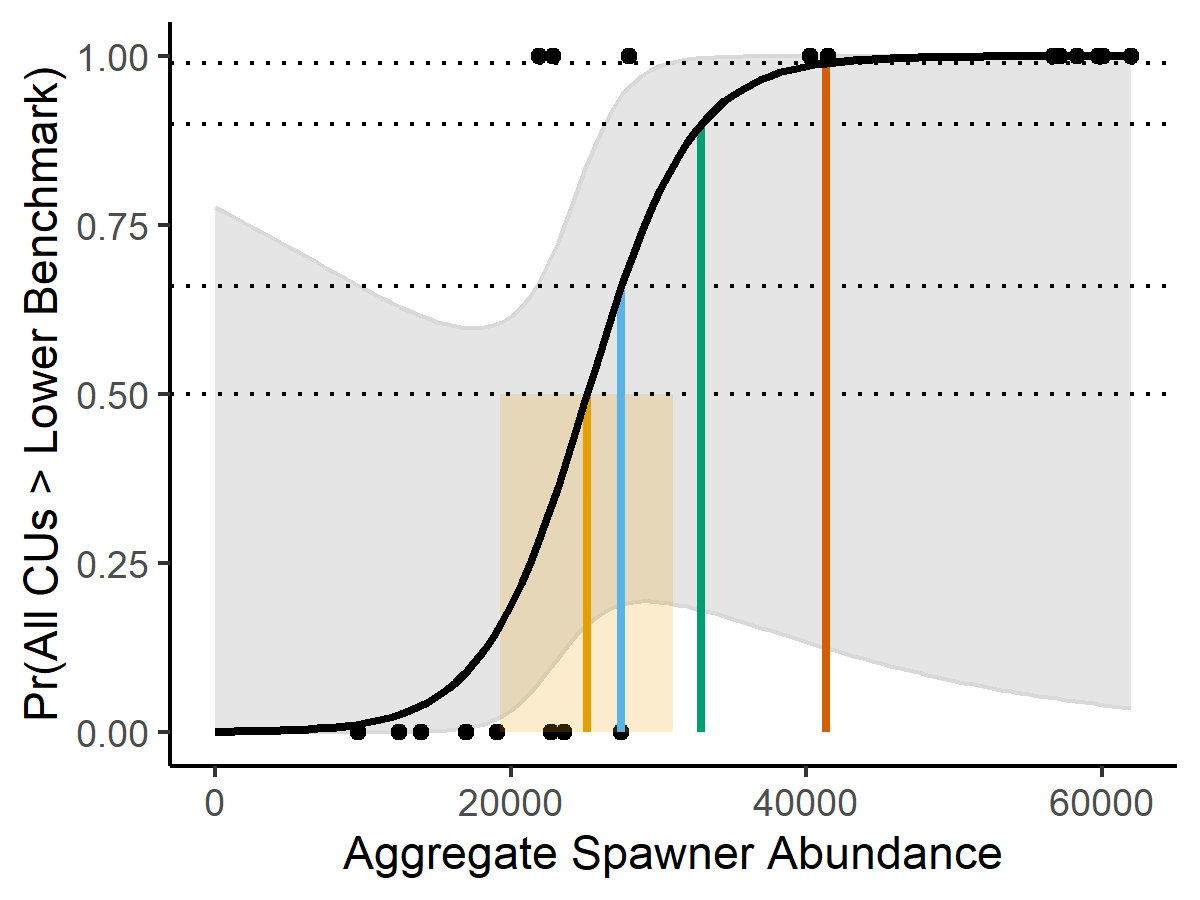


Figure 3.7: Logistic regression fit from the integrated Logistic:Sgen-priorCap LRP model using data from 1998 - 2020. See Figure 9 caption for additional details.

When CU status was based on the IFCRT distributional target, the fit logistic curve was more gradual than the two Sgen 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 3.8). As a result, LRPs based on the IFCRT distributional target were more uncertain than those based on . LRPs based on this model also became increasingly large at high probability thresholds (Table 3.2. The LRP based on a 99% probability was 44,403 spawners, with a 95% confidence interval extending from 15,102 - 73,703 spawners.

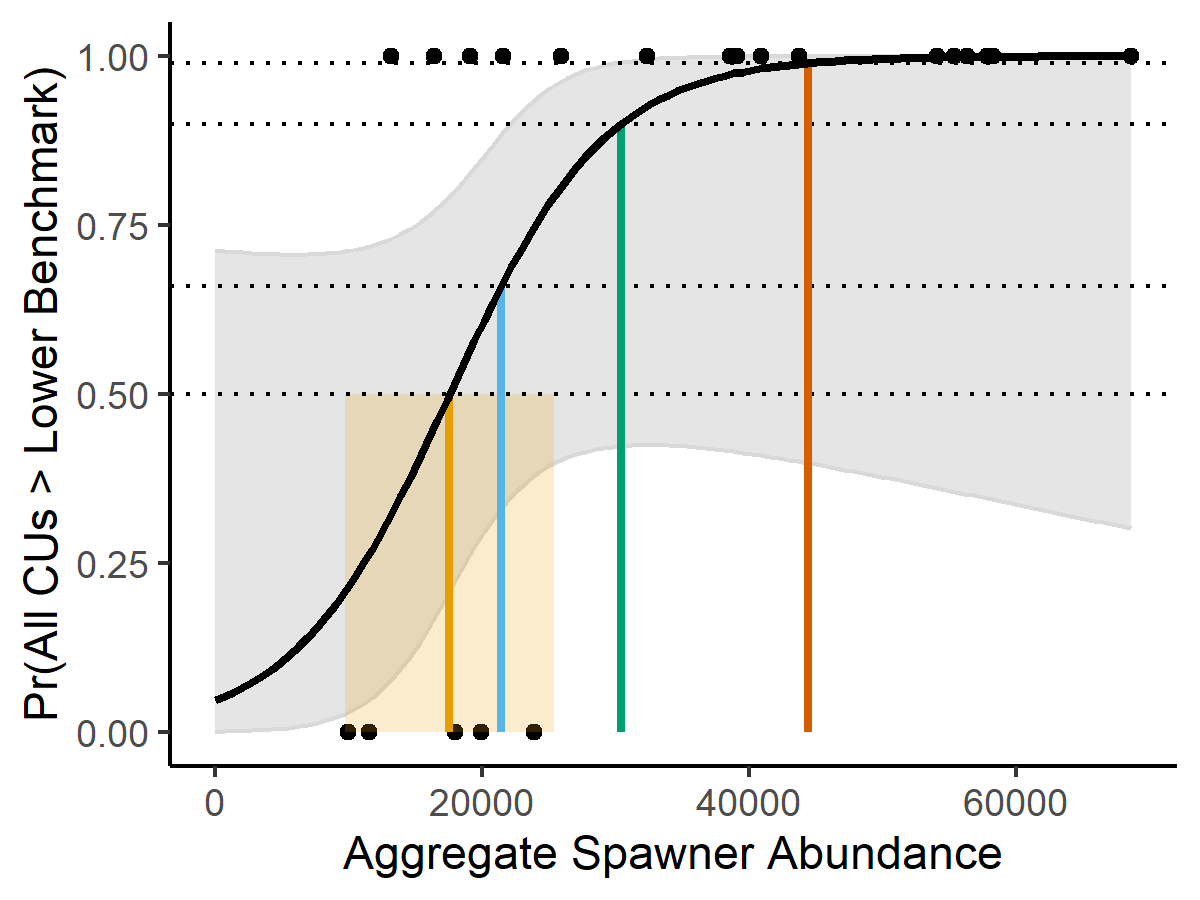


Figure 3.8: Logistic regression fit from the Logistic:IFCRT LRP model using data from 1998 - 2020. See Figure 9 caption for additional details.

Table 3.2: Aggregate abundance based LRPs (with 95% confidence intervals) from three different logistic regression-based 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) | 15,395 (11,187-19,603) | 25,677 (20,683-30,672) | 17,515 (9,695-25,336) |
| 66% (Likely) | 16,685 (12,454-20,916) | 26,424 (20,478-32,369) | 21,396 (13,418-29,375) |
| 90% (Very likely) | 19,668 (13,752-25,584) | 31,969 (21,414-42,523) | 30,372 (15,711-45,033) |
| 99% (Virtually certain) | 24,331 (13,924-34,738) | 40,637 (21,288-59,936) | 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-based LRPs from all three models(Table ([**ref?**](#ref-ref))(tab:logisticDiagIFC2020)). Assumptions of linearity and lack of large outliers were met for all models. 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. An examination of deviance residuals did not show any large outliers, i.e. no residual values were greater than 2 standard deviations. Observations were independent at all year lags examined for the Logistic:Sgen-priorCap and Logistic-IFCRT models. For the Logistic:Sgen-Ricker model, observations were independent at 1 and 2-year lags and marginally significant at a 3-year lag suggesting generational-scale trends (Figure ([**ref?**](#ref-ref))(fig:coho-logisticACF-IM)). The Wald Test showed that logistic model coefficient for aggregate abundance was marginally significant (p < 0.10). Psuedo- 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 model which had a hit ratio of 0.95 at probability thresholds of 50% and 66%. Classification accuracy was lowest for all models at the 99% probability threshold.

Table 3.3: 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 | 0.81 | 1.0 | 0.79 |
| Max. deviance residual | 1.52 | 1.68 | 1.66 |
| AR-1 | -0.20 | 0.16 | 0.05 |
| Wald p-values | 0.09^\* + | 0.08^\* + | 0.09^\* |
| Goodness-of-fit p-value | <0.01 | <0.01 | <0.01 |
| Pseudo- | 0.68 | 0.63 | 0.41 |
| Hit Ratio (p= 50%, 60%, 90%, 99%) | 0.91, 0.91 0.91, 0.74 | 0.87, 0.91, 0.87, 0.78 | 0.76, 0.81, 0.76, 0.52 |

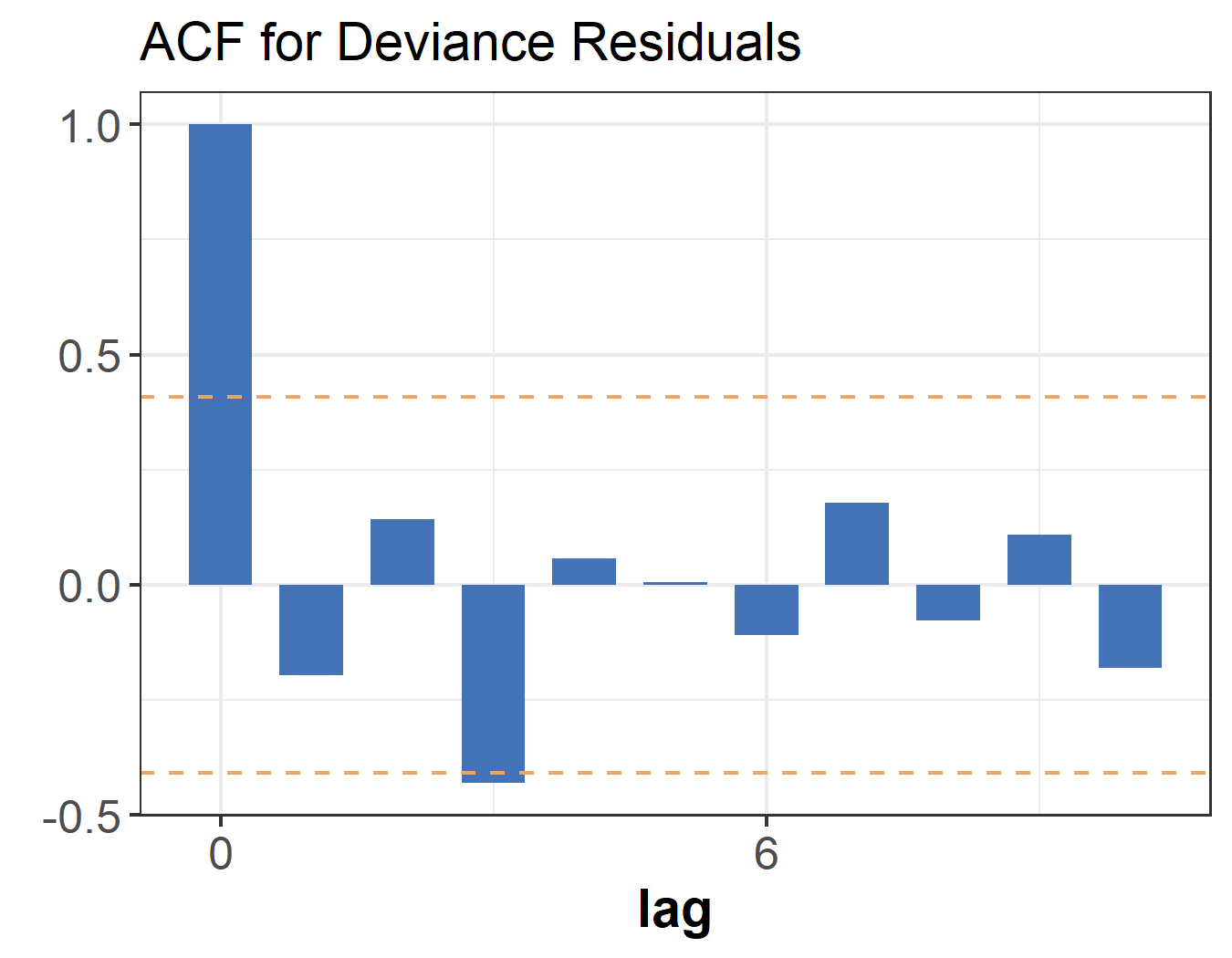


Figure 3.9: Autocorrelation in aggregate spawner abundance at 1- to 10-year lags for the Integreated Sgen:LRP model. Orange dashed lines inidcate whether autocorrelations are significantly different from zero based on a 95% confidence interval

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.](#ref-peduzziSimulationStudyNumber1996) ([1996](#ref-peduzziSimulationStudyNumber1996)) 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 3, 9, 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.](#ref-peduzziSimulationStudyNumber1996) ([1996](#ref-peduzziSimulationStudyNumber1996)) ranged from 26 to 77 years. However, despite small sample sizes, hit ratios are high for all models at p = 50%. As a result, we suggest that logistic regression-based 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***

2015 was the first year in which the available IFC time series was long enough to estimate logistic regression-based LRPs using the Logistic:Sgen-priorCap and Logistic:IFCRT models. However, the Logistic:Sgen-priorCap model was unable to converge on an LRP estimate in 2018. The Logistic:Sgen-Ricker model required an additional two years of data before LRP estimates were first available in 2017. As a result, only 4-6 years of retrospective analyses were available, depending on the model being considered. All three models showed some fluctuations in LRP estimates over time (Figure 3.10). The Logistic:IFCRT distribution model (Dist:LRP in Figure 3.10) tended to produce the most stable LRPs over time.

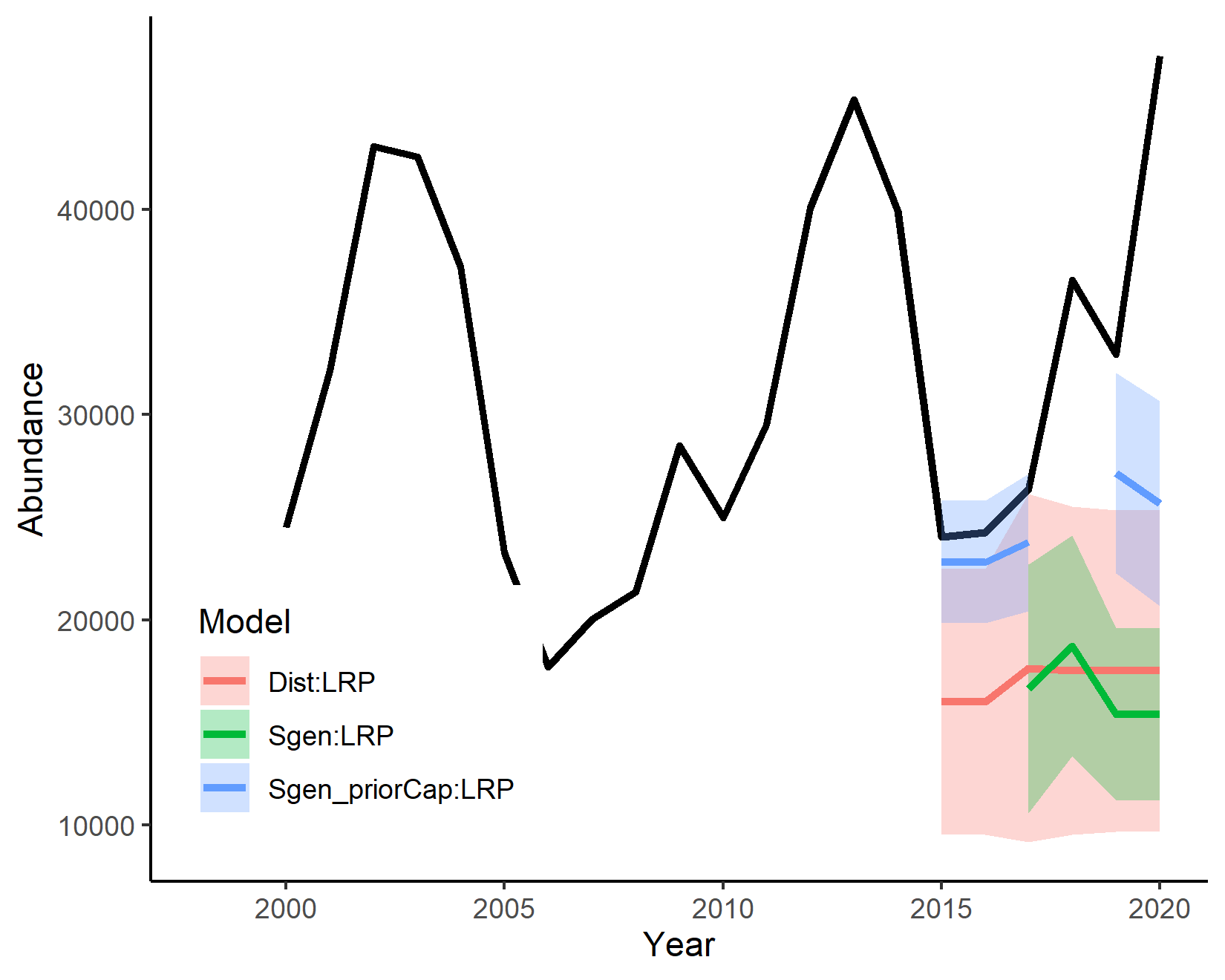


Figure 3.10: Three-year geometric mean of aggregate spawning abundance for the Interior Fraser Coho SMU (black line) and associated time series of retrospective LRPs from logistic regression-based estimation methods. LRPs are based on a 50% probability that all CUs will be above their lower benchmarks. 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 four out of the five CUs, only a subset of scenarios had LRP estimates that converged on a solution (Figure 3.11). Four of the five possible combinations of four CUs had estimates in 2017, while only three had estimates in 2019 and 2020. For scenarios in which LRP estimates were possible, estimates of aggregate status (Equation (3.6)) were often close to the estimate obtained when all 5 CUs were used, and always fell within 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 three CUs were used. This pattern was especially true for 2019 and 2020 when only 4 out of the 10 possible combinations had estimates. For scenarios that were able to converge, aggregate status estimates from 3 CUs tended to be more uncertain than 4- and 5-CU estimates, and showed larger deviations from estimated status when all CUs were used. One missing data scenario in 2018 had a status estimate that fell outside of the 95% confidence interval of the full data estimate.

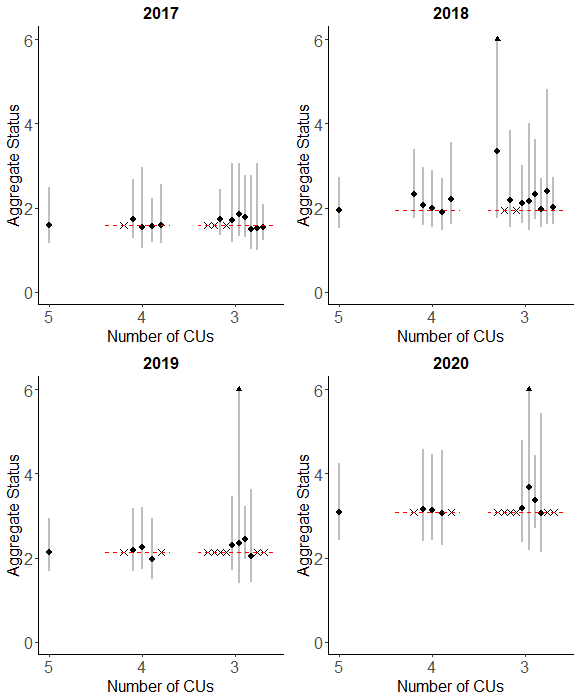


Figure 3.11: Retrospective estimates of aggregate status (with 95% confidence intervals, triangles indicate that the upper bound is greater than the shown axis) from the Sgen:LRP model under different scenarios about missing CUs, where aggregate status is characterized as the recent generational mean 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.

When the Logistic:Sgen-priorCap model was applied to missing data scenarios in which four out of five CUs had data, LRP estimates were only available for two to three of the five CU combinations, depending on the year (Figure 3.12). 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 three CUs were used, estimates had high uncertainty and were variable among scenarios. Several of the status estimates from three-CU scenarios fell outside of the 95% confidence interval for the full data case.

The failure of both the Logistic:Sgen-Ricker and Logistic:Sgen-priorCap models to converge in some years is a function of low sample sizes in the available data set, such that the removal of one or two CUs results in a failure of the logistic regression model to converge on a solution. For example, for the Logistic:Sgen-Ricker model, the South Thompson CU is an influential CU. Removing it from the characterization of ‘successful’ and ‘failure’ years, as well as the aggregate abundance used to fit the logistic regression, means that the model cannot converge on a solution because there was no overlap in aggregate abundance levels associated with ‘successes’ and ‘failures,’ which is a requirement for logistic regression model fits. For the Logistic:Sgen-priorCap model, several CUs are influential due to higher estimates compared to the Logistic:Sgen-Ricker model. Because several different CUs contribute to ‘failure’ years, in which CU-level abundances drop below , there is higher sensitivity to the removal of any one of these CUs.

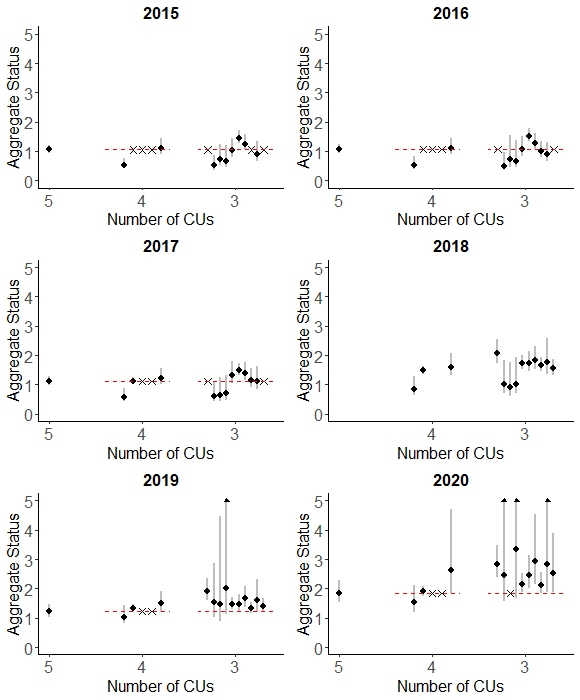


Figure 3.12: Retrospective estimates of aggregate status (with 95% confidence intervals) from the Sgen\_priorCap:LRP model under different scenarios about missing CUs, where status is characterized as the recent generational mean of aggregate abundance / LRP. LRPs are based on a 50% probability that all CUs will be above their lower benchmarks. See Figure xx caption for more details.

LRPs based on the Logistic:IFCRT model could be estimated for all four-CU data scenarios in all years (Figure 3.13). Resulting estimates of SMU status were similar to the full data estimate for four of the five 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 four-CU combinations shown for each year in Figure 3.13). This pattern is due the 2015 data point for South Thompson CU being an influential observation that has a large impact on the shape of the fit model . For missing data scenarios in which only three CUs were included, status estimates often had higher uncertainty than the four-CU or full data scenarios, and showed high variability among scenarios in estimated status.



## 3.6 LRP ESTIMATION: AGGREGATE ABUNDANCE PROJECTION-BASED LRPS

### 3.6.1 Methods

Forward projections of each of the five CUs with the Interior Fraser Coho SMU were done using the samSim modelling tool (Appendix 8). Parameters characterizing population dynamics, marine survival rates, and exploitation rate 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 ??. Additional details on key model parameterizations and sensitivity analyses are also described in text below.

Projection model outputs were used to estimate projection-based LRPs using the methods described on Section 2.3.2. Forward projections were run for 30 years over 20,000 simulation trials. 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. We found that running projections over longer periods, such as 100 years, gave similar results as our 30 year time horizon.

***Stock recruitment dynamics***

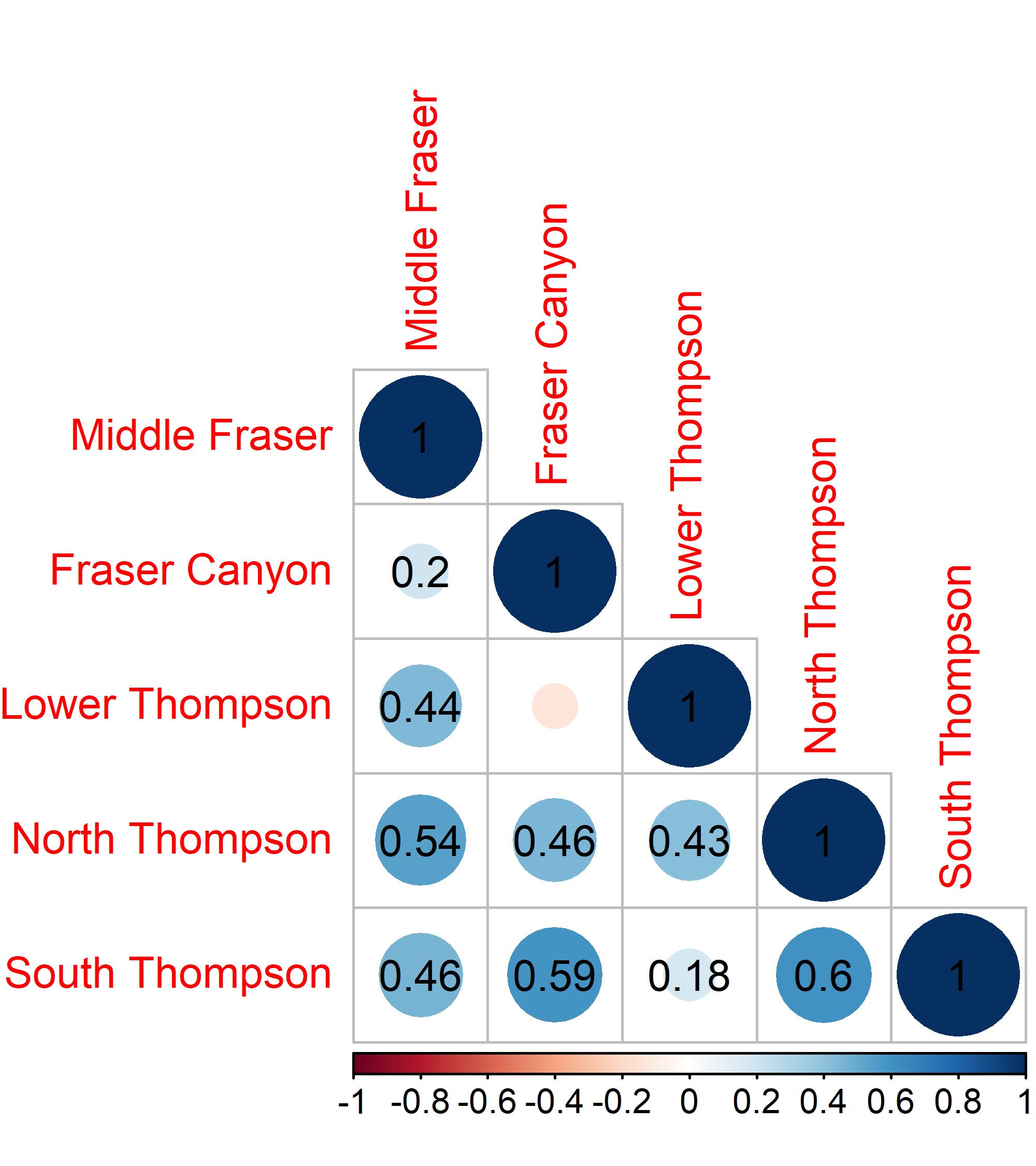
Stock recruitment parameters for all five CUs were drawn from joint posterior distributions obtained by fitting the two stock recruit models described in Section 3.3.1 (Ricker and Ricker\_priorCap) to available spawner-recruit data using Bayesian Markov Chain Monte Carlo (MCMC) estimation. Bayesian estimation was done using tmbStan (Kristensen 2019), which is an R package that allows MCMC samples to be drawn from a TMB model object using rStan (Guo et al. 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 Rhat 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 (, , , and ) is provided in Appendix ??.

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-based LRP. Additional sensitivity analyses described below were only done using the base Ricker model.

***Covariance in recruitment residuals***

We parameterized correlations in recruitment residuals among CUs from MLE predictions of pairwise correlations from spawner recruit model fits. The correlation matrix from the base Ricker model fit is shown in Figure 3.14. 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 marine rate coefficient dominating among-CU variability in recruitment. We therefore used sensitivity analyses of the level of variability in marine 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 @ref(#WCVIchinookChapter).



***Variability in marine survival coefficient among CUs***

When fitting spawner recruit models to data, we followed the approach of [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) and [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) in assuming that all CUs experienced the same marine survival rate for given sea-entry year, and that the marine survival coefficient, , was constant both among CUs and among years. When projecting CUs forward, we maintained this assumption in our base case by generating a single marine survival rate for each sea entry year and setting = 0, where is the standard deviation of among-CU variability in such that . We used sensitivity analyses on to test the effect of changes in spawner abundance covariation among CUs on projected LRP estimates. Three alternative levels of were used in sensitivity analyses: = 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 from our Ricker stock recruitment model fit.

The resulting correlations in spawner abundances from the projections are shown in Figure 3.15. In the forward projections, pairwise correlations in projected spawner abundances among CUs for the base case assumption of = 0 were similar to observed pairwise correlations in spawner abundances among CUs. Increasing resulted in decreased among-CU correlation in projected spawner abundances.



Figure 3.15: Distribution of correlations of spawner abundances among CUs for observed data between 1998 and 2021 and projected time-series under alternative assumptions about the standard deviation on the marine survival co-efficient among CUs for the base Ricker model formulation.

***Variability in age proportions of recruits 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 , 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 co-variation in proportions at age seen in available time series for Interior Fraser Coho, especially since 2010 (Figure 3.14). 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 recruits has not been included in other recent projection analyses for this SMU. Both [Korman et al.](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca) ([2019](#X48d76e42f3bfb5bffa7f7b73f62fa3cf22421ca)) and [Arbeider et al.](#ref-arbeiderInteriorFraserCoho2020) ([2020](#ref-arbeiderInteriorFraserCoho2020)) assumed a constant age structure over time.

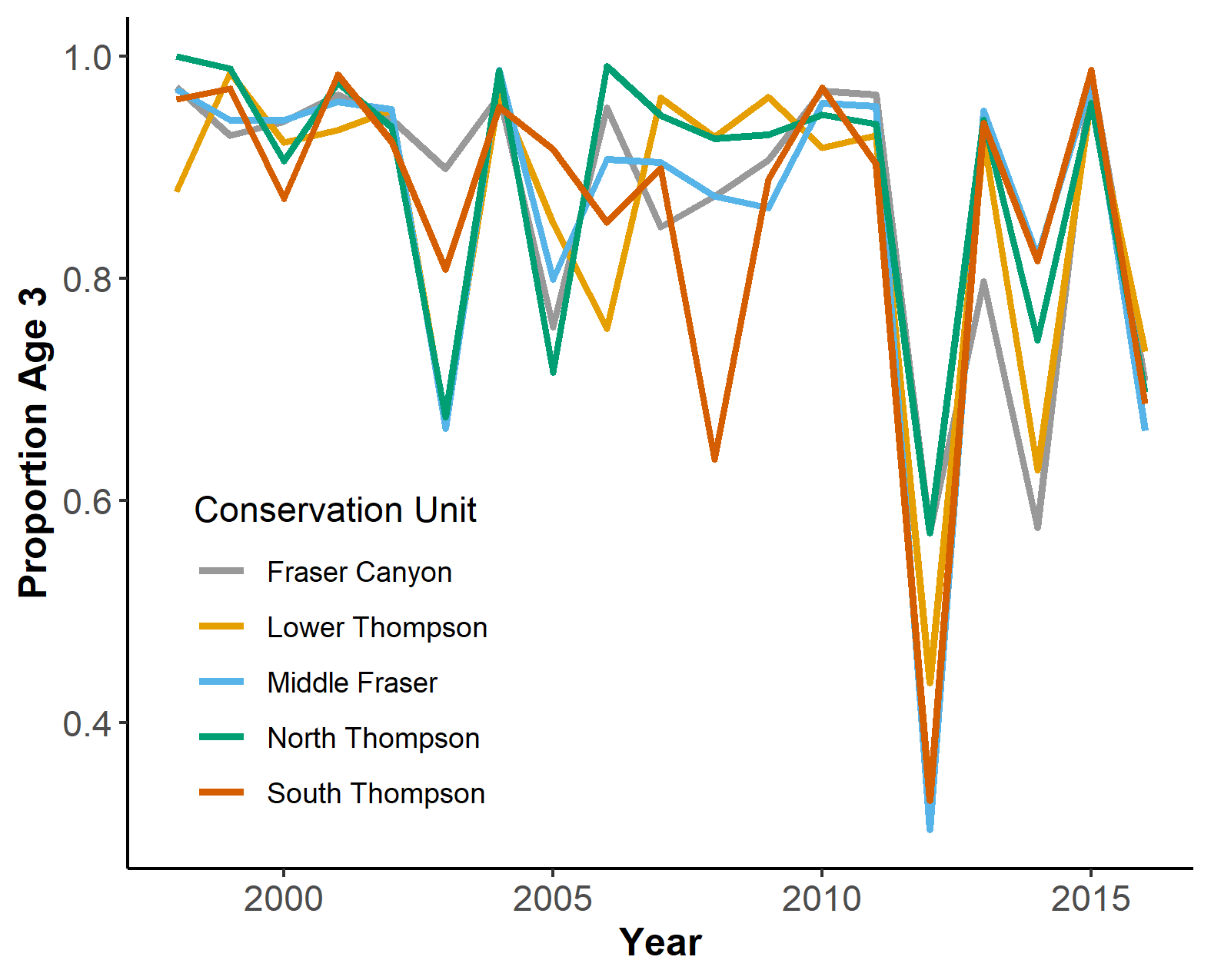


Figure 3.16: Proportion of recruits returning at age 3 for 1998 - 2016 brood years. Only two age classes (age 3 and age 4) are present in the age structure, so the proportion of recruits returning at age 4 will account for the remainder of returns in each year.

***Covariance in exploitation***

We assumed an average exploitation rate of 12.5% for all CUs in forward projections based on average historical 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 stocks (1-2 CUs with indicators / year) and variation in which indicator stocks were operational in a given year. 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-based 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 to derive the LRP (Figure 3.17; Table 3.4). This result is similar to the logistic regression-based LRPs, where LRPs derived using estimates from the Ricker\_priorCap model were higher due to higher values. The projected curve showing the probability of all CUs being above was more gradual and further to the right for the Ricker\_priorCap model compared to the base Ricker model (Figure 3.17). When projection outputs from both stock recruit 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.

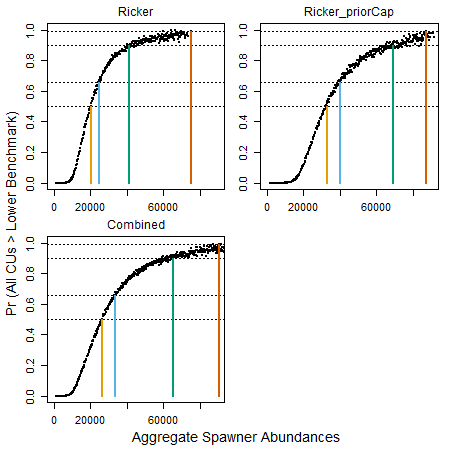


Figure 3.17: Probability of all CUs being above their lower benchmark of Sgen along a gradient in aggregate abundances within bins of 200 fish for two different stock recruit model options (Ricker and Ricker\_priorCap) as well as a model averaged case (Combined) in which results from both stock recruit 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. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue), 0.90 (green), and 0.99 (orange) are highlighted.

Table 3.4: Projection-based 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 .

|  |  |  |  |
| --- | --- | --- | --- |
| 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 |

Generational average spawning abundance (based on a 3-year geometric mean) remained above the projection-based 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 in which aggregate spawning abundance dropping below the LRP: 2006 and 2007 (Figure @ref:fig(coho-AggEscpSeries-wProjLRP). In comparison, when projection-based 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.

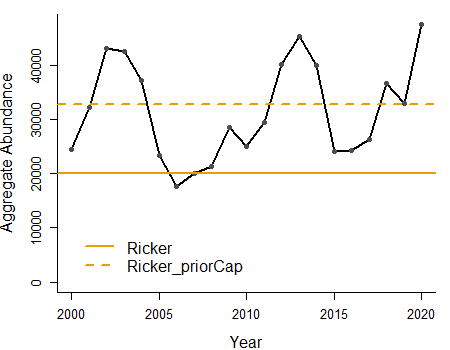


Figure 3.18: Three-year geometric mean of aggregate spawning abundance for the Interior Fraser Coho SMU (black line) relative to projection-based LRP estimates using two different stock recruitment model formulations, Ricker and Ricker\_priorCap, with a probability threshold of p=0.5. Forward projections used to estimate reference points were parameterized using available 1998-2020 time series under base model assumptions.

***Sensitivity Analyses***

Increasing , which corresponded with reduced between-CU correlation in spawner abundances over time (Figure 3.15), resulted in a flattening of the projected relationship between aggregate spawer abundances and the probability of all CUs being above their lower benchmarks. LRP estimates corresponding to a given probability threshold increased as increased as curves shifted to the right and became more gradual (i.e., less steep). For the two highest scenarios examined (=0.0675 and 0.09), a 99% probability of all CUs being above their lower benchmark was never achieved.

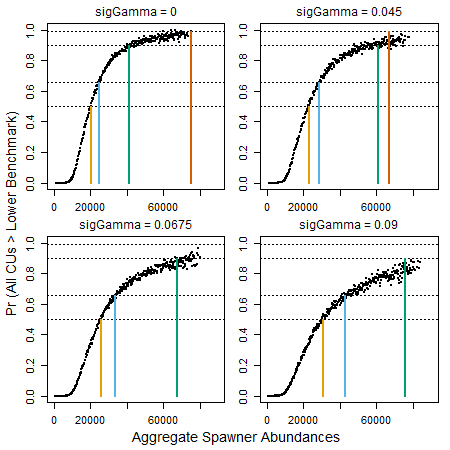


Figure 3.19: Probability of all CUs being above their lower benchmark of Sgen along a gradient in aggregate abundances (within bins of 200 fish) for alternative scenarios about the value of sigGamma. The baseline value used for forward projections was sigGamma = 0. Results are derived from projections over 30 years and 20,000 MC Trials. Each dot is the proportion of MC trials where all CUs were > Sgen. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue), 0.90 (green), and 0.99 (orange) are highlighted.

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 (Figure 3.20). 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 benchmarks.

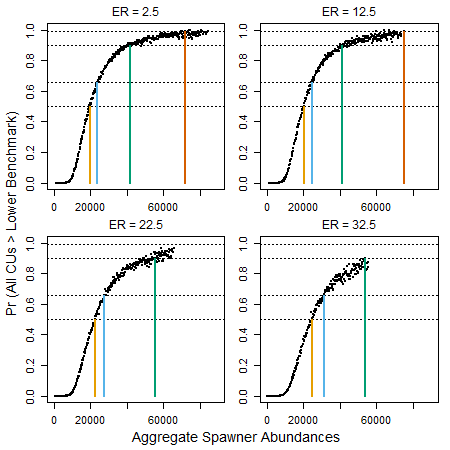


Figure 3.20: Probability of all CUs being above their lower benchmark of Sgen along a gradient in aggregate abundances (within bins of 200 fish) for alternative scenarios about average exploitation rates (ER) in forward projections. The baseline value used for forward projections was ER = 12.5%. Results are derived from projections over 30 years and 20,000 MC Trials. Each dot is the proportion of MC trials where all CUs were > Sgen. Candidate LRPs at p=0.5 (yellow) and p=0.66 (blue), 0.90 (green), and 0.99 (orange) are highlighted.

## 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 3.21). For all aggregate abundance-based LRPs, we used LRPs estimated using 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 labelling 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 ‘poor’ CU status (Prop) or on aggregate SMU-level abundance (Abund). The ‘LRP’ method only applies to aggregate-abundance based LRPs, for which is can be logistic regression (Logistic) or projection-based (Proj). Finally, the ‘CU Status Method’ can be based on the rapid multidimensional scanning tool in in which CU abundance-based benchmarks are based on one of the two Ricker models (Multidim-Ricker or Multidim-priorCap). Or, when only a single benchmark is used to characterize CU status, it can be based on 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-based LRP that is estimated via a logistic regression fit to historical CU status, with CU status estimated relative to from the base Ricker model, we label it as “Abund: Logistic: Sgen\_Ricker.”

We show historical results for two types of proportional LRP methods: one that uses the proportion of CUs with rapid multidimensional status > red (e.g., Prop: Multidim-Ricker) and one that uses the proportion of CUs with abundance > Sgen (e.g., Prop: Sgen-Ricker). Holt et al. (in review) recommend that only the multidimensional approach should be used to assess status; however, we show results for the single metric approach here to demonstrate how the two approaches differ. This comparison is of interest because our aggregate abundance-based LRPs use status estimates based on a single metric rather than the multidimensional status estimates.

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 proportion-based LRP. We label this case “Prop : WSP-2014.” SMU status would have been assessed as being above the LRP at this time as all CUs were assessed as amber or green.

In general, estimated LRP breaches coincided with low points in the aggregate abundance time series (2000, 2005 - 2006 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 few methods for which status was never estimated to be below the LRP (Prop: Sgen-Ricker, Abund: Logistic: Sgen-Ricker, Abund: Logistic: IFCRT).

Comparison of SMU status estimates over time for all LRP estimation methods that used estimates from the base Ricker model (first group of four methods in Figure 3.21), showed that the LRP was only breached in years 2015-2017 under the Prop: Multidim-Ricker method. The other three Ricker methods estimated status to remain above the LRP over this period. The latter three methods are similar in that they all assess CU status based on a direct comparison of CU-level abundance to . In contrast, the decision tree for the rapid multidimensional scanning tool includes a step in which CU status is designated as ‘red’ anytime the generational mean spawning abundance drops below 1500 spawners (Figure 2.1). Because estimated 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 remains above . This situation occurs for this CU in 2015-2017. Therefore, LRP methods that use the rapid multi-dimensional scanning tool to characterize CU status can be more precautionary than methods that rely on a single benchmark.

In the years 2005-2006, SMU status estimates from the ‘Abund: Proj: Sgen-Ricker’ method fell below the LRP, while the other two Sgen-Ricker methods 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 estimates). Declines in the lower abundance Fraser Canyon CU were not as drastic. As a result, while SMU-level aggregate abundance dropped below the abundance-based LRP, the Fraser Canyon CU that triggered ‘red’ status in 2015-2017 remained above 1500 spawners and did not trigger the Prop: Multidim-Ricker method. The aggregate abundance-based 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 instead of the base Ricker model, both 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 (see second group of four methods in Figure 3.21) compared to when the base Ricker model was used. 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 13 out of the 21 years between 2000 and 2020. In comparison, the LRP was triggered in 8, 7, and 5 of the 21 years for the ‘Abund: Proj:Sgen-Ricker,’ ‘Prop: Multidim-priorCap,’ and ‘Prop: Sgen-priorCap’ methods, respectively. LRP estimates based on the proportional LRPs estimated using the rapid multidimensional scanning tool were therefore the least precautionary of the thee priorCap methods.

Finally, SMU status remained above the LRP in all years under the Abund: Logistic: IFCRT method. Because the aggregate abundance-based LRP estimated using the Abund: Logistic: IFCRT method was similar to that of the Abund: Logistic: Sgen-Ricker (17,515 and 15,395 spawners, respectively), performance for these methods was similar. In comparison, the aggregate abundance-based LRP estimated using a logistic regression combined with the Ricker-priorCap model (Abund: Logistic: Sgen-priorCap) was higher (25,677 spawners).

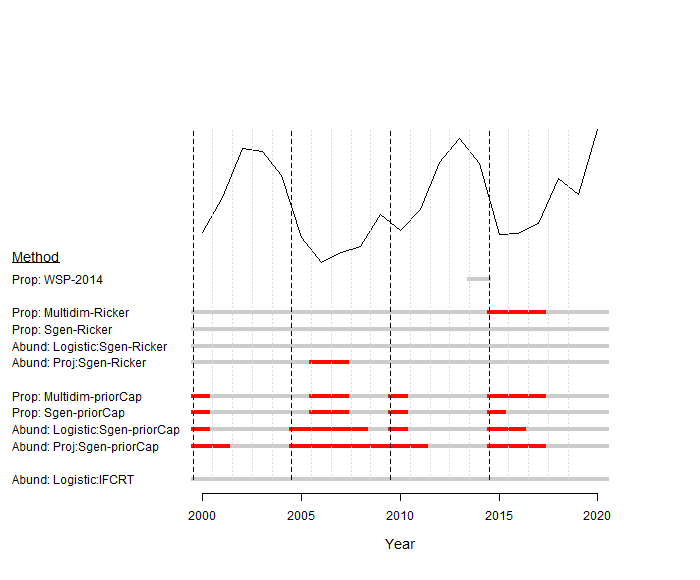


Figure 3.21: Historical evaluation of status relative to LRP options considered for Interior Fraser Coho. The black line shows the 2000-2020 generational mean aggregate spawning abundance to the SMU. Red bars indicate years in which SMU status would have been assessed as being below the LRP. Estimates of Sgen benchmarks and aggregate abundance-based LRPs were based on data available up to 2020

## 3.8 DISCUSSION

(Still in rough note form)

Discussion topic 1: What are the unique characteristics of this case study that can inform the development of guidelines

* Data rich SMU; while the number of years of data are limited, full SR time series are available for all 5 CUs. These have previously been used to develop forward simulations for individual CUs within the SMU.
* Long history of using aggregate abundance-based recovery targets and fisheries reference points that were developed based on an underlying relationship between aggregate abundance and the distribution of abundance among sub-populations and CUs. As a result, it was well suited to looking at the application of aggregate abundance-based LRPs, as well as how they compared historically to the preferred proportional approach.

Discussion topic 2: How well do aggregate abundance-based LRPs perform retrospectively compared to proportional LRPs?

* The abundance-based methods we considered often matched the proportional methods in a historical comparison of SMU status relative to LRPs. For a given assumption about SR model structure, LRPs tended to be triggered in similar periods of times under the aggregate abundance-based and proportional options; however, there were some differences.
* Our results highlight the complexities in predicting how well aggregate abundance-based LRPs will do at tracking proportion-based LRPs. For example, when estimates of Sgen were obtained using the base Ricker model, proportion-based LRPs using rapid multidimensional status were more precautionary than the two aggregate abundance-based LRP options; especially in years 2015-2017. This result is partially a function of the different methods used to estimate CU status (rapid multidiensional scanning tool vs. single metric) rather than the choice of proportion vs aggregate abundance approach. When aggregate abundance-based LRPs are compared to proportion-based LRPs using a single metric, they are better aligned over this period. This result occurs because under the multidimensional approach, CUs can be above Sgen but still assessed as red status when their Sgen estimates are < 1500 spawners.
* In comparison, when estimates of Sgen were obtained using the Ricker\_priorCap model, which produced higher Sgen and LRP estimates than the Ricker model, both types of proportion-based LRPs were less precautionary than aggregate abundance-based LRPs. This result was especially pronounced when aggregate abundance-based LRPs were estimated using the projection-based LRP approach. LRP breaches using the multidimensional scanning tool with Ricker-priorCap estimates in earlier years (i.e., before 2015) were based CU abundance relative to , meaning that the two proportional methods were aligned. There were however additional years in which aggregate abundance LRPs were triggered but neither proportional LRP was. This pattern occurred when aggregate abundance dropped below abundance-based LRPs, but all CUs remained above red status based on CU-level abundances all being greater than . While this pattern occurred for both types of estimates (Ricker and Ricker-priorCap), it was more common for the Ricker-priorCap model.

Discussion topic 3: Importance of SR model choice in characterizing SMU status in all approaches.

* All methods (with the exception of IFCRT) relied heavily on assessment of CU status relative to Sgen. This is even true for the Prop methods using the rapid mutlidimensional scanning tool because the decision tree relies heavily on estimates of Sgen when available, which they are for Interior Fraser Coho.
* As a result, the method used to estimate Sgen had a large impact on results. Sgen estimates tended to be higher for the Ricker\_priorCap model compared to the base Ricker model, which meant that LRPs were more frequently triggered under this formulation.
* We considered alternative Ricker models for Interior Fraser Coho because previous analyses for this SMU have done so. Arbeider et al. (2020) used a model averaging approach with 3 SR models equally weighted when assessing recovery potential (the base Ricker and Ricker\_priorCap models we used, as well as a third depensatory mortality version that we did not consider).
* Implementation of LRPs when considerable uncertainty in underlying model structure exists will require methods to integrate estimates of LRP status over alternative model structures. We demonstrate one approach when using projection-based estimates of aggregate abundance-based LRPs, in which we combine projections under each SR model scenario before calculating the LRP. This approach is basically a model-average approach in which both scenarios are equally weighted. However, other methods of assigning weights among model are possible. For example …. (TO DO: reference model selection / averaging papers from Carrie). In other cases, such at the proportional approach using WSP assessments or the multi-dimensional scanning tool, uncertainty in model structure may best be dealt with through expert opinion. For example, under the planned expert workshops that will be used to confirm rapid multidimensional status estimates, participants could be given two sets of status results based on two different Sgen models, and then be asked to converge on a single status estimate. (can we pers. comm. Sue Grant as a reference for this process?).

Discussion topic 4: What was learned from retrospective analysis of logistic regression-based methods?

* Retrospective analyses of logistic regression-based LRP options showed that LRPs were sensitive to data availability. 2015 was the first year that that regression-based LRPs could be estimated, indicating that at least 18 years of data were required. (Although, note that the Logistic regression with the Base Ricker model could not estimate an LRP until 2017, so required 20 years of data). However, slight shifts in Sgen estimates in some years meant that logistic models were sometimes unable to converge on a solution even with more data.
* For years in which LRPs could be estimated, LRP estimates did vary over time; especially when Sgen was estimated each year within an integrated modelling framework. LRP estimates were more stable when CU status was based on the IFCRT recovery target of at least half of all sub-populations within a CU having more than 1000 fish. This result is likely because CU-level SR parameters and lower benchmarks in a given historic year were not changing annually in the same way the did in the integrated Sgen-logistic regression model fits.
* Missing data scenarios, in which 1 or 2 CUs were removed from the data set, 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 the data used as inputs to the logistic regression. Estimates of aggregate SMU status, characterized as generational mean escapement / LRP, were also sensitive to the combination of CUs used. Removal of one or two influencial CUs often resulted in very different characterizations of CU status.
* Taken together, these retrospective results highlight that caution should be used when applying logistic regression-based LRPs. While they did provide similar estimates of SMU status as proportion-based methods using the rapid multidimesional scanning tool 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 becomes available to improve the statistical power of logistic regression fits.

Discussion topic 5: What we learned from sensitivity analysis of projection-based methods?

* Projection-based LRPs were higher, and therefore more precautionary, than logistic regression-based LRPs when forward projections were parameterized using base case parameters. Given that the estimation of logistic regression-based LRPs were sensitive to data availability, projection-based LRPs may provide more reliable estimates for cases in which population and fishery dynamics can be modelled.
* Projection-based LRPs also have the advantage of being able to incorporate hypotheses about current population and / or fishery dynamics into forward projections, whereas logistic regression-based LRPs are constrained by conditions that have been previously experienced.
* The sensitivity of projection-based LRPs to exploitation rate means that these LRPs are specific to the management context. In our Interior Fraser Coho projections, it made sense to set exploitation rates at the recent average as fishery restrictions since 1998 have maintained relatively stable harvest dynamics. In this case, the LRP represents the level of aggregate abundance that would be required to ensure all CUs were above Sgen given a specified fixed ER policy. If a decision was made to increase the exploitation rate, the LRP would also be increased accordingly to ensure that the underlying objective of all CUs above Sgen 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 Sgen. This effect is demonstrated in Appendix 10. As a result, projection-based LRPs are not static measures of serious harm, as commonly developed for other stocks/species.
* Projection-based LRPs were also sensitive to the level of co-variation in spawner abundances among CUs over time. Reductions in covariation resulted in increased LRP estimates. This pattern will result in more precautionary LRPs as the relationship between aggregate abundance and CU status weakens. Projected LRPs therefore have a built-in buffer that will help avoid the situation where aggregate abundance remains above the LRP despite several CUs having poor realized status.

# 4 CASE STUDY 2: WEST COAST VANCOUVER ISLAND CHINOOK

## 4.1 CONTEXT

The West Coast of Vancouver Island (WCVI) Chinook SMU is comprised of 3 CUs ([Holtby and Ciruna 2007](#ref-holtbyConservationUnitsPacific2007)), 7 large inlets (or sounds), and 20 indicators stocks, which are stocks with relatively complete time-series and consistent observation methodology (Figure 4.1; Table 4.1, [Riddell et al.](#ref-riddellReview2001Chinook2002) ([2002](#ref-riddellReview2001Chinook2002))). Hatchery enhancement is an important component of many of these stocks. Hatcheries are a conservation tool for wild salmon populations and can increase the availability of fish for harvest, but they can also reduce wild genetic diversity and are considered a risk factor for the long-term sustainability of CUs ([Withler et al. 2018](#ref-withlerGeneticallyBasedTargets2018)). Therefore only indicator stocks without significant enhancement were included in our analyses. Proportionate Natural Influence, PNI, is a metric of the genetic risk of hatcheries on natural populations, with values < 0.5 indicating Integrated-Hatchery populations where most fish are hatchery origin ([Withler et al. 2018](#ref-withlerGeneticallyBasedTargets2018)). Only stocks with PNI values 0.5 were included in the development of LRPs and assessment against those LRPs (J. Bokvist, pers. comm. DFO South Coast Stock Assessment).

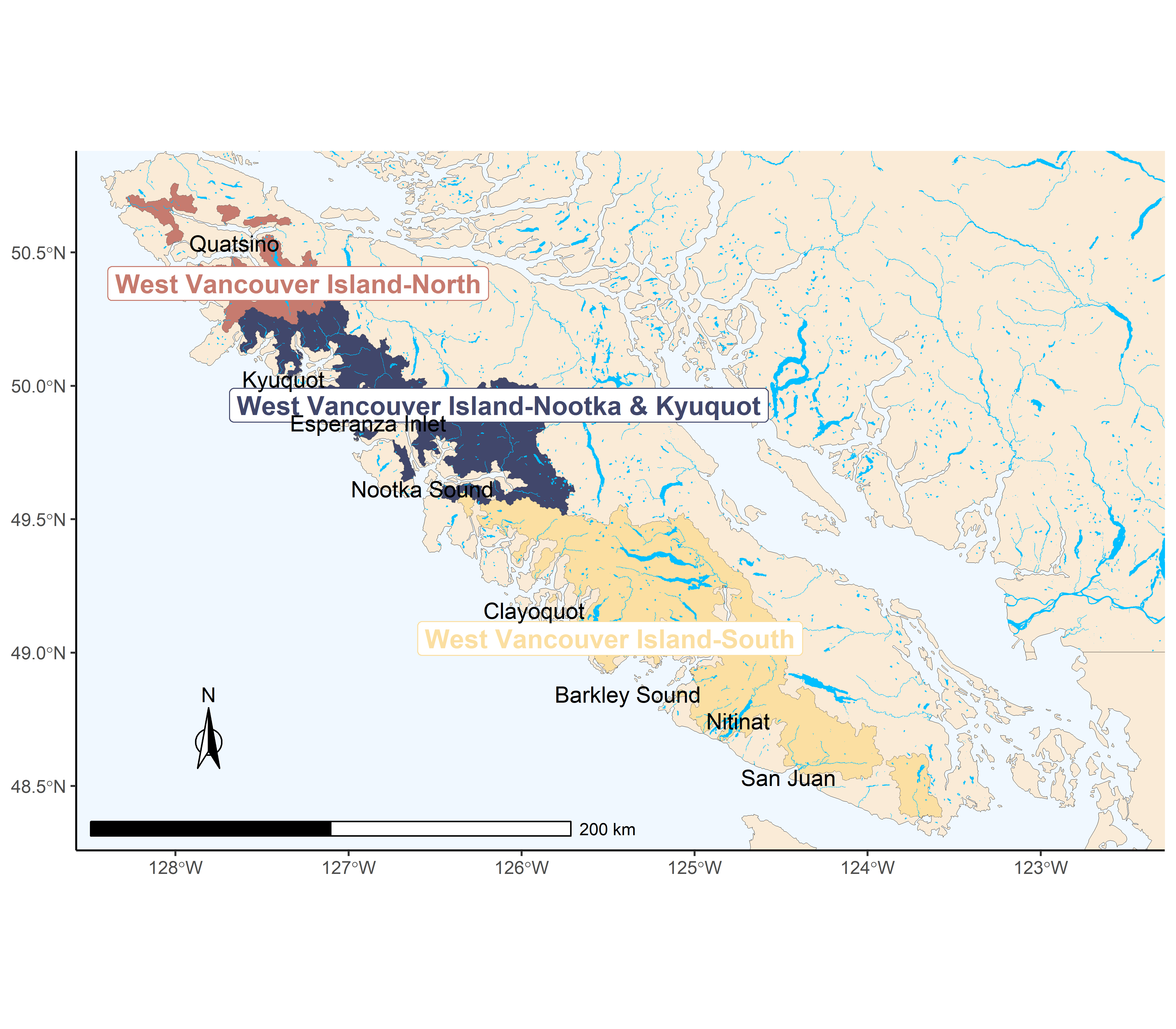


Table 4.1: Overview of WCVI Chinook Stock Management Unit. Italics represent indicators with average PNI values < 0.5. Note, the inlets, San Juan and Nitinat do not contain indicator stocks with PNI < 0.5 and are not included in these analyses. WCVI is West Coast of Vancouver Island.

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

This SMU was included as a case study to demonstrate the development of LRPs under data limitations when stock-recruitment relationships are not available to develop stock-recruitment based benchmarks, but habitat-based benchmarks are, as is common for Chinook salmon in BC. WCVI Chinook is also included in the first batch of major stocks proposed for regulation under the Fish Stock Provisions of the revised Fisheries Act, necessitating the development of LRPs for this SMU.

Most Chinook in this SMU are ‘ocean type,’ entering the ocean 1-3 months after emergence from spawning gravel ([**dfoAssessmentWestCoast2012?**](#ref-dfoAssessmentWestCoast2012)). ‘Stream type’ fish, those that stay in the river for one year after emergence, are rare. After entering the ocean, WCVI Chinook migrate into northern BC and southeast Alaska waters to rear for 2 to 7 years, returning to spawn predominantly at ages 4 and 5 ([**dfoAssessmentWestCoast2012?**](#ref-dfoAssessmentWestCoast2012)).

### 4.1.1 Previous assessments

Two of the 3 CUs in this SMU, WCVI-South and WCVI-Nootka & Kyuquot, were assessed as ‘red’ status in an integrated Wild Salmon Policy assessment ([DFO 2016](#ref-dfoIntegratedBiologicalStatus2016)). For these CUs, assessments were based on component stocks without hatchery enhancement within the most recent 12 years, omitting stocks with enhancement during that period. For WCVI-South, red status was based primarily on threats of genetic introgression from strays from nearby large-scale hatcheries. For WCVI-Nootka & Kyuoquot, 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, WCVI-North, was not assessed by DFO in 2016 because all component stocks had some level of enhancement over the most recent 12 years (other metrics of hatchery enhancement, e.g., Proportionate Natural Influence or PNI were not considered). A list of indicator and non-indicator stocks within each CU is available in [Brown et al.](#ref-brown2020SummaryAbundance2020) ([2020](#ref-brown2020SummaryAbundance2020)).

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](#ref-dfoIntegratedFisheriesManagement2021)). Poor marine survival rates for WCVI Chinook and low spawner levels over the past 2 decades are highlighted as reasons for conservation concern in the IFMP ([DFO 2021a p. 129](#ref-dfoIntegratedFisheriesManagement2021)). A variety of management measures have been implemented to restrict harvest on WCVI Chinook and address these concerns, described in the IFMP ([DFO 2021a](#ref-dfoIntegratedFisheriesManagement2021)).

Biological benchmarks have been estimated for WCVI indicator stocks using an empirical relationship between watershed area and common stock-recruitment reference points, spawner abundances at replacement, , and , from a meta-analysis of 25 Chinook stocks across North America ([Parken et al. 2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)). Lack of rigorous recruitment data for WCVI Chinook stocks has precluded the use of stock-recruitment based benchmarks. For the development of LRPs for WCVI Chinook, the empirical relationship between watershed area and was re-estimated using a hierarchical Bayesian model (as in [Liermann et al.](#ref-liermannUsingAccessibleWatershed2010) ([2010](#ref-liermannUsingAccessibleWatershed2010))), and applied to inlets of WCVI Chinook (Appendix X, to be included).

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](#ref-holtbyConservationUnitsPacific2007)). For WCVI Chinook, inlets nested within CUs are another important spatial scale of diversity for sustainability given 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 that preserved CU-scale diversity, while also considering inlet-scale diversity. Specifically, 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 indicators stock without significant hatchery influence. The lack of indicators without significant hatchery influence for inlets Nitinat and San Juan is due to large-scale hatcheries and infrequent monitoring of sites with natural spawning. Because the remaining 5 inlets with significant natural spawning are nested within the 3 WCVI Chinook CUs, preserving this inlet-scale biodiversity 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 indicators for Nitinat and San Juan, if they are developed.

## 4.2 DATA

### 4.2.1 Watershed Areas

To derive habitat-based benchmarks, watershed areas were updated for WCVI Chinook using methods described in [Parken et al.](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb) ([2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)) 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](https://catalogue.data.gov.bc.ca/dataset/provincial-obstacles-to-fish-passage) (Appendix X, to be included). Only watershed areas for indicator stocks were included in the current analyses, and these watershed areas were then summed within inlets (Table 4.2). 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 as a base case because of large uncertainties in abundances of non-indicator stocks.

Table 4.2: Sum of watershed areas for indicator stocks within inlets, km. Only indicator stocks that are not highly enhanced are included.

|  |  |
| --- | --- |
| Inlet | Watershed Area |
| Barkley | 42 |
| Clayoquot | 460 |
| Kyuquot | 336 |
| Nootka/Esperanza | 77 |
| Quatsino | 217 |

### 4.2.2 Spawner Abundances

Spawner abundances were provided for 20 WCVI indicators stocks, (D. Dosbon and D. McHugh pers .comm.; Table 4.1; Figure 4.2). These time-series are compiled annually by DFO Area Staff for local and international assessment and management (e.g., [DFO](#ref-dfoWCVISalmonBulletin2021) ([2021b](#ref-dfoWCVISalmonBulletin2021))). Missing values were not infilled. In future work, infilled time-series of indicators within inlets (or CUs) could be developed to extend the available time-series.

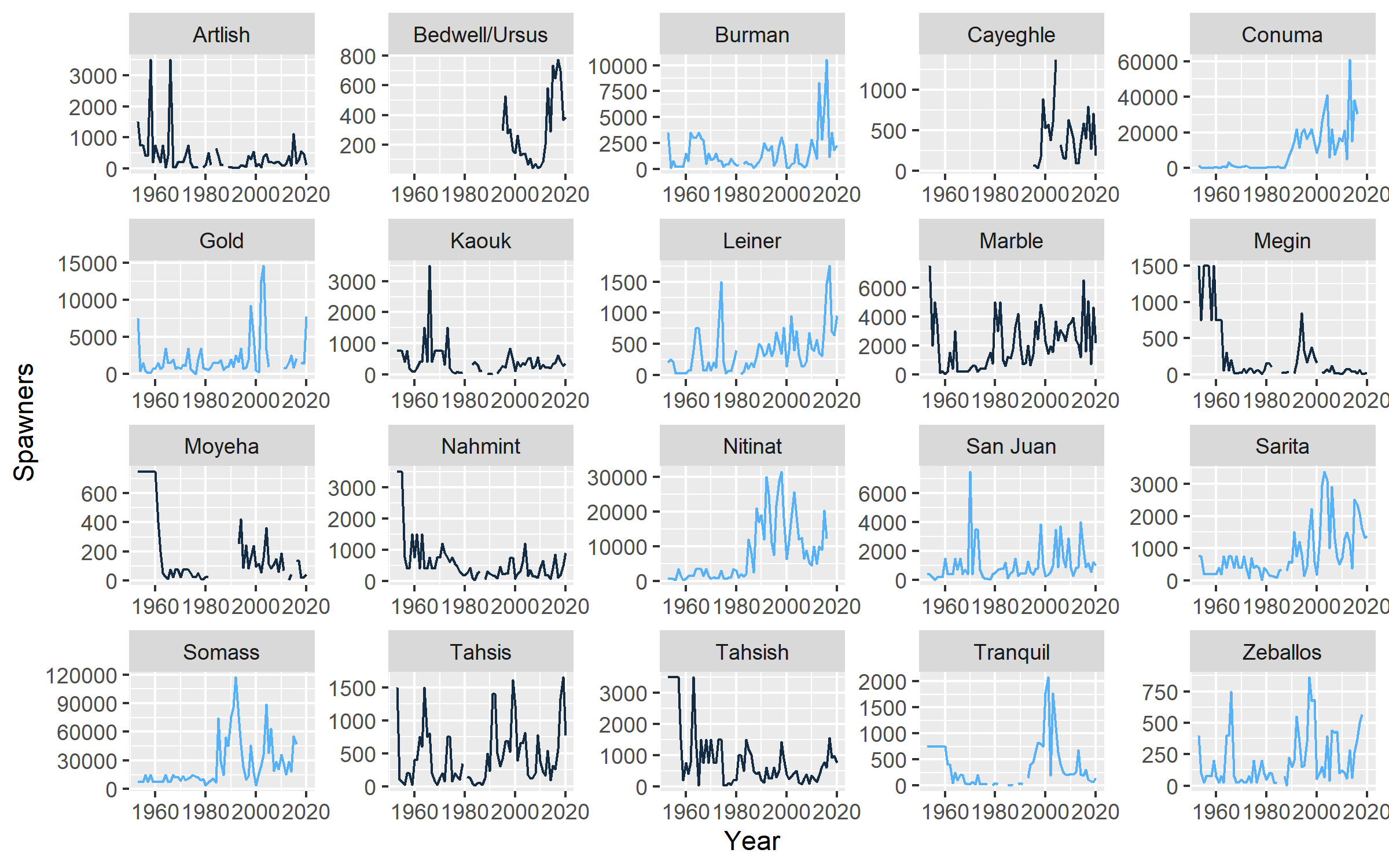


Figure 4.2: Time-series of spawner abundances by indicator stock. Dark blue time-series are indicator stocks with Proportionate Natural Index (PNI) values <= 0.5; light blue time-series are indicator stocks with PNI < 0.5, i.e., are highly enhanced.

### 4.2.3 Proportionate Natural Influence, PNI

PNI values for 14 WCVI indicator stocks were provided to DFO South Coast Stock Assessment by DFO’s Salmonid Enhancement Program (J. Bokvist, pers. comm. DFO South Coast Salmon Assessment). Stocks were considered significantly enhanced if average PNI values over available time-series were < 0.5, representing integrated-hatchery stocks where most fish are hatchery origin ([Withler et al. 2018](#ref-withlerGeneticallyBasedTargets2018)). 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 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. There is no evidence of the original natural spawners in this system, so it was excluded from our analyses. Five of the remaining 6 indicator stocks 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). One indicator stock without PNI data, Tranquil, was considered significantly enhanced and was grouped with the PNI <0.5 stocks (D. McHugh, pers. comm., DFO South Coast Stock Assessment). Guidelines and methods for estimating PNI values are currently being documented by DFO’s Salmonid Enhancement Program.

## 4.3 PROPORTION OF CUS

### 4.3.1 METHODS

values were derived from the watershed-area model adapted from [Parken et al.](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb) ([2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)) (Appendix X, to be included). The Wild Salmon Policy lower benchmark on abundances, , the spawner abundances required to achieve within one generation without fishing under equilibrium conditions, was derived by optimizing the Ricker equation with recruitment set to ,

where,

and is recruits-per-spawner at low productivity. Ricker values were approximated for WCVI Chinook 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. Life-stage specific survival rates were then combined to derive an overall survival from spawners to recruitment (W. Luedke pers. comm. DFO South Coast Stock Assessment). 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 ([Parken et al. 2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)), (>7 recruits/spawner). From the life-stage model, mean was estimated at ~ 1 (~=2.72 recruits/spawner), with standard errors (1.96 SDs) +/- 0.5 ( ranging from 1.6 to 4.5), representing relatively large uncertainty in productivity. Bootstrapped confidence intervals in (Equation (3.5)) were estimated by repeated sampling from normal distributions of and , with standard deviations in 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.

Our approach to estimating differed from that of [Parken et al.](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb) ([2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)), because we derived productivity independently from the life-stage specific models, whereas [Parken et al.](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb) ([2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)) estimated both and from the watershed-area model thereby inferring mean estimates of productivity which were deemed unrealistically high for WCVI Chinook.

Table 4.3: Benchmarks and boostrapped 95% confidence intervals (labelled, lwr and upr) for five inlets, including only indicator stocks that are not highly enhanced.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Stock or inlet | Sgen | Sgen.lwr | Sgen.upr | SREP | SREP.lwr | SREP.upr |
| Barkley | 111 | 33 | 373 | 630 | 283 | 1277 |
| Clayoquot | 1390 | 399 | 3969 | 7265 | 4348 | 12556 |
| Kyuquot | 1050 | 234 | 2940 | 5333 | 2898 | 9375 |
| Nootka/Esperanza | 241 | 56 | 739 | 1205 | 572 | 2579 |
| Quatsino | 658 | 165 | 2073 | 3425 | 1744 | 6142 |

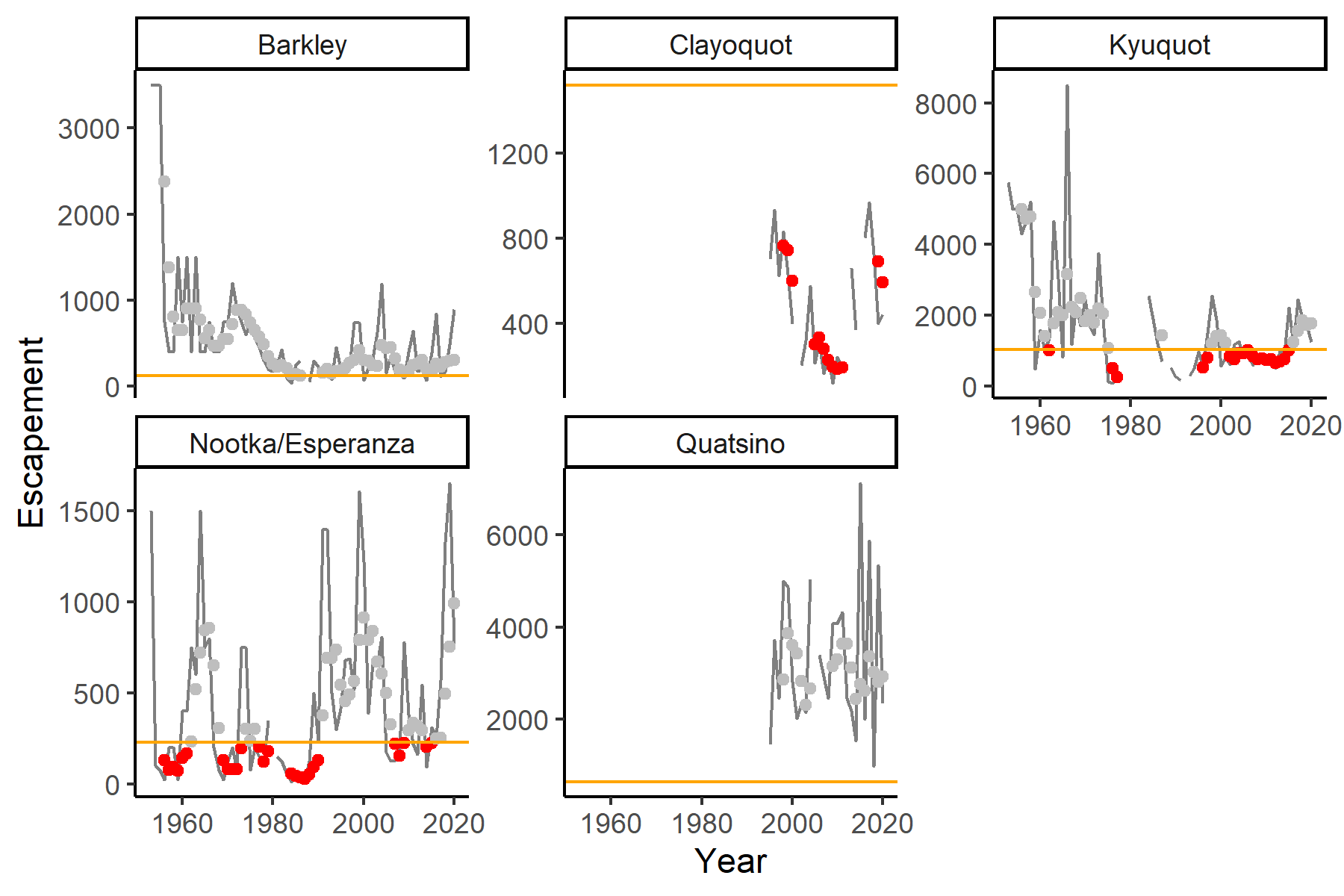


Figure 4.3: Time-series of spawner abundances by inlet, including only indicators stocks that are not highly enhanced. Horizontal yellow line is Sgen and dots are generational geometric average spawner abundances coloured by red (below Sgen) and grey (above Sgen).

The LRP on the proportion of CUs was identified as all 3 CUs containing inlets with current statuses exclusively above their lower benchmarks. For this SMU, serious harm was identified as any one inlet within each of the 3 CUs dropping below its lower benchmark or in the red zone under the Wild Salmon Policy. Because inlets are nested within CUs, this LRP accounts for the distribution of spawning within CUs. Status of inlets within CUs was identified in two ways: spawner abundances relative to and multi-dimensional status assessments developed by the DFO’s State of the Salmon program (S. Grant. pers. comm. DFO Science; Figure 2.1).

### 4.3.2 RESULTS: PROPORTION OF CUs

In the most recent year with data, 2020, 4 of 5 inlets are above their abundance-based lower benchmark, (Figure 4.3). Therefore, 2 of 3 CUs contain 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 3/3 CUs.

Using the multidimensional approach, the status was the same as for the abundance-based lower benchmarks. For this SMU, time-series of abundances for WCVI Chinook are not absolute (only indicator stocks are monitored consistently) and relative-abundance benchmarks can be identified ( and ), and so according to the multidimensional decision tree (Figure 2.1, status is derived from abundance-based benchmarks as above. Therefore, similar to above, 2 of 3 CUs met the criteria of containing inlets with status above the red zone under the multi-dimensional approach, falling below the LRP of 3/3 CUs.

## 4.4 AGGREGATE-ABUNDANCE, EMPIRICAL LRPS

Empirical LRPs based on the probability of all component inlets (nested within CUs) being above their lower benchmarks 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 4.3). In order to estimate a logistic regression, data points of successes (years when all inlets were > lower benchmarks) and failures (years when all inlets were not > lower benchmarks) are required. The estimation of empirical LRPs is limited to SMUs with historical records that demonstrate contrast in status over time.

## 4.5 AGGREGATE-ABUNDANCE, PROJECTION-BASED LRPS

### 4.5.1 METHODS

Projection-based LRPs were derived for WCVI Chinook by projecting inlet-specific population dynamics using the samSim modelling tool (Appendix 8). We chose to project inlet-specific rather than CU-specific population dynamics to reflect the importance of the inlet scale of diversity for long-term sustainability of the SMU. 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 stocks, and exploitation rates from the Robertson Creek hatchery indicator stock (D. Dobson & D. McHugh, pers. comm. DFO South Coast Stock Assessment). CU-specific parameters were applied across all component inlets. Inlet-specific capacities, or spawner abundances at replacement, were estimated from the watershed-area model ([Parken et al. 2006](#Xa50ddd5116e80abdcf5cfb9a25187a8dc0c8bbb)) (Table 4.2) and applied in projections of recruitment. The model was projected for 30 years from initial equilibrium abundances, and 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 capacity). Base-case parameters are provided in Table ??; sensitivity analyses from base case parameterizations are described in the text. Projection-based LRPs were identified from the aggregate abundances with specified probabilities of all component inlets being above lower benchmarks.

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 4.4). Specifically, model parameters were adjusted 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 4.4. Starting in 1995, the first boxplot displays the distribution of pair-wise correlations among 5 inlets for the time-period 1995-2015; the second box-plot 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.

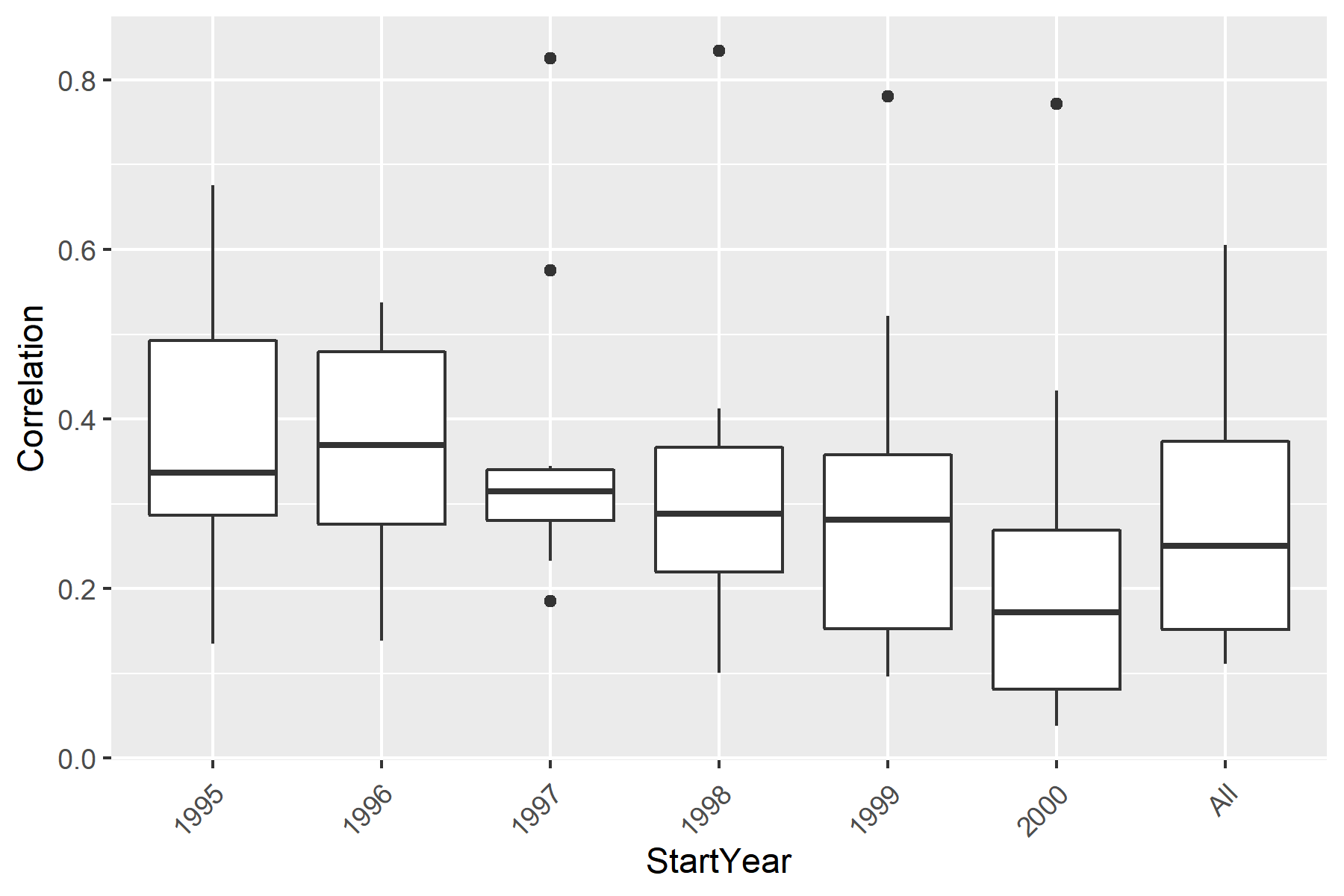


Figure 4.4: Running correlations in spawner abundances among inlets in 20-year time periods, with the start year of the 20-year period on the X-axis. Each boxplot shows the distribution of pairwise correlations among the 5 inlets (n=10 pairwise correlations).

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, which is determined from a common interannual exploitation (due to shared exploitation offshore, parameterized from pre-terminal exploitation on Robertson Creek hatchery fish), and additional inlet-specific variability in exploitation due to inlet-specific vulnerability to exploitation, (2) covariance in recruitment residuals among inlets, and (3) covariance in age proportions of recruits among inlets.

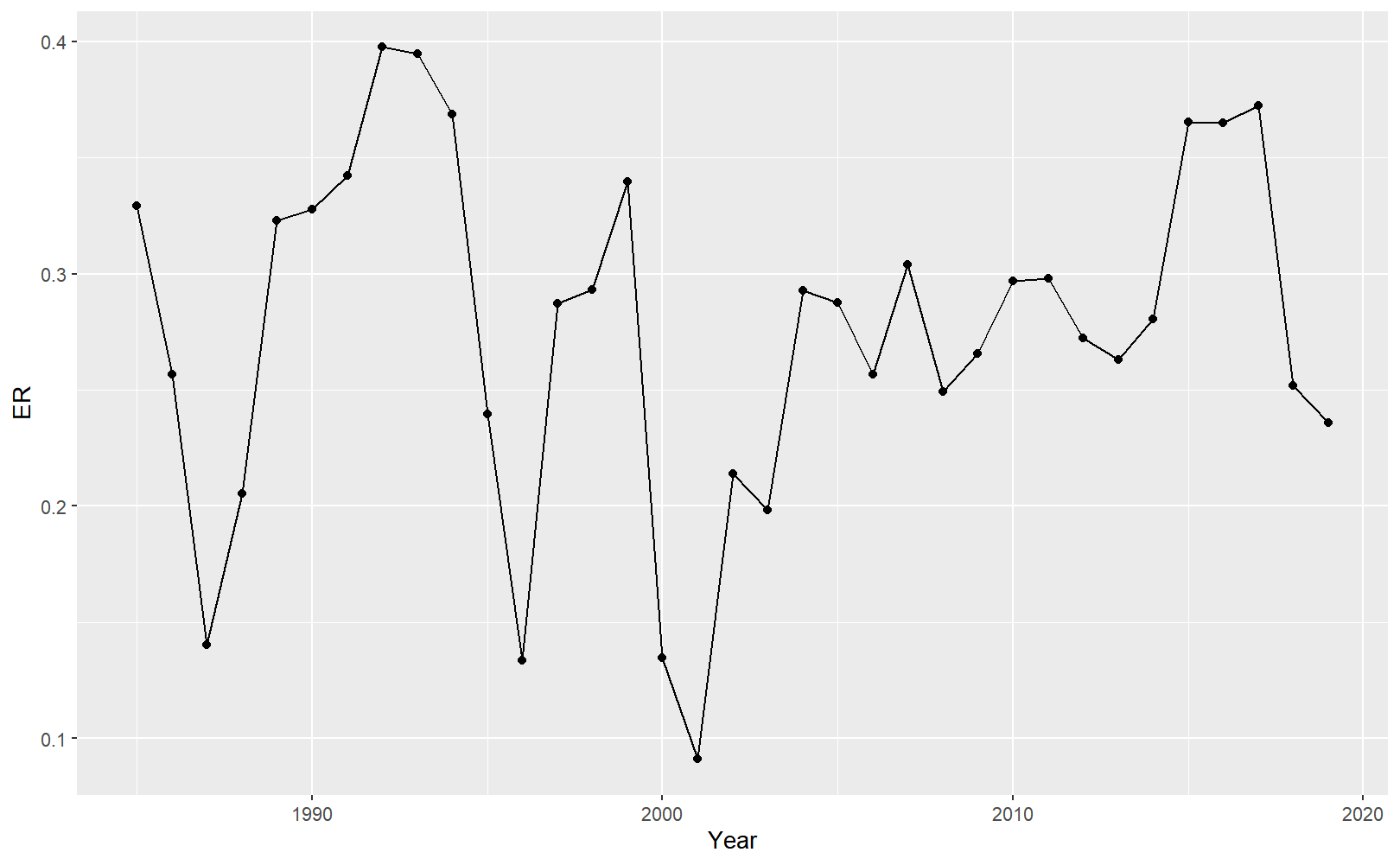


Figure 4.5: Pre-terminal exploitation rates for Robertson Creek CWT indicator.

*Covariance in exploitation*

We assumed an average exploitation rate as observed for WCVI Chinook in recent years (2010-2019, Robertson Creek indicator, 30%, Figure 4.5, with common interannual variability in exploitation rates due to shared exploitation history offshore.

In forward 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 ??). 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 4.6).

 We assumed that inlets were either consistently under- or over-exploited relative to the average over the entire time-series (e.g., due to the spatial and temporal variability in inlet-specific migration patterns affecting vulnerability to fisheries), but that this bias 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).

In the forward projections, pairwise correlations in projected spawner abundances among inlets were similar to observed pairwise correlations in spawner abundances among inlets (Figure 4.7). 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.

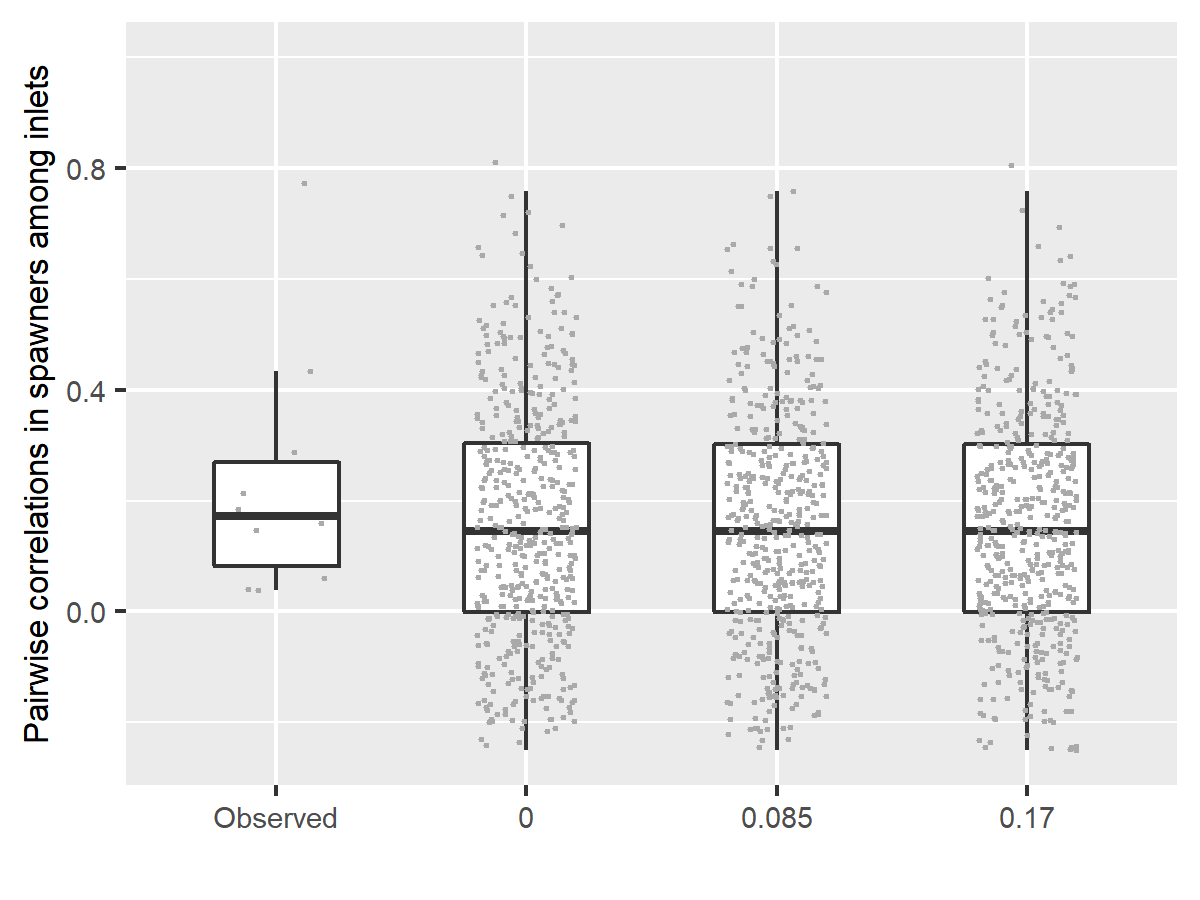


Figure 4.7: Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations) and projected time-series, with a cv in exploitation rates among inlets = 0, 0.085 or 0.17 (0.17 is equal to the estimated interannual variablity in exploitation rates).

*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 Figure 4.8). In sensitivity analyses, we scaled the 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 ground-truth our assumption and evaluate the extent to which the model provided realistic projections.



Figure 4.8: Bubble plot of correlations in spawner abundances among inlets over time, 1994-2020.

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 4.9), 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.

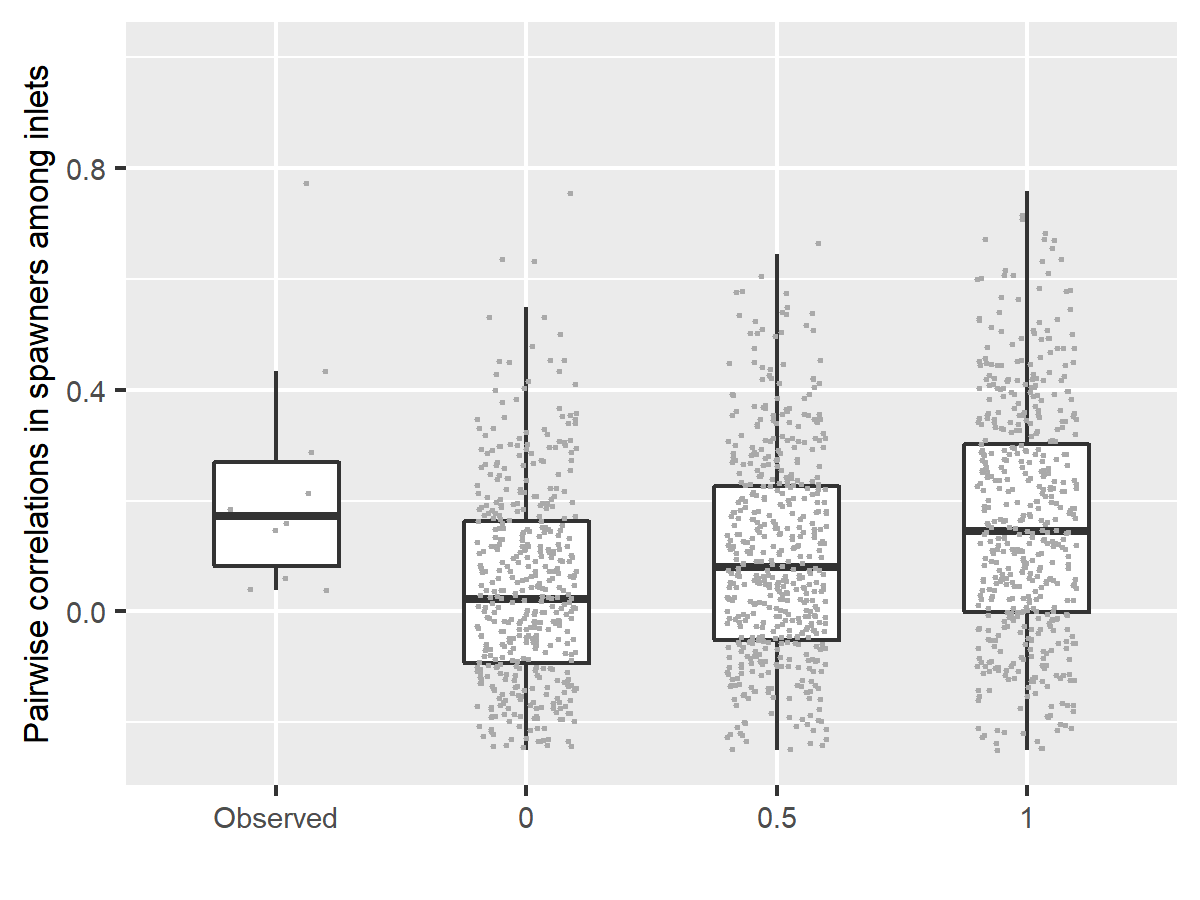
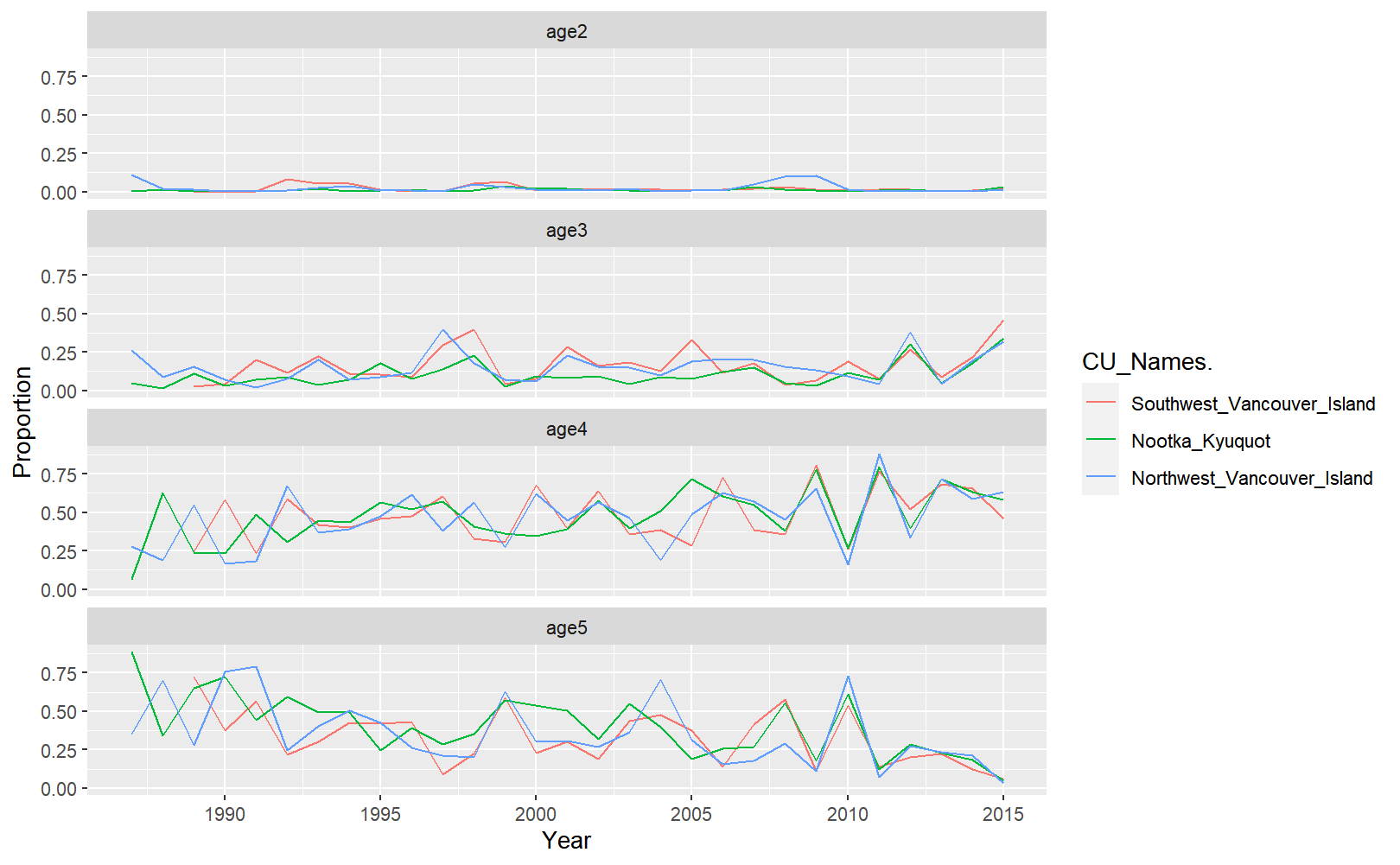


Figure 4.9: Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations) and projected time-series, assuming a scalar on covariance in recruitment residuals from 1 (equal to observed spawner correlations), 0.5 and 0 (no correlation in recruitment residuals). Projections assume a cv in exploitation rates among inlets = 0.085 (half that of estimated interannual variablity in exploitation rates).

*Variability in age proportions recruits among inlets*

For the base case, we assumed that age proportions of recruits varied over time and among inlets parameterized from age proportions of recruits calculated for each CU in the WCVI Chinook run reconstruction (D. Dobson pers. comm. DFO Science; inlet-specific age-proportions were not available) (Figure 4.10). 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. 

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 4.11), generating time-series that were unrealistic.

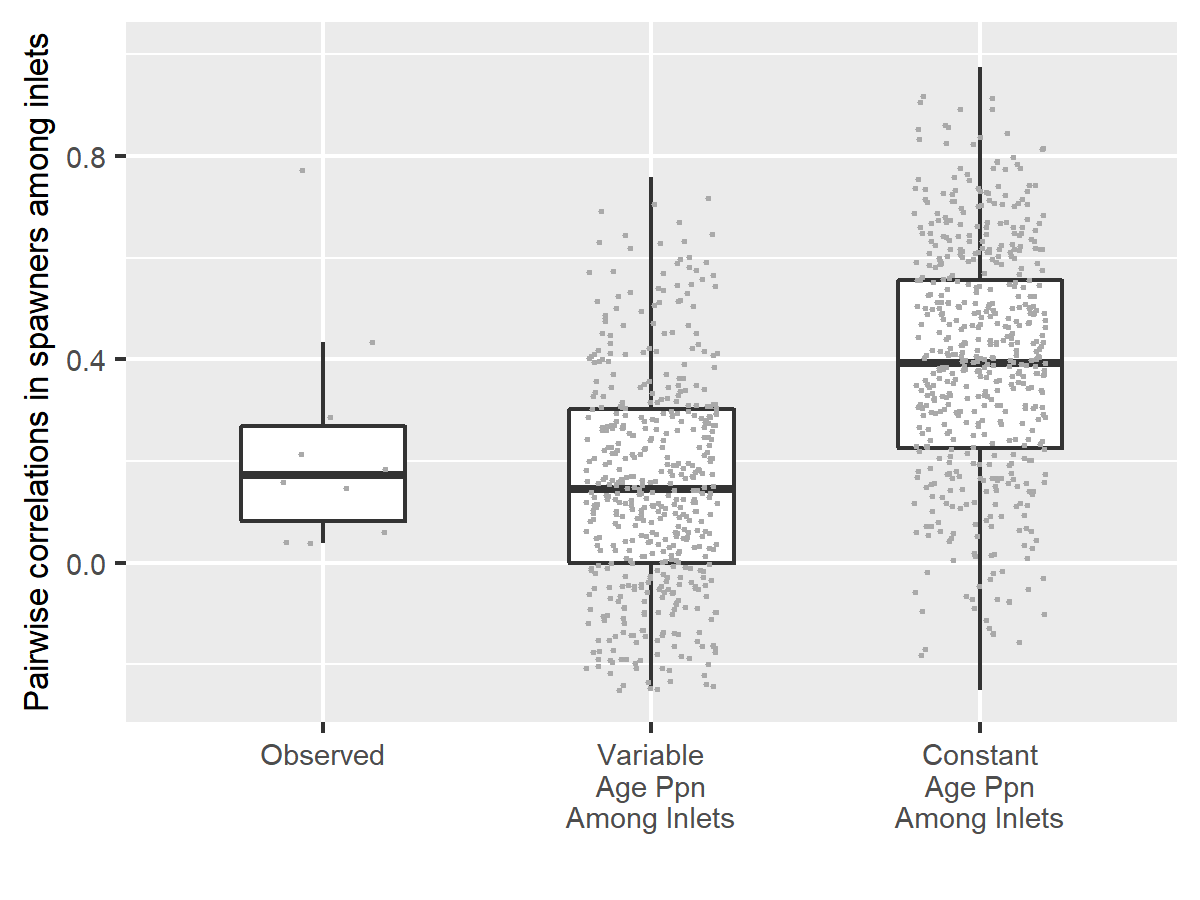


Figure 4.11: Distribution of correlations of spawner abundances among inlets for observed data over the most recent 20 years (n=10 pairwise correlations) and projected time-series under the assumptions of variable age proportions among CUs and constant proportions among CUs. We assumed a cv in exploitation rates among inlets = 0.085 (half that of estimated interannual variablity in exploitation rates) in the projections.

### 4.5.2 RESULTS: AGGREGATE-ABUNDANCE, PROJECTION-BASED LRPS

Projection-based 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 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 4.12). Provisional LRPs at p=0.66 (“likely” that all inlets are above their lower benchmarks) is also shown, near 20 000 (Figure 4.12). Probabilities that all inlets exceeded lower benchmarks did not exceed 0.9 so LRPs at higher p values could not be estimated. Note, the LRP at p=0.66 requires more MC trials for full stabilization and is shown here for demonstration purposes only.

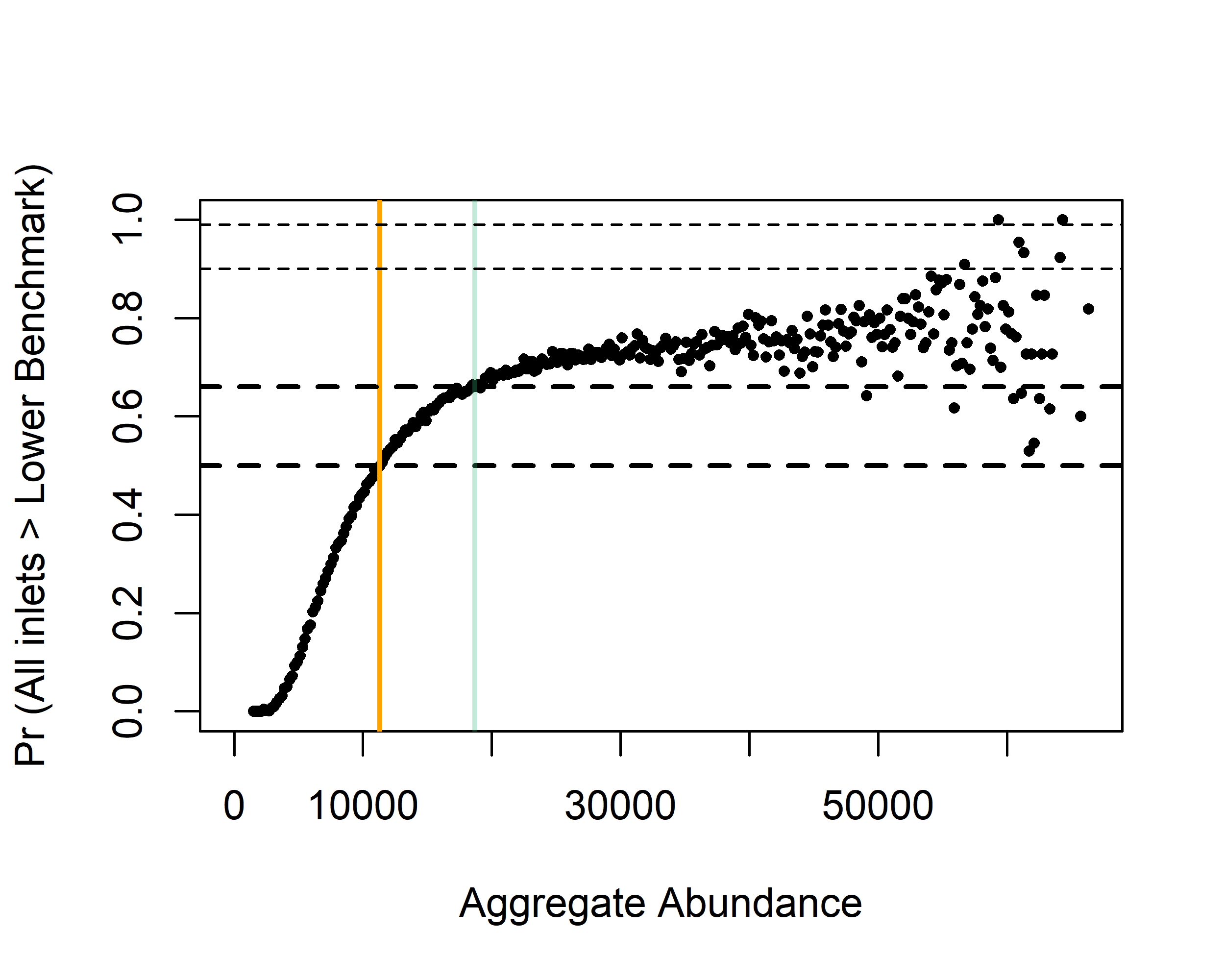


Figure 4.12: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials. Candidate LRPs at p=0.5 (yellow) and p=0.66 (pale green) are highlighted. Each dot is the proportion of MC trials where all inlets were > lower benchmarks.

For the base case parameters, the candidate projection-based LRPs were compared against time-series of aggregate abundances observed for WCVI Chinook salmon (sum of indicator stocks 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 4.13).

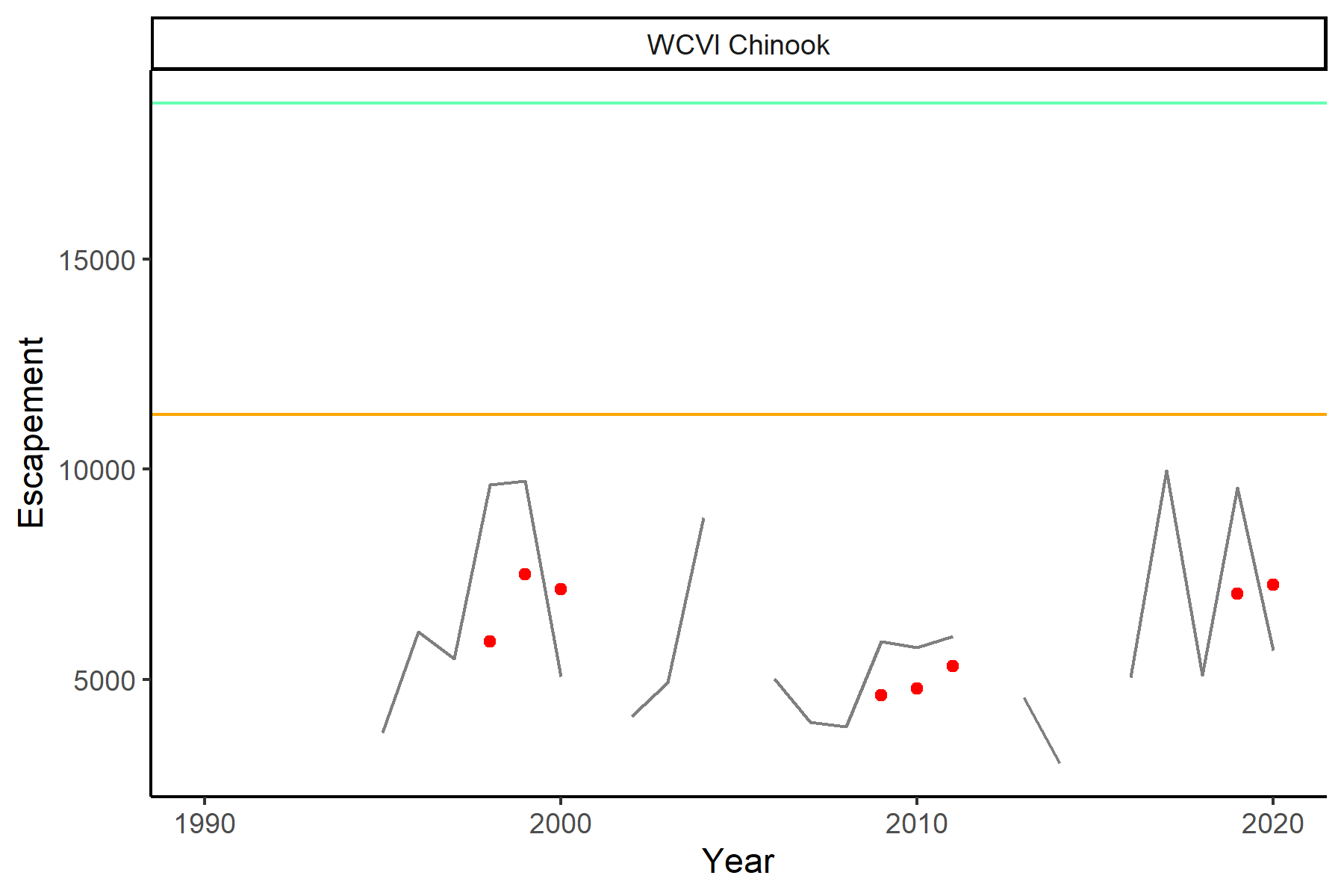


Figure 4.13: Time-series of aggregate escapement for WCVI Chinook (indicator stocks with PNI > 0.5), with projection-based LRPs associated with component inlets being > lower benchmarks at p=0.5 (yellow) and p=0.66 (pale green). Red points are the generational average escapement (geometric mean), red indicating status below LRPs

### 4.5.3 Sensitivity Analyses

We considered sensitivity analyses on interannual variability in exploitation rates among inlets with cv = 0 and 0.17 (Figure 4.14), and found LRPs at 50% probability were not sensitive to this assumption.

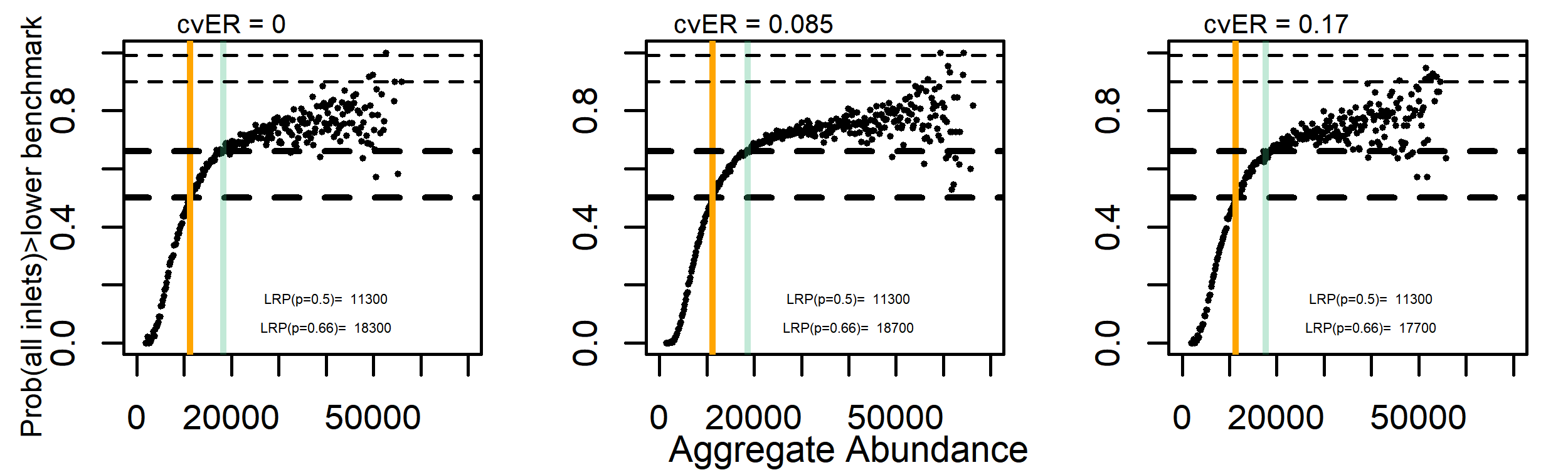


Figure 4.14: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials. The projections assumed variability in ERs among inlets with a cv=0, 0.085, and 0.17.

We further considered sensitivity analyses on average exploitation rates from 5-45% (Figure 4.15), 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, the depletion of any given inlet was more frequent despite often relatively high aggregate abundances on the remaining inlets.

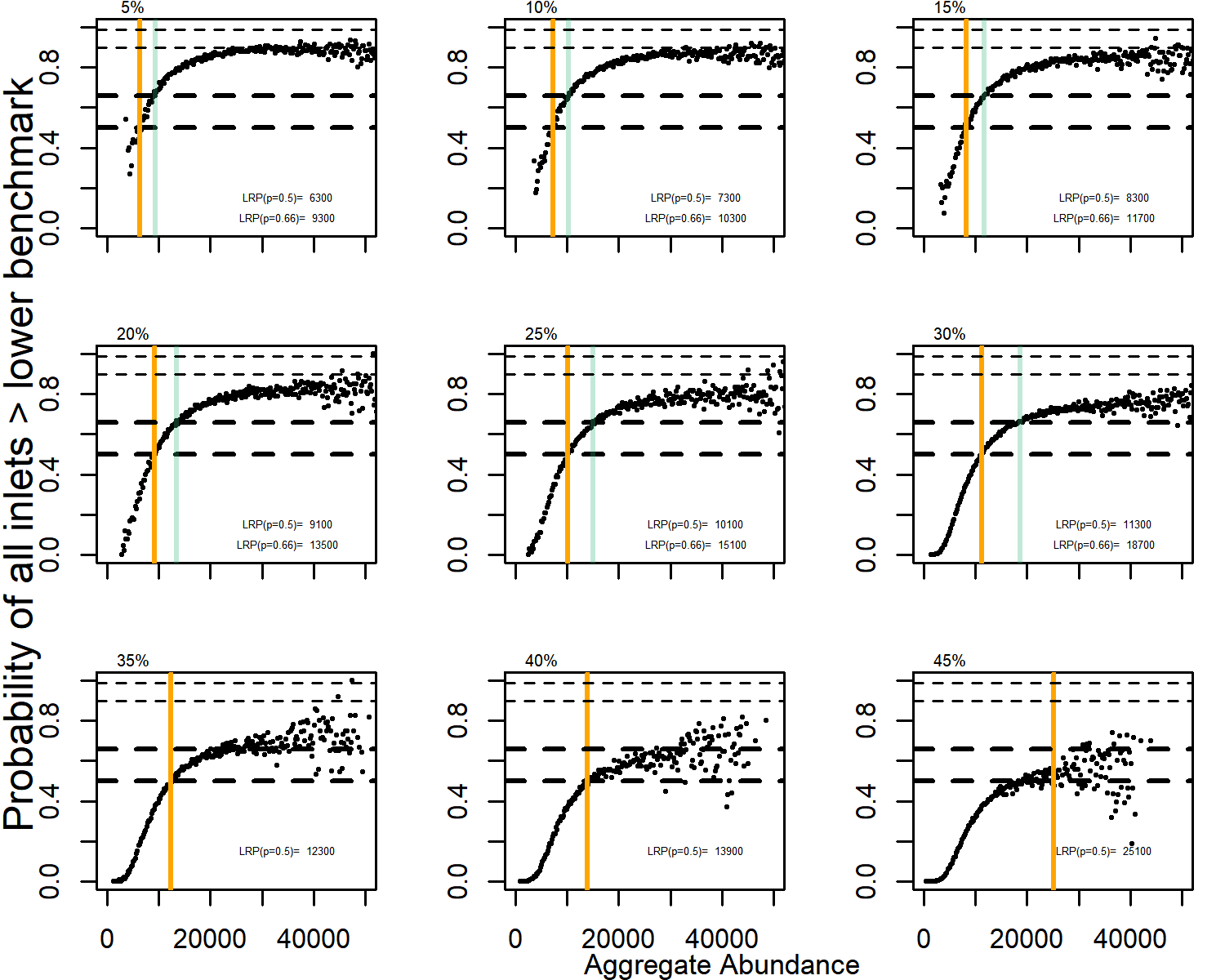


Figure 4.15: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 50,000 MC Trials, under a range of average exploitation rates from 5-45%.

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

Projection-based LRPs tended to increase under low productivity and vice versa, a trend that was expected due to the inverse relationship between productivity and inlet-specific values ([Holt and Folkes 2015](#ref-holtCautionsUsingPercentilebased2015)). At low productivity, the spawner abundances required to achieve (), tends to increase, thereby becoming more precautionary. The sensitivity of LRPs to productivity highlights the value of updating benchmarks and projection-based LRPs as productivity changes (Figure 4.16). 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 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 (though estimation may be possible with more Monte Carlo trials). More detailed analyses of LRPs along the entire range of productivities and exploitation was beyond the scope of this case study.

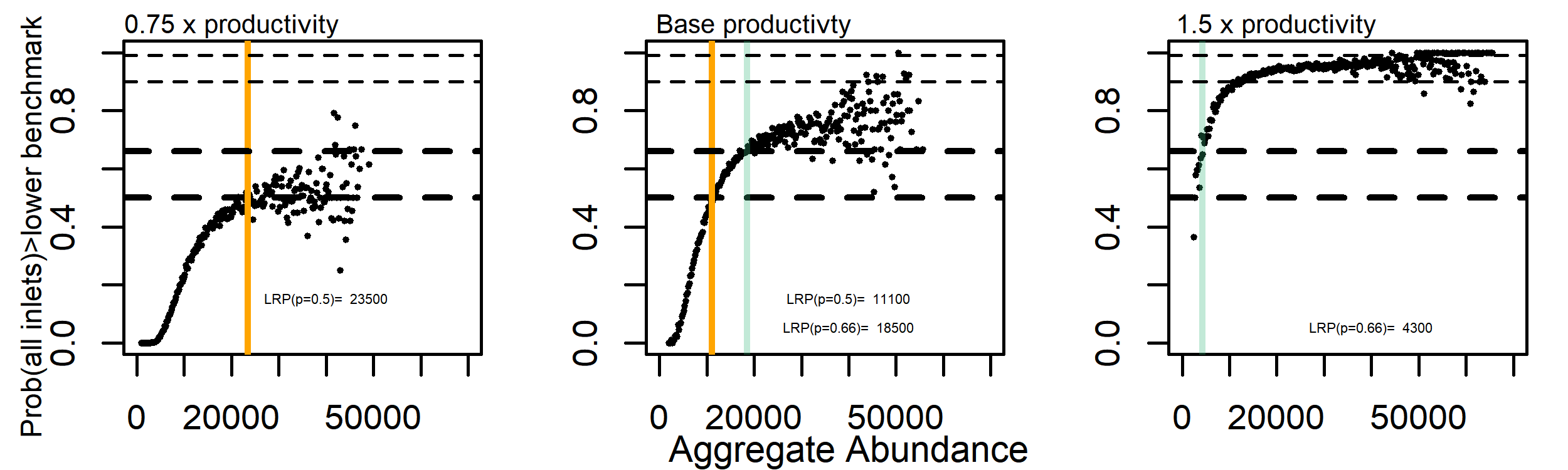


Figure 4.16: Projection-based LRPs estimated under assumptions of reduced producitivty (0.75x of current levels) and increased productivity (1.5x current levels). More MC trials are required for stabilization of LRPs at low productivity.

## 4.6 HISTORICAL EVALUATION OF STATUS ACROSS LRP METHODS

We evaluated status of WCVI Chinook using LRPs estimated using the proportion of CUs with all inlets above and projection-based LRPs, as well as the previously published WSP integrated assessment (status in 2014 only, [DFO](#ref-dfoIntegratedBiologicalStatus2016) ([2016](#ref-dfoIntegratedBiologicalStatus2016))) (Figure 4.17). All methods indicate this SMU being below its LRP for years where data are available.

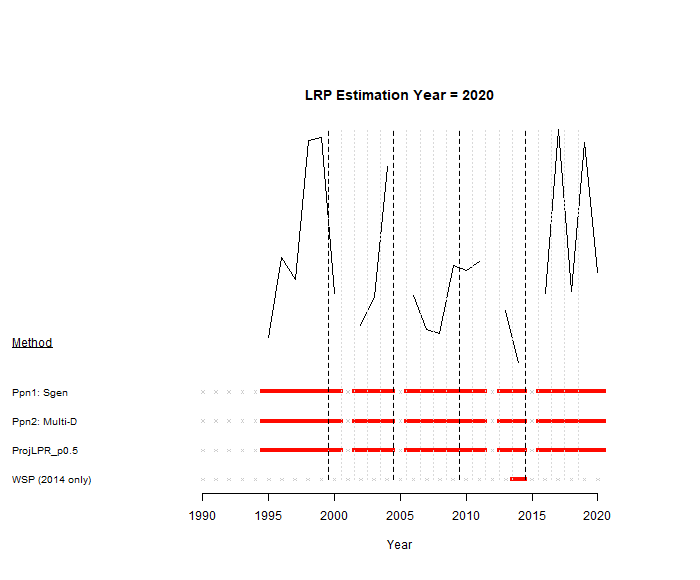


Figure 4.17: Historical evaluation of status using available methods for estimating LRPs. Red bars indicate status below LRP; grey x’s indicate status not available

## 4.7 OVERALL CONCLUSIONS AND FUTURE ANALYSES

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.
* Aggregate-abundance based LRP derived from empirical logistic regression was not possible due to lack of contrast in the time-series.
* Aggregate-abundance based LRPs derived from projections were highly sensitivity to average exploitation. LRPs derived from the base case assumption can not be applied in situations where exploitation has changed, and so cannot be used as a management target *per se*.
* Aggregate-abundance based LRPs derived from projections were also highly sensitivity to underlying population productivities. As productivity declined, LRPs became more precautionary and vice versa.

In the development of projection-based 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. Furthermore, future iterations of the multidimensional status assessment approach could include information on the distribution of spawners across sites within CUs or inlets to incorporate additional scales of diversity.

In addition, if projection-based LRPs are considered for this SMU, further work exploring their sensitivity to productivity and exploitation is warranted with increased number of Monte Carlo trials.

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

## 5.1 CONTEXT

The ‘Inside South Coast Chum - Non-Fraser’ (ISC-NF Chum) SMU includes seven CUs of chum salmon (*Oncorhynchus keta*) 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 5.1; [Holtby and Ciruna](#ref-holtbyConservationUnitsPacific2007) ([2007](#ref-holtbyConservationUnitsPacific2007))). 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.

The ISC Chum SMU is considered data-limited. While escapement 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). 60% of observations (count of spawners for an individual stream, in a given year) were missing and needed to be infilled. 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.](#ref-debertinMarineGrowthPatterns2017) ([2017](#ref-debertinMarineGrowthPatterns2017))). 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.

Benchmarks based on spawner recruit relationships are unreliable if there is uncertainty in the spawner and recruit data. One alternative is benchmarks calculated as a percentile of the historical CU-level spawner abundance time series (percentile benchmarks). Previous work on developing WSP benchmarks for Inner South Coast Chum has shown that percentile benchmarks can be comparable to those based on stock-recruit relationships when productivity is relatively high and harvest is relatively low ([Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f))). In other cases, percentile benchmarks may be inappropriate due to low productivity, high harvest, and because they do not account for non stationarity in recruitment dynamics ([Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f))).

We chose the ISC-NF Chum SMU as a case study because we were interested in exploring LRP options for a data-limited SMU. We applied LRPs based on two methods: proportions of CUs above their lower benchmark, and logistic regression based on aggregate abundance. For proportions, we used percentile benchmarks and multi-dimensional status assessment to determine the status of component CUs. For the logistic regressions, we used percentile .



Figure 5.1: The seven Conservation Units that make up the Inside South Coast Chum Stock Management Unit (not including Lower Fraser and Fraser Canyon Conservation Units).

## 5.2 DATA

We used the same data used in [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)), but updated to 2018. [Van Will](#ref-vanwillInnerSouthCoast2014) ([2014](#ref-vanwillInnerSouthCoast2014)) 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 7.

## 5.3 METHODS

Data and methods are available at: <https://github.com/Pacific-salmon-assess/SalmonLRP_RetroEval>.

### 5.3.1 Determining the Status of Conservation Units

For this case study, we consider two approaches for characterizing CU status: (i) percentile benchmarks and (ii) multi-dimensional status assessment ([Pestal et al.](#ref-pestalAlgorithmsRapidStatus2021) ([2021](#ref-pestalAlgorithmsRapidStatus2021)), in prep).

In addition to abundance-based benchmarks, other benchmarks would also be considered as part of an integrated status assessment (e.g., trends, distribution of abundance; [Holt et al.](#ref-holtIndicatorsStatusBenchmarks2009) ([2009](#ref-holtIndicatorsStatusBenchmarks2009))). At this time, an integrated status assessment has not been developed for ISC chum.

One limitation of percentile benchmarks and the multi-dimensional assessment method used here is the assumption of constant productivity.

There are studies showing that a range of factors may affect the productivity of ISC Chum. These include competition with other salmon in the ocean and ocean conditions ([Debertin et al.](#ref-debertinMarineGrowthPatterns2017) ([2017](#ref-debertinMarineGrowthPatterns2017)), [Litz et al.](#ref-litzCompetitionOddyearPink2021) ([2021](#ref-litzCompetitionOddyearPink2021))). This application of percentile benchmarks does not account for changing productivity.

**Abundance-Based Benchmarks**

Abundance-based benchmarks can be calculated in several ways. They can be informed by stock-recruit relationships when appropriate data are available. Where there are no reliable stock-recruit data available, an alternate method is using percentiles of recorded abundance ([Clark et al.](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd) ([2014](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd)), [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f))). The suitability of percentile benchmarks was evaluated for ISC Chum by [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)), who tested how well percentile benchmarks matched benchmarks from stock-recruit parameters, using retrospective and simulation analyses. [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)) also calculated benchmarks based on stock-recruit model parameters for ISC Chum stocks, but did not recommend them due to uncertainty in spawner and recruit data. They tested how well a 25% percentile benchmark (and higher values up to 50%) compared to estimates of 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’ 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. They also found that time series bias tends to under-estimate .

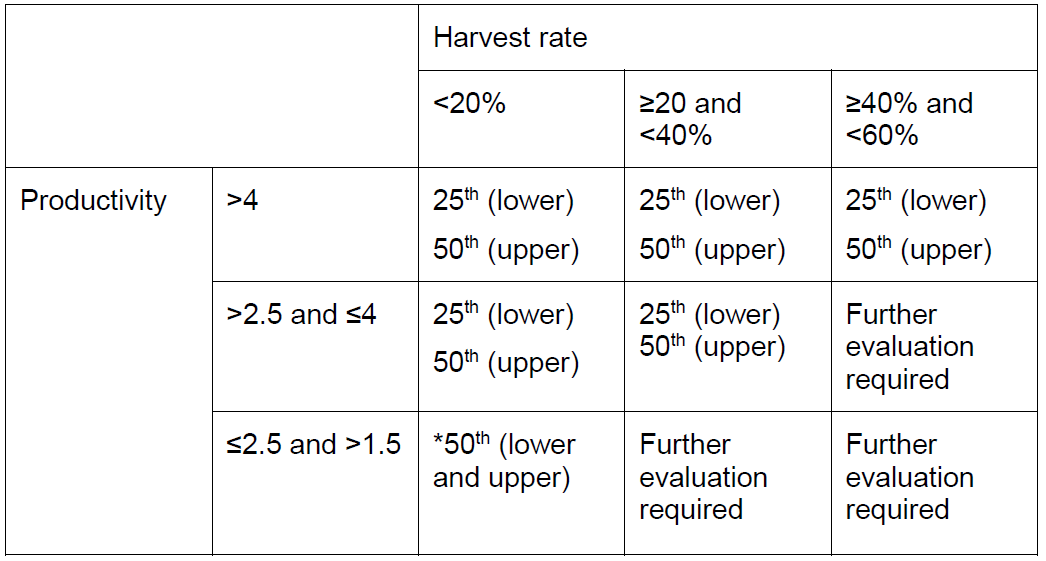


Figure 5.2: Selected percentile-based lower and upper benchmarks identified to be similar or higher in value than stock-recruitment based benchmarks under the WSP, along gradients in productivity (recruits/spawner) and average harvest rates. \* denotes the low-productivity scenario where lower and upper Ricker-based benchmarks are very close to one another, resulting in lower and upper percentile-based benchmarks that are the same. From Holt et al. 2018.

[Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)) recommended different percentiles to be used based on Ricker and average harvest rate (figure 5.2). Based on these recommendations, Georgia Strait and Howe Sound Burrard Inlet fall in the category of using 25th percentile as a lower benchmark (Ricker 2.5-4, harvest rate 20-40%). Loughborough, Northeast Vancouver Island, and Upper Knight ( 1.5-2.5 and harvest rate 0-20%) had a 50th percentile lower benchmark recommended. Bute Inlet ( 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 ( <1.5). Thus, we used 25% of spawner abundance as a benchmark for Georgia Strait and Howe Sound Burrard Inlet, 50% for Loughborough, Northeast Vancouver Island, Upper Knight, and did not use percentile benchmarks for Bute Inlet and Southern Coastal Streams.

**Multi-dimensional CU Status Assessment**

The methods for applying the multi-dimensional status assessment for CU status is described in Chapter 2.

In applying the multi-dimensional rapid status assessment to ISC Chum, we used the percentile benchmarks as recommended in [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)) for relative abundance benchmarks for the five CUs that have appropriate percentiles identified. For Bute Inlet and Southern Coastal Streams, we did not use relative abundance benchmarks. When relative abundance benchmarks are not available, the decision tree was used assesses trends instead.

### 5.3.2 LRP Estimation for ISC-NF Chum

**LRPs Based on Proportion of CU Status**

A simple method to set a LRP for a group of CUs is to set the LRP trigger as being a certain proportion of component CUs as being in the red zone. For example, for ISC chum (7 CUs), the LRP could be defined as being breached when one CU is in the red zone. For this case study, we set this as the rule - if any CUs entered the red zone, the SMU was considered to be below the LRP.

We evaluated six different combinations of data and LRP methods (table 5.1). For scenarios 1 and 2, we used CU status based on percentile benchmarks. For this comparison, we used static benchmarks (not retrospective) using the full data set, and percentile benchmarks based on [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)). This method used the raw annual escapement values to calculate the benchmarks and the generational mean (geometric mean of 4 years) of escapement in the given year and previous 3 years to assess status in a given year. For scenarios 3-6, we used multi-dimensional status of CUs. The multi-dimensional assessment used percentile benchmarks as relative abundance benchmarks, and also compares the generational geometric mean to assess status relative these benchmarks for each year.

Table 5.1: 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). 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 | SCS | NEVI | UK | L | BI | GS | HSBI |
| 1. Percentile- 4 CUs full | - | Y | - | Y | - | Y | Y |
| 2. Percentile- 5 CUs partial | - | Y | YP | Y | - | Y | Y |
| 3. Decision Tree- 4 CUs full | - | Y | - | Y | - | Y | Y |
| 4. Decision Tree-  5 CUs full | Y | Y | - | Y | - | Y | Y |
| 5. Decision Tree- 7 CUS partial | Y | Y | YP | Y | YP | Y | Y |
| 6. Decision Tree- 5 CUs partial | - | Y | YP | Y | - | Y | Y |

**LRPs Based on Aggregate Abundance and Logistic Regression**

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 and benchmarks. These methods used 5 CUs with over 50 years of data (Bute Inlet and Upper Knight both had CU-level infilling in recent years and thus were left out of this analysis).

These methods were applied retrospectively. For a series of years up to a given year, the benchmarks and logistic regressions were calculated with all years up to that year. This was done for all successive years to see how the LRP (and benchmarks, and underlying stock-recruit parameters) would have changed over time as more data was collected.

Due to poor logistic model fits using the entire 1953-2018 time series for both and percentile benchmarks, we did not conduct full retrospective analyses for this SMU. The characteristics of the data that led to poor logistic model fits are highlighted in the results section below.

## 5.4 RESULTS

### 5.4.1 LRP Based on Proportion of CU Status

**CU Status Based on Percentile Benchmarks**

Two out of four CUs were below their percentile lower benchmark in 2018 (Figure 5.3. Howe Sound-Burrard Inlet and Georgia Strait had status above their lower benchmarks.

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 9.2). Percentile benchmarks decreased by a small amount for Loughborough and North East Vancouver Island.

Percentile approaches were not used for the other three CUs for the purpose of the logistic regression of aggregate abundance because they were not appropriate based on productivity and harvest rates (see [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)) Table 6), CU-level infilling, or both (although they are shown in Figure 9.2). Among these three CUs, Southern Coastal Streams and Upper Knight show evidence of shifting baselines if percentile approaches are used.

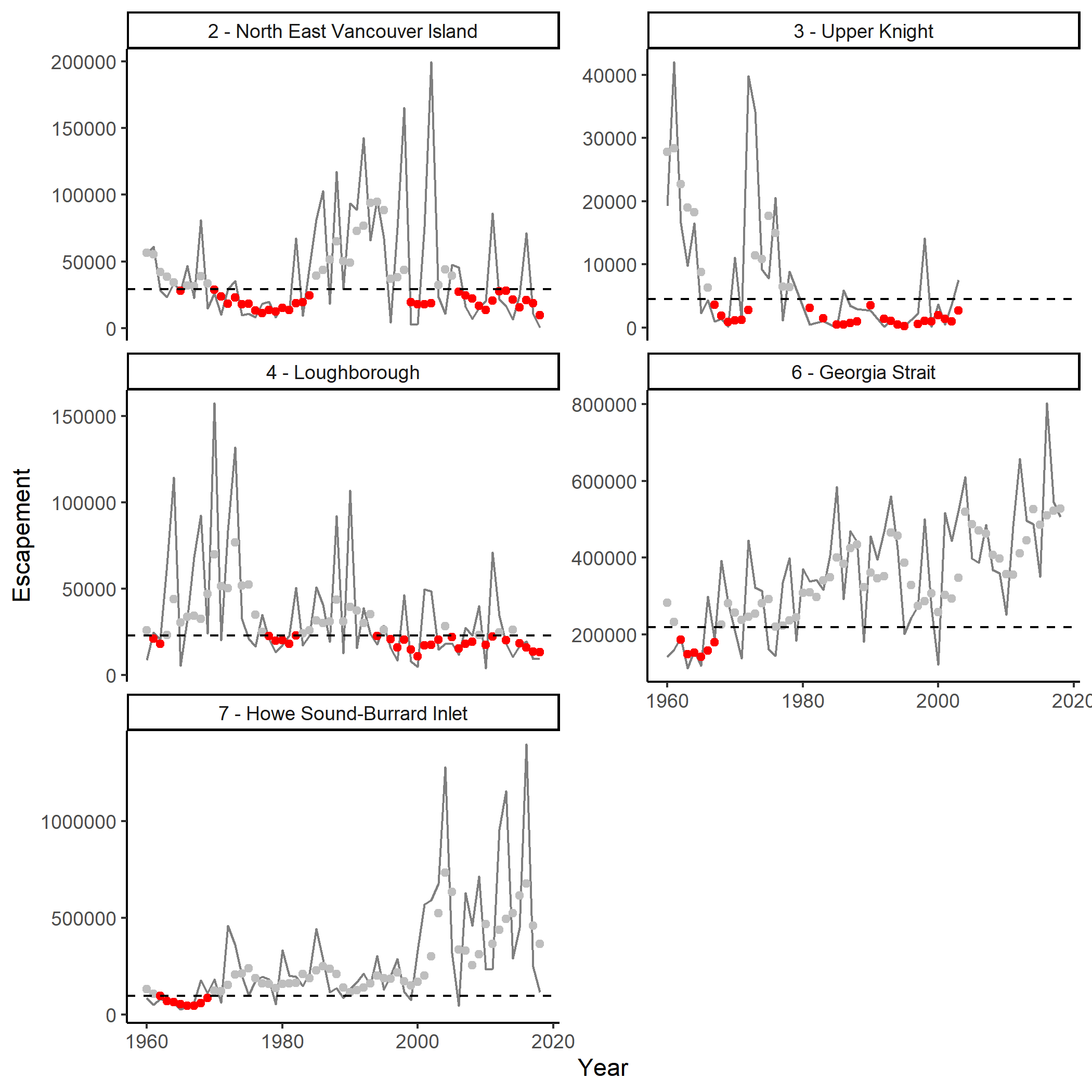


Figure 5.3: Spawner escapement (solid black line) with generational mean (4 year rolling geometric mean) of escapement in points.

**CU Status Based on Multi-Dimensional Status**

Using this method, 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 3 would be below (red zone. 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.

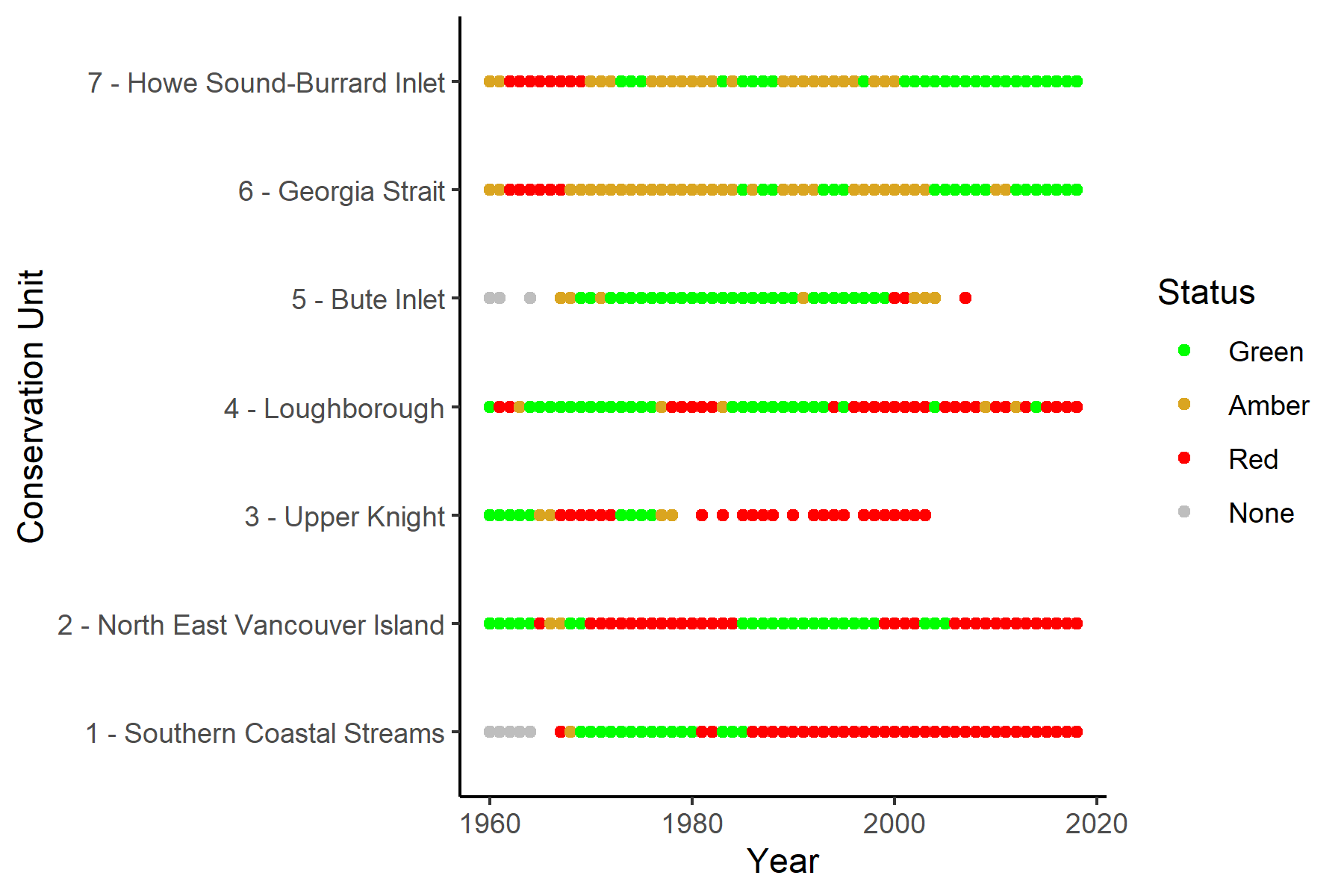


Figure 5.4: Status of CUs based on multi-dimensional status assessment (decision tree). Years with CU-level infilling were not included.

**Comparison of Percentile and Multi-Dimensional Methods**

LRP status based on percentile benchmarks had more years below the LRP multi-dimensional status (Figure 5.5, Table 5.1). Comparing scenarios 1 and 3 (same data) in a given year, ISC Chum were below the LRP based on percentile benchmarks but above it based on decision tree. Scenarios 2 and 6 (same data, more data than 1 and 3) show a similar pattern.

In this case study, adding more data changed the number of years that the SMU was below the LRP. Scenario 5 (most data) had the most years below the LRP. Comparing scenarios 1 and 2, which are both based on percentile benchmarks, including more data (scenario 2) results in more years below the LRP. Comparing scenarios 4 and 5 (decision tree only), including more observations results in one year switching from above the LRP to below it. Comparing scenarios 5 and 6 (6 drops two CUs completely), including the two CUs in scenario 5 results in three years switching from above the LRP to below. Other applications may result in different outcomes of including more data based on the status of additional CUs or years.

We found that SMU status can be below the LRP even if the aggregate abundance is going up. For ISC Chum, this is mainly due to years with high abundances of Georgia Strait and Burrard Inlet-Howe Sound and low abundances and red status in other, smaller CUs, such as Southern Coastal Streams. This highlights the importance of including a metrics of status at the CU level, which influence the overall SMU status.

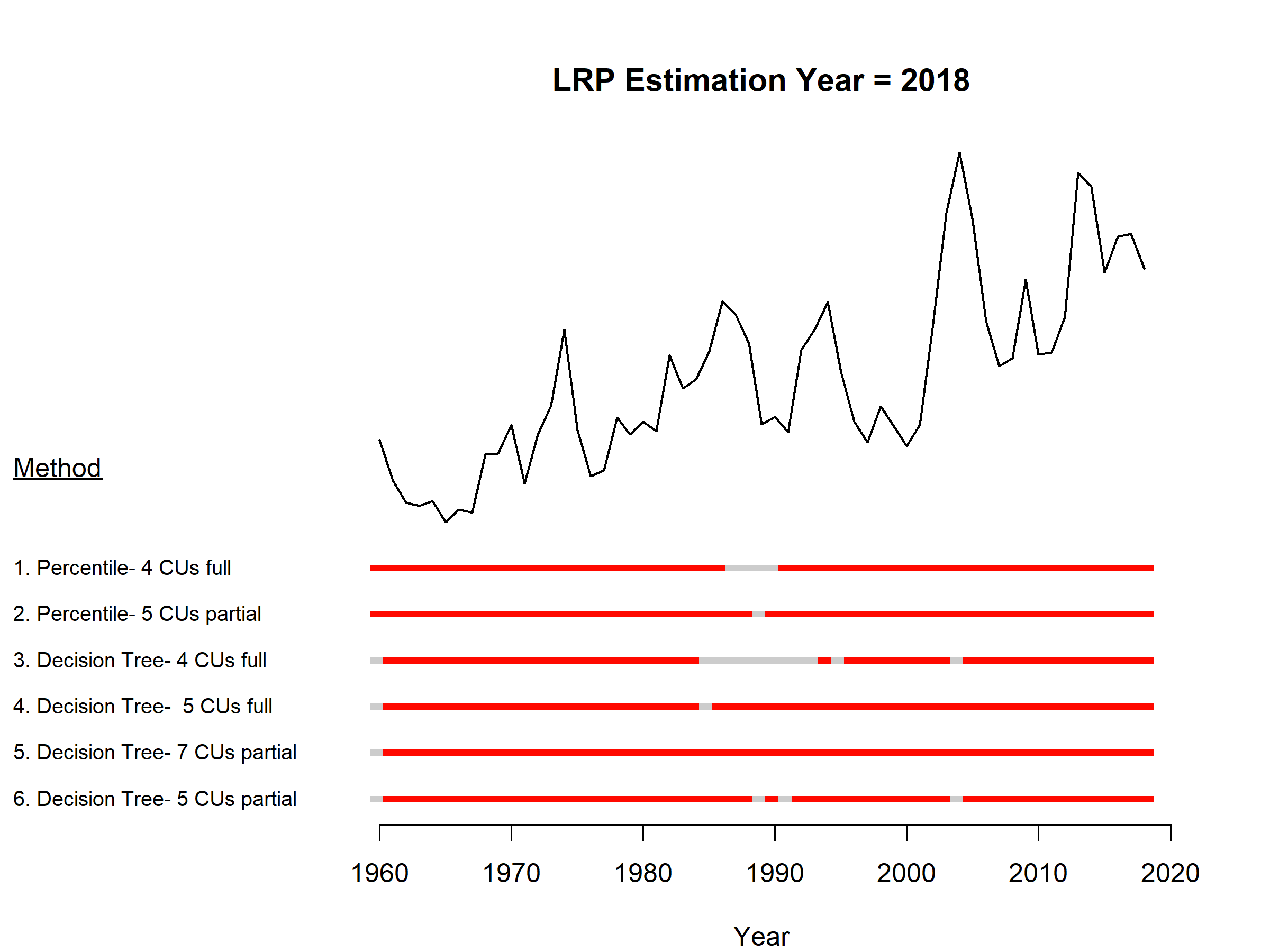


Figure 5.5: Comparison of LRP status (red = below LRP, gray = above LRP) for six scenarios. The black line shows aggregate abundance. Scenarios 1-3 and 6 do not include Bute Inlet or Southern Coastal Streams (no appropriate percentile benchmarks). ‘Full’ scenarios use only years with full time series (no CU-level infilled CUs) and ‘partial’ scenarios include CU-level infilled CUs but drop years with CU-level infilling for those CUs.

### 5.4.2 LRPs Based on Logistic Regression and SMU Aggregate Abundance

The logistic models predicting whether all CUs were above their benchmark based on aggregate abundance fit the data poorly (Figures 9.3, 5.6). In both cases, 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. Note that these regressions used the aggregate abundance of only the CUs used in the regressions, and excluded the other CUs.

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. In addition, the correlation in escapement among these seven CUs is low. 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. This makes sense because this SMU covers a large area with many different populations affected by both local and regional factors. These seven CUs also have different numbers of populations. There are also differences in actual productivity (recruits per spawner) among CUs.

![Figure 5.6: 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)](data:application/pdf;base64,)

Figure 5.6: 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)

The diagnostics for the logistic regression indicated that the model fit was poor for percentile benchmarks (Figure 5.6). The Box-Tidwell test indicated a significant lack of linearity in the relationship between aggregate abundance and log-odds, which means that an assumption of logistic regression was not met. There was not a significant improvement in the model fit when aggregate abundance was included, compared to the null model. There was no evidence of outliers, and there was a sufficient sample size. The ratio of correct classification based on a confusion matrix was 0.7. Note that this method tends to have overly optimistic values. The p-value was significant for the estimation of , but not for . There was no evidence for autocorrelation in residuals. Regressions based on had similarly poor model fits (Figure 9.3.

## 5.5 DISCUSSION

### 5.5.1 Suitability of LRP based on status of component CUs (proportion)

Something about portfolio effects/ theory. Paper on Alaska shifting productivity areas from year to year.

(Note: not using percentile benchmarks for relative abundance benchmark for decision tree gives the same results as scenario 5 at the SMU level)

**Limitations of Percentile Benchmarks**

There are some assumptions and limitations when using benchmarks based on percentiles of abundance. One of the largest is the influence of shifting baselines on percentile benchmarks. If abundance has decreased over time, the resulting percentile benchmark will also decrease over time as more data is included (Figure 9.2). This means that the benchmark shifts downward, reinforcing a shifting baseline. A population size that used to be below the benchmark can become above the benchmark, as the benchmark decreases. This can arise from a decrease in abundance in the period of data, and by an unrecorded high level of abundance before the period of data followed by a decrease before data are available.

The concept of percentile benchmarks also assumes productivity is stationary. Otherwise, if productivity was decreasing, a larger abundance of spawners would be required to produce the same number of recruits. Contrary to this assumption, there is evidence that the productivity of chum salmon is not stationary. The productivity of BC chum salmon is lower when the abundance of North American salmon like pink, sockeye, and chum is greater ([Debertin et al.](#ref-debertinMarineGrowthPatterns2017) ([2017](#ref-debertinMarineGrowthPatterns2017)), [Litz et al.](#ref-litzCompetitionOddyearPink2021) ([2021](#ref-litzCompetitionOddyearPink2021))). The percentile benchmark is also only informed by the data available, which may be for a short time period. Those using percentile benchmarks should also consider whether they are calculated using a percentile of recruits or escapement.

Estimating relative-abundance benchmarks for salmon populations without a long time series and without data on productivity (only escapement, no recruits/smolt production) is challenging. Previous evaluations of Inside South Coast chum population status used a 25% benchmark ([Hilborn et al.](#ref-hilbornBritishColumbiaChum2012) ([2012](#ref-hilbornBritishColumbiaChum2012))). This was based on previous work by the Alaska Department of Fish and Game that defined four tiers of populations based on contrast in spawner abundances, harvest rate, and precision of escapement data ([Bue and Hasbrouck](#ref-bueEscapementGoalReview2001) ([2001](#ref-bueEscapementGoalReview2001)), [Otis and Hasbrouck](#ref-otisEscapementGoalsSalmon2004) ([2004](#ref-otisEscapementGoalsSalmon2004))). The goal of these tiers was to choose a Sustainable Escapement Goal (an upper and lower percentile) to use as a goal for escapement to represent a proxy for keeping escapement within a range that includes ([Clark et al.](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd) ([2014](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd))). These SEGs were calculated for each major river/system and are still done that way in Alaska ([McKinley et al.](#ref-mckinleyReviewSalmonEscapement2020) ([2020](#ref-mckinleyReviewSalmonEscapement2020))). Tier 1 of this method was for high escapement contrast (greater than 8 ) and at least moderate harvest rate, with a SEG of 25th to 75th percentiles. [Bue and Hasbrouck](#ref-bueEscapementGoalReview2001) ([2001](#ref-bueEscapementGoalReview2001)) assessed this method on 11 populations of sockeye salmon and Chinook salmon from Upper Cook Inlet and Bristol Bay (in [Clark et al.](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd) ([2014](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd)) ). [Clark et al.](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd) ([2014](#Xac6a400d07a0b275e3bfcc6c352975dadf1eddd)) tested the suitability of this 4 tier percentile approach with theoretical, simulation, and meta-analysis methods using 76 stock-recruitment data sets from Alaska (7 pink salmon, 7 coho salmon, 43 sockeye salmon, 6 chum salmon, and 13 Chinook salmon populations). They recommended a revised 3 tier system, which changed the Tier 1 lower percentile to 20%. Moving to British Columbia, [Hilborn et al.](#ref-hilbornBritishColumbiaChum2012) ([2012](#ref-hilbornBritishColumbiaChum2012)) adopted the previous 25% lower limit of SEG as a benchmark for evaluating the status of Inside South Coast Chum in BC for the purpose of certification with the Marine Stewardship Council ([Hilborn et al.](#ref-hilbornBritishColumbiaChum2012) ([2012](#ref-hilbornBritishColumbiaChum2012))), despite its lack of testing for populations of chum salmon in British Columbia. Further, SEGs were and still are applied to individual rivers in Alaska, compared to the application of this method to entire CUs by [Hilborn et al.](#ref-hilbornBritishColumbiaChum2012) ([2012](#ref-hilbornBritishColumbiaChum2012)), [Holt et al.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)), and this study. ISC chum includes 296 streams among the seven CUs, with 126 in Strait of Georgia alone. By aggregating spawners and recruits across many rivers before estimating benchmarks of percentile or stock-recruit parameters, the following problems may arise:

* Error in fitting stock-recruit curves because it is at aggregate level instead of by river
* Sum of calculated for individual rivers may not equal calculated using aggregated spawner and recruit data
* Non-stationarity of productivity in individual systems may be hidden by aggregating spawners and recruits
* Spawner abundance at CU level may not be a good predictor of status of individual rivers compared to SEGs at the river scale, depending on the contrast in size between rivers and the correlation (or lack thereof) in escapement and/or productivity

**Multidimensional**

Useful for mixture of data qualities/types/BM e.g., some CUs didn’t have appropriate RelAbdundance benchmarks. This approach has been tested on a variety of data types, including those with and without relative abundance benchmarks. Like any approach to assess LRP’s, the underlying data, and benchmarks applied if relative abundance benchmarks can be used should be verified by experts. There are examples in Fraser Sockeye or with Fraser IFC, where it relied on trend metrics only, so can relate to data types that are data limited for Chum.

### 5.5.2 Suitability of Logistic Regression LRPs Based on Aggregate Abundance

Did not work for ISC Chum SMU.

Data was not suited to logistic regression - aggregate abundance was not a good predictor of the status of component CUs.

Some reasons why (summarise from Results): - large differences in abundnace between CUs - 2 orders of magnitude gor Goergia Strait, Howe Sound-Burrard Inlet compared to others. Not high correlation between escapements between CUs. -

Why (further) ? - Large geographical range of SMU / component CUs - Lots of different populations - CUs have different numbers of populations (big differences), and those populations have big differences in abundance - Differences in productivity among CUs/populations

In the retrospective analysis, the logistic model fits were more appropriate to the data in some years (e.g., 1980s). Although logistic regression could be used to estimated LRPs based on aggregate abundance in some SMUs where abundance is more even among CUs and escapements are more correlated, these relationships may not remain static and could become unreasonable over time. Care should be taken to regularly reassess the validity of aggregate abundance-based LRPs where they are implemented in the future.

### 5.5.3 Assumptions and limitations

The CUs that required CU-level infilling (Upper Knight and Bute Inlet) were not used for the retrospective analysis because the assumption that escapement is correlated between CUs ignores diversity between CUs and the potential for uncorrelated escapements. The reality of uncorrelated escapements must be taken into account to evaluate whether aggregate escapement is a meaningful predictor for the status of individual CUs. It should also be noted that these two CUs do not represent a random subset of the seven CUs in the Inside South Coast Chum SMU. Both have fewer streams than the other CUs and a higher proportion of summer-run populations of chum. These CUs also include long fjord systems with glaciers and watersheds that go deep into the mainland with headwaters in the Cariboo region. The hydrology, geomorphology, and marine conditions when smolts enter the ocean in these systems may vary from that of the other five CUs, leading to differences in productivity and responses to the regional climate. For example, productivity (recruits per spawner) of the Upper Knight and Bute Inlet CUs (using CU-level infilling, which introduces error) have the largest magnitude of variability in the SMU, with very productive years (>100 recruits per spawner) and low productivity years, and boom and bust cycles of abundance. In other SMUs where the quality of data differs for a subset of CUs, careful consideration should be given to whether abundance, productivity, and their trends can be reliably estimated using data from CUs with data of higher quality.

### 5.5.4 Other sources of information to inform LRPs / benchmarks

Indigenous Knowledge

* Two-Eyed Seeing - Etuaptmumk(Mi’kmaw) [Reid et al.](#ref-reidTwoEyedSeeingIndigenous2020) ([2020](#ref-reidTwoEyedSeeingIndigenous2020))
* Historical baseline before records from western science [Eckert et al.](#ref-eckertDivingBackTime2018) ([2018](#ref-eckertDivingBackTime2018)), [Lee et al.](#ref-leeDiverseKnowledgeSystems2019) ([2019](#ref-leeDiverseKnowledgeSystems2019)), [Ban et al.](#X2e73f4d087e5cbb6ed1fcd225c03e59fe3ca58f) ([2018](#X2e73f4d087e5cbb6ed1fcd225c03e59fe3ca58f))

Genetic tools and historical records

* Skeena sockeye [Price et al.](#ref-priceGeneticsCenturyOld2019) ([2019](#ref-priceGeneticsCenturyOld2019)), [Price et al.](#X7f953f57dcd3fd1caf89680dcd111a8edd4c00b) ([2021](#X7f953f57dcd3fd1caf89680dcd111a8edd4c00b))
* Skeena chum [Price et al.](#ref-priceAbundanceSkeenaRiver2013) ([2013](#ref-priceAbundanceSkeenaRiver2013))
* Cannery records (**[meengs\_estimating\_2005?](#ref-meengs_estimating_2005)**)

Archaeological records

* BC herring [McKechnie et al.](#X7c0b148a133f238157c8ad2ef69e802d44db7f8) ([2014](#X7c0b148a133f238157c8ad2ef69e802d44db7f8))

# 6 LESSONS LEARNED FROM CASE STUDY APPLICATIONS

To be completed.

* Synthesize main results and conclusions from case studies

## 6.1 Proportion-based LRPs

The proportion-based LRPs are the simplest assessment method presented. It consists in verifying is all CUs within the SMU of interest are assessed to be above their lower benchmarks or above the red zone. Complications related to applying proportion-based LRPs arise when considering the range of data availability for salmon CUs. The data availability will determine what metrics are used for the CU status assessment and whether an assessment can be made at all. Recommendations on when it may be appropriate to use a subset of CUs as proxy for all CUs within an SMU are provided in the companion Guidelines paper (Holt et al. In review).

The case studies in this paper considered a variety of metrics and assessment methods for determining status of individual CUs. We found that using as single metric lower benchmark resulted in similar status assessments to using the rapid multidimensional scanning tool. This similarities occur because, when estimates are available, the rapid multidimensional scanning tool will almost always default to the estimates to assess status, as was seen on both Interior Fraser coho and WCVI chinook study cases. Exceptions occur when the estimates are below the absolute population thresholds (e.g., below 1500 spawners), as occurred in the interior Fraser coho study case. The status assessments, however, are sensitive to the method and recruitment model used to estimate . The decision on which method to consider depends on the interpretation of the data and prior knowledge for each CU, highlighting the importance of considering expert knowledge and peer-reviewed WSP assessments for determining CU status. In data poor scenarios, it may not be possible to estimate , as was seen in the Inside South Coast Chum - Non-Fraser study case. When estimates are not available and alternative single metric benchmarks are used, e.g. abundance percentiles, the status assessments between the rapid multidimensional scanning tool and single metric approach diverge more often. For example, in the Inside South Coast Chum - Non-Fraser study case, the LRP was triggered more often when percentile benchmarks were used. Whereas when the distributional target was used as a metric for the Interior Fraser coho study case, the LRP was triggered less often when compared to rapid multidimensional scanning tool. This is likely associated with the fact that alternative single metric benchmarks are usually more volatile then assessments results based on or the rapid multidimensional scanning tool. In addition, using the rapid multidimensional scanning tool allows for the consideration of CUs that would otherwise be considered data deficient, thus allowing cor a more complete assessment of the SMU status. This was illustrated in the Inside South Coast Chum - Non-Fraser study case, as the exclusion of CUs with incomplete time series led to overoptimistic assessments.

## 6.2 Aggregate abundance-based LRPs

### 6.2.1 Logistic regression-based LRPs

The Logistic regression-based LRPs are empirically derived from the past observations of SMU abundance and CU statuses. In this method we apply a logistic regression to identify historical abundance levels associated with probabilities that all CUs within an SMU have statuses above the red zone or above their lower benchmarks. Similarly to the proportion-based LRP, this aggregate abundance method depends on the outcomes of individual CU assessments, which are sensitive to the method chosen for the assessment and the data availability. We found that the logistic regression-based LRPs were only estimable when Cu assessment was based on single-metric assessments, such as or the distributional target method pplied to the IF coho study case.

The Logistic regression-based LRP is only estimable when there are years when all CUs or sub-populations are above their lower benchmark and years when at least one CU is below their lower benchmarks. This was not the case for the WCVI Chinook study case due to one inlet always been below its lower benchmark. In addition, individual CU must have moderate to high level of correlation, so that the aggregate abundance of the SMU is a good indicator of individual CU status. The case studies shown in this paper show that logistic regression-based LRPs were estimable for interior Fraser coho (average correlation within CUS of 0.43) but not estimable for Inside South Coast Chum - Non-Fraser (average correlation within CUs of XX). Additional factors for the poor fit of the logistic regression-based LRPs for the Inside South Coast Chum - Non-Fraser study case include the presumed wide range of productivity and capacity values for the CUs within that SMU.

Missing data for individual CUs within an SMU may also pose a problem for the estimation of logistic regression-based LRPs. When data is missing for one or more CUs within and SMU, it may still be appropriate to apply the logistic regression-based LRP to the remaining CUs with data to assess status for the entire SMU. This is particularly true if there are high levels of covariation between the CUs. However, the logistic regression model fit will degenerate as the number of CUs with missing data increases. Sensitivity analysis for the Interior Fraser Coho study case showed that the model fit degenerated when two CU data sets were removed from the analysis. The influence of missing data was also dependent on the status of the CU for which data was missing. The omission of a CU with red status will be more influential that omitting data for a CU with amber or green status because the red status would trigger the LRP and change the SMU status for the logistic regression, biasing the aggregate abundance LRP to lower values.

Finally, it is important to inspect model diagnostics and statistically test the model assumptions whenever applying the logistic regression-based LRPs. In chapter 2 we provide a list of model diagnostics that should be checked when applying this aggregate abundance LRP estimation method. In addition, we illustrate how the diagnostics are used in support of the model fit in chapter 3, and against the model fit in the 5.

### 6.2.2 Projection based LRPs

The projection-based LRPs approach relies on closed-loop simulation model to project future CU abundances. These projections are then used to identify the 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 requirement for the application of projection-based LRPs is the availability of information on productivity and capacity for the CUs within an SMU. Parameter estimates for productivity and capacity can be provided based on single parameter estimates, e.g., parameters derived based on expert input, life-stage models or watershed model estimates (see WCVI Chinook study case, chapter 4) or posterior distributions from stock recruitment analyses (see interior Fraser Coho study case, chapter 3). We did not estimate projection-based LRPs for Inside South Coast Chum - Non-Fraser study case because estimates of capacity and productivity were not available for the CUs within that SMU.

The projection-based LRP approach is flexible and allows for consideration of structural uncertainty in the SMU population dynamics via consideration of alternative future scenarios. For example, for the WCVI chinook study case, 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, sensitivity analyses were performed regarding the variability in marine survival coefficient among CUs. Future implementations of the projection-based LRPs could also take into consideration shifts in stock recruitment parameters, and future changes in fishery exploitation rates.

We also demonstrated that the projection-based LRPs is sensitive to the assumed levels of exploitation rate 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 among stock-recruitment parameters increase, and also as uncertainty in parameter estimates increase. This property of projection-based LRPs is explored in Appendix ??. This feature of the approach could be used in future exercises to identify the optimum levels of exploitation, to ensure that the aggregate abundance LRP is in line with current observed abundances.

# REFERENCES

# Appendix

# 7 Data Sources & Treatment for Innter South Coast Non-Fraser Chum Salmon

## 7.1 Spawner counts / 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. Biologists from Fisheries and Oceans Canada and First Nations including … (Island Marine Aquatic Working Group) generate these data by walking streams and counting fish, and using fences or weirs on some rivers. Total escapement for each stream is usually a peak counts or estimated using the area under the curve (AUC) method.

## 7.2 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.

## 7.3 Data treatment

We removed the summer run fish because all of the data that goes into the run reconstruction work is associated with populations that return in the fall.

To get wild escapement, we kept only wild spawners and removed hatchery-origin spawners (with clipped adipose fins), spawners harvested at a facility, and spawners collected for brood stock.

We also removed spawners for the Qualicum River, Little Qualicum River, and Puntledge River, as these systems have been nearly 100% enhanced at least since enhancement began at these locations. We made the assumption that these streams had 100% hatchery origin spawners.

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:
  + Add fishery catch by CU and Area to total escapement to estimate total returns
  + Use proportion of wild:total escapement 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

### 7.3.1 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.](#X3b081672c1abb3cf386e8d680f27c38edd8b66f) ([2018](#X3b081672c1abb3cf386e8d680f27c38edd8b66f)); Figure 7.1). 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.

#### 7.3.1.1 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 (can have figure in appendix or quote correlation values).

#### 7.3.1.2 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, 1991,1996,2004-18) and Bute Inlet (13 years: 2005-2006, 2008-2018).

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.

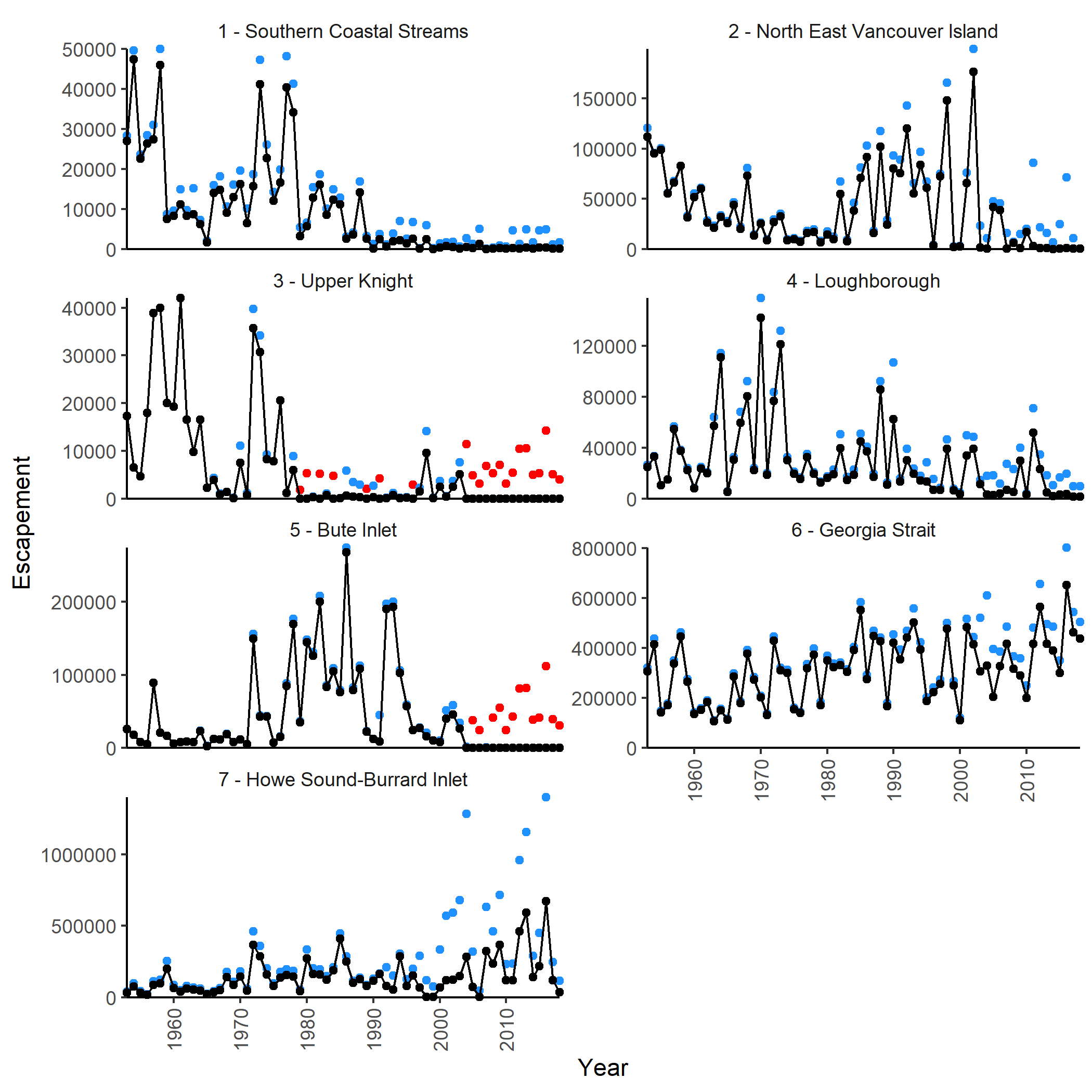


Figure 7.1: Chum salmon escapement for the seven Conservation Units. Black points indicate actual counts, blue points are infilled by stream, and red points are infilled by Conservation Unit.

### 7.3.2 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). Using CU benchmarks based on stock-recruit parameters - in this case, Sgen - 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 5.1). 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 totoal stock by CU and Fishery Management Area for each spawning year. This total stock 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 total wild stock (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 this total stock 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.

# 8 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](https://github.com/Pacific-salmon-assess/samSim/tree/LRP). samSim has been previously used to evaluate harvest control rule performance relative to recovery potential (([Holt et al. 2020](#ref-holtQuantitativeToolEvaluating2020); [Freshwater et al. 2020](#X05d0642f7bbce859a84f3071e0897945c1c2212))). 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 no historical recruitment data are 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.
* The option to include a log-normal bias-correction factor of 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*^ is *e*^} rather than zero when recruitment deviations are normally distributed ([Cox et al.](#ref-coxCandidateLimitReference2019) ([2019](#ref-coxCandidateLimitReference2019)), [Ohlberger et al.](#ref-ohlbergerBayesianLifecycleModel2019) ([2019](#ref-ohlbergerBayesianLifecycleModel2019)), [Olmos et al.](#ref-olmosEvidenceSpatialCoherence2019) ([2019](#ref-olmosEvidenceSpatialCoherence2019)), [Forrest et al.](#ref-forrestAssessmentPacificCod2020) ([2020](#ref-forrestAssessmentPacificCod2020)), Weir et al., in press). When input parameters have been corrected for this log-normal bias, the bias correction must also be added to projections. 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 aims at describing the samSim model equations and the model’s internal logic. We focus on providing detailed descriptions of the modeling options used for LRP study cases but include brief mentions of other model extentions already implemented within samSim. samsim includes two population levels, it could be applied to one Conservation Unit (CU) with component sites, or one Stock Management Unit (SMU) with component CUs, or even one region with component SMUs. 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 five CUs) and the Interior Fraser Coho Salmon SMU (with three 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 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. The model indexes are defined in Table ??, the model parameters and model input are defined in Table ?? and the modeled quantities are defined in Table ??. Detailed definitions of the input data and parameters are provided in the project [README](https://github.com/Pacific-salmon-assess/samSim/tree/LRP#readme).

## 8.1 MODEL PRIMING

The priming phase, or model initialization, represents the past data for CUs being modeled. It is used to represent real 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 is not available.

### 8.1.1 Recruitment data is available

If spawner-recruitment data is 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.

### 8.1.2 Recruitment data is not available

When Recruitment data is 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, tipically from mcmc samples. If mcmc samples are provided, a different set of parameters is used for each simulation trial.

The spawner 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, , the capacity parameter , and the recruitment standard deviations, . 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, the covariance matrix is calculated based on the variance-covariance matrix, which is calculated based on CU-specific recruitment variances, and the correlation matrix 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 and then calculated based on recruitment and exploitation rates in the previous years (Equations (8.1) and (8.1)). 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.

The age structure of the returns is computed following a multivariate logistic error structure based on the long term average age structure for each CU, and the CU-specific variability parameter ([Schnute and Richards 1995](#ref-schnuteInfluenceErrorPopulation1995)) (Equation (8.3). The age structure error can vary or be held constant among CUs. Calendar year recruitment is only calculated after the sixth year of the priming phase. It is the product of the brood year recruitment and the age structure of the returns (Equation (8.4).

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 (8.5) when ), Ricker curve with temporal autocorrelation in recruitment error (equation (8.5)), and Ricker curve with a smolt-to-adult marine survival covariate (Equations (8.7) and (8.8), 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 (8.6)).

For the Ricker model with the marine survival covariate, the covariates for each calendar year are generated following a normal distribution with user defined mean and variance (Equation (8.10)). The distribution of survival covariates is truncated between maximum and minimum values provided in the input files. The brood year survival covariates, , 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 (8.9)). The exception is the first two years of the priming loop, when no lag is applied to the covariates.

Recruitment estimates produced for either formulation of the Ricker model are capped. The default maximum recruitment value is , but the scalar can be modified by the user via the variable (Equation (8.11)). In addition, if the generated recruitment is lower than the user defined extinction threshold, then recruitment is set to zero.

### 8.1.3 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, , from the notation used for the management quantities.

If the “stockRecruit” option is used, the management quantities are and calculated based on the stock-recruitment parameters. When the model with the survival covariate is used, the parameter is modified to incorporate the survival component (Equation (8.12)). In order to keep the management benchmarks constant through time, the long term average of the survival covariate is used. is calculated following the explicit solution provided by [Scheuerell](#Xc42d04c48da523ac8df8573b3cd717b3dd480a5) ([2016](#Xc42d04c48da523ac8df8573b3cd717b3dd480a5)) using the Lambert W function (Equation (8.13)). is estimated by solving Equation (8.14) numerically, as described by [Holt et al.](#ref-holtIndicatorsStatusBenchmarks2009) ([2009](#ref-holtIndicatorsStatusBenchmarks2009)). The Lower management benchmark is set to and the upper benchmark is set to 80% of .

If the “percentile” benchmark option is chosen, the upper benchmark is set to the 50th percentile of historical spawners (). The lower benchmark is set to the 25th percentile of historical spawners. 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.

### 8.1.4 Infill missing data

The last step of the model priming is infilling, which is only relevant if stock recruitment data is 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.

## 8.2 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.

### 8.2.1 Specify stock recruitment parameters

Similarly to the priming phase, the first step on the projection loop is to define the stock recruitment parameters. The and 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 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 () for the parameter in the sections to follow.

### 8.2.2 Project management benchmarks

Once is specified, the true management quantities and for the projection year are computed following Equations (8.13) and (8.14). 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.

### 8.2.3 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](#ref-schnuteInfluenceErrorPopulation1995) ([1995](#ref-schnuteInfluenceErrorPopulation1995)). Observation error for the proportions of returns at age is not included in the LRP study cases, i.e., the variability parameter, , is set to zero.

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 (8.16)).

### 8.2.4 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 (8.17) and (8.18)). 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.

### 8.2.5 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 (8.24)). 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 (8.19)-(8.20) ).

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 (8.22)-(8.23). The Catches are then computed by multiplying the CU specific and the calendar year recruits Equation (8.24).

The catch for Canada is further divided in two components, mixed stock fishery and single stock fisheries (Equations (8.25) and (8.26)).

The next step is to compute the aggregate exploitation rate and the remaining number of Spawners (Equations (8.27) and (8.28)).

### 8.2.6 Project observed data

In this step, observation error is added to the quantities calculated in the current time step. Catch observation error is given by a log normal distribution (Equations (8.29)-(8.30)), 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 (8.31)).

Canadian mixed stock fisheries observed catches:

Canadian single stock fisheries observed catches:

Observed number of spawners is given by a log normal distribution truncated between the 0.0001 and 0.9999 quantiles (Equation (8.32)). The observed recruitment is the sum of observed catches and observed spawner numbers (Equation (8.34)). The observed exploitation rate is directly calculated by dividing the observed catches by the observed recruitment (Equation (8.35)).

### 8.2.7 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 and are estimated.

The management quantities, i.e., and or Spawners quantiles, can then be re-estimated based on the estimated stock recruitment parameters and the observed time series of spawners using the same procedure described in section 8.1.3. The LRP study cases, however, set the management benchmarks to the normative period, and for this reason the management quantities are kept constant and equal to the management benchmark at the last year of the priming period.

### 8.2.8 Project population dynamics

In this section the brood year recruitment for the current projection year is computed. The first step is to generate the marine survival estimates which are used to project recruitment when the Ricker model with survival covariates is used. The survival covariates are generated using the method described in Section 8.1.2 and Equations (8.10) and (8.9). Marine survival covariates are considered to be constant across CUs.

The following step is compute the age structure of the returns with random error, which follows the same procedure described in Section 8.1.2. 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, the recruitment deviations are computed with multivariate normal distribution, reflecting the recruitment covariance among CUs. Recruitment is then calculated following the same procedure described in Section8.1.2 and using Equation (8.5) for the simple ricker model, or Equation (8.7) 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 8.2.7. These are either stock-recruit or percentile benchmarks, as described in section 8.1.3 computed based on the true and observed spawner abundances.

# 9 Retrospective analysis of CU benchmarks based on Sgen and percentiles

*\textcolor{cyan}{LT: open to other name of this appendix*

In the retrospective analysis, the estimates of , , and changed as pregressively more years of data were included (Figures 9.1). Note that these are not estimates based on a model that accounts for time-varying paramters. Rather, the estimates of , , and 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 , , and may change. These results should be interpreted with caution due to the large residuals in observed vs. predicted recruits. Since and are correlated, the meaning of any trends in one parameter should be interpreted with the other parameter in mind, escpecially when model fits have large residuals. Similarly, since and determine and , changes in these derived parameters can be challenging to interpret and can be due to changes in , , and their relative values.

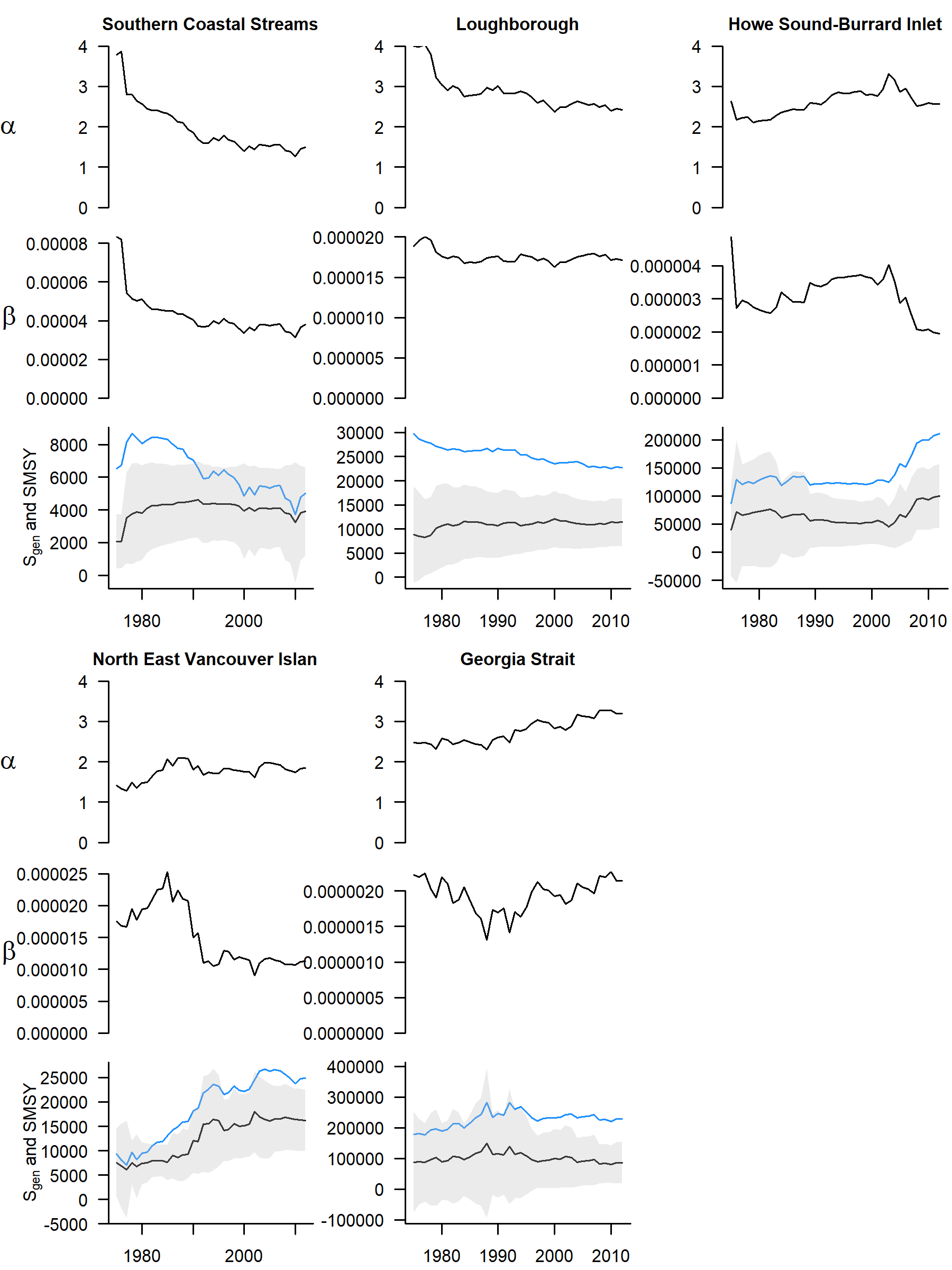


Figure 9.1: Retrospective estimates of , , (black line with gray confidence intervals) and (blue line) for five CUs in the Inside South Coast Chum SMU. Note y axis is identical across CUs for but varies for other parameters.

Retrospective estimates of and for Southern Coastal Streams show declines over time. and increase sharply in the first few years due to large decreases in and . then decreases over time, while stays relatively stable. This is because as decreases below ~2.5, decreases, but as decreases, decreases, so that a simultaneous decrease in and can cancel out. However, the lower alpha is below 2.5, the less influence has on .

Increasing for North East Vancouver Island is mainly due to an increase in from <1.5 to >2 and then a decrease in .

for Loughborough showed modest decreases over time, and was fairly stable.

The Georgia Strait CU shows evidence of increasing , and its estimate was fairly stable.

Howe Sound-Burrard Inlet was fairly stable, and then increased due to decreases in and .

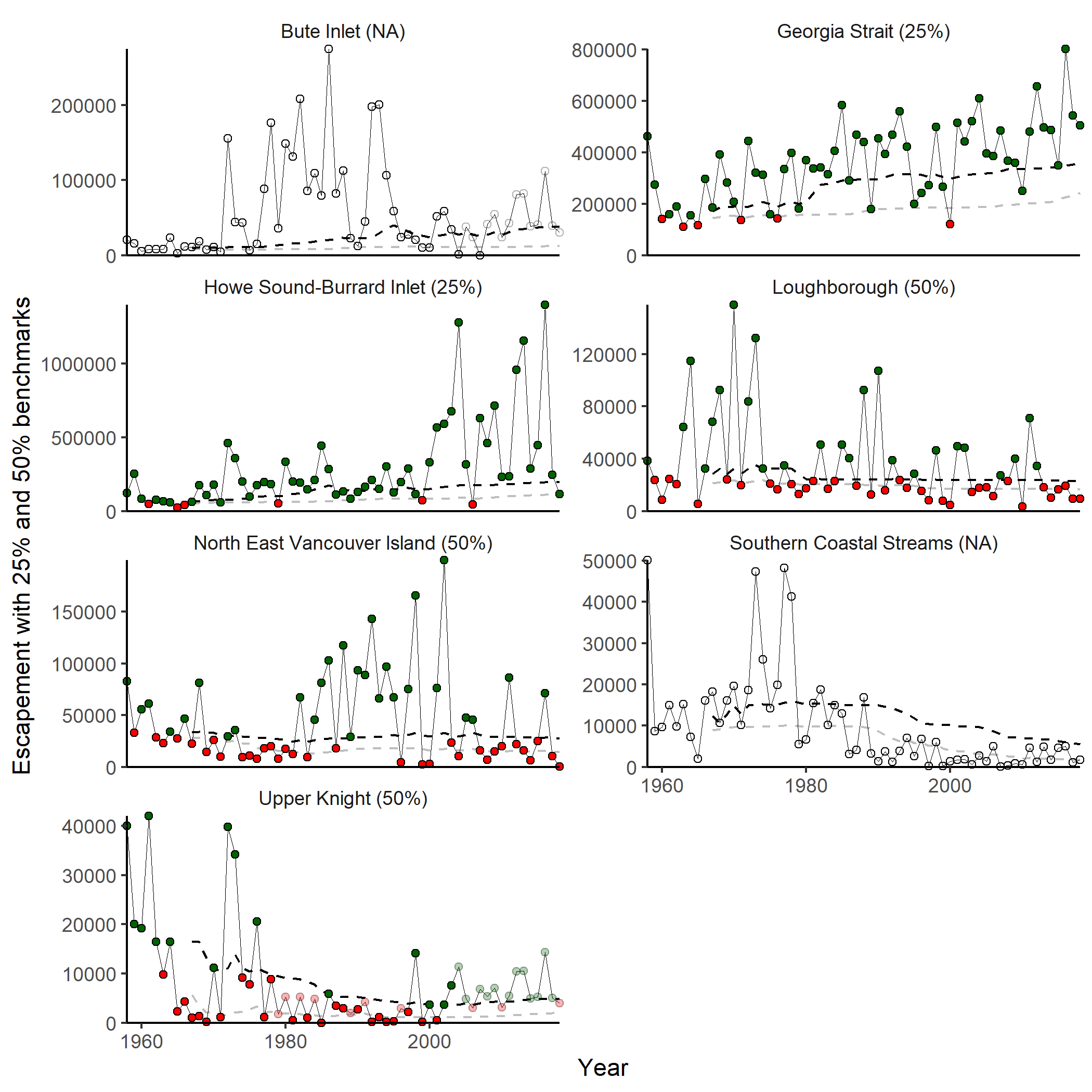


Figure 9.2: Escapement with 25th and 50th percentile benchmarks shown by gray and black dotted lines, respectively. Benchmarks are calculated using escapements up to the given year. Values following the CU names indicate the appropriate percentile benchmark. Green and red points indicate status above or below benchmark, respectively. Transparent points are years with CU-level infilling.

![Figure 9.3: 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)](data:application/pdf;base64,)

Figure 9.3: Logistic regression of whether escapement of all component CUs were above their 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)

# 10 Sensitivity of Projection-Based LRPs to Exploitation Rates

To explain the initially counter-intuitive result of sensitivity of projection based LRPs to exploitation rates, we ran an additional analysis where the spawner-recruitment parameters, productivity (log()) and spawners at replacement, (log()/) 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:

1. All inlets were assumed to have stock-recruitment parameters drawn from the same distributions (the mean and standard deviation for productivity and as estimated for Quatsino, Westcoast 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 choose to draw from a random distributions instead of Ricker or (1/) because the parameter was drawn randomly in projections for this case study from the watershed-area model. However, in preliminary sensitivity analyses, we sampled from a random distribution of 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 value of the assumed distribution for all inlets and trials. was drawn from its distribution and allowed to vary across inlets and trials. The same distribution of was used across inlets and trials, as in Scenario 1.
3. was fixed at the mean value 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 among inlets. In Scenario 1, productivity and tended to be lower for random trials and inlets that dropped below the lower benchmark in at least one year. Random trials and inlets with abundances that remained above the lower benchmark over the time-series tended to be more productive and slightly larger (Fig. 10.1).

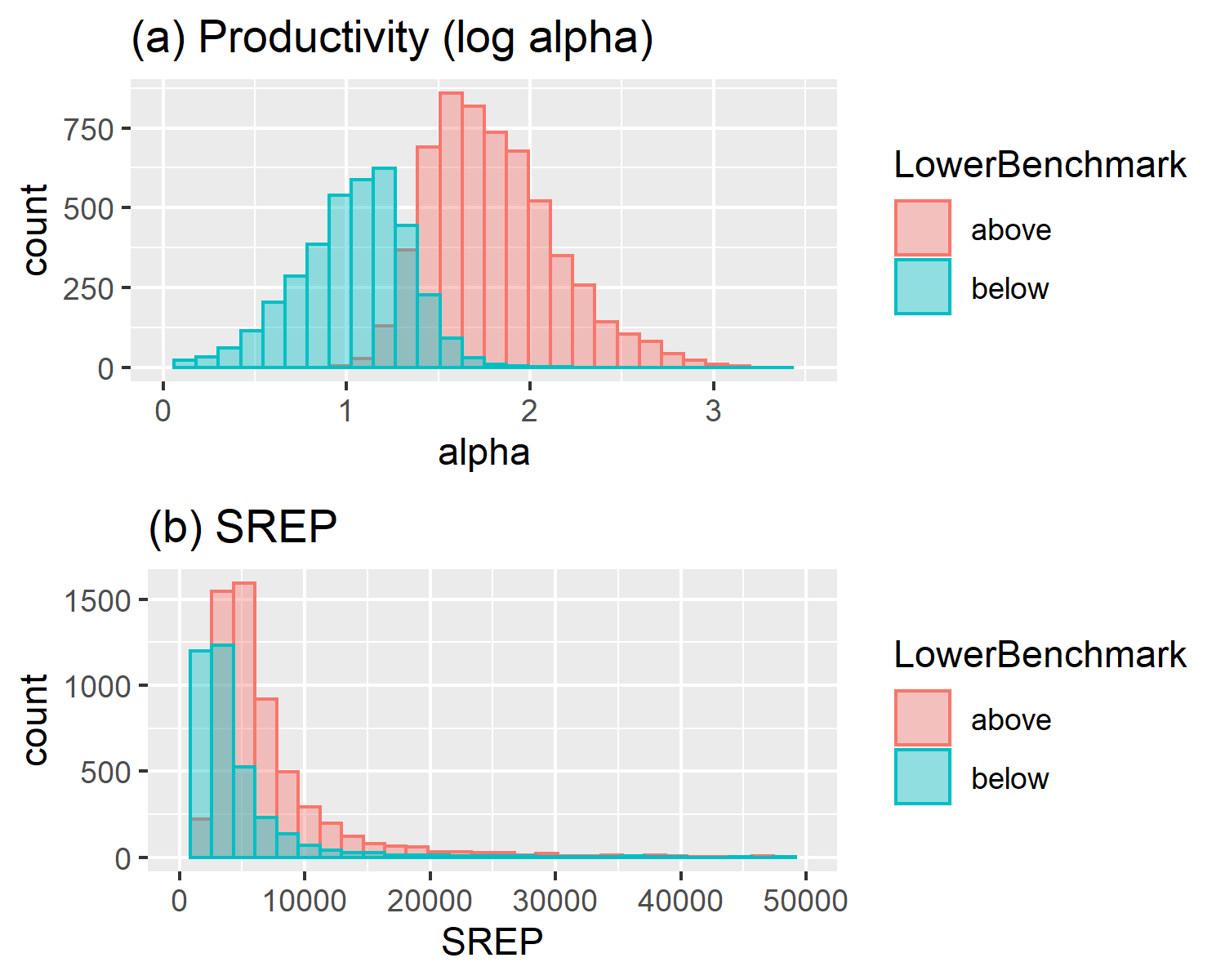


Figure 10.1: Distribution of (a) productivity (log alpha) and (b) spawners at replacement, SREP among MC trials, coloured by whether abundances in that trial remained above the lower benchmark (red) or not (blue), under a 45% exploitation. Productivity and SREP varied among inlets and trials and were drawn from common distributions.

Inlets and Monte Carlo trials with low productivity tended to have relatively high (lower benchmark) values (as described in [Holt and Folkes](#ref-holtCautionsUsingPercentilebased2015) ([2015](#ref-holtCautionsUsingPercentilebased2015))), 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. 10.2).

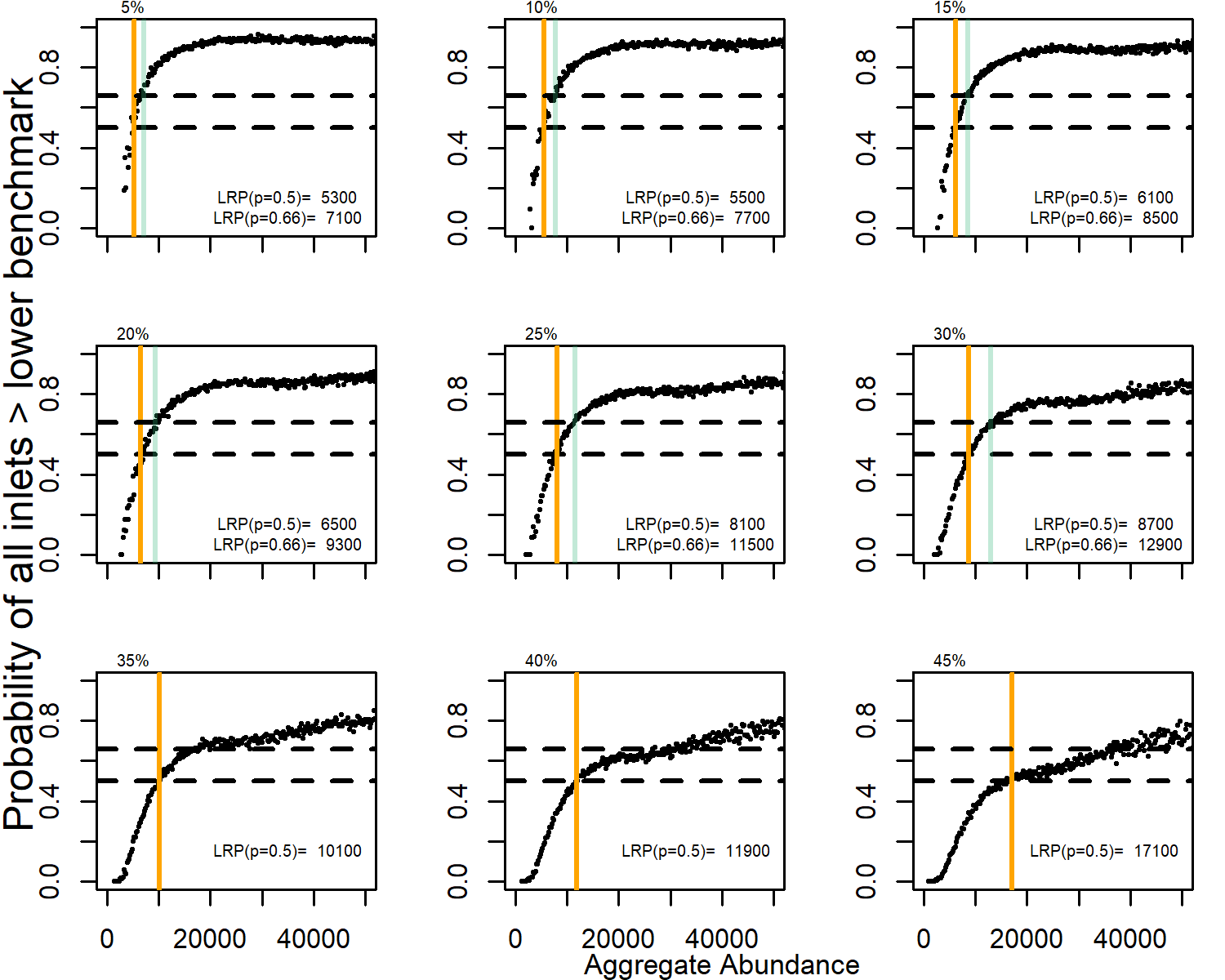


Figure 10.2: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 10,000 MC Trials, under a range of average exploitation rates from 5-45%, assuming productivity and SREP varied across inlets and trials, and are drawn from common distributions. Horizontal dashed lines at 50% and 66% represent equal and likely probabilities of all inlets being above lower benchmarks. 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.

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, and the LRP was insensitive to exploitation rate (Fig. 10.3 and 10.4).

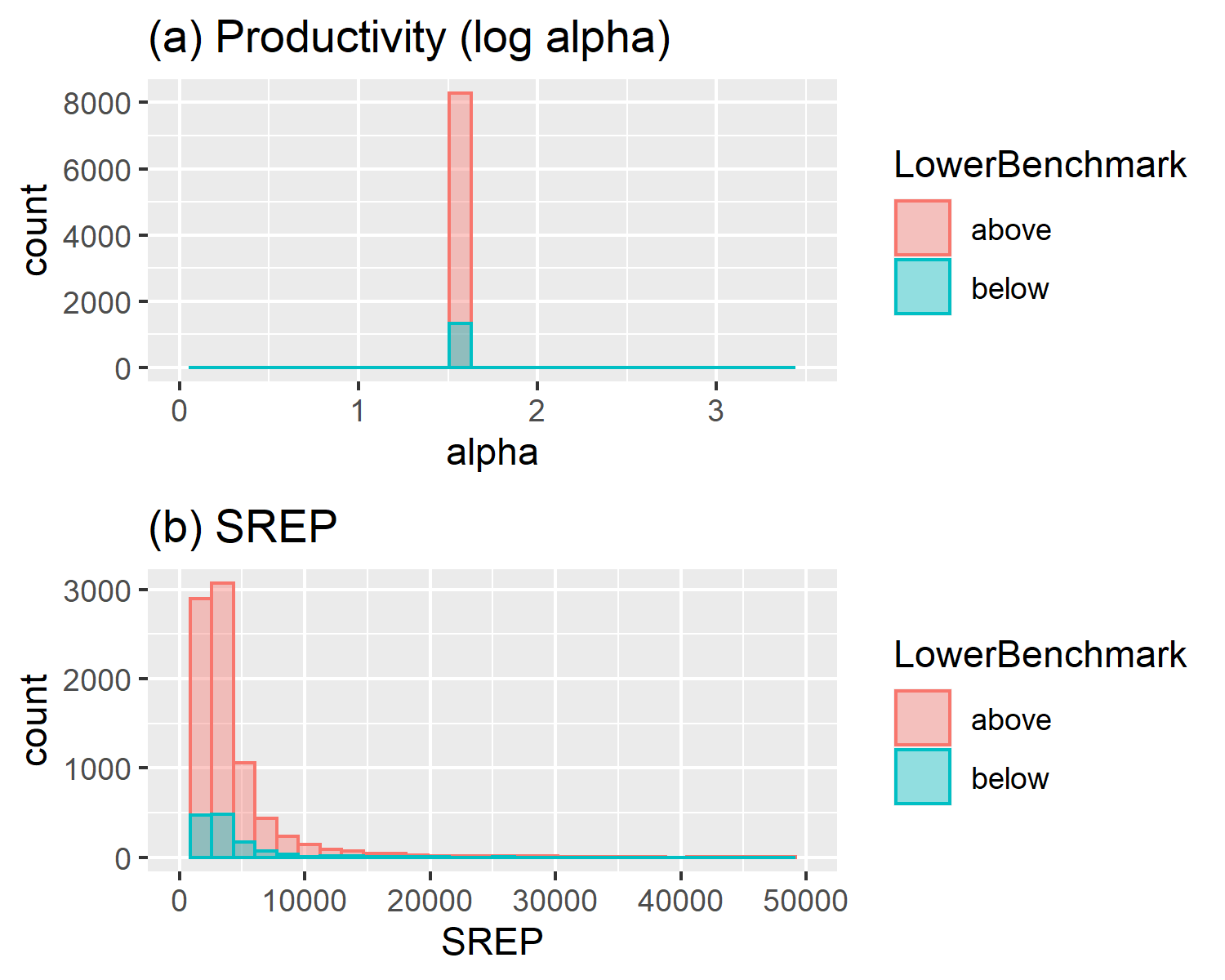


Figure 10.3: Distribution of (a) productivity (log alpha) and (b) spawners at replacement, SREP among MC trials, coloured by whether abundances in that trial remained above the lower benchmark (red) or not (blue), under a 45% exploitation and constant productivity among inlets and trials. SREP was drawn from a common distribution across inlets and trials.

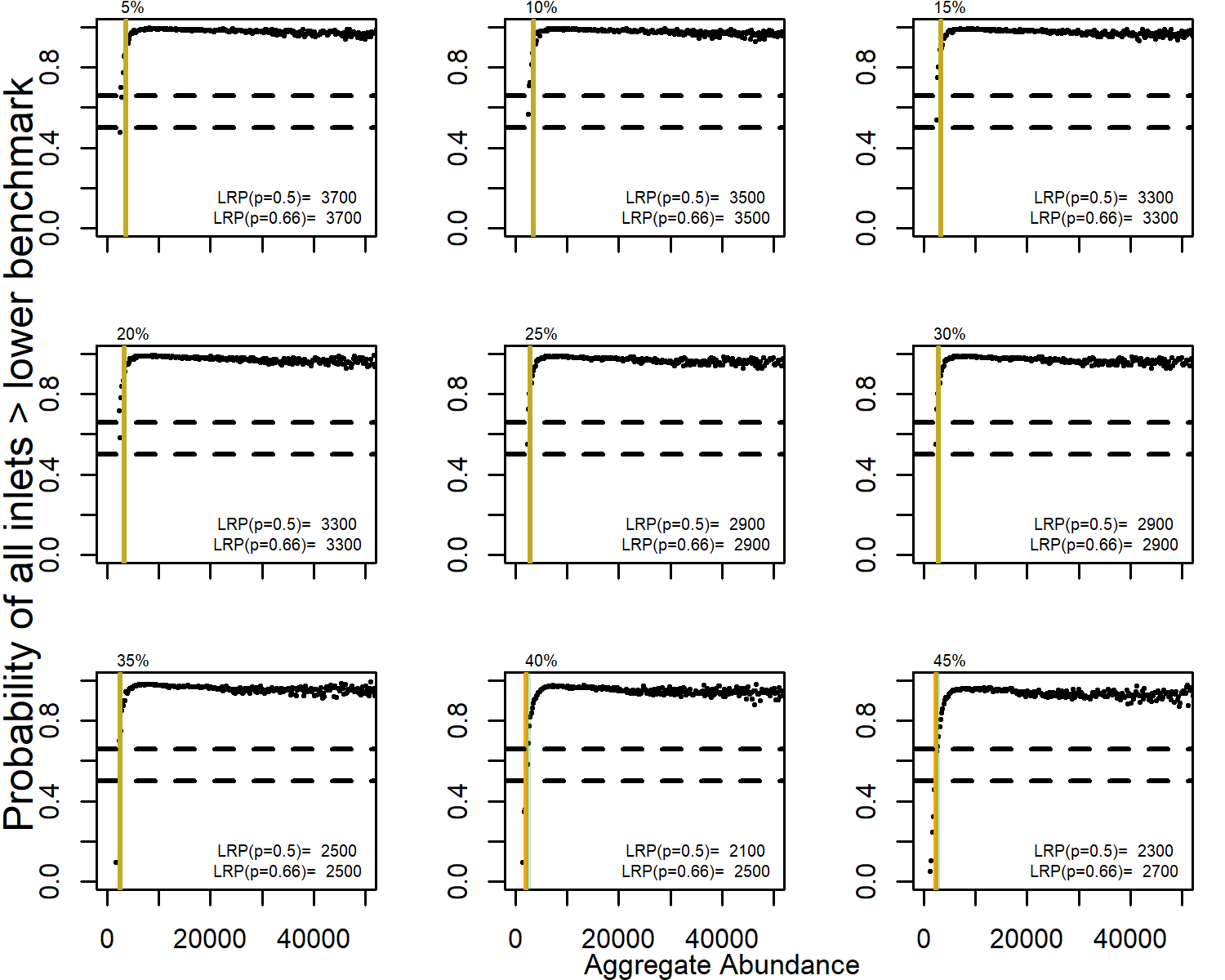


Figure 10.4: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 10,000 MC Trials, under a range of average exploitation rates from 5-45% (across 9 panels), assuming the same productivity for each inlet and trial and an SREP that varied across inlets and trials, drawn from a common disribution. Horizontal dashed lines at 50% and 66% represent equal and likely probabilities of all inlets being above lower benchmarks. 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.

When was fixed at the mean value among inlets and random trials in Scenario 3, productivity was higher for inlets and trials that remained above the benchmarks compared to those that dropped below them, though the overlap in the distributions above and below the lower benchmarks was slightly greater than when both and productivity varied (Scenario 1). The LRP varied with exploitation rates but to a lesser extent than when both productivity and varied (Fig. 10.5 and 10.6).

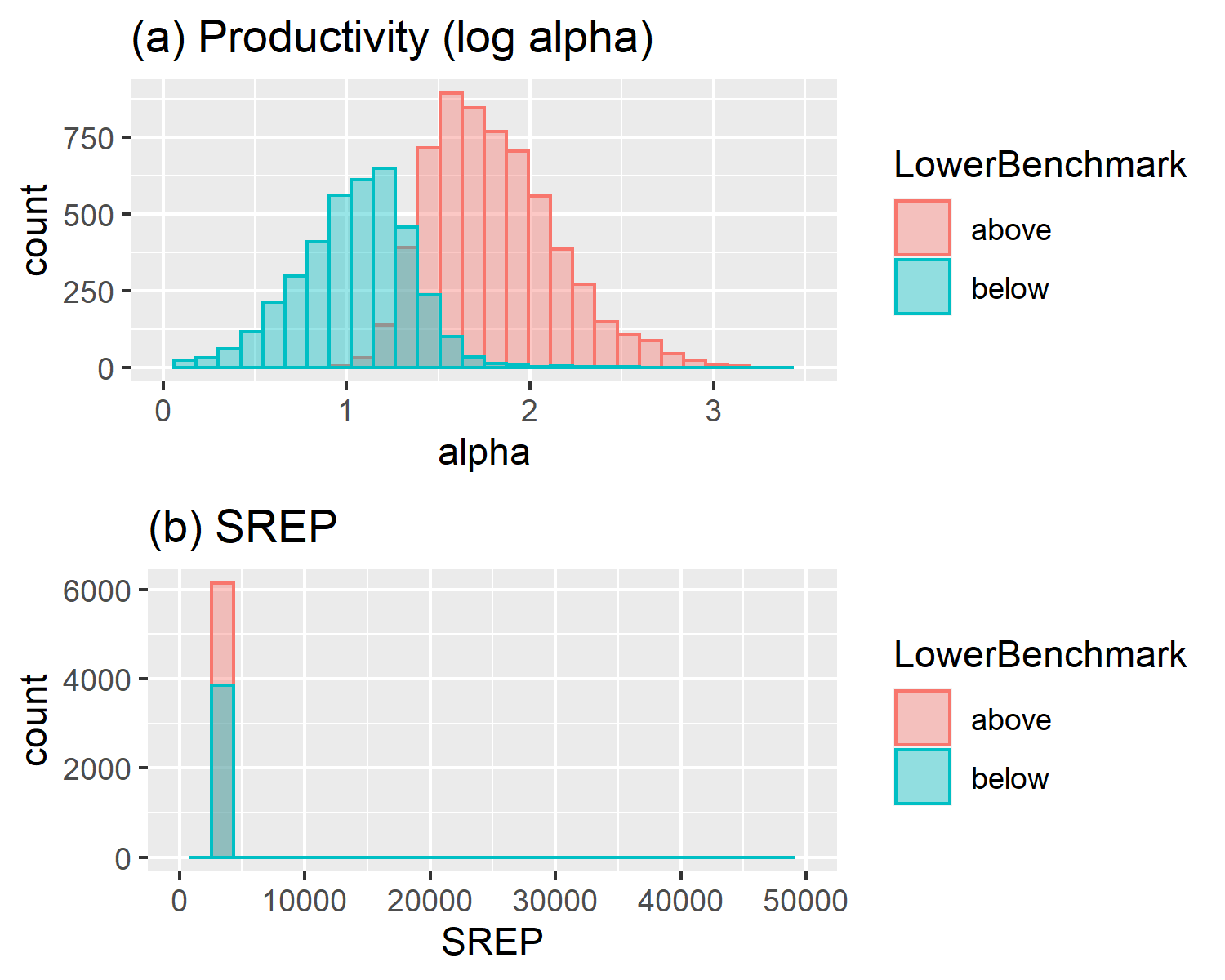


Figure 10.5: Distribution of (a) productivity (log alpha) and (b) spawners at replacement, SREP among MC trials, coloured by whether abundances in that trial remained above the lower benchmark (red) or not (blue), under a 45% exploitation and constant SREP among inlets and trials. Productivity was drawn from a common distribution across inlets and trials.

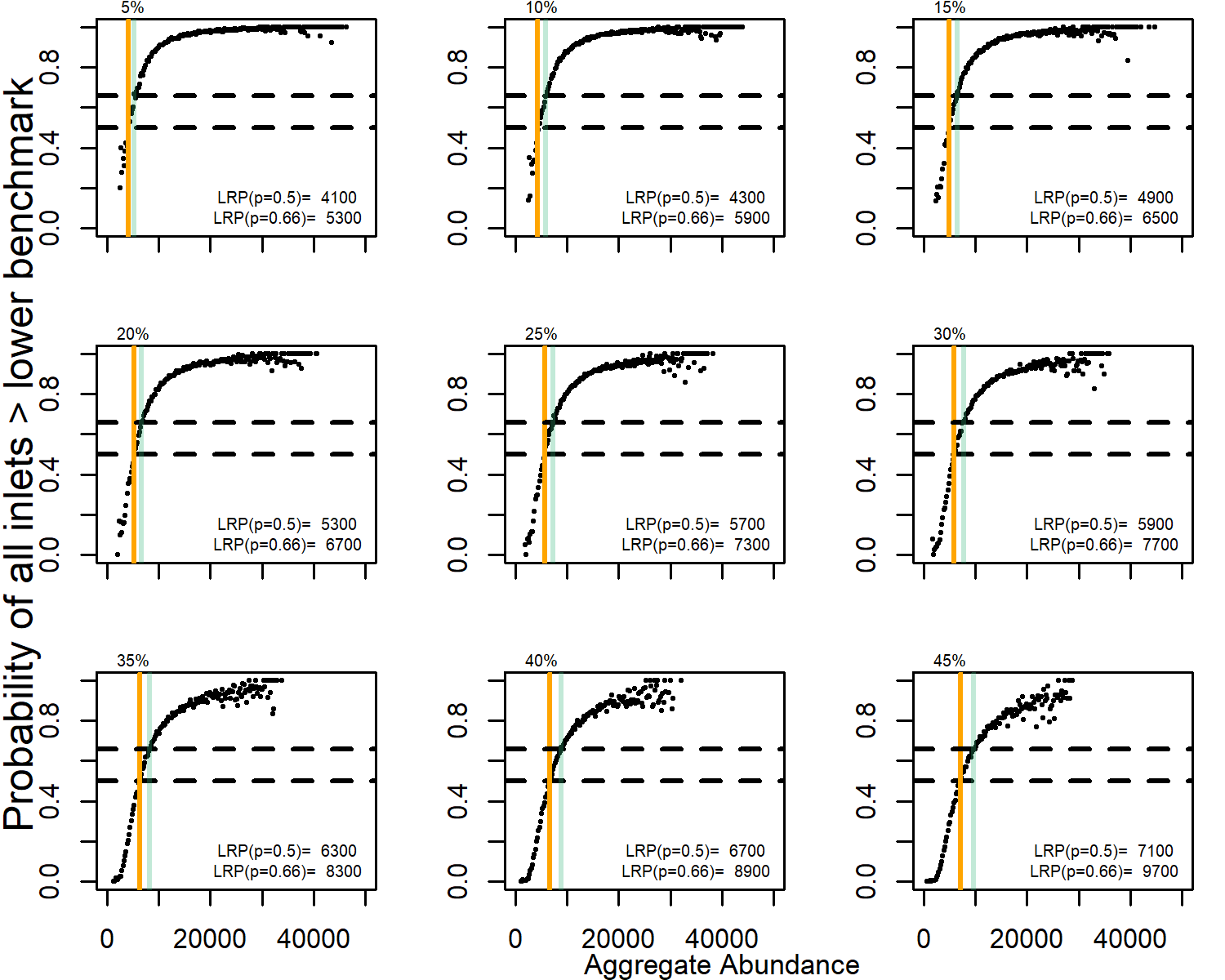


Figure 10.6: Probability of all inlets being above their lower benchmark along a gradient in aggregate abundances within bins of 200 fish, derived from projections over 30 years and 10,000 MC Trials, under a range of average exploitation rates from 5-45% (across 9 panels), assuming the same SREP for each inlet and trial, and productivity that varied across inlets and trials, drawn from a common disribution. Horizontal dashed lines at 50% and 66% represent equal and likely probabilities of all inlets being above lower benchmarks. Orange and pale green vertical lines are the LRPs associated with 50% and 66% probability of all inlets being above their lower benchmarks, respectively.

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 status among inlets and a higher aggregate abundances required for all inlets to be above their lower benchmarks (i.e., higher LRP).

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